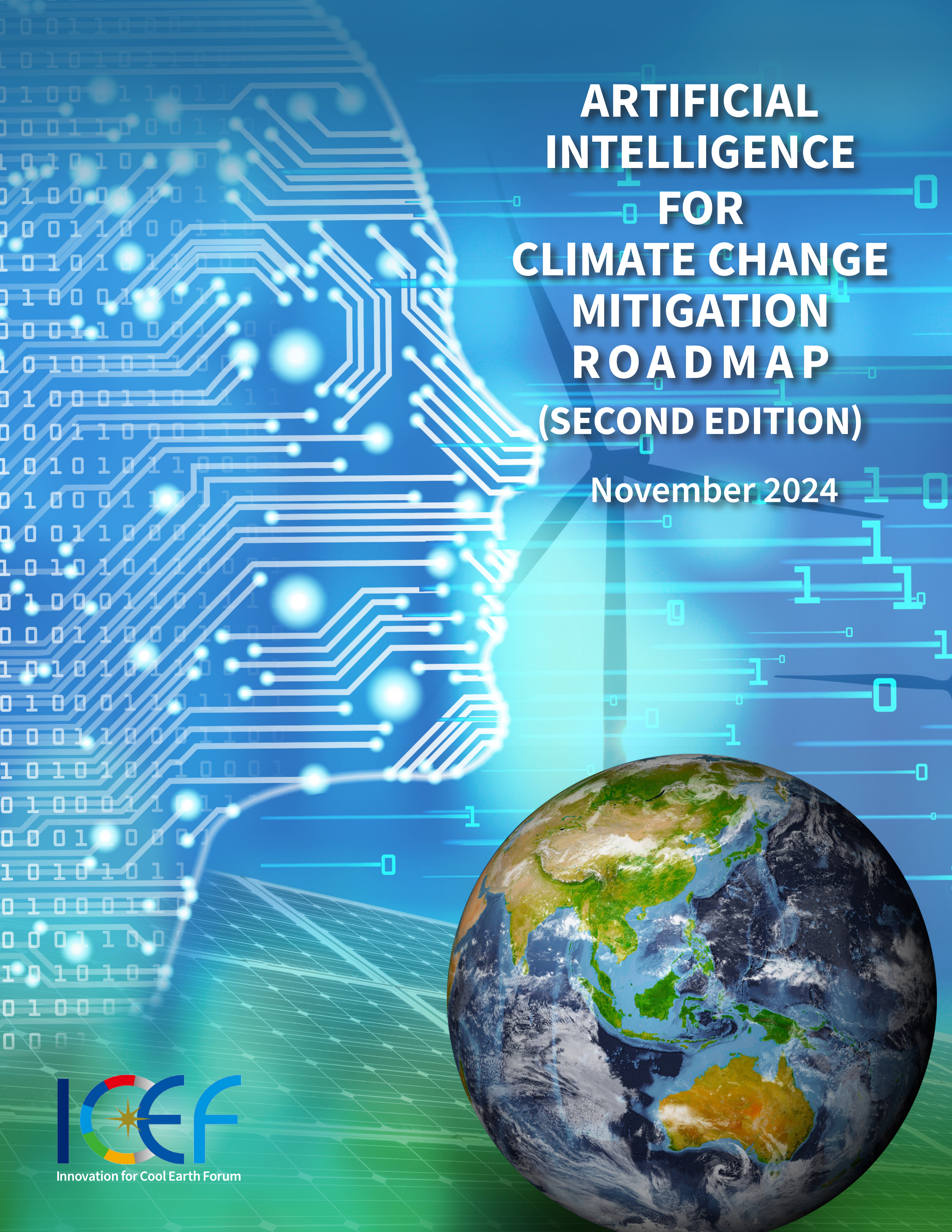


ARTIFICIAL INTELLIGENCE FOR CLIMATE CHANGE MITIGATION ROADMAP

(SECOND EDITION)

November 2024

Innovation for Cool Earth Forum

AUTHORS

LEAD AUTHOR

David Sandalow
Columbia University
Chair, ICEF Innovation Roadmap Project

PRINCIPAL CO-AUTHORS

Colin McCormick
Georgetown University and Carbon Direct

Alp Kucukelbir
Columbia University and Fero Labs

Julio Friedmann
Carbon Direct

Michal Nachmany
Climate Policy Radar and London School of Economics

DISTINGUISHED CO-AUTHOR

Hoesung Lee
Carbon-Free Alliance
former Chair, Intergovernmental Panel on Climate Change

CO-AUTHORS

Alice Hill
Council on Foreign Relations

Matthew Wald
Breakthrough Institute

Ruben Glatt
Lawrence Livermore National Laboratory

Kevin Karl
Columbia University and
NASA Goddard Institute for Space Studies

Daniel Loehr
Georgetown University

Antoine Halff
Columbia University and Kayrros

Philippe Benoit
Global Infrastructure Advisory Services 2050

Fan Zhiyuan
Columbia University

CO-AUTHORS

Trishna Nagrani
Climeworks

Ivo Steklac
ConnectDER

Mariah Frances Carter
Lumora Technologies

Rama Ponangi
Columbia University

Alex C. Ruane
NASA Goddard Institute for Space Studies

Lily-belle Sweet
Helmholtz Centre for Environmental Research

Cameron Kruse
Earth Genome

Matteo Turchetta
Kora Labs

Sarah Garland
Triple Helix Institute

Elena Méndez Leal
Columbia University

Ranveer Chandra
Microsoft Corporation

This roadmap was prepared to facilitate dialogue at the 11th Innovation for Cool Earth Forum (October 2024), for final release at COP29 in November 2024. We are deeply grateful to the Ministry of Economy, Trade and Industry (METI) and New Energy and Industrial Technology Development Organization (NEDO), Japan for launching and supporting the ICEF Innovation Roadmap Project of which this is a part.

Cite report as: David Sandalow, Colin McCormick, Alp Kucukelbir, Julio Friedmann, Michal Nachmany, Hoesung Lee, Alice Hill, Daniel Loehr, Matthew Wald, Antoine Halff, Ruben Glatt, Philippe Benoit, Kevin Karl, et al., *Artificial Intelligence for Climate Change Mitigation Roadmap (Second Edition)* (ICEF Innovation Roadmap Project, November 2024) https://doi.org/10.7916/2j4p-nw61.
Available at icef.go.jp/roadmap and transitiondigital.org/ai-climate-roadmap.

PREFACE

The first ICEF *Artificial Intelligence for Climate Change Mitigation Roadmap* was released in December 2023. Since that time, attention to artificial intelligence (AI) has continued to grow at a rapid pace. Tens of billions of dollars have poured into AI projects, policymakers around the world have considered new AI policies, and OpenAI reports that each month more than 200 million people now use ChatGPT.

Signs of a changing climate continue to grow as well. Based on global average temperatures, July 22, 2024 was the warmest day ever recorded; 2023 was the warmest year ever recorded; and the 10 warmest years on record are the past 10 years. Yet global emissions of greenhouse gases continue to climb.

Can AI help cut emissions of greenhouse gases? This Roadmap explores that question. In this second edition of the *Artificial Intelligence for Climate Change Mitigation Roadmap*, a team of 25 co-authors builds on last year's roadmap—comprehensively updating all old chapters, adding six new chapters and offering 5–10 specific, actionable recommendations in each chapter.

Our goal is to provide a useful resource for experts and non-experts alike. In Part I of this Roadmap, we provide brief introductions to both AI and climate change. In Part II, we explore eight sectors in which AI is helping respond to climate change and could do much more. In Part III, we explore cross-cutting issues. We close with findings and recommendations.

This roadmap builds on the body of literature produced annually in connection with the ICEF conference. Previous roadmaps have addressed the following topics:

- Artificial Intelligence for Climate Change Mitigation (2023)
- Low-Carbon Ammonia (2022)
- Blue Carbon (2022)
- Carbon Mineralization (2021)
- Biomass Carbon Removal and Storage (BiCRS) (2020)
- Industrial Heat Decarbonization (2019)
- Direct Air Capture (2018)
- Carbon Dioxide Utilization (2017 and 2016)
- Energy Storage (2017)
- Zero Energy Buildings (2016)
- Solar and Storage (2015)

This roadmap is a team effort. We are grateful to the many experts who reviewed draft chapters and/or helped with research for this Roadmap in the past six months. Special thanks to Laura Cozzi, Antonia Gawel, Savannah Goodman, Mars Hanna, Nicole Iseppi, Noah Kauffman, Meg King, Cheryl Lafleur, Amy Luers, Matthew Lundgren, Priyanka Mahat, Ning Qi, Josh Parker, David Patterson, Nicolas Schunck, James Slider, Thomas Spencer, Jed Sundwall and Tess Turner. Any mistakes are of course our own. We are especially grateful for the support provided by the ICEF Secretariat, the ICEF Steering Committee (including in particular its chair, Nobuo Tanaka), the New Energy and Industrial Technology Development Organization (NEDO), experts at the Institute of Energy Economics – Japan, and our superb copy edit and design team (including in particular Dr. Kathryn Lindl, Ms. Janelle Cataldo and Ms. Jeannette Yusko).

The ICEF Innovation Roadmap Project aims to contribute to the global dialogue about solutions to the challenge of climate change. We welcome your thoughts, reactions and suggestions.

David Sandalow

Columbia University
Chair, ICEF Innovation Roadmap Project

TABLE OF CONTENTS

FIVE KEY TAKEAWAYS

EXECUTIVE SUMMARY........1

PART I – INTRODUCTION

CHAPTER 1: INTRODUCTION TO AI........1-1

Alp Kucukelbir

A. What is AI?........1-2
B. What Can AI Do?........1-3
C. How Does AI Work?........1-4
D. What Is AI's Potential?........1-5
E. How Much Energy Does AI Need?........1-7
F. What Kind Of Data Does AI Need?........1-8
G. Why Is AI Developing So Rapidly?........1-10
H. Readings........1-11
I. References........1-12

CHAPTER 2: INTRODUCTION TO CLIMATE CHANGE........2-1

Hoesung Lee, David Sandalow, Julio Friedmann and Trishna Nagrani

A. Climate Change Background........2-2
B. Contributions of Artificial Intelligence to Climate Science........2-4
C. Readings........2-6
D. References........2-7

PART II – SECTORS

CHAPTER 3: POWER SYSTEM........3-1

David Sandalow, Fan Zhiyuan and Mariah Frances Carter

A. Generation........3-4
B. Transmission and Distribution........3-6
C. End-Use Devices........3-8
D. Energy Storage........3-10

E. Barriers 3-11
F. Risks 3-12
G. Conclusion 3-12
H. Recommendations 3-14
I. References 3-15

CHAPTER 4: FOOD SYSTEMS 4-1

Kevin Karl, Lily-belle Sweet, Cameron Kruse, Matteo Turchetta, Sarah Garland, Elena Mendez Leal, Ranveer Chandra and Alex C. Ruane

A. Food System and Climate Change Overview 4-2
B. Examples of AI Applications in Food Systems and Climate Change 4-4
C. Barriers 4-11
D. Risks 4-13
E. Recommendations 4-15
F. References 4-17

CHAPTER 5: MANUFACTURING SECTOR 5-1

Alp Kucukelbir

A. How Can AI Help Decarbonize Manufacturing? 5-2
B. What Are Common Applications of AI In Manufacturing? 5-3
C. Barriers 5-8
D. Risks 5-9
E. Recommendations 5-10
F. References 5-11

CHAPTER 6: ROAD TRANSPORT 6-1

Ruben Glatt, David Sandalow and Ivo Steklac

A. Vehicle Electrification 6-3
B. Alternative Fuels 6-5
C. Intelligent Transportation Systems (ITSs) 6-6
D. Modal shifts 6-9
E. Autonomous Vehicles (AVs) 6-10
F. Barriers 6-11
G. Risks 6-11

H. Recommendations 6-13

I. References 6-15

CHAPTER 7: AVIATION 7-1

Colin McCormick

A. Use of AI For Emissions Mitigation in Commercial Aviation 7-2

B. Barriers 7-6

C. Risks 7-6

D. Recommendations 7-8

E. References 7-9

CHAPTER 8: BUILDINGS SECTOR 8-1

Philippe Benoit and Alp Kucukelbir

A. AI for Reducing Building Emissions 8-2

B. Buildings as Clean Energy Producers 8-6

C. Barriers 8-8

D. Risks 8-8

E. Recommendations 8-10

F. References 8-11

CHAPTER 9: CARBON CAPTURE 9-1

Julio Friedmann

A. Capture Technology 9-3

B. Transportation and Storage 9-4

C. CO_2 Conversion to Products 9-6

D. Other Carbon Capture, Utilization and Storage (CCUS)-related AI Applications 9-7

E. Barriers 9-8

F. Risks 9-8

G. Recommendations 9-10

H. References 9-12

CHAPTER 10: NUCLEAR POWER 10-1

Matthew L. Wald, Julio Friedmann, Alp Kucukelbir, Rama Ponangi and David Sandalow

A. Operating Reactors 10-3
B. Advanced Reactor Design 10-7
C. Nuclear Waste 10-9
D. Nuclear Regulatory Process 10-11
E. Barriers 10-15
F. Risks 10-16
G. Recommendations 10-18
H. References 10-19

PART III – CROSS-CUTTING TOPICS

CHAPTER 11: LARGE LANGUAGE MODELS 11-1

Daniel Loehr

A. Background 11-2
B. General Uses of LLMs 11-6
C. Using LLMs to Mitigate Climate Change 11-8
D. Barriers 11-11
E. Risks 11-12
F. Recommendations 11-13
G. References 11-14

CHAPTER 12: GREENHOUSE GAS EMISSIONS MONITORING 12-1

Antoine Halff and Colin McCormick

A. Background 12-2
B. Methane Emissions 12-5
C. Carbon Dioxide (CO_2) Emissions 12-7
D. Policy and Market Impacts 12-10
E. Barriers 12-12
F. Risks 12-13
G. Recommendations 12-14
H. References 12-16

CHAPTER 13: MATERIALS INNOVATION 13-1

Colin McCormick

A. Materials innovation in Climate Technologies 13-3
B. Computational Materials Development 13-5
C. Applications of AI in Materials Discovery and Design 13-6
D. Barriers 13-8
E. Risks 13-9
F. Recommendations 13-10
G. References 13-11

CHAPTER 14: EXTREME WEATHER RESPONSE 14-1

Alice C. Hill and Colin McCormick

A. Forecasting and Early Warning 14-2
B. Changing Risk Picture 14-3
C. How Can AI Improve Forecasting? 14-4
D. Barriers 14-8
E. Risks 14-10
F. Recommendations 14-11
G. References 14-12

CHAPTER 15: GREENHOUSE GAS EMISSIONS FROM AI 15-1

David Sandalow

A. Background 15-2
B. Data Center Power Demand 15-3
C. Current GHG Emissions from AI 15-9
D. Future Greenhouse Gas (GHG) Emissions from AI 15-13
E. Conclusion 15-20
F. Recommendations 15-21
G. References 15-22

TEXT BOX: DATA CENTER WATER USE

Julio Friedmann

A. Recommendations 15.5-3

B. References 15.5-4

CHAPTER 16: GOVERNMENT POLICY 16-1

David Sandalow and Michal Nachmany

A. General AI Policies 16-2

B. Realizing AI's Potential for Climate Mitigation 16-4

C. Managing Risks 16-11

D. Recommendations 16-18

E. References 16-23

CHAPTER 17: FINDINGS AND RECOMMENDATIONS 17-1

David Sandalow, Colin McCormick, Alp Kucukelbir, Julio Friedmann and Michal Nachmany

A. Findings 17-1

B. Recommendations 17-3

C. References 17-6

APPENDIX A: ADDITIONAL READING A-1

APPENDIX B: RECOMMENDATIONS FROM EACH CHAPTER B-1

FIVE KEY TAKEAWAYS

This second edition of the *Artificial Intelligence for Climate Change Mitigation Roadmap* explores many topics in considerable detail. For those of you interested in a quick summary of our main messages, here are five.

1. Artificial intelligence (AI) has the potential to make very significant contributions to climate change mitigation in the years ahead. This includes incremental gains (such as increasing output at solar farms and improving energy efficiency in buildings) and transformational gains (such as helping discover important new materials for clean energy technologies).

2. Greenhouse gas (GHG) emissions from computing operations for AI are less than 1%—and perhaps much less than 1%—of global GHG emissions. These emissions will very likely increase in the years ahead, in amounts that could be modest or significant.

3. The main barriers to realizing AI's potential to help reduce GHG emissions are lack of data and lack of trained personnel. Governments, companies and educational institutions should work together to overcome these barriers.

4. Trust in AI systems is essential for AI to deliver substantial benefits for climate change mitigation. For AI to be trustworthy and trusted, risks related to bias, privacy, misinformation, disinformation, safety, security and other issues must be addressed.

5. Every organization with a role in climate change mitigation should consider opportunities for AI to contribute to its work.

The 17 chapters and 334 pages of this Roadmap explore these topics and others, discussing current applications of AI in reducing GHG emissions, future possibilities, risks, barriers, policy options and other topics, noting the limits of current knowledge. We hope the Roadmap is a useful resource for you.

EXECUTIVE SUMMARY

PART I – INTRODUCTION

Chapter 1 – INTRODUCTION TO ARTIFICIAL INTELLIGENCE (AI)

Artificial intelligence (AI) is the science of making computers perform complex tasks typically associated with human intelligence. Modern AI relies on machine learning (ML)—a type of software in which algorithms detect patterns from large data sets without being explicitly programmed. This differs from traditional software, which requires explicit programming of domain knowledge. AI instead relies on implicit programming by using historical data and simulations to train models to extract patterns.

AI has far-reaching capabilities. It can detect patterns, make forecasts, optimize systems and simulate what-if scenarios. Access to large, high-quality data sets is important for complex real-world applications of AI. These data can come from various public and private sector organizations. Tabular, time series, geospatial and text data are all commonly used in AI. Data must be properly measured, digitized and accessible to enable effective AI applications.

The release of ChatGPT in November 2022 generated extraordinary public attention to AI. ChatGPT quickly became the most rapidly adopted product in human history. Large language models (LLMs), like ChatGPT, demand significant amounts of energy to train and use. In contrast, not all AI systems are as resource-intensive, with many being efficient to deploy at scale.

Chapter 2 – INTRODUCTION TO CLIMATE CHANGE

Atmospheric concentrations of heat-trapping gases are now higher than at any time in human history. This is changing the Earth's climate. July 22, 2024 was the hottest day ever recorded; 2023 was the warmest year ever recorded; and the 10 warmest years on record are the last 10 years. Severe storms, droughts, floods and wildfires—all made more likely by global warming—have caused extraordinary damage in recent years. Sea-level rise threatens coastal cities around the world.

The Paris Agreement—adopted by over 190 nations in 2015—calls for holding the global average temperature increase to well below 2 °C (3.6 °F) above pre-industrial levels and pursuing efforts to limit the increase to 1.5 °C (2.7 °F). The world is not on a path to achieve these goals. Policies currently in place would result in a global average temperature increase of roughly 3 °C (5.4 °F) by 2100, and many of these policies are not being fully implemented.

AI is making important contributions to scientific understanding of climate change. AI is improving climate-model performance, providing more advanced warning of extreme weather events and helping attribute extreme weather events to the increase in heat-trapping gases in the atmosphere. AI's contributions to climate science will grow in the years ahead.

PART II – SECTORS

Chapter 3 – POWER SYSTEM

In 2023, carbon dioxide (CO_2) emissions from the power sector were roughly 28% of greenhouse gas (GHG) emissions globally. Most strategies for deep decarbonization foresee growing reliance on the power sector as vehicles, industry, space heating and other sectors shift from fossil fuels to electricity. To achieve global climate change goals, the power sector must grow and decarbonize at the same time.

AI is a key tool in addressing these challenges. At solar and wind power plants, for example, AI can help improve siting decisions, speed permitting and increase output with better weather forecasting. On long-distance transmission lines, AI can increase capacity with dynamic line rating. Virtual power plants and demand response programs are starting to rely heavily on AI tools. AI can accelerate innovations in battery chemistry, optimize battery usage and support vehicle-to-grid systems. In all these areas and more, AI's potential to help reduce greenhouse gas (GHG) emissions from the power sector is significant.

However, barriers including inaccessible data, lack of trained personnel and poor market design could hinder progress. Safety and security risks require priority attention. Data center power demand is growing faster than low-carbon power sources in some regions. Collaboration between governments, regulators and the private sector will be essential to realize AI's significant potential to contribute to power sector decarbonization.

Chapter 4 – FOOD SYSTEM

Food systems—including food production, processing, distribution, consumption and disposal—are critical to health and livelihood worldwide. Food systems are responsible for more than 30% of global GHG emissions. Climate change, in turn, poses substantial risks to food systems, threatening agricultural productivity, food security and supply chain stability.

AI has significant potential to help reduce GHG emissions from food systems, while enhancing resilience. Key AI application areas include remote sensing for agricultural monitoring, modeling to optimize farm management decisions and accelerated breeding programs for climate-resilient crops. However, significant challenges persist, such as limitations in model interpretability and transferability, data biases and the risk of exacerbating existing inequalities in food systems.

To promote responsible AI deployment, AI guardrails (e.g., human-in-the-loop model improvement) and AI accelerators (e.g., collaborative data ecosystems) are both needed. Steps that would help AI reduce GHG emissions from the food system include increasing public research and development (R&D) funding, developing standardized benchmarks and data sets, investing in adaptive data collection systems and adopting participatory approaches for AI model development.

Chapter 5 – MANUFACTURING

The manufacturing sector accounts for roughly one-third of global GHG emissions. AI has significant potential to help decarbonize manufacturing by optimizing existing industrial processes and operations in cost-effective ways.

For example, AI can play an important role in steelmaking with electric arc furnaces—an important decarbonization technology in which steel is made with recycled scrap metal instead of coal. AI can help address the variability in each batch of scrap metal, recommending optimal production settings to adapt to the variability. Using AI tools, one Brazilian steel manufacturer achieved an 8% reduction in alloy additive consumption using AI, cutting both costs and emissions.

More broadly, AI can help decarbonize manufacturing by enabling manufacturers to adapt to production issues faster and better, avoid past mistakes by leveraging historical data, improve production yields, promote recycling and circularity by adapting to variable recycled feedstocks, minimize energy consumption, adopt alternative energy sources and optimize manufacturing schedules and supply chains to reduce logistical overhead.

Chapter 6 – ROAD TRANSPORT

Road transport is a critical part of the global economy. Current modes of road transport rely heavily on fossil fuels, producing roughly 12% of global GHG emissions.

AI has significant potential to help reduce GHG emissions from road transport. AI can speed deployment of electric vehicles (EVs) by improving siting of charging infrastructure, extending EV battery life and helping operate vehicle-to-grid networks. AI has significant potential to accelerate innovation in batteries, electric motors and alternative fuels. AI provides critical support for intelligent transportation systems, helps promote modal shifts and plays a central role in operating autonomous vehicles (which can reduce GHG emissions through platooning and other measures).

Several barriers could hinder progress. Lack of data, the absence of uniform data standards and a shortage of trained personnel are among the most significant. Using AI in road transport also creates risks, including bias, invasion of privacy and—in the case of autonomous vehicles—increasing GHG emissions as the use of individual vehicles becomes easier. To realize the full potential of AI to reduce emissions from road transport, governments should invest in smart transportation infrastructure; industry and standards organizations should work together on data standards for smart transportation technologies; and governments, industry and academia should work together on AI tools to accelerate innovation in batteries and other technologies that reduce GHG emissions from road transport.

Chapter 7 – AVIATION

Emissions from aviation are rapidly growing as both passenger and cargo demand continues to climb. AI has the potential to reduce aviation emissions and climate impacts in several ways. One especially promising approach is using AI to help predict when aircraft-induced condensation trails (contrails) will form and enable minor flight route changes to avoid them. (Emerging science has demonstrated that climate impacts from contrails are quite large—comparable to radiative forcing from direct CO_2

emissions from aviation.) AI can also predict key properties of novel formulations of sustainable aviation fuel (SAF), helping accelerate adoption of non-fossil-based fuels.

AI-based tools can improve engine and aircraft design to increase fuel efficiency. Using AI to simulate fuel combustion within aircraft engines can help optimize engine design and allow for testing of entirely novel design concepts. Similar approaches can improve engine cooling designs, increasing engine longevity. AI methods can also help design and test aircraft bodies, wings and nacelles to minimize aerodynamic drag and reduce weight, further boosting overall fuel efficiency. During aircraft operations, near-real-time decisions must be made about runway allocation, take-off/landing timing, and climb/descend trajectories. AI tools can help optimize all of these, boosting overall efficiency and reducing unnecessary fuel burn.

Regulatory frameworks for aviation are appropriately focused on safety and may inadvertently present a barrier to adopting some AI-based methods. Industry, innovators and governments must work together closely to realize the benefits of AI for climate mitigation in aviation. Work on contrails should be a top priority. Towards that end, national governments should increase the coverage and quality of publicly available meteorological data, require all commercial and private aircraft to report non-CO_2 climate impacts (including contrail formation) and release these data publicly.

Chapter 8 – BUILDINGS

Buildings are responsible for roughly 18% of global GHG emissions. This includes emissions throughout the building life-cycle—from design to steel and cement manufacturing to construction to operation to demolition.

AI can play an important role in reducing CO_2 emissions from buildings. In the design stage, AI can help improve energy efficiency, site placement and material choices. During construction, AI can assist in waste management, facilitate prefabrication and help identify emission-reduction opportunities on site. When a building is operational, AI can optimize HVAC (heating, ventilation and air conditioning) and other mechanical systems, reducing energy consumption based on real-time data on building occupancy and usage patterns. AI has the potential to help buildings generate clean energy on-site, optimizing solar panel placement and integrating building-generated energy with broader grid demands. AI can enable efficient categorization of construction waste, facilitating reuse of materials.

Approaches must be adapted to diverse local contexts, especially to conditions in developing economies, where the vast majority of building construction will take place in the decades ahead. Key stakeholders' lack of familiarity with AI technologies is a significant barrier. Governments, the private sector and professional associations should develop a platform to disseminate best practices regarding implementing AI in reducing building energy use and emissions. Multilateral development banks, national/bilateral organizations and other donor agencies should develop a program of technical assistance and funding to increase stakeholders' capacity to develop AI innovation programs for the buildings sector.

Chapter 9 – CARBON CAPTURE

Ambitious climate goals require widespread deployment and safe operation of carbon management, including carbon capture, use and storage (CCUS). Today, CCUS faces challenges in deployment, including project economics, permitting and public acceptance. AI has the potential to significantly reduce costs and accelerate deployment of CCUS, including radical improvements in performance and dramatically faster project implementation.

AI could improve every aspect of CCUS research, development and deployment. From an early innovation perspective, AI can help identify new materials for carbon capture and use, including sorbents, catalysts and membranes. AI applications, such as digital twinning, could dramatically improve efficiency and costs of facility design and operations. Pipeline routing and subsurface characterization could benefit from AI tools reducing risks, costs and local impacts. Non-technical concerns could also benefit from AI applications. For example, AI could speed drafting and review of air permits and approval of injection wells and could facilitate environmental monitoring or maintain environmental justice standards.

To manifest these benefits, decision-makers must ensure adequate access to key data volumes to train these advanced tools and applications. Similarly, a workforce—from researcher to regulator—must be trained in AI to ensure good outcomes and avoid challenges of AI bias or hallucination.

Chapter 10 – NUCLEAR POWER

Nuclear reactors could make a larger contribution to reducing carbon emissions if the costs could be lowered. AI is already being used to optimize fueling and maintenance of current-generation reactors, and shows promise in aiding in the design of the advanced reactors that are moving toward commercialization. AI may also improve efficiency of nuclear safety regulation.

Boiling water reactors (BWRs) are already using AI in core design and monitoring, reducing enrichment requirements and cutting the volume of spent fuel, as well as avoiding unnecessary shutdowns. AI shows promise in helping plants move away from maintenance based on operating hours or calendar days and towards intervals based on interpretation of plant data to pinpoint the likelihood of future equipment failure. AI can also interpret scans of irradiated concrete to reduce uncertainty about its condition, and it can be helpful in equipment design for advanced fission reactors and even for fusion reactors.

But the application of AI to nuclear power faces challenges. The industry does not have large volumes of readily accessible data about operations and component performance, for example. Further, bringing AI into a complex, tightly linked safety-critical system will require careful planning and vetting of software tools.

PART III – CROSS-CUTTING TOPICS

Chapter 11 – LARGE LANGUAGE MODELS (LLMs)

Large language models (LLMs) have captured the public's imagination through the human-like output of popular products like ChatGPT. These LLMs are already helping mitigate climate change. LLMs are helping make sense of vast repositories of climate change information from many sources in multiple languages, identifying sentiment and argument structure in climate change discussions, and summarizing climate change risks and impacts described in the growing body of climate research.

In the future, LLMs can do even more to fight climate change. They can serve as tutors in climate education, depict personalized climate consequences and suggest individualized climate actions. They can advance basic science in climate change mitigation, from materials discovery for better batteries and carbon capture to sophisticated management of the power grid. They can help shortcut the current maze of permitting requirements that are slowing deployment of carbon-free power.

Barriers to using LLMs to mitigate climate change include issues with trusting "black boxes," which can "hallucinate" incorrect information. Risks include bias, security threats, harmful use and LLMs' own emissions of GHGs. National governments, LLM developers and other stakeholders should create and share LLMs trained on climate data while establishing benchmarks and training programs to ensure their effective use in addressing climate change. They should increase R&D efforts, promote transparency in tracking LLMs' carbon footprint and work to advance LLM applications in fighting climate change.

Chapter 12 – GREENHOUSE GAS (GHG) EMISSIONS MONITORING

Accurate information about GHG emissions is vital for addressing climate change. Historically, GHG data have been fragmented and sometimes incomplete, with significant time lags, limiting the ability to design effective mitigation strategies. AI is now playing a critical role in overcoming this limitation by analyzing vast amounts of data from satellites and other technologies to provide more complete, near-real-time emissions monitoring.

AI's contributions are particularly notable in monitoring methane emissions. Methane is increasingly monitored by AI-driven tools that use satellite imagery to detect, quantify and attribute emission events. This approach has allowed policymakers and companies to identify "super-emitters" and pinpoint chronic methane leaks from industries like fossil fuel extraction and waste management, which were previously mostly unreported. AI is also revolutionizing CO_2 emissions tracking by integrating large data sets from different sectors, such as transportation and industry, to provide real-time data. AI is also facilitating transparency in carbon-offset markets by enabling detailed monitoring of natural carbon sinks, such as forests, through satellite imagery.

To help realize AI's potential to revolutionize emissions monitoring, national governments should encourage the United Nations Framework Convention on Climate Change (UNFCCC) to update guidance on preparing national emissions inventories so that it explicitly allows the use of AI-enabled data rather than just emissions factor–based assessments. National governments and appropriate international bodies should continue ongoing efforts toward standardizing AI-enabled emissions data and should consider setting up formal processes to certify AI-assisted emissions data and data providers.

Chapter 13 – MATERIALS INNOVATION

Advanced materials with special properties are vital for decarbonization because they underpin many low-emitting technologies. Examples include catalysts, battery anodes, solar photovoltaics, wind turbine blades, HVAC refrigerants, superconductors, carbon-capture sorbents and high-strength magnets.

Historically, advanced materials were discovered through accident or tedious, expensive trial and error. Several decades ago, advances in materials science theory and computing power enabled a transition to a more computational basis for materials discovery. However, the standard methods for identifying new advanced materials through computation require large computing resources and are still too slow to fully meet the needs of materials innovation for decarbonization.

Recently, computational materials science has begun using AI methods. These methods are already having an important impact. In some cases, AI models can fully replace conventional science-based approaches, greatly speeding up processing times. In other cases, AI can help quickly interpret results of materials-characterization experiments, enabling rapid, high-throughput testing of advanced materials candidates. One especially promising development is using natural-language AI to synthesize the vast materials-science technical literature and to quickly produce accurate literature reviews and precise processing steps for materials production. Most recently, generative AI methods have been able to propose entirely new classes of advanced materials that had not previously been envisioned as relevant to decarbonization. While these advances are highly promising, much better integration between materials science and AI research is needed to fully realize the potential of this technology for climate mitigation.

Chapter 14 – EXTREME WEATHER PREDICTION

AI can help build resilience to extreme weather events fueled by climate change, such as severe droughts, intense storms and powerful wildfires. It can also strengthen resilience to flooding caused by accelerating sea-level rise. These events have caused thousands of deaths and major economic damage, with global losses estimated at $2.86 trillion from 2000 to 2019.

Adaptation strategies range from long-term infrastructure improvements to short-term emergency response. AI-based forecasting models are becoming increasingly accurate, using far less time and energy and costing less than conventional forecast models. Thanks to these emerging capabilities, the role of AI in enhancing forecasting and enabling better early warning systems for extreme weather events is becoming increasingly important. AI is providing vital tools for disaster preparedness and response, especially in regions with limited forecasting capabilities today.

Despite these advances, significant barriers to the widespread adoption of AI-enhanced forecasting remain. Insufficient data, technical expertise and financial resources limit progress. Transparent and interpretable AI models are critical to building trust and confidence among meteorologists and emergency responders. Governments and international organizations must invest in AI-driven weather models, support infrastructure development and ensure equitable access to early warning systems globally. Collaboration between the public and private sectors is essential to harness the full potential of AI in mitigating the growing risks of climate change and safeguarding vulnerable populations.

Chapter 15 – GREENHOUSE GAS (GHG) EMISSIONS FROM AI

AI systems need energy for manufacturing silicon chips, training and running AI models, and more. This energy use does not necessarily result in significant GHG emissions. When the electricity at a data center comes from new solar, wind or nuclear power, for example, the GHG emissions from data-center operations are modest. GHG emissions from AI computation are currently less than 1%—and perhaps much less than 1%—of the global total. Better data collection and assessment methodologies are needed to provide a more precise estimate with high confidence.

Data center power demand is growing steeply in many places around the world, due in part to demand for AI. Estimates of near-term growth vary widely. Sharply growing demand for AI computation will very likely lead to increased GHG emissions in the near-term. Efficiency improvements in AI hardware and software, as well as the use of low-carbon energy in the AI supply chain, will constrain but not prevent this emissions growth.

In the medium- to long-term, AI could result in either net increases or net decreases in GHG emissions. In part because AI is a transformational technology in the early stages of deployment, the range of uncertainty is enormous. Future GHG emissions from AI depend on a number of factors, including (1) growth in demand for AI, (2) improvements in the energy efficiency of AI hardware, (3) improvements in the energy efficiency of AI software, (4) use of low-carbon electricity in computation for AI, (5) use of AI to reduce production costs in the fossil fuel sector and (6) use of AI to reduce GHG emissions throughout the economy—such as the many AI applications discussed in this Roadmap. Each of these factors is highly uncertain, and they interact in complex ways.

Chapter 16 – GOVERNMENT POLICY

Governments play an important role in using AI for climate change mitigation—collecting data used in AI models, funding clean energy research programs that use AI tools, establishing policies that shape the use of AI in the power and transport sectors, and more. Governments also play an increasing role in managing risks from AI, which is essential in promoting trust in well-functioning AI systems.

Government AI policies vary widely. Europe's approach has been called "rights-driven," the US approach "market-driven" and China's approach "state-driven." Government attention to AI has grown rapidly in the past several years, with discussions on topics including liability rules, labeling requirements, data privacy protections, workforce training programs and safety standards. Although government policies with respect to AI are evolving rapidly, these policies tend to change much more slowly than AI technologies themselves.

Governments can help realize AI's potential to contribute to climate change mitigation with policies and programs in a range of areas. Governments should invest in data collection, curation and standardization; fund development of large-scale open-source foundational models tailored to address climate challenges; incentivize AI applications that contribute to climate mitigation with regulatory frameworks, financial incentives and public recognition programs; invest in education and training programs to develop a skilled AI workforce; facilitate knowledge sharing and collaboration between experts in climate mitigation and experts in AI; and establish ethical guidelines for developing and deploying AI applications to help foster trust in well-functioning AI applications for climate change mitigation.

Chapter 17 – FINDINGS AND RECOMMENDATIONS

A. Findings

1. AI is contributing to climate change mitigation in important ways.
2. AI has the potential to make very significant contributions to climate change mitigation in the years ahead.
3. The principal barriers to using AI for climate change mitigation are (i) the lack of available, accessible and standardized data and (ii) the lack of trained personnel.
4. Other barriers to using AI for climate mitigation include cost, lack of available computing power and institutional issues.
5. GHG emissions from AI computation are currently less than 1%—and perhaps much less than 1%—of the global total.
6. GHG emissions from AI computation will very likely rise in the near-term.
7. In the medium- to long-term, AI could result in either net increases or net decreases in GHG emissions. In part because AI is a transformational technology in the early stages of deployment, the range of uncertainty is enormous.
8. Only a tiny fraction of GHG emissions associated with AI operations are related to AI applications for climate change mitigation.
9. Trust in AI is essential for AI to deliver substantial benefits in mitigating climate change. To earn this trust, AI applications must undergo risk assessments that address a range of concerns. Risks related to safety, security, model accuracy, misinformation and disinformation require the closest attention.
10. Open-source foundation models have the potential to contribute to climate change mitigation by providing more organizations opportunities to access AI tools.
11. Significant resources and sustained focus—by governments, corporations, philanthropies and other stakeholders—will be required for AI to reach its potential in helping mitigate climate change.

12. Several recommendations in last year's ICEF *Artificial Intelligence for Climate Change Mitigation Roadmap* have been adopted by key stakeholders.

B. Recommendations

1. *Every organization working on climate change mitigation should consider opportunities for AI to contribute to its work.*
2. *Governments, businesses and philanthropies should fund fora in which AI experts and climate change experts jointly explore ways AI could contribute to climate change mitigation.*
3. *Governments should assist in developing and sharing data for AI applications that mitigate climate change.*
    a. *Governments should systematically consider opportunities to generate and share data that may be useful for climate mitigation.*
    b. *Governments should establish policies to promote standardization and harmonization of climate and energy-transition data.*
    c. *Governments should establish climate data task forces composed of key stakeholders and experts.*
4. *Companies with datasets relevant to climate change mitigation should consider sharing portions of these datasets publicly.*
5. *Every organization working on climate mitigation should prioritize AI skills-development and capacity-building.*
    a. *Governments and foundations should launch AI-climate fellowship programs.*
    b. *Government agencies with responsibility for climate issues should regularly review the capabilities of their staff with respect to AI.*
    c. *Every organization working on climate change mitigation should require minimum AI literacy from a broad cross-section of employees.*
6. *Educational institutions should offer courses that provide familiarity with AI and its uses in climate mitigation.*
7. *Governments should adopt policies to minimize GHG emissions from AI's computing infrastructure, including requiring AI developers and data center operators to disclose GHG emissions associated with their operations on a full life-cycle basis.*
8. *Organizations that use AI for climate change mitigation should assess and address potential risks of AI tools.*

9. *All government agencies with responsibility for climate change, including environment and energy ministries, should create an Artificial Intelligence Office, responsible for assessing opportunities, barriers and risks with respect to AI in all aspects of the agency's mission.*

10. *Governments should provide substantial funding for developing and applying AI applications for climate mitigation.*

    a. *Governments should fund AI for climate change mitigation programs with a focus on emissions reduction potential, not just new AI methods*

    b. *Governments should help increase the availability of computing power for AI projects related to climate change mitigation.*

11. *Governments, philanthropies and information technology companies should play a pivotal role in funding development of large-scale open-source foundation models tailored to address climate challenges.*

12. *Governments should launch international platforms to support cooperative work on AI for climate change mitigation.*

    a. *Member countries in the Clean Energy Ministerial (CEM) and Mission Innovation (MI), as well as other stakeholders, should participate actively in the CEM/MI AI initiative.*

    b. *The United Nations Framework Convention on Climate Change (UNFCCC), International Energy Agency (IEA) and Food and Agriculture Organization of the United Nations (FAO), among other organizations, should build AI-for-climate issues centrally into their work programs.*

    c. *One or more global organizations should be tasked with helping reconcile any conflicting AI-enabled data on GHG emissions.*

PART I - INTRODUCTION

Chapter 1 – INTRODUCTION TO ARTIFICIAL INTELLIGENCE (AI)

Chapter 2 – INTRODUCTION TO CLIMATE CHANGE

CHAPTER 1:

INTRODUCTION TO AI

Alp Kucukelbir

A. What is AI? 1-2

B. What Can AI Do? 1-3

C. How Does AI Work? 1-4

D. What Is AI's Potential? 1-5

E. How Much Energy Does AI Need? 1-7

F. What Kind Of Data Does AI Need? 1-8

G. Why Is AI Developing So Rapidly? 1-10

H. Readings 1-11

I. References 1-12

Artificial intelligence (AI) is part of our everyday lives. Email providers use AI to filter spam. Postal services apply AI to route hand-written envelopes. Technology companies leverage AI to identify faces in photographs, while radiologists reach for AI to interpret medical scans. Economists use AI to forecast elections, and digital retailers turn to AI to optimize prices.[1,2]

The release of ChatGPT in November 2022 generated extraordinary public attention to AI. ChatGPT quickly became the most rapidly adopted product in human history, with more than 100 million users by January 2023. Its operator claims that 200 million people are now using ChatGPT on a weekly basis.[3] This increased attention has led to questions about how AI could help address major global challenges, including climate change—the topic of this report.

A. What Is AI?

AI is the science of making computers perform complex tasks typically associated with human intelligence. Modern AI relies on a branch of computer science called machine learning (ML). ML refers to a set of algorithms that detects patterns from large and sometimes messy data without explicit programming (i.e., without a human-crafted description of each pattern). This is a task often associated with human learning—for example, learning to walk, speak or identify objects.

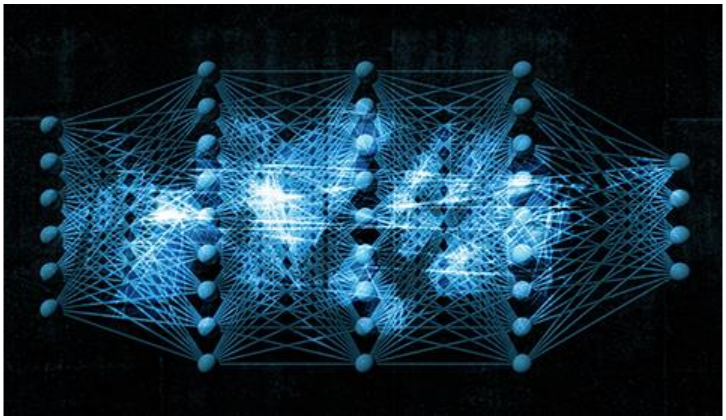


Figure 1-1. *A visualization of a deep neural network, a type of AI model that powers popular AI systems such as ChatGPT.*

How does AI differ from traditional computation? Consider a computer program that plays chess. The traditional approach to building such an algorithm involves explicitly programming the rules of chess, encoding basic principles of good game play, and specifying a method to search over all possible moves to pick the best one. Even in a game as seemingly simple as chess, this is an enormous task for a computer—the number of chess positions is about the same as the number of atoms on Earth.[4] (For the curious, that is about 1,000,000,000,000,000,000,000,000,000,000,000, 000,000,000,000,000,000 positions.) No existing computer, even the most powerful supercomputing clusters, can efficiently play chess this way.

Now consider an AI approach to playing chess. The core idea is to replace human input on what constitutes good strategy with a system that only uses the rules of the game to play against itself to find good strategies. Leveraging clever mathematics that significantly reduce the need to search over all possible moves, an AI system can efficiently simulate games against itself millions of times. This repeated simulation enables the AI system to "learn" the principles of good play, in a way that exceeds the ability of human programmers to explicitly encode them in software. This approach to AI uses branches of ML known as deep neural networks (see Figure 1-1) and reinforcement learning, which are ideally suited to problems where simulation plays a prominent role.[5] Table 1-1 summarizes the key difference between AI and traditional computation.

Supervised and unsupervised ML are two other ways to build AI systems—both rely on historical data to "learn" patterns.

- Supervised learning requires historical data with labels or explicit targets. One common example includes handwritten digit recognition—used by many postal services around the world—which pairs many thousands of scanned pictures of written digits with their corresponding number to "train" the AI system.
- Unsupervised learning only requires historical data, without any corresponding labels. The AI system is trained to search for patterns and associations hidden in the data. This form of AI is commonly used in recommendation engines, which can suggest movies you might like based on movies you have previously watched and historical patterns of the likes and dislikes of other people watching similar movies.

Table 1-1. *AI differs from traditional software in its requirements and its outputs.*

	TRADITIONAL SOFTWARE	ARTIFICIAL INTELLIGENCE (AI)
Requirements	• No historical data needed • Explicit programming of domain knowledge • No "training" needed (everything is explicitly programmed)	• Historical data or simulator • Implicit programming of expectations of patterns from data • Need to "train" the AI algorithm to extract patterns
Outputs	• Deterministic results • Can efficiently solve simpler problems	• Statistical results: can sometimes make mistakes • Can offer solutions to more complex problems

B. What Can AI Do?

Modern AI systems have far-reaching capabilities in at least four areas.

Detection. AI can detect patterns and anomalies in vast and complex data sets. This capability enables AI to perform tasks such as detecting faces in images and pinpointing greenhouse gas (GHG) leaks from satellite data. Monitoring combines continuous detection with alerting capabilities. In this context, AI facilitates continuous detection of unusual patterns or anomalies within data sets, which is different from traditional monitoring methods that involve periodic checks and human intervention. Classic examples of monitoring include tracking financial transactions for signs of fraud and surveying gas extraction asset data to detect methane leaks, both of which benefit from AI-powered detection and monitoring.

Prediction. AI systems can learn from historical patterns to make predictions and forecasts about how a system might behave in the future. This capability enables AI to perform tasks such as guessing what movies you might like to watch and forecasting complex weather patterns for the upcoming week. Forecasting typically implies a prediction over time (almost always in the future). But the ability to make predictions is a fundamental part of AI systems, one that enables the capabilities below.

Optimization. AI systems can leverage their predictions to optimize systems and recommend actions that achieve specific goals. For instance, AI can identify the minimum amount of fertilizer needed for a particular crop by predicting its effect on production yield. Similarly, AI can optimize steel production by predicting how different recipes will impact its final strength properties. The output of AI-based optimization are action recommendations, which are typically implemented by human experts. (See the example below on AI's potential.)

Simulation. AI systems can create complex simulations and scenario plans, allowing organizations to test hypotheses in situations where running real-world experiments are not practical. AI-powered simulations can sift through millions of new material candidates, helping identify promising candidates for empirical validation. Scenario planning identifies future "what-if" situations, assesses risks and provides actionable insights for strategic decision-making. This can enable energy providers to plan for supply and demand scenarios that their grids may have never experienced before, minimizing operational costs and risks.

Many AI systems offer capabilities that fall into more than one category above.

C. How Does AI Work?

With AI, there is no longer a need to explicitly program every detail of how to solve a problem. Instead, we rely on data, a model and computation.

Data. To replace explicit programming, supervised and unsupervised AI methods require historical data—observations and measurements that pertain to the problem at hand. In postal routing, these are images of handwritten letters and digits mapped to their correct digital representations. In facial recognition, these are many photographs of the same individual, labeled with their name. Access to high-quality data is essential for AI training. More data directly improves the odds of finding useful patterns—up to a point, after which more data provide diminishing benefits. (In reinforcement learning, data sets are typically simulated.)

Model. AI methods require implicit programming of the types of patterns that lie hidden in data. This part of an AI program is called the "model"—a mathematical description of pattern types expected in data. For example, if a sequence of chess moves appears frequently in winning games, the model should pick this up as a successful strategy. If some people write the letter "t" with a straight line and others with a curve at the bottom, the model should identify both as valid forms of a "t." The scientific community has been steadily developing increasingly sophisticated models over the past several decades.

Computation. Models by themselves are useless—they provide nonsense answers—until they are "trained" on data. Collectively, the various statistical approaches to achieving this goal and the hardware that enables such algorithms fall under the term "computation"—a set of mathematical methods to use a model to find and evaluate the quality of patterns ("training"), while simulating multiple scenarios. In chess, this involves making thousands of clever hypothetical moves to evaluate a particular strategy. In postal routing, this involves quantifying the uncertainty in differentiating a "3" from an "8" to recognize such digits reliably. Computation integrates the idea that AI programs do not contain explicitly programmed rules; rather, computation is the mechanism by which AI unravels and leverages implicit patterns from data (Figure 1-2).

AI has been steadily improving since its inception in the early days of computing. A combination of better access to rich data sources, better models for complex applications and better computing technology (software and hardware) for simulation has led to AI's proliferation.

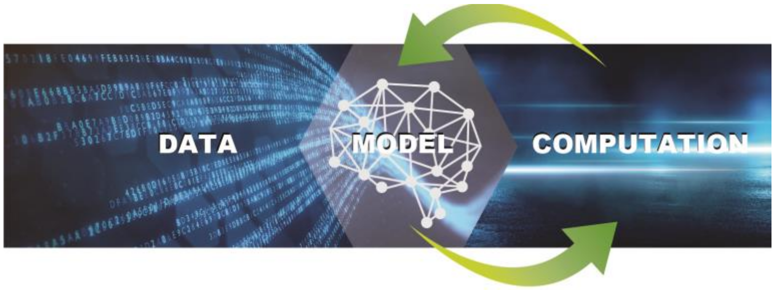


Figure 1-2. *AI systems work by using a model to identify patterns in data. Models by themselves are not useful and must be "trained" on data through computation. Computation integrates the idea that AI systems do not contain explicit information, rather computation is the mechanism by which AI unravels and leverages implicit patterns from data.*

D. What Is AI's Potential?

While chess contrasts AI to traditional software, it does not fully capture AI's potential; a chess program is effectively playing a game. To dive deeper into a practical discipline that is evolving with AI,[6] we turn to radiology—a branch of medicine in which specialist doctors use medical imaging (data) to diagnose and treat diseases.

Radiologists are experts at pattern recognition. After years of training, these doctors spend much of their time detecting anatomical and physiological deviations from blurry and noisy medical scans—which are themselves proxies for tissue and biology, not the real thing itself. AI can provide an important boost to performing this task.

In cancer medicine, for instance, medical imaging data sets with expert-verified labeling of the location and type of tumors are increasingly available. Armed with these data sets, AI systems can be trained to detect patterns in the medical images that expert humans have labeled as a tumor. Once trained, these systems can be directed to examine new medical images, searching for similar patterns in the data that would imply the existence of a tumor.

Once a tumor has been identified, an AI system can begin to simulate various treatment scenarios. How big would the tumor be after one session of radiotherapy? How about after the second? What if the parameters of the radiotherapy are slightly different? Do we end up with a better outcome? These are the types of questions radiologists can explore using AI to assist them in designing a treatment plan, which they execute using tested traditional software that operates medical equipment. The AI outputs a series of outcome probabilities, which themselves recommend treatment actions.

AI technologies not only help radiologists in their practice but also help push the scientific boundaries of their field. AI is enabling radiologists to process and search for patterns across huge databases, paving the way toward personalized treatments. This movement is so significant, it has its own name: radiomics.[7]

The rise of AI in radiology has neither usurped traditional software nor displaced its practitioners. But it highlights a particular type of AI success story. When AI is combined with traditional software and human domain experts, the results are stronger than what AI can produce alone. Keeping “humans in the loop” is key to using AI to solve many real-world problems (Figure 1-3).

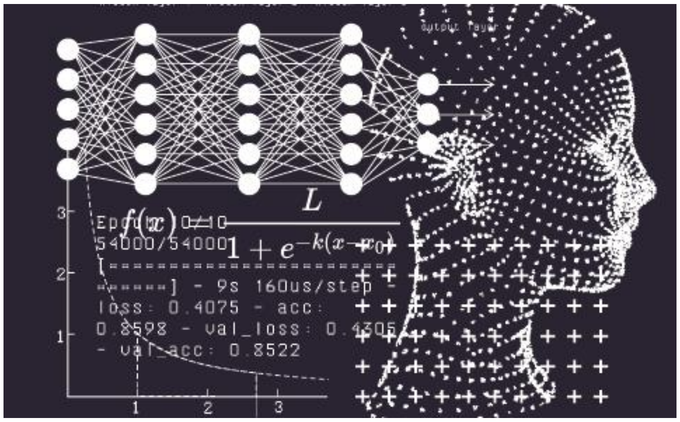


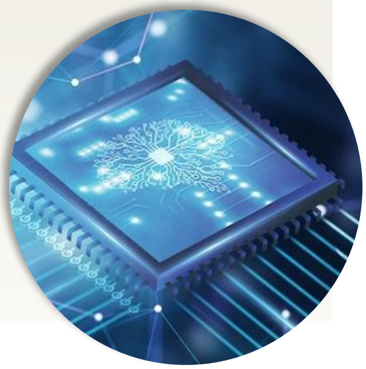
Figure 1-3. *Keeping "humans in the loop" is essential to using AI to solve real-world problems.*

Box 1-1

LARGE LANGUAGE MODELS (LLMS) AND THE FUTURE OF AI

Large language models (LLMs), such as ChatGPT, are one type of AI system. LLMs analyze vast amounts of text data and can string together responses to queries by predicting the most likely next word in a sentence. The user interface is similar to conversing with a human, expanding the potential user base for such technology to anyone who can type a question into a mobile phone or computer.

The success of these systems has revived questions around the future capabilities of AI. ML and AI experts are divided on the transformational potential of LLMs and the best balance between rapid innovation and caution. Chapter 11 of this Roadmap discusses LLMs in greater detail.



E. How Much Energy Does AI Need?

In the past year the energy needs of generative AI models, such as ChatGPT, have received considerable media attention.[8-10] But not all AI systems require as much computing power as generative AI. Some types of AI, such as simple statistical models, neural networks and reinforcement learning, require much less energy. The amount of energy an AI system needs is dictated by its model type and how frequently it is trained and used.

Most AI models require relatively modest energy inputs, even with large data sets. However recently popular generative AI models, such as LLMs and image/video diffusion models, are far more energy-intensive than other AI systems. This is because they require substantial energy both to train and to use.

Training AI Models. In general, training is the most energy-intensive part of building an AI system. Yet for most AI systems, energy demands are not enormous. Some AI systems that analyze medical data, forecast manufacturing sensor outputs and process agricultural drone imagery can be trained on a laptop, often in a matter of minutes. In generative AI systems, however, the type of model (e.g., LLMs) and scale of data (e.g., billions of web pages) can require enormous amounts of computation. Training can become a weeks-long energy-intensive task, executed on supercomputers housed in data centers.

Using AI Models. Once an AI system has been trained, it becomes ready for use—detecting patterns, predicting the future, optimizing systems and simulating "what-if" scenarios. In most AI systems, this is reasonably cheap to do. However, generative AI systems have introduced a new dynamic: they are energy-intensive both to train *and* to use. Enormous (and fiercely secretive) training costs have effectively priced out all but the largest technology firms from developing popular systems, like LLMs. But using such models is also very expensive, with ChatGPT rumored to cost OpenAI $700,000 per day.[11]

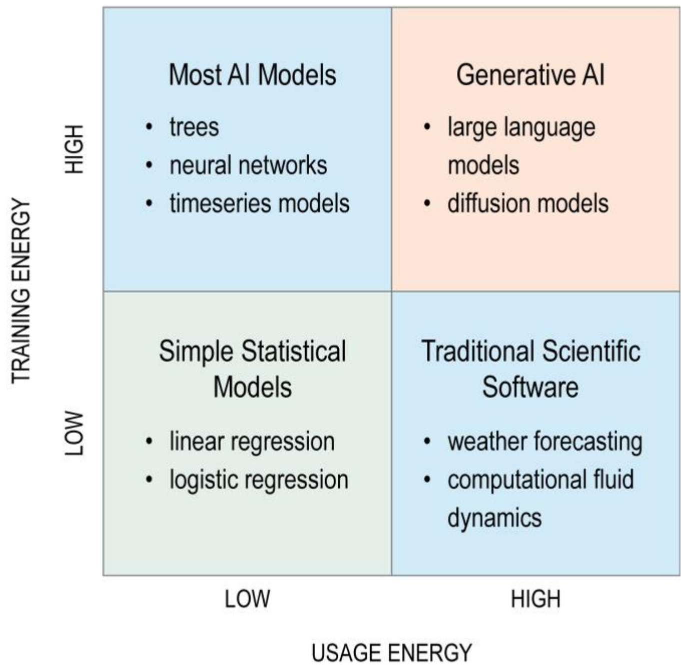


Figure 1-4. *AI systems differ in how much energy they require to train and to use.*

F. What Kind Of Data Does AI Need?

Unlike traditional software, AI requires access to historical data. These data can come in many different forms and be hosted by different types of entities. The availability and accessibility of these data are both important considerations for their potential role in AI systems.

i. Data types

AI systems can work with many different data types.

- Tabular data. Measurements that follow a generic row and column structure. Often associated with spreadsheet applications, tabular data can represent multiple measurements (rows) of a set of things (columns). Common across many applications.
- Time-series data. Measurements that have a time ordering and can be plotted over time. While small time-series data sets can also be considered tabular, they are often stored in database software that can handle large volumes of data. Common in signal processing (audio, remote sensing), finance and econometrics.
- Geospatial and raster data. Measurements that have a spatial ordering and can often be viewed as images. This kind of data no longer looks tabular; they are often stored as files or in special databases. Common in satellite imaging and climate science.
- Network data. Measurements that come with a graph of nodes and edges. This kind of data is often stored in special graph databases. Common in power systems and social networks.
- Text and sequential data. Measurements that comprise sequences of symbols, such as words. This kind of data is typically stored as text files but can also be encoded in databases. Common in language applications.

Box 1-2

HOW MUCH DATA DOES AI NEED?

The answer to this important question depends on the “resolution” of the problem AI is solving. In chess, the number of moves in each game in a data set has no effect—the “resolution” of the task is at the game-level. The more games, the better.

In time-series tasks, if a common event is being studied, a few days of data may be sufficient. But for rare events, years if not decades of historical measurements will be needed. In general, data size is not a useful metric—the amount of data to drive successful AI applications can range from megabytes[12] to terabytes.[13]

ii. Data hosts and owners

Data that can be used for AI applications may be hosted by different organizations and entities. Public sector data hosts include government agencies, state-owned enterprises, public universities, national research laboratories and multilateral institutions. Private sector data hosts include for-profit companies, not-for-profit organizations (e.g., private universities, think tanks, private research laboratories) and individuals. For both public sector and private sector organizations, data can have varying degrees of availability and accessibility.

iii. Data availability

The term "data" loosely refers to some amount of measured information. But for AI applications, the way in which data are measured and digitized matters (Figure 1-5).

- Measured and well-digitized. Properly designed and deployed instrumentation will provide high-quality data that can power AI applications. Such data typically exhibit a high degree of spatial and temporal resolution, covering relevant areas in sufficient precision over an appropriate number of experiments and amount of time. Examples include industrial production data, high-fidelity weather data and fine-resolution satellite data.
- Measured but poorly digitized. Data where instrumentation is either insufficient or improperly configured may not be able to drive successful AI applications. These cases can occur in underfunded application areas (biodiversity studies), rapidly changing application areas (agriculture) and broader geographies (weather data in developing nations). For example, digitizing the monthly total energy usage at the building-level is not sufficient to drive AI-based individual household energy optimization.
- Measured but not digitized. Measurements that could support AI applications may be measured but not digitized. Digital instruments without connectivity, analog instrumentation and manual observations constitute much of this category. Examples include digital thermometers without internet connectivity, analog pressure gauges and visual observations of local weather.
- Not measured. Facts and quantities that would be required to drive an AI application may not be measured at all. In these situations, the ideal outcome is to leapfrog to measured and well-digitized data.

iv. Data accessibility

Data that are measured and (ideally well) digitized may have varying levels of accessibility (Figure 1-5).

- Open-source data. These are the most easily accessed data. Open-source data sets are often hosted on public websites or other public data services. While open-source data sets are widely accessible, they may be subject to licensing[9] agreements that limit their use. Such data may also lack the specificity required in AI applications, as they may have been anonymized to protect individual privacy or trade secrets. Examples include government databases, academic data repositories and data sets shared for data-science competitions.

- Data at cost. These are data that are governed by some sort of usage agreement at a cost dictated by their host. Such data are often high-quality and specific to application areas and may also be governed by additional licensing agreements. Examples include imaging data sold by satellite-operating corporations, curated data for self-driving vehicle development and transportation data from shipping corporations.

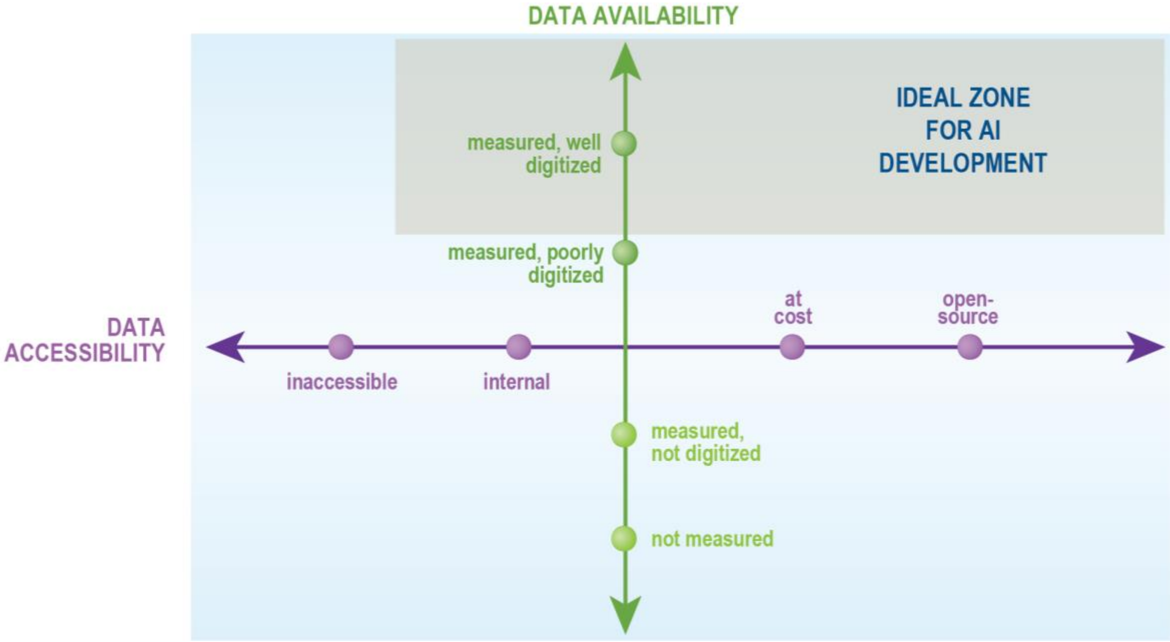


Figure 1-5. Data availability and accessibility are key aspects of enabling AI applications. The ideal zone for AI development relies on accessible, measured and well digitized data.

- Internal data. These data are kept by their hosts to be used internally. Such data are typically proprietary, containing confidential or private information. Examples include industrial production data, material-science research and development records, and GPS location data at the individual level.
- Inaccessible data. These data are generated but not stored. Such data are often temporarily created by computer programs and used in some way. Derived results may be stored, but the raw data are frequently discarded. Examples include physical system simulators and intermediate data used in the processing of other data. Inaccessible data prevents AI development.

G. Why Is AI Developing So Rapidly?

The speed and scale of recent AI development and deployment are remarkable. Improvements in computational technology and exponential reductions in cost are fueling larger and more complex AI systems.[10] The sharing of pre-trained models has also lowered costs by enabling transfer learning instead of building AI systems from scratch. These decreasing costs are enabling more widespread use of advanced AI like large language models for chatbots.

H. Readings

There is a vast literature on AI, including many books and articles introducing computation, ML and AI to non-experts. The following sources may be helpful:

1. Stuart Russell. *Human Compatible: Artificial Intelligence and the Problem of Control*. (Penguin Publishing Group, London, UK, 2020)
2. Nate Silver. *The Signal and the Noise: Why So Many Predictions Fail-but Some Don't*. (Penguin Publishing Group, London, UK, 2012)
3. Judea Pearl & Dana Mackenzie. *The Book of Why: The New Science of Cause and Effect*. (Basic Books, New York, NY, 2018)
4. Brian Christian & Tom Griffiths. *Algorithms to Live By: The Computer Science of Human Decisions*. (Henry Holt and Company, New York, NY, 2016)

The following textbooks may be helpful to those seeking additional technical depth in AI and ML:

1. Kevin P. Murphy. *Probabilistic Machine Learning: An Introduction*. (MIT Press, Cambridge, Massachusetts, 2022)
2. Moritz Hardt & Benjamin Recht. *Patterns, Predictions, and Actions: Foundations of Machine Learning*. (Princeton University Press, Princeton, New Jersey, 2022)
3. Stuart Jonathan Russell & Peter Norvig. *Artificial Intelligence: A Modern Approach*. (Pearson, London, UK, 2020)
4. Richard S. Sutton & Andrew G. Barto. *Reinforcement Learning, second edition: An Introduction*. (MIT Press, Cambridge, Massachusetts, 2018)

I. References

1 Postal Facts. *Optical character recognition;* US Postal Service (USPS), Washington, D.C., https://facts.usps.com/98-percent-of-hand-addressed-letters/ (Accessed August 2024).

2 Bibb Allen *et al.* 2020 ACR Data Science Institute Artificial Intelligence Survey. *Journal of the American College of Radiology* 18, 1153-1159 (2021). https://doi.org/10.1016/j.jacr.2021.04.002.

3 Ina Fried. *OpenAI says ChatGPT usage has doubled since last year;* Axios, Arlington, Virginia, https://www.axios.com/2024/08/29/openai-chatgpt-200-million-weekly-active-users?utm_source=newsletter&utm_medium=email&utm_campaign=newsletter_axiosam&stream=top (2024).

4 Stefan Steinerberger. On the number of positions in chess without promotion. *International Journal of Game Theory* 44, 761-767 (2015). https://doi.org/10.1007/s00182-014-0453-7.

5 David Silver *et al.* A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. *Science* 362, 1140-1144 (2018). https://doi.org/10.1126/science.aar6404.

6 Garry Choy *et al.* Current Applications and Future Impact of Machine Learning in Radiology. *Radiology* 288, 318-328 (2018). https://doi.org/10.1148/radiol.2018171820.

7 Kaustav Bera *et al.* Predicting cancer outcomes with radiomics and artificial intelligence in radiology. *Nature Reviews Clinical Oncology* 19, 132-146 (2022). https://doi.org/10.1038/s41571-021-00560-7.

8 Brian Calvert. *AI already uses as much energy as a small country. It's only the beginning;* Vox, Washington, D.C., https://www.vox.com/climate/2024/3/28/24111721/climate-ai-tech-energy-demand-rising (2024).

9 Seth Fiegerman & Matt Day. *Why AI Is So Expensive;* Bloomberg, New York, New York, https://www.bloomberg.com/news/articles/2024-04-30/why-artificial-intelligence-is-so-expensive (2024).

10 Ariel Cohen. *AI Is Pushing The World Toward An Energy Crisis;* Forbes, Jersey City, New Jersey, https://www.forbes.com/sites/arielcohen/2024/05/23/ai-is-pushing-the-world-towards-an-energy-crisis/ (2024).

11 Aaron Mok. *ChatGPT could cost over $700,000 per day to operate. Microsoft is reportedly trying to make it cheaper.;* Business Insider, New York, New York, https://www.businessinsider.com/how-much-chatgpt-costs-openai-to-run-estimate-report-2023-4 (2023).

12 Creative Commons. *Creative Commons;* Mountain View, CA, https://creativecommons.org/ (Accessed August 2024).

13 OpenAI. *AI and compute;* San Francisco, California, https://openai.com/research/ai-and-compute (2018).

CHAPTER 2:
INTRODUCTION TO CLIMATE CHANGE

Hoesung Lee, David Sandalow, Julio Friedmann and Trishna Nagrani

A. Climate Change Background 2-2

B. Contributions of Artificial Intelligence to Climate Science 2-4

C. Readings 2-6

D. References 2-7

A. Climate Change Background

Concentrations of heat-trapping gases in the atmosphere are now higher than at any time in human history.[1] This is changing the Earth's climate.[2] (See Figures 2-1 and 2-2.)

The Earth's average global temperature has risen by more than 1 °C (almost 2 °F) since the second half of the 19th century.[a] (See Figure 2-3.) Based on global average temperatures:

- July 22, 2024 was the hottest day ever recorded[4]
- July 2023 was the warmest month ever recorded[3]
- 2023 was the warmest year on record, by a substantial margin (the average temperature was 1.45 ± 0.12 °C above pre-industrial levels)[3]
- The last decade is likely the warmest 10-year period on record[3]

The principal heat-trapping gases are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and fluorinated gases (such as HFCs and SF_6). These are commonly called greenhouse gases (GHGs). (See Figure 2.) CO_2 is responsible for roughly 76% of the warming impact of GHGs globally. Methane is responsible for roughly 18%, nitrous oxide for 4% and fluorinated gasses for 2%.[5]

Human activities are the principal cause of the buildup of GHGs in the atmosphere.[1] Those activities include burning fossil fuels (coal, oil and gas), land use and land-use change, and patterns of consumption and production.[1] Roughly 34% of global GHG emissions come from electricity and heat production; 24% from industry; 22% from agricultural, forestry and other land use; 15% from transport and 5% from buildings.[5]

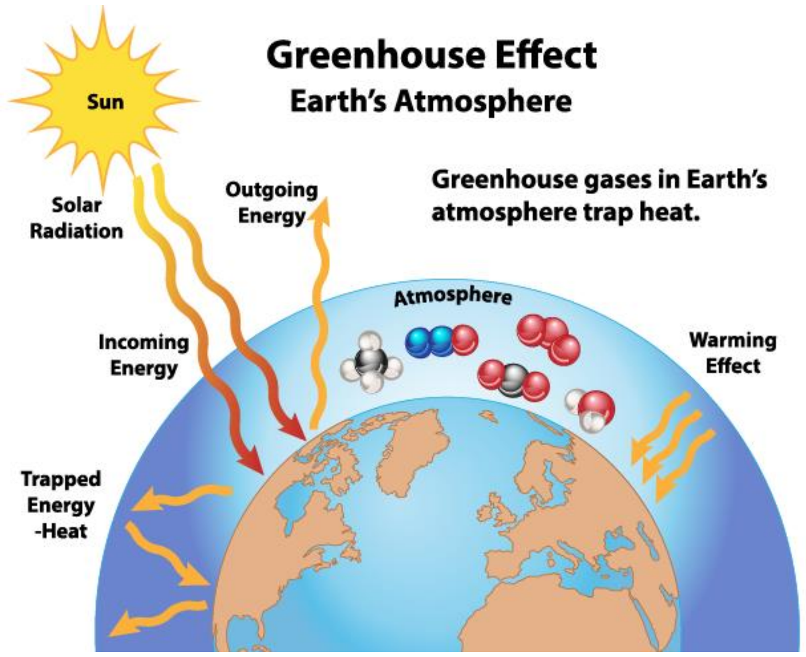


Figure 2-1. Greenhouse Effect.

[a] To be precise, the Earth's average global temperature from 2014-2023 was 1.2°C (1.9°F) above the 1850-1900 average.[3]

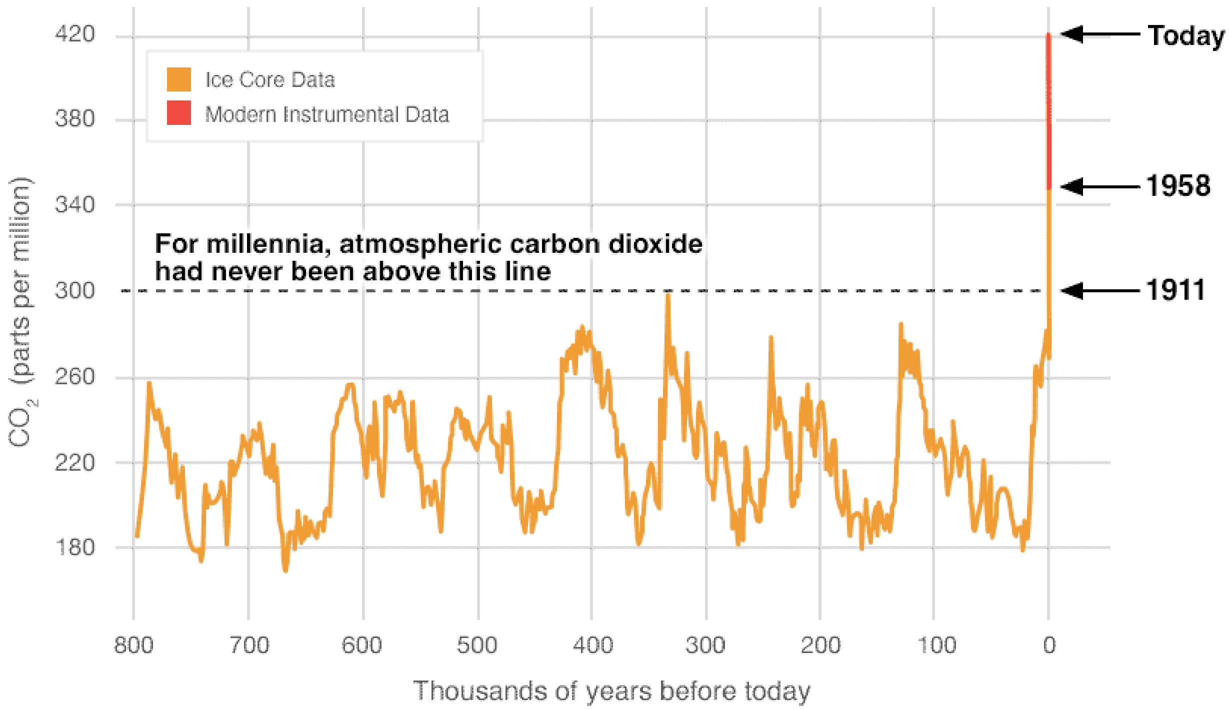


Figure 2-2. *NASA, Global Climate Change, Vital Signs of the Planet, Carbon Dioxide.*[6]

Since 1850, cumulative net CO_2 emissions have been 2400 ± 240 $GtCO_2$, 42% of which occurred during the last 30 years (see IPCC, 2023 *Summary for Policymakers* at p. 5[1]).

The impacts of a changing climate are being felt across the globe:

- Storms, heat waves and droughts have increased in frequency and intensity in recent decades. Scientists are increasingly able to attribute these increases directly to human activities—in particular the burning of fossil fuels.[7,8]
- Warming air temperatures and droughts, made more likely by climate change, have directly contributed to increased fire risk in many parts of the world. For example, changes in the climate over the past 30 years are associated with a doubling of extreme fire weather conditions in California.[9]
- Approximately 3.3–3.6 billion people are highly vulnerable to climate hazards, including acute food insecurity and reduced water security.[1]
- Between June and August 2022, Pakistan experienced unprecedented floods, which affected 33 million individuals. Over 1700 lives were lost and more than 2.2 million houses were destroyed or damaged.[10]

Billions of people face extraordinary risks unless the buildup of heat-trapping gases in the atmosphere slows and then reverses in the decades ahead.[11] Those risks include even more severe and frequent storms, floods, droughts and heat waves, as well as sea-level rise.[12] One study found

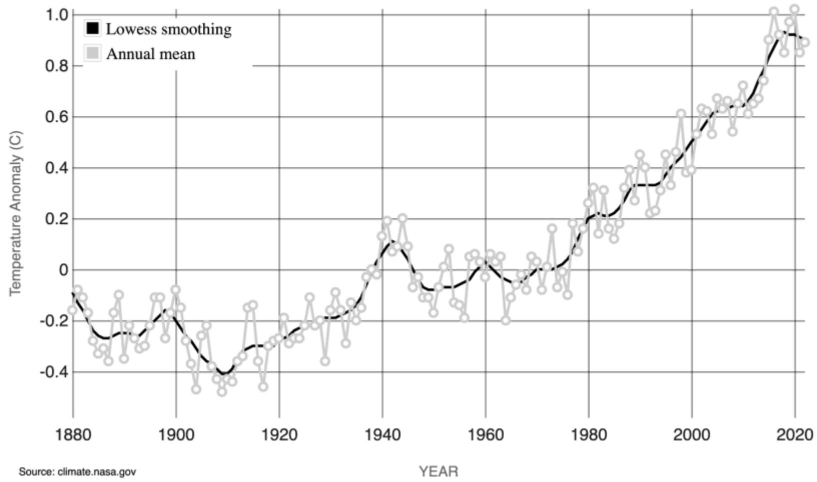


Figure 2-3. *Global average temperatures 1880-2022.*[13]

that, in roughly a dozen locations across the Mediterranean and Middle East, temperatures are likely to reach 50 °C every year in the latter part of this century. Such temperatures were extremely rare or impossible in these locations in the pre-industrial world.[14]

Climate change is expected to increase heat-related mortality rates and the incidence of lung and heart disease associated with poor air quality. Higher temperatures and more frequent flooding events caused by climate change contribute to the spread of infectious and vector-borne communicable diseases, such as dengue, malaria, hantavirus and cholera.[15]

In 2015, more than 190 nations adopted the Paris Agreement, which calls for "holding the increase in global average temperature to well below 2 °C (3.6 °F) above pre-industrial levels" and "pursuing efforts to limit the temperature increase to 1.5 °C (2.7 °F) above pre-industrial levels."[16] However, policies currently in place around the world would result in a global average temperature increase of 2.2–3.5 °C (4–6.3 °F) (see IPCC, 2023 at p. 11[1]) above preindustrial levels by 2100,[1] and many policies to limit emissions are not being fully implemented.[17] The world is not on a path to meet globally agreed upon climate change goals.

In April 2022, the Intergovernmental Panel on Climate Change (IPCC) Working Group 1 (WGI) concluded that it is almost inevitable that the Earth's average temperature will temporarily exceed the Paris Agreement's 1.5 °C threshold in the short-term, although global average temperatures could return to below that level by the end of the century. The IPCC also found that a return to levels below the 1.5 °C threshold can only be achieved with rapid and deep reduction in GHG emissions and enhanced CO_2 removal (see IPCC, 2023 at p. 23[1]).

B. Contributions of Artificial Intelligence to Climate Science

Artificial intelligence (AI) is making important contributions to the scientific understanding of climate change. While AI applications are still in relatively early stages of development, the progress to date suggests real opportunity for better monitoring of anthropogenic climate impacts, better understanding of how the Earth's climate is likely to evolve and better predictions of climate impacts.

i. Improving climate model performance

The best scientific understanding of climate dynamics and forecasts of climate impacts are based on computer simulations of complex climate models. To validate these simulations, results are compared across models ("model intercomparison") and to historical weather data ("hindcasting"). AI can help improve this comparison process, identifying biases in specific models and extracting the most useful physical results from increasingly massive amounts of climate model output data.[18]

AI can also complement conventional physics-based climate modeling in hybrid approaches, dramatically reducing the need for certain very intensive computations[19] or improving the resolution of model outputs.[20] In some cases, AI can analyze the voluminous output of high-resolution climate models and assess potential biases in their predictions. A Stanford study using AI to analyze maps of temperature anomalies, for example, suggested that climate models underestimate the average rate of warming and that temperature increases are likely to exceed 1.5 °C by 2030–2035.[21] Already, AI has improved both the pre-processing[22] and post-processing[23] of climate models and numerical weather prediction.

A potential drawback of incorporating AI into climate simulations is less reproducibility (meaning that calculations cannot necessarily be repeated and arrive at essentially identical results). The complexity and probabilistic nature of some AI and machine learning (ML) techniques make this more challenging.[24]

ii. Improving the understanding of climate processes and feedbacks

The ability of AI to ingest and interpret immense volumes of climate and weather data has helped illuminate natural processes and important hidden feedbacks within the climate system. For example, one study identified the role of US Midwestern precipitation in modulating North Atlantic salinity.[25] Another AI-driven analysis of river floods illustrated that data-driven, empirical modeling using AI could perform as well as science-based simulations in many situations.[26] AI can also reduce uncertainties in certain key climate drivers. For example, a recent study improved the understanding of the interactions between aerosols and clouds, which has long been challenging for climate models to accurately represent.[27]

Figure 2-4. *Svalbard, Norway. (photo: David Sandalow)*

iii. Providing more advanced warning for extreme weather

Already, AI is beginning to improve weather forecasts associated with extreme events, providing accurate, near-term advanced warning in critical contexts.[28] This work has made major strides in the past two years and could ultimately transform climate adaptation responses. Some of the most crucial areas in which this AI-enabled "nowcasting" (within 6 hours) capability is being applied include extreme precipitation[29] and extreme wind speeds,[30] with additional work on predicting extreme heat over timescales of days to weeks.[31]

iv. Attributing extreme events to human influence

Climate attribution is a rapidly changing field, and understanding how climate change leads to extreme events is important for governments, companies and public stakeholders. AI has already provided insights into human attribution around specific phenomena and mechanisms. These include river flooding in Europe,[32] tropical cyclone intensity,[33] periods of frost occurrence[34] and many more. New organizations and government programs like Europe's XAIDA[35] are dedicated to this important task.

v. Revealing additional climate drivers

The ability of AI to analyze visual and numerical data for patterns has greatly improved the understanding of certain man-made climate drivers. For example, AI-based analysis of satellite data from the US National Aeronautics and Space Administration (NASA) revealed much higher ship-track cloud formation than was previously known (10 times greater) and detected a long-term reduction over 20 years due to sulfur reductions in maritime fuels.[36]

C. Readings

There is a vast literature on climate change, including many books and articles introducing climate change to non-experts. The following sources may be helpful:

Books

1. Bill Gates. *How to Avoid a Climate Disaster: The Solutions We Have and the Breakthroughs We Need.* (Knopf Doubleday Publishing Group, New York, NY, 2021)
2. Christiana Figueres & Tom Rivett-Carnac. *The Future We Choose: Surviving the Climate Crisis.* (Alfred A. Knopf, New York, NY, 2020)
3. Vaclav Smil. *How the World Really Works: The Science Behind How We Got Here and Where We're Going.* (Penguin Publishing Group, London, UK, 2022)
4. John Doerr & Ryan Panchadsaram. *Speed & Scale: An Action Plan for Solving Our Climate Crisis Now.* (Penguin Publishing Group, London, UK, 2021)
5. David Wallace-Wells. *The Uninhabitable Earth: Life After Warming.* (Crown Publishing Group, New York, NY, 2020)

Reports

1. Intergovernmental Panel on Climate Change (IPCC), *Climate Change 2023: Synthesis Report* (2023)
2. International Energy Agency (IEA), *World Energy Outlook 2023* (2023)
3. World Meteorological Organization (WMO), *State of Climate Services Report* (2023)
4. United Nations Environment Programme (UNEP), *Emissions Gap Report 2022* (2022)

D. References

1 Intergovernmental Panel on Climate Change (IPCC). *Summary for Policymakers. In: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change;* DOI; 10.59327/IPCC/AR6-9789291691647.001; https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_SPM.pdf (2023).

2 Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change;* Cambridge University Press, Cambridge, https://doi.org/10.1017/9781009157896 (2023).

3 World Meteorological Organization (WMO). *State of the Global Climate 2023;* Geneva, Switzerland, https://wmo.int/publication-series/state-of-global-climate-2023 (2024).

4 Goddard Digital Team. *NASA Data Shows July 22 Was Earth's Hottest Day on Record;* NASA, Greenbelt, Maryland, https://www.nasa.gov/earth/nasa-data-shows-july-22-was-earths-hottest-day-on-record/#:~:text=July%2022%2C%202024%2C%20was%20the,record%2C%20set%20in%20July%202023 (2024).

5 Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2022 - Mitigation of Climate Change: Working Group III Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change;* Cambridge University Press, Cambridge, https://doi.org/10.1017/9781009157926 (2023).

6 The National Aeronautics and Space Administration (NASA). *Carbon Dioxide;* Washington, D.C., https://climate.nasa.gov/vital-signs/carbon-dioxide/ (Accessed August 2024).

7 Intergovernmental Panel on Climate Change (IPCC). *Summary for Policymakers;* Cambridge University Press, Cambridge, UK, https://doi.org/10.1017/9781009157896.001 (2023).

8 Matthew Rodell & Bailing Li. Changing intensity of hydroclimatic extreme events revealed by GRACE and GRACE-FO. *Nature Water* 1, 241-248 (2023). https://doi.org/10.1038/s44221-023-00040-5.

9 Michael Goss *et al.* Climate change is increasing the likelihood of extreme autumn wildfire conditions across California. *Environmental Research Letters* 15, 094016 (2020). https://doi.org/10.1088/1748-9326/ab83a7.

10 United Nations Children's Fun (UNICEF). *Devastating floods in Pakistan;* New York, New York, https://www.unicef.org/emergencies/devastating-floods-pakistan-2022 (2023).

11 Intergovernmental Panel on Climate Change (IPCC). *Summary for Policymakers;* Cambridge University Press, Cambridge, https://doi.org/10.1017/9781009325844.001 (2023).

12 Intergovernmental Panel on Climate Change (IPCC). *Summary for Policymakers;* Cambridge University Press, Cambridge, https://doi.org/10.1017/9781009157940.001 (2022).

13 The National Aeronautics and Space Administration (NASA). *Global Temperature;* Washington, D.C., https://climate.nasa.gov/vital-signs/global-temperature/?intent=121 (Accessed August 2024).

14 Nikolaos Christidis, Dann Mitchell & Peter A. Stott. Rapidly increasing likelihood of exceeding 50 °C in parts of the Mediterranean and the Middle East due to human influence. *npj Climate and Atmospheric Science* 6, 45 (2023). https://doi.org/10.1038/s41612-023-00377-4.

15 Marina Romanello *et al.* The 2022 report of the Lancet Countdown on health and climate change: health at the mercy of fossil fuels. *The Lancet* 400, 1619-1654 (2022). https://doi.org/10.1016/S0140-6736(22)01540-9.

16 United Nations. *Paris Agreement;* Paris, France, https://unfccc.int/sites/default/files/english_paris_agreement.pdf (2015).

17 Climate Action Tracker. *Temperatures;* Climate Analytics and NewClimate Institute, Berlin and Cologne, Germany, https://climateactiontracker.org/global/temperatures/ (Accessed August 2024).

18 Ophelie and Plancherel Meuriot, Yves and Nieves, Veronica. *Unsupervised machine learning techniques for multi-model comparison: A case study on Antarctic Intermediate Water in CMIP6 models;* https://www.climatechange.ai/papers/iclr2023/16 (2023).

19 L. J. Slater *et al.* Hybrid forecasting: blending climate predictions with AI models. *Hydrol. Earth Syst. Sci.* 27, 1865-1889 (2023). http://doi.org/10.5194/hess-27-1865-2023.

20 M. Witte, Filippou, D., Plésiat, É., Meuer, J., Thiemann, H., Hall, D., Ludwig, T., and Kadow, C. From Super-Resolution to Downscaling - An Image-Inpainting Deep Neural Network for High Resolution Weather and Climate Models. (2023). https://doi.org/10.5194/egusphere-egu23-13196.

21 Noah S. Diffenbaugh & Elizabeth A. Barnes. Data-driven predictions of the time remaining until critical global warming thresholds are reached. *Proceedings of the National Academy of Sciences* 120, e2207183120 (2023). https://doi.org/10.1073/pnas.2207183120.

22 Sid-Ahmed Boukabara *et al.* Leveraging Modern Artificial Intelligence for Remote Sensing and NWP: Benefits and Challenges. *Bulletin of the American Meteorological Society* 100, ES473-ES491 (2019). https://doi.org/10.1175/BAMS-D-18-0324.1.

23 Amy McGovern *et al.* Using Artificial Intelligence to Improve Real-Time Decision-Making for High-Impact Weather. *Bulletin of the American Meteorological Society* 98, 2073-2090 (2017). https://doi.org/10.1175/BAMS-D-16-0123.1.

24 R. Bush, Dutton, A., Evans, M., Loft, R., & Schmidt, G. A. . Perspectives on Data Reproducibility and Replicability in Paleoclimate and Climate Science. *Harvard Data Science Review* 2 (2020). https://doi.org/10.1162/99608f92.00cd8f85.

25 Laifang Li *et al.* Implications of North Atlantic Sea Surface Salinity for Summer Precipitation over the U.S. Midwest: Mechanisms and Predictive Value. *Journal of Climate* 29, 3143-3159 (2016). https://doi.org/10.1175/JCLI-D-15-0520.1.

26 Anne Jones *et al.* AI for climate impacts: applications in flood risk. *npj Climate and Atmospheric Science* 6, 63 (2023). https://doi.org/10.1038/s41612-023-00388-1.

27 Fangqun Yu *et al.* Use of Machine Learning to Reduce Uncertainties in Particle Number Concentration and Aerosol Indirect Radiative Forcing Predicted by Climate Models. *Geophysical Research Letters* 49, e2022GL098551 (2022). https://doi.org/10.1029/2022GL098551.

28 Zied Ben Bouallegue Matthew Chantry, Linus Magnusson, Michael Maier-Gerber, Jesper Dramsch. *The rise of machine learning in weather forecasting;* https://www.ecmwf.int/en/about/media-centre/science-blog/2023/rise-machine-learning-weather-forecasting (2023).

29 Yuchen Zhang *et al.* Skilful nowcasting of extreme precipitation with NowcastNet. *Nature* 619, 526-532 (2023). https://doi.org/10.1038/s41586-023-06184-4.

30 Sandy Chkeir *et al.* Nowcasting extreme rain and extreme wind speed with machine learning techniques applied to different input datasets. *Atmospheric Research* 282, 106548 (2023). https://doi.org/10.1016/j.atmosres.2022.106548.

31 Ignacio Lopez-Gomez *et al.* Global Extreme Heat Forecasting Using Neural Weather Models. *Artificial Intelligence for the Earth Systems* 2, e220035 (2023). https://doi.org/10.1175/AIES-D-22-0035.1.

32 S. Jiang, E. Bevacqua & J. Zscheischler. River flooding mechanisms and their changes in Europe revealed by explainable machine learning. *Hydrol. Earth Syst. Sci.* 26, 6339-6359 (2022). https://doi.org/10.5194/hess-26-6339-2022.

33 Davide Faranda *et al.* Correcting biases in tropical cyclone intensities in low-resolution datasets using dynamical systems metrics. *Climate Dynamics*, https://link.springer.com/article/10.1007/s00382-00023-06794-00388 (2023). https://doi.org/10.1007/s00382-023-06794-8.

34 Carl J Talsma *et al.* Frost prediction using machine learning and deep neural network models. *Frontiers in Artificial Intelligence* 5, 963781 (2023). https://doi.org/10.3389/frai.2022.963781.

35 Xaida. *Home Page – eXtreme events : Artificial Intelligence for Detection and Attribution;* European Union–Funded Project, https://xaida.eu/ (Accessed August 2024).

36 Tianle Yuan *et al.* Global reduction in ship-tracks from sulfur regulations for shipping fuel. *Science Advances* 8, eabn7988 (2022). https://doi.org/10.1126/sciadv.abn7988.

PART II - SECTORS

Chapter 3 – POWER SECTOR

Chapter 4 – FOOD SYSTEMS

Chapter 5 – MANUFACTURING

Chapter 6 – ROAD TRANSPORT

Chapter 7 – AVIATION

Chapter 8 – BUILDING SECTOR

Chapter 9 – CARBON CAPTURE

Chapter 10 – NUCLEAR POWER

CHAPTER 3:

POWER SYSTEM

David Sandalow, Fan Zhiyuan and Mariah Frances Carter

A. Generation 3-4

B. Transmission and Distribution 3-6

C. End-Use Devices 3-8

D. Energy Storage 3-10

E. Barriers 3-11

F. Risks 3-12

G. Conclusion 3-12

H. Recommendations 3-14

I. References 3-15

In 2023, carbon dioxide (CO_2) emissions from the global power sector were almost 15 Gt—roughly 28% of greenhouse gas (GHG) emissions globally.[1,2]

The power sector will play a central role in decarbonizing the global economy. Most strategies for deep decarbonization foresee growing reliance on the power sector as vehicles, industry, space heating and other sectors shift from fossil fuels to electricity. In the *Net Zero by 2050* scenario released by the International Energy Agency (IEA), for example, the share of electricity in final energy use increases from 20% in 2020 to 50% in 2050.[3] The amount of final energy use changes very little during this period, so the electric power sector more than doubles in size in the decades ahead in this scenario. Other scenarios are similar.[4]

For global climate change goals to be achieved, the power sector must grow and decarbonize at the same time. The scale of the challenge is enormous.

- Despite the extraordinary fall in the price of renewable power in the past 30 years, fossil fuels still dominate the global power sector. In 2023, fossil fuels (coal, oil and natural gas) generated 61% of the electricity produced globally. (In 1990, the figure was 65%.)[5]
- The impressive and record-breaking deployment of renewable power in the past decade has not been enough to meet the growth in the world's power demand in the same period.[6]
- Trillions of dollars are currently invested in legacy fossil fuel infrastructure globally. The average life of much of this infrastructure is several decades.[7-9]
- IEA analysis suggests that achieving net-zero emissions by mid-century will require global power sector investment to surge to roughly $3 trillion by 2030 (almost triple current levels) and stay at or near that level for decades.[3,10]

A challenge of this magnitude requires new technologies and approaches. The rapid advances in artificial intelligence (AI) have the potential to make a meaningful difference.[11,12] Indeed they are already starting to do so. For example:

- AI algorithms are predicting solar radiation and wind speeds more accurately than traditional methods, allowing for better scheduling and dispatch of renewable energy

- Dynamic line rating and other AI-driven techniques have started to optimize transmission and distribution of electricity, ensuring that renewable energy is transmitted efficiently from generation sites to consumers
- AI is facilitating demand response programs by analyzing consumption patterns and incentivizing consumers to shift their usage to periods of high renewable energy generation
- AI is accelerating innovation in energy storage, evaluating new battery chemistries far more rapidly than traditional methods and accelerating deployment of vehicle-to-grid (V2G) and other distributed storage technologies[13,14]

These steps are just a beginning. In the years ahead, AI could do much more to help reduce GHG emissions from the power sector, including in permitting reform, optimal power flow analyses, V2G charging and more.

At the same time, the rapid growth of AI creates challenges for decarbonizing the power sector. AI currently uses less than 1% of electricity generated globally, but power demand for AI is growing quickly. In many locations, demand for new data centers—driven in part by AI—is increasing faster than low-carbon power sources can be deployed. Power demand from new data centers is creating challenges for some utilities that are committed to decarbonizing their generation mix in the years ahead. This topic is discussed in more detail in Chapter 15 of this Roadmap.

This chapter explores how AI can contribute to decarbonizing the power sector. The chapter begins by exploring AI's current and potential impact in decarbonizing four parts of the power sector: (1) generation infrastructure, (2) transmission and distribution networks, (3) end-use sectors and (4) energy storage. The chapter then turns to barriers, risks, concluding thoughts and recommendations.

(This chapter mostly uses the term "AI" when referring to programs that perform tasks through inference of patterns and learning from data. In the technical literature, the term "machine learning" ("ML") is more common.)

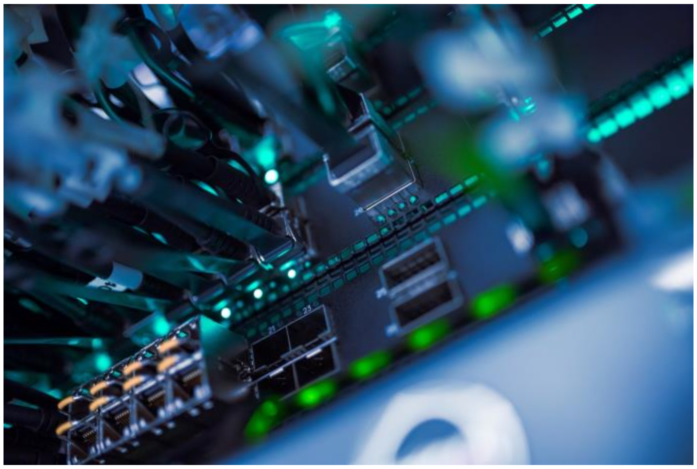
A. Generation

Planning and operating power generation infrastructure are complex tasks. Many factors require attention, including renewable resource availability, permitting constraints and the condition of physical assets. AI can help improve performance, speed deployment timelines and cut costs.

i. Planning

AI can be especially valuable in planning large-scale renewable projects:

- AI can recommend the optimal size and location of solar power projects, which requires complex calculations on topics such as weather patterns, equipment type and grid constraints.[15,16]
- AI can help with wind farm planning, which requires complex calculations on topics such as terrain, wind speed and direction, and turbine type.[17,18]
- AI can help accelerate deployment of non-conventional renewables, including wave energy[19] and geothermal energy.[20] In geothermal energy, AI can help improve numerical reservoir modeling, exploration, drilling and production.[19]



Permitting timelines are often a challenge for renewable projects. Large language models (LLMs) can extract text from past permit applications and decisions to help applicants improve application quality (see Benes et al., 2024[21] at p. 12–16). LLMs also help permitting authorities review permits more quickly and thoroughly (see e.g., Symbium[22]). At the US Department of Energy (DOE), several National Labs have initiated a pilot project using foundation models and other AI to systematically improve siting permitting and environmental reviews for renewables projects.[23]

AI can also help accelerate innovation in nuclear reactor design, speed the nuclear permitting process and cut costs in the operations of nuclear reactors.[24] (These topics are discussed in Chapter 10 of this Roadmap.)

ii. Operations

After renewable generation capacity is installed, operational decisions can have significant impacts on power output and costs. Predicting variable solar and wind power is one of the most well-studied topics in the use of AI in the power sector (see Figure 3-1).[25] For example:

- AI can predict weather relevant to wind/solar generation, such as cloud cover,[26] wind speed[27] and solar radiation[28]

- AI can integrate weather forecasts and power production forecasts (these forecasts typically focus on short-term predictions (<72 hours, mostly 24 hours) that rely on robust historical and real-time data)[29]
- Other applications for maximizing renewable power generation using AI include reinforcement learning control for wind turbines,[30,31] solar system operation[29] and solar shading[32]

Recent advances in AI-based weather forecasting are especially promising. In traditional weather forecasting, numerical models use sophisticated physics equations and historical weather data to predict atmospheric behavior. This is computationally expensive, requiring supercomputers for each prediction. In newer AI-based weather forecasting, ML techniques are used to train a model on historical weather data. Once the model is trained, the computational requirements to forecast atmospheric behavior are significantly less than with traditional methods.

Researchers around the world have made significant performance improvements using these new AI-based tools. In July 2023, scientists at Huawei Cloud released a paper in Nature[33] presenting AI-driven weather forecasting models that outperformed numerical methods. In November 2023, Google DeepMind released a paper[34] showing even more accurate results, especially for medium-range weather forecasts. Government agencies are starting to incorporate these new methods into their standard forecasts.[35]

As AI-based weather models become more accurate and less expensive, the use cases for these types of models will grow. In the power sector, AI-based weather models can increase output from solar and wind farms, help prepare for extreme weather events and contribute to system resilience. In North America, for example, AI is being used to help predict wildfires, synthesizing satellite images and LIDAR feeds in ways that can help grid operators make decisions on managing transmission lines through forests during periods of high wildfire risk.[36] (See Chapter 14 of this Roadmap, which explores how AI can help respond to extreme weather events.)

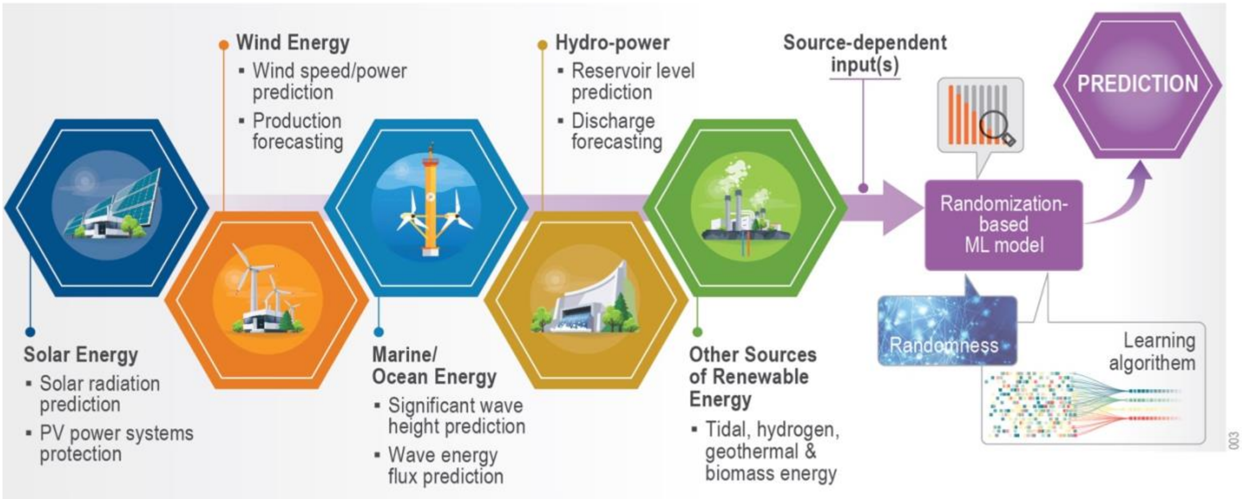


Figure 3-1. *AI predictions in renewable energy.*

AI can be especially helpful in operating rooftop solar photovoltaic (PV). AI can predict the power generation potential of rooftop solar panels,[37] generate forecasts[38] and reduce customer acquisition costs.[39]

Federated learning (FL)—a special type of AI—can be very useful in operating distributed power generation infrastructure. Federated learning is an AI technique where multiple decentralized devices collaboratively train a shared model while keeping the training data on the devices themselves, preserving data privacy and security.[40] FL is well-suited to tasks such as predicting rooftop solar generation[41] and can perform a number of tasks in the “smart city” and “smart grid” context.[42]

AI can also be used for preventive maintenance at power generation infrastructure. Data-driven predictions of maintenance and repair needs can minimize cost and production downtime. These predictions can be especially useful at wind power facilities, which are often located in difficult environments and must endure high wind speed, extreme temperatures and other challenges, making maintenance expensive.[43] AI can be used to schedule preventive maintenance, reducing turbine failure and repair costs.[43,44] AI can also be used to improve maintenance at solar,[45] nuclear[46] and hydro[47] power plants.

Finally, AI can assist with integrating the electric grid and emerging low-carbon hydrogen networks. Green hydrogen production will consume enormous power. Optimizing integration of the electric grid with green hydrogen production can deliver significant savings.[48] AI can help optimize green hydrogen production by predicting renewable power potential,[49] curtailed renewable energy[50] and water sustainability.[51] AI can also help plan hydrogen refueling stations, optimizing station-based production and storage.[52] AI can be used to integrate renewable power with hydrogen-energy storage to increase grid stability and lower peak loads.[53]

B. Transmission and Distribution

Investing in transmission and distribution infrastructure is essential for integrating high volumes of renewable power into the electric grid. Renewable resources are often located far away from load centers, requiring long-distance transmission. Planning and operating this infrastructure involves solving complicated nonlinear problems. AI tools can help with many aspects of electricity transmission and distribution—cutting costs, increasing capacity and helping reduce GHG emissions.[54]

AI can be especially helpful with transmission expansion planning (TEP). Determining the best location and capacity of new transmission lines involves large-scale complex optimization problems in which finding a feasible solution can be difficult.[55] These difficulties, along with a large increase in the number of interconnection requests, are causing significant delays and uncertainties in permitting renewable power projects in the United States and other geographies.

Several studies highlight the potential for AI to contribute to TEP:

- Borozan et al. (2023) integrated AI with well-established TEP decomposition methods to improve computational efficiency while preserving solution quality[56]
- Wang et al. (2021a and b) showed that AI can be used to solve multi-stage TEP based on a static model, which can be flexibly adjusted and incorporate uncertainties in wind power and demand projections[57,58]
- Fu et al. (2020) studied the stochastic optimal planning of distribution networks using AI, considering both renewable power and demand variability[59]

AI can be especially helpful in optimal power flow (OPF) analysis—an integral part of TEP that evaluates the most efficient and reliable flow of electricity through a transmission network while meeting operational constraints and minimizing costs. AI can significantly improve the process of solving alternating current optimal power flow (AC-OPF) problems by evaluating transmission expansion results much more efficiently than current methods.[60,61] This improvement not only increases accuracy over traditional direct current optimal power flow (DC-OPF) systems but also has the potential to make transmission permitting faster. Leveraging AI for AC-OPF can lead to better transmission expansion planning, helping reduce emissions from the power system.[62,63]

Another promising application of AI is for dynamic line rating -- a method of determining the maximum capacity of transmission lines based on current weather and line conditions instead of static, conservative estimates.[64] Dynamic line rating can increase the capacity of transmission lines by at least 30%.[65,66] Increasing the capacity of existing transmission lines is especially valuable where permitting new transmission lines to bring renewable power to load centers is difficult. AI-driven dynamic line rating can help maximize utilization of renewable resources and support integration of more renewable power into the electric grid.[67]

AI can also help distribution network operations. Historically, the distribution grid was too complex to be mapped accurately, leading to difficulties with fault detection. Recent progress in digitalization has increased the observability and controllability of the distribution grid, enabling AI to assist in fault detection.[68] Studies have shown that AI methods outperform traditional methods in fault detection accuracy but demand large amounts of data and significant computational resources.[68,69] Better fault detection can reduce GHG emissions by minimizing downtime, reducing the need for carbon-intensive backup power and ensuring grid stability, which supports integration of renewable power.[70,71]

In conclusion, AI is being used in transmission and distribution infrastructure to improve expansion planning, renewables integration and core operations. As costs decline and AI capabilities continue to improve, AI can play an increasingly important role in transmission and distribution.[72]

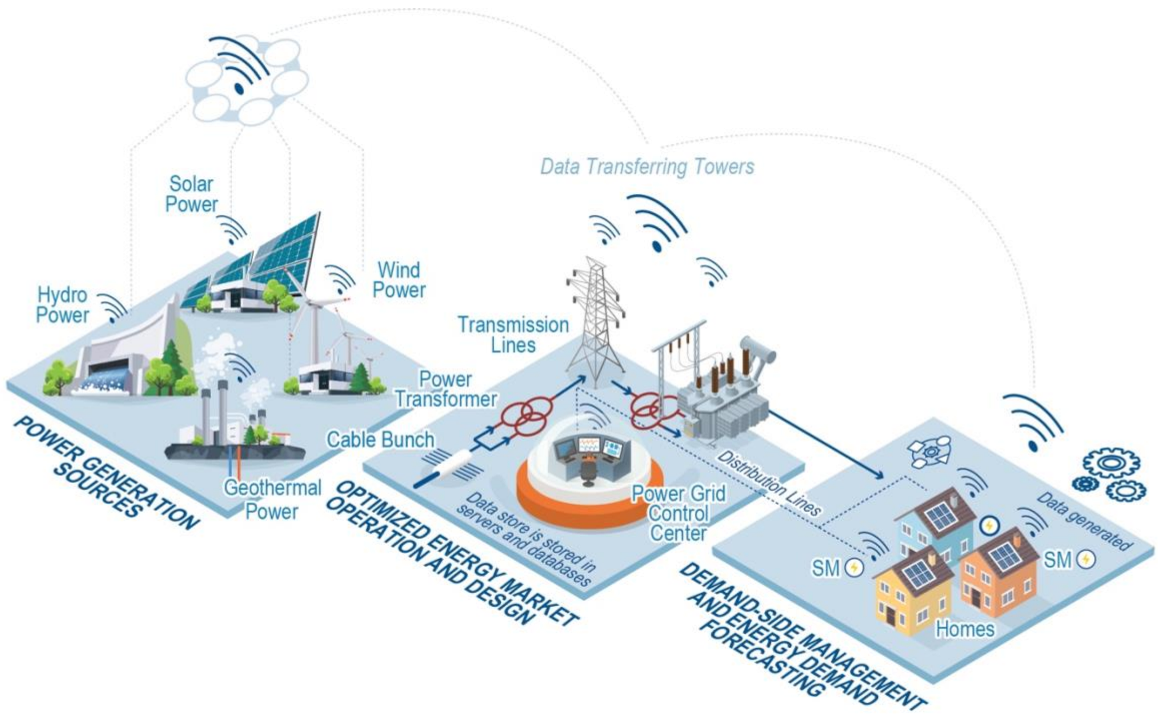


Figure 3-2. Power grid with data transfer

C. End-Use Devices

"End-use devices" include appliances, lighting, electric vehicles (EVs), air conditioning and any other equipment that consumes electricity. In 2023, there were roughly 13 billion end-use devices with automated sensors and controls globally.[73] Better management of these end-use devices can help significantly improve energy efficiency and reduce GHG emissions.

AI can play a central role in managing end-use devices. Indeed, AI tools are essential for leveraging the enormous quantities of data from end-use devices into performance gains. AI can predict energy demand patterns and adjust device settings to improve efficiency, cut energy use and reduce emissions. AI can optimize operation of smart devices, such as appliances, lighting systems and thermostats, to ensure these devices consume less energy during periods of high demand or low renewable power supplies. AI can facilitate demand response programs, virtual power plants, EV charging and peer-to-peer energy trading.

Demand prediction using AI already exhibits great potential. AI can predict general energy demand patterns[74] and demand patterns for specific sectors, such as buildings[75] and EV charging.[76] These demand predictions can be used for system operations, including for unit commitment (short-term) and system planning (long-term).

Aside from passively predicting electricity demand, AI can also be used to actively reshape demand profiles. In demand response programs, volunteers agree to limit electricity consumption for financial reward. This helps reduce GHG emissions by avoiding the need to turn on peaker plants for additional electricity generation. Antonopoulos et al. (2020) reviewed AI approaches for demand response, finding that AI can capture human feedback and motivate electricity users to participate in demand response programs.[77] Demand-side AI tools require significant data with high spatiotemporal resolution, which requires enabling infrastructure (such as smart meters) and can create privacy concerns.

AI plays an especially important role in virtual power plants (VPPs) -- networks of decentralized, distributed energy resources including end-use devices that are integrated and managed using advanced software.[78,79] VPPs reduce GHG emissions by helping integrate renewable power into electric grids and (like demand response programs) helping limit the need for peaker plants. Many VPPs combine AI-driven demand predictions and the ability to manipulate the power demand of end-use devices:

- Several US states facing peak demand problems have programs to combine consumer assets, including home batteries, smart thermostats, EVs and more, into a VPP. By controlling these devices in aggregate and making small changes to their operational programming, utilities and retailers can shift load from times of peak demand and peak prices, reducing overall costs.[80]
- In Japan, the Kyocera Corporation has implemented an AI-driven VPP system that aggregates energy from numerous distributed sources, including solar panels and battery storage, to optimize energy distribution and balance supply and demand in real time.[81]
- In Germany, Next Kraftwerke operates a VPP that uses AI to manage over 10,000 decentralized energy units.[82]
- One report suggests the savings from VPPs in California could help utilities save up to $755 million in power system costs, while consumers could save up to $550 million per year by 2035 if the current trajectory of VPP deployment continues.[83]

AI can be especially helpful with EV charging. AI tools can help optimize EV charging station locations, predict EV power demand, increase EV charger utilization, schedule EV charging to reduce costs and implement V2G programs.[84-86] (See discussion of V2G programs below.)

Finally, AI can help establish intelligent peer-to-peer energy trading platforms and predictive analysis.[87,88] Peer-to-peer energy can help reduce GHG emissions in several ways, such as by allowing households and businesses with solar PV panels to sell excess clean energy directly to other consumers and by reducing the distance electricity needs to travel, cutting transmission and distribution losses.[89,90]

In conclusion, AI could play an important role in managing end-use devices—helping to optimize their operation, increase energy efficiency and reduce GHG emissions.

D. Energy Storage

As more solar and wind power is deployed, energy storage is becoming an essential part of the electric grid. Energy storage balances temporal mismatch in supply and demand, serving as both generation and load. AI can help plan for energy storage, schedule its operation and optimize its lifetime value. AI can also help accelerate innovation in energy storage.

Energy storage is growing significantly around the world. In the United States, the investment tax credit for stand-alone storage in the Inflation Reduction Act of 2022 creates powerful new incentives for utility scale battery storage, and deployment is growing rapidly.[91,92] In China, battery storage featured prominently in the 14th Five Year Plan (2021–2025), which directed more than 100 billion RMB to the market. In 2023, newly installed capacity was nearly 50 GWh, an increase of more than 60% from the end of 2022.[93] In Europe, battery storage installations are led by the United Kingdom, Germany and Italy, where policy incentives and high energy prices are creating ideal market conditions for rapid deployment, especially alongside renewable power generation.[94,95]

Types of energy storage systems include (1) electrochemical storage, such as lithium-ion batteries, flow batteries and capacitors; 2) pumped hydro energy; 3) chemical storage, such as hydrogen; 4) thermal storage, such as molten salt, paraffin and metals and 5) mechanical storage, such as flywheels and compressed air.[96]

AI can help integrate energy storage into power grids, predicting when renewable power will be curtailed and supporting energy storage scheduling more broadly.[50,97,98] AI can also help battery owners plan for maintenance and replacement of energy storage assets.[99,100]

AI is especially well-suited to energy storage due to the dynamic nature of the optimization needed for battery management. Battery storage operators must consider many factors in making decisions, including safety, market signals and weather at the site of related solar and wind power facilities. Multi-factor models with this level of complexity are well-suited to AI algorithms for finding optimal variables on very short timeframes. Many AI algorithms are fast to train and deploy and can be very effective in helping operators respond to real-time market conditions to maximize revenue and optimize asset usage.

AI has a range of other benefits for energy storage, including preventive maintenance and optimization of consumable components, such as rolling bearings of flywheel-battery hybrid storage.[101] AI can be used to optimize combined systems, such as those with wind, pumped hydro and hydrogen[102]; integrate price and energy forecasts for hydrogen energy storage operation and control[103]; and (as discussed in Chapter 13) accelerate innovation in battery chemistry.

EVs have significant potential as distributed energy storage, sometimes referred to as mobile energy storage, V2G or vehicle-to-everything (V2X).[104] Aggregated volumes of energy storage in EV are very large in scale—many times greater than deployed amounts of stationary storage. Most vehicles are parked most of the time. However, to use EVs as grid assets, grid managers must understand and pay careful attention to drivers' use of their vehicles for mobility services, which will be a priority for most drivers in most situations. AI can be used for predicting user charging behaviors,[105] helping solve vehicle routing optimization problems[106] and improving V2G performance.[107,108] AI can maximize the value of data collected from vehicles, facilitating deployment of V2G technologies.

E. Barriers

Several barriers limit the adoption of AI for decarbonization of the power sector.

First, the use of AI in the power sector is limited by poor data quality and governance. The accuracy and efficacy of any AI modeling technique depends on clean, well-organized and well-governed data. Many parts of the power sector will need to invest in making their data available in an industry-standard way. The myriad benefits of AI discussed above will be limited unless the underlying inputs can be cleaned, organized and deployed in a way that AI models can consume.

In the United States, for example, standardized data (in tables with descriptions and access points that are the same across each organization) do not exist in the power sector today. Utilities, independent system operators (ISOs) and regional transmission organizations (RTOs) make data available in slightly different ways—across different time horizons, in different formats and with different frequencies—thus making it impossible to do analysis across all the relevant players in the power system. Private companies and the US Energy Information Administration (EIA) are doing some of this standardization work, but getting comparable data sets across all major US regions at a granular level remains very onerous from a data engineering perspective. Thoughtful governance to reduce privacy risks and model bias stemming from poor quality data is also essential.

Second, the lack of AI-training in the workforce is a significant barrier. AI's application in grid infrastructure requires a workforce that is knowledgeable on both the electric grid and AI. This knowledge base is important for research and development (R&D), technology deployment and policy design. The rapid advance of AI in software and technology systems will yield the best results if workers are equipped with a baseline of strong technical skills to understand the appropriate and safe use cases for AI.

Finally, poor market design can hinder adoption of AI in the power sector. When market structures do not adequately reward innovation or the integration of advanced technologies like AI, utilities and other stakeholders may be reluctant to invest in AI-driven solutions. Fragmented markets and inconsistent regulations across regions can complicate the deployment of AI, limiting its potential to optimize energy systems, reduce emissions and enhance grid reliability.

F. Risks

Deploying AI in the power sector creates a number of serious risks, including those related to bias, invasions of privacy, safety and security.

First, AI can lead to biased outcomes when training data do not accurately represent real-world conditions. For example, an AI model trained on power system data without adequate information on poor communities could recommend infrastructure investments that fail to adequately serve those communities. A model trained on data from the Global North could produce inaccurate information or suboptimal outcomes when used in the Global South. Data sets from one region could work poorly in another region due to differences in weather conditions, topographies or other factors.

Second, use of AI in the power sector could result in privacy breaches. AI systems require large amounts of data to function well. Data collection on topics such as energy consumption patterns and customer payment histories may be important for some AI applications but creates a risk of unauthorized access, identity theft and related problems. (This risk principally occurs with respect to AI in end-use devices and with distribution utilities—not with use of AI in generation, transmission or energy storage.)

Third, catastrophic failures could result if an AI system recommends or makes an incorrect decision due to a flaw in its algorithm or an unforeseen situation. Such failures could include equipment damage, power outages or worse. Rigorous testing, continuous monitoring and robust fail-safe mechanisms are crucial to ensure the safety of AI-operated energy systems. Transparency and interpretability of AI models are essential to create trust in AI systems.

Fourth, AI systems are susceptible to cyberattacks, including adversarial attacks where malicious actors manipulate the AI's input data to cause harmful outputs. Such attacks can compromise the integrity of the AI system, leading to incorrect decisions that could disrupt power supply, damage infrastructure or even facilitate further attacks on the grid. Robust cybersecurity measures, regular updates and stringent access controls are essential to protect AI systems from such threats.

In April 2024, the US DOE released a report on *Potential Benefits and Risks of Artificial Intelligence for Critical Energy Infrastructure,* which found that:

> *"while a number of significant risks exist if AI is used or deployed naïvely, most risks can be mitigated through best practices, putting appropriate protections around important data and models, and in some cases, funding further research on mitigation techniques."*[109]

G. Conclusion

In summary, AI has significant potential to help decarbonize the power sector in several areas.

- Short-term predictions based on time-series data. Predictions of electricity demand, solar availability and wind speed are necessary for operating electric grids and power markets. These types of data follow certain physical laws and patterns of human behavior but are intrinsically stochastic. Prediction is possible but difficult with conventional non-AI algorithms. AI can detect patterns in historical data that improve predictive abilities enormously.

- Scenario development, such as for EV charging and renewable power deployment*.* These scenarios are important to guide grid planning, especially in light of uncertainties related to climate change impacts and the deployment of new technologies. If rich historical data are available, AI tools can help significantly with these tasks.
- Improving optimization, such as for planning problems. Many power grid optimization problems involve work with large, nonlinear models. AI can speed computation, improve feature extraction and help solve "optimization unsolvable" problems, such as stochastic planning. Data support for these model-based problems is generally less critical than in other areas.
- System integration and operation. The grid infrastructure is becoming more and more inclusive and increasingly exposed to real-time uncertainties, such as wind/solar fluctuation. Taking a systematic view, instead of focusing on certain grid components, is more critical than in the past. Furthermore, grid operations have objectives related to cost, reliability, resilience, equity GHG emissions. AI shows great promise in helping grid managers understand more complex and quickly evolving grid infrastructure.

AI has potential application in nearly all aspects of power-sector management, including planning, monitoring, maintenance and operations. AI is becoming an important tool to help decarbonize the power sector. However, AI tools for decarbonization are not yet widely deployed. Barriers must be overcome and several risks must be addressed to realize AI's full potential to contribute to power sector decarbonization.

H. Recommendations

1. *Utilities and independent power producers should use AI tools for a wide range of purposes, including helping to plan renewables projects, monitor the condition of power equipment, integrate distributed energy resources into the grid, run demand response programs and optimize the use of energy storage systems. In doing so, utilities and independent power producers should prioritize rigorous testing, continuous monitoring and robust fail-safe mechanisms, setting benchmarks for the transparency of AI systems.*
2. *Electricity regulators should create clear regulatory frameworks to support using AI in energy management. These frameworks should include rates that provide cost recovery for AI-related investments, such as smart meters, sensors and open-source grid management software. The frameworks should address risks related to data privacy, safety and cybersecurity.*
3. *National governments, electricity regulators and utilities should work together to develop and enforce data standards for all aspects of grid operations. Regional governing bodies, such as the US ISOs and RTOs, should prioritize standardization of data to enable cross-regional analysis. These data should be available in industry standard formats in free and publicly available portals for use in AI modeling and research.*
4. *Utilities, regulatory agencies and academic experts should work together to develop AI-driven AC-OPF (alternating current-optimal power flow) models and permitting reforms. These models should be used to reduce delays in the interconnection process and accelerate deployment of new renewable generation sources to the grid.*
5. *Academic experts should emphasize geographic specificity in AI-driven weather models to increase the utility of weather forecasting for renewable energy production within specific boundaries (e.g., ISOs, climate zones). These experts should develop models that forecast within a smaller range than nearby weather station radii, focusing on wind direction, wind speed, solar radiation and cloud cover.*
6. *Utilities and electricity regulators should launch programs for training workers in the power sector to assess and use AI-driven technologies.*
7. *National governments should encourage and fund collaborative R&D projects between academic institutions, industry and utilities focused on AI and related applications for renewable power, energy efficiency and emissions reduction, including AI-driven forecasting tools and grid management systems.*

I. References

1 Statista. *Distribution of carbon dioxide emissions worldwide in 2023, by sector;* Hamburg, Germany, https://www.statista.com/statistics/1129656/global-share-of-co2-emissions-from-fossil-fuel-and-cement/ (Accessed October 2024).

2 EDGAR - Emissions Database for Global Atmospheric Research. *GHG emissions of all world countries;* European Commission Joint Research Centre, Brussels, Belgium, https://edgar.jrc.ec.europa.eu/report_2023 (Accessed October 2024).

3 International Energy Agency (IEA). *Net Zero by 2050: A Roadmap for the Global Energy Sector;* Paris, France, https://www.iea.org/reports/net-zero-by-2050 (2021).

4 Net-Zero America. *Net-Zero America: Potential Pathways, Infrastructure, and Impacts;* Princeton University, Princeton, New Jersey, https://netzeroamerica.princeton.edu/?explorer=year&state=national&table=2020&limit=200 (Accessed August 2024).

5 Hannah Ritchie & Pablo Rosado. *Electricity Mix: Explore data on where our electricity comes from and how this is changing;* Our World in Data, Oxford, England, https://ourworldindata.org/electricity-mix (2020 (Updated 2024)).

6 Peter Lovegrove. *Energy Transition Outlook: Renewables still not replacing fossil fuels in the global energy mix;* Det Norske Veritas (DNV), Høvik, Norway, https://www.dnv.com/news/energy-transition-outlook-renewables-still-not-replacing-fossil-fuels-in-the-global-energy-mix-247880/ (2023).

7 International Energy Agency (IEA). Overview and key findings in *World Energy Investment 2023* (Paris, France, 2023, https://www.iea.org/reports/world-energy-investment-2023/overview-and-key-findings).

8 Ryna Yiyun Cui *et al.* Quantifying operational lifetimes for coal power plants under the Paris goals. *Nature Communications* 10, 4759 (2019). https://doi.org/10.1038/s41467-019-12618-3.

9 Valentin Vogl, Olle Olsson & Björn Nykvist. Phasing out the blast furnace to meet global climate targets. *Joule* 5, 2646-2662 (2021). https://doi.org/10.1016/j.joule.2021.09.007.

10 International Energy Agency (IEA). *World Energy Investment 2024;* Paris, France, https://www.iea.org/reports/world-energy-investment-2024 (2024).

11 David Rolnick *et al.* Tackling Climate Change with Machine Learning. *ACM Comput. Surv.* 55, Article 42 (2022). https://doi.org/10.1145/3485128.

12 Claus Daniel *et al. Advanced Research Directions on AI for Energy: Report on Winter 2023 Workshops;* US Department of Energy (DOE), Washington, D.C., https://doi.org/10.2172/2340139 (2024).

13 Vladimir Franki, Darin Majnarić & Alfredo Višković. A Comprehensive Review of Artificial Intelligence (AI) Companies in the Power Sector. *Energies* 16, 1077 (2023). https://doi.org/10.3390/en16031077.

14 Sonal Patel. *AI's Paradox in the Power Sector—Unleashing Potential but Confronting Uncertainty;* Power Magazine, Houston, Texas, https://www.powermag.com/ais-paradox-in-the-power-sector-unleashing-potential-but-confronting-uncertainty/ (2024).

15 E. Engel & N. Engel. A Review on Machine Learning Applications for Solar Plants. *Sensors-Basel* 22 (2022). https://doi.org/10.1016/j.nexus.2021.10001110.3390/s22239060.

16 R. Ahmed *et al.* A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization. *Renew Sust Energ Rev* 124 (2020). https://doi.org/10.1016/j.rser.2020.109792.

17 L. Ekonomou *et al.* Estimation of wind turbines optimal number and produced power in a wind farm using an artificial neural network model. *Simul Model Pract Th* 21, 21-25 (2012). https://doi.org/10.1016/j.simpat.2011.09.009.

18 S. A. Renganathan *et al.* Data-driven wind turbine wake modeling via probabilistic machine learning. *Neural Comput Appl* 34, 6171-6186 (2022). https://doi.org/10.1007/s00521-021-06799-6.

19 S. Y. Zou *et al.* Optimization of the electricity generation of a wave energy converter using deep reinforcement learning. *Ocean Eng* 244 (2022). https://doi.org/10.1016/j.oceaneng.2021.110363.

20 E. R. Okoroafor *et al.* Machine learning in subsurface geothermal energy: Two decades in review. *Geothermics* 102 (2022). https://doi.org/10.1016/j.geothermics.2022.102401.

21 Keith J. Benes, Joshua E. Porterfield & Charles Yang. *AI for Energy: Opportunities for a Modern Grid and Clean Energy Economy;* US Department of Energy (DOE), Washington, D.C., https://www.energy.gov/sites/default/files/2024-04/AI%20EO%20Report%20Section%205.2g%28i%29_043024.pdf (2024).

22 Symbium. *Symbium Solar Permits: Join Symbium's solar permitting pilot;* San Francisco, California, https://symbium.com/instantpermitting/solar/california/sb379 (Accessed August 2024).

23 US Department of Energy (DOE). *DOE Announces New Actions to Enhance America's Global Leadership in Artificial Intelligence;* Washington, D.C., https://www.energy.gov/articles/doe-announces-new-actions-enhance-americas-global-leadership-artificial-intelligence#:~:text=DOE%20is%20investing%20%2413%20million,used%20to%20develop%20software%20to (2024).

24 Electric Power Research Institute (EPRI). *Quick Insight Brief: Leveraging Artificial Intelligence for the Nuclear Energy Sector;* Palo Alto, California, https://www.epri.com/research/products/000000003002021067 (2021).

25 J. Del Ser *et al.* Randomization-based machine learning in renewable energy prediction problems: Critical literature review, new results and perspectives. *Appl Soft Comput* 118 (2022). https://doi.org/10.1016/j.asoc.2022.108526.

26 Quentin Paletta *et al.* Advances in solar forecasting: Computer vision with deep learning. *Advances in Applied Energy* 11, 100150 (2023). https://doi.org/10.1016/j.adapen.2023.100150.

27 S. X. Lv & L. Wang. Deep learning combined wind speed forecasting with hybrid time series decomposition and multi-objective parameter optimization. *Appl Energ* 311 (2022). https://doi.org/10.1016/j.apenergy.2022.118674.

28 G. Etxegarai *et al.* An analysis of different deep learning neural networks for intra-hour solar irradiation forecasting to compute solar photovoltaic generators' energy production. *Energy Sustain Dev* 68, 1-17 (2022). https://doi.org/10.1016/j.esd.2022.02.002.

29 P. L. Donti & J. Z. Kolter. Machine Learning for Sustainable Energy Systems. *Annu Rev Env Resour* 46, 719-747 (2021). https://doi.org/10.1146/annurev-environ-020220-061831.

30 C. Wei *et al.* Reinforcement-Learning-Based Intelligent Maximum Power Point Tracking Control for Wind Energy Conversion Systems. *Ieee T Ind Electron* 62, 6360-6370 (2015). https://doi.org/10.1109/Tie.2015.2420792.

31 A. Saenz-Aguirre *et al.* Performance enhancement of the artificial neural network-based reinforcement learning for wind turbine yaw control. *Wind Energy* 23, 676-690 (2020). https://doi.org/10.1002/we.2451.

32 N. Padmavathi, A. Chilambuchelvan & N. R. Shanker. Maximum Power Point Tracking During Partial Shading Effect in PV System Using Machine Learning Regression Controller. *J Electr Eng Technol* 16, 737-748 (2021). https://doi.org/10.1007/s42835-020-00621-4.

33 Kaifeng Bi *et al.* Accurate medium-range global weather forecasting with 3D neural networks. *Nature* 619, 533-538 (2023). https://doi.org/10.1038/s41586-023-06185-3.

34 Remi Lam *et al.* Learning skillful medium-range global weather forecasting. *Science* 382, 1416-1421 (2023). https://doi.org/10.1126/science.adi2336.

35 Sergey Frolov *et al.* Integration of emerging data-driven models into the NOAA research to operation pipeline for numerical weather prediction. *Bulletin of the American Meteorological Society* (2024). https://doi.org/10.1175/BAMS-D-24-0062.1.

36 Nina Raffio. *USC scientists use AI to predict a wildfire's next move;* United Nations Office for Disaster Risk Reduction (UNDRR) Prevention Web, Geneva, Switzerland, https://www.preventionweb.net/news/usc-scientists-use-ai-predict-wildfires-next-move (2024).

37 K. Mukilan *et al.* Prediction of Rooftop Photovoltaic Solar Potential Using Machine Learning. *Int J Photoenergy* 2022 (2022). https://doi.org/10.1155/2022/1541938.

38 M. Cordeiro-Costas *et al.* Machine Learning and Deep Learning Models Applied to Photovoltaic Production Forecasting. *Appl Sci-Basel* 12 (2022). https://doi.org/10.3390/app12178769.

39 C. G. Dong *et al.* Machine learning reduces soft costs for residential solar photovoltaics. *Sci Rep-Uk* 13 (2023). https://doi.org/10.1038/s41598-023-33014-4.

40 L. Li *et al.* A review of applications in federated learning. *Comput Ind Eng* 149 (2020). https://doi.org/10.1016/j.cie.2020.106854.

41 P. Hosseini *et al.* Privacy-preserving federated learning: Application to behind-the-meter solar photovoltaic generation forecasting. *Energ Convers Manage* 283 (2023). https://doi.org/10.1016/j.enconman.2023.116900.

42 J. C. Jiang *et al.* Federated Learning in Smart City Sensing: Challenges and Opportunities. *Sensors-Basel* 20 (2020). https://doi.org/10.3390/s20216230.

43 C. H. Yeh *et al.* Machine Learning for Long Cycle Maintenance Prediction of Wind Turbine. *Sensors-Basel* 19 (2019). https://doi.org/10.3390/s19071671.

44 A. A. Jimenez *et al.* Maintenance management based on Machine Learning and nonlinear features in wind turbines. *Renew Energ* 146, 316-328 (2020). https://doi.org/10.1016/j.renene.2019.06.135.

45 Isaac Segovia Ramírez, Fausto Pedro García Márquez & Jesús Parra Chaparro. Convolutional neural networks and Internet of Things for fault detection by aerial monitoring of photovoltaic solar plants. *Measurement* 234, 114861 (2024). https://doi.org/10.1016/j.measurement.2024.114861.

46 H. A. Gohel *et al.* Predictive maintenance architecture development for nuclear infrastructure using machine learning. *Nucl Eng Technol* 52, 1436-1442 (2020). https://doi.org/10.1016/j.net.2019.12.029.

47 K Kumar *et al.* Daily Plant Load Analysis of a Hydropower Plant Using Machine Learning in *In Applications of Artificial Intelligence in Engineering* (eds X.Z. Gao, R. Kumar, S. Srivastava, & B.P Soni) 819-826 (https://doi.org/810.1007/1978-1981-1033-4604-1008_1065) (Springer, Singapore, 2021, https://link.springer.com/chapter/10.1007/978-981-33-4604-8_65).

48 Fabian Neumann *et al.* The potential role of a hydrogen network in Europe. *Joule* 7, 1793-1817 (2023). https://doi.org/10.1016/j.joule.2023.06.016.

49 Guishi Cheng *et al.* Analysis and prediction of green hydrogen production potential by photovoltaic-powered water electrolysis using machine learning in China. *Energy* 284, 129302 (2023). https://doi.org/10.1016/j.energy.2023.129302.

50 Mohammad H. Shams *et al.* Machine learning-based utilization of renewable power curtailments under uncertainty by planning of hydrogen systems and battery storages. *J Energy Storage* 41, 103010 (2021). https://doi.org/10.1016/j.est.2021.103010.

51 Mohammad Mahbub Kabir *et al.* Machine learning-based prediction and optimization of green hydrogen production technologies from water industries for a circular economy. *Desalination* 567, 116992 (2023). https://doi.org/10.1016/j.desal.2023.116992.

52 R. Venkatasatish & C. Dhanamjayulu. Reinforcement learning based energy management systems and hydrogen refuelling stations for fuel cell electric vehicles: An overview. *International Journal of Hydrogen Energy* 47, 27646-27670 (2022). https://doi.org/10.1016/j.ijhydene.2022.06.088.

53 Amirmohammad Behzadi *et al.* An efficient renewable hybridization based on hydrogen storage for peak demand reduction: A rule-based energy control and optimization using machine learning techniques. *J Energy Storage* 57, 106168 (2023). https://doi.org/10.1016/j.est.2022.106168.

54 The Economist. *AI and other tricks are bringing power lines into the 21st century;* London, UK, https://www.economist.com/business/2024/05/05/ai-and-other-tricks-are-bringing-power-lines-into-the-21st-century (2024).

55 M. Mahdavi *et al.* Transmission Expansion Planning: Literature Review and Classification. *Ieee Syst J* 13, 3129-3140 (2019). https://doi.org/10.1109/Jsyst.2018.2871793.

56 Stefan Borozan *et al.* A Machine Learning-Enhanced Benders Decomposition Approach to Solve the Transmission Expansion Planning Problem under Uncertainty. *arXiv* (2023). https://doi.org/10.48550/arXiv.2304.07534.

57 Y. H. Wang *et al.* Flexible Transmission Network Expansion Planning Based on DQN Algorithm. *Energies* 14 (2021). https://doi.org/10.3390/en14071944.

58 Y. H. Wang *et al.* Transmission Network Expansion Planning Considering Wind Power and Load Uncertainties Based on Multi-Agent DDQN. *Energies* 14 (2021). https://doi.org/10.3390/en14196073.

59 X. Q. Fu, Q. L. Guo & H. B. Sun. Statistical Machine Learning Model for Stochastic Optimal Planning of Distribution Networks Considering a Dynamic Correlation and Dimension Reduction. *Ieee T Smart Grid* 11, 2904-2917 (2020). https://doi.org/10.1109/Tsg.2020.2974021.

60 Pascal Van Hentenryck. Machine Learning for Optimal Power Flows. *Emerging Optimization Methods and Modeling Techniques with Applications*, 62-82 (2021). https://doi.org/10.1287/educ.2021.0234.

61 F. Hasan, A. Kargarian & A. Mohammadi. “A Survey on Applications of Machine Learning for Optimal Power Flow” in *2020 IEEE Texas Power and Energy Conference (TPEC)*, College Station, Texas. 1-6, https://doi.org/10.1109/TPEC48276.2020.9042547,(2020).

62 Hooman Khaloie *et al.* Review of Machine Learning Techniques for Optimal Power Flow. *Preprint submitted to Elsevier* (2024). http://dx.doi.org/10.13140/RG.2.2.31375.36008.

63 D. Owerko, F. Gama & A. Ribeiro. “Unsupervised Optimal Power Flow Using Graph Neural Networks” in *ICASSP 2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Seoul, South Korea. 6885-6889, https://doi.org/10.1109/ICASSP48485.2024.10446827,(2024).

64 National Renewable Energy Laboratory (NREL). *On the Road to Increased Transmission: Dynamic Line Ratings: How Dynamic Line Ratings Can Adapt to Changing Weather Conditions To Enhance Transmission;* Golden, Colorado, https://www.nrel.gov/news/program/2024/on-the-road-to-increased-transmission-dynamic-line-ratings.html (2024).

65 A. Mansour Saatloo *et al.* Hierarchical Extreme Learning Machine Enabled Dynamic Line Rating Forecasting. *Ieee Syst J* 16, 4664-4674 (2022). https://doi.org/10.1109/JSYST.2021.3128213.

66 Jeff St. John. *Better real-time data for the country’s congested transmission lines;* Canary Media, New York, New York, https://www.canarymedia.com/articles/transmission/better-real-time-data-for-the-countrys-congested-transmission-lines (2024).

67 Abdelrahman Sobhy, Tamer F. Megahed & Mohammed Abo-Zahhad. Overhead transmission lines dynamic rating estimation for renewable energy integration using machine learning. *Energy Reports* 7, 804-813 (2021). https://doi.org/10.1016/j.egyr.2021.07.060.

68 P. Stefanidou-Voziki *et al.* A review of fault location and classification methods in distribution grids. *Electr Pow Syst Res* 209 (2022). https://doi.org/10.1016/j.epsr.2022.108031.

69 M. Shafiullah, K. A. AlShumayri & M. S. Alam. Machine learning tools for active distribution grid fault diagnosis. *Adv Eng Softw* 173 (2022). https://doi.org/10.1016/j.advengsoft.2022.103279.

70 Safegrid. *Electrical Grid Fault Detection;* Espoo, Finland, https://safegrid.io/electrical-grid-fault-detection/ (2023).

71 Jorge De La Cruz *et al.* Fault Location for Distribution Smart Grids: Literature Overview, Challenges, Solutions, and Future Trends. *Energies* 16, 2280 (2023). https://doi.org/10.3390/en16052280.

72 J. Xie, I. Alvarez-Fernandez & W. Sun. A Review of Machine Learning Applications in Power System Resilience. *Ieee Pow Ener Soc Ge* (2020). https://doi.org/10.1109/PESGM41954.2020.9282137.

73 Pauline Henriot. *Unleashing the benefits of data for energy systems;* International Energy Agency (IEA), Paris, France, https://www.iea.org/commentaries/unleashing-the-benefits-of-data-for-energy-systems (2023).

74 B. Hrnjica & A.D. Mehr. Energy Demand Forecasting Using Deep Learning in *Smart Cities Performability, Cognition, and Security* (ed Fadi Al-Turjman) 71-104 (https://doi.org/110.1007/1978-1003-1030-14718-14711_14714) (Springer, Cham, 2020, https://link.springer.com/chapter/10.1007/978-3-030-14718-1_4#citeas).

75 R. Olu-Ajayi *et al.* Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. *J Build Eng* 45 (2022). https://doi.org/10.1016/j.jobe.2021.103406.

76 Z. Y. Yi *et al.* Electric vehicle charging demand forecasting using deep learning model. *J Intell Transport S* 26, 690-703 (2022). https://doi.org/10.1080/15472450.2021.1966627.

77 I. Antonopoulos *et al.* Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. *Renew Sust Energ Rev* 130 (2020). https://doi.org/10.1016/j.rser.2020.109899.

78 Anna Demeo. *Why We Need True AI-Driven Virtual Power Plants;* Energy Changemakers, Charlottesville, Virginia, https://energychangemakers.com/ai-driven-virtual-power-plants/ (2024).

79 Energies Media Staff. *Why We Need AI-Driven Virtual Power Plants: A Step Towards Sustainable Energy;* Energies Media, Galveston, Texas, https://energiesmagazine.com/why-we-need-ai-driven-virtual-power-plants-a-step-towards-sustainable-energy/ (2024).

80 Brian Lips. *What are States Doing to Make Virtual Power Plants a Reality?;* N.C. Clean Energy Technology Center (NCCETC), Raleigh, North Carolina, https://nccleantech.ncsu.edu/2024/04/26/what-are-states-doing-to-make-virtual-power-plants-a-reality/ (2024).

81 Kyocera. *Virtual Power Plants: Connecting Homes and Tackling Energy Problems (Interview);* Kyoto, Japan, https://global.kyocera.com/be_innovation/environment-and-energy/interview2/ (Accessed August 2024).

82 Next Kraftwerke. *The Power of Many;* Cologne, Germany, https://www.next-kraftwerke.com/vpp (Accessed August 2024).

83 Ryan Hledik, Kate Peters & Sophie Edelman. *Virtual Power Plants Can Be a Solution for California's Growing Need for Affordable Capacity, According to a New Brattle Report;* Brattle (Prepared for

GridLab), Boston, Massachusetts, https://www.brattle.com/insights-events/publications/californias-virtual-power-potential-how-five-consumer-technologies-could-improve-the-states-energy-affordability/ (2024).

84 S. Deb. Machine Learning for Solving Charging Infrastructure Planning Problems: A Comprehensive Review. *Energies* 14 (2021). https://doi.org/10.3390/en14237833.

85 Y. M. Saputra *et al.* Energy Demand Prediction with Federated Learning for Electric Vehicle Networks. *Ieee Glob Comm Conf* (2019). https://doi.org/10.1109/globecom38437.2019.9013587.

86 Z. Teimoori, A. Yassine & M. S. Hossain. A Secure Cloudlet-Based Charging Station Recommendation for Electric Vehicles Empowered by Federated Learning. *Ieee T Ind Inform* 18, 6464-6473 (2022). https://doi.org/10.1109/Tii.2022.3148997.

87 F. Jamil *et al.* Peer-to-Peer Energy Trading Mechanism Based on Blockchain and Machine Learning for Sustainable Electrical Power Supply in Smart Grid. *IEEE Access* 9, 39193-39217 (2021). https://doi.org/10.1109/ACCESS.2021.3060457.

88 Dawei Qiu *et al.* Scalable coordinated management of peer-to-peer energy trading: A multi-cluster deep reinforcement learning approach. *Appl Energ* 292, 116940 (2021). https://doi.org/10.1016/j.apenergy.2021.116940.

89 Chathuri Lakshika Gunarathna *et al.* Reviewing global peer-to-peer distributed renewable energy trading projects. *Energy Research & Social Science* 89, 102655 (2022). https://doi.org/10.1016/j.erss.2022.102655.

90 Sachinkumar Suthar, S. Hari Charan Cherukuri & Naran M. Pindoriya. Power loss reduction in peer-to-peer energy trading-enabled distribution network. *Electr Pow Syst Res* 229, 110161 (2024). https://doi.org/10.1016/j.epsr.2024.110161.

91 Suparna Ray. *Solar and battery storage to make up 81% of new U.S. electric-generating capacity in 2024 (In-Brief Analysis);* US Energy Information Administration (EIA), Washington, D.C., https://www.eia.gov/todayinenergy/detail.php?id=61424 (2024).

92 Andy Colthorpe. *US sees 84% year-on-year rise in Q1 energy storage deployments, three states dominant;* Energy Storage News, London, UK, https://www.energy-storage.news/us-sees-84-year-on-year-rise-in-q1-energy-storage-deployments-three-states-dominant/ (2024).

93 National Energy Administration (NEA). *Transcript of the National Energy Administration's press conference for the first quarter of 2024;* The Stat Council of the People's Republic of China, Beijing, China, https://www.nea.gov.cn/2024-01/25/c_1310762019.htm (2024).

94 Directorate-General for Energy. *Recommendations on energy storage* European Commission, Brussels, Belgium, https://energy.ec.europa.eu/topics/research-and-technology/energy-storage/recommendations-energy-storage_en (Accessed August 2024).

95 Jacopo Tosoni. *EMMES 8.0 - March 2024 (Market Analysis);* European Association for Storage of Energy (EASE), Brussels, Belgium, https://ease-storage.eu/publication/emmes-8-0-march-2024/ (2024).

96 S. Koohi-Fayegh & M. A. Rosen. A review of energy storage types, applications and recent developments. *J Energy Storage* 27, 101047 (2020). https://doi.org/10.1016/j.est.2019.101047.

97 P. Moutis, S. Skarvelis-Kazakos & M. Brucoli. Decision tree aided planning and energy balancing of planned community microgrids. *Appl Energ* 161, 197-205 (2016). https://doi.org/10.1016/j.apenergy.2015.10.002.

98 K. S. Zhou, K. L. Zhou & S. L. Yang. Reinforcement learning-based scheduling strategy for energy storage in microgrid. *J Energy Storage* 51 (2022). https://doi.org/10.1016/j.est.2022.104379.

99 M. Aykol *et al.* Perspective-Combining Physics and Machine Learning to Predict Battery Lifetime. *J Electrochem Soc* 168 (2021). https://doi.org/10.1149/1945-7111/abec55.

100 Y. Z. Zhang & M. Y. Zhao. Cloud-based in-situ battery life prediction and classification using machine learning. *Energy Storage Mater* 57, 346-359 (2023). https://doi.org/10.1016/j.ensm.2023.02.035.

101 Zhenhua Wen *et al.* A novel machine learning model for safety risk analysis in flywheel-battery hybrid energy storage system. *J Energy Storage* 49, 104072 (2022). https://doi.org/10.1016/j.est.2022.104072.

102 Junsong Wang *et al.* Optimal design of combined operations of wind power-pumped storage-hydrogen energy storage based on deep learning. *Electr Pow Syst Res* 218, 109216 (2023). https://doi.org/10.1016/j.epsr.2023.109216.

103 Alexander Dreher *et al.* AI agents envisioning the future: Forecast-based operation of renewable energy storage systems using hydrogen with Deep Reinforcement Learning. *Energ Convers Manage* 258, 115401 (2022). https://doi.org/10.1016/j.enconman.2022.115401.

104 A Zahedi. "Electric Vehicle as distributed energy storage resource for future smart grid" in *2012 22nd Australasian Universities Power Engineering Conference (AUPEC)*, Bali, Indonesia. 1-4 (https://ieeexplore.ieee.org/document/6360205), 2012).

105 Y. W. Chung *et al.* Ensemble machine learning-based algorithm for electric vehicle user behavior prediction. *Appl Energ* 254 (2019). https://doi.org/10.1016/j.apenergy.2019.113732.

106 R. Basso, B. Kulcsar & I. Sanchez-Diaz. Electric vehicle routing problem with machine learning for energy prediction. *Transport Res B-Meth* 145, 24-55 (2021). https://doi.org/10.1016/j.trb.2020.12.007.

107 C. Scott, M. Ahsan & A. Albarbar. Machine Learning Based Vehicle to Grid Strategy for Improving the Energy Performance of Public Buildings. *Sustainability-Basel* 13 (2021). https://doi.org/10.3390/su13074003.

108 M. Shibl, L. Ismail & A. Massoud. Electric Vehicles Charging Management Using Machine Learning Considering Fast Charging and Vehicle-to-Grid Operation. *Energies* 14 (2021). https://doi.org/10.3390/en14196199.

109 Office of Cybersecurity U.S. Department of Energy (DOE), Energy Security, and Emergency Response (CESER). *Potential Benefits and Risks of Artificial Intelligence for Critical Energy Infrastructure (Summary Report);* Washington, D.C., https://www.energy.gov/sites/default/files/2024-04/DOE%20CESER_EO14110-AI%20Report%20Summary_4-26-24.pdf (2024).

CHAPTER 4:

FOOD SYSTEMS

Kevin Karl, Lily-belle Sweet, Cameron Kruse, Matteo Turchetta, Sarah Garland, Elena Mendez Leal, Ranveer Chandra and Alex C. Ruane

A. Food Systems and Climate Change Overview 4-2

B. Examples of AI Applications in Food Systems and Climate Change 4-4

C. Barriers 4-11

D. Risks 4-13

E. Recommendations 4-15

F. References 4-17

A. Food Systems and Climate Change Overview

Food systems—encompassing activities in agricultural production, land use change, supply chain activities and waste management—are critical to sustaining livelihoods and delivering nutrition worldwide (Figure 4-1). Food systems also contribute significantly to climate change. Recent estimates suggest that food systems produce about 30% of annual anthropogenic greenhouse gas (GHG) emissions: over 20% of carbon dioxide, 50% of methane and 75% of nitrous oxide.[1] Climate change, in turn, has a significant and growing impact on food systems. For example, climate change is poised to increase heat stress for crops and livestock, accelerate soil moisture loss and reduce the nutritional content of food.[2,3] The increasing frequency and duration of climate extremes, such as severe droughts and extreme rain events, endanger global food and nutrition security.

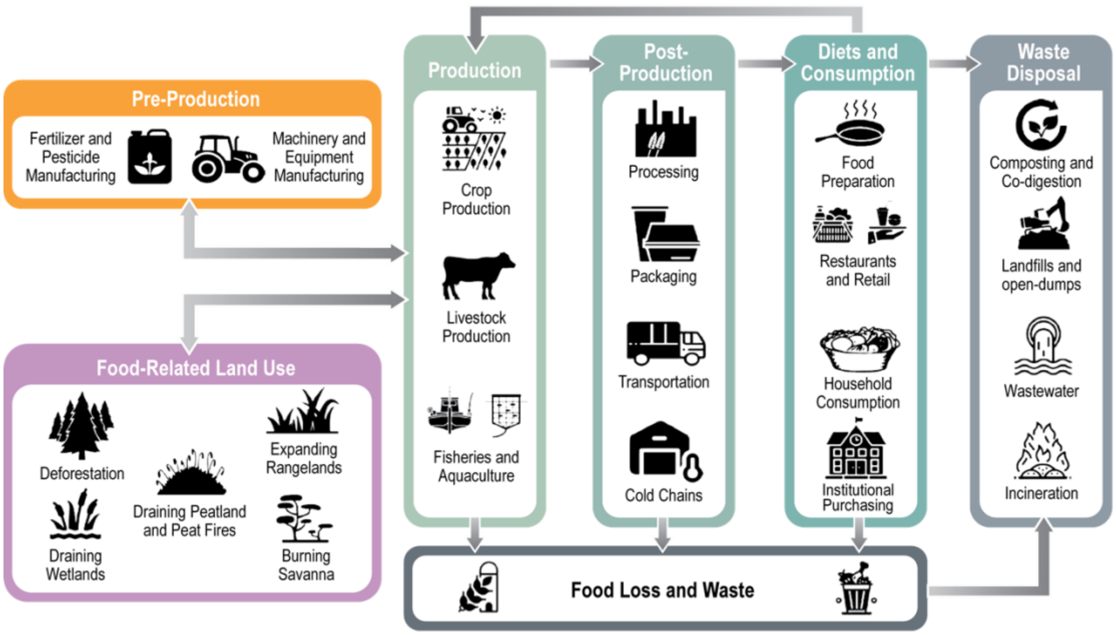


__Figure 4-1. An integrated overview of food systems.__ Food systems comprise a wide variety of inter-related activities, from the production of agricultural inputs (pre-production), food-related land use change, agricultural production and fisheries, post-farm-gate supply chains, consumption activities, and waste disposal. Adapted from Rosenzweig et al. (2020).[4]

A grand challenge lies in transforming food systems to be more sustainable, resilient and equitable, while increasing food security for a growing population in the face of climate change. Artificial intelligence (AI) technologies and processes offer significant potential to address this challenge by enabling more efficient, data-driven decision-making across food system activities. Recent advancements in AI, such as deep learning, computer vision, and natural language processing, combined with the increasing availability of large-scale agriculture and land use data, have created a unique opportunity to harness AI for transforming food systems.[5]

However, AI applications carry significant risks if models are developed and used without considerable caution. For example, an AI model trained to achieve a specific target (such as improving near-term agricultural yields) could produce results that ignore other objectives (e.g., social, nutritional, economic, cultural, environmental or ethical goals). The result could be suboptimal or even harmful outcomes.

Close collaboration between AI researchers, food system experts, farmers, policymakers and the private sector is necessary to ensure that AI solutions are aligned with broader goals in sustainability and justice. An ideal AI information ecosystem would feature coordination across various nodes of information transfer, supported by a series of guardrails and accelerators that ensure AI models are adaptive to changing conditions, inclusive of diverse and representative perspectives, and embedded in appropriate context (Figure 4-2).

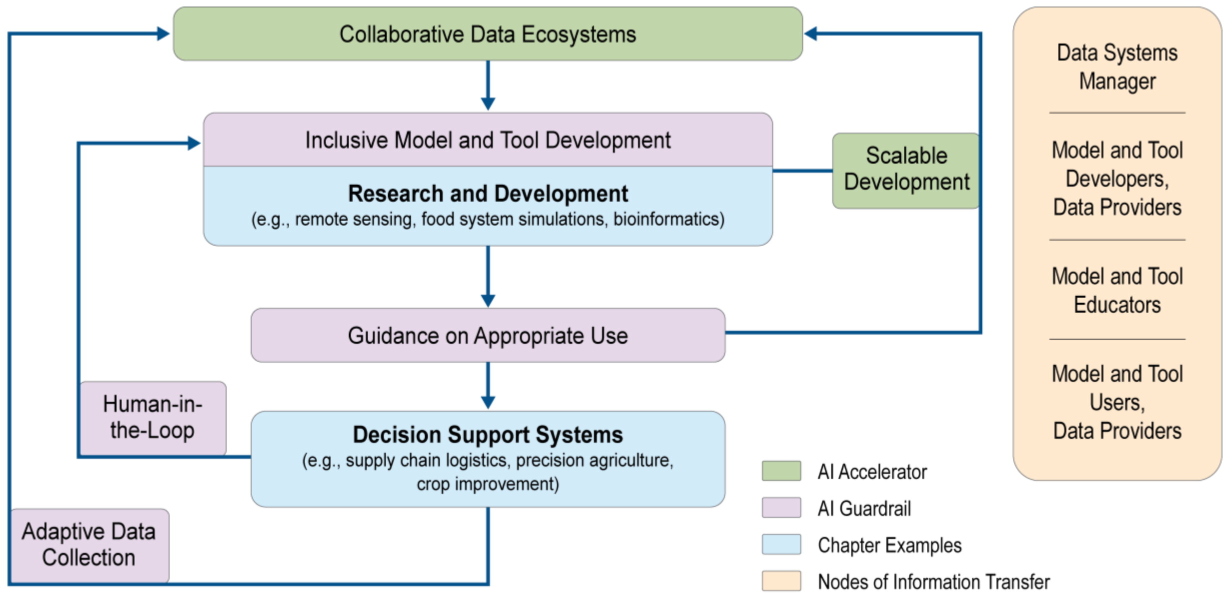


Figure 4-2. A coordinated, adaptive and inclusive AI information ecosystem for food systems. *A responsible and effective AI information chain is supported by AI acceleration processes (green) as well as process that establish AI guardrails (pink). Blue boxes represent examples of specific food systems applications or processes highlighted in this chapter. Red boxes represent where different groups of people fit into the picture as nodes of information synthesis and transfer.*

This chapter will describe example AI applications at the nexus of climate change and food systems, explore key components of an effective and responsible AI information chain, and conclude with recommendations for governments, businesses, scientists, international organizations, and civil society to ensure the appropriate use of this promising suite of technologies.

B. Examples of AI Applications in Food Systems and Climate Change

i. Overview

AI applications in food systems run the gamut from establishing early warning systems for pest and disease pressure on crops, optimizing energy use during food transportation and storage, and enhancing soil carbon sequestration efforts, among other transformational application areas.[6-8] AI tools are also used to rapidly develop novel alternative protein products with much lower carbon footprints than many animal-sourced foods, which are a key source of emissions from food systems.[9-13] AI-enhanced supply chain monitoring and solid waste management practices—such as improved resource recovery through computer vision—can greatly improve circularity in food systems and significantly reduce emissions from food waste in landfills (which contributes roughly 8% of global anthropogenic methane emissions).[14,15] Recent studies show that large language models, like GPT-4, perform well on agricultural exams and questions, sometimes outperforming humans.[16] AI models demonstrate potential in supporting agricultural education, assessment, and management decisions, offering new tools to assist farmers and agricultural professionals as they navigate novel challenges posed by climate change. There are myriad examples of promising use cases for AI to enhance food systems decision-making, reduce emissions, and enhance climate resilience. This chapter will focus on just a few.

ii. Remote sensing

Remote sensing involves synthesizing and analyzing satellite, drone and/or ground-based imagery to facilitate a wide array of food systems decisions.[17] Use cases span a variety of spatial scales—from field level monitoring of crop health, soil conditions, and land use change to regional monitoring of agricultural conditions to provide early warning for international trade markets.[18,19] There are currently roughly 50–100 remote sensing specific foundation models, each with unique architectures and strengths.[20] In Table 4-1, we break these use cases into three broad categories: object recognition, land use identification and temporal monitoring.

Table 4-1. *AI-Enhanced Remote Sensing Applications for Mitigation and Adaptation in Food Systems*

CATEGORY	USE CASE	VALUE
Object recognition	• Identifying concentrated animal feeding operations (CAFOs) and landfills • Estimating and anticipating crop yields using satellite imagery	• To better monitor and account for methane emissions from point sources (including from food waste in landfills) for improved decision-making in climate mitigation • To improve adaptation planning by accurately assessing crop production levels in historical conditions and improving satellite-based seasonal projections

CATEGORY	USE CASE	VALUE
Land use Identification	• Monitoring soil erosion and land degradation • Identifying the use of climate-smart agricultural practices	• To advance soil carbon sequestration potential and land suitability assessments (e.g., to support sustainable intensification and reduce land conversion pressure) • To monitor the prevalence of climate-smart practices, such as cover cropping, reduced tillage and no-till systems; can also be used to monitor and encourage the climate impact of agricultural land use through the albedo effect
Temporal monitoring	• Monitoring coastal erosion affecting agricultural lands • Tracking changes in water bodies affecting irrigation systems • Monitoring heat and water stress on crop and grassland productivity • Tracking the spread of plant diseases and pests over seasons	• To facilitate adaptive coastal management strategies that protect agricultural areas from the impacts of coastal erosion • To optimize irrigation management and water allocation by monitoring changes in water availability and distribution • To develop early warning systems for timely food security interventions • To facilitate early detection and control measures to mitigate the spread of diseases and pests, thus minimizing crop losses

As the success of OpenAI's ChatGPT demonstrated, applications that connect users with AI models are just as important as the models themselves. Figure 4-3 illustrates a tool called Earth Index, a product designed to connect users to geospatial AI models to increase accessibility for earth monitoring. The tool transforms satellite imagery into machine learning (ML) embeddings and makes them interactable by allowing users to select features of interest. Based on the embeddings, the model predicts where similar features would be located. After a few labeling iterations, the model can accurately predict new features that match. Earth Index has been used to identify illegal gold mining in the Amazon, find unregistered concentrated animal feeding operations (CAFOs), quantify plastic in landfills and much more.

AI Guardrail

HUMAN-IN-THE-LOOP MODEL AND TOOL IMPROVEMENT

Developing effective human-in-the-loop model-user interfaces is crucial for adopting and using AI tools in food systems applications, especially given the diverse backgrounds, expertise levels and information needs of end-users in this domain. These interfaces should be intuitive, user-friendly and adaptable, providing clear and actionable insights while allowing users to explore and interrogate the underlying data and assumptions behind AI model outputs. Moreover, these interfaces should incorporate mechanisms for user feedback and input. Such features would enable users to validate, refine and improve AI model performance over time by flagging inaccurate or irrelevant outputs, suggesting new data sources or features, and sharing their domain expertise and local knowledge. By actively engaging users in the iterative process of model improvement, human-in-the-loop interfaces can build trust, transparency and accountability in AI tools. This process would also ensure that such tools are tailored to the specific contexts and needs of end users.

Remote sensing benefits from large-scale, non-invasive monitoring of agricultural land use with high spatiotemporal and spectral resolution. Data are frequently updated, with near-global coverage, and can be integrated with physical models to enhance decision-making capabilities. However, challenges in gathering ground-truth data to validate analyses, combined with difficulties in obtaining consistent, high-quality imagery (e.g., due to cloud cover), can significantly reduce the robustness of decisions based solely on remotely sensed data.[21] The relatively short historical record also limits long-term climate change impact analysis. These factors necessitate careful consideration in implementing AI for remote sensing in food systems, such as developing human-in-the-loop processes as a guardrail.

iii. Agricultural simulations

Agricultural simulations, such as process-based climate-crop models, can project crop growth, yield, runoff and emissions under various genetic, environmental and management regimes. Process-based models form these projections by simulating biophysical processes in both current and future climate scenarios.[22] These models have been used to optimize yields, improve grain quality, reduce the environmental impacts of farming and increase profitability.[23] However, crop growth is influenced by complex interactions across myriad biophysical factors, and many of these compound effects are not yet well-understood, nor are they fully represented in process-based models.[24,25]

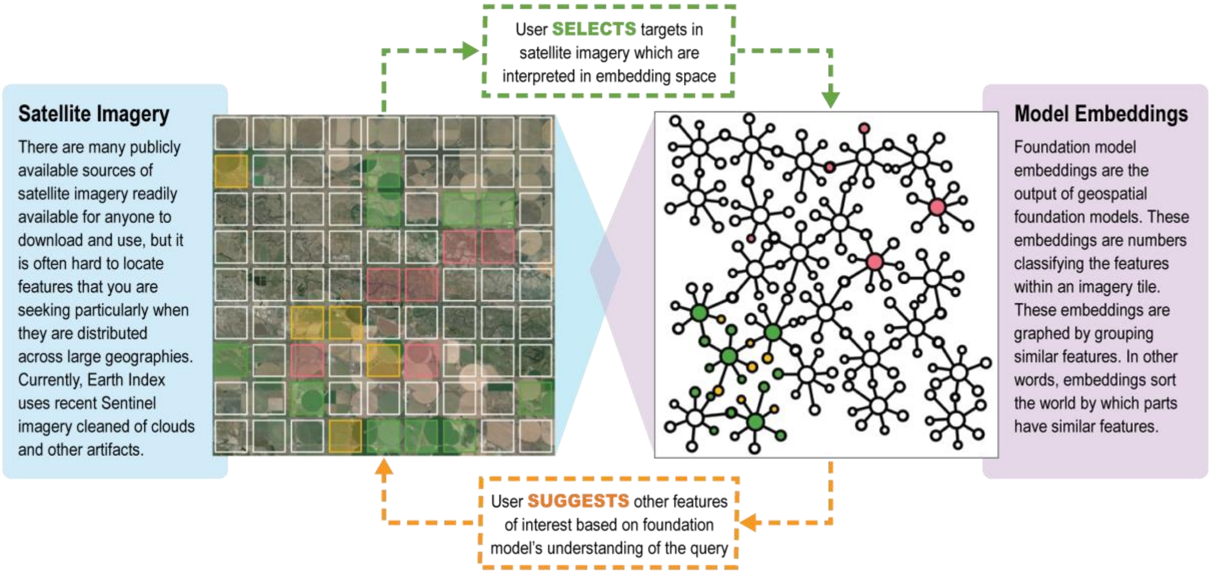


Figure 4-3. Efficient human-in-the-loop learning for AI-enhanced remote sensing analysis. *This schematic illustrates how Earth Index connects users to interactive geospatial AI models.*

ML models have emerged with new capabilities to predict global and regional crop yields based on climate conditions, satellite vegetation indices and other drivers.[26-28] These forecasts can be used to estimate regional or national crop production, assess potential supply chain disruptions, quantify high-resolution soil organic carbon changes, and guide allocation of resources to support farmers in adapting to changing climate conditions.[29] ML methods can also benefit from pre-training on available data from other crops and regimes or even on synthetic data from process-based models when dealing with data-limited crops or regions.[30-32] Recent research has experimented with novel ways to combine traditional process-based models with powerful ML models, resulting in hybrid models that are more likely than standalone ML models to produce plausible predictions when exposed to situations outside of the training set.[29,33,34] The Agricultural Model Intercomparison and Improvement Project (AgMIP) Machine Learning Activity (AgML) is coordinating efforts to build a collaborative community, including developing approaches that make the best combined use of process-based and data-driven models for agricultural impacts and adaptation analysis.

Precision Agriculture

OPTIMIZING RESOURCE USE FOR CLIMATE-SMART AGRICULTURE

Farmers can utilize the latest AI advances in remote sensing and agricultural simulations to optimize their use of inputs, such as irrigation, fertilizers and pesticides. For example, an AI-based decision support system for precision irrigation in a lettuce crop used a combination of soil moisture sensors, weather data and ML algorithms to optimize irrigation scheduling.[35] The results showed a 20% reduction in water use compared to traditional irrigation methods while maintaining crop yield and quality.

Reinforcement learning (RL) methods have recently been used to inform agricultural decision-making based on complex and high-dimensional data, such as historic weather, soil information, forecast and remote sensing data. Coupled with crop simulation models, RL interfaces can combine to create virtual farms by simulating different crops, weather conditions and soil properties.[36-39] By simulating a variety of management scenarios, researchers and farmers can set customized parameters and optimization algorithms. These simulations explore various crop growth and environmental outcomes, aiming to balance economic viability, GHG emission mitigation and other elements of environmental sustainability in food production.

AI applications in precision agriculture benefit from the availability of low-cost, reliable sensors and internet-connected farm equipment, the increased availability of agricultural drones and the growing adoption of digital platforms for farm management.[40] However, barriers exist, such as high upfront costs of the new technologies, limited data availability in some regions, and the need for technical expertise among farmers. Risks include the possibility of short-term over-optimization leading to reduced farming system diversity, data privacy and security concerns, potential unintended environmental consequences, job displacement, and the loss of traditional agricultural knowledge. Additionally, the highly contextual nature of precision agriculture systems means that successful AI approaches in one field may not be easily transferable to others.

Simulation models are flexible enough to incorporate multi-modal data (e.g., from remote sensing, biophysical crop models, newspaper articles and crowd-sourced images) for more accurate and timely predictions, potentially incorporating relationships not captured by current process-based models alone. Foundation models trained on large agricultural datasets can be fine-tuned to perform well on a diverse range of downstream tasks where data are more limited. However, ML methods often perform poorly in conditions different from the training data— for example, data-driven prediction models that exploit spatiotemporal correlations often fail to perform well in future years or new locations.[41,42] No matter how good a simulation is, it will always be some distance from reality, especially in extremely complex systems. Additionally, an uneven distribution of sufficient, high-quality data for model validation and training across locations and farming systems, could potentially results in inequitable distribution of model performance across geographical regions and socioeconomic strata. Further, there is a risk that AI methods rely on spurious correlations, leading to inaccurate estimations of intervention effects or physically implausible simulated behavior.[43]

AI Guardrail

INCLUSIVE MODEL AND TOOL DEVELOPMENT

To ensure that AI tools are relevant and applicable across diverse contexts, it is crucial to prioritize inclusive and iterative AI development. This involves engaging local stakeholders—such as farmers, extension agents and community organizations—in designing, training and validating AI models. By incorporating local knowledge, preferences and priorities into the development process, AI tools can be better tailored to the specific needs and constraints of different agroecological regions, production systems and sociocultural contexts. Inclusive AI development also requires using diverse and representative training datasets that capture the variability of food systems across different locations and scales. Initiatives to support collecting and sharing localized data from food systems, such as participatory sensing networks or community-driven data platforms, can help develop more context-specific AI solutions.

iv. Crop breeding

Developing crops with increasingly higher yields and enhanced stress tolerance is crucial for feeding a growing population in the face of climate change.[44] AI can help accelerate the crop breeding process.[45-49] On the macro-scale, developments in robotics and computer vision have revolutionized the collection and synthesis of data on plant size, shape, color and other visible characteristics, allowing researchers and farmers to assess crop performance much faster than traditional methods.[50] On the micro-scale, AI can help analyze genetic sequencing information. The genomes of many crops have yet to be fully annotated, which means that their genomes have not been fully assembled and functions have not been identified for all genes.[51,52] When presented with a genetic sequence, AI can help predict gene function, speeding up the annotation process and unlocking potential crop improvement targets for diverse species.[53]

Combining macro-level phenotypic data with genetic sequencing information generates rich and extensive datasets that link the expression of specific genetic regions to traits displayed in the field across various environmental conditions.[54,55] Modern AI algorithms are capable of discovering strongly non-linear patterns in high-dimensional data. Thus, they can be trained on these datasets to predict complex traits of new cultivars in various environments based solely on genomic information.[56] These predictions are fed into optimization algorithms for autonomous decision-making (e.g., reinforcement learning algorithms) to optimize critical factors of breeding programs by making data-driven choices.[57,58] This prediction can cut down on the time and uncertainty involved with traditional plant breeding.[54]

AI Guardrail

ADAPTIVE DATA COLLECTION SYSTEMS

Developing adaptive data collection systems is essential for ensuring that AI tools in food systems are continuously updated with relevant, accurate and timely data from on-the-ground sources. This is particularly important in the context of climate change, where rapid shifts in weather patterns, crop yields and market conditions require agile and responsive data collection processes. These systems should be designed to collect data from across the supply chain on local conditions, practices and challenges. For example, farmers can share data on pest and disease outbreaks through mobile apps or online platforms, which can be used to refine AI models for precision agriculture and pest and disease modeling. Data collection systems should also leverage crowdsourcing and citizen science approaches to gather large-scale, fine-grained data on food system dynamics, such as food prices, consumption patterns and waste levels, which can be used to improve AI models for supply chain optimization and food security monitoring. Large-language-model interfaces can gather timely insights into emerging practices and challenges under evolving climate conditions.

In addition to assisting traditional breeding processes, AI can also be instrumental in supporting modern biotechnological breeding methods like gene editing.[59] Gene editing techniques make precise changes in a crop's genetic code that lead to a desired characteristic. Well-identified genomic information produced with the help of AI, as described above, is key for selecting regions for editing that will have a functional effect on the crop. Within that region, AI tools can help choose which specific sequence to target for high editing efficacy, as well as ensuring that any potential off-target effects are minimized.[60,61] AI can also help improve gene editing methods overall by designing new proteins for increased editing ability, continuing to evolve the field to be ever more efficient and precise.[62]

AI applications in crop breeding can significantly reduce costs and time for labor-intensive phenotyping. They can also enhance breeding efficiency through early identification of promising climate-resilient cultivars and precise design of genetic engineering techniques. However, barriers exist, such as limited access to high-quality genomic datasets for under-researched crops, the need for substantial computational resources, and limited transferability across different crop species or environments given that the complexity of plant-environment interactions cannot be fully captured by genetic data alone. Risks include an over-reliance on ML predictions without sufficient field validation, the possibility of further narrowing genetic diversity, and the potential misuse of ML-generated intellectual property. These risks need to be addressed in order to manage further consolidation of genetic control in the seed industry and to ensure that generated crop varieties effectively support local communities and agroecosystems.

C. Barriers

i. Lack of interpretability

Many advanced AI models operate as "black boxes" to inexperienced users, making it difficult for end users to understand how the model arrives at its predictions or recommendations. This lack of interpretability can hinder the adoption of AI tools—for instance, a farmer might be reluctant to follow an AI-recommended planting schedule or fertilizer application rate without understanding the underlying reasoning. Care must be taken to generate accurate explanations of AI recommendations wherever possible, as users may be more inclined to trust a model's predictions about crop management or food distribution when given some kind of explanation, even if the prediction, or explanation, is incorrect.

AI Guardrail

GUIDANCE ON APPROPRIATE USE

Providing clear and comprehensive guidance on the appropriate use of AI tools is essential for ensuring their responsible and effective application in food systems. This is particularly important given the potential for AI tools to influence critical decisions related to agricultural production, supply chain management and policy development, which can have significant implications for food security, livelihoods and environmental sustainability. Guidance should cover key considerations, such as data privacy and security, as well as potential biases and limitations of AI tools. It should also provide practical advice on how to select, implement and evaluate AI tools based on specific use cases, user needs and contextual factors. This can involve developing best practice guides, case studies and decision support frameworks that help users navigate the complex landscape of AI tools and make informed choices about their application. Moreover, guidance should emphasize the importance of using AI tools in conjunction with other forms of knowledge and expertise, such as local and indigenous knowledge systems, to advance a truly context-sensitive decision-making approach.

ii. Limited transferability of agricultural data

Agricultural AI models are highly dependent on the specific spatiotemporal context in which they are trained. Correlative factors established in one location or time-period may not be reliably transferred to another due to differences in climate, soil, socioeconomic conditions or management practices. Even high-resourced and high-producing regions may experience challenges with model transferability due to contextual differences that are not immediately noticeable in the underlying datasets. Efforts to enhance transferability— such as the collection and publication of data from multi-environment trials, with wide spatial, temporal and production system coverage— are crucial for developing AI tools that can support decision-making across diverse contexts.

iii. Lack of available and accessible agricultural data

The development of AI applications in food systems often relies on collecting and sharing sensitive data, such as individual farm-level information on production practices, yields and financial performance. Ensuring the privacy and security of these data is crucial for protecting the interests of producers and maintaining trust in AI systems. Furthermore, some datasets may be proprietary, expensive, restricted or even classified, and some models may not have open-source code. Clear frameworks for data ownership and access rights are necessary to ensure equitable distribution of the benefits of AI applications and that producers maintain control over their data.

AI Accelerator

SCALABLE DATA-MODEL DEVELOPMENT

Integrated and scalable data-model systems are particularly critical for AI applications in food systems, given the complexity and diversity of data sources involved. Model developers would benefit tremendously from seamlessly integrated data from various stages of the food supply chain, including input distribution (e.g., fertilizers, seeds), agricultural production, food processing, distribution, consumption and waste management. For example, data from farm-management systems, precision-agriculture sensors, food-processing equipment and retail point-of-sale systems could be harmonized to enable end-to-end visibility. This integration could also allow optimization of food systems to effectively reduce food loss and waste. Additionally, managers of data systems must build platforms that are deployable at scale to handle the massive volumes of data generated by food systems, all while ensuring data quality, security and privacy.

D. Risks

i. Counterproductive results for some objectives

AI applications in food systems are often designed to help achieve specific, quantifiable targets, such as near-term crop yields. However, this singular focus can lead to damaging results unless a broader range of objectives is considered. For instance, an AI decision support system designed to maximize immediate crop output might recommend management practices that deplete soil nutrients, reduce biodiversity or increase vulnerability to pests and diseases over time. Similarly, AI-driven supply chain optimizations focusing solely on improving energy efficiency might inadvertently reduce system redundancy, leaving food distribution networks more vulnerable to disruptions from climate shocks or other unforeseen events. The challenge lies in developing AI models that optimize across multiple and sometimes competing objectives, such as productivity, environmental sustainability, economic viability, social equity and long-term resilience to climate change.

ii. Bias in agricultural data collection

The quality, availability and representativeness of the data used to train AI models can significantly impact their performance and applicability. In research and development (R&D) for food systems, data collection bias can arise from self-selection issues, in which only well-resourced producers with established best practices choose to participate in data collection efforts or publicize results. This can lead to models that are skewed toward better-performing systems and may not accurately represent the challenges and opportunities faced by a wider range of producers. Additionally, using data from already suitable agricultural areas to predict agricultural production in less suitable environments can result in overly optimistic projections and inadequate adaptation planning.

iii. Reinforcement of existing societal inequalities

Adopting AI technologies in food systems may exacerbate existing societal inequalities due to unequal access to education, digital infrastructure, data generation, data holdings and financial resources. Smallholder farmers and marginalized rural communities may face significant barriers in accessing and benefiting from AI tools, such as limited internet connectivity, low digital literacy, lack of affordable computing devices and lack of access to AI-enhanced inputs (such as improved seeds). Furthermore, many agricultural regions do not have the resources to collect, clean and digitize data. This digital divide can widen the gap between well-resourced and under-resourced communities, concentrating AI benefits among a small group of already advantaged stakeholders. Efforts to promote inclusive AI adoption, such as investments in rural digital infrastructure, digital literacy training programs and development of low-cost, user-friendly AI tools, are crucial for ensuring that the benefits of AI in food systems are distributed equitably.

AI Accelerator

COLLABORATIVE DATA ECOSYSTEMS

Establishing collaborative data ecosystems that bring together diverse stakeholders, including farmers, researchers, agribusinesses, supply chain managers and policymakers, can help to address issues of data bias, privacy and ownership in developing AI tools for food systems. These ecosystems should prioritize creation of shared, interoperable and secure data platforms that enable the pooling of diverse food system datasets while protecting the rights and interests of agricultural data providers. Collaborative data governance frameworks, such as data cooperatives or trust frameworks, can help to ensure that data is collected, shared and used in an equitable and transparent manner.

E. Recommendations

Food systems are highly decentralized, with an estimated 570 million farms worldwide, each operating in specific agroecological and socioeconomic contexts, challenging the notion of one-size-fits-all AI solutions. To address the myriad unique issues associated with AI applications in food systems and to ensure their responsible and effective deployment across contexts, we recommend the following priorities targeted at a range of institutional structures (Table 4-3):

1. *National governments should expand public R&D funding to develop and study AI applications in remote sensing, agricultural systems modeling, crop breeding and other high impact application areas.*
2. *Researchers, industry associations and standards development organizations should collaborate to develop and share benchmark datasets, sample algorithms and standard performance metrics for AI applications.*
3. *National governments and businesses should invest in developing adaptive data collection technology, such as Internet of Things sensors and mobile apps, to enable continuous updating of AI models with relevant, accurate and timely data.*
4. *Academic institutions and research organizations should prioritize inclusive and participatory approaches to developing AI models and tools, such as engaging farmers, extension agents and community organizations, to ensure that AI solutions are context-specific, user-centered and aligned with local needs and priorities.*
5. *Professional societies, academic institutions and international organizations should develop and promote guidelines, best practices and training programs on the appropriate use of AI in food systems, covering issues such as data privacy, model transparency, potential biases, risks and limitations.*
6. *National governments, private companies and civil society organizations should establish collaborative data ecosystems for food systems that have clear frameworks for data sharing, ownership and access rights.*
7. *Research funding agencies and philanthropy should support interdisciplinary research on ethical, legal and social implications of AI in food systems, as well as development of responsible AI governance frameworks and accountability mechanisms.*
8. *Private companies and model developers should prioritize development of human-in-the-loop model improvement approaches, incorporating user feedback and local knowledge to iteratively refine AI solutions and ensure their adaptability to evolving climate challenges and food system dynamics.*

9. *International organizations and multi-stakeholder platforms should facilitate knowledge exchange, capacity building and coordination of AI R&D with a focus on promoting inclusive innovation and equitable access to AI technologies.*

A responsible AI information ecosystem is based on the principles of true multi-stakeholder collaboration, the incorporation of local knowledge and priorities, the prioritization of transparency and accountability, and an emphasis on continuous, adaptive improvement. A coordinated approach can support the critical transition to more sustainable, resilient and equitable food systems that are bolstered against the impending challenges of climate change.

Table 4-3. *Recommendations*

GOVERNMENTS	CIVIL SOCIETY	INTERNATIONAL ORGANIZATIONS	BUSINESS	SCIENCE
Convene consortia exchanging food system data Ensure equitable access to AI tools in food systems Establish oversight and accountability mechanisms Create forums for stakeholder feedback on AI policies Support participatory collection initiatives for agricultural data Invest in rural connectivity infrastructure	Monitor data use and privacy issues Advocate for inclusive and transparent data governance Provide training in digital literacy to marginalized groups Create resources on ethics in AI for food systems Monitor AI adoption and impacts	Coordinate global data-sharing efforts in food systems Develop privacy and security frameworks for data in food systems Promote inclusive AI development Facilitate technology transfer and capacity building Identify and fill data gaps Share pre-competitive research and data	Participate in industry data consortia and standards bodies Ensure diversity in AI teams and training data Invest in Internet of Things and mobile data collection Develop scalable, accessible data architecture Co-develop tools that help identify barriers and limits to adaptation Develop open-source libraries, platforms, models and tools	Study the ethical, legal and social elements of AI in food systems Advance explainable, interpretable AI techniques Establish model evaluation protocols using open benchmark datasets Standardize data formats for ease of interoperability Identify and fill data gaps

F. References

1 Francesco N. Tubiello *et al.* Greenhouse gas emissions from food systems: building the evidence base. *Environmental Research Letters* 16, 065007 (2021). https://doi.org/10.1088/1748-9326/ac018e.

2 Matias Heino *et al.* Increased probability of hot and dry weather extremes during the growing season threatens global crop yields. *Scientific Reports* 13, 3583 (2023). 10.1038/s41598-023-29378-2.

3 Richard D. Semba *et al.* The Potential Impact of Climate Change on the Micronutrient-Rich Food Supply. *Advances in Nutrition* 13, 80-100 (2022). https://doi.org/10.1093/advances/nmab104.

4 Cynthia Rosenzweig *et al.* Finding and fixing food system emissions: the double helix of science and policy. *Environmental Research Letters* 16, 061002 (2021). 10.1088/1748-9326/ac0134.

5 Stéphanie Camaréna. Artificial intelligence in the design of the transitions to sustainable food systems. *Journal of Cleaner Production* 271, 122574 (2020). https://doi.org/10.1016/j.jclepro.2020.122574.

6 Tiago Domingues, Tomás Brandão & João C. Ferreira. Machine Learning for Detection and Prediction of Crop Diseases and Pests: A Comprehensive Survey. *Agriculture* 12, 1350 (2022). https://doi.org/10.3390/agriculture12091350

7 Jonas L. Vilas-Boas, Joel J. P. C. Rodrigues & Antonio M. Alberti. Convergence of Distributed Ledger Technologies with Digital Twins, IoT, and AI for fresh food logistics: Challenges and opportunities. *Journal of Industrial Information Integration* 31, 100393 (2023). https://doi.org/10.1016/j.jii.2022.100393.

8 Luca G. Bernardini *et al.* Learning vs. understanding: When does artificial intelligence outperform process-based modeling in soil organic carbon prediction? *New Biotechnology* 81, 20-31 (2024). https://doi.org/10.1016/j.nbt.2024.03.001.

9 Zane Swanson, Caitlin Welsh & Joseph Majkut. Mitigating Risk and Capturing Opportunity: The Future of Alternative Proteins. (Center for Strategic and International Studies (CSIS), 2023; https://www.csis.org/analysis/mitigating-risk-and-capturing-opportunity-future-alternative-proteins).

10 Rebecca Carroll. *NASA Helps Serve Yellowstone Fungi for Breakfast;* NASA's Spinoff Publication, https://www.nasa.gov/technology/tech-transfer-spinoffs/nasa-helps-serve-yellowstone-fungi-for-breakfast/ (2022).

11 Sezin Kircali Ata *et al.* Predicting the Textural Properties of Plant-Based Meat Analogs with Machine Learning. *Foods* 12, 344 (2023). https://doi.org/10.3390/foods12020344

12 Firmenich. *The World's First AI-Created Flavor;* https://www.firmenich.com/taste-and-beyond/blog-article/worlds-first-ai-created-flavor (Accessed July 2024).

13 Richard Twine. Emissions from Animal Agriculture—16.5% Is the New Minimum Figure. *Sustainability* 13, 6276 (2021). https://doi.org/10.3390/su13116276.

14 Helen Onyeaka *et al.* Using Artificial Intelligence to Tackle Food Waste and Enhance the Circular Economy: Maximising Resource Efficiency and Minimising Environmental Impact: A Review. *Sustainability* 15, 10482 (2023). https://doi.org/10.3390/su151310482.

15 F. N. Tubiello *et al.* Pre- and post-production processes increasingly dominate greenhouse gas emissions from agri-food systems. *Earth Syst. Sci. Data* 14, 1795-1809 (2022). 10.5194/essd-14-1795-2022.

16 Bruno Silva *et al.* GPT-4 as an Agronomist Assistant? Answering Agriculture Exams Using Large Language Models. arXiv:2310.06225 (2023). https://doi.org/10.48550/arXiv.2310.06225.

17 M. Weiss, F. Jacob & G. Duveiller. Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment* 236, 111402 (2020). https://doi.org/10.1016/j.rse.2019.111402.

18 Tetsuji Tanaka *et al.* Satellite forecasting of crop harvest can trigger a cross-hemispheric production response and improve global food security. *Communications Earth & Environment* 4, 334 (2023). https://doi.org/10.1038/s43247-023-00992-2.

19 Inbal Becker-Reshef *et al.* The GEOGLAM crop monitor for AMIS: Assessing crop conditions in the context of global markets. *Global Food Security* 23, 173-181 (2019). https://doi.org/10.1016/j.gfs.2019.04.010.

20 Jack-bo1220. *Awesome Remote Sensing Foundation Models [Computer software];* https://github.com/Jack-bo1220/Awesome-Remote-Sensing-Foundation-Models (2024; Original work published 2023).

21 Catherine Nakalembe & Hannah Kerner. Considerations for AI-EO for agriculture in Sub-Saharan Africa. *Environmental Research Letters* 18, 041002 (2023). https://doi.org/10.1088/1748-9326/acc476.

22 Jonas Jägermeyr *et al.* Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. *Nature Food* 2, 873-885 (2021). https://doi.org/10.1038/s43016-021-00400-y.

23 Karine Chenu *et al.* Contribution of Crop Models to Adaptation in Wheat. *Trends in Plant Science* 22, 472-490 (2017). https://doi.org/10.1016/j.tplants.2017.02.003.

24 Heidi Webber *et al.* Framework to guide modeling single and multiple abiotic stresses in arable crops. *Agriculture, Ecosystems & Environment* 340, 108179 (2022). https://doi.org/10.1016/j.agee.2022.108179.

25 Corey Lesk *et al.* Compound heat and moisture extreme impacts on global crop yields under climate change. *Nature Reviews Earth & Environment* 3, 872-889 (2022). https://doi.org/10.1038/s43017-022-00368-8.

26 F. Lin *et al.* "MMST-ViT: Climate Change-aware Crop Yield Prediction via Multi-Modal Spatial-Temporal Vision Transformer" in *2023 IEEE/CVF International Conference on Computer Vision (ICCV)*, 5751-5761, https://doi.org/10.1109/ICCV51070.2023.00531,(2023).

27 Dilli Paudel *et al.* Machine learning for large-scale crop yield forecasting. *Agricultural Systems* 187, 103016 (2021). https://doi.org/10.1016/j.agsy.2020.103016.

28 Sem Vijverberg, Raed Hamed & Dim Coumou. Skillful U.S. Soy Yield Forecasts at Presowing Lead Times. *Artificial Intelligence for the Earth Systems* 2, e210009 (2023). https://doi.org/10.1175/AIES-D-21-0009.1.

29 Licheng Liu *et al.* Knowledge-guided machine learning can improve carbon cycle quantification in agroecosystems. *Nature Communications* 15, 357 (2024). https://doi.org/10.1038/s41467-023-43860-5.

30 Christos Pylianidis, Michiel G. J. Kallenberg & Ioannis N. Athanasiadis. Domain adaptation with transfer learning for pasture digital twins. *Environmental Data Science* 3, e8 (2024). https://doi.org/10.1017/eds.2024.6.

31 Ruben Cartuyvels *et al.* Spatiotemporal self-supervised pre-training on satellite imagery improves food insecurity prediction. *Environmental Data Science* 2, e48 (2023). https://doi.org/10.1017/eds.2023.42.

32 Yuchi Ma *et al.* Improving the Transferability of Deep Learning Models for Crop Yield Prediction: A Partial Domain Adaptation Approach. *Remote Sensing* 15, 4562 (2023). https://doi.org/10.3390/rs15184562.

33 Taewon Moon *et al.* Process-Based Crop Modeling for High Applicability with Attention Mechanism and Multitask Decoders. *Plant Phenomics* 5, 0035 (2023). https://doi.org/10.34133/plantphenomics.0035.

34 Ioannis Droutsas *et al.* Integration of machine learning into process-based modelling to improve simulation of complex crop responses. *in silico Plants* 4 (2022). https://doi.org/10.1093/insilicoplants/diac017.

35 H. Navarro-Hellín *et al.* A decision support system for managing irrigation in agriculture. *Computers and Electronics in Agriculture* 124, 121-131 (2016). https://doi.org/10.1016/j.compag.2016.04.003.

36 Michiel G. J. Kallenberg *et al.* Nitrogen management with reinforcement learning and crop growth models. *Environmental Data Science* 2, e34 (2023). https://doi.org/10.1017/eds.2023.28.

37 Romain Gautron *et al.* Reinforcement learning for crop management support: Review, prospects and challenges. *Computers and Electronics in Agriculture* 200, 107182 (2022). https://doi.org/10.1016/j.compag.2022.107182.

38 Matteo Turchetta *et al.* Learning long-term crop management strategies with cyclesgym. *Advances in neural information processing systems* 35, 11396-11409 (2022). https://proceedings.neurips.cc/paper_files/paper/2022/hash/4a22ceafe2dd6e0d32df1f7c0a69ab68-Abstract-Datasets_and_Benchmarks.html.

39 Malvern Madondo *et al.* A SWAT-based Reinforcement Learning Framework for Crop Management. arXiv:2302.04988 (2023). https://ui.adsabs.harvard.edu/abs/2023arXiv230204988M.

40 Mohd Javaid *et al.* Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Advanced Agrochem* 2, 15-30 (2023). https://doi.org/10.1016/j.aac.2022.10.001.

41 Holger R. Maier *et al.* On how data are partitioned in model development and evaluation: Confronting the elephant in the room to enhance model generalization. *Environmental Modelling & Software* 167, 105779 (2023). https://doi.org/10.1016/j.envsoft.2023.105779.

42 Lily-belle Sweet *et al.* Cross-Validation Strategy Impacts the Performance and Interpretation of Machine Learning Models. *Artificial Intelligence for the Earth Systems* 2, e230026 (2023). https://doi.org/10.1175/AIES-D-23-0026.1.

43 Davide Cammarano *et al.* Models can enhance science–policy–society alignments for climate change mitigation. *Nature Food* 4, 632-635 (2023). https://doi.org/10.1038/s43016-023-00807-9.

44 Mario Herrero *et al.* Innovation can accelerate the transition towards a sustainable food system. *Nature Food* 1, 266-272 (2020). https://doi.org/10.1038/s43016-020-0074-1.

45 Mohsen Niazian & Gniewko Niedbała. Machine Learning for Plant Breeding and Biotechnology. *Agriculture* 10, 436 (2020). https://doi.org/10.3390/agriculture10100436

46 Mohsen Yoosefzadeh Najafabadi, Mohsen Hesami & Milad Eskandari. Machine Learning-Assisted Approaches in Modernized Plant Breeding Programs. *Genes* 14, 777 (2023). https://doi.org/10.3390/genes14040777

47 Kyung Do Kim, Yuna Kang & Changsoo Kim. Application of Genomic Big Data in Plant Breeding: Past, Present, and Future. *Plants* 9, 1454 (2020). https://doi.org/10.3390/plants9111454.

48 Hai Wang *et al.* Deep learning for plant genomics and crop improvement. *Current Opinion in Plant Biology* 54, 34-41 (2020). https://doi.org/10.1016/j.pbi.2019.12.010.

49 Saritha V. Kuriakose, Ravindra Pushker & Ebenezer M. Hyde. Data-Driven Decisions for Accelerated Plant Breeding in *Accelerated Plant Breeding, Volume 1: Cereal Crops* (eds Satbir Singh Gosal & Shabir Hussain Wani) 89-119 (Springer International Publishing, Cham, 2020; https://doi.org/10.1007/978-3-030-41866-3_4, https://doi.org/10.1007/978-3-030-41866-3_4).

50 Abbas Atefi *et al.* Robotic Technologies for High-Throughput Plant Phenotyping: Contemporary Reviews and Future Perspectives. *Frontiers in Plant Science* 12 (2021). https://doi.org/10.3389/fpls.2021.611940

51 Lorena Y. Ramírez Gonzales *et al.* The role of omics in improving the orphan crop tef. *Trends in Genetics* 40, 449-461 (2024). https://doi.org/10.1016/j.tig.2024.03.003.

52 Nicholas Furnham, Tjaart A. P. de Beer & Janet M. Thornton. Current challenges in genome annotation through structural biology and bioinformatics. *Current Opinion in Structural Biology* 22, 594-601 (2012). https://doi.org/10.1016/j.sbi.2012.07.005.

53 Zhaojia Chen *et al.* From tradition to innovation: conventional and deep learning frameworks in genome annotation. *Briefings in Bioinformatics* 25 (2024). https://doi.org/10.1093/bib/bbae138.

54 Kelin Wang *et al.* DNNGP, a deep neural network-based method for genomic prediction using multi-omics data in plants. *Molecular Plant* 16, 279-293 (2023). https://doi.org/10.1016/j.molp.2022.11.004.

55 Aalt Dirk Jan van Dijk *et al.* Machine learning in plant science and plant breeding. *iScience* 24 (2021). https://doi.org/10.1016/j.isci.2020.101890.

56 Osval Antonio Montesinos-López *et al.* A review of deep learning applications for genomic selection. *BMC Genomics* 22, 19 (2021). https://doi.org/10.1186/s12864-020-07319-x.

57 Omar G. Younis *et al.* Breeding Programs Optimization with Reinforcement Learning. arXiv:2406.03932 (2024). https://doi.org/10.48550/arXiv.2406.03932.

58 Saba Moeinizade, Guiping Hu & Lizhi Wang. A reinforcement Learning approach to resource allocation in genomic selection. *Intelligent Systems with Applications* 14, 200076 (2022). https://doi.org/10.1016/j.iswa.2022.200076.

59 Emily Waltz. With CRISPR and machine learning, startups fast-track crops to consume less, produce more. *Nature Biotechnology*, 1251-1253 (2019). https://doi.org/10.1038/d41587-019-00027-2.

60 Xi Xiang *et al.* Enhancing CRISPR-Cas9 gRNA efficiency prediction by data integration and deep learning. *Nature Communications* 12, 3238 (2021). https://doi.org/10.1038/s41467-021-23576-0.

61 Jutan Das *et al.* Machine learning in the estimation of CRISPR-Cas9 cleavage sites for plant system. *Frontiers in Genetics* 13 (2023). https://doi.org/10.3389/fgene.2022.1085332.

62 Ewen Callaway. 'ChatGPT for CRISPR'creates new gene-editing tools. *Nature* 629, 272-272 (2024). https://doi.org/10.1038/d41586-024-01243-w.

CHAPTER 5:

MANUFACTURING SECTOR

Alp Kucukelbir

A. How Can AI Help Decarbonize Manufacturing? 5-2

B. What Are Common Applications of AI In Manufacturing? 5-3

C. Barriers 5-8

D. Risks 5-9

E. Recommendations 5-10

F. References 5-11

The manufacturing sector makes products on which the modern world depends. Billions of tons of steel and cement are used in buildings, bridges and roads each year. Chemicals, including ammonia, provide fertilizers and other essential building blocks for modern society.[1]

At the same time, the manufacturing sector is responsible for roughly one third of global greenhouse gas (GHG) emissions. Steelmaking has the largest carbon footprint in the manufacturing sector, followed by cement-making and then chemicals. The remaining emissions come from aluminum, glass, paper and other light manufacturing.[2-5]

Decarbonizing the manufacturing sector will be challenging. Many industrial processes require high and sustained heat, which fossil fuels are well-suited to delivering. Some industrial processes, including cement-making, rely on chemical reactions that emit CO_2. Many industrial products are globally traded commodities, subject to significant loss of market share due to small increases in production costs.[6,7]

Artificial intelligence (AI) is showing promise in helping address the challenge of decarbonizing the manufacturing sector. This chapter discusses that potential and explores opportunities for further work.

A. How Can AI Help Decarbonize Manufacturing?

Consider the following example: AI can play a central role in reducing costs and emissions for electric arc furnaces (EAFs)—a key technology for decarbonizing steelmaking. EAFs melt scrap metal using electricity instead of coal. Using recycled/circular feedstock, such as scrap, is a core idea that pervades the effort to decarbonize all types of manufacturing. This idea introduces a novel challenge: how to manage new sources of variability.

Virgin raw materials are stable. Mining operators control their operations, packaging and shipping raw ingredients that meet specific quality criteria. Steelmakers are accustomed to this stability. But every batch of scrap is different. One batch of scrap may contain too much of an alloy, another possibly too little of it. Modern steelmakers can adjust for this variation by enhancing the scrap with costly additives. The most common strategy is simple: plan for the “worst batch” scenario.

This strategy has led to a consistent, industry-wide overuse of additives. No matter what scrap metal comes in, unnecessary amounts of additives are added. The extent of this practice is such that the biggest portion of EAF steel’s carbon footprint is the upstream emissions from sourcing these additives.[8]

AI offers a better approach to this challenge: instead of over-designing for the “worst batch,” AI can help steelmakers “adapt to each batch” with predictions that have higher accuracy than traditional software systems (Figure 5-1). The idea is to use AI to recommend optimal production settings, adapting to the variability in each batch.

Manufacturing remains a challenging segment of the economy to decarbonize and will require significant long-term hardware research and investments. Many governments are sponsoring capital-expenditure-heavy projects to adopt recycled feedstock, switch to greener sources of fuel, and make clever use of industrial heat.[9,10]

AI provides a complementary benefit that is (1) available today and (2) can be applied to existing manufacturing infrastructure. In many cases, AI can be applied today without any capital equipment change-out—it is ultimately just an operational change. As a result, AI can be orders of magnitude faster and cheaper to adopt than deeper decarbonization pathways that require significant capital expenditures.

Figure 5-1. *Factories are increasingly digitalizing their operations.*

B. What Are Common Applications of AI In Manufacturing?

i. Decarbonizing the process of making things

The steelmaking example highlights one way AI can reduce a manufacturer's emissions. There are many more. Here are a few proven ways AI can help reduce emissions across many sectors:

- Adapt to volatility faster. Manufacturing plants are designed to minimize variation and consistently produce high-quality goods. The idea of using data to control quality variation dates to Walter A. Shewhart, who established the field of statistical process control at Bell Laboratories in the 1920s.[11] AI extends the notion of statistical process control, enabling manufacturers to adapt to issues more quickly—any amount of time avoided making low-quality goods reduces scrap and minimizes a plant's waste and energy usage.
- Adapt to volatility better. Without AI, reducing the time wasted making low-quality commodities may be difficult because existing statistical methods may not be accurate enough to explain the root cause of production issues. AI-based production can pinpoint the specific root cause of an issue in real-time during production. AI's precision and ability to handle large numbers of potential root-cause factors is what drives this capability.
- Avoid past mistakes and enable expertise retention. Over three quarters of manufacturing firms are concerned about their aging workforces.[12] A primary component of their concern is losing the expertise that their skilled workers have amassed at specific manufacturing sites (e.g., the exact setting for a temperature for a particular product type). These sorts of insights are rarely recorded in an accessible manner, but skilled engineers and operators leave their marks in historical production data. Thus, while the experienced operator may know what to do in any scenario, a novice may leverage AI to sift through prior production runs and extract insights that resemble an issue at hand. AI can map challenges happening today to historical periods, filtering out interventions that did not work and focusing on those that did. In this way, AI can help new talent perform more efficiently, reducing waste and energy consumption during onboarding and beyond.

- Improve yield. Production at scale is never 100% efficient: while 10 grams of ingredients may yield 10 grams of a final product in the laboratory, 10 tonnes of ingredients may yield only 9 tonnes of final product at scale. Scaling production introduces inefficiencies caused by the challenge of operating large-scale machinery and prioritizing production speed.[13] AI can help minimize this yield loss. By analyzing historical production data, AI can identify unexpected points in production where complex operational changes may lead to improved yields. AI is uniquely suited to learning the idiosyncrasies of large-scale manufacturing facilities and can provide specific recommendations on how to improve production yield for each site individually.

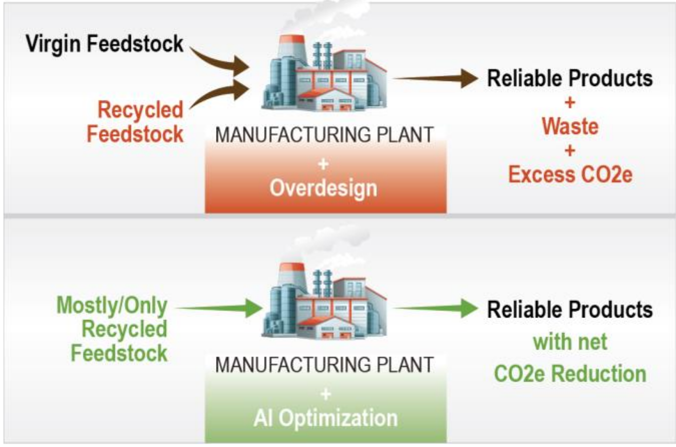


Figure 5-2. *AI enables manufacturers to adapt to recycled feedstock. Factories typically address the increased variability of recycled feedstock by planning for the "worst case" scenario; this leads to unnecessary waste and excess emissions. Instead, factories can use AI to optimize operations and produce equally reliable products with net CO2e reductions.*

- Enable recycling and circularity. Having traditionally relied on high-quality, low-variability raw ingredients, many industrial sectors are embracing recycled feedstock to reduce their carbon footprint, as well as increasing use of prior components and parts. Both could be considered increased circularity, potentially helping with cost, as well as carbon intensity. However, recycled and circular feedstocks typically exhibit low quality and certainly have high variability. This is the example from the steelmaking case study, with direct parallels in the chemicals, aluminum, glass, and paper sectors, among others. Embracing recycled feedstock not only reduces emissions during manufacturing, but also relieves demand on mining virgin ingredients in the first place. This aligns with the materials-efficiency objective highlighted in the sixth assessment report[14] of the Intergovernmental Panel on Climate Change (IPCC).

- Minimize energy consumption. Manufacturing facilities are not designed to minimize energy consumption; they are designed for safety. This means plants operate with conservative safety margins factored into all parts of production. This presents an opportunity for energy improvements while maintaining safety standards. This topic is a focus of the fifth assessment report[15] of the IPCC and serves as an optimization target for AI as well. Digital control systems which automatically operate much of the machinery at modern manufacturing sites, can be orchestrated using AI to adapt to operating conditions to safely reduce energy consumption. Reinforcement learning techniques can explore energy efficiencies in a gradual and safe way, exploiting operating set points that provide the biggest energy savings while operating with the safety margins that matter. Applications like these can provide net energy emissions reductions for plants with no hardware changes needed.

- **Adopt alternative energy sources.** In some sectors, such as scrap-based steelmaking, production is shifting to using clean electricity, which provides a pathway to shifting towards green production. In other cases, however, the switch may not be so simple. In direct steelmaking, manufacturers are shifting towards hydrogen, biomass, and carbon capture. In cement, the use of alternative fuels at the kiln is steadily increasing, including hydrogen and biomass, as well as carbon capture. Adopting alternative energy sources, however, comes with its own new source of volatility. Alternative cement fuels can negatively impact clinker quality, forcing cement mills to continue using hydrocarbon-based fuels for stability.[16] AI can help adapt to this new source of variability, enabling an increased, if not full conversion, to newer greener sources of fuels during production.

Box 5-1

CASE STUDY: ALLOY ADDITIVE REDUCTION IN STEELMAKING

In 2022, a Brazilian steel manufacturer using AI achieved 8% reduction in alloy additive consumption. This reduction came with a commensurate $3/metric ton cost savings and a 7.5% reduction in CO_2e/metric ton.[17]

This company achieved these results by

- Acquiring recycled scrap metal for their production
- Measuring the chemical composition of each batch of scrap
- Leveraging AI recommendations during melting to add as little (if any) additives as possible
- Predicting the risk of producing each batch of steel, trading off potential quality issues with emissions
- Reducing the quality variation of their final product.

Adopting AI as part of a plant's operating workflow, manufacturers can progressively target high-opportunity use cases within their production.

- **Adopt smaller and quicker batch manufacturing.** Batch production, which encapsulates much of the steel and chemicals sectors, embodies a tradeoff between size and speed. Larger batches offer more opportunity to correct for mistakes and adapt to production issues, while smaller and quicker batches use less energy and offer production flexibility. Reducing the cycle time—the amount of time it takes to make a batch from start to finish—is a common challenge, compounded by the switching between different product types between batches. AI can help analyze patterns in high-dimensional historical production data and recommend operational set points as production shifts quickly from batch to batch. Reducing cycle time comes with direct emissions reduction along with energy minimization, and typically requires no hardware changes to the plant.

ii. Decarbonizing supply chains and adopting dematerialization strategies

- Optimize manufacturing schedules. The production and storage of commodities are driven by market demands. Factories optimize their production schedules to minimize order wait-time while reducing switching costs between product types or grades. Inefficiencies in scheduling lead to superfluous production being stored on-site (leading to unnecessary emissions associated with moving large volumes of material) and switching costs (leading to unnecessary emissions due to keeping equipment running without producing any goods). AI can help with this scheduling process by optimizing complex production schedules to minimize such transitions and it can do so at greater speeds and accuracy than manual approaches. AI can also help forecast market demands, enabling manufacturers to prepare for anticipated market demand ahead of time.[18]
- Minimize logistics overhead. Manufacturers and shipping companies collaborate to deliver billions of tonnes of material across the globe. Handling and routing such large amounts of material with precision is a complex operational task. Shipments that are kept in storage and/or unnecessarily shuffled around during this process lead to energy waste. Poorly planned shipping routes can add to the indirect emissions that come with transporting goods to their final destinations. AI can help with this process in two ways. First, AI can optimize shipping operations, such as terminals and ports, to minimize container movement while correctly loading and unloading shipments from one mode of transport to another. Second, AI can help with forecasting both weather conditions and market demand, enabling logistics companies to plan and reduce operational inefficiencies.[19]
- Evaluate and adopt dematerialization strategies. The 6th IPCC Assessment Report highlights material efficiency as a key strategy in reducing the carbon footprint of manufacturing. This strategy involves increasing circularity of materials used during production, while consuming the smallest amount of new ingredients possible. It also involves designing and manufacturing of stronger, lighter, and better materials to reduce how much is needed for downstream applications. AI can assist with both objectives by targeting production practices that reduce waste—increasing stability with recycled feedstock—and precisely matching product specifications to production.[20] AI can also be used to design materials for easier disassembly and recycling. However, material efficiency is not tracked the same way as energy efficiency, which poses a systematic challenge in this endeavor.[21]

iii. Decarbonizing the impact of maintaining industrial equipment

- Monitor processes. Industrial facilities are typically designed to operate for long stretches of time, ranging from chemical plants that operate with one day of downtime per week, to steel blast furnaces that can operate continuously for years at a time. Any unexpected issues or downtime cause unnecessary and often preventable additional emissions. Aluminum smelters can sometimes unexpectedly fail in a way that releases perfluorocarbons—a potent GHG. AI forecasting models can predict when this is about to happen, enabling operators an opportunity to proactively avoid such scenarios.[22] Similarly, silicon levels in tapped iron of blast furnaces can indicate an unexpected cooling of the furnace—but only when it is too late to act. AI can forecast silicon levels in a blast furnace, enabling operators to pre-emptively avoid any furnace cooldowns that would cause avoidable emissions.[23]

Figure 5-3. *Factories comprise thousands of interconnected sensors.*

- Plan for maintenance. Scheduling maintenance for batch production is reasonably straightforward since downtime between batches can be used to service equipment. However, continuous-process machinery requires regular maintenance that causes a reduction in capacity, if not direct downtime for the plant. Like cleaning a filter that clogs over time, these maintenance procedures are typically conducted on a regular basis—regardless of the state of the equipment. However, as manufacturing plants adopt increasing variable feed- and fuel-stock, continuous-process machinery can degrade at wildly differing rates. AI can be used to forecast the optimal time to service machinery, thus reducing downtime and the resulting unnecessary emissions that come from winding a plant down and up again.[24]

- Manage alerts at scale. Highly instrumented production sites have thousands of sensors that raise alerts if their measurements are out of expected ranges. These alerts can sometimes refer to mild warnings that operators can ignore if they know the underlying cause is temporary (e.g., a particularly cold or hot day). Other alerts can be critical and require initiating costly plant shutdowns and other safety protocols. Handling such alerts, when hundreds may be going off at a time, is a challenging task for manufacturing operators. AI can contextualize these alerts to help manage them at scale. AI software can automatically detect patterns of common alerts that may be used to reconfigure underlying sensor limits. AI can also highlight very unusual alerts and raise additional awareness in the rare cases they occur. These techniques are already being applied in cybersecurity,[25] and can help manufacturing operators detect and minimize emissions with better accuracy and speed.

C. Barriers

Several barriers prevent the widespread adoption of AI in the decarbonization of manufacturing. They include the following:

- Lack of incentive to decarbonize. A threshold issue is the incentive of manufacturers to decarbonize, which can involve expense, market risk, adoption of unfamiliar technologies and disruption of longstanding ways of doing business. Regulatory requirements or clear market rewards are the two reasons why most factories and logistics companies pursue decarbonization, but such requirements or rewards are often lacking. In the absence of incentives to decarbonize, AI tools that could help with this process will rarely be considered or adopted.
- Lack of investment in digitalization. Manufacturing companies are often—culturally and operationally—anchored to the pre-digital era of the industrial revolution. While large manufacturing companies are at various stages of embracing digitalization across their production and supply chains, small- to medium-sized businesses may need to first invest in digitizing their operations. This process may involve installing sensors, connecting them to databases, and maintaining an information technology foundation to support connecting all parts of the business.
- Low digital literacy. Digitalization requires manufacturers to develop, hire or outsource personnel with expertise. Developing such talent in-house involves training internal domain experts with data literacy, storage, and manipulation skills. Hiring for digital talent often involves recruiting data scientists and data engineers to enhance existing staff in their work in this field. Some manufacturers may prefer to outsource such activities to consulting groups and other companies that provide such services.
- Need for coordination across large organizations. Adopting AI in day-to-day workflows requires buy-in from many stakeholders. Manufacturing companies execute complex workflows that can involve up to dozens of departments. Team members must be given sufficient resources and time to build trust in AI-based strategies, which in turn should have clear deployment ownership. Results should be quantified and shared among stakeholders to further incentivize adoption.
- Availability of recycled feedstock. Not every geography and economic market may have access to the same levels or quality of recycled feedstock. Individual recycling is an important challenge in recycling plastic products.26 Commercial recycling of commodities, such as steel, is well established in the United States, Europe, and Japan; similar workflows and markets are developing in South America, China, and India. Companies that lack consistent access to recycled feedstock may hesitate to adopt workflows, with or without AI, that rely on such sources.

D. Risks

The adoption of AI in manufacturing also comes with a variety of risks.

- Increased emissions due to lack of AI maintenance. Factories and logistics change over time. Any AI-based system that operates on real-time data must be carefully maintained and updated. Static AI solutions carry the risk of quickly producing inaccurate analyses, predictions and optimizations, which in turn can lead factories to carry out actions that increase their emissions. Factories that fail to adopt the workflows necessary to update and maintain AI systems raise the risk working with inaccurate AI systems over time.
- Industrial accidents due to improper use. Factories can be dangerous places. Industrial accidents can harm workers and neighboring communities. If properly used, AI can reduce risks at factories, but the opposite could occur with improper use. If AI is tested improperly or implemented incorrectly or if humans are not kept in the loop, the risk of industrial accidents could increase. In adopting AI-based solutions, companies must develop new safety procedures with additional training to mitigate the risk of negative human health and safety outcomes.
- Use of AI in processes that increase emissions. As a general-purpose technology, AI can also be used to reduce costs or speed deployment of industrial processes that increase GHG emissions. Regulatory pressure and market dynamics, along with other incentives, are ways to minimize this risk.

E. Recommendations

1. *Private companies should engage with governments, non-profits and academia to develop, release and maintain AI-ready datasets that pertain to industrial operations. This effort should leverage best practices for data sharing and hosting. Private companies should encourage those interested in leveraging their data to explore high-impact AI applications.*
2. *Private companies should develop clear processes to accelerate the adoption of digitalization within their organizations, from streamlining vendor evaluation to incentivizing internal adoption of AI in high impact use cases.*
3. *Technical societies should develop educational assets and programs to increase digital and AI literacy within industrial workforces. These initiatives should scale across the workforce, from operators up to executives. Emphasis should be on developing a foundational skill set that will enable the manufacturing sector to adopt AI-based solutions.*
4. *Governments and standards organizations should incentivize market demand for AI-optimized products that exhibit increased material circularity and lower carbon footprints. Governments should offer financial incentives to adopt such goods.*
5. *Governments and academia should develop and deploy education opportunities at the intersection of AI and manufacturing as part of computer science and engineering programs.*
6. *Governments should incentivize the market of recycled feed and fuel stock to increase their supply and reduce their costs. This reduces a barrier for adopting AI to increase material circularity.*

F. References

1 Peter John Turnbull Morris. *From classical to modern chemistry: The instrumental revolution*. (Royal Society of Chemistry, Great Britain, 2002).

2 Intergovernmental Panel on Climate Change (IPCC) Working Group III. *Climate Change 2022: Mitigation of Climate Change - Summary for Policymakers (Sixth Assessment Report);* https://www.ipcc.ch/report/sixth-assessment-report-working-group-3/ (2022).

3 United Nations Economic Commission for Europe (UNECE). *COP27: UN report shows pathways to carbon-neutrality in "energy intensive" steel, chemicals and cement industries* UNECE, https://unece.org/climate-change/press/cop27-un-report-shows-pathways-carbon-neutrality-energy-intensive-steel (2022).

4 The Economist. *The truth about recycling;* https://www.economist.com/technology-quarterly/2007/06/09/the-truth-about-recycling (2007).

5 RC Ziegler. *Environmental Impacts of Virgin and Recycled Steel and Aluminum;* US Environmental Protection Agency (EPA), https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=9101LWZP.txt (1976).

6 David Sandalow *et al. ICEF Industrial heat decarbonization roadmap;* Innovation for Cool Earth Forum (ICEF), https://www.icef.go.jp/pdf/summary/roadmap/icef2019_roadmap.pdf (2019).

7 Caleb M Woodall *et al.* Technology options and policy design to facilitate decarbonization of chemical manufacturing. *Joule* (2022). https://doi.org/10.1016/j.joule.2022.10.006.

8 Steel Manufacturers Association & CRU International Limited. *Emissions Analysis: Executive Summary;* https://steelnet.org/steelmaking-emissions-report-2022/ (2022).

9 New Energy and Industrial Technology Development Organization (NEDO) Evaluation Department. *NEDO Project Success Stories;* NEDO, Kanagawa, Japan, https://www.nedo.go.jp/content/100899120.pdf (2023).

10 US Department of Energy (DOE). *DOE Industrial Decarbonization Roadmap* US DOE, https://www.energy.gov/industrial-technologies/doe-industrial-decarbonization-roadmap (Accessed September 2023).

11 Richard E. Barlow & Telba Z. Irony. Foundations of Statistical Quality Control. *Lecture Notes-Monograph Series* **17**, 99-112 (1992). https://www.jstor.org/stable/4355628.

12 The Manufacturing Institute. *The Aging of the Manufacturing Workforce;* https://www.themanufacturinginstitute.org/research/the-aging-of-the-manufacturing-workforce/ (2019).

13 Jonathan Worstell. *Scaling chemical processes: practical guides in chemical engineering*. (Butterworth-Heinemann, 2016; https://doi.org/10.1016/C2015-0-01809-3).

14 International Panel on Climate Change (IPCC). *Sixth Assessment Report;* https://www.ipcc.ch/assessment-report/ar6/ (2021).

15 International Panel on Climate Change (IPCC). *Fifth Assessment Report;* https://www.ipcc.ch/assessment-report/ar5/ (2014).

16 Azad Rahman *et al.* Impact of Alternative Fuels on the Cement Manufacturing Plant Performance: An Overview. *Procedia Engineering* **56**, 393-400 (2013). https://doi.org/10.1016/j.proeng.2013.03.138.

17 Pamir Ozbay & Carter Almquist. Adopting Machine-Learning-Based Workflows for Reducing Production Risk and Cost in *AISTech 2023 Iron & Steel Technology Conference*, Detroit, MI. 2086-2100, https://www.proceedings.com/69204.html, (2023).

18 Pietro De Giovanni. Smart Supply Chains with vendor managed inventory, coordination, and environmental performance. *European Journal of Operational Research* **292**, 515-531 (2021). https://doi.org/10.1016/j.ejor.2020.10.049.

19 Reza Toorajipour *et al.* Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research* **122**, 502-517 (2021). https://doi.org/10.1016/j.jbusres.2020.09.009.

20 Lara Waltersmann *et al.* Artificial Intelligence Applications for Increasing Resource Efficiency in Manufacturing Companies—A Comprehensive Review. *Sustainability* **13**, 6689 (2021). https://doi.org/10.3390/su13126689.

21 Sasha Shahbazi *et al.* Material efficiency in manufacturing: swedish evidence on potential, barriers and strategies. *Journal of Cleaner Production* **127**, 438-450 (2016). https://doi.org/10.1016/j.jclepro.2016.03.143.

22 Ron Kremser *et al.* Anode Effect Prediction in Hall-Héroult Cells Using Time Series Characteristics. *Applied Sciences* **10**, 9050 (2020). https://doi.org/10.3390/app10249050.

23 Wandercleiton Cardoso, Renzo di Felice & Raphael Colombo Baptista. Artificial Neural Network for Predicting Silicon Content in the Hot Metal Produced in a Blast Furnace Fueled by Metallurgical Coke. *Materials Research* **25** (2022). https://doi.org/10.1590/1980-5373-MR-2021-0439

24 Alexandros Bousdekis *et al.* A Review of Data-Driven Decision-Making Methods for Industry 4.0 Maintenance Applications. *Electronics* **10**, 828 (2021). https://doi.org/10.3390/electronics10070828.

25 Tao Ban *et al.* Combat Security Alert Fatigue with AI-Assisted Techniques in *Proceedings of the 14th Cyber Security Experimentation and Test Workshop*, Virtual, CA, USA. 9–16, https://doi.org/10.1145/3474718.3474723, (2021).

26 Renee Cho. *Recycling in the U.S. Is Broken. How Do We Fix It?;* Columbia Climate School State of the Planet, https://news.climate.columbia.edu/2020/03/13/fix-recycling-america/ (2020).

CHAPTER 6:

ROAD TRANSPORT

Ruben Glatt, David Sandalow and Ivo Steklac

A. Vehicle Electrification 6-3

B. Alternative Fuels 6-5

C. Intelligent Transportation Systems (ITSs) 6-6

D. Modal Shifts 6-9

E. Autonomous Vehicles (AVs) 6-10

F. Barriers 6-11

G. Risks 6-11

H. Recommendations 6-13

I. References 6-15

Road transport is a critical part of the global economy. Current modes of road transport rely heavily on fossil fuels, producing roughly 18% of global energy-related carbon dioxide (CO_2) emissions.[1,2] Strategies for reducing CO_2 emissions from road transport include deploying electric vehicles (EVs), using alternative fuels, adopting intelligent transportation systems (ITSs), shifting to shared modes of transport and deploying autonomous vehicles (AVs).

Plug-in electric vehicle

Vehicle electrification is the dominant strategy for reducing CO_2 emissions from road transport. Life-cycle greenhouse gas (GHG) emissions from EVs are already significantly lower than those from comparable vehicles with internal combustion engines. (Emission benefits vary based on regional differences in energy generation. One recent study found EV life-cycle emissions were lower by 66–69% in Europe, 60–68% in the United States, 37–45% in China and 19–34% in India.[3]) As electric grids decarbonize and EVs become more efficient in terms of distance per kWh and manufacturing materials employed, EVs will contribute even more to reducing emissions. Barriers to accelerated deployment of EVs include their up-front purchase price and driving range, both of which can be addressed with battery and electric motor innovations.

Other important strategies for reducing CO_2 emissions from road transport include:

- **Alternative fuels.** The energy properties of biofuels, synthetic fuels, hydrogen and natural gas make them attractive options for many kinds of transport, including heavy duty vehicles carrying large loads over long distances.
- **Intelligent transportation systems (ITSs).** Sensor and communication technologies combined with data processing can analyze vast amounts of real-time data to plan, monitor and control transit and congestion.
- **Modal shifts.** Shifts from personal vehicles to shared vehicles and/or public transport are also important for changing the transportation landscape.
- **Autonomous vehicles (AVs).** AVs have the potential to reduce CO_2 emissions by accelerating EV adoption and facilitating platooning, among other changes, but could also increase CO_2 emissions by making it easier to use individual vehicles, leading to longer trips and displacing walking, cycling and mass transit.

Artificial intelligence (AI) has significant potential to help reduce GHG emissions in all these areas. Many solutions are still in research and pilot stages but show great promise. To realize AI's immense potential to reduce road transport emissions, AI solutions must be built into commercial products, integrated into public infrastructure and deployed in a safe and responsible manner.

In this chapter we discuss how emerging capabilities of AI are opening up new opportunities to reduce CO_2 emissions from road transport.[4]

A. Vehicle Electrification

AI has the potential to play a major role in reducing carbon emissions by improving battery and electric motor design, optimizing battery usage and promoting battery recycling.

i. Material discovery

One especially promising example is AI's ability to help improve battery and electric motor design by speeding the process of material discovery. Discovering new materials is a complex task comprising two core challenges.[5] The first challenge involves determining the right chemical components that, in combination, exhibit certain desired characteristics and properties. The second challenge involves finding a structure that provides a stable solution. The key to this process often lies in reducing the very large number of possible solutions to a small number that can be evaluated in real-world experiments in a more cost- and time-effective manner.[6] AI can increase accuracy when predicting the properties of materials and accelerate down-selection of possible solutions.[7]

Indeed this is already happening. Google has discovered 2.2 million new crystals—including 380,000 stable materials—via Graph Networks for Materials Exploration (GNoME). Google researchers estimate this discovery is equivalent to nearly 800 years' worth of non AI-based research, dramatically increasing the speed and efficiency of discovery by predicting the stability of new materials.[8] Major AI-driven breakthroughs and innovations in battery materials—including in nickel cathodes, silicon anodes and novel electrolytes—are already increasing capacity and reducing the cost of EV batteries.[9]

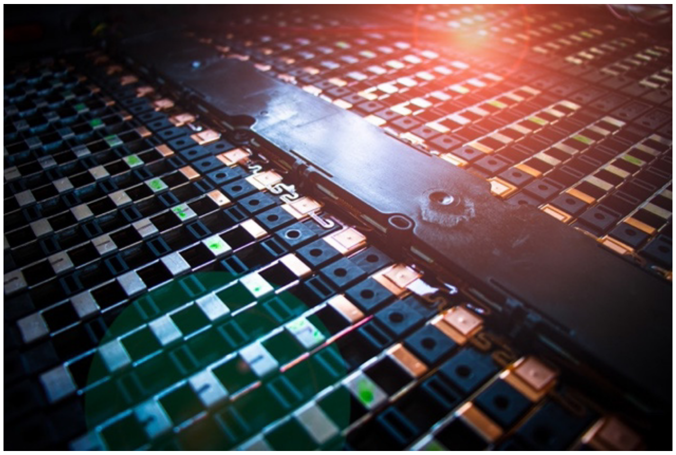
More progress could be achieved through AI investments that support collaborations between industry and academia based on data, model and knowledge sharing. Such work is underway at the US Joint Center for Energy Storage Research and the European Battery 2030+ Initiative.[10]

Similar materials research is being applied to electric motors. A United Kingdom company recently developed a rare-earth-free permanent magnet by identifying, synthesizing and testing more than 100 million compositions of rare-earth-free permanent magnet candidates within 3 months, a 200x increase over traditional methods. The process addresses industry challenges, such as supply chain security, cost, performance and environmental issues, and the resulting material reduces material costs by 80% and carbon emissions by 30% compared to current commercial rare-earth permanent magnets.[11]

ii. Battery efficiency and lifespan

AI can significantly enhance battery efficiency and lifespan. With data on energy prices, grid load, driving patterns, battery health and other factors, AI methods can optimize charging schedules for EVs with reinforcement learning.[12] AI-assisted battery charging can cut electricity costs, prevent overburdening the power grid, prolong battery lifespans and increase vehicle availability, particularly for EV fleet providers.[13] AI tools can also optimize the charging process directly while considering battery-aging effects and environmental conditions (such as temperature) that prevent chemical aging. Examples include (1) replacing rule-based charging strategies with Bayesian optimization combined with a linear-regression prediction model to define an extreme fast-charging protocol that maximizes battery cycle-life and reduces the traditional experimental-based approach from 500 to 16 days and (2) employing adaptive multistage constant current/constant voltage charging strategies based on a particle swarm optimization approach.[14]

AI-based battery monitoring provides various innovative methodologies to enhance battery efficiency and lifespan. Examples include: AI-empowered digital twin technology to create a digital replica of the battery system for real-time monitoring and predictive analysis. The digital twin works alongside the battery management system, using AI algorithms like long short-term memory (LSTM) for precise state-of-charge predictions and time-series generative adversarial networks (TS-GAN) for generating synthetic data. This integration enhances the monitoring process, predicts battery behavior accurately, and improves overall battery performance and safety.[15] Additionally, research into driving behavior–guided battery health monitoring focuses on the importance of incorporating real-world driving behaviors into battery health monitoring. By evaluating various health indicators and their acquisition probability under actual driving conditions, the state of battery health can be predicted with high accuracy. This approach balances performance and practicality, ensuring accurate and applicable battery health assessments in real-world scenarios.[16]



Automotive batteries

iii. Battery recycling and reuse

Another way to decrease the carbon footprint of EV batteries is to improve recycling and reuse.[17] AI can improve processes based on pyrometallurgical, hydrometallurgical and biological recycling to recover precious raw materials, while supporting diagnostics to evaluate the fit and expected characteristics for a second life. Examples of these applications are (1) useful-life forecasting,[18] (2) machine learning (ML)-enhanced automated disassembly and quality control that integrates computer vision and time- series prediction,[19] (3) optimal parameter setting for bioleaching processes for material recovery based on a random forest regression model[20] and (4) applications for battery life-cycle, waste recycling and material recovery.[21]

iv. Bidirectional charging

AI can play an important role in bidirectional EV charging.[22] With bidirectional charging capabilities, EVs can deliver power to homes (V2H), businesses (V2B) or the electric grid (V2G). Together, these applications are sometimes referred to as V2X or "vehicle-to-everything". V2X technologies provide homeowners and businesses with energy security and help grid managers overcome shortages or deliver ancillary grid services. Reinforcement learning algorithms based on user preference and price signals are a potent tool for guiding the charging and discharging in V2X systems.[23] AI can also be used in charge-management systems to guide EVs to charging stations to reduce negative effects during peak charging times.[24] The mobile storage can also be used to improve energy performance of public buildings by using an AI-based V2G strategy to reduce the carbon footprint of buildings supported by energy consumption and cost predictions.[25]

To realize AI's full potential to contribute to vehicle electrification, interoperability of AI systems will be important. Defining protocols for interoperability of AI systems across different EV models and charging infrastructures can help ensure seamless integration and operational efficiency.

EV fleet charging

B. Alternative Fuels

Alternative fuels can play an important role in reducing CO_2 emissions from road transport. Synthetic fuels and biofuels provide transitional solutions that can leverage existing infrastructure and reduce emissions in the near term. Compressed natural gas (CNG) and liquefied natural gas (LNG) serve as lower-emission alternatives to conventional fuels, particularly in regions with abundant natural gas resources. The optimal mix of these technologies will depend on regional resources, infrastructure and specific transportation needs. Each technology has its own strengths and challenges, and their importance varies by application and context. These alternative fuels also have applications beyond road transport, including in air and marine travel.

Biofuels can help decarbonize road transport. The most promising applications are with heavy duty vehicles, such as trucks carrying large loads over long distances. Although caution is required. When feedstocks other than waste biomass are used for biofuels, indirect effects of land use change can reduce or even eliminate the GHG benefits of using biofuels. AI can play an important role in developing sustainable biofuels. Applications include image segmentation for cell analysis in microalgae and modeling time series in the bioenergy conversion process. For new biofuels, AI already plays an important role in predicting and optimizing highly complex non-linear bioenergy systems. When it comes to producing biofuels from biomass, so far most of the literature involving AI focuses on thermochemical processes,[26] however biological processes offer a promising research direction.[27] AI models can also help evaluate biofuel infrastructure requirements and support policy making and long-term planning.[28]

Synthetic Fuels, also known as synfuels, are produced through chemical processes, such as Fischer-Tropsch synthesis, which converts carbon monoxide and hydrogen into liquid hydrocarbons suitable for vehicle engines.[29] Audi's "e-diesel" is an example of a synthetic diesel fuel produced using renewable energy, suitable for standard diesel engines without modifications. The production process involves electrolysis to separate hydrogen from water molecules, combined with CO_2 to create liquid hydrocarbons. AI enhances the efficiency of Fischer-Tropsch synthesis by optimizing reaction conditions and developing more effective catalysts.[30] AI-driven process simulations help identify and mitigate inefficiencies, reducing the carbon footprint of synthetic fuel production and usage in road transport.

Hydrogen Fuel Cells generate electricity by combining hydrogen gas stored in high-pressure tanks with oxygen, producing only water vapor as an emission. The Toyota Mirai is a hydrogen fuel cell vehicle (FCV) that uses this technology, offering a driving range comparable to gasoline vehicles with refueling times of about five minutes. AI optimizes fuel cell design and the hydrogen production process, particularly electrolysis, by predicting the performance of materials and operational parameters.[31] Predictive maintenance and integration with renewable energy sources are enhanced by AI, reducing the carbon footprint of hydrogen production and fuel cell operation.

Compressed Natural Gas (CNG) is a cleaner-burning alternative to gasoline, producing fewer emissions and often used in fleets for companies or municipal services. The Honda Civic Natural Gas vehicle is an example, featuring a modified engine and fuel system to accommodate CNG. AI improves CNG technology by optimizing combustion processes, analyzing real-time engine data, and enhancing natural gas extraction and processing.[32] AI-driven analytics also help design efficient storage and distribution systems, reducing the carbon emissions associated with CNG production, distribution and consumption in road transport.

Liquefied Natural Gas (LNG) is used in heavy-duty trucks for long-haul trucking due to its higher energy density compared to CNG. The Freightliner Cascadia is a heavy-duty truck equipped with an LNG fuel system, providing a cleaner alternative to diesel-powered trucks. AI optimizes the LNG liquefaction process, improves plant performance and enhances routing and scheduling of LNG shipments. Predictive maintenance extends the lifespan of LNG infrastructure, while AI-driven improvements in the regasification process reduce energy input and emissions, making the LNG supply chain more sustainable and environmentally friendly.[33]

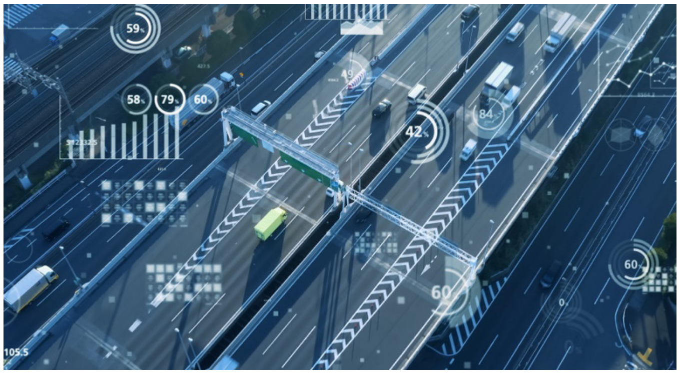
C. Intelligent Transportation Systems (ITSs)

AI, sensors and communications networks can be used in combination to manage transportation infrastructure. An ITS with these components can help plan transportation infrastructure, coordinate traffic, manage EV charging networks and predict maintenance needs. ITSs can adjust digital signs, traffic signals and public transportation schedules to react to forecasted congestion. They can schedule maintenance to avoid material failure and increase road safety. ITSs have great potential to help reduce congestion, optimize vehicle and infrastructure usage, and improve safety while reducing emissions from road transport.[34] These technologies could be at the heart of a more sustainable and carbon-free transportation system.

i. Traffic management

AI can help optimize traffic flow, decrease congestion, enable dynamic traffic-light sequencing, suggest smart multi-modal public/private routes and model traffic to foresee and alleviate congestion. These AI strategies have substantial potential sustainability benefits, including reduced fuel consumption and GHG emissions, which in turn enhance urban air quality and support environmental sustainability goals.

Some cities have implemented pilot studies to investigate real-world implications of using AI for traffic management. The city of Phoenix in the United States saw a 40% decrease in vehicle delay time after implementing an AI-driven traffic management system. In Calabria, Italy, a pilot program reduced total travel time by up to 55% through adaptive real-time control of traffic signals for connected vehicles (CV).[35] Case studies have shown that AI-driven traffic management systems can reduce traffic congestion by up to 30% during peak times and 15–20% overall by providing 45- to 60-minute congestion-prediction lead times.[36]



Vehicles connected by intelligent transportation system

AI can predict traffic congestion through advanced analytics by leveraging historical and real-time data from various sources, such as sensors, GPS devices and traffic cameras. Techniques based on deep learning enable AI systems to learn intricate traffic patterns and accurately forecast congestion and traffic anomalies. Real-time data integration allows these systems to provide timely insights, enhancing their predictive accuracy.[37] AI also plays a critical role in incident detection and response, where AI-powered surveillance systems can identify accidents or road hazards in real-time, allowing for immediate alerts to authorities and rapid response to minimize traffic disruptions. Dynamic routing optimization further helps alleviate congestion by using reinforcement learning algorithms, such as Q-learning, to adjust vehicle routes in real-time, thereby optimizing traffic flow and reducing travel times. AI-driven traffic signal coordination, exemplified by initiatives like Google's Project Green Light,[38] enhances traffic efficiency by optimizing signal timings based on current conditions.

In public transport, AI can be used to predict passenger loads and optimize schedules and routes, enhancing service efficiency and user satisfaction.[39] AI's role in predictive maintenance can also help foresee potential infrastructure issues in public transit, preventing failures or delays. In addition, AI traffic congestion prediction can be used to schedule increases in public transport capacity. Finally, by processing and analyzing ITS data, AI will be able to aid informed policy decisions and strategic planning, leading to greener, more efficient public transit systems. Infusion of AI into ITSs is emerging as a cornerstone strategy in shifting toward lower emissions and heightened efficiency in public transit.

ii. Data needs

The data needed for successful AI applications can be provided by static or mobile sensors. Sensor-driven infrastructure components—collecting and transmitting data—are essential.[40] These include traffic sensors at intersections or along roadways, smart traffic lights with sensors to monitor traffic and pedestrian activity, road weather information systems that track atmospheric and pavement conditions, and smart parking sensors that detect vehicle presence. Sensors on bridges, tunnels and roads to facilitate predictive maintenance, as well as environmental sensors to monitor conditions like air quality and emissions, are also important. In the realm of CVs, sensor-driven infrastructure can dynamically integrate vehicle sensors—such as LiDAR, radar and cameras—in ITSs to perceive the surrounding environment through edge (distributed) analytics.[41] By offering continuous, real-time data, a sensor-driven infrastructure enables AI systems to significantly enhance operational capabilities of infrastructure, helping route emergency services, control traffic and respond to demand changes in public transport. However, the massive amounts of data require smart integration with cloud-based storage and potentially large computing capabilities that may have a negative impact on net emissions.[42]

Digital connectivity and emerging technologies, such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, are cornerstones of Cooperative Intelligent Transport Systems (C-ITS). Such systems enable coordinated exchange of data for real-time analytics and collection of data to train the next generation of intelligent systems.[43] New sensors for C-ITS have been shown to increase resilience for transportation systems, with immediate impact on operation and infrastructure robustness.[44] However, interconnectedness between individual vehicles, roadside units and central data processing may increase the risk of data exploitation and invasions of privacy, warranting new methods for privacy protection in these systems through emerging technologies, such as blockchain[45] and federated learning.[46]

iii. Simulations

AI-driven simulation has significant potential to reduce road transport emissions, delivering better results than conventional algorithm-based simulations by capturing complex patterns and relationships in transportation data.[47] This can provide a wealth of insights, including in optimizing infrastructure planning, forecasting energy demand and evaluating potential transportation system policies.[48] AI simulations can help identify where investments in charging stations and bicycle lanes can best reduce emissions, for example. Linking transportation and energy systems in AI-driven simulations can significantly advance the evolution of ITSs, contributing to more sustainable and efficient transport networks. A 2021 Latvian study, for example, showed the potential of different policy instruments to reduce CO_2 emissions 30% by 2030, concluding that more research and a tighter coupling between the transportation and energy sectors are needed to reach the ambitious goals of the European Green Deal.[49]

As simulations become more powerful, more data are needed, and real-world experiences can provide the best insights. Communities, utility providers, fleet operators and vehicle manufacturers could initiate more pilot projects, such as dynamic traffic light control systems, which leverage real-time data from GPS, traffic flow sensors, transportation network health and weather updates to optimize the sequence and timing of traffic lights using ML methods. These pilot projects can enhance traffic flow, reduce congestion and curtail fuel consumption. However, securing a large enough number of participants will be key to gaining meaningful insights. Other initiatives could involve predictive maintenance of road infrastructure using sensors that monitor wear and tear, schedule preemptive maintenance and mitigate critical failures.[50] Such collaborative, large-scale projects not only improve transportation efficiency, safety and user experience, but also contribute significantly to reducing carbon emissions.

iv. Foundation models

As a final consideration, the advent of foundation models, prompted by recent advances in large-language and vision models, has marked a significant shift in our approach to problem-solving. These models, with their capacity to handle multi-modal input and domain-specific expertise, have the potential to revolutionize numerous fields. However, their applicability in the realm of road transport is relatively uncharted. Potential applications for foundation models may include autonomous driving and control of intelligent transportation infrastructure, however their impact is not yet clear.[43]

D. Modal Shifts

Modal shifts—moving from one type of transportation to another—can significantly reduce emissions from road transport. Leading examples include shifts from private vehicles to public transit and from solo driving to car sharing. Such modal shifts require behavior changes and often depend on transit systems that offer an array of mobility options.

AI can serve as a powerful tool in driving behavioral change that contributes to sustainable mobility. AI-driven approaches encourage the use of public transportation in several ways:

- First, by harnessing AI algorithms to analyze various data sources, AI-driven approaches can predict public transit demand, allowing for optimal route planning and strategic relocation that enhances the convenience of public transit.
- Second, by underpinning integrated mobility platforms, which process real-time information from multiple transport modes and propose optimal route options, AI platforms can nudge users toward public or shared transport. In addition, AI-guided autonomous public transit could extend the reach of public transport to regions where traditional services may not be economically viable, thus decreasing reliance on private vehicles.
- Third, by producing personalized recommendations and effective gamification techniques, such as reward systems, challenges or social competitions, AI-driven approaches can incentivize and engage commuters in choosing sustainable transportation options.
- Finally, by predicting maintenance issues in public transportation vehicles, AI-driven approaches can improve the dependability of these services by minimizing downtime. Consequently, AI can make public transportation more efficient, reliable and appealing, playing a crucial role in curtailing private vehicle usage and overall transport activity.

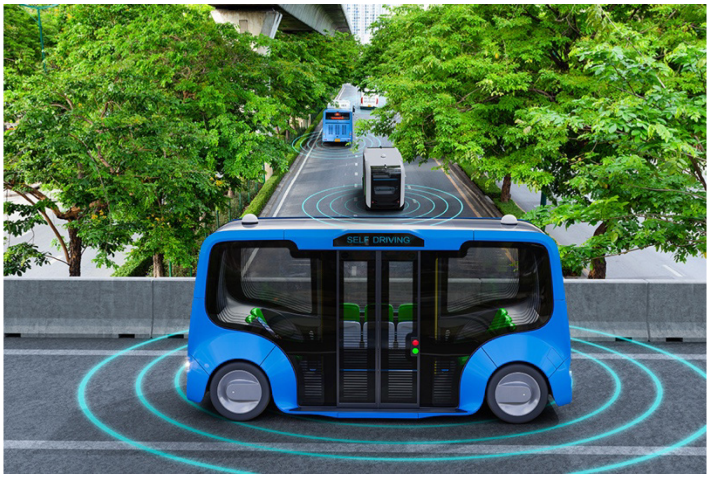
AI can also enable shared mobility solutions, which can significantly cut down on energy consumption and GHG emissions.[51]

- AI can help manage shared vehicle fleets, ensuring that vehicles are distributed effectively based on anticipated demand, reducing waiting times, and making shared mobility more effective and attractive.[52]
- AI can also personalize the shared mobility experience by understanding users, suggesting the most suitable shared options and facilitating dynamic pricing with prices based on supply and demand to balance resource utilization and maintain service attractiveness.[53]
- AI-driven predictive maintenance can keep shared vehicles in optimal condition, maintaining energy efficiency, reducing downtime and enhancing reliability of shared mobility services.[53]

Thus, through these measures, AI can make shared mobility a more appealing alternative to private vehicle use, leading to a significant reduction in overall transport activity.

E. Autonomous Vehicles (AVs)

One of the most important emerging uses of AI in the road transport sector to date is with AVs.[54] AVs have made significant progress in real-world deployments, with companies like Waymo and Cruise operating commercial robo taxi services in select US cities, while autonomous trucking firms, such as TuSimple and Kodiak Robotics, have conducted extensive on-road testing.[55] As of 2023, AVs had driven over 80 million miles on US public roads, demonstrating the scale of ongoing testing and development efforts.[56] However, widespread deployment remains limited, with most autonomous vehicle operations restricted to specific geographic areas and operating conditions.[57]



Autonomous shuttle bus

AVs and more specifically autonomous electric vehicles (AEVs) have the potential to reduce CO_2 emissions by reducing dependence on conventional, individual-owned internal combustion engine vehicles and promoting shared electric and autonomous transport. AI can be used to enhance accessibility and convenience, as route optimization and vehicle distribution make AEVs that are integrated into shared mobility platforms highly reliable and accessible. Furthermore, AEVs can lower operating costs due to their electric drivetrains, a benefit that AI can augment by optimizing energy usage. AI also enables AEVs to operate more efficiently, through measures such as platooning, smart parking management and route selection. This efficiency reduces congestion, energy use and urban space requirements. Additionally, the environmental impact is minimized as AEVs produce no tailpipe emissions and AI aids in optimizing energy usage. Lastly, AI can facilitate integration of AEVs with public transit, enhancing first-mile and last-mile connectivity, making public transit a more appealing choice and further driving the modal shift.

Studies show that AVs are expected to bring noticeable changes to road transport and, through them, reduce environmental impacts and CO_2 emissions.[58] However, AVs could also increase emissions of CO_2.

- Cheap, convenient on-demand mobility may overshadow alternatives, such as walking, cycling and public transport. Drivers may be more prone to take longer trips when driving requires little attention. The result could be more vehicle kilometers traveled and greater emissions.[59]
- In addition, rebound effects can occur when savings from efficiency improvements lead to increased demand for a product, reducing or even negating the original savings.[60]
- As AVs and smart infrastructure are algorithm-driven, malfunctions could result in significant inefficiencies, unexpected behaviors or accidents that require corrective actions, potentially leading to additional carbon emissions.

F. Barriers

While AI has immense potential to help reduce GHG emissions from road transport, several barriers must be addressed to realize this potential.

A first barrier is lack of data. Data on a wide range of topics are required to deploy AI in integrated road transportation systems. Sensors, smart infrastructure and other tools will be needed to collect such data. While algorithm development and improved computing hardware are important, near- to mid-term advances primarily depend on availability and accessibility of data.

Second, uniform standards and protocols for sensor data collection and communication are essential. In a modern grid, a vehicle can serve as a communication node and operate as a channel to interconnect the electricity grid, traffic network and communication network.[61] In this context, developing common standards in V2V and V2I communication is important for promoting seamless interoperability. A standardized communication framework enables vehicles to exchange information effectively with their environment. This capability provides additional data that can inform local predictions and decision making, reducing emissions while increasing the efficiency and safety of the transportation system.

A third barrier is a shortage of personnel with the needed training in and familiarity with AI. AI experts and software developers are needed, but—at least as important—transport operators and regulators must be equipped with the necessary skills to consider and evaluate AI options.

G. Risks

Using AI in road transport also creates risks that must be addressed.

First, privacy interests can be threatened by the extensive data collection needed for many applications. Those data could potentially reveal a great deal about individuals' habits and actions.

Societal norms are only beginning to be established with respect to collecting, distributing and using data in this area.

Second, using AI in road transport creates risks of bias. For example, training data sets may sample more heavily from wealthy neighborhoods than poor ones. Inadvertent discrimination against certain groups or areas is possible. Close attention is required to minimize the risk of inadvertent bias emerging from use of AI.

A third and serious risk is higher emissions as a result of deploying AVs, as noted above. AVs might lead to far more driving, increasing emissions from driving and vehicle manufacturing.[62]

Predicting the impact of AVs on road transport emissions is challenging due to several factors, including ongoing technological development, market evolution and regulatory actions. To address potential negative impacts, a holistic and sustainable approach to integrating AI in the transportation sector is crucial. Careful planning will be necessary to prevent unintended consequences and manage potential increases in vehicle usage.

H. Recommendations

Vehicle Electrification

1. *Local governments should promote development and deployment of AI-optimized EV charging stations, update building codes that require incorporating such systems in new installations, and run public awareness campaigns to educate residents and businesses about the benefits of intelligent EV infrastructure.*

2. *Industry and academia should form partnerships to drive innovation in AI-enhanced EV technologies. These collaborations should focus on developing AI-driven solutions to improve battery lifespan, efficiency and recycling methods.*

3. *National governments, industry and academia should invest in AI research for battery and motor advancements, leveraging HPC for materials discovery; integrating AI methods to enhance performance, safety and lifespan; and promoting collaborations such as the US Joint Center for Energy Storage Research and the European Battery 2030+ Initiative.*

4. *National governments should establish comprehensive regulations for AI applications in EV technology on topics including data privacy, usage and storage. These regulations should align with global standards to facilitate international cooperation and ensure responsible and ethical use of AI tools.*

5. *Industry and standards development organizations should work together to develop standards for AI applications in EVs, covering topics such as battery monitoring, charging optimization and communication protocols.*

Alternative Fuels

1. *National governments should implement incentive programs such as subsidies and grants, to encourage AI-driven research and development of alternative fuels. They should also increase simulation capabilities to evaluate the life-cycle and infrastructure impact of innovative fuels.*

2. *Industry and academia should increase collaborative research efforts to enhance efficiency and reduce the environmental impact of alternative fuels based on AI methods, for example by establishing innovation hubs and providing funding and support for startups working on AI-driven technologies in these fields.*

3. *Governments, academia and industry should develop centralized data-sharing platforms where researchers can access and share datasets related to alternative fuels to facilitate data exchange, enhance research quality and speed up discoveries.*

Intelligent Transportation Systems (ITSs)

1. *National governments and intergovernmental organizations should establish comprehensive data privacy regulations for AI applications in transportation following examples such as the United Nations' global AI resolution. These regulations should ensure clear guidelines to safeguard human rights, protect personal data and support AI use to mitigate climate impact in road transport.*
2. *Local governments should invest in smart infrastructure and develop long-term strategic plans, implementing procurement policies, conducting public awareness campaigns and investing in sensor-driven infrastructure for AI-based real-time decision making.*
3. *Industry and standards development organizations should collaborate to establish standards for smart transportation technologies, including V2X communication, data security, EV charging connectors and harmonized communication networks leveraging 5G and satellite technology to ensure integration and distributed interoperability.*
4. *National governments, industry, and academia should increase research and data collection for intelligent transportation systems to support AI in mitigating climate impact in road transport, enabling complex simulations using HPC, and launching large-scale collaborations and pilot projects for smart infrastructure development.*

Modal Shift

1. *National governments should allocate funding for AI projects that optimize multi-modal transit routes, predict demand and improve shared mobility services, ensuring a streamlined and transparent application process for research institutions and private companies to access these funds.*
2. *Governments, industry, and academia should form consortia to develop AI-driven mobility platforms in major cities, integrate pilot projects to test strategies like dynamic pricing and optimized public transit schedules, and publish findings for wider implementation.*

Autonomous Vehicles (AVs)

1. *Local and national governments should collect and share data on the GHG impacts of AVs, including data on supply chain emissions.*
2. *Local governments should develop regulations and run pilot projects to facilitate integration of AI-driven autonomous mobility solutions that reduce CO_2 emissions.*
3. *Industry and academia should expand research efforts and develop improved simulation capacities to help develop AI-based methods that offer a safe test bed for evolving autonomous driving capabilities, focusing in particular on ensuring that AVs help reduce CO_2 emissions.*

I. References

1 Arizona Public Service Company (APS). *2023 Integrated Resource Plan;* Phoenix, Arizona, https://www.aps.com/-/media/APS/APSCOM-PDFs/About/Our-Company/Doing-business-with-us/Resource-Planning-and-Management/APS_IRP_2023_PUBLIC.pdf?la=en&sc_lang=en&hash=DF34B49033ED43FF0217FC2F93A0BBE6 (2023).

2 Statista. *Distribution of carbon dioxide emissions produced by the transportation sector worldwide in 2022, by sub sector;* Hamburg, Germany, https://www.statista.com/statistics/1185535/transport-carbon-dioxide-emissions-breakdown/ (Accessed November 2024).

3 Georg Bieker. *A global comparison of the life-cycle greenhouse gas emissions of combustion engine and electric passenger cars;* International Council on Clean Transportation (ICCT), https://www.team-bhp.com/forum/attachments/electric-cars/2310712d1653112667-things-consider-when-buying-electric-car-global-lca-passenger-cars-jul2021-0.pdf (2021).

4 S. P. Sathiyan *et al.* Comprehensive Assessment of Electric Vehicle Development, Deployment, and Policy Initiatives to Reduce GHG Emissions: Opportunities and Challenges. *IEEE Access* 10, 53614-53639 (2022). https://doi.org/10.1109/ACCESS.2022.3175585.

5 Scott M. Woodley & Richard Catlow. Crystal structure prediction from first principles. *Nature Materials* 7, 937-946 (2008). https://doi.org/10.1038/nmat2321.

6 Peter M. Attia *et al.* Closed-loop optimization of fast-charging protocols for batteries with machine learning. *Nature* 578, 397-402 (2020). https://doi.org/10.1038/s41586-020-1994-5.

7 Yue Liu *et al.* Machine learning assisted materials design and discovery for rechargeable batteries. *Energy Storage Materials* 31, 434-450 (2020). https://doi.org/10.1016/j.ensm.2020.06.033.

8 Amil Merchant *et al.* Scaling deep learning for materials discovery. *Nature* 624, 80-85 (2023). 10.1038/s41586-023-06735-9.

9 Mohamed S. E. Houache *et al.* On the Current and Future Outlook of Battery Chemistries for Electric Vehicles—Mini Review. *Batteries* 8, 70 (2022). https://doi.org/10.3390/batteries8070070.

10 Muratahan Aykol, Patrick Herring & Abraham Anapolsky. Machine learning for continuous innovation in battery technologies. *Nature Reviews Materials* 5, 725-727 (2020). https://doi.org/10.1038/s41578-020-0216-y.

11 Ben Crome. *Materials Nexus Uses AI-Based Materials Discovery Platform to Create MagNex, a Novel Rare Earth-Free Permanent Magnet;* Materials Nexus, London, UK, https://www.materialsnexus.com/news/magnex-rare-earth-free-permanent-magnet (2024).

12 X. Hu *et al.* Reinforcement Learning for Hybrid and Plug-In Hybrid Electric Vehicle Energy Management: Recent Advances and Prospects. *IEEE Industrial Electronics Magazine* 13, 16-25 (2019). https://doi.org/10.1109/MIE.2019.2913015.

13 Oliver Frendo *et al.* Data-driven smart charging for heterogeneous electric vehicle fleets. *Energy and AI* 1, 100007 (2020). https://doi.org/10.1016/j.egyai.2020.100007.

14 Yunjian Li *et al.* Optimized charging of lithium-ion battery for electric vehicles: Adaptive multistage constant current–constant voltage charging strategy. *Renewable Energy* 146, 2688-2699 (2020). https://doi.org/10.1016/j.renene.2019.08.077.

15 Mitra Pooyandeh & Insoo Sohn. Smart Lithium-Ion Battery Monitoring in Electric Vehicles: An AI-Empowered Digital Twin Approach. *Mathematics* 11, 4865 (2023). https://doi.org/10.3390/math11234865

16 Nanhua Jiang *et al.* Driving behavior-guided battery health monitoring for electric vehicles using extreme learning machine. *Applied Energy* 364, 123122 (2024). https://doi.org/10.1016/j.apenergy.2024.123122.

17 Karlo Hainsch *et al.* Energy transition scenarios: What policies, societal attitudes, and technology developments will realize the EU Green Deal? *Energy* 239, 122067 (2022). https://doi.org/10.1016/j.energy.2021.122067.

18 Prabhakar Sharma & Bhaskor J. Bora. A Review of Modern Machine Learning Techniques in the Prediction of Remaining Useful Life of Lithium-Ion Batteries. *Batteries* 9, 13 (2023). https://doi.org/10.3390/batteries9010013.

19 Yingqi Lu *et al.* A novel disassembly process of end-of-life lithium-ion batteries enhanced by online sensing and machine learning techniques. *Journal of Intelligent Manufacturing* 34, 2463-2475 (2023). https://doi.org/10.1007/s10845-022-01936-x.

20 Parastou Mokarian *et al.* The advanced design of bioleaching process for metal recovery: A machine learning approach. *Separation and Purification Technology* 291, 120919 (2022). https://doi.org/10.1016/j.seppur.2022.120919.

21 Agnieszka Pregowska, Magdalena Osial & Weronika Urbańska. The Application of Artificial Intelligence in the Effective Battery Life Cycle in the Closed Circular Economy Model—A Perspective. *Recycling* 7, 81 (2022). https://doi.org/10.3390/recycling7060081.

22 Francis Mwasilu *et al.* Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration. *Renewable and Sustainable Energy Reviews* 34, 501-516 (2014). https://doi.org/10.1016/j.rser.2014.03.031.

23 David Rolnick *et al.* Tackling Climate Change with Machine Learning. *ACM Comput. Surv.* 55, Article 42 (2022). https://doi.org/10.1145/3485128.

24 Tehseen Mazhar *et al.* Electric Vehicle Charging System in the Smart Grid Using Different Machine Learning Methods. *Sustainability* 15, 2603 (2023). https://doi.org/10.3390/su15032603.

25 Connor Scott, Mominul Ahsan & Alhussein Albarbar. Machine Learning Based Vehicle to Grid Strategy for Improving the Energy Performance of Public Buildings. *Sustainability* 13, 4003 (2021). https://doi.org/10.3390/su13074003.

26 Muzammil khan *et al.* Applications of machine learning in thermochemical conversion of biomass-A review. *Fuel* 332, 126055 (2023). https://doi.org/10.1016/j.fuel.2022.126055.

27 Ahmed I. Osman *et al.* Conversion of biomass to biofuels and life cycle assessment: a review. *Environmental Chemistry Letters* 19, 4075-4118 (2021). https://doi.org/10.1007/s10311-021-01273-0.

28 Jakob Wachsmuth *et al.* The European Commission's 2050 Vision "A clean planet for all"–Implications for Sector Strategies and Climate Governance. Final report. (Dessau-Roßlau: German Environment Agency, 2022).

29 Hans Schulz. Short history and present trends of Fischer–Tropsch synthesis. *Applied Catalysis A: General* 186, 3-12 (1999). https://doi.org/10.1016/S0926-860X(99)00160-X.

30 Qian-Yu Liu, Cheng Shang & Zhi-Pan Liu. In Situ Active Site for CO Activation in Fe-Catalyzed Fischer–Tropsch Synthesis from Machine Learning. *Journal of the American Chemical Society* 143, 11109-11120 (2021). https://doi.org/10.1021/jacs.1c04624.

31 Amani Al-Othman *et al.* Artificial intelligence and numerical models in hybrid renewable energy systems with fuel cells: Advances and prospects. *Energy Conversion and Management* 253, 115154 (2022). https://doi.org/10.1016/j.enconman.2021.115154.

32 Dmitry Koroteev & Zeljko Tekic. Artificial intelligence in oil and gas upstream: Trends, challenges, and scenarios for the future. *Energy and AI* 3, 100041 (2021). https://doi.org/10.1016/j.egyai.2020.100041.

33 Ozowe Chinwe *et al.* Technological innovations in liquefied natural gas operations: Enhancing efficiency and safety. *Engineering Science & Technology Journal* 5, 1909-1929 (2024). https://doi.org/10.51594/estj.v5i6.1188.

34 Kashif Naseer Qureshi & Abdul Hanan Abdullah. A Survey on Intelligent Transportation Systems. *Middle-East Journal of Scientific Research* 15, 629-642 (2013). https://doi.org/10.5829/idosi.mejsr.2013.15.5.11215.

35 Vittorio Astarita *et al.* Floating Car Data Adaptive Traffic Signals: A Description of the First Real-Time Experiment with "Connected" Vehicles. *Electronics* 9, 114 (2020). https://doi.org/10.3390/electronics9010114.

36 Toon Bogaerts *et al.* A graph CNN-LSTM neural network for short and long-term traffic forecasting based on trajectory data. *Transportation Research Part C: Emerging Technologies* 112, 62-77 (2020). https://doi.org/10.1016/j.trc.2020.01.010.

37 Geraldo P. Rocha Filho *et al.* Enhancing intelligence in traffic management systems to aid in vehicle traffic congestion problems in smart cities. *Ad Hoc Networks* 107, 102265 (2020). https://doi.org/10.1016/j.adhoc.2020.102265.

38 Google Research. *Green Light: Reduce Traffic Emissions with AI;* Mountain View, California, https://sites.research.google/greenlight/ (Accessed August 2024).

39 Tielle Alexandre *et al.* Machine Learning Applied to Public Transportation by Bus: A Systematic Literature Review. *Transportation Research Record* 2677, 639-660 (2023). https://doi.org/10.1177/03611981231155189.

40 J. A. Guerrero-ibanez, S. Zeadally & J. Contreras-Castillo. Integration challenges of intelligent transportation systems with connected vehicle, cloud computing, and internet of things technologies. *IEEE Wireless Communications* 22, 122-128 (2015). https://doi.org/10.1109/MWC.2015.7368833.

41 A. Ferdowsi, U. Challita & W. Saad. Deep Learning for Reliable Mobile Edge Analytics in Intelligent Transportation Systems: An Overview. *IEEE Vehicular Technology Magazine* 14, 62-70 (2019). https://doi.org/10.1109/MVT.2018.2883777.

42 D. Nallaperuma *et al.* Online Incremental Machine Learning Platform for Big Data-Driven Smart Traffic Management. *IEEE Transactions on Intelligent Transportation Systems* 20, 4679-4690 (2019). https://doi.org/10.1109/TITS.2019.2924883.

43 Yifeng Shi *et al.* "Open-TransMind: A New Baseline and Benchmark for 1st Foundation Model Challenge of Intelligent Transportation" in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Vancouver, Canada; https://openaccess.thecvf.com/content/CVPR2023W/WFM/html/Shi_Open-TransMind_A_New_Baseline_and_Benchmark_for_1st_Foundation_Model_CVPRW_2023_paper.html. 6327-6334, 2023).

44 Muhammet Deveci *et al.* Evaluation of Cooperative Intelligent Transportation System scenarios for resilience in transportation using type-2 neutrosophic fuzzy VIKOR. *Transportation Research Part A: Policy and Practice* 172, 103666 (2023). https://doi.org/10.1016/j.tra.2023.103666.

45 R. Kumar *et al.* A Privacy-Preserving-Based Secure Framework Using Blockchain-Enabled Deep-Learning in Cooperative Intelligent Transport System. *IEEE Transactions on Intelligent Transportation Systems* 23, 16492-16503 (2022). https://doi.org/10.1109/TITS.2021.3098636.

46 Ruben Glatt *et al.* A Study on Efficient Reinforcement Learning Through Knowledge Transfer in *Federated and Transfer Learning* (eds Roozbeh Razavi-Far, Boyu Wang, Matthew E. Taylor, & Qiang Yang) 329-356 (Springer International Publishing, Cham, 2023, https://doi.org/10.1007/978-3-031-11748-0_14).

47 Saraju Mohanty. Everything You Wanted to Know About Smart Cities. *IEEE Consumer Electronics Magazine* 5, 60-70 (2016). https://doi.org/10.1109/MCE.2016.2556879.

48 Rocio de la Torre *et al.* Simulation, Optimization, and Machine Learning in Sustainable Transportation Systems: Models and Applications. *Sustainability* 13, 1551 (2021). https://doi.org/10.3390/su13031551.

49 Aiga Barisa, Vladimirs Kirsanovs & Alina Safronova. "Renewable Transport Challenge: A Comprehensive Policy Assessment Model" in *International Conference on Applied Energy*, Thailand/Virtual*.* 1-5 (Paper ID 858), https://www.energy-proceedings.org/wp-content/uploads/icae2021/1642955253.pdf,(2021).

50 Angie Ruiz & Jose Guevara. Sustainable Decision-Making in Road Development: Analysis of Road Preservation Policies. *Sustainability* 12, 872 (2020). https://doi.org/10.3390/su12030872.

51 Fahimeh Golbabaei, Tan Yigitcanlar & Jonathan Bunker. The role of shared autonomous vehicle systems in delivering smart urban mobility: A systematic review of the literature. *International Journal of Sustainable Transportation* 15, 731-748 (2021). https://doi.org/10.1080/15568318.2020.1798571.

52 Stefano Mariani, Giacomo Cabri & Franco Zambonelli. Coordination of Autonomous Vehicles: Taxonomy and Survey. *ACM Comput. Surv.* 54, Article 19 (2021). https://doi.org/10.1145/3431231.

53 Berkay Turan, Ramtin Pedarsani & Mahnoosh Alizadeh. Dynamic pricing and fleet management for electric autonomous mobility on demand systems. *Transportation Research Part C: Emerging Technologies* 121, 102829 (2020). https://doi.org/10.1016/j.trc.2020.102829.

54 Darsh Parekh *et al.* A Review on Autonomous Vehicles: Progress, Methods and Challenges. *Electronics* 11, 2162 (2022). https://doi.org/10.3390/electronics11142162.

55 Autonomous Vehicle Industry Association (AVIA). *State of AV 2024;* Washington, D.C., https://theavindustry.org/resources/2024_StateOfAV.pdf (2024).

56 Derek Chiao *et al. Autonomous vehicles moving forward: Perspectives from industry leaders;* McKinsey's Automotive and Assembly Practice and McKinsey Center for Future Mobility (McKInsey & Company), San Francisco, California, https://www.mckinsey.com/features/mckinsey-center-for-future-mobility/our-insights/autonomous-vehicles-moving-forward-perspectives-from-industry-leaders (2024).

57 Nick Reed. *OPINION: Are autonomous vehicles ready to deploy at scale?;* Traffic Technology International (TTI), Kent, UK, https://www.traffictechnologytoday.com/news/autonomous-vehicles/opinion-are-autonomous-vehicles-ready-to-deploy.html (2024).

58 Pantelis Kopelias *et al.* Connected & autonomous vehicles – Environmental impacts – A review. *Science of The Total Environment* 712, 135237 (2020). https://doi.org/10.1016/j.scitotenv.2019.135237.

59 Andrea Chicco & Marco Diana. Air emissions impacts of modal diversion patterns induced by one-way car sharing: A case study from the city of Turin. *Transportation Research Part D: Transport and Environment* 91, 102685 (2021). https://doi.org/10.1016/j.trd.2020.102685.

60 Kara Kockelman *et al.* An assessment of autonomous vehicles : traffic impacts and infrastructure needs : final report. (2017; https://rosap.ntl.bts.gov/view/dot/31990).

61 H. S. Das *et al.* Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review. *Renewable and Sustainable Energy Reviews* 120, 109618 (2020). https://doi.org/10.1016/j.rser.2019.109618.

62 Christina Pakusch *et al.* Unintended Effects of Autonomous Driving: A Study on Mobility Preferences in the Future. *Sustainability* 10, 2404 (2018). https://doi.org/10.3390/su10072404.

CHAPTER 7:

AVIATION

Colin McCormick

A. Use of AI For Emissions Mitigation in Commercial Aviation 7-2
B. Barriers 7-6
C. Risks 7-6
D. Recommendations 7-8
E. References 7-9

The aviation industry is a major sector of the global economy, with almost $1 trillion in revenue in 2024.[1] After a steep decline during the COVID pandemic, airline traffic returned to pre-COVID levels in 2024.[2,3] The sector has consistently grown faster than the global economy, with an average annual growth rate of 5% over the past 30 years.[4]

CO_2 emissions from the aviation sector were approximately 800 Mt in 2022, roughly 80% of pre-pandemic levels.[5] Emissions from aviation grew faster over recent decades than emissions from shipping, road or rail.[5] Member states of the International Civil Aviation Organization (ICAO) have adopted an aspirational goal of achieving net-zero carbon emissions by 2050.[6] In addition to CO_2, the industry is paying increasing attention to non-CO_2 impacts, including NO_x and methane (CH_4) emissions. This also includes persistent contrails.[7,8] While significant uncertainties remain, there is growing scientific consensus that aviation contrails result in an equivalent or greater amount of climate radiative forcing as that caused by aviation CO_2 emissions, making contrails a particularly important area of focus for mitigation efforts.[9,10]

The aviation industry is no stranger to artificial intelligence (AI) and has adopted AI in many areas. However, these uses of AI have primarily focused on areas such as customer satisfaction and cost reduction.[11,12] Specific uses of AI for emissions mitigation are relatively recent and limited in comparison, but they are growing and may have a significant impact in the future.

A. Use of AI For Emissions Mitigation in Commercial Aviation

i. Improving aircraft design

Aviation's CO_2 emissions are overwhelmingly driven by burning fossil-derived aviation fuel in jet engines. The fuel efficiency of new commercial jet aircraft has steadily improved over the past four decades (see Figure 7-1), but AI can help to continue this trend. One key approach is using AI/machine learning (ML) methods to enhance computational modeling of jet engine combustion physics and chemistry, potentially enabling engine designs with improved combustion efficiency.[13] Similar AI/ML techniques can also improve modeling of the advanced methods used to cool critical jet engine components (partly replacing the need for intensive computational fluid dynamics (CFD) calculations). This can enable development of designs that better balance fuel efficiency with engine longevity.[14] A related challenge in jet engine design is efficiently predicting the performance of novel engine concepts—designed by humans or AI systems—without expensive physical testing. AI/ML methods have been used to rapidly develop these performance assessments for next-generation turbofan concepts, accelerating the ability of aerospace design teams to efficiently iterate through novel designs.[15]

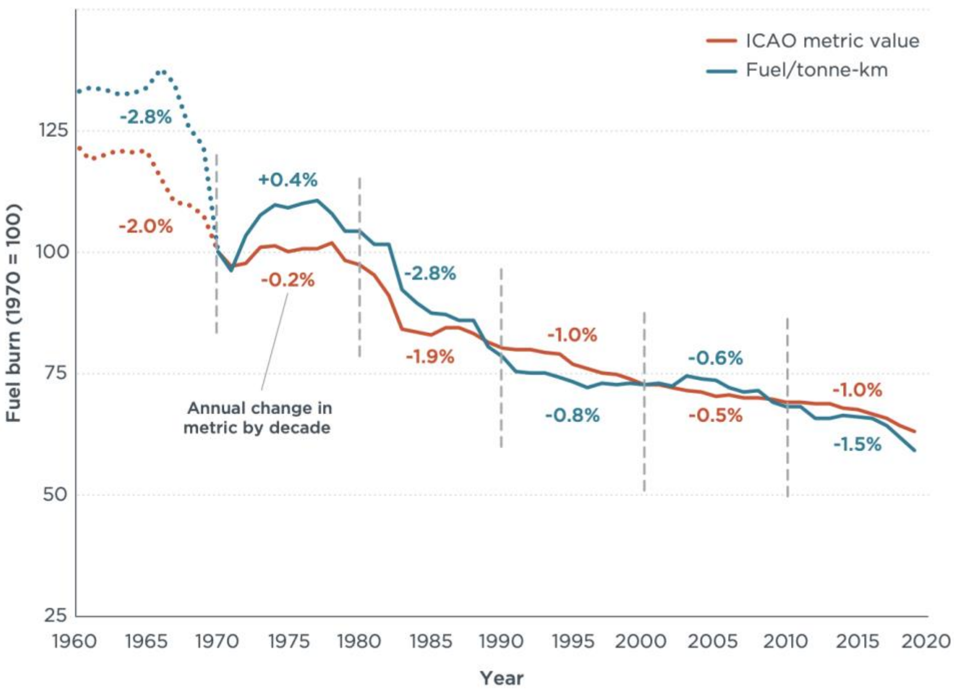


Figure 7-1. *Improvement in fuel efficiency of new commercial jet aircraft, 1980-2020. Credit: The International Council on Clean Transportation.*[21]

While engine efficiency is a crucial component of overall aircraft fuel efficiency, the shape of components, such as wings, fuselage and engine nacelles, can also have a major impact by reducing drag. AI/ML methods can help with aerodynamic shape optimization problems, such as designing highly efficient airfoil (wing) shapes that provide high lift and low drag and designing optimal engine nacelles to reduce drag.[16-18]. The design cycle for aircraft traditionally includes computational simulations that look at how both component shape and turbulent airflow (which often occurs during take-off/landing and in some atmospheric conditions) would affect lift and drag, prior to performing expensive physical testing in a wind tunnel. Conventional CFD methods are accurate but extremely compute-intensive/costly. AI/ML methods can dramatically reduce the computational requirements for modeling turbulent (highly complex) flows[19,20] and the lift and drag of different component designs, arriving at equivalent solutions more quickly and easily. This allows much more experimentation and iterative design-test cycles.

The structural materials used in aircraft, such as aluminum alloys, must meet high performance specifications because they are subject to high stresses under flight conditions. Understanding these stresses quantitatively is challenging. AI/ML methods can increasingly be used to calculate stresses/loads throughout an aircraft during flight and to predict the performance of various alloys used in aircraft construction.[22] The primary use of this method is to ensure aircraft safety, but it could potentially lead to the use of lighter-weight materials and/or novel designs that reduce the total amount of structural materials required, reducing aircraft weight and thus improving fuel efficiency.

ii. Optimizing air operations

Another approach to minimizing emissions from aviation is to optimize the use of the existing aircraft fleet, matching specific aircraft to specific routes and passenger demand as efficiently as possible. A closely related issue is ensuring optimal airport operations, given changing wind conditions, impacts of weather at other airports, and constrained runway count. AI/ML methods have been tested as part of the pre-planning phase of air operations, helping assess demand-capacity balancing for various runway configurations for US airports.[23] NASA and the US Federal Aviation Administration (FAA) have begun implementing an AI/ML-based air traffic management planning tool (the Collaborative Digital Departure Reroute tool) that can improve projections of runway availability and reduce on-tarmac airplane idling time.[24] Carriers such as Alaska Airlines and SWISS have begun using AI/ML-based systems to optimize real-time flight route planning and general flight operations.[25,26] Other carriers, including TUI Airlines, have begun using AI/ML methods calibrated to individual aircraft to develop customized climb rates and speed profiles for lift-off and climb phases of a flight, helping reduce unnecessary fuel burn.[27]

iii. Reducing aviation-induced contrails

When aircraft fly through regions of the atmosphere that are particularly cold, they can form condensation trails ("contrails"), which are essentially artificially induced cirrus clouds. Under specific meteorological conditions, these contrails can persist for many hours and can spread, resulting in a net climate warming effect by blocking thermal radiation (heat) that would otherwise radiate out into space. This effect is quite large, roughly the same as warming effects from the CO_2 emitted by burning jet fuel, although uncertainties remain.[8,10]

Projections for contrail radiative forcing in future years are uncertain but could rise significantly, given increased air traffic and an overall shift in flight altitudes.[28]

One method for reducing this warming effect is "navigational avoidance," which involves predicting where contrail-forming meteorological conditions will occur before or during specific flights and then redirecting aircraft to different altitudes to avoid those atmospheric regions. (Because only a small fraction of flights generates contrails, the use of this method would be limited to a small number of flights annually.) The majority of contrail radiative forcing can be avoided with navigational changes that add only ~0.1% additional cost and fuel burn.[29,30]

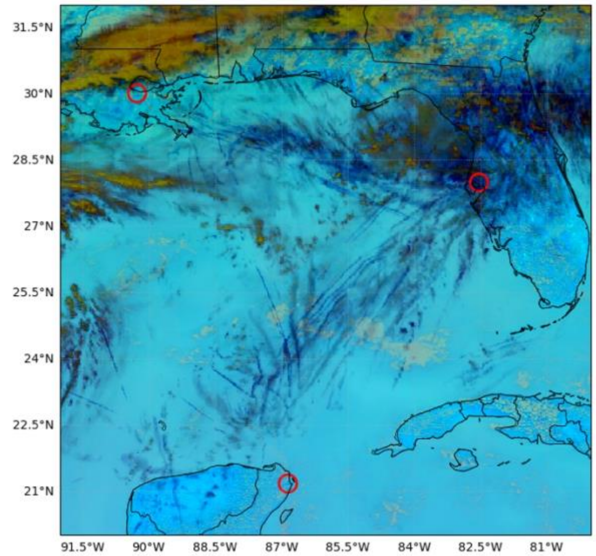


Figure 7-2. False-color image of aviation-induced contrails in the Gulf of Mexico, derived from GOES-16 imagery. Red circles are major airports (MSY, TPA, CUN) and contrails appear as thin, dark-blue lines between them. (Credit: Colin McCormick).

Research is underway to evaluate the use of advanced conventional algorithms and remote sensing imagery to predict where contrail-forming regions will occur. This would support navigational avoidance (Fig. 7-2). However, AI/ML methods may be able to improve on the performance of these conventional algorithms, particularly by leveraging AI-enabled improvements in meteorological forecasting. AI/ML methods have already been developed that can detect contrails in satellite imagery, as well as estimate their altitude, using a variety of deep learning methods.[31-33] Data pipelines based on these methods of detecting contrails can form the basis of validation systems to confirm in near-real-time whether a particular flight successfully avoided forming a contrail, in some cases leveraging aircraft position data via Automatic Dependent Surveillance-Broadcast (ADS-B).[34,35]

Google, Breakthrough Energy and American Airlines recently collaborated to demonstrate AI-based contrail navigational avoidance in a series of 70 test flights, confirming the ability of this approach to avoid contrail formation at a very low cost.[36,37] Because contrail navigational avoidance is entirely an operational change—there are no capital costs for modified equipment or new supply chain requirements—it has the potential to be implemented extremely rapidly.

iv. Advancing Sustainable Aviation Fuel (SAF)

A key strategy for decarbonizing aviation is adopting sustainable aviation fuel (SAF), a (mostly) drop-in replacement fuel for aviation kerosene that is based on non-petroleum feedstocks. As the industry assesses novel chemical compositions of various types of SAF, AI/ML methods can be used to predict key physicochemical properties, such as flash point, density and heat capacity, to identify specific fuel blends that have high enough technical potential for synthesis and physical testing.[38,39] One important barrier to using SAF in conventional aviation fuel systems is the presence of nitrile O-ring seals in many fuel lines, which are designed to swell in the presence of specific conventional jet fuel components. This issue has led to a 50% blend limit of SAF in most current aircraft.[40] However, AI/ML methods have been used to better understand how different O-ring materials would swell in the presence of various different compositions of SAF, potentially helping resolve this issue and eliminating the need for the blend limit.[41,42]

B. Barriers

The multiple regulatory frameworks and industry standards in commercial aviation are a potential barrier to AI/ML adoption. These frameworks have been developed to ensure safety throughout the process of aircraft design, manufacture and operations and are updated on timescales that tend to be significantly slower than the rapid pace of advances in AI/ML. If key regulations do not keep up with advances in AI, they may slow the industry's ability to adopt these emerging technologies.

Another potential barrier is a lack of technical familiarity with modern AI/ML methods within key regulatory agencies, such as the US FAA, the European Union Aviation Safety Agency (EASA) and the Japan Civil Aviation Bureau (JCAB). These agencies may lack staff capacity to assess emerging AI/ML methods, as well as the resources to train existing staff or hire new talent.

Encouragingly, some of these regulators have begun actively considering how AI/ML can be used within aviation through roadmaps[43] and webinars.[44] The work to date has principally focused on safety, which is appropriate given their core mandates.[45] However, if regulators focus exclusively on AI/ML safety issues, this may obscure or preclude consideration of opportunities for emissions reductions, creating an additional barrier to their use in this context.

C. Risks

As with all aerospace design processes, any novel designs for engines, airframe components or structural materials that are developed by AI must be rigorously tested to meet safety criteria. However, if AI/ML methods identify highly novel designs or configurations, it may be challenging to fully test them within existing protocols. If these protocols are not appropriately updated to accommodate an expanded range of designs that may result from AI/ML methods, this could create safety risks.

When using AI for planning and operations, an AI model may identify highly efficient solutions that have less available margin for error than current operational strategies (for example, very tight timing for aircraft turn-around or runway reconfiguration). These solutions could make the overall system more “brittle” or vulnerable to any unanticipated disruptions. Minimizing the effects of these disruptions and fully recovering from them may therefore be more difficult in scenarios in which air operations are guided by AI/ML models.

The use of AI in real-time operations may also introduce cybersecurity risks because of increased complexity in the data systems used.[46] This is a similar challenge to that encountered when using AI in other industries, in the context of real-time decision making for physical assets. Improved testing and cybersecurity response protocols are likely needed to manage this risk.

D. Recommendations

1. *National governments should expand public research and development (R&D) funding for applying AI/ML methods to aircraft design, engine design and aircraft operations, with a focus on improving fuel efficiency, enabling the use of SAF, and reducing non-CO_2 impacts (including contrails). To ensure this funding targets priority areas, the relevant funding ministries should enhance the AI/ML expertise of program management staff through training and/or hiring.*

2. *Aviation technical societies, associations and standards development organizations should expand technical resources available for AI/ML-enabled aircraft design and operations, including developing benchmark datasets, releasing sample algorithms and publishing standard performance metrics.*

3. *National governments should increase the coverage and quality of publicly available meteorological data (temperature, pressure, humidity) in commonly traveled air spaces to enable improved modeling of the non-CO_2 climate impacts of aviation, including contrail formation.*

4. *National governments, philanthropy and private companies should collaborate to improve the state of the art on digital modeling of atmospheric contrail formation by aircraft, including use of advanced AI/ML techniques. High-quality models should be made publicly available.*

5. *National governments should require all commercial and private aircraft to track and report non-CO_2 impacts, including contrail formation. This should be through public-facing data portals or similar methods that minimize the burden of data collection and computation on the private actors covered by these requirements. Aggregated results should be publicly released.*

6. *Carbon accounting bodies should update accounting rules to include the full set of climate impacts of aviation, including contrails. Private companies with aviation-based supply chains should adopt the use of these updated rules in measuring supply chain greenhouse gas (GHG) emissions.*

7. *National governments should ensure that the regulatory frameworks for approving novel aircraft and engine design are compatible with using AI/ML methods and should update them accordingly if necessary. Aviation regulatory bodies should collaborate directly on these topics to ensure that regulations are harmonized as much as possible across national borders.*

E. References

1 International Air Transport Association (IATA). Industry Statistics: Fact Sheet; https://www.iata.org/en/iata-repository/pressroom/fact-sheets/industry-statistics/ (2024).

2 International Civil Aviation Organization (ICAO). Passenger air traffic surpasses pre-pandemic levels; ICAO Newsroom, Montréal, Québec, Canada, https://www.icao.int/Newsroom/Pages/Passenger-air-traffic-surpasses-pre-pandemic-levels.aspx (2024).

3 International Air Transport Association (IATA). Air Passenger Market Analysis; https://www.iata.org/en/iata-repository/publications/economic-reports/air-passenger-market-analysis-february-2024/ (2024).

4 International Civil Aviation Organization (ICAO). Facts and Figures: World Aviation and the World Economy ICAO – Economic Development of Air Transport, Montréal, Québec, Canada, https://www.icao.int/sustainability/pages/facts-figures_worldeconomydata.aspx (Accessed August 2024).

5 International Energy Agency (IEA). Aviation; Paris, France, https://www.iea.org/energy-system/transport/aviation (Accessed August 2024).

6 International Civil Aviation Organization (ICAO). States adopt net-zero 2050 global aspirational goal for international flight operations; ICAO Newsroom, Montréal, Québec, Canada, https://www.icao.int/Newsroom/Pages/States-adopts-netzero-2050-aspirational-goal-for-international-flight-operations.aspx (2022).

7 Richard C. Miake-Lye & Didier Hauglustaine. Impacts of Aviation NOx Emissions on Air Quality, Health, and Climate (within Chapter 3: Local Air Quality) in ICAO Environmental Report Ch. 3, 74–76 (International Civil Aviation Organization (ICAO), Montréal, Québec, Canada, 2022, https://www.icao.int/environmental-protection/Documents/EnvironmentalReports/2022/ENVReport2022_Art18.pdf).

8 International Air Transport Association (IATA). Aviation contrails and their climate effect: Tackling uncertainties and enabling solutions; https://www.iata.org/contentassets/726b8a2559ad48fe9decb6f2534549a6/aviation-contrails-climate-impact-report.pdf (2024).

9 D. S. Lee et al. The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018. Atmospheric Environment 244, 117834 (2021). https://doi.org/10.1016/j.atmosenv.2020.117834.

10 R. Teoh et al. Global aviation contrail climate effects from 2019 to 2021. Atmos. Chem. Phys. 24, 6071-6093 (2024). https://doi.org/10.5194/acp-24-6071-2024.

11 Amina Zaoui et al. Impact of artificial intelligence on aeronautics: An industry-wide review. Journal of Engineering and Technology Management 71, 101800 (2024). https://doi.org/10.1016/j.jengtecman.2024.101800.

12 Julie Weed. Did You Make Your Connecting Flight? You May Have A.I. to Thank.; NY Times, New York, NY, https://www.nytimes.com/2024/05/10/travel/airlines-artificial-intelligence.html (2024).

13 Soledad Le Clainche et al. Improving aircraft performance using machine learning: A review. Aerospace Science and Technology 138, 108354 (2023). https://doi.org/10.1016/j.ast.2023.108354.

14 Argonne National Laboratory. Accelerating Gas Turbine Engine Design by Fusing Physics-Guided Machine Learning and Supercomputing; Lemont, Illinois, https://www.anl.gov/aet/accelerating-gas-turbine-engine-design-by-fusing-physicsguided-machine-learning-and-supercomputing (Accessed August 2024).

15 Michael T Tong. Machine learning-based predictive analytics for aircraft engine conceptual design; NASA – Glenn Research Center, Cleveland, Ohio, https://ntrs.nasa.gov/citations/20205007448 (2020).

16 Jichao Li, Xiaosong Du & Joaquim R. R. A. Martins. Machine learning in aerodynamic shape optimization. Progress in Aerospace Sciences 134, 100849 (2022). https://doi.org/10.1016/j.paerosci.2022.100849.

17 Thomas P. Dussauge et al. A reinforcement learning approach to airfoil shape optimization. Scientific Reports 13, 9753 (2023). https://doi.org/10.1038/s41598-023-36560-z.

18 Zilan Zhang et al. An adaptive machine learning-based optimization method in the aerodynamic analysis of a finite wing under various cruise conditions. Theoretical and Applied Mechanics Letters 14, 100489 (2024). https://doi.org/10.1016/j.taml.2023.100489.

19 H. Jane Bae & Petros Koumoutsakos. Scientific multi-agent reinforcement learning for wall-models of turbulent flows. Nature Communications 13, 1443 (2022). https://doi.org/10.1038/s41467-022-28957-7.

20 Ricardo Vinuesa. Perspectives on predicting and controlling turbulent flows through deep learning. Physics of Fluids 36 (2024). https://doi.org/10.1063/5.0190452.

21 Sola Zheng & Dan Rutherford. Fuel burn of new commercial jet aircraft: 1960 to 2019 (White Paper); The International Council on Clean Transportation (ICCT), https://theicct.org/publication/fuel-burn-of-new-commercial-jet-aircraft-1960-to-2019/ (2020).

22 Chenxi Sun et al. A multi-model architecture based on deep learning for aircraft load prediction. Communications Engineering 2, 47 (2023). https://doi.org/10.1038/s44172-023-00100-4.

23 Christopher J. Lloyd et al. Operationalizing Machine Learning Models for Strategic Planning in AIAA AVIATION 2023 Forum (https://arc.aiaa.org/doi/abs/10.2514/6.2023-4213).

24 Hillary Smith. NASA Machine Learning Air Traffic Software Saves Fuel; NASA, https://www.nasa.gov/centers-and-facilities/ames/nasa-machine-learning-air-traffic-software-saves-fuel/ (2023).

25 Alaska Airlines. Alaska Airlines and Airspace Intelligence announce first-of-its-kind partnership to optimize air traffic flow with artificial intelligence and machine learning; https://news.alaskaair.com/newsroom/alaska-airlines-and-airspace-intelligence-announce-first-of-its-kind-partnership-to-optimize-air-traffic-flow-with-artificial-intelligence-and-machine-learning/ (2021).

26 Google Cloud. SWISS: Making air travel more sustainable and improving operational quality with Google Cloud; Mountain View, California, https://cloud.google.com/customers/swiss (Accessed October 2024).

27 The Weather Network. Airline uses Ai to cut carbon emissions during flight take-off; Deutsche Presse-Agentur GmbH via Reuters Connect, Berlin, Germany, https://www.theweathernetwork.com/en/news/climate/solutions/airline-uses-ai-to-cut-carbon-emissions-during-flight-take-off (2023).

28 D. K. Singh, S. Sanyal & D. J. Wuebbles. Understanding the Role of Contrails and Contrail Cirrus in Climate Change: A Global Perspective. EGUsphere 2024, 1-50 (2024). https://doi.org/10.5194/egusphere-2024-127.

29 Denis Avila, Lance Sherry & Terry Thompson. Reducing global warming by airline contrail avoidance: A case study of annual benefits for the contiguous United States. Transportation Research Interdisciplinary Perspectives 2, 100033 (2019). https://doi.org/10.1016/j.trip.2019.100033.

30 A. Martin Frias et al. Feasibility of contrail avoidance in a commercial flight planning system: an operational analysis. Environmental Research: Infrastructure and Sustainability 4, 015013 (2024). https://dx.doi.org/10.1088/2634-4505/ad310c.

31 Luke Kulik. Satellite-based detection of contrails using deep learning, Massachusetts Institute of Technology, Department of Aeronautics and Astronautics, (2019; https://dspace.mit.edu/handle/1721.1/124179).

32 Rémi Chevallier et al. Linear Contrails Detection, Tracking and Matching with Aircraft Using Geostationary Satellite and Air Traffic Data. Aerospace 10, 578 (2023). https://doi.org/10.3390/aerospace10070578.

33 Vincent Meijer, Sebastian David Eastham & Steven R H Barrett. A31D-2428 Contrail Height Estimation Using Geostationary Satellite Imagery; American Geophysical Union (AGU) at AGU23, San Francisco, CA and Virtual, https://agu.confex.com/agu/fm23/meetingapp.cgi/Paper/1430793 (2023).

34 Federal Aviation Administration (FAA). Automatic Dependent Surveillance-Broadcast (ADS-B); US Department of Transportation (DOT), Washington, D.C., https://www.faa.gov/air_traffic/technology/adsb (Accessed August 2024).

35 Scott Geraedts et al. A scalable system to measure contrail formation on a per-flight basis. Environmental Research Communications 6, 015008 (2024). https://dx.doi.org/10.1088/2515-7620/ad11ab.

36 Google Research. Project Contrails; https://sites.research.google/contrails/ (Accessed August 2024).

37 Breakthrough Energy. How Breakthrough Energy's Contrails Team is helping to reduce aviation's climate impact; Kirkland, Washington, https://www.breakthroughenergy.org/news/contrails/ (2023).

38 Clemens Hall et al. Predictive Capability Assessment of Probabilistic Machine Learning Models for Density Prediction of Conventional and Synthetic Jet Fuels. Energy & Fuels 35, 2520-2530 (2021). https://doi.org/10.1021/acs.energyfuels.0c03779.

39 Ji-Hun Oh et al. Learning to predict sustainable aviation fuel properties: A deep uncertainty quantification viewpoint. Fuel 356, 129508 (2024). https://doi.org/10.1016/j.fuel.2023.129508.

40 Conor Faulhaber et al. Measurements of Nitrile Rubber Absorption of Hydrocarbons: Trends for Sustainable Aviation Fuel Compatibility. Energy & Fuels 37, 9207-9219 (2023). https://doi.org/10.1021/acs.energyfuels.3c00781.

41 Shane Kosir, Joshua Heyne & John Graham. A machine learning framework for drop-in volume swell characteristics of sustainable aviation fuel. Fuel 274, 117832 (2020). https://doi.org/10.1016/j.fuel.2020.117832.

42 Benoit Creton, Benjamin Veyrat & Marie-Hélène Klopffer. Fuel sorption into polymers: Experimental and machine learning studies. Fluid Phase Equilibria 556, 113403 (2022). https://doi.org/10.1016/j.fluid.2022.113403.

43 Federal Aviation Administration (FAA). Roadmap for Artificial Intelligence Safety Assurance: Version I; US Department of Transportation (DOT), Washington, D.C., https://www.faa.gov/aircraft/air_cert/step/roadmap_for_AI_safety_assurance (2024).

44 Scot Campbell, Andrés Bucchi & Abdulla Al-Asam. AI in International Civil Aviation (Webinar); International Civil Aviation Organization (ICAO), Montréal, Québec, Canada, https://www.icao.int/Meetings/innovation-series/Pages/AI-in-International-Civil-Aviation.aspx (2024).

45 Rebecca Heilweil. In deploying AI, the Federal Aviation Administration faces unique challenges; Scoop News Group – Fedscoop, Washington, D.C., https://fedscoop.com/in-deploying-ai-the-federal-aviation-administration-faces-unique-challenges/ (2024).

46 Anna Ribeiro. Aviation industry faces rising cybersecurity risks as new technologies drive adoption, says Aviation ISAC survey; Industrial Cyber, https://industrialcyber.co/reports/aviation-industry-faces-rising-cybersecurity-risks-as-new-technologies-drive-adoption-says-aviation-isac-survey/ (2024).

CHAPTER 8:

BUILDINGS SECTOR

Philippe Benoit & Alp Kucukelbir

A. AI for Reducing Building Emissions 8-2

B. Buildings as Clean Energy Producers 8-6

C. Barriers 8-8

D. Risks 8-8

E. Recommendations 8-10

F. References 8-11

Building operations generate about one quarter of global carbon dioxide (CO_2) emissions. Roughly 8% are direct emissions from buildings (Scope 1) and 18% are indirect emissions from electricity and heat consumed in buildings but produced elsewhere (Scope 2).[1] Embedded emissions related to the manufacture, construction and demolition of buildings are also significant, potentially representing over 50% of life-cycle carbon for new buildings.[2]

Artificial intelligence (AI) is already helping reduce the carbon footprint of the buildings sector, from design to demolition, with significant opportunities for improving operations and energy efficiency. In the future, AI could do much more. One recent study found that adopting AI could reduce energy consumption and CO_2 emissions from commercial buildings by 8–19% from business-as-usual forecasts in 2050.[3]

This chapter presents current trends and promising directions to deploy AI in residential and commercial buildings, including in heating, ventilation and air conditioning (HVAC) systems as well as elevators and other appliances and equipment. The chapter also touches on the interaction of the buildings sector with broader urban development elements, including transport. In particular, the placement of buildings in relation to other buildings and key infrastructure (such as roads and mass transit) will impact a region's carbon footprint.[a]

Significantly, most future building construction and urban expansion will take place in developing countries, driven by rising populations, incomes, migration and other forces. These countries present different challenges than developed countries for the deployment of AI solutions.

A. AI for Reducing Building Emissions

AI can help reduce CO_2 emissions generated by a building in ways that cut across the three main stages of its lifecycle: design, construction & demolition, and operation. These reductions mostly involve increasing the impact of energy efficiency initiatives and other emission reduction activities, but they also include activities such as fuel switching and increasing the capacity of buildings to produce renewable energy.

i. Design & materials

The design of a building and the materials used in constructing it can have significant impacts on the building's carbon footprint. (That footprint includes both the carbon emissions embedded in buildings and carbon emitted in their subsequent operations.) This section presents several of the many opportunities for AI to help in designing buildings and using such materials.

---

[a] See Chapter 6 of this Roadmap (Road Transport).

- AI for lower-carbon and sustainable construction materials. AI can help reduce the carbon footprint of common construction materials such as steel and cement/concrete.[b] In addition, AI is being used to explore and encourage the use of sustainable construction materials, showing a strong potential to reduce the carbon footprint of industrial buildings.[5] AI is also being used to optimize the use of recycled concrete aggregate.[6]
- Optimizing the location of building siting. Identifying and quantifying the geophysical, ecological (including carbon) and economic properties of potential building sites involve integrating many disparate data sources and complex objectives. Explainable AI can help quickly process large amounts of data, identifying the properties of potential sites of interest, while also revealing new sites that may have been missed by traditional approaches.[7]
- Optimizing passive design of buildings. The shape, orientation, window-to-wall ratio and selection of construction materials are all factors in determining the carbon footprint of buildings. AI is being used to quickly and efficiently optimize these design parameters without adding costs or reducing comfort. One application in India reported a 46% reduction of energy consumption and 8% reduction in discomfort hours.[8]
- Optimizing ventilation properties of buildings. Indoor ventilation can also help reduce a building's carbon footprint. Designing windows to encourage pressure differences that drive natural ventilation typically involves computationally expensive simulations that are beyond the reach of all but the most sophisticated building design projects. AI is reducing the barrier

[b] See Chapter 5 of this Roadmap (Manufacturing Sector), which explores opportunities for AI to reduce the carbon footprint of materials such as steel. Sixty percent of the steel used by the construction industry is used in buildings.[4] See also Chapter 13 of this Roadmap (Materials Innovation), which describes how AI could accelerate discovery of new materials, including those that could help reduce the carbon footprint of building construction.

to designing good indoor ventilation, with one example that optimizes rooms with one-sided windows showing a 10× speedup in design time over traditional techniques.[9]

- Modeling heating and cooling loads during design. Traditional modeling tools enable designers to simulate the energy their buildings would require to heat and cool through various HVAC systems. The complexity of these tools, along with their computational expense, makes it challenging for designers to optimize their designs for energy efficiency. AI has been reducing this barrier by offering fast and accurate approximations of heating and cooling loads, encouraging designers to adopt energy-efficient options early in the design process.[10]

ii. Construction & demolition

AI offers opportunities to mitigate the climate impact of a building throughout its lifecycle. Once its design is finalized and decisions around what materials to use are made, its construction (and eventual demolition) offer additional avenues for carbon reduction. This is also an interactive process: construction opportunities can influence the choice of materials (e.g., weight of materials relative to distance to be transported to the construction site).

- AI for traditional construction and waste management. Construction managers plan, direct and coordinate construction projects, ensuring compliance with building safety codes and other regulations. Construction technology and software vendors offer a variety of digital solutions that help detect defects during construction, perform root cause analysis of issues, and ensure workplace safety and compliance. New data sources at traditional construction sites, such as image and video data from drones, are creating opportunities for AI to help to better integrate and process such data streams, thereby creating opportunities to reduce operational emissions and waste.[11]
- Creating visibility into construction emissions. The carbon footprint of construction activities is hard to measure and quantify. A large component is created by heavy machinery, which are typically not equipped with direct emissions measurement mechanisms. AI offers a way to indirectly estimate the carbon footprint of on-site heavy equipment using accelerometer and gyroscope data, creating the visibility necessary to start optimizing operations to minimize emissions.[12]
- AI for accelerating prefabrication methods. Prefabricating buildings, which are manufactured off-site in a factory then installed on site, offers a promising pathway to reduce the carbon footprint of construction. AI-based robotics are particularly well suited for prefabrication facilities, as robots can be installed in the factory and AI can operate them efficiently with high throughput.[13] AI can also help optimize prefabrication techniques and scheduling,[14] while simultaneously matching designs to the specific capabilities of prefabrication manufacturers, thereby reducing construction times and material waste.[15]
- AI for reducing quantity and improving management of demolition waste. In South Korea, construction and demolition waste represent approximately 50% of total waste, including municipal solid waste and commercial and industrial waste.[16] AI can enable efficient categorization of construction waste from image data, which can increase identification,

segregation and reuse of materials in the circular material economy of recycled feed and fuel stocks.[c]

iii. Operations

Building operations generate considerable Scope 1 emissions and even larger Scope 2 emissions. AI can assist with two strategies for reducing these emissions: lowering demand for heat and electricity (both on and off site) [d] and increasing on-site zero-carbon energy production.

- Optimizing HVAC and other building mechanical systems. Making HVAC, elevators and other building mechanical systems operate in a better, more efficient manner would reduce a buildings' carbon footprint. This includes understanding where people are and where they are not (e.g., in a commercial building) at different times of the day and adjusting heating and cooling accordingly. AI can monitor and enhance HVAC operations at increasing scales, incorporating all factors mentioned above.[18] But nobody uses systems they do not trust, which drives a recent focus to make such AI systems interpretable.[19]
- Minimizing the energy requirements of appliances and office equipment. Appliances are major drivers of energy use in buildings. Governments run a variety of appliance efficiency programs, including those that "nudge" consumers to buy energy efficient products (such as Japan's Top Runner and US Energy Star programs). AI can help to make operation of these products even more efficient.[20] It can also increase information flows through digitalization (including in appliances) which can improve the efficiency of buildings. This includes communication between appliances and the power system to lower demand from individual appliances at times of peak demand that would potentially call on the need for deployment of fossil fuel–based power generation. These systems already exist (e.g., refrigerators), and AI can improve their design and operation.[21] One of the expanding sources of demand from within buildings is for the servers they contain to power AI and other computational functions. This is an emerging issue of concern in efforts to reduce emissions and will require increasing attention as the use of AI increases.[22]
- Raising knowledge regarding existing space usage. AI is enabling building owners, developers and investors to better understand and adapt their existing assets to shifting usage and market demands. By leveraging data from wireless networks and other sensors, building usage can be analyzed and visualized in a way that allows owners to make better decisions for lowering their

---

[c] See Chapter 5 of this Roadmap (Manufacturing Sector)

[d] Measures that reduce the amount of energy required to maintain an adequate level of comfort and other emissions-related actions should also generate other important co-benefits, such as reducing energy poverty by reducing the need of poorer families to consume energy to heat their homes. (See, e.g., US DOE 2024[17]).

operational carbon footprint and encourage them to consider alternative uses for their existing spaces.[23]

- Automating sustainability reporting. AI-powered cloud-based reporting can help construction companies and building operators automatically track their performance and adjust as needed, making it easier to measure and transparently report their environmental impact and make adjustments to lower impacts, which in turn they can also track.[24]

B. Buildings as Clean Energy Producers

Reducing the emissions impact of buildings involves looking not only at the demand-side aspects, but also the capacity of buildings to generate low-carbon energy for use by the building or even potentially other offsite consumers. Crafting buildings to produce low-carbon energy can be integrated into the various aspects regarding buildings enumerated in the previous subsection, including notably their design, as well as the operation of onsite solar and other clean energy production capacity.

AI can integrate additional layers of information (including dynamic hourly data regarding solar radiation and the placement of other structures) to build systems that optimize available solar and other resources (including wind, geothermal and other).

In addition, AI can help to better match demand and supply at the building level. Adding the energy production dimension to the consumption of buildings increases operational complexity. AI can help buildings adapt to dynamic load and demand, optimally allocating clean energy production to building demand[25] and tightly coupling the specific energy requirements of a building with the power it generates and consumes.[26]

FROM BUILDINGS TO TOWNS AND CITIES

Individual buildings do not exist in isolation but are built and operate within a larger environment that includes other buildings, infrastructure (such as roads, bridges and mass transit) and natural terrain. The areas around a building can affect its energy usage and emissions. For example, the location of nearby buildings will affect the amount of solar radiation a building will receive (e.g., by casting shadows). So, in designing a building at a specific site, the surrounding built environment is also a factor—one that injects additional complexity.

This is also true when designing a new block of buildings, such as a townhouse development or a commercial building complex. This adds additional levels of complexity. And this complexity is further increased when extending it to the construction of new neighborhoods (or efforts to redesign existing ones), let alone new cities. Moreover, cities themselves produce higher temperatures than surrounding areas, at times up to 4° C higher.[27] This increases the demand for electricity for cooling, an anticipated major driver of future emissions, as well as presenting the challenge of using materials and urban design technique specifically to reduce the extent of this "heat island" phenomenon.

The computational power of just several years ago provided the ability to address the interaction of these larger sets of variables but to a degree that was substantially more limited than what AI can provide today. Areas where AI can help when thinking beyond the single building to a block or a broader city include the following:

- Placement and design of a series of buildings (both residential and commercial).
- Structure of utility services, including electricity, water and sewage.
- Design and placement of residential versus commercial and retail services.
- Design of urban transport systems, including bus routes and commuter rail systems, as well as bike routes (invoking the framework of avoid/shift/improve).
- Operation of heating and other systems, including beyond the single building unit, such as district heating and district cooling systems.
- Interaction of all the above: the design of new neighborhoods or even entire new cities (e.g., in Egypt and Indonesia) provide an opportunity to deploy AI technologies to reduce emissions and improve sustainability.[28]

The data-driven insights that AI potentially provides can help make environmental strategies more effective, leading to better, more sustainable urban environments. Bibri et al. (2024)[29] highlight AI's applications to energy and water conservation, sustainable transportation management, waste management and environmental monitoring.

C. Barriers

- Geography. Significantly, most new construction is projected to take place in emerging economies and other developing countries. The IEA posits that building floor–area equivalent to that of the city of Paris will be added every week globally between 2020 and 2030,[30] 80% of which will be in emerging market and developing economies (See page 58, IEA's *Energy Efficiency 2022*[31]). Opportunities to apply AI would be squandered if geography is not considered in this construction, including adapting solutions to the on-the-ground realities in these countries, such as capacity and financial constraints that typically differ from those in advanced economies.
- Low digital penetration. The degree of familiarity with digitalization and AI techniques within the building sector (like in many others) will constrain the ability to fully exploit theoretical opportunities. Closing the gap between the potential and the actual will require raising the degree of expertise, either in house or alternatively through the use of specialized outside suppliers. To date, both areas are immature, especially as the potential of AI has, naturally, outpaced the rate of change in the industry. Digitalization and application of AI techniques specifically require governments, designers and developers to build, hire or outsource personnel with expertise. Developing such talent in house involves training internal domain experts with data literacy, storage and manipulation skills. Hiring for digital talent often involves recruiting data scientists and data engineers to enhance the work of existing staff in this field. Some entities within the building sector may prefer to outsource such activities to consulting groups and other companies that provide such services.
- Rapid pace of urbanization. One of the barriers to deploying innovative AI solutions is the rapid pace at which urbanization is taking place. The pressure of numerous real-world forces driving increased urbanization are not leaving city planners with the time to adopt new technologies to optimize emissions. This pressure is compounded by the fact that many of these expanding urban populations are in countries with limited technical and other capacities, notably in some of the largest cities in the developing world. This limits time and opportunity required to develop, vet and deploy AI-based solutions, particularly on construction sites.

D. Risks

- Rebound effect. One of the main challenges in using AI to reduce emissions related to the built environment is the possibility of a rebound effect, namely that the improved efficiency afforded by AI will lead to greater consumption that negates the emissions gains generated by AI.
- Distracting from other decarbonization strategies. AI is a "high-end" approach that has the possibility to distract from less sophisticated but more attainable approaches. AI is good but not if you deprioritize more accessible technological solutions (such as improved insulation, etc.) that can generate, in practice, a stronger impact (particularly in developing countries and settings with some of the capacity issues described above).

- AI in energy production brings operational risks. AI dependent systems present operational risks. While HVAC, appliances and other systems can generate important emissions savings, they are also exposed to software and internet-based operational, safety and security risks.
- AI can justify decisions that are worse than alternatives. AI can be used to "optimize" a solution of a particular input that results in a larger life-cycle carbon footprint for the building than an alternative. For example, AI can be used to marginally reduce the carbon footprint of using a particular construction material (e.g., cement) while an alternative material (with or without the use of AI) would have led to a lower overall carbon footprint (e.g., one that involves lower transport emissions). Failing to move toward lifecycle approaches can result in AI being misapplied to produce the mirage of emissions gains (an issue that also affects non-AI interventions).

E. Recommendations

1. *Governments at all levels working with the private sector should identify and pilot AI-supported technological improvements in design, materials, construction and demolition that reduce the embedded carbon in buildings.*

2. *National governments should develop research and development programs for AI improvements in emissions efficiency of building operations (including HVAC systems, lighting, elevators and other mechanical systems). Municipalities should explore more restrictive commercial-building energy use and emissions standards (including for Scope 2 emissions) that become attainable through AI. These efforts should combine a "pull" strategy of government support paired with a "push" effort of more restrictive norms.*

3. *Public and private construction organizations should engage government research agencies, academia and the nonprofit community in providing support for developing and deploying AI. Sharing data, encouraging the development of standards and best practices, and creating venues for dissemination and discussion of these results can help accelerate development and deployment of AI in this sector. In particular, using AI to build more sophisticated life-cycle analytic tools can help optimize AI's impact and reduce the possibility of its misapplication.*

4. *Governments, the private sector and professional associations should develop a platform to disseminate best practices regarding improving digitalization and other data collection to support the deployment of AI to reduce building energy use and emissions (including Scope 2). This platform should be tied into the areas of action for AI identified under recommendations 1, 2 and 3. These groups should also work with suppliers to increase the availability and improve the affordability of related sensors and other equipment.*

5. *Multilateral development banks, national/bilateral organizations and other donor agencies should develop a program of technical assistance and funding to increase the capacity of stakeholders both (1) to develop domestic AI innovation programs for the buildings sector in urban areas and (2) to implement AI-enhancements, whether designed locally or abroad. AI in the buildings sector should be adapted to the opportunities and constraints presented by developing economies, including designing and deploying technology-appropriate solutions (such as low-tech approaches where country conditions present constraints), as well as encouraging data gathering in those geographies.*

6. *Governments, in association with city associations and academia, and supported by international development agencies, should identify and develop one or more urban development pilot programs to explore using AI to lower embedded carbon and operational emissions. The new cities being built in emerging economies (such as Indonesia's new capital, Nusantara) provide a possible opportunity for targeted cooperation between donor agencies, such as the World Bank and Japan's JBIC, together with developing-country national and municipal authorities (e.g., Egypt's new administrative capital).*

F. References

1 International Energy Agency (IEA). *Buildings;* IEA, Paris, https://www.iea.org/energy-system/buildings (Accessed August 2024).

2 Thomas Lützkendorf & Maria Balouktsi. Embodied carbon emissions in buildings: explanations, interpretations, recommendations. *Buildings and Cities* 3(1), 964–973 (2022). https://doi.org/10.5334/bc.257.

3 Chao Ding *et al.* Potential of artificial intelligence in reducing energy and carbon emissions of commercial buildings at scale. *Nature Communications* 15, 5916 (2024). https://doi.org/10.1038/s41467-024-50088-4.

4 Muiris C. Moynihan & Julian M. Allwood. Utilization of structural steel in buildings. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 470, 20140170 (2014). https://doi.org/10.1098/rspa.2014.0170.

5 Wes Mills. *Purdue, Google announce sustainability and AI research partnership;* Purdue University – News, West Lafayette, IN, https://www.purdue.edu/newsroom/releases/2024/Q2/purdue-google-announce-sustainability-and-ai-research-partnership.html (2024).

6 Sabrina C. Shen *et al.* Computational Design and Manufacturing of Sustainable Materials through First-Principles and Materiomics. *Chemical Reviews* 123, 2242-2275 (2023). https://doi.org/10.1021/acs.chemrev.2c00479.

7 Dhafer Alqahtani *et al.* Optimizing Residential Construction Site Selection in Mountainous Regions Using Geospatial Data and eXplainable AI. *Sustainability* 16, 4235 (2024). https://doi.org/10.3390/su16104235.

8 Tripti Singh Rajput & Albert Thomas. Optimizing passive design strategies for energy efficient buildings using hybrid artificial neural network (ANN) and multi-objective evolutionary algorithm through a case study approach. *International Journal of Construction Management* 23, 2320-2332 (2023). https://doi.org/10.1080/15623599.2022.2056409.

9 Yun Kyu Yi *et al.* Application of machine learning (ML) and genetic algorithm (GA) to optimize window wing wall design for natural ventilation. *Journal of Building Engineering* 68, 106218 (2023). https://doi.org/10.1016/j.jobe.2023.106218.

10 Jui-Sheng Chou & Dac-Khuong Bui. Modeling heating and cooling loads by artificial intelligence for energy-efficient building design. *Energy and Buildings* 82, 437-446 (2014). https://doi.org/10.1016/j.enbuild.2014.07.036.

11 Limao Zhang *et al. Artificial intelligence in construction engineering and management*. (Springer Singapore, 2021; https://doi.org/10.1007/978-981-16-2842-9, https://www.springerprofessional.de/en/artificial-intelligence-in-construction-engineering-and-manageme/19274334).

12 Farid Shahnavaz & Reza Akhavian. Automated Estimation of Construction Equipment Emission Using Inertial Sensors and Machine Learning Models. *Sustainability* 14, 2750 (2022). https://doi.org/10.3390/su14052750.

13 Mi Pan *et al.* Artificial Intelligence and Robotics for Prefabricated and Modular Construction: A Systematic Literature Review. *Journal of Construction Engineering and Management* 148, 03122004 (2022). https://doi.org/10.1061/(ASCE)CO.1943-7862.0002324.

14 Leila Farahzadi & Mahdi Kioumarsi. Application of machine learning initiatives and intelligent perspectives for CO2 emissions reduction in construction. *Journal of Cleaner Production* 384, 135504 (2023). https://doi.org/10.1016/j.jclepro.2022.135504.

15 Peter Caulfield. *Artificial intelligence and the future of modular and pre-fab construction;* Daily Commercial News by ConstructConnect – Technology,

https://canada.constructconnect.com/dcn/news/technology/2023/07/artificial-intelligence-and-the-future-of-modular-and-pre-fab-construction (2023).

16 Seunguk Na *et al.* Development of an Artificial Intelligence Model to Recognise Construction Waste by Applying Image Data Augmentation and Transfer Learning. *Buildings* 12, 175 (2022). https://doi.org/10.3390/buildings12020175.

17 US Department of Energy (DOE). *DOE Announces National Definition of a Zero Emissions Building;* Washington, D.C., https://www.energy.gov/articles/doe-announces-national-definition-zero-emissions-building?ref=ctvc.co (2024).

18 Paige Wenbin Tien *et al.* Machine Learning and Deep Learning Methods for Enhancing Building Energy Efficiency and Indoor Environmental Quality – A Review. *Energy and AI* 10, 100198 (2022). https://doi.org/10.1016/j.egyai.2022.100198.

19 Zhe Chen *et al.* Interpretable machine learning for building energy management: A state-of-the-art review. *Advances in Applied Energy* 9, 100123 (2023). https://doi.org/10.1016/j.adapen.2023.100123.

20 Claudio Tomazzoli, Simone Scannapieco & Matteo Cristani. Internet of Things and artificial intelligence enable energy efficiency. *Journal of Ambient Intelligence and Humanized Computing* 14, 4933-4954 (2023). https://doi.org/10.1007/s12652-020-02151-3.

21 Hari Prasanna Das *et al.* Machine Learning for Smart and Energy-Efficient Buildings. *Environmental Data Science* 3, e1 (2024). https://doi.org/10.1017/eds.2023.43.

22 Philippe Benoit. *AI policy can't ignore climate change: We need net zero AI emissions;* The Hill, Washington, D.C., https://thehill.com/opinion/energy-environment/4583242-ai-policy-cant-ignore-climate-change-we-need-net-zero-ai-emissions/ (2024).

23 Sabina Wex. Build IT Series – AI sensors and WiFi networks that provide workplace insights are antidotes for some companies combating 'zombie offices'; Business Insider, https://www.businessinsider.com/office-spaces-empty-ai-sensors-wifi-network-optimization-2023-9 (2023).

24 Carol Dunn. *5 Tips on Harnessing Artificial Intelligence in Sustainable Construction;* Applied Software Graitec Group (ASTI), https://asti.com/blog/5-tips-on-harnessing-artificial-intelligence-in-sustainable-construction/ (2024).

25 Md Romyull Islam *et al.* in *Proceedings of the 2024 ACM Southeast Conference* 95–103 (Association for Computing Machinery, Marietta, GA, USA, 2024; https://doi.org/10.1145/3603287.3651202).

26 Xueyuan Cui *et al.* Data-driven aggregation of thermal dynamics within building virtual power plants. *Applied Energy* 353, 122126 (2024). https://doi.org/10.1016/j.apenergy.2023.122126.

27 Hannah Druckenmiller. *Urban Heat Islands 101;* Resources for the Future, Washington, D.C., https://www.rff.org/publications/explainers/urban-heat-islands-101/ (2023).

28 Nell Lewis. *A new city is rising in Egypt. But is it what the country needs?;* CNN World - Connecting Africa, https://edition.cnn.com/world/egypt-new-administrative-capital-spc-intl/index.html (2024).

29 Simon Elias Bibri *et al.* Smarter eco-cities and their leading-edge artificial intelligence of things solutions for environmental sustainability: A comprehensive systematic review. *Environmental Science and Ecotechnology* 19, 100330 (2024). https://doi.org/10.1016/j.ese.2023.100330.

30 United Nations Environment Programme (UNEP). *As buildings and construction sector grows, time running out to cut energy use and meet Paris climate goals (Press Release);* Nairobi, Kenya, https://www.unep.org/news-and-stories/press-release/buildings-and-construction-sector-grows-time-running-out-cut-energy# (2017).

31 International Energy Agency (IEA). *Energy Efficiency 2022;* IEA, Paris, https://www.iea.org/reports/energy-efficiency-2022 (2022).

CHAPTER 9:

CARBON CAPTURE

Julio Friedmann

A. Capture Technology 9-3

B. Transportation and Storage 9-4

C. CO_2 Conversion to Products 9-6

D. Other Carbon Capture, Utilization and Storage (CCUS)-related AI Applications 9-7

E. Barriers 9-8

F. Risks 9-8

G. Recommendations 9-10

H. References 9-12

Carbon capture is an essential technology for climate change mitigation. Analysis by dozens of organizations, most notably the Intergovernmental Panel on Climate Change (IPCC)[1] and the International Energy Agency (IEA),[2] confirm the need for carbon capture to decarbonize key sectors (including steel, concrete, chemicals and aviation). As global greenhouse gas (GHG) emissions have continued to rise in recent years, carbon capture has received growing acceptance and been featured in international agreements, including the Dubai Consensus[3] and Sunnylands Agreement.[4]

Many governments, including those in the United States,[5,6] the European Union,[7,8] China[9] and Germany,[10] have included carbon capture as a key strategy to help achieve ambitious climate targets. National and international carbon capture programs include grants and loans for project demonstration, fiscal incentives (including tax credits and contracts for differences), infrastructure investment and robust investments in innovation. As a consequence, the number of operating and announced projects have increased significantly.[11,12]

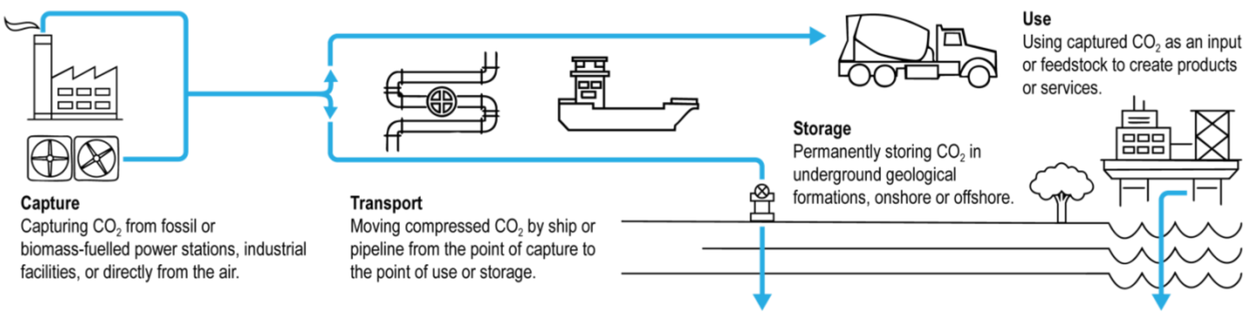


Figure 9-1. Components of the carbon capture value chain including technology and infrastructure elements. Source: IEA, 2024[13]

The field of carbon capture includes many forms of technology and cuts across many energy and climate sectors.[14] The core technology sets include many parts (Figure 9-1):

- separation of CO_2 from points source, the air and the ocean;
- transportation of CO_2, including pipeline construction and operation, barges, ships and trucks;
- storage of CO_2 in dedicated geological formations, including saline aquifers, depleted oil and gas fields, and basaltic formations;
- conversion of CO_2 into new building materials, chemicals and fuels and
- removal of CO_2 from the air and oceans using biomass and minerals as vectors for removal and storage to achieve climate neutrality[15]

Carbon capture systems can reduce the GHG footprint of existing fuels (e.g., bioethanol, aviation fuels), feedstocks (e.g., hydrogen) and energy sources (e.g., natural gas, biomass), as well as provide critically important climate services independent of energy production.

Despite some core technologies being quite mature,[16] integrated carbon capture systems are not widely commercialized and new technologies—including novel electrochemical means of CO_2 conversion and direct air capture operations—enter the field often. Although the costs for some applications are modest (below \$50/tonne CO_2), others are substantial (>\$100/tonne CO_2),[17] prompting decision makers to support means of reducing capital and operating expenses.

Small wonder, then, that AI could improve many aspects of this field, including technical elements (efficiency, performance, environmental benefits), commercial aspects (cost, routing) and policy concerns (equity and justice, resource allocation). The literature on AI applications in carbon capture is young, but the potential for AI to improve carbon capture appears significant, based on both primary manuscripts and reviews.[18,19]

This chapter describes some promising applications of AI in the broad field and specific subfields of carbon capture, including specific recommendations for key actors in climate and energy.

A. Capture Technology

Separating CO_2 from industrial waste streams, ambient air or the oceans requires chemical, physical or electrical processes, such as electrical-swing adsorption, humidity-swing adsorption and phase-change systems. These processes use chemical agents (e.g., liquid solvents and solid sorbents), functional components (e.g., contactors and membranes), well-functioning reactors and integration with other systems. For each of these steps, AI can play a role and already has begun to do so.

i. Materials discovery and functionalization

AI can assist in discovering new materials with properties that enable profound improvements in energy use, efficiency, strength and other key properties.[20,21] (See Chapter 6 of this Roadmap.) Carbon capture is particularly well suited for these approaches,[22] in part because of the key role materials (including liquid solvents, solid sorbents and membranes) play in CO_2 separation. AI speeds up the discovery of new materials[23,24] that can improve performance, including in the CO_2 loading of chemical systems, heat capacity,[25] energy consumption in CO_2 regeneration and longevity. In particular, metal-organic frameworks (MOFs) have proven well-suited to discovery through AI tools, which can collapse the range of possible materials into promising options in terms of structure, composition and design.[26]

However, having a library of suitable materials will not lead to deployment if the materials are not made or functionalized. AI has proven helpful in prioritizing which materials to fabricate and test based on their estimated performance, but benefits of these materials cannot be realized until they are built into filters, monoliths and other gas-contact media. AI has already proposed ways to improve functionalization (e.g., ways to structure solid sorbents to improve loading and performance).[27] Studies that demonstrate how AI can enhance manufacturing and functioning of other materials (e.g., carbon nanotubes[28]) show promise for carbon capture materials, as well. Given the very large range of approaches to manufacturing and functionalizing carbon capture materials, AI could help identify processes and pathways with high performance and chance of success.

ii. Novel capture system

AI can also accelerate development of novel processes for capture, regeneration and CO_2 conversion. Many novel processes are still designed through trial and error, including novel fluidized bed reactors, use of ionic liquids and dual-function processes that perform both CO_2 capture and conversion to chemicals like methanol. AI has proven useful in accelerating system design and testing—for example by helping identify and improve a novel regeneration process (electrochemically mediated amine regeneration).[29] Exploration of these process engineering and design options is only at the earliest stages.

iii. Capture system operation, optimization and integration

AI tools have already been applied to manufacturing and industrial production processes to good effect. (See Chapter 5 of this Roadmap.) Carbon capture systems can benefit from similar applications. This includes the use of digital twins of existing or planned facilities to assess and implement tools for efficiency gains. One study found that, by improving clean electricity delivery from the grid, AI tools could help carbon capture systems improve capture rates by >16% and reduce energy use by >35%.[30] Additional approaches include efficiency improvements through heat integration and reactor design optimization. Another study used AI to better optimize temperature, pressure and composition to enhance CO_2 solubility to increase uptake and reduce energy costs.[31] These tools have the potential to dramatically improve system performance, reducing capital cost, operating expense and energy consumption (Figure 9-2).

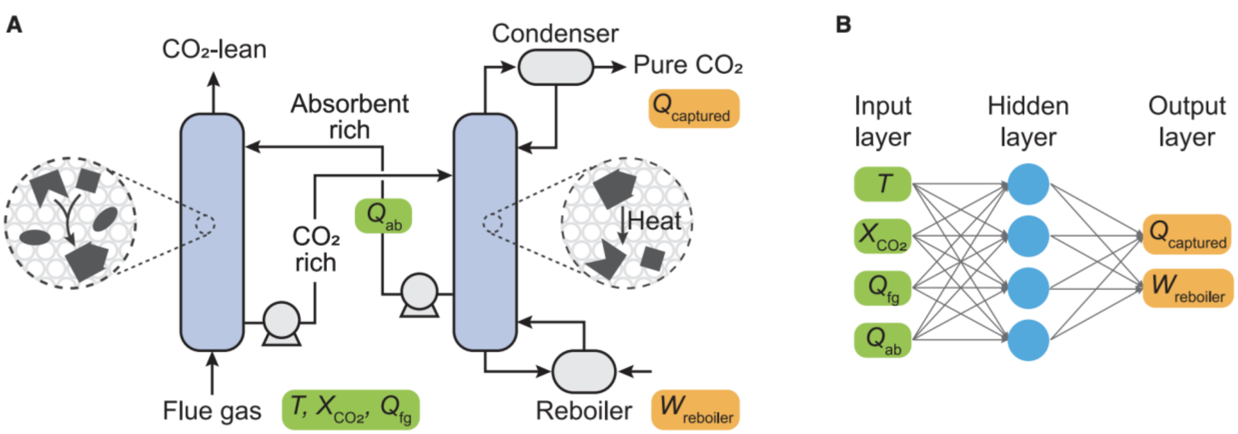


Figure 9-2. An example of an implementation of machine learning (ML) for a CO_2-capture process. (A) Simplified flow diagram of an absorbent-based CO_2-capture process. (B) Illustration of an artificial neural network serving as an ML algorithm to correlate the reboiler-specific duty ($W_{reboiler}$) and CO_2-capture rate ($Q_{captured}$) as model outputs to the key operational parameters, including the flue gas temperature (T), CO_2 fraction (X_{CO2}) and flow rate (Q_{fg}), and the absorbent flow rate (Q_{ab}) as inputs. Source: Rahimi et al, 2021.[27]

B. Transportation and Storage

i. Transportation

Once captured, CO_2 is moved to storage sites using a mix of approaches, including pipelines, ships and barges, and trucks. AI tools have already begun to help governments, private industry and communities develop plans for CO_2 transport that maximize CO_2 volume while minimizing cost and risks.[32,33] One study in China—a country with many large point-sources and very few CO_2 pipelines—

estimated total cost and network size for pipelines could be reduced by 12.5% using AI tools,[34] reducing embodied carbon emissions in fabrication and construction, as well as capital cost.

ii. Geological storage

Manipulating fluids in deep geological formations involves uncertainty, inference, interpretation of monitoring tools and making choices that require trade-offs. For geological storage of CO_2, critical uncertainties can involve the presence or absence of storage porosity (pore volume), the permeability of storage formations, the ability of overlying units to trap CO_2, and connectivity between units, across rock bodies and faults. In some cases, local data (field scale) and regional data (decades of exploration and production) are abundant and can help shape key choices. In other cases, geological data are scarce and operators face greater uncertainties.

AI can help in both cases. Where data are relatively abundant, workers have used AI to assess critical components of CO_2 storage systems, including geological storage efficiency,[35] trapping and overall site performance,[36,37] and monitoring[38] (Figure 9-3). In locations with lower data quality or volume, studies have used synthetic data volumes to train AI.[39] Although initial results have been impressive, the lack of large data volumes risks generating hallucinations in greenfield sites or frontier basins, requiring greater human intervention and validation. Finally, AI can serve to identify prospective new sites for CO_2 storage—an approach piloted by Microsoft[40] and others, where data availability may be either abundant or scarce.

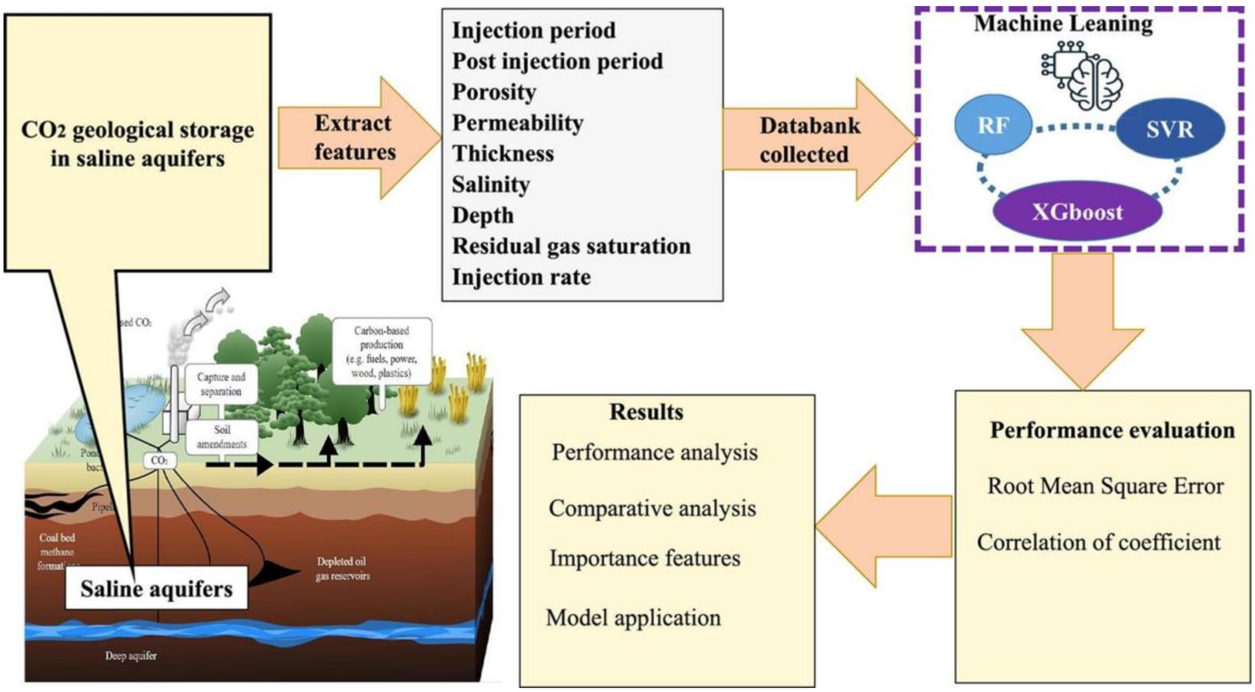


Figure 9-3. A representative process flow for using machine learning (ML) systems to predict and manage performance of subsurface CO_2 storage systems. From Thanh et al., 2022.37

AI approaches are likely to prove useful and accurate for traditional energy companies with large, complex in-house data sets. Already, industry has begun to pursue research and operational collaborations using AI tools. For example, Total Energies has partnered with Cerebras[41] and IBM[42] to identify and de-risk high-quality CO_2 storage sites. Similarly, Halliburton has developed an AI based analytical system to understand subsurface risks,[43] which could be used to predict the performance of geological CO_2 storage systems. In some cases, these specific tools began as means to optimize oil and gas production and have been converted or modified for geological CO_2 storage (e.g., optimizing CO_2-enhanced oil recovery (EOR) for oil production or for geological storage with AI).[44,45] These serve as an example of how AI only delivers climate benefits when asked to deliver them.

C. CO_2 Conversion to Products

Like CO_2 separation, CO_2 recycling and conversion processes involve chemical agents and materials, functional components (e.g., contactors), and fit-for-purpose reactors. AI can play similar roles in these endeavors as it plays in capture technologies, including material discovery, reactor optimization and system integration. Opportunities are many and broad,[46] involving direct chemical synthesis, biological intermediaries, novel reactors and materials, and mineralization (Figure 9-4).

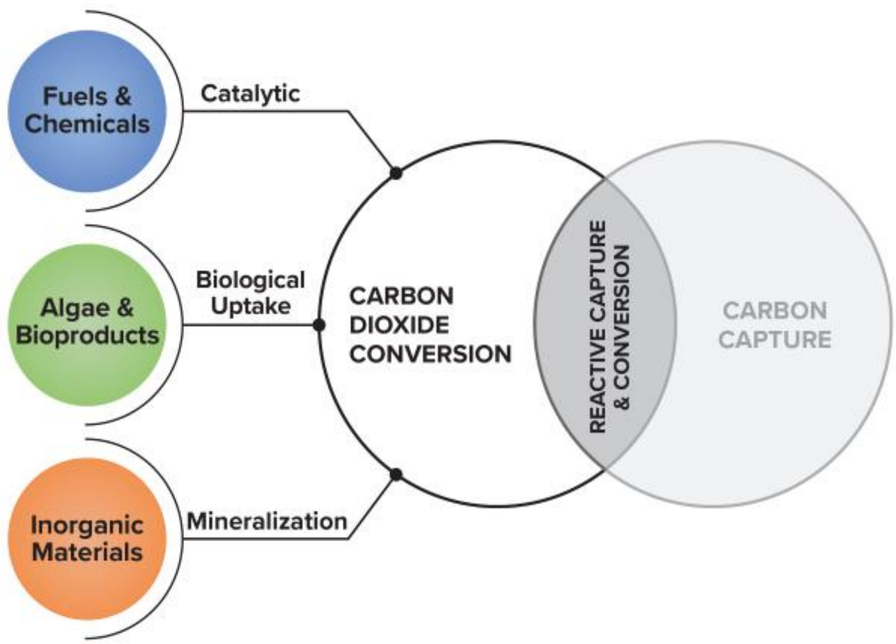


Figure 9-4. *Potential applications of AI for CO_2 conversion and recycling, including subdisciplines of high interest. From NETL.47*

- Chemical reduction of CO_2: Many CO_2 recycling pathways begin by converting CO_2 (carbon dioxide) to CO (carbon monoxide) or other simple organic compounds, such as methanol (CH_3OH). AI has already discovered special materials and processes that chemically reduce CO_2 through electrocatalysis,[48] photocatalysis,[49] enhanced biological processes[50] and multi-phase thermal catalysis.[51]

- Novel chemical synthesis: AI has begun to recognize novel approaches to making compounds out of CO_2. This includes turning CO_2 into starches, proteins and complex hydrocarbons.[22,52,53] One intriguing use of AI involved identifying "dual-purpose" materials that combine capture and conversion in one chemical step.[54,55]
- Characterizing waste and input streams: Industrial and municipal waste streams are often complicated mixes of many materials, compounds and substances. In some cases, these waste streams have substantial fractions of reactive compounds that could be well-suited to mineralization or other CO_2 utilization pathways.[56] AI can simplify and streamline these wastes for improved use.[57]

D. Other Carbon Capture, Utilization and Storage (CCUS)-related AI Applications

A cross-cutting technical concern with deploying carbon capture, utilization and storage (CCUS) involves accurately characterizing and understanding the full life-cycle assessment. Since new CCUS facilities commonly require energy, materials, land, construction and water, it is important to both understand the likely life-cycle implications, including both construction and operational phases, as well as to identify potential pathways to improve life-cycle. In the case of some CO_2 utilization pathways, this can be particularly complicated, as they include multiple supply chains and complex displacement pathways. AI can help provide life-cycle analysis, including initial life-cycle estimates, assessments of improvement opportunities and quantification, and trade-offs in design and operation of facilities between cost, carbon intensity and key environmental attributes (e.g., water consumption).[58]

AI could also help address non-technical issues associated with deploying CCUS. For example, existing facilities may need to update air or water permits when retrofitting for carbon capture or use. This process can be cumbersome, with long timelines and high expense. Similarly, permits for CO_2 storage wells require substantial data and analysis and are often backlogged. AI, including both large language models (LLMs) and digital twinning, could help facilitate both drafting and reviewing of permits, reducing time and costs. AI could help prepare the necessary written documents to receive tax credits for carbon storage or utilization under programs such as those in the US Inflation Reduction Act.[59]

Finally, AI can help ensure that local stakeholders do not suffer environmental burdens or health risks associated with CO_2 pipelines or siting other carbon capture facilities. Specifically, AI can help assess and provide environmental baselines[60] and monitor changes in the environment[61] from construction or pollution. AI can help consider the trade-offs in CO_2 transportation options, including cost, risks and environmental burdens. Initial work at the US National Energy Technology Lab (NETL) and the US Environmental Protection Agency (EPA) suggest potential AI applications and tools to help planners, regulators, investors and community stakeholders develop projects of all kinds in ways that are equitable and just.

E. Barriers

In addition to the many barriers confronting CCUS, increasing adoption and use of AI in CCUS presents specific challenges. The first and most critical issues, as is often the case, are data-related, including *access*, *quality* and *volume*. *Data access* involves the availability of specific compounds (catalysts, sorbents, solvents), reactors and facilities that might benefit from AI applications, which are likely to be limited due to intellectual property constraints, operational security and other commercial concerns. *Data quality* issues are related, including ensuring accurate metadata population and tracking and avoiding duplication of results and analyses, which require time, attention and specific coding to resolve. *Data volume* issues will most likely involve insufficient data, especially given the relatively small number of operating CCUS companies and facilities. While these could be overcome over time, these issues will likely prove challenging in the near- to mid-term.

The second set of challenges are workforce-related. CCUS broadly faces workforce shortfalls,[62,63] which are likely to be compounded by lack of training or familiarity with AI tools, methodologies and potential application. Although some corners of the CCUS enterprise are relatively familiar with AI tools and approaches (e.g., molecular discovery, digital mirroring), many groups in the ecosystem and value chain are unlikely to have the facility and sensibility to seek or employ AI-based tools today, whether for permitting or for reactor design.

F. Risks

Some of the barriers described above may manifest specific risks of AI use. For example, the lack of data for some applications could lead to generation of pseudo-data, which can increase the chance of hallucinations or simple errors. Similarly, the lack of trained workforce could introduce bias and fail to recognize specious results (e.g., in financial or regulatory affairs).

Some risks, independent of other barriers, could prove substantial. Since almost all CCUS projects and developments are taking place in countries within the Organization for Economic Co-operation and Development (OECD), geographic bias is an enormous risk, ranging from estimated costs to permitting ability or climate justice concerns. This could prove particularly true for subsurface studies and planning, where lack of subsurface data in key geographies or applications (e.g., *in situ* mineralization) could limit the ability of AI tools to generate useful and accurate results. Since geology varies greatly from region to region, misapplying Ai results could prove devastating to project success, which in turn might risk the CCUS enterprise.

Such risks could be mitigated at relatively low costs through a combination of management, training and review, but they would most likely require additional human and financial resources, which could prove hard to find.

G. Recommendations

1. *National governments and private companies should expand current research, development and demonstration (RD&D) programs in carbon capture to include AI methodologies, with commensurate increased funding.*
   a. *Specific use-inspired research topics would include material discovery (especially sorbents and solvents for carbon capture), functionalization of materials, and novel reactor design (including catalysts for CO_2-to-products). They should consider prioritizing efforts beyond simple material discovery and focus on more applied and operational aspects of CO_2 capture. Near-Medium term*
   b. *Applied research topics could include optimizing systems (including heat integration, use of digital twins, minimization of heat and electricity demands) and designing key infrastructure pathways (including location, size and operation for CO_2 transportation and storage design), operation and MMRV (measurement, monitoring, reporting and verification)). Near and medium term, with near term emphasis.*
   c. *Government granting entities must hire and/or train personnel that are sufficiently trained and knowledgeable to be able to review AI-related proposals well. Near and medium term.*
2. *Asset owners, utility owners and operators, industrial manufacturers and key state-owned enterprises should use AI tools and methodologies to accelerate assessment of CCUS pathways for existing and planned assets. This should include cost-benefit determinations in comparison with other decarbonization options, with the goal of establishing a ranking of opportunities. Near term.*
3. *National governments should use AI, including LLMs and other generative AI platforms, to streamline permitting processes for carbon capture in all forms. This includes permitting wells for CO_2 injection and processing pipeline rights of way, power electronic designs, and processing revisions to air permits for facility retrofits. Near term.*
4. *National governments and private companies should use AI to improve resource characterization for carbon capture, with emphasis on characterizing geological storage resources. AI-enabled resource characterization should extend beyond bulk storage terms and volume estimates to include understanding of injectivity, permeability fields and risks posed by pre-existing wells. Where possible, national and state governments and some private companies should make data available for training, either through voluntary sharing and federation or mandates. Near term.*
5. *Professional societies, academic experts and carbon accounting bodies should launch training programs on the potential for AI in carbon capture. This could include use of AI for life-cycle assessments of carbon capture systems, as well as the RD&D topics stated above. Near and medium term.*

6. *National governments, private companies and academic researchers should immediately commence with identifying key data requirements for enabling AI in carbon capture. Once identified, these three groups should work to gather, federate and share these data while providing fair, judicious access. Near term.*

H. References

1 Intergovernmental Panel on Climate Change (IPCC). Summary for Policymakers in *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (ed H. Lee and J. Romero Core Writing Team) pp. 1-3 (IPCC, Geneva, Switzerland; https://doi.org/10.59327/IPCC/AR6-9789291691647.001, 2023).

2 International Energy Agency (IEA). *CCUS in Clean Energy Transitions;* IEA, Paris, France, https://www.iea.org/reports/ccus-in-clean-energy-transitions (2020).

3 28th Conference of Parties (COP 28). COP28: The UAE Concensus in *Dubai Climate Change Conference*, Dubai, UAE. (2023; https://cop28.com/UAEconsensus).

4 US Department of State – Office of the Spokesperson. *Sunnylands Statement on Enhancing Cooperation to Address the Climate Crisis (Media Note);* https://www.state.gov/sunnylands-statement-on-enhancing-cooperation-to-address-the-climate-crisis/ (2023).

5 Council on Environmental Quality (CEQ). *Council on Environmental Quality Report to Congress on Carbon Capture, Utilization, and Sequestration;* Executive Office of the President of the United States – CEQ, Washington, D.C., https://whitehouse.gov/wp-content/uploads/2021/06/CEQ-CCUS-Permitting-Report.pdf (2021).

6 The White House. *Voluntary Carbon Markets Joint Policy Statement and Principles;* https://www.whitehouse.gov/wp-content/uploads/2024/05/VCM-Joint-Policy-Statement-and-Principles.pdf (2024).

7 European Commission. *2040 Climate Target: Reducing net emissions by 90% by 2040;* European Commission – Directorate-General for Communication, https://climate.ec.europa.eu/eu-action/climate-strategies-targets/2040-climate-target_en (Accessed August 2024).

8 European Commission. *Questions and Answers on the EU Industrial Carbon Management Strategy;* European Commission – Directorate-General for Communication, https://ec.europa.eu/commission/presscorner/detail/en/qanda_24_586 (2024).

9 Daniela Peta. *2024 Europe Forum on Carbon Capture and Storage: Recap;* Global CCS Institute, Melbourne, Australia, https://www.globalccsinstitute.com/news-media/insights/2024-europe-forum-on-carbon-capture-and-storage-recap/ (2024).

10 Franca Quecke & Julian Wettengel. *Q&A – CCS makes comeback as Germany and the EU strive for climate neutrality;* Clean Energy Wire, Berlin, Germany, https://www.cleanenergywire.org/factsheets/quest-climate-neutrality-puts-ccs-back-table-germany (2024).

11 Global CCS Institute. *Global Status of CCS Report 2023;* Melbourne, Australia, https://status23.globalccsinstitute.com/ (2023).

12 International Energy Agency (IEA). *CCUS Projects Explorer;* Paris, France, https://www.iea.org/data-and-statistics/data-tools/ccus-projects-explorer (Accessed August 2024).

13 International Energy Agency (IEA). *Carbon Capture, Utilisation and Storage;* Paris, France, https://www.iea.org/energy-system/carbon-capture-utilisation-and-storage (Accessed August 2024).

14 Eslam G. Al-Sakkari *et al.* Carbon capture, utilization and sequestration systems design and operation optimization: Assessment and perspectives of artificial intelligence opportunities. *Science of The Total Environment* 917, 170085 (2024). https://doi.org/10.1016/j.scitotenv.2024.170085.

15 Gregor Erbach & Gema Andreo Victoria. *Carbon dioxide removal: Nature-based and technological solutions;* European Parliamentary Research Service (EPRS),

https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/689336/EPRS_BRI(2021)689336_EN.pdf (2021).

16 Intergovernmental Panel on Climate Change (IPCC). *Carbon Dioxide Capture and Storage*. (eds Bert Metz *et al.*), (Cambridge University Press, Cambridge, UK, 2005, https://www.ipcc.ch/report/carbon-dioxide-capture-and-storage/).

17 David Kearns, Harry Liu & Chris Consoli. *Technology Readiness and Cost of CCS;* Global CCS Institute, Melbourne, Australia, https://www.globalccsinstitute.com/wp-content/uploads/2021/03/Technology-Readiness-and-Costs-for-CCS-2021-1.pdf (2021).

18 A. K. Priya *et al.* Artificial intelligence enabled carbon capture: A review. *Science of The Total Environment* 886, 163913 (2023). https://doi.org/10.1016/j.scitotenv.2023.163913.

19 Yongliang Yan *et al.* Harnessing the power of machine learning for carbon capture, utilisation, and storage (CCUS) – a state-of-the-art review. *Energy & Environmental Science* 14, 6122-6157 (2021). http://dx.doi.org/10.1039/D1EE02395K.

20 Keith T. Butler *et al.* Machine learning for molecular and materials science. *Nature* 559, 547-555 (2018). https://doi.org/10.1038/s41586-018-0337-2.

21 David Sandalow *et al. Artificial Intelligence for Climate Change Mitigation Roadmap;* Innovation for Cool Earth Forum (ICEF) Innovation Roadmap Project, https://www.icef.go.jp/wp-content/uploads/2024/02/AI-Climate-Roadmap-ICEF-Dec-1-2023.pdf (2023).

22 Honghao Chen *et al.* AI for Nanomaterials Development in Clean Energy and Carbon Capture, Utilization and Storage (CCUS). *ACS Nano* 17, 9763-9792 (2023). https://doi.org/10.1021/acsnano.3c01062.

23 Jared Sagoff. *Beckman scientists use AI to identify new materials for carbon capture;* University of Illinois Urbana-Champaign – Beckman Institute, Urbana, Illinois, https://beckman.illinois.edu/about/news/article/2024/02/14/beckman-scientists-use-ai-to-identify-new-materials-for-carbon-capture#:~:text=In%20collaboration%20with%20researchers%20from,new%20materials%20for%20carbon%20capture (2024).

24 Jared Sagoff. *Argonne scientists use AI to identify new materials for carbon capture;* Argonne National Laboratory, Lemont, Illinois, https://www.anl.gov/article/argonne-scientists-use-ai-to-identify-new-materials-for-carbon-capture (2024).

25 Seyed Mohamad Moosavi *et al.* A data-science approach to predict the heat capacity of nanoporous materials. *Nature Materials* 21, 1419-1425 (2022). https://doi.org/10.1038/s41563-022-01374-3.

26 Hasan Can Gulbalkan *et al.* Accelerated Discovery of Metal–Organic Frameworks for CO2 Capture by Artificial Intelligence. *Industrial & Engineering Chemistry Research* 63, 37-48 (2024). https://doi.org/10.1021/acs.iecr.3c03817.

27 Mohammad Rahimi *et al.* Toward smart carbon capture with machine learning. *Cell Reports Physical Science* **2** (2021). https://doi.org/10.1016/j.xcrp.2021.100396.

28 Abd-Alkhaliq Salih Mijwel *et al.* Artificial intelligence models for methylene blue removal using functionalized carbon nanotubes. *Scientific Reports* 13, 18260 (2023). https://doi.org/10.1038/s41598-023-45032-3.

29 Liu Helei *et al.* Technology development and applications of artificial intelligence for post-combustion carbon dioxide capture: Critical literature review and perspectives. *International Journal of Greenhouse Gas Control* 108, 103307 (2021). https://doi.org/10.1016/j.ijggc.2021.103307.

30 Oliver J. Fisher *et al.* Responsive CO2 capture: predictive multi-objective optimisation for managing intermittent flue gas and renewable energy supply. *Reaction Chemistry & Engineering* 9, 235-250 (2024). http://dx.doi.org/10.1039/D3RE00544E.

31 Ahmed M. Nassef. Improving CO2 Absorption Using Artificial Intelligence and Modern Optimization for a Sustainable Environment. *Sustainability* 15, 9512 (2023). https://doi.org/10.3390/su15129512.

32 National Energy Technology Laboratory (NETL). *Artificial Intelligence, Machine Learning, and Data Analytics at NETL;* US Department of Energy (DOE) NETL, https://netl.doe.gov/sites/default/files/CompSciEng/NETL-AI-ML-DA-Infosheet.pdf (2020).

33 National Energy Technology Laboratory (NETL). *NETL Develops Pipeline Route Planning Database To Guide CO2 Transport Decisions;* US Department of Energy (DOE) NETL, https://netl.doe.gov/node/12580 (2023).

34 Qi Zhang *et al.* A new optimization model for carbon capture utilization and storage (CCUS) layout based on high-resolution geological variability. *Applied Energy* 363, 123065 (2024). https://doi.org/10.1016/j.apenergy.2024.123065.

35 Youngmin Kim *et al.* Prediction of storage efficiency on CO2 sequestration in deep saline aquifers using artificial neural network. *Applied Energy* 185, 916-928 (2017). https://doi.org/10.1016/j.apenergy.2016.10.012.

36 Hung Vo Thanh & Kang-Kun Lee. Application of machine learning to predict CO2 trapping performance in deep saline aquifers. *Energy* 239, 122457 (2022). https://doi.org/10.1016/j.energy.2021.122457.

37 Hung Vo Thanh *et al.* Knowledge-based machine learning techniques for accurate prediction of CO2 storage performance in underground saline aquifers. *Applied Energy* 314, 118985 (2022). https://doi.org/10.1016/j.apenergy.2022.118985.

38 Zhi Zhong *et al.* A deep learning approach to anomaly detection in geological carbon sequestration sites using pressure measurements. *Journal of Hydrology* 573, 885-894 (2019). https://doi.org/10.1016/j.jhydrol.2019.04.015.

39 Siddharth Misra, Hao Li & Jiabo He. *Machine Learning for Subsurface Characterization*. (Gulf Professional Publishing (an imprint of Elsevier), Cambridge, MA and Oxford, United Kingdom, 2020; https://doi.org/10.1016/C2018-0-01926-X).

40 IEEE Spectrum. Better Carbon Sequestration With AI in *Fixing the Future. (IEEE Spectrum, New York, NY, 2023; https://spectrum.ieee.org/carbon-sequestration-with-ai) https://spectrum.ieee.org/carbon-sequestration-with-ai.*

41 Tiernan Ray. *AI computer maker Cerebras nabs TotalEnergies SE as first energy sector customer;* ZDNet – Innovation, https://www.zdnet.com/article/ai-computer-maker-cerebras-nabs-totalenergies-se-as-first-energy-sector-customer/ (2022).

42 Mackenzie Komeshak. *Using AI To Optimize Mechanical Carbon Capture & Storage Systems;* Xyonix, Inc., Seattle, WA, https://www.xyonix.com/blog/using-ai-to-optimize-mechanical-carbon-capture-amp-storage-systems (2022).

43 Dr. Satyam Priyadarshy & Duane Moonsammy. *A maching learning risk management framework for sustainable oil and gas solutions;* Halliburton – Energy Pulse, https://www.halliburton.com/en/energy-pulse/a-machine-learning-risk-management-framework-for-sustainable-oil-and-gas-solutions (2021).

44 Damian Janiga, Jerzy Stopa & Pawel Wojnarowski. Application of artificial intelligence in CO2-EOR process optimization in *Surveying Geology & Mining Ecology Management (SGEM) 2016*, Albena Resort, Bulgaria. https://www.researchgate.net/publication/316664691, (2016).

45 Hung Vo Thanh, Yuichi Sugai & Kyuro Sasaki. Application of artificial neural network for predicting the performance of CO2 enhanced oil recovery and storage in residual oil zones. *Scientific Reports* 10, 18204 (2020). 10.1038/s41598-020-73931-2.

46 Office of Fossil Energy and Carbon Management (FECM). *Carbon Conversion: Roles for Artificial Intelligence in Support of FECM RDD&D Priorities;* U.S. Department of Energy (DOE) FECM, https://www.energy.gov/sites/default/files/2024-04/carbon-dioxide-conversion.pdf (2024).

47 National Energy Technology Laboratory (NETL). *Carbon Dioxide Conversion Program;* US Department of Energy (DOE) NETL, https://netl.doe.gov/carbon-management/carbon-conversion (Accessed August 2024).

48 Miao Zhong *et al.* Accelerated discovery of CO2 electrocatalysts using active machine learning. *Nature* 581, 178-183 (2020). https://doi.org/10.1038/s41586-020-2242-8.

49 Parameswaram Ganji, Ramesh Kumar Chowdari & Blaž Likozar. Photocatalytic Reduction of Carbon Dioxide to Methanol: Carbonaceous Materials, Kinetics, Industrial Feasibility, and Future Directions. *Energy & Fuels* 37, 7577-7602 (2023). https://doi.org/10.1021/acs.energyfuels.3c00714.

50 Wim Vermaas. *DOE Bioenergy Technologies Office (BETO) 2021 Project Peer Review: Multi-pronged approach to improving carbon utilization by cyanobacterial cultures;* US Department of Energy (DOE) Bioenergy Technologies Office (BETO), https://www.energy.gov/sites/default/files/2021-04/beto-35-peer-review-2021-algae-vermaas.pdf (2021).

51 Ho Seok Whang *et al.* Heterogeneous catalysts for catalytic CO2 conversion into value-added chemicals. *BMC Chemical Engineering* 1, 9 (2019). https://doi.org/10.1186/s42480-019-0007-7.

52 Tao Cai *et al.* Cell-free chemoenzymatic starch synthesis from carbon dioxide. *Science* 373, 1523-1527 (2021). https://doi.org/10.1126/science.abh4049.

53 Hao Li *et al.* Prediction of CO2 absorption by physical solvents using a chemoinformatics-based machine learning model. *Environmental Chemistry Letters* 17, 1397-1404 (2019). https://doi.org/10.1007/s10311-019-00874-0.

54 Martha A. Arellano-Treviño *et al.* Catalysts and adsorbents for CO2 capture and conversion with dual function materials: Limitations of Ni-containing DFMs for flue gas applications. *Journal of CO2 Utilization* 31, 143-151 (2019). https://doi.org/10.1016/j.jcou.2019.03.009.

55 Melis S. Duyar, Martha A. Arellano Treviño & Robert J. Farrauto. Dual function materials for CO2 capture and conversion using renewable H2. *Applied Catalysis B: Environmental* 168-169, 370-376 (2015). https://doi.org/10.1016/j.apcatb.2014.12.025.

56 Caleb M. Woodall *et al.* Utilization of mineral carbonation products: current state and potential. *Greenhouse Gases: Science and Technology* 9, 1096-1113 (2019). https://doi.org/10.1002/ghg.1940.

57 Yi Liu *et al.* Machine learning-guided optimization of coarse aggregate mix proportion based on CO2 intensity index. *Journal of CO2 Utilization* 85, 102862 (2024). https://doi.org/10.1016/j.jcou.2024.102862.

58 Almando Morain *et al.* Artificial Intelligence for Water Consumption Assessment: State of the Art Review. *Water Resources Management* 38, 3113-3134 (2024). https://doi.org/10.1007/s11269-024-03823-x.

59 US Internal Revenue Service (IRS). *IRS issues guidance for the procedures to claim a credit for utilization of carbon oxide;* Washington, D.C., https://www.irs.gov/newsroom/irs-issues-guidance-for-the-procedures-to-claim-a-credit-for-utilization-of-carbon-oxide (2024).

60 Jagabondhu Hazra *et al.* AI for Environmental Intelligence in the Digital Economy. *Ubiquity* 2023, Article 2 (2023). https://doi.org/10.1145/3623296.

61 Yassine Himeur *et al.* Using artificial intelligence and data fusion for environmental monitoring: A review and future perspectives. *Information Fusion* 86-87, 44-75 (2022). https://doi.org/10.1016/j.inffus.2022.06.003.

62 Carbon Capture Coalition. *Carbon Capture Jobs and Project Development Status;* https://carboncapturecoalition.org/wp-content/uploads/2020/06/Carbon-Capture-Jobs-and-Projects.pdf (2020).

63 Rhodium Group. *Carbon Capture and Storage Workforce Development: State-by-State;* New York, NY, https://rhg.com/research/carbon-capture-and-storage-workforce-development-state-by-state/ (2023).

CHAPTER 10:

NUCLEAR POWER

Matthew L. Wald, Julio Friedmann, Alp Kucukelbir, Rama Ponangi and David Sandalow

A. Operating reactors ... 10-3
B. Advanced reactor design ... 10-7
C. Nuclear waste ... 10-9
D. Nuclear regulatory process ... 10-11
E. Barriers ... 10-15
F. Risks ... 10-16
G. Recommendations ... 10-18
H. References ... 10-19

Nuclear power provides low-carbon, dispatchable power in large quantities. It has the potential to contribute significantly to achieving the goals of the Paris Agreement.[1] At the 28th Conference of the Parties to the UN Framework Convention on Climate Change (COP28) in December 2023, 25 countries pledged to triple their nuclear power capacity by mid-century.

Meeting this pledge will be a challenge. High costs, public opposition and other factors have limited the growth of nuclear power for decades. Indeed in 2023, nuclear power output globally was two percent *below* its 2006 peak.[2] China leads the world in new nuclear power capacity but has added only 2–3 GW per year—a stark contrast with the 210 GW of new solar power capacity added in China last year.[3] Japan has reopened only 12 of the 53 reactors that were operating before the 2011 Fukushima accident.[4] New nuclear reactors recently opened in the United States for the first time in eight years.[5] Germany has closed its last reactors, and Spain may soon follow.[2,6] France—which leads the world in the percentage of nuclear power on the electric grid—has seen extensive delays and cost overruns in constructing a new reactor type (the European Pressurized Reactor) and may replace some nuclear reactors with solar and wind power.[7] Many developing countries aspire to nuclear power but lack the resources, and the political situation in many developed countries remains murky. All this taken together has resulted in the global share of primary energy that comes from nuclear sources remaining flat at about nine percent in the last few years.[2]

If nuclear power is going to make a bigger contribution to the world's growing energy needs, the industry will need to reduce the time and cost required to build new reactors and to optimize operations of legacy reactors and new models. One way to accomplish this goal is to harness technological improvements from outside the nuclear industry, such as artificial intelligence (AI).[9]

AI could raise the productivity of reactors already in service, increasing their annual hours of operation. It could reduce the amount of uranium enrichment these reactors require, cut the volume of nuclear waste they produce and assist in evaluations needed to extend their lives. AI could also cut the cost of electricity produced by new reactors by optimizing the design of their cores. Proponents are hopeful that AI could shorten the time needed to license new reactors, reduce the staffing requirements for those reactors and eliminate unnecessary radiation exposure to plant staff.

Figure 10-1. *Boiling water reactors at the Enrico Fermi Nuclear Plant in Newport, Michigan, USA.*[8]

AI could be a key part of a "faster/better/cheaper" approach.

But there are barriers to these potential contributions. One is that existing nuclear plants are largely analog and create far less data than digitized industries do. Also many nuclear databases are proprietary and may not be in a usable form. In addition, regulators are quite conservative about incorporating new tools into nuclear design and operations. (These problems are related. One reason legacy reactors in the United States do not have large databases of their performance is that the US Nuclear Regulatory Commission (NRC) has held back licensees' efforts to digitize controls.)

AI is a fast-moving technology; nuclear power is a slow-moving industry with especially slow-moving regulators. AI has just begun to demonstrate its value in operating nuclear power plants. Whether AI can ease or speed deployment of additional nuclear reactors remains unclear.

This chapter explores how AI could add value in the nuclear power sector. The chapter explores AI applications in operating reactors, advanced reactor design, nuclear waste management and the nuclear regulatory process, discusses barriers and risks and offers nine recommendations.

A. Operating reactors

AI can help improve operations in a number of ways at nuclear reactors that are already operating. The US Department of Energy's (DOE's) Idaho National Laboratory has suggested that AI can support nuclear power in the following ways:

- "Detecting process anomalies in a nuclear power plant before they develop into significant events
- Automating paperwork activities of nuclear power plant operators by applying natural language processing methods to documents that are generated daily
- Applying classical and machine learning (ML)-based image processing to automate manual and visual tasks in a plant
- Creating risk-informed predictive maintenance strategies for nuclear power plants that are based on predictive models developed to monitor an identified plant asset
- Developing intelligent operator aids to enhance the operator's ability to monitor nuclear plant systems and components
- Preventing and managing corrosion
- Creating virtual operators to run simulations so reviewers can identify human factors that affect performance"[10]

The US Electric Power Research Institute has observed growth in the deployment of sensors and other instruments at nuclear power plants. These tools provide a vast amount of information about a nuclear power plant's operational status. This growth of information about operational performance provides an opportunity to use AI tools to increase reliability and efficiency.[11]

i. Fuel management

One consulting firm (Blue Wave) has been using AI since 2016 to reduce the number of fuel assemblies needing premature replacement at boiling water reactors (BWRs). The firm also uses AI to help find sensors whose out-of-calibration readings could have led to shutdowns or reduced energy production.[12,13]

The design of BWR cores is complex due to uneven water density between the top and bottom (more of the water is steam near the top). AI may be better than humans at specifying optimum distribution of the more fissile type of uranium within the core, allowing full power operation until a refueling outage and ensuring the fuel is completely used up at the time of scheduled refueling.[13]

AI can avoid another problem: having to replace a fuel bundle early because the bundle does not have enough energy potential left to last until the next scheduled refueling. Replacing assemblies early increases the volume of nuclear waste. Blue Wave says it has saved 110 assemblies across the 16 units that use its software. (BWRs have between 300 and 800 fuel assemblies.)

Figure 10-2. *Boiling water reactor fuel bundle.*[8]

ii. Sensor and camera readings

AI can also optimize reactor operations by analyzing sensor readings. In one instance, a utility reported that its reactor was producing more and more steam and was projected to exceed its licensed limit within days. The utility proposed to insert control rods to reduce energy output. Instead, using a digital model and AI tools, Blue Wave concluded that of the 172 sensors that measured power in different spots in the core, 7 were giving inaccurate readings. (In-core sensors in a BWR have limited lifetimes.) Turning off the inaccurate sensors allowed the utility to calculate that it was operating well within its thermal limits, and the plant avoided losing production.[13]

Blue Wave sees other potential uses for AI:

- Nuclear plants make extensive use of security cameras, but human beings do not always notice what the cameras capture
- AI does not get bored and could categorize everything on the screen, sorting the images as normal or not normal and flagging the ones that need human attention

Likewise, plants use remotely controlled cameras to scrutinize reactor vessels and other components. AI could be taught to look for images on screen that merit follow-up and flag them for human operators. Both these examples are machine assistance to human decision-makers, and as such, proponents say they may avoid triggering NRC licensing requirements.[13,14] This is important because reactor owners are reluctant to make any changes that force them to go to regulators for license amendments or other rulings. In the United States, changes that require NRC approval can take a year or more and cost a licensee thousands of dollars in NRC review fees.

iii. Operator tasks and robotics

Other companies have been developing AI tools for use at nuclear power plants. NuclearN[15] provides products to automate the tasks and challenges operators typically face. The idea of automating nuclear operations and maintenance dates back to the 1980s.[16] Some labeled the "lack of intelligence" the Achilles heel of nuclear robotic technology. But today, AI is driving configuration and operation in robotics in sectors ranging from automobile manufacturing to household vacuum cleaners and from medical surgical equipment to aerial drones used in agriculture and defense. AI can enhance the functionality, versatility and precision of robots. AI-powered robots can have advanced software, computer vision and decision-making capabilities that allow them to operate more autonomously and effectively than those not powered by AI. In some nuclear facilities, AI-controlled unmanned platforms (e.g., quadrupeds, such as SPOT)[17] are already at work.

These developments are gradually being ported to the nuclear sector, with a focus on robotics first and software second. The United Kingdom's Research and Innovation agency sponsored a five-year research program at this interface.[18] The European Union's Robotics for Inspection and Maintenance project focused on nuclear facilities.[19] The Organization for Economic Cooperation and Development's Nuclear Energy Agency has an ongoing initiative focused around decommissioning,[20] while recent nuclear robotics deployments in Japan have been well documented.[21]

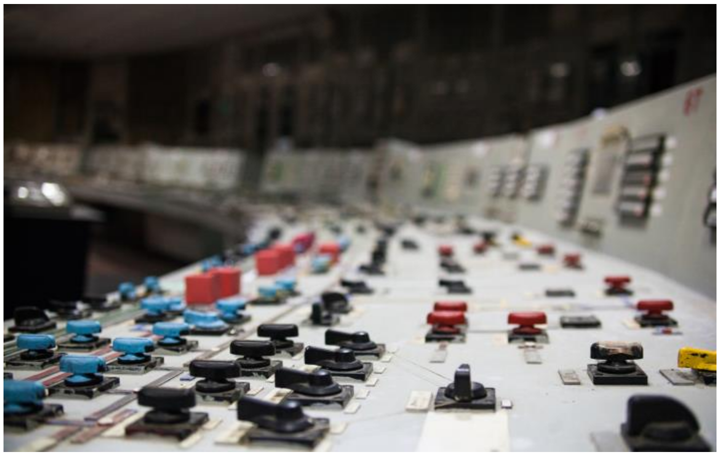


Figure 10-3. *Nuclear power plant control panel*

These initiatives and deployments encourage research into the modifications needed to adapt these technologies to nuclear requirements. Some examples of research at this interface include:

- A semi-autonomous pipe-cutting robot in radiological environments[22]
- The role of AI in remote glovebox operations in nuclear settings[23]
- AI for nuclear decommissioning projects[24]

iv. Corrosion

Material corrosion is one of the nuclear industry's great challenges. Annual costs from corrosion-related aging and degradation due to radiation exposure are significant, even for advanced metals (e.g., Zircaloy). The risks and challenges with corrosion have increased as reactors' licenses are extended, demanding longer and better performance from plants and operating systems. AI could help extend the lifetimes of reactors already operating and improve operations in reactors now being designed, saving operators cost and reducing maintenance outages (planned and unplanned).

Materials discovery presents a terrific opportunity for AI-driven improvements in nuclear power, as in other fields. (Chapter 13 of this Roadmap discusses this opportunity in depth.) This is particularly true with respect to advanced alloys used in pressure vessels, specialty welding and reactor claddings, which can be damaged by direct radiation exposure and interaction with advanced coolants (e.g., molten salts). Discovery of new alloys or optimal production of existing alloys could deliver significant improvements and would likely have applications to both reactor design and waste storage systems.

The same is true for AI applications in process and control systems. For example, using operational data from sensors and controls, AI could help detect corrosion earlier and improve maintenance cycles. (Chapter 5 presents similar applications of AI within the manufacturing industry.)

v. Life extensions

In many countries, nuclear power plants face challenges due to declining prices of electricity in wholesale markets, driven by technical improvements in competing sources of energy and subsidies for them. AI can help reactors meet this financial challenge by cutting the cost of producing electricity in a nuclear plant, by improving fuel utilization (using less and wasting less), reducing unnecessary shutdowns and making it more feasible to extend the life of a reactor.

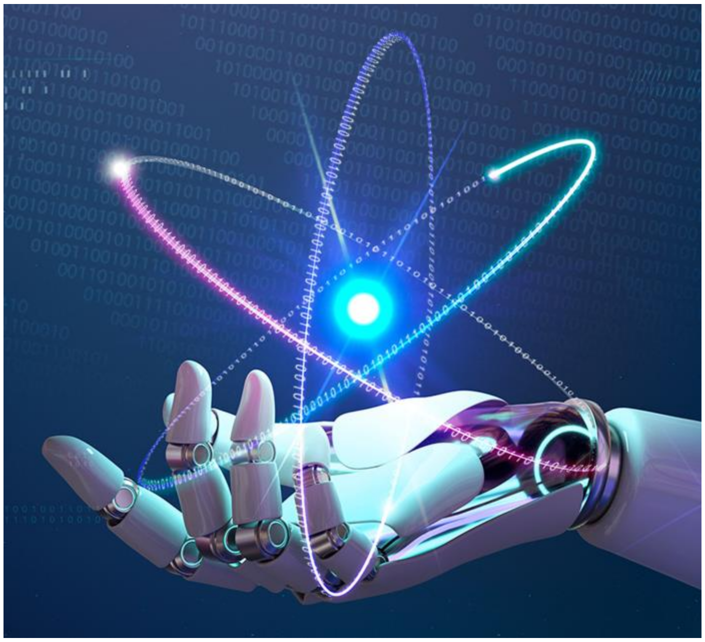


Figure 10-4. *AI can manage nuclear processes efficiently.*

Indeed at nuclear reactors that are currently operating, AI can help analyze the potential for life extension. For example, AI can help measure the extent of radiation damage to concrete—a prerequisite for life extension. The aggregates used in concrete often include quartz, and when quartz is hit by a neutron, its structure is damaged. Technicians can use a technology called x-ray computed tomography to look deep inside concrete structures and see the extent of damage. However, the images are low contrast, and the work is so tedious that the accuracy of a human analyst interpreting the images may not be high enough. Researchers at DOE's Oak Ridge National Laboratory have used AI to scan the images more accurately.[25]

ARTIFICIAL INTELLIGENCE (AI) CAN SAVE NUCLEAR FUEL

As discussed above, when operators of a US boiling water reactor (BWR) saw that sensors indicated power levels were rising beyond license limits, they thought they would have to change rod patterns within a few days to reduce energy production. However, they used AI to determine that 7 of the 92 sensors were giving inaccurate readings and that excluding them from analysis of the core would improve accuracy. They kept power at 100 percent, just below the license limit.

Engineers' initial analyses of the cores of several reactors showed that they would have to replace 104 assemblies after just 2 cycles, rather than the standard 3, but AI analysis of just how many megawatt-hours of energy each fuel assembly in a BWR had actually produced allowed operators to leave them in place for a third 2-year cycle. This reduced their costs and the volume of nuclear waste.

B. Advanced reactor design

AI can assist in designing advanced nuclear reactors.[26]

i. Thorium-Fueled Fission Reactors

Thorium is a radioactive element whose main isotope, Th-232, is four times more abundant than most uranium and about four hundred times more abundant that U-235 (used in nuclear fuel). The current favored design for thorium-fueled reactors is a molten salt-cooled reactor, in which the thorium fuel would be mixed directly with the molten salt coolant.[27] The design does not use cooling water, a distinct environmental advantage, and is believed to have a smaller risk of core damage compared to water-based nuclear reactors. Other advantages include low risk of weaponization or proliferation, high efficiency, high-temperature heat generation and reduced production of waste.[28] China has built a thorium reactor, and other nations are considering it as well.[29]

AI could potentially contribute positively to many aspects of thorium reactors. AI could optimize fuel, coolant and reactor design against multiple objectives (cost, safety, performance). Digital twins could serve to further improve thorium reactor designs and to identify potential operational challenges and faults.

ii. Traveling Wave Reactors

In traveling wave reactors, a small quantity of *enriched* uranium or plutonium triggers a chain reaction, which showers a larger volume of *natural* and *depleted* uranium (which are abundant) with neutrons. These neutrons convert the uranium to plutonium, which is a reactor fuel.[28,30] Designs vary between static fuel systems, in which the reaction wave moves through stationary fuel arrays, and standing wave designs, in which the reaction front is maintained in place by moving the fuel.

Given the early status of design and operation, an enormous number of potential AI applications could serve to test and improve traveling wave reactors. First, AI could help determine how to blend and configure the fissile trigger. It could help assess the potential for adding wastes from nuclear weapons or medical isotopes. As with thorium reactors, it could help design better, cheaper, safer reactors. And it could help anticipate novel challenges and risks from extended operation of traveling wave reactors, including potential environmental and commercial challenges.

iii. Sodium-cooled fast reactor

Sodium-cooled fast reactors (SFRs) are advanced nuclear reactors that use liquid sodium as a coolant, allowing for higher operating temperatures and lower pressures compared to water-cooled reactors. SFR technology has been demonstrated in several countries, but deployment remains limited, with only a handful of SFRs reactors currently operating. Their "fast" neutrons have more energy, so they can split more kinds of atoms as fuel.[31]

Terrapower, a US company developing an SFR design, is using AI to optimize the placement and enrichment level of fuel elements.[32] AI may also be used to find weak spots in the design before construction by running multiple operating scenarios in a quick fashion.

iv. Graphite Gas-Cooled Reactors

Nuclear engineers from the University of Tennessee, Oak Ridge National Laboratory and UltraSafe Nuclear Corporation have optimized the design for a graphite-moderated, gas-cooled reactor with a core manufactured via 3-D printing. Use of 3-D printing has liberated designers from uniformly shaped components. The technique, also called additive manufacturing, allows fabrication of cooling channels of varying radius—even variable radius over its length—and the channel's path through the graphite does not have to be straight. Their design is for a 3-megawatt core, measuring 1 meter high and 80 centimeters in diameter. Its size gave rise to the informal name, "the trash can reactor." At the moment, this design is conceptual under DOE's Transformational Challenge Reactor program.

In developing their "trash can reactor," researchers at the University of Tennessee used AI to help optimize their design. "A human can do it, but it's difficult for the human to do it precisely," said Vladimir Sobes, assistant professor of nuclear engineering at the University of Tennessee, Knoxville and lead author of a paper describing the process. "The human gets the intuition very well in terms of directionality, but not in terms of precise numbers." In their case, the AI program applied computational fluid dynamics techniques to 750 designs to find the best configuration.[33]

v. Networking fleets of new reactors

Part of making nuclear power cost-competitive is getting economies of scale in reactor operations—not just construction—and making best use of human resources across a fleet. Today, nuclear power plants differ enough from each other that each needs its own engineering and maintenance.

Maintenance is conducted mostly based on the condition of components, as observed by local staff. But a family of new reactors could pool their data, and some engineering and maintenance functions could be centralized. Utilities that operate fleets of reactors have already centralized their engineering and maintenance to improve efficiency, but AI may allow additional centralization.

X-energy, for example, is developing a gas-cooled, graphite-moderated small reactor, which it intends to deploy in four-packs. However, all the four-packs will be wired together, and AI at a regional plant support center will analyze their pooled data.[34] This arrangement should permit predictive maintenance based on data gathered from components, including temperature, vibration and similar parameters, which will indicate whether to increase or decrease the maintenance interval. This approach contrasts with the legacy approach of refurbishing solely based on time intervals or equipment cycles.

The system can also optimize the supply chain, determining what parts need to be kept in inventory and how fast they will be consumed. Humans will still be in the loop, according to the company, and it does not plan to use AI in the moment-to-moment operation of the plants.[a]

FUSION

Can AI help make fusion energy practical? The date predicted for that milestone is has always been floating a few years in the future, and the pathway is still unclear. There is, however, some early work in applying AI to this challenge.

Researchers at the Princeton Plasma Physics Laboratory have used AI to attack a central problem of magnetic fusion, which is to keep the plasma field together, a prerequisite for maintaining the terrific temperatures and pressures needed to fuse atoms. AI has analyzed previous experimental work in making plasma fields in a tokamak and can now predict one type of instability that causes plasma fields to break down, called tearing mode instabilities. AI can give notice of 300 milliseconds, which is short (about three times the duration of a blink of an eye), but potentially long enough for a computer-controlled system to make adjustments to prevent the tearing. Researchers have used AI to change the shape of the plasma and the strength of the beams that add power to it. Thus far, they have applied AI to one type of instability at one tokamak, which uses a magnetic field to keep the plasma together, so the work is still preliminary.[36]

AI has also been used to help with another approach to fusion—inertial confinement. Engineers at Lawrence Livermore National Laboratory used AI to study hundreds of thousands of computer simulations to improve the way the fuel is confined.[37] Lawrence Livermore sustained a fusion reaction in December 2022 that produced more energy than was used to create the event.

C. Nuclear waste

One of the most vexing and persistent concerns about nuclear energy is the back end of the fuel cycle: waste management. Although nuclear waste is safely managed today through a variety of approaches, public concerns persist regarding safe handling and disposal of waste fuel and nuclear residues. Advances in AI can potentially improve the end of the nuclear fuel cycle

[a] NRC Chairman, Christopher T. Hanson, reiterated in testimony before a House Energy & Commerce subcommittee on July 23 that his agency's position is that humans must remain in the loop.[35]

i. Dry Cask Storage

Most operating plants around the world have on-site interim storage of spent fuel rods in specially designed and operated pools. When pools become full, the rods are most commonly placed into dry casks, comprising a metal sheath and concrete. The dry casks are designed to hold fuel rods indefinitely, with most common dry-cask performance estimates of ~100 years of storage, with some estimates of 1800 years.[38] Dry casks are commonly stored above ground and can be shipped safely.

AI has the potential to improve the design and performance of dry cask storage. In part, this is due to the long history and sustained study and monitoring of the casks, which produced data that might serve as AI training data sets. For example, AI has helped better identify damage and functional anomalies,[39] and is a central component of systems for automatic damage detection.[40] AI tools could also optimize storage system components in terms of pressure, temperature, composition and loadings; improve material design for storage cladding and casing alloys; and predict the performance of existing systems. [41,42]

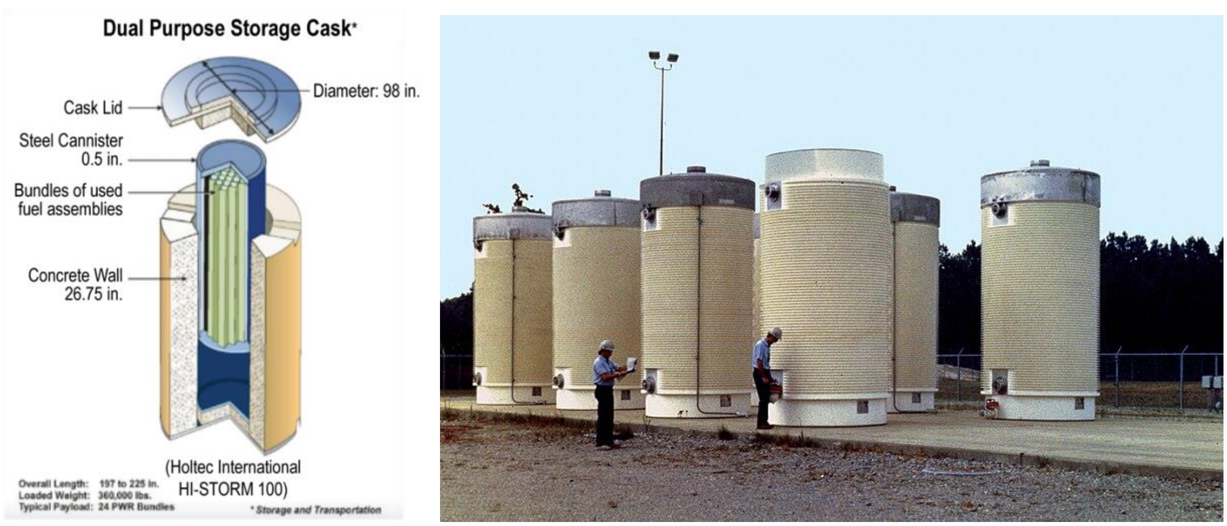


Figure 10-5. *Dry casks for spent nuclear fuel. Left: Schematic diagram of a cask for storage and shipping and description of the materials used in its construction. Right: Dry-cask storage containers in the field. Source: US NRC*[43]

ii. "Conventional" Geological Repositories

The scientific consensus is that the long-term solution for containing and disposing of spent nuclear fuel is dedicated geological repositories. According to the Nuclear Energy Association (NEA), "Deep geological disposal is widely agreed to be the best solution for final disposal of the most radioactive waste produced".[44] Today, some long-lived waste from weapons production and maintenance is buried at the Waste Isolation Pilot Plant (WIPP) facility in New Mexico,[45,46] which has operated since 1999 and has received over 14,000 shipments of trans-uranic waste. The Onkalo facility in Finland,[47] the first facility dedicated to civilian high-level nuclear waste storage, could open as early as 2026 with the goal of 100,000-year containment.

These facilities are highly complicated in design, site characterization, operation, fault detection, monitoring (sensors and controls) and performance assurance. AI applications across these disciplines could deliver improvements in materials, design and operational performance.[48] Potential improvements could include understanding mineralogical response,[49] better corrosion resistance and management (see below), improved fault detection, heat management, optimized loading of storage cannisters[50] and rapid assessment of environmental hazards. AI could also help find the most promising locations for geological repositories.[51] To better understand these potential opportunities, the NEA convened a working group in 2023 to explore applications to radioactive waste storage,[52] with its report and recommendations anticipated in 2025.

iii. Alternative Waste Management Strategies

Finally, AI might help operators, managers and regulators consider novel approaches to nuclear waste storage. One promising approach, deep borehole disposal (DBD), would place waste containers into specially designed boreholes that are 5 km deep or more. AI has many potential applications in this approach, including identifying promising borehole sites, optimizing container design, or far-field detecting of disposal breaches.

Another potential approach involves separating certain radioactive isotopes in nuclear waste and transmuting them into new elements that do not need to be isolated for so long (e.g., by bombarding long-lived isotopes with neutrons to convert them to materials with shorter half-lives).[53] Possible benefits of processing and partitioning wastes followed by transmutation include recovering some elements for re-use in fuels and reducing total waste volumes.[54,55] Although promising, transmutation is an immature technology that needs advanced technology.[56,57] In considering functional transmutation systems, some workers have already turned to AI and ML applications to provide insight.[58] Potential applications include optimizing energy and performance for isotope separation and designing neutron beams and specialty materials for transmutation system components.

D. Nuclear regulatory process

Regulators enforce the obligation of plant operators to ensure that power reactors remain safe. As technology advances, the integration of AI into regulatory activities represents a promising avenue for enhancing oversight and efficiency of enforcement. AI algorithms could be deployed to analyze maintenance and performance data from nuclear power reactors, enabling more predictive decision-making. For instance, AI-powered analytics could identify emerging safety trends or anomalies in reactor performance, allowing regulators to prompt the licensees to take preemptive measures to address issues before they escalate. Additionally, AI-driven automation could streamline regulatory processes, such as inspections and licensing reviews, by focusing regulators on the most important areas, optimizing resource allocation and accelerating assessment of compliance with safety standards.

However, integrating AI into regulatory activities also presents challenges. Ensuring reliability and transparency of AI algorithms used in regulatory decision-making will be paramount to maintaining public trust and confidence in the regulatory process. Rigorous testing, validation and monitoring of

AI systems will be necessary to mitigate the risk of biases, errors or unintended consequences. Furthermore, regulatory bodies will need to develop robust frameworks and standards for ethical and responsible use of AI, particularly concerning data privacy, security and accountability. Collaborative efforts with industry stakeholders, research institutions and AI experts will be essential for navigating these challenges and harnessing the full potential of AI to enhance nuclear safety and regulatory oversight.

A few regulatory bodies have already started exploring and testing AI systems through hosting workshops, engaging industry stakeholders, seeking public input and using "sandboxing" techniques.

AI sandboxing is an activity in a controlled environment where AI algorithms and new technologies are tested, validated and refined virtually before deploying them in the real world. The primary objective of AI sandboxing is to mitigate risks associated with adopting AI, such as algorithmic bias, safety lapses and regulatory non-compliance, while also fostering innovation and collaboration within the AI ecosystem.[59]

AI sandboxing is not limited to nuclear power. In October 2023, President Biden issued an executive order on the use of AI that called for "robust, reliable, repeatable and standardized evaluations of AI systems." The order requires the Secretary of Energy to establish a plan for developing AI testbeds and to develop tools to evaluate AI's "capabilities to generate outputs that may represent nuclear, nonproliferation, biological, chemical, critical infrastructure and energy-security threats."[60]

Here are initiatives taken in several countries:

i. United States

The NRC's work to understand AI developments in the US nuclear industry dates to at least 2021, when the NRC issued a Federal Register notice to solicit comments from the industry about AI and organized a series of workshops on data science and AI regulatory applications. This created a forum for NRC, the nuclear industry and various stakeholders to discuss the state of knowledge on AI applications in the nuclear industry.[61]

In 2022, the NRC issued NUREG/CR-7274, "Exploring Advanced Computational Tools and Techniques and Artificial Intelligence and Machine Learning in Operating Nuclear Power Plants," which documented the state of practice of AI applications in the nuclear industry. In the same year, the NRC published the "Artificial Intelligence Strategic Plan" for fiscal years 2023–2027. The AI Strategic Plan established "the vision and goals for the NRC to cultivate an AI-proficient workforce, keep up pace with AI technological innovations, and ensure the safe and secure use of AI in NRC-regulated activities."[62] The AI Strategic Plan includes five goals[62]:

1. Ensure NRC readiness for regulatory decision-making
2. Establish an organizational framework to review AI applications
3. Strengthen and expand AI partnerships
4. Cultivate an AI-proficient workforce
5. Pursue use cases to build an AI foundation across the NRC[62]

There are some roles for AI that do not appear to raise safety implications. The NRC maintains the Agency-wide Documents Access and Management System, known as ADAMS, that is notoriously hard to use. In an age when other documents can be located by commercial search engines, ADAMS remains mostly opaque because search engines like Google work by examining links between documents, and ADAMS does not link documents.

But two companies have downloaded the entire ADAMS corpus and are using AI tools to make it searchable. Microsoft has done this on behalf of TerraPower, which is building a reactor plus storage project in Wyoming. And a startup called Atomic Canyon is seeking to make ADAMS searchable so that companies preparing license applications can find useful precedents. Similar to other technical fields like medicine and law, regulating nuclear energy is a specialized field with specialized vocabulary. This adds a layer of challenge in making ADAMS searchable since general purpose large language models (LLMs) may struggle with correctly interpreting and processing technical language, such as that found in the 50 million documents in ADAMS. (See Chapter 11 for a discussion of LLMs.)

A more easily searchable ADAMS would help applicants for licenses find relevant precedents—and solutions—for the technical issues they face.

A 2024 workshop report from Argonne National Laboratory identified three areas where AI could assist nuclear power to make a larger contribution to addressing energy and environmental challenges: (1) accelerating the licensing and regulatory process, (2) accelerating deployment and (3) facilitating maintenance scheduling and autonomous operation. (AI control of robotic maintenance or cleanup equipment seems more likely, though, than AI replacing control room operators.) Regarding the analysis and licensing of new reactors, studies have looked at the potential for digital engineering and digital twinning technologies (a nuclear digital twin is the virtual representation of a nuclear power system) to be applied to reactor design and construction, which could help with the economics of future reactors.

ii. United Kingdom

The United Kingdom's Office for Nuclear Regulation (ONR) is a leader in exploring the potential benefits and challenges of AI in nuclear power. ONR and the UK Environment Agency have consulted with a wide range of stakeholders on AI and are piloting an AI sandboxing initiative aimed at fostering innovation and exploring the potential applications of AI in nuclear regulatory processes "in the interest of safety, security and environmental protection."[63](See ONR, 2023 at p. 5[64]) In November 2022, the UK Department for Business, Energy and Industrial Strategy awarded ONR and the Environment Agency a grant of £170,950 through the Regulators' Pioneer Fund to deliver the sandboxing pilot project (see ONR, 2023 at p. 5[64]).

The ONR has been exploring regulatory sandboxing for AI, consulting with the UK Environment Agency, the UK Civil Aviation Authority and others on topics including the use of AI-enabled robots in constrained spaces (see ONR, 2023 at p. 9 and 11[64]). Engagement sessions conducted during the project have sparked increasing stakeholder interest in the sandboxing approach and AI integration. Key findings include the necessity to clearly articulate AI benefits compared to traditional technologies, the importance of understanding and managing AI-related risks and of phased deployment for confidence-building, and the need for a principles-based regulatory approach. Stakeholders also highlighted challenges in substantiating AI reliability. They stressed the importance of thorough hazard analysis for different AI deployment modes and identified three key areas for skill and guidance development: access to AI expertise, operational experience and fostering a safety-centric culture. Moreover, stakeholders underscored the complexity of human/system interaction in AI deployment and advocated for disseminating guidance and good practices, focusing initially on principles and case studies to aid stakeholders in navigating AI deployment and regulation (see ONR, 2023 at p. 6–7[64]).

iii. Canada

The Canadian Nuclear Safety Commission (CNSC) has taken several steps with regards to AI. From 2019 to 2020 the CNSC established a working group to assess the implications of disruptive, innovative and emerging Technologies (DIET) for its regulatory framework.[65,66] In 2023, under the DIET initiative, CNSC along with Candu Energy, Inc. released a report titled "A Study for the Canadian Nuclear Safety Commission on Artificial Intelligence Applications and Implications for the Nuclear Industry"(See CNSC, 2023 at p. 5[67]). The report reviews current applications of AI in the nuclear industry and regulatory efforts by the International Atomic Energy Agency (IAEA), US NRC and UK ONR. The report assesses the regulatory framework of the CNSC, providing strategic recommendations on how it can better support licensees in safely and effectively integrating AI technologies "(see CNSC, 2023 at p. 15[67]) and analyzes AI applications in safety-centric industries, including nuclear power, oil and gas, medicine, and aviation. The report highlights data integrity as crucial to preventing AI failures, maintaining performance and meeting safety standards in these industries (see CNSC, 2023 at p. 15[67]).

Three areas have emerged as regulatory challenges for CSNC with respect to AI: reliability, trustworthiness and security. The 2023 report provides recommendations to address all three (see CNSC, 2023 at p. 48–49[67]):

1. AI reliability in nuclear facilities. Prior to deployment, demonstrate that AI performance meets established metrics. Implement use of AI in phases, with parallel human-in-the-loop validation. Transition to fully autonomous operation once AI reliability is confirmed. Implement real-time monitoring to continuously assess algorithm and data reliability.
2. AI trustworthiness in nuclear facilities. AI engineers and technicians should collaborate with standard-setting bodies to develop uniform practices and software evaluation methodologies. Personnel should be educated continuously to stay updated with technological advancements and regulatory requirements, ensuring safe and effective AI integration in nuclear activities.
3. AI security. Develop algorithms in secure environments, conduct pre-implementation evaluations for malicious code, continuously monitor model access and usage to prevent manipulation, and enforce strict access controls to protect sensitive information.

The report by CNSC, the UK ONR and the US NRC published in September 2024 emphasizes the importance of applying safety and security systems engineering principles when integrating AI into nuclear applications. Since current regulations do not specifically address AI, regulators require nuclear licensees to identify applicable standards and potential gaps. A recommended strategy is to utilize the simplest technologies alongside AI to reduce uncertainty and enhance safety. This includes performing gap analyses to explore both AI-based and conventional risk mitigation strategies, especially in scenarios where AI failures could have severe consequences. The report advocates for robust recovery plans, risk management principles such as diversity and redundancy, and a multilayered defense approach to avoid reliance on any single aspect of the AI system (see Lee et al., 2024 at p. 6[68]).

The report stresses that human and organizational factors play a critical role in AI deployment within nuclear operations. Clear definitions of human and AI roles are essential for human-machine collaboration, as many AI systems are designed to augment rather than replace human decision-making. Concerns regarding the "black box" nature of AI necessitate monitoring AI performance and allowing for human intervention when needed (see Lee et al., 2024 at p. 9–10[68]). Ongoing training programs and evaluations of safety culture are vital for ensuring that AI integration aligns with safety priorities. Additionally, the report outlines high-level principles for managing the AI life-cycle, highlighting the importance of iterative processes in design, development and deployment, while stressing the need for continuous monitoring to address issues like data drift and model biases. Finally, the report emphasizes the need for thorough documentation and innovative testing methods for demonstrating the safety and reliability of AI (see Lee et al., 2024 at p. 15[68]).

iv. Japan

The Japanese Nuclear Regulation Authority (NRA) has been using AI since 2019 for automated transcription of meetings with industry representatives. The AI tools are used to help increase transparency of NRA operations.[69] The NRA is also expected to use AI tools to help process data collected under an agreement with the IAEA regarding inspection procedures at Japanese research reactors and other nuclear research and development (R&D) facilities (see Siserman-Gray et al, 2023 at p. 7[70]). In response to a request from a member of the NRA, the NRA’s Technology Platform Group conducted a survey on technological trends in the nuclear power sector, which was released in March 2024.[71]

The Japan Atomic Energy Agency and Nagoya University have developed AI tools to create radiation maps from data collected by drones. These tools significantly improve accuracy and reduce analysis time, helping map radiation in the Fukushima Daiichi Nuclear Power Plant evacuation zone.[72]

The Japanese government is using AI to identify social media postings it believes to be incorrect regarding the release of treated wastewater from the Fukushima nuclear power plant.[73] The Japanese government’s AI Strategy, released in 2022, highlights potential roles for AI in the power sector but does not specifically mention nuclear power.[74]

E. Barriers

Several barriers limit the use of AI for nuclear power. In an industry that relies on a public confidence in both the nuclear plants and the regulators, employing a technology susceptible to “hallucinations” could be counterproductive, even if experts were convinced that the technology was being used in safe ways. A text-based system that urges a user to divorce his wife because she does not really love him[75] or includes glue in a pizza recipe[76] could make members of the public who are already skeptical or opposed to nuclear power even more so. Additional barriers include:

- Development of AI technology in the nuclear sector is severely inhibited by lack of data in digital format from power reactors. The data that do exist are mostly for non-power reactors operated by national laboratories and other institutions.
- Lack of domain awareness and expertise within the AI community also impedes development of AI for nuclear power. With nuclear expertise strongly concentrated in a handful of highly specialized institutions, it is challenging for non-experts to gain knowledge about nuclear power, which limits scalable development of AI within this application area. Overall, interfacing between the highly specialized nature of both AI and nuclear power requires significant training and skills-development. Professional societies could ameliorate the problem by providing educational opportunities and supporting development of best practices and standards.
- Nuclear power has, by far, the most stringent regulatory oversight in the energy sector. The safety and security requirements of nuclear power are a high barrier for AI applications to overcome, deterring AI development and deployment.
- Current rules flatly forbid using AI in one place where advanced reactor developers say it could be very useful: operating micro-reactors. The industry is moving toward reactors that put out only a few megawatts, but these cannot be an economic success if they carry the full complement of control room operators that big plants do today. In fact, they might be able to run with no more than a local "monitor," someone at the plant or on call, as some diesel generators and gas turbines do. But this would require a new mindset at the NRC, which has not given any public indication that it is moving in that direction. The current rule says only a licensed operator can adjust the power level.[77]
- The nuclear sector has a conservative professional culture and late-adopter strategy when it comes to new technologies such as AI, a technology subject to rapid change and improvements

F. Risks

The use of AI for nuclear power creates a number of risks:

- AI methods used as part of nuclear planning, simulation and other off-line activities that involve close human scrutiny pose little or no additional risk over existing approaches. Additional risk arises only if the "humans-in-the-loop" give too much or misplaced weight to results derived from AI.
- The primary risk of AI in nuclear operations pertains to on-line applications. If AI-based analyses, predictions or optimizations are used in time-constrained "real-time" decision-

making workflows, their reliability must be taken into account to minimize the risk of catastrophic operational failure.

- AI methods that adapt to real-time conditions require data networks that pipe data from sensors to servers. If these networks are exposed to other networks or the internet broadly, the application of AI can introduce a new set of cybersecurity risks. Nuclear operators and regulators must clearly evaluate and mitigate these risks.
- AI methods are traditionally tested against plentiful data, which enables rigorous evaluation of their expected performance once deployed. Data scarcity within the nuclear sector raises a risk of insufficient validation of AI methods prior to deployment. Prematurely deployed AI methods may lead to insights, predictions and optimizations that are less effective than traditional approaches. In real-time applications, prematurely deployed AI carries additional operational safety and security risks.
- The potential negative consequences of catastrophic operational failure at nuclear power plants are very high. As a result, extreme caution is required by all parties, from regulators to operators, in introducing any new technology, including AI, into nuclear power operations. For example, the consequences of AI-induced hallucinations could be very large. In addition, AI-operated control systems could present a new vector for cyberattacks with new vulnerabilities to their specific design and function. Additional care is needed to harden such systems, and additional points of intervention and override may be needed to avoid dangerous or poor outcomes.
- Deploying AI within nuclear operations and maintenance may eventually eliminate certain jobs in the nuclear sector. While this is likely a net positive in terms of minimizing human health and safety risk within nuclear operations, it may be perceived as an economic and political risk.

G. Recommendations

1. *Nuclear regulators should be open to AI playing a role in reactor design, safety analyses and recommendations for operating procedures. The operative question is the quality of the work product, not the identity of the designer. All designs, analyses and procedures, whatever their origin, should be run through rigorous reviews. Additional oversight, checks and security hardening may be part of this work.*

2. *Plant owners and regulators should assure that AI will be used only in advisory and alerting roles. Nuclear plant operators should play the same role in a plant that uses AI as in a plant that does not. The operator should not become like a car driver who plays video games while driving; humans must remain in the loop, engaged and active, despite the routine work performed by AI. Nuclear plant owners should look at the experience in aviation, power and other relevant industries.*

3. *The civilian nuclear industry should scrutinize AI technologies funded by government dollars through science R&D agencies for applicability to their operations.*

4. *Nuclear regulatory bodies should be preparing for license requests from microreactor companies that include a role for AI in remote control.*

5. *Regulators should consider employing the UK ONR's initiative to test different AI technologies in a controlled environment to understand AI's potential to enhance various aspects of nuclear operation and regulation ("sandboxing"). Through sandboxing, regulators can test, refine and evaluate the algorithms within the context of nuclear safety.*

6. *Government innovation agencies should integrate AI into their research, development and demonstration (RD&D) plans. Key foci of innovation investments should include sustaining the existing fleet, advanced reactors, and non-electric applications of nuclear energy*

7. *Plant owners should engage with the scientific community to provide access to high-quality data that can drive AI development and deployment. Professional societies should support development and dissemination of best practices in gathering, annotating, hosting and sharing such data.*

8. *Professional societies should offer educational resources and training to attract the attention of the AI community to the nuclear sector. These societies should also reach out to computer science academic departments, professional computer science societies and government agencies to encourage development of AI skills within the nuclear sector.*

9. *Nuclear regulatory agencies should hire staff with AI expertise to efficiently evaluate and recommend adoption of high value-add AI applications in nuclear power.*

H. References

1 Brent Wanner & Ryota Taniguchi. *Nuclear Power;* International Energy Agency (IEA), Paris, France, https://www.iea.org/energy-system/electricity/nuclear-power (Accessed August 2024).

2 Energy Institute. *Statistical Review of World Energy;* London, UK, https://www.energyinst.org/statistical-review (Accessed August 2024).

3 Slade Johnson & Jonathan Russo. *China continues rapid growth of nuclear power capacity;* US Energy Information Administration, Washington, D.C., https://www.eia.gov/todayinenergy/detail.php?id=61927 (2024).

4 World Nuclear Association. *Country Profiles: Nuclear Power in Japan;* London, UK, https://world-nuclear.org/information-library/country-profiles/countries-g-n/japan-nuclear-power (Accessed August 2024).

5 Jennifer Hiller. *A Massive U.S. Nuclear Plant Is Finally Complete. It Might Be the Last of Its Kind.;* The Wall Street Journal, New York, New York, https://www.wsj.com/business/energy-oil/a-massive-u-s-nuclear-plant-is-finally-complete-it-might-be-the-last-of-its-kind-0c0f6e44 (2024).

6 World Nuclear Association. *Country Profiles: Nuclear Power in Spain;* London, UK, https://world-nuclear.org/information-library/country-profiles/countries-o-s/spain (Accessed August 2024).

7 Rumyana Vakarelska. *Flamanville-3 / Fuel Loading Begins At France's Delayed EPR Nuclear Power Plant;* NucNet, Brussels, Belgium, https://www.nucnet.org/news/fuel-loading-begins-at-flamanville-3-epr-nuclear-plant-in-normandy-5-4-2024 (2024).

8 Energy Education. *Boiling water reactor;* University of Calgary, Calgary, Alberta, Canada, https://energyeducation.ca/encyclopedia/Boiling_water_reactor (Accessed August 2024).

9 Derjew Ayele Ejigu, Yanjie Tuo & Xiaojing Liu. Application of artificial intelligence technologies and big data computing for nuclear power plants control: a review. *Frontiers in Nuclear Engineering* 3 (2024). 10.3389/fnuen.2024.1355630.

10 Idaho National Laboratory. *Artificial Intelligence and Machine Learning;* Idaho Falls, Idaho, https://inl.gov/artificial-intelligence/ (Accessed August 2024).

11 Rob Austin & Thiago Seuaciuc-Osorio. *Quick Insight Brief: Leveraging Artificial Intelligence for the Nuclear Energy Sector;* Electric Power Research Institute (EPRI), Palo Alto, California, https://www.epri.com/research/products/000000003002021067 (2021).

12 Blue Wave AI Labs. *Home Page;* West Lafayette, Indiana, https://www.bluewaveailabs.com/ (Accessed August 2024).

13 Jonathan Nistor Chief Operating Officer of Blue Wave Labs & Tom Gruenwald Co-Founder and Senior Vice President of Blue Wave Labs. (Zoom interview, April 11, 2024).

14 David McIntire of the US Nuclear Regulatory Commission (NRC). (ed Matthew L. Wald) (July 31, 2024).

15 NuclearN. *Home Page: NuclearN isArtificial Intelligence for the Nuclear Industry;* Phoenix, Arizona, https://nuclearn.ai/ (Accessed August 2024).

16 D. K. Wehe *et al.* 10. Intelligent robotics and remote systems for the nuclear industry. *Nuclear Engineering and Design* 113, 259-267 (1989). https://doi.org/10.1016/0029-5493(89)90077-0.

17 Boston Dynamics. *Home Page: Spot® - The Agile Mobile Robot;* Waltham, Massachusetts, https://bostondynamics.com/products/spot/ (Accessed August 2024).

18 Barry Lennox at University of Manchester. *Robotics and Artificial Intelligence for Nuclear (RAIN);* UK Research and Innovation, Swindon, UK, https://gtr.ukri.org/projects?ref=EP%2FR026084%2F1 (Accessed August 2024).

19 RIMA Network Alliance. *RIMA: Robotics for Inspection and Maintenance;* https://rimanetwork.eu/ (Accessed August 2024).

20 Organisation for Economic Co-operation and Development (OCED) Nuclear Energy Agency (NEA). *Expert Group on the Application of Robotics and Remote Systems in the Nuclear Back-end (EGRRS);* Boulogne-Billancourt, France, https://www.oecd-nea.org/jcms/pl_25235/expert-group-on-the-application-of-robotics-and-remote-systems-in-the-nuclear-back-end-egrrs (Accessed August 2024).

21 Erico Guizzo. *Fukushima Robot Operator Writes Tell-All Blog;* Institute of Electrical and Electronics Engineers (IEEE) Spectrum, New York, New York, https://spectrum.ieee.org/fukushima-robot-operator-diaries (2011).

22 Stephen D. Monk *et al.* Implementation and Evaluation of a Semi-Autonomous Hydraulic Dual Manipulator for Cutting Pipework in Radiologically Active Environments. *Robotics* 10, 62 (2021). https://doi.org/10.3390/robotics10020062.

23 Ozan Tokatli *et al.* Robot-Assisted Glovebox Teleoperation for Nuclear Industry. *Robotics* 10, 85 (2021). https://doi.org/10.3390/robotics10030085.

24 Declan Shanahan, Ziwei Wang & Allahyar Montazeri. Robotics and Artificial Intelligence in the Nuclear Industry: From Teleoperation to Cyber Physical Systems in *Artificial Intelligence for Robotics and Autonomous Systems Applications* (eds Ahmad Taher Azar & Anis Koubaa) 123-166 (Springer International Publishing, Cham, 2023, https://doi.org/10.1007/978-3-031-28715-2_5).

25 Amani Cheniour, Amir Koushyar Ziabari & Yann Le Pape. A mesoscale 3D model of irradiated concrete informed via a 2.5 U-Net semantic segmentation. *Construction and Building Materials* 412, 134392 (2024). https://doi.org/10.1016/j.conbuildmat.2023.134392.

26 Richard Vilim & Lander Ibarra. Artificial Intelligence/Machine Learning Technologies for Advanced Reactors (Workshop Summary Report). Medium: ED; Size: 32 p. (United States, 2022; https://doi.org/10.2172/1861306).

27 Isabelle Dumé. *Can thorium compete with uranium as a nuclear fuel?;* Polytechnique Insights (A Review by Insititut Polytechnique de Paris), Palaiseau, France, https://www.polytechnique-insights.com/en/braincamps/energy/the-latest-technological-advances-in-nuclear-energy/can-thorium-compete-with-uranium-as-a-nuclear-fuel/ (2022).

28 Wikipedia. *Thorium-based nuclear power;* San Francisco, California, https://en.wikipedia.org/wiki/Thorium-based_nuclear_power#:~:text=Thorium%2Dbased%20nuclear%20power%20generation,A%20sample%20of%20thorium (Accessed August 2024).

29 International Atomic Energy Agency (IEAE). *Thorium's Long-Term Potential in Nuclear Energy: New IAEA Analysis;* Vienna, Austria, https://www.iaea.org/newscenter/news/thoriums-long-term-potential-in-nuclear-energy-new-iaea-analysis (2023).

30 T. Ellis *et al. Traveling-wave reactors: A truly sustainable and full-scale resource for global energy needs*. (American Nuclear Society - ANS, United States, 2010, http://inis.iaea.org/search/search.aspx?orig_q=RN:42097751).

31 The Generational IV (GenIV) International Forum (GIF). *Sodium-Cooled Fast Reactor (SFR);* https://www.gen-4.org/gif/jcms/c_42152/sodium-cooled-fast-reactor-sfr#:~:text=The%20SFR%20uses%20liquid%20sodium,requires%20a%20sealed%20coolant%20system (Accessed August 2024).

32 Eric Williams Senior Vice President of Engineering at Terrapower. (ed Matthew L. Wald) (Telephone Interview, May 1 2024).

33 University of Tennessee Assistant Professor Vladimir Sobes. (ed Matthew L. Wald) (Telephone Communication, May 9 2024).

34 X-energy. *X-energy to Open First Plant Support Center for Xe-100 Advanced Small Modular Reactor Fleet;* Rockville, Maryland, https://x-energy.com/media/news-releases/x-energy-to-open-first-plant-support-center-for-xe-100-advanced-small-modular-reactor-fleet (2023).

35 US House on Committee on Energy and Commerce. *Energy Hearing: The Fiscal Year 2025 Nuclear Regulatory Commission Budget;* YouTube, San Bruno, California, https://www.youtube.com/watch?v=cxgja_3ndDohttps://www.youtube.com/watch?v=cxgja_3ndDo (2024).

36 Jaemin Seo *et al.* Avoiding fusion plasma tearing instability with deep reinforcement learning. *Nature* 626, 746-751 (2024). https://doi.org/10.1038/s41586-024-07024-9.

37 Jeremy Thomas. *High-performance computing, AI and cognitive simulation helped LLNL conquer fusion ignition;* Lawrence Livermore National Laboratory (LLNL), Livermore, California, https://www.llnl.gov/article/49911/high-performance-computing-ai-cognitive-simulation-helped-llnl-conquer-fusion-ignition (2023).

38 US Nuclear Regulatory Commission. *Questions and Answers – Spent Fuel Pool Safety;* Rockville, Maryland, https://www.nrc.gov/waste/spent-fuel-storage/faqs.html#gen7 (Accessed August 2024).

39 Bozhou Zhuang *et al.* Machine learning-aided damage identification of mock-up spent nuclear fuel assemblies in a sealed dry storage canister. *Engineering Applications of Artificial Intelligence* 128, 107484 (2024). https://doi.org/10.1016/j.engappai.2023.107484.

40 Theodore Papamarkou *et al.* Automated detection of corrosion in used nuclear fuel dry storage canisters using residual neural networks. *Nuclear Engineering and Technology* 53, 657-665 (2021). https://doi.org/10.1016/j.net.2020.07.020.

41 Hee Sang Yoo, Seung Hun Yoo & Eung Soo Kim. Heat transfer enhancement in dry cask storage for nuclear spent fuel using additive high density inert gas. *Annals of Nuclear Energy* 132, 108-118 (2019). https://doi.org/10.1016/j.anucene.2019.04.018.

42 Kristina Yancey Spencer, Pavel V. Tsvetkov & Joshua J. Jarrell. Optimization of dry cask loadings for used nuclear fuel management strategies. *Progress in Nuclear Energy* 108, 11-25 (2018). https://doi.org/10.1016/j.pnucene.2018.04.029.

43 U.S. Nuclear Regulatory Commission Division of Spent Fuel Storage and Transportation. *Dry Cask Storage of Nuclear Spent Fuel;* Rockville, Maryland, https://csgmidwest.org/wp-content/uploads/2022/08/Easton.pdf (2022).

44 World Nuclear Association. *Nuclear Fuel Cycle: Storage and Disposal of Radioactive Waste;* London, UK, https://world-nuclear.org/information-library/nuclear-fuel-cycle/nuclear-waste/storage-and-disposal-of-radioactive-waste (Accessed August 2024).

45 Waste Isolation Pilot Plant (WIPP). *Home Page;* Carlsbad, New Mexico, https://www.wipp.energy.gov/ (Accessed August 2024).

46 Waste Isolation Pilot Plant (WIPP). *WIPP Site;* Carlsbad, New Mexico, https://wipp.energy.gov/wipp-site.asp (Accessed August 2024).

47 World Nuclear Association. *Country Profiles: Nuclear Power in Finland;* London, UK, https://world-nuclear.org/information-library/country-profiles/countries-a-f/finland (Accessed August 2024).

48 Guang Hu & Wilfried Pfingsten. Data-driven machine learning for disposal of high-level nuclear waste: A review. *Annals of Nuclear Energy* 180, 109452 (2023). https://doi.org/10.1016/j.anucene.2022.109452.

49 Chunhui Li, Elijah O. Adeniyi & Piotr Zarzycki. Machine learning surrogates for surface complexation model of uranium sorption to oxides. *Scientific Reports* 14, 6603 (2024). https://doi.org/10.1038/s41598-024-57026-w.

50 Virginie Solans *et al.* Optimisation of used nuclear fuel canister loading using a neural network and genetic algorithm. *Neural Computing and Applications* 33, 16627-16639 (2021). https://doi.org/10.1007/s00521-021-06258-2.

51 Federal Office for the Safety of Nuclear Waste Management. *Research: Artificial intelligence in the search for a final repository?;* Government of Germany, Berlin, Germany, https://www.base.bund.de/SharedDocs/Kurzmeldungen/BASE/EN/2022/artificial-intelligence.html (2022).

52 Organisation for Economic Co-operation and Development (OCED) Nuclear Energy Agency (NEA). *The role of artificial intelligence in the future of radioactive waste management;* Boulogne-Billancourt, France, https://www.oecd-nea.org/jcms/pl_78672/the-role-of-artificial-intelligence-in-the-future-of-radioactive-waste-management (2023).

53 Organisation for Economic Co-operation and Development (OCED) Nuclear Energy Agency (NEA). *Transmutation of Radioactive Waste;* Boulogne-Billancourt, France, https://www.oecd-nea.org/trw/ (Accessed August 2024).

54 International Atomic Energy Agency (IEAE). *Implications of Partitioning and Transmutation in Radioactive Waste Management (Technical Reports Series No. 435);* Vienna, Austria, https://www.iaea.org/publications/7112/implications-of-partitioning-and-transmutation-in-radioactive-waste-management (

55 Palash Kumar Bhowmik, Md. Shafiqul Islam & Piyush Sabharwall. *Partitioning and Transmutation of Used Nuclear Fuel in Support of Geological Waste Disposal;* Idaho National Laboratory (Prepared for the U.S. Department of Energy), https://inldigitallibrary.inl.gov/sites/sti/sti/Sort_66409.pdf (2023).

56 X. Y. Sun *et al.* Transmutation of long-lived fission products in an advanced nuclear energy system. *Scientific Reports* 12, 2240 (2022). https://doi.org/10.1038/s41598-022-06344-y.

57 Cosima Paul. *Transmutation of High-Level Nuclear Waste;* (Submitted as coursework for PH241, Stanford University), Stanford, California, http://large.stanford.edu/courses/2024/ph241/paul2/ (2024).

58 Jin Whan Bae *et al.* Deep learning approach to nuclear fuel transmutation in a fuel cycle simulator. *Annals of Nuclear Energy* 139, 107230 (2020). https://doi.org/10.1016/j.anucene.2019.107230.

59 Jon Truby *et al.* A Sandbox Approach to Regulating High-Risk Artificial Intelligence Applications. *European Journal of Risk Regulation* 13, 270-294 (2022). https://doi.org/10.1017/err.2021.52.

60 The White House. *FACT SHEET: President Biden Issues Executive Order on Safe, Secure, and Trustworthy Artificial Intelligence;* Washington, D.C., https://www.whitehouse.gov/briefing-room/statements-releases/2023/10/30/fact-sheet-president-biden-issues-executive-order-on-safe-secure-and-trustworthy-artificial-intelligence/ (2023).

61 US Nuclear Regulatory Commission (NRC). *Artificial Intelligence Strategic Plan: Fiscal Years 2023-2027;* Rockville, Maryland, https://www.nrc.gov/docs/ML2313/ML23132A305.pdf (2023).

62 US Nuclear Regulatory Commissions (NRC). *Artificial Intelligence;* Rockville, Maryland, https://www.nrc.gov/about-nrc/plans-performance/artificial-intelligence.html (Accessed April 2024).

63 Office for Nuclear Regulation (ONR). *Artificial Intelligence;* Bootle, UK, https://www.onr.org.uk/our-expertise/innovation/artificial-intelligence/ (Accessed August 2024).

64 Office for Nuclear Regulation (ONR). *Regulators' Pioneer Fund (Department for Science, Innovation and Technology): Pilot of a regulatory sandbox on artificial intelligence in the nuclear sector;* Bootle, UK, Report available at https://onr.org.uk/news/all-news/2023/11/outcomes-of-nuclear-ai-regulatory-sandbox-pilot-published/ (2023).

65 Canadian Nuclear Society (CNS). *The Canadian Nuclear Society's Disruptive, Innovative and Emerging Technology (DIET) Division;* Toronto, Ontario, https://www.cns-snc.ca/about-cns/divisions/the-canadian-nuclear-societys-disruptive-innovative-and-emerging-technology-diet-division/ (Accessed August 2024).

66 Seamus O'Rega. *CNSC Departmental Results Report 2019–20 (at p. 10);* Canadian Nuclear Safety Commission (CNSC), Ottawa, Ontario, https://api.cnsc-ccsn.gc.ca/dms/digital-medias/CNSC_s_2019-20_Departmental_Results_Report.pdf/object (2020).

67 Canadian Nuclear Safety Commission (CNSC). *R760.1 - A Study for the Canadian Nuclear Safety Commission on Artificial Intelligence Applications and Implications for the Nuclear Industry;* Ottawa, Ontario, https://www.cnsc-ccsn.gc.ca/eng/resources/research/research-and-support-program/research-report-abstracts/research-report-summaries-2022-2023/#R760.1 (2023).

68 Kevin Lee *et al. Considerations for Developing Artificial Intelligence Systems in Nuclear Applications;* Canadian Nuclear Safety Commission (CNSC), United Kingdom Office for Nuclear Regulation (UK ONR), United States Nuclear Regulatory Commission (US NRC), https://www.nrc.gov/docs/ML2424/ML24241A252.pdf (2024).

69 Riki Iwama. *Japan's nuclear authority using AI to help make closed meetings more transparent;* The Mainichi, Osaka, Japan, https://mainichi.jp/english/articles/20190409/p2a/00m/0na/019000c (2019).

70 Cristina Siserman-Gray *et al. Regulatory Challenges Related to the Use of Artificial Intelligence for IAEA Safeguards Verification (PNNL-SA-184813);* Pacific Northwest National Laboratory (PNNL), Richland, Washington, https://resources.inmm.org/sites/default/files/2023-07/finalpaper_379_0512065638.pdf (2023).

71 Japan Nuclear Regulation Authority Technology Platform Group. *Survey Report on Technological Trends of Artificial Intelligence and Advanced Manufacturing Technology in the Nuclear Energy Sector;* Tokyo, Japan, https://www.da.nra.go.jp/view/NRA100000236?contents=NRA100000236-002-023#pdf=NRA100000236-002-023 (2024).

72 Japan Atomic Energy Agency (JAEA). *Press Releases: Creating radiation maps smarter with AI;* Tokai, Japan, https://www.jaea.go.jp/english/news/press/2021/012902/ (2021).

73 Rieko Miki. *Japan deploys AI to detect false info on Fukushima water release;* Nikkei Asia, Tokyo, Japan, https://asia.nikkei.com/Business/Technology/Japan-deploys-AI-to-detect-false-info-on-Fukushima-water-release (2023).

74 Cabinet Office (CAO) agency of the Cabinet Office of Japan. *AI Strategy 2022 (tentative translation);* Tokyo, Japan, https://www8.cao.go.jp/cstp/ai/aistratagy2022en.pdf (2022).

75 Kevin Roose. *A Conversation With Bing's Chatbot Left Me Deeply Unsettled;* The New York Times, New York, New York, https://www.nytimes.com/2023/02/16/technology/bing-chatbot-microsoft-chatgpt.html (2023).

76 Nico Grant. *Google's A.I. Search Errors Cause a Furor Online;* The New York Times, New York, New York, https://www.nytimes.com/2024/05/24/technology/google-ai-overview-search.html (2024).

77 US Nuclear Regulatory Commission (NRC). *50.54 Conditions of licenses;* Rockville, Maryland, https://www.nrc.gov/reading-rm/doc-collections/cfr/part050/part050-0054.html (Accessed August 2024).

PART III – CROSS-CUTTING TOPICS

Chapter 11 – LARGE LANGUAGE MODELS (LLMs)

Chapter 12 – GREENHOUSE GAS (GHG) EMISSIONS MONITORING

Chapter 13 – MATERIALS INNOVATION

Chapter 14 – EXTREME WEATHER PREDICTION

Chapter 15 – GREENHOUSE GAS (GHG) EMISSIONS FROM AI

Chapter 16 – GOVERNMENT POLICY

Chapter 17 – FINDINGS AND RECOMMENDATIONS

CHAPTER 11:
LARGE LANGUAGE MODELS

Daniel Loehr

A. Background ... 11-2
B. General Uses of LLMs ... 11-6
C. Using LLMs to Mitigate Climate Change ... 11-8
D. Barriers ... 11-11
E. Risks ... 11-12
F. Recommendations ... 11-13
G. References ... 11-14

In November 2022, the general public became aware of the power of artificial intelligence (AI) when OpenAI released a browser-based chat interface to its generative pre-trained transformer (GPT), a type of large language model (LLM). The generated text was so human-like the world experienced a "ChatGPT moment," in which many felt that AI (represented by LLMs) had now reached human performance.

LLMs have significant potential to help mitigate climate change. Already, LLMs are used in a variety of ways toward this goal. They help humans search and make sense of vast repositories of climate change information, from a variety of sources and in multiple languages. They identify sentiment and argument structure in human discussions of climate change. They find, classify and summarize climate change risks and impacts described within the growing breadth of climate literature.

In the future, LLMs hold even greater potential. They can serve as tutors in climate education, depict personalized climate consequences, and suggest individualized climate actions. They can advance basic science in climate change mitigation, from materials science for developing better batteries or carbon capture materials to sophisticated power grid management for incorporating dynamic renewable energy sources. They could also serve as guides to shortcut the current maze of permitting requirements that are causing a backlog in bringing carbon-free energy to the grid.

A. Background

i. Evolution of Natural Language Processing (NLP)

LLMs are an evolution of the 70-year-old field of natural language processing (NLP), in which computers process natural (human) languages. Table 11-1 shows common types of NLP.

Table 11-1. *Common types of natural language processing (NLP)*

NLP TYPE	DESCRIPTION
Machine Translation	Automatic language translation
Named Entity Recognition	Identifying entities in text, such as people, places and organizations
Sentiment Analysis	Identifying sentiment (opinion/viewpoint) in text
Search	Finding and retrieving user-relevant information in a specific set of text documents
Question Answering	Providing answers to specific questions, e.g. the answer "316 ppm" to the question "What was atmospheric CO2 concentration in January 1960?" (vs. searching on e.g. "historic atmospheric CO2" and receiving relevant documents)
Dialogue Management	Chat
Summarization	Generating summaries of longer texts
Topic Modeling	Identifying topics in documents
Argument Mining	Extracting argument structure from text

NLP TYPE	DESCRIPTION
Optical Character Recognition	Converting images of text into digital text
Speech Recognition	Converting speech into digital text
Speech Synthesis	Converting digital text into speech

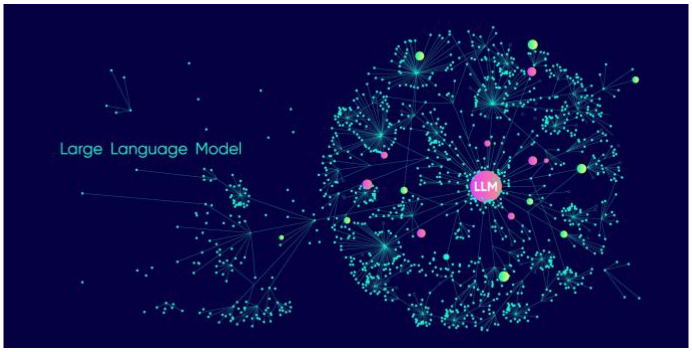
The general methodology of NLP can be divided into three historical paradigms.

- The earliest was rule-based, coding explicit instructions in the form of rules. For example, a Spanish-English translation system would include a rule to convert "casa" to "house." However, these rules are difficult to write explicitly and often fail to capture nuances or unusual cases.
- The next paradigm, starting in the 1980s, was statistical, jettisoning explicit rules and taking advantage of the increasing amount of digital data. Here, the translation system would learn patterns from the available body of human-translated documents. For example, "house" is typically found in English translations of Spanish sentences containing "casa," so the system learns to choose "house" as the translation.
- The current paradigm, LLMs, started in the early 2010s and is also essentially statistical but takes advantage of much more powerful statistical models based on neural nets. As described below, LLMs handle the translation task by converting text in one language into a mathematical representation of the words (an "embedding") that captures their core meaning. The LLM then converts that representation into text in another language.

ii. Understanding Language Models (LMs)

LLMs are more directly evolved from a statistical-paradigm model called a language model (LM). LMs originally developed in the 1980s to enable a variety of NLP tasks. They are probabilistic models of a natural language. That is, LMs capture the probabilities of the sequences of words (or sometimes sub-words or characters) in a language.

LMs use sequences of words to derive *embeddings*, one of their core features. Embeddings are based on the idea that a word is defined "by the company it keeps."[1] For example, two common senses of the word "bank"—a financial bank and a river bank—will occur in different contexts of surrounding words (e.g., near words like "loan" or "water"). A word is thus *embedded* in its context, and by capturing the surrounding words of every word in a body of text, an LM stores each word's embedding.



Amazingly, embeddings allow the meaning of words to be treated like mathematical equations. A well-known example is that when the mathematical value of the word "man" is subtracted from the value for "king," and the value for "woman" is added, the resulting value is near the value for "queen."[2] Embeddings thus capture something essential about words, transferred out of the specific human language in which they occur. Specifically, embeddings are represented mathematically as vectors. The embedding vector for each word in a language is created by calculating which words it appears with most frequently. Further, a variety of downstream tasks use the *de facto* semantics that embeddings provide. For example, because words with similar embeddings are found in similar contexts, search algorithms can expand search terms with synonyms, by including words with vectors similar to those of the original search terms.

iii. Growing from Language Models (LMs) to *Large* Language Models (LLMs)

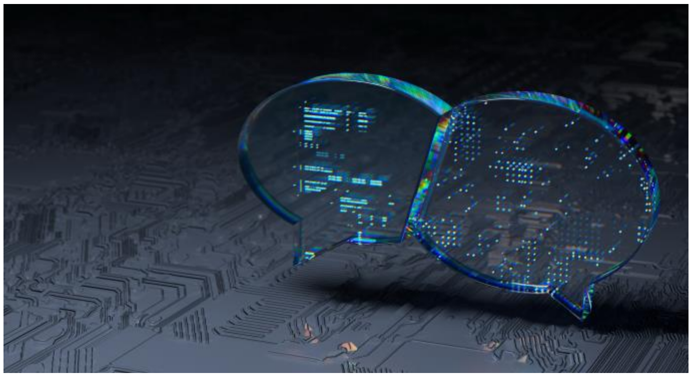
Large LMs (LLMs) are LMs of a much greater size than the original class of LMs. Though "large" is a relative term, it was first used in 2018 to describe a model called BERT (Bidirectional Encoder Representations from Transformers),[3] which contained 340 million parameters. A parameter is roughly equivalent to a connection or node in a neural network.

BERT made use of an effective new type of neural network, a transformer.[4] The original transformer, developed in 2017 to translate from English into German, had two parts. An encoder converted English text into its embeddings (capturing the semantics of the source text). A decoder converted the embeddings into the German text.

BERT used only the encoder part of transformers to generate high-quality embeddings. In contrast, LLMs, such as GPT, use only the decoder part of transformers to generate text from pretrained embeddings; hence the name generative pre-trained transformer (GPT).

Since BERT, the largest LLMs have grown to over a trillion parameters (though others have been designed to reduce parameter size while maintaining similar performance). Modern LLMs also use faster parallel processing methods than earlier word-by-word sequential approaches. The immense scale and speed of LLMs has driven much higher performance on language-related tasks than previous types of models.

There now exist dozens of LLMs, both proprietary and open source. Furthermore, though LLMs (as *language* models) started with text, embeddings need not be restricted to words. Pixels in images, audio clips, video frames, DNA sequences, computer code and many other types of data are best interpreted by models that are "aware" of the surrounding context. For this reason, LLMs can be multimodal, handling images, audio, video and other modalities, in addition to text.



Because LLMs are typically used to *generate* text, images and other modalities, the technology is a type of Generative AI or GenAI. Another common term is foundation model

(FM), which refers to systems with a general functionality (a "foundation") on which more specific applications can be built. For instance, ChatGPT is a specific chat system built on GPT, a general foundation. Though these three terms—LLM, GenAI and FM—describe slightly different types of systems, they overlap significantly and are often used interchangeably.

Note that while LLMs are often the most effective tool for many NLP tasks, thanks to their foundational capabilities, this is not always the case. For example, traditional optical character recognition (OCR) tools currently outperform the OCR capabilities of image-enabled LLMs.

iv. Improving and Evaluating Large Language Models (LLMs)

An ecosystem of new technologies has arisen to improve the output of LLMs:

- Prompt Engineering: LLMs generate output in response to prompts. Since the complexity of LLMs can yield greatly different responses to only slightly different prompts, a new discipline has emerged to create the most effective prompts for a given task. This can include providing the LLM with multiple examples (or "shots") of the desired response type.
- Retrieval-Augmented Generation (RAG): In RAG, the LLM searches a traditional database or trusted web source for information that it combines with its response. This can update the recency of information (incorporating information that has become available since the LLM was trained), allow companies to incorporate proprietary data, and reduce (but not eliminate) incorrect "hallucinations" to which LLMs are prone.
- Agentic Workflows: LLMs can act as agents in a collection of multiple LLMs working with each other and with external tools, such as search engines, to achieve a goal. New programming languages have been created to develop these systems.
- Fine Tuning: LLMs are typically trained as general-purpose models, which are then applied to a variety of specific domains. Yet they can also be fine-tuned by further training on domain-specific data. ClimateBert[5] and ClimateGPT[6] are two examples in the climate domain.

An important aspect of LLMs is evaluation of their performance, which not only records their astonishing progress but also drives their improvement by providing benchmarks to develop against. Dozens of evaluation frameworks have been created to test a variety of knowledge capabilities, such as question answering in a variety of subjects (e.g., logic, mathematics, commonsense reasoning and more). An example is Massive Multitask Language Understanding (MMLU), which contains 16,000 multiple-choice questions from 57 academic topics.[7] Figure 11-1 shows the performance of LLMs over four years on MMLU, revealing remarkable improvement, now reaching a human performance baseline of 90%. This also underscores how benchmarks are quickly being saturated and require replacement by more difficult ones.

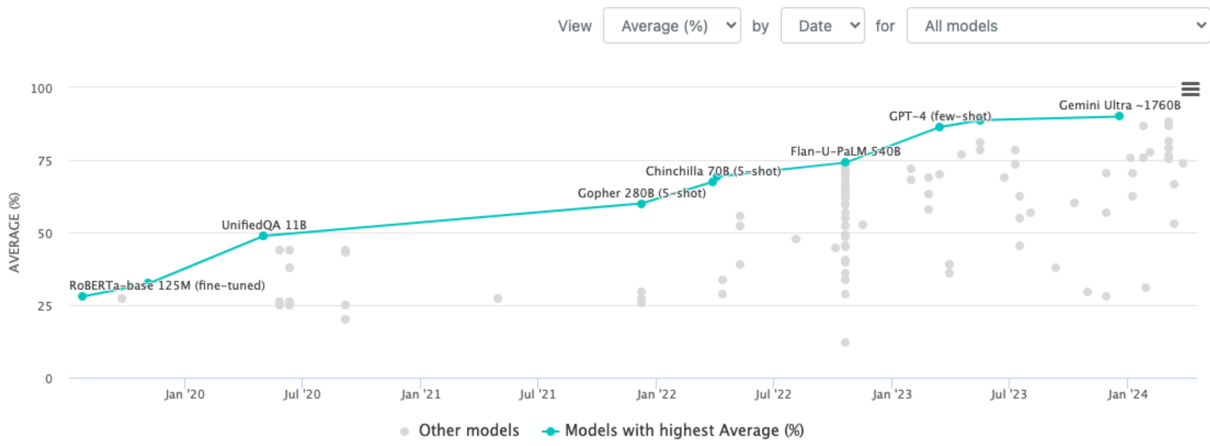


Figure 11-1. *Large language model (LLM) performance on Massive Multitask Language Understanding (MMLU) over time. From paperswithcode.com.*[8]

Templates called Winograd schemas are another evaluation framework used to evaluate LLMs. They are often used to test reasoning that is simple for humans but difficult for LLMs. In these templates, an answer depends on commonsense knowledge. For example, in the sentence "The trophy doesn't fit in the suitcase because it's too small," does "it" refer to the trophy or the suitcase? Does the answer change if "small" is replaced by "large"?[9]

LLMs have recently been evaluated specifically for their knowledge in the climate domain and have shown clear gaps in knowledge content and recency.[10,11] Newer LLMs such as ClimateGPT,[6] fine-tuned on climate data, are an effort to fill these gaps.

It is also necessary to evaluate more than knowledge capability. Equally important is assessing what is called *alignment*, meaning the extent to which LLMs are aligned with human values, such as helpfulness, harmlessness and honesty. This includes aspects such as ethics and morality, bias, toxicity, truthfulness and safety, including robustness against attacks. Benchmarks have been created to evaluate all these qualities.[12] Assessing human-aligned values is difficult by its very nature, as human judgments, often the source of the content of these benchmarks, are subjective and variable. Thus, the ability to evaluate LLMs' alignment with human values typically lags the ability to evaluate their knowledge capabilities.

B. General Uses of LLMs

Because of the hype surrounding LLMs, it can be difficult to determine exactly how they are currently being used. A 2024 Harvard Business Review[13] article researched actual usage by individuals, via online forums, and came up with six overall themes. These are listed in the first part of the table below, along with example use cases for each. Following those are an additional set of attested uses by organizations.

Table 11-2. *Uses of LLMS*

INDIVIDUAL USE OF LLMS	
Technical Assistance & Troubleshooting • Debugging software code • Writing Excel formulas • Manipulating data	*Learning & Education* • Generating a lesson plan • Giving simple explainers • Summarizing content
Content Creation & Editing • Generating ideas • Drafting emails • Writing and editing cover letters	*Creativity & Recreation* • Getting past writer's block • Recommending movies, books, etc. • Writing poems
Personal & Professional Support • Providing therapy/companionship • Providing business advice • Planning workouts	*Research Analysis & Decision-Making* • Conducting specific searches • Performing fact-checking • Developing critiques & counterarguments
ORGANIZATIONAL USE OF LLMS	
Software development assistance	*Creation of images and videos*
Business analytics	*Business analytics*
Personalized experiences • Marketing • Recommender systems	*Translation* *Search* *Data management*
Education • General training • Personalized tutoring	*Summarization* • Search results • Product reviews • Documents • Meeting notes
Generating documents • Business documents • Product descriptions	*User support (via chat, Q&A, or search)* • Customer support • Helpdesk • Product information

It is important to note that while LLMs are being *used* for these purposes and others, it is not yet clear how *useful* they are for these tasks. Nor is it clear whether LLMs are more useful than existing task-specific tools. For example, the search use case may be better served by traditional search engines optimized for the task. Interestingly, only 11% of companies had adopted LLMs at scale as of May 2024, according to McKinsey.[14]

It is also worth noting that in most use cases above, the LLM assists humans in carrying out tasks, rather than replacing them. This may be the real value of LLMs, in which artificial intelligence augments human intelligence. For example, LLMs can generate software code for common short programming tasks or write job application cover letters, but it cannot be relied on to guarantee the correctness of those products. Because the *presentation* of LLM output can appear so human-like, humans often assume LLMs' *content* is human-quality. Yet LLM content can be incorrect and even harmful, and human over-reliance on LLM output can be dangerous (see Section E). Nonetheless, humans can clearly benefit from LLM *assistance* with common tasks, in which humans provide a quality check before incorporating LLM output.

C. Using LLMs to Mitigate Climate Change

The use of natural language processing in studying climate change is not new. Traditional NLP has been used to help understand views expressed in online discussions and other texts concerning climate change for several decades.[15,16] However the advent of LLMs six years ago greatly enhanced the ability of NLP to help mitigate climate change. In light of their remarkable effectiveness and rapid evolution, LLMs have the potential to play a helpful and important role in climate change mitigation. In fact, LLMs are already being applied to climate change in a number of ways. Examples are shown in Table 11-3, categorized by NLP type.

Table 11-3. *Existing applications of large language models (LLMs) to climate change, categorized by natural language processing (NLP) type*

NLP TYPE	APPLICATION OF LLM TO CLIMATE CHANGE
Machine Translation	• Providing climate change information in Arabic[17] • Translating windmill operational codes to textual maintenance instructions[18] • Translating climate model components from Fortran to Python, to improve performance[19]
Named Entity Recognition	• Identifying specific geographic locations in climate literature and tracking regional impacts of climate change[20]

NLP TYPE	APPLICATION OF LLM TO CLIMATE CHANGE
Sentiment Analysis	• Determining stance on climate in news media[21] • Assessing human expert confidence in climate statements[22] • Estimating public opinion about global warming[23]
Search	• Improving search of climate laws and policies[24] • Mining the scientific literature for functional materials design[25] • Searching product descriptions against industry estimates of similar products' embodied carbon footprints[26]
Question Answering	• Answering questions about climate information in corporate earnings calls[27]
Dialogue Management	• Providing climate information from corporate sustainability reports via chat[28] • Providing organizations' and nations' net-zero information via chat[29]
Summarization	• Providing summaries of climate information from authoritative UN documents[30,31] or tailored to the user's specific geography[32]
Topic Modeling	• Detecting climate change topics in public documents[33] • Identifying environmental, social and governance (ESG) topics in news media[34] • Identifying climate change topics in insurance, carbon disclosure[35] and Nationally Determined Contribution documents[36] • Finding topics in the climate literature related to climate-induced infrastructure hazards[37]
Argument Mining	• Identifying narrative techniques in climate skeptic texts[38,39] • Using evidence-based reasoning for fact-checking of climate change claims[40,41]

LLMs provide another capability: classification. Indeed, the largest category of work applying LLMs to climate change involves classification, as listed below.

- Classifying evidence in building a dataset for verification of climate claims[42]
- Classifying climate risks in corporate disclosure reports to track trends[43] and analyze their impact on the credit default swap market[44]
- Classifying Task Force on Climate-related Financial Disclosure (TCFD) categories in corporate disclosure documents[45,46]
- Classifying presence/absence of net-zero claims[47] and climate risk type in corporate earnings calls[48]
- Classifying presence/absence of net-zero claims in laws and policies[49]
- Classifying environmental, social and governance (ESG) categories in corporate documents[47]

- Classifying presence/absence of climate-related text[50] or environmental claims[51] in a variety of document types
- Classifying climate change impacts found in the scientific literature[52]
- Classifying financial activities to estimate emissions of investments[53]
- Classifying climate change claims to benchmark a corporate greenwashing dataset[54]

Finally, the productivity enhancements provided by LLMs can speed up routine tasks, freeing humans to focus on innovation (e.g., allowing a chemistry lab to more quickly predict molecular structures with better carbon absorption capability).[55]

The ways in which LLMs are currently used to help mitigate climate change give good insight into the many ways they might be used for this purpose in the future. For example:

- LLMs can be especially helpful in education about climate change. LLMs can help develop accessible materials on climate change and act as personalized “climate tutors” to bring individuals up to speed on various climate topics.
- LLMs can also personalize the potential impacts of climate change. Non-LLM GenAI technologies can already create images of a user’s home or neighborhood under flood conditions to personalize climate change impacts.[56] Generative AI using LLMs could enable depictions of climate impacts in myriad other ways.
- In addition, LLMs can be monetized in business to develop personalized experiences in advertising and marketing. In this spirit, LLMs can be tuned so their responses include sustainability “nudges” (e.g., suggesting lower-carbon options when asked about recipes, investments, travel or other general topics).[57]

Other potential use cases of LLMs include:

- Summarizing policy documents
- Monitoring the extent of natural disaster impacts via social media
- Providing laypersons a natural language interface to specialized climate information tools and resources
- Creating synthetic data to stand in for privacy-containing data, such as residential smart meters to further smart grid research
- Identifying chemical names in scientific literature to assist in materials discovery
- Shortening the grid interconnection queue with predictive planning to help operators manage increasingly renewable energy sources[58]

More generally, the ability of LLMs to help with common tasks, such as data manipulation and software development, could augment AI practitioners’ technical efforts in the above use cases.

Finally, an important contribution of LLMs could lie in accelerating permitting for renewable energy (RE) siting, construction, storage and transmission—an urgent need in the United States and other geographies. In the United States, federally funded RE projects require an Environmental Impact Statement (EIS), and the average duration from initial notice to final decision is 4.5 years.[59] In addition, there is an "interconnection queue" of RE power and storage plants seeking connection to the national grid. Currently in queue is an active capacity of nearly 2.6 TW (~1.6 TW power and ~1 TW storage), twice the installed capacity of the entire US power plant fleet (~1.3 TW), and 95% of that queue is zero-carbon. However, the median duration from initial request to commercial operation is ~5 years.[60]

Part of the permitting delay is the work proposers must undertake to navigate the dozens of potential required permits at the local, state, tribal, interstate and federal levels.[61,62] LLMs are well suited for summarizing and extracting information from lengthy and complex documents, which could accelerate permitting. For example, LLMs could assist in processing voluminous public comments, automate application completeness checks, and extract and organize information from past permits, reviews and approvals to create a reference dataset useful for all stakeholders.[63,64] LLMs also estimate solar permitting risk for developers, based on zoning information.[65,66] LLMs can also help draft lengthy permit applications (an EIS alone averages over 600 pages[67]), by generating application text. For instance, Microsoft is using LLMs to generate documents for nuclear power regulatory approval.[68,69]

Such work would respond to federal permitting directives. For example, the 2022 White House Permitting Action Plan directs federal agencies to "identify, share, or develop … tools to assist project sponsors, permit applicants, affected communities, Tribal communities, and other stakeholders to navigate the environmental review and permitting process effectively."[70] In addition, the 2022 Inflation Reduction Act includes DOE funding for "actions that may improve the chances of, and shorten the time required for, approval by the siting authority of the application relating to the siting or permitting of the covered transmission project,"[71] and DOE is piloting the use of LLMs to streamline RE permitting.[72]

D. Barriers

Barriers to using LLMs to mitigate climate change include the following.

- Limited Interpretability: LLMs, which can contain hundreds of billions of numbers as parameters, are to a large extent "black boxes." It is difficult to understand how they arrive at their output, eroding trust in their answers related to climate change. Though work on AI interpretability is making LLMs somewhat more understandable, they are still largely opaque.
- Incorrect Information: LLMs are well known for "hallucinating" or making up incorrect information, also eroding trust and willingness to apply them to climate change. This can be mitigated using some of the techniques described above (e.g., RAG). But the opacity of LLMs makes it difficult to guarantee that information they supply is correct.
- Access Barriers: LLMs require huge capital investments for training and are thus currently concentrated within a few technology companies. This investment requirement can shut out the majority of potential climate mitigation practitioners, including smaller companies, the

global south and academia. Fortunately, a growing number of open-source and smaller-footprint LLMs are showing good performance.

- Intellectual Property Issues: Current litigation alleges copyright infringement of certain training data. Although many repositories of LLM training data in the climate domain actively encourage their dissemination, other climate information sources belong to organizations, such as the media, that protect their intellectual property. Thus, copyright issues could limit LLMs' current and future use of climate-related data.

E. Risks

Risks of using LLMs to mitigate climate change include the following.

- Bias: LLMs are trained on society's data (e.g., the Internet) and reflect society's biases. In the climate domain, much of the available training data are skewed toward the global north, which has a greater representation on the Internet. Recent work has tried to correct bias, but it is difficult and over-correction can yield factually incorrect output.
- Security Threats: Like any software, LLMs can be exploited. They can be subject to "jailbreaks" and tricked into operating outside their prescribed instructions. They are also vulnerable to leaking personal or proprietary information, such as residential smart meter data, which could be used to maliciously target household residents. It is difficult to enforce LLM guardrails, given their complexity and opacity.
- Greenhouse Gas (GHG) Emissions: LLMs are compute-intensive. The carbon footprint of AI in general is currently modest, but there is potential for growth. (See Chapter 15.) Mitigation gains achieved by LLMs in the fight against climate change could be partially undercut by their own GHG emissions.
- Incorrect Use: Though LLMs have captured the public's imagination and are thus turned toward a variety of uses, they are often not the right tool for the job. Consequences of incorrect use in the climate domain can range from simply being not as effective as other tools to disillusionment at not living up to hyped expectations to real-world damage if improperly used in critical applications, such as the power sector.
- Harmful Use: For every beneficial purpose of LLMs, there can be an opposite harmful purpose they are turned toward. For instance, in the climate domain, LLMs can be positively directed toward mitigation via education, marketing, content creation or software development. Yet LLMs could also use these capabilities for climate change denial, misinformation, or encouragement and development of GHG-emitting activities.

These issues are real obstacles to furthering application of LLMs in climate change mitigation, and work overcoming them requires as much focus as continued development of LLM capabilities.

F. Recommendations

1. *Private companies and academic researchers should continue to develop LLMs specifically trained on climate data and ensure they are openly available so the public can both improve them and benefit from them.*

2. *National governments, private companies, academic researchers and standards development organizations should cooperate on developing further benchmarks for evaluating LLMs' knowledge in the climate domain, thus extending the existing ecosystem for evaluating LLMs' knowledge in general.*

3. *Professional societies and academic experts should develop training programs on the proper use and limits of LLMs in mitigating climate change to help the public better understand the benefits and risks of using LLMs in the climate domain.*

4. *National governments, private companies and academic researchers should cooperate on developing public challenge competitions on proposed climate mitigation use cases of LLMs to advance their development.*

5. *National governments and private companies should expand current research and development (R&D) programs in addressing known issues with LLMs, so the public can place greater trust in LLMs, especially when applied to climate change.*

6. *LLM developers and users should publish fine-grained measurements of LLMs' carbon footprint by adopting tools to track and report the GHGs emitted by their compute time.*

7. *National governments should fund R&D for public-facing prototypes to advance the use of LLMs for accelerating permitting of renewable energy.*

G. References

1 J. Firth. A Synopsis of Linguistic Theory, 1930-1955 in *Studies in Linguistic Analysis* (ed J.R. Firth) pgs. 10-32 (Philological Society – Blackwell, Oxford, 1957, https://cs.brown.edu/courses/csci2952d/readings/lecture1-firth.pdf).

2 Emerging Technology from the arXiv. *King – Man + Woman = Queen: The Marvelous Mathematics of Computational Linguistics;* MIT Technology Review – Artificial Intelligence, https://www.technologyreview.com/2015/09/17/166211/king-man-woman-queen-the-marvelous-mathematics-of-computational-linguistics/ (2015).

3 Jacob Devlin *et al.* BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv:1810.04805 (2018). https://doi.org/10.48550/arXiv.1810.04805.

4 Ashish Vaswani *et al.* Attention Is All You Need. arXiv:1706.03762 (2017). https://doi.org/10.48550/arXiv.1706.03762.

5 Nicolas Webersinke *et al.* ClimateBert: A Pretrained Language Model for Climate-Related Text. arXiv:2110.12010 (2021). https://doi.org/10.48550/arXiv.2110.12010.

6 David Thulke *et al.* ClimateGPT: Towards AI Synthesizing Interdisciplinary Research on Climate Change. arXiv:2401.09646 (2024). https://doi.org/10.48550/arXiv.2401.09646.

7 Dan Hendrycks *et al.* Measuring Massive Multitask Language Understanding. arXiv:2009.03300 (2020). https://doi.org/10.48550/arXiv.2009.03300.

8 Papers with Code. *Multi-task Language Understanding on MMLU;* https://paperswithcode.com/sota/multi-task-language-understanding-on-mmlu (Accessed August 2024).

9 Ernest Davis. *Collection of Winograd Schemas;* https://cs.nyu.edu/~davise/papers/WinogradSchemas/WSCollection.html (Accessed August 2024).

10 Jannis Bulian *et al.* Assessing Large Language Models on Climate Information. arXiv:2310.02932 (2023). https://doi.org/10.48550/arXiv.2310.02932.

11 Hongyin Zhu & Prayag Tiwari. Climate Change from Large Language Models. arXiv:2312.11985 (2023). https://doi.org/10.48550/arXiv.2312.11985.

12 Zishan Guo *et al.* Evaluating Large Language Models: A Comprehensive Survey. arXiv:2310.19736 (2023). https://doi.org/10.48550/arXiv.2310.19736.

13 Marc Zao-Sanders. *How People Are Really Using GenAI;* Harvard Business Review – Technology and Analytics, https://hbr.org/2024/03/how-people-are-really-using-genai (2024).

14 Aamer Baig *et al. Moving past gen AI's honeymoon phase: Seven hard truths for CIOs to get from pilot to scale;* McKinsey Digital, https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/moving-past-gen-ais-honeymoon-phase-seven-hard-truths-for-cios-to-get-from-pilot-to-scale (2024).

15 Andrés Alonso, José Manuel Carbó & J Manuel Marqués. Machine Learning methods in climate finance: a systematic review. *Banco de Espana* Working Paper No. 2310 (2023). http://dx.doi.org/10.2139/ssrn.4352569

16 Manfred Stede & Ronny Patz. The Climate Change Debate and Natural Language Processing in *Proceedings of the 1st Workshop on NLP for Positive Impact*, Bangkok, Thailand. pgs. 8–18, (2021; https://aclanthology.org/2021.nlp4posimpact-1.2.pdf).

17 Sahal Shaji Mullappilly *et al.* Arabic Mini-ClimateGPT : A Climate Change and Sustainability Tailored Arabic LLM in *Findings of the Association for Computational Linguistics: EMNLP 2023*, Singapore. (eds

Houda Bouamor, Juan Pino, & Kalika Bali) 14126–14136, https://doi.org/10.18653/v1/2023.findings-emnlp.941, (2023).

18 Joyjit Chatterjee & Nina Dethlefs. Natural language generation for operations and maintenance in wind turbines in *NeurIPS 2019 Workshop on Tackling Climate Change with Machine Learning, Vancouver, Canada*, https://www.climatechange.ai/papers/neurips2019/9, (2019).

19 Anthony Zhou, Linnia Hawkins & Pierre Gentine. Proof-of-concept: Using ChatGPT to Translate and Modernize an Earth System Model from Fortran to Python/JAX. arXiv:2405.00018 (2024). https://doi.org/10.48550/arXiv.2405.00018.

20 Tanwi Mallick *et al.* Analyzing Regional Impacts of Climate Change using Natural Language Processing Techniques. arXiv:2401.06817 (2024). https://doi.org/10.48550/arXiv.2401.06817.

21 Yiwei Luo, Dallas Card & Dan Jurafsky. Detecting Stance in Media on Global Warming. arXiv:2010.15149 (2020). https://doi.org/10.48550/arXiv.2010.15149.

22 Romain Lacombe, Kerrie Wu & Eddie Dilworth. ClimateX: Do LLMs Accurately Assess Human Expert Confidence in Climate Statements? , arXiv:2311.17107 (2023). https://doi.org/10.48550/arXiv.2311.17107.

23 Sanguk Lee *et al.* Can large language models estimate public opinion about global warming? An empirical assessment of algorithmic fidelity and bias. *PLOS Climate* 3, e0000429 (2024). https://doi.org/10.1371/journal.pclm.0000429.

24 Climate Policy Radar – Blog. *Building natural language search for climate change laws and policies;* https://climatepolicyradar.org/latest/building-natural-language-search-for-climate-change-laws-and-policies (Accessed August 2024).

25 Yifei Duan *et al.* Literature Mining with Large Language Models to Assist the Development of Sustainable Building Materials (Papers Track) in *International Conference on Learning Representations (ICLR) 2024 – Workshop: Tackling Climate Change with Machine Learning*, Vienna, Austria. https://www.climatechange.ai/papers/iclr2024/39, (2024).

26 Bharathan Balaji *et al.* CaML: Carbon Footprinting of Household Products with Zero-Shot Semantic Text Similarity in *Proceedings of the ACM Web Conference 2023*, Austin, TX, USA. pgs. 4004–4014, https://doi.org/10.1145/3543507.3583882, (2023).

27 Alexandra Luccioni, Emily Baylor & Nicolas Duchene. Analyzing Sustainability Reports Using Natural Language Processing in *Neural Information Processing Systems (NeurIPS) – Tackling Climate Change with Machine Learning workshop*, https://www.climatechange.ai/papers/neurips2020/31, (2020).

28 Jingwei Ni *et al.* CHATREPORT: Democratizing Sustainability Disclosure Analysis through LLM-based Tools. arXiv:2307.15770 (2023). https://doi.org/10.48550/arXiv.2307.15770.

29 ChatNetZero. *ChatNetZero: Helping to demystify net zero (Home Page);* Fremont, California, https://chatnetzero.ai/ (Accessed October 2024).

30 Natalia de la Calzada *et al.* ClimateQ&A : bridging the gap between climate scientists and the general public (Papers Track) in *International Conference on Learning Representations (ICLR) 2024 – Workshop: Tackling Climate Change with Machine Learning*, Vienna Austria. https://www.climatechange.ai/papers/iclr2024/3; https://arxiv.org/pdf/2403.14709, (2024).

31 Saeid Ashraf Vaghefi *et al.* ChatClimate: Grounding conversational AI in climate science. *Communications Earth & Environment* 4, 480 (2023). https://doi.org/10.1038/s43247-023-01084-x.

32 Nikolay Koldunov & Thomas Jung. Local climate services for all, courtesy of large language models. *Communications Earth & Environment* 5, 13 (2024). https://doi.org/10.1038/s43247-023-01199-1.

33 Francesco S. Varini *et al.* ClimaText: A Dataset for Climate Change Topic Detection. arXiv:2012.00483 (2020). https://doi.org/10.48550/arXiv.2012.00483.

34 Tim Nugent, Nicole Stelea & Jochen L. Leidner. Detecting Environmental, Social and Governance (ESG) Topics Using Domain-Specific Language Models and Data Augmentation in *Flexible Query Answering Systems: 14th International Conference (FQAS 2021) Proceedings*, Bratislava, Slovakia. pgs. 157–169, https://doi.org/10.1007/978-3-030-86967-0_12, (2021).

35 Tanmay Laud *et al.* ClimaBench: A Benchmark Dataset For Climate Change Text Understanding in English. *ArXiv* (2023). https://doi.org/10.48550/arXiv.2301.04253.

36 Tom Corringham *et al.* Bert classification of paris agreement climate action plans in *International Conference on Machine Learning (ICML) 2021 – Workshop on Tackling Climate Change with Machine Learning*, Paper #45, https://www.climatechange.ai/papers/icml2021/45, (2021).

37 Tanwi Mallick *et al.* Analyzing the impact of climate change on critical infrastructure from the scientific literature: A weakly supervised NLP approach. arXiv:2302.01887 (2023). https://doi.org/10.48550/arXiv.2302.01887.

38 Shraey Bhatia, Jey Han Lau & Timothy Baldwin. Automatic classification of neutralization techniques in the narrative of climate change scepticism in *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pgs. 2167-2175, https://aclanthology.org/2021.naacl-main.175/, (2021).

39 Travis G. Coan *et al.* Computer-assisted classification of contrarian claims about climate change. *Scientific Reports* 11, 22320 (2021). https://doi.org/10.1038/s41598-021-01714-4.

40 Markus Leippold *et al.* Automated Fact-Checking of Climate Change Claims with Large Language Models. arXiv:2401.12566 (2024). https://doi.org/10.48550/arXiv.2401.12566.

41 Saeid A Vaghefi *et al.* Deep climate change: a dataset and adaptive domain pre-trained language models for climate change related tasks in *Conference on Neural Information Processing Systems (NeurIPS) 2022 – Workshop on tackling climate change with machine learning*, New Orleans, Louisiana, USA. Paper #27, https://www.climatechange.ai/papers/neurips2022/27, (2022).

42 Thomas Diggelmann *et al.* CLIMATE-FEVER: A Dataset for Verification of Real-World Climate Claims. arXiv:2012.00614 (2020). https://doi.org/10.48550/arXiv.2012.00614.

43 David Friederich *et al.* Automated Identification of Climate Risk Disclosures in Annual Corporate Reports. arXiv:2108.01415 (2021). https://doi.org/10.48550/arXiv.2108.01415.

44 Julian F Kölbel *et al.* Ask BERT: How Regulatory Disclosure of Transition and Physical Climate Risks Affects the CDS Term Structure*. *Swiss Finance Institute (Journal of Financial Econometrics, forthcoming)*, Research Paper No. 21-19 (2022). http://dx.doi.org/10.2139/ssrn.3616324.

45 Julia Anna Bingler *et al.* Cheap talk and cherry-picking: What ClimateBert has to say on corporate climate risk disclosures. *Finance Research Letters* 47, 102776 (2022). https://doi.org/10.1016/j.frl.2022.102776.

46 Rylen Sampson, Aysha Cotterill & Quoc Tien Au. TCFD-NLP: Assessing alignment of climate disclosures using NLP for the financial markets in *Conference on Neural Information Processing Systems (NeurIPS) 2022 – Tackling Climate Change with Machine Learning: workshop at NeurIPS 2022*, New Orleans, Louisiana, USA. https://s3.us-east-1.amazonaws.com/climate-change-ai/papers/neurips2022/49/paper.pdf, (2022).

47 Tobias Schimanski *et al.* Bridging the gap in ESG measurement: Using NLP to quantify environmental, social, and governance communication. *Finance Research Letters* 61, 104979 (2024). https://doi.org/10.1016/j.frl.2024.104979.

48 Ming Deng *et al.* War and Policy: Investor Expectations on the Net-Zero Transition. *Swiss Finance Institute*, Research Paper No. 22-29 (2023). http://dx.doi.org/10.2139/ssrn.4080181

49 Matyas Juhasz *et al.* Identifying Climate Targets in National Laws and Policies using Machine Learning in *International Conference on Learning Representations (IRCL) 2024*, Vienna, Austria. https://s3.us-east-1.amazonaws.com/climate-change-ai/papers/iclr2024/26/paper.pdf, (2024).

50 Eduardo Garrido-Merchán, Cristina González-Barthe & Maria Coronado. Fine-tuning ClimateBert transformer with ClimaText for the disclosure analysis of climate-related financial risks. (2023). http://dx.doi.org/10.21203/rs.3.rs-3600821/v1.

51 Dominik Stammbach *et al.* Environmental Claim Detection. arXiv:2209.00507 (2022). https://doi.org/10.48550/arXiv.2209.00507.

52 Max Callaghan *et al.* Machine-learning-based evidence and attribution mapping of 100,000 climate impact studies. *Nature Climate Change* 11, 966-972 (2021). https://doi.org/10.1038/s41558-021-01168-6.

53 Ayush Jain *et al.* Empowering Sustainable Finance: Leveraging Large Language Models for Climate-Aware Investments in *International Conference on Learning Representations (ICLR) 2024 – Tackling Climate Change with Machine Learning workshop*, Vienna, Austria. https://s3.us-east-1.amazonaws.com/climate-change-ai/papers/iclr2024/27/paper.pdf, (2024).

54 Gaku Morio & Christopher D. Manning. An NLP benchmark dataset for assessing corporate climate policy engagement in *Proceedings of the 37th International Conference on Neural Information Processing Systems*, New Orleans, LA, USA. Article 1724, https://dl.acm.org/doi/10.5555/3666122.3667846, (2024).

55 Zhiling Zheng *et al.* ChatGPT Research Group for Optimizing the Crystallinity of MOFs and COFs. *ACS Central Science* 9, 2161-2170 (2023). https://doi.org/10.1021/acscentsci.3c01087.

56 A. Luccioni *et al.* Using Artificial Intelligence to Visualize the Impacts of Climate Change. *IEEE Computer Graphics and Applications* 41, 8-14 (2021). https://doi.org/10.1109/MCG.2020.3025425.

57 Cesar Ilharco *et al. Open-source LLM Alignment for Promoting Sustainability | Accelerating Climate Change Action;* Applied Machine Learning Days, EPFL, Switzerland, https://www.youtube.com/watch?v=KV0UWyZlcko (2024).

58 Beret Walsh. *AI & the Interconnection Queue: The Newest Intersection in Renewable Energy;* Landgate, https://www.landgate.com/news/ai-the-interconnection-queue-the-newest-intersection-in-renewable-energy (Accessed August 2024).

59 Executive Office of the President – Council on Environmental Quality. *Environmental Impact Statement Timelines (2010-2018);* National Environmental Policy Act - Department of Energy, Washington, D.C., https://ceq.doe.gov/docs/nepa-practice/CEQ_EIS_Timeline_Report_2020-6-12.pdf (2020).

60 Joseph Rand *et al. Queued Up: 2024 Edition – Characteristics of Power Plants Seeking Transmission Interconnection As of the End of 2023;* Lawrence Berkeley National Laboratory, https://emp.lbl.gov/sites/default/files/2024-04/Queued%20Up%202024%20Edition_R2.pdf (2024).

61 Shawn Enterline, Andrew Valainis & Ben Hoen. *Laws in Order: An Inventory of State Renewable Energy Siting Policies;* Lawrence Berkeley National Laboratory – Energy Markets and Policy, https://emp.lbl.gov/publications/laws-order-inventory-state-renewable (2024).

62 Rayan Sud & Sanjay Patnaik. *How does permitting for clean energy infrastructure work?;* Brookings – Research, https://www.brookings.edu/articles/how-does-permitting-for-clean-energy-infrastructure-work/ (2022).

63 Keith J. Benes, Joshua E. Porterfield & Charles Yang. *AI for Energy: Opportunities for a Modern Grid and Clean Energy Economy;* US Department of Energy (DOE), Washington, D.C., https://www.energy.gov/sites/default/files/2024-04/AI%20EO%20Report%20Section%205.2g%28i%29_043024.pdf (2024).

64 PolicyAI. *LLM for Environmental Review;* Kaggle, https://www.kaggle.com/competitions/llm-for-environmental-review/ (2024).

65 Symbium. *Symbium Solar Permits: Join Symbium's solar permitting pilot;* San Francisco, California, https://symbium.com/instantpermitting/solar/california/sb379 (Accessed August 2024).

66 Paces. *Quantifying Solar Permitting Risk with Large Language Models;* https://www.paces.com/post/permitting-risk-with-large-language-models (2023).

67 Executive Office of the President – Council on Environmental Quality. *Length of Environmental Impact Statements (2013-2018);* National Environmental Policy Act - Department of Energy, Washington, D.C., https://ceq.doe.gov/docs/nepa-practice/CEQ_EIS_Length_Report_2020-6-12.pdf (2020).

68 Solomon Klappholz. *Microsoft is using AI to get its nuclear projects approved in the US;* ITPro – Technology: Artificial Intelligence, https://www.itpro.com/technology/artificial-intelligence/microsoft-is-using-ai-to-get-its-nuclear-projects-approved-in-the-us (2023).

69 Jennifer Hiller. *Microsoft Targets Nuclear to Power AI Operations;* Microsoft Start, https://www.msn.com/en-us/money/other/microsoft-targets-nuclear-to-power-ai-operations/ar-AA1loccZ (2024).

70 The White House. *The Biden-Harris Permitting Action Plan to Rebuild America's Infrastructure, Accelerate the Clean Energy Transition, Revitalize Communities, and Create Jobs;* https://www.whitehouse.gov/wp-content/uploads/2022/05/Biden-Harris-Permitting-Action-Plan.pdf (2022).

71 117th Congress. *H.R.5376 - Inflation Reduction Act of 2022;* Congress.gov, https://www.congress.gov/bill/117th-congress/house-bill/5376/text (2022).

72 US Department of Energy (DOE). *DOE Announces New Actions to Enhance America's Global Leadership in Artificial Intelligence;* Washington, D.C., https://www.energy.gov/articles/doe-announces-new-actions-enhance-americas-global-leadership-artificial-intelligence#:~:text=DOE%20is%20investing%20%2413%20million,used%20to%20develop%20software%20to (2024).

CHAPTER 12:

GREENHOUSE GAS EMISSIONS MONITORING

Antoine Halff and Colin McCormick

A. Background 12-2

B. Methane Emissions 12-5

C. Carbon Dioxide (CO_2) Emissions 12-7

D. Policy and Market Impacts 12-10

E. Barriers 12-12

F. Risks 12-13

G. Recommendations 12-14

H. References 12-16

Good information on the sources of greenhouse gas (GHG) emissions is essential for responding to climate change. Accurate and timely data are needed to design mitigation strategies, prioritize abatement opportunities and track the effectiveness of climate policies. Historically, however, data concerning sources of GHG emissions have often been partial and approximate, with significant time lags. In many cases, a lack of definitive information on GHG emissions has been an important hurdle to climate action.

Artificial intelligence (AI) is helping address this challenge. AI tools are now analyzing vast amounts of data from Earth-observation satellites, airplanes, drones, land-based monitors, the Internet of Things (IoT), social media and other technologies. This capability dramatically improves our ability to monitor GHG emissions from specific sources accurately in near real-time.

AI's impact on GHG emissions monitoring will likely grow in the near future as machine learning (ML) algorithms used to analyze and process satellite imagery at scale continue to evolve from relatively early-stage computer vision technologies to powerful deep learning (DL) models trained on ever-growing amounts of data. In addition, large language models (LLMs) and generative AI may play an important role in building detailed and comprehensive asset databases (needed to attribute GHG emissions to their sources), while making it easier for end-users to use digital data.

A. Background

i. From GHG concentrations to emissions

Scientists began regularly measuring GHG concentrations in the atmosphere in the 1950s. These measurements, from ground-mounted instruments and Earth-observation satellites, have shown a steady increase in GHG concentrations and been foundational for climate science (see Figures 12-1

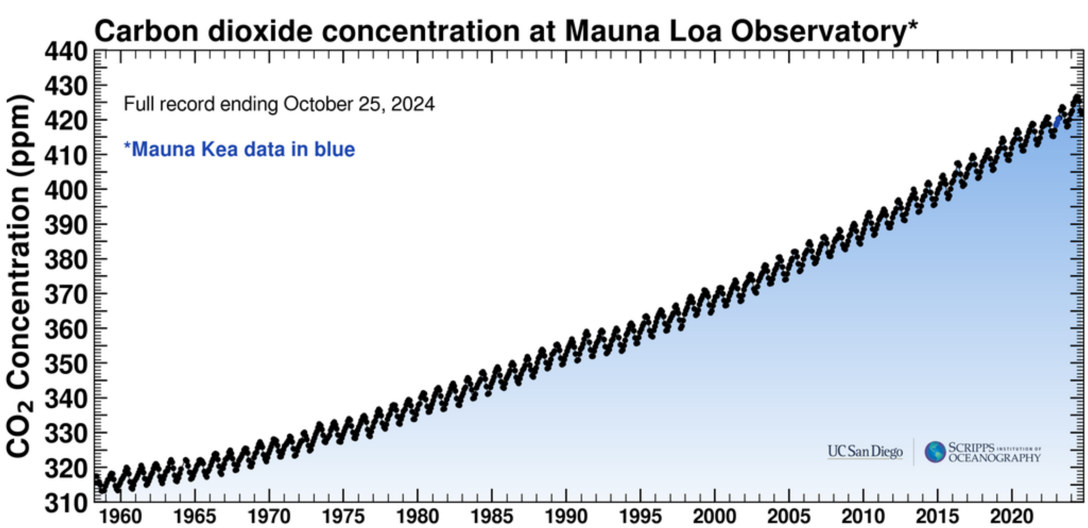


Figure 12-1. The Keeling Curve, showing measurements of CO_2 concentrations at the Mauna Loa Observatory in Hawaii since 1958, is named after the scientist Charles David Keeling who started the monitoring program.
Source: https://keelingcurve.ucsd.edu/

and 12-2). However, the data on GHG concentrations provide very limited or no information on the sources, location, timing and rates of GHG emissions.

To understand sources and amounts of GHG emissions, the climate community has often relied on estimated emission factors based on categories of equipment and processes. Unfortunately, these emission factors often systematically underestimate real emissions.[1-5] (This is especially true of anthropogenic methane emissions, which unlike CO_2 emissions are not a necessary byproduct of fossil fuel combustion.) In addition, the use of emission factors creates no incentive for improving operational performance. For example, a natural gas pipeline operator will be assigned the same level of methane emissions—based on pipeline length and diameter—whether or not it engages in routine venting, flaring or other climate-adverse, high-emitting and avoidable practices.

Different GHGs pose very different detection and measurement challenges:

- CO_2 emissions are mainly caused by fossil fuel combustion and deforestation. CO_2 emissions from fossil fuel combustion can be estimated with reasonable accuracy using fuel-consumption data, while deforestation emissions can be estimated with a lower level of accuracy using land-use-change data. However, neither fuel-consumption nor land-use-change data are readily available in all jurisdictions with sufficient frequency and granularity.
- Methane (CH_4) emissions, in contrast, come from a range of anthropogenic sources (the energy sector, food system and waste management) in addition to natural sources, such as melting of the permafrost, and are less correlated with consumption. Energy-related methane emissions are largely avoidable byproducts of fossil fuel production and transport, uncorrelated with consumption rates and unevenly distributed across fossil-fuel supply chains. Agriculture-related methane emissions are mainly a result of livestock biology and rice cultivation. They have long been deemed relatively difficult to avoid, although emerging technologies may change that. Technologies also exist to reduce waste methane emissions through better landfill management practices.

Figure 12-2. *Japan's Greenhouse gas observing satellite "IBUKI-2" (GOSAT-2).*
Source: https://global.jaxa.jp/projects/sat/gosat2/

ii. AI-enabled greenhouse gas (GHG) emissions monitoring

The use of satellites, drones and ground sensors to monitor GHG emissions at the source has increased significantly in recent years. These instruments produce vast amounts of data that can be processed and analyzed with AI algorithms to yield accurate emissions measurements.

A growing constellation of government and private satellites now monitors GHGs. Japan launched the first such satellite in 2009—the Greenhouse Gases Observing Satellite "IBUKI" (GOSAT).[6] Other government satellites include the European Space Agency's (ESA's) Copernicus Sentinel program; NASA's Landsat, OCO-2 and-3, EMIT and GOES missions; the German Space Agency's (DLR) Environmental Mapping and Analysis Program (EnMAP)[7]; the Italian Space Agency's (ASI) PRISMA[8]; China's Gaofen, Ziyuan and Huanjing missions[9]; and many others.

On the private-sector front, GHG-tracking satellites include, *inter alia*, the GHGSat constellation and Maxar's WorldView program. Several private start-ups, such as the French company Absolut Sensing, are planning to launch new Earth-observation nanosatellites. Oil and gas companies, including Exxon Mobil[10,11] and Saudi Aramco,[12] have announced plans to operate their own GHG monitoring satellites.

Non-governmental organizations (NGOs) have recently been adding to this ecosystem of Earth-observation satellites. The Environmental Defense Fund (EDF), a US NGO, launched MethaneSat in March 2024. Carbon Mapper, a public-private coalition composed of Planet, NASA's Jet Propulsion Laboratory (JPL), the State of California, the University of Arizona, Arizona State University, the Rocky Mountain Institute, the High Tide Foundation and other sponsors launched Tanager-1 in August 2024,[13] the first of several dedicated GHG-tracking satellites.

AI technologies are essential for processing the vast amount of imagery these satellites generate, analyzing it at scale and speedily converting it into precise, accurate and actionable data. Thanks in part to the falling cost of data storage and the dramatic increase in compute power achieved in recent years, scientists have developed powerful algorithms to process and analyze terabytes of raw satellite imagery and other data at scale in near-real time. This "software" development is a critical enabler of advances on the "hardware" side.

Further progress in AI, together with new satellites, will continue to improve methane emissions monitoring and will open up new abatement opportunities. Progress in real-time CO_2-emissions monitoring, as well as in measurement and monitoring of natural carbon sinks—such as vegetation—offers the same potential.

B. Methane Emissions

Methane has more than 80 times the warming power of CO_2 in the first 20 years after release and is as big a source of near-term warming as CO_2.[14] Although methane emissions account for an estimated 30% of global warming to date, the lack of good information on sources of methane emissions has limited the ability of policymakers and emitters to address this problem.

In recent years, the convergence of AI and satellite imagery has significantly improved methane-emissions monitoring. ML algorithms now make it possible to analyze raw satellite imagery at scale in record time. This is accomplished in three main stages. First, AI tools help identify abnormal concentrations of methane. Next, AI tools convert these static measurements into dynamic emissions events. Finally, detailed databases of infrastructure and industrial assets and advanced emissions dispersion models are used to connect ("attribute") these emission events to their point sources. These tools provide policymakers and emitters with important new information for methane abatement by attributing observations of excess methane in the atmosphere to the specific sources that are responsible.

i. Processing data at scale

AI algorithms that process large amounts of remote-sensing data related to methane have been developed by scientists at research institutions, such as the Netherlands Institute for Space Research (SRON), the French Laboratory for Climate and Environmental Science (LSCE) and the Wofsy group at Harvard University (to name just a few), often working in partnership with private actors, such as French environmental intelligence firm Kayrros SAS or Canadian company GHGSat. (One co-author of this chapter is a principal of Kayrros.) Kayrros has been particularly active in further developing and operationalizing research advances, which has enabled automatic detection and measurement of large methane emissions events at scale on a global basis (Figure 12-3). The International Methane Emissions Observatory (IMEO), established in 2021 by the United Nations Environment Programme (UNEP) and the European Union, has been using methane detection data from Kayrros, SRON and GHGSat as feeds for its Methane Alert and Response System (MARS), which collects and disseminates information on super-emitters and works with the responsible parties and their governments to reduce emissions. More recently, the IMEO has been developing its own capability to process and analyze satellite imagery in-house.[15]

Advances in AI-enabled image-processing capacity help squeeze ever more methane information from satellite imagery, including from sensors that may not have been originally designed for that purpose. Thanks to this progress, satellites can now detect methane at the same spatial resolution and emission threshold as aerial surveys (down to 3 meters and 100 tons per hour or less), at a much lower cost and higher temporal resolution (frequency).[16] The combination of new satellites and increased processing capacity results in a growing number of GHG emission detections and facilitates their attribution to point sources on the ground. There is a trade-off among spatial resolution, temporal resolution (frequency) and spectral resolution (sensitivity) in most satellites—optimizing for two of these variables usually comes at the expense of the third. However, integrating inputs from multiple sensors (often called "data fusion") can overcome these limitations by creating an ideal, multi-scale monitoring platform that combines the best of all instruments.

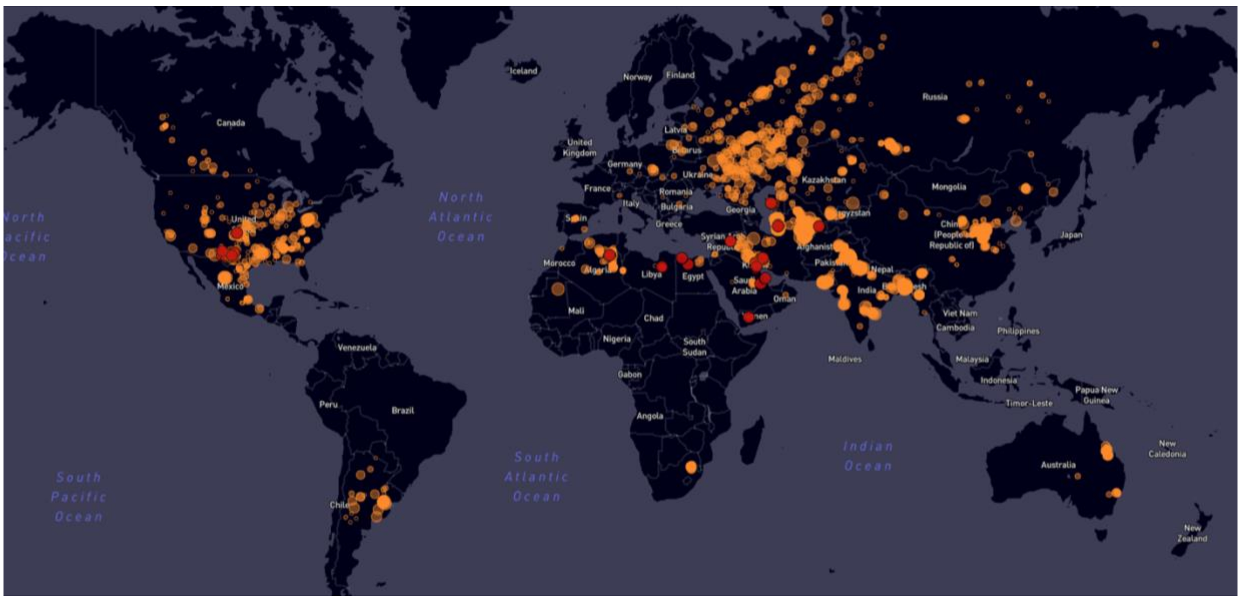


Figure 12-3. Methane super-emitters identified from satellite data processed with AI algorithms. Source: Kayrros.

ii. Use cases and takeaways

AI-enabled methane monitoring can be used in two ways: to identify large but sporadic emissions events, known as "super-emitters," or to assess total overall methane emissions from a country, sub-national region or fossil-fuel basin over a more prolonged period of time.

The transparency provided by AI and satellites has already significantly changed our understanding of anthropogenic methane emissions. For example, large emissions events from fossil fuel extraction and transportation have been shown to be far more ubiquitous than previously thought. Eliminating these super-emitters is "low-hanging fruit" for climate action: their eradication could be achieved at a relatively low cost,[17-19] significantly reducing anthropogenic methane emissions and cutting the increase in global average temperatures by 0.3 °C by 2045 and by 0.5 °C by 2100.[20,21] This set of abatement measures—the fastest known way to reduce global warming—is entirely dependent on the use of AI.

AI-enabled monitoring also has revealed large-scale, chronic methane emissions from landfills, with a disproportionate share in South Asia (India, Bangladesh and Pakistan)—another promising abatement opportunity.[22] In these countries, methane abatement could also provide substantial health benefits and reduce the need for imported, high cost liquefied natural gas (LNG). Similarly, AI-enabled monitoring using airborne detectors has uncovered large, ongoing methane emissions from US landfills.[23] In addition, AI can be used to analyze satellite imagery to track methane emissions from cattle feedlots.[24]

Basin-level or regional methane emission assessments can also help establish national or subnational methane inventories, set abatement targets and monitor the effect of mitigation policies. Saudi Arabia's King Abdullah Petroleum Research and Studies Center (KAPSARC), a government think-tank, conducted an AI-enabled study of Saudi methane emissions from oil and gas production and landfills. Their findings have confirmed the accuracy of earlier government assessments compared to those of the International Energy Agency (IEA) and the European Commission's Emissions Database for Global Atmospheric Research (EDGAR).[25]

C. Carbon Dioxide (CO_2) Emissions

AI is increasingly used to better understand and quantify sources of CO_2 emissions. At present, CO_2 emissions are monitored by assessing levels of carbon-emitting activities, such as industrial production and deforestation. AI helps build on existing datasets and dramatically improves the timeliness, granularity, comprehensiveness and accessibility of CO_2 emissions information.

i. Methodology: Bringing granular, real-time accountability to carbon emissions

AI can analyze and integrate large quantities of data from highly diverse real-time or near-real-time datasets from industry, power generation, ground transportation and other sectors. This approach has produced near-real-time trackers of CO_2 emissions by sector, company or even individual asset, with continuous improvements made to the underlying datasets and AI-based emissions analysis methods.[26,27]

ii. Current applications and emerging opportunities

AI-enabled CO_2 emissions data allow policymakers, industries and other carbon-market participants to monitor demand for carbon allowances in near real-time, better understand the drivers of carbon emissions and assess the effectiveness of emissions-abatement policies with timeliness and precision. For example, AI can model and monitor CO_2 emissions from urban environments with high spatial and temporal resolution, helping city managers and urban planners assess the effects of abatement measures, sharpen their toolkit and respond to changing circumstances in a timely manner.[28-30]

More use-cases for AI-enabled CO_2 emissions data will undoubtedly emerge as AI algorithms continue to improve, helped in part by new underlying data from Earth-observation satellites scheduled to be launched soon.

iii. Use case: Providing near-real-time information on CO_2 emissions from transport and industry

Climate Trace, Carbon Monitor and other organizations are using AI to more accurately monitor CO_2 emissions. Their methods include combining computer vision with data from remote-sensing satellites, such as detecting water vapor (a proxy for CO_2 emissions) released from large natural-draft cooling towers at power plants[31,32]; measuring daily vehicle traffic on roads over large regions and GHG emissions these vehicles collectively produce[33]; and improving plume-inversion techniques to translate direct CO_2 concentration measurements into estimates of CO_2 emissions rates at large power plants.[34]

Related work has used AI to create a much more accurate estimate of GHG emissions per nautical mile from cargo ships and has combined this information with satellite-relayed ship tracking data from automated identification system (AIS) transponders.[35]

Such transparency carries far-reaching consequences for carbon abatement. In particular, AI-enabled measurements can support and improve carbon markets, such as the EU Emissions Trading System or the California Cap-and-Trade Program, amplifying their impact by providing carbon-market participants with up-to-date information on implied demand for carbon credits.

In operational contexts, AI tools are increasingly able to make real-time predictions of the CO_2 emissions that will result from different vehicle duty cycles,[36] industrial process changes[37] and industrial boiler use.[38] This can help optimize operations to reduce on-site emissions and can highlight specific operating conditions that lead to excessive emissions.

AI-enabled measurement of carbon emissions could also help assess lifecycle emissions of commodities and other products. This type of information may be critically important for carbon border adjustment mechanisms. For example, AI-enabled measurements could be used to assess the amount of carbon (and methane) emissions embedded in products (e.g., crude oil, gasoline, LNG, electric vehicles (EVs) or wind turbines) by collecting data on emissions associated with each link of their respective supply chains. Countries importing the product could use this information to assess its GHG intensity and any associated GHG tariff.

Finally, AI tools can provide policymakers with a powerful resource for tracking effects of emissions regulations, identifying and prioritizing CO_2 abatement opportunities, detecting swings in CO_2 emissions and crafting appropriate reaction measures in a timely manner. This is particularly the case for urban CO_2 emissions, which are estimated to account for up to 60% of total CO_2 emissions and which can be analyzed with AI technologies in great detail.[39]

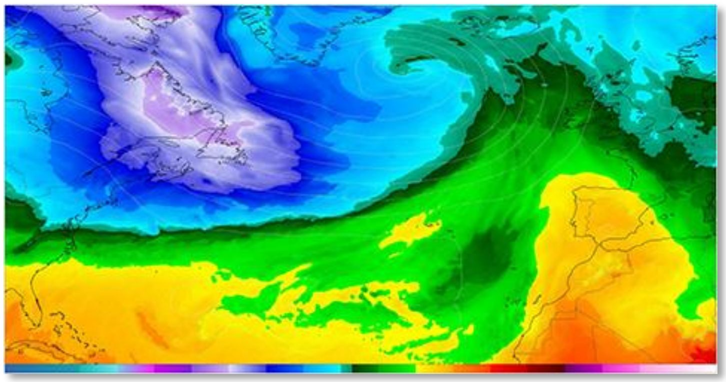
iv. Use case: Achieving near-real-time transparency on negative CO_2 emissions and carbon credit demand

In its Sixth Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) highlights the importance of vegetation to achieving our climate goals. Forestry and other forms of vegetation constitute a vital carbon sink. Monitoring this carbon sink has been challenging with traditional techniques. However, AI algorithms can be trained to survey the world's vegetation at high spatial resolution with radar and optical satellite imagery and can precisely measure the amount of biomass carbon sequestered in forestry and other forms of vegetation, at scale and at reasonable cost.

Traditional monitoring of forest projects involves sending teams of inspectors on the ground at large intervals of 5 to 10 years to inspect sample sections of the forests, measure the circumference of their tree trunks, and extrapolate from those measurements. Inspections are (1) too few and far between to detect deforestation or degradation in time to take corrective measures, (2) do not account for carbon leakage (whereby deforestation is pushed from carbon-offset projects to surrounding areas) and (3) do not provide sufficient data to assess the baselines used to set the number of carbon credits issued (i.e., the assumed growth trajectory of the forest parcel in the absence of a carbon offset project).

In contrast, AI can be used to process radar and optical satellite imagery to survey forests and build a strong monitoring, reporting and verification (MRV) architecture around carbon-offset projects. AI technologies make it possible to monitor entire projects comprehensively, cost-efficiently and non-intrusively at relatively high frequency. They are also able to detect carbon leakage virtually from the onset and to test the projects' baselines by using archival imagery to observe underlying trends in their respective areas over extended periods of time.[40] This transparency has the potential to rebuild confidence in carbon-offset projects, prevent and crack down on unsavory practices in nature-based solutions (NBS) markets, set strong safeguards around our shared forestry endowment and safely channel capital from North to South.

Many start-up companies are currently engaged in AI-assisted biomass carbon monitoring, competing commercially in this emerging sector. As with monitoring positive carbon emissions, this application of AI technology has several use cases. These include strengthening forest protection through robust MRV of carbon offsetting projects, supporting carbon markets with provision of near real-time data on the supply of carbon credits and facilitating implementation of anti-deforestation policies.



These AI-assisted technologies are a potential game changer for developing a robust and transparent NBS sector. NBS projects have been plagued by a lack of transparency that has shielded dubious and sometimes fraudulent business practices, caused market inefficiencies and failures, and severely undermined market confidence in NBS as a viable climate tool.[41,42] AI technologies can provide carbon traders with near-real-time information about the supply of carbon offsets, supplementing implied demand data produced from monitoring carbon emissions. Near-real-time transparency on carbon-credit supply and demand fundamentals can facilitate price formation in carbon markets and can help send price signals needed to support investment in offset projects.[43]

D. Policy and Market Impacts

Policymakers and private-sector companies around the world are already beginning to avail themselves of AI-enabled emissions-tracking tools. This is especially true of EU and US methane policies.

i. Methane

By shining a light on methane emissions, AI has sparked a revolution in global governance of these emissions. The full impact of such changes have yet to be felt, but they have the potential to start reducing global methane emissions relatively soon.

In the United States, these policies include both new methane regulations of the US Environmental Protection Agency (EPA) and the methane provisions of the Inflation Reduction Act of 2022. Both sets of rules recognize AI-enabled satellite technologies as a way to independently track the methane footprint of oil and gas operators without having to rely on their self-reporting. To that end, and in a departure from past practice, the US EPA has invited third-party notifiers to provide methane detection data that may be used as a basis for enforcement actions and other measures. These third-party agents, which will be subject to formal EPA certification, may include users of AI-enabled satellite monitoring technologies.

The US Government has also tasked NASA with supervising the launch of the US GHG Center, a multi-agency unit of NASA, the US EPA, the National Institute of Standards and Technology (NIST) and the National Oceanic and Atmospheric Administration (NOAA).[44] The US GHG Center is expected to provide a wealth of information on GHG emissions, including AI-enabled methane measurements.

Similarly, the EU Methane Strategy is imposing both new methane reporting standards for European energy producers and new due-diligence requirements for European importers of fossil energy. It has considered a "border adjustment mechanism" that would place a tariff on methane emissions associated with EU imports from countries that do not already penalize methane emissions. Companies may use AI-enabled satellite monitoring technologies for compliance purposes, and EU member countries may use them for enforcement.

Meanwhile, as noted above, the IMEO has been developing the MARS platform, which uses AI and satellite imagery to track global methane emissions.

In parallel with these developments, AI-enabled satellite monitoring of methane emissions has been instrumental in the birth of multilateral coalitions and initiatives to reduce methane emissions from the oil and gas sector, such as the Global Methane Pledge, launched at COP26 in Glasgow in 2022 and joined by more than 155 participants.[45] AI-enabled detections of large methane emissions in Turkmenistan played a role in getting Ashgabat to agree to work with the United States and other countries to reduce its methane footprint.

AI-enabled satellite monitoring can empower countries to report their methane emissions to the United Nations Framework Convention on Climate Change (UNFCCC) more accurately than is possible with the prevailing method of emission factors. However, while this use of AI technology for GHG inventories or "stocktake" purposes is not expressly disallowed by the United Nations, it is not explicitly encouraged. This is unfortunate, since satellite studies often show large discrepancies between “bottom up” inventories based on emission factors and “top down” measurements with AI and satellites. On rare occasions, AI monitoring has made it possible to validate the accuracy of national inventories and disprove higher third-party estimates (see, e.g., KAPSARC 2023 study).[26]

Once methane abatement policies have been adopted by countries and/or corporations, AI technologies can help verify their implementation, assess their effectiveness and evaluate what works best or what does not work. For example, the Permian basin (the United States’ most prolific oil and gas basin) straddles the line between Texas and New Mexico, two states with very different methane regulations. Here, AI monitoring could help empirically measure the impact of these policies on the basin’s GHG footprint.[46]

In commodities markets, methane emissions (or the lack thereof) are becoming an important differentiating factor, with products deemed “clean” or “low emissions” already commanding or set to command a premium. AI-enabled technologies hold promise as a key tool for helping establish the methane footprint of individual oil and gas producers or cargoes of oil or LNG and could become an important building block in “responsible gas“ certification.[47]

In equities and fixed-income markets, several banks and asset managers have announced AI-assisted initiatives to factor methane measurements and other climate-related metrics into their decision-making for investments or loans. Here too AI-assisted technologies could prove pivotal in helping financial actors integrate climate considerations into their workflows.

ii. Carbon dioxide (CO_2)

Policymakers are increasingly considering the need to adjust international trade practices to avoid “carbon leakage” (i.e. “imported emissions” from exporting countries with loose carbon regulations to importing economies with more stringent rules). At the national level, this can mean a “carbon border adjustment mechanism” (CBAM) – a carbon tariff on imported goods from countries with lower carbon emissions standards than the destination market.

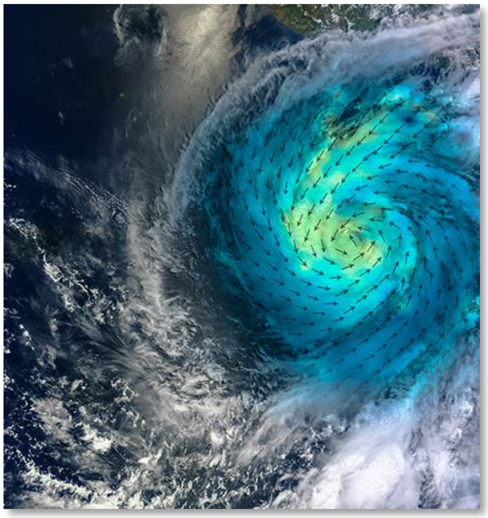
An EU CBAM is due to take effect in its definitive regime in 2026. In the United States, there is bipartisan support for a proposed US version of the European CBAM. (In California, a CBAM is already effectively in place regarding the inter-state movement of electricity from neighboring states under the California Air Resources Board’s Cap-and-Trade Program.)

One of the challenges raised by proposed CBAM regulations is to accurately assess the carbon footprint of internationally traded commodities and goods—a challenge that AI-enabled technologies might help to overcome. Not surprisingly, there is strong interest in both the European Union and the United States in studying the usefulness of these technologies for determining the carbon intensity of imports.

E. Barriers

The use of AI to harness satellite imagery and other data sources is one of the most promising developments for GHG emissions monitoring. However, there are important barriers.

i. Lack of AI literacy



Lack of AI literacy limits the ability of data users to analyze GHG data, integrate these data into their operations and generate customized products and applications based on these data. Lack of AI literacy could also inhibit the willingness of national governments to avail themselves of AI-enabled Earth-observation tools in the absence of guidelines from the UNFCCC, even if these technologies could greatly enhance the accuracy of their GHG inventories and support their stocktake efforts. Finally, lack of AI literacy could also adversely affect public trust in AI-enabled GHG data and create a fertile ground for misuse of data. To realize the full potential benefits of AI for GHG emissions monitoring, AI literacy must be broadly improved, including in developing economies.

The growth of generative AI and large language models (LLMs) could help overcome this barrier by making it easier for users to leverage AI-enabled data. This could however prove to be a double-edged sword. Distrust of generative AI and the tendency of some LLMs to "hallucinate" could undermine user confidence and emerge as barriers to adoption in their own right.

ii. Sovereignty concerns

Sovereignty concerns may emerge as a significant impediment to using AI-enabled GHG emissions data. Some countries may object to foreign monitoring and analysis of emissions within their territories. AI-enabled analysis of GHG emissions data may face a trust deficit if it is perceived as biased in favor of certain economic actors, especially if these data are used as the basis for imposing international tariffs or trade restrictions.

Independent verification of global GHG data and international consensus about the accuracy of AI-enabled analyses will be required to fully realize the potential benefits of AI tools in GHG emission monitoring.[48]

iii. Emitter pushback

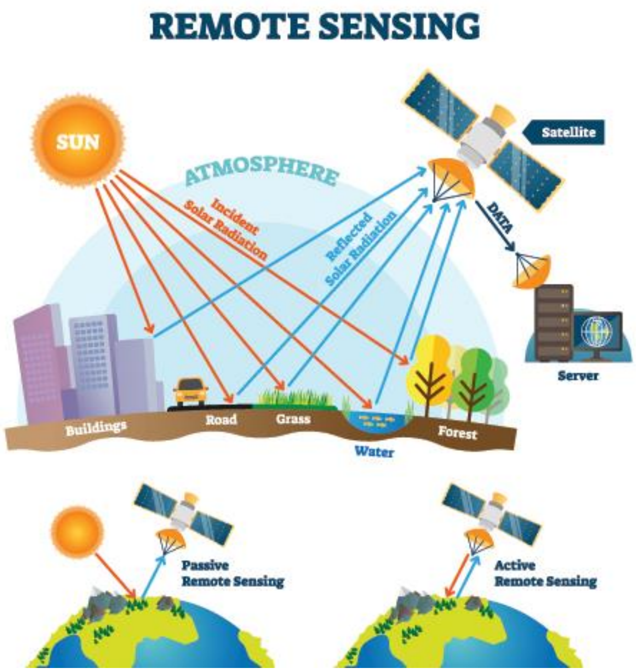
Industry participants whose true climate footprint might be exposed by AI technologies as larger than reported or whose short-term interests might otherwise be harmed by the transparency brought by AI technologies might be naturally inclined to push back against these measurements. National governments whose GHG inventories might be shown as understating actual emissions might be inclined to react by challenging the maturity and reliability of AI-enabled monitoring technologies.

iv. Uncertain financial models

A tension exists in current development of AI-enabled GHG monitoring tools. While these tools rely strongly on data provided by publicly funded satellites, much of their technological innovation is the result of intense competition between private-sector companies, including many start-ups. These companies are profit-seeking and must generate revenue from the sale of data to recoup their investments and fund further research and development (R&D). At the same time, the data must be shared as widely as possible and ideally made publicly available in open access to maximize their impact and facilitate global acceptance of their accuracy. Protecting the intellectual property in many AI-enabled technologies is essential to the financial success of these private-sector enterprises and thus to innovation in AI technologies but may limit public acceptance of GHG emissions data.

F. Risks

Risks with respect to using AI for GHG emissions monitoring are modest. Safety and bias concerns that arise with using AI in other sectors are not major issues when using AI for monitoring GHGs. However, two categories of risks require attention.



Privacy concerns may arise when AI enables remote monitoring. For example, manufacturers may be concerned that AI-enabled remote GHG emissions measurements could provide confidential information about factory operations to competitors. However, the technologies underlying AI-enabled emissions data (high-resolution remote sensing and advanced AI algorithms) can be used to obtain competitive industrial information regardless of whether they are also used to assess emissions. Mitigation of this concern ultimately relies on policies that address those underlying technologies.

Lack of confidence arising from data inconsistency. Lack of confidence in AI-enabled data could emerge among key stakeholders due to a variety of factors, such as naturally occurring differences in GHG emissions detections and measurements, inaccurate measurements or seemingly conflicting results. Natural differences in data could be misconstrued as conflicting when they in fact simply stem from the intermittency of some emissions and timing differences in collecting satellite imagery. Inaccurate or conflicting results could result from the proliferation of imagery transmitted by a growing constellation of Earth-observation satellites, as well as from new start-up companies competing in the AI-for-climate space, with different providers releasing different measurements.

G. Recommendations

Several measures could help address the barriers and overcome the risks described above, promoting the use of AI tools for GHG emissions monitoring.

1. *National governments should encourage the UNFCCC to update guidance on preparing national emissions inventories to explicitly allow the use of AI-enabled data rather than primarily emissions factor–based assessments. This would provide for more accurate baselines and thus make it easier to optimize climate policies and to better tailor them to specific national conditions, while also better recognizing the progress of countries in reducing their climate footprint.*
2. *Carbon accounting bodies, such as the GHG Protocol of the World Resources Institute (WRI) and World Business Council for Sustainable Development (WBCSD) or the Science Based Targets Initiative (SBTI), should develop rules for including AI-enabled data as part of corporate carbon footprints, supply chain emissions estimates and related emissions-tracking efforts. When feasible, they should encourage or prioritize the use of validated AI-enabled emissions data over generic emissions factors. In tandem with this, other relevant multilateral institutions, such as the World Trade Organization (WTO) and IEA, should continue[49] explicitly addressing the topic of using AI-enabled emissions data and should identify roles they can productively play in advancing its use in a scientifically robust manner.*
3. *National governments and appropriate international bodies should consider how best to set up the housing and governance regime of AI-enabled emissions data, including such questions as whether one or several national or international organizations or private entities should function as de facto or de jure central data repositories or clearinghouses. Clear options should be defined and decisions made in the short-term. To the extent that the market or regulations require information on GHG emissions in supply chains, the quality of emissions data will be of paramount importance. To be effective, emissions data will need buy-in from as many stakeholders as possible and must be independently replicable. Governments and multilateral organizations should consider the role of existing institutions, such as the IMEO, the World Meteorological Organization and the Food and Agriculture Organization, as well as major philanthropic organizations and for-profit companies, in providing repository and clearinghouse services for AI-enabled GHG emissions data.*
4. *National governments and appropriate international bodies should continue ongoing efforts toward standardizing AI-enabled emissions data and should consider whether to set up formal processes to certify AI-assisted emissions data and data providers. In the last two years, NIST at the US Department of Commerce and the UK Space Agency have spearheaded a series of brainstorming workshops and consultations with leading scientists and industry participants from around the world, with the goal of achieving greater standardization and consistency in AI-assisted measurements of methane and other GHG emissions and of preempting the risk of future conflicting data.[50] These efforts are highly worthwhile and ought to be continued so as to guarantee the scientific integrity and comparability of emissions data and to build public trust. To*

the extent possible, participation should be broadened to include more representatives from emerging and newly developed economies and major exporters of commodities and manufactured goods.

5. *National governments, philanthropic organizations and private-sector companies should support ongoing "ground truthing" efforts by research universities and scientific organizations that aim to independently assess the performance of AI-assisted GHG monitoring technologies. Because AI-enabled GHG monitoring technologies often detect and measure emissions that cannot be otherwise detected or measured, proving their accuracy can be challenging. Hence, there is a need to support public research to develop ways of independently replicating and corroborating AI-enabled data and verifying their accuracy based on well-calibrated ground-truth experiments.*
6. *National governments and private-sector organizations should enhance their in-house AI proficiency, whether by requiring minimum AI literacy standards from a broad cross-section of employees or by building up dedicated AI-focused units and data-science centers within their organizations. Minimum AI literacy may be essential for these organizations to deploy AI-enabled GHG emissions data and to integrate those data into public and proprietary databases and operational systems. Professional standards bodies should update accreditation requirements for professions, such as public accounting and civil engineering, to require demonstration of minimal AI proficiency and the ability to use basic AI technologies. This would serve as a step to support adoption and implementation of emissions abatement targets by industry and carbon accounting by corporations. Trade and professional organizations, such as the Society of Petroleum Engineers (SPE) or the International Association for Energy Economics (IAEE), should support AI literacy among their members and the adoption of AI-enabled GHG monitoring, including through training programs in countries where these technologies are not widely available.*
7. *Banks, asset managers and other private-sector actors should use AI-enabled methane emissions data to quantify the embedded emissions of fossil fuel shipments, following the lead of some financial institutions who have already begun this practice.*

H. References

1 A. R. Brandt *et al.* Methane Leaks from North American Natural Gas Systems. *Science* 343, 733-735 (2014). https://doi.org/10.1126/science.1247045.

2 Stuart N. Riddick & Denise L. Mauzerall. Likely substantial underestimation of reported methane emissions from United Kingdom upstream oil and gas activities. *Energy & Environmental Science* 16, 295-304 (2023). https://doi.org/10.1039/D2EE03072A.

3 International Energy Agency (IEA). (International Energy Agency (IEA), 2022).

4 M. Saunois *et al.* The Global Methane Budget 2000–2017. *Earth Syst. Sci. Data* 12, 1561-1623 (2020). https://doi.org/10.5194/essd-12-1561-2020.

5 Giulia Zazzeri *et al.* Radiocarbon Measurements Reveal Underestimated Fossil CH4 and CO2 Emissions in London. *Geophysical Research Letters* 50, e2023GL103834 (2023). https://doi.org/10.1029/2023GL103834.

6 GOSAT Project. *Greenhouse gases observing satellite GOSAT "IBUKI";* Tsukuba-shi, Ibaraki, Japan, https://www.gosat.nies.go.jp/en/#:~:text=The%20Greenhouse%20Gases%20Observing%20Satellite,been%20operating%20properly%20since%20then (Accessed August 2024).

7 Deutsches Zentrum für Luft- und Raumfahrt (DLR). *German satellite EnMAP launches successfully;* DLR (German Aerospace Center), Köln, Germany, https://www.dlr.de/en/latest/news/2022/02/20220401_german-satellite-enmap-launches-successfully (2022).

8 Agenzia Spaziale Italiana (ASI). *Prisma – Hyperspectral satellite, capable of observing from the optical to the near infrared;* Rome, Italy, https://www.asi.it/en/earth-science/prisma/ (Accessed August 2024).

9 China National Space Administration (CNSA). *China launches new Earth observation satellite;* Beijing, China, https://www.cnsa.gov.cn/english/n6465652/n6465653/c6801815/content.html (2018).

10 Exxon Mobil. *ExxonMobil and Scepter, Inc. to deploy satellite technology for real-time methane emissions detection (News Release);* Spring, Texas, https://corporate.exxonmobil.com/news/news-releases/2021/1213_exxonmobil-and-scepter-to-deploy-satellite-technology-for-real-time-methane-emissions-detection (2021).

11 CERAWeek. *Exxon Mobil | Using High-altitude Platforms to Monitor Methane;* S&P Global, Houston, Texas, https://ceraweek.com/agora/program/exxon-mobil-using-highaltitude-platforms-to-monitor-methane-18865-813079/Exxon Mobil | Using High-altitude Platforms to Monitor Methane (2024).

12 Ahmad Al Khowaiter. *Space Age Forum 2024 – Opening Remarks by Ahmad Al Khowaiter, EVP for Technology & Innovation (Speech);* Aramco, Dhahran, Saudi Arabia, https://www.aramco.com/en/news-media/speeches/2024/space-age-forum-2024---remarks-by-ahmad-al-khowaiter (2024).

13 NASA Jet Propulsion Laboratory (JPL). *Tanager-1 First Methane and Carbon Dioxide Plume Detections;* Pasadena, California, https://www.jpl.nasa.gov/images/pia26416-tanager-1-first-methane-and-carbon-dioxide-plume-detections/ (2024).

14 Climate Change IPCC Working Group III. Mitigation of Climate Change - Summary for Policymakers (Sixth Assessment Report). 7 (2022).

15 Luis Guanter. *International Methane Emissions Observatory, Methane Alert and Response System (MARS)"*

16 Evan Sherwin *et al.* Single-blind test of nine methane-sensing satellite systems from three continents (Preprint). *EGUsphere* 2023, 1 (2023). https://doi.org/10.31223/X56089.

17 T. Lauvaux *et al.* Global assessment of oil and gas methane ultra-emitters. *Science* 375, 557-561 (2022). https://doi.org/10.1126/science.abj4351.

18 Damian Carrington. *Revealed: 1,000 super-emitting methane leaks risk triggering climate tipping points;* The Guardian, New York, New York, https://www.theguardian.com/environment/2023/mar/06/revealed-1000-super-emitting-methane-leaks-risk-triggering-climate-tipping-points (2023).

19 Tomas de Oliveira Bredariol & Christophe McGlade. *Methane Abatement;* https://www.iea.org/energy-system/fossil-fuels/methane-abatement (2023).

20 Tiy Chung. *Global Assessment: Urgent Steps Must Be Taken to Reduce Methane Emissions This Decade;* United Nations Framework Convention on Climate Change (UNFCCC), Bonn, Germany, https://unfccc.int/news/global-assessment-urgent-steps-must-be-taken-to-reduce-methane-emissions-this-decade (2021).

21 Environmental Defense Fund (EDF). *Benefits of measurement-based methane estimates and timely emissions reductions for reaching the long-term global goal on temperature: Submission to the Global Stocktake by the Environmental Defense Fund;* https://www4.unfccc.int/sites/SubmissionsStaging/Documents/202208040943---Environmental%20Defense%20Fund_GST%2004.08.22.pdf (2022).

22 Joannes D. Maasakkers *et al.* Using satellites to uncover large methane emissions from landfills. *Science Advances* 8, eabn9683 (2022). https://doi.org/10.1126/sciadv.abn9683.

23 Daniel H. Cusworth *et al.* Quantifying methane emissions from United States landfills. *Science* 383, 1499-1504 (2024). https://doi.org/10.1126/science.adi7735.

24 Valerie Volcovici. *Californian cow burps have been detected by satellites. Here's why that matters;* World Economic Forum in collaboration with Reuters, Cologny, Switzerland, https://www.weforum.org/agenda/2022/05/satellites-california-cows-cattle-methane-agriculture/ (2022).

25 Walid Matar and Abdelrahman Muhsen Anwar Gasim. *Using Satellite Technology to Measure Greenhouse Gas Emissions in Saudi Arabia (Discussion Paper);* King Abdullah Petroleum Studies and Research Center (KAPSARC), Riyadh, Saudi Arabia, https://www.kapsarc.org/research/publications/using-satellite-technology-to-measure-greenhouse-gas-emissions-in-saudi-arabia/ (2023).

26 Zhu Liu *et al.* Carbon Monitor, a near-real-time daily dataset of global CO2 emission from fossil fuel and cement production. *Scientific Data* 7, 392 (2020). http://doi.org/10.1038/s41597-020-00708-7.

27 Carbon Monitor. *Homepage;* https://carbonmonitor.org/ (Accessed August 2024).

28 Yi Gao *et al.* in *Proceedings of the 5th International Conference on Information Technologies and Electrical Engineering* 232–237 (Association for Computing Machinery, Changsha, China, 2023; https://doi.org/10.1145/3582935.3582972).

29 Angel Hsu *et al.* Predicting European cities' climate mitigation performance using machine learning. *Nature Communications* 13, 7487 (2022). https://doi.org/10.1038/s41467-022-35108-5.

30 Chuanlong Zhou *et al.* "Building Integral Gridded Carbon Emission Disaggregating Model (BIGCarbonEDM): Near real-time community-level CO2 emission evaluations for twelve cities in Egypt, South Africa, and Turkey" in *General Assembly 2023 of the European Geosciences Union (EGU)*, Vienna, Austria and Online. https://doi.org/10.5194/egusphere-egu23-4138,(2023).

31 Heather D Couture *et al.* "Towards tracking the emissions of every power plant on the planet" in *NeurIPS 2020 Workshop: Tackling Climate Change with Machine Learning*, Virtual. https://www.climatechange.ai/papers/neurips2020/11,(2020).

32 Heather D. Couture *et al.* Estimating Carbon Dioxide Emissions from Power Plant Water Vapor Plumes Using Satellite Imagery and Machine Learning. *Remote Sensing* 16, 1290 (2024). https://doi.org/10.3390/rs16071290.

33 Derek Rollend *et al.* Machine learning for activity-based road transportation emissions estimation. *Environmental Data Science* 2, e38 (2023). https://doi.org/10.1017/eds.2023.32

34 J. Dumont Le Brazidec *et al.* Deep learning applied to CO2 power plant emissions quantification using simulated satellite images. *Geosci. Model Dev. Discuss.* 2023, 1-30 (2023). https://doi.org/10.5194/gmd-2023-142.

35 Brett Mayes *et al. Transportation Sector: Domestic and International Shipping Emissions;* https://github.com/climatetracecoalition/methodology-documents/blob/main/2023/Transportation/Transportation%20sector-%20Domestic%20and%20International%20Shipping%20Emissions%20methodology.docx.pdf (2023).

36 Shengwei Li, Zeping Tong & Muhammad Haroon. Estimation of transport CO2 emissions using machine learning algorithm. *Transportation Research Part D: Transport and Environment* 133, 104276 (2024). https://doi.org/10.1016/j.trd.2024.104276.

37 Rojiar Haddadian, Chennan Li & Lanyon Carr. *Monitor carbon emissions through real-time machine learning;* Schneider Electric, Rueil-Malmaison, France, https://blog.se.com/industry/energies-and-chemicals/2024/04/18/emissions-monitoring-through-real-time-machine-learning/ (2024).

38 Bárbara D. Ross-Veitía *et al.* Machine learning regression algorithms to predict emissions from steam boilers. *Heliyon* 10, e26892 (2024). https://doi.org/10.1016/j.heliyon.2024.e26892.

39 Da Huo *et al.* Carbon Monitor Cities near-real-time daily estimates of CO2 emissions from 1500 cities worldwide. *Scientific Data* 9, 533 (2022). https://doi.org/10.1038/s41597-022-01657-z.

40 Van Butsic. *The role of improved forest management for carbon dioxide removal;* Carbon Direct, New York, New York, https://www.carbon-direct.com/insights/the-role-of-improved-forest-management-for-carbon-dioxide-removal (2023).

41 Monica Guy. *COP26: Is corruption on the agenda?;* Basel Institute on Governance, Basel, Switzerland, https://baselgovernance.org/blog/cop26-corruption-agenda (2021).

42 Patrick Greenfield. *Revealed: more than 90% of rainforest carbon offsets by biggest certifier are worthless, analysis shows;* The Guardian, New York, New York, https://www.theguardian.com/environment/2023/jan/18/revealed-forest-carbon-offsets-biggest-provider-worthless-verra-aoe (2023).

43 International Panel on Climate Change. *AR6 Synthesis Report: Climate Change 2023;* Geneva, Switzerland, https://www.ipcc.ch/report/sixth-assessment-report-cycle/ (2023).

44 US GHG Center. *Exploration Page;* https://earth.gov/ghgcenter/exploration?datasets=%5B%5D&taxonomy=%7B%22Gas%22%3A%22ch%E2%82%84%22%2C%22Product+Type%22%3A%22satellite-observations%22%2C%22Topics%22%3A%22anthropogenic-emissions%22%7D (Accessed August 2024).

45 Global Methane Pledge. *Fast action on methane to keep a 1.5°C future within reach;* Climate and Clean Air Coalition (CCAC), Paris, France, https://www.globalmethanepledge.org/ (Accessed August 2024).

46 State of New Mexico – Office of the Governor: Michelle Lejan Grisham. *Independent study shows New Mexico's emissions from oil and gas are HALF those of Texas' industry (Press Release);* Sante Fe, https://www.governor.state.nm.us/2023/11/14/independent-study-shows-new-mexicos-emissions-from-oil-and-gas-are-half-those-of-texas-industry/ (2023).

47 Arvind P. Ravikumar *et al.* Measurement-based differentiation of low-emission global natural gas supply chains. *Nature Energy* 8, 1174-1176 (2023). https://doi.org/10.1038/s41560-023-01381-x.

48 Kit Million Ross. *China clamps down on information leaks in energy sector;* https://www.power-technology.com/news/china-clamps-down-on-information-leaks-in-energy-sector/?cf-view (2023).

49 International Energy Agency (IEA). Progress on data and lingering uncertainties in *Global Menthane Tracker 2024* (Paris, France, 2024, https://www.iea.org/reports/global-methane-tracker-2024/progress-on-data-and-lingering-uncertainties).

50 Committee on Earth Observation Satellites (CEOS). *International Methane Standards Workshop;* UK Space Agency and US National Institute of Standards and Technology (NIST), London, UK, https://ceos.org/meetings/uksa-methane-workshop/ (2024).

CHAPTER 13:
MATERIALS INNOVATION

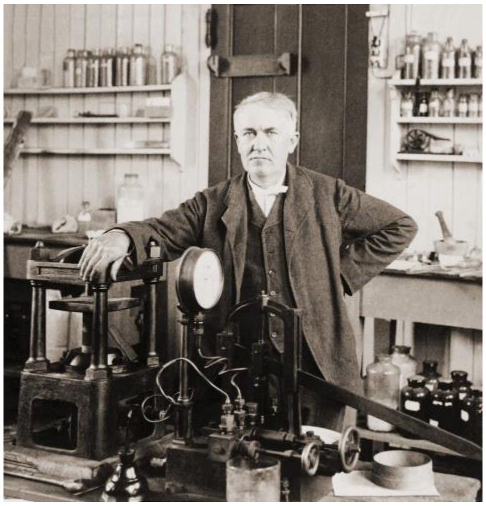
Colin McCormick

A. Materials Innovation in Climate Technologies 13-3
B. Computational Materials Development 13-5
C. Applications of AI in Materials Discovery and Design 13-6
D. Barriers 13-8
E. Risks 13-9
F. Recommendations 13-10
G. References 13-11

Materials innovation is important for decarbonization, and artificial intelligence (AI) can play a major role in accelerating it. This chapter examines how improved materials can reduce emissions and enable carbon management, as well as specific areas in which AI can help.

Roman concrete enabled extraordinary construction projects, including the Pantheon, the world's oldest building still in active use.

The search for novel materials with useful properties has been central to technology innovation for centuries. Ancient Romans developed novel concrete for bridges, aquifers and other structures, some of which have survived for millennia.[1] In the modern era, Thomas Edison's discovery of carbon filament for electric light bulbs in 1879 enabled these bulbs to last for long enough to be practical, leading to a fundamental transformation of lighting technologies and the eventual phase-out of whale oil and kerosene lamps.[2] Similarly, Charles Goodyear's discovery of a process to vulcanize rubber in the 1830s helped overcome the limitations of natural rubber, which melts in heat and cracks in cold. Goodyear (among others) worked for years to address this challenge, eventually discovering how to cross-link the long molecules in natural rubber to create a much stronger and more durable material.[3]



Thomas Edison's discovery of carbon filament for electric light bulbs in 1879 fundamentally transformed lighting.

These examples illustrate that most materials innovation throughout history has relied on insight, experimentation and serendipity. Edison's search for an appropriate filament depended on general scientific insight and exhaustive material testing: his laboratory tried thousands of carbonized plants before finally identifying one that worked well. Goodyear's discovery of vulcanization was largely due to a stroke of luck. Many other key materials—including carbon steel, ceramics, catalysts and polymers—have followed similar paths. Without a systematic, quantitative framework for determining how a material's properties depend on its chemical and structural nature, there is only one feasible approach: innovators must laboriously find or synthesize many different materials (or many variations of the same basic material with slight modifications) and exhaustively test them. This is costly and time-consuming and creates a barrier to technological progress.

A. Materials Innovation in Climate Technologies

The performance of many clean-energy technologies is limited by the properties of key materials, including photovoltaics (PVs), semiconductors, magnets, catalysts, polymers, alloys and composites. Identifying new materials with improved properties could enable these technologies to achieve higher energy efficiency, lower costs, greater performance, longer service lifetime, higher energy densities and many other desirable characteristics. This in turn would allow these technologies to provide identical or improved services with lower net greenhouse gas emissions (GHG).

Materials innovation enabled the development of lithium-ion batteries for electric vehicles (EVs), long-duration grid storage and other low-carbon technologies.

Lithium-ion batteries are a good example of a technology that was greatly improved through discovery of novel materials. Specifically, the cathode, anode and electrolyte materials in modern lithium-ion batteries are all the result of extensive fundamental and applied research. This includes identification of lithium cobalt oxide ($LiCoO_2$), lithium iron phosphate ($LiFePO_4$) and other cathode materials beginning in the 1970s, as well as identification of graphite for anodes and a variety of liquid and solid materials for the electrolyte.[4] Before these materials were identified and successfully integrated into full systems, the performance of batteries was much worse than today (lower energy density and total capacity). The cost of building battery-enabled technologies was correspondingly higher. Advances in these key materials therefore improved performance and thus brought batteries into new applications, such as electric vehicles (EVs) and bulk storage of renewable electricity. Research into advanced battery materials is still ongoing and may open a path to even higher-performing batteries, such as all-solid-state[5] and sodium-ion technologies.[6]

Solar photovoltaic (PV) systems are the product of years of materials innovation and optimization.

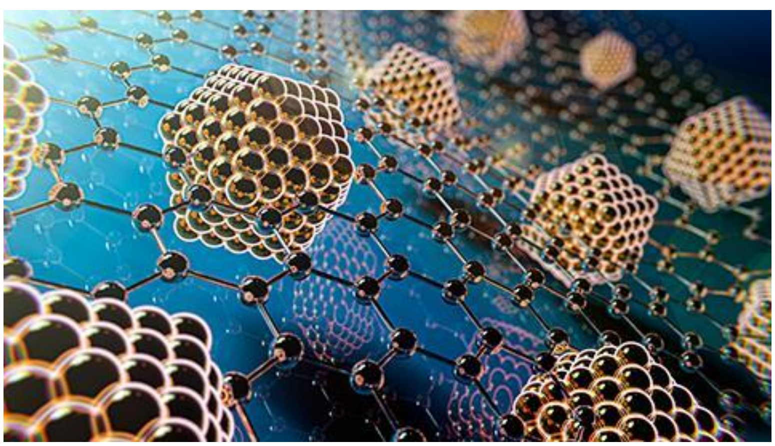
Advanced materials also play important roles in carbon capture and management technologies. Properties such as CO_2-binding energy and kinetics, as well as long-term stability, determine the overall performance of materials used as sorbents and solvents for carbon capture and direct air capture (DAC) applications.[7] Similar properties also determine the performance of catalyst materials in applications such as electrocatalytic reduction of CO_2.[8] Even in the case of CO_2 transport for sequestration or utilization, material properties influence the durability and overall performance of bulk transport systems. [9]

Box 13-1

INNOVATION IN MATERIALS SYNTHESIS

In some cases, a well-known material with superior properties could potentially overcome limitations to a technology's performance, but no practical method is known for producing this material. One such case is the general illumination LED bulb, now in common use. Although LEDs were originally invented in the 1960s, they were based on a material (gallium arsenide, GaAs) that can only emit red light. Researchers knew that gallium nitride (GaN) and zinc selenide (ZnSe) could enable white LEDs that could be used for general applications like building and street lighting. However, it was not until the development of the two-flow MOCVD (metal organic chemical vapor deposition) reactor in the 1990s that GaN crystals could be reliably produced.[10]

This development led directly to commercial, white-colored LED lights with dramatically higher energy efficiency than incandescent and fluorescent bulbs, which are now gradually being replaced. Notably, although LEDs have reduced the energy intensity of lighting significantly, global CO_2 emissions from lighting have not fallen because the demand for more lighting has offset these efficiency gains.[11]



There are many other use cases of advanced materials that are, or would be, valuable in enabling technologies to reduce GHG emissions in energy, industrial, transportation and other applications. These include solar PVs,[12] wind turbine blades,[13] hydrogen storage,[14] fuel-cell electrodes and electrolytes,[15] lightweight alloys and composites for vehicles,[16] low-GWP (global warming potential) refrigerants,[17] thermal-barrier coatings,[18] desiccants for advanced HVAC,[19] high-voltage direct-current (HVDC) power transmission,[20] high-temperature superconductors,[21] and high-strength permanent magnets (used in everything from wind turbines to fusion reactors).[22]

Innovative materials are important for enabling point-source carbon capture systems and CO_2 removal systems, such as this direct air capture (DAC) plant in Iceland (photo credit: Julio Friedmann).

B. Computational Materials Development

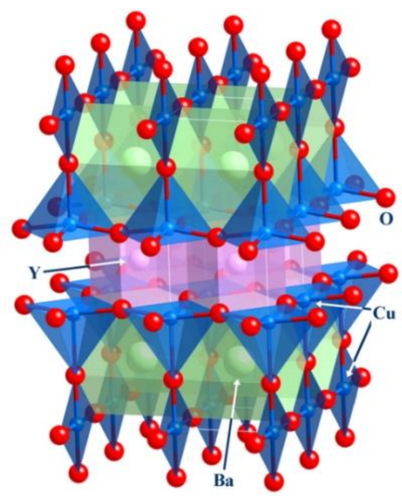
Key scientific advances in the 1960s changed the way materials are designed and discovered. New computational methods finally enabled researchers to go beyond simply relying on intuition and incremental experiments; these methods allowed them to directly calculate the properties of new materials just from their chemical makeup and structure ("*ab initio*"). For example, following the discovery of the first high-temperature superconductor (which was largely an Edisonian process guided by intuition), other researchers quickly applied computational modeling to better understand the superconducting effect. This approach led to the discovery of other, better high-temperature superconductors.[23,24] *Ab initio* modeling also led to materials discoveries for batteries, hydrogen storage, thermoelectrics, nuclear fuels and semiconductors.[25]

As a result, materials research has increasingly shifted to computation. Advances in computing power, algorithms and data science have accelerated this trend. Governments have funded broadly integrated materials science projects that leverage information-science tools to share advanced algorithms, provide compute resources and disseminate the results of computations and experiments in increasingly massive materials property databases. Some examples include The Materials Project coordinated by U.C. Berkeley,[26] the NOMAD database hosted by Humboldt University of Berlin,[27] and the MateriApps project hosted by the University of Tokyo.[28] These projects contain hundreds of thousands to millions of entries on material properties and provide methods for users to run numerical calculations of materials properties on high-performance computers. The scale of materials datasets is a consequence of the enormous number of stable materials that could theoretically exist by the laws of chemistry and physics (estimated to be more than the number of atoms on Earth[29]), even though only a tiny fraction of these have actually been synthesized.

Notably, modern computational materials science consumes enormous computing resources. In recent years, roughly one-third of available supercomputing has been dedicated to these materials-related calculations.[30]

C. Applications of AI in Materials Discovery and Design

The complex nature of materials property predictions and the enormous amount of available data have sparked interest in using AI methods in computational materials science for several years. One key area where AI has been applied is directly predicting properties of new materials without performing full *ab initio* calculations. This approach trains AI models on large databases of previously computed and/or tested materials to learn quantitative relationships between atomic structure and relevant properties. This can save enormous compute time and cost. A recent application of this was the use of graph neural networks trained on data from the Materials Project to screen 31 million hypothetically possible crystal structures to identify roughly two thousand of them with promising properties for further investigation.[31] This AI approach can provide major benefits by down-selecting a small number of candidate materials for more intensive, high-accuracy studies. An important recent variation of this approach combined AI algorithms with *ab initio* calculations to generate and then filter potential new inorganic crystals, discovering more than 380,000 new, previously unknown stable materials.[32]



Yttrium barium copper oxide (YBCO) was one of the first high-temperature superconductors to be discovered. Image was created using published crystallographic information and the Crystalmaker® program. Author: Gadolinist

This type of materials prediction and screening relies on large datasets, so ongoing efforts to develop AI-ready massive materials datasets are crucial. The recently released Open DAC 2023 dataset containing millions of high-accuracy calculations of the properties of thousands of sorbent materials for DAC is a good example of this kind of dataset, enabling multiple teams to train AI models for more extensive and focused rapid materials discovery for DAC.[33]

While *ab initio* calculations will probably remain the most accurate method of predicting materials properties for some time, AI methods have begun to produce impressive results compared to first-principles calculations. For example, an artificial neural network was recently developed to predict key characteristics of the surfaces of binary and ternary oxides, materials that may be useful as PVs and photocatalysts.[34] AI can also be used to accelerate experimental characterization of materials, leading to much more efficient use of limited experimental resources. For example, x-ray diffraction (XRD), which measures the pattern of diffraction of x-rays that hit a sample, is a common technique for examining the crystal structure of materials (such as changes in cathode phases during battery charging). AI models trained on large experimental datasets of diffraction patterns and material crystal structures can directly interpret new XRD data in real time, dramatically speeding up experiments.[35]

An enormous amount of prior materials research is available in scientific journal articles. Researchers typically survey the scientific literature before approaching a new problem, but the large number of relevant articles (often tens of thousands for a single material subtype) makes this process extremely difficult and prone to error and bias. AI in the form of natural language processing (NLP) can be used to extract information from these research articles and structure it systematically, known as "knowledge discovery."[36,37] NLP models trained on non-technical language struggle to handle scientific text, but materials-research-specific language models with better performance have begun to emerge.[38] With the broad introduction of large language models (LLMs) in 2022, progress in materials-science knowledge discovery has begun to accelerate dramatically.[39]

The complexity of advanced materials means that the process used to synthesize (produce) them must be tightly controlled. Small changes in process parameters can result in different, less useful materials, so identifying and optimizing synthesis parameters is crucial. AI-based knowledge-discovery techniques have been successfully applied to the materials research literature to identify precise synthesis steps for key materials from thousands of research papers. For example, researchers used a neural-network-based NLP method to search 22,000 journal articles and extract precise synthesis parameters for optimized titania nanotubes.[40]

Researchers are increasingly working to combine these use cases in integrated "autonomous materials" laboratories. These laboratories combine novel material formulations discovered by AI with physical synthesis guided by specific steps that other AI models summarize from the scientific literature. One recent example allowed the direct synthesis and testing of 41 novel compounds over 17 continuous days of operation.[41] However, designing these autonomous materials laboratories is challenging and requires new thinking about reproducibility and robust handling of various types of errors that can occur in real-world experimental settings.[42] Ultimately, these types of laboratories should aim to achieve a positive feedback loop that integrates AI-guided theoretical materials design, automated chemical synthesis of physical samples, and automated materials characterization.[43]

The use of generative AI is also growing rapidly within materials discovery and design. Generative AI can propose new hypothetical materials that are not currently in any materials database and may be dramatically different from those that are. This is particularly powerful for the "inverse design" problem of materials, which starts with a desired property and uses an AI method to propose possible materials structures that may have it. As an example, researchers used a generative adversarial network (GAN) to propose 23 entirely novel structures made from three atoms (magnesium, manganese and oxygen) that displayed excellent properties as photoanodes for water splitting.[44] Similarly, researchers recently used a generative AI method to rapidly design and partially validate novel materials for carbon capture, identifying six candidates with very high capacity for further testing.[45]

D. Barriers

Some important progress has already been made in applying AI techniques to computational materials discovery and design. Expanded research budgets, including additional funding for AI-specific applications in materials science, would make even more progress possible.

While high-speed internet connections have partly equalized access to materials datasets and high-performance computing across the globe (with notable exceptions), the same is not true for physical materials-testing facilities. Real breakthroughs will ultimately depend on coupling AI-enabled computational materials discovery with high-throughput synthesis and testing/characterization.

The vast and growing network of materials databases also poses a challenge for progress. Better integration of these datasets, including better harmonization of their metadata, is needed. This would improve the ability of researchers to train models and query materials properties across the full spectrum of existing data, avoiding silos and misinterpretations due to conflicting definitions. Explicitly encouraging inclusion of null results or failed experiments on materials—an uncommon step in most scientific research—could broaden the value of these datasets and provide more balanced training data for AI models. Governments have difficulty acting on these issues unilaterally since the global materials-science community must align on data exchange and metadata protocols. However, international standards bodies and scientific societies can lead the way through cooperative standards-setting efforts, potentially with government funding for support.[46]

At a system level, the full life-cycle emissions implications of advanced materials are dependent on both the key property of interest (e.g., PV efficiency, CO_2-adsorption capacity, etc.) and the emissions caused by synthesizing (producing) the material. Unfortunately, relatively little attention has been paid to synthesis emissions when discovering or optimizing novel materials, even though different synthesis pathways can have significantly different emissions.[47] More use of AI tools is needed in predicting GHG emissions that would be caused by synthesizing novel materials, preferably in parallel with materials discovery and design efforts. This application of AI would allow better understanding of the complete life-cycle emissions that would result from using a novel material in energy and related technologies.

Finally, advances in accelerating materials discovery and design with AI depend on improving the AI knowledge and skills of the materials-science workforce. Key issues in AI, such as understanding the applicability of trained AI models to problems outside the domain of their training data and quantifying the uncertainty of model predictions, are challenging and likely unfamiliar to conventionally trained materials scientists.[46] AI tools should therefore be incorporated as a central part of materials-science education, and training should also be offered to AI experts who are interested in applying their skills to developing novel materials. These education and training efforts could take place within traditional materials-science curricula or as part of external courses that can ensure the most recent models, numerical algorithms and datasets are presented and continually updated.

E. Risks

Powerful AI-enabled tools and techniques developed for materials innovation could be used to advance materials that enable highly emitting activities. For example, these tools could discover new high-temperature alloys for gas turbines[48] or stronger, more durable alloys for drill bits used in oil and gas drilling.[49] This means that advanced AI models for materials innovation may be "dual use" and lead to the development of high-performance materials that lower the cost of emissions-intensive technologies, undermining momentum toward decarbonization. Policy guardrails are unlikely to be sufficient to address this issue. However, because many emerging decarbonized technologies depend on high-performance materials (as noted above), it may be the case that advanced materials-innovation capabilities are, on balance, more beneficial for low-emitting technologies.

Separately, the pursuit of AI-enabled materials innovation at scale will require resources, and the appropriate allocation of research focus areas may be more challenging than in traditional materials-discovery contexts. In particular, the inherent scaling advantages of AI may make it optimal to concentrate research efforts and data into a smaller number of larger research groups than is currently the case. This concentration could lead to "neglected" areas of materials innovation that fall outside of the increasingly centralized research agendas. Reasonable efforts to maintain a diversity of research teams leveraging AI models for materials innovation that are focused on enabling low-emissions technologies should be sufficient to address this risk.

F. Recommendations

1. *National governments should increase R&D budgets for AI-enabled materials discovery, with a focus on holistic design considerations that include full life-cycle GHG emissions. Support should also be made available for creating new automated and partly autonomous materials-testing laboratories in a variety of locations around the world. By combining AI and robotics, these facilities could unlock broad global access to rapid iterations in materials design and testing, reducing the challenges of participating in advanced materials development for researchers in resource-limited countries.*[50]
2. *Private companies should engage directly with AI-guided materials-discovery efforts by clarifying manufacturability constraints and offering embedded emissions guidelines. This could also include articulating specific materials classes of interest for commercially relevant low-carbon technologies and issuing benchmarks and/or targets for key performance thresholds.*
3. *National governments, academia and private companies should collaborate to develop and release (or expand existing) AI-ready datasets of material properties that can be used by other research teams to train high-performance models. This effort should use standard data formats and be at least loosely coupled to materials-synthesis and -testing facilities to validate results.*
4. *National governments and academia should support increased education in AI techniques as part of materials-science and related degree programs.*
5. *Scientific publishers should ensure that research publications are fully compatible with AI-guided research synthesis methods, including retroactively converting historical publications.*

G. References

1 Seymour 2023. Hot mixing: Mechanistic insights into the durability of ancient Roman concrete. 1-13 (2023). https://www.science.org/doi/10.1126/sciadv.add1602

2 Rebecca Matulka & Daniel Wood. *History of the Light Bulb;* DOE, https://www.energy.gov/articles/history-light-bulb (2013).

3 Cai Guise-Richardson. Redefining Vulcanization: Charles Goodyear, patents, and industrial control, 1834-1865. *Technology and Culture* 51, 357-387 (2010). https://doi.org/10.1353/tech.0.0437.

4 M. V. Reddy *et al.* Brief History of Early Lithium-Battery Development. *Materials (Basel)* 13 (2020). https://doi.org/10.3390/ma13081884.

5 Jürgen Janek & Wolfgang G. Zeier. Challenges in speeding up solid-state battery development. *Nature Energy* 8, 230-240 (2023). https://doi.org/10.1038/s41560-023-01208-9.

6 Ivana Hasa, Nuria Tapia-Ruiz & Montserrat Galceran. Editorial: Sodium-ion batteries: From materials discovery and understanding to cell development. *Frontiers in Energy Research* 10 (2022). https://doi.org/10.3389/fenrg.2022.1076764.

7 Tanay Sahu, Kulbir K. Ghuman & Paul G. O'Brien. in *Progress in Sustainable Development* (eds David Ting & Paul O'Brien) 205-232 (Elsevier, 2023, https://doi.org/10.1016/B978-0-323-99207-7.00003-8).

8 Yuhou Pei, Heng Zhong & Fangming Jin. A brief review of electrocatalytic reduction of CO2—Materials, reaction conditions, and devices. *Energy Science & Engineering* 9, 1012-1032 (2021). https://doi.org/10.1002/ese3.935.

9 Luca Ansaloni, Ben Alcock & Thijs A. Peters. Effects of CO2 on polymeric materials in the CO2 transport chain: A review. *International Journal of Greenhouse Gas Control* 94, 102930 (2020). https://doi.org/10.1016/j.ijggc.2019.102930.

10 Shuji Nakamura. Background story of the invention of efficient blue InGaN light emitting diodes (Nobel Lecture). *Annalen der Physik* 527, 335-349 (2015). https://doi.org/10.1002/andp.201500801.

11 Kevin Lane. *LIGHTING;* https://www.iea.org/energy-system/buildings/lighting (accessed October 2024).

12 Modupeola Dada & Patricia Popoola. Recent advances in solar photovoltaic materials and systems for energy storage applications: a review. *Beni-Suef University Journal of Basic and Applied Sciences* 12, 66 (2023). https://doi.org/10.1186/s43088-023-00405-5.

13 A. V. Pradeep *et al.* A comprehensive review on contemporary materials used for blades of wind turbine. *Materials Today: Proceedings* 19, 556-559 (2019). https://doi.org/10.1016/j.matpr.2019.07.732.

14 Michael Hirscher *et al.* Materials for hydrogen-based energy storage – past, recent progress and future outlook. *Journal of Alloys and Compounds* 827, 153548 (2020). https://doi.org/10.1016/j.jallcom.2019.153548.

15 Ahmed Sajid *et al.* A perspective on development of fuel cell materials: Electrodes and electrolyte. *International Journal of Energy Research* 46, 6953-6988 (2022). https://doi.org/10.1002/er.7635.

16 Wen Zhang & Jun Xu. Advanced lightweight materials for Automobiles: A review. *Materials & Design* 221, 110994 (2022). https://doi.org/10.1016/j.matdes.2022.110994.

17 D. C. Savitha *et al.* Refrigerants for sustainable environment – a literature review. *International Journal of Sustainable Energy* 41, 235-256 (2022). https://doi.org/10.1080/14786451.2021.1928129.

18 S. T. Vagge & Suraj Ghogare. Thermal barrier coatings: Review. *Materials Today: Proceedings* 56, 1201-1216 (2022). https://doi.org/10.1016/j.matpr.2021.11.170.

19 R. P. Singh, V. K. Mishra & R. K. Das. Desiccant materials for air conditioning applications - A review. *IOP Conference Series: Materials Science and Engineering* 404, 012005 (2018). https://dx.doi.org/10.1088/1757-899X/404/1/012005.

20 Christoph Felix Niedik *et al.* Improvement of high voltage direct current material properties upon tailoring the morphology of crosslinked polyethylenes. *Polymer Crystallization* 4, e10208 (2021). https://doi.org/10.1002/pcr2.10208.

21 Alexander Molodyk & David C. Larbalestier. The prospects of high-temperature superconductors. *Science* 380, 1220-1222 (2023). https://doi.org/10.1126/science.abq4137.

22 J. M. D. Coey. Perspective and Prospects for Rare Earth Permanent Magnets. *Engineering* 6, 119-131 (2020). https://doi.org/10.1016/j.eng.2018.11.034.

23 J. Georg Bednorz & K. Alex Müller. Perovskite-Type Oxides—the New Approach to High-Tc Superconductivity. Nobel Lecture. *Angewandte Chemie International Edition in English* 27, 735-748 (1988). https://doi.org/10.1002/anie.198807351.

24 Warren E. Pickett. Electronic structure of the high-temperature oxide superconductors. *Reviews of Modern Physics* 61, 433-512 (1989). https://doi.org/10.1103/RevModPhys.61.433.

25 R. Ramprasad *et al.* Recent advances in first principles computations in materials research. *Journal of Materials Science* 47, 7313-7316 (2012). https://doi.org/10.1007/s10853-012-6736-0.

26 The Materials Project. *The Materials Project: A materials genome approach to accelerating materials innovation;* https://next-gen.materialsproject.org/ (Acessed August 2024).

27 NOMAD. *Materials science data managed and shared;* Humbolt University of Berlin, https://nomad-lab.eu/nomad-lab/ (2023).

28 University of Tokyo. *MateriApps;* https://ma.issp.u-tokyo.ac.jp/en (2023).

29 Peter Kirkpatrick & Clare Ellis. Chemical space. *Nature* 432, 823-823 (2004). https://doi.org/10.1038/432823a.

30 Stefan Heinen *et al.* Machine learning the computational cost of quantum chemistry. *Machine Learning: Science and Technology* 1, 025002 (2020). https://doi.org/10.1088/2632-2153/ab6ac4.

31 Chi Chen & Shyue Ping Ong. A universal graph deep learning interatomic potential for the periodic table. *Nature Computational Science* 2, 718-728 (2022). https://doi.org/10.1038/s43588-022-00349-3.

32 Amil Merchant *et al.* Scaling deep learning for materials discovery. *Nature* 624, 80-85 (2023). https://doi.org/10.1038/s41586-023-06735-9.

33 Anuroop Sriram *et al.* The Open DAC 2023 Dataset and Challenges for Sorbent Discovery in Direct Air Capture. *ACS Central Science* 10, 923-941 (2024). https://doi.org/10.1021/acscentsci.3c01629.

34 Shin Kiyohara, Yoyo Hinuma & Fumiyasu Oba. Band Alignment of Oxides by Learnable Structural-Descriptor-Aided Neural Network and Transfer Learning. *Journal of the American Chemical Society* 146, 9697-9708 (2024). https://doi.org/10.1021/jacs.3c13574.

35 Nathan J. Szymanski *et al.* Adaptively driven X-ray diffraction guided by machine learning for autonomous phase identification. *npj Computational Materials* 9, 31 (2023). https://doi.org/10.1038/s41524-023-00984-y.

36 Olga Kononova *et al.* Opportunities and challenges of text mining in materials research. *iScience* 24, 102155 (2021). https://doi.org/10.1016/j.isci.2021.102155.

37 Edward O. Pyzer-Knapp *et al.* Accelerating materials discovery using artificial intelligence, high performance computing and robotics. *npj Computational Materials* 8, 84 (2022). https://doi.org/10.1038/s41524-022-00765-z.

38 Tanishq Gupta *et al.* MatSciBERT: A materials domain language model for text mining and information extraction. *npj Computational Materials* 8, 102 (2022). https://doi.org/10.1038/s41524-022-00784-w.

39 Yiwen Hu & Markus J. Buehler. Deep language models for interpretative and predictive materials science. *APL Machine Learning* 1 (2023). https://doi.org/10.1063/5.0134317.

40 Edward Kim *et al.* Materials Synthesis Insights from Scientific Literature via Text Extraction and Machine Learning. *Chemistry of Materials* 29, 9436-9444 (2017). https://doi.org/10.1021/acs.chemmater.7b03500.

41 Nathan J. Szymanski *et al.* An autonomous laboratory for the accelerated synthesis of novel materials. *Nature* 624, 86-91 (2023). https://doi.org/10.1038/s41586-023-06734-w.

42 Zhichu Ren *et al.* Autonomous experiments using active learning and AI. *Nature Reviews Materials* 8, 563-564 (2023). https://doi.org/10.1038/s41578-023-00588-4.

43 Santiago Miret *et al.* Perspective on AI for accelerated materials design at the AI4Mat-2023 workshop at NeurIPS 2023. *Digital Discovery* 3, 1081-1085 (2024). http://dx.doi.org/10.1039/D4DD90010C.

44 Sungwon Kim *et al.* Generative Adversarial Networks for Crystal Structure Prediction. *ACS Central Science* 6, 1412-1420 (2020). https://doi.org/10.1021/acscentsci.0c00426.

45 Hyun Park *et al.* A generative artificial intelligence framework based on a molecular diffusion model for the design of metal-organic frameworks for carbon capture. *Communications Chemistry* 7, 21 (2024). https://doi.org/10.1038/s42004-023-01090-2.

46 Dane Morgan & Ryan Jacobs. Opportunities and Challenges for Machine Learning in Materials Science. *Annual Review of Materials Research* 50, 71-103 (2020). https://doi.org/10.1146/annurev-matsci-070218-010015.

47 Carlos A. Grande *et al.* Life-cycle assessment as a tool for eco-design of metal-organic frameworks (MOFs). *Sustainable Materials and Technologies* 14, 11-18 (2017). https://doi.org/10.1016/j.susmat.2017.10.002.

48 D. Sauceda *et al.* High throughput exploration of the oxidation landscape in high entropy alloys. *Materials Horizons* 9, 2644-2663 (2022). http://dx.doi.org/10.1039/D2MH00729K.

49 Ruizhi Zhong, Cyrus Salehi & Ray Johnson. Machine learning for drilling applications: A review. *Journal of Natural Gas Science and Engineering* 108, 104807 (2022). https://doi.org/10.1016/j.jngse.2022.104807.

50 Nature Synthesis Editorial. Automate and digitize. *Nature Synthesis* 2, 459-459 (2023). https://doi.org/10.1038/s44160-023-00354-y.

CHAPTER 14:

EXTREME WEATHER RESPONSE

Alice C. Hill and Colin McCormick

A. Forecasting and Early Warning 14-2

B. Changing Risk Picture 14-3

C. How Can AI Improve Forecasting? 14-4

D. Barriers 14-8

E. Risks 14-10

F. Recommendations 14-11

G. References 14-12

In 2023, the Earth experienced its hottest year in recorded history, primarily due to the burning of fossil fuels and land-use change.[1] To reduce future heating, more than 190 nations have agreed on the necessity of reducing the greenhouse gas (GHG) pollution that causes climate change.[2] Yet that pollution—and temperatures—continue to rise. With higher temperatures have come more extreme weather events, such as deeper droughts, more intense storms, bigger wildfires and extended heat waves. Sea-level rise has also accelerated. These climate-worsened events have caused economic damage. Researchers estimate that from 2000 to 2019, 185 climate-worsened events caused $2.86 trillion in global damages, averaging $143 billion per year, a figure the researchers say likely underestimates the full harm.[3]

Even if nations succeed in aggressively cutting GHG emissions, accumulated atmospheric pollution will continue to drive new climate-worsened extremes for at least the next few decades. Those extremes require humans to adapt. Climate adaptation involves preparing for and building resilience to the current and looming impacts of climate change. Adaptation efforts can protect lives, livelihoods, infrastructure and ecosystems. They can also save money. According to the Global Commission on Adaptation, investments in adaptation carry a high rate of return: an estimated $2 to $10 or more for every $1 spent.[4]

Adaptation can take many forms, over many different timescales. On the scale of years to decades, the construction of climate-resilient physical infrastructure—such as power grids, roads, and flood and heat protection measures—can ensure continuity of critical services during extreme weather. On the scale of months, improved management of seasonal agriculture planting and harvesting can ensure food supplies. And on short timescales (days to weeks) improved forecasting and early warning serves as one of the most important adaptation measures to reduce economic damage and save lives. This chapter explores how artificial intelligence (AI) can enhance adaptation in the essential area of forecasting and early warning of extreme weather events, including wildfires and extreme flooding.

A. Forecasting and Early Warning

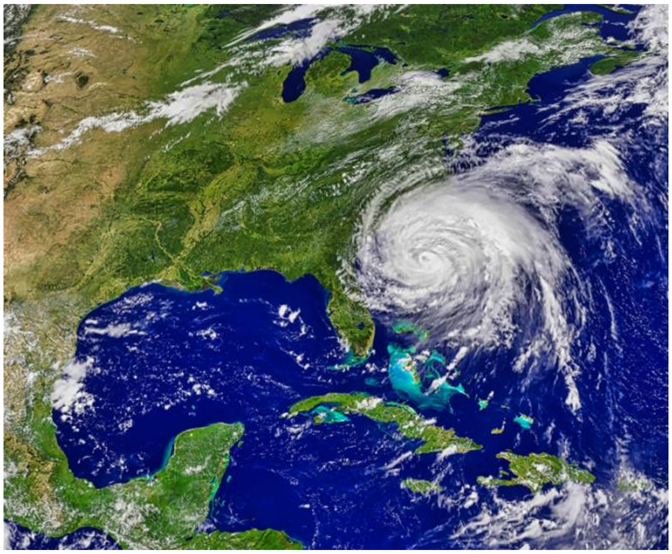
Accurate weather data and forecasting can assist people in adapting to climate change by giving them additional time to prepare for damaging events. For example, in the near term, storm forecasts can provide people time to seek shelter or evacuate and take resilience measures to reduce damage to structures, like removing flammable materials outside and protecting windows from high winds. Similarly, near-term forecasts can aid utilities in managing electricity production and transmission during extreme heat events. Seasonal forecasts can assist farmers in making better decisions as to when to irrigate, plant and harvest. They can also inform continuity planning for businesses worried about weather disruptions to supply chains. Multi-year forecasts can help building owners and city planners make informed decisions about where and how to build facilities that can withstand climate-worsened extremes.

In recent years, near-term forecasting has attracted significant attention. Improved forecasting of impending extreme events saves lives when coupled with early warning. These systems can also empower people to take action to reduce the risk of economic harm from worsening climate extremes. For example, people could move livestock to higher ground as storms approach or shut down electricity production as winds increase the risk of downed wires sparking wildfire.

The safety and economic benefits of improved weather forecasts are large. One World Bank analysis estimated that early warning systems could reduce annual deaths from weather events and cut economic losses from disasters by $35 billion per year.[5] In the US, forecasting improvements since 2007 have saved an average of $5 billion per hurricane.[6] However, about a third of the world's population lives in areas without early warning systems.[7] Countries that have limited or only modest weather forecasting and early warning coverage suffer disaster-related deaths at nearly six times the rate of countries with better coverage.[8]

In 2022, the United Nations called for a concerted global effort to improve early warnings for all by 2027.[9] The number of countries with early warning systems has increased since 2015 when the World Meteorological Organization (WMO) and other international groups launched the Climate Risk and Early Warning Systems initiative. This initiative aimed at increasing the capacity of least-developed and small-island nations to generate early warnings for seventeen hazards, ranging from flood to drought to sand and dust storms. In some places coverage includes seasonal outlooks.[10] But only about half of all nations currently have adequate systems, with many countries in Africa, the Caribbean, the Americas and the Pacific experiencing significant gaps in coverage.[8]

Weather forecasting has improved in recent years with the help of increased satellite data, better algorithms and evolving understanding of weather patterns.[8] However, climate change has made forecasting more complex because it is shifting traditional weather patterns and changing the frequency and intensity of extreme weather events.[11] There is considerable uncertainty about whether this shift will impact the accuracy of weather forecasting. Stanford University researchers found that for every Celsius degree of warning, the reliable forecast window may decrease in certain locations.[12] However, other researchers argue that a changing climate does not inherently lead to more difficulty in making predictions or less accurate weather predictions.[13] The introduction of AI-based weather forecasting models further complicates this picture.



B. Changing Risk Picture

Despite continuing improvements in forecasting, escalating risks and damage from climate-worsened events sharpens the need for improved forecasting and early warning. Damage from climate extremes has climbed in recent years and is predicted to continue to rise. In 2023 alone, the United States suffered almost $95 billion dollars in damages from 28 separate extreme events.[14] By 2050, "global annual damages are estimated to be at 38 trillion dollars

annually.”[15] According to World Bank data, five health risks worsened by a warmer climate could lead to at least 21 million deaths by 2050.[16]

Consider the changing risk picture for wildfire. Climate change brings higher temperatures that can reduce humidity in the air, which in turn can dry out vegetation and lower soil moisture content. It also can produce intense winds. All these factors can lead to bigger and more intense wildfires. According to an analysis of satellite data, the frequency of extreme fires has more than doubled from 2003 to 2023. An explosion of extreme fires has occurred in Canada, the United States and Russia.[17] Some parts of the western United States experience two more months of wildfire weather than a century ago.[18] The UN Environment Programme estimates the number of wildfires will increase 50 percent by 2100.[19]

Climate change has similarly altered the risk picture for flooding. A warmer atmosphere can hold more moisture. This increase can lead to extreme rainfall, otherwise known as “rain bombs,” that overwhelm existing flood infrastructure. Changing snowmelt patterns from higher temperatures can extend flood seasons in some areas. Higher ocean temperatures mean that storms can pull in more water vapor and heat, leading to stronger winds, higher storm surge and heavier rainfall. All of this can lead to more flooding when storms make land fall. Rising sea levels also add to tidal and coastal flood risk. Ocean warming can cause hurricanes to intensify more rapidly, leaving people less time to prepare. Scientists predict that climate change will drive greater flooding in the future. For example, according to the Human Climate Horizons platform, a collaboration between the Climate Impact Lab and the United Nations Development Programme (UNDP), in the past two decades, sea level rise alone has expanded the areas prone to flooding to places where over 14 million people live. By 2100, flood-prone areas will expand to places populated by over 73 million people.[19]

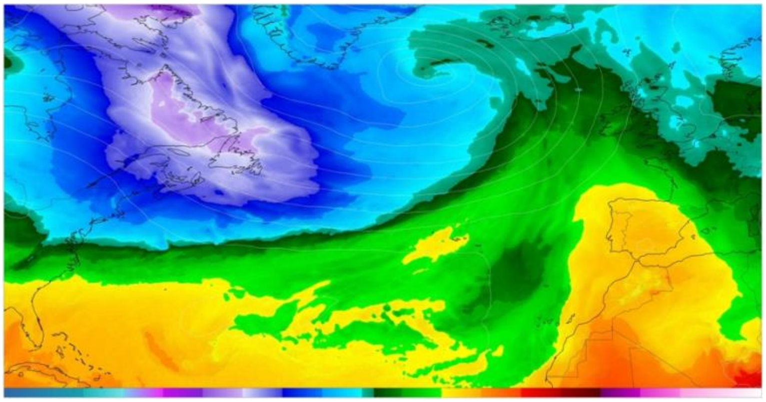
C. How Can AI Improve Forecasting?

AI can significantly enhance the accuracy of weather forecasting and reduce the cost and energy consumption of running forecasting computer models. Current state-of-the-art conventional medium-range weather forecasting models include the Global Forecast System (GFS) of the US National Oceanic and Atmospheric Administration (NOAA)[14] and the Integrated Forecasting System (IFS) of the European Centre for Medium-Range Weather Forecasts (ECMWF).[20] These numerical weather prediction (NWP) models solve complex physics-based equations for atmospheric, ocean and land behavior using best available science for the underlying interactions of heat, pressure, moisture and other fundamental physical and chemical parameters.

Typically, a single "run" of these models starts with the most recent observational data from satellites and weather stations and then calculates solutions for the equations at each hour in the future, up to 10–14 days in advance. Because weather systems are constantly changing, the error in the forecast grows dramatically at later times, using current models.[21] Spatially, the model calculates the solutions at each location on a global grid with horizontal spacing of ~13 km at the surface and roughly 100 vertical layers throughout the atmosphere. The solution outputs include temperature, pressure, wind speed, precipitation, soil moisture and many other variables.

National weather services, such as NOAA, run their primary medium-range weather model several times in a single day, using updated observational data each time, and continually release revised forecasts. Because of the size and complexity of these models, they require supercomputers and may take several hours to complete, consuming large amounts of energy in the process. (See Box 14-1.) These models could run faster if they used a sparser grid (e.g., only producing solutions every 20–30 km) or less frequent time intervals (e.g., only producing solutions for 2-hour intervals rather than hourly), but this would reduce the quality and value of the forecasts.

Many countries are unable to afford the supercomputing facilities and expert meteorology teams required to run these state-of-the-art weather models. The high cost and large energy consumption of conventional weather models has driven much of the interest in developing AI-based weather models. In general, these models run with vastly smaller computing power, meaning they could potentially use higher-resolution spatial grids and shorter time steps and/or be updated more frequently compared to conventional models. However, for this to be a widely accepted approach, AI-based weather models must demonstrate that they can achieve similar or better accuracy than conventional models, which use a full simulation of key atmospheric physics and chemistry equations.



In 2023, Huawei, a Chinese communications technology conglomerate, released the first AI-based weather model that not only matched the accuracy of conventional models, but significantly outperformed them.[22] Instead of using physics-based equations, Huawei's PanguWeather (PGW) is based on a deep neural network trained on almost 40 years of historical observed weather data (ERA5[23]). This enables it to emulate the statistical patterns hidden in that dataset. Compared to the ECMWF's IFS model, it has smaller error in most cases (i.e., the forecasted weather vs the actual weather). Given the need for accuracy in forecasts, this result helped galvanize interest in AI-based weather forecasting.

PGW also runs approximately 10,000 times faster than IFS, a huge reduction in cost and energy consumption. Ongoing studies of PGW (which is open source for noncommercial use) in an operational environment show that, for many tasks, its accuracy is comparable to IFS or better (still at vastly lower compute cost), although it underperforms in others.[24]

Since the release of PGW, several other companies have released AI-based weather forecasting models, including GraphCast by Google, an American technology company. GraphCast also performs very well compared to IFS in many contexts.[25] While private technology companies have largely driven the development of these models, government agencies have directly collaborated on their development in some cases. For example, the ECMWF worked with Google to develop GraphCast, and NASA is collaborating with IBM to release the Prithvi-weather-climate model.[26]

AI-based weather forecasting models can assist in a variety of adaptation-related tasks, including extreme weather forecasting coupled with early warnings. The low cost and improved accuracy of AI-based weather forecasting could potentially make the UN goal of "early warning for all by 2027" more achievable.

Box 14-1

Energy Consumption of AI-Based Weather Forecasting Models

AI-based weather models consume much less energy on a life-cycle basis than conventional weather models. Although they require large amounts of energy to train, they consume very little energy to use for weather forecasting (approximately 1000x less than conventional models). This dramatic energy benefit can translate into lower costs and can help improve access to weather forecasting globally.

AI models consume energy during two main phases of their life-cycle: *training* and *use* (or "inference"). During training, the parameters of an AI model (which may number in the billions) are gradually adjusted to make the model's output match patterns in a set of training data. In the case of weather forecasting, the training data are historic weather observations, and the goal of training is to "tune" the AI model to be able to output the weather patterns that were observed in the past. (In the case of LLMs, the training data are thousands to millions of documents spanning many types of writing.)

Training an AI weather model can consume large amounts of energy. For example, training Google's GraphCast model took approximately 4 weeks (28 days) of continuous processing on 32 TPU v4 devices (similar to GPUs).[25] Because these devices have an average power consumption of 200 W, the electricity consumed in training one version of the model was about 4.3 MWh.[27] If this electricity was supplied by average US grid power, it would have resulted in 1.7 tCO_2 of emissions.[28] The overall model creation process typically involves repeating this training process several times (at least four versions of GraphCast were trained, for comparison), so the total energy consumption could be an order of magnitude larger. However, Google (like many other data center operators) supplies some of its data center power using renewable energy, so the CO_2 emissions may have been substantially lower.[29] AI weather models will need to be retrained occasionally, consuming additional energy, but this is likely to be infrequent.

Using a trained AI weather model to make a single forecast consumes far less energy than the training phase. The GraphCast model can calculate a 10-day weather forecast in under 1 minute on a single TPU,[25] implying that the electricity consumption for making this forecast is only a few Watt-hours, or approximately 1 million times less than the training phase. Of course, under normal forecasting operations the model would run multiple times a day to update forecasts, repeated every day for the foreseeable future. Nevertheless, the cumulative electricity consumed during the use phase would likely be quite small.

By contrast, current leading medium-range weather models, such as the European Centre for Medium-Range Weather Forecasts' (ECMWF's) Integrated Forecast System (IFS), take multiple hours to run on a large supercomputer and consume tens of kWh per run.[30] These models do not require training, so the only energy consumption is during the use phase (although there are embedded CO_2 emissions from producing the dedicated supercomputing equipment). These comparisons must be viewed carefully because the models do not necessarily produce solutions at the same spatial resolution; however, the general comparison is broadly correct.

In addition to predicting extreme weather events, related AI-based models can increasingly provide early warning for river flooding and wildfires. For example, Google and ECMWF recently collaborated to demonstrate a flood prediction model based on a deep neural network that can predict river flood events with a five-day lead time and comparable accuracy to same-day lead time predictions from the conventional Global Flood Awareness System.[31,32] Google now makes predictions available for free and in real time to dozens of countries.[33]

Companies have also developed AI models to predict where wildfires are likely to ignite. For example, Athena Intelligence's model aims to identify the probability of a wildfire occurring within a specific geographic area, the potential severity and intensity of that wildfire, and the potential losses if such a wildfire were to happen. AI-driven prediction models primarily use remote sensing data, and recent results are quite promising in terms of both high accuracy and low computational cost.[20,34] Some emerging use cases of AI for wildfire focus more on early/rapid detection of new wildfires. This includes systems in several US states, including California and Oregon, that use networks of cameras and AI to automatically identify wildfires soon after they ignite. These systems aim to optimize allocation of scarce firefighting resources and potentially extinguish fires before they spread.[35,36] In Türkiye, the World Economic Forum (WEF) has worked to develop the FireAId program, which uses AI to create an interactive map of fire risk. That initiative has predicted wildfire outbreaks 24 hours in advance with high accuracy.[37]

Longer-term forecasts also help climate adaptation, including efforts to limit crop failures during droughts. The time horizon for useful predictions of these events runs from weeks to months since adaptation actions, such as food shipments or water conservation, take this long to implement. Application of AI to drought prediction has begun to make significant progress, although important challenges remain.[38-41] Several government-led projects focus on applying AI to prediction of drought, including the European Space Agency's AI for Drought project[42] and NASA's TERRAHydro software system.[43] The AI for Drought initiative has downscaled existing satellite-based drought prediction estimates to make them higher resolution and thus more geographically precise.[44]

D. Barriers

Despite the ability of AI to improve forecasting and early warnings, barriers to adoption remain. Those barriers include insufficient data and technical expertise and capacity, lack of confidence, lack of supporting infrastructure, and financial constraints.

i. Insufficient Data

AI systems are only as good as the data used to train them.[45] Limited or incomplete data for certain weather conditions can impair accuracy. Since AI models rely on historical data, they may struggle with the more extreme, record-breaking events that climate change brings.[46] This challenge becomes even more acute in developing countries that lack high-resolution observational data about atmospheric or other conditions. For example, India has close to 10,000 glaciers in the Himalayas, yet it has detailed *in situ* data on only 30 of those.[47] Inaccurate or incomplete data can degrade the quality of predictions.[48] While satellite-derived datasets on important parameters, such as land

surface temperature and vegetation, are globally available, other important input parameters for training data sets are far more available in developed countries than in developing ones.[49]

Although the WMO has pushed for greater standardization of observing practices and instrumentation, when it comes to weather forecasting, different countries use different technologies and have different hardware standards. Differences arise in the level of resolution, with some countries prioritizing high-resolution localized forecasts while others focus on broader forecasting. Countries also use different combinations of data sources, be it on-the-ground observations or satellite data. And of course, some countries lack sufficient resources and technology to support robust weather forecasting, with high-income countries enjoying more accurate forecasts as a result.

ii. Insufficient Technical Expertise and Capacity

Human expertise is essential for interpreting results and handling complexities that AI models may not be able to interpret. Currently only a limited pool of human capital and expertise exists. The lack of talent is particularly challenging for public agencies since they often cannot compete with private salaries. This will make it imperative for governments to invest in recruiting, training and retaining AI experts.

iii. Lack of Confidence

With AI weather-forecasting models, results are not easily traced back to the tens of millions of underlying assumptions upon which they rest.[46] These models are a "black box", often lacking transparency as to how conclusions are reached. Thus, some meteorologists may be hesitant to rely on AI-based predictions since, if they are wrong, it is difficult to understand why. This issue is the focus of substantial research, and more "interpretable" AI models may eventually be developed.[50] For example, in the United States, NOAA has taken a cautious approach to adopting recent technologies, including AI, although it is working to integrate AI and understand the opportunities and obstacles.[51]

iv. Lack of Supporting Infrastructure

Translating forecasts into actionable information requires supporting infrastructure. For example, ready access to the internet can speed dissemination and receipt of warnings based on a storm forecast. But some communities and individuals may lack internet access, or power failures may impede dissemination.[8] Currently only about 20 percent of poor nations have a plan to act on early warnings as compared to about half of the nations in the Asia-Pacific region.[52]

v. Financial Constraints

Lack of adequate funding will remain a challenge, both for research and development (R&D) of early warning systems and for their deployment and use. Establishing an early warning system takes money. So does maintenance of the system. Developing complex AI models requires significant computational resources (although they require far fewer to use operationally).[48] Because weather patterns and climate conditions are dynamic, AI models also need updating and retraining to capture the latest information.[48]

Government agencies will likely require additional funding to evaluate emerging technologies for accuracy and reliability. Given the speed with which these technologies are changing, the need for funding could increase over time.

E. Risks

While the accuracy of some flagship AI medium-term weather models is high, they do not currently perform as well as conventional models in some areas, such as forecasting tropical cyclone intensity.[24] They may need to be deployed in combination with conventional models, with the forecasts integrated or synthesized.

The relative ease and low cost of AI-based weather forecasting may undermine support for public meteorological agencies, as some policymakers may conclude that they are no longer necessary. Lack of adequate funding could undermine the ability of public meteorological agencies to assess and understand the performance of AI-based models and to collect the observational data on which these models are based. This in turn could increase dependency on private sector companies for the public service of weather forecasting.

While major private companies currently offer these flagship AI weather models as open source, that could change in the future. Legislators should carefully weigh the appropriate role of public funding as opposed to private development.

F. Recommendations

1. *National governments, international organizations, and the private sector should invest in AI models that increase accuracy, improve the timeliness and reduce the cost of extreme weather event forecasts. They should also collaborate on ways to evaluate accuracy and to develop frameworks that promote long-term sustainability.*
2. *National governments should:*
   - *continue collecting and publishing weather data as a foundational public service;*
   - *provide a base level of access for poorer communities and countries;*
   - *explore innovative programs to attract the necessary talent to lead public AI systems (this could include government-sponsored fellowships, additional compensation and opportunities for continued education);*
   - *integrate AI training into professional development programs for meteorologists and climate scientists working in public sector weather agencies;*
   - *ensure robust understanding of the limitations and opportunities of AI-assisted forecasting and early warning; and*
   - *promote and construct necessary infrastructure to disseminate forecasts and warnings effectively.*
3. *National governments and international organizations should develop the capacity to build and use cutting-edge AI-based weather models as those models improve in the years ahead. Public-private partnerships are important for equity. National governments and international organizations should also support the expansion of AI-based early warning systems for extreme weather to underserved regions, ensuring equitable access and bridging the gap in global forecasting capabilities.*
4. *National governments, international organizations, and the private sector should prioritize collection and integration of weather and climate data from the global south and provide technical support for adopting AI-based forecasting models to countries that have previously lacked advanced forecasting capabilities due to resource constraints.*
5. *Research institutions and AI developers should prioritize creating AI models that are transparent and interpretable to help meteorologists and emergency responders gain trust in AI-generated weather predictions.*
6. *Emergency management and humanitarian aid agencies should implement AI-driven decision support systems to optimize response strategies during extreme weather events, such as evacuations or resource allocation, based on real-time data and predictions.*

G. References

1 Angela Colbert & Sally Younger. *Five Factors to Explain the Record Heat in 2023;* NASA Earth Observatory, Greenbelt, Maryland, https://earthobservatory.nasa.gov/images/152313/five-factors-to-explain-the-record-heat-in-2023#:~:text=But%20what%20caused%202023%2C%20especially,gases%20is%20the%20primary%20driver (2023).

2 United Nations Framework Convention on Climate Change (UNFCCC). *The Paris Agreement;* Bonn, Germany, https://unfccc.int/process-and-meetings/the-paris-agreement (Accessed August 2024).

3 Rebecca Newman & Ilan Noy. The global costs of extreme weather that are attributable to climate change. *Nature Communications* 14, 6103 (2023). https://doi.org/10.1038/s41467-023-41888-1.

4 Susannah Fisher, Sophie Dicker & Georgina Kyriacou. *What is climate change adaptation?;* Grantham Research Institute on Climate Change and the Environment at the London School of Economics and Political Science (LSE) (republished from The Guardian), London, UK, https://www.lse.ac.uk/granthaminstitute/explainers/what-is-climate-change-adaptation/ (2021).

5 Stéphane Hallegatte. *Early Warning Weather Systems Have Very Real Benefits;* World Bank Blogs, Washington, D.C., https://blogs.worldbank.org/en/developmenttalk/early-warning-weather-systems-have-very-real-benefits (2012).

6 Renato Molina & Ivan Rudik. *The Social Value of Hurricane Forecasts;* National Bureau of Economic Research (NBER), Cambridge, Massachusetts, http://www.nber.org/papers/w32548; https://www.doi.org/10.3386/w32548 (2024).

7 Lara Loussert *et al. Scaling up early warning systems for communities in fragile and conflict zones;* World Bank Blogs, Washington, D.C., https://blogs.worldbank.org/en/dev4peace/scaling-early-warning-systems-communities-fragile-and-conflict-zones (2024).

8 United Nations Office for Disaster Risk Reduction and World Meteorological Organization. *Global status of multi-hazard early warning systems 2023;* Geneva, Switzerland, https://www.undrr.org/reports/global-status-MHEWS-2023 (2023).

9 Amina J. Mohammed. *Secretary-General's message on World Meteorological Day;* United Nations, New York, New York, https://www.un.org/sg/en/content/sg/statement/2022-03-23/secretary-generals-message-world-meteorological-day (2022).

10 Climate Risk & Early Warning Systems Initiative (CREWS). *Annual Report 7 - 2023;* Geneva, Switzerland, https://crews-initiative.org/wp-content/uploads/2024/06/20240605_CREWS_AR_2023_ENG_webspread.pdf (2024).

11 Rebecca Hersher. *FAQ: 5 things to know about weather forecasts and climate change;* National Public Radio (NPR), Washington, DC, https://www.wfae.org/energy-environment/2024-06-11/faq-5-things-to-know-about-weather-forecasts-and-climate-change (2024).

12 Josie Garthwaite. *Climate of chaos: Stanford researchers show why heat may make weather less predictable;* Stanford Report, Stanford, California, https://news.stanford.edu/stories/2021/12/warming-makes-weather-less-predictable (2021).

13 Andrew Moseman. *Will climate change make weather forecasting less accurate?;* Massachusetts Institution of Technology (MIT), Boston, Massachusetts, https://climate.mit.edu/ask-mit/will-climate-change-make-weather-forecasting-less-accurate (2023).

14 NOAA National Centers for Environmental Information (NCEI). *U.S. Billion-Dollar Weather and Climate Disasters;* Stennis Space Center, Mississippi, https://www.ncei.noaa.gov/access/billions/; https://www.doi.org/10.25921/stkw-7w73 (2024).

15 Potsdam Institute for Climate Impact Research (PIK). *38 trillion dollars in damages each year: World economy already committed to income reduction of 19 % due to climate change;* ScienceDaily, Rockville, Maryland, https://www.sciencedaily.com/releases/2024/04/240417131138.htm#:~:text=Overall%2C%20global%20annual%20damages%20are,in%20rainfall%20and%20temperature%20variability (2024).

16 World Bank Group. *Health and Climate Change;* Washington, D.C., https://www.worldbank.org/en/topic/health/brief/health-and-climate-change (2024).

17 Jeff Tollefson. You're not imagining it: extreme wildfires are now more common. *Nature News* (2024). https://www.nature.com/articles/d41586-024-02071-8.

18 Climate Central. *Longer, More Intense Fire Weather Seasons;* Princeton, New Jersey, https://www.climatecentral.org/climate-matters/longer-more-intense-fire-weather-seasons (2024).

19 United Nations Environment Programme. *Spreading like Wildfire: The Rising Threat of Extraordinary Landscape Fires;* A UNEP Rapid Response Assessment, Nairobi, Kenya, https://www.unep.org/resources/report/spreading-wildfire-rising-threat-extraordinary-landscape-fires (2022).

20 European Centre for Medium-Range Weather Forecasts (ECMWF). *Integrated Forecasting System;* Reading, UK, https://www.ecmwf.int/en/forecasts/documentation-and-support/changes-ecmwf-model (Accessed June 2024).

21 Rosella (Qian-Ze) Zhu. *A Sky Full of Data: Weather forecasting in the age of AI;* Harvard Graduate School of Arts and Sciences – Science in the News, Boston, Massachusetts, https://sitn.hms.harvard.edu/flash/2024/ai_weather_forecasting/ (2024).

22 Kaifeng Bi *et al.* Accurate medium-range global weather forecasting with 3D neural networks. *Nature* 619, 533-538 (2023). https://doi.org/10.1038/s41586-023-06185-3.

23 European Centre for Medium-Range Weather Forecasts (ECMWF). *ECMWF Reanalysis v5 (ERA5);* Reading, UK, https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5 (Accessed August 2024).

24 Zied Ben Bouallègue *et al.* The Rise of Data-Driven Weather Forecasting: A First Statistical Assessment of Machine Learning–Based Weather Forecasts in an Operational-Like Context. *Bulletin of the American Meteorological Society* 105, E864-E883 (2024). https://doi.org/10.1175/BAMS-D-23-0162.1.

25 Remi Lam *et al.* Learning skillful medium-range global weather forecasting. *Science* 382, 1416-1421 (2023). https://doi.org/10.1126/science.adi2336.

26 Josh Blumenfeld. *NASA and IBM Research Apply AI to Weather and Climate;* NASA: Earth Data, Washington, D.C., https://www.earthdata.nasa.gov/learn/blog/nasa-ibm-weather-climate-foundation-model (2024).

27 Norm Jouppi & David Patterson. *Google's Cloud TPU v4 provides exaFLOPS-scale ML with industry-leading efficiency;* Google Cloud, Mountain View, California, https://cloud.google.com/blog/topics/systems/tpu-v4-enables-performance-energy-and-co2e-efficiency-gains (2023).

28 US Energy Information Administration (EIA). *Frequently Asked Questions (FAQs): How much carbon dioxide is produced per kilowatthour of U.S. electricity generation?;* Washington, D.C., https://www.eia.gov/tools/faqs/faq.php?id=74&t=11 (Accessed August 2024).

29 Google. *2024 Environmental Report;* Mountain View, California, https://sustainability.google/reports/google-2024-environmental-report/ (2024).

30 Peter Bauer *et al. The ECMWF scalability programme: Progress and plans;* European Centre for Medium Range Weather Forecasts, https://doi.org/10.21957/gdit22ulm (2020).

31 Grey Nearing *et al.* Global prediction of extreme floods in ungauged watersheds. *Nature* 627, 559-563 (2024). https://doi.org/10.1038/s41586-024-07145-1.

32 Copernicus Programme. *Global Flood Awareness System;* European Union, Vincennes, France, https://global-flood.emergency.copernicus.eu/ (Accessed August 2024).

33 Google Research. *Flood Hub;* Mountain View, California, https://sites.research.google/floods/l/0/0/3 (Accessed August 2024).

34 Younes Oulad Sayad, Hajar Mousannif & Hassan Al Moatassime. Predictive modeling of wildfires: A new dataset and machine learning approach. *Fire Safety Journal* 104, 130-146 (2019). https://doi.org/10.1016/j.firesaf.2019.01.006.

35 Caitlin Scully. *ALERTCalifornia and CAL FIRE's Fire Detection AI Program Named One of TIME's Best Inventions of 2023;* UC Sand Diego Today, San Diego, California, https://today.ucsd.edu/story/alertcalifornia-and-cal-fires-fire-detection-ai-program-named-one-of-times-best-inventions-of-2023 (2023).

36 University of Oregon. *Wildfire Cameras: A 21st Century Firespotting System;* Eugene, Oregon, https://ohaz.uoregon.edu/wildfire-cameras/ (2024).

37 Marco Aguilar. *The power of AI in wildfire prediction and prevention;* World Economic Forum, Cologny, Switzerland, https://www.weforum.org/impact/artificial-intelligence-wildfire-prediction-and-prevention/ (2023 (Updated 2024)).

38 A. AghaKouchak *et al.* Status and prospects for drought forecasting: opportunities in artificial intelligence and hybrid physical–statistical forecasting. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 380, 20210288 (2022). https://doi.org/10.1098/rsta.2021.0288.

39 Lincoln Laboratory - Massachusetts Institute of Technology. *Artificial Intelligence–Based Drought Prediction;* Lexington, Massachusetts, https://www.ll.mit.edu/r-d/projects/artificial-intelligence-based-drought-prediction (Accessed August 2024).

40 Aldo Márquez-Grajales *et al.* Characterizing drought prediction with deep learning: A literature review. *MethodsX* 13, 102800 (2024). https://doi.org/10.1016/j.mex.2024.102800.

41 Neeta Nandgude *et al.* Drought Prediction: A Comprehensive Review of Different Drought Prediction Models and Adopted Technologies. *Sustainability* 15, 11684 (2023). https://doi.org/10.3390/su151511684.

42 AI for Drought. *Explainable AI and Earth Observation for seasonal drought prediction;* Eurpean Space Agency, Paris, France, https://www.ai4drought.com/ (Accessed August 2024).

43 Gage Taylor. *AI-powered TERRAHydro could help hydrologists better understand the water cycle;* NASA Earth Science Techbology Office (ESTO), Washington, D.C., https://esto.nasa.gov/ai-powered-terrahydro-could-help-hydrologists-better-understand-the-water-cycle/ (2023).

44 Nazanin Behfar *et al.* Drought index downscaling using AI-based ensemble technique and satellite data. *Theoretical and Applied Climatology* 155, 2379-2397 (2024). https://doi.org/10.1007/s00704-023-04822-5.

45 Rob Carey. *Trusted data is the heart of trustworthy AI;* NextGov/FCW (Washington Technology), Washington, D.C., https://www.nextgov.com/ideas/2024/02/trusted-data-heart-trustworthy-ai/394460/ (2024).

46 Lauren Leffer. *AI Weather Forecasting Can't Replace Humans—Yet;* Scientific American, New York, New York, https://www.scientificamerican.com/article/ai-weather-forecasting-cant-replace-humans-yet/ (2024).

47 Nidhi Jamwal. *Data drought: The challenge of AI weather forecasting in India;* Eco-Business, Rochester Commons, Singapore, https://www.eco-business.com/news/data-drought-the-challenge-of-ai-weather-forecasting-in-india/?t&utm_source=perplexity (2024).

48 Snezhanaszillat. *The Role of Artificial Intelligence in Modern Weather Prediction;* Enago Academy, Mumbai, India, https://www.enago.com/academy/guestposts/snezhanaszillat/the-role-of-artificial-intelligence-in-modern-weather-prediction/ (2024).

49 NOAA National Centers for Environmental Information (NCEI). *Integrated Global Radiosonde Archive (IGRA);* Stennis Space Center, Mississippi, https://www.ncei.noaa.gov/products/weather-balloon/integrated-global-radiosonde-archive (Accessed August 2024).

50 Ruyi Yang *et al.* Interpretable Machine Learning for Weather and Climate Prediction: A Survey. arXiv:2403.18864 (2024). https://ui.adsabs.harvard.edu/abs/2024arXiv240318864Y.

51 Sergey Frolov *et al.* Integration of emerging data-driven models into the NOAA research to operation pipeline for numerical weather prediction. *Bulletin of the American Meteorological Society* (2024). https://doi.org/10.1175/BAMS-D-24-0062.1.

52 Early Warnings for All. *Early Warnings for All Dashboard;* World Meteorological Organization (WMO), Geneva, Switzerland, https://earlywarningsforall.org/site/early-warnings-all/early-warnings-all-dashboard (Accessed August 2024).

CHAPTER 15:
GREENHOUSE GAS EMISSIONS FROM AI

David Sandalow

A. Background 15-2

B. Data Center Power Demand 15-3

C. Current GHG Emissions from AI 15-9

D. Future Greenhouse Gas (GHG) Emissions from AI 15-13

E. Conclusion 15-20

F. Recommendations 15-21

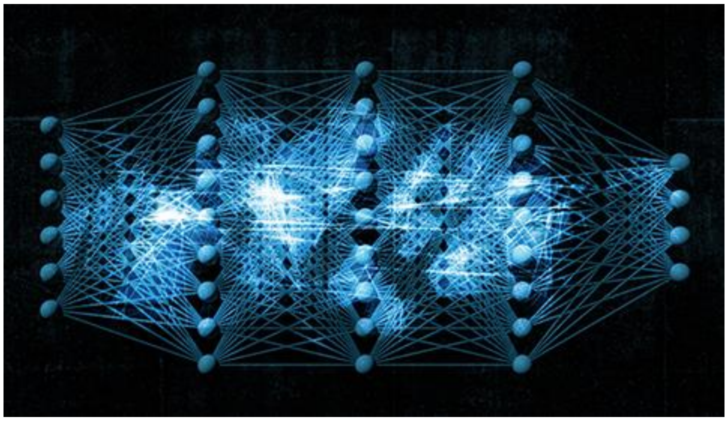
G. References 15-22

AI systems need energy. Manufacturing silicon chips requires energy for mining minerals and operating complex machinery. Building data centers requires energy for making steel and concrete. Training and running AI models requires energy for electricity to power servers. Lighting and cooling data centers requires energy for electricity as well.

This energy use does not necessarily result in significant greenhouse gas (GHG) emissions. When the electricity for a data center comes from new solar, wind or nuclear power, for example, the GHG emissions from data-center operations are modest. Amazon, Microsoft, Google and Meta—the world's largest data center operators—are among the world's largest purchasers of renewable power.[1] However some activities essential for AI—such as making steel and concrete—use only modest amounts of low-carbon energy.

A review of the current literature suggests the following conclusions:

- Current overall impacts of AI on GHG emissions could be positive or negative. Much better data collection is needed to assess overall impacts with confidence.
- GHG emissions from generating power for AI operations at data centers and on edge devices ("AI operational emissions") are less than 1%—and perhaps much less than 1%—of global GHG emissions.
- AI operational emissions will likely increase in the years ahead. This increase could be modest or quite substantial.
- In the medium- to long-term, the overall impacts of AI on GHG emissions could be positive or negative. The GHG benefits of using AI throughout the economy could significantly outweigh GHG emissions increases due to AI. However, the opposite could occur as well. The impact of AI on GHG emissions will depend on decisions by policymakers, business leaders, researchers and others in the years ahead.



This chapter starts with background on GHG emissions from AI and data center power demand. With that foundation, the chapter examines current and future GHG emissions from AI, concluding with recommendations.

A. Background

The phrase "GHG emissions from AI" is quite broad. It includes:

- AI operational emissions,
- GHG emissions from manufacturing equipment and building infrastructure used for AI ("AI upstream emissions") and

- The emissions impacts of applying AI in countless thousands of ways throughout the economy, some of which reduce GHG emissions (such as the many applications of AI discussed in this Roadmap) and some of which increase GHG emissions (such as when AI is used to cut the cost of some polluting activities).

Estimating GHG emissions from AI is challenging, for several reasons.

First, data collection and assessment methodologies are inadequate. The lack of standardized reporting practices and metrics across the AI industry makes it difficult to provide precise and confident emissions estimates.[2-4]

Second, the shared use of computing resources in cloud environments can make it difficult to isolate and accurately attribute emissions to AI-related activities. Data center operators do not routinely keep records distinguishing the time a server is running AI-based software from the time a server is running non-AI-based software. (Doing so would be difficult.) As a result, it can be challenging to correctly allocate overall GHG emissions from computing infrastructure to the subcategory of AI applications.

This challenge is diminished by the increasing use of specialized computing chips, such as graphics processing units (GPUs) and tensor processing units (TPUs), which are used almost exclusively for AI-based software. However allocating emissions from other AI hardware can be a challenge.

Third, data center emissions are location-specific. A data center's GHG emissions depend on the fuels used to generate electricity for that data center. Many data centers purchase electricity from local power grids, and the fuel mix in local power grids varies greatly around the world. To project future GHG emissions from data centers, one must make assumptions about not only the increase in overall data center power demand but also the locations where data centers will be built and the sources of electricity data centers will use.

Finally, AI is a transformational technology at an early stage of deployment. Forecasting how AI will impact many economic processes and societal patterns in the years and decades ahead is difficult if not impossible. As a result, forecasting the GHG impacts of AI deployment with high confidence is challenging as well.[5]

Despite these challenges, a growing body of literature seeks to estimate current and future GHG emissions. These studies are essential for understanding and managing AI's GHG impacts. After reviewing the related topic of data center power demand, we examine these studies below.

B. Data Center Power Demand

There are roughly 11,000 data centers globally (Aljbour et al, 2024[6] at p. 11). Roughly half of global data center capacity is in the United States, 15% is in Europe and 15% is in China.[7]

Data centers are central to the AI industry. Most AI models are trained, tuned and run at data centers. Although some AI computation is beginning to move to edge devices, most AI takes place at data centers and will continue to do so for the foreseeable future.[8-10]

Data centers perform many functions other than AI—hosting websites, processing financial transactions, running email networks and much more. Only a fraction of data center workload is attributable to AI. Recent estimates of that fraction vary widely:

- KKR Insights estimates that, today, roughly 35% of the workload at Amazon, Google, Meta and Microsoft data centers is for AI and that this figure will rise to more than 50% by 2030.[11]
- A 2022 paper in *Nature Climate Change* by Lynn Kaack et al. estimates that “less than one-quarter” of the workloads and traffic of cloud and hyperscale data centers is related to machine learning (ML).[3]
- FTI Consulting estimates that roughly 10% of data center power demand globally is for AI, growing to roughly 25% by 2030.[12]
- The Electric Power Research Institute (EPRI) estimates that about 10–20% of data center electricity use comes from AI applications.[13]
- A 2024 paper in *Communications of the ACM* by David Patterson et al. estimates that, from 2019 to 2021, ML “represented between 10% and 15% of the total annual operational energy use in the Google cloud” (Patterson et al., 2024[14] at p. 88).
- Goldman Sachs estimates that the percentage of data center workload attributable to AI globally was less than 1% in 2024 but will increase to roughly 19% by 2028 (see “Data center power demand graph[15]).
- A paper published in *Nature* by Amy Luers et al. in April 2024 estimates that roughly 1% of data center power demand in 2023 came from AI processors.[5]

The wide differences in these estimates reflect different definitions of “AI” (with some studies focused on generative AI and others on ML more broadly), data gaps, the lack of standard measurement protocols and other factors.

In the past year, data center power demand has received considerable media attention, often in the context of the growth of AI.[16-18] We explore that topic below.

i. Current data center power demand

Data centers use substantial amounts of electricity. To operate a data center, electric power is needed for servers, data storage equipment, networking equipment, cooling systems, lighting and more.

In 2023, roughly 1.5% of global electricity demand came from data centers (IEA 2024[19] at p. 19). In the United States, data centers were responsible for 3% of electricity demand.[20] The figure was 1–2% in Japan,[21] 3.5% in China[22] and 3.5% in the European Union.[23]

Although these amounts are significant, they are smaller than the electricity used in some other sectors. In 2023, for example, 4% of global electricity demand came from aluminum smelters (IEA 2024[19] at p. 19). According to IEA experts, “annual electricity consumption from data centers globally is about half of the electricity consumption from household IT appliances, like computers, phones and TVs."[24]

Data centers tend to be built in clusters. In places where data centers are concentrated, their share of power demand is much greater than the global average. In Loudon County, Virginia, USA—which has the world's largest number of data centers by far—roughly a quarter of electricity demand comes from data centers.[25] In Ireland (the largest data center hub in Europe), 21% of electricity demand came from data centers in 2023.[26] In Singapore (one of the leading data center hubs in Asia), 7% of electricity demand comes from data centers.[27]

ii. Future data center power demand

Data center power demand is growing rapidly. Goldman Sachs Research projects 160% growth globally by 2030.[15] EPRI projects 5–15% annual growth in the United States until 2030 (EPRI 2024[6] at p. 5), several research firms project annual growth in the 7–9% range in the European Union[23,28,29] and the Open Data Center Committee projects annual growth of roughly 10% in China.[30]

The growth in data center power demand is coming from many sources, not just AI. Streaming services, 5G networks, social media and online gaming are all fueling surging data center demand.[11,31] Yet AI is an important (and perhaps the most important) factor.[30]

Although power demand from data centers is growing rapidly, it is smaller than power demand growth from several other sectors. In the IEA's Stated Policies Scenario, power demand growth for electric vehicles (EVs) and space cooling in buildings are each more than three times greater than power demand growth for data centers. According to IEA, "data centers look set to remain a relatively small driver of overall electricity demand growth at the global level in the decade to come. Nonetheless, constraints at the local level may be significant." (IEA 2024[32] at p. 188.)

Those constraints are especially significant in countries including the United States, Ireland, Singapore and Japan. In the past several years, electric utilities in these countries and other locations have received a record-breaking number of requests from data center operators for electricity interconnections. These requests are creating significant challenges. In Loudon Country, Virginia, for example, applications for electricity interconnection from data center operators are currently facing several years of delay. These applications are experiencing similar delays in many other locations as well.[12,33]

However, many of the applications for electricity interconnection submitted by data center operators do not represent actual demand. Due to delays and uncertain prospects for approvals, many data center operators have applied for more interconnections than they need, hoping that some applications will be successful. This “application frenzy” has some similarities to a run on a bank or the panic buying of essential goods at the start of the COVID epidemic.[34]

Still, data center power demand is rising rapidly.[35] In the past year, many research organizations, investment banks, consultancies and energy companies have released forecasts for increased power demand from data centers. Table 1 summarizes the results of some of these studies.

Table 1. Power consumption projections for data centers.

AUTHOR	PROJECTED ANNUAL GROWTH RATE	TIMEFRAME	REMARKS
Global			
IEA, *Electricity 2024* (January 2024)[36] at p.31	21%	2022–2026	Electricity consumption by data centers, cryptocurrencies and AI globally increases from 460 TWh in 2022 to 620–1050 TWh by 2026
IEA, *Electricity Mid-Year Report* (July 2024)[19] at p.19	19%	2022–2026	Electricity consumption of data centers increases from 1–1.3% of global demand in 2022 to 1.5–3% by 2026
Goldman Sachs Research, 2024 (May 14, 2024)[15]	14.5%	2023–2030	Electricity consumption by global data centers increases from 411 TWh in 2023 to 1063 TWh in 2030; AI’s percent of global data center load increases from 3% in 2023 to 20% in 2030 Data centers increase from 1–2% of global electricity consumption now to 3–4% by end of the decade
SemiAnalysis, 2024[37]	25%	2024–2030	Electricity consumption by data centers reaches 4.5% of global consumption by 2030
Morgan Stanley, 2024[38]	70% (GenAI only)	2024–2027	Global power usage from GenAI grows by 70% CAGR (compound annual growth rate) in 2024–2027 to 224 TWh

United States[33]			
EPRI, 2024 (May 28, 2024)[6]	5–15%	2023–2030	Electricity consumption by US data centers increases from 150 TWh in 2023 to 196–404 TWh by 2030, taking 5–9.1% of 2030 electricity consumption
BCG, 2024[39]	15–20%	2024–2030	Electricity consumption by US data centers increases to 800–1050 TWh (100–130 GW capacity) by 2030
McKinsey, 2023[40]	9.5%	2022–2030	Electricity consumption by US data centers increases from 149 TWh (17 GW capacity) in 2022 to 307 TWh (35 GW capacity) in 2030
Columbia Center on Global Energy Policy, 2024[41]		2024–2027	In 2027, GPUs will be roughly 4% of total US electricity sales and roughly 1.7% of total electric capacity
European Union			
Joint Research Centre EU, 2024 at pp.3,8[23]	5–17%	2022–2030	Electricity consumption by EU data centers increases from 45–65 TWh in 2022 to 98.5–160 TWh in 2030
Savills, 2024[29]	8.3%	2024–2027	27% increase to 13.1 GW capacity in 2027
Mordor Intelligence, 2024[28]	7.4%	2024–2029	Data centers reach 3.2% of EU electricity consumption in 2030, citing official EU sources
China			
China State Grid Energy Research Institute, 2021[42]	7.1%	2020–2030	Electricity consumption by data centers increases from 200 TWh in 2020 (2.7% of total power demand) to 400 TWh in 2030 (3.7% of total power demand)
China Com-service White paper, 2023[43]	6%	2022–2025	Electricity consumption by data centers in China increases from 101 TWh in 2022 to 120 TWh in 2025
Japan			
Japan Transmission Operators, 2024[21]	6–12%	2022–2050	Electricity consumption by data centers owned by three leading communications companies in Japan increases from 8.6 TWh in 2022 (slightly less than 1% of total power demand) to 43–211 TWh in 2050

RESOURCE ADEQUACY

by Mariah Frances Carter and David Sandalow

"Resource adequacy" is the ability of an electric utility to meet the needs of its customers even during periods of peak usage or unexpected disruptions.

When a utility experiences resource adequacy problems, several issues can arise:

- First, blackouts or brownouts become more likely, especially during extreme weather events and other periods of high demand. This occurs because the utility may not have enough generation capacity or demand response resources to meet the peak electric load.
- Second, higher electricity prices are possible because the utility may need to purchase power at premium prices or rely on expensive, less efficient and more polluting peaker plants to meet demand.
- Third, the stability and resilience of the electricity system can be compromised, causing operational problems with grid management.

Surging power demand—in part due to data centers—is causing resource adequacy problems in some regions around the world. This demand surge contrasts sharply with the experience in most developed countries in recent years. For most of the past two decades, power consumption in the United States, Europe and Japan was mostly flat. However, this is changing dramatically as new factories, EVs, data centers, crypto currencies and other sources create significant new demand for electric power. The International Energy Agency (IEA) projects power demand in the United States will grow 1.5% per year in 2024–2026, with a third of that growth due to data centers (IEA, 2024[36] at p. 111). The Japanese government recently released a report forecasting an increase in long term electricity demand for the first time in twenty years, due in significant part to semiconductor plants and data centers. The report estimates that electricity demand will grow from 1 trillion kilowatt-hours (kWh) in this decade to about 1.35-1.5 trillion kWh in 2050.[44]

Power demand is growing especially fast in regions where data centers are clustered. In the United States, this includes Northern Virginia, Dallas-Ft. Worth, Chicago, Silicon Valley and Phoenix. (The Phoenix-based Arizona Public Service recently estimated average load growth in its service territory of 3.7% per year from 2023 to 2038. This is an additional 24 TWh of annual electricity consumption, with more than half of that increase coming from data centers.)[45] Globally, top areas include Frankfurt, London, Paris, Singapore, Tokyo, Hong Kong, Sydney and Querétaro (Mexico). All of these regions are facing 20–25% annual growth in data center capacity with significant related power demands.[46]

Utilities in regions with high concentrations of data centers are responding to this increased demand with new generation, demand response and other tools. In Ohio, one utility is asking permission to impose special tariffs on data center customers to help pay for expanding and strengthening the grid.[47] However the growth in power demand is outpacing the utilities' ability to respond in some places. Power connections for new data centers will need to be delayed—in some cases for years—to address resource adequacy concerns.[12]

C. Current GHG Emissions from AI

Current overall impacts of AI on GHG emissions could be positive or negative. Assessing those impacts with confidence is difficult due to gaps in data collection, a lack of standard assessment methodologies and the rapid pace of AI deployment in recent years.

Recent studies suggest the following:

- AI operational emissions are less than 1%—and perhaps much less than 1%—of total GHG emissions.
- AI upstream emissions contribute to AI's GHG footprint. Much better data are needed to assess the magnitude of these emissions with confidence.
- The GHG impacts of applying AI in countless thousands of processes throughout the economy are difficult to assess. These impacts could be beneficial on a net basis, outweighing AI operational emissions, AI upstream emissions and other GHG increases associated with AI. However, these impacts could also be negative on a net basis, increasing global emissions.

This section discusses each of these topics in turn.

i. AI operational emissions

Based on the existing literature, it is reasonable to conclude that GHG emissions from computing operations for AI are less than 1%—and perhaps much less than 1%—of global GHG emissions.

Relevant studies include the following.

- In a 2024 *Nature* article, Amy Luers et al. wrote that "in terms of total global greenhouse-gas emissions, we calculate that AI today is responsible for about 0.01%."[5] The estimate is based on the power consumption of AI processors in 2023.
- In a 2022 *Nature Climate Change* article, Lynn Kaack et al. estimated that cloud and hyperscale data centers are responsible for 0.1–0.2% of global GHG emissions and that roughly 25% of their workloads are related to ML.[3]
- In a 2022 study, Sasha Luccioni et al. found that GHG emissions from training several current large language models (LLMs), including GPT-3 and BLOOM, ranged from roughly 30 to 550 tonnes CO_2e.[48] In a 2021 paper, David Patterson et al. provided similar estimates (noting that

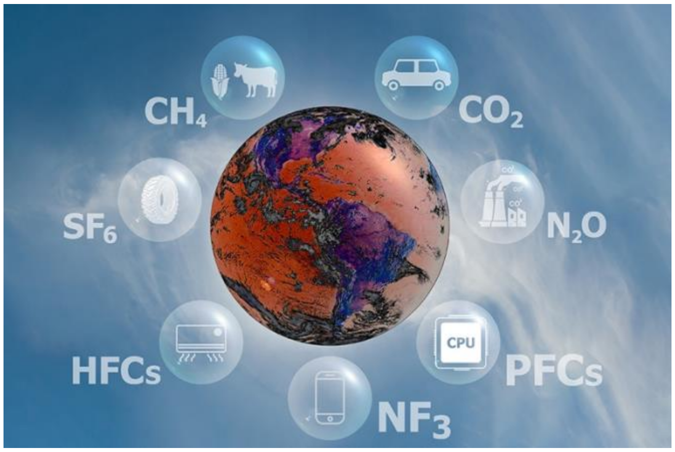
the average commercial plane emits roughly 180 tonnes CO_2e flying from San Francisco to New York).[49] (550 tonnes CO_2e is roughly 0.000001% ($1x10^{-8}$) of global GHG emissions, which were roughly 54 $GtCO_2$e in 2022.)[50]

- In a 2023 report, IEA estimated that "Data centres and data transmission networks are responsible for 1% of energy-related GHG emissions." The estimate included both upstream and operational emissions.[51]
- In a 2021 paper in *Patterns*, Charlotte Freitag et al. estimated that 1.8–2.8% of global GHG emissions came from the information, communications and technology sector. This estimate included both upstream and operational emissions.[52]

These studies explore related but somewhat different topics, offering a range of results. Some of the studies are based on data that are several years old and therefore partly out of date. (The AI market is growing rapidly—at compound annual growth rates in the range of 35% according to some estimates.[53-55]) However, combined with the estimates of AI's share of data center workload (summarized in Section B of this chapter above), these studies suggest that 1% is a likely upper bound for the share of global GHG emissions from computing operations for AI and that the actual share could be much less.

ii. AI upstream emissions

Upstream emissions from AI must be part of any complete GHG accounting for AI; however, the literature on upstream emissions from AI is sparse.[56,57] A research agenda to better assess the magnitude of AI upstream emissions should consider several factors, including the following.



First, many upstream AI activities, such as manufacturing silicon chips and making steel and cement for data centers, rely heavily on fossil fuels for energy. This contrasts with AI operations at data centers, where power use is often matched with renewable energy.

Second, major data center operators, including Google and Microsoft, report that the vast majority of their emissions are Scope 3 emissions (defined as "indirect emissions in the value chain of a company, other than emissions from the generation of purchased energy").[58] For Google, the figure is 75% (Google, 2024[59] at p. 38), and for Microsoft it is 96% (Microsoft 2024[60] at p. 15). Scope 3 is a broad category that includes many sources of emissions beyond AI upstream emissions, but still these corporate reports suggest the possibility that upstream emissions from AI could be significant and merit attention. (Again, more research is needed.)

Third, studies that have begun to explore topics related to upstream emissions from AI include:

- A 2024 paper in *Communications of the ACM* by David Patterson et al., which found that "embodied server CO2e was ~115x larger than ML operational CO2e in Google datacenters in 2021" (at p.95).[14]
- A 2024 IEEE paper by Carole-Jean Wu et al., which found that upstream GHG emissions for University LM, a multilingual language translation model, were roughly 50% of operational emissions.[61]
- A 2021 study in *HAL Open Science* by Maxime Pelcat, which found that annual emissions from semiconductor manufacturing were roughly 76.5 Mt CO2e globally (0.15% of global GHG emissions).[62] Semiconductor manufacturing is an important part of the value chain for AI, although semiconductor chips are used in countless thousands of products and only a small fraction of semiconductor chips manufactured each year are used in AI.

iii. Impacts of AI applications on emissions

Data quantifying the current impacts of AI applications on GHG emissions are sparse.

The phrase "impacts of AI applications on GHG emissions" is potentially confusing. In this context, it means how use of AI impacts GHG emissions, not including AI operational emissions or AI upstream emissions. For example:

- When a municipality uses AI tools to help with traffic management, how much do vehicle emissions fall?
- When a commercial building uses AI tools to help with energy management, how much do emissions at that building and at the local power grid fall?
- When an industrial facility uses AI tools in its operations, how much do emissions at that facility rise or fall?

A few studies have estimated the current GHG emission benefits that come from using AI in some settings.

- In a 2021 report, BCG experts reported that their clients had achieved 5–10% emissions reductions using AI[63]
- In a 2021 report, Capgemini reported that organizations had reduced GHG emissions by 13% using AI[64]

However, the literature on this topic is sparse. Qualitative and anecdotal assessments are more common than quantitative assessments. Few if any studies have attempted to quantify the potential emissions benefits of AI-enabled breakthroughs in areas such as battery chemistry or carbon capture. Chapters 3–13 of this Roadmap contain many examples of ways in which AI is currently being used to reduce GHG emissions, including the use of AI to monitor methane emissions, optimize fertilizer application, improve low-carbon steel manufacturing and much more. Taken together, these and other AI applications may already be having a meaningful impact in reducing GHG emissions. However, much more data collection and analysis are needed to provide rigorous estimates.

The literature on the extent to which AI applications may be increasing GHG emissions is especially sparse. When AI is used in carbon-intensive industries, such as mining, manufacturing and oil-and-gas production, AI could increase GHG emissions by making carbon-emitting activities more cost-competitive. In recent years, the oil and gas industry has rapidly adopted AI tools in exploration and production activities, improving operational efficiencies and cutting costs.[65-67] Lower-cost oil and gas production seems likely to lead to higher GHG emissions, although the analysis is complicated by (1) the potential for cheap natural gas to reduce GHG emissions by displacing coal, if leakage rates for that natural gas are kept to a minimum, and (2) the partially-managed nature of global oil markets. (See text box below.)

Some AI applications are currently reducing GHG emissions. Other AI applications are probably increasing GHG emissions. Comprehensive data on the cumulative impacts of AI applications on GHG emissions are lacking.

iv. Further study

In an interesting 2024 paper in *Scientific Reports*, Bill Tomlinson et al. compare (1) GHG emissions that come from using AI for writing and drawing tasks (both upstream and operational emissions) with (2) the GHG footprint of humans performing the same tasks. Tomlinson et al. found that "AI systems emit between 130 and 1500 times less CO_2e per page of text generated compared to human writers, while AI illustration systems emit between 310 and 2900 times less CO_2e per image than their human counterparts."[68]

The literature on GHG emissions from AI is growing.[69-71] However there are no widely used protocols or standards for measuring GHG emissions from AI systems or the GHG benefits of AI applications. Improved measurement protocols and standards—and much more research—are needed to provide precise and confident estimates of current emissions.

AI IN THE OIL AND GAS INDUSTRY

AI is widely used in the oil and gas industry.[72-74] Some ways AI is used may increase GHG emissions; other ways may decrease emissions. On a net basis, AI appears likely to be increasing GHG emissions from the oil and gas industry, however no studies have rigorously analyzed this topic to date.

Use of AI use in the oil and gas industry has grown rapidly in recent years. AI is being used for predictive maintenance, supply chain optimization, performance improvements at refineries and much more. AI is increasing yields from reservoirs, expanding areas where drilling is economic and cutting costs in exploring for oil and gas. Many industry testimonials cite the benefits of AI for oil and gas production.[75-77]

To the extent that AI is helping oil and gas companies produce more oil and gas at lower cost, higher GHG emissions are likely to be one result. In general, lower production costs for goods put downward pressure on prices for those goods, increasing consumption. More consumption of fossil fuels, such as oil and gas, generally increases GHG emissions.

However, several factors complicate the analysis of AI's impact on GHG emissions from the oil and gas sector.

First, natural gas replaces coal in many places, with cheaper natural gas leading to less coal use. Natural gas produces roughly half the GHG emissions per unit of energy as coal when burned, so more natural gas use and less coal use can reduce GHG emissions—although only if natural gas leaks are kept to a minimum. Thus, while cheaper natural gas production due to AI creates significant risks of higher GHG emissions, there are scenarios in which it could do the opposite. The results will depend on a number of factors that vary by location.

Second, the global oil market is not a classic competitive market. Prices are determined in substantial part by the decisions of key producers (including in particular the Kingdom of Saudi Arabia), who adjust supply with the goal of keeping prices within ranges they consider desirable. In the partially managed global oil market, lower production costs enabled by AI may lead to lower prices and greater consumption but less directly and immediately than in more competitive markets.

Third, AI is also used in the oil and gas industry to help reduce GHG emissions. AI is helping to detect and control methane leaks, improve carbon capture processes and address supply chain emissions. Although these efforts appear to be smaller in scale than the use of AI to enhance oil and gas production, they have the potential to offset some of the GHG emissions increases from AI use in the industry.[78-80]

The bottom-line is that use of AI in the oil and gas sector has the potential to both increase and decrease GHG emissions. AI appears likely to be increasing GHG emissions from the oil and gas sector on a net basis, but a confident assessment requires more rigorous analysis.

D. Future Greenhouse Gas (GHG) Emissions from AI

Future GHG emissions from AI are highly uncertain. AI has the potential to increase or decrease GHG emissions in the years ahead, in amounts that could be small or significant. The results will depend on a range of policy and investment decisions.

In the short-term, the surging demand for AI seems likely to increase GHG emissions.

- Although major data center operators would like to buy 100% low-carbon power, new data center demand exceeds the supply of low-carbon power in many locations. Growing demand for data center use, driven in part by AI, has led to deferral of some coal plant retirements in the US[17,81] and to construction of new natural gas plants in several locations, including Dublin and Phoenix.[82,83]
- Decarbonization of the processes and industries central to AI upstream emissions—including manufacturing silicon chips, steel and cement—is moving slowly.[84,85]
- Adoption of emissions-reducing applications of AI may not keep pace with increases in AI operational emissions and AI upstream emissions (although data on this topic are sparse).

In the medium- to long-term, AI could increase or decrease GHG emissions. While AI operational emissions and AI upstream emissions may both grow, AI will also be deployed in countless ways to accelerate decarbonization and reduce emissions. (See Chapters 3–13 of this Roadmap.) The net impact of AI on GHG emissions is uncertain.

A few studies have estimated future GHG emissions from AI.

- In a 2024 report, Morgan Stanley projected that CO_2 emissions from generative AI will reach 0.2–0.3% of global power sector CO_2 emissions (which is 0.1–0.15% of global CO_2 emissions) in 2027. Morgan Stanley said it expects the "net sustainability benefits from GenAI to be positive" (Morgan Stanley, 2024[38] at p. 4).
- In a 2021 study, BCG experts estimated that AI could reduce 5–10% of global GHG emissions by 2030, based on experiences with BCG clients.[63,86]

Several other studies have estimated future GHG emissions from data centers (including GHG emissions from data center operations unrelated to AI).

- In a 2024 report, Goldman Sachs found that "carbon dioxide emissions of data centers may more than double between 2022 and 2030."[87]
- In a 2024 blog post, International Monetary Fund (IMF) experts projected that CO_2 emissions from data centers could reach 0.5% of the global total by 2027.[88]

Future GHG emission from AI will be the sum of (1) AI operational emissions, (2) AI upstream emissions and (3) the GHG emissions impacts of AI applications (which could be positive or negative). The uncertainty with respect to each of these categories is significant. We consider each of them—as well as future demand for AI—below.

i. AI operational emissions

Emissions from computing operations for AI in the years ahead will be a function of (1) improvements in the energy efficiency of AI hardware, (2) improvements in the energy efficiency of AI software, (3) rebound effects from these improvements and (4) the percentage of computing operations powered by new low-carbon sources. There is considerable uncertainty with respect to all these factors.

a) Hardware efficiency

The energy efficiency of AI equipment has improved significantly in the past decade. This trend continues today and is likely to continue in the future. However, predicting the precise pace of improvements in the energy efficiency of AI equipment is challenging.

Some recent improvements in energy efficiency have been dramatic. Between 2015 and 2021, for example, data center workload increased by 260% while data center energy use increased by only 10%.[15,89]

Similar improvements continue today. NVIDIA's new Blackwell GPU trains large AI models with roughly 25% of the power needed for comparable tasks by older GPUs.[90,91] NVIDIA reports an astounding 45,000x improvement in the energy efficiency of their GPUs running LLMs in the past eight years.[91] In 2020, average power use effectiveness (PUE) across the industry was 1.58. (PUE is the ratio of total energy use at a data center to the energy used by its computing equipment.) Newer data centers have demonstrated PUEs of 1.1.[61,92-96]

These improvements in energy efficiency are likely to continue. Miniaturization and architectural optimization will likely drive continued energy efficiency in GPUs in the years ahead.[90,91,97] More efficient and higher-performing computational equipment, such as tensor processing units (TPUs), also offer the promise of continued improvements in energy efficiency.[92-94] More radical design concepts, such as analog-AI chips, may also result in major improvements in energy efficiency.[98] Studies of PUE at data centers suggest continued energy-efficiency improvements are possible.[61,92-96]

Yet predicting the pace at which the energy efficiency of AI equipment will improve is challenging. Hardware advances, such as new chip architectures, often follow unpredictable innovation cycles, making it difficult to forecast specific gains. Breakthroughs in quantum computing, neuromorphic

chips or AI itself could drastically improve efficiency. Supply chain disruptions or geopolitical forces could slow innovation. Significant energy efficiency gains in AI equipment are likely, but precise projections are challenging.

b) Software efficiency

Advances in AI models have significantly improved the energy efficiency of AI in recent years. These advances include development of more efficient algorithms, such as sparse models and pruning techniques, which reduce the number of computations required to achieve the same or better results. Optimization strategies like quantization and knowledge distillation have also enabled AI models to run more efficiently on existing hardware. As a result, AI systems now require less computational power and energy to perform complex tasks, reducing their overall carbon footprint.[99,100]

Significant work is underway to further improve model architectures using these techniques and others.[92,101] Nodal and clustering optimization could have significant impacts on the overall carbon intensity of compute-heavy parts of an AI model's lifecycle. Researchers across major markets (e.g., the United States and China) have begun to investigate this potential, but more analysis is needed as new hardware becomes available.[102]

As with hardware efficiency improvements, projecting the pace of change in software development is challenging. The development of new algorithms and optimization techniques is inherently uncertain, as breakthroughs in AI often come from unexpected research directions and can be difficult to foresee.

The International Standards Organization (ISO) recently published a methodology for evaluating a software system's "software carbon intensity (SCI)." The methodology is intended to "help software practitioners make better, evidence-based decisions during system design, development, and deployment, that will ultimately minimize carbon emissions."[103] Widespread attention to the SCI methodology could help reduce emissions from AI systems.

c) Rebound effects

In combination, the hardware and software energy advances described above offer the potential for significant—indeed extraordinary—improvement in the energy efficiency of AI in the years ahead. Whether these energy efficiency gains will have a significant impact on GHG emissions from AI is uncertain.

A core challenge in projecting GHG emissions from AI is the rebound effect (sometimes called "Jevons Paradox").[104,105] As AI tools become more energy efficient and therefore cost less, use cases for AI will expand. The power demand for AI from these new use cases could offset the energy savings from hardware and software energy efficiency improvements in part or in whole.

The rebound effect is a well-studied phenomenon in other contexts, including automotive fuel efficiency standards, where the rebound effect is estimated to offset 10–30% of a fuel efficiency standard's benefits.[106-108] A 2014 paper in the *American Economic Journal* by Lucas Davis et al. found significant rebound effects in Mexican programs to replace energy inefficient air conditioners and refrigerators.[109]

There is little research on the likely rebound effect as the energy efficiency of AI hardware and software improves in years ahead. Yet general trends in the industry suggest rebound effects may be significant. As significant energy efficiency improvements in the latest generation of GPUs were being announced in 2024, commercial orders for those GPUs skyrocketed and applications for new data center capacity continued to climb. A wide range of industry participants appear to believe that cheaper and more efficient computing power will open up new potential applications for AI, not cut back on overall power demand from the industry.[39,57]

d) Low-carbon power

The amount of GHG emissions from AI operations in the years ahead will be determined in significant part by the amount of low-carbon power used for these operations.

Many large data center operators are deeply committed to using low-carbon power. Indeed the world's largest data center operators—Amazon, Microsoft, Google and Meta—are among the world's largest purchasers of renewable power.[1,110-112] However data center operators face significant constraints in procuring sufficient low-carbon power. Permitting delays, inadequate transmission infrastructure and land-use constraints are among the major barriers.[35]

These constraints complicate forecasting. The amount of GHG emissions from AI operations depends not just on the pace at which power demand for AI grows, but on how that power is generated. A data center or edge device powered by a grid with significant coal generation will emit far more GHGs than a data center co-located with a new low-carbon power plant.

The indirect effects of data center operators purchasing low-carbon power are also a complicating factor. If the supply of low-carbon power in a region is constrained, the purchase of low-carbon power by a data center operator may force other electricity consumers to purchase power from higher-carbon sources, indirectly increasing GHG emissions. This may currently be happening in the eastern United States.[113,114]

(Similar concerns have been raised with respect to hydrogen produced with renewable power, known as "green hydrogen." The European Union and United States have both adopted rules requiring that green hydrogen facilities use new or additional renewable power in order to receive favorable regulatory or tax treatment. There are proposals that data centers be subject to similar additionality requirements.)[115-118]

A potential solution to the problem of indirect GHG emissions increases is for data center operators to develop new low-carbon power sources for new data centers. One innovative approach is the Clean Transition Tariff developed by Google and others, in which utility regulators establish a rate structure under which data centers and other large customers pay more for new low-carbon power projects using emerging clean energy technologies.[119,120]

Another important development is the emergence of "carbon-aware computing," which schedules intensive computing tasks based on the carbon intensity of the power available to perform the computation.[121] By leveraging near-real-time data and models about renewable generation, a carbon-aware computing system can defer intensive, non-urgent AI model training tasks for time periods when renewable generation is abundant or curtailed. Intensive computing tasks could also be transferred to data centers in different locations where low-carbon electricity is available (taking into account the emissions associated with the data transfer).[122-124]

The strong commitment of leading data center operators to buying low-carbon power will help minimize the growth of GHG emissions in connection with AI in the years ahead. But there are constraints on the ability of data center operators to buy low-carbon power. Projections of low-carbon power's role in AI computing operations in the years ahead should allow for a range of possible outcomes.

ii. AI upstream emissions

Upstream emissions from AI include emissions from manufacturing silicon chips, making steel and cement for data centers, and taking other steps necessary to build the physical infrastructure for AI operations. Many of these activities rely heavily on fossil fuel combustion and have significant GHG footprints. Future upstream emissions from AI will depend on growth in demand for AI and the pace at which these activities decarbonize.

Progress in decarbonizing some of these activities has been slow. Some forms of silicon production have a higher carbon footprint today than 20 years ago.[125] Steel and cement making are often considered "hard-to-abate" sectors, which are difficult to decarbonize.[126] (Fortunately AI could help accelerate decarbonization of some of these sectors. See Chapter 5 of this Roadmap.) The prospects for decarbonizing many of these sectors faster than AI scales may not be good, suggesting that upstream GHG emissions from AI may rise in the years ahead. However much more research is needed to make confident projections on this topic.

iii. Emissions impacts of AI applications

In the years ahead, the impacts of AI applications on GHG emissions could be positive or negative. Indeed, these impacts could be very positive or very negative. The range of uncertainty is enormous.

As noted in Section C (iii) above, the phrase "impacts of AI applications on GHG emissions" is potentially confusing. In this context, it means how use of AI impacts GHG emissions, not including AI operational emissions or AI upstream emissions. For example, when a municipality uses AI tools to help with traffic management, how much do vehicle emissions fall? When an industrial facility uses AI tools in its operations, how much do emissions at that facility rise or fall?

A few studies have attempted to project the potential emissions benefits of AI applications in the years ahead.

- A 2023 report by BCG and Google found that "AI has the potential to unlock insights that could help mitigate 5–10% of GHG emissions by 2030"[127]
- A 2021 Capgeminii study found that executives interviewed believed AI could reduce overall GHG emissions 16% by 2024–2026[64]
- A 2019 report by PricewaterhouseCoopers (PwC)/Microsoft found that AI could reduce global GHG emissions by 1.5–4% by 2030 compared to business-as-usual pathways

However, the literature on this topic is sparse, and challenges in making projections are considerable. Data with respect to the impacts of AI applications on GHG emissions are limited. Evaluating the benefits of AI applications involves considering a counterfactual—what would happen in the same setting without AI? Such counterfactuals are often difficult to define with rigor. The potential for rebound effects from efficiencies introduced by AI creates analytic difficulties. Finally, AI is a transformational technology at early stages of development. Confidently predicting its capabilities or how it will be deployed beyond the short-term is difficult at best.

The dozens of AI applications discussed in this roadmap highlight the enormous potential for AI applications to reduce GHG emissions in the years and decades ahead. Some of these reductions are likely to be incremental—gains of perhaps 10–20% through improved operations. Other reductions could be transformational—such as dramatically reducing GHG emissions by discovering novel materials. At the same time, using AI in carbon-intensive industries could significantly increase emissions, if AI helps carbon-emitting activities become cheaper or more competitive.

iv. Demand for AI

The pace of AI demand growth will help determine future GHG emissions in all three of the categories discussed above (AI operational emissions, AI upstream emissions and the emissions impacts of AI application). Demand for AI has been growing quickly for the past decade and is surging today. Private sector investment in AI grew 18x between 2013 and 2021,[128] and private sector demand for AI more than doubled from 2017 to 2022.[129] With the explosion of interest in AI following the release of ChatGPT in November 2022, demand for AI began to grow even faster. Many forecasters predict that AI will grow dramatically in the years ahead—at compound annual growth rates in the range of 30–35% or more.[11,53-55]

However, the pace at which demand for AI grows in the years and decades ahead is very uncertain. Some analysts question whether AI will deliver productivity benefits consistent with the enormous current investments in the technology,[130] suggesting that projections of rapid demand growth could be overstated. Regulatory frameworks, public attitudes, economic conditions, technology development and geopolitical trends will all shape demand growth. AI is a transformational, general-use technology at an early stage of adoption in most sectors. High growth rates are likely, but the range of uncertainty with respect to these rates is considerable.

E. Conclusion

AI’s impacts on GHG emissions could be positive or negative, both today and in the years ahead. Estimating with precision is challenging due to limited data and other challenges.[4]

However, there is significant potential for the overall GHG benefits of AI to exceed its costs. This could happen if (1) some of the emissions-reducing applications of AI discussed in this Roadmap deliver significant results and (2) AI operational emissions and AI upstream emissions grow slowly or fall in the years ahead. However, the opposite result is possible as well: AI applications could fail to reduce GHG emissions and AI operational emissions and AI upstream emissions could climb in the years ahead.

Supportive policies and commitment on the part of key stakeholders are needed to realize the full potential of AI to reduce GHG emissions.

F. Recommendations

1. *AI developers, data center owners, energy experts, GHG emissions experts and standards organizations should establish robust methodologies and standards for reporting energy use and GHG emissions across the AI value chain.*

2. *AI developers and data center owners should report energy use and GHG emissions associated with their AI workloads.*

3. *Governments should adopt regulations that require AI developers and data centers owners to report their energy use and GHG emissions.*

4. *AI developers should take steps to reduce the carbon intensity of their models, using the ISO's methodology for evaluating their models' Software Carbon Intensity (SCI).*[103]

5. *Data center owners should prioritize adoption of energy-efficient hardware for AI operations and optimize AI workloads based on carbon-aware computing strategies.*

6. *Governments should promote and support policies that enable and incentivize data center owners to purchase low-carbon energy, including supporting new low-carbon power generation and grid expansion in regions with high concentrations of AI-driven data center growth.*

7. *National governments, AI developers, data center owners and philanthropies should fund researchers to develop a set of scenarios to quantify the effects that AI could have on greenhouse gas emissions under a range of assumptions. These scenarios should combine quantitative models with expert consultations, rigorously exploring a range of possible futures. The Intergovernmental Panel on Climate Change (IPCC) should include these scenarios in a special report on AI to be released within two years.*[5]

8. *All stakeholders should review and consider the dozens of other recommendations throughout this Roadmap to help reduce GHG emissions using AI tools.*

G. References

1 Oktavia Catsaros. *Corporate Clean Power Buying Grew 12% to New Record in 2023, According to BloombergNEF;* BloombergNEF (BNEF), London, UK, https://about.bnef.com/blog/corporate-clean-power-buying-grew-12-to-new-record-in-2023-according-to-bloombergnef/ (2024).

2 Eric Masanet, Nuoa Lei & Jonathan Koomey. To better understand AI's growing energy use, analysts need a data revolution. *Joule* https://doi.org/10.1016/j.joule.2024.07.018.

3 Lynn H. Kaack *et al.* Aligning artificial intelligence with climate change mitigation. *Nature Climate Change* 12, 518-527 (2022). https://doi.org/10.1038/s41558-022-01377-7.

4 Peter Henderson *et al.* Towards the systematic reporting of the energy and carbon footprints of machine learning. *J. Mach. Learn. Res.* 21, Article 248 (2020). https://doi.org/10.48550/arXiv.2002.05651.

5 Amy Luers *et al.* Will AI accelerate or delay the race to net-zero emissions? *Nature* 628(8009), 718–720 (2024). https://doi.org/10.1038/d41586-024-01137-x.

6 Jordan Aljbour, Tom Wilson & Poorvi Patel. *Powering Intelligence: Analyzing Artificial Intelligence and Data Center Energy Consumption* Electric Power Research Institute (EPRI), Palo Alto, California, https://www.epri.com/research/products/000000003002028905 (2024).

7 Statista. *Share of worldwide hyperscale data center capacity in 2nd quarter 2022, by region* New York, New York, https://www.statista.com/statistics/1350992/global-hyperscale-data-center-capacity/ (Accessed August 2024).

8 Shandra Earney. *The Advantages and Disadvantages of Edge AI Simply Explained;* Xailient, Dover, Delaware, https://xailient.com/blog/the-advantages-and-disadvantages-of-edge-ai-simply-explained/ (2022).

9 Wevolver. Edge AI Market Analysis and Trends in *2024 State of Edge AI Report* Ch. 1, (Wevolver, Amsterdam, North Holland, 2024, https://www.wevolver.com/article/2024-state-of-edge-ai-report/edge-ai-market-analysis-and-trends).

10 Wevolver. Edge AI Challenges and Real-World Mitigations in *2024 State of Edge AI Report* Ch. 10, (Wevolver, Amsterdam, North Holland, 2024, https://www.wevolver.com/article/2024-state-of-edge-ai-report/edge-ai-challenges-and-real-world-mitigations).

11 Waldemar Szlezak & Andrew Peisch. *Data Centers: The Hubs of Digital Infrastructure;* Kohlberg Kravis Roberts & Co. L.P. (KKR), New York, New York, https://www.kkr.com/insights/hubs-digital-infrastructure#:~:text=Two%20megatrends%20are%20driving%20the,of%20artificial%20intelligence%20(AI) (2024).

12 Fengrong Li *et al. Current Power Trends and Implications for the Data Center Industry;* FTI Consulting, Washington, D.C., https://www.fticonsulting.com/insights/articles/current-power-trends-implications-data-center-industry (2024).

13 Jordan Aljbour, Tom Wilson & Poorvi Patel. *Executive Summary – Powering Intelligence: Analyzing Artificial Intelligence and Data Center Energy Consumption;* Electric Power Research Institute (EPRI), Palo Alto, California, https://www.epri.com/research/products/000000003002028905 (2024).

14 David Patterson *et al.* Energy and Emissions of Machine Learning on Smartphones vs. the Cloud. *Commun. ACM* 67, 86–97 (2024). https://doi.org/10.1145/3624719.

15 Goldman Sachs. *AI is poised to drive 160% increase in data center power demand;* New York, New York, https://www.goldmansachs.com/insights/articles/AI-poised-to-drive-160-increase-in-power-demand (2024).

16 Sayumi Take. *Boom in data centers challenges clean power goals in Asia;* Nikkei Asia, Tokyo, Japan, https://asia.nikkei.com/Business/Energy/Boom-in-data-centers-challenges-clean-power-goals-in-Asia (2024).

17 Antonio Olivo. *Internet data centers are fueling drive to old power source: Coal;* The Washington Post, Washington, D.C., https://www.washingtonpost.com/business/interactive/2024/data-centers-internet-power-source-coal/ (2024).

18 Melody Petersen. *Power-hungry AI data centers are raising electric bills and blackout risk;* Los Angeles Times, Los Angeles, California, https://www.latimes.com/environment/story/2024-08-12/california-data-centers-could-derail-clean-energy-goals (2024).

19 International Energy Agency (IEA). *Electricity Mid-Year Update – July 2024;* Paris, France, https://www.iea.org/reports/electricity-mid-year-update-july-2024Electricity Mid-Year Update - July 2024 (2024).

20 Carly Davenport *et al. Generational Growth: AI, data centers and the coming US power demand surge;* Goldman Sachs Group, Inc., New York, New York, https://www.goldmansachs.com/insights/goldman-sachs-research/generational-growth-ai-data-centers-and-the-coming-us-power-demand-surge (2024).

21 Nanako Takehara. *OCCTO Panel: Communications-Related Electricity Demand Expected to Increase Sharply to 2050;* Japan Atomic Industrial Forum, Inc (JAIF), Tokyo, Japan, https://www.jaif.or.jp/en/news/7022 (2024).

22 Jefferies' Equity Research Team. *How Data Centers Are Shaping the Future of Energy Consumption;* Jeffries Global Research & Strategy, New York, New York, https://insights.jefferies.com/the-big-picture/how-data-centers-are-shaping-the-future-of-energy-consumption (2024).

23 European Commission: Joint Research Centre, George Kamiya & Paolo Bertoldi. *Energy consumption in data centres and broadband communication networks in the EU;* Publications Office of the European Union, Luxembourg, Luxembourg, https://data.europa.eu/doi/10.2760/706491 (2024).

24 International Energy Agency (IEA). *What the data centre and AI boom could mean for the energy sector;* Paris, France, https://www.iea.org/commentaries/what-the-data-centre-and-ai-boom-could-mean-for-the-energy-sector (2024).

25 Dominion Energy. *Powering Your Every Day – 2023 Annual Report;* Richmond, Virginia, https://s2.q4cdn.com/510812146/files/doc_downloads/2024/2024/03/21/Dominion-Energy-2023-Annual-Report-and-Annual-Report-on-Form-10-K-1.pdf (2023).

26 Eoin Burke-Kennedy. *Data centres now account for 21% of all electricity consumption;* The Irish Times, Dublin, Ireland, https://www.irishtimes.com/business/2024/07/23/electricity-consumption-by-data-centres-rises-to-21-eclipsing-urban-households/ (2024).

27 National University of Singapore (NUS) College of Design and Engineering. *Taking a byte out of data centre emissions;* Singapore, https://cde.nus.edu.sg/taking-a-byte-out-of-data-centre-emissions/Taking a byte out of data centre emissions (2024).

28 Mordor Intelligence. *Europe Data Center Power Market Size & Share Analysis - Growth Trends & Forecasts (2024 - 2029);* Hyderabad, India, https://www.mordorintelligence.com/industry-reports/europe-data-center-power-market (2024).

29 Lydia Brissy *et al. Spotlight: European Data Centre – 2024;* Savills, London, UK, https://www.savills.com/research_articles/255800/362604-0 (2024).

30 Xuemei Xie, Yuhang Han & Hao Tan. Greening China's digital economy: exploring the contribution of the East–West Computing Resources Transmission Project to CO2 reduction. *Humanities and Social Sciences Communications* 11, 466 (2024). https://doi.org/10.1057/s41599-024-02963-0.

31 Aaron Tilley & Yang Jie. *Apple Is Developing AI Chips for Data Centers, Seeking Edge in Arms Race;* The Wall Street Journal, New York, New York, https://www.wsj.com/tech/ai/apple-is-developing-ai-chips-for-data-centers-seeking-edge-in-arms-race-0bedd2b2 (2024).

32 International Energy Agency (IEA). *World Energy Outlook 2024;* Paris, France, https://www.iea.org/reports/world-energy-outlook-2024 (2024).

33 John D. Wilson & Zach Zimmerman. *The Era of Flat Power Demand is Over (at slide 10);* Grid Strategies, LLC (sponsored by Clean Grid Initiative), Bethesda, Maryland, https://gridstrategiesllc.com/wp-content/uploads/2023/12/National-Load-Growth-Report-2023.pdf (2023).

34 Shayle Kann. Under the hood of data center power demand in *Catalyst. (Latitute Media, 2024) https://podcasts.apple.com/lu/podcast/under-the-hood-of-data-center-power-demand/id1593204897?i=1000658881876*.

35 Vijay V. Vaitheeswaran. *Big tech's great AI power grab;* The Economist, London, England, https://www.economist.com/business/2024/05/05/big-techs-great-ai-power-grab (2024).

36 International Energy Agency (IEA). *Electricity;* Paris, France, https://www.iea.org/reports/electricity-2024 (2024).

37 Dylan Patel, Daniel Nishball & Jeremie Eliahou Ontiveros. *AI Datacenter Energy Dilemma - Race for AI Datacenter Space;* SemiAnalysis, https://www.semianalysis.com/p/ai-datacenter-energy-dilemma-race (2024).

38 Morgan Stanley. *Powering the AI Revolution;* New York, New York, https://www.morganstanley.com/ideas/ai-energy-demand-infrastructure (2024).

39 Vivian Lee *et al. U.S. Data Center Power Outlook: Balancing competing power consumption needs;* Boston Consulting Group (BCG) on LinkedIn, Sunnyvale, CA, https://www.linkedin.com/pulse/us-data-center-power-outlook-balancing-competing-consumption-lee-iz4pe/ (2024).

40 Srini Bangalore *et al. Investing in the rising data center economy;* McKinsey & Company – Technology, Media & Telecommunications Practice, New York, New York, https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/investing-in-the-rising-data-center-economy (2023).

41 Taiba Jafari *et al. Projecting the Electricity Demand Growth of Generative AI Large Language Models in the US;* Columbia University School of International and Public Affairs (SIPA) Center on Global Energy Policy, New York, New York, https://www.energypolicy.columbia.edu/projecting-the-electricity-demand-growth-of-generative-ai-large-language-models-in-the-us/ (2024).

42 China Daily. *Green data centers in focus;* The State Council of the People's Republic of China, Beijing, China, https://english.www.gov.cn/statecouncil/ministries/202112/09/content_WS61b13edac6d09c94e48a1f81.html#:%7E:text=According%20to%20a%20report%20from%20China%27s%20State%20Grid,for%202.7%20percent%20of%20the%20country%27s%20electricity%20consumption. (2021).

43 China Com-Service. *White Paper;* https://aimg8.dlssyht.cn/u/551001/ueditor/file/276/551001/1684888884683143.pdf (2023).

44 Katya Golubkova, Chang-Ran Kim & Sonali Paul. *Japan sees need for sharp hike in power output by 2050 to meet demand from AI, chip plants;* Reuters, Toronto, Canada, https://www.reuters.com/business/energy/japan-sees-need-sharp-hike-power-output-by-2050-meet-demand-ai-chip-plants-2024-05-14/ (2024).

45 Arizona Public Service Company (APS). *2023 Integrated Resource Plan;* Phoenix, Arizona, https://www.aps.com/-/media/APS/APSCOM-PDFs/About/Our-Company/Doing-business-with-us/Resource-Planning-and-Management/APS_IRP_2023_PUBLIC.pdf?la=en&sc_lang=en&hash=DF34B49033ED43FF0217FC2F93A0BBE6 (2023).

46 CBRE (Coldwell Banker Richard Ellis). *Global Data Center Trends 2024;* Dallas, Texas, https://www.cbre.com/insights/reports/global-data-center-trends-2024 (2024).

47 Matthew Connatser. *Ohio power plants want special tariffs on datacenters to protect regional grid;* The Register, London, England, https://www.theregister.com/2024/05/21/ohio_datacenter_power/ (2024).

48 Alexandra Sasha Luccioni, Sylvain Viguier & Anne-Laure Ligozat. Estimating the carbon footprint of bloom, a 176b parameter language model. *arXiv preprint arXiv:2211.02001* (2022). https://doi.org/10.48550/arXiv.2211.02001.

49 David Patterson *et al.* Carbon emissions and large neural network training. *arXiv preprint arXiv:2104.10350* (2021). https://doi.org/10.48550/arXiv.2104.10350.

50 Hannah Ritchie, Pablo Rosado & Max Roser. *Greenhouse gas emissions;* Our World in Data, Oxford, England, https://ourworldindata.org/greenhouse-gas-emissions (2020 (updated 2024)).

51 International Energy Agency (IEA). *Data Centres and Data Transmission Networks;* https://www.iea.org/energy-system/buildings/data-centres-and-data-transmission-networks (Accessed September 2023).

52 Charlotte Freitag *et al.* The real climate and transformative impact of ICT: A critique of estimates, trends, and regulations. *Patterns* 2, 100340 (2021). https://doi.org/10.1016/j.patter.2021.100340.

53 Grand View Research. *Artificial Intelligence Market Size & Trends;* San Francisco, California, https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market (2024).

54 Markets and Markets Research Private Ltd. *Artificial Intelligence (AI) Market;* Hadapsar, India, https://www.marketsandmarkets.com/Market-Reports/artificial-intelligence-market-74851580.html (Accessed August 2024).

55 Bergur Thormundsson. *Artificial intelligence (AI) market size worldwide from 2020 to 2030;* Statista, New York, New York, https://www.statista.com/forecasts/1474143/global-ai-market-size#:~:text=AI%20market%20size%20worldwide%20from,2030%20(in%20billion%20U.S.%20dollars)&text=The%20market%20for%20artificial%20intelligence,billion%20U.S.%20dollars%20in%202030 (2024).

56 THe Salata Institute for Climate and Sustainability. *Cutting the carbon footprint of future computer chips;* Harvard University, Boston, Massachusetts, https://salatainstitute.harvard.edu/cutting-the-carbon-footprint-of-future-computer-chips/ (2024).

57 Gauthier Roussilhe, Anne-Laure Ligozat & Sophie Quinton. A long road ahead: a review of the state of knowledge of the environmental effects of digitization. *Current Opinion in Environmental Sustainability* 62, 101296 (2023). https://doi.org/10.1016/j.cosust.2023.101296.

58 Greenhouse Gas Protocol. *FAQ;* World Resources Institute, Washington, D.C., https://ghgprotocol.org/sites/default/files/2022-12/FAQ.pdf (Accessed August 2024).

59 Google. *2024 Environmental Report;* Mountain View, California, https://sustainability.google/reports/google-2024-environmental-report/ (2024).

60 Microsoft. *2024 Environmental Sustainability Report;* Redmond, Washington, https://www.microsoft.com/en-us/corporate-responsibility/sustainability/report (2024).

61 Carole-Jean Wu *et al.* Beyond Efficiency: Scaling AI Sustainably. arXiv:2406.05303 (2024). https://ui.adsabs.harvard.edu/abs/2024arXiv240605303W.

62 Maxime Pelcat. GHG emissions of semiconductor manufacturing in 2021. (Univ Rennes, INSA Rennes, CNRS, IETR – UMR 6164, F-35000 Rennes (hal-04112708v1), 2023; https://hal.science/hal-04112708v1/file/semiconductor_ghg.pdf).

63 Charlotte Degot *et al. Reduce Carbon and Costs with the Power of AI;* Boston Consulting Group (BCG), Boston, Massachusetts, https://www.bcg.com/publications/2021/ai-to-reduce-carbon-emissions (2021).

64 Anne-Laure Thieullent *et al. Climate AI: How artificial intelligence can power your climate action strategy;* Capgemini Research Institute, Paris, France, https://www.capgemini.com/insights/research-library/climate-ai/ (2020).

65 Gaurav Sharma. *How Multibillion Dollar Investments In AI Are Driving Oil And Gas Sector Innovation;* Forbes Media, Jersey City, New Jersey, https://www.forbes.com/sites/gauravsharma/2023/08/14/how-multibillion-dollar-investments-in-ai-are-driving-oil-and-gas-sector-innovation/ (2023).

66 Sudeep Srivastava. *Unleashing the Potential of Artificial Intelligence in the Oil and Gas Industry – 10 Use Cases, Benefits, Examples;* Appinventiv, Noida, Uttar Pradesh, India, https://appinventiv.com/blog/artificial-intelligence-in-oil-and-gas-industry/ (2024).

67 Karen Hao. *Microsoft's Hypocrisy on AI;* The Atlantic, Washington, D.C., https://www.theatlantic.com/technology/archive/2024/09/microsoft-ai-oil-contracts/679804/ (2024).

68 Bill Tomlinson *et al.* The carbon emissions of writing and illustrating are lower for AI than for humans. *Scientific Reports* 14, 3732 (2024). https://doi.org/10.1038/s41598-024-54271-x.

69 Renee Cho. *AI's Growing Carbon Footprint;* Columbia Climate School: State of the Planet, https://news.climate.columbia.edu/2023/06/09/ais-growing-carbon-footprint/ (2023).

70 U. Gupta *et al.* "Chasing Carbon: The Elusive Environmental Footprint of Computing" in *2021 IEEE International Symposium on High-Performance Computer Architecture (HPCA)*, 854-867, https://www.doi.org/10.1109/HPCA51647.2021.00076,(2021).

71 Eric Masanet *et al.* Recalibrating global data center energy-use estimates. *Science* 367, 984-986 (2020). https://www.doi.org/10.1126/science.aba3758.

72 Dmitry Koroteev & Zeljko Tekic. Artificial intelligence in oil and gas upstream: Trends, challenges, and scenarios for the future. *Energy and AI* 3, 100041 (2021). https://doi.org/10.1016/j.egyai.2020.100041.

73 Adogioye Monigha. AI-Driven Cost Optimization in Oil and Gas Projects. *International Journal of Petroleum and Gas Engineering Research* 7(2), 17-32 (2024). https://eajournals.org/ijpger/vol-7-issue-2-2024/ai-driven-cost-optimization-in-oil-and-gas-projects/.

74 Abdulhamid Musa. Review Paper Revolutionizing Oil and Gas Industries with Artificial Intelligence Technology. *International Journal of Computer Sciences and Engineering* 11(5), 20–30 (2023). https://www.researchgate.net/publication/374380602_Review_Paper_Revolutionizing_Oil_and_Gas_Industries_with_Artificial_Intelligence_Technology.

75 C3.ai. *C3 AI Addresses Key Issues Across the Oil and Gas Value Chain;* Redwood City, California, https://c3.ai/industries/enterprise-ai-for-oil-and-gas/ (Accessed October 2024).

76 Lance Mortlock *et al. AI in oil and gas: Extracting collective value by humanizing data;* Ernst & Young LLP, London, UK, https://assets.ey.com/content/dam/ey-sites/ey-com/en_gl/topics/oil-and-gas/ey-ai-in-oil-and-gas.pdf (2019).

77 Wassim Ghadban. *The journey of AI in the oil & gas industry;* Oil & Gas Middle East, Dubai, United Arab Emirates, https://www.oilandgasmiddleeast.com/business/insights/the-journey-of-ai-in-the-oil-gas-industry (2024).

78 Mike Lyons *et al. The AI Angle in Solving the Oil and Gas Emissions Challenge;* Boston Consulting Group (BCG), Boston, Massachusetts, https://www.bcg.com/publications/2021/ai-in-oil-and-gas-emissions-challenge (2021).

79 Jim Magill. *Oil, Gas Companies Deploy AI In The Fight To Reduce Carbon Emissions;* Forbes, Jersey City, New Jersey, https://www.forbes.com/sites/jimmagill/2021/03/28/oil-gas-companies-deploy-ai-in-the-fight-to-reduce-carbon-emissions/ (2021).

80 Charlie Fazzino *et al. Building a Lower-Carbon Future With HPC and AI in Energy;* NVIDIA, Santa Clara, California, https://resources.nvidia.com/en-us-upstream-energies/gtc24-s62121 (

81 Matthew Connatser. *Surging datacenter power demand slows the demise of US coal plants;* The Register, London, England, https://www.theregister.com/2024/05/31/datacenter_power_crunch/ (2024).

82 Peter Judge. *Microsoft granted permission to run its Dublin data center on gas;* Data Center Dynamics (DCD), London, UK, https://www.datacenterdynamics.com/en/news/microsoft-granted-permission-to-run-its-dublin-data-center-on-gas/ (2023).

83 Catherine Boudreau. *Phoenix plans to build gas plants to help power new data centers;* Business Insider, New York, New York, https://www.businessinsider.com/phoenix-expanding-its-natural-gas-plants-to-power-data-centers-2023-10 (2023).

84 Jan-Hinnerk Mohr *et al. For Chip Makers, the Decarbonization Challenge Lies Upstream;* Boston Consulting Group (BCG), Boston, Massachusetts, https://www.bcg.com/publications/2023/why-chip-makers-need-to-focus-on-the-upcoming-decarbonization-challenges (2023).

85 Canary Media. *The Tough Stuff: Decarbonizing steel, cement and chemicals;* New York, New York, https://www.canarymedia.com/the-tough-stuff-decarbonizing-steel-cement-and-chemicals (Updated 2023; Accessed August 2024).

86 Amane Dannouni *et al. Accelerating Climate Action with AI;* Boston Consulting Group (commissioned by Google), Boston, Massachusetts, https://web-assets.bcg.com/72/cf/b609ac3d4ac6829bae6fa88b8329/bcg-accelerating-climate-action-with-ai-nov-2023-rev.pdf (2023).

87 . (!!! INVALID CITATION !!! 15,75).

88 Shafik Hebous & Nate Vernon-Lin. *Carbon Emissions from AI and Crypto Are Surging and Tax Policy Can Help;* International Monetary Fund (IMF), Washington, D.C., 2024).

89 Ciaran Flanagan. *How Data Centers Are Driving The Renewable Energy Transition;* Forbes, https://www.forbes.com/sites/siemens-smart-infrastructure/2023/03/13/how-data-centers-are-driving-the-renewable-energy-transition/?sh=1396b0fb4214 (2023).

90 Shar Narasimhan. *Beyond 'Data-Driven': How Energy-Efficient Computing for AI Is Propelling Innovation and Savings Across Industries;* Nvidia – Blogs, Santa Clara, California, https://blogs.nvidia.com/blog/energy-efficient-ai-industries/ (2024).

91 Dion Harris. *Sustainable Strides: How AI and Accelerated Computing Are Driving Energy Efficiency;* Nvidia – Blogs, Santa Clara, California, https://blogs.nvidia.com/blog/accelerated-ai-energy-efficiency/ (2024).

92 Meredith Fowlie. *Data Centers Are Booming;* Energy Institute Blog by the Energy Institute at Haas (University of California (UC) Berkeley), https://energyathaas.wordpress.com/2023/10/09/data-centers-are-booming/ (2023).

93 D. Patterson *et al.* The Carbon Footprint of Machine Learning Training Will Plateau, Then Shrink. *Computer* 55, 18-28 (2022). https://www.doi.org/10.1109/MC.2022.3148714.

94 Ashish Dandekar. *8 power usage effectiveness (PUE) best practices for your data center;* Computer Weekly, https://www.computerweekly.com/tip/8-power-usage-effectiveness-PUE-best-practices-for-your-data-center (2011).

95 Colleen Josephson *et al.* The Sky is Not the Limit: Untapped Opportunities for Green Computing. *SIGENERGY Energy Inform. Rev.* 3, 33–39 (2023). https://doi.org/10.1145/3630614.3630621.

96 T. Hernandez *et al.* "Energy Efficiency in Data Center Management" in *2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE)*, 1214-1218, https://doi.org/10.1109/CSCE60160.2023.00203,(2023).

97 Nvidia. *Glossary: Power Efficiency;* Santa Clara, California, https://www.nvidia.com/en-us/glossary/power-efficiency/ (Accessed August 2024).

98 Antonella Gina Fleitas. *What Is Data Center PUE? Defining Power Usage Effectiveness;* Data Center Knowledge, https://www.datacenterknowledge.com/sustainability/what-data-center-pue-defining-power-usage-effectiveness (2023).

99 Torsten Hoefler *et al.* Sparsity in Deep Learning: Pruning and growth for efficient inference and training in neural networks. arXiv:2102.00554 (2021). https://doi.org/10.48550/arXiv.2102.00554.

100 Everton Gomede. *Sparse Neural Networks and Pruning: Trimming the Fat for Efficient Machine Learning;* Medium, San Fancisco, California, https://medium.com/aimonks/sparse-neural-networks-and-pruning-trimming-the-fat-for-efficient-machine-learning-5b9d2920c526 (2023).

101 S. Ambrogio *et al.* An analog-AI chip for energy-efficient speech recognition and transcription. *Nature* 620, 768-775 (2023). https://doi.org/10.1038/s41586-023-06337-5.

102 Wenli Ni *et al.* CO2 emission-mitigation pathways for China's data centers. *Resources, Conservation and Recycling* 202, 107383 (2024). https://doi.org/10.1016/j.resconrec.2023.107383.

103 International Organization for Standardization (ISO). *ISO/IEC 21031:2024 Information technology — Software Carbon Intensity (SCI) specification;* Geneva, Switzerland, https://www.iso.org/standard/86612.html (2024).

104 David Owen. *The Efficiency Dilemma (in Annals of Environmentalism);* The New Yorker, New York, New York, https://www.newyorker.com/magazine/2010/12/20/the-efficiency-dilemma?_sp=c1f8b808-3111-41ce-a832-08891ee99fa5.1723848270771 (2010).

105 Mario Giampietro & Kozo Mayumi. Unraveling the Complexity of the Jevons Paradox: The Link Between Innovation, Efficiency, and Sustainability. *Frontiers in Energy Research* 6 (2018). https://doi.org/10.3389/fenrg.2018.00026.

106 Ruiwen Lee, Gernot Wagner & Environmental Defense Fund. *The Rebound Effect in a More Fuel Efficient Transportation Sector (Working Paper No. 2012/3);* New York University School of Law – Institute for Policy Integrity, New York, New York, https://policyintegrity.org/files/publications/The_Rebound_Effect.pdf (2013).

107 Kenneth Gillingham, David Rapson & Gernot Wagner. *The Rebound Effect and Energy Efficiency Policy;* Yale School of the Environment, New Haven, Connecticut, https://resources.environment.yale.edu/gillingham/GillinghamRapsonWagner_Rebound.pdf (2015).

108 David Berreb. *As Use of A.I. Soars, So Does the Energy and Water It Requires;* Yale School of the Environment – Yale Environment 360, New Haven, Connecticut, https://e360.yale.edu/features/artificial-intelligence-climate-energy-emissions (2024).

109 Lucas W. Davis, Alan Fuchs & Paul Gertler. Cash for Coolers: Evaluating a Large-Scale Appliance Replacement Program in Mexico. *American Economic Journal: Economic Policy* 6, 207–238 (2014). http://dx.doi.org/10.1257/pol.6.4.207.

110 Amazon – Sustainability. *Carbon-Free Energy;* Seattle, Washington, https://sustainability.aboutamazon.com/climate-solutions/carbon-free-energy?energyType=true (Accessed August 2024).

111 Google Data Centers. *24/7 Carbon-Free Energy by 2030;* Council Bluff, Iowa, https://www.google.com/about/datacenters/cleanenergy/#:~:text=A%20sustainability%20moonshot,with%20purchases%20of%20renewable%20energy (Accessed August 2024).

112 Michelle Patron. *Advocating for decarbonization of the power sector;* Microsoft, Redmond, Washington, https://blogs.microsoft.com/on-the-issues/2023/08/16/apec-sustainability-decarbonization-fusion-energy/ (2023).

113 Jackson Morris. *Data Centers Gobbling Up Existing Nukes Threatens Grid Decarb Goals;* Natural Resources Defense Council (NRDC), New York, New York, https://www.nrdc.org/bio/jackson-morris/data-centers-gobbling-existing-nukes-threatens-grid-decarb-goals-0 (2024).

114 Jeff St. John. *Data centers want to tap existing nuclear power. Is that good or bad?;* Canary Media, New York, New York, https://www.canarymedia.com/articles/nuclear/data-centers-want-to-tap-existing-nuclear-power-is-that-good-or-bad (2024).

115 Directorate-General for Energy. *Renewable hydrogen production: new rules formally adopted;* European Commission, Brussels, Belgium, https://energy.ec.europa.eu/news/renewable-hydrogen-production-new-rules-formally-adopted-2023-06-20_en (2023).

116 US Department of Energy (DOE). *Clean Hydrogen Production Tax Credit (45V) Resources;* Washington, D.C., https://www.energy.gov/articles/clean-hydrogen-production-tax-credit-45v-resources (2023).

117 Brian Deese & Lisa Hansmann. *America Needs an Energy Policy for AI;* Heatmap News Inc., Larchmont, New York, https://heatmap.news/technology/ai-additionality-framework (2024).

118 Cy McGeady. *AI Additionality Is the Wrong Solution to a Real Problem;* Center for Strategic & International Studies, Washington, D.C., https://www.csis.org/analysis/ai-additionality-wrong-solution-real-problem (2024).

119 Lisa Martine Jenkins. *Can Google's clean transition tariff remake utility incentives?;* Latitude Media, Mount Pleasant, Michigan, https://www.latitudemedia.com/news/the-clean-transition-tariff-is-googles-play-to-remake-utility-incentives#:~:text=Dubbed%20the%20%E2%80%9Cclean%20transition%20tariff,passing%20costs%20on%20to%20ratepayers (2024).

120 Duke Energy. *Responding to growing demand, Duke Energy, Amazon, Google, Microsoft and Nucor execute agreements to accelerate clean energy option;* PR Newswire, New York, New York, https://www.prnewswire.com/news-releases/responding-to-growing-demand-duke-energy-amazon-google-microsoft-and-nucor-execute-agreements-to-accelerate-clean-energy-options-302158155.html (2024).

121 Philipp Wiesner *et al.* Vessim: A Testbed for Carbon-Aware Applications and Systems. arXiv:2306.09774 (2023). https://doi.org/10.48550/arXiv.2306.09774.

122 Green Software Foundation. *Carbon-Aware Computing Whitepaper - How UBS succeeded in measuring and reducing carbon emissions of their core risk platform;* San Francisco, California, https://greensoftware.foundation/articles/carbon-aware-computing-whitepaper-how-ubs-succeeded-in-measuring-and-reducing-car (2023).

123 A. Radovanović *et al.* Carbon-Aware Computing for Datacenters. *IEEE Transactions on Power Systems* 38, 1270-1280 (2023). https://doi.org/10.1109/TPWRS.2022.3173250.

124 Dan Benitah. *Green-Software-Foundation / carbon-aware-sdk* GitHub, San Francisco, California, https://github.com/Green-Software-Foundation/carbon-aware-sdk (Accessed August 2024).

125 Gudrun Sævarsdottir, Halvor Kvande & Thordur Magnusson. Greenhouse Gas Emissions from Silicon Production -Development of Carbon Footprint with Changing Energy Systems. *Proceedings of the 16th International Ferro-Alloys Congress (INFACON XVI)* (2021). http://dx.doi.org/10.2139/ssrn.3926088

126 Chris Bataille. Decarbonizing Steel and Cement in *Columbia Energy Exchange. (Columbia University School of International and Public Affairs – Center on Global Energy Policy, New York, New York, 2023) https://www.energypolicy.columbia.edu/decarbonizing-steel-and-cement/.*

127 Amane Dannouni *et al. How AI Can Speed Climate Action;* Boston Consulting Group (BCG), Boston, Massachusetts, https://www.bcg.com/publications/2023/how-ai-can-speedup-climate-action (2023).

128 Emma Chervek. *Hyperscaler sustainability scorecard: Rating Google's, Microsoft's and AWS' environmental strategies;* SDxCentral, https://www.sdxcentral.com/articles/analysis/hyperscaler-sustainability-scorecard-rating-google-microsoft-and-aws/2023/07/ (2023).

129 Quantum Black AI by McKinsey. *The state of AI in 2022—and a half decade in review;* https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review (2022).

130 Goldman Sachs. *Top of Mind – Gen AI: too much spend, too little benefit? (Report);* New York, New York, Report available at https://www.goldmansachs.com/insights/top-of-mind/gen-ai-too-much-spend-too-little-benefit (2024).

DATA CENTER WATER USE

Julio Friedmann

Most modern data centers use water to cool the computer servers, which generate huge volumes of heat. The servers preferred by AI applications generate even more heat than standard servers and therefore use more water as a coolant. In addition, generating electricity for data centers often consumes water (Figure 15.5-1). Since many new data centers are being built in water-stressed areas, minimizing water usage for data centers is a priority in many locations.

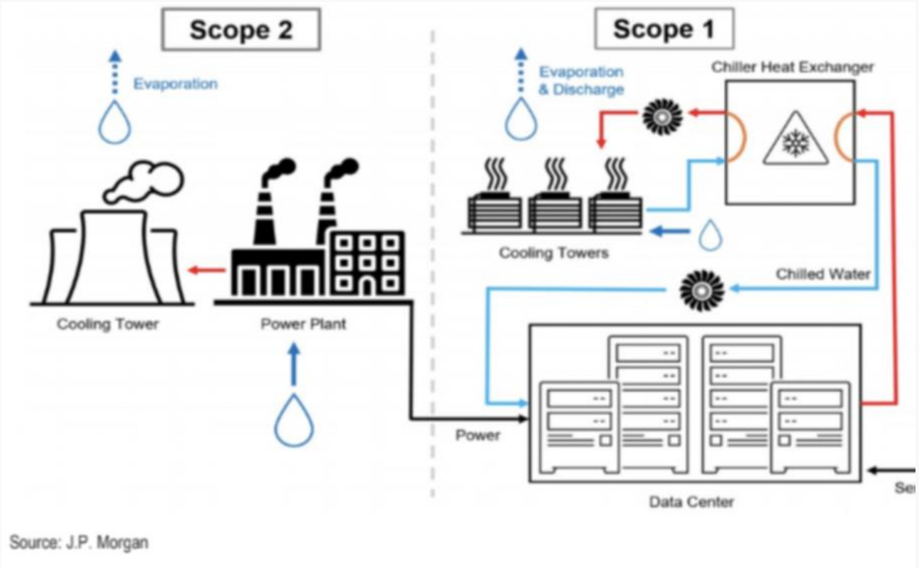


Figure 15.5-1. *Major sources of water consumption associated with data center operation and AI.*[1]

Magnitude

Data on the magnitude of water use by data centers are limited, as are projections about near-term consumption. Bluefield Research found that data centers consumed 292 million gallons per day (roughly 1.1 million m^3/d) globally in 2022 (Figure 15.5-2). They project global use will increase to roughly 450 million gallons/d (~1.7 million m^3/d)—a 5.5% annual increase.[1] (Only a portion of data center workloads, and therefore water use, is for AI applications.) In a 2023 paper, Li et al. project greater water consumption by 2027 (4.2–6.6 million m^3/d, depending largely on the cooling requirements for power systems and estimated growth rate).[2]

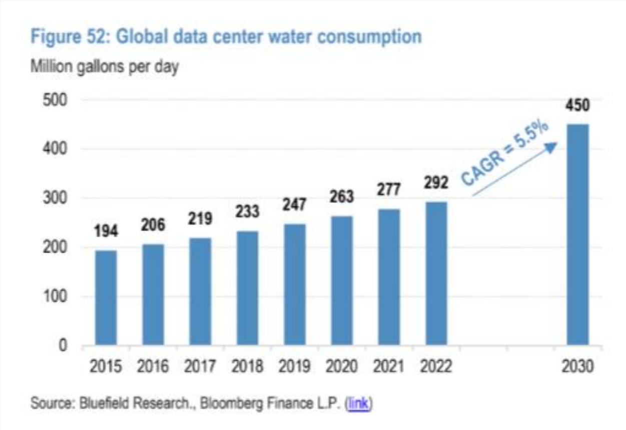


Figure 15.5-2. *Global water use for data centers. Source: JP Morgan Chase, based on original data from Bluefield Research[1]*

By way of comparison:

- The agricultural irrigation load of just the United States alone is ~140 billion gal/d,[3] or 300 times more than the 450 million gal/d forecast for global data center water use in 2030.
- The Amazon discharges ~4800 billion gal/d (almost 5 trillion/day),4 which is more than 10,000 times larger than the projected 2030 global data center water use.

Although 0.001% of one river could provide all the world's water consumption for all data centers, ultimately water is managed and consumed regionally. In water scarce regions, such as the Middle East or the western United States, local impacts could be substantial and unmanaged growth of data centers could lead to subsidence, local water shortages, and competition between agriculture and AI. In a 2021 paper on US data centers, Siddik et al. found that "one-fifth of data center servers' direct water footprint comes from moderately to highly water stressed watersheds, while nearly half of servers are fully or partially powered by power plants located within water stressed regions."[5]

Options and possible solutions

Many providers and operators of data centers are considering ways to reduce water consumption or water stress. For example, the computer maker Lenovo has begun to market a novel cooling system that significantly decreases water consumption.[6] Data-center builder and operator Nautilus Data Technologies typically operates on closed-loop cooling systems in sea water,[7] consuming no fresh water at all. In addition, some operators have begun exploring opportunities to use waste heat rather than rejecting it for cooling, including using it for district heating and running industrial processes (e.g., direct air capture).[8] And, of course, AI can be directly harnessed to optimize for minimal water consumption.

Policy options include mandatory water usage reporting, water efficiency standards, incentives for sustainable practices, water pricing mechanisms and water recycling mandates. (See Chapter 16 of this Roadmap.)

Data center water consumption will not be a major concern in many places but could be a significant concern in other locations. Water is a scarce resource and should be managed well in all circumstances. More data collection and research are needed.

Recommendations

1. *<u>Data center operators and governments</u> should collect and share data on water consumption to understand potential issues and determine risk. More and better data are needed to identify potential risks in terms of the magnitude and acuteness of community or environmental stresses.*
2. *<u>Data center operators</u> should explore potential pathways to reduce water consumption and mitigate risks. There are many promising, practical ways to manage water use and reduce total water consumption. The economic and technical viability of these options will vary by region. Especially in water stressed areas, <u>data center operators</u> should begin to track, review and explore options to responsibly and reasonably mitigate water consumption stresses and concerns.*
3. *<u>National and local governments</u> should consider policy options, including mandatory water usage reporting, water efficiency standards, incentives for sustainable practices, water pricing mechanisms and water recycling mandates.*

References

1 Tyler Durden. *JPM Predicts Global AI Data Centers Will Consume 681 Olympic-Sized Pools Of Fresh Water Daily;* Zero Hedge, Omaha, Nebraska, https://www.zerohedge.com/commodities/jpm-predicts-global-ai-data-centers-will-consume-681-olympic-sized-pools-fresh-water (2024).

2 Pengfei Li *et al.* Making AI Less "Thirsty": Uncovering and Addressing the Secret Water Footprint of AI Models. arXiv:2304.03271 (2023). https://doi.org/10.48550/arXiv.2304.03271.

3 Water Resources Mission Area. *Irrigation Water Use;* US Geological Survey (USGS), Reston, Virginia, https://www.usgs.gov/mission-areas/water-resources/science/irrigation-water-use (2019).

4 Wikipedia. *List of rivers by discharge;* San Francisco, California, https://en.wikipedia.org/wiki/List_of_rivers_by_discharge (Accessed August 2024).

5 Md Abu Bakar Siddik, Arman Shehabi & Landon Marston. The environmental footprint of data centers in the United States. *Environmental Research Letters* 16, 064017 (2021). https://dx.doi.org/10.1088/1748-9326/abfba1.

6 Matthew T. Ziegler. *The world's AI generators: rethinking water usage in data centers to build a more sustainable future;* Lenovo, San Jose, California, https://news.lenovo.com/data-centers-worlds-ai-generators-water-usage/#:~:text=NPR%20reports%20the%20average%20data,generated%20by%20the%20IT%20equipment (2024).

7 Nautilus Data Technologies. *Home Page: Energy Efficient Water Wise AI Ready;* San Ramon, California, https://nautilusdt.com/ (Accessed August 2024).

8 Sebastian Moss. *Meta and Alphabet's X developing direct air capture systems using data center waste heat;* Data Centre Dynamics Ltd (DCD), London, UK, https://www.datacenterdynamics.com/en/news/meta-and-alphabets-x-developing-direct-air-capture-systems-using-data-center-waste-heat/ (2024).

CHAPTER 16:

GOVERNMENT POLICY

David Sandalow and Michal Nachmany

A. General AI Policies 16-2

B. Realizing AI's Potential for Climate Mitigation 16-4

C. Managing Risks 16-11

D. Recommendations 16-18

E. References 16-23

European Parliament -- Strasbourg, France

Governments play an important role in the use of artificial intelligence (AI) for climate change mitigation. Governments collect environmental data used to train AI models, fund clean energy research programs that use AI tools, establish policies that shape the use of AI in the power and transport sectors, and facilitate international cooperation on AI for climate action. Other examples abound.

Governments are playing an increasing role in addressing risks from AI, including content risks (such as bias, invasions of privacy and misinformation/disinformation), resource risks (such as increased greenhouse gas (GHG) emissions, strains on the power grid and water stress) and safety/security risks. These risks may affect the use of AI for climate change mitigation, diminishing the impact of AI tools designed to help reduce greenhouse gas emissions and/or undermining public trust in AI more broadly.

These policies and programs have important impacts. Yet governments could do much more, using their convening powers, vast spending, regulatory authorities and other tools to speed and steer the use of AI for climate change mitigation.

This chapter explores government's role in AI for climate change mitigation. After a background section on government AI policies broadly, we pose two broad questions:

1. What can governments do to promote the use of AI for climate change mitigation?
2. What can governments do to address risks related to the use of AI for climate mitigation.

We conclude with recommendations.

A. General AI Policies

Government policies with respect to AI are evolving rapidly. Policymakers around the world are considering a range of AI topics, including liability rules, labeling requirements, intellectual property protections, data privacy restrictions, workforce training programs, security and safety standards and data sovereignty issues.

AI first began to receive widespread attention from policymakers during the latter part of the 2010s, due in part to the growing capabilities of AI models and emergence of applications such as facial recognition and autonomous vehicles. The release of ChatGPT in fall 2022 focused extraordinary public attention on AI, with rapid recognition of AI's revolutionary potential and serious risks. This recognition has led to unprecedented interest in AI from policymakers. Important recent policy developments include:

- the European Union's *Artificial Intelligence Act* (May 2024)[1];
- the Biden administration's *Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence* (October 2023)[2];
- the *G7 Hiroshima Process International Guiding Principles* (October 2023)[3] and
- the *Shanghai Declaration on Global AI Governance* (July 2024).[4]

The text box at the end of this chapter summarizes recent AI policy developments in key jurisdictions around the world.

AI policies around the world vary widely, reflecting different political cultures. Europe's approach to regulating digital issues (including AI) has been called "rights-driven," emphasizing privacy, data protection and ethical standards; the US approach has been called "market-driven," emphasizing innovation with minimal regulatory constraints; and China's approach has been called "state-driven," emphasizing government oversight and control to help achieve national security and economic objectives. (The terms are from Anu Bradford's *Digital Empires* (2023).)[5]

Although government policies with respect to AI are evolving rapidly, those policies tend to change much more slowly than AI technologies themselves. Government institutions in many countries tend to move slowly, and many policy makers lack basic familiarity with AI. Finding ways for government policies to respond to fast-moving developments in AI is a challenge.[6,7]

Still, government policies can play an important role in shaping AI for positive social outcomes. Governments can, for example, incentivize development of AI technologies that promote public goods by offering innovators grants or tax breaks. Governments can adopt regulations to prevent premature deployment of AI in mission-critical settings, which poses privacy and security risks. By setting clear ethical standards and requiring transparency in AI development, governments can mitigate biases and discrimination that might arise from poorly designed AI systems.

For AI to achieve its full potential in benefiting society, key stakeholders must trust AI systems where appropriate and also critically evaluate their strengths and weaknesses. Yet the varying quality of AI systems, coupled with concerns about job displacement, privacy, algorithmic bias and energy use, have led to varying levels of trust and willingness to use AI-based systems.

Governments can play a pivotal role in promoting trust in well-functioning AI systems and a questioning attitude about AI more broadly. By setting standards to minimize risks, governments can enhance the trustworthiness of AI systems. By implementing transparency measures, governments can help foster public understanding of AI. Governments can both promote open-source models, helping mitigate concerns about "black box" algorithms, and set transparency standards for closed-source models, allowing the public to scrutinize the models' training data, identify potential biases and improve the models' performance.

At the G7 Summit in June 2024, the heads of state held a "Special Session on Artificial Intelligence." Pope Francis delivered remarks that concluded with the statement "It is up to everyone to make good use of [artificial intelligence], but the onus is on politics to create the conditions for such good use to be possible and fruitful."[8]

B. Realizing AI's Potential for Climate Mitigation

AI is already contributing significantly to climate mitigation and has the potential to contribute much more. Today, for example, AI algorithms play a central role in monitoring methane emissions and help increase productivity of solar and wind power plants. Large language models (LLMs) help summarize and interpret climate-related documents from governments, financial institutions and others.[9] In the years ahead, AI could accelerate discovery of new materials for batteries and biofuels, dramatically increase the capacity of transmission lines, reduce emissions from traffic congestion and much more.[10,11] (Chapters 3–13 of this roadmap explore these topics in greater detail.)

As opportunities to use AI for climate mitigation grow in the years ahead, the role of governments will be important. Some AI projects will have emissions reductions benefits but little, if any, near-term commercial return, requiring governments to help move the projects forward. Other AI projects will have commercial returns but will not be designed to achieve optimal climate change benefits. Investing in projects to help maximize social benefits (such as those related to climate change) is a classic and important governmental function.

Realizing AI's full potential to contribute to climate mitigation will not be easy. Available, accessible, high-quality and interoperable data are essential. So are people with the skills to develop AI tools and the vision to identify the many ways AI can help accelerate decarbonization. Computing power is needed to train and run AI models, institutions must adapt to transformational new technologies, and funding is required for all this work. Government policies could help overcome barriers in all these areas.

i. Data

Data are essential for AI models. Complete, representative and reliable data provide a foundation for models that can support and accelerate the transition to net-zero emissions. Partial, unrepresentative and unreliable data produce bad models that could complicate or slow the transition. Unavailable or inaccessible data (especially from the global south), biased data and the lack of interoperable data can all cause problems.

U.S. Capitol -- Washington, DC, USA

Governments can play an important role in addressing these challenges in at least three areas: collecting data, standardizing data and making it interoperable, and addressing the digital divide.

a) Data collection

Governments collect significant amounts of data related to climate change. The European Space Agency (ESA), the US National Aeronautics and Space Administration (NASA), the Japan Meteorological Agency and the China Meteorological Administration, for example, all collect large amounts of historical and current weather data. Several government programs, including ESA's Climate Change Initiative and NASA's Climate Data Service, specifically focus on ways that weather data can contribute to understanding climate change.

Government agencies collect other types of data related to climate mitigation as well. NASA collects data on forest loss.[12] The Japan Meteorological Agency collects data on sea-level rise.[13] Hundreds of cities around the world collect traffic data.[14] Most national governments—as well as the World Bank, the International Monetary Fund (IMF) and the Organization for Economic Co-operation and Development (OECD)—collect economic data.[15] The UN Climate Framework Convention on Climate Change (UNFCCC), UN Environment Program (UNEP),UN Office for Disaster Risk Reduction (UNDRR) and others collect data on countries' GHG emissions and climate action.

In addition, governments support collection of climate-related data sets by others. Many universities, for example, rely on government grants for data collection and analysis with respect to climate change. The United States, European Union, Japanese and Chinese governments, among others, provide extensive grant funding for climate change and clean-energy research, which often involves data collection.[16-18]

More and better data could contribute to climate change mitigation. Priorities include LiDAR data for topography, flood maps for urban planning, and more frequent and granular economic and emissions data. (Climate Change AI has published a Dataset Wishlist that includes considerable detail on data sets that would be helpful.[19]) Further, some of the currently available data suffer from quality problems and biases.

Governments play an important role in helping address these gaps. Government policies can include:

- Collecting, curating and hosting climate-related data;
- Funding the collection, curation and hosting of climate-related data by others with grants, tax incentives or other fiscal tools;
- Developing governance mechanisms for climate-related data on topics such as IP rights, legacy data, protection from deletion, data provenance and interoperability;
- Convening task forces or similar groups to encourage standardization and interoperability of climate-related data and
- Adopting regulations that encourage or require disclosure of climate-related data.

b) Data standardization and interoperability

Governments play a growing role in promoting standardization and interoperability of data for climate change mitigation. Current initiatives focused specifically on climate change and energy data include:

- The ESA Climate Change Initiative's Data Standards, which set forth requirements "to ensure consistency, harmonization and ease of use" of varied climate data sets[20]
- The UK Energy Data Task Force, established in 2019 as a collaboration between government, industry and academia, which develops standards and best practices with respect to data quality, interoperability and data sharing protocols in the energy sector.[21]

Broader data initiatives with a climate change component include:

- The German Standardization Roadmap, which establishes "data infrastructure and data quality standards for the development and validation of AI systems," specifically noting that "[data] standardization contributes to Germany's transformation into a climate-neutral industrialized country"[22];
- Global Open Data for Agriculture and Nutrition (GODAN), which brings together governments, organizations and individuals to advocate for data standardization, sharing and interoperability[23];
- The Open Government Partnership, a government–civil society collaboration aimed at enhancing data transparency, civic participation and public accountability, including with respect to climate-related data and
- The European Telecommunications Standards Institute (ETSI), a European standard-setting organization supported in part by the European Union that sets Internet of Things (IoT) standards, including those for "achieving the green and digital transformation."[24]

Governments could do more to help increase standardization and interoperability of climate data. Steps governments could take include:

- Recommending stakeholders follow data management guidelines, such as the "FAIR Guiding Principles" (Findability, Accessibility, Interoperability and Reusability)25;
- Imposing data standardization and harmonization requirements in connection with government-funded research and development (R&D) and tax incentives;
- Enacting regulations to ensure transparency, including access to metadata and core data;
- Providing funding for data standardization organizations and activities, including for developing standards and raising awareness and
- Fostering collaboration and knowledge-sharing among stakeholders, thereby promoting standardization and harmonization of climate-related data.

Government participation in standardization bodies and initiatives focused on data for climate mitigation can be especially helpful. By joining international organizations—such as the International Standards Organization (ISO)—and supporting industry-specific groups, governments contribute to development of data standards, protocols and best practices. Governments can also provide resources, expertise and endorsements to encourage adoption of these standards by industries and organizations.[24]

c) Addressing the digital divide

Finally, governments can take steps to address the global digital divide. Today, more than 2.5 billion people globally are not connected to the Internet, and roughly half the world's population lacks access to high-speed broadband.[26] That creates two problems with respect to using AI for climate change mitigation. First, the lack of digital connectivity significantly limits data creation on a range of topics relevant to climate change mitigation, including energy usage, travel patterns and more.[27] Second, the lack of digital connectivity prevents businesses and others from accessing AI tools that could help cut emissions.(Of course, connecting people to high-speed Internet has wide-ranging economic and social benefits and should be pursued for many reasons beyond those related to climate change mitigation.)

Some intergovernmental bodies and government programs currently work to address the digital divide. These programs include:

- The International Telecommunication Union, a UN agency whose mission is "connecting the world"[28]
- The World Bank's Digital Development Partnership, which works to "to leverage digital technologies and data as a means to accelerate green, inclusive and resilient social and economic development"[29]
- The US Infrastructure Investment and Jobs Act (IIJA) of 2021, which allocated $42 billion to close the digital divide in the US by improving broadband access.[30]

Additional steps governments can take include providing more funding for broadband infrastructure in remote and underserved areas; establishing public WiFi hotspots in community centers, libraries and schools; launching digital literacy training programs to teach basic digital skills; and sharing best practices with other governments concerning policies and programs in this area.[31]

ii. People

Developing AI tools for climate change mitigation requires a diverse team of professionals. Data scientists, climate scientists, data engineers, software engineers, designers, product managers, climate policy experts and others may all have roles. These professionals must work together, often bridging differences in professional backgrounds and approach.

One of the principal barriers to using AI for climate change mitigation is a lack of trained personnel. Trained data scientists and engineers are in short supply. (LinkedIn data suggest a 74% increase in the demand for AI specialists in the past four years.[32,33]) In addition, many professionals working on climate issues lack basic familiarity with AI. They may miss opportunities for AI to contribute significantly to their work and/or be unable to utilize AI tools for maximum advantage.

Governments could help overcome these barriers in several ways.[33]

First, governments could launch skills-development programs for professionals working on AI and climate issues. Some programs would target professionals with climate expertise, teaching them about AI; other programs would target professionals with AI expertise, teaching them about climate.

The programs could be workshops, short lecture series or full courses. Government agencies could run such programs or fund others to do so.

Second, governments could launch AI-climate fellowship programs. The programs would identify promising university graduates (perhaps focusing on those from developing countries) and fund residential fellowships to study topics related to AI and climate change. Governments could explore partnerships with leading foundations for these programs.[34-36]

Third, governments could pay for the education of university students learning skills related to using AI for climate mitigation. In some countries, paying the tuition and living expenses of university students developing such skills could help significantly increase enrollment in relevant courses.

Fourth, governments could integrate AI and climate change–related topics into educational curricula at all levels. AI skills rest on a foundation of science, technology, engineering and math (STEM) education, with a curriculum that includes quantitative reasoning, logic, computer programming and related topics. Governments could commit to strengthening STEM education as a platform for developing a new generation prepared for AI-specific education/training, with particular applications related to climate change.

Fifth, government agencies working on climate mitigation could systematically review the capabilities of their own staff with respect to AI and launch programs to ensure their staff remain up-to-date regarding AI developments. This could be especially beneficial for grant managers, helping them ensure government funds are disbursed with an up-to-date understanding of AI's potential and attention to AI-related data management practices.

Great Hall of the People -- Beijing, China

Sixth, governments could commit extra funds to recruiting and retaining skilled AI professionals. AI specialists often command high salaries in the private sector, making it challenging for government agencies to hire them. Providing government human resources (HR) departments with the authority and resources to compete (at least partially) with the private sector for the best AI professionals could deliver significant benefits.

Finally, as a core feature of education and training programs for AI and climate change, governments could pay attention to the global digital divide. As noted, billions of people globally currently lack Internet connectivity. Education and training programs focusing on basic digital skills in many regions will contribute enormously to a workforce able to fully utilize AI for climate change mitigation over the long-term.

iii. Computing power

AI projects require computing power—for training models, running models and storing data. Lack of adequate computing power can be a barrier to AI projects related to climate change, especially in training foundation models that require enormous compute. Governments can take several steps to address this challenge.

Governments could help increase the availability of computing power for climate change–related AI projects by (1) investing in its own computing infrastructure; (2) making its computing infrastructure available for projects that use AI for climate change mitigation and (3) funding research organizations, civil society and private sector companies working on climate change–related projects to use computing infrastructure owned by others.

Governments already play an important role in this regard. Within the US Department of Energy (DOE), for example, some of the world's most powerful supercomputers support a global network of partners as part of the Earth System Grid Federation (above). In connection with this project, Oak Ridge National Laboratory (ORNL), Lawrence Livermore National Laboratory (LLNL) and other US DOE National Labs provide computational services for climate change modeling and analysis—including simulations and projections—in part using AI tools.[37-39]

Government investment could take several forms. Governments could invest in their own computing infrastructure, provide grants for others to develop such infrastructure and/or provide tax incentives to encourage development. The approaches that work best will vary from country to country.

One powerful tool could be to (1) solicit proposals for projects that use AI for climate change mitigation and then (2) make computing power available without cost for the proposals that offer the greatest potential benefits. Microsoft AI for Earth and other private companies already do this[40]; governments could play an important role as demand for computing time increases in the years ahead. Government high-performance computing (HPC) facilities could expand their review process and reviewer pool to include more AI expertise and emphasize allocating HPC time for AI-enabled research with direct impacts on climate mitigation.[41]

iv. Cost

Cost is a cross-cutting barrier, relevant to each of the three barriers discussed above (data, people and computing power). Each of these three barriers could be mostly addressed, at least in the medium-term, with greater funding.

As noted above, many climate change–related AI projects will have little if any near-term commercial return, making government funding essential. Many advances in using AI for climate mitigation will depend on government funding in the years ahead.

A key question will be how such government funding for AI will be allocated. Some governments may focus funding on new and innovative AI methods, including open foundational models. Other governments may prioritize GHG reductions, which will often be achievable with existing AI methods. The allocation of funding between these two types of projects—those investigating new AI methods and those targeting maximum emission reduction—could have a significant impact.[42]

Governments also have an important role in ensuring that electric utilities that use AI tools to reduce emissions receive compensation for such projects. Electric utilities that are paid a regulated return based on their capital spending may lack the incentive to invest in AI tools that reduce emissions and costs. Unless regulators approve rules that provide compensation for the value created by AI, electric utilities may not pursue emissions-reducing projects, such as those for demand response or vehicle-grid integration.[43]

National Diet Building – Tokyo, Japan

v. Institutions

Institutional structures will play a significant role in realizing AI's potential for climate mitigation.

Some recent history provides useful background. The modern computing era began in the 1960s, as mainframe computers became increasingly central to many business functions. But the term "Chief Information Officer" was not coined until 1981. Until the 1980s, few large organizations had executives solely responsible for information and communications technologies in their top leadership teams.[44]

In a similar manner, despite significant recent advances in AI, many institutions are only beginning to incorporate AI into their organization and mission. They could do so in a number of ways. For government agencies with responsibility for climate change mitigation, possible steps include:

- creating an Artificial Intelligence Office, with responsibility for assessing opportunities, barriers and risks with respect to AI in all aspects of the agency's mission;[45]
- hiring a Special Advisor responsible for advising the head of the agency on all matters related to AI;
- creating a unit to improve AI skills throughout the agency; and/or
- launching a strategic planning process to consider ways that topics related to AI can best be addressed within the agency on an ongoing basis.

Several governments are taking steps in these directions. In March 2024, for example, US Vice President Kamala Harris announced that all US government agencies would be required to name a chief AI officer.[46]

Governments can also create or help create public-private partnerships or other stakeholder groups, bringing together diverse groups to discuss and implement opportunities for using AI for climate mitigation. Governments could help fund such public-private partnerships and/or provide the convening power to help assemble and sustain such groups.

Finally, intergovernmental organizations can play an important role in AI for climate mitigation. The International Energy Agency (IEA) produces leading research and convenes important meetings on AI/energy issues.[47-49] The U.N. Framework Convention on Climate Change has an Initiative on AI for Climate Action.[50] The Clean Energy Ministerial and Mission Innovation are launching an initiative on using AI to promote clean energy. The World Meteorological Organization (WMO) is using AI to improve understanding of Earth systems.[51] These and other programs can help support the use of AI for climate mitigation.

C. Managing Risks

Risks related to using AI include content risks (such as bias, invasions of privacy and misinformation/disinformation), resource risks (such as increased GHG emissions, strains on the power grid and water stress) and safety/security risks.

These risks arise from using AI generally, not from using AI for climate change mitigation in particular. Yet, there are two reasons why addressing these risks is important to successfully using AI for climate change mitigation. First, failure to address these risks could undermine public trust and confidence in AI, making adoption of AI for climate change mitigation less likely. Second, failure to address these risks could diminish the impact of AI tools designed to help mitigate climate change.

In this section we discuss risks of using AI, government policies that could help address these risks and steps taken by governments to date.

i. Bias

Unrepresentative data, poorly designed algorithms and other factors create risks of bias in many AI applications. These biases can distort AI recommendations on a range of topics, including (for example) on infrastructure siting. An AI algorithm trained on historical data might suggest that new polluting infrastructure be located in low-income communities and new electric vehicle (EV) charging infrastructure be located in high-income communities because that is where such infrastructure is found in existing data sets. AI can produce poor or inaccurate results when developers fail to realize that data collected from one socioeconomic group is not representative of patterns in another socioeconomic group.

These biases often result from uneven data availability across regions. For example, LLMs are trained on vast amounts of data, but these data are overwhelmingly from the Global North and primarily in English—the prevalent language on the Internet. This imbalance can lead to LLMs that are biased toward Western perspectives and struggle to understand or respond appropriately to languages and cultures from the global south.[27]

Governments can address risks of bias with a range of tools:

- Data collection standards. Governments could set data collection standards for AI models, highlighting the importance of diverse and representative data sets. These standards could be binding or non-binding.

- Transparency. Similarly, governments could set standards with respect to transparency in developing AI models, giving all stakeholders a better opportunity to identify possible biases. These standards could be binding or non-binding. For example, disclosure requirements could be established for training and evaluation data sets.
- Third-party audits. Governments could recommend or require that AI developers retain third party auditors to assess any bias in their products and establish accreditation standards for organizations conducting such audits.
- Legal accountability. Governments could establish legal frameworks that hold entities accountable for biased or discriminatory outcomes resulting from AI applications.
- Convening. Governments could convene diverse stakeholders to evaluate AI products, bringing people with a wide range of views together and making sure all are heard.
- Education and training. Governments could offer AI developers, data scientists and other stakeholders training programs on the importance of bias recognition and mitigation
- Research and development (R&D). Governments could allocate funding for research into reducing bias in AI generally and for climate mitigation.

There is emerging regulation attempting to address bias in AI. For example, the US Federal Trade Commission (FTC) and Equal Employment Opportunity Commission have introduced initiatives aimed at establishing guardrails around AI and its potential impact on the constituencies those agencies are charged with protecting.[52] The FTC has already taken enforcement action against using biased data.[53] The EU's AI Act specifically addresses bias, requiring data governance and management practices for AI systems classified as high-risk—including human oversight and risk management practices to mitigate likely risks to fundamental rights. The Act does not prevent deploying biased systems.[54]

ii. Privacy

Privacy risks related to using AI for climate mitigation include surveillance, personal identification and data sharing. First, increasing use of sensors, drones and IoT devices to monitor environmental change and human behaviors related to carbon emissions creates a risk that some data could be used for unauthorized surveillance. Second, when data from multiple sources are aggregated (such as smart meter data and property records), individuals who were previously anonymous in isolated datasets could become identifiable. Third, data on energy consumption patterns or other topics could be shared with third parties, either by the host of that data or as the result of a cyberattack.

Governments can address these risks with policies including:

- Data protection regulations. Governments could enact laws requiring organizations to ensure the privacy and protection of personal data, provide transparency on how data are processed and give individual's rights to access, correct and delete their data. The EU's General Data Protection Regulation (GDPR) is widely considered to be the strongest such law passed globally to date.[55]

- Privacy by design for all AI models. Governments could require that privacy considerations be expressly integrated in the design of AI models throughout development and during use.
- Cybersecurity standards. Governments could mandate cybersecurity measures for organizations that collect, process or store climate-related data.
- Anonymization. Governments could require use of techniques that render personal data less identifiable.
- Oversight and governance bodies. Governments could establish independent oversight boards or agencies responsible for monitoring and ensuring privacy protections related to AI and climate mitigation.

Some of these policies are already being incorporated into national laws:

- Some data protection law frameworks, while not addressing AI specifically, lay a foundation for managing AI-related risks. The EU *General Data Protection Regulation* is an example.
- AI-specific privacy regulation is emerging in multiple countries. In some countries, this is done by integrating explicit AI provisions into existing general data protection measures. Examples include Brazil's *General Data Protection Law* (LGPD), South Africa's *Protection of Personal Information Act (POPIA)* and India's draft *Personal Data Protection Bill.*
- In addition, privacy provisions can be introduced into AI regulation, such as integrating data protection measures into the EU AI Act.

iii. Misinformation/disinformation

Misinformation is false or misleading information. Disinformation is false or misleading information spread deliberately to deceive or cause harm. (Critically, misinformation or disinformation can include the omission of information necessary for statements to be complete and accurate.)[56]

AI enables creation and dissemination of misinformation and disinformation at an unprecedented scale. Advanced AI technologies can generate fake text, images and videos that are difficult to distinguish from authentic content. These tools can be exploited to spread false narratives, manipulate public opinion and undermine trust in legitimate sources of information.

AI contributes to misinformation and disinformation in other ways as well. AI-driven algorithms on social media platforms exacerbate the spread of misinformation by prioritizing content that maximizes user engagement without regard to whether the information is authentic. This creates echo chambers where users are exposed primarily to information that confirms their existing beliefs, further entrenching misinformation and making it harder to correct false narratives. In addition, incomplete data or flawed weights in AI models can lead to "algorithmic bias," causing AI tools to spread false or misleading information.[27]

AI-driven misinformation and disinformation is a potentially serious problem with respect to climate change mitigation. Misinformation and disinformation can erode public confidence in scientific judgments that are at the core of effective climate change policies, create false or polarizing narratives that undercut public support for climate change policies and create significant impediments to sustaining climate change policies over the medium- to long-term.[57-59]

There are no easy solutions to AI-driven misinformation and disinformation. Having governments serve as the arbiter of truth creates significant risks—arguably greater than allowing AI-based misinformation and disinformation to proceed unchecked.[60]

Policies designed to mitigate AI-driven misinformation and disinformation include:

- Labeling requirements for manipulated text, images or video;
- Requirements that media platforms provide prompts or warnings suggesting that users consider the credibility of content before sharing or engaging with it;
- Media literacy education in schools, equipping students with skills to critically evaluate information;
- Government-led and independent watchdog fact-checking organizations and
- Prohibitions on content that governments consider to be misinformation or disinformation.[61]

Governments have begun to adopt policies in this area. The EU AI Act requires AI systems intended to inform the public on a matter of public interest to disclose when text has been manipulated, subject to some exceptions, including when human editors have reviewed and taken responsibility for the content.[62] Several countries have established government-funded fact-checking entities to combat misinformation, including AFP in France[63] and Singapore's Fact Check Media.[64] The G7 has established a Rapid Response Mechanism on Disinformation.[65] The Chinese government prohibits dissemination of information it considers to be false or misleading, with initiatives that focus on AI-driven content in particular.[66,67] (Strong disagreements between the Chinese government and many Western governments on what constitutes false or misleading information underscores the challenges of government regulation on this topic.)

iv. Greenhouse gas (GHG) emissions

At present, GHG emissions from AI operations are less than 1% of total GHG emissions—and perhaps much less.[68,69] Yet as the use of AI grows in the years ahead, GHG emissions from AI operations could increase significantly. (This topic is explored in detail in Chapter 15 of the Roadmap.)

A number of policies can help limit growth in GHG emissions from AI operations in the years ahead. Those include the following:

- Research & development (R&D). Governments could invest in R&D on energy-efficient AI algorithms and hardware. That could include research on methods that require less data or computational power for training AI models, such as few-shot learning or transfer learning.
- Low-carbon data centers. Governments can promote data centers that emit little or no carbon dioxide (CO_2) through a range of measures, including (1) tax incentives or subsidies for data centers powered with zero-carbon electricity (renewables, nuclear or fossil generation with carbon capture), (2) regulations requiring data centers to use a certain percentage of zero-

carbon power, (3) guidelines and incentives for energy-efficient data centers and (4) measures to increase supply of clean electricity (such as accelerated permitting).

- Disclosures. Governments could require AI companies to disclose GHG emissions associated with their operations on a full life-cycle basis. Disclosure requirements can apply to model cards (fact sheets that include information about how models are trained) and AI applications.
- Government procurement. Governments can prioritize AI systems with low GHG emissions when procuring AI solutions for their own use.

Recent legislation on these topics includes Germany's Energy Efficiency Act of 2023, which requires data centers to use 50% renewable energy by early 2024, rising to 100% by 2027.[70] In 2024, the EU Commission introduced a new regulatory framework mandating sustainability reporting for data centers consuming 0.5 MW or more. Beginning in 2026, operators must disclose total electricity consumption and the proportion sourced from renewable energy, including on-site generation and grid-supplied renewable energy backed by Guarantees of Origin.[71,72]

In the United States, Senator Ed Markey and several co-sponsors introduced the "Artificial Intelligence Environmental Impacts Act of 2024."[73] This act mandates that the Environmental Protection Agency (EPA) conduct a comprehensive study on the environmental impacts of AI, including energy consumption, pollution and electronic waste. The bill also requires that the National Institute of Standards and Technology (NIST) establish a consortium to develop standards and a voluntary reporting system for the environmental impacts of AI.

v. Strains on the power grid

In the past year, data center owners and operators have submitted a record number of requests for electricity interconnections in many places around the world. These requests are due in significant part to increasing demand for AI.[74,75] Due to uncertain prospects for approvals, many data center operators have submitted more interconnection requests than they need. Yet even accounting for this "application frenzy," data center power demand is still rising rapidly.[76,77] (This topic is explored in detail in Chapter 15B of the Roadmap.)

In many locations, electric utilities are unable to provide sufficient electric power to meet data center demand. In some locations, electric utilities do not anticipate being able to meet this demand for many years. Data center power demand is creating challenges with respect to resource adequacy (the ability of a power system to ensure sufficient generation capacity and other resources to reliably meet electricity demand at all times). Problems with resource adequacy increase risks of blackouts and brownouts, can lead to higher electricity prices, and compromise the reliability of an electric grid.

Government policy can play an important role in responding to these challenges. Potential approaches include:

- Construction moratoria halting approvals of new data centers until resource adequacy concerns are fully addressed;

- Suspension of data center tax incentives, slowing development that could raise resource adequacy concerns;
- Permitting reforms that streamline approval processes for new projects, allowing faster deployment of generation and transmission infrastructure;
- Locational incentives, such as zonal pricing and zoning rules for new data centers;
- Demand response programs, which reduce peak load on the grid by incentivizing consumers to lower their energy usage during high-demand periods[78];
- Proactive transmission planning to anticipate future energy needs and strategically develop transmission networks that accommodate load growth from data centers and
- Approval of infrastructure upgrades, such as expanding transmission lines and enhancing substations, thus increasing the grid's capacity to handle higher loads and reducing the risk of blackouts and brownouts.[78]

Regulators and utilities are starting to adopt some of these measures. Ireland, Singapore and the Netherlands have each at times imposed construction moratoria on data centers to prevent grid-related problems.[79,80] The state of Georgia in the United States suspended a tax break for data centers pending analysis of power demand issues.[81]

vi. Water stress

Data centers are critical infrastructure for the digital economy, powering everything from cloud storage to AI computations. However, some data centers consume significant amounts of water, primarily for cooling the servers, which generate substantial heat. This water usage can strain local water resources, especially in regions already facing water scarcity. The impact on local water resources can be severe, leading to competition between industrial and municipal water needs and potentially exacerbating existing water stress. To mitigate this impact, some data centers are exploring alternative cooling methods, such as using recycled or non-potable water or adopting more efficient air-cooling technologies that reduce water dependency.[82,83]

To address the environmental impacts of water consumption by data centers, governments can implement the following policy measures:

- Mandatory water usage reporting. Enforce transparent reporting of both direct and indirect water usage by data centers on AI model cards. The EU Data Center Directive includes water usage reporting.
- Water efficiency standards and targets. Establish water efficiency standards and clear targets for data center operations, mandating adoption of water-saving technologies like advanced cooling systems.
- Water pricing mechanisms. Implement tiered water pricing systems that reflect the true cost of water, encouraging data centers to optimize their water use and reduce unnecessary consumption.

- Location-based restrictions. Impose restrictions on the location of new data centers in water-scarce regions, directing development toward areas with abundant water resources to prevent strain on local water supplies.
- Water recycling and reuse mandates. Mandate or promote using recycled or non-potable water for cooling purposes in data centers.

Current examples of these policies include the EU-wide delegated regulation for rating sustainability of data centers,[71] which includes mandatory water usage reporting for data centers, and the Singapore Building and Construction Authority's Green Mark Certification scheme, which includes water efficiency criteria for data centers.[84]

vii. Safety/security

AI systems can create safety risks when they fail to operate as intended or have unintended consequences. Risks are especially acute when AI is used not only to inform human decision making, but to make decisions with limited or no human oversight. This can be especially dangerous in real-time operations in industrial facilities, the power grid and autonomous vehicles. In addition, AI tools are subject to attack by hackers or others with malicious intent, creating security risks. AI systems expand the "attack surface" for hackers beyond that found in conventional hardware and software, increasing security risks.[85,86]

Government policy can play an important role in addressing AI safety and security risks:

- Regulatory frameworks. Governments can establish regulations that require safety assessments, security protocols and risk management procedures for AI systems, as well as independent testing and verification to ensure these standards are met before AI systems are deployed.
- Certification and compliance. Governments can implement certification processes for AI systems that meet safety and security criteria.
- Public-private partnerships. Governments can collaborate with industry stakeholders and research institutions to develop best practices, guidelines and tools for ensuring AI safety and security, funding research focused on AI safety and security.
- Global cooperation and governance. Governments can engage in dialogue and cooperate with other governments around the world to establish global norms and standards for AI safety and security.
- Public awareness and education. Governments can initiate public awareness campaigns and educational programs about the potential safety and security risks of AI.

D. Recommendations

1. *Governments should prioritize development of a climate-relevant data ecosystem. This should include the following:*
    a. *Governments should invest significant funds in data collection, curation and standardization. The climate-relevant data collected by governments should be easily accessible by all stakeholders. In developing climate-relevant data, governments should particularly focus on data-gathering from underrepresented regions and sectors, as well as on data types that have previously been unavailable or insufficient.*
    b. *Governments should adopt and promote data interoperability standards and invest in secure, scalable infrastructure for storing and disseminating climate-relevant data. Governments should also adopt clear data governance frameworks to ensure data privacy, security and ethical use.*
    c. *Governments should employ a combination of direct funding, low-interest loans, tax incentives, advanced market commitments and regulatory frameworks to help.*
2. *Governments should help fund large-scale open-source foundational models tailored to addressing climate challenges. These models, in domains such as climate science, energy systems, food security and oceanography, could serve as the bedrock for a new generation of climate mitigation applications. By using existing open-source models and investing in new open-source models, governments can accelerate innovation, foster public-private partnerships and help develop solutions to pressing climate issues. International collaboration in funding and research will be essential to maximizing the impact of these models.*
3. *Governments should incentivize AI applications that contribute to climate mitigation with (1) regulatory frameworks that prioritize climate-friendly AI; (2) financial incentives, such as grants, tax breaks and procurement preferences and (3) public recognition programs. In connection with these programs, governments should establish clear evaluation criteria to assess the climate impact of AI systems to help ensure that incentives are targeted effectively.*
4. *Governments should invest in education and training programs to develop a skilled AI workforce. This should include supporting AI research, curriculum development and upskilling programs for both students and professionals.*
5. *In shaping policies and programs on AI and climate change, governments should seek input from and work closely with a wide range of stakeholders, including technology companies, energy companies, academia and civil society.*
6. *Governments should facilitate knowledge-sharing and collaboration between experts in climate mitigation and experts in AI. Governments should use their convening power (by organizing roundtables, task forces, advisory bodies and hackathons) and other tools for this purpose.*

7. *Governments should establish ethical guidelines for developing and deploying AI applications to help foster the trust and confidence in AI that will be important for using AI in climate change mitigation. These guidelines should address issues such as data privacy, bias, transparency, truthfulness and accountability. Governments should develop these guidelines in collaboration with industry, civil society and academia.*

RECENT AI POLICIES IN BRIEF

as of November 2024

UNITED STATES

Leading AI policy announcements from the US federal government include:

- The *Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence*, released in October 2023, which requires developers of large AI models to share information about their products with the US government, streamlines visa processes for noncitizens working on AI and directs federal agencies to issue AI guidelines, among dozens of provisions[2];
- The *AI Risk Management Framework,* released by NIST in January 2023 to help "manage risks to individuals, organizations, and society associated with artificial intelligence"[87] and
- The *Blueprint for an AI Bill of Rights*, released by the White House in October 2022 to guide design and use of AI with five principles—safe and effective systems; algorithmic discrimination protection; data privacy; notice and explanation; and human alternatives, considerations and fallback.[88]

In July 2023, President Biden met at the White House with the CEOs of leading AI companies, who pledged "to develop and deploy advanced AI systems to help address society's greatest challenges," including climate change.[89]

In May 2024, the Bipartisan Senate Artificial Intelligence Working Group released its *Roadmap for Artificial Intelligence Policy in the US Senate*.[90] The roadmap recommends that the federal government spend up to $32 billion for annual nondefense AI R&D and encourages Congressional committees to consider legislation on a wide range of AI topics including workforce training, transparency of AI systems, liability of AI developers and standards for using AI in critical infrastructure.

In the past several years, many bills on AI have been introduced in the US Congress:

- The Artificial Intelligence Environmental Impacts Act of 2024, which would mandate several measures to ensure environmental consequences of AI are thoroughly studied and reported[91];
- The CREATE AI Act of 2023, which would establish the National Artificial Intelligence Research Resource (NAIRR)[92] and

- The AI Labeling Act of 2023, which would require all generative AI systems to include a clear and conspicuous disclosure that identifies content as AI-generated.[93]

EUROPEAN UNION

The European Union's Artificial Intelligence Act entered into force on August 1, 2024. The Act comprehensively regulates AI in Europe, applying a risk-based approach. High-risk AI systems are subject to the most stringent controls. Activities considered to be especially risky—including live facial recognition and scraping of biometric data from social media platforms—are prohibited.[1,94]

The European Union's Energy Efficiency Directive, adopted in 2023, requires data centers with more than 500 kW of power demand to report energy consumption, renewable energy use, water use and related topics.[95] Germany's revised Energy Efficiency Act, also adopted in 2023, incorporates the EU reporting obligations, requires data centers to buy 50% of their power from renewable sources (rising to 100% by 2027) and sets other standards for data center operations.[70]

In September 2022, the European Commission proposed the AI Liability Directive, which is intended to ensure that AI operators can be held liable for damages caused by AI systems. (In the absence of such a directive, the lack of transparency and complexity of AI systems could make recovery of damages difficult.) The European Parliament and Council of the European Union have not yet acted on the European Commission's proposal. If the AI Liability Directive is adopted, EU Member States would then be required to incorporate its terms into national laws.[96-101]

Other important EU AI policies include (1) the Coordinated Plan on Artificial Intelligence, updated in 2021, which aims to accelerate investments in AI technologies and align AI throughout the European Union[102] and (2) the General Data Protection Regulation (GDPR) of 2016. AI is not explicitly mentioned in the GDPR, but many of its provisions—including those on purpose limitation, data minimization, the special treatment of "sensitive data" and limitations on automated decisions—are relevant to AI.[103,104]

CHINA

In July 2023, the Cyberspace Administration of China (CAC) and other entities published the Provisional Regulations on Management of Generative Artificial Intelligence Services. The Provisional Regulations require that any generative AI technologies used to provide services to the public in the China "reflect socialist core values" and prohibit content that "may harm national security and hurt the national image."[67]

In June 2023, China's State Council announced that it will submit a draft AI law to the Standing Committee of the National People's Congress by the end of the year.[105] This would be China's first national AI legislation.

In the past several years, the Chinese government has released a number of binding policy documents on AI:

- *Provisions on the Administration of Deep Synthesis Internet Information Services*, released by the CAC, the Ministry of Industry and Information Technology (MIIT) and the Ministry of Public Security (MPS) in November 2022. This policy document requires the labeling of synthetically generated content and prohibits AI tools from generating "fake news information."[106]
- *Provisions on the Management of Algorithmic Recommendations in Internet Information Services*, released by CAC, MIIT, MPS and the State Administration for Market Regulation in December 2021. This document includes provisions for content control and worker protection and created China's "algorithm registry," an online database. Developers are required to submit information to the registry on the training and deployment of their algorithms.[107,108]

JAPAN

In their May 2023 meeting in Hiroshima, Japan, G7 heads of state agreed to launch an initiative to strengthen collaboration on governance of generative AI. The initiative will be known as the "Hiroshima AI process."[109] Also in May 2023, the Japanese government held the first meeting of its Artificial Intelligence Strategy Council, attended by Prime Minister Fumio Kishida.[110]

In April 2023, Japan's governing Liberal Democratic Party released an *AI White Paper* with more than two dozen recommendations for promoting and managing the development of AI in Japan:

- "Accelerate applied research and development by accumulating domestic knowledge on foundation models"
- "Immediately initiate multiple pilot projects with visible results in a short period of time as specific examples of utilizing AI for basic administrative services"
- "Provide strong support for AI-based smart city initiatives by local governments"
- "Position the improvement of AI literacy in the public education curriculum in anticipation of the AI native era, when active use of AI in daily socioeconomic activities will be the norm"[111,112]

The *AI White Paper* builds on Japan's *AI Strategy 2022*, released in April 2022 by the Secretariat of Science, Technology and Innovation Policy within the Cabinet office. The *AI Strategy 2022* sets forth five strategic objectives for AI development in Japan:

- "A technological infrastructure that will enable Japan to protect its people in the face of imminent crises such as pandemics and large-scale disasters"
- "Japan should become the world's most capable country in the AI era by developing human resources"
- "Japan should become a top runner in the application of AI in real-world industries"
- "In Japan, a series of technology systems to realize a sustainable society with diversity is established and a mechanism to operate them is realized"
- "Japan should lead in building an international network in the AI field for research, education and social infrastructure"[111,113]

INDIA

In April 2023, India's Ministry of Electronics and Information Technology announced that the Indian government "is not considering bringing a law or regulating the growth of artificial intelligence in the country." The ministry referred to AI as a "kinetic enabler of the digital economy."[114,115] In February 2023, the Indian government announced the establishment of three new Centers of Excellence for Artificial Intelligence.[116]

In 2021, Nitii Ayog published a Responsible AI/AIforALL report, proposing seven "principles for the responsible management of AI systems: (1) safety and reliability, (2) equality, (3) inclusivity and non-discrimination, (4) privacy and security, (5) transparency, (6) accountability and (7) protection and reinforcement of positive human values."[117]

In 2018, Nitii Ayog released an AI Strategy calling for investment in education and training, privacy protections, and use of AI across the value chain.[117] The Indian Government maintains an AI website at https://indiaai.gov.in/.[118,119]

E. References

1 The Artifical Intelligence Act. *Homepage;* https://artificialintelligenceact.eu/ (Accessed September 2023).

2 The White House. *Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence;* https://www.whitehouse.gov/briefing-room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/ (2023).

3 G7 Hiroshima Summit. *Hiroshima Process International – Guiding Principles for Organizations Developing Advanced AI System;* https://www.mofa.go.jp/files/100573471.pdf (2023).

4 Ministry of Foreign Affairs – The People's Republic of China. *Shanghai Declaration on Global AI Governance;* https://www.fmprc.gov.cn/eng/wjdt_665385/2649_665393/202407/t20240704_11448349.html (2024).

5 Anu Bradford. *Digital Empires – The Global Battle to Regulate Technology*. (Oxford University Press, Oxford, UK, 2023, https://global.oup.com/academic/product/digital-empires-9780197649268?cc=us&lang=en&).

6 Tom Wheeler. *The three challenges of AI regulation;* The Brookings Institute, Washington, D.C., https://www.brookings.edu/articles/the-three-challenges-of-ai-regulation/ (2023).

7 Isabelle Bousquette. *AI Is Moving Faster Than Attempts to Regulate It. Here's How Companies Are Coping;* The Wall Street Journal, New York, New York, https://www.wsj.com/articles/ai-is-moving-faster-than-attempts-to-regulate-it-heres-how-companies-are-coping-7cfd7104 (2024).

8 Pope Francis Attends the G7 Session on Artificial Intelligence. *Address of his Holiness Pope Francis;* Borgo Egnazia (Puglia), https://www.vatican.va/content/francesco/en/speeches/2024/june/documents/20240614-g7-intelligenza-artificiale.html (2024).

9 Climate Policy Radar. *Building the evidence base for evidence-based decision-making;* London, UK, https://climatepolicyradar.org/ (Accessed August 2024).

10 Columbia Univerity: Climate Earth and Society. *Landscape Assessment of AI for Climate and Nature (Report);* Columbia University and Bexos Earth Fund with University at Albany (SUNY) and Environmental Systems Research Institute, Inc. (ESRI), New York, New York, https://www.climate.columbia.edu/ai-climate-nature-landscape-assessment (2024).

11 David B. Olawade *et al.* Artificial intelligence potential for net zero sustainability: Current evidence and prospects. *Next Sustainability* 4, 100041 (2024). https://doi.org/10.1016/j.nxsust.2024.100041.

12 Kate Ramsayer. *Global Forest Cover, Loss, and Gain 2000-2012;* NASA Scientific Visualization Studio, https://svs.gsfc.nasa.gov/11393 (2023).

13 Japan Meteorological Agency. *Sea level (around Japan);* https://www.data.jma.go.jp/gmd/kaiyou/english/sl_trend/sea_level_around_japan.html (2023).

14 Data World. *Traffic Datasets;* https://data.world/datasets/traffic (Accessed September 2023).

15 University of California (UC) San Diego. *Economics: Country Statistics & Data Sources;* https://ucsd.libguides.com/econguide/countrydata (2023).

16 Environmental Protection Agency (EPA). *Climate Change Research Grants* https://www.epa.gov/research-grants/climate-change-research-grants (Accessed September 2023).

17 Earth and Environmental Systems Modeling (EESM). *DOE Announces Funding for Climate Resilience Centers;* https://climatemodeling.science.energy.gov/news/doe-announces-funding-climate-resilience-centers (2022).

18 National Institutes of Health. *Funding Opportunities: Notice of Special Interest (NOSI): Climate Change and Health NOT-ES-22-006;* https://www.nih.gov/climateandhealth#funding-opportunities (Accessed September 2023).

19 Climate Change AI. *Climate Change AI Dataset Wishlist;* Pittsburgh, Pennsylvania, https://www.climatechange.ai/dataset-wishlist.pdf (Accessed August 2024).

20 The European Space Agency (ESA) Climate Office. *ESA CCI data standards;* https://climate.esa.int/en/explore/esa-cci-data-standards/ (Accessed September 2023).

21 GOV.UK. *Energy Data Taskforce* https://www.gov.uk/government/groups/energy-data-taskforce (2019).

22 Deutsches Institut für Normung (DIN). *Second edition of the German Standardization Roadmap AI;* https://www.din.de/en/innovation-and-research/artificial-intelligence/ai-roadmap (Accessed September 2023).

23 Global Open Data for Agriculture and Nutrition (GODAN). *Harnessing Open Data to Achieve Global Food Security;* https://www.godan.info/ (Accessed September 2023).

24 Sophia Antipolis. *ETSI IoT conference: standards are key to achieving green and digital transformation;* European Telecommunications Standards Institute (ETSI), https://www.etsi.org/newsroom/news/2258-etsi-iot-conference-standards-are-key-to-achieving-green-and-digital-transformation (2023).

25 Mark D. Wilkinson *et al.* The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data* 3, 160018 (2016). https://doi.org/10.1038/sdata.2016.18.

26 Landry Signé. *Fixing the global digital divide and digital access gap;* Brookings Institution, https://www.brookings.edu/articles/fixing-the-global-digital-divide-and-digital-access-gap/#:~:text=While%20this%20growth%20indicates%20that,of%20compounding%20negative%20effects%20in (2023).

27 Ramit Debnath *et al.* Harnessing human and machine intelligence for planetary-level climate action. *npj Climate Action* 2, 20 (2023). https://doi.org/10.1038/s44168-023-00056-3.

28 International Telecommunication Union (ITU). *About International Telecommunication Union (ITU);* Geneva, Switzerland, https://www.itu.int/en/about/Pages/default.aspx (Accessed August 2024).

29 Digital Development Partnership (DDP). *About DDP;* Administered by World Bank Group, Washington, D.C., https://www.digitaldevelopmentpartnership.org/about.html (Accessed August 2024).

30 Marc S. Martin & Tyler D. Robbins. *How the New Infrastructure Act Aims to Bridge the Digital Divide;* Perkins Coie, Washington, D.C., https://www.perkinscoie.com/en/news-insights/how-the-new-infrastructure-act-aims-to-bridge-the-digital-divide.html (2021).

31 Digital Development Partnership and World Bank Group. *Launch of the Guinea-Bissau Digital Economy Diagnostic;* https://www.digitaldevelopmentpartnership.org/index.html?ddp=news-10-11-01 (2022).

32 Stewart Townsend. *The Growing Demand for AI Experts: The Shortage of Workers in 2024;* Medium – AI for the next century, San Francisco, California, https://medium.com/ai-for-the-next-century/the-growing-demand-for-ai-experts-the-shortage-of-workers-in-2024-37727134b4b7 (2024).

33 Team DigitalDefynd. *Is There a Shortage of AI Engineers? How to Fix It? ;* San Francisco, California, https://digitaldefynd.com/IQ/how-to-fix-ai-engineers-shortage/ (2024).

34 US Department of State. *Fellowships;* https://www.state.gov/subjects/fellowships/ (Accessed September 2023).

35 Marshall Scholarships. *Homepage;* https://www.marshallscholarship.org/ (Accessed September 2023).

36 Schwarzman Schoalrs. *Homepage;* https://www.schwarzmanscholars.org/ (Accessed September 2023).

37 Anne M. Stark. *Earth System Grid Federation launches effort to upgrade global climate data system;* Lawrence Livermore National Laboratory (LLNL), https://www.llnl.gov/archive/news/earth-system-grid-federation-launches-effort-upgrade-global-climate-data-system (2022).

38 Lawrence Livermore National Laboratory (LLNL). *ESGF: Supporting Climate Research Collaboration;* Livermore, California, https://computing.llnl.gov/projects/esgf-supporting-climate-research-collaboration (Accessed August 2024).

39 US Department of Energy (DOE). *Digital Climate Solutions Inventory;* https://www.energy.gov/sites/default/files/2022-09/Digital_Climate_Solutions_Inventory.pdf (Accessed September 2023).

40 Microsoft AI. *AI for Earth;* https://www.microsoft.com/en-us/ai/ai-for-earth (Accessed September 2023).

41 Argonne National Laboratory. U.S. Department of Energy's INCITE program seeks proposals for 2024 to advance science and engineering at U.S. leadership computing facilities https://www.anl.gov/article/us-department-of-energys-incite-program-seeks-proposals-for-2024-to-advance-science-and-engineering (2023).

42 Peter Clutton-Brock *et al.* Climate Change and AI: Recommendations for Government Action. (Global Partnership on AI (GPAI), Climate Change AI, and Centre for AI & Climate, 2021; https://www.gpai.ai/projects/climate-change-and-ai.pdf).

43 World Economic Forum, BloombergNEF & Deutsche Energie-Agentur. Harnessing Artificial Intelligence to Accelerate the Energy Transition (White Paper). (2021; https://www3.weforum.org/docs/WEF_Harnessing_AI_to_accelerate_the_Energy_Transition_2021.pdf).

44 Jonathan Huer. *A Brief History of the CIO;* Educase Review, https://er.educause.edu/articles/2018/8/a-brief-history-of-the-cio (2018).

45 Office of Critical and Emerging Technologies. *Artificial Intelligence and Technology Office;* US Department of Energy (DOE), Washington, D.C., https://www.energy.gov/ai/artificial-intelligence-technology-office (Accessed August 2024).

46 Emilia David. *Every US federal agency must hire a chief AI officer;* The Verge (A Vox Media Network), New York, New York, https://www.theverge.com/2024/3/28/24114105/federal-agencies-ai-responsible-guidance-omb-caio (2024).

47 International Energy Agency (IEA). *Electricity 2024: Analysis and forecast to 2026* Paris, France, https://www.iea.org/reports/electricity-2024 (2024).

48 Thomas Spencer & Siddharth Singh. *What the data centre and AI boom could mean for the energy sector;* International Energy Agency (IEA), Paris, France, https://www.iea.org/commentaries/what-the-data-centre-and-ai-boom-could-mean-for-the-energy-sector (2024).

49 International Energy Agency (IEA). *Global Conference on Energy & AI;* Paris, France, https://www.iea.org/events/global-conference-on-energy-and-ai (December 2924).

50 United Nations Framework Convention on Climate Change (UNFCCC). *Workplan for the Technology Mechanism Initiative on AI for Climate Action (2024–2027);* Bonn, Germany,

https://unfccc.int/ttclear/misc_/StaticFiles/gnwoerk_static/artificial_intelligence_cms_slot/e1673478d26041fb84b40a1b4c0ddb5d/cc306226d72e4dc9b52a1604bdf49a09.pdf (Accessed October 2024).

51 World Meteorological Organization (WMO). *Advancing Earth System Science with Artificial Intelligence;* Geneva, Switzerland, https://wmo.int/media/magazine-article/advancing-earth-system-science-artificial-intelligence (2024).

52 US Equal Employment Opportunity Commission (EEOC). *Artificial Intelligence and Algorithmic Fairness Initiative;* Washington, D.C., https://www.eeoc.gov/ai (Accessed August 2021).

53 Federal Trade Commission (FTC). Rite Aid Banned from Using AI Facial Recognition After FTC Says Retailer Deployed Technology without Reasonable Safeguards (Press Release); Washington, D.C., https://www.ftc.gov/news-events/news/press-releases/2023/12/rite-aid-banned-using-ai-facial-recognition-after-ftc-says-retailer-deployed-technology-without (2023).

54 European Parliament. *EU AI Act: first regulation on artificial intelligence;* Strasbourg, France, https://www.europarl.europa.eu/topics/en/article/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence (2023 (Accessed August 2024)).

55 Ben Wolford. *What is GDPR, the EU's new data protection law?;* GDPR.eu (Horizon 2020 Framework Programme of the European Union and Proton AG). Plan-les-Ouates , Switzerland, https://gdpr.eu/what-is-gdpr/ (Accessed August 2024).

56 Aspen Digital. *Commission on Information Disorder – Final Report;* Tsim Sha Tsui East, Hong Kong, https://www.aspeninstitute.org/wp-content/uploads/2021/11/Aspen-Institute_Commission-on-Information-Disorder_Final-Report.pdf (2021).

57 Tushar Choudhary. *The Climate Misinformation Crisis*. (Hopespring Press, Rosenberg, Texas, 2024, https://www.amazon.com/Climate-Misinformation-Crisis-mistruths-smarter/dp/B0CR9Q6YJ4).

58 Katie Worth. *Miseducation: How Climate Change Is Taught in America*. (Columbia Global Reports, New York, New York, 2021, https://globalreports.columbia.edu/books/miseducation/).

59 Naomi Oreskes & Erik M. Conway. *Merchants of Doubt: How a Handful of Scientists Obscured the Truth on Issues from Tobacco Smoke to Climate Change*. (Bloomsbury Press, New York, New York, 2011, https://www.amazon.com/Merchants-Doubt-Handful-Scientists-Obscured/dp/1608193942).

60 Daniel Lyons. *Government-Funded Blacklist Highlights Danger of Regulating "Disinformation";* American Enterprise Institute (AEI) – AEIdeas, Washington, D.C., https://www.aei.org/technology-and-innovation/government-funded-blacklist-highlights-danger-of-regulating-disinformation/ (2023).

61 Jon Bateman & Dean Jackson. *Countering Disinformation Effectively: An Evidence-Based Policy Guide;* Carnegie Endowment for International Peace, Washington, D.C., https://carnegieendowment.org/research/2024/01/countering-disinformation-effectively-an-evidence-based-policy-guide?lang=en (2024).

62 Gernot Fritz, Theresa Ehlen & Tina Fokter Cuvan. *EU AI Act unpacked #8: New rules on deepfakes;* Freshfields Bruckhaus Deringer, London, UK, https://technologyquotient.freshfields.com/post/102jb19/eu-ai-act-unpacked-8-new-rules-on-deepfakes (2024).

63 Agence France-Presse (AFP) Fact Check. *Home page;* AFP, Paris, France, https://factcheck.afp.com/ (Accessed August 2024).

64 Factually. *Home page;* Singapore Government, Singapore, https://www.gov.sg/factually (Accessed August 2024).

65 Ministero degli Affari Esteri e della Cooperazione Internazionale. *G7 Working Group Meeting on disinformation at the Farnesina (Press Release);* Italian Government, Rome, Italy,

https://www.esteri.it/en/sala_stampa/archivionotizie/comunicati/2024/07/riunione-alla-farnesina-del-gruppo-di-lavoro-g7-su-disinformazione/ (2024).

66 Hayley Wong. *China steps up crackdown on 'misleading' AI-generated content, 'troubling phenomena';* South China Morning Post, Beijing, China, https://www.scmp.com/news/china/politics/article/3255578/china-steps-crackdown-misleading-ai-generated-content-troubling-phenomena (2024).

67 Latham & Watkins Privacy and Cyber Practice. *China's New AI Regulations (Client Alert Commentary);* https://www.lw.com/admin/upload/SiteAttachments/Chinas-New-AI-Regulations.pdf (2023).

68 Amy Luers *et al.* Will AI accelerate or delay the race to net-zero emissions? *Nature* 628(8009), 718–720 (2024). https://doi.org/10.1038/d41586-024-01137-x.

69 Lynn H. Kaack *et al.* Aligning artificial intelligence with climate change mitigation. *Nature Climate Change* 12, 518-527 (2022). https://doi.org/10.1038/s41558-022-01377-7.

70 Carlos Robles y Zepf & Philipp Schaefer. *Sustainable data centers—The German Energy Efficiency Act: What data center operators need to consider now and in the future;* Mayor Brown, Frankfurt, Germany, https://www.mayerbrown.com/en/insights/publications/2024/02/sustainable-data-centers-the-german-energy-efficiency-act-what-data-center-operators-need-to-consider-now-and-in-the-future (2024).

71 European Commission. *Data centres in Europe – reporting scheme;* https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/13818-Data-centres-in-Europe-reporting-scheme_en (Act adopted 2024).

72 Directorate-General for Energy. *Commission adopts EU-wide scheme for rating sustainability of data centres;* European Commission, Brussels, Belgium, https://energy.ec.europa.eu/news/commission-adopts-eu-wide-scheme-rating-sustainability-data-centres-2024-03-15_en (2024).

73 Congress.gov. *Text – S.3732 – 118th Congress (2023–2024): Artificial Intelligence Environmental Impacts Act of 2024;* https://www.congress.gov/bill/118th-congress/senate-bill/3732/text (2024).

74 Goldman Sachs. *AI is poised to drive 160% increase in data center power demand;* New York, New York, https://www.goldmansachs.com/insights/articles/AI-poised-to-drive-160-increase-in-power-demand (2024).

75 Ethan Howland. *MISO: 49 GW has received interconnection approval, but projects face major delays;* Utility Drive (Operated by Industry Dive), Washington, D.C., https://www.utilitydive.com/news/midcontinent-miso-interconnection-queue-supply-chain-transmission-expansion-mtep/693652/ (2023).

76 Shayle Kann. Under the hood of data center power demand in *Catalyst. (Latitude Media, 2024) https://podcasts.apple.com/lu/podcast/under-the-hood-of-data-center-power-demand/id1593204897?i=1000658881876.*

77 Vijay V. Vaitheeswaran. *Big tech's great AI power grab;* The Economist, London, UK, https://www.economist.com/business/2024/05/05/big-techs-great-ai-power-grab (2024).

78 HDR Inc. *Overcoming Data Center Power Interconnection Challenges;* Omaha, Nebraska, https://www.hdrinc.com/insights/rethinking-data-center-power (2023).

79 Kenddrick Chan *et al. Greening AI: A Policy Agenda for the Artificial Intelligence and Energy Revolutions;* Tony Blair Institute for Global Change (TBI), London, UK, https://www.institute.global/insights/climate-and-energy/greening-ai-a-policy-agenda-for-the-artificial-intelligence-and-energy-revolutions (2024).

80 Alexandra Gorin, Roberto Zanchi & Mark Dyson. *How Data Centers Can Set the Stage for Larger Loads to Come;* Rocky Mountain Institute (RMI), Basalt, Colorado, https://rmi.org/how-data-centers-can-set-the-stage-for-larger-loads-to-come/ (2024).

81 Lulu Ramadan & Sydney Brownstone. *Data Centers Demand a Massive Amount of Energy. Here's How Some States Are Tackling the Industry's Impact;* ProPublica's Local Reporting Network and The Seattle Times, New York, New York, https://www.propublica.org/article/data-centers-power-usage-washington-virginia (2024).

82 Pengfei Li *et al.* Making AI Less "Thirsty": Uncovering and Addressing the Secret Water Footprint of AI Models. arXiv:2304.03271 (2023). https://ui.adsabs.harvard.edu/abs/2023arXiv230403271L.

83 Shaolei Ren. *How much water does AI consume? The public deserves to know;* OCED (Organisation for Economic Co-operation and Development) AI Policy Observatory (OCED AI), Paris, France, https://oecd.ai/en/wonk/how-much-water-does-ai-consume (2023).

84 Building and Construction Authority (BCA). *Green Mark Certification Scheme;* Singapore, https://www1.bca.gov.sg/buildsg/sustainability/green-mark-certification-scheme (Accessed August 2024).

85 Daniel Miessler. *The AI Attack Surface Map v1.0: A visual map for understanding attacks against AI and AI systems;* Unsupervised Learning, San Francisco Bay Area, California, https://danielmiessler.com/p/the-ai-attack-surface-map-v1-0 (Accessed August 2024).

86 Krishnakumar Kottekkat. *Connectsecure: Your Solution to Reducing Attack Surface in an AI-driven World;* ConnectSecure, Tampa, FL, https://connectsecure.com/blog/connectsecure-your-solution-to-reducing-attack-surface-in-an-ai-driven-world (2024).

87 Natonal Institute of Standards and Technology (NIST) Information Technology Laboratory (ITL). *AI Risk Management Framework;* https://www.nist.gov/itl/ai-risk-management-framework (Accessed September 2023).

88 The White House. *Blueprint for an AI Bill of Rights: Making Automated Systems Work for the American People;* https://www.whitehouse.gov/ostp/ai-bill-of-rights/ (Accessed September 2023).

89 The White House. FACT SHEET: Biden-Harris Administration Secures Voluntary Commitments from Leading Artificial Intelligence Companies to Manage the Risks Posed by AI https://www.whitehouse.gov/briefing-room/statements-releases/2023/07/21/fact-sheet-biden-harris-administration-secures-voluntary-commitments-from-leading-artificial-intelligence-companies-to-manage-the-risks-posed-by-ai/ (2023).

90 The Bipartisan Senate AI Working Group *et al. A Roadmap for Artificial Intelligence Policy in the U.S. Senate;* US Senate, Washington, D.C., https://www.young.senate.gov/wp-content/uploads/One_Pager_Roadmap.pdf (Accessed August 2024).

91 Ed Markey. Markey, Heinrich, Eshoo, Beyer Introduce Legislation to Investigate, Measure Environmental Impacts of Artificial Intelligence (Press Release); Washington, D.C., https://www.markey.senate.gov/news/press-releases/markey-heinrich-eshoo-beyer-introduce-legislation-to-investigate-measure-environmental-impacts-of-artificial-intelligence (2024).

92 US Senate Artificial Intelligence Caucus. *CREATE AI Act of 2023;* Martin Heinrich Website, Washington, D.C., https://www.heinrich.senate.gov/imo/media/doc/create_ai_act_fact_sheet1.pdf (2023).

93 Brian Schatz. *Schatz, Kennedy Introduce Bipartisan Legislation To Provide More Transparency On AI-Generated Content (Press Release);* Washington, D.C., https://www.schatz.senate.gov/news/press-releases/schatz-kennedy-introduce-bipartisan-legislation-to-provide-more-transparency-on-ai-generated-content (2023).

94 Wilson Sonsini Goodrich & Rosati. *10 Things You Should Know About the EU Artificial Intelligence Act;* https://www.wsgr.com/a/web/5mGbBqgzQyQoCFJz72ZYCC/10-things-eu-artificial-intelligence-act.pdf (2023).

95 Directorate-General for Energy. *New Energy Efficiency Directive published;* European Commission, Brussels, Belgium, https://energy.ec.europa.eu/news/new-energy-efficiency-directive-published-2023-09-20_en (2023).

96 European Commission. DIRECTIVE OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL on adapting non-contractual civil liability rules to artificial intelligence (AI Liability Directive); https://commission.europa.eu/system/files/2022-09/1_1_197605_prop_dir_ai_en.pdf (2022).

97 European Parliament. *Artificial intelligence liability directive;* https://www.europarl.europa.eu/RegData/etudes/BRIE/2023/739342/EPRS_BRI(2023)739342_EN.pdf (2023).

98 Giangiacomo Olivi & Chiara Bocchi. *Regulating AI in EU: three things that you need to know, and three reasons why you have to know them!;* Dentons, https://www.dentons.com/en/insights/articles/2023/february/1/regulating-ai-in-eu-three-things-that-you-need-to-know (2023).

99 European Institute of Public Administration. *An In-Depth Look at the EU's AI Regulation and Liability Directive;* https://www.eipa.eu/blog/an-in-depth-look-at-the-eus-ai-regulation-and-liability/ (2023).

100 Simon Bollans. *EU Artificial Intelligence Liability Directive* Stephenson Harwood, https://www.shlegal.com/insights/eu-artificial-intelligence-liability-directive#:~:text=The%20AI%20Liability%20Directive%20would,alleged%20to%20have%20caused%20damage. (2023).

101 Cynthia Kroet. *Incoming European Parliament to work on AI liability rules, despite tech lobby concerns;* Euronews, Lyon, France, https://www.euronews.com/next/2024/07/12/incoming-parliament-to-work-on-ai-liability-rules-despite-tech-lobby-concerns (2024).

102 European Commission. *Coordinated Plan on Artificial Intelligence* https://digital-strategy.ec.europa.eu/en/policies/plan-ai (Accessed September 2023).

103 European Parliament. *The impact of the General Data Protection Regulation (GDPR) on artificial intelligence;* https://www.europarl.europa.eu/RegData/etudes/STUD/2020/641530/EPRS_STU(2020)641530_EN.pdf (2020).

104 European Commission. *A European approach to artificial intelligence;* https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence (Accessed September 2023).

105 Liu Caiyu. *Draft AI law to be reviewed by China's top legislature;* People's Daily Online, http://en.people.cn/n3/2023/0609/c90000-20029571.html (2023).

106 China Law Translate. *Provisions on the Administration of Deep Synthesis Internet Information Services;* https://www.chinalawtranslate.com/en/deep-synthesis/ (2022).

107 China Law Translate. *Provisions on the Management of Algorithmic Recommendations in Internet Information Services;* https://www.chinalawtranslate.com/en/algorithms/ (2022).

108 Matt Sheehan. *China's AI Regulations and How They Get Made;* Carnegie Endowment for International Peace, https://carnegieendowment.org/research/2023/07/chinas-ai-regulations-and-how-they-get-made?lang=en (2023).

109 Kazuaki Nagata. *G7 aims to beef up collaboration for AI governance;* The Japan Times, https://www.japantimes.co.jp/news/2023/05/21/business/generative-ai/ (2023).

110 The Japan News. *Japan's Artificial Intelligence Strategy Council Holds 1st Meeting with Aim to Create Rules for AI Use;* https://japannews.yomiuri.co.jp/politics/politics-government/20230511-109145/ (2023).

111 Japanese Cabinet Office. *AI Strategy 2022;* https://www8.cao.go.jp/cstp/ai/aistratagy2022en.pdf (2022).

112 LDP Headquarters for the Promotion of Digital Society Project Team on the Evolution and Implementation of AIs. *The AI White Paper: Japan's National Strategy in the New Era of AI;* https://www.taira-m.jp/ldp%e2%80%99s%20ai%20whitepaper_etrans_2304.pdf (2023).

113 Secretariat of Science. *AI Strategy 2022;* Government of Japan – Technology and Innovation Policy Cabinet Office, Tokyo, Japan, https://www8.cao.go.jp/cstp/ai/aistratagy2022en_ov.pdf (2022).

114 Manish Singh. *India opts against AI regulation;* TechCrunch, https://techcrunch.com/2023/04/05/india-opts-against-ai-regulation/ (2023).

115 Indian Bureaucracy. *AI will be kinetic enabler of India's Digital Economy says Rajeev Chandrasekhar;* https://www.indianbureaucracy.com/ai-will-be-kinetic-enabler-of-indias-digital-economy-says-rajeev-chandrasekhar/ (2023).

116 Verdict.co.uk. *India: AI centers of excellence will boost the start-up ecosystem;* https://www.verdict.co.uk/india-ai-centers-of-excellence/ (2023).

117 Government of India: NITI Aayog. *Responsible AI: #AIFORALL;* https://www.niti.gov.in/sites/default/files/2021-02/Responsible-AI-22022021.pdf (2021).

118 Umesh Rathod. *AI policies across the world: Key lessons for India;* Forbes India, https://www.forbesindia.com/article/isbinsight/ai-policies-across-the-world-key-lessons-for-india/85163/1#:~:text=Unlike%20other%20countries%2C%20India%20has,adoption%20of%20AI%20in%20India (2023).

119 Jibu Elias. *AI for All: How India is carving its own path in the global AI race* Organisation for Economic Co-operation and Development (OECD) AI, https://oecd.ai/en/wonk/india (2023).

CHAPTER 17:

FINDINGS AND RECOMMENDATIONS

David Sandalow, Colin McCormick, Alp Kucukelbir, Julio Friedmann and Michal Nachmany

A. Findings

1. Artificial intelligence (AI) is contributing to climate change mitigation in important ways. AI tools are helping integrate solar and wind power into electric grids, improve the energy efficiency of industrial operations, monitor methane emissions and deforestation, implement sustainable agricultural practices, speed innovations in battery chemistry and reduce greenhouse gas (GHG) emissions in many other ways.

2. AI has the potential to make very significant contributions to climate change mitigation in the years ahead. This includes incremental gains in many areas (e.g., renewable energy generation and building energy management) and transformational gains in other areas (e.g., materials innovation).

3. The principal barriers to using AI for climate change mitigation are (i) the lack of available, accessible and standardized data and (ii) the lack of trained personnel.
   - Successful AI applications are built on data that are available, accessible and standardized. Poor data limit the quality of AI development.
   - Policymakers, business leaders, factory operators and many others with a role in climate mitigation need greater familiarity with the potential for AI to contribute to their work. More computer programmers and data engineers with the skills to create AI applications for climate change mitigation are needed as well.

4. Other barriers to using AI for climate mitigation include cost, lack of available computing power and institutional issues. More resources are needed for training programs, RD&D (research, development and demonstration) and other purposes. Some promising ideas may falter from lack of access to the computing power needed to fully develop them. Many organizations working on climate mitigation—including government agencies, businesses and nongovernmental organization (NGOs)—are only beginning to incorporate AI into their operations and organizational structures.

5. GHG emissions from AI computation are currently less than 1%—and perhaps much less than 1%—of the global total. Better data collection and assessment methodologies are needed to provide a more precise estimate with high confidence.

6. GHG emissions from AI computation will very likely rise in the near-term. Sharply growing demand for AI computation will very likely lead to increased GHG emissions in the near-term. Efficiency improvements in AI hardware and software, as well as use of low-carbon energy in the AI supply chain, will constrain but not prevent this growth in emissions.

7. In the medium- to long-term, AI could result in either net increases or net decreases in GHG emissions. In part because AI is a transformational technology in the early stages of deployment, the range of uncertainty is enormous. Future GHG emissions from AI depend on a number of factors, including (i) growth in demand for AI, (ii) improvements in the energy efficiency of AI hardware, (iii) improvements in the energy efficiency of AI software, (iv) the use of low-carbon electricity in computation for AI, (v) the use of AI to reduce production costs in the fossil fuel sector, and (vi) the use of AI to reduce GHG emissions throughout the economy—such as the many AI applications discussed in this Roadmap. Each of these factors is highly uncertain and interacts with the others in complex ways.

8. Only a tiny fraction of GHG emissions associated with AI operations are related to AI applications for climate change mitigation. There is little to no risk that using AI applications to reduce GHG emissions will increase GHG emissions from AI operations in amounts that would meaningfully reduce the GHG benefits of those applications.

9. Trust in AI is essential for AI to deliver substantial benefits in mitigating climate change. To earn this trust, AI must undergo risk assessments that address a range of concerns. Risks related to safety, security, model accuracy, misinformation and disinformation require the closest attention.
   - Safety and security risks arise when AI is used in real-time in some industrial operations, but they can be addressed by keeping "humans-in-the-loop" at key stages.
   - Hallucinations and other inaccurate results from AI models can cause problems, but they can be addressed with education on how best to use AI models and their results.
   - Misinformation/disinformation can undercut political support for climate change mitigation but arise mainly in the context of large language models (LLMs) and not in most applications of AI for climate change mitigation discussed in this Roadmap.

10. Open-source foundation models have the potential to contribute to climate change mitigation by providing more organizations opportunities to access AI tools. Foundation models dramatically lower the computational power required to use AI in new contexts because they only need minimal "fine tuning" to be useful and avoid redundant re-training by multiple organizations.

11. Significant resources and sustained focus—by governments, corporations, philanthropies and other stakeholders—will be required for AI to reach its potential in helping mitigate climate change. Providing the human resources needed will require hiring and mission priority. Expansion of both funding and personnel are essential for delivering climate solutions at scale, as well as for building institutional knowledge, practice and processes.

12. Several recommendations in last year's ICEF *Artificial Intelligence for Climate Change Mitigation Roadmap* have been adopted by key stakeholders. For example, in March 2024, US Vice President Kamala Harris announced a directive requiring all federal agencies to name a chief AI officer[1] (as suggested in Recommendation 6 in last year's Roadmap). Also, member countries in the Clean Energy Ministerial (CEM) have launched an AI initiative under the CEM (as suggested in Recommendation 8A in last year's Roadmap).

B. Recommendations

1. *Every organization working on climate change mitigation should consider opportunities for AI to contribute to its work. This process should receive high priority within the organization. Government agencies should explore ways AI could contribute to policy making, funding decisions and permitting processes. Businesses should explore ways AI could contribute to sustainability programs and low-carbon product development. Universities and non-governmental organizations should explore ways AI could contribute to research and public outreach.*

2. *Governments, businesses and philanthropies should fund fora in which AI experts and climate change experts jointly explore ways AI could contribute to climate change mitigation. Sessions should be dedicated to potential AI applications, data requirements, personnel training and timelines to deployment, among other topics.*

3. *Governments should assist in developing and sharing data for AI applications that mitigate climate change.*

    a. *Governments should systematically consider opportunities to generate and share data that may be useful for climate mitigation. This should include data with respect to weather patterns, electricity generation and use, manufacturing, crop and livestock production, hydrocarbon production and consumption, and transport.*

    b. *Governments should establish policies to promote standardization and harmonization of climate and energy-transition data. These policies should include (i) data management guidelines, such as the "FAIR Guiding Principles" (Findability, Accessibility, Interoperability and Reusability); (ii) data standardization and harmonization requirements in connection with government-funded RD&D; (iii) measures to ensure transparency, including access to metadata and core data and (iv) funding for data standardization organizations and activities.*

    c. *Governments should establish climate data task forces composed of key stakeholders and experts. The UK's Energy Data Task Force provides a good model. Climate data task forces should start by inventorying data gaps and identifying potential barriers to data access. They should plan ways to federate, share and anonymize data for AI applications relevant to climate mitigation.*

4. *Companies with datasets relevant to climate change mitigation should consider sharing portions of these datasets publicly. Public release of a company's datasets can provide direct benefits to that company by encouraging development of algorithms helpful to the company, attracting AI talent and facilitating integration with related datasets. Public release may provide broader social benefits, as well. In releasing datasets, companies must anonymize and strictly protect personally identifiable information.*

5. *Every organization working on climate mitigation should prioritize AI skills-development and capacity-building.*

   a. *Governments and foundations should launch AI-climate fellowship programs. These programs should identify promising students (from developing countries and underrepresented communities, in particular) and fund fellowships in AI and climate-focused topics.*

   b. *Government agencies with responsibility for climate issues should regularly review the capabilities of their staff with respect to AI. The goals should be to continually enhance these capabilities and to ensure that opportunities for AI to advance their mission are recognized and accurately evaluated.*

   c. *Every organization working on climate change mitigation should require minimum AI literacy from a broad cross-section of employees. Understanding of AI's capabilities and experience working with AI will contribute to employees' impact and effectiveness in the years ahead.*

6. *Educational institutions should offer courses that provide familiarity with AI and its uses in climate mitigation. Primary and secondary schools should teach basic skills. Universities and continuing education programs should offer courses, fellowships, internships and certification programs.*

7. *Governments should adopt policies to minimize GHG emissions from AI's computing infrastructure, including requiring AI developers and data center operators to disclose GHG emissions associated with their operations on a full lifecycle basis. Governments should (i) work with standard-setting bodies, AI developers and data center operators to standardize GHG emissions reporting protocols, (ii) prioritize AI systems with low GHG emissions when procuring AI solutions; (iii) invest in RD&D on energy-efficient AI algorithms and hardware, (iv) promote data centers that emit minimal GHGs through a range of measures, including regulations, guidelines and/or financial incentives; and (v) implement ambitious emissions-reduction programs that incentivize all companies, including AI and data center operators, to reduce their GHG emissions.*

8. *Organizations that use AI for climate change mitigation should assess and address potential risks of AI tools. These organizations should pay close attention to (i) safety and security risks, especially if AI is being used in real-time operations in industrial settings or grid management and (ii) AI model accuracy, especially with AI systems that require up-to-date data to function correctly. Organizations should address the risk of misinformation and disinformation from LLMs, with worker training and adhering to best practices around adopting and using LLMs.*

9. *All government agencies with responsibility for climate change, including environment and energy ministries, should create an Artificial Intelligence Office, responsible for assessing opportunities, barriers and risks with respect to AI in all aspects of the agency's mission. These agencies should also consider (1) hiring an advisor to the head of the agency who has responsibility for advising on all matters related to AI, (2) creating a unit to improve AI skills throughout the organization and*

(3) launching a strategic planning process to consider ways that topics related to AI can best be addressed within the ministry on an ongoing basis.

10. *Governments should provide substantial funding for developing and applying AI applications for climate mitigation.*

    a. *Governments should fund AI for climate change mitigation programs with a focus on emissions reduction potential, not just new AI methods. Innovations in AI methodologies are important but may not be required for high-impact climate mitigation programs. Some funding programs should prioritize emissions-reduction potential using AI as a selection criterion.*

    b. *Governments should help increase the availability of computing power for AI projects related to climate change mitigation. They should do so by (i) investing in computing infrastructure, (ii) soliciting proposals for projects that use AI for climate change mitigation and (iii) making computing power available without cost for proposals that offer the greatest potential benefits. This could include solicitations from the private sector in partnership with governments.*

11. *Governments, philanthropies and information technology companies should play a pivotal role in funding development of large-scale open-source foundation models tailored to address climate challenges. These models, in domains such as climate science, energy systems, food security and oceanography, could serve as the bedrock for a new generation of climate mitigation applications. By investing in this critical infrastructure, governments can accelerate innovation, foster public-private partnerships and create a fertile environment for developing solutions to pressing climate issues. International collaboration in funding and research will be essential for maximizing the impact of these models.*

12. *Governments should launch international platforms to support cooperative work on AI for climate change mitigation.*

    a. *Member countries in the Clean Energy Ministerial (CEM) and Mission Innovation (MI), as well as other stakeholders, should participate actively in the CEM/MI AI initiative.*

    b. *The United Nations Framework Convention on Climate Change (UNFCCC), International Energy Agency (IEA) and Food and Agriculture Organization of the United Nations (FAO), among other organizations, should build AI-for-climate issues centrally into their work programs.*

    c. *One or more global organizations should be tasked with helping reconcile any conflicting AI-enabled data on GHG emissions. The International Methane Emissions Observatory (IMEO) could fulfill this role with respect to methane emissions. The World Meteorological Organization (WMO) and FAO could fulfill this role for CO_2 and some other GHG emissions datasets.*

C. References

1 The White House. *Fact Sheet: Vice President Harris Announces OMB Policy to Advance Governance, Innovation, and Risk Management in Federal Agencies' Use of Artificial Intelligence;* Washington, D.C., https://www.whitehouse.gov/briefing-room/statements-releases/2024/03/28/fact-sheet-vice-president-harris-announces-omb-policy-to-advance-governance-innovation-and-risk-management-in-federal-agencies-use-of-artificial-intelligence/ (2024).

Appendix A:

ADDITIONAL READING

For anyone interested in additional reading on artificial intelligence and climate change, we especially recommend these sources:

1. Pierre Gentine, et al. *AI for Climate and Nature: Landscape Assessment;* Columbia University & Bezos Earth Fund, New York, New York, https://www.climate.columbia.edu/ai-climate-nature-landscape-assessment (2024).
2. Kenddrick Chan *et al. Greening AI: A Policy Agenda for the Artificial Intelligence and Energy Revolutions;* Tony Blair Institute for Global Change (TBI), London, UK, https://institute.global/insights/climate-and-energy/greening-ai-a-policy-agenda-for-the-artificial-intelligence-and-energy-revolutions (2024)
3. Keith J. Benes, Joshua E. Porterfield & Charles Yang. *AI for Energy: Opportunities for a Modern Grid and Clean Energy Economy;* US Department of Energy (DOE), Washington, D.C., https://www.energy.gov/cet/articles/ai-energy (2024).
4. Amy Luers *et al.* Will AI accelerate or delay the race to net-zero emissions? *Nature* 628, 718-720 (2024). https://doi.org/10.1038/d41586-024-01137-x.
5. David B. Olawade *et al.* Artificial intelligence potential for net zero sustainability: Current evidence and prospects. *Next Sustainability* 4, 100041 (2024). https://doi.org/10.1016/j.nxsust.2024.100041.
6. Amane Dannouni *et al. How AI Can* Speed *Climate Action;* Boston Consulting Group (BCG) and Google, Boston, Massachusetts, https://www.bcg.com/publications/2023/how-ai-can-speedup-climate-action (2023).
7. Lynn H. Kaack *et al.* Aligning artificial intelligence with climate change mitigation. *Nature Climate Change* 12, 518-527 (2022). https://doi.org/10.1038/s41558-022-01377-7.
8. David Rolnick *et al.* Tackling Climate Change with Machine Learning. *ACM Comput. Surv.* 55, Article 42 (2022). https://doi.org/10.1145/3485128.

In addition, we recommend exploring the References sections of the 17 chapters in this Roadmap, which contain many hundreds of sources on a wide variety of topics related to artificial intelligence and climate change.

Appendix B:

RECOMMENDATIONS FROM EACH CHAPTER

Part II: Sectors 2

Chapter 3 – Power System 2
Chapter 4 – Food Systems 2
Chapter 5 – Manufacturing Sector 4
Chapter 6 – Road Transport 4
Chapter 7 – Aviation 5
Chapter 8 – Buildings Sector 7
Chapter 9 – Carbon Capture 7
Chapter 10 – Nuclear Power 8

Part III: Cross-Cutting Issues 10

Chapter 11 – Large Language Models 11
Chapter 12 – Greenhouse Gas Emissions Monitoring 11
Chapter 13 – Materials Innovation 13
Chapter 14 – Extreme Weather Response 14
Chapter 15 – Greenhouse Gas Emissions from AI 14
Text Box: Data Center Water Use 15
Chapter 16 – Government Policy 15

Part II: SECTORS

Chapter 3 – Power System

1. *Utilities and independent power producers should use artificial intelligence (AI) tools for a wide range of purposes, including helping to plan renewables projects, monitor the condition of power equipment, integrate distributed energy resources into the grid, run demand response programs and optimize the use of energy storage systems. In doing so, utilities and independent power producers should prioritize rigorous testing, continuous monitoring and robust fail-safe mechanisms, setting benchmarks for the transparency of AI systems.*

2. *Electricity regulators should create clear regulatory frameworks to support using AI in energy management. These frameworks should include rates that provide cost recovery for AI-related investments, such as smart meters, sensors and open-source grid management software. The frameworks should address risks related to data privacy, safety and cybersecurity.*

3. *National governments, electricity regulators and utilities should work together to develop and enforce data standards for all aspects of grid operations. Regional governing bodies, such as the US independent system operators (ISOs) and regional transmission organizations (RTOs), should prioritize standardization of data to enable cross-regional analysis. These data should be available in industry standard formats in free and publicly available portals for use in AI modeling and research.*

4. *Utilities, regulatory agencies and academic experts should work together to develop AI-driven AC-OPF (alternating current-optimal power flow) models and permitting reforms. These models should be used to reduce delays in the interconnection process and accelerate deployment of new renewable generation sources to the grid.*

5. *Academic experts should emphasize geographic specificity in AI-driven weather models to increase the utility of weather forecasting for renewable energy production within specific boundaries (e.g., ISOs, climate zones). These experts should develop models that forecast within a smaller range than nearby weather station radii, focusing on wind direction, wind speed, solar radiation and cloud cover.*

6. *Utilities and electricity regulators should launch programs for training workers in the power sector to assess and use AI-driven technologies.*

7. *National governments should encourage and fund collaborative research and development (R&D) projects between academic institutions, industry and utilities focused on AI and related applications for renewable power, energy efficiency and emissions reduction, including AI-driven forecasting tools and grid management systems.*

Chapter 4 – Food Systems

Food systems are highly decentralized, with an estimated 570 million farms worldwide, each operating in specific agroecological and socioeconomic contexts, challenging the notion of one-size-fits-all AI solutions. To address the myriad unique issues associated with AI applications in food systems and to ensure their responsible and effective deployment across contexts, we recommend the following priorities targeted at a range of institutional structures (Table 4-3):

1. *National governments should expand public R&D funding to develop and study AI applications in remote sensing, agricultural systems modeling, crop breeding and other high impact application areas.*
2. *Researchers, industry associations and standards development organizations should collaborate to develop and share benchmark datasets, sample algorithms and standard performance metrics for AI applications.*
3. *National governments and businesses should invest in developing adaptive data collection technology, such as Internet of Things sensors and mobile apps, to enable continuous updating of AI models with relevant, accurate and timely data.*
4. *Academic institutions and research organizations should prioritize inclusive and participatory approaches to developing AI models and tools, such as engaging farmers, extension agents and community organizations, to ensure that AI solutions are context-specific, user-centered and aligned with local needs and priorities.*
5. *Professional societies, academic institutions and international organizations should develop and promote guidelines, best practices and training programs on the appropriate use of AI in food systems, covering issues such as data privacy, model transparency, potential biases, risks and limitations.*
6. *National governments, private companies and civil society organizations should establish collaborative data ecosystems for food systems that have clear frameworks for data sharing, ownership and access rights.*
7. *Research funding agencies and philanthropy should support interdisciplinary research on ethical, legal and social implications of AI in food systems, as well as development of responsible AI governance frameworks and accountability mechanisms.*
8. *Private companies and model developers should prioritize development of human-in-the-loop model improvement approaches, incorporating user feedback and local knowledge to iteratively refine AI solutions and ensure their adaptability to evolving climate challenges and food system dynamics.*
9. *International organizations and multi-stakeholder platforms should facilitate knowledge exchange, capacity building and coordination of AI R&D with a focus on promoting inclusive innovation and equitable access to AI technologies.*

A responsible AI information ecosystem is based on the principles of true multi-stakeholder collaboration, the incorporation of local knowledge and priorities, the prioritization of transparency and accountability, and an emphasis on continuous, adaptive improvement. A coordinated approach can support the critical transition to more sustainable, resilient and equitable food systems that are bolstered against the impending challenges of climate change.

Table 4-3. *Recommendations*

GOVERNMENTS	CIVIL SOCIETY	INTERNATIONAL ORGANIZATIONS	BUSINESS	SCIENCE
Convene consortia exchanging food system data Ensure equitable access to AI tools in food systems Establish oversight and accountability mechanisms Create forums for stakeholder feedback on AI policies Support participatory collection initiatives for agricultural data Invest in rural connectivity infrastructure	Monitor data use and privacy issues Advocate for inclusive and transparent data governance Provide training in digital literacy to marginalized groups Create resources on ethics in AI for food systems Monitor AI adoption and impacts	Coordinate global data-sharing efforts in food systems Develop privacy and security frameworks for data in food systems Promote inclusive AI development Facilitate technology transfer and capacity building Identify and fill data gaps Share pre-competitive research and data	Participate in industry data consortia and standards bodies Ensure diversity in AI teams and training data Invest in Internet of Things and mobile data collection Develop scalable, accessible data architecture Co-develop tools that help identify barriers and limits to adaptation Develop open-source libraries, platforms, models and tools	Study the ethical, legal and social elements of AI in food systems Advance explainable, interpretable AI techniques Establish model evaluation protocols using open benchmark datasets Standardize data formats for ease of interoperability Identify and fill data gaps

Chapter 5 – Manufacturing Sector

1. *Private companies should engage with governments, non-profits and academia to develop, release and maintain AI-ready datasets that pertain to industrial operations. This effort should leverage best practices for data sharing and hosting. Private companies should encourage those interested in leveraging their data to explore high-impact AI applications.*

2. *Private companies should develop clear processes to accelerate the adoption of digitalization within their organizations, from streamlining vendor evaluation to incentivizing internal adoption of AI in high impact use cases.*

3. *Technical societies should develop educational assets and programs to increase digital and AI literacy within industrial workforces. These initiatives should scale across the workforce, from*

operators up to executives. Emphasis should be on developing a foundational skill set that will enable the manufacturing sector to adopt AI-based solutions.

4. *Governments and standards organizations should incentivize market demand for AI-optimized products that exhibit increased material circularity and lower carbon footprints. Governments should offer financial incentives to adopt such goods.*
5. *Governments and academia should develop and deploy education opportunities at the intersection of AI and manufacturing as part of computer science and engineering programs.*
6. *Governments should incentivize the market of recycled feed and fuel stock to increase their supply and reduce their costs. This reduces a barrier for adopting AI to increase material circularity.*

Chapter 6 – Road Transport

A. Vehicle Electrification

1. *Local governments should promote development and deployment of AI-optimized electric vehicle (EV) charging stations, update building codes that require incorporating such systems in new installations, and run public awareness campaigns to educate residents and businesses about the benefits of intelligent EV infrastructure.*
2. *Industry and academia should form partnerships to drive innovation in AI-enhanced EV technologies. These collaborations should focus on developing AI-driven solutions to improve battery lifespan, efficiency and recycling methods.*
3. *National governments, industry and academia should invest in AI research for battery and motor advancements, leveraging high-performance computing (HPC) for materials discovery; integrating AI methods to enhance performance, safety and lifespan; and promoting collaborations such as the US Joint Center for Energy Storage Research and the European Battery 2030+ Initiative.*
4. *National governments should establish comprehensive regulations for AI applications in EV technology on topics including data privacy, usage and storage. These regulations should align with global standards to facilitate international cooperation and ensure responsible and ethical use of AI tools.*
5. *Industry and standards development organizations should work together to develop standards for AI applications in EVs, covering topics such as battery monitoring, charging optimization and communication protocols.*

B. Alternative Fuels

1. *National governments should implement incentive programs such as subsidies and grants, to encourage AI-driven research and development of alternative fuels. They should also increase simulation capabilities to evaluate the life-cycle and infrastructure impact of innovative fuels.*
2. *Industry and academia should increase collaborative research efforts to enhance efficiency and reduce the environmental impact of alternative fuels based on AI methods, for example by*

establishing innovation hubs and providing funding and support for startups working on AI-driven technologies in these fields.

3. *Governments, academia and industry should develop centralized data-sharing platforms where researchers can access and share datasets related to alternative fuels to facilitate data exchange, enhance research quality and speed up discoveries.*

C. Intelligent Transportation Systems (ITSs)

1. *National governments and intergovernmental organizations should establish comprehensive data privacy regulations for AI applications in transportation following examples such as the United Nations' global AI resolution. These regulations should ensure clear guidelines to safeguard human rights, protect personal data and support AI use to mitigate climate impact in road transport.*
2. *Local governments should invest in smart infrastructure and develop long-term strategic plans, implementing procurement policies, conducting public awareness campaigns and investing in sensor-driven infrastructure for AI-based real-time decision making.*
3. *Industry and standards development organizations should collaborate to establish standards for smart transportation technologies, including V2X ("vehicle-to-everything") communication, data security, EV charging connectors and harmonized communication networks leveraging 5G and satellite technology to ensure integration and distributed interoperability.*
4. *National governments, industry, and academia should increase research and data collection for intelligent transportation systems to support AI in mitigating climate impact in road transport, enabling complex simulations using HPC, and launching large-scale collaborations and pilot projects for smart infrastructure development.*

D. Modal Shift

1. *National governments should allocate funding for AI projects that optimize multi-modal transit routes, predict demand and improve shared mobility services, ensuring a streamlined and transparent application process for research institutions and private companies to access these funds.*
2. *Governments, industry, and academia should form consortia to develop AI-driven mobility platforms in major cities, integrate pilot projects to test strategies like dynamic pricing and optimized public transit schedules, and publish findings for wider implementation.*

E. Autonomous Vehicles (AVs)

1. *Local and national governments should collect and share data on the greenhouse gas (GHG) impacts of AVs, including data on supply chain emissions.*
2. *Local governments should develop regulations and run pilot projects to facilitate integration of AI-driven autonomous mobility solutions that reduce carbon dioxide (CO_2) emissions.*

3. *Industry and academia should expand research efforts and develop improved simulation capacities to help develop AI-based methods that offer a safe test bed for evolving autonomous driving capabilities, focusing in particular on ensuring that AVs help reduce CO_2 emissions.*

Chapter 7 – Aviation

1. *National governments should expand public R&D funding for applying AI/machine learning (ML) methods to aircraft design, engine design and aircraft operations, with a focus on improving fuel efficiency, enabling the use of sustainable aviation fuel (SAF), and reducing non-CO_2 impacts (including contrails). To ensure this funding targets priority areas, the relevant funding ministries should enhance the AI/ML expertise of program management staff through training and/or hiring.*

2. *Aviation technical societies, associations and standards development organizations should expand technical resources available for AI/ML-enabled aircraft design and operations, including developing benchmark datasets, releasing sample algorithms and publishing standard performance metrics.*

3. *National governments should increase the coverage and quality of publicly available meteorological data (temperature, pressure, humidity) in commonly traveled air spaces to enable improved modeling of the non-CO_2 climate impacts of aviation, including contrail formation.*

4. *National governments, philanthropy and private companies should collaborate to improve the state of the art on digital modeling of atmospheric contrail formation by aircraft, including use of advanced AI/ML techniques. High-quality models should be made publicly available.*

5. *National governments should require all commercial and private aircraft to track and report non-CO_2 impacts, including contrail formation. This should be through public-facing data portals or similar methods that minimize the burden of data collection and computation on the private actors covered by these requirements. Aggregated results should be publicly released.*

6. *Carbon accounting bodies should update accounting rules to include the full set of climate impacts of aviation, including contrails. Private companies with aviation-based supply chains should adopt the use of these updated rules in measuring supply chain greenhouse gas (GHG) emissions.*

7. *National governments should ensure that the regulatory frameworks for approving novel aircraft and engine design are compatible with using AI/ML methods and should update them accordingly if necessary. Aviation regulatory bodies should collaborate directly on these topics to ensure that regulations are harmonized as much as possible across national borders.*

Chapter 8 – Buildings Sector

1. *Governments at all levels working with the private sector should identify and pilot AI-supported technological improvements in design, materials, construction and demolition that reduce the embedded carbon in buildings.*

2. *National governments should develop research and development programs for AI improvements in emissions efficiency of building operations (including HVAC systems, lighting, elevators and other*

mechanical systems). Municipalities should explore more restrictive commercial-building energy use and emissions standards (including for Scope 2 emissions) that become attainable through AI. These efforts should combine a "pull" strategy of government support paired with a "push" effort of more restrictive norms.

3. *Public and private construction organizations should engage government research agencies, academia and the nonprofit community in providing support for developing and deploying AI. Sharing data, encouraging the development of standards and best practices, and creating venues for dissemination and discussion of these results can help accelerate development and deployment of AI in this sector. In particular, using AI to build more sophisticated life-cycle analytic tools can help optimize AI's impact and reduce the possibility of its misapplication.*
4. *Governments, the private sector and professional associations should develop a platform to disseminate best practices regarding improving digitalization and other data collection to support the deployment of AI to reduce building energy use and emissions (including Scope 2). This platform should be tied into the areas of action for AI identified under recommendations 1, 2 and 3. These groups should also work with suppliers to increase the availability and improve the affordability of related sensors and other equipment.*
5. *Multilateral development banks, national/bilateral organizations and other donor agencies should develop a program of technical assistance and funding to increase the capacity of stakeholders both (1) to develop domestic AI innovation programs for the buildings sector in urban areas and (2) to implement AI-enhancements, whether designed locally or abroad. AI in the buildings sector should be adapted to the opportunities and constraints presented by developing economies, including designing and deploying technology-appropriate solutions (such as low-tech approaches where country conditions present constraints), as well as encouraging data gathering in those geographies.*
6. *Governments, in association with city associations and academia, and supported by international development agencies, should identify and develop one or more urban development pilot programs to explore using AI to lower embedded carbon and operational emissions. The new cities being built in emerging economies (such as Indonesia's new capital, Nusantara) provide a possible opportunity for targeted cooperation between donor agencies, such as the World Bank and Japan's JBIC, together with developing-country national and municipal authorities (e.g., Egypt's new administrative capital).*

Chapter 9 – Carbon Capture

1. *National governments and private companies should expand current research, development and demonstration (RD&D) programs in carbon capture to include AI methodologies, with commensurate increased funding.*

a. *Specific use-inspired research topics would include material discovery (especially sorbents and solvents for carbon capture), functionalization of materials, and novel reactor design (including catalysts for CO_2-to-products). They should consider prioritizing efforts beyond simple material discovery and focus on more applied and operational aspects of CO_2 capture. Near-Medium term*

b. *Applied research topics could include optimizing systems (including heat integration, use of digital twins, minimization of heat and electricity demands) and designing key infrastructure pathways (including location, size and operation for CO_2 transportation and storage design), operation and MMRV (measurement, monitoring, reporting and verification)). Near and medium term, with near term emphasis.*

c. *Government granting entities must hire and/or train personnel that are sufficiently trained and knowledgeable to be able to review AI-related proposals well. Near and medium term.*

2. *Asset owners, utility owners and operators, industrial manufacturers and key state-owned enterprises should use AI tools and methodologies to accelerate assessment of carbon capture, utilization and storage (CCUS) pathways for existing and planned assets. This should include cost-benefit determinations in comparison with other decarbonization options, with the goal of establishing a ranking of opportunities. Near term.*

3. *National governments should use AI, including large language models (LLMs) and other generative AI platforms, to streamline permitting processes for carbon capture in all forms. This includes permitting wells for CO_2 injection and processing pipeline rights of way, power electronic designs, and processing revisions to air permits for facility retrofits. Near term.*

4. *National governments and private companies should use AI to improve resource characterization for carbon capture, with emphasis on characterizing geological storage resources. AI-enabled resource characterization should extend beyond bulk storage terms and volume estimates to include understanding of injectivity, permeability fields and risks posed by pre-existing wells. Where possible, national and state governments and some private companies should make data available for training, either through voluntary sharing and federation or mandates. Near term.*

5. *Professional societies, academic experts and carbon accounting bodies should launch training programs on the potential for AI in carbon capture. This could include use of AI for life-cycle assessments of carbon capture systems, as well as the RD&D topics stated above. Near and medium term.*

6. *National governments, private companies and academic researchers should immediately commence with identifying key data requirements for enabling AI in carbon capture. Once identified, these three groups should work to gather, federate and share these data while providing fair, judicious access. Near term.*

Chapter 10 – Nuclear Power

1. *Nuclear regulators should be open to AI playing a role in reactor design, safety analyses and recommendations for operating procedures. The operative question is the quality of the work product, not the identity of the designer. All designs, analyses and procedures, whatever their origin, should be run through rigorous reviews. Additional oversight, checks and security hardening may be part of this work.*
2. *Plant owners and regulators should assure that AI will be used only in advisory and alerting roles. Nuclear plant operators should play the same role in a plant that uses AI as in a plant that does not. The operator should not become like a car driver who plays video games while driving; humans must remain in the loop, engaged and active, despite the routine work performed by AI. Nuclear plant owners should look at the experience in aviation, power and other relevant industries.*
3. *The civilian nuclear industry should scrutinize AI technologies funded by government dollars through science R&D agencies for applicability to their operations.*
4. *Nuclear regulatory bodies should be preparing for license requests from microreactor companies that include a role for AI in remote control.*
5. *Regulators should consider employing the UK Office for Nuclear Regulation's (ONR's) initiative to test different AI technologies in a controlled environment to understand AI's potential to enhance various aspects of nuclear operation and regulation ("sandboxing"). Through sandboxing, regulators can test, refine and evaluate the algorithms within the context of nuclear safety.*
6. *Government innovation agencies should integrate AI into their RD&D plans. Key foci of innovation investments should include sustaining the existing fleet, advanced reactors, and non-electric applications of nuclear energy*
7. *Plant owners should engage with the scientific community to provide access to high-quality data that can drive AI development and deployment. Professional societies should support development and dissemination of best practices in gathering, annotating, hosting and sharing such data.*
8. *Professional societies should offer educational resources and training to attract the attention of the AI community to the nuclear sector. These societies should also reach out to computer science academic departments, professional computer science societies and government agencies to encourage development of AI skills within the nuclear sector.*
9. *Nuclear regulatory agencies should hire staff with AI expertise to efficiently evaluate and recommend adoption of high value-add AI applications in nuclear power.*

Part III: CROSS-CUTTING ISSUES

Chapter 11 – Large Language Models

1. *Private companies and academic researchers should continue to develop LLMs specifically trained on climate data and ensure they are openly available so the public can both improve them and benefit from them.*

2. *National governments, private companies, academic researchers and standards development organizations should cooperate on developing further benchmarks for evaluating LLMs' knowledge in the climate domain, thus extending the existing ecosystem for evaluating LLMs' knowledge in general.*

3. *Professional societies and academic experts should develop training programs on the proper use and limits of LLMs in mitigating climate change to help the public better understand the benefits and risks of using LLMs in the climate domain.*

4. *National governments, private companies and academic researchers should cooperate on developing public challenge competitions on proposed climate mitigation use cases of LLMs to advance their development.*

5. *National governments and private companies should expand current R&D programs in addressing known issues with LLMs, so the public can place greater trust in LLMs, especially when applied to climate change.*

6. *LLM developers and users should publish fine-grained measurements of LLMs' carbon footprint by adopting tools to track and report the GHGs emitted by their compute time.*

7. *National governments should fund R&D for public-facing prototypes to advance the use of LLMs for accelerating permitting of renewable energy.*

Chapter 12 – Greenhouse Gas Emissions Monitoring

Several measures could help address the barriers and overcome the risks described above, promoting the use of AI tools for GHG emissions monitoring.

1. *National governments should encourage the United Nations Framework Convention on Climate Change (UNFCCC) to update guidance on preparing national emissions inventories to explicitly allow the use of AI-enabled data rather than primarily emissions factor–based assessments. This would provide for more accurate baselines and thus make it easier to optimize climate policies and to better tailor them to specific national conditions, while also better recognizing the progress of countries in reducing their climate footprint.*

2. *Carbon accounting bodies, such as the GHG Protocol of the World Resources Institute (WRI) and World Business Council for Sustainable Development (WBCSD) or the Science Based Targets*

Initiative (SBTI), should develop rules for including AI-enabled data as part of corporate carbon footprints, supply chain emissions estimates and related emissions-tracking efforts. When feasible, they should encourage or prioritize the use of validated AI-enabled emissions data over generic emissions factors. In tandem with this, other relevant multilateral institutions, such as the World Trade Organization (WTO) and International Energy Agency (IEA), should continue[1] explicitly addressing the topic of using AI-enabled emissions data and should identify roles they can productively play in advancing its use in a scientifically robust manner.

3. *National governments and appropriate international bodies should consider how best to set up the housing and governance regime of AI-enabled emissions data, including such questions as whether one or several national or international organizations or private entities should function as de facto or de jure central data repositories or clearinghouses. Clear options should be defined and decisions made in the short-term. To the extent that the market or regulations require information on GHG emissions in supply chains, the quality of emissions data will be of paramount importance. To be effective, emissions data will need buy-in from as many stakeholders as possible and must be independently replicable. Governments and multilateral organizations should consider the role of existing institutions, such as the International Methane Emissions Observatory (IMEO), the World Meteorological Organization and the Food and Agriculture Organization, as well as major philanthropic organizations and for-profit companies, in providing repository and clearinghouse services for AI-enabled GHG emissions data.*

4. *National governments and appropriate international bodies should continue ongoing efforts toward standardizing AI-enabled emissions data and should consider whether to set up formal processes to certify AI-assisted emissions data and data providers. In the last two years, National Institute of Standards and Technology (NIST) at the US Department of Commerce and the UK Space Agency have spearheaded a series of brainstorming workshops and consultations with leading scientists and industry participants from around the world, with the goal of achieving greater standardization and consistency in AI-assisted measurements of methane and other GHG emissions and of preempting the risk of future conflicting data.[2] These efforts are highly worthwhile and ought to be continued so as to guarantee the scientific integrity and comparability of emissions data and to build public trust. To the extent possible, participation should be broadened to include more representatives from emerging and newly developed economies and major exporters of commodities and manufactured goods.*

5. *National governments, philanthropic organizations and private-sector companies should support ongoing "ground truthing" efforts by research universities and scientific organizations that aim to independently assess the performance of AI-assisted GHG monitoring technologies. Because AI-enabled GHG monitoring technologies often detect and measure emissions that cannot be otherwise detected or measured, proving their accuracy can be challenging. Hence, there is a need to support public research to develop ways of independently replicating and corroborating AI-enabled data and verifying their accuracy based on well-calibrated ground-truth experiments.*

6. *National governments and private-sector organizations should enhance their in-house AI proficiency, whether by requiring minimum AI literacy standards from a broad cross-section of employees or by building up dedicated AI-focused units and data-science centers within their organizations. Minimum AI literacy may be essential for these organizations to deploy AI-enabled GHG emissions data and to integrate those data into public and proprietary databases and operational systems. Professional standards bodies should update accreditation requirements for professions, such as public accounting and civil engineering, to require demonstration of minimal AI proficiency and the ability to use basic AI technologies. This would serve as a step to support adoption and implementation of emissions abatement targets by industry and carbon accounting by corporations. Trade and professional organizations, such as the Society of Petroleum Engineers (SPE) or the International Association for Energy Economics (IAEE), should support AI literacy among their members and the adoption of AI-enabled GHG monitoring, including through training programs in countries where these technologies are not widely available.*
7. *Banks, asset managers and other private-sector actors should use AI-enabled methane emissions data to quantify the embedded emissions of fossil fuel shipments, following the lead of some financial institutions who have already begun this practice.*

1) International Energy Agency (IEA). Progress on data and lingering uncertainties in *Global Menthane Tracker 2024* (Paris, France, 2024, https://www.iea.org/reports/global-methane-tracker-2024/progress-on-data-and-lingering-uncertainties).
2) Committee on Earth Observation Satellites (CEOS). *International Methane Standards Workshop;* UK Space Agency and US National Institute of Standards and Technology (NIST), London, UK, https://ceos.org/meetings/uksa-methane-workshop/ (2024).

Chapter 13 – Materials Innovation

1. *National governments should increase R&D budgets for AI-enabled materials discovery, with a focus on holistic design considerations that include full life-cycle GHG emissions. Support should also be made available for creating new automated and partly autonomous materials-testing laboratories in a variety of locations around the world. By combining AI and robotics, these facilities could unlock broad global access to rapid iterations in materials design and testing, reducing the challenges of participating in advanced materials development for researchers in resource-limited countries.[1]*
2. *Private companies should engage directly with AI-guided materials-discovery efforts by clarifying manufacturability constraints and offering embedded emissions guidelines. This could also include articulating specific materials classes of interest for commercially relevant low-carbon technologies and issuing benchmarks and/or targets for key performance thresholds.*
3. *National governments, academia and private companies should collaborate to develop and release (or expand existing) AI-ready datasets of material properties that can be used by other research teams to train high-performance models. This effort should use standard data formats and be at least loosely coupled to materials-synthesis and -testing facilities to validate results.*

4. *National governments and academia should support increased education in AI techniques as part of materials-science and related degree programs.*

5. *Scientific publishers should ensure that research publications are fully compatible with AI-guided research synthesis methods, including retroactively converting historical publications.*

1) Nature Synthesis Editorial. Automate and digitize. *Nature Synthesis* 2, 459-459 (2023). 10.1038/s44160-023-00354-y.

Chapter 14 – Extreme Weather Response

1. *National governments, international organizations, and the private sector should invest in AI models that increase accuracy, improve the timeliness and reduce the cost of extreme weather event forecasts. They should also collaborate on ways to evaluate accuracy and to develop frameworks that promote long-term sustainability.*

2. *National governments should:*
   - *continue collecting and publishing weather data as a foundational public service;*
   - *provide a base level of access for poorer communities and countries;*
   - *explore innovative programs to attract the necessary talent to lead public AI systems (this could include government-sponsored fellowships, additional compensation and opportunities for continued education);*
   - *integrate AI training into professional development programs for meteorologists and climate scientists working in public sector weather agencies;*
   - *ensure robust understanding of the limitations and opportunities of AI-assisted forecasting and early warning; and*
   - *promote and construct necessary infrastructure to disseminate forecasts and warnings effectively.*

3. *National governments and international organizations should develop the capacity to build and use cutting-edge AI-based weather models as those models improve in the years ahead. Public-private partnerships are important for equity. National governments and international organizations should also support the expansion of AI-based early warning systems for extreme weather to underserved regions, ensuring equitable access and bridging the gap in global forecasting capabilities.*

4. *National governments, international organizations, and the private sector should prioritize collection and integration of weather and climate data from the global south and provide technical support for adopting AI-based forecasting models to countries that have previously lacked advanced forecasting capabilities due to resource constraints.*

5. *Research institutions and AI developers should prioritize creating AI models that are transparent and interpretable to help meteorologists and emergency responders gain trust in AI-generated weather predictions.*

6. *Emergency management and humanitarian aid agencies should implement AI-driven decision support systems to optimize response strategies during extreme weather events, such as evacuations or resource allocation, based on real-time data and predictions.*

Chapter 15 – Greenhouse Gas Emissions from AI

1. *AI developers, data center owners, energy experts, GHG emissions experts and standards organizations should establish robust methodologies and standards for reporting energy use and GHG emissions across the AI value chain.*

2. *AI developers and data center owners should report energy use and GHG emissions associated with their AI workloads.*

3. *Governments should adopt regulations that require AI developers and data centers owners to report their energy use and GHG emissions.*

4. *AI developers should take steps to reduce the carbon intensity of their models, using the International Standards Organization's (ISO's) methodology for evaluating their models' Software Carbon Intensity (SCI).*[1]

5. *Data center owners should prioritize adoption of energy-efficient hardware for AI operations and optimize AI workloads based on carbon-aware computing strategies.*

6. *Governments should promote and support policies that enable and incentivize data center owners to purchase low-carbon energy, including supporting new low-carbon power generation and grid expansion in regions with high concentrations of AI-driven data center growth.*

7. *National governments, AI developers, data center owners and philanthropies should fund researchers to develop a set of scenarios to quantify the effects that AI could have on greenhouse gas emissions under a range of assumptions. These scenarios should combine quantitative models with expert consultations, rigorously exploring a range of possible futures. The Intergovernmental Panel on Climate Change (IPCC) should include these scenarios in a special report on AI to be released within two years.*[2]

8. *All stakeholders should review and consider the dozens of other recommendations throughout this Roadmap to help reduce GHG emissions using AI tools.*

1) International Organization for Standardization (ISO). *ISO/IEC 21031:2024 Information technology — Software Carbon Intensity (SCI) specification;* Geneva, Switzerland, https://www.iso.org/standard/86612.html (2024).
2) Amy Luers *et al.* Will AI accelerate or delay the race to net-zero emissions? *Nature* 628(8009), 718–720 (2024). https://doi.org/10.1038/d41586-024-01137-x.

Text Box: Data Center Water Use

1. *Data center operators and governments should collect and share data on water consumption to understand potential issues and determine risk. More and better data are needed to identify potential risks in terms of the magnitude and acuteness of community or environmental stresses.*

2. *Data center operators should explore potential pathways to reduce water consumption and mitigate risks. There are many promising, practical ways to manage water use and reduce total water consumption. The economic and technical viability of these options will vary by region. Especially in water stressed areas, data center operators should begin to track, review and explore options to responsibly and reasonably mitigate water consumption stresses and concerns.*

3. *National and local governments should consider policy options, including mandatory water usage reporting, water efficiency standards, incentives for sustainable practices, water pricing mechanisms and water recycling mandates.*

Chapter 16 – Government Policy

1. *Governments should prioritize development of a climate-relevant data ecosystem. This should include the following:*

    a. *Governments should invest significant funds in data collection, curation and standardization. The climate-relevant data collected by governments should be easily accessible by all stakeholders. In developing climate-relevant data, governments should particularly focus on data-gathering from underrepresented regions and sectors, as well as on data types that have previously been unavailable or insufficient.*

    b. *Governments should adopt and promote data interoperability standards and invest in secure, scalable infrastructure for storing and disseminating climate-relevant data. Governments should also adopt clear data governance frameworks to ensure data privacy, security and ethical use.*

    c. *Governments should employ a combination of direct funding, low-interest loans, tax incentives, advanced market commitments and regulatory frameworks to help.*

2. *Governments should help fund large-scale open-source foundational models tailored to addressing climate challenges. These models, in domains such as climate science, energy systems, food security and oceanography, could serve as the bedrock for a new generation of climate mitigation applications. By using existing open-source models and investing in new open-source models, governments can accelerate innovation, foster public-private partnerships and help develop solutions to pressing climate issues. International collaboration in funding and research will be essential to maximizing the impact of these models.*

3. *Governments should incentivize AI applications that contribute to climate mitigation with (1) regulatory frameworks that prioritize climate-friendly AI; (2) financial incentives, such as grants, tax breaks and procurement preferences and (3) public recognition programs. In connection with these programs, governments should establish clear evaluation criteria to assess the climate impact of AI systems to help ensure that incentives are targeted effectively.*

4. *Governments should invest in education and training programs to develop a skilled AI workforce. This should include supporting AI research, curriculum development and upskilling programs for both students and professionals.*
5. *In shaping policies and programs on AI and climate change, governments should seek input from and work closely with a wide range of stakeholders, including technology companies, energy companies, academia and civil society.*
6. *Governments should facilitate knowledge-sharing and collaboration between experts in climate mitigation and experts in AI. Governments should use their convening power (by organizing roundtables, task forces, advisory bodies and hackathons) and other tools for this purpose.*

7. *Governments should establish ethical guidelines for developing and deploying AI applications to help foster the trust and confidence in AI that will be important for using AI in climate change mitigation. These guidelines should address issues such as data privacy, bias, transparency, truthfulness and accountability. Governments should develop these guidelines in collaboration with industry, civil society and academia.*

DISCLAIMER

Ruben Glatt contributed to the technical evaluations but not the policy recommendations in this document.