

ARTIFICIAL INTELLIGENCE FOR CLIMATE CHANGE MITIGATION ROADMAP

December 2023



Innovation for Cool Earth Forum

AUTHORS

David Sandalow

Chair, ICEF Innovation Roadmap Project

Columbia University

Colin McCormick

Georgetown University and Carbon Direct

Alp Kucukelbir

Columbia University and Fero Labs

Julio Friedmann

Carbon Direct

Trishna Nagrani

Climeworks

Zhiyuan Fan

Columbia University

Antoine Halff

Columbia University and Kayrros

Alexandre d'Aspremont

Centre National de la Recherche Scientifique and Kayrros

Ruben Glatt

Lawrence Livermore National Laboratory

Elena Méndez Leal

Columbia University

Kevin Karl

Columbia University

Alex Ruane

NASA Goddard Institute for Space Studies

Cite report as: David Sandalow, Colin McCormick, Alp Kucukelbir, Julio Friedmann, Trishna Nagrani, Zhiyuan Fan, Antoine Halff, Alexandre d'Aspremont, Ruben Glatt, Elena Méndez Leal, Kevin Karl and Alex Ruane, *Artificial Intelligence for Climate Change Mitigation Roadmap* (ICEF Innovation Roadmap Project, December 2023). Available at <https://www.icef.go.jp/roadmap/>.

PREFACE

Artificial intelligence (AI) is a hot topic. One business leader recently called it “the defining technology of our time.” Another said “It is difficult to think of a major industry that AI will not transform.”¹

Meanwhile countries around the world are struggling to respond to the challenge of climate change. Despite encouraging developments, including steep declines in the price of renewable power, global emissions of greenhouse gases keep rising. Scientists warn that heat waves, floods, droughts and severe storms will get far worse in the decades ahead unless we change course.

Can AI help cut emissions of greenhouse gases? This roadmap explores that question. Our goal is to provide a useful resource for experts and non-experts alike. In Part I of the roadmap, we provide brief introductions to both AI and climate change. In Part II, we explore six areas in which AI is helping respond to climate change and could do much more. In Part III, we explore cross-cutting barriers, risks and policies. We finish with findings and recommendations, including the following:

- AI could make significant contributions to climate mitigation. Areas of especial opportunity include greenhouse gas emissions monitoring, the power sector, manufacturing, materials innovation, the food system and road transport.
- Barriers to AI helping reduce greenhouse gas emissions include the lack of trained personnel and access to high-quality data. All institutions with a role in climate change mitigation should prioritize AI skills-development and explore ways to develop and share relevant data.
- Risks related to AI – including bias, privacy and safety issues – require careful attention when AI is used to reduce emissions.
- Greenhouse gas emissions from computing infrastructure for AI are currently modest. The amount of such emissions in the years ahead is highly uncertain.
- All government agencies with responsibility for climate change should create an Artificial Intelligence Office with responsibility for assessing opportunities, barriers and risks with respect to AI in all aspects of the agency’s mission.

The relationship between AI and climate change is a big topic. Among the questions we do not explore in this roadmap are (1) how AI could contribute to climate change adaptation (an important area for work and study) and (2) whether the broad societal forces that AI may unleash are more likely to help or hinder the response to climate change (a difficult question in light of the many uncertainties with respect to AI’s impacts in the years ahead). Instead, we aim to provide a resource that will make favorable outcomes more likely, pointing toward ways in which AI can contribute to climate solutions.

¹ “15 Quotes,” ai.nl (January 3, 2022). <https://www.ai.nl/artificial-intelligence/15-quotes-from-technology-leaders-about-artificial-intelligence-ai/>

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

- [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 deeply 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 design and copy edit team (including in particular Ms. Jeannette Yusko, Dr. Kathryn Lindl, Dr. Melanie Mendez and Ms. Cat Lee).

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

*Chair, ICEF Innovation Roadmap Project
Inaugural Fellow, Center on Global Energy Policy,
Columbia University*

TABLE OF CONTENTS

EXECUTIVE SUMMARY	1
PART I – BACKGROUND	
Chapter 1. INTRODUCTION TO ARTIFICIAL INTELLIGENCE	8
<i>Alp Kucukelbir</i>	
A. What is AI?	8
B. How does AI work?	10
C. What is AI capable of?	11
D. What kind of data does AI need?	12
E. Why is AI developing so rapidly?	15
F. Further reading	16
Chapter 2. INTRODUCTION TO CLIMATE CHANGE	18
<i>David Sandalow, Trishna Nagrani and Julio Friedman</i>	
A. Climate change background	18
B. Contributions of artificial intelligence to climate science	20
C. Further reading	22
<hr/>	
PART II – HIGH-POTENTIAL OPPORTUNITIES	
Chapter 3. GREENHOUSE GAS EMISSIONS MONITORING	25
<i>Antoine Halff, Colin McCormick and Alexandre d'Aspremont</i>	
A. Incumbent GHG emissions monitoring	25
B. AI-enabled GHG emissions monitoring	26
(i) Methane emissions	
(ii) Carbon dioxide emissions	
(iii) Barriers	
(iv) Next Steps	
C. Conclusion	34

Chapter 4. POWER SECTOR	37
<i>Zhiyuan Fan and David Sandalow</i>	
A. Generation infrastructure	38
B. Transmission and distribution infrastructure	40
C. End uses	41
D. Energy-storage infrastructure	42
E. Barriers and risks	43
F. Conclusion	44
Chapter 5. MANUFACTURING SECTOR	49
<i>Alp Kucukelbir</i>	
A. How can AI help decarbonize manufacturing?	49
B. Common applications of AI in manufacturing	50
(i) Decarbonizing the process of making things	
(ii) Decarbonizing supply chains and adopting dematerialization strategies	
(iii) Decarbonizing the impact of maintaining industrial equipment	
C. Barriers and risks for AI in manufacturing	54
Chapter 6. MATERIALS INNOVATION	58
<i>Colin McCormick</i>	
A. Materials innovation in climate technologies	59
B. Computational materials development	61
C. Applications of AI in materials discovery and design	62
D. Barriers	63
Chapter 7. FOOD SYSTEMS	67
<i>Elena Méndez Leal, Kevin Karl and Alex Ruane</i>	
A. Food system greenhouse gas emissions	67
B. Using AI to mitigate food system emissions	68
C. Barriers and risks to AI applications in food systems	71
D. Key considerations in using AI to mitigate food-system emissions	72

Chapter 8. ROAD TRANSPORT	75
<i>Ruben Glatt and David Sandalow</i>	
A. Using AI to cut road transport emissions	76
(i) Batteries	
(ii) Biofuels	
(iii) Intelligent transportation systems and smart infrastructure	
(iv) Modal shift	
B. Barriers and Risks	82

PART III – CROSS-CUTTING TOPICS

Chapter 9. BARRIERS	87
<i>Alp Kucukelbir and David Sandalow</i>	
A. Data	87
B. People	88
C. Computing power	88
D. Cost	89
E. Institutions	89
Chapter 10. RISKS	91
<i>David Sandalow, Julio Friedmann and Alp Kucukelbir</i>	
A. Bias	91
B. Privacy	92
C. Security	93
D. Safety	94
E. Greenhouse gas emissions	95
(i) Background	
(ii) Current GHG emissions from AI	
(iii) Future GHG emissions from AI	
(iv) Conclusion	

Chapter 11. POLICY	102
<i>David Sandalow</i>	
A. Promoting use of AI for climate mitigation	103
(i) Data	
(ii) People	
(iii) Computing power	
(iv) Cost	
(v) Institutions	
B. Managing Risks	108
(i) Bias	
(ii) Privacy	
(iii) Greenhouse gas emissions	
Box: AI Policies in Brief	111
Chapter 12. FINDINGS AND RECOMMENDATIONS	118
A. Findings	118
B. Recommendations	120

EXECUTIVE SUMMARY

Chapter 1 – INTRODUCTION TO ARTIFICIAL INTELLIGENCE

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 datasets 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.

Access to large, high-quality datasets 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 for 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, with more than 100 million users by January 2023. The website now receives roughly 1.8 billion visits per month. Large language models (LLMs), such as ChatGPT, are one type of AI system.

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 2023 was the hottest month ever recorded. The nine warmest years ever recorded have been the last nine 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.

Chapter 3 – GREENHOUSE GAS EMISSIONS MONITORING

Good information on the sources of greenhouse gas (GHG) emissions is essential for responding to climate change. AI is helping to significantly improve such information by analyzing vast amounts of data from earth-observation satellites, airplanes, drones, land-based monitors, the Internet of Things (IoT), social media and other technologies.

AI has been particularly important for improving methane-emissions monitoring. AI helps to (1) process data from methane sensors at scale, (2) combine input from multiple satellites to overcome each particular satellite's limitations and (3) integrate satellite information with data generated by other types of sensors to build multi-scale monitoring and reporting systems.

AI is being used to better understand the sources of CO₂ emissions as well. AI algorithms can be trained to survey the world's vegetation at high spatial resolution and to precisely measure the amount of biomass carbon sequestered in forestry and other forms of vegetation, at scale and at a negligible cost.

Barriers to using AI for emissions monitoring include lack of AI literacy, conflicting data, sovereignty concerns and uncertain financial models for providing AI-enabled GHG emissions data. Measures to help address these barriers include promoting AI literacy, establishing best practices and mechanisms to validate AI-enabled GHG emissions data, setting up one or more global "owners" of AI-enabled GHG emissions data and elevating AI for climate in international dialogue and negotiations.

Chapter 4 – POWER SECTOR

More than a third of global carbon dioxide (CO₂) emissions come from the power sector. AI is becoming an essential part of this sector due to the power grid's complexity and rapid growth in power sector data. AI can help with scenario development, short-term predictions based on time-series data, optimization problems and systems integration.

AI has the potential to make decarbonization of the power sector cheaper, faster and smoother. Opportunities abound in generation infrastructure, transmission and distribution networks, end-use sectors and energy storage. Examples include:

- determining the optimal size and location of solar- and wind-power projects;
- predicting weather relevant to solar and wind generation;
- improving fault detection, outage forecasting and stability assessments on distribution grids and
- facilitating deployment of demand response and vehicle-to-grid programs

Several barriers limit adoption of AI for decarbonizing the power sector. AI models and methods are not yet sufficiently robust or well-developed for widespread deployment, standards for performance evaluation are lacking, and knowledgeable workers are in short supply. Security risks must be studied and properly addressed before deploying AI for most grid infrastructure.

Chapter 5 – MANUFACTURING SECTOR

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 – MATERIALS INNOVATION

Advanced materials with special properties are essential for decarbonizing many parts of the economy. Products including catalysts, battery anodes, solar photovoltaics, wind turbine blades, refrigerants, superconductors, carbon-capture sorbents and high-strength magnets depend on advanced materials.

Historically, advanced materials have been discovered through accident or tedious, expensive trial and error. Advances in computing power and material-science theory enabled a transition to a more computational basis for materials discovery several decades ago. However, the methods for identifying potentially valuable novel materials through computation require large computing resources and are still too slow to fully meet the needs of materials innovation for a decarbonized economy.

Computational materials science has begun using AI methods, and they are already having an important impact. In some cases, AI models can replace fully science-based computations, greatly speeding up processing times. AI can also help interpret results of material-characterization experiments, enabling rapid, high-throughput testing of advanced materials candidates. Natural-language AI can scour the vast materials-science technical literature, summarizing thousands of published research articles to enable rapid, accurate literature reviews and surface harmonized process steps for materials production. Most recently, generative AI methods have begun to suggest entirely novel classes of advanced materials that had not previously been envisioned as relevant to emissions-reduction applications. While these advances are highly promising, much better integration between materials science and AI research is still needed to realize the full potential for climate mitigation.

Chapter 7 – FOOD SYSTEMS

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, has a significant impact on food systems.

AI has significant potential to help reduce GHG emissions in food systems, including by (1) integrating data from multiple sources—such as soil sensors and satellites—to recommend fertilizer application schedules that mitigate nitrous oxide emissions while maximizing crop yields; (2) anticipating future needs for precision fertilizer applications under a range of projected climate conditions; (3) analyzing

data on biomass characteristics, growth rates and carbon-sequestration potential to optimize feedstocks for biomass carbon removal and storage (BiCRS); (4) increasing renewable energy generation by optimizing land use for multiple purposes; (5) forecasting pest and disease pressure; (6) developing alternative protein products, which have a much lower carbon footprint than animal-sourced foods, and (7) reducing food loss and waste through intelligent harvest-timing to prevent food spoilage.

AI provides a set of complementary tools for reducing food-system emissions, not a solution in itself. Proper use of AI technologies should be grounded in scientific knowledge, physical constraints, well-defined public-policy objectives, ethical considerations and a nuanced understanding of the complex operations of food-system stakeholders.

Chapter 8 – ROAD TRANSPORT

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 CO₂ emissions.

AI has significant potential to help reduce GHG emissions from road transport. AI can play an important role in several important areas including (1) batteries, (2) sustainable biofuels, (3) intelligent transportation systems and (4) shifts toward modes of transportation that emit less carbon.

While the potential of AI in revolutionizing road transportation is immense, several barriers and risks must be addressed. Barriers include a lack of data, the absence of uniform standards for data and a shortage of personnel with training in AI. Risks include bias, invasion of privacy and increases in GHG emissions caused by deployment of autonomous vehicles, which are likely to increase total vehicle miles traveled.

Chapter 9 – BARRIERS

Five groups of barriers impede the use of AI for climate change mitigation: data, people, computation, cost and institutions.

Data and people barriers are among the most significant. AI depends on available, accessible and standardized data; such data are often lacking. The shortage of trained personnel can also be a significant barrier. AI for climate mitigation requires skilled AI developers, collaboration between those developers and experts in diverse fields (such as atmospheric chemistry, materials science, electrical engineering, finance and political science), and users who are broadly educated on the basics of AI.

Other important barriers can include a lack of computing power to train, tune and run AI models; a lack of financial resources; and a lack of leadership attention or clear AI policies within organizations.

Chapter 10 – RISKS

Risks from using AI can include bias, invasion of privacy, security, safety and increased GHG emissions.

Bias-related risks when using AI for climate mitigation include prioritizing certain groups due to differences in data availability. Privacy-related risks include unauthorized data leaks to third parties, personal identification and even surveillance. Security risks can arise when AI systems expand the attack surface for hackers beyond that found in conventional software programs. Safety risks can be serious when AI systems fail to work as intended or have unintended consequences. Security and safety risks are especially acute if AI is used for real-time decision-making (such as in operating factories or the electric grid).

GHG emissions from AI computing operations are currently modest—significantly less than 1% of the global total. Better data collection and assessment methodologies are needed to provide a more precise estimate with high confidence. The amount of future GHG emissions related to AI is highly uncertain. In some scenarios, GHG emissions from AI decline in the years ahead. In other scenarios, such emissions increase significantly.

Chapter 11 – POLICY

Government policies with respect to AI are evolving rapidly. Policymakers around the world are considering a range of topics with respect to AI, including security, bias, privacy, job displacement and international competitiveness.

Very few policies that specifically address the use of AI for climate mitigation have been adopted to date. Those policies fall into two broad categories: (1) policies that promote the use of AI for climate mitigation and (2) policies that manage risks related to the use of AI for climate mitigation.

Governments could promote the use of AI for climate mitigation by addressing barriers related to data, people, computing power, cost and institutions. Such policies could include funding collection of climate-related data, encouraging or requiring standardization and harmonization of climate-related data, launching AI skills-development programs, making computing infrastructure available for projects that use AI for climate change mitigation, creating AI offices within government ministries, and using international institutions—such as the Clean Energy Ministerial and World Meteorological Organization—as platforms for international cooperation on using AI for climate mitigation.

Governments could help manage risks related to the use of AI for climate mitigation, including bias, privacy and increased emissions. Such policies could include standards requiring diverse and representative data sets for AI models; standards with respect to transparency in the development of AI models; legal frameworks that hold entities accountable for biased outcomes resulting from AI applications; requiring that privacy considerations be expressly integrated in the design of AI models; establishing independent oversight boards responsible for monitoring privacy protections related to AI and climate mitigation; investing in research and development on energy-efficient AI algorithms and hardware; and promoting low-carbon data centers.

Chapter 12 – FINDINGS AND RECOMMENDATIONS

FINDINGS

1. AI is currently contributing to climate change mitigation in important ways.
2. AI has the potential to make significant additional contributions to climate change mitigation in the years ahead.
3. AI is not a panacea when it comes to climate change.
4. The lack of trained and experienced personnel is a critical barrier to using AI for climate mitigation.
5. The lack of access to high-quality data is a critical barrier to using AI for climate mitigation.
6. Other barriers to using AI for climate mitigation include cost, lack of available computing power and institutional issues.
7. Significant resources—by governments, corporations and other stakeholders—will be required for AI to reach its potential in helping mitigate climate change.
8. General risks of using AI include bias, invasion of privacy and security issues. These risks also exist when using AI for climate mitigation.
9. GHG emissions from computing infrastructure for AI are currently modest—significantly less than 1% of the global total.
10. The amount of future GHG emissions from AI computing infrastructure is highly uncertain.

RECOMMENDATIONS

1. AI tools should be integrated into many aspects of climate change mitigation.
2. AI skills-development and capacity-building should be a priority in all institutions with a role in climate mitigation.
 - A. Educational institutions at all levels should offer courses relevant to AI.
 - B. Governments and foundations should launch AI-climate fellowship programs.
 - C. Government agencies with responsibility for climate issues should regularly review their staffs' AI capabilities.
 - D. All organizations working on climate mitigation should require minimum AI literacy from a broad cross-section of employees.
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 those datasets publicly.
5. Governments should provide substantial funding for developing and applying AI tools for climate mitigation.
 - A. Government funding for AI in the climate area should focus on emissions-reduction potential, not just new AI methods.
 - B. Governments should help increase the availability of computing power for climate change-related AI projects.
6. All government agencies with responsibility for climate change, including environment and energy ministries, should create an Artificial Intelligence Office, with responsibility for assessing opportunities, barriers and risks with respect to AI in all aspects of the agency's mission.
7. Electric utilities should be incentivized to deploy AI, with regulated returns for investments in AI and other tools.
8. Governments should launch international platforms to support cooperative work on AI for climate change mitigation.
 - A. One or more member countries should launch a Clean Energy Ministerial initiative on AI and climate mitigation.
 - B. The UN Framework Convention on Climate Change (UNFCCC), International Energy Agency (IEA) and Food and Agriculture Organization (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 to reconcile any conflicting AI-enabled data on GHG emissions.
9. Governments should work to minimize GHG emissions from AI's computing infrastructure.
10. Avoiding unfair bias should be a core, high-priority principle guiding development of all AI tools for climate change mitigation.
11. Governments should address privacy risks related to AI-climate programs with data-protection regulations, cybersecurity standards, oversight boards and techniques that make personal data less identifiable.

Chapter 1:

INTRODUCTION TO ARTIFICIAL INTELLIGENCE

Alp Kucukelbir

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. The website now receives more than 1.5 billion visits per month.^{3, 4} 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.

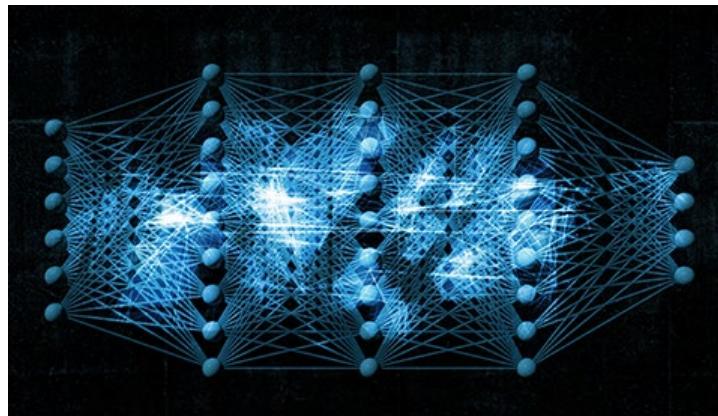


Figure 1-1. A visualization of a deep neural network, a type of AI model that powers popular AI systems such as ChatGPT.

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.⁶ Table 1 summarizes the key difference between AI and traditional software.

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 itself. 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.

	Traditional software	Artificial intelligence (AI)
Requirements	No historical data needed	Historical data or simulator
Outputs	Deterministic results	Statistical results: can sometimes make mistakes
	Can efficiently solve simpler problems	Can offer solutions to more complex problems

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

B. 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 simulation.

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 for using 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.

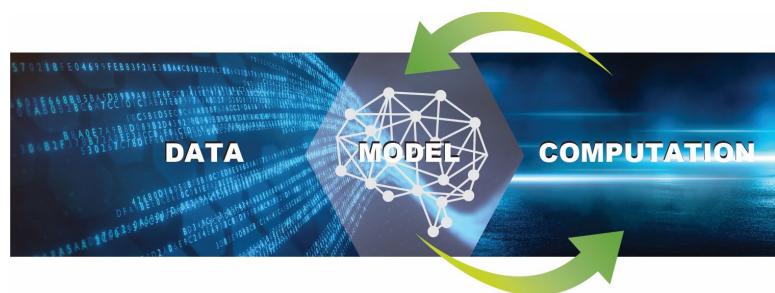


Figure 1-2. AI systems work by using a model to identify patterns in data. Models by themselves are not useful and must be “trained” on data through computation. Computation integrates the idea that AI systems do not contain explicit information, rather computation is the mechanism by which AI unravels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

C. What is AI capable of?

While chess contrasts AI to traditional software, it does not fully capture AI's capabilities; a chess program is effectively playing a game. To dive deeper into a practical discipline that is evolving with AI,⁷ 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 the 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.⁸

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).

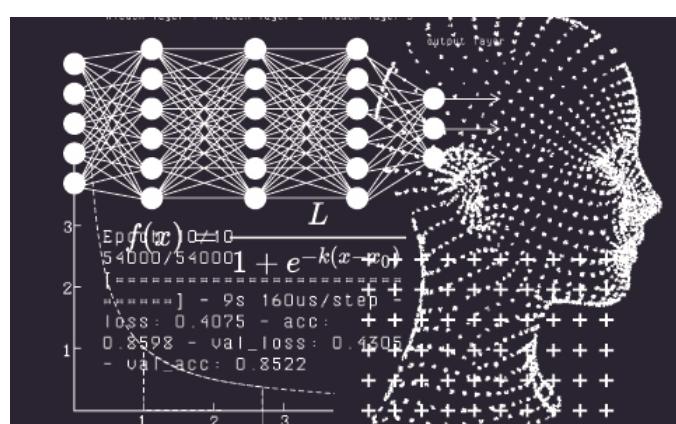


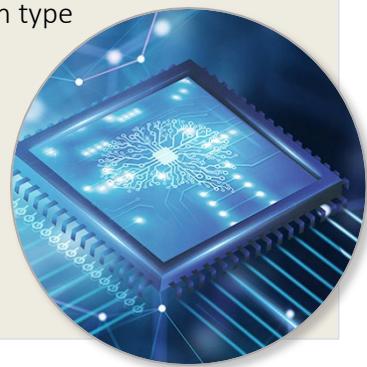
Figure 1-3. Keeping “humans in the loop” is essential to using AI to solve real-world problems.

Box 1-1

LARGE LANGUAGE MODELS 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 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.



D. 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 IS NEEDED FOR AI?

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 megabytes⁹ to terabytes.¹⁰



(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 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 1-4).

- **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 the 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 1-4).

- **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 licensing⁹ 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.

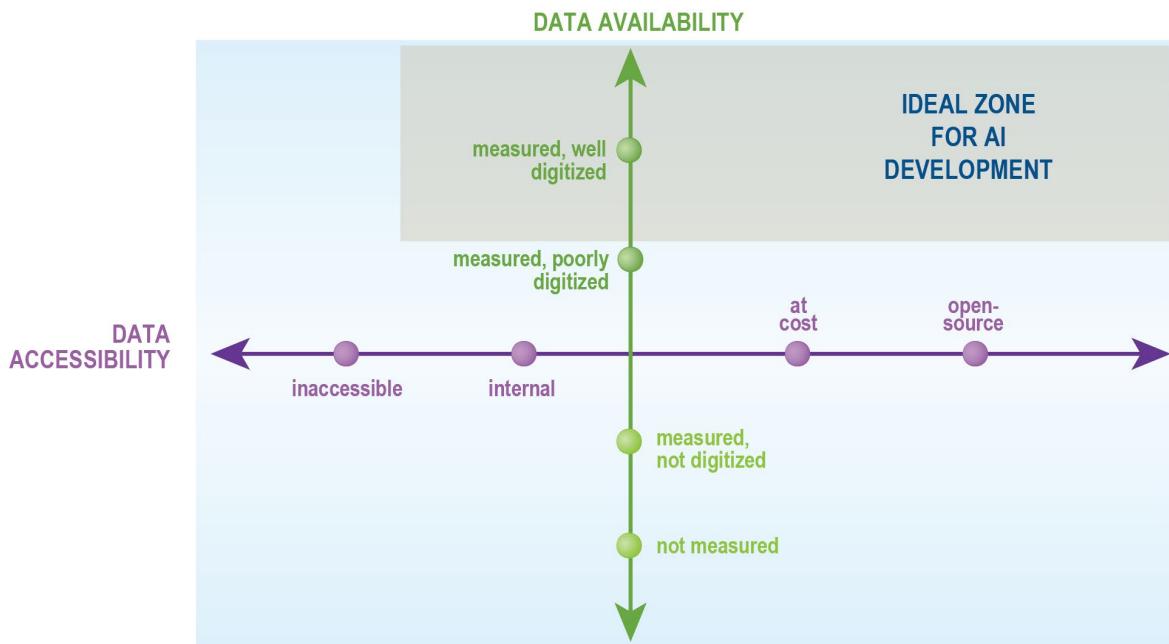


Figure 1-4. Data availability and accessibility are key aspects of enabling AI applications. The ideal zone for AI development relies on accessible, measured and well digitized data.

- **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.
- **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.

E. 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.

F. Further reading

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:

- New York City Mayor's Office, *AI Primer* (2021)
- Silver, N., *The Signal and the Noise: Why So Many Predictions Fail—but Some Don't* (Penguin Publishing Group, 2012)
- Pearl, J., Mackenzie, D., *The Book of Why: The New Science of Cause and Effect* (Penguin Books Limited, 2018)
- Christian, B., Griffiths, T., *Algorithms to Live By: The Computer Science of Human Decisions* (Henry Holt and Company, 2016)

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

- Kevin P. Murphy, *Probabilistic Machine Learning: An introduction* (MIT Press, 2022)
- Moritz Hardt, & Benjamin Recht, *Patterns, predictions, and actions: Foundations of machine learning*. (Princeton University Press 2022)
- Russell, S., Russell, S., & Norvig, P., *Artificial Intelligence: A Modern Approach*. (Pearson, 2020)
- Sutton, R. S., Barto, A. G. *Reinforcement Learning: An Introduction* (MIT Press, 2018)

REFERENCES

1. *Optical character recognition*. Available from <https://facts.usps.com/98-percent-of-hand-addressed-letters/>.
2. Bibb Allen, et al., *2020 ACR Data Science Institute Artificial Intelligence Survey*. Journal of the American College of Radiology, 2021. **18**(8): p. 1153-1159, <https://doi.org/10.1016/j.jacr.2021.04.002>.
3. Robert & Cai. *ChatGPT Statistics* 2023. 2023 Available from <https://www.tooltester.com/en/blog/chatgpt-statistics/>.
4. Rohit Shewale. *32 Detailed ChatGPT Statistics — Users, Revenue and Trends*. 2023 Available from <https://www.demandsgage.com/chatgpt-statistics/>.
5. Stefan Steinerberger, *On the number of positions in chess without promotion*. International Journal of Game Theory, 2015. **44**(3): p. 761-767, <https://doi.org/10.1007/s00182-014-0453-7>.
6. David Silver, et al., *A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play*. Science, 2018. **362**(6419): p. 1140-1144, <https://doi.org/10.1126/science.aar6404>.
7. Garry Choy, et al., *Current Applications and Future Impact of Machine Learning in Radiology*. Radiology, 2018. **288**(2): p. 318-328, <https://doi.org/10.1148/radiol.2018171820>.

8. Kaustav Bera, et al., *Predicting cancer outcomes with radiomics and artificial intelligence in radiology*. Nature Reviews Clinical Oncology, 2022. **19**(2): p. 132-146, <https://doi.org/10.1038/s41571-021-00560-7>.
9. Creative Commons. Available from <https://creativecommons.org/>.
10. *AI and compute*. 2018 Available from <https://openai.com/research/ai-and-compute>.

CHAPTER 2:

INTRODUCTION TO CLIMATE CHANGE

David Sandalow, Trishna Nagrani and Julio Friedmann

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 at least 1.1 °C (1.9 °F) since 1880.³ (See Figure 2-3.) Based on global average temperatures:

- July 6, 2023 was the hottest day ever recorded.⁴
- July 2023 was the hottest month ever recorded.⁵
- The nine hottest years on record are the past nine years.⁶

The principal heat-trapping gases are carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O) and fluorinated gases (such as HFCs and SF₆). (These are commonly called greenhouse gases or GHGs. See Figure 2) Carbon dioxide 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%.⁷

Human activities are the principal cause of the buildup of GHGs in the atmosphere.¹ Human activities are responsible for more than 50 Gt CO₂e of emissions each year—an increase of roughly 40% since 1990.⁸ Those activities include burning fossil fuels (coal, oil and gas), land use and land-use change, and lifestyles 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.⁷

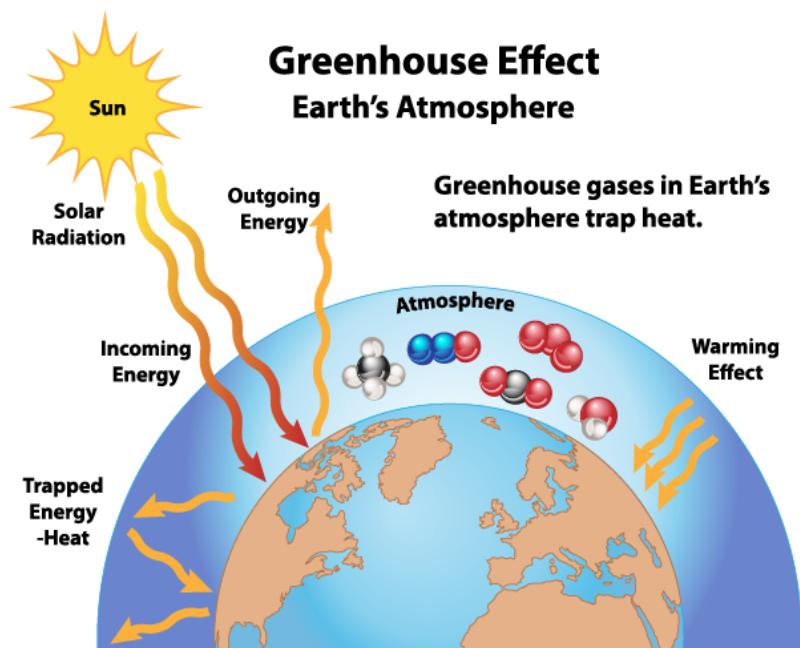


Figure 2-1. Greenhouse Effect.

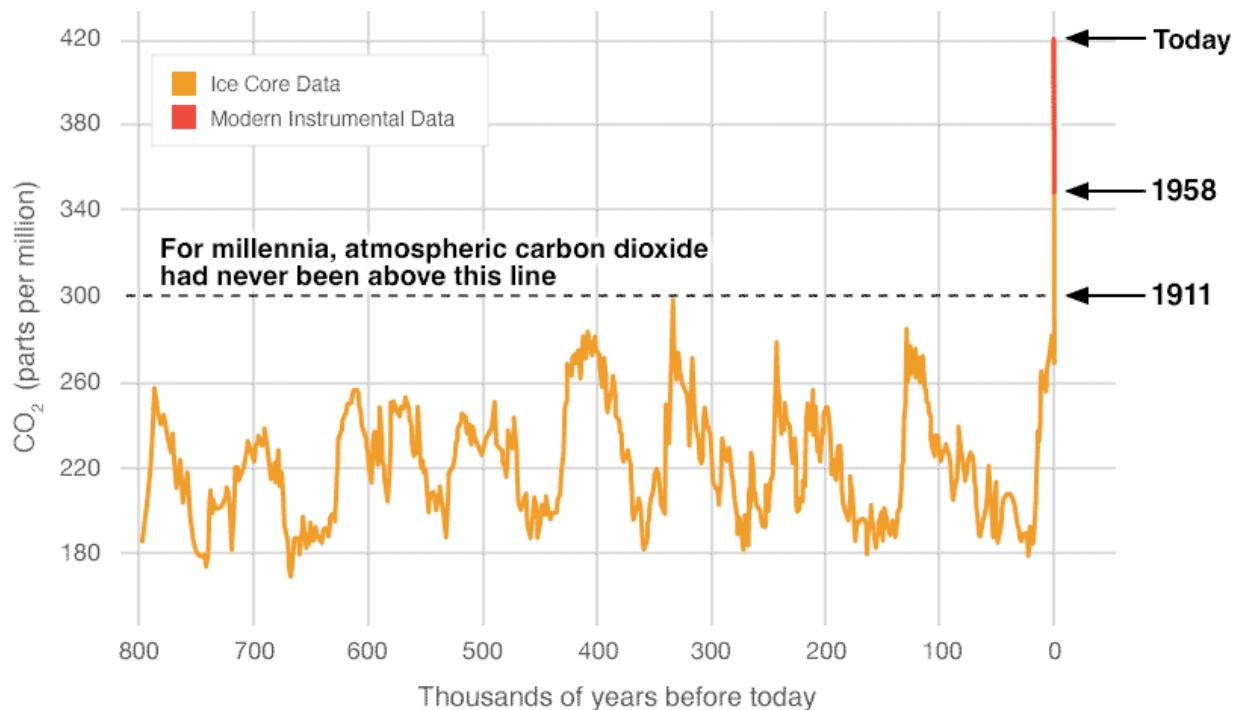


Figure 2-2. Carbon dioxide concentrations for past 800,000 years. Source: NASA, Global Climate Change, Vital Signs of the Planet, Carbon Dioxide, <https://climate.nasa.gov/vital-signs/carbon-dioxide/>

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.^{9, 10}
- Warming air temperatures and droughts made more likely by climate change have directly contributed to increased fire risk in many parts of the world. Changes in the climate over the past 30 years are associated with a doubling of extreme fire weather conditions in California.¹¹
- Between June and August 2022, Pakistan experienced unprecedented floods, which affected 33 million individuals. Over 1,700 lives were lost and more than 2.2 million houses were destroyed or damaged.¹²

Billions of people face extraordinary risks unless the buildup of heat-trapping gases in the atmosphere slows and then reverses in the decades ahead.¹³ Those risks include even more severe and frequent storms, floods, droughts and heat waves, as well as sea-level rise.¹⁴ One study found 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.¹⁵

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.¹⁶

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.”¹⁷ However, policies currently in place around the world would result in a global average temperature increase of 2.9 °C (5.2 °F) by 2100, and many policies to limit emissions are not being fully implemented.¹⁸ The world is not on a path to meet globally-agreed climate change goals.

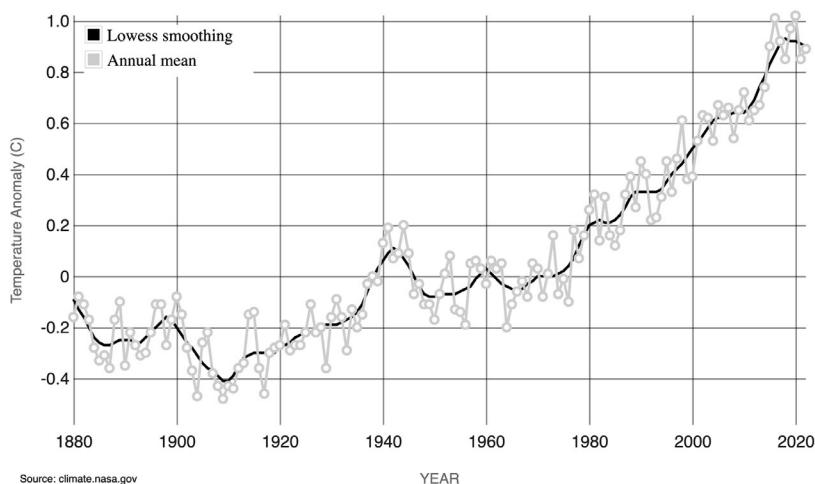


Figure 2-3. Global average temperatures 1880-2022. Source: NASA Global Climate Change, Vital Signs of the Planet, Carbon Dioxide, <https://climate.nasa.gov/vital-signs/carbon-dioxide/>

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, their results are compared across models (“model intercomparison”) and to historical actual 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.¹⁹

AI can also complement conventional physics-based climate modeling in hybrid approaches, dramatically reducing the need for certain very intensive computations²⁰ or improving the resolution of model outputs.²¹ 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 2030–2035.²² Already, AI has improved both the pre-processing²³ and post-processing²⁴ 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.²⁵

(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.²⁶ 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.²⁷ 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 a challenge for climate models to accurately represent.²⁸

(iii) Providing more advanced warning for extreme weather

Already, AI is beginning to improve the weather forecasts associated with extreme events, providing accurate, near-term advanced warning in critical contexts.²⁹ 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 are being applied include extreme precipitation³⁰ and extreme wind speeds,³¹ with additional work on predicting extreme heat over timescales of days to weeks.³²

(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,³³ tropical cyclone intensity,³⁴ growing period frost occurrence³⁵ and many more. New organizations and government programs like Europe’s XAIDA³⁶ 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 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.³⁷ (See Chapter 3 for additional examples.)

C. Further reading

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

- Gates, B., *How to Avoid a Climate Disaster* (Penguin Books Limited, 2021)
- Figuères, C., Rivett-Carnac, T., *The Future We Choose: Surviving the Climate Crisis* (Alfred A. Knopf, 2020)
- Smil, V., *How the World Really Works: The Science Behind How We Got Here and Where We're Going* (Penguin Publishing Group, 2022)
- Doerr, J., Panchadsaram, R., *Speed and Scale: An Action Plan for Solving Our Climate Crisis Now* (Penguin Publishing Group, 2021)
- Wallace-Wells, D., *The Uninhabitable Earth: Life After Warming* (Crown, 2020)

Reports

- International Panel on Climate Change (IPCC), *Sixth Assessment Report* (2023)
- International Energy Agency (IEA), *World Energy Outlook 2023* (2023)
- World Meteorological Organization (WMO), *State of Climate Services Report* (2023)
- United Nations Environment Programme (UNEP), *Emissions Gap Report 2022* (2022)

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.* 2023: p. 34, <https://doi.org/10.59327/IPCC/AR6-9789291691647.001>.
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.* 2023 Available from <https://www.cambridge.org/core/books/climate-change-2021-the-physical-science-basis/415F29233B8BD19FB55F65E3DC67272B>.
3. NASA. *World of Change: Global Temperatures.* Available from [https://earthobservatory.nasa.gov/world-of-change/global-temperatures#:~:text=According%20to%20an%20ongoing%20temperature,1.9%C2%B0%20Fahrenheit\)%20since%201880.](https://earthobservatory.nasa.gov/world-of-change/global-temperatures#:~:text=According%20to%20an%20ongoing%20temperature,1.9%C2%B0%20Fahrenheit)%20since%201880.)
4. World Meteorological Organization (WMO). *July 2023 is set to be the hottest month on record.* 2023 Available from <https://public.wmo.int/en/media/press-release/july-2023-set-be-hottest-month-record>.
5. Copernicus Climate Change Service. *July 2023 sees multiple global temperature records broken.* 2023 Available from https://climate.copernicus.eu/july-2023-sees-multiple-global-temperature-records-broken?utm_source=press&utm_medium=referral&utm_campaign=CBjuly23.
6. Roxana Bardan. *NASA Says 2022 Fifth Warmest Year on Record, Warming Trend Continues.* NASA. 2023. Available from <https://www.nasa.gov/press-release/nasa-says-2022-fifth-warmest-year-on-record-warming-trend-continues>.
7. 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.* 2023. Available from <https://www.cambridge.org/core/books/climate-change-2022-mitigation-of-climate-change/2929481A59B59C57C743A79420A2F9FF>.
8. Hannah Ritchie, Max Roser, Pablo Rosado. *Greenhouse gas emissions*. Our World in Data. 2020 Available from <https://ourworldindata.org/greenhouse-gas-emissions>.
 9. Intergovernmental Panel on Climate Change (IPCC), *Summary for Policymakers*. In: *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. 2021. Available from <https://www.cambridge.org/core/books/climate-change-2021-the-physical-science-basis/summary-for-policymakers/8E7A4E3AE6C364220F3B76A189CC4D4C>.
 10. Matthew Rodell and Bailing Li, *Changing intensity of hydroclimatic extreme events revealed by GRACE and GRACE-FO*. Nature Water, 2023. **1**(3): p. 241-248, <https://doi.org/10.1038/s44221-023-00040-5>.
 11. Michael Goss, et al., *Climate change is increasing the likelihood of extreme autumn wildfire conditions across California*. Environmental Research Letters, 2020. **15**(9): p. 094016, <https://doi.org/10.1088/1748-9326/ab83a7>.
 12. UNICEF. *Devastating floods in Pakistan*. 2023. Available from <https://www.unicef.org/emergencies/devastating-floods-pakistan-2022>.
 13. Intergovernmental Panel on Climate Change (IPCC), *Summary for Policymakers*. In: *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. 2022. Available from <https://www.cambridge.org/core/books/climate-change-2022-impacts-adaptation-and-vulnerability/summary-for-policymakers/016527EADEE2178406C4A7CE7DEAEACA>.
 14. Intergovernmental Panel on Climate Change (IPCC), *Summary for Policymakers*. In: *Global Warming of 1.5°C: IPCC Special Report on Impacts of Global Warming of 1.5°C above Pre-industrial Levels in Context of Strengthening Response to Climate Change, Sustainable Development, and Efforts to Eradicate Poverty*. 2018. Available from <https://www.cambridge.org/core/books/global-warming-of-15c/summary-for-policymakers/31C38E590392F74C7341928B681FF668>.
 15. Nikolaos Christidis, Dann Mitchell, and 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, 2023. **6**(1): p. 45, <https://doi.org/10.1038/s41612-023-00377-4>.
 16. 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, 2022. **400**(10363): p. 1619-1654, [https://doi.org/10.1016/S0140-6736\(22\)01540-9](https://doi.org/10.1016/S0140-6736(22)01540-9).
 17. United Nations Framework Convention on Climate Change (UNFCCC). *Paris Agreement*. 2015. Available from https://unfccc.int/sites/default/files/english_paris_agreement.pdf.
 18. Climate Action Tracker. *Temperatures*. Accessed October 2023. Available from <https://climateactiontracker.org/global/temperatures/>.
 19. Ophelie Meuricot, Yves Plancherel, and Veronica Nieves. *Unsupervised machine learning techniques for multi-model comparison: A case study on Antarctic Intermediate Water in CMIP6 models*. International Conference on Learning Representations (ICLR) 2023 Workshop on Tackling Climate Change with Machine Learning. 2023. Available from <https://www.climatechange.ai/papers/iclr2023/16>.
 20. L. J. Slater, et al., *Hybrid forecasting: blending climate predictions with AI models*. Hydrol. Earth Syst. Sci., 2023. **27**(9): p. 1865-1889, <http://doi.org/10.5194/hess-27-1865-2023>.
 21. 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*. European Geoscience Union (EGU) General Assembly, Vienna, Austria, EGU23-13196. 2023, <https://doi.org/10.5194/egusphere-egu23-13196>.
 22. Noah S. Diffenbaugh and Elizabeth A. Barnes, *Data-driven predictions of the time remaining until critical global warming thresholds are reached*. Proceedings of the National Academy of Sciences, 2023. **120**(6): p. e2207183120, <https://doi.org/10.1073/pnas.2207183120>.

23. Sid-Ahmed Boukabara, et al., *Leveraging Modern Artificial Intelligence for Remote Sensing and NWP: Benefits and Challenges*. Bulletin of the American Meteorological Society, 2019. **100**(12): p. ES473-ES491, <https://doi.org/10.1175/BAMS-D-18-0324.1>.
24. Amy McGovern, et al., *Using Artificial Intelligence to Improve Real-Time Decision-Making for High-Impact Weather*. Bulletin of the American Meteorological Society, 2017. **98**(10): p. 2073-2090, <https://doi.org/10.1175/BAMS-D-16-0123.1>.
25. 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, 2020. **2**, <https://doi.org/10.1162/99608f92.00cd8f85>.
26. 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, 2016. **29**(9): p. 3143-3159, <https://doi.org/10.1175/JCLI-D-15-0520.1>.
27. Anne Jones, et al., *AI for climate impacts: applications in flood risk*. npj Climate and Atmospheric Science, 2023. **6**(1): p. 63, <https://doi.org/10.1038/s41612-023-00388-1>.
28. 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, 2022. **49**(16): p. e2022GL098551, <https://doi.org/10.1029/2022GL098551>.
29. Matthew Chantry, Zied Ben Bouallegue, Linus Magnusson, Michael Maier-Gerber, Jesper Dramsch. *The rise of machine learning in weather forecasting*. European Centre for Medium-Range Weather Forecasts (ECMWF). 2023. Available from <https://www.ecmwf.int/en/about/media-centre/science-blog/2023/rise-machine-learning-weather-forecasting>.
30. Yuchen Zhang, et al., *Skilful nowcasting of extreme precipitation with NowcastNet*. Nature, 2023. **619**(7970): p. 526-532, <https://doi.org/10.1038/s41586-023-06184-4>.
31. Sandy Chkeir, et al., *Nowcasting extreme rain and extreme wind speed with machine learning techniques applied to different input datasets*. Atmospheric Research, 2023. **282**: p. 106548, <https://doi.org/10.1016/j.atmosres.2022.106548>.
32. Ignacio Lopez-Gomez, et al., *Global Extreme Heat Forecasting Using Neural Weather Models*. Artificial Intelligence for the Earth Systems, 2023. **2**(1): p. e220035, <https://doi.org/10.1175/AIES-D-22-0035.1>.
33. S. Jiang, E. Bevacqua, and J. Zscheischler, *River flooding mechanisms and their changes in Europe revealed by explainable machine learning*. Hydrol. Earth Syst. Sci., 2022. **26**(24): p. 6339-6359, <https://doi.org/10.5194/hess-26-6339-2022>.
34. Davide Faranda, et al., *Correcting biases in tropical cyclone intensities in low-resolution datasets using dynamical systems metrics*. Climate Dynamics, 2023, <https://doi.org/10.1007/s00382-023-06794-8>.
35. Carl J Talsma, et al., *Frost prediction using machine learning and deep neural network models*. Frontiers in Artificial Intelligence, 2023. **5**: p. 963781, <https://doi.org/10.3389/frai.2022.963781>.
36. XAIDA, *eXtreme events: Artificial Intelligence for Detection and Attribution*. Accessed October 2023. Available from <https://xaida.eu/>.
37. Tianle Yuan, et al., *Global reduction in ship-tracks from sulfur regulations for shipping fuel*. Science Advances, 2022. **8**(29): p. eabn7988, <https://doi.org/10.1126/sciadv.abn7988>.

Chapter 3:

GREENHOUSE GAS EMISSIONS MONITORING

Antoine Halff, Colin McCormick and Alexandre d'Aspremont

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 to address this challenge. AI tools can analyze 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-enabled emissions monitoring has the potential to accelerate climate mitigation in many areas.

A. Incumbent GHG emissions monitoring

Scientists began regularly measuring GHG concentrations in the atmosphere in the 1950s. These measurements have shown a steady increase in GHG concentrations (see Figure 3-1) and have been

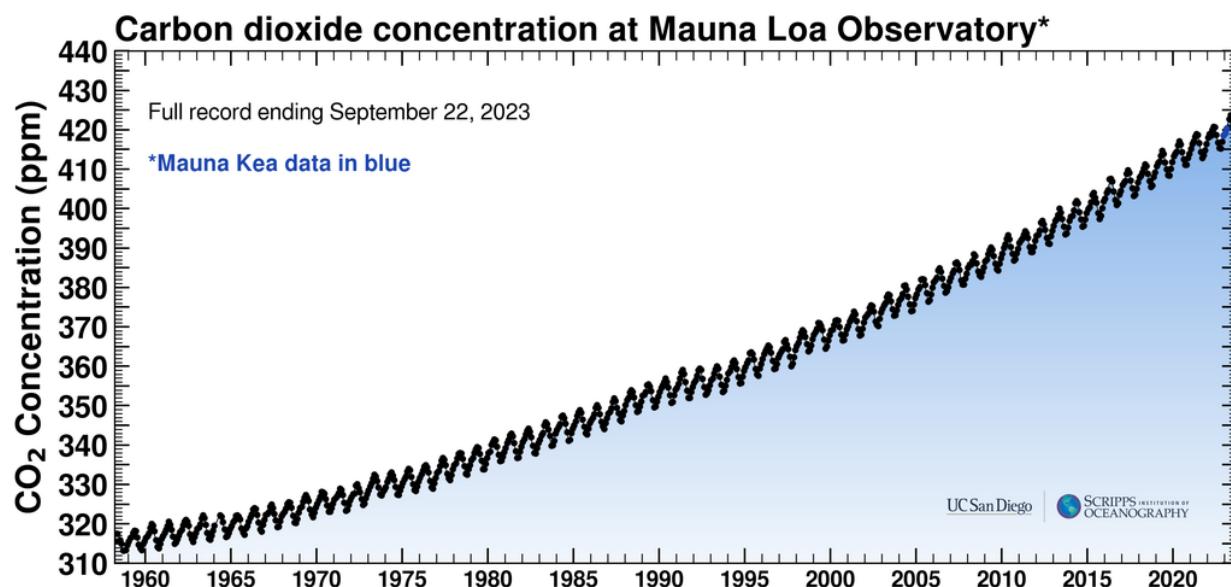


Figure 3-1. The Keeling Curve, showing measurements of CO₂ concentrations at the Mauna Loa Observatory in Hawaii since 1958, is named after the scientist Charles David Keeling who started the monitoring program.

Source: <https://keelingcurve.ucsd.edu/>

instrumental in raising awareness of the climate crisis. These data, from ground-mounted instruments and Earth-observation satellites, such as NASA's OCO series and JAXA's GOSAT/IBUKI series (see Figure 3-

2), are foundational for climate science. However, they provide very limited or no information on the sources, spatial distribution, timing and rates of GHG emissions.

To understand the sources of GHG emissions, the climate community primarily uses estimated emission factors based on generic categories of equipment and processes. Unfortunately, these emission factors often systematically underestimate real emissions.¹⁻⁵ 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 emissions—based on pipeline length and diameter—whether or not its operators engage in routine venting, flaring or other climate-adverse, high-emitting and avoidable practices.

Different GHGs pose very different detection and measurement challenges.

- CO₂ emissions are mainly caused by fossil fuel combustion and deforestation. CO₂ 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.
- CH₄ emissions, in contrast, come from a range of sources (the energy sector, food system and waste management) and are much less correlated with consumption. Energy-related methane emissions are largely avoidable byproducts of fossil fuel production and transport, uncorrelated with consumption rates and very unevenly distributed across fossil-fuel supply chains.

AI tools are critical for overcoming these challenges.



Figure 3-2. Japan's GHG-observing satellite "IBUKI-2" (GOSAT-2).

Source: <https://global.jaxa.jp/projects/sat/gosat2/>

B. AI-enabled GHG emissions monitoring

The use of satellites, drones and ground sensors to measure GHG emissions at the source has increased significantly in recent years. These instruments produce vast amounts of data. AI technologies are essential to process and analyze these data. Progress on the “software” side—the capacity to process and analyze raw satellite imagery and other data at scale in near-real time—is a critical enabler of advances on the “hardware” side.

Further progress in AI, together with a new generation of satellites, will further improve methane-emissions monitoring and abatement. Progress in real-time carbon-emissions monitoring, as well as in measurement and monitoring of natural carbon sinks—such as vegetation—offers the same potential.

(i) Methane emissions

Methane has more than 80 times the warming power of CO₂ in the first 20 years after release and is as big a source of near-term warming as CO₂.⁶

AI has been particularly important in improving methane-emissions monitoring. AI helps to (1) process data from methane sensors at scale, (2) combine input from multiple satellites to overcome each particular satellite's limitations and (3) integrate satellite information with data generated by other types of sensors to build multi-scale monitoring and reporting systems.

a. Processing data at scale

AI algorithms that process large amounts of remote-sensing data related to methane have been developed by scientists at leading research institutions, including the Netherlands Institute for Space Research (SRON), the French Laboratory for Climate and Environmental Science (LSCE) and the Wofsy group at Harvard University. These algorithms have been further developed and operationalized by Kayrros, a French-based start-up company, which has enabled the automatic detection and measurement of large methane emission events at scale on a global basis (Figure 3-3). (Two of the co-authors of this chapter are principals of Kayrros.) The International Methane Emissions Observatory (IMEO), launched by the UN Environment Programme (UNEP) and the European Union in 2021, has contracted with Kayrros, SRON and GHGSat (a Canadian company that operates methane-tracking satellites) to collect information on super-emitters and work with the responsible parties and their governments to reduce emissions.⁷

Advances in AI-enabled image processing capacity have considerably advanced the monitoring power of satellites, which can now detect methane at the same spatial resolution as aerial surveys at much lower cost and much higher temporal resolution.⁸ AI-enabled global methane monitoring has shown that super-emitters are more ubiquitous than previously thought and that eliminating most super-emitters from the oil and gas industry could be achieved at negligible cost.⁹⁻¹¹

Eliminating energy-related super-emitters would help significantly reduce anthropogenic methane emissions, which could cut the increase in global average temperatures by 0.3 °C by 2045 and by 0.5 °C by 2100.^{12, 13} This set of abatement measures—the fastest known way to reduce global warming—is entirely dependent on the use of AI.

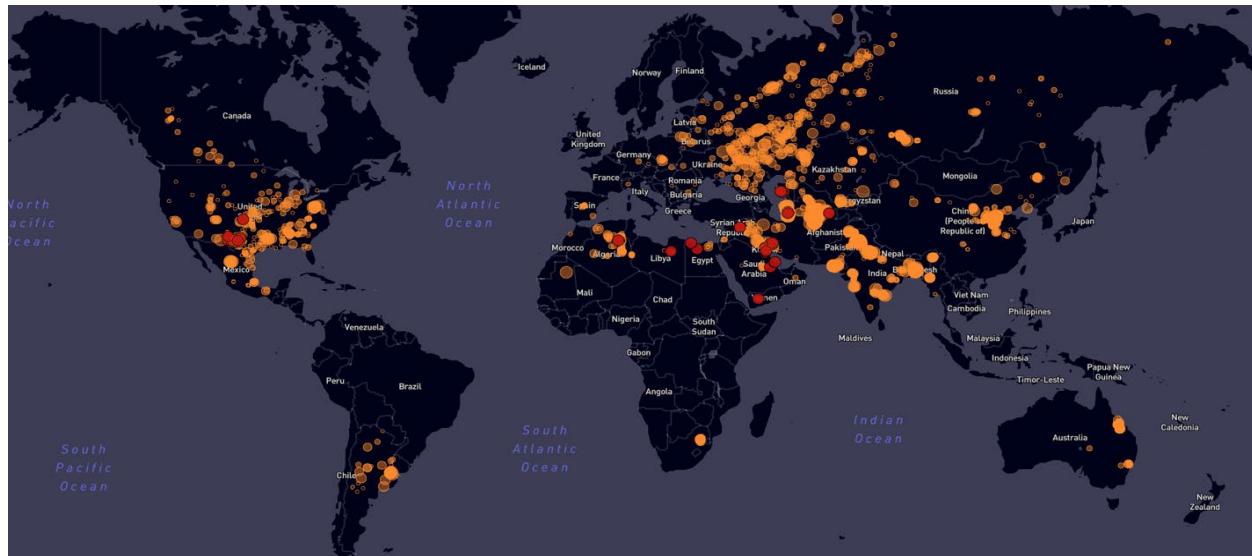


Figure 3-3. Methane super-emitters identified from satellite data processed with AI algorithms. Source: Kayrros.

The policy implications of these developments are already being felt. AI breakthroughs have played an important role in advancing understanding of methane emissions and have enabled climate policy initiatives, including the Global Methane Pledge, the EU Methane Strategy, the methane provisions of the US Inflation Reduction Act, upcoming new methane regulations from the US Environmental Protection Agency (EPA) and IMEO and its Methane Alert and Response System (MARS).

b. Combining data from multiple satellites

AI has been particularly valuable in enabling GHG monitoring based on data from satellites with diverse capabilities, including satellites that were not initially intended for GHG monitoring.¹⁴ For example, satellites such as Sentinel-5P and Sentinel-2 from the European Space Agency, PRISMA from the Italian Space Agency, EnMAP from the German space agency DLR and Landsat 8 and 9 from the National Aeronautics and Space Administration (NASA) have different orbital timing (days between revisiting a given location), spatial resolutions (the ground size of a single image pixel) and spectral (color) sensitivity. Input from these and other satellites, with distinct sets of benefits and disadvantages, has been combined to build a more powerful and comprehensive monitoring and reporting system.¹⁵ This system makes it possible to confidently attribute methane emissions at the facility level (versus basin-level), overcome terrain challenges (such as mountainous terrain in China's coal-producing Shanxi province) and even pinpoint the individual pieces of equipment responsible for methane emissions (such as specific elevators or ventilation units in mines).

c. Integrating satellite data with other data

Some regulations call for very low detection thresholds at the asset level that cannot be detected via satellite and can only be detected with local *in situ* sensors. However, the latter have inherently limited range and are not configured to detect large intermittent events. AI can be used to integrate data from various types of sensors to build comprehensive, multi-scale monitoring and reporting

systems. This capability is critical for establishing differentiated natural gas and liquified natural gas (LNG) markets based on lifecycle GHG emissions and for establishing carbon border adjustment mechanisms.

(ii) Carbon dioxide emissions

AI is increasingly being used to better understand and quantify the sources of CO₂ emissions. AI is helping to build on existing datasets and dramatically improve the timeliness, granularity and accessibility of CO₂ information.

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 been used to produce near-real-time trackers of CO₂ emissions by sector, with continuous improvements made to the underlying datasets and AI-based emissions analysis methods.^{16, 17}

AI-enabled CO₂ emissions data allow policymakers to assess the effects of emission-abatement measures with timeliness and precision. For example, AI can model and monitor CO₂ 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.¹⁸⁻²⁰

More use-cases for AI-enabled CO₂ 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.

a. Providing near real-time information on CO₂ emissions and demand for carbon credits

Climate Trace, Carbon Monitor and other organizations are using AI to more accurately monitor CO₂ emissions. Their methods include:

- combining computer vision with data from remote-sensing satellites, such as detecting water vapor (a proxy for CO₂ emissions) that is released from large natural-draft cooling towers at power plants;^{21, 22}
- measuring the daily amount of vehicle traffic on roads over large regions and the GHG emissions that these vehicles collectively produce,²³ and
- improving plume-inversion techniques to translate direct CO₂ concentration measurements into estimates of CO₂ emissions rates at large power plants.²⁴

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 with satellite-relayed ship tracking data from automated identification system (AIS) transponders.²⁵

Such transparency carries far-reaching consequences for carbon abatement. In particular, AI-enabled measurements can support and improve cap-and trade systems, amplifying their impact by providing carbon-market participants with up-to-date information on implied demand for carbon credits.

AI-enabled measurements of carbon emissions can also be deployed across extended supply chains to assess the lifecycle emissions of commodities and other products. This type of information may be of critical importance 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 including crude oil, gasoline, LNG, electric vehicles or wind turbines, by collecting emissions associated with each link of their respective supply chains. This information could be used by importing countries to assess the product's GHG intensity and any associated GHG tariff.

Finally, AI tools can provide policymakers with a powerful resource to track the effect of emissions regulations, identify and prioritize CO₂ abatement opportunities, detect swings in CO₂ emissions and craft appropriate reaction measures in a timely manner. This is particularly the case for urban CO₂ emissions, which are estimated to account for up to 60% of total CO₂ emissions and which can be analyzed with AI technologies in great detail.²⁶

b. Achieving near real-time transparency on negative CO₂ emissions

In its Sixth Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) highlights the critical 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, but 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 ways of monitoring forest projects involve 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 data sufficient 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 forestry and build a strong monitoring, reporting and verification (MRV) architecture around carbon-offset projects. AI technologies make it possible to not only monitor entire projects comprehensively at relatively high frequency, cost-efficiently and non-intrusively, but also 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. This transparency has the potential to rebuild confidence in carbon-offset projects, prevent and crack down on unsavory practices in 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 the monitoring of positive carbon emissions, there are several use cases for this application of AI technology. These include

strengthening forest protection through robust MRV of carbon offsetting projects, supporting carbon markets with the provision of near real-time data on the supply of carbon credits, and facilitating the implementation of anti-deforestation policies.

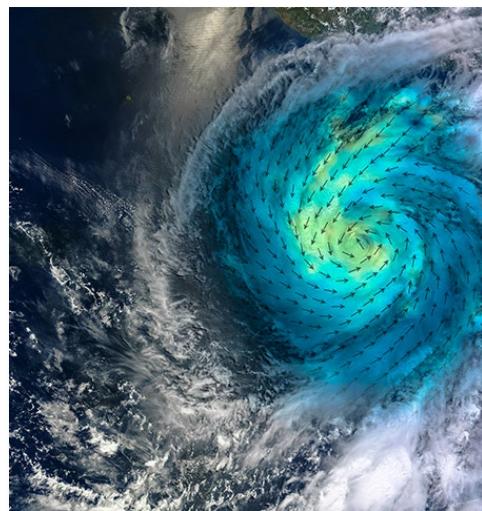
These AI-assisted technologies are a potential game changer for developing a robust and transparent nature-based solutions (NBS) sector. NBS projects have been plagued by a lack of transparency that has shielded dubious and sometimes fraudulent business practices, caused market inefficiencies and failures, and severely undermined market confidence in NBS as a viable climate tool.^{27,28} AI technologies can provide carbon traders with real-time information about the supply of carbon offsets, supplementing implied demand data produced from the monitoring of carbon emissions. Near-real-time transparency on carbon-credit supply and demand fundamentals can facilitate price formation in carbon markets and help send the price signals needed to support investment in offset projects.²⁹

(iii) Barriers

The use of AI to harness satellite imagery and other data sources is one of the most promising developments for GHG emissions abatement. However, there are important barriers.

a. Barrier: 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 adversely affect public trust in GHG data and create a fertile ground for the 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.



b. Barrier: Conflicting AI-enabled greenhouse gas (GHG) emissions data

With a proliferation of Earth-observation satellites being launched in the near future and new start-up companies competing in the AI-for-climate space, different providers could potentially release conflicting measurements. This could undermine public confidence in the accuracy of AI-enabled GHG emissions data.

This challenge could emerge with respect to methane emissions, in particular, in the years ahead. The Environmental Defense Fund plans to launch MethaneSat in 2024; Carbon Mapper, a public-private joint venture between the California Air Resources Board (CARB), NASA, Planet Labs and others is also set to launch in 2024; GHGSat will expand its fleet; Absolut Sensing, a French private company, is preparing to launch its own fleet of methane tracking nano-satellites; and many new start-up companies are seeking to tap into the wealth of raw data from multiple satellite constellations to generate actionable methane data. The proliferation of methane tracking sources could lead to real or apparent data inconsistencies, requiring integration and harmonization.

c. Barrier: Sovereignty concerns

Sovereignty concerns may emerge as a significant impediment to the use of 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 come under assault or face a trust deficit if it is perceived as biased in favor of certain economic actors.

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.³⁰

d. Barrier: Uncertain financial models

A tension exists in the current development of AI tools for GHG emissions data. The technological innovations behind these new tools are developed by private-sector enterprises that must generate revenue from the sale of data to recoup their investments and fund further research and development. However the data must be as widely-shared as possible and ideally made available to the public in open access to facilitate global acceptance of their accuracy. Protecting the intellectual property in many AI-enabled data technologies is essential to the financial success of these private-sector enterprises and thus to innovation in AI data technologies but may limit public acceptance of GHG emissions data.

(iv) Next steps

Several measures could help address the barriers described above and could promote the use of AI tools for GHG emissions monitoring.

a. Promote AI literacy

AI literacy could be promoted in education worldwide, both by integrating AI into students' broad curriculum and by establishing AI as an independent, specialized field of study. In addition, professional accreditation standards could include AI literacy metrics. For example, certified public accountants and civil engineers could be required to demonstrate minimal AI proficiency and the ability to use basic AI technologies for professional certification.

Furthermore, organizations in both the public and private sectors could enhance 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 integrate those data into proprietary databases and operational systems.

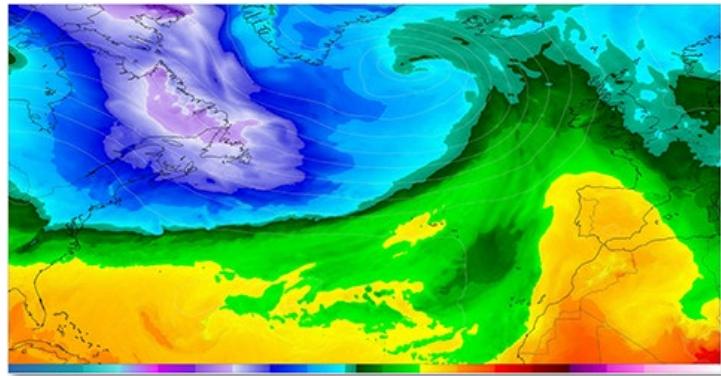
b. Promote mechanisms to validate AI-enabled greenhouse gas (GHG) emissions data

Because AI-enabled data often detect and measure things that cannot be otherwise detected or measured, proving their accuracy can be challenging. Governments could encourage public research to develop ways of independently replicating and corroborating these data and documenting their accuracy based on well-calibrated ground-truth measurements. For example, a team of scientists at Stanford University recently performed controlled blind releases of methane in the Arizona desert to test the capacity of various companies to detect and accurately measure

these releases. Similar studies could be funded and their findings disseminated to build confidence in AI-enabled data.

c. Establish best practices/regulations for AI-enabled data

To strengthen public trust in AI-enabled GHG data and foster their use, firewalls could be built between companies in the data-generation business and those selling low-carbon certification products based on these measurements. If the business model of companies that measure GHG emissions with their proprietary AI technologies is based on the sale of low-emission guarantees or other “certificates of origin” (e.g., certificates offering the “guaranty” that certain volumes of LNG or petroleum products have been “responsibly” produced and are free of methane or other emissions) that creates an incentive for the data provider to boost sales by providing favorable data. Data generation and certification could be decoupled, so that the sale of AI-enabled GHG measurements is not conditioned on the favorability of the outcome to customers.



AI data providers could also be subject to some degree of regulatory oversight, similar to the way energy Price Reporting Agencies methodologies were subjected to some form of regulatory guidance from the International Energy Agency (IEA), the Organization of the Petroleum Exporting Countries (OPEC) and the International Organization of Securities Commissions (IOSCO) under a G20 mandate in the wake of the 2011 London Interbank Offered Rate (LIBOR) scandal.³¹ For example, regulations could seek to address and avoid any conflict of interest from AI data providers that would also engage in the certification of so-called “responsibly produced liquefied natural gas,” requesting that the functions of emissions measurement and responsible gas certification be performed by separate actors.

d. Set up one or several global “owners” of AI-enabled greenhouse gas (GHG) emissions data

To manage the risk of conflicting AI-enabled data on GHG emissions, one or several global “owners” of these data could be established and tasked with reconciling potentially contradictory measurements. These data owners may also be tasked with identifying and adopting best practices.

In the area of methane emissions measurement, the IMEO may fulfill this role. A challenge for the IMEO and other such multilateral organizations is to engage with and ensure the participation and buy-in of a broad diversity of energy consuming and producing countries and state and non-state actors, notably to get buy-in from key stakeholders, including major oil and gas exporting countries and large economies, such as China and India.

Existing organizations such as the World Meteorological Organization and Food and Agriculture Organizations could handle CO₂ and other GHG emissions datasets, as well. Alternatively, a single new, centralized organization could be set-up to serve as a one-stop clearinghouse for all climate data.

Finally, the data “owner” in charge of harmonizing and reconciling data may not necessarily warehouse all types of GHG data but may choose instead to focus only on high-level data, while also providing a form of certification for private providers of more granular GHG measures.

e. Elevate AI for climate in international dialogue and negotiations

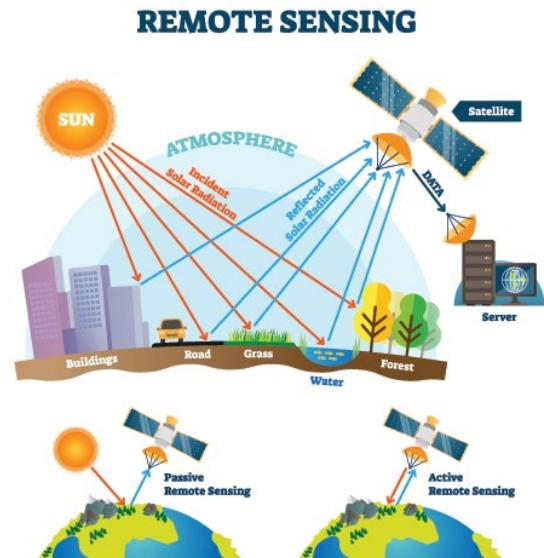
A first step in managing some of the issues above may be to foster international cooperation on addressing them. Climate policy hinges to a large extent on sound international policies with respect to these AI issues. For example, it is important to acknowledge and address AI-for-climate issues in such institutions as the UN Framework Convention on Climate Change (UNFCCC), the World Trade Organization (WTO) and IEA.

C. Conclusion

AI is making great strides in providing near-real-time transparency on GHG emissions by enabling data collection on metrics that were previously unavailable (with CH₄) and by enhancing the timeliness, coverage and accuracy of existing datasets (with CO₂ emissions). This information is provided at scale, globally and cost-efficiently.

Rapid developments in the use of AI for GHG emissions measurements are opening new opportunities for climate action on many fronts and at many levels. AI-enabled GHG emissions data provide fresh fodder for climate research and may lead to new and more effective climate policies, such as the methane rules currently under development in various jurisdictions. AI-enabled emissions data are also providing key metrics and key performance indicators (KPIs) to guide environmental, social and governance (ESG) practices in the financial sector. For example, banks can use data on methane emissions from oil and gas companies as criteria for lending decisions or investors could use them to monitor the footprint of their portfolio companies and help them reduce their emissions. Industrial actors in carbon-intensive sectors and energy producers can use AI-enabled data to monitor their own footprint and improve their operating practices. The fast-growing volume of AI-enabled data on GHG emissions in open access also helps raise public awareness of climate change, empowering civil society to hold public officials and private companies accountable for their climate footprint.

Progress in AI-enabled GHG emissions data technologies is ongoing, enabled by new algorithms, cloud computing and the falling cost of data storage, growing computing capacity, and a proliferation of new sources of raw data, including satellite imaging, geolocation data, the IoT, etc. The growth of underlying



Earth-observation data is itself fueled by falling costs in satellite construction and launching. AI technologies are also supported by the promotion of AI literacy in education and across all sectors of society.

Because the GHG emissions data enabled by AI are often new, their use cases are still being established and are highly versatile. But the wealth and breadth of potential applications of these technologies are already apparent, making AI-enabled GHG data services a critical “climate tech” sector that is vitally important to the energy transition.

REFERENCES

1. A. R. Brandt, et al., *Methane Leaks from North American Natural Gas Systems*. Science, 2014. **343**(6172): p. 733-735, <https://doi.org/10.1126/science.1247045>.
2. Stuart N. Riddick and Denise L. Mauzerall, *Likely substantial underestimation of reported methane emissions from United Kingdom upstream oil and gas activities*. Energy & Environmental Science, 2023. **16**(1): p. 295-304, <https://doi.org/10.1039/D2EE03072A>.
3. International Energy Agency (IEA). *Methane emissions from the energy sector are 70% higher than official figures*. 2022. International Energy Agency (IEA). Available from <https://www.iea.org/news/methane-emissions-from-the-energy-sector-are-70-higher-than-official-figures>.
4. M. Saunois, et al., *The Global Methane Budget 2000–2017*. Earth Syst. Sci. Data, 2020. **12**(3): p. 1561-1623, <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, 2023. **50**(15): p. e2023GL103834, <https://doi.org/10.1029/2023GL103834>.
6. IPCC Working Group III, Climate Change. *Mitigation of Climate Change - Summary for Policymakers (Sixth Assessment Report)*. 2022. <https://www.ipcc.ch/report/sixth-assessment-report-working-group-3/>.
7. Luis Guanter, *International Methane Emissions Observatory, Methane Alert and Response System (MARS), PowerPoint presentation* (in possession of authors).
8. Evan Sherwin, et al., *Single-blind test of nine methane-sensing satellite systems from three continents*. EGUsphere, 2023. **2023**: p. 1, <https://doi.org/10.31223/X56089>.
9. T. Lauvau, et al., *Global assessment of oil and gas methane ultra-emitters*. Science, 2022. **375**(6580): p. 557-561, <https://doi.org/10.1126/science.abj4351>.
10. Damian Carrington, *Revealed: 1,000 super-emitting methane leaks risk triggering climate tipping points*, in *The Guardian*. 2023. Available from <https://www.theguardian.com/environment/2023/mar/06/revealed-1000-super-emitting-methane-leaks-risk-triggering-climate-tipping-points>.
11. Christophe McGlade Tomas de Oliveira Bredariol. *Methane Abatement*. 2023 Available from <https://www.iea.org/energy-system/fossil-fuels/methane-abatement>.
12. Tiy Chung. *Global Assessment: Urgent Steps Must Be Taken to Reduce Methane Emissions This Decade*. 2021. United Nations Climate Change. Available from <https://unfccc.int/news/global-assessment-urgent-steps-must-be-taken-to-reduce-methane-emissions-this-decade>.
13. 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*. 2022 Available from https://www4.unfccc.int/sites/SubmissionsStaging/Documents/202208040943---Environmental%20Defense%20Fund_GST%2004.08.22.pdf.
14. European Space Agency. *Mapping high-resolution methane emissions from space*. Available from https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-5P/Mapping_high-resolution_methane_emissions_from_space.

15. Sudhanshu Pandey, et al., *Daily detection and quantification of methane leaks using Sentinel-3: a tiered satellite observation approach with Sentinel-2 and Sentinel-5p*. *Remote Sensing of Environment*, 2023. 296: p. 113716, <https://doi.org/10.1016/j.rse.2023.113716>.
16. Zhu Liu, et al., *Carbon Monitor, a near-real-time daily dataset of global CO2 emission from fossil fuel and cement production*. *Scientific Data*, 2020. 7(1): p. 392, <http://doi.org/10.1038/s41597-020-00708-z>.
17. *Carbon Monitor*. 2023 Available from <https://carbonmonitor.org/>.
18. Yi Gao, et al., *A High-Frequency Monitoring Method for Urban Carbon Emissions Based on Vertical Federated Deep Learning and Multi-Source Heterogeneous Data Fusion Methods*, in *Proceedings of the 5th International Conference on Information Technologies and Electrical Engineering*. 2023, Association for Computing Machinery: Changsha, China. p. 232–237, <https://doi.org/10.1145/3582935.3582972>.
19. Angel Hsu, et al., *Predicting European cities' climate mitigation performance using machine learning*. *Nature Communications*, 2022. 13(1): p. 7487, <https://doi.org/10.1038/s41467-022-35108-5>.
20. 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*. 2023. Copernicus Meetings, <https://doi.org/10.5194/egusphere-egu23-4138>.
21. Heather D Couture, et al. *Towards tracking the emissions of every power plant on the planet*. (2020). 3; pgs. NeurIPS Workshop, <https://www.climatechange.ai/papers/neurips2020/11>.
22. Madison Hobbs, Ali Rouzbeh Kargar, Heather Couture, Jeremy Freeman, Isabella Söldner-Rembold, André Ferreira, Jeyavinoth Jeyaratnam, Joseph O'Connor, Jordan Lewis, Hannes Koenig, Colin McCormick, Tiffany Nakano, Charmaine Dalisay, Aaron Davitt, Lee Gans, Christy Lewis, Gabriela Volpato, Matthew Gray, Gavin McCormick, *Inferring carbon dioxide emissions from power plants using satellite imagery and machine learning*. 2023, https://2023.ieeeigarss.org/view_paper.php?PaperNum=5326.
23. Derek Rollend, Tomek Kott, Kevin Foster, Rohita Mocharla, Rai Muñoz, Neil Fendley, Chase Ashcraft, Marisa Hughes, *Transportation Sector: Road transportation (asset)*. 2022, [https://github.com/climatetracecoalition/methodology-documents/blob/main/2022/Transportation/Transportation%20Sector-%20Road%20transportation%20\(asset\)%20Methodology.pdf](https://github.com/climatetracecoalition/methodology-documents/blob/main/2022/Transportation/Transportation%20Sector-%20Road%20transportation%20(asset)%20Methodology.pdf).
24. J. Dumont Le Brazidec, et al., *Deep learning applied to CO2 power plant emissions quantification using simulated satellite images*. *Geosci. Model Dev. Discuss.*, 2023. 2023: p. 1-30, <https://doi.org/10.5194/gmd-2023-142>.
25. Brett Mayes, Mark Powell, Dan Knights, Max Schofield, Ted Mackereth, *Transportation sector: Shipping*. 2023, <https://github.com/climatetracecoalition/methodology-documents/blob/main/2023/Transportation/Transportation%20sector-%20Domestic%20and%20International%20Shipping%20Emissions%20methodology.docx.pdf>.
26. Da Huo, et al., *Carbon Monitor Cities near-real-time daily estimates of CO2 emissions from 1500 cities worldwide*. *Scientific Data*, 2022. 9(1): p. 533, <https://doi.org/10.1038/s41597-022-01657-z>.
27. Monica Guy. *COP26: Is corruption on the agenda?* 2021 Available from <https://baselgovernance.org/blog/cop26-corruption-agenda>.
28. Patrick Greenfield. *Revealed: more than 90% of rainforest carbon offsets by biggest certifier are worthless, analysis shows*. 2023 Available from <https://www.theguardian.com/environment/2023/jan/18/revealed-forest-carbon-offsets-biggest-provider-worthless-verra-aoe>.
29. International Panel on Climate Change. *AR6 Synthesis Report: Climate Change 2023*. 2023 Available from <https://www.ipcc.ch/report/sixth-assessment-report-cycle/>.
30. Kit Million Ross. *China clamps down on information leaks in energy sector*. 2023 Available from <https://www.power-technology.com/news/china-clamps-down-on-information-leaks-in-energy-sector/?cf-view>.
31. Board of the International Organization of Securities Commissions. *Implementation of the Principles for Oil Price Reporting Agencies*. 2015 Available from <https://www.iosco.org/library/pubdocs/pdf/IOSCOPD506.pdf>.

Chapter 4:

POWER SECTOR

Zhiyuan Fan and David Sandalow

The power sector will play a central role in meeting economy-wide decarbonization targets. The scale of the challenge is enormous.

- In 2022, global emissions of carbon dioxide (CO₂) from the power sector were 14.5 Gt—roughly 40% of energy-related CO₂ emissions globally.¹
- Most strategies for deep decarbonization foresee growing reliance on the power sector in the decades ahead. In the *Net Zero by 2050* scenario prepared by the International Energy Agency (IEA), for example, the share of electricity in final energy use increases from 20% in 2020 to 50% in 2050.² To achieve economy-wide net-zero emissions targets, the power sector must grow significantly as it decarbonizes.
- In 2022, global investment in the power sector was about \$1 trillion.³
- In IEA's *Net Zero by 2050* scenario, annual power sector investment surges to roughly \$3 trillion by 2030 and stays at or near that level for decades.²

Artificial intelligence (AI) provides an important set of tools to help decarbonize the power sector. The growing capabilities of AI tools and increasing amounts of power sector data both play a role.



Figure 4-1. Data and AI applications for power grid infrastructure.⁵

Machine learning (ML) tools use data from satellites to predict solar and wind power generation and data from the “Internet of things” to forecast electricity demand.⁴ Indeed due to the profound complexity of the power grid’s structure and operations, AI is becoming an essential component of power-grid infrastructure. Power-sector management is one of the most important opportunities for using AI to counter climate change.^{5, 6}

This chapter gives an overview of AI’s current and potential impact on four parts of the power system: (1) generation infrastructure (both utility-scale and distributed), (2) transmission and distribution networks, (3) end-use sectors and (4) energy storage.

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

A. Generation infrastructure

The planning, operation and maintenance of generation infrastructure are complex tasks, requiring attention to a variety of factors including the size and expected lifespan of equipment, renewable resource availability and transmission congestion. AI can play an important role in performing these tasks.

AI can be especially valuable in siting large-scale renewable projects.

- Determining the optimal size and location of solar projects requires complex calculations, which must consider weather patterns, grid constraints and other factors. Engel and Engel (2022) reviewed AI’s application for optimal sizing of solar plants.⁷ Ahmed et al. (2020) summarized how both short-term (<1 day) and long-term (seasonal) solar-potential predictions can help optimize site-specific solar plant planning.⁸
- Similar complex planning challenges also exist for wind farm planning, which must consider terrain morphology, wind speed and direction, turbine type and costs.⁹ Ashwin Renganathan et al. (2022) applied AI models to study economic performance of wind farm design and wind farm wake interactions for planning decisions.¹⁰

AI also has significant potential to assist with integrated electric-grid planning. This is an important area for research and innovation.

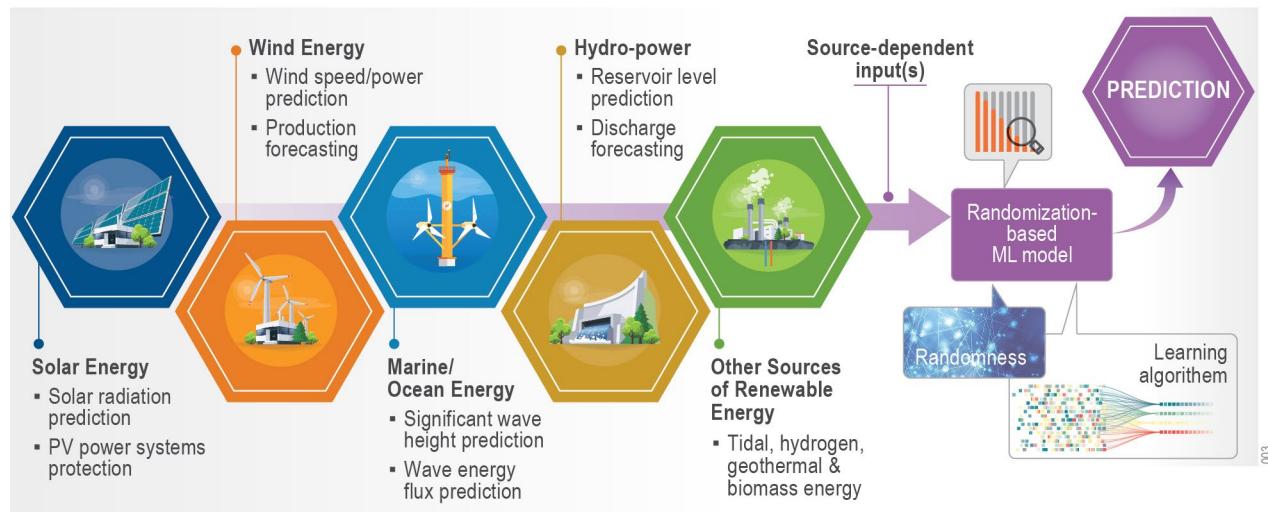


Figure 4-2. AI for renewable predictions.¹¹

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 4-2).¹¹ For example:

- AI can predict weather relevant to wind/solar generation, such as wind speed¹² and solar radiation.¹³
- 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).¹⁴
- Other applications for maximizing renewable power generation using AI include reinforcement learning control for wind turbines,^{15, 16} solar system operation⁴ and solar shading.¹⁷
- AI can help accelerate deployment of non-conventional renewables such as wave energy¹⁸ and geothermal energy.¹⁹ In geothermal energy, AI can help improve numerical reservoir modeling, exploration, drilling and production.¹⁸

AI can also be applied for power generation infrastructure maintenance. Wind power facilities are often located in tough environments and must endure high wind-speed, extreme temperatures and/or low population density, making maintenance expensive (usually higher than procurement costs).²⁰ AI can be used for maintenance prediction and scheduling to minimize turbine failure and malfunction, as well as for reducing maintenance frequency and costs.^{20, 21} Similarly, maintenance optimization using AI can be used for solar,²² nuclear,²³ hydropower,²⁴ and general power plants.²⁵ AI for utility-scale infrastructure maintenance applies data-driven predictions for failure, risk detection and age/life predictions to minimize cost and production downtime.

AI can be especially helpful in operating rooftop solar PV. AI can predict rooftop solar installation potential,²⁶ generate forecasts²⁷ and reduce customer acquisition costs.²⁸ Overall, AI can help with deployment of rooftop PV by predicting assets' production and reducing uncertainty that may damage the grid.

Federated learning (FL)—a special type of AI—can be very useful in distributed infrastructure. FL is a collaboratively decentralized privacy-preserving learning method that allows training to be performed on local devices.²⁹ In FL, only training output (updated model parameters) is shared with the global model while data are kept private within users' local devices. FL can also perform tasks such as rooftop solar generation prediction,³⁰ which provides an alternative to AI models based on centralized data and can perform various tasks in the “smart city” and “smart grid” context.³¹

In summary, AI can help improve power generation infrastructure, especially wind and solar, from all phases of the project lifetime: planning, operation and maintenance. Compared to operation and maintenance, generation-infrastructure planning using AI is less well-studied and potentially a point for innovation. Data support is critical for predictive approaches and proposed AI-based methods are rarely deployed for commercial applications.

B. Transmission and distribution infrastructure

Transmission and distribution infrastructure is needed to bring electricity to end-users.

Interconnected lines form the transmission and distribution network is the backbone of the electric grid. Planning and operating this infrastructure involves solving complicated nonlinear problems. AI can improve optimization methods and provide completely new perspectives.

Transmission expansion planning (TEP) is a process that determines the optimal location and capacity of new transmission lines, as well as the best timing for new construction. TEP involves large-scale combinatorial and nonconvex optimization problems in which finding a feasible solution can be difficult.³² As a result, heuristic methods are sometimes adopted to search line-by-line to locate a “good solution.” Recent 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.³³



- Wang et al. (2021a and b) showed that AI can be used to solve multi-stage TEP based on the static model, which can be flexibly adjusted and incorporate uncertainties on wind power and demand projections.^{34, 35}
- Similarly for transmission networks, Fu et al. (2020) studied the stochastic optimal planning of distribution networks using AI, considering both renewable power and demand variability.³⁶

Although AI has been used to investigate TEP problems since at least 2002,³⁷ its application for transmission and distribution planning is not widely studied. This topic is an opportunity for innovation.

In grid operation, AI can be used to improve both economics and resilience. The famous optimal power flow (OPF) problem is a good example of AI's application for grid operation. As Hasan et al. (2020) mention in their review, the research community is still in search of reliable and computationally efficient OPF solution techniques 60 years after its initial formulation.³⁸ AI can obtain a more cost-effective solution and reduce the computational burden.³⁸ Xie et al. (2020) summarize AI's application in power system resilience, showing AI's great potential in outage forecasting, stability assessment, power system control and power restoration.³⁹

AI can also help distribution network operations. Historically, the distribution grid is too complex and tangled to be mapped accurately, leading to difficulties with fault detection. Recent progress in digitalization has increased the observability and controllability of the distribution grid and enabled AI to assist in fault detection.⁴⁰ Studies have shown that AI methods outperform traditional methods in fault detection accuracy but demand large amounts of data and significant computational resources.^{40, 41}

In conclusion, AI can be applied to transmission and distribution infrastructure to improve planning/operational economics and resilience. As the optimization-based solution is largely limited by computational load and expansion in problem size/complexity, AI is becoming increasingly important in providing not just better but potentially more robust solutions.

C. End uses

Analyses of electric grid infrastructure sometimes treat end-use sectors such as buildings and industrial facilities as out of scope. These sectors are often studied as separate research questions. However, electricity-demand forecasting, demand side management and new end-use infrastructure (such as EV charging stations and hydrogen systems) are becoming increasingly important to the electric grid. AI can play an important role in these areas.

Demand prediction and scenario projections using AI already exhibit great potential. AI can be used to perform general demand prediction (time-series decomposition and prediction),⁴² national long-term demand scenario forecasting⁴³ and demand predictions for specific sectors such as buildings⁴⁴ and EV charging.⁴⁵ These demand predictions can be used for system operation such as unit commitment (short-term) and system planning (long-term).

Aside from passively predicting electricity demand, AI can also be used to actively manipulate demand in limited scope. Known as demand response, this refers to programs in which certain users

volunteer to limit electricity consumption for financial reward, providing the grid operator more flexibility and minimizing the need for capacity charges, spinning reserves and ancillary service storage purchases. Antonopoulos et al. (2020) reviewed AI approaches for demand response, demonstrating that AI can capture human feedback, cluster users and tasks without prior knowledge, and activate participants in demand response programs.⁴⁶ Demand-side AI research requires significant data support with high spatial-temporal resolution.

EV charging infrastructure offers another great example of AI's value. In addition to predicting EV charging demand (see above), AI can help with EV charging infrastructure planning. Deb (2021) reviewed ML approaches to solving charging infrastructure planning problems, highlighting that AI can be used to optimize charging station placement, charger utilization (station size) and scheduling for minimum pricing.⁴⁷ Federated learning can perform tasks such as EV demand prediction⁴⁸ and optimal EV charging station location.⁴⁹



AI can also 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.⁵⁰ AI can help optimize green hydrogen production by predicting renewable power potential,⁵¹ curtailed renewable energy⁵² and water sustainability.⁵³ AI can also help plan hydrogen refueling stations, optimizing station-based production and storage.⁵⁴ AI can be used to integrate renewable power with hydrogen-energy storage to increase grid stability and lower peak loads.⁵⁵

In summary, AI for demand prediction and demand-side response can assist with planning and operating other grid infrastructure components. AI can also help plan new end-use infrastructure, such as EV charging stations and low-carbon hydrogen networks.

D. Energy-storage infrastructure

With more and more variable renewables in the power system, energy storage is becoming an essential part of grid infrastructure. Energy storage balances supply-demand temporal mismatch, serving as both generation and load. The scale of energy storage, although quickly expanding, is still limited. AI can help plan for energy storage, schedule its operation and optimize its lifetime value.

AI has demonstrated ability to help predict and plan for the energy storage that will be required on a power grid.⁵⁶ Shams et al. (2021) used ML-based prediction of curtailed renewable power to plan hydrogen and battery energy storage systems.⁵⁷ Zhou et al. (2022) applied AI for energy storage

scheduling.⁵⁸ AI has also been used to help battery owners plan for maintenance, replacement and optimal use of their energy storage assets.^{59, 60}

EVs have significant potential as distributed energy storage, sometimes referred to as “vehicle to grid (V2G)” or “vehicle to everything (V2X)”.⁶¹ EV sales are growing rapidly. 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 in order 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,⁶² helping solve vehicle routing optimization problems,⁶³ and improving vehicle-to-grid performance.^{64, 65} AI can maximize the value of data collected from vehicles, facilitating deployment of V2G technologies.



E. Barriers and risks

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

First, AI models and methods are not yet sufficiently robust or well-developed for widespread deployment. Notwithstanding some studies that date back to the early 2000s, most studies on this topic are very recent and applications of AI for the grid are at an early stage of research and technology readiness level (TRL). Further, actual deployment timelines and impacts on commercial systems are still highly uncertain. AI applications have greatly benefited from both the explosion of power-grid system data and AI algorithm research. As the “digital infrastructure” of the grid becomes more universal, AI is increasingly necessary to effectively use the growing amount of grid-related data. However, more fundamental work on models and methods is needed for large-scale deployment.

Second, a lack of general guidance and standards for performance evaluation is another barrier to AI deployment. Nearly all types of AI methods (e.g., supervised, unsupervised and reinforcement learning) explored in the literature can be applied to grid infrastructure. These methods have the potential to deliver big improvements over non-AI methods. Quantifying the improvements in a systematic way requires guidance and standards.

Finally, the lack of a knowledgeable workforce is an important 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.

As AI is deployed in the power sector, security risks will be an important topic. Grid security is a paramount concern for grid operators. In most literature on the use of AI in the power sector, security risks receive scant attention. Important questions include (1) Is there a security risk from using AI in the proposed way?; (2) If not, how does one prove that?; and (3) If yes, how does one minimize it? Whether AI will introduce security risks to grid infrastructure remains unclear, but risk assessment and minimization strategies are essential. Security risks must be studied and properly addressed before deploying AI for most grid infrastructure. (See Chapter 10.)

F. 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, operation and optimization.* 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 operation have objectives related to cost, reliability, resilience, equity and greenhouse gas 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 risks addressed before that happens.

REFERENCES

1. International Energy Agency (IEA). *CO2 Emissions in 2022*. 2023. International Energy Agency; Available from <https://iea.blob.core.windows.net/assets/3c8fa115-35c4-4474-b237-1b00424c8844/CO2Emissionsin2022.pdf>.
2. International Energy Agency (IEA). *Net Zero by 2050: A Roadmap for the Global Energy Sector*. 2021. Available from <https://www.iea.org/reports/net-zero-by-2050>.
3. International Energy Agency (IEA). *World Energy Investment 2022*. 2022. Available from <https://iea.blob.core.windows.net/assets/b0beda65-8a1d-46ae-87a2-f95947ec2714/WorldEnergyInvestment2022.pdf>.
4. T. Ahmad, et al., *Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities*. Journal of Cleaner Production, 2021. **289**, <https://doi.org/10.1016/j.jclepro.2021.125834>.
5. R. Singh, et al., *Energy System 4.0: Digitalization of the Energy Sector with Inclination towards Sustainability*. Sensors, 2022. **22**(17), <https://doi.org/10.3390/s22176619>.
6. D. Rolnick, et al., *Tackling Climate Change with Machine Learning*. Acm Computing Surveys, 2023. **55**(2), <https://doi.org/10.1145/3485128>.
7. E. Engel and N. Engel, *A Review on Machine Learning Applications for Solar Plants*. Sensors, 2022. **22**(23), <https://doi.org/10.1016/j.nexus.2021.1000110.3390/s22239060>.
8. R. Ahmed, et al., *A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization*. Renewable & Sustainable Energy Reviews, 2020. **124**, <https://doi.org/10.1016/j.rser.2020.109792>.
9. L. Ekonomou, et al., *Estimation of wind turbines optimal number and produced power in a wind farm using an artificial neural network model*. Simulation Modelling Practice and Theory, 2012. **21**(1): p. 21-25, <https://doi.org/10.1016/j.simpat.2011.09.009>.
10. S. A. Renganathan, et al., *Data-driven wind turbine wake modeling via probabilistic machine learning*. Neural Computing & Applications, 2022. **34**(8): p. 6171-6186, <https://doi.org/10.1007/s00521-021-06799-6>.
11. J. Del Ser, et al., *Randomization-based machine learning in renewable energy prediction problems: Critical literature review, new results and perspectives*. Applied Soft Computing, 2022. **118**, <https://doi.org/10.1016/j.asoc.2022.108526>.
12. S. X. Lv and L. Wang, *Deep learning combined wind speed forecasting with hybrid time series decomposition and multi-objective parameter optimization*. Applied Energy, 2022. **311**, <https://doi.org/10.1016/j.apenergy.2022.118674>.
13. 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 for Sustainable Development, 2022. **68**: p. 1-17, <https://doi.org/10.1016/j.esd.2022.02.002>.
14. P. L. Donti and J. Z. Kolter, *Machine Learning for Sustainable Energy Systems*. Annual Review of Environment and Resources, Vol 46, 2021, 2021. **46**: p. 719-747, <https://doi.org/10.1146/annurev-environ-020220-061831>.
15. C. Wei, et al., *Reinforcement-Learning-Based Intelligent Maximum Power Point Tracking Control for Wind Energy Conversion Systems*. Ieee Transactions on Industrial Electronics, 2015. **62**(10): p. 6360-6370, <https://doi.org/10.1109/Tie.2015.2420792>.
16. A. Saenz-Aguirre, et al., *Performance enhancement of the artificial neural network-based reinforcement learning for wind turbine yaw control*. Wind Energy, 2020. **23**(3): p. 676-690, <https://doi.org/10.1002/we.2451>.
17. N. Padmavathi, A. Chilambuchelvan, and N. R. Shanker, *Maximum Power Point Tracking During Partial Shading Effect in PV System Using Machine Learning Regression Controller*. Journal of Electrical Engineering & Technology, 2021. **16**(2): p. 737-748, <https://doi.org/10.1007/s42835-020-00621-4>.
18. S. Y. Zou, et al., *Optimization of the electricity generation of a wave energy converter using deep reinforcement learning*. Ocean Engineering, 2022. **244**, <https://doi.org/10.1016/j.oceaneng.2021.110363>.

19. E. R. Okoroafor, et al., *Machine learning in subsurface geothermal energy: Two decades in review*. Geothermics, 2022. **102**, <https://doi.org/10.1016/j.geothermics.2022.102401>.
20. C. H. Yeh, et al., *Machine Learning for Long Cycle Maintenance Prediction of Wind Turbine*. Sensors, 2019. **19**(7), <https://doi.org/10.3390/s19071671>.
21. A. A. Jimenez, et al., *Maintenance management based on Machine Learning and nonlinear features in wind turbines*. Renewable Energy, 2020. **146**: p. 316-328, <https://doi.org/10.1016/j.renene.2019.06.135>.
22. A. M. Del Rio, I. S. Ramirez, and F. P. G. Marquez, *Photovoltaic Solar Power Plant Maintenance Management based on IoT and Machine Learning*, in *2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)*. 2021, IEEE: Zallaq, Bahrain. p. 423-428 (<https://doi.org/10.1109/3ICT53449.2021.9581504>).
23. H. A. Gohel, et al., *Predictive maintenance architecture development for nuclear infrastructure using machine learning*. Nuclear Engineering and Technology, 2020. **52**(7): p. 1436-1442, <https://doi.org/10.1016/j.net.2019.12.029>.
24. K Kumar, et al., *Daily Plant Load Analysis of a Hydropower Plant Using Machine Learning*, in *In Applications of Artificial Intelligence in Engineering*, X.Z. Gao, et al., Editors. 2021, Springer: Singapore. p. 819-26 (https://doi.org/10.1007/978-981-33-4604-8_65).
25. S. D. Milic, Z. Durovic, and M. D. Stojanovic, *Data science and machine learning in the IIoT concepts of power plants*. International Journal of Electrical Power & Energy Systems, 2023. **145**, <https://doi.org/10.1016/j.ijepes.2022.108711>.
26. K. Mukilan, et al., *Prediction of Rooftop Photovoltaic Solar Potential Using Machine Learning*. International Journal of Photoenergy, 2022. **2022**, <https://doi.org/10.1155/2022/1541938>.
27. M. Cordeiro-Costas, et al., *Machine Learning and Deep Learning Models Applied to Photovoltaic Production Forecasting*. Applied Sciences-Basel, 2022. **12**(17), <https://doi.org/10.3390/app12178769>.
28. C. G. Dong, et al., *Machine learning reduces soft costs for residential solar photovoltaics*. Scientific Reports, 2023. **13**(1), <https://doi.org/10.1038/s41598-023-33014-4>.
29. L. Li, et al., *A review of applications in federated learning*. Computers & Industrial Engineering, 2020. **149**, <https://doi.org/10.1016/j.cie.2020.106854>.
30. P. Hosseini, et al., *Privacy-preserving federated learning: Application to behind-the-meter solar photovoltaic generation forecasting*. Energy Conversion and Management, 2023. **283**, <https://doi.org/10.1016/j.enconman.2023.116900>.
31. J. C. Jiang, et al., *Federated Learning in Smart City Sensing: Challenges and Opportunities*. Sensors, 2020. **20**(21), <https://doi.org/10.3390/s20216230>.
32. M. Mahdavi, et al., *Transmission Expansion Planning: Literature Review and Classification*. Ieee Systems Journal, 2019. **13**(3): p. 3129-3140, <https://doi.org/10.1109/Jsyst.2018.2871793>.
33. Stefan Borozan, et al. *A Machine Learning-Enhanced Benders Decomposition Approach to Solve the Transmission Expansion Planning Problem under Uncertainty*. 2023 2023-04-15; Available from <https://arxiv.org/abs/2304.07534>.
34. Y. H. Wang, et al., *Flexible Transmission Network Expansion Planning Based on DQN Algorithm*. Energies, 2021. **14**(7), <https://doi.org/10.3390/en14071944>.
35. Y. H. Wang, et al., *Transmission Network Expansion Planning Considering Wind Power and Load Uncertainties Based on Multi-Agent DDQN*. Energies, 2021. **14**(19), <https://doi.org/10.3390/en14196073>.
36. X. Q. Fu, Q. L. Guo, and H. B. Sun, *Statistical Machine Learning Model for Stochastic Optimal Planning of Distribution Networks Considering a Dynamic Correlation and Dimension Reduction*. Ieee Transactions on Smart Grid, 2020. **11**(4): p. 2904-2917, <https://doi.org/10.1109/Tsg.2020.2974021>.
37. T. Al-Saba and I. El-Amin, *The application of artificial intelligent tools to the transmission expansion problem*. Electric Power Systems Research, 2002. **62**(2): p. 117-126, [https://doi.org/10.1016/S0378-7796\(02\)00037-8](https://doi.org/10.1016/S0378-7796(02)00037-8).

38. F. Hasan, A. Kargarian, and A. Mohammadi, *A Survey on Applications of Machine Learning for Optimal Power Flow*, in *2020 IEEE Texas Power and Energy Conference (TPEC)*. 2020, IEEE: College Station, TX, USA. p. 1-6 (<https://doi.org/10.1109/TPEC48276.2020.9042547>).
39. J. Xie, I. Alvarez-Fernandez, and W. Sun, *A Review of Machine Learning Applications in Power System Resilience*. 2020 IEEE Power & Energy Society General Meeting (PESGM), 2020, <https://doi.org/10.1109/PESGM41954.2020.9282137>.
40. P. Stefanidou-Voziki, et al., *A review of fault location and classification methods in distribution grids*. Electric Power Systems Research, 2022. **209**, <https://doi.org/10.1016/j.epsr.2022.108031>.
41. M. Shafiullah, K. A. AlShumayri, and M. S. Alam, *Machine learning tools for active distribution grid fault diagnosis*. Advances in Engineering Software, 2022. **173**, <https://doi.org/10.1016/j.advengsoft.2022.103279>.
42. B. Hrnjica and A.D. Mehr, *Energy Demand Forecasting Using Deep Learning*, in *Smart Cities Performability, Cognition, and Security*, F. Al-Turjman, Editor. 2020, Springer, Cham. p. 71-104 (https://doi.org/10.1007/978-3-030-14718-1_4).
43. S. Y. Shin and H. G. Woo, *Energy Consumption Forecasting in Korea Using Machine Learning Algorithms*. Energies, 2022. **15**(13), <https://doi.org/10.3390/en15134880>.
44. R. Olu-Ajayi, et al., *Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques*. Journal of Building Engineering, 2022. **45**, <https://doi.org/10.1016/j.jobe.2021.103406>.
45. Z. Y. Yi, et al., *Electric vehicle charging demand forecasting using deep learning model*. Journal of Intelligent Transportation Systems, 2022. **26**(6): p. 690-703, <https://doi.org/10.1080/15472450.2021.1966627>.
46. I. Antonopoulos, et al., *Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review*. Renewable & Sustainable Energy Reviews, 2020. **130**, <https://doi.org/10.1016/j.rser.2020.109899>.
47. S. Deb, *Machine Learning for Solving Charging Infrastructure Planning Problems: A Comprehensive Review*. Energies, 2021. **14**(23), <https://doi.org/10.3390/en14237833>.
48. Y. M. Saputra, et al., *Energy Demand Prediction with Federated Learning for Electric Vehicle Networks*. 2019 IEEE Global Communications Conference (Globecom), 2019, <https://doi.org/10.1109/globecom38437.2019.9013587>.
49. Z. Teimoori, A. Yassine, and M. S. Hossain, *A Secure Cloudlet-Based Charging Station Recommendation for Electric Vehicles Empowered by Federated Learning*. IEEE Transactions on Industrial Informatics, 2022. **18**(9): p. 6464-6473, <https://doi.org/10.1109/TII.2022.3148997>.
50. Fabian Neumann, et al., *The potential role of a hydrogen network in Europe*. Joule, 2023. **7**(8): p. 1793-1817, <https://doi.org/10.1016/j.joule.2023.06.016>.
51. Guishi Cheng, et al., *Analysis and prediction of green hydrogen production potential by photovoltaic-powered water electrolysis using machine learning in China*. Energy, 2023. **284**: p. 129302, <https://doi.org/10.1016/j.energy.2023.129302>.
52. Mohammad H. Shams, et al., *Machine learning-based utilization of renewable power curtailments under uncertainty by planning of hydrogen systems and battery storages*. Journal of Energy Storage, 2021. **41**: p. 103010, <https://doi.org/10.1016/j.est.2021.103010>.
53. Mohammad Mahbub Kabir, et al., *Machine learning-based prediction and optimization of green hydrogen production technologies from water industries for a circular economy*. Desalination, 2023. **567**: p. 116992, <https://doi.org/10.1016/j.desal.2023.116992>.
54. R. Venkatasatish and C. Dhananjayulu, *Reinforcement learning based energy management systems and hydrogen refuelling stations for fuel cell electric vehicles: An overview*. International Journal of Hydrogen Energy, 2022. **47**(64): p. 27646-27670, <https://doi.org/10.1016/j.ijhydene.2022.06.088>.
55. 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*. Journal of Energy Storage, 2023. **57**: p. 106168, <https://doi.org/10.1016/j.est.2022.106168>.

56. P. Moutis, S. Skarvelis-Kazakos, and M. Brucoli, *Decision tree aided planning and energy balancing of planned community microgrids*. Applied Energy, 2016. **161**: p. 197-205, <https://doi.org/10.1016/j.apenergy.2015.10.002>.
57. M. H. Shams, et al., *Machine learning-based utilization of renewable power curtailments under uncertainty by planning of hydrogen systems and battery storages*. Journal of Energy Storage, 2021. **41**, <https://doi.org/10.1016/j.est.2021.103010>.
58. K. S. Zhou, K. L. Zhou, and S. L. Yang, *Reinforcement learning-based scheduling strategy for energy storage in microgrid*. Journal of Energy Storage, 2022. **51**, <https://doi.org/10.1016/j.est.2022.104379>.
59. M. Aykol, et al., *Perspective-Combining Physics and Machine Learning to Predict Battery Lifetime*. Journal of the Electrochemical Society, 2021. **168**(3), <https://doi.org/10.1149/1945-7111/abec55>.
60. Y. Z. Zhang and M. Y. Zhao, *Cloud-based in-situ battery life prediction and classification using machine learning*. Energy Storage Materials, 2023. **57**: p. 346-359, <https://doi.org/10.1016/j.ensm.2023.02.035>.
61. A Zahedi, *Electric Vehicle as distributed energy storage resource for future smart grid*, in *2012 22nd Australasian Universities Power Engineering Conference (AUPEC)*. 2012, IEEE: Bali, Indonesia. p. 1-4 (<https://ieeexplore.ieee.org/document/6360205>).
62. Y. W. Chung, et al., *Ensemble machine learning-based algorithm for electric vehicle user behavior prediction*. Applied Energy, 2019. **254**, <https://doi.org/10.1016/j.apenergy.2019.113732>.
63. R. Basso, B. Kulcsar, and I. Sanchez-Diaz, *Electric vehicle routing problem with machine learning for energy prediction*. Transportation Research Part B-Methodological, 2021. **145**: p. 24-55, <https://doi.org/10.1016/j.trb.2020.12.007>.
64. C. Scott, M. Ahsan, and A. Albarbar, *Machine Learning Based Vehicle to Grid Strategy for Improving the Energy Performance of Public Buildings*. Sustainability, 2021. **13**(7), <https://doi.org/10.3390/su13074003>.
65. M. Shibli, L. Ismail, and A. Massoud, *Electric Vehicles Charging Management Using Machine Learning Considering Fast Charging and Vehicle-to-Grid Operation*. Energies, 2021. **14**(19), <https://doi.org/10.3390/en14196199>.

Chapter 5:

MANUFACTURING SECTOR

Alp Kucukelbir

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 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 CO₂. 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



Figure 5 – 1. Factories are increasingly digitalizing their operations.

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 a prediction that has accuracy unavailable in existing 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.

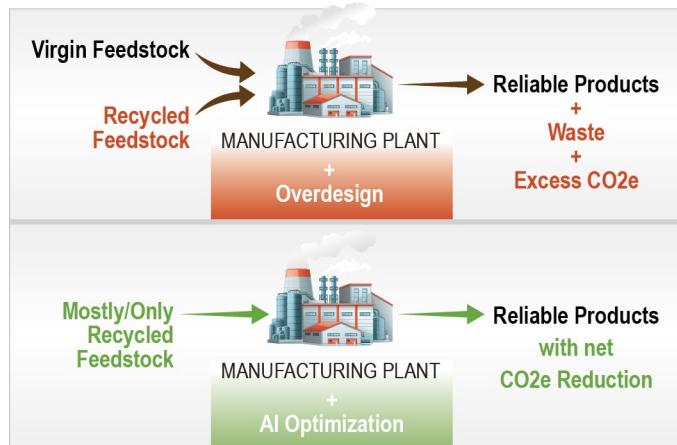


Figure 5 – 2. AI enables manufacturers to adapt to recycled feedstock. Factories typically address the increased variability of recycled feedstock by planning for the “worst case” scenario; this leads to unnecessary waste and excess emissions. Instead, factories can use AI to optimize operations and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

B. 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.
- **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 report¹⁴ 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 report¹⁵ 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.
- **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 the¹⁷ 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.

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 CO₂e/metric ton.¹⁷

This company achieved these results by

1. Acquiring recycled scrap metal for their production
2. Measuring the chemical composition of each batch of scrap
3. Leveraging AI recommendations during melting to add as little (if any) additives as possible
4. Predicting the risk of producing each batch of steel, trading off potential quality issues with emissions
5. 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.



(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 greenhouse gas. 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
- **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



Figure 5 – 3. Factories comprise thousands of interconnected sensors.

C. Barriers and risks for AI in manufacturing

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.²⁵ 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.

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

- **Need for regular maintenance.** Factories and logistics change over time. Any AI-based system that operates on real-time data must be carefully maintained. Deployed AI models should be checked regularly and updated based on the requirements of their applications. This may be a new workflow to which existing information technology groups may not be accustomed. Regular workflows to assess and maintain software systems apply to AI-based applications.
- **Additional/new safety procedures.** Manufacturing and logistics facilities are dangerous places to work. Any change to a workflow must be accompanied with a careful investigation of any source of risk to human safety and health. AI-based systems must be validated to perform as expected under normal and abnormal operating conditions. Any personnel working with AI systems may require additional training.
- **Application of AI to maintain or increase emissions.** As a general-purpose technology, we have no way of stopping bad manufacturing actors from applying AI toward use cases that either maintain or increase their carbon footprint. Regulatory pressure and market dynamics, along with other incentivization, are ways to minimize this risk.

REFERENCES

1. Peter JT Morris, *From classical to modern chemistry: The instrumental revolution*. 2002: Royal Society of Chemistry; 347 p.
2. Intergovernmental Panel on Climate Change (IPCC) Working Group III. *Climate Change 2022: Mitigation of Climate Change - Summary for Policymakers (Sixth Assessment Report)*. 2022. <https://www.ipcc.ch/report/sixth-assessment-report-working-group-3/>.
3. United Nations Economic Commission for Europe (UNECE). *COP27: UN report shows pathways to carbon-neutrality in “energy intensive” steel, chemicals and cement industries*. 2022 Published by UNECE; Available from <https://unece.org/climate-change/press/cop27-un-report-shows-pathways-carbon-neutrality-energy-intensive-steel>.
4. The Economist. *The truth about recycling*. 2007. Available from <https://www.economist.com/technology-quarterly/2007/06/09/the-truth-about-recycling>.
5. RC Ziegler. *Environmental Impacts of Virgin and Recycled Steel and Aluminum*. 1976. Published by US Environmental Protection Agency (EPA); Available from <https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=9101LWZP.txt>.
6. David Sandalow, et al. *ICEF Industrial heat decarbonization roadmap*. 2019. Innovation for Cool Earth Forum (ICEF): Tokyo, Japan; https://www.icef.go.jp/pdf/summary/roadmap/icef2019_roadmap.pdf.
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. CRU International Limited. *Emissions Analysis Executive Summary*. 2022 Published by Steel Manufacturers Association; Available from <https://steelnets.org/steelmaking-emissions-report-2022/>.
9. New Energy and Industrial Technology Development Organization (NEDO) Evaluation Department. *NEDO Project Success Stories*. 2023. Published by NEDO; Available from <https://www.nedo.go.jp/content/100899120.pdf>.
10. US Department of Energy (DOE). *DOE Industrial Decarbonization Roadmap*. Accessed September 2023. Published by US DOE; Available from <https://www.energy.gov/industrial-technologies/doe-industrial-decarbonization-roadmap>.
11. Richard E. Barlow and Telba Z. Irony, *Foundations of Statistical Quality Control*. Lecture Notes-Monograph Series, 1992. **17**: p. 99-112, <https://www.jstor.org/stable/4355628>.
12. The Manufacturing Institute. *The Aging of the Manufacturing Workforce*. 2019. Available from <https://www.themanufacturinginstitute.org/research/the-aging-of-the-manufacturing-workforce/>.
13. Jonathan Worstell, *Scaling chemical processes: practical guides in chemical engineering*. 2016: Butterworth-Heinemann; <https://doi.org/10.1016/C2015-0-01809-3>; 177 p.
14. Intergovernmental Panel on Climate Change (IPCC). *Sixth Assessment Report*. 2021. <https://www.ipcc.ch/assessment-report/ar6/>.
15. Intergovernmental Panel on Climate Change (IPCC). *Fifth Assessment Report*. <https://www.ipcc.ch/assessment-report/ar5/>.
16. Azad Rahman, et al., *Impact of Alternative Fuels on the Cement Manufacturing Plant Performance: An Overview*. Procedia Engineering, 2013. **56**: p. 393-400, <https://doi.org/10.1016/j.proeng.2013.03.138>.
17. Pamir Ozbay and Carter Almquist. *Adopting Machine-Learning-Based Workflows for Reducing Production Risk and Cost*. (2023). pgs. 2086-2100. AISTech 2023 Iron & Steel Technology Conference. Detroit, MI <https://www.proceedings.com/69204.html>.
18. Pietro De Giovanni, *Smart Supply Chains with vendor managed inventory, coordination, and environmental performance*. European Journal of Operational Research, 2021. **292**(2): p. 515-531, <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, 2021. **122**: p. 502-517, <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*, 2021. **13**(12): p. 6689, <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*, 2016. **127**: p. 438-450, <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*, 2020. **10**(24): p. 9050, <https://doi.org/10.3390/app10249050>.
23. Wandercleiton Cardoso, Renzo di Felice, and 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*, 2022. **25**, <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*, 2021. **10**(7): p. 828, <https://doi.org/10.3390/electronics10070828>.
25. Renee Cho. *Recycling in the U.S. Is Broken. How Do We Fix It?* 2020. Published by Columbia Climate School State of the Planet; Available from <https://news.climate.columbia.edu/2020/03/13/fix-recycling-america/>.

CHAPTER 6:

MATERIALS INNOVATION

Colin McCormick

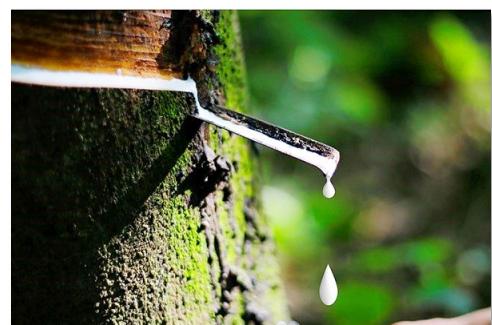
Materials innovation is important for decarbonization, and artificial intelligence (AI) can play a major role in accelerating it. This chapter examines how improved materials can reduce emissions and enable carbon management, as well as specific areas in which AI can help.

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.³ 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.⁵

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.



Roman concrete enabled extraordinary construction projects, including the Pantheon, the world's oldest building still in active use.



The discovery of the vulcanization process transformed natural rubber into a highly durable, extremely useful material.

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.

Lithium-ion batteries are a good example of a technology that was greatly improved through the 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 the identification of lithium cobalt oxide (LiCoO_2), lithium iron phosphate (LiFePO_4) and other cathode materials beginning in the 1970s, as well as the identification of graphite for anodes and a variety of liquid and solid materials for the electrolyte.⁶ 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 enabled improved performance that 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-state⁷ and sodium-ion technologies.⁸

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.⁹ Similar properties also determine the performance of catalyst materials in applications such as electrocatalytic reduction of CO_2 .¹⁰ Even in the case of CO_2 transport for sequestration or utilization, material properties influence the durability and overall performance of bulk transport systems.¹¹



Materials innovation enabled the development of lithium-ion batteries for electric vehicles (EVs), long-duration grid storage and other low-carbon technologies.



Solar photovoltaic (PV) systems are the product of years of materials innovation and optimization.

Box 6-1

INNOVATION IN MATERIALS SYNTHESIS

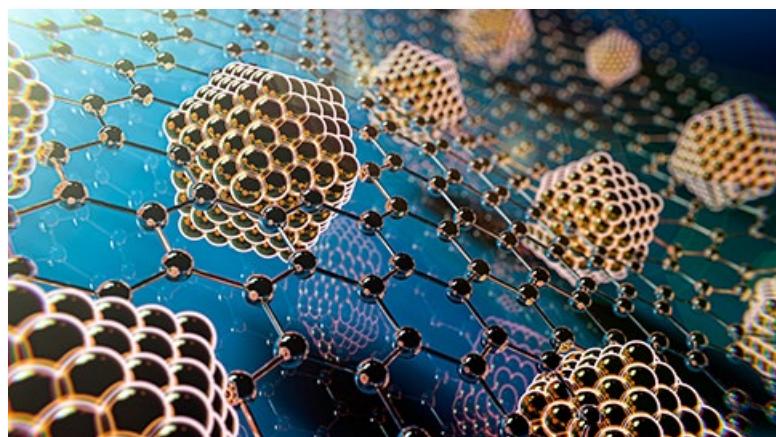
In some cases, the limitation to the performance of a technology could be overcome by a well-known material that has superior properties, but a practical method to produce this material is not known. One such case is the general illumination LED bulb, now in common use. Although LEDs were originally 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.²

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 CO₂ emissions from lighting have not fallen because the demand for more lighting has offset these efficiency gains.⁴)



There are many other use cases of advanced materials that are, or would be, valuable in enabling technologies to reduce greenhouse gas 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-global warming potential (GWP) 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



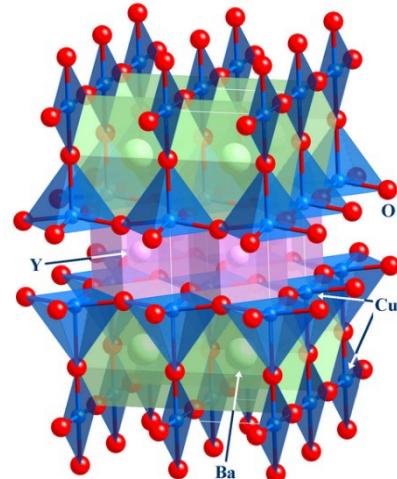


Innovative materials are important for enabling carbon capture and removal systems, such as this direct air capture (DAC) plant in Iceland (photo credit: Julio Friedmann).

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



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

algorithms, provide compute resources, and disseminate the results of computations and experiments in increasingly massive material property databases. Some examples include The Materials Project coordinated by UC 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 material 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 Earth²⁹) even though only a tiny fraction have actually been synthesized.

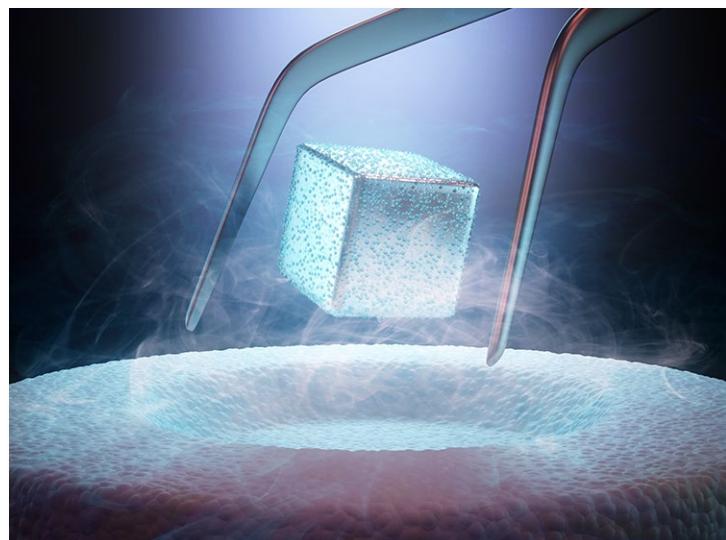
Notably, modern computational materials science consumes enormous computing resources. In recent years, roughly one-third of available supercomputing has been dedicated to these materials-related calculations.³⁰

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 will probably remain less accurate than *ab initio* calculations for a long time but can provide enormous benefits by down-selecting candidate materials for more intensive, high-accuracy studies.

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) is a common technique for examining the crystal structure of materials (such as changes in cathode phases during battery charging) by measuring the pattern of diffraction of x-rays that hit a sample. 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.³²





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.”^{33, 34} 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.³⁵ With the broad introduction of large language models in 2022, progress in materials science knowledge discovery has begun to accelerate dramatically.³⁶

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 published materials literature to identify precise synthesis steps for key materials from thousands of research papers. For example, a neural-network-based NLP method was used to search 22,000 journal articles and extract precise synthesis parameters for optimized titania nanotubes.³⁷

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 materials “inverse design” problem, which starts with a desired property and uses an AI method to propose possible material structures that may have it. As an example, a generative adversarial network (GAN) was used to propose 23 entirely novel structures made from three atoms (magnesium, manganese and oxygen) that displayed excellent properties as photoanodes for water splitting.³⁸

D. Barriers

Some important progress has already been made in applying AI techniques to computational materials discovery and design. More progress would be possible with expanded research budgets, including additional funding for AI-specific applications in materials science.

While access to materials datasets and high-performance computing has been partly equalized across the globe thanks to high-speed internet connections (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. To enable this capability and broaden access to physical testing facilities, new automated and partly autonomous materials testing laboratories are needed, which would allow remote operation for materials characterization experiments. By combining machine learning (ML), 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.³⁹

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 material properties across the full spectrum of existing data, avoiding silos and misinterpretations due to conflicting definitions. Explicitly encouraging the 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.⁴⁰

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, CO₂ adsorption capacity, etc.) and the emissions caused by synthesis (production) of 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.⁴¹ More use of AI tools is needed in predicting greenhouse gas 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.⁴⁰ 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 novel materials development. 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.



REFERENCES

1. Linda M. Seymour, et al., *Hot mixing: Mechanistic insights into the durability of ancient Roman concrete.* Science Advances, 2023. **9**(1): eadd1602, <https://doi.org/10.1126/sciadv.add1602>.
2. Shuji Nakamura, *Background story of the invention of efficient blue InGaN light emitting diodes (Nobel Lecture).* ANNALEN DER PHYSIK, 2015. 527: 335-349, <https://doi.org/10.1002/andp.201500801>.
3. Rebecca Matulka and Daniel Wood. *History of the Light Bulb.* 2013. US Department of Energy (DOE). Available from <https://www.energy.gov/articles/history-light-bulb>.
4. Kevin Lane. *Lighting.* International Energy Agency (IEA) 2023 Available from <https://www.iea.org/energy-system/buildings/lighting>.
5. Cai Guise-Richardson, *Redefining Vulcanization: Charles Goodyear, patents, and industrial control, 1834-1865.* Technology and Culture, 2010. **51**(2): p. 357-387, <https://doi.org/10.1353/tech.0.0437>.
6. M. V. Reddy, et al., *Brief History of Early Lithium-Battery Development.* Materials (Basel), 2020. **13**(8), <https://doi.org/10.3390/ma13081884>.
7. Jürgen Janek and Wolfgang G. Zeier, *Challenges in speeding up solid-state battery development.* Nature Energy, 2023. **8**(3): p. 230-240, <https://doi.org/10.1038/s41560-023-01208-9>.
8. Ivana Hasa, Nuria Tapia-Ruiz, and Montserrat Galceran, *Editorial: Sodium-ion batteries: From materials discovery and understanding to cell development.* Frontiers in Energy Research, 2022. **10**, <https://doi.org/10.3389/fenrg.2022.1076764>.
9. Tanay Sahu, Kulbir K. Ghuman, and Paul G. O'Brien, *Chapter 7 - A review of materials used for carbon dioxide capture,* in *Progress in Sustainable Development*, D. Ting and P. O'Brien, Editors. 2023, Elsevier. p. 205-232, Available at <https://www.sciencedirect.com/book/9780323992077/progress-in-sustainable-development>.
10. Yuhou Pei, Heng Zhong, and Fangming Jin, *A brief review of electrocatalytic reduction of CO₂—Materials, reaction conditions, and devices.* Energy Science & Engineering, 2021. **9**(7): p. 1012-1032, <https://doi.org/10.1002/ese3.935>.
11. Luca Ansaldi, Ben Alcock, and Thijs A. Peters, *Effects of CO₂ on polymeric materials in the CO₂ transport chain: A review.* International Journal of Greenhouse Gas Control, 2020. **94**: p. 102930, <https://doi.org/10.1016/j.ijggc.2019.102930>.
12. Modupeola Dada and 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, 2023. **12**(1): p. 66, <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, 2019. **19**: p. 556-559, <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, 2020. **827**: p. 153548, <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, 2022. **46**(6): p. 6953-6988, <https://doi.org/10.1002/er.7635>.
16. Wen Zhang and Jun Xu, *Advanced lightweight materials for Automobiles: A review.* Materials & Design, 2022. **221**: p. 110994, <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, 2022. **41**(3): p. 235-256, <https://doi.org/10.1080/14786451.2021.1928129>.
18. S. T. Vagge and Suraj Ghogare, *Thermal barrier coatings: Review.* Materials Today: Proceedings, 2022. **56**: p. 1201-1216, <https://doi.org/10.1016/j.matpr.2021.11.170>.
19. R. P. Singh, V. K. Mishra, and R. K. Das, *Desiccant materials for air conditioning applications - A review.* IOP Conference Series: Materials Science and Engineering, 2018. **404**(1): p. 012005, <https://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, 2021. **4**(6): p. e10208, <https://doi.org/10.1002/pcr2.10208>.
21. Alexander Molodyk and David C. Larbalestier, *The prospects of high-temperature superconductors*. Science, 2023. **380**(6651): p. 1220-1222, <https://doi.org/10.1126/science.abg4137>.
22. J. M. D. Coey, *Perspective and Prospects for Rare Earth Permanent Magnets*. Engineering, 2020. **6**(2): p. 119-131, <https://doi.org/10.1016/j.eng.2018.11.034>.
23. J. Georg Bednorz and K. Alex Müller, *Perovskite-Type Oxides—the New Approach to High-Tc Superconductivity. Nobel Lecture*. Angewandte Chemie International Edition in English, 1988. **27**(5): p. 735-748, <https://doi.org/10.1002/anie.198807351>.
24. Warren E. Pickett, *Electronic structure of the high-temperature oxide superconductors*. Reviews of Modern Physics, 1989. **61**(2): p. 433-512, <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, 2012. **47**(21): p. 7313-7316, <https://doi.org/10.1007/s10853-012-6736-0>.
26. The Materials Project. *The Materials Project*. Available from <https://next-gen.materialsproject.org/>.
27. NOMAD. *Materials science data managed and shared*. Accessed September 2023, Available from <https://nomad-lab.eu/nomad-lab/>
28. University of Tokyo. *MateriApps*. Accessed September 2023; Available from <https://ma.issp.u-tokyo.ac.jp/en>.
29. Peter Kirkpatrick and Clare Ellis, *Chemical space*. Nature, 2004. **432**(7019): p. 823-823, <https://doi.org/10.1038/432823a>.
30. Stefan Heinen, et al., *Machine learning the computational cost of quantum chemistry*. Machine Learning: Science and Technology, 2020. **1**(2): p. 025002, <https://doi.org/10.1088/2632-2153/ab6ac4>.
31. Chi Chen and Shyue Ping Ong, *A universal graph deep learning interatomic potential for the periodic table*. Nature Computational Science, 2022. **2**(11): p. 718-728, <https://doi.org/10.1038/s43588-022-00349-3>.
32. Nathan J. Szymanski, et al., *Adaptively driven X-ray diffraction guided by machine learning for autonomous phase identification*. npj Computational Materials, 2023. **9**(1): p. 31, <https://doi.org/10.1038/s41524-023-00984-y>.
33. Olga Kononova, et al., *Opportunities and challenges of text mining in materials research*. iScience, 2021. **24**(3): p. 102155, <https://doi.org/10.1016/j.isci.2021.102155>.
34. Edward O. Pyzer-Knapp, et al., *Accelerating materials discovery using artificial intelligence, high performance computing and robotics*. npj Computational Materials, 2022. **8**(1): p. 84, <https://doi.org/10.1038/s41524-022-00765-z>.
35. Tanishq Gupta, et al., *MatSciBERT: A materials domain language model for text mining and information extraction*. npj Computational Materials, 2022. **8**(1): p. 102, <https://doi.org/10.1038/s41524-022-00784-w>.
36. Yiwen Hu and Markus J. Buehler, *Deep language models for interpretative and predictive materials science*. APL Machine Learning, 2023. **1**(1), <https://doi.org/10.1063/5.0134317>.
37. Edward Kim, et al., *Materials Synthesis Insights from Scientific Literature via Text Extraction and Machine Learning*. Chemistry of Materials, 2017. **29**(21): p. 9436-9444, <https://doi.org/10.1021/acs.chemmater.7b03500>.
38. Sungwon Kim, et al., *Generative Adversarial Networks for Crystal Structure Prediction*. ACS Central Science, 2020. **6**(8): p. 1412-1420, <https://doi.org/10.1021/acscentsci.0c00426>.
39. Nat. Synth, *Automate and digitize*. Nature Synthesis, 2023. **2**(6): p. 459-459, <https://doi.org/10.1038/s44160-023-00354-y>.
40. Dane Morgan and Ryan Jacobs, *Opportunities and Challenges for Machine Learning in Materials Science*. Annual Review of Materials Research, 2020. **50**(1): p. 71-103, <https://doi.org/10.1146/annurev-matsci-070218-010015>.
41. Carlos A. Grande, et al., *Life-cycle assessment as a tool for eco-design of metal-organic frameworks (MOFs)*. Sustainable Materials and Technologies, 2017. **14**: p. 11-18, <https://doi.org/10.1016/j.susmat.2017.10.002>.

Chapter 7: FOOD SYSTEMS

Elena Méndez Leal, Kevin Karl and Alex Ruane

Food systems—including food production, distribution, consumption, and waste disposal—are critical to sustaining livelihoods and delivering nutrition worldwide. However, food systems contribute significantly to the climate crisis, accounting for over 30 percent of human-caused global greenhouse gas emissions¹ (e.g., methane, carbon dioxide, and nitrous oxide). Climate change, in turn, has a significant and growing impact² on food systems. Climate change increases heat stress and can lead to deteriorating soil health, for example, slowing agricultural productivity and reducing the nutritional content of crops and livestock. The cascading impacts of climate extremes on agricultural production are likely to destabilize global food security, endangering the livelihoods of billions of people and threatening public health.



A. Food system greenhouse gas emissions

All parts of the food system – from land use change to waste disposal – result in greenhouse gas emissions.

(i) Land-use change *The conversion³ of natural ecosystems such as forests, marshes and grasslands into land for agriculture*. Eighty percent of deforestation and land degradation is due to land-use change intended for agricultural production. This is a significant contributor⁴ to carbon dioxide and nitrous oxide emissions. Sustainable intensification can spare land from conversion and take land out of agricultural production. Well-designed land-use management strategies⁵—such as agroforestry, cover cropping and reductions in tillage—can preserve soil health and enhance carbon sequestration in working lands.

(ii) Production *The inputs and operations needed to produce food with agriculture.* For example, existing agricultural practices⁶ contribute to copious⁷ methane production (e.g., through flooded rice fields and enteric fermentation in livestock) and nitrous oxide production (e.g., over-application of synthetic fertilizers). Improving livestock management, including rotational grazing and optimized feed, and implementing precision agriculture techniques to reduce fertilizer and pesticide use can help lower total emissions.

(iii) Supply chains *The processing, distribution, storage, trade, marketing and handling of food following production and before consumption.* Food-system supply chains have considerable potential to employ more sustainable strategies, from increasing penetration of renewable energy into food cold chains⁸ and decreasing energy expenditures across all steps of the food supply chain via improved logistics and reductions in post-harvest food loss.

(iv) Consumption and Waste *Processes related to consumer food preparation and to the disposal of food waste.* Substantial carbon dioxide emissions occur⁹ in the production and combustion of biomass and fossil fuels for cooking. The disposal of food waste in landfills emits significant amounts of methane¹⁰ globally. Food waste and consequent emissions also occur during food production, storage, and transportation.

There is substantial opportunity to mitigate the climate impact of food systems while improving the resilience of food systems to climate shocks. Mitigating greenhouse gas emissions from food systems will require, among other efforts, the adoption and improvement of sustainable practices⁶ in land use, agriculture, supply chains and consumption processes. Integrating renewable energy sources and energy-efficient technologies will also be essential to reducing greenhouse gas emissions. All these efforts could benefit from leveraging technological innovation to optimize the dual needs of improving food security and reducing food system greenhouse gas emissions. With sufficient, relevant and accessible data, the emergence of artificial intelligence (AI) carries unique potential to complement existing strategies to improve food-system mitigation efforts.

B. Using AI to mitigate food system emissions

AI tools represent a sea change in terms of how data are identified, defined, interpreted and optimized. By leveraging AI technologies, real-time and historical data can be efficiently harnessed to model and anticipate outcomes and drive significant improvements in each stage of the food system in order to minimize environmental impacts.

AI can make food systems more efficient. For instance, AI can optimize agricultural practices by integrating data from various sources like soil sensors and satellite imagery to create precise nutrient and fertilizer management plans. Machine learning (ML) simulations¹¹ can further analyze these data to recommend fertilizer application schedules that minimize nitrous oxide emissions while maximizing crop yields. ML simulations can also analyze optimal fertilizer applications across a range of projected climate conditions. AI can aid in monitoring and predicting soil health, moisture levels and disease risks, enabling proactive crop management and minimizing the demand for agricultural inputs. Similarly,



AI applications can explore optimal feedstock for Biomass with Carbon Removal and Storage (BiCRS)¹² by analyzing data on biomass characteristics, growth rates and carbon sequestration potential. AI can identify the most suitable biomass species or crop varieties for efficient carbon removal and storage by considering factors such as regional climate. Such analyses can accelerate the development climate-smart systems in ways that are both traditional and completely novel—for example, AI models can test combinations of farm management, equipment, breeding, financing, and policy instruments that do not yet exist.

Another example of precision agriculture is CYCLESGYM, an innovative tool that employs simulations¹³ (i.e., reinforcement learning) to improve crop management strategies. CYCLESGYM can create virtual farms simulating different crops, weather conditions and soil properties. With adjustments to different agriculture management strategies, researchers and farmers can set custom observational spaces and reward mechanisms that explore various crop growth and environmental outcomes over short-term intervals that provide a balance between economic viability, greenhouse gas emission mitigation and general environmental sustainability in food production. For example, the CYCLESGYM environment can fine-tune the use of nitrogen-based fertilizers and water supply, strategize how to minimize nitrogen loss and environmental impact, maintain crop yield objectives and reduce crop wastage.

Other applications of AI in food systems include augmenting renewable energy generation by optimizing land use for multiple purposes, forecasting pest and disease pressure for proactive controls, identifying opportunities for multi-cropping or intercropping, improving logistics and energy consumption during food transportation and storage and enhancing soil carbon sequestration efforts. AI tools are also used to rapidly develop alternative protein products¹⁴ with a much lower carbon footprint than most animal-sourced foods. AI is being used to scale food loss and waste reduction, such as intelligent harvest timing to prevent food spoilage. As an overarching technology for data identification and integration, AI can also help compile information¹⁵ on successful greenhouse gas mitigation strategies in food systems to evaluate best practices across a variety of contexts (see Table 1 below).

Title	Description
Land-use change	Map renewable energy solutions and classify land. Through AI methods, such as deep learning, AI is improving land classifications ¹⁶ , which can improve efforts to integrate biomass production (as a renewable energy source) into agricultural landscapes. Other models using simulations can indicate ¹⁷ land use as the climate changes as well as analyze ¹⁸ and optimize future land uses to assist in emission-reduction efforts
	Balance solar resources for food and energy production. AI models can predict how to use land for both sustainable food and energy production. When solar panels are located over crop fields, for example, AI can predict optimal tilt and shading ¹⁹ to maximize power production while protecting crop growth
	Observe and predict deforestation events. Deforestation is a significant contributor to greenhouse gas emissions. Monitoring and predicting deforestation and related events ²⁰ for agricultural expansion could help minimize the carbon footprint of food production
Food Production	Soil carbon sequestration to reduce emissions and mitigate climate change. Satellite data fed into an image-based simulation model ²¹ can accurately predict the storage potential and management of carbon dioxide in soils and inform policy and agricultural practices around land-use change and regenerative agriculture activities (e.g., agroforestry and tillage)
	Enhance productivity. Precision agriculture employing AI can increase efficiency and conservation gains without sacrificing yield outcomes. Examples include watering and feed management, controlled crop management ^{22, 23} , automation ²⁴ , and advanced livestock and crop health monitoring, including identifying field stresses and impacts from pests and pathogens ²⁵ through image processing and neural networks. In addition, AI can help decrease food loss during harvest ²⁶ and maximize the potential of using bioenergy and biomass ²⁷ for greener farming inputs, such as fertilizer
	Derive new or enhanced models of farming systems²⁸. This can include exploration of alternative solutions, filling observational gaps to better calibrate existing models, creating low-cost model emulators to scale analyses, and develop data-driven hybrid models that enhance predictive power
Supply Chains	Forecast crop yield and loss. With remote sensing and AI, farmers can better prepare for crop and yield loss to weather ²⁹ events or other impacts of climate change (e.g., reducing on-farm and post-harvest loss).
	Develop alternative proteins. AI methods can be leveraged to improve innovation ³⁰ around plant-based and cultivated meat, which can lead to the consumption ³¹ of food with smaller environmental footprints ³² . Nonetheless, at scale, the production of alternative proteins also carries an emission risk and currently depends on limited crops that could be at risk in future climate scenarios
	Optimize food supply chains. AI can increase the efficiency ³³ of food supply chains using current and historical data. Through simulations, AI can predict and reduce actual energy usage in procedures needed for transportation ³⁴ , such as in cold chains ³⁵ . This application can include providing optimal routes while weighing other relevant considerations, such as transportation resources and route maintenance
Consumption and Waste	Improve food packaging. Through simulations and predictive analytics, AI can assist in improving the design, materials and energy usage for packaging ³⁶ food items
	Forecast consumption patterns. AI simulations can help predict and emulate food demand, nutritional needs, product shelf life and actual restocking ³⁷ requirements to limit food disposal ³⁸ and reduce overallocation of products ³⁸ . Accurately meeting real needs for consumption can improve unnecessary ³⁹ emission-contributing activities
	Streamline disposal processes and sort waste. AI can assist in improving ⁴⁰ management of disposal processes, including forecasting waste amounts, sorting recyclables and compostable waste, and decreasing methane gas emissions ⁴¹ from landfills

Table 1: Selected examples of current AI applications for food-system emission reduction.

AI is best conceived as a set of complementary tools, rather than a solution in itself. To ensure sustainable and equitable outcomes, proper implementation of AI technologies should be grounded in scientific knowledge, physical constraints, well-defined public policy objectives, ethical considerations and a nuanced understanding of the complex operations of food system actors and changing baselines. AI models are susceptible to misuse and misinterpretation if not applied correctly or if used in an incorrect context, leading to unsuccessful interventions or maladaptation. For example, an AI model that seeks to maximize crop yields in the short-term with limited information on sustainable agriculture practices, local knowledge, or climate and weather variations could over-emphasize the promotion of monoculture crop production and harmful fertilizer use. As such, AI models must be trained with diverse datasets, consider optimization across multiple objectives and implement policy interventions that promote sustainable and responsible AI use in food systems. Nonetheless, the possibilities for integration and application are limitless—by strategically harnessing the potential of AI within a comprehensive framework, we can accelerate progress in mitigating food-system emissions and foster a resilient and sustainable global food system.

C. Barriers and risks to AI applications in food systems

Using AI simulations and models for food-system emission mitigation is associated with barriers and risks that require careful attention. First, a lack of capital may constrain widespread adoption of AI technology since the cost of AI tools (e.g., remote sensing monitors, computational power), data availability, maintenance needs and other



access limitations are likely to prevent resource-constrained farmers from employing them. Moreover, concerns surrounding data privacy, security and market competitiveness may limit the willingness of food-system actors across the supply chain to employ AI-driven solutions and participate in data-sharing.

Importantly, the efficacy of AI models heavily relies on the quality and availability of input and output datasets. Insufficient or incomplete data on food-system processes can lead to inaccurate or misleading forecasts, especially under novel climate scenarios, potentially undermining the efficacy of emission-reduction strategies. Data access and intellectual property barriers from agribusinesses can impede the use of AI in designing comprehensive and inclusive mitigation strategies. In some cases, just because AI models could be applied does not mean they should be applied, or that they are an improvement on existing empirical models and analyses. Establishing proficient technical expertise and knowledge-sharing across food-system actors is important to ensure appropriate and effective application of AI technologies.

Finally, striking a balance between food-emission reduction objectives and other food-security imperatives is both a key design constraint and a significant obstacle. Finding a way to limit our footprint while increasing food security globally is not straightforward, especially with many regions relying on imports for general access and nutrition security.

D. Key considerations in using AI to mitigate food-system emissions

- (i) **Develop protocols for stakeholder-driven AI applications and tools** across food systems. AI solutions should employ human-centered design principles focusing on the end user, such as farmers, factory managers and retailers. In addition, applications should be developed with input from relevant experts, scientists, engineers and policymakers to increase opportunities for seamless and effective AI use in food systems.
- (ii) **Increase transparency, accountability and standardization** in AI decision-making and data collection in food systems. Encouraging larger and more shareable data collection alongside standardized AI approaches to food-system problems can increase understanding of factors influencing emission-reduction strategies and knowledge sharing around practical AI applications and methods. Such practices lead to more informed and targeted interventions across the food supply chain.
- (iii) **Expand and scale existing technologies** to effectively mitigate food-system emissions. Capitalizing on existing AI technologies and initiatives that have demonstrated promise in curtailing emissions and improving food-system processes is crucial. Scaling AI-driven interventions in areas such as precision agriculture and energy-efficient supply chains can lead to more sustainable and efficient resource management and global food provision.
- (iv) **Invest in AI research and innovation explicitly tailored to food systems.** By dedicating resources to developing cutting-edge AI technologies and models for food production, distribution, consumption and waste disposal networks, novel and more effective approaches for mitigating food-system emissions can be identified and implemented.
- (v) **Promote collaboration and public-private partnerships** to facilitate scalable emission-reduction strategies across land use, production, distribution, consumption and waste. Collaboration between government, researchers, private companies, farmers and other relevant stakeholders allows for more seamless integration of AI technologies and practices across various stages of the food supply chain, such as optimizing transportation logistics, accurately predicting demand and reducing food waste.
- (vi) **Ensure inclusivity and accessibility** so relevant stakeholders within the food system have the opportunity to benefit from AI-driven strategies and contribute to a lower-emission future. Efforts should consider improving access, knowledge sharing and technical assistance for small-scale farmers and marginalized communities. Initiatives to reduce food-system emissions using AI technologies should also align and consider other objectives of food security, health and safety.

By optimizing agriculture practices through AI, embracing data-driven decision making, investing in AI research for food systems, fostering collaborative partnerships and prioritizing technology access for all stakeholders, AI can play a transformative role in mitigating food-system emissions, enabling a more sustainable and resilient global food and climate future.

REFERENCES

1. F. N. Tubiello, et al., *Pre- and post-production processes increasingly dominate greenhouse gas emissions from agri-food systems*. Earth Syst. Sci. Data, 2022. **14**(4): p. 1795-1809, <https://doi.org/10.5194/essd-14-1795-2022>.
2. C. Mbow, C. Rosenzweig, L.G. Barioni, T.G. Benton, M. Herrero, M. Krishnapillai, E. Liwenga, P. Pradhan, M.G. Rivera-Ferre, and F.N. Tubiello T. Sapkota, Y. Xu, *Food security*, in *Climate Change and Land: IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*, Intergovernmental Panel on Climate Change, Editor. 2019, Cambridge University Press: Cambridge. <https://doi.org/10.1017/9781009157988.007>. p. 437-550.
3. ScienceDirect. *Land Use Change*. Accessed September 2023. Available from <https://www.sciencedirect.com/topics/earth-and-planetary-sciences/land-use-change>.
4. Aruna Chandrasekhar, Daisy Dunne, and Giuliana Viglione. *UN land report: Five key takeaways for climate change, food systems and nature loss*. 2022. Published by CarbonBrief; Available from <https://www.carbonbrief.org/un-land-report-five-key-takeaways-for-climate-change-food-systems-and-nature-loss/>.
5. Peter H. Verburg, et al., *Land system change and food security: towards multi-scale land system solutions*. Current Opinion in Environmental Sustainability, 2013. **5**(5): p. 494-502, <https://doi.org/10.1016/j.cosust.2013.07.003>.
6. Cynthia Rosenzweig, et al., *Climate change responses benefit from a global food system approach*. Nature Food, 2020. **1**(2): p. 94-97, <https://doi.org/10.1038/s43016-020-0031-z>.
7. Intergovernmental Panel on Climate Change, *Summary for Policymakers*, in *Climate Change and Land: IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*, I.P.O.C. Change, Editor. 2019, Cambridge University Press: Cambridge. <https://doi.org/10.1017/9781009157988.001>. p. 1-36.
8. UNEP and FAO. *Sustainable Food Cold Chains: Opportunities, Challenges and the Way Forward*. 2022. U. FAO, Nairobi, Kenya; Rome, Italy; <https://doi.org/10.4060/cc0923en>.
9. FAO. *Food Loss and Food Waste*. Published by Available from <https://www.fao.org/policy-support/policy-themes/food-loss-food-waste/en/>.
10. S. Kenny, J. Stephenson, and K. Jaglo. *From Farm to Kitchen: Environmental Impacts of Food Waste (Part 1)*. 2021. U.S. EPA Office of Research and Development, Washington, DC; <https://www.epa.gov/land-research/farm-kitchen-environmental-impacts-us-food-waste>.
11. Luís Silva, et al., *Digitization of Crop Nitrogen Modelling: A Review*. Agronomy, 2023. **13**(8): p. 1964, <https://doi.org/10.3390/agronomy13081964>.
12. David Sandalow, et al. *Biomass Carbon Removal and Storage (BiRCS) Roadmap*. 2021. Innovation for Cool Earth Forum (ICEF), https://www.icef.go.jp/pdf/summary/roadmap/icef2020_roadmap.pdf.
13. Matteo Turchetta, et al., *Learning long-term crop management strategies with CyclesGym*. Advances in Neural Information Processing Systems, 2022. **35**: p. 11396-11409, https://proceedings.neurips.cc/paper_files/paper/2022/file/4a22ceafe2dd6e0d32df1f7c0a69ab68-Paper-Datasets_and_Benchmarks.pdf.
14. Caitlin Welsh Zane Swanson , and Joseph Majkut. *Mitigating Risk and Capturing Opportunity: The Future of Alternative Proteins*. 2023. Center for Strategic and International Studies (CSIS), <https://www.csis.org/analysis/mitigating-risk-and-capturing-opportunity-future-alternative-proteins>.
15. Havos.ai. *Homepage*. Accessed September 2023. Available from <https://www.havos.ai/>.
16. Manuel Campos-Taberner, et al., *Understanding deep learning in land use classification based on Sentinel-2 time series*. Scientific Reports, 2020. **10**(1): p. 17188, <https://doi.org/10.1038/s41598-020-74215-5>.
17. Jonas Jägermeyr, et al., *Climate impacts on global agriculture emerge earlier in new generation of climate and crop models*. Nature Food, 2021. **2**(11): p. 873-885, <https://doi.org/10.1038/s43016-021-00400-y>.
18. F. E. Sfa, M. Nemiche, and R. P. Lopez. *A generic model of reinforcement learning combined with macroscopic cellular automata to simulate land use change*. (2019). pgs. 1-5. 2019 4th World Conference on Complex Systems (WCCS). <https://doi.org/10.1109/ICoCS.2019.8930751>.
19. DAWNBREAKER. *AGRIVOLTAICS*. 2022. <https://science.osti.gov/-/media/sbir/pdf/Market-Research/SETO--Agrivoltaics-August-2022-Public.pdf>.
20. Adriana Erthal Abdenur. *How Can Artificial Intelligence Help Curb Deforestation in the Amazon?* 2020. Published by The Global Observatory. Available from <https://theglobalobservatory.org/2020/11/how-can-artificial-intelligence-help-curb-deforestation-amazon/>.

21. Ken CL Wong, et al. *Image-Based Soil Organic Carbon Estimation from Multispectral Satellite Images with Fourier Neural Operator and Structural Similarity*. Accessed September 2023. Available from <https://s3.us-east-1.amazonaws.com/climate-change-ai/papers/neurips2022/2/paper.pdf>.
22. Catherine Early. *From indoor farming to alternative proteins: the entrepreneurs looking to feed the world*. 2023. Published by Reuters; Available from <https://www.reuters.com/sustainability/land-use-biodiversity/indoor-farming-alternative-proteins-entrepreneurs-looking-feed-world-2023-06-26/>.
23. Romain Gautron, et al., *Reinforcement learning for crop management support: Review, prospects and challenges*. Computers and Electronics in Agriculture, 2022. **200**: p. 107182, <https://doi.org/10.1016/j.compag.2022.107182>.
24. WAXInvest. *Apple Harvesting, Automated*. Accessed September 2023. Available from <https://waxinvest.com/projects/abundant-robots/>.
25. Plantix. *Homepage*. Accessed September 2023. Available from <https://plantix.net/en/>.
26. Maurice Günder, et al., *Evolutionary Hierarchical Harvest Schedule Optimization for Food Waste Prevention*. arXiv preprint arXiv:2112.10712, 2021, <https://doi.org/10.48550/arXiv.2112.10712>.
27. Mochen Liao and Yuan Yao, *Applications of artificial intelligence-based modeling for bioenergy systems: A review*. GCB Bioenergy, 2021. **13**(5): p. 774-802, <https://doi.org/10.1111/gcbb.12816>.
28. C. Rosenzweig, et al., *The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies*. Agricultural and Forest Meteorology, 2013. **170**: p. 166-182, <https://doi.org/10.1016/j.agrformet.2012.09.011>.
29. Carnegie Mellon University (CMU) Software Engineering Institute (SEI). *xView 2 Challenge*. 2020 Published by SMU SEI; Available from https://www.sei.cmu.edu/our-work/projects/display.cfm?customel_datapageid=4050=295280.
30. Firmenich. *The World's First AI-Created Flavor*. Accessed September 2023. Available from <https://www.firmenich.com/taste-and-beyond/blog-article/worlds-first-ai-created-flavor>.
31. Matthew N. Hayek, et al., *The carbon opportunity cost of animal-sourced food production on land*. Nature Sustainability, 2021. **4**(1): p. 21-24, <https://doi.org/10.1038/s41893-020-00603-4>.
32. Michael B. Eisen and Patrick O. Brown, *Rapid global phaseout of animal agriculture has the potential to stabilize greenhouse gas levels for 30 years and offset 68 percent of CO2 emissions this century*. PLOS Climate, 2022. **1**(2): p. e0000010, <https://doi.org/10.1371/journal.pclm.0000010>.
33. I. Santoso, et al., *Machine learning application for sustainable agri-food supply chain performance: a review*. IOP Conference Series: Earth and Environmental Science, 2021. **924**(1): p. 012059, <https://doi.org/10.1088/1755-1315/924/1/012059>.
34. N. N. Misra, et al., *IoT, Big Data, and Artificial Intelligence in Agriculture and Food Industry*. IEEE Internet of Things Journal, 2022. **9**(9): p. 6305-6324, <https://doi.org/10.1109/JIOT.2020.2998584>.
35. David Shillingford. *Reducing Waste in Food Supply Chains*. 2022 Published by Food Logistics; Available from <https://www.foodlogistics.com/sustainability/waste-reduction/article/22197400/everstream-analytics-reducing-waste-in-food-supply-chains>.
36. Y Dai, *Research on the design of green and low-carbon food packaging based on artificial intelligence technology*. Global NEST Journal, 2023. **25**(5): p. 90-97, <https://doi.org/10.30955/gnj.004705>.
37. Sami Jullien, et al., *GLDQN: Explicitly Parameterized Quantile Reinforcement Learning for Waste Reduction*. arXiv preprint arXiv:2205.15455, 2022, <https://doi.org/10.48550/arXiv.2205.15455>.
38. TOMRA. *Homepage*. Accessed September 2023 Published by Available from <https://www.tomra.com/en>.
39. Clarisse Magnin. *How AI can unlock a \$127B opportunity by reducing food waste*. 2019 Published by McKinsey Sustainability; Available from <https://www.mckinsey.com/capabilities/sustainability/our-insights/sustainability-blog/how-ai-can-unlock-a-127b-opportunity-by-reducing-food-waste>.
40. Puneet Sharma and Upma Vaid, *Emerging role of artificial intelligence in waste management practices*. IOP Conference Series: Earth and Environmental Science, 2021. **889**(1): p. 012047, <https://doi.org/10.1088/1755-1315/889/1/012047>.
41. M. C. Anggraeni, et al. *Role of Artificial Intelligence in the Management of Food Waste*. (2021). pgs. 1-6. 2021 2nd International Conference on Artificial Intelligence and Data Sciences (AiDAS). <https://doi.org/10.1109/AiDAS53897.2021.9574167>.

Chapter 8:

ROAD TRANSPORT

Ruben Glatt and David Sandalow

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 (CO₂) emissions.^{1,2} Strategies for reducing CO₂ emissions from road transport include deploying electric vehicles (EVs), sustainable biofuels and intelligent transportation systems, as well as greater use of more efficient modes of transit.



Vehicle electrification is an especially important strategy. Life-cycle greenhouse gas emissions from EVs are already significantly lower than those from comparable vehicles with internal combustion engines. (Emissions benefits vary based on regional differences in energy generation. One recent study found EV lifecycle 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, EVs will contribute even more to reducing emissions. Barriers to more rapid deployment of EVs include their up-front purchase price and driving range, both of which can be addressed with battery innovations.

Sustainable biofuels also have an important potential role in decarbonizing road transport. The energy density of biofuels make them an attractive option for heavy duty vehicles, including trucks carrying large loads over long distances.

Intelligent transportation systems (ITSs) also have potential to reduce carbon emissions from road transport. ITSs integrate sensor and communication technologies with data processing, analyzing vast amounts of real-time data to plan, monitor and control transit. Shifts from personal vehicles to shared vehicles or public transport are also important. Data-driven algorithms can be used to promote this shift by optimizing public transport to make sure riders have low wait times and can get to their destinations in a timely and cost-effective manner.

A. Using artificial intelligence (AI) to cut road transport emissions

AI has significant potential to help reduce greenhouse gas emissions from road transport. Many solutions are still in the research stage but show great promise in experimental settings or simulations. 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.



The emerging capabilities of machine learning (ML) are opening up new opportunities to reduce emissions throughout the road transport value chain.⁴ AI can play an important role in three core areas: (1) batteries and biofuels, (2) intelligent transportation systems and smart infrastructure and (3) shifts towards modes of transportation that emit less carbon.

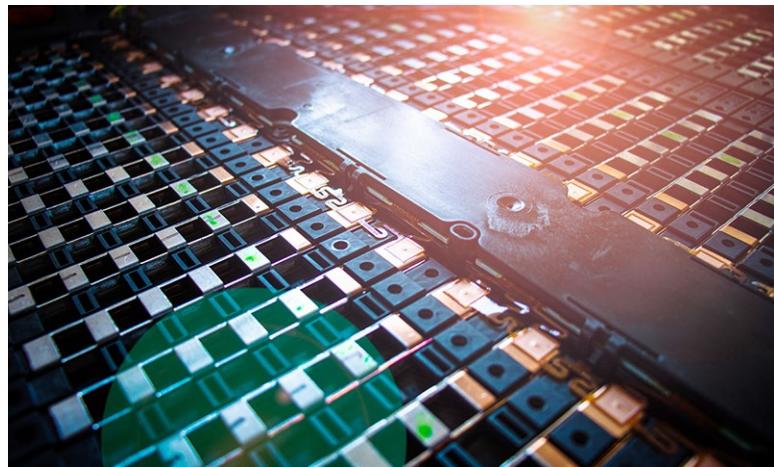
Realizing the full potential of AI in these areas will require more data and improved ML methods. Together, they can provide a robust foundation for predictive analytics and decision-making in scenario simulations. While algorithm development and improved computing hardware are important, near- to mid-term advances primarily depend on the availability of data. In combination, new data sources and cutting-edge theoretical insights can maximize the impact of recent ML advances.

(i) Batteries

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

For instance, AI has been shown to help improve battery 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 characteristics and develop desired 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 ML can increase accuracy when predicting the properties of materials and speed down-selection of possible solutions.⁷

Major ML-driven breakthroughs and innovations in battery materials – including nickel cathodes, silicon anodes and novel electrolytes – are already increasing capacity and reducing the cost of EV batteries.⁸ More progress could be achieved through ML investments that support collaborations between industry and academia based on data, model and knowledge sharing such as the *U.S. Joint*



Center for Energy Storage Research and the European *Battery 2030+* Initiative.⁹

AI can significantly enhance battery use-phase processes. 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.¹⁰ AI-assisted battery charging can cut electricity costs, prevent overburdening of the power grid, prolong battery lifespans and increase vehicle availability, particularly for EV fleet providers.¹¹ AI tools can also optimize the charging process directly while considering battery-aging effects and environmental conditions (such as temperature) to 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 days⁶ and (2) adaptive multistage constant current/constant voltage charging strategies based on a particle swarm optimization approach.¹²

Another way to decrease the carbon footprint of EV batteries is to improve recycling and reuse.¹³ 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,¹⁴ (2) ML-enhanced automated disassembly and quality control that integrates computer vision and time-series prediction,¹⁵ (3) optimal parameter setting for bioleaching processes for material recovery based on a random forest regression model,¹⁶ and (4) applications for battery life-cycle, waste recycling and material recovery.¹⁷

Box 8-1

RECOMMENDATIONS

- Encourage collaboration between industry and academia to build better data sets and encourage joint model development and knowledge exchange for material research
- Support development of large-scale non-linear surrogate models to improve prediction of material properties
- Integrate AI-driven management systems in the battery life-cycle to extend time of use and optimize raw material efficiency
- Increase simulation capabilities to evaluate life-cycle and infrastructure impact of innovative fuels



(ii) Biofuels

Sustainable biofuels can help decarbonize road transport. The most promising applications are with heavy duty vehicles, such as trucks carrying large loads long distances. (Sustainable biofuels can also help decarbonize air and marine travel.)

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,¹⁸ however biological processes offer a promising research direction.¹⁹ AI models can also help evaluate biofuel infrastructure requirements and support policy making and long-term planning.²⁰

(iii) Intelligent transportation systems and smart infrastructure

ITSs integrate advanced information collection, data processing, communication and sensor technologies into transportation networks. ITSs include technologies such as real-time traffic data analysis, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, automatic number plate recognition and advanced vehicle control systems.²¹

Smart infrastructure refers to physical infrastructure embedded with sensor technology, digital connectivity and data analytics. In the context of road transport, smart infrastructure includes intelligent traffic signals that adjust to real-time traffic conditions, road sensors that detect and report issues such as potholes or icy conditions, and digital signs that provide real-time information to drivers.

ITSs and smart infrastructure have significant potential to help reduce carbon emissions in road transport. These technologies could be at the heart of a more sustainable and carbon-free transportation system.

AI plays a central role in maximizing the potential of ITSs and smart infrastructure. AI's power to analyze extensive real-time data from multiple sources could be a game-changer. Theoretical studies have shown AI's ability to optimize traffic flow, decrease congestion, enable dynamic traffic light sequencing, suggest smart routes and model traffic predictively to foresee and alleviate congestion. While real-world adoption and insights are still scarce and not well-documented, some cities already have implemented pilot studies to investigate real-world implications. 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).²²



In public transport, AI can be used to predict passenger loads and optimize schedules and routes, enhancing service efficiency and user satisfaction.²³ AI's role in predictive maintenance can also help foresee potential infrastructure issues in public transit, preventing failures or delays. Finally, by processing and analyzing ITS data, AI will be able to aid in informed policy decisions and strategic planning, leading to greener, more efficient public transit systems. The infusion of AI into ITSs is emerging as a cornerstone strategy in the shift toward lower emissions and heightened efficiency in public transit.

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.²⁴ 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 analytics.²⁵ By offering continuous, real-time data, a sensor-driven infrastructure enables AI systems to significantly enhance the 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.²⁶

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.²⁷ This can provide a wealth of insights, including in optimizing infrastructure planning, forecasting energy demand and evaluating potential transportation system policies.²⁸ 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 CO₂ 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.²⁹

AI can play an important role in bidirectional EV charging.³⁰ With bidirectional charging capabilities, EVs can deliver power to homes (V2H), businesses (V2B) or the electric vehicle 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.³¹ ML can also be used in charge-management systems to guide EVs to charging stations to reduce negative effects during peak charging times.³² The mobile storage can also be used to improve energy performance of public buildings by using an ML-based V2G strategy to reduce the carbon footprint of buildings supported by energy consumption and cost predictions.³³

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

Box 8-2

RECOMMENDATIONS

- Increase investment in sensor-driven infrastructure components that can provide data for ML models to support real-time decision making and planning efforts
- Establish privacy regulations for data collection, storage and use in AI applications in transportation.
- Support infrastructure research that extends simulation capabilities to better capture the interactions between transportation and energy infrastructure
- Establish large-scale pilot projects for intelligent transportation systems in collaboration with utility provider, fleet operator and vehicle manufacturer
- Establish standards for communication technology and protocols for vehicle-infrastructure communication



involve predictive maintenance of road infrastructure with sensors that monitor wear and tear, schedule preemptive maintenance and mitigate critical failures.³⁴ Such collaborative, large-scale projects not only improve transportation efficiency, safety and user experience, but also contribute significantly to reducing carbon emissions.

(iv) Promoting modal shift

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 ML 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 towards 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 transport 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 greenhouse gas emissions.³⁵

- 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.³⁶
- 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.³⁷
- AI-driven predictive maintenance can keep shared vehicles in optimal condition, maintaining energy efficiency, reducing downtime and enhancing the reliability of shared mobility services.³⁸

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.

Autonomous vehicles (AVs) and more specifically autonomous electric vehicles (AEVs) have the potential to significantly shift transportation modalities, steering us away from a dependence on conventional, individual-owned internal combustion engine vehicles and toward a new era of 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. These features encourage a shift away from private vehicle ownership. Furthermore, AEVs can potentially lower operating costs due to their electric drivetrains, a benefit that AI can augment by optimizing energy usage. In terms of infrastructure use, AI enables AEVs to operate more efficiently, through measures like 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 the 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.

Box 8-3

RECOMMENDATIONS

- Encourage technology adoption in public transport to increase analytics capabilities
- Develop regulations and incentives to facilitate the use of shared mobility solutions
- Support development and implementation of AEVs to increase vehicle efficiency



B. Barriers and risks

While the potential of AI in revolutionizing road transportation is immense, several barriers must be addressed to realize this potential.

A first barrier is lack of data. As noted above, data on a wide range of topics are required to deploy AI in integrated road transportation systems. Sensors, smart infrastructure, CVs and other tools will be needed to collect such 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.³⁹ 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.

The use of 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 an individual's habit and actions. Societal norms are only beginning to be established with respect the collection, distribution and use of data in this area.

Second, the use of 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.⁴⁰

- 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.⁴¹
- 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.⁴²
- 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.

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.

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 the control of intelligent transportation infrastructure, however their impact is not yet clear.⁴³

REFERENCES

1. International Energy Agency (IEA). *Greenhouse Gas Emissions from Energy Data Explorer*. 2023. Available from <https://www.iea.org/data-and-statistics/data-tools/greenhouse-gas-emissions-from-energy-data-explorer>.
2. International Energy Agency (IEA). *Energy Efficiency 2022*. 2022. Available from <https://www.iea.org/reports/energy-efficiency-2022>.
3. Georg Bicker. *A global comparison of the life-cycle greenhouse gas emissions of combustion engine and electric passenger cars*. 2021. Published by The International Council on Clean Transportation (ICCT); Available from <https://www.team-bhp.com/forum/attachments/electric-cars/2310712d1653112667-things-consider-when-buying-electric-car-global-lca-passenger-cars-jul2021-0.pdf>.
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, 2022. **10**: p. 53614-53639, <https://doi.org/10.1109/ACCESS.2022.3175585>.
5. Scott M. Woodley and Richard Catlow, *Crystal structure prediction from first principles*. Nature Materials, 2008. **7**(12): p. 937-946, <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, 2020. **578**(7795): p. 397-402, <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, 2020. **31**: p. 434-450, <https://doi.org/10.1016/j.ensm.2020.06.033>.
8. Mohamed S. E. Houache, et al., *On the Current and Future Outlook of Battery Chemistries for Electric Vehicles—Mini Review*. Batteries, 2022. **8**(7): p. 70, <https://doi.org/10.3390/batteries8070070>.
9. Muratahan Aykol, Patrick Herring, and Abraham Anapolsky, *Machine learning for continuous innovation in battery technologies*. Nature Reviews Materials, 2020. **5**(10): p. 725-727, <https://doi.org/10.1038/s41578-020-0216-y>.
10. X. Hu, et al., *Reinforcement Learning for Hybrid and Plug-In Hybrid Electric Vehicle Energy Management: Recent Advances and Prospects*. IEEE Industrial Electronics Magazine, 2019. **13**(3): p. 16-25, <https://doi.org/10.1109/MIE.2019.2913015>.
11. Oliver Frendo, et al., *Data-driven smart charging for heterogeneous electric vehicle fleets*. Energy and AI, 2020. **1**: p. 100007, <https://doi.org/10.1016/j.egyai.2020.100007>.
12. Yunjian Li, et al., *Optimized charging of lithium-ion battery for electric vehicles: Adaptive multistage constant current–constant voltage charging strategy*. Renewable Energy, 2020. **146**: p. 2688-2699, <https://doi.org/10.1016/j.renene.2019.08.077>.
13. Karlo Hainsch, et al., *Energy transition scenarios: What policies, societal attitudes, and technology developments will realize the EU Green Deal?* Energy, 2022. **239**: p. 122067, <https://doi.org/10.1016/j.energy.2021.122067>.
14. Prabhakar Sharma and Bhaskor J. Bora, *A Review of Modern Machine Learning Techniques in the Prediction of Remaining Useful Life of Lithium-Ion Batteries*. Batteries, 2023. **9**(1): p. 13, <https://doi.org/10.3390/batteries9010013>.
15. 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, 2023. **34**(5): p. 2463-2475, <https://doi.org/10.1007/s10845-022-01936-x>.
16. Parastou Mokarian, et al., *The advanced design of bioleaching process for metal recovery: A machine learning approach*. Separation and Purification Technology, 2022. **291**: p. 120919, <https://doi.org/10.1016/j.seppur.2022.120919>.
17. Agnieszka Pregowska, Magdalena Osial, and Weronika Urbańska, *The Application of Artificial Intelligence in the Effective Battery Life Cycle in the Closed Circular Economy Model—A Perspective*. Recycling, 2022. **7**(6): p. 81, <https://doi.org/10.3390/recycling7060081>.
18. Muzammil khan, et al., *Applications of machine learning in thermochemical conversion of biomass—A review*. Fuel, 2023. **332**: p. 126055, <https://doi.org/10.1016/j.fuel.2022.126055>.

19. Ahmed I. Osman, et al., *Conversion of biomass to biofuels and life cycle assessment: a review.* Environmental Chemistry Letters, 2021. **19**(6): p. 4075-4118, <https://doi.org/10.1007/s10311-021-01273-0>.
20. Jakob Wachsmuth, et al. *The European Commission's 2050 Vision "A clean planet for all"—Implications for Sector Strategies and Climate Governance.* Final report. 2022. Dessau-Roßlau: German Environment Agency, <https://www.ecologic.eu/18577>.
21. Kashif Naseer Qureshi and Abdul Hanan Abdullah, *A Survey on Intelligent Transportation Systems.* Middle-East Journal of Scientific Research, 2013. **15**: p. 629-642, <https://doi.org/10.5829/idosi.mejsr.2013.15.5.11215>.
22. Vittorio Astarita, et al., *Floating Car Data Adaptive Traffic Signals: A Description of the First Real-Time Experiment with "Connected" Vehicles.* Electronics, 2020. **9**(1): p. 114, <https://doi.org/10.3390/electronics9010114>.
23. Tielle Alexandre, et al., *Machine Learning Applied to Public Transportation by Bus: A Systematic Literature Review.* Transportation Research Record, 2023. **2677**(7): p. 639-660, <https://doi.org/10.1177/03611981231155189>.
24. J. A. Guerrero-ibanez, S. Zeadally, and J. Contreras-Castillo, *Integration challenges of intelligent transportation systems with connected vehicle, cloud computing, and internet of things technologies.* IEEE Wireless Communications, 2015. **22**(6): p. 122-128, <https://doi.org/10.1109/MWC.2015.7368833>.
25. A. Ferdowsi, U. Challita, and W. Saad, *Deep Learning for Reliable Mobile Edge Analytics in Intelligent Transportation Systems: An Overview.* IEEE Vehicular Technology Magazine, 2019. **14**(1): p. 62-70, <https://doi.org/10.1109/MVT.2018.2883777>.
26. D. Nallaperuma, et al., *Online Incremental Machine Learning Platform for Big Data-Driven Smart Traffic Management.* IEEE Transactions on Intelligent Transportation Systems, 2019. **20**(12): p. 4679-4690, <https://doi.org/10.1109/TITS.2019.2924883>.
27. Saraju Mohanty, *Everything You Wanted to Know About Smart Cities.* IEEE Consumer Electronics Magazine, 2016. **5**: p. 60-70, <https://doi.org/10.1109/MCE.2016.2556879>.
28. Rocio de la Torre, et al., *Simulation, Optimization, and Machine Learning in Sustainable Transportation Systems: Models and Applications.* Sustainability, 2021. **13**(3): p. 1551, <https://doi.org/10.3390/su13031551>.
29. Aiga Barisa, Vladimirs Kirsanovs, and Alina Safronova. *Renewable Transport Challenge: A Comprehensive Policy Assessment Model.* (2021). pgs. 1-5 (Paper ID 858). International Conference on Applied Energy. Thailand/Virtual: Energy Proceedings; <https://www.energy-proceedings.org/wp-content/uploads/icae2021/1642955253.pdf>.
30. 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, 2014. **34**: p. 501-516, <https://doi.org/10.1016/j.rser.2014.03.031>.
31. David Rolnick, et al., *Tackling Climate Change with Machine Learning.* ACM Comput. Surv., 2022. **55**(2): p. Article 42, <https://doi.org/10.1145/3485128>.
32. Tehseen Mazhar, et al., *Electric Vehicle Charging System in the Smart Grid Using Different Machine Learning Methods.* Sustainability, 2023. **15**(3): p. 2603, <https://doi.org/10.3390/su15032603>.
33. Connor Scott, Mominul Ahsan, and Alhussein Albarbar, *Machine Learning Based Vehicle to Grid Strategy for Improving the Energy Performance of Public Buildings.* Sustainability, 2021. **13**(7): p. 4003, <https://doi.org/10.3390/su13074003>.
34. Angie Ruiz and Jose Guevara, *Sustainable Decision-Making in Road Development: Analysis of Road Preservation Policies.* Sustainability, 2020. **12**(3): p. 872, <https://doi.org/10.3390/su12030872>.
35. Fahimeh Golbabaei, Tan Yigitcanlar, and 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, 2021. **15**(10): p. 731-748, <https://doi.org/10.1080/15568318.2020.1798571>.
36. Stefano Mariani, Giacomo Cabri, and Franco Zambonelli, *Coordination of Autonomous Vehicles: Taxonomy and Survey.* ACM Comput. Surv., 2021. **54**(1): p. Article 19, <https://doi.org/10.1145/3431231>.

37. Berkay Turan, Ramtin Pedarsani, and Mahnoosh Alizadeh, *Dynamic pricing and fleet management for electric autonomous mobility on demand systems*. Transportation Research Part C: Emerging Technologies, 2020. **121**: p. 102829, <https://doi.org/10.1016/j.trc.2020.102829>.
38. Patrick Killeen, et al., *IoT-based predictive maintenance for fleet management*. Procedia Computer Science, 2019. **151**: p. 607-613, <https://doi.org/10.1016/j.procs.2019.04.184>.
39. H. S. Das, et al., *Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review*. Renewable and Sustainable Energy Reviews, 2020. **120**: p. 109618, <https://doi.org/10.1016/j.rser.2019.109618>.
40. Christina Pakusch, et al., *Unintended Effects of Autonomous Driving: A Study on Mobility Preferences in the Future*. Sustainability, 2018. **10**(7): p. 2404, <https://doi.org/10.3390/su10072404>.
41. Andrea Chicco and 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, 2021. **91**: p. 102685, <https://doi.org/10.1016/j.trd.2020.102685>.
42. 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>.
43. Yifeng Shi, et al. *Open-TransMind: A New Baseline and Benchmark for 1st Foundation Model Challenge of Intelligent Transportation*. (2023). pgs. 6327-6334. 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.

Chapter 9:

BARRIERS

Alp Kucukelbir and David Sandalow

Five groups of barriers impede the development and application of artificial intelligence (AI) to climate change mitigation: data, people, computation, cost and institutions.

A. Data

AI requires significant amounts of data, from which it extracts patterns. Data-related barriers to the use of AI for climate change mitigation include the following:

- **Data availability.** This is a threshold issue for AI. Without available data, AI tools have limited value. Data quality¹ can be as important as data quantity, as more data is typically good but not always better.²
- **Data accessibility.** To be useful for AI, data must not only exist but also be accessible. Inaccessible data inhibits application of AI. Both AI experts and domain experts will struggle to conceive of AI applications without access to key data. Inaccessible data may further impede deployment of AI, even if it has been developed using alternative data sources. For example, power-network optimization software may need regular access to real-time data from a specific grid to make an impact on that grid's carbon emissions.
- **Data standardization.** Climate applications of AI, particularly those that require collaborative efforts by stakeholders, can be severely impeded by lack of data standardization. Standardization is especially important when data are gathered in a distributed fashion. The parties who gather and store data can remove significant barriers to the use of their data by adhering to standard practices in their individual efforts.

Data-related barriers can be overcome with a range of strategies. ClimateChangeAI has released a *Data Set Wishlist*—“a list of datasets whose availability could accelerate progress or remove bottlenecks” in using AI to fight climate change.³ Such guidance can help spur development and release of datasets with high potential for impact. In addition, some businesses may find it helpful to release datasets while protecting personally identifiable information. A leading example is Netflix, which released anonymized user data and offered a prize for the development of the best recommender system using those data. The “Netflix Prize” accelerated the development of machine learning algorithms important to the company’s business model and beneficial to the entire media sector.⁴

B. People

The success of AI depends on the people who develop, use and evaluate it. Three primary groups of people are involved:

- **AI developers.** Developing AI requires a mixture of specialized skills: a strong fluency in statistics and information theory, built upon a foundation of computer science and software engineering. Many AI developers have graduate-level degrees in computer science, statistics, engineering and applied sciences, applied mathematics, and operations research. Like any other highly technical field, the reliance on such specialist skill-sets poses a barrier to scaling the development and deployment of AI, as the difficulty of the topic and the time required for its study produces a small group of people every year with these credentials. Moreover, AI developers are under significant market demand from non-climate-focused institutions, such as technology, finance and media companies, leading to extraordinary competition to attract and retain such individuals.⁵
- **Climate application experts.** AI developers cannot address climate change mitigation alone. Expertise in many domains is needed. For AI to have an impact on climate change mitigation, AI developers must work closely with experts in fields such as atmospheric chemistry, materials science, electrical engineering, finance and political science.⁶ A lack of collaboration between AI developers and these experts poses a barrier for successfully developing and deploying AI. Such collaborations are catalyzed when groups of skilled workers develop an elementary understanding of each others' fields. These collaborations are stymied when these groups lack experience working together or organizational structures that facilitate common efforts.
- **AI users.** AI users can be anyone who makes decisions based on the output of AI systems. This can include chemists exploring novel materials, economists evaluating policy impacts, pilots making decision on flight paths and many others.⁷ The training needed to interact effectively with AI systems will vary from application to application. In general, the more familiarity AI users have with basic AI principles, the more likely they are to be able to use AI tools effectively for climate change mitigation.

C. Computing power

The ability to simulate and run computations is a fundamental building block for AI. Obstacles to computation include the following:

- **Computation hardware access.** As the amount of data continues to grow across all application areas, so does the demand on AI computation.⁸ This includes access to hardware, either physically or through an online computation platform. With access to computation hardware comes costs associated with executing simulations; for physical hardware, this includes energy costs and the need to maintain computational infrastructure. With online computational platforms, such as cloud computing vendors, these costs are typically charged by the vendors based on the amount of time taken for computation and the quantity of data processed during that time.

- **Infrastructure maintenance and upkeep.** Institutions that decide to procure and operate computational infrastructure must also plan for its maintenance and upkeep. Computational infrastructure comprises many electronic components, ranging from servers to networking and temperature-control equipment. All components are subject to gradual degradation, which requires redundancy in their design and a well-executed maintenance workflow. Upkeep of individual components may include using chips with lower energy requirements and increasing the capabilities of computation infrastructure as demand for AI increases.

D. Cost

Cost is a fundamental barrier that permeates and compounds the barriers discussed above:

- **Financing data for AI.** Insufficient financial resources can pose a significant obstacle to data availability. Collecting, standardizing and digitizing the data that are needed to power a broad range of AI applications for climate use-cases requires funds to buy and operate measurement equipment; pay salaries of technicians and data analysts; and pay for data processing, transfer and storage.
- **Financing people for AI.** With AI-developer talent in strong demand, institutions seeking to draw such skilled workers to climate applications require commensurate funding to compete in the recruitment market. Climate-application experts are also in demand; lack of sufficient funding can impede the ability to bring both sets of people together.
- **Financing computation for AI.** Whether institutions choose to procure their own infrastructure or outsource their computation to third-party vendors, cost is a primary obstacle to gaining access to computation.⁹ Without sufficient funding, lack of access to computation can bring AI development and deployment to a standstill.
- **Financing access to AI.** In many climate applications, end-users of AI will likely need to procure AI systems and software from vendors. Institutions may decide to build these AI systems “in house,” financing the people and computation as above. Or they may choose to buy the AI systems from a vendor, in which case lack of funding can prohibit adoption of AI into these climate applications.

E. Institutions

AI is poised to transform the work of many organizations that have a role in climate change mitigation, including government agencies, private companies and non-governmental organizations (NGOs). A lack of leadership attention and thoughtful internal policies in these organizations could be a barrier to realizing AI’s potential to help reduce emissions. Potential barriers include the following:

- **Lack of institutional focus.** To integrate AI into operations, many organizations will require senior-management commitment and an organizational structure that ensures attention to AI (such as an AI department).
- **Internal policies around AI.** Good data practices, adopting AI-based workflows and committing to requisite investments, both human and technical, are all essential.
- **Lack of standard-setting.** Effective scaling of AI requires data standardization, but the institutions with responsibility for setting these standards may be unclear.

REFERENCES

1. Andy McDonald. *Data Quality Considerations for Machine Learning Models*. 2022. Medium. Available from <https://towardsdatascience.com/data-quality-considerations-for-machine-learning-models-dcbe9cab34cb>.
2. Rhys Compton, et al., *When More is Less: Incorporating Additional Datasets Can Hurt Performance By Introducing Spurious Correlations*. arXiv preprint arXiv:2308.04431, 2023, <https://doi.org/10.48550/arXiv.2308.04431>.
3. Climate Change AI. *Climate Change AI Dataset Wishlist*. Accessed November 2023. Available from <https://www.climatechange.ai/dataset-wishlist.pdf>.
4. Medium. *Medium: Sign up to discover human stories that deepen your understanding of the world*. Accessed November 2023. Available from <https://medium.com/codex/hybrid-recommender-system-netflix-prize-dataset-e9f6b4a875aa>.
5. Chris Cutter. *The \$900,000 AI Job Is Here*. 2023. The Wall Street Journal. Available from <https://www.wsj.com/articles/artificial-intelligence-jobs-pay-netflix-walmart-230fc3cb>.
6. Dong Kwan Kim. *How cross-sector collaboration is driving the global climate agenda*. 2020. World Economic Forum. Available from <https://www.weforum.org/agenda/2020/01/how-cross-sector-collaboration-is-driving-the-global-climate-agenda/>.
7. Carl Elkin and Dinesh Sanekommu. *How AI is helping airlines mitigate the climate impact of contrails*. 2023. Google Blog. Available from <https://blog.google/technology/ai/ai-airlines-contrails-climate-change/>.
8. Erin Griffith. *The Desperate Hunt for the A.I. Boom's Most Indispensable Prize*. 2023. The New York Times. Available from <https://www.nytimes.com/2023/08/16/technology/ai-gpu-chips-shortage.html>.
9. Aaron Mok. *AI is expensive. A search on Google's chatbot Bard costs the company 10 times more than a regular one, which could amount to several billion dollars*. 2023. Business Insider. Available from <https://www.businessinsider.com/ai-expensive-google-chatbot-bard-may-cost-company-billions-dollars-2023-2>.

Chapter 10: **RISKS**

David Sandalow, Julio Friedmann and Alp Kucukelbir

Risks from using artificial intelligence (AI) can include bias, invasion of privacy, security, safety and increased greenhouse gas emissions.

A. Bias

Bias in AI refers to discrimination that can arise when algorithms make decisions that perpetuate prejudices, reflect stereotypes or amplify social inequalities. The causes of bias include skewed training data and flawed algorithm design. Prominent examples include (1) an AI-enabled hiring tool that favored male over female applicants because it was trained on historic data in which men were favored in the hiring process and (2) a healthcare algorithm that prioritized healthier white patients over sicker black patients because the algorithm used health care spending as a proxy for health care needs.^{1, 2}

When using AI in the context of climate mitigation, risks related to bias include:

Unrepresentative data: Data used to train AI models can be biased due to the very different levels of data availability in different countries. For example, data on vehicle traffic patterns in Organization for Economic Cooperation and Development (OECD) countries is relatively rich because of the ability to collect measurements from radio frequency identification (RFID), connected vehicles and *in situ* traffic sensors. However, these data may be significantly different from measurements that would be collected in non-OECD countries if more sensor systems were available in those countries. As a result, AI models for improving traffic flow trained on the most accessible data might be badly adapted or entirely unusable in many countries.^{3, 4}

Misaligned Objectives: AI models are designed to optimize specific objectives. If these objectives are not carefully aligned with broad, inclusive climate goals, the models might inadvertently favor certain groups or regions over others.

- **Undermining personal autonomy.** AI may increasingly be used to provide climate mitigation “nudges,” subtly encouraging people to choose options resulting in lower emissions. An example of this is Google Maps’ decision to bias route recommendations toward those with lower projected greenhouse gas emissions, even at the expense of slightly longer travel times.⁵ These biases in recommendations can be quite powerful at influencing behavior, especially when informed by AI algorithms. However, there is no clear line between “minor” nudges and more intrusive provision of information that excessively manipulates individual decision-making. Without clearer guidelines, AI-enabled “green nudges” may exceed reasonable safeguards and undermine personal autonomy in decision-making.⁶
- **Reinforcing environmental injustice in communities.** AI will increasingly be used to determine the optimal locations for siting green infrastructure, such as electric transmission lines and low-

carbon fuel production facilities. However, the process of optimization includes many different goals, including reducing overall costs and minimizing additional (marginal) environmental impacts to air and water quality. Based on those criteria, an AI optimal-siting algorithm may conclude that low-income communities with low land values that are already burdened by extensive air and water pollution are the “optimal” sites for further industrial development. Without appropriate safeguards, this would further reinforce historical environmental injustices in those communities. AI-enabled algorithms used to identify sites for beneficial green infrastructure may suffer from similar issues. For example, when siting electric vehicle (EV) charging stations, an AI algorithm that prioritizes high rates of EV ownership in siting decisions may neglect low-income communities, making EV ownership in those communities more difficult.

Economic Bias: AI solutions could be developed with economic motivations that prioritize wealthier nations or communities. As a result, mitigation strategies might overlook developing countries, which might be more vulnerable to climate change but less represented in global data sets, even when viable, cost-effective strategies are available.

Cultural Bias: Climate-related AI models might inadvertently prioritize or deprioritize certain mitigation strategies based on the cultural biases of the researchers or developers. This could overlook indigenous knowledge or local practices.

Feedback Loops: AI models that use real-time data to adapt can sometimes create feedback loops that reinforce existing biases. For example, if renewable energy installations are primarily in wealthier areas due to economic factors, an AI system optimizing for energy distribution might continue to prioritize these areas, further widening the gap.

B. Privacy

Collection and analysis of vast amounts of data are essential for AI to contribute to climate change mitigation. Some of these data may be sensitive, proprietary or personal, presenting privacy concerns. Privacy risks related to using AI for climate mitigation include:

Surveillance: With the increasing use of sensors, drones and Internet of Things (IoT) devices to monitor environmental change and human behaviors related to carbon emissions, some data could be used for unauthorized surveillance of individuals or businesses.

Personal identification: When data from multiple sources are aggregated, individuals who were previously anonymous in isolated data sets could become identifiable. For example, combining smart-meter data with property records or other public data sets can reveal detailed information about an individual's habits.

Data Sharing: Data collected for climate-mitigation purposes, such as energy-consumption patterns, might be shared with third parties like advertisers, insurers or utilities, potentially without the explicit consent of the individuals involved. The data could be shared by the host of the data or as the result of a data breach or cyberattack by a third party.

These risks may have repercussions beyond the realm of commerce or privacy. For example, criminals could use these data to gain access to personal information. AI-based systems that leverage distributed data collection could be appropriated for political use. For example, AI models that optimize crop growth in developing countries (increasing food production per unit of total greenhouse gas emissions) may inadvertently provide previously unavailable network and data collection infrastructure for government surveillance systems.⁷ While private developers may initially build data-collection and analysis technology for purely climate mitigation systems, they may be unable to prevent a repurposing of these system.

Ultimately, any kind of data that are granular enough to contain information at the individual level are of concern. Examples may include information about individuals (gathered through their usage of a device connected to the internet), including personal and potentially private aspects, such as their medical history, age or gender.

Not all data about people are of concern. Examples include data aggregated to the point where individuals cannot be identified or data about individuals where they cannot be identified, such as satellite images of people in cars. Some operational and mathematical tools can fully anonymize data, allowing for safe and insightful derivative data and results.

Practical applications are possible without overstepping important privacy bounds. Workers using and developing AI tools can start with design around specific use cases (e.g., traffic or power use). This can start first with awareness-building and operational guides, as well as training and education regarding privacy concerns. In addition, straightforward technical approaches, such as federating data, restricted access, differential privacy and encryption, can assist workers in both maintaining privacy and delivering high-impact mitigation outcomes.

C. Security

All software programs are subject to attacks by hackers, creating security risks. AI systems expand the “attack surface” for hackers beyond that found in conventional software programs, increasing such risks. For example, AI systems ingest large amounts of data from potentially many different sources. Attacking these data sources can steer an AI system’s behavior in unpredictable ways. The consequences can be especially serious when AI is used in real-time workflows.

Using AI for planning/static use cases poses similar security risks to regular software infrastructure. AI systems store and process data, thereby exposing such data to parties without authorized access, both within and outside of organizations. AI systems produce results that are themselves data subject to similar risks. Both can be managed with data security protocols that are well established in organizations that produce and operate with data.

Using AI in real-time/live workflows carries additional security risks beyond regular software systems. AI systems that are integrated into real-time workflows may be subject to stringent reliability requirements. Since AI systems are so complex, it becomes difficult to fully audit them for potential issues when adopted into live workflows. Risks specific to AI include but are not limited to:

- Cases where data are accepted as an input during operations. For example, researchers have identified security risks in large language models (LLMs) by adding extra text in clever ways to drive AI systems to act unpredictably.⁸
- Cases where the environment in which an AI system operates is modified. For example, researchers were able to spoof street signs and confuse a self-driving AI autopilot system using subtle stickers. By printing modified copies of signs or adding small black and white strips, they could reliably cause a stop sign to be misread as a speed limit sign.⁹
- Cases where systems must be regularly and carefully updated with new data to maintain their effectiveness, giving attackers the opportunity to introduce data that may steer the AI system astray.¹⁰

The rapid development of new AI technologies also means security risks may emerge faster than organizations can address them.¹¹ Many of the AI applications in this report pertain to critical infrastructure sectors¹² which are accompanied by additional security risk-mitigation requirements.

Overall, while promising significant climate mitigation opportunities, AI systems share similarities to regular software in how vulnerabilities can inadvertently be introduced if not properly managed from a security perspective.

The key is for both governments and organizations to take a proactive approach focused on transparency, oversight, education and governance to manage the faster-moving security challenges associated with adopting AI.

D. Safety

AI systems can create safety risks when they fail to operate as intended or have unintended consequences. (This is different than the security risks discussed above, in which someone intentionally uses an AI system to cause harm.)

The Cybersecurity and Infrastructure Security Agency of the United States maintains a list of sectors considered “so vital [...] that their incapacitation or destruction would have a debilitating effect on security, national economic security, national public health or safety, or any combination thereof.”¹² More than half of these sectors, such as chemicals, manufacturing and energy, are covered in this roadmap. Some of these sectors, such as manufacturing, have dangerous workplaces. Others, such as food and agriculture, carry public health risks.

Almost every application of AI described in this roadmap could create safety risks. For example:

- AI systems in real-time grid-optimization operations could lead to unsafe physical conditions and/or other threats to human safety in the field.
- Manufacturing facilities under AI-driven recommendations could lead to unstable operating conditions and increase the risk of injury in physical facilities.
- Agricultural AI applications with inadequate data or poorly developed models could lead to over-utilization of arable land and/or adverse public-health consequences.
- Transportation systems optimized by AI could increase the risk of accidents by proposing unsafe routes and traffic patterns.

In each of these examples, the safety risk can be minimized with several strategies:

- First, AI systems should be fully tested and validated in static (non-real-time) settings, where the above-mentioned risks are mitigated because no live action is taken based on the AI system's outputs. This validation phase must be carefully conducted to properly represent "real-world" conditions of what the AI system would encounter once deployed live.
- Second, AI systems in dangerous settings should be deployed under the same safeguards that apply to regular software. The outputs of AI systems should pass through deterministic and vetted workflows that ensure these outputs cannot lead to dangerous physical conditions.
- Finally, AI systems should be deployed in phased rollouts across large systems. This enables enough resources to be dedicated to the required monitoring and validation of real-time AI systems, before scaling across entire systems, such as large power grids. Existing guidelines for adopting new workflows apply to AI systems and can help mitigate the risk to public health and safety.

E. Greenhouse gas emissions

At present, greenhouse gas emissions from AI are modest—significantly less than 1% of the global total. (See discussion below.) Better data collection and assessment methodologies are needed to provide a more precise estimate with high confidence.

The amount of future greenhouse gas emissions related to AI is highly uncertain. In some scenarios, greenhouse gas emissions from AI decline in the years ahead. In other scenarios, such emissions increase significantly.

This section discusses current and future greenhouse gas emissions from AI, explaining the uncertainties.

(i) Background

AI systems require energy. Manufacturing integrated circuitry for AI systems requires energy for mineral extraction, construction of complex machinery and sophisticated operations. Training and tuning of AI models requires energy for electricity. AI inference (in which users query models for results) also requires energy for electricity. Infrastructure supporting these tasks, including data storage, data transfer and cooling of hardware, adds to AI's energy footprint.

This energy use does not necessarily result in significant greenhouse gas emissions. When the electricity at a data center comes from solar, wind or nuclear power, for example, the direct greenhouse gas emissions from data-center operations are modest. Current data centers are major consumers of renewable power. Indeed in 2021, Amazon, Microsoft, Meta and Google—which operate a significant percentage of the world's data centers—led the world in renewable-power purchase agreements.¹³ However other parts of the AI value chain—including mineral extraction for equipment manufacturing—rely much less heavily on low-carbon power.

The term “emissions from AI” is potentially quite broad. The term could include emissions from:

- 1) manufacturing hardware for AI;
- 2) training and tuning of AI models;

- 3) AI inference (i.e., use of AI models);
- 4) applications of AI, some of which may increase emissions (e.g., those that make burning fossil fuels cheaper or easier) and some of which may reduce emissions (e.g., the AI applications discussed in this roadmap); and
- 5) broad societal changes caused by AI, such as in labor markets or political dialogue.¹⁴

Estimating current and future greenhouse gas emissions from each of these processes is challenging for several reasons:

- Data collection and assessment methodologies are generally inadequate for providing precise and confident estimates.^{14, 15}
- In modern cloud-based computing, computer hardware and its associated infrastructure (including HVAC) are frequently shared among many software programs. While some of these software programs use AI-based algorithms, many do not. As a result, it is difficult to correctly allocate overall emissions from computing infrastructure to the subcategory of AI applications. (In some cases, specialized computing chips are used for purely AI-based software, but the use of chips for both AI-based and non-AI-based software is more common.) This leads to significant uncertainty in emissions estimates, although the overall emissions from the information, communications and technology (ICT) sector serves as an upper bound on AI's emissions.
- Estimating greenhouse gas emissions from items 4 and 5 above is especially challenging due to the considerable unknowns with respect to how AI will be used in the years ahead.

In this section, we focus on items 1-3 above. Using the terminology of greenhouse gas accounting, these are Scope 1, Scope 2 and upstream Scope 3 emissions related to computing operations for AI.

(ii) Current greenhouse gas emissions from AI

There are no precise, widely accepted estimates of current lifecycle greenhouse gas emissions from computing operations for AI. However, the existing literature suggests that such emissions are significantly less than 1% of total global greenhouse gas emissions.

- According to the International Energy Agency (IEA), in 2020, data centers and data transmission networks were responsible for 0.6% of global greenhouse gas emissions (330 Mt CO₂e). This figure includes embodied emissions (i.e., emissions from the manufacturing of equipment used in data centers and data transmission networks).¹³
 - No figure is available for the percentage of data-center and data-transmission-network activity that relates to AI. However, that figure is less than 100% and likely much less than 100%.
 - On the other hand, AI activity has grown significantly since 2020—including most notably with the development and public release of ChatGPT, which has roughly 100 million active users.^{16, 17}

- In a *Nature Climate Change* paper published in 2022, Lynn Kaack et al. estimate that cloud and hyperscale data centers are responsible for 0.1–0.2% of global greenhouse gas emissions and that roughly 25% of their workloads were related to machine learning (ML).¹⁴
 - This estimate is based on data that are now several years old. AI activity has increased significantly in the past several years.
- In a 2022 study, Sasha Luccioni et al. found that greenhouse gas emissions from training several current LLMs, including GPT-3 and BLOOM, ranged from roughly 30 to 550 tonnes CO₂e.¹⁸ In a 2021 paper, David Patterson et al. provided similar estimates (noting that the average commercial plane emits roughly 180 tonnes CO₂e flying from San Francisco to New York).¹⁹ 550 tonnes CO₂e is 0.000001% (1×10^{-8}) of global greenhouse gas emissions. (Global greenhouse gas emissions were 55 ± 5.2 GtCO₂e in 2021.)²⁰
- In 2021, Scope 1 and Scope 2 emissions from semiconductor manufacturing were roughly 76.5 Mt CO₂e globally (0.15% of global emissions).²¹ The share of this manufacturing that related to AI is unknown, but in light of the pervasive use of semiconductors in countless products, it is likely not significant.

The literature on greenhouse gas emissions from AI is growing.²²⁻²⁴ Unfortunately, no clear, uniform standards exist for measuring greenhouse gas emissions from AI systems. Improved measurement standardization and more research are needed to provide precise and confident estimates of current emissions.

(iii) Future greenhouse gas emissions from AI

Future greenhouse gas emission from computing operations for AI depend on a number of factors, including:

- 1) the processes used to manufacture AI computing equipment,
- 2) the energy efficiency of AI computing equipment,
- 3) optimization techniques used to reduce the size of AI models and make training them more efficient,
- 4) the use of zero carbon electricity in AI operations, and
- 5) demand for AI applications.

Projecting most of these five variables over the medium- to long-term is very challenging. Each is discussed below.

- 1) **Manufacturing AI equipment.** The demand for hardware related to AI is likely to grow significantly in the years ahead. That could lead to an increase in greenhouse gas emissions from manufacturing AI hardware, although energy efficiency improvements have the potential to slow that increase and renewable-power deployment has the potential to reverse the increase. With sufficient deployment of low-carbon power, greenhouse gas emissions from manufacturing AI hardware could fall even as demand grows.²⁵
- 2) **Energy efficiency of computation.** Between 2015 and 2021, data center workload increased by 260% while data center energy use increased by only 10%.²⁶ If such improvements

continue, they would help to significantly limit AI's greenhouse gas footprint. Studies of power usage effectiveness (PUE) at data centers suggest significant continued energy-efficiency improvements are possible.²⁷ In 2020, average PUE (defined as the ratio of total energy use at a data center divided by the energy used by its computing equipment) across the industry was 1.58, while newer data centers demonstrated PUEs of 1.1. More efficient and higher-performing computational equipment such as tensor processing units (TPUs) offer the promise of continued energy-efficiency improvements as well.²⁸⁻³⁰ More radical design concepts, such as analog-AI chips, may also result in major improvements in energy efficiency.³¹

- 3) **AI model improvement.** Historically, advances in ML model architectures (such as sparse models versus dense models) have reduced computation needs by 5–10 times while improving quality. Significant work is underway to further improve model architectures, such as by reducing the size and improving efficiency with techniques such as pruning, low-rank factorization, quantization and knowledge distillation.^{28, 32} Whether these improvements outpace the growth in demand for AI is uncertain.
- 4) **Use of low-carbon electricity.** Electricity for data centers is the single largest source of energy consumption related to AI. Many operators of large data centers are committed to the use of low-carbon electricity and have committed to achieving net-zero emissions.³³ However achieving those commitments could be difficult due to a number of factors, including land-use constraints, inadequate transmission infrastructure, permitting delays and the cost of energy storage. The ability of data-center operators to use 24/7 low-carbon electricity in the years ahead will vary from jurisdiction to jurisdiction and will have a significant impact on greenhouse gas emissions from AI.
- 5) **Demand for AI.** Between 2017 and 2022, companies' demand for AI applications more than doubled.²⁵ Total AI-related private investment grew 18 times from 2013 to 2021.³⁴ Many forecasters predict that AI will grow dramatically in the years ahead—at compound annual growth rates in the range of 20–40% or more.³⁵⁻³⁷

Each of the factors above will have a material impact on greenhouse gas emissions from computing operations for AI in the years ahead. The range of uncertainty with respect to each of them is significant. If demand for AI increases at an exponential rate in the years ahead but energy efficiency, model improvements and/or renewable power deployment proceed slowly, greenhouse gas emissions could be quite large. If AI grows slowly and energy efficiency, model improvements and/or renewable-power deployment proceed rapidly, greenhouse gas emissions from computing operations from AI could be modest. Many intermediate scenarios are possible as well.

(iv) Conclusion

Widening the aperture to include the greenhouse gas impacts of AI applications and broad societal impacts of AI, the uncertainties become even greater.

There is significant potential for the overall greenhouse gas benefits of AI to exceed its costs. This could happen, for example, if strategies for minimizing emissions from AI succeed and some of the emissions-reducing applications of AI discussed in this roadmap deliver significant results. However,

the opposite is possible as well. AI could increase greenhouse gas emissions if strategies for reducing emissions from AI fail and applications of AI that increase emissions overwhelm beneficial applications, such as those discussed in this roadmap.

Rigorous analysis of the broad sweep of AI's impact on greenhouse gas emissions will require further research, as well as better data and assessment methodologies than exist today.¹⁵

REFERENCES

1. Ninareh Mehrabi, et al., *A survey on bias and fairness in machine learning*. ACM computing surveys (CSUR), 2021. **54**(6): p. 1-35, <https://doi.org/10.48550/arXiv.1908.09635>.
2. Lindsey Andersen. *Artificial Intelligence in International Development: Avoiding Ethical Pitfalls*. 2019. Published by Princeton University Journal of Public and International Affairs; Available from <https://jpiia.princeton.edu/news/artificial-intelligence-international-development-avoiding-ethical-pitfalls>.
3. Ramit Debnath, et al., *Harnessing human and machine intelligence for planetary-level climate action*. npj Climate Action, 2023. **2**(1): p. 20, <https://doi.org/10.1038/s44168-023-00056-3>.
4. Md. Aktaruzzaman Pramanik, et al. *Modeling Traffic Congestion in Developing Countries Using Google Maps Data*. (2021). Advances in Information and Communication; pgs. 513-531. Cham: Springer International Publishing; https://doi.org/10.1007/978-3-030-73100-7_36.
5. Jacob Sweet. *Would You Drive an Extra Five Minutes to Save the Planet?* 2023. Published by The Atlantic; Available from <https://www.theatlantic.com/technology/archive/2023/08/google-maps-eco-mode-driving-efficiency/674904/>.
6. Marius Bartmann, *The Ethics of AI-Powered Climate Nudging—How Much AI Should We Use to Save the Planet?* Sustainability, 2022. **14**(9): p. 5153, <https://www.mdpi.com/2071-1050/14/9/5153>.
7. Carnegie Endowment for International Peace. *AI Global Surveillance Technology*. Accessed September 2023. Available from <https://carnegieendowment.org/publications/interactive/ai-surveillance>.
8. Cade Metz. *Researchers Poke Holes in Safety Controls of ChatGPT and Other Chatbots*. 2023. Published by The New York Times; Available from <https://www.nytimes.com/2023/07/27/business/ai-chatgpt-safety-research.html>.
9. Jonathan M. Gitlin. *Hacking street signs with stickers could confuse self-driving cars*. 2017. Published by ArsTechnica; Available from <https://arstechnica.com/cars/2017/09/hacking-street-signs-with-stickers-could-confuse-self-driving-cars>.
10. Ami Daniel. *The Impact Of Retraining AI In Vertical Software*. 2023. Published by Forbes; Available from <https://www.forbes.com/sites/forbestechcouncil/2023/02/22/the-impact-of-retraining-ai-in-vertical-software>.
11. Belle Lin. *AI Is Generating Security Risks Faster Than Companies Can Keep Up*. 2023. Published by The Wall Street Journal: Cybersecurity; Available from <https://www.wsj.com/articles/ai-is-generating-security-risks-faster-than-companies-can-keep-up-a2bdedd4>.
12. US Cybersecurity and Infrastructure Security Agency (CISA). *Critical Infrastructure Sectors*. Accessed September 2023. Available from <https://www.cisa.gov/topics/critical-infrastructure-security-and-resilience/critical-infrastructure-sectors>.
13. International Energy Agency (IEA). *Data Centres and Data Transmission Networks*. Accessed September 2023. Available from <https://www.iea.org/energy-system/buildings/data-centres-and-data-transmission-networks>.
14. Lynn H. Kaack, et al., *Aligning artificial intelligence with climate change mitigation*. Nature Climate Change, 2022. **12**(6): p. 518-527, <https://doi.org/10.1038/s41558-022-01377-7>.
15. Peter Henderson, et al., *Towards the systematic reporting of the energy and carbon footprints of machine learning*. J. Mach. Learn. Res., 2020. **21**(1): p. Article 248, <https://doi.org/10.48550/arXiv.2002.05651>.

16. Sawdah Bhaimiya. *ChatGPT may be the fastest-growing consumer app in internet history, reaching 100 million users in just over 2 months, UBS report says.* 2023. Published by Business Insider: Markets Insider; Available from <https://markets.businessinsider.com/chatgpt-may-be-fastest-growing-app-in-history-ubs-study-2023-2>.
17. Rohit Shewale. *32 Detailed ChatGPT Statistics — Users, Revenue and Trends.* 2023. Published by Demandsage; Available from <https://www.demandsage.com/chatgpt-statistics/>.
18. Alexandra Sasha Luccioni, Sylvain Viguier, and 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>.
19. 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>.
20. P. M. Forster, et al., *Indicators of Global Climate Change 2022: annual update of large-scale indicators of the state of the climate system and human influence.* Earth Syst. Sci. Data, 2023. **15**(6): p. 2295-2327, <https://www.doi.org/10.5194/essd-15-2295-2023>.
21. Maxime Pelcat. *GHG emissions of semiconductor manufacturing in 2021.* 2023. Univ Rennes, INSA Rennes, CNRS, IETR – UMR 6164, F-35000 Rennes (hal-04112708v1), https://hal.science/hal-04112708v1/file/semiconductor_ghg.pdf.
22. Renee Cho. *AI's Growing Carbon Footprint.* 2023. Published by Columbia Climate School: State of the Planet; Available from <https://news.climate.columbia.edu/2023/06/09/ais-growing-carbon-footprint/>.
23. U. Gupta, et al. *Chasing Carbon: The Elusive Environmental Footprint of Computing.* (2021). pgs. 854-867. 2021 IEEE International Symposium on High-Performance Computer Architecture (HPCA). <https://www.doi.org/10.1109/HPCA51647.2021.00076>.
24. Eric Masanet, et al., *Recalibrating global data center energy-use estimates.* Science, 2020. **367**(6481): p. 984-986, <https://www.doi.org/10.1126/science.aba3758>.
25. Quantum Black AI by McKinsey. *The state of AI in 2022—and a half decade in review.* 2022. Available from <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review>.
26. Ciaran Flanagan. *How Data Centers Are Driving The Renewable Energy Transition.* 2023. Published by Forbes; Available from <https://www.forbes.com/sites/siemens-smart-infrastructure/2023/03/13/how-data-centers-are-driving-the-renewable-energy-transition/?sh=1396b0fb4214>.
27. Meredith Fowlie. *Data Centers Are Booming.* 2023 Published by Energy Institute Blog by the Energy Institute at Haas (University of California (UC) Berkeley); Available from <https://energyathaas.wordpress.com/2023/10/09/data-centers-are-booming/>.
28. D. Patterson, et al., *The Carbon Footprint of Machine Learning Training Will Plateau, Then Shrink.* Computer, 2022. **55**(7): p. 18-28, <https://www.doi.org/10.1109/MC.2022.3148714>.
29. Ashish Dandekar. *8 power usage effectiveness (PUE) best practices for your data center.* 2011. Published by Computer Weekly; Available from <https://www.computerweekly.com/tip/8-power-usage-effectiveness-PUE-best-practices-for-your-data-center>.
30. Antonella Gina Fleitas. *What Is Data Center PUE? Defining Power Usage Effectiveness.* 2023. Published by Data Center Knowledge; Available from <https://www.datacenterknowledge.com/sustainability/what-data-center-pue-defining-power-usage-effectiveness>.
31. S. Ambrogio, et al., *An analog-AI chip for energy-efficient speech recognition and transcription.* Nature, 2023. **620**(7975): p. 768-775, <https://doi.org/10.1038/s41586-023-06337-5>.
32. Leonie Monigatti. *Towards Green AI: How to Make Deep Learning Models More Efficient in Production.* 2023. Published by Medium; Available from <https://towardsdatascience.com/towards-green-ai-how-to-make-deep-learning-models-more-efficient-in-production-3b1e7430a14>.
33. Emma Chervek. *Hyperscaler sustainability scorecard: Rating Google's, Microsoft's and AWS' environmental strategies.* 2023. Published by SDxCentral; Available from <https://www.sdxcentral.com/articles/analysis/hyperscaler-sustainability-scorecard-rating-google-microsoft-and-aws/2023/07/>.

34. Nestor Maslej, et al. *Artificial Intelligence Index Report 2023*. 2023. Stanford University Human-Centered Artificial Intelligence (HAI), https://aiindex.stanford.edu/wp-content/uploads/2023/04/HAI_AI-Index-Report_2023.pdf.
35. Fortune: Business Insights. *Artificial Intelligence Market Size, Share & COVID-19 Impact Analysis, By Component (Hardware, Software/Platform, and Services), By Function (Human Resources, Marketing & Sales, Product/Service Deployment, Service Operation, Risk, Supply-Chain Management, and Others (Strategy and Corporate Finance)), By Deployment (Cloud and On-premises), By Industry (Healthcare, Retail, IT & Telecom, BFSI, Automotive, Advertising & Media, Manufacturing, and Others), and Regional Forecast, 2023-2030*. 2023. Available from <https://www.fortunebusinessinsights.com/industry-reports/artificial-intelligence-market-100114>.
36. Grand View Research. *Artificial Intelligence Market Size, Share & Trends Analysis Report By Solution, By Technology (Deep Learning, Machine Learning), By End-use, By Region, And Segment Forecasts, 2023 - 2030*. Available from <https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market>.
37. Bloomberg. *Generative AI to Become a \$1.3 Trillion Market by 2032, Research Finds*. 2023. Available from <https://www.bloomberg.com/company/press/generative-ai-to-become-a-1-3-trillion-market-by-2032-research-finds/>.

Chapter 11: **POLICY**

David Sandalow

Government policies with respect to artificial intelligence (AI) are evolving rapidly. Policymakers around the world are considering a range of topics with respect to AI including security, bias, privacy, job displacement and international competitiveness.

AI policy began to receive considerable attention 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. Important developments included:

- a White House report on *Preparing for the Future of Artificial Intelligence* (2016),¹
- China State Council's *Artificial Intelligence Development Plan* (2017),²⁻⁴
- the European Union's *General Data Protection Regulation* (2018),⁵ and
- the *OECD AI Principles*, issued by the Organization for Economic Cooperation and Development (OECD) (2019).⁶



The release of ChatGPT in fall 2022 focused extraordinary public attention on AI, leading to unprecedented interest from policymakers. The text box at the end of this chapter summarizes recent AI policy developments in key jurisdictions around the world.

This chapter examines policies that specifically address the use of AI for climate mitigation. Few such policies have been adopted to date. Some general AI policies have implications for climate change, and some climate change policies will be implemented using AI, but policies specifically designed to promote or manage the use of AI in climate mitigation are only beginning to emerge. Against that mostly blank slate, this chapter explores two questions:

1. What policy tools could governments use to promote the use of AI for climate mitigation?
2. What policies could governments use to manage risks related to the use of AI for climate mitigation?

These questions are discussed below.

A. Promoting use of AI for climate mitigation

Barriers to the use of AI for climate mitigation include those related data, people, computing power, cost and institutions. (See Chapter 9.) Government policies could help overcome barriers in all these areas.

(i) Data

Data issues can be a significant barrier to the use of AI for climate mitigation. Such issues can include the absence of data, the failure to digitize data, the lack of standardized or harmonized data, and shortfalls in funding for data collection and management.

Governments can play an important role in addressing these challenges.

Possible measures include:

- collecting, curating and hosting climate-related data;
- funding the collection and hosting of climate-related data by others;
- convening task forces or similar groups to encourage the collection, standardization and harmonization of climate-related data;
- adopting regulations that encourage or require the collection, standardization and harmonization of climate-related data; and
- addressing the global digital divide, which limits the creation of relevant data relevant to billions of people worldwide.



Governments already collect and host significant amounts of data related to climate change. The European Space Agency, US National Aeronautics and Space Administration (NASA), Japan Meteorological Agency and China Meteorological Administration, for example, all collect and host large amounts of historical and current weather data. Multilateral organizations, including the World Meteorological Organization, do the same. Several government programs, including the European Space Agency's Climate Change Initiative and NASA's Climate Data Service focus specifically on ways that weather data can contribute to understanding of climate change.

Government agencies collect other types of data related to climate mitigation as well. NASA collects data on forest loss.⁷ The Japan Meteorological Agency collects data on sea-level rise.⁸ Hundreds of cities around the world collect traffic data.⁹ Most national governments—as well as the World Bank, International Monetary Fund (IMF) and OECD—collect economic data.¹⁰

Governments often support the collection of climate-related data sets with grants, procurement or other spending. Many universities, for example, rely on government grants for data collection and analysis with respect to climate change. The US, EU, Japanese and Chinese governments,

among others, provide extensive grant funding for climate change and clean-energy research, which often involves data collection.¹¹⁻¹³

Governments can also play a central role in promoting standardization and harmonization of data for climate mitigation.

First, governments can establish policies that emphasize the importance of standardization and harmonization of climate data. These policies could include:

- data management guidelines, such as the “FAIR Guiding Principles” (Findability, Accessibility, Interoperability and Reusability) proposed by a diverse group of stakeholders in 2016;¹⁴
- data standardization and harmonization requirements in connection with government-funded research and development (R&D);
- measures to ensure transparency, including access to metadata and core data; and
- funding for data standardization organizations and activities.

Examples of such data standardization policies today 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”¹⁵; and
- the European Space Agency’s Climate Change Initiative Data Standards, which set forth requirements “to ensure consistency, harmonization and ease of use” of varied climate data sets.¹⁶

Second, governments can participate in standardization bodies and initiatives focused on data for climate mitigation. By joining international organizations—such as the International Standards Organization—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 the adoption of these standards by industries and organizations. One example is 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.”¹⁷

Third, governments can foster collaboration and knowledge-sharing among stakeholders, thereby promoting standardization and harmonization of climate-related data. The UK Energy Data Task Force is a good example. Established in 2019 as a collaboration between government, industry and academia, the Task Force develops standards and best practices with respect to data quality, interoperability and data sharing protocols in the energy sector.¹⁸ Similarly, Global Open Data for Agriculture and Nutrition (GODAN) is an international initiative that promotes the use of open data in the agriculture and nutrition sectors. GODAN brings together governments, organizations and individuals to advocate for data standardization, sharing and interoperability.¹⁹

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.²⁰ That significantly limits the creation of data on a range of topics relevant to climate mitigation, including energy usage, travel patterns and more. Connecting people to high-speed Internet has far-reaching benefits for economic development, of course, and should be pursued for many reasons far more immediate than creating useful data for AI-climate applications. Steps that governments can take include investing in broadband infrastructure in remote and underserved areas; establishing public wifi hotspots in community centers, libraries and schools; and launching digital literacy training programs to teach basic digital skills.²¹

(ii) People

One of the principal barriers to the use of AI for climate mitigation is a lack of trained personnel. Not only are trained data scientists and engineers in short supply, but many professionals working on climate issues lack basic familiarity with AI issues.

Governments could help overcome these barriers in several ways.

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, modeled after Marshall Scholarships, Schwarzman Scholarships and similar 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.²²⁻²⁴

Third, governments could pay for the education of university students learning skills related to the use of AI for climate mitigation. In some countries, paying the tuition and living expenses of university students developing such skills could help significantly to 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 can 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 with respect to AI developments. This could be especially beneficial for grant managers, to ensure government funds are disbursed with an up-to-date understanding of AI's potential and attention to AI-related data management practices.



Sixth, governments could commit extra funds to recruit and retain 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. The lack of adequate computing power can be a barrier limiting the ability to pursue valuable AI projects related to climate change. 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 computing infrastructure and (2) making computing infrastructure available for projects that use AI for climate change mitigation.

Governments already play an important role in this regard. Within the US Department of Energy (US 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—including baselining, simulations and projections—in part using AI tools.²⁵⁻²⁷

As opportunities to use AI for climate mitigation grow in the years ahead, the role of governments in helping provide computing power for such opportunities will be important. Many climate change-related AI projects will have large potential public benefits but little, if any, near-term commercial return. (Examples include projects that analyze satellite data to identify deforestation

and traffic data to help minimize congestion.) Investing in such projects is a classic governmental function.

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 (i) solicit proposals for projects that use AI for climate change mitigation and then (ii) 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,²⁸ 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.²⁹

(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 the use of 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. Other governments may prioritize greenhouse gas (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 targeting maximum emissions reduction—could have a significant impact.³⁰

Governments also have an important role in making sure 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.³¹

(v) Institutions

A final barrier to the deployment of AI for climate mitigation is institutional.

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” wasn’t coined until 1981. Until the 1980s, few large organizations had executives solely responsible for information and communications technologies in their top leadership teams.³²

In a similar manner, despite significant recent advances in AI, many institutions are only beginning to incorporate AI into their organization and mission. A range of steps to do so are possible. For governmental organizations with responsibility for climate change mitigation, including environment and energy ministries, such steps could include:

- creating an Artificial Intelligence Office, with responsibility for assessing opportunities, barriers and risks with respect to AI in all aspects of the ministry’s mission;³³
- hiring a Special Advisor to the Minister or Cabinet Secretary, with responsibility for advising the Minister on all matters related to AI;
- creating a unit to improve AI skills throughout the organization; and/or
- launching a strategic planning process to consider ways that topics related to AI can best be addressed within the ministry on an ongoing basis.

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, international cooperation could also pay dividends. The Clean Energy Ministerial could launch an initiative on the use of AI in promoting clean energy. The World Meteorological Organization could launch a program to reconcile potentially contradictory GHG emissions data using AI tools. (See Chapter 3.) Other international fora could launch work programs in this area as well.

B. Managing risks

Risks related to the use of AI for climate mitigation include those related to bias, privacy and increased emissions. Government policies can play an important role in helping manage each of these risks.

(i) Bias

Unrepresentative data, poorly-designed algorithms and other factors create risks of bias in many AI applications. These biases can affect siting recommendations, suggesting (for example) that new polluting infrastructure be located in low-income communities and new electric vehicle (EV) charging infrastructure be located in high-income communities, in part because that’s where such infrastructure is found in existing data sets. AI modes 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.

Governments can address these risks with a range of tools.

- **Data collection standards.** Governments could set 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
- **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

(ii) Privacy

As set forth in Chapter 10, privacy risks related to the use of AI for climate mitigation include surveillance, personal identification and data sharing. First, the 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 European Union's General Data Protection Regulation (GDPR) is the strongest such law passed globally to date.
- **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 of the models.
- **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.

(iii) Greenhouse gas (GHG) emissions

As set forth in Chapter 10, AI systems consume energy and, therefore, create a risk of increased GHG emissions. A number of policies can help mitigate this risk and lower GHG emissions from AI systems.

- **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 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 and (3) guidelines and incentives for energy-efficient data centers, accelerating the adoption of energy-efficient cooling, energy-management systems and other technologies.
- **Energy consumption disclosures.** Governments could require AI companies to disclose GHG emissions associated with their operations on a full lifecycle basis.
- **Government procurement.** Governments can prioritize AI systems with low GHG emissions when procuring AI solutions for their own use.
- **Carbon pricing.** Governments can implement carbon taxes or cap-and-trade systems to incentivize a wide range of companies, including AI and data center operators , to reduce their GHG emissions.

AI POLICIES IN BRIEF

as of November 2023

UNITED STATES

The Biden administration has devoted considerable attention to AI. Leading announcements 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;³⁴
- the *AI Risk Management Framework*, released by the National Institute for Standards and Technology (NIST) in January 2023 to help “manage risks to individuals, organizations, and society associated with artificial intelligence;”³⁵ and
- the *Blueprint for an AI Bill of Rights*, released by the White House in October 2022 to guide the 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.³⁶

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.³⁷ The National Artificial Intelligence Initiative Office, part of the White House Office of Science and Technology Policy, coordinates the federal government’s National AI Initiative.³⁸

Members of the US Congress have been paying attention as well, with high-profile hearings and briefings, as well as bills introduced on a number of AI-related topics.³⁹ Legislation to date has focused on the use of AI within the federal government. This includes:

- the Advancing American AI Act of 2022, which defines principles for government use of AI;
- the AI Training for the Acquisition Workforce Act of 2022, which requires AI training for government acquisition employees;
- the National AI Initiative Act of 2020, which established the National Artificial Intelligence Initiative Office and directed NIST to develop the AI Risk Management Framework; and
- the AI in Government Act of 2020, which created the AI Center of Excellence within the General Services Administration (GSA) and directed the Office of Management and Budget (OMB) to develop guidance on AI for federal agencies.⁴⁰

EUROPEAN UNION

As of November 2023, the European Parliament, European Commission and Member State governments were in negotiations concerning an Artificial Intelligence Act that would comprehensively regulate AI in Europe. If enacted, the legislation would apply a risk-based approach to AI, with high-risk AI systems subject to the most stringent controls. Drafts of the AI Act include provisions prohibiting some activities considered to be especially risky, such as live

facial recognition and scraping biometric data from social media platforms. Final action is expected in late 2023 or early 2024.^{41, 42}

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.⁴³⁻⁴⁷

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 Union⁴⁸ 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.^{49, 50}

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 China “reflect socialist core values” and prohibit content that “may harm national security and hurt the national image.”⁵¹

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.⁵² 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. These include:

- *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.”⁵³
- *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.^{54, 55}

JAPAN

In their May 2023 meeting in Hiroshima, Japan, G7 heads of state agreed to launch an initiative to strengthen collaboration on the governance of generative AI. The initiative will be known as the “Hiroshima AI process.”⁵⁶ Also in May 2023, the Japanese government held the first meeting of its Artificial Intelligence Strategy Council, attended by Prime Minister Fumio Kishida.⁵⁷

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, including:

- “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”^{58, 59}

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”⁶⁰

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.”^{61, 62} In February 2023, the Indian government announced the establishment of three new Centers of Excellence for Artificial Intelligence.⁶³

In 2021, Nitii Ayog published a Responsible AI/AlforALL 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 7. Protection and Reinforcement of Positive Human Values.”⁶⁴ 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.⁶⁵ The Indian Government maintains an AI website at <https://indiaai.gov.in/>.^{66, 67}

REFERENCES

1. National Science and Technology Council Executive Office of the President. *National Science and Technology Council Report: Preparing for the Future of Artificial Intelligence* 2016. Available from <https://publicintelligence.net/white-house-preparing-artificial-intelligence/>.
2. Graham Webster, et al. *Full Translation: China's 'New Generation Artificial Intelligence Development Plan'* 2017. Available from <https://www.newamerica.org/cybersecurity-initiative/digichina/blog/full-translation-chinas-new-generation-artificial-intelligence-development-plan-2017/>.
3. International Research Center for AI Ethics and Governance. *Beijing Artificial Intelligence Principles*. Accessed September 2023. Available from <https://ai-ethics-and-governance.institute/beijing-artificial-intelligence-principles/>
4. Matt Sheehan. *Beijing's Approach to Trustworthy AI Isn't So Dissimilar from the World's*. 2021. Published by Macro Polo; Available from <https://macropolo.org/beijing-approach-trustworthy-ai/?rp=e>.
5. Ben Wolford. *What is GDPR, the EU's new data protection law?* Accessed September 2023. Published by General Data Protection Regulation (GDPR.EU); Available from <https://gdpr.eu/what-is-gdpr/>.
6. Organisation for Economic Co-operation and Development (OECD) AI. *OECD AI Principles overview* Accessed September 2023. Available from <https://oecd.ai/en/ai-principles>.
7. Kate Ramsayer. *Global Forest Cover, Loss, and Gain 2000-2012*. 2023. Published by NASA Scientific Visualization Studio; Available from <https://svs.gsfc.nasa.gov/11393>.
8. Japan Meteorological Agency. *Sea level (around Japan)*. 2023. Available from https://www.data.jma.go.jp/gmd/kaiyou/english/sl_trend/sea_level_around_japan.html.
9. Data World. *Traffic Datasets*. Accessed September 2023. Available from <https://data.world/datasets/traffic>.
10. University of California (UC) San Diego. *Economics: Country Statistics & Data Sources*. 2023. Available from <https://ucsd.libguides.com/econguide/countrydata>.
11. Environmental Protection Agency (EPA). *Climate Change Research Grants*. Accessed September 2023. Available from <https://www.epa.gov/research-grants/climate-change-research-grants>.
12. Earth and Environmental Systems Modeling (EESM). *DOE Announces Funding for Climate Resilience Centers*. 2022. Available from <https://climatedmodeling.science.energy.gov/news/doe-announces-funding-climate-resilience-centers>.
13. National Institutes of Health. *Funding Opportunities: Notice of Special Interest (NOSI): Climate Change and Health NOT-ES-22-006*. Accessed September 2023. Available from <https://www.nih.gov/climateandhealth#funding-opportunities>.
14. Mark D. Wilkinson, et al., *The FAIR Guiding Principles for scientific data management and stewardship*. *Scientific Data*, 2016. **3**(1): p. 160018, 10.1038/sdata.2016.18.
15. Deutsches Institut für Normung (DIN). *Second edition of the German Standardization Roadmap AI*. Accessed September 2023. Available from <https://www.din.de/en/innovation-and-research/artificial-intelligence/ai-roadmap>.
16. The European Space Agency (ESA) Climate Office. *ESA CCI data standards*. Accessed September 2023. Available from <https://climate.esa.int/en/explore/esa-cci-data-standards/>.
17. Sophia Antipolis. *ETSI IoT conference: standards are key to achieving green and digital transformation*. 2023. European Telecommunications Standards Institute (ETSI); Available from <https://www.etsi.org/newsroom/news/2258-etsi-iot-conference-standards-are-key-to-achieving-green-and-digital-transformation>.
18. GOV.UK. *Energy Data Taskforce* 2019. Available from <https://www.gov.uk/government/groups/energy-data-taskforce>.
19. Global Open Data for Agriculture and Nutrition (GODAN). *Harnessing Open Data to Achieve Global Food Security*. Accessed September 2023. Available from <https://www.godan.info/>.
20. Landry Signé. *Fixing the global digital divide and digital access gap*. 2023. Published by Brookings Institution; Available from <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.
21. Digital Development Partnership and World Bank Group. *Launch of the Guinea-Bissau Digital Economy Diagnostic*. 2022. Available from <https://www.digitaldevelopmentpartnership.org/index.html?ddp=news-10-11-01>.
 22. US Department of State. *Fellowships*. Accessed September 2023. Available from <https://www.state.gov/subjects/fellowships/>.
 23. Marshall Scholarships. *Homepage*. Accessed September 2023. Available from <https://www.marshallscholarship.org/>.
 24. Schwarzman Scholars. *Homepage*. Accessed September 2023. Available from <https://www.schwarzmanscholars.org/>.
 25. Anne M. Stark. *Earth System Grid Federation launches effort to upgrade global climate data system*. 2022 Published by Lawrence Livermore National Laboratory (LLNL); Available from <https://www.llnl.gov/archive/news/earth-system-grid-federation-launches-effort-upgrade-global-climate-data-system>.
 26. *ESGF: Supporting Climate Research Collaboration*. Accessed September 2023. Available from <https://computing.llnl.gov/projects/esgf-supporting-climate-research-collaboration>.
 27. US Department of Energy (DOE). *Digital Climate Solutions Inventory*. Accessed September 2023. Available from https://www.energy.gov/sites/default/files/2022-09/Digital_Climate_Solutions_Inventory.pdf.
 28. Microsoft AI. *AI for Earth*. Accessed September 2023. Available from <https://www.microsoft.com/en-us/ai/ai-for-earth>.
 29. 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* 2023. Available from <https://www.anl.gov/article/us-department-of-energy-incite-program-seeks-proposals-for-2024-to-advance-science-and-engineering>.
 30. Peter Clutton-Brock, et al. *Climate Change and AI: Recommendations for Government Action*. 2021. Global Partnership on AI (GPAI), Climate Change AI, and Centre for AI & Climate, <https://www.gpai.ai/projects/climate-change-and-ai.pdf>.
 31. World Economic Forum, BloombergNEF, and 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.
 32. Jonathan Huer. *A Brief History of the CIO*. 2018. Educase Review; Available from <https://er.educause.edu/articles/2018/8/a-brief-history-of-the-cio>.
 33. *Artificial Intelligence and Technology Office*. Accessed September 2023. Available from <https://www.energy.gov/ai/artificial-intelligence-technology-office>.
 34. The White House. *Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence*. 2023. Available from <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/>.
 35. National Institute of Standards and Technology (NIST) Information Technology Laboratory (ITL). *AI Risk Management Framework*. Accessed September 2023. Available from <https://www.nist.gov/itl/ai-risk-management-framework>.
 36. The White House. *Blueprint for an AI Bill of Rights: Making Automated Systems Work for the American People*. Accessed September 2023. Available from <https://www.whitehouse.gov/ostp/ai-bill-of-rights/>.
 37. The White House. *FACT SHEET: Biden-Harris Administration Secures Voluntary Commitments from Leading Artificial Intelligence Companies to Manage the Risks Posed by AI* 2023. Available from <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/>.
 38. AI.gov. *National Artificial Intelligence Initiative*. Accessed September 2023. Available from <https://www.ai.gov/>.

39. Ritchie Torres. *U.S. Rep. Ritchie Torres Introduces Federal Legislation Requiring Mandatory Disclaimer for Material Generated by Artificial Intelligence*. 2023. Available from <https://ritchietorres.house.gov/posts/u-s-rep-ritchietorres-introduces-federal-legislation-requiring-mandatory-disclaimer-for-material-generated-by-artificial-intelligence>.
40. Hadrien Pouget and Matt O'Shaughnessy. *Reconciling the U.S. Approach to AI*. 2023. Published by Carnegie Endowment for International Peace; Available from <https://carnegieendowment.org/2023/05/03/reconciling-u.s.-approach-to-ai-pub-89674>.
41. Wilson Sonsini Goodrich & Rosati. *10 Things You Should Know About the EU Artificial Intelligence Act*. 2023. Available from <https://www.wsgr.com/a/web/5mGbBqgzQyQoCFJz72ZYCC/10-things-eu-artificial-intelligence-act.pdf>.
42. The Artificial Intelligence Act. *Homepage*. Accessed September 2023. Available from <https://artificialintelligenceact.eu/>.
43. European Commission. *DIRECTIVE OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL on adapting non-contractual civil liability rules to artificial intelligence (AI Liability Directive)*. 2022. Available from https://commission.europa.eu/system/files/2022-09/1_1_197605_prop_dir_ai_en.pdf.
44. European Parliament. *Artificial intelligence liability directive*. 2023. Available from [https://www.europarl.europa.eu/RegData/etudes/BRIE/2023/739342/EPRS_BRI\(2023\)739342_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/BRIE/2023/739342/EPRS_BRI(2023)739342_EN.pdf)
45. Giorgio Olivi and Chiara Bocchi. *Regulating AI in EU: three things that you need to know, and three reasons why you have to know them!* 2023. Published by Dentons; Available from <https://www.dentons.com/en/insights/articles/2023/february/1/regulating-ai-in-eu-three-things-that-you-need-to-know>.
46. European Institute of Public Administration. *An In-Depth Look at the EU's AI Regulation and Liability Directive*. 2023. Available from <https://www.eipa.eu/blog/an-in-depth-look-at-the-eus-ai-regulation-and-liability/>.
47. Simon Bollans. *EU Artificial Intelligence Liability Directive*. 2023. Published by Stephenson Harwood; Available from <https://www.shlegal.com/insights/eu-artificial-intelligence-liability-directive#:~:text=The%20AI%20Liability%20Directive%20would,alleged%20to%20have%20caused%20damage>.
48. European Commission. *Coordinated Plan on Artificial Intelligence*. Accessed September 2023. Available from <https://digital-strategy.ec.europa.eu/en/policies/plan-ai>.
49. European Parliament. *The impact of the General Data Protection Regulation (GDPR) on artificial intelligence*. 2020. Available from [https://www.europarl.europa.eu/RegData/etudes/STUD/2020/641530/EPRS_STU\(2020\)641530_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/STUD/2020/641530/EPRS_STU(2020)641530_EN.pdf).
50. European Commission. *A European approach to artificial intelligence*. Accessed September 2023. Available from <https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence>.
51. Latham and Watkins Privacy and Cyber Practice. *China's New AI Regulations (Client Alert Commentary)*. 2023. Available from <https://www.lw.com/admin/upload/SiteAttachments/Chinas-New-AI-Regulations.pdf>.
52. Liu Caiyu. *Draft AI law to be reviewed by China's top legislature*. 2023. Published by People's Daily Online; Available from <http://en.people.cn/n3/2023/0609/c90000-20029571.html>.
53. China Law Translate. *Provisions on the Administration of Deep Synthesis Internet Information Services*. 2022. Available from <https://www.chinalawtranslate.com/en/deep-synthesis/>.
54. China Law Translate. *Provisions on the Management of Algorithmic Recommendations in Internet Information Services*. 2022. Available from <https://www.chinalawtranslate.com/en/algorithms/>.
55. Matt Sheehan. *China's AI Regulations and How They Get Made*. 2023. Published by Carnegie Endowment for International Peace. Available from <https://carnegieendowment.org/2023/07/10/china-s-ai-regulations-and-how-they-get-made-pub-90117#:~:text=Over%20the%20past%20two%20years,Al%20systems%20like%20OpenAI's%20ChatGPT>.
56. Kazuaki Nagata. *G7 aims to beef up collaboration for AI governance*. 2023. Published by The Japan Times. Available from <https://www.japantimes.co.jp/news/2023/05/21/business/generative-ai/>.

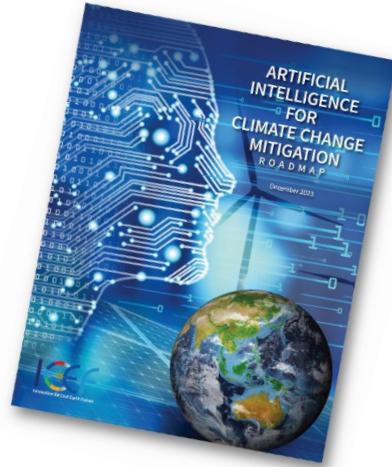
57. "Japan's Artificial Intelligence Strategy Council Holds 1st Meeting with Aim to Create Rules for AI Use," *The Japan News* (May 11, 2023). Available from <https://japannews.yomiuri.co.jp/politics/politics-government/20230511-109145/>.
58. Japanese Cabinet Office. *AI Strategy 2022*. 2022. Available from <https://www8.cao.go.jp/cstp/ai/aistratagy2022en.pdf>.
59. 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*. 2023. Available from https://www.taira-m.jp/ldp%e2%80%99s%20ai%20whitepaper_etrans_2304.pdf.
60. Technology and Innovation Policy Cabinet office Secretariat of Science, Government of Japan. *AI Strategy 2022*. 2022. Available from https://www8.cao.go.jp/cstp/ai/aistratagy2022en_ov.pdf.
61. Manish Singh. *India opts against AI regulation*. 2023. Published by TechCrunchAvailable from <https://techcrunch.com/2023/04/05/india-opts-against-ai-regulation/>.
62. Indian Bureaucracy. *AI will be kinetic enabler of India's Digital Economy says Rajeev Chandrasekhar*. 2023. Available from <https://www.indianbureaucracy.com/ai-will-be-kinetic-enabler-of-indias-digital-economy-says-rajeev-chandrasekhar/>.
63. Verdict.co.uk. *India: AI centers of excellence will boost the start-up ecosystem*. 2023. Available from <https://www.verdict.co.uk/india-ai-centers-of-excellence/>.
64. Government of India: NITI Aayog. *Responsible AI: #AIFORALL*. 2021. Available from <https://www.niti.gov.in/sites/default/files/2021-02/Responsible-AI-22022021.pdf>.
65. Government of India: NITI Aayog. *National Strategy for AI Discussion*. 2018. Available from <https://niti.gov.in/sites/default/files/2019-01/NationalStrategy-for-AI-Discussion-Paper.pdf>.
66. Umesh Rathod. *AI policies across the world: Key lessons for India*. 2023. Published by Forbes India; Available from <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>.
67. Jibu Elias. *AI for All: How India is carving its own path in the global AI race*. 2023. Published by Organisation for Economic Co-operation and Development (OECD) AI; Available from <https://oecd.ai/en/wonk/india>.

Chapter 12:

FINDINGS AND RECOMMENDATIONS

A. Findings

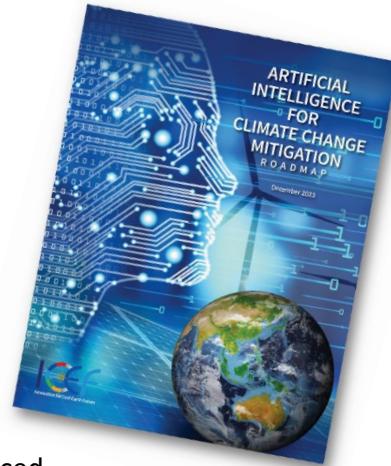
1. **Artificial intelligence is currently contributing to climate change mitigation in important ways.** AI tools play a central role in monitoring methane emissions and deforestation; in integrating solar and wind power into electric grids; in improving the energy efficiency of industrial operations; in optimizing agricultural practices to reduce emissions and increase yields; and much more.
2. **Artificial intelligence has the potential to make significant additional contributions to climate change mitigation in the years ahead.** Areas in which artificial intelligence could make significant contributions include greenhouse gas emissions monitoring; decarbonization of the power sector; the discovery of novel materials; and reducing emissions from manufacturing, the food system and road transport.
3. **Artificial intelligence is not a panacea when it comes to climate change.** Significant changes beyond the scope of artificial intelligence will be required to achieve net zero emissions. AI does not build infrastructure, move molecules or shift supply chains. While emissions reduction from the use of AI may be substantial, these savings alone cannot deliver deep decarbonization.
4. **The lack of trained and experienced personnel is a critical barrier to the use of AI for climate mitigation.** More computer programmers and data engineers with the skills to create AI applications for climate mitigation are needed. Equally important, policymakers, business leaders, factory operators, climate professionals and many others need greater familiarity with the potential for AI to contribute to their work and risks posed by AI.
5. **The lack of access to high-quality data is a critical barrier to the use of AI for climate mitigation.** Successful AI applications are built on data that is available, accessible, and standardized. Poorly measured and non-standardized data will limit the quality of AI development, while private ownership and the cost of accessing data will limit the scale of AI deployment. In addition, current limits of data gathering may introduce bias to AI analyses and conclusions. Strong policy, investment in education, and public sector action will be needed to overcome these barriers.



6. **Other barriers to the use of AI for climate mitigation include cost, lack of available computing power and institutional issues.** More resources are needed for training programs, RD&D 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 NGOs – are only beginning to incorporate AI into their operations and organizational structures.
7. **Significant resources—by governments, corporations 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.
8. **Risks of using AI include bias, invasions of privacy and security issues. These risks exist when using AI for climate mitigation.** Bias in AI data and algorithms can lead to injustice, failure to achieve program objectives, unneeded expense and many other harmful outcomes. Failures to build in privacy safeguards can lead to unauthorized data sharing, personal identification and surveillance. Negligence or misuse of AI technologies can lead to accidents and serious security problems.
9. **Greenhouse gas emissions from the computing infrastructure for AI are currently modest – significantly less than 1% of the global total.** Better data collection and assessment methodologies are needed to provide a more precise estimate with high confidence.
10. **The amount of future greenhouse gas emissions from AI computing infrastructure is highly uncertain.** Such emissions could rise or fall in the years ahead. Future greenhouse gas emission from computing operations for AI depend on a number of factors, including: (i) the processes used to manufacture AI computing equipment, (ii) the energy efficiency of AI computing equipment, (iii) optimization techniques used to reduce the size of AI models, (iv) the use of zero carbon electricity in AI operations, and (v) demand for AI applications. Each of these is highly uncertain.

B. Recommendations

1. **Artificial intelligence tools should be integrated into many aspects of climate change mitigation.** Government agencies should use AI tools in policy making and funding decisions. Businesses should use AI tools in sustainability programs. All institutions with a role in climate mitigation should examine opportunities for AI to support their mission and identify priority areas in which AI could contribute.
2. **AI skills-development and capacity-building should be a priority in all institutions with a role in climate mitigation.**
 - A. **Educational institutions at all levels should offer courses relevant to AI.** This should include basic skills development in primary and secondary schools, more advanced courses in universities and continuing education for professionals of all kinds. Academic institutions should develop classes, internships, certification programs and executive training programs that provide familiarity with AI.
 - B. **Governments and foundations should launch AI-climate fellowship programs.** These programs should identify promising students (from developing countries in particular) and fund fellowships in AI and climate-focused topics.
 - C. **Government agencies with responsibility for climate issues should regularly review the capabilities of their staffs with respect to AI.** The goals should be to continually enhance these capabilities and ensure that opportunities for AI to advance their mission are recognized and accurately evaluated.
 - D. **All organizations working on climate 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. Training and education are essential.
3. **Governments should assist in the development and sharing of 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 forecasting, electricity generation and use, manufacturing, 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 as well as 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. The climate data task forces should start by identifying potential barriers to data access. They should plan ways to federate, share and anonymize data for AI climate applications.
4. **Companies with datasets relevant to climate change mitigation should consider sharing portions of those 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. **Governments should provide substantial funding for the development and application of AI tools for climate mitigation.**
- Government funding for AI in the climate area should 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 make emissions reduction potential using AI a priority selection criterion.
 - Governments should help increase the availability of computing power for climate change-related AI projects.** 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 the proposals that offer the greatest potential benefits. This could include solicitations from the private sector in partnership with governments.
6. **All government agencies with responsibility for climate change, including environment and energy ministries, should create an Artificial Intelligence Office, with responsibility for assessing opportunities, barriers and risks with respect to AI in all aspects of the agency's mission.** These agencies should also consider (i) hiring a Special Advisor to the head of the agency, with responsibility for advising the head on all matters related to AI, (ii) creating a unit to improve AI skills throughout the organization; and (iii) launching a strategic planning process to consider ways that topics related to AI can best be addressed within the ministry on an ongoing basis.
7. **Electric utilities should be incentivized to deploy artificial intelligence, with regulated returns for investments in AI and other tools.** Governments should provide utilities, generators and balancing authorities with financial incentives and technical support to integrate AI into grid systems. These programs should recognize the significant benefits AI tools can provide in grid planning as well as risks related to the use of AI in grid operations.
8. **Governments should launch international platforms to support cooperative work on AI for climate change mitigation.**
- One or more member countries should launch a Clean Energy Ministerial initiative on AI and climate mitigation.**

- B. **The UNFCCC, International Energy Agency and Food and Agriculture Organization, 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 to 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 Food and Agriculture Organizations (FAO) could fulfill this role for CO₂ and some other GHG emissions datasets. Alternatively, a single new, centralized organization could be set-up to serve as a one-stop clearinghouse for all AI-enabled GHG emissions data.
9. **Governments should work to minimize greenhouse gas emissions from AI's computing infrastructure.** This should include (i) investing in RD&D on energy-efficient AI algorithms and hardware; (ii) requiring reporting on GHG emissions in all government-funded AI work; (iii) prioritizing AI systems with low greenhouse gas emissions when procuring AI solutions; (iv) promoting data centers that emit little or no carbon dioxide through a range of measures including regulations, guidelines and/or financial incentives, (v) establishing standardized methods for measuring emissions from AI; (vi) requiring AI companies to disclose greenhouse gas emissions associated with their operations, on a full lifecycle basis; and (vii) implementing ambitious climate programs that incentivize all companies, including AI and data center operators, to reduce their greenhouse gas emissions.
10. **Avoiding unfair bias should be a core, high-priority principle guiding the development of all AI tools for climate change mitigation.** Businesses, governments, and researchers should continually pay attention to the possibility of data and algorithmic bias in their work. Governments should address the risk of bias with tools including (i) standards for the collection of data for AI models, highlighting the importance of diverse and representative data sets; (ii) standards with respect to transparency in the development of AI models, giving all stakeholders a better opportunity to identify possible biases; (iii) legal frameworks that hold entities accountable for biased or discriminatory outcomes resulting from AI applications; (iv) regular reviews to consider the potential for bias in all AI programs related to climate change; and (v) training programs on the importance of bias recognition and mitigation.
11. **Governments should address privacy risks related to AI-climate programs with data protection regulations, cybersecurity standards, oversight boards and techniques that make personal data less identifiable.**

This roadmap was prepared to facilitate dialogue at the Tenth Innovation for Cool Earth Forum (October 2023), for final release at COP28 in December 2023.

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.

