CLIMATE CHANGE AND AI

Recommendations for Government Action

Global Partnership on AI Report

In collaboration with Climate Change AI and the Centre for AI & Climate

GPAI

Climate Change AI

CENTRE FOR AI & CLIMATE

Climate Change & AI: Recommendations for Government
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Co-Leads Foreword

Climate change and digital transformation are the two most powerful trends of our century. The way in which we manage them, and their increasing interaction, will play a significant role in humanity's future in the 21st century and beyond. We need to create pathways to combine the climate and digital transitions in a way that upholds our social and democratic values.

Recent scientific reports, including from the IPCC[1], highlight that we are in a climate emergency. This calls for the mobilization of all actors across politics, business, science, and civil society. In this context, the rise of AI is showing promising signs of being able to support climate action. However, AI's potential to address climate change is not well understood, and it potentially carries some climate risk itself.

AI needs to be developed responsibly in all contexts. In the context of climate action, responsible AI means rejecting "techno-solutionism" and not overblowing its potential. It means not underestimating its risks and drawbacks. A growing body of evidence suggests that the least-well-resourced actors (such as those in the Global South) stand to suffer most from both climate change (they bear the brunt of climate impacts) and digital transformation-related transfers of power (loss of agency and control). Therefore, a responsible AI-for-climate strategy needs to mitigate the risks of these transitions to those least-well resourced to adapt to them.

There is a general market failure of not properly pricing the negative impacts of greenhouse gas emissions. This yields a specific market failure regarding the research, innovation and deployment of AI technologies that can help fight climate change. As such, it is essential that governments directly support the research, innovation, and deployment of these technologies.

In this context, we are calling for governments to devote targeted resources for the responsible adoption of AI for climate solutions. However, money on its own is not enough. Governments need to develop bespoke support packages that seek to improve access to relevant data and digital infrastructure, facilitate deployment in climate-relevant sectors, target research and innovation programs at key challenges in this space, and ensure the incentives in relevant industries are aligned with climate-focussed innovation. There is also a huge capacity-building challenge required to empower businesses, communities and individuals with the knowledge, tools, and skills needed for the responsible adoption of AI-for-Climate solutions. We need to mobilize more international cooperation on this, and align it with broader efforts on climate change.

[1] *Sixth Assessment Report* of the IPCC, the United Nations body of the world's leading climate scientists.

The Global Partnership on AI (GPAI) is a forum where governments and experts can come together to discuss the development of AI. In December 2020, GPAI proposed the creation of a Committee on Climate Action and Biodiversity Preservation to start to address questions regarding AI's potential to support climate action. This report represents the first output of this committee, however it is not a delivery plan and further work is needed to build on the recommendations in this report and provide details on how the recommendations can be delivered. Beyond climate change, further work is also needed to assess how AI can help preserve biodiversity, and how GPAI and its community can support work in this space.

This report is intended to help guide the action of governments of GPAI Member States and beyond about how to support the responsible adoption of AI for climate action. It is the first step of a program of activities that GPAI would support in this space that we hope would forge concrete international cooperation programs in the form of joint investment in research, development, innovation, regulation, and capacity-building.

Raja Chatila and Nicolas Miailhe

Co-Leads, Committee on Climate Action & Biodiversity Preservation

Executive Summary

Climate change is one of the most pressing issues of our time, requiring rapid action spanning many communities, approaches, and tools.[2] Artificial intelligence (AI) has been proposed as one such tool, with significant opportunities to accelerate climate action via applications such as forecasting solar power production, optimizing building heating and cooling systems, pinpointing deforestation from satellite imagery, and analyzing corporate financial disclosures for climate-relevant information.[3] At the same time, AI is a general-purpose technology with many applications across society, which means it has also been applied in ways that impede climate action both through immediate effects and broader systemic effects.[4]

In this report, we provide **actionable recommendations as to how governments can support the responsible use of AI in the context of climate change.** These recommendations were obtained via consultation with a broad set of stakeholders, and span three primary categories: (a) supporting the responsible use of AI for climate change mitigation and adaptation, (b) reducing the negative impacts of AI where it may be used in ways that are incompatible with climate goals, and (c) building relevant implementation, evaluation, and governance capabilities for and among a wide range of entities.

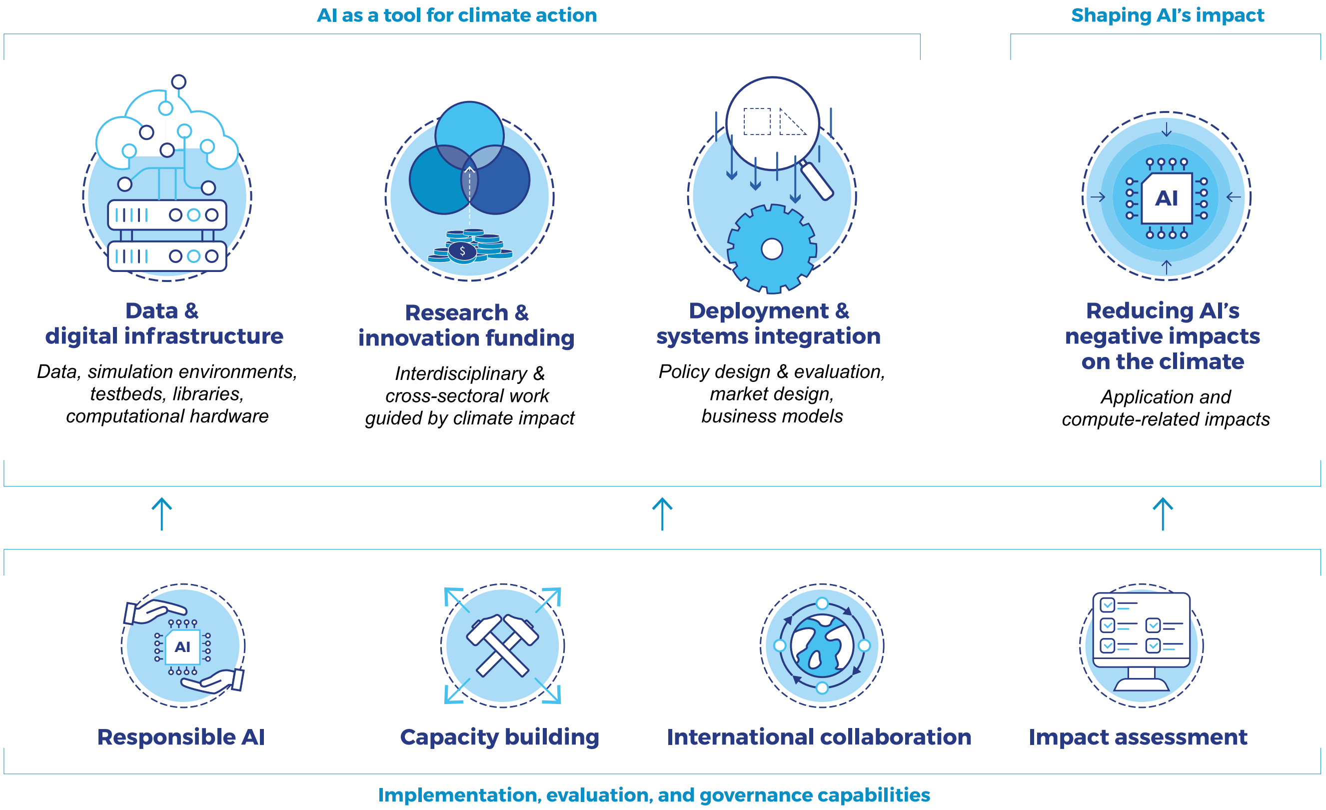
Our full list of recommendations is provided in Table E-1. To illustrate these recommendations, we additionally provide **a booklet of high-potential AI-for-climate use cases** illustrating the capabilities of AI for climate action across different sectors, and describing policy-relevant bottlenecks such use cases may face in terms of development, deployment, and scaling.

Supporting AI applications in climate change mitigation and adaptation

Given the short time scales on which society must address climate change, it will be critical that responsible climate solutions be rapidly deployed and scaled across key sectors. However, many such solutions often get stuck in research or early stages of technological readiness, and even after initial deployment, often face difficulties scaling. We propose that governments can take leadership in supporting the use of AI to address climate change by:

- Fostering the responsible development of and access to **data and digital infrastructure** — e.g., relevant data, simulation environments, testbeds, model libraries, and computational hardware — that can support the development and adoption of AI-for-climate applications.
- Targeting **research and innovation funding** to enable interdisciplinary

[2] *Special Report: Global Warming of 1.5 °C,* Intergovernmental Panel on Climate Change (2018).
[3] *Tackling Climate Change with Machine Learning,* Rolnick et al. (2019).
[4] *AI and Climate Change: How they're connected, and what we can do about it,* Dobbe and Whittaker (2019).



Areas of action for governments in supporting the responsible use of AI in the context of climate change

and cross-sectoral work at the intersection of AI and climate change that is guided by climate impact.

- Supporting **deployment and systems integration** of AI-for-climate applications via targeted policy design and evaluation, market design, and business models, including within highly-regulated sectors such as energy, transportation, agriculture, and heavy industry.

Reducing AI's negative impacts on the climate

Every application of AI affects the climate, which means aligning AI with climate change strategies involves not only facilitating beneficial applications of AI, but also shaping the space of AI overall so that business-as-usual applications are more climate-aligned. Notably, there are three principal ways in which AI can increase greenhouse gas emissions: (a) via its use for applications with immediate negative impacts on emissions, (b) via system-level impacts such as induced demand or lock-in effects associated with AI applications, and (c) via the carbon footprint associated with the life-cycle impacts of the associated software and hardware.[5] Governments can work to reduce the negative impacts of AI by **incorporating climate impact considerations into AI regulation,**

[5] *Aligning artificial intelligence with climate change mitigation*, Kaack et al. (2021, working paper).

strategies, funding mechanisms, and procurement programs.

Building implementation, evaluation, and governance capabilities

Cutting across the previous recommendations is the need to build institutional capabilities aimed at the responsible implementation, evaluation, and governance of AI in the context of climate change. Such capabilities must be built across a wide range of organizations, including governmental entities at the international, national, and local levels, as well as private and civil society organizations in climate-relevant sectors (e.g., energy, transport, heavy industry, or agriculture). We propose that governments can support the development of relevant institutional capabilities by:

- Embedding **responsible AI principles** into the design of initiatives and governance structures (e.g., those recommended in this report), which includes fostering inclusion of participants from civil society, local governments, the Global South, and marginalized groups.
- Fostering **climate-cognizant impact assessment of AI** via collection of data on AI's emissions impacts, and by establishing standard measurement and reporting frameworks.
- Building **capacity for implementation, evaluation, and governance** in the form of literacy, skills and talent, standards, tools, and best practices.

A roadmap for action

As the use of AI grows rapidly across society, it is imperative that governments be proactive in helping shape these developments with climate action in mind. Within individual countries, meaningful action on these initiatives will require **collaborations among multiple branches or arms of government** — e.g., agencies focused on AI or digitalization, agencies focused on climate change or climate-relevant sectors, standards bodies, regulators, and local governments — in addition to participation from civil society, academia, and the private sector. **Multilateral or international collaborations** — e.g., via the development of cross-functional consortia or capacity building within existing international organizations — can also prevent unnecessary duplication, facilitate knowledge sharing, and strengthen overall efforts. We hope the recommendations and enumeration of existing bottlenecks contained in this report will provide a launching point for these initiatives.

Table E-1: Summary of recommendations

Theme	Recommendations for governments
Supporting AI applications in climate change mitigation and adaptation	
Data and digital infrastructure	• Establish data task-forces in climate-critical sectors • Facilitate data creation and open data standards, where appropriate, in climate-critical industries • Rapidly create data portals to increase data access and sharing • Collaborate with GPAI member countries (and others) to fund the development of an international catalogue for open-source climate-relevant data, models, and software • Oversee the development of data collection systems and digital twins for energy, transport, and other physical infrastructure • Support cloud compute resources that are affordable for academic researchers, civil society, and small and medium enterprises
Research and innovation funding	• Ensure decisions on research and innovation funding for AI-for-climate projects are impact-driven, rather than technology-driven • Accommodate AI within wider climate "grand challenges" • Develop targeted AI-for-climate challenges where AI can offer particularly high impact results • Encourage open IP, open data, and open model development within innovation funding for AI-for-climate solutions • Develop innovation funding for AI-for-climate solutions so as to foster greater diversity and equity in the AI-for-climate community • Fund the development of research compute and simulation assets for AI-for-climate research • Deploy AI-for-climate innovation support in a manner that aligns the incentives of innovators and market incumbents • Channel primarily AI research and innovation funding, rather than climate funding, to developing energy efficient AI
Deployment and systems integration	• Embed digitalization and AI experts into governmental climate policy teams and advisor groups • Launch digital innovation pathway initiatives within industries in climate-relevant sectors • Set up and co-fund public-private investment groups with regulated industries to co-invest in startups offering digital services • Develop cross-sectoral innovation centers to incubate AI-for-climate projects and facilitate collaborations • Develop and maintain non-commercial public interest applications

Reducing AI’s negative impacts on the climate

Reducing AI’s negative impacts on the climate	• Avoid direct governmental funding of applications that run counter to climate goals • Make climate change a central consideration when fostering the development of AI-enabled technologies • Ensure that cloud compute is appropriately included in reporting and carbon pricing policies • Procure AI and compute services only from companies that have signed up to a net zero target covering scopes 1, 2, and 3

Building implementation, evaluation, and governance capabilities

Responsible AI implementation and assessment	• Establish and implement standards or best practices guiding responsible practice and participatory design of AI in climate contexts • Include participation stipends for experts and civil society participants within the budgets of governmental task forces and committees aimed at shaping AI-for-climate initiatives • Incorporate climate and environmental assessment and reporting into AI regulation and strategies more broadly
Assessing AI’s overall impacts on the climate	• Set reporting requirements, where appropriate, for the life-cycle emissions associated with the development and use of AI • Ensure funding for research in developing impact assessment methodologies and gathering relevant information • Ensure funding and capacity for impartial third party impact assessment • Set methodological standards for impact assessments at the national and international level • Facilitate availability of relevant data on compute-related greenhouse gas emissions and application impacts of AI
Capacity building	• Rapidly implement large scale AI literacy and “upskilling” programs for governments, climate-relevant industries, and civil society • Fund interdisciplinary higher education, research, and professional programs bridging AI and individual climate-relevant sectors • Incorporate elements on data and on climate, including both technical and socio-technical components, into educational curricula • Fund or facilitate secondment programs for AI experts within climate-relevant sectors • Fund or incentivize the creation of trusted AI-for-climate solutions providers and auditors • Develop and/or facilitate sharing of standards for scoping, developing, deploying, maintaining, and evaluating AI-for-climate work • Develop and employ tools and instruments for monitoring, impact assessment, benchmarking, and certification of AI-for-climate solutions, and for climate impact assessment of AI • Ensure global access to the above programs and resources across a wide variety of countries and local contexts

International collaboration	• Support knowledge sharing on policy design and implementation between governments, industries, and key stakeholders • Pool limited government RD&D resources via, e.g., coordinated funding or cross-functional consortium institutions • Bring together researchers and innovators to address common and cross-border AI-for-climate challenges • Support shared AI-for-climate capacity-building activities • Pool data for common or cross-border AI-for-climate challenges and agree on data standards internationally • Coordinate on the development and use of specific physical and digital assets to support development of AI-for-climate solutions • Coordinate government support for the development and maintenance of non-commercial public interest applications • Support existing international initiatives with the capacity to advance AI-for-climate applications • GPAI could champion the development of an international AI-for-Climate Partnership made up of governments, relevant international organizations, and a network of businesses and NGOs from both the climate and AI communities to support the coordination and delivery of international AI-for-climate work

Introduction

CASE STUDIES

Throughout the text, we will provide brief snapshots of case studies illustrating opportunities and bottlenecks in the space of AI and climate change. Full descriptions of these case studies are available at the end of the report.

Climate change is one of the most pressing issues of our time. Its impacts are already being felt globally and promise to grow exponentially, with disproportionate consequences for the world's most marginalized communities.[6] Tackling climate change requires action from across society, spanning many communities, approaches, and tools.[7]

Artificial intelligence (AI) is one such tool, with significant opportunities to accelerate strategies for climate change mitigation and adaptation, across areas such as energy, land use, and disaster response (see *Key Areas*). However, there currently exist a number of bottlenecks and challenges that impede AI from realizing its full potential in this regard.

In this report, we aim to provide an actionable set of recommendations for what governments can do to facilitate AI for climate impact. We discuss broader considerations for the *responsible use* of AI in a climate context, then consider bottlenecks and policy levers in *data and digital infrastructure*, *research and innovation funding*, and *deployment and systems integration*. While our primary focus is on applications of AI to support climate action, we note that AI is a general-purpose tool that can also be applied in ways that impede climate action. There is a role for governments in helping align the broader use of AI with climate goals, by taking steps to *reduce negative impacts of AI* and via holistic *impact assessment* of AI from a climate perspective. To conclude our recommendations, we consider how to build *capacity* and *international collaboration* at the intersection of AI and climate change. The report closes with a set of short case studies on highly impactful AI-for-climate projects, with a discussion of what bottlenecks can be alleviated to catalyze the further growth of such work.

Our report is designed to provide actionable insights for governmental entities at the local, national, and international levels in shaping policy both in AI and in climate-relevant domains. We believe our recommendations will be of interest to GPAI member countries, as well as those outside of GPAI.

It is worth noting that we focus strictly on the intersection of AI with climate action, which is already a very broad topic. There are numerous uses of AI in advancing sustainability more generally,[8] as well as many points of intersection between other digital technologies and climate change.[9] Both of these topics, however, extend beyond the scope of this report.

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[6] *Climate Change 2021: The Physical Science Basis,* Intergovernmental Panel on Climate Change, Working Group I (2021)..

[7] *Special Report: Global Warming of 1.5 °C,* Intergovernmental Panel on Climate Change (2018).

[8] *Computational Sustainability: Computing for a better world and a sustainable future,* Gomes et al. (2019).

[9] See e.g. *Digital technology and the planet,* The Royal Society (2020) and *Computing research for the climate crisis,* Bliss et al. (2021).

Methodology

This report was authored by members of Climate Change AI (CCAI) and the Centre for AI & Climate (CAIC) with the close consultation of GPAI. CCAI and CAIC are nonprofit organizations focused on facilitating impactful work at the intersection of climate change and AI. The structure of the report drew on the authors' own prior work in this space, as well as that of other experts (see *Further Reading*). A preliminary set of key points was drafted and presented for feedback at a stakeholder workshop including 50 experts representing a diversity of geographies, sectors, and areas of expertise (see *Acknowledgments*). Featured case studies were sourced via an open call, which was filtered and supplemented by the authors with a focus on high Technology Readiness Level and diversity across sectors and geographies. Throughout the revision process, the writing was overseen by a Steering Group of the GPAI Committee on Climate Action & Biodiversity Preservation under the GPAI Responsible AI Working Group; and the draft was presented for feedback at relevant GPAI working groups and committees. These various experts offered iterative suggestions and additions to the draft report, which the authors revised repeatedly.

Introduction to AI

Artificial intelligence encompasses any computer algorithm that makes predictions, recommendations, or decisions on the basis of a defined set of objectives.[10] AI methods can loosely be divided into symbolic approaches, which rely on predefined rules and logic to derive results, and statistical approaches, which rely on induction from data rather than deduction from rules. Both approaches can be powerful depending on the setting; however, the recent growth of AI in effectiveness and popularity is due largely to a branch of statistical AI known as machine learning (ML). Throughout this report, most AI techniques referenced will fall under the category of machine learning.

In an ML algorithm, the exact nature of the computations performed is not specified in advance, but instead is "learned" by the algorithm by identifying patterns within the data, which can then be used to make predictions on new data. Thus, an ML algorithm might learn from thousands of labeled satellite images to identify which patterns constitute trees, and would be able to identify the trees if given a new set of satellite images without labels.

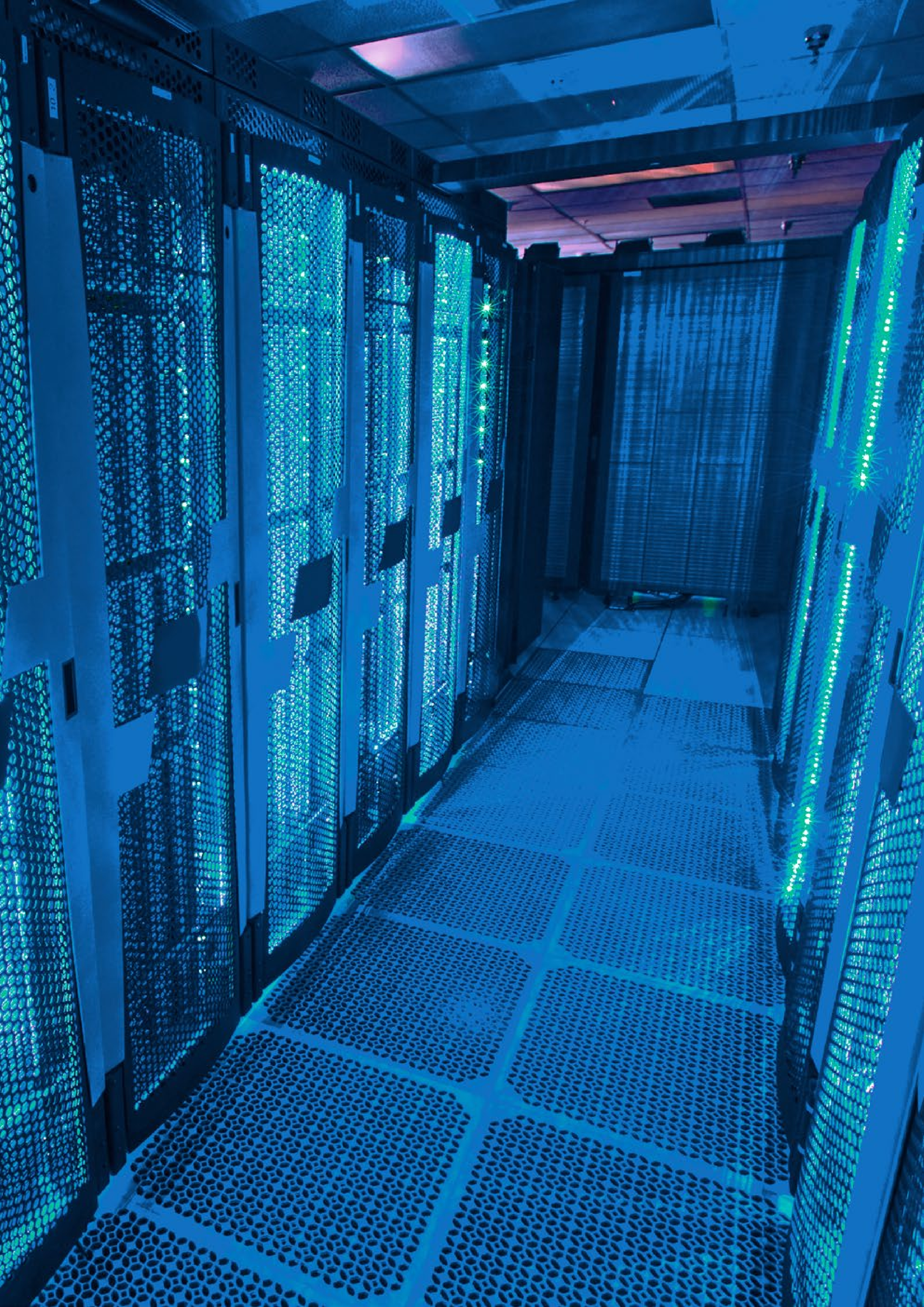
ML algorithms can perform extremely well on certain kinds of problems. Generally, these are problems for which large amounts of data are available and where the answer involves finding correlations between the solution and subtle patterns within the data. This makes ML good at automating various tasks that humans would find easy (such as picking out the forested areas in a satellite image), as well as solving problems where there is more data than a human would be able to wrap their head around (such as identifying the settings needed to control

[10] *OECD AI Principles,* OECD AI Policy Observatory (2019).

industrial equipment with the least possible energy).

The weak points of ML algorithms are also instructive. They find patterns in the data they are given, which means they generally fail or find only spurious correlations if the data they have learned from is inaccurate, biased, or skewed towards certain situations or contexts. Current ML methods are also generally unable to solve problems requiring broader conceptual understanding or creativity. And ML methods are also often inapplicable for problems where it is necessary to "show one's work" - many machine learning algorithms in particular are "black boxes" where the answer appears without much explanation of why it is true, or of how uncertain the answer is.

Recent years have seen many breakthroughs in ML and other AI algorithms, leading to a rapid growth in their adoption across society. Besides the climate-relevant applications we detail in the following section, other areas where AI is being adopted widely include text correction and translation, image tagging, robotics, healthcare, advertising, and finance.



Key areas where AI can facilitate climate action

Key AI capabilities for climate

There are several key themes for how AI can accelerate climate action:

Distilling raw data into actionable information. AI can identify useful information within large amounts of unstructured data, often by scaling up annotations that humans could provide more laboriously. For example, AI can analyze satellite imagery in order to pinpoint deforestation or identify areas of cities vulnerable to coastal inundation, or can filter large databases of corporate financial disclosures for climate-relevant information.

Improving predictions. AI can use past data to predict what will happen in the future, sometimes also incorporating auxiliary information. For example, AI can provide minute-level forecasts of solar power generation to help balance the electrical grid, or predictions of agricultural yield as extreme weather threatens food security.

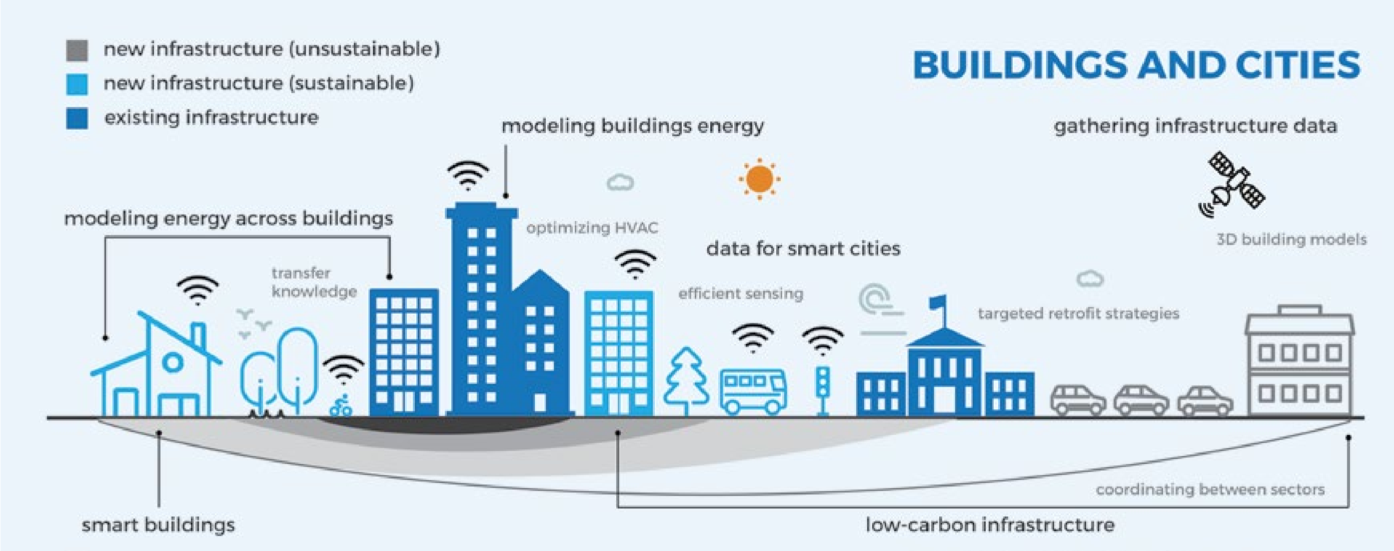
Optimizing complex systems. AI methods are good at optimizing for a specific objective given a complicated system with many variables that can be controlled simultaneously. For example, AI can be used to reduce the energy needed to heat and cool a building, or to optimize freight transportation schedules.

Accelerating scientific modeling and discovery. AI can accelerate the process of scientific discovery itself, often by blending known physics-based constraints with approximations learned from data. For example, AI can suggest promising candidate materials for batteries and catalysts to speed up experimentation, and can quickly simulate portions of climate and weather models to make them more computationally tractable.

Key AI applications within relevant sectors

Having summarized the overall roles that AI can play within strategies for climate change mitigation and adaptation, we now provide a sector-by-sector high-level overview of some of the specific applications by which AI can achieve climate impact. Most of these applications are the subject of active development, and many are already beginning to be deployed. For a more detailed treatment of numerous specific applications of AI in climate action, and recommendations on especially high-leverage applications, see work by Climate Change AI and the citations therein.[11]

[11] *Tackling Climate Change with Machine Learning,* Rolnick et al. (2019).



Selected AI-for-climate applications within buildings and cities.
Figure reproduced with permission from Tackling Climate Change with Machine Learning (Rolnick et al. 2019)

Electricity systems.[12] AI can enable significant emissions reductions in electricity systems, across a wide range of applications. To balance power grids efficiently, and thereby enable the integration of large amounts of renewables, it is essential to forecast both electricity supply and demand, a function that AI can provide. AI can also improve algorithms for electricity scheduling and storage, as well as management of microgrids in areas with decentralized systems. AI can improve the operations of renewable energy generators such as wind turbines and solar panels, and can pinpoint methane leaks in natural gas pipelines. AI is also being used to accelerate discovery of new energy-relevant materials, such as those used in photovoltaic cells, batteries, and electrofuels.

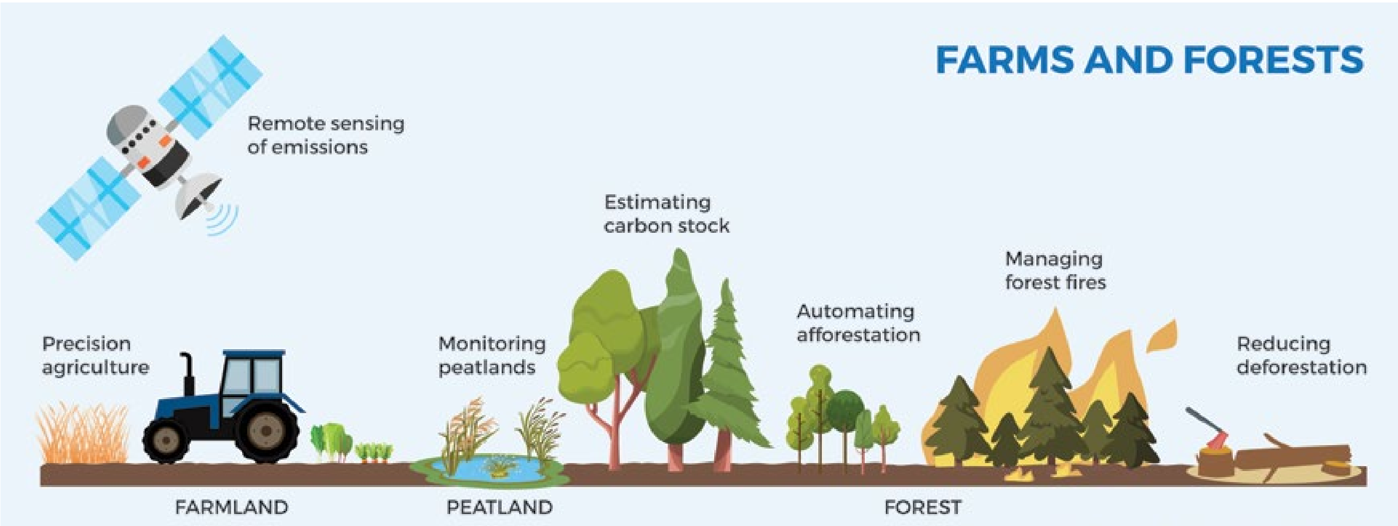
Buildings and cities. AI can increase the efficiency of energy use in buildings and urban environments. In cases where certain data on the built environment has not been collected, AI can be used to label infrastructure in satellite imagery. AI can infer energy use from building properties, as well as interpreting data from smart meters. Within smart buildings, AI can optimize building functions such as heating and lighting to conserve energy. For city-scale optimization, AI can be used in soft sensor systems and data mining. AI can also help cities with waste management to reduce methane emissions associated with landfill and wastewater.

Transportation. AI can help decarbonize transportation in many ways. AI can improve

[12] See also: *Harnessing Artificial Intelligence to Accelerate the Energy Transition*, World Economic Forum (2021).

estimates of transportation usage, as well as model demand for public transportation and infrastructure. AI can optimize freight routing and scheduling, and can increase utilization of low-carbon options such as trains. To advance the adoption of electric vehicles, AI can optimize charging protocols and locations, as well as informing the design of batteries and next-generation fuels. AI is also an integral part of autonomous vehicle technologies, though the climate impacts here are uncertain: self-driving personal vehicles may increase emissions by making driving easier, while autonomous buses could decrease emissions by pooling passengers and integrating with public transportation.

Heavy industry and manufacturing. AI can reduce emissions associated with heavy industry in numerous ways. AI can be used in adaptive control and process optimization to reduce the energy consumed by industrial processes, as well as in demand response to schedule such processes to reduce emissions intensity. AI-enabled predictive maintenance and digital twins can also boost efficiency and in some cases reduce leaks of greenhouse gases such as methane. Increasingly, AI is being used in the discovery of materials such as catalysts, which may reduce the energy needs of certain chemical processes. AI can also help optimize recycling processes and waste sorting for energy-intensive materials such as aluminum and steel, which can help avoid emissions associated with mining and processing virgin material.



Selected AI-for-climate applications within agriculture, forestry, and other land use.
Figure reproduced with permission from Tackling Climate Change with Machine Learning (Rolnick et al. 2019)

Agriculture. AI can support both mitigation and adaptation efforts in agriculture. Precision agriculture involves the use of AI in automated tools that are responsive to variability within a crop, offering the potential for increased efficiency and reduced greenhouse gas emissions associated with agricultural chemicals and land use. (It is worth noting that incentives in agriculture are not always aligned with GHG emissions reduction, though there can be significant overlap.) From the standpoint of adaptation, remote sensing tools for crop monitoring and yield prediction can advance food security in the face of droughts and other extreme weather.

Forestry and other land use. AI can facilitate responsible land use practices and nature-based solutions for carbon sequestration, in several ways. AI tools are being used together with satellite imagery in carbon stock estimation for informing land management decisions and for calculating carbon offsets. AI is also being used to help track deforestation and other land use changes, as well as in drones to accelerate afforestation. There are also numerous uses of AI in predicting the risk and spread of wildfires.

Climate science. AI can advance models of climate, weather, and other Earth systems. It can help provide data for such models by calibrating sensors or by inferring properties such as ice cover from raw data like satellite imagery. AI can also provide fast approximations to certain physics simulations within climate and weather models that would otherwise be prohibitively time-intensive to run. Such approximate simulations can be useful both in improving overall models and in increasing the spatial resolution at which they can practically be run, thereby providing more localized predictions of risk.

Societal adaptation. AI can aid in societal resilience to the effects of climate change. AI tools can pinpoint vulnerable locations and target infrastructure improvements where they are most needed, as well as enabling predictive maintenance to avert failures. Methods from AI for healthcare can improve public health models as well as societal response to climate-influenced pandemics and other diseases. In the event of disasters such as storms, floods, and fires, AI can inform relief efforts by improving maps and identifying at-risk individuals.

Ecosystems and biodiversity. AI can support biodiversity preservation in the face of a changing climate. AI methods are increasingly being incorporated into sensors used to monitor wildlife, remote sensing tools for assessing ecosystem change, and recognition systems used to identify species from visual or audio data. AI is also beginning to be used in parsing ecological information, for example from citizen science databases.

Climate policy. Many of the above applications of AI can be valuable for policymaking by providing data useful in informing policy decisions. However, AI can also inform climate policy in other ways. AI can be incorporated in models used for assessing policy options, and can also be used in causal inference to help assess the efficacy of policies that have been executed.

Markets and finance. AI can be used within markets and finance in ways aligned with climate action. In carbon markets, AI can provide data such as carbon stock estimation to inform pricing, as well as forecasting prices and analyzing factors driving these prices. In non-carbon markets, AI can be used to analyze and model behavior patterns to align market design with climate impact. AI can also inform insurance and financial policy by quantifying climate-associated risks and parsing climate-related corporate disclosures.

Responsible AI in the context of climate change

While AI has great potential to enable climate mitigation and adaptation strategies, it also comes with many pitfalls and risks that are inextricably connected with the opportunities. This leads to the need for the responsible development, deployment, and governance of AI in the context of climate change.[13] The considerations detailed below are vitally important to ensuring ethical research and deployment; they are relevant throughout the rest of the report and should be a central consideration for any policies adopted on this topic.

Important considerations

AI is a means, not an end: AI is a tool, not an end goal, and the way we use it — and whether we use it — should fundamentally be informed by problems and societal contexts which we are trying to address. Careful attention should also be given to the problem framing, recognizing AI as a component of solutions and not a solution in and of itself.

AI can have both positive and negative impacts on climate and the environment: AI has a multi-faceted relationship with climate change and the environment, through both its compute-related impacts (including energy use and life-cycle hardware impacts) and those impacts, both positive and negative, relating to how it is used.[14] It is important to quantify and consider both negative and positive impacts when shaping the development and use of AI, both within and outside of climate change contexts. (See also: *Assessing Overall Impacts*.)

AI's relationship to equity and climate justice: Climate change cannot be addressed without addressing colonialism, racism, and global power structures. Notably, the frameworks of climate equity and climate justice acknowledge that the harms of climate change are unevenly distributed and that equitable participation in climate change strategies is required. With this in mind, it is worth noting that the use of AI may centralize power among those select institutions and entities with the knowledge and resources to develop and deploy it, and otherwise exacerbate the digital divide.[15] It is important that AI be leveraged

[13] See also: *Areas for Future Action in the Responsible AI Ecosystem,* The Future Society in collaboration with the GPAI Responsible Development, Use and Governance of AI Working Group and CEIMIA (2020).
[14] *Aligning artificial intelligence with climate change mitigation,* Kaack et al. (2021, working paper).
[15] *Decolonial AI: Decolonial Theory as Sociotechnical Foresight in Artificial Intelligence,* Mohamed et al. (2020).

in ways that address, rather than widen, societal inequities — e.g., through choice of problems and stakeholders addressed.

Avoiding techno-solutionism, greenwashing, and diversion: AI is not a silver bullet — it is not always applicable, and there is a real danger that it may distract or divert resources from less "flashy" tools or approaches. AI should only be employed in places where it is actually needed and truly impactful.

Considerations shared across many areas of applied AI: Many principles of responsible AI — such as fairness and equity, accountability, safety, privacy, security, and robustness — are common across areas of application, and are each already the subject of extensive policy recommendations.[16,17,18] The forms these principles take within climate-relevant contexts are, however, noteworthy. For instance, avoiding implicit and explicit biases is highly relevant in cases where data may be available only for certain parts of the world — an AI model trained using data on buildings from the US may not apply to buildings in India, or may perform poorly. Safety considerations are particularly important in contexts such as power grids and industrial operations where errors can have serious consequences, or where digitalization may impose new cybersecurity risks. Explainability is also especially relevant in these contexts to mitigate barriers operators and policymakers may have to trusting the outputs of AI systems. Equity and justice considerations are often overlooked in collecting large datasets, including undervaluing or exploiting human labor, or framing a problem without stakeholder consultation.

Responsible AI is not a one-off consideration: The implementation and evaluation of the responsible AI considerations detailed above must be a continuous, rather than a one-off, process. Notably, these considerations should be a central and continued part of scoping, developing, deploying, and maintaining AI and AI-for-climate projects to ensure that projects are well-founded and that no new harms or unintended consequences arise later on the project lifecycle.

[16] *Outcome document: first draft of the Recommendation on the Ethics of Artificial Intelligence*, UNESCO (2020).
[17] *Draft NIST Special Publication 1270: A Proposal for Identifying and Managing Bias within Artificial Intelligence*, National Institute of Standards and Technology (2021).
[18] *Trustworthy AI*, Chatila et al. (2021).

RECOMMENDATIONS

- **Establish and implement standards and/or best practices guiding the responsible practice and participatory design of AI in climate contexts.** This includes standards for assessing whether AI is relevant or well-suited for a particular problem; for repeated iteration with stakeholders and impacted communities throughout problem scoping, development, deployment, and maintenance; and for auditing the impacts of solutions from the climate and broader social perspectives.[17] Such standards could, for example, be established within the context of broader initiatives on ethical and responsible AI within international bodies, professional organizations, or other contexts. This should also include locally-focused initiatives, as some aspects may vary or need tailoring to different geographical and cultural contexts.

- **Include participation stipends for experts and civil society participants within the budgets of governmental task forces and committees aimed at shaping AI-for-climate initiatives** (such as those detailed throughout the rest of this report). In particular, this can help support the participation of a wider range of stakeholders — including participants from Indigenous communities,[18] the Global South, and other marginalized communities in both local and global contexts — and help better ensure that their perspectives are fundamentally represented in the design of the AI-for-climate landscape.

- **Incorporate climate and environmental assessment and reporting into AI regulation and strategies more broadly** to better align the use of AI with global climate pathways and environmental goals. Notably, many uses of AI — even those that are not explicitly labeled as climate-relevant — have the potential for significant influence on climate mitigation or adaptation goals (e.g., targeted advertising systems that affect global patterns of consumption). Thus, the responsible use of AI involves shaping the overall use of AI technologies in a way that is cognizant of their impacts on climate change mitigation, adaptation, and climate and environmental equity (see also: *Reducing Negative Impacts* of and *Assessing Overall Impacts*).

[19] See also: *OECD Working Papers on Public Governance No. 36: "Hello, World: Artificial intelligence and its use in the public sector"*, Berryhill et al. (2019).
[20] See also: *Indigenous Protocol and Artificial Intelligence*, Indigenous Protocol and Artificial Intelligence Working Group (2020).

Data and digital infrastructure

Introduction

AI algorithms work alongside a stack of other technologies, inputs, and processes that are prerequisites to its success. These include everything from raw data, to big data processing techniques and platforms, to computational infrastructure, to a range of more domain-specific digital infrastructure. The successes AI applications have achieved in recent years are as much a function of advances in big data processing and computation as they are of fundamental advances in AI itself. While progress on data processing and compute have enabled AI in general to do more, many of the bottlenecks that are holding back the application of AI for climate specifically are related to the absence of domain-specific technologies and inputs. There is an important role for governments and international organizations in supporting the creation of this stack of prerequisites in a way that unlocks the potential that AI offers and fosters innovation in every climate related field.

Climate-relevant AI algorithms need valuable data and simulation environments. At the core of the stack of inputs for AI algorithms is data. AI algorithms learn from data. They identify relationships between variables, develop predictions, make decisions, and evaluate their performance from the data they are fed with (e.g., via fixed datasets or simulation environments). The better the data the algorithm learns from, the better the algorithm performs. For any particular application, data goes through a range of processes. It can be created, compiled, pooled with other data, stored, cleaned and labeled, used to train an AI algorithm, occasionally shared, and finally sometimes deleted. Many, if not all, of these processes need to be better supported within climate-relevant sectors (e.g. energy, transport, land-use, industry, and buildings) to facilitate AI applications.

Climate-relevant data needs to be managed responsibly. Data needs to be collected, shared, and governed in a way that maintains trust and is appropriately cognizant of privacy and security. Certain data that is relevant for climate applications can be highly sensitive from a privacy perspective. There is a risk that if AI projects in the climate space are irresponsible with data access or handling, they may undermine trust in AI within climate-relevant sectors. In addition, open data ecosystems should be designed in a way that respects the needs and interests of the communities from which data is derived, particularly in the case of historically marginalized or minoritized communities.[19]

Data is often unequally distributed, as there is more capacity for gathering it in certain sectors and geographies than others. Data collection infrastructure and funding in lower income and traditionally under-represented countries tends

[21] *CARE Principles for Indigenous Data Governance,* The Global Indigenous Data Alliance (2019).

to be less developed, which risks exacerbating inequities in access to AI solutions as well as bias in the AI algorithms themselves.[20] Data is also more available in sectors where there are the strongest incentives to collect it. As a result, we see greater adoption in finance and adtech, and lower uptake in sectors where there are conventionally fewer incentives for adoption, including many climate related areas. The unequal distribution can also lead to bias in the algorithms.

Beyond data, there is a need for non-commercial, public-interest digital infrastructure to support the adoption of AI-for-climate applications. In some circumstances, there is a role for the public sector to support the development of models and platforms that facilitate wider adoption of AI-for-climate applications. This is likely to be highly sector-specific. Such digital infrastructure might include data portals, model libraries, digital twins and data trusts.

Affordable access to increasingly powerful compute will unlock AI-for-climate applications. Computing and big data processing have been improving substantially over the last decade and have enabled the implementation of large-scale AI applications that have emerged. Increasingly, data scientists working in the climate space are using cloud compute services, which have improved rapidly. But, the affordability of compute services also is not equal across sectors/geographies. While there are a few compute-heavy climate-relevant applications where advances in compute technologies might unlock advances (such as large scale simulations of physical systems and molecular level simulation for climate-relevant material science), these represent a minority. The more important issue is how to support affordable and equitable access to compute to support research and innovation in non-commercial contexts, such as among researchers and civil society.

[22] *Use and Impact of Artificial Intelligence on Climate Change Adaptation in Africa,* Rutenberg et al. (2021).

Bottlenecks

Countries and companies around the world have been realizing the importance of data and digital infrastructure, and are starting to prioritize support for their development. However in many cases modern data strategies and digital infrastructure are still nascent. This section details the key bottlenecks that are holding back greater adoption

DATA BOTTLENECKS

Data required for AI-for-climate applications often does not exist. Across all sectors identified, data is often unavailable because data collection and availability is not being incentivized by the market. Data across all climate-relevant sectors will need to be collected, including e.g. energy system topologies (where grid wires and assets are) and high resolution land use data that are needed to address some of the challenges in climate-relevant sectors. In many sectors there is a need for sensor hardware equipment to be improved and rolled out (e.g., devices to measure soil carbon quickly and easily).

Current climate-related data discovery and access is slow and inefficient. The starting point for many data science projects involves an extended process to ascertain what datasets are available and from where, whether they are publically available, and if so on what license. This process is time consuming and inefficient, and creates barriers to entry in each sector. Datasets are often held privately or are offered without license, and lack APIs, which limits the potential for achieving efficiencies by making it hard to access, combine, or link datasets from different private actors.

Climate-relevant data quality is often low and there is a lack of data standards. There are substantial costs associated in cleaning and labeling datasets to allow for them to be used by machine learning algorithms. It is often said that approximately 70-80% of time spent on machine learning projects is spent on cleaning and labeling data. The market inefficiencies caused by a lack of applied data standards results in substantial inefficiencies and often puts researchers off from working in this field.

The incentives for organizations in climate-relevant sectors to open up or share data are outweighed by the costs and risks of doing so. Opening up data can come with a range of privacy, security and reputational costs and risks, whereas often the benefits are unknown and hard to quantify. Even where there is interest in data sharing, the protocols and standards for sharing data either do not exist or are nascent.

Climate-relevant data collection is unequal. Climate-relevant data collection and hence availability for use by AI algorithms, is concentrated in the Global North, and international organizations could usefully consider supporting the development of data collection processes in lower income countries and the Global South to widen the geographic distribution of data.

Insufficient protection against the development of climate-relevant data monopolies. In many climate-relevant sectors there is a risk of some companies building up a closed monopoly of data, creating barriers to entry and so reducing competition and innovation. Regulators often do not have sufficient awareness about the risk of data monopolies, or the technical or legal capacity to understand the risks fully.

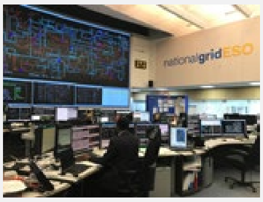
DOMAIN SPECIFIC DIGITAL INFRASTRUCTURE BOTTLENECKS

Lack of real time digital representations (e.g., digital twins) of physical systems relevant to climate action. The transition to net zero will require very significant changes to key systems (energy, transport, land use, industry, buildings, etc.). Digital representations of these systems that integrate real time data inputs could allow for both massively improved situational awareness across these systems, allowing system operators to improve system management, as well as offer opportunities to optimize these systems in real time. Such representations may also offer system designers opportunities to simulate alternative system designs and inputs to properly understand the implications of different courses of action, and how to choose the optimum system design.

Lack of climate-relevant AI model libraries. For responsible climate-specific AI applications to be developed quickly and efficiently, data scientists need to be able to learn from, compare against, and/or directly use the best available AI models in any climate-related field at that time, rather than starting from scratch for each project. At present there is neither an easy way to find existing well benchmarked climate-relevant AI models, nor the incentive for making them.

COMPUTE AND HARDWARE BOTTLENECKS

Lack of affordable scalable compute for non-commercial climate applications. While cloud compute providers have been offering some support for climate relevant applications, this support is generally low, and as a result scaling non-commercial AI applications can be challenging because the cost of compute can spiral rapidly.



CASE STUDY

National Grid ESO (UK) *has used AI to double the accuracy of its forecasts of electricity demand, enabling better integration of renewables. Improving standards for sharing data on electricity demand could enable broader adoption of such methods.* *Full description on page 73*

Image license: National Grid ESO

RECOMMENDATIONS

- **Establish data task-forces in climate-critical sectors,** including energy, transport, land-use, industry, buildings, and climate science. These task forces should establish what data is needed to support climate action, what data currently exists and is accessible (and on what license), what data standards exist and whether they are adequate, and what incentives there are for data sharing, and should propose regulations to incentivize greater data collection and sharing where needed. This can help inform government funding and regulation decisions to help address the gaps in data processes. The UK Government's Energy Data Task Force offers a successful model that could be applied more widely.[21]

- **Facilitate data creation and open data standards, where appropriate, in climate-critical industries,** with the expectation that all data should be made open except where there are privacy, security, commercial, or governance concerns that can not be mitigated. Regulators should support the development of standards and protocols for data sharing. The EU's INSPIRE Directive,[22] aimed at enabling the sharing of environmental spatial information among public sector organizations, is a good example of leadership in this space. Governments should also fund research into how best to facilitate the sharing of private data accessible via advanced encryption and other privacy-preserving measures.

- **Rapidly create data portals to increase data access and sharing:** Sectoral government data portals are an important first step. Such portals need to be able to link to and interface with other portals, have common standards across countries, and support easy access to the data required for high value climate problems. Further public-private collaboration is required to strengthen the underlying cloud infrastructure to support real time data flows (via APIs) and support a range of user interfaces for such portals. Governments can also usefully learn from Open Banking approaches and help develop and test data sharing mechanisms such as data trusts. Donor governments and international organizations should support the development and maintenance of data portals for climate-relevant sectors in lower income countries to ensure equitable access to data.

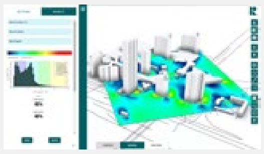
[23] *Energy Data Taskforce: A Strategy for a Modern Digitalised Energy System,* Energy Systems Catapult (2019)
[24] INSPIRE Knowledge Base: *https://inspire.ec.europa.eu*

- **GPAI member countries (and others) could collaborate to jointly fund the development of an international catalogue for open-source climate-relevant data, models and software,** which would link practitioners to datasets and data portals available from disparate sources and would offer a catalogue for AI models for climate-relevant tasks to allow projects to build on top of each other's work. See, e.g., the AI Commons initiative.[25]

- **Oversee the development of data collection systems and digital twins for energy, transport, and other physical infrastructure:** Many climate-relevant systems will need to undergo fundamental change to achieve net zero, requiring large public spending programs on safety-critical infrastructure. In a number of cases, simulation and optimization environments as such systems can inform decision makers regarding the optimal deployment of physical infrastructure in a low-risk way, thereby reducing costs and improving future syste m designs. There is a need for public-private partnerships to ensure such digital twins are developed efficiently, are accessible to innovators, and have appropriate governance to maximize their system-wide value and avoid the development of monopolies that might stifle innovation. Further work is needed to offer guidance on how digital twins in this context should be developed, governed, tested, certified, accessed and maintained.

- Governments should also work with private sector cloud compute providers to **support cloud compute resources that are affordable** for academic researchers, civil society, and small and medium enterprises.

[25] *Democratizing AI for Humanity: A Common Goal*, Banifatemi et al. (2021).



CASE STUDY

The ***InFraRed*** *project at the Austrian Institute of Technology uses AI to model the effect of urban design on the microclimate in cities, allowing simulations to run in seconds instead of hours. The impact of such methods can be boosted via standards for integration of AI tools with design platforms. Full description on* *page 83*.

Image license: InFraRed City Intelligence Lab, Austrian Institute of Technology GmbH

CASE STUDY

The ***UN Satellite Centre (UNOSAT)*** *FloodAI system delivers high-frequency flood reports, based on Copernicus satellite data, which have improved disaster response in Asia and Africa. Ensuring the availability of computational power and data storage servers to public sector players could boost the adoption of similar methods. Full description on* *page 82*.

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LI-ION BATTERY
ENERGY
Lithium ion batteries
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Research and innovation funding

Introduction

For AI to achieve its potential to accelerate action on climate change, governments need to carefully consider how best to support research and innovation within this emerging and cross-disciplinary area. Existing government research and innovation funding for AI is very occasionally relevant to climate, and research and innovation funding for climate sometimes accommodates AI-related proposals. However, despite some notable exceptions (for example in the US,[26] Sweden,[27] Austria,[28] and Germany[29]), few governments have dedicated significant funding to the intersection of these two fields.

Technology research is predominantly funded by governments through universities or research institutes, or by companies with sufficient funding to develop long-term research programs. Funding of early-stage technology **innovation** for AI and climate projects is currently offered by a combination of angel investors, venture capital firms, commercial innovation funds, philanthropic foundations and governments. Governments can add value in this space by addressing gaps in funding where financial risks have resulted in a lack of private investment, highlighting strategically important AI innovations required to meet a policy outcome or system change, and more widely in ensuring there is a supportive environment in which AI-for-climate innovations can be deployed responsibly and succeed. Support for research and innovation needs to be seen in a wider context and hence this section should be considered in connection with all the other sections in this report, but particularly the *Deployment and Systems Integration* section.

While there are significant opportunities where research and innovation funding can support the development of AI solutions that support climate action, it is important to emphasize that government funders will need to be discerning in their support. There are many instances where AI will not play a role, might be a distraction, or can come with risks to society (see e.g. the *Responsible AI* section), and funding programs have a role to provide guidance and direction regarding meaningful work in this area.

[26] *DOE Announces USD34.5 Million for Data Science and Computation Tools to Advance Climate Solutions*, US Department of Energy (April 8, 2020).
[27] AI in the service of climate, *2020 call* and *2021 call*, Vinnova, total approx. USD7.8 million
[28] *AI for Green – Ausschreibung 2021*, Austrian Ministry for Climate Action (2021), approx. USD8.2 million
[29] *Federal Ministry for the Environment publishes Five-Point-Program for environmentally and socially just AI development and application (in German)*, German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (June 23, 2021), total approx. USD170 million

Bottlenecks

Countries and companies around the world have been realizing the importance of data and digital infrastructure, and are starting to prioritize support for their development. However in many cases modern data strategies and digital infrastructure are still nascent. This section details the key bottlenecks that are holding back greater adoption of AI for climate applications.

There is a lack of integration of AI and sectoral climate-relevant research and innovation funding programs. AI-specific research funding is typically focused on AI methodological innovation and algorithmic novelty and less on the application of existing AI methods in new domains. Funding for climate action on the other hand has had little focus on AI technologies and is mostly directed through sector-specific funding channels (for low-carbon transport, energy, agriculture, etc.). Often, AI for climate-related research and innovation support falls outside the scope of these existing funding schemes, and specific financing mechanisms that can improve work in this area are scarce.

Limited prioritization within AI-for-climate research and innovation funding. There is a range of emerging academic research at the intersection between AI and all sector-specific climate fields, from the power sector to climate science. Building on existing work,[30] there remain opportunities to determine more precisely what research has already been conducted, where the important gaps are that need to be filled, and what stage of technology readiness has been achieved, as well as building coalitions of research bodies to help address these gaps.

AI-for-climate innovation funding recipients in regulated sectors may "fizzle out" if there is no route to market. Support for the deployment of AI solutions in the context of regulated climate-critical systems (e.g. electricity and transport) requires a bespoke approach. While there is significant potential for AI innovation funding to support the transition of regulated climate-critical sectors, there are challenges for innovators to work in this space. In the *Deployment and Systems Integration* section we discuss in more detail the need for innovation pathways to ensure that there are routes for digital innovators to deliver and scale revenue from their innovations. Innovation funders need to ensure that innovation support is offered as part of a wider package of support in regulated sectors to build a supportive environment for digital innovation.

[30] *Tackling Climate Change with Machine Learning,* Rolnick et al. (2019).

There is a risk that high-risk "silver bullet" funding challenges could draw limited AI talent from lower-risk "low-hanging-fruit" projects with more certain climate benefits. There are a range of "silver bullet" climate solutions that have been proposed over the years, ranging from radical new energy sources to geo-engineering projects, which are unlikely to provide feasible solutions given economic, social or time constraints. There is a risk that AI could raise similar hopes. While there are also valid cases where moonshot challenges can focus attention on critical areas of the climate challenge and advances could help unlock more rapid climate action, there is a need to ensure balance between such high profile moon-shot challenges and less "exciting" but critical innovation.

There is insufficient funding available for AI-for-climate research and innovation in lower income countries, and funding for international AI projects aimed at supporting stakeholders from the Global South is often implicitly chosen by stakeholders in the Global North. Funding provision for AI for climate, like other sectors, is dominated by higher income countries. Given the disproportionate impacts of climate change in lower income countries, and the importance of local knowledge about climate-related challenges, there is a particular need to increase AI-for-climate research and innovation funding in lower income countries and the Global South. Such funding needs to be delivered in a way that puts stakeholders from low income countries in the Global South at the center for decision making. Often, the problems that are prioritized for technology development and investment are those that are highly visible to stakeholders in the Global North, rather than problems at a similar or larger scale that primarily affect people in the Global South. For example, locust swarms are being exacerbated by climate change and are a threat to large portions of Africa, the Middle East, and South Asia, but AI solutions for monitoring and predicting their movement are often not sufficiently prioritized.[31] Furthermore, the recent availability of high resolution global satellite imagery can lead to failure modes such as well-funded teams of AI researchers in higher income countries or cities being funded to work on climate problems in lower income countries or on Indigenous lands, sometimes without local expert collaborators.

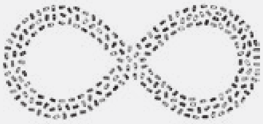
[31] *Use and Impact of Artificial Intelligence on Climate Change Adaptation in Africa,* Rutenberg et al. (2021).

RECOMMENDATIONS

- **Ensure decisions on research and innovation funding at the intersection of AI and climate are impact-driven, rather than technology-driven.** There is a risk that both funders and funding recipients pursue the use of advanced AI systems when a much simpler approach would address a problem more effectively. Governments should seek to focus on supporting projects with high impact for addressing climate change, and require justification that the approach leverages the most appropriate tools for the specific climate challenge. There is a vast amount of AI-for-climate innovation that is possible using existing AI technology without further innovation on AI methods. Funding calls should make the pathway to impact a clear and important selection criteria, require simple baseline comparisons, and welcome well-tested negative results.

- **Accommodate AI within wider climate "grand challenges."** Governments can play an important and unique role in outlining and popularizing key "grand challenges" required to support climate action, and identifying how specifically AI experts (and likewise experts from other scientific and engineering fields) can usefully apply their skills to address these challenges. Such "grand challenges" can also help foster collaboration and communication across disciplines. While there is a strong case that such innovation support should be technology-neutral and seek to support the solution that can best address the challenge (which may or may not involve AI), there is also a need to draw in digital and AI experts when designing and judging such challenges to ensure that data science and AI solutions are being judged by innovation funders that understand what they can offer.

- **Develop targeted AI-for-climate challenges where AI can offer particularly high impact results.** In addition to integrating AI into wider climate grand challenges, there are some challenges where the potential for AI to support climate action is so high that it warrants a specific challenge to bring together the AI community with that sector's community. Governments could fund or develop cross-functional multi-university research coalitions around these challenges combining AI and sector-specific researchers. Such challenges could include:
    - AI for electricity supply and demand forecasting;
    - AI for accelerated materials science, e.g., for renewable energy, electricity storage, or alternative fuels;
    - AI for carbon stock estimation from satellite imagery.



CASE STUDY

US-based startup ***Aionics*** *uses AI to provide a 10x speedup in the process of designing better batteries, a critical bottleneck to the wider adoption of electric vehicles and renewable energy. Applications of AI for accelerated materials discovery represent a "grand challenge" for which government support could be broadly catalytic.* *Full description on page 77.*

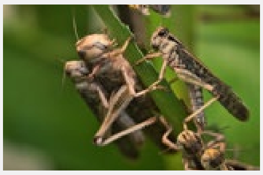
- **Innovation funding for AI-for-climate solutions should encourage open IP, open data, and open model development.** Where public money is used to support innovation at the intersection between AI and climate, there should be a presumption that the outputs generated and the methodology behind them will be made available for others to learn from so as to accelerate the wider use of such solutions.

- **Innovation funding for AI-for-climate solutions should foster greater diversity and equity in the AI-for-climate community.** This includes ensuring diverse research teams and appropriate collaboration with local knowledge experts, increasing AI-for-climate research and innovation funding in the Global South, and prioritizing problems that are relevant to stakeholders outside traditional technology and finance hubs.

- **Fund the development of compute and simulation assets for AI-for-climate research.** Many domain-specific research teams lack the digital infrastructure (compute, data management and annotation tools, etc.) to develop AI approaches, as well as test-beds and simulation environments to integrate them into climate-relevant sectors. Countries should consider developing affordable scalable compute services, either independently or in collaboration with commercial providers or other countries, to address this bottleneck and ensure these resources are made equitably available. This is discussed further in the *Data and Digital Infrastructure* section.

- **Deploy AI-for-climate innovation support in a manner that aligns the incentives of innovators and market incumbents.** There is currently a risk that government innovation grants are being spent on pilot projects that have no potential to become commercially viable because there is no available route to market. This is discussed further in the *Deployment and Systems Integration* section.

- **Channel primarily AI research and innovation funding, rather than climate funding, to developing energy efficient AI.** To address compute-related emissions impacts, the fields of AI and machine learning are increasingly working on models that are more energy efficient. Such approaches rely on cutting edge algorithmic innovation typically done by AI research groups, and such research has the potential for support through "traditional" AI funding mechanisms from the public and private sector. Before diverting resources from government-funded climate programs to this area, the value and substitutability of additional public funding in this area should be considered carefully.



CASE STUDY

Kuzi, *a tool by Kenyan company Selina Wamucii, uses AI to predict locust outbreaks, a devastating threat to farmers that has intensified with climate change. It is essential that funding in AI-for-climate be available to teams based in the Global South, and that funding priorities be defined with reference to the needs of stakeholders globally.* *Full description on page 75.*

Deployment and systems integration

Introduction

Given the short time scales on which society must address climate change, it will be critical that responsible climate solutions be rapidly deployed and scaled across key sectors. However, many such solutions **get stuck in research or early stages of technological readiness, and even after deployment, often face difficulties scaling.** In part, this is connected to the fact that many sectors relevant to climate change are heavily regulated with embedded incumbents, thereby creating integration challenges.

Policy and market designs play a critical role in supporting, slowing down, or even blocking AI-for-climate deployments in key climate-relevant sectors. As systems, markets, and incentives are updated to support the transition to net zero, it is critical that these policy and regulatory updates properly accommodate a wide suite of tools and approaches, including AI and digital innovation within climate-relevant sectors. However, as climate policy development is complex with a wide array of stakeholders, there is a risk that policymakers do not always fully understand the potential that AI and digital innovation offers to support the transition in these sectors, as well as how policy and regulatory changes could support such innovation. In particular, **AI-driven solutions often face a unique set of challenges** — such as a need for large quantities of high-quality data, and potential and/or perceived reliability concerns — that create new industry challenges, and must be accommodated within policy and regulatory designs.

Business models, playbooks, and value chains for AI are also needed in key climate-relevant sectors to foster deployment and integration. However, such business models are nascent, and there are often many barriers preventing companies that are developing AI solutions from sharing the value of their work with incumbent industries interested in adopting them. For instance, tech companies (who can offer AI solutions) and incumbent companies in climate-relevant sectors (who have access to industry data and the infrastructure to deploy solutions) offer naturally complementary sets of skills and resources for AI-for-climate projects. However, both sets of entities often have stringent requirements surrounding in-house ownership of intellectual property, leading to difficulties forming collaborations between these entities in practice.

In formulating new policy designs, market designs, and business models, it is worth noting that **some climate-relevant sectors have higher barriers to entry than others.** In particular, sectors with highly regulated markets (e.g., energy, transportation, agriculture and heavy industry), where incentives are set in regulation or legislation (due to a range of safety, monopoly, or environmental concerns), often have the highest barriers to entry for innovators. There has also been a disparity in the extent to which different sectors have focused on addressing integration challenges, often due to a combination of capital, incentives, and reliability considerations. For example, there has been more discussion of how to integrate digital solutions into the energy sector than in heavy industry.

In addition to sectoral differences, **disparities in capacity and resources across different countries and local contexts must crucially be accounted for** in policy, market, and business designs. Notably, stakeholders with fewer resources (e.g., NGOs or those in the Global South) may experience difficulties accessing or benefiting from AI-for-climate innovations due, e.g., to lack of access to capital or inclusion in innovation processes, which may concentrate developments among select stakeholders.

Bottlenecks

Countries around the world have been supporting the development of AI in general, but are starting to understand that applications in e.g. more regulated sectors, many of which are relevant to climate action, require bespoke incentives and support to enable AI integration into these systems. This section details the bottlenecks that are holding back AI deployment and systems integration in climate-relevant sectors.

Inadequate financial incentives for climate action. Some AI-for-climate applications may be held back by policy or market failures, such as inadequate carbon pricing, that make climate action less attractive from a financial perspective. AI innovators typically have many options for applications to work on, which means AI-for-climate applications that are less financially attractive may garner less attention. For instance, the preservation of ecosystem services in the face of climate change is an important public good, but there has been relatively little commercial work using AI in this area, except where such work is monetizable via carbon offset markets. Even in cases where AI is already employed within a climate-relevant industry, misalignment between profits and climate impacts can lead to AI being used in ways that are not necessarily climate-aligned; for example, there has been an explosion of interest in the use of AI to optimize agricultural processes, but these developments often focus on increasing profits instead of (or even at the expense of) resilience or reducing emissions.

Slow adoption of new technologies due to organizational culture and capacity. Key players in particular climate-relevant sectors may be slow to adopt technological innovations for cultural reasons. For instance, system reliability is justifiably at the heart of the electric power sector, especially in cases of critical infrastructure (discussed further below). This means entities in this sector tend to use "waterfall" software development approaches where software is sequentially developed and then deployed according to rigid system requirements, as opposed to "agile" approaches that allow for faster iteration and feedback on new approaches via intermediate deployments, but which may not be as reliable. These issues can be exacerbated by a lack of internal capacity to assess and implement AI (see *Capacity Building*).

Technical integration with legacy infrastructure. Many climate-relevant industries have a great amount of legacy infrastructure that is aging or slowly updated, making integration of AI and modern software challenging. For instance, incumbent industries face challenges creating "ecosystems" of digital solutions within the context of legacy systems, as integrating digital components from multiple providers can be difficult, especially where such systems need to be able to share information. For example, in power systems, system operators will need systems related to voltage regulation to be able to interact with those related to dispatch. As a result there is a tendency to work with large technology providers, rather than an ecosystem of smaller players, to limit the extent of integration required.

Old or outdated market designs. Many market designs for regulated sectors were developed prior to the availability of advanced, real-time digital optimization techniques, and have not yet been updated. This can provide an "upper bound" on the efficiency gains that can be realized through these markets. For instance, electricity markets often require power generators to forecast the amount of power they will produce several hours ahead, posing challenges to the integration of renewable energy sources such as solar and wind whose output varies truly in real time. Updating markets to more "real-time" designs that leverage modern real-time digital optimization capabilities could facilitate renewables integration and provide efficiency gains.

Private funding for startups in regulated markets is limited due to a challenging route to market. Venture capitalists and other early stage-funders believe there is significant value in AI for climate in regulated sectors such as electricity and transport, but because of the long time scales, lack of market incentives, and regulatory barriers to market entry, are often wary about investing. Governments could help align the incentives of incumbents and innovators to de-risk financing of innovation in this sector by e.g. enabling incumbents to take equity stakes in AI-for-climate startups.

Opaque innovation processes. The processes for innovation in highly regulated climate-relevant sectors are often opaque, without a clear path for how innovations can transition from concept to scaled solution. For example, innovation support processes in many energy sectors is often grant-funded, but lacks clarity on

CASE STUDY

The ***Arup Neuron*** *system, deployed in buildings around Hong Kong and elsewhere, uses AI-based optimization tools and sensor data to boost building energy efficiency by 10-30%. Greater adoption of such technologies is held back by the slow pace of building refurbishments to accommodate smart control systems. Full description on* *page 87*.

Image license:
Neuron - 2 - © Arup.jpg

how solution developers can build ongoing revenue streams from their innovations.

Safety and national security considerations. Some of the sectors where AI could be applied for climate impact involve safety-critical or nationally-critical infrastructure (e.g., energy and transport). Supporting AI deployment in these areas may require specific implementation models where solutions are developed and deployed in multiple stages. This could include solutions going through thorough safety and cybersecurity audits to ensure all necessary safety requirements are met, then simulating these solutions virtually, and then deploying them in either a "human-in-loop" or fully automated manner as appropriate. For security-sensitive areas, there may be a need to create bridges between infrastructure managers and classified research and innovation teams.

Lack of non-commercial public-service models and applications. There are some areas — such as adaptation, emissions monitoring, ecosystem services, and climate science — where there are inadequate commercial incentives to support the development and deployment of AI-for-climate solutions. In these areas, there is a need for governments and international organizations to go beyond providing a facilitating environment and the right incentives, and to actually provide financial and infrastructural support to the development of specific public interest applications. We have seen projects such as Climate TRACE[32] leverage philanthropic funding to get off the ground, but arguably there is a role for governments to provide ongoing funding for such public interest applications.

[32] Climate TRACE, "the platform for independent emissions reporting": *https://www.climatetrace.org*

RECOMMENDATIONS

- **Embed digitalization and AI experts into governmental climate policy teams and advisor groups** to help ensure that digitalization and AI considerations are incorporated into policies designed to support the transition to net zero where applicable. Policymakers leading updates to market regulation towards net zero should also engage the digital and AI communities more widely to support the development of these strands.

- **Launch digital innovation pathway initiatives with industries in climate-relevant sectors,** to develop innovation pathways and business models that can support digital and AI projects throughout their whole journey from concept to scaled solution. Innovation funding should be provided at each stage it is required. Support for sandboxes, testbeds, pilots, and demonstration projects should be expedited such that pilots should be allowed to proceed ahead of regulatory approval for the final proposed solution. There should be a strong emphasis on developing pathways for successful pilots to scale up rapidly, and to retain ongoing revenue streams from their innovations.

- **Governments and regulated industries should set up and co-fund public-private investment groups to co-invest in startups offering digital services to regulated industries.** Regulated industries often lack substantive incentives to facilitate the integration of innovations developed by startups. To align incentives between incumbents and innovators, governments should consider establishing financial mechanisms that incentivize regulated industry bodies to take equity stakes in digital and AI startups for climate-relevant sectors. Due to their low risk-profile, regulated industries are perhaps unlikely to be able to do this without co-investment from governments whose involvement would de-risk such investments. This can further serve to reduce the investment risk for the private funding community, by providing more confidence that innovations may actually be deployed (see also: *Research and Innovation Funding*).

- **Develop cross-sectoral innovation centers to incubate AI-for-climate projects, facilitate collaborations, and build a shared understanding of opportunities and needs** among a diverse set of stakeholders. Such centers could bring together those working on AI in climate-relevant sectors to support cross-fertilization of ideas, coordinate support and advice, create novel business models and playbooks, and engage with governments to support them in thinking about how to align incentives.

CASE STUDY

Recently developed **tools in natural language processing (NLP)** *by researchers in Canada, Switzerland, and Germany can automatically analyze corporate reports for disclosures of climate-related risks, helping evaluate the impacts of climate change on companies and assess the effects of green financial policies. AI literacy within climate policy bodies can help ensure such tools are leveraged impactfully. Full description on* *page 89*.

CASE STUDY

France's electricity transmission system operator, **RTE,** *leads a competition series called Learning to Run a Power Network (L2RPN). This innovative platform provides essential opportunities to validate the potential of reinforcement learning algorithms to optimize power grids in real time. Full description on* *page 80*.

CASE STUDY

Climate TRACE, *a global coalition of organizations, has radically improved the transparency and accuracy of emissions monitoring by leveraging AI algorithms and data from more than 300 satellites and 11,000 sensors. Strengthening non-commercial incentive structures will boost the adoption of such technologies for public benefit.* *Full description on page 71.*

As an illustrative example, Confiance.ai, a community launched by the French Innovation Council, brings together leaders from academia and industry to develop standards and best practices for the integration of AI into safety-critical sectors.[33] International organizations, including the multilateral development banks, UN Agencies, and Overseas Development Aid donors, could usefully support the development of such centers in the Global South to ensure that AI capacity is widely distributed.

- **Develop and maintain non-commercial public interest applications.** There are some areas where there are no commercial incentives to support the development of AI-for-climate solutions, and in these areas, there is a need for governments and international organizations to go beyond providing a facilitating environment and the right incentives, and to actually providing funding, infrastructure, and other support for the development of specific applications. Examples that governments should consider providing ongoing support for include: AI-enabled international forest monitoring service for carbon stock estimation and deforestation monitoring, AI-enabled food and water risk monitoring service, AI-enabled international emissions monitoring service, and AI for policy impact planning and assessment service.

[33] Confiance.ai, "the technological pillar of the Grand Défi 'Securing, certifying and enhancing the reliability of systems based on artificial intelligence'" launched by the French Innovation Council: https://www.confiance.ai/en

Reducing AI's negative impacts on the climate

Introduction

Every application of AI affects the climate, and aligning AI with climate change strategies does not only involve facilitating beneficial applications of AI (the focus of most of this report). It also means **shaping the space of AI overall so that business-as-usual applications are more climate-aligned,** as well as **reducing explicitly negative impacts.**[34]

There are three principal ways in which AI can adversely affect decarbonization strategies and result in an increase in greenhouse gas (GHG) emissions, following a framework previously introduced by the authors.[35] (See also *Assessing Overall Impacts*.)

1. First, there are the **effects associated with computation.** Developing and running AI algorithms uses energy and requires hardware with its own embodied emissions. These effects are independent of what problem the algorithms are being used to solve, and instead depend on (i) the exact AI method (some methods require minimal energy, but some are computationally expensive) and the data involved, (ii) the hardware running the computations, and (iii) the carbon intensity of the energy used. (It is worth noting that the production of computing hardware can also be associated with various other environmental harms, though these are outside the scope of this report.)

2. Second, **AI may be used to facilitate activities associated with high GHG emissions.** For example, AI and other advanced analytics techniques have been used extensively in oil and gas exploration and extraction, and are estimated to contribute an estimated $425 billion in profits for the fossil fuel industry by 2025.[36] More subtly, perhaps, AI has become ubiquitous in digital recommender systems, resulting in highly personalized advertising. It is plausible that this increases consumption and therefore comes with a significant (though unattributed) carbon footprint.

3. Third, **AI can have system-level impacts on society that affect the climate.** These impacts are the hardest to quantify, but are potentially significant. For example, even though autonomous vehicle technology can introduce efficiency gains for driving, the technology also lowers the barrier to driving and can induce new demand for individualized transportation. It is thus possible that self-driving cars will cause the total emissions associated with transportation to increase.

[34] *Artificial Intelligence and Climate Change: Opportunities, considerations, and policy levers to align AI with climate change goals,* Kaack et al. (2020).
[35] *Aligning artificial intelligence with climate change mitigation*, Kaack et al. (2021, working paper).
[36] *AI In Oil and Gas Market - Global Industry Analysis,* Zion Market Research (2018).

Bottlenecks

There is a lack of data on the life-cycle impacts of AI use cases. This includes a lack of data on the compute-related impacts of AI (computational energy use and hardware) and on the downstream climate effects of AI applications (negative as well as positive). We discuss further these challenges, and recommendations for alleviating them, under *Assessing Overall Impacts*.

The AI sector is moving fast. Applications and methodology in AI are changing rapidly from year to year, and it is difficult to develop policies for assessing, facilitating, and regulating technologies that have only recently been deployed and will continue to change. In sectors that have a direct impact on GHG emissions (such as energy, manufacturing, and agriculture) AI is still not yet widely integrated but is developing fast.[37] While designing policies for fast-moving technologies may be difficult, it is vital that governments be proactive.[38]

Most emissions associated with AI fall under scope 3 emissions and therefore risk being deprioritized. Many stakeholders prioritize reductions in scope 1 and scope 2 emissions, while AI-associated emissions typically either (a) arise from the use of AI to accelerate an emissions-intensive activity, and hence are scope 3, or (b) come from the computation itself, and therefore can be considered scope 3 if outsourced to a cloud compute provider.[379]

There is often a disproportionate focus on computational emissions compared to other negative climate impacts. While data are lacking, it is plausible that the negative climate impacts associated with applications of AI are significantly greater than the direct negative impacts associated with computation. However, since computational emissions are easier to measure, they often garner more focus. In addition, some stakeholders may have an interest in diverting attention away from the question of how their AI algorithms are being used by instead focusing on computational energy efficiency. Even as large technology companies increasingly switch to renewable energy, many are simultaneously building AI algorithms designed to be applied to fossil fuel extraction.[40]

[37] *The AI Index 2021 Annual Report,* Zhang et al. (2021).
[38] See also: *OECD Working Papers on Public Governance No. 36: "Hello, World: Artificial intelligence and its use in the public sector",* Berryhill et al. (2019).
[39] *Aiding greenhouse gas emissions in the cloud,* Mytton (2020).
[40] *Oil in the Cloud,* Greenpeace (2020).

RECOMMENDATIONS

- **Avoid direct governmental funding of AI applications that run counter to climate goals** (e.g., accelerating fossil fuel extraction and development). While governments may not wish to directly restrict the use of AI to accelerate applications strongly detrimental to the climate, it would seem inappropriate for governmental funding to actively support such work - for example, AI methods designed specifically for oil and gas extraction. Moreover, existing or proposed regulations pertaining to high-risk AI systems should consider including the impact on the climate and the environment in how they define risks.

- **Make climate change a central consideration when fostering the development of AI-enabled technologies.** Governments have often lagged in developing policies for new technologies until after they are widely adopted. However, some emerging technologies (for example autonomous vehicles) have an uncertain impact on GHG emissions, and implicit choices in the technology design or use can shape their impact. For example, incentives for self-driving technology that improves public transportation (for example, via self-driving buses or shared cars that provide short-distance transport to train stations) could help make this AI-enabled technology overall more beneficial than detrimental to the climate. Ensuring that the implicit choices behind new technologies are explored from the outset can have long-term impacts, since once society is "locked in" to a new technology, changes can be slow even if other options are later developed with a lower carbon footprint.

- **Ensure that cloud compute is appropriately included in reporting and carbon pricing policies.** Many stakeholders use cloud compute providers instead of in-house computing, which can allow such computation to fall under scope 3 emissions and thus be subject to less stringent regulation, or can be subject to carbon leakage across national borders. Appropriately accounting for cloud compute is essential to decarbonizing data centers, and will be valuable for the entire ICT sector, including AI.

- **Procure AI and compute services only from companies that have signed up to a net zero target covering scopes 1, 2, and 3.** Governments can use their procurement power to shift markets. If tier 1 government suppliers of AI and compute were required to set net zero targets in order to secure government contracts, and were required to ask their suppliers to do so as well, this provision can be passed onto a wide range of suppliers creating a chain reaction of target setting and transparency. Governments such as the UK are already deploying such an approach for all government suppliers.[41]

[41] *UK Government Net Zero Procurement Requirement,* UK Government (2021).

Assessing AI's overall impacts on the climate

Introduction

Throughout this report, we have considered how best to align AI with climate goals, both through facilitating impactful AI-for-climate applications and through reducing negative impacts. In parallel with such interventions, **it is essential to develop effective tools and frameworks for quantitatively assessing the positive and negative impacts of AI on greenhouse gas (GHG) emissions.** Concrete and holistic data on AI's impact on GHG emissions will be critical in informing technological priorities and guiding the recommendations we have set forth. Furthermore, understanding the dynamics and trends for how these impacts will develop is critical to accounting for AI appropriately in overall climate scenarios and decarbonization pathways.

In this section, we consider how to effectively assess the GHG emissions impacts related to AI, describing gaps in reporting and data collection, as well as the need for innovations in measurement methodologies.[42] While we focus here on GHG emissions impacts, it is important to note that assessing and managing other societal and environmental impacts is also essential in the context of applying AI to climate change; we have endeavored to discuss these other considerations throughout this report (see *Responsible AI*).

As detailed further in *Reducing Negative Impacts*, the impacts of AI on GHG emissions include both compute-related impacts (energy use from computation and embodied emissions from hardware) and application-related impacts (from accelerating activities that are beneficial or harmful to GHG emissions, as well as from shaping societal activities more broadly). **It is often easier to estimate the compute-related impacts of AI than those related to how AI is applied; however, central information is missing about both.**

For compute-related impacts, quantitative assessment has often focused on analysis of individual instances of an AI method. This neglects consideration of how many times different AI methods are "trained" vs. "tuned" vs. employed, on what infrastructure, using what energy sources, and with what data, all of which are essential to estimating total emissions. Often, analysis has attempted to extrapolate trends in AI GHG emissions from either (i) trends in the most computation-intensive methods, which may not be representative of methods commonly used in practice or (ii) GHG emissions associated with digital infrastructure as a whole, of which AI represents an unknown fraction with potentially different dynamics. Treating the IT sector as a single black box will prevent decision-makers from picking up early on different dynamics within subsectors (including AI) that could be important for decarbonization strategies.

For application-related impacts, quantitative assessment has largely been limited to domain-specific case

[42] This section is largely based on *Aligning artificial intelligence with climate change mitigation*, Kaack et al. (2021, working paper).

studies. Such studies have typically focused on either use cases designed for climate benefit or those with clear negative effects on GHG emissions (e.g. fossil fuel exploration and extraction), while not considering the vast majority of AI applications, which do not fall into either category but may still impact the climate significantly. For example, automatic recommender systems may increase global consumption and thus GHG emissions, while autonomous vehicle technologies may either increase or decrease GHG emissions depending on how they are used.[43]

Essential information

Relevant data for impact assessment includes information needed for both macro-level ("top-down") and project-level ("bottom-up") estimates of compute-related greenhouse gas emissions, as well as quantitative estimates for AI applications and system-level effects.

Compute-related greenhouse gas emissions:

- **Top-down reporting by data center operators:** A central data point for top-down estimates of AI's compute related impacts is the share of data center loads by type of computing application, and for AI the model stage of ML (e.g., development, training, inference). Enabling reporting by cloud compute providers, by requiring it or through approaches such as joint research programs, would provide valuable insights for understanding the total impact and dynamics of AI's energy use.
- **Bottom-up reporting by stakeholders using AI-systems:** For estimating compute-related impacts bottom-up, data could be required from stakeholders using AI-systems, especially when those are already subject to reporting requirements such as proposed in the EU. Such information should include, at a minimum, specifics on computing power needed for system development, training/fine-tuning, and inference at appropriate time resolutions, as well as information about the type, time, and location of computing infrastructure used. If permissible, such information should also include specifics about the model, training requirements for system development (or pre-trained systems used), frequency of training/retraining/fine-tuning, and as well as average number of inference uses per unit of time.

Current and future potential impacts of AI in each sector as well as the economy at large, as reported by stakeholders: To obtain better data on the application impacts of AI, research needs to move beyond case studies and obtain more robust estimates of the current and future potential impacts of AI in each sector as well as the economy at large. For that, stakeholders can report important information about how their AI systems affect or may affect climate change mitigation

[43] *Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles,* Wadud et al. (2016).

or adaptation more broadly, including of the greenhouse gas emissions resulting from the applications of the AI system. The assessment should be as quantitative as possible, and should describe the methodology and assumptions used.

System-level indirect effects of AI on energy consumption and greenhouse gas emissions: A particular challenge lies in estimating the (potentially significant) system-level effects of AI on energy consumption and greenhouse gas emissions, including adverse effects that could counteract decarbonization efforts. Examples here include increased fossil fuel production efficiency, cost-effectiveness and longevity of emissions-intensive infrastructure, and effects of targeted advertising on consumption. Assessment of system-level impacts will require cross-disciplinary efforts prominently featuring social scientists and economists, as well as technologists.

Bottlenecks

Data on aggregate compute-related GHG emissions from AI are largely unavailable. While it is relatively straightforward to estimate the compute-related GHG emissions resulting from individual runs of AI systems, the usage patterns in practice (encompassing how often a machine learning model is used or re-trained using new data) are typically opaque. In addition, data center operators currently do not publish the shares of AI loads on their servers. These issues make it very hard to obtain aggregate numbers on the emissions associated with the computational energy requirements of AI.

Reliable quantifications of the application-related climate impacts of AI (both positive and negative) are scarce. Assessing the overall emissions impacts of AI involves understanding the direct and systemic effects of AI applications, including both those designed with GHG emissions savings as the objective (e.g., see *Key Areas*) and those designed with other goals but which still may impact the climate. Full assessment of such impacts poses numerous challenges, such as estimation of rebound effects and lock-in to first-mover technologies, and requires sector-specific knowledge as well as tools from life-cycle assessment and the social sciences.

In addition to a lack of data, there is a lack of standardized measurement methodology. In particular, estimating the marginal and/or counterfactual benefit that AI has if it is introduced in established processes requires application-specific domain knowledge, but could be greatly accelerated by a "playbook" of best practices and established methodologies.

There is also currently a lack of methodology for how to include AI into climate change scenarios and forecasts. AI can be a driving force that influences many input factors of such large system models, such as efficiency, production and consumption rates, and learning rates. Appropriately factoring in these influences will require standardized methodology.

While compute-related impacts of AI are generally easier to measure than application-related impacts, this does not mean they are larger or even comparable. There is often a bias towards over-weighting the importance/saliency of things that are easy to quantify. In many cases, application-related effects are plausibly much larger than those from computational energy, and effort needs to be made to estimate both appropriately.

RECOMMENDATIONS

- **Set reporting requirements, where appropriate, for the life-cycle emissions associated with the development and use of AI,** including hardware, compute, and application-related impacts, which will both provide relevant data as well as spur more innovation on impact assessment in practice.[44] Such reporting requirements are most effective when implemented together with incentives for emissions reductions. While it is important to require impact assessment for many AI systems, the costs might outweigh the benefits for many other cases, as impact assessment is cumbersome and can come with high cost and time commitment. A process of how to distinguish where impact assessment should or should not be required also needs to be established, and voluntary reporting should be encouraged.

- **Ensure funding for research in developing impact assessment methodologies and gathering relevant information.** The impact assessment community, in particular researchers concerned with information and communication technologies (ICT) and computing, will be invaluable for tackling this problem, particularly in helping develop and standardize methodology. ML researchers can provide technical knowledge of AI systems to enable meaningful impact assessment.

[44] *AI and Climate Change: How they're connected, and what we can do about it,* Dobbe and Whittaker (2019).

- **Ensure funding and capacity for impartial third party impact assessment,** potentially in partnership or as part of audits of systems involving AI. Impact assessment for this purpose should also be conducted on a continuous basis across the life-cycle of the AI system (throughout scoping, development, and deployment).

- **Set methodological standards for impact assessments at the national and international level.** This includes developing a taxonomy that can help decide how to assess different types of systems and application areas, building on for example the OECD's taxonomy of AI.[45] National and sub-national governments can also contribute testbeds and useful case-studies toward the development of standards. Such standards could be implemented as part of required or voluntary reporting mechanisms, and can integrate with existing frameworks such as developed by the International Telecommunication Union, the Global Reporting Initiative, CDP, and the Sustainability Accounting Standards Board.

[45] *A first look at the OECD's Framework for the Classification of AI Systems,* Perset et al. (2020).

Capacity building

Introduction

As the emergence of the nexus of AI and climate change is relatively recent, many entities salient to the development, deployment, and governance of work at this nexus often lack access to needed skills and capacity. Such entities include governmental entities at national and local levels, as well as private and civil society organizations working in climate-relevant sectors (e.g., energy, transport, or agriculture). Cutting across the previous recommendations, therefore, is the need to build capacity for and within relevant organizations, both in the short and longer terms.

Our recommendations in this section focus on three aspects of capacity building in particular. The first is **building literacy** regarding the opportunities and pitfalls associated with AI in the context of climate change, **spanning both technical and socio-technical considerations.** Such literacy-building is essential to identifying when and whether AI-for-climate solutions are relevant, to facilitating the integration of these solutions within climate-relevant sectors where appropriate, and to framing and implementing effective policies and governance strategies at the intersection of AI and climate change more broadly.

The second relates to the **building of skills and talent** among relevant individuals and organizations. In particular, developing and deploying AI-for-climate solutions requires a combination of AI-related technical capabilities (e.g., in data science, data engineering, and software engineering), domain expertise in salient climate-relevant sectors (e.g., an understanding of the relevant problems, stakeholder landscape, regulatory landscape, and deployment pathways), and approaches from the humanities and social sciences (e.g., participatory design and governance strategies). The building of such skills and talent can take a number of different forms, such as supporting the creation of in-house capacity within a given organization, building stronger connections between organizations with different sets of expertise (e.g., between data science organizations and organizations in climate-relevant sectors), or even supporting the creation of new entities with fundamentally cross-functional expertise in e.g. data science and a given climate-relevant domain.

The third relates to **tools, standards, and best practices.** The availability of tools, standards, and best practices for the scoping, development, deployment, integration, maintenance, evaluation, and governance of AI-for-climate solutions is critical to ensuring that work is conducted responsibly, and can facilitate progress across a heterogeneous set of organizations by preventing the “reinvention of the wheel.” In addition, tools, standards, and best practices for evaluating and governing the climate impacts of AI more generally can support governments in shaping those impacts. Relevant tools, standards, and best practices include those associated with the responsible collection and use of data, scoping the applicability of AI in particular climate-relevant contexts, participatory design and stakeholder engagement, agile software development, data science and engineering methodologies, impact assessment, and regulation of relevant organizations and projects.

In developing this capacity, is it important to ensure it is built **across multiple countries and local contexts** to ensure that progress is fundamentally equitable and inclusive. For instance, AI and data science expertise today is often concentrated within a small set of entities and geographies (e.g., tech companies in the Global North), which means that data science solutions are more likely to reflect the needs of the demographics who develop them and can contribute to the widening of digital divides. Fostering the responsible use of AI for climate, and shaping the climate impacts of AI more broadly, thereby entails broadening the set of people empowered to participate in these developments. This requires, for instance, a concerted focus on capacity building within the Global South, as well as the inclusion of smaller or traditionally less well-resourced entities (e.g., local governments, civil society organizations, and small and medium enterprises) across all contexts.46

Bottlenecks

This section details several key bottlenecks relating to capacity and capacity building for work at the intersection of AI and climate change.

Lack of knowledge within the public sector at the nexus of AI and climate change: As the emergence of the nexus of AI and climate change is relatively recent, knowledge and understanding of how to govern and shape developments in this area is nascent.

Lack of AI and AI-for-climate knowledge within private and civil society organizations working in climate-relevant areas: This includes knowledge about the capabilities and pitfalls of AI, how to support the development and deployment of AI-for-climate solutions where appropriate (e.g., via the procurement of internal vs. external talent), how to evaluate AI-for-climate solutions, and how to build data management and governance capabilities and procedures. This results in AI not being properly accounted for in budget planning processes, and leads to integration challenges.

Lack of cross-disciplinary and cross-functional teams: Successful AI-for-climate projects require a combination of deep technical expertise in AI, skills in data and software engineering, deep understanding of the sector in

[46] See also: *AI for Sustainable Development Goals*, Miailhe et al. (2020).

CASE STUDY

UK-based company **DeepMind** *has built AI algorithms that reduce the energy needed to cool Google's data centers by about 30-40%. There is significant scope for similar algorithms to improve the efficiency of industrial facilities, but this requires teams combining expertise in AI and the application setting. Full description on* *page 90*.

which the project is operating, and deep understanding of the socio-technical considerations associated with a particular project. Similarly, efforts to shape the climate impacts of AI more broadly require cross-disciplinary and cross-functional expertise. There is often difficulty in forming teams spanning relevant disciplines and sectors.

Lack of cross-disciplinary and cross-sectoral experts: In addition to people with expertise in either data science or a climate-relevant sector, interdisciplinary teams working at the nexus of AI and climate change also need experts who are trained in both and can translate between areas. There are currently few people who have both AI expertise and domain expertise in a climate-relevant sector, as well as relevant socio-technical expertise needed to foster responsible development, deployment, and governance. In addition, recognition and incentive structures that appropriately value such “translational” experts are not yet in place.

Lack of incentives and missing role model careers for AI experts and practitioners: Compensation packages and organizational cultures within governments and traditional climate-relevant industries are (either in reality or perception) not as attractive as those in the financial or tech sectors, affecting the flow of AI talent. While there is separately some growth in climate tech startups, there are still relatively few career opportunities at this intersection, as well as associated stability risks.

Low capacity to develop or procure AI-for-climate solutions: Small- and medium-sized enterprises (SMEs), local governments, civil society organizations, and many other climate-relevant problem owners might not have the financial and institutional resources to build in-house AI capacity, and may face high risks or costs in procuring external capacity. This is particularly acute for many climate-relevant industries and public entities that are under-funded and/or lack in-house AI literacy and expertise.

Risk of capture when procuring external capacity: There is a risk that where organizations (including central and local governments) exclusively rely on external data science and engineering capacity, they become reliant on the expertise and systems of the companies providing it, which creates system capture, monopoly risk, and potentially high costs.

Lack of availability of and access to standards, playbooks, and best practices: Given the relatively recent emergence of the nexus of AI and climate change, there is often a lack of standards, playbooks, and best practices that are tailored towards work in this area. Some illustrative examples include sector-specific playbooks for stakeholder engagement and systems integration; standards for assessing the efficacy and impact of an AI-for-climate application; best practices for scoping, selecting, and auditing AI methodologies in climate-relevant contexts (considering, e.g., domain-specific requirements such as safety, auditability, and access); and best practices for assessing the climate impacts of AI applications in general. Many of these standards, playbooks, and best practices are yet to be developed. Even in cases where these resources may exist, they may not always be easily discoverable or accessible. For instance, while mature methodologies for data science, data engineering, and agile software development exist within the tech sector, data teams within the energy sector may not always have access to them.

RECOMMENDATIONS

To address the bottlenecks identified, we recommend that governments take the following actions to improve education and literacy, and to build research, development, deployment, and governance capacity, at the nexus of AI and climate change.

EDUCATION AND LITERACY

- **Rapidly implement large scale AI literacy and "upskilling" programs for policymakers, leaders in climate-relevant industries, and civil society** to help "demystify" AI and build understanding in how organizations can concretely develop, deploy, and govern work in AI and climate change. This should include education on both AI theory and practice, and also on socio-technical aspects pertinent to AI. As an example, the Wilson Center[47] and the Stanford Institute for Human-Centered AI[48] in the US both host AI training programs geared specifically towards policymakers.

- **Fund interdisciplinary higher education, research, and professional programs** bridging AI and individual climate-relevant sectors (e.g., energy, heavy industry, transportation, agriculture, and forestry), in order

CASE STUDY

German railway company **Deutsche Bahn** *uses AI to improve reliability, detecting failures and maintenance needs early, as well as improving the scheduling of trains. Upskilling programs in the rail sector could enable broader adoption of such methods by building AI expertise within experienced teams.* *Full description on page 88.*

[47] Wilson Center Artificial Intelligence Lab: *https://www.wilsoncenter.org/artificial-intelligence-lab*

[48] Stanford Institute for Human-Centered AI's training programs for policymakers: *https://hai.stanford.edu/policy*

CASE STUDY

US-based company **Fero Labs** *uses AI to help steel manufacturers reduce the use of mined ingredients by up to 34%, preventing an estimated 450,000 tons of CO2 emissions per year. Building secondment programs for AI experts within industrial sectors could spur significant innovations by enabling needed collaboration and knowledge-sharing.* *Full description on page 85.*

Image license: Adobe Stock Standard License (Fero Labs)

to help build experts who can translate between fields. In particular, governments should fund master's programs, professional training programs, and interdisciplinary research grants (see *Research and Innovation Funding*) at the intersection of AI and key climate-relevant sectors.

- **Incorporate curricular elements on data and on climate into primary, secondary, and higher education, including both technical and socio-technical components.** This can help build a longer-term pipeline of climate-literate data scientists, and of data-literate professionals in climate-relevant sectors and the public sector. Socio-technical approaches in particular — i.e., approaches that appropriately situate the study of technical topics within their broader societal and policy contexts — can ensure that individuals have a fundamental understanding of what it means to approach climate-related AI work ethically and responsibly. In addition, given the pressing and cross-cutting nature of climate change, as well as the increasing relevance of data across many sectors, the creation of such curricular elements may also have significant co-benefits outside the context of AI-for-climate.

- **Ensure global access** to the above programs and resources across a wide variety of countries and contexts, including the Global South — e.g., via collaborative co-development across countries, scholarship programs, or exchange programs.

RESEARCH, DEVELOPMENT, DEPLOYMENT, AND GOVERNANCE CAPACITY

- **Fund or facilitate secondment programs for AI experts within climate-relevant sectors.** Secondment or fellowship programs, where AI experts work in climate-relevant sectors for a limited time, could help build cross-disciplinary expertise, allow organizations in climate-relevant sectors to explore AI-for-climate solutions at lower costs and risks to their business, and allow AI experts to gain additional exposure to climate-relevant careers. Governments can play an important role by providing primary or supplementary funding in order to make such programs more financially attractive, especially in contexts with low financial resources (given competition against high-paying sectors such as the tech or financial sectors).

- **Fund or incentivize the creation of trusted AI-for-climate solutions providers and auditors.** Climate-focused data science and engineering organizations could provide high-quality data analytics, auditing, and evaluation capabilities for climate-relevant applications in different sectors. Governments can play an important role by providing financial incentives for the creation of trusted entities, and (where appropriate) creating public solutions providers that can enable organizations in climate-relevant sectors to experiment with AI approaches without undue financial or institutional risk.

- **Develop and/or facilitate sharing of standards for scoping, developing, deploying, maintaining, and evaluating AI-for-climate work.** These include standards for the responsible collection and use of data, the scoping and design of AI methodologies, participatory design and stakeholder engagement (see *Responsible AI*), data science and software engineering methodologies (see *Data and Digital Infrastructure*), systems integration (see *Deployment and Systems Integration*), and impact assessment (see *Assessing Overall Impacts*). Standards will likely need to be tailored to or adapted for the different climate-relevant sectors in which they are used, given the heterogeneity of these sectors. Such standards should be co-developed with participants from industry and civil society, to ensure feasibility and foster adoption.

- **Develop and employ tools and instruments for monitoring, impact assessment, benchmarking, and certification of AI-for-climate solutions, and for climate impact assessment of AI.** Given the rapidly-evolving nature of the AI and AI-for-climate spaces, there is a danger that policy and governance approaches may lag progress in these areas. Such tools and instruments could enable governments to more effectively monitor and track developments, and proactively develop regulations and incentives on that basis.[48] (See also *Reducing Negative Impacts* and *Assessing Overall Impacts*.)

[49] See also: Why and How Governments Should Monitor AI Development, Whittlestone and Clark (2021).

International collaboration

Introduction

Stronger international cooperation on AI-for-climate applications will be important in unlocking the full potential of this area. Climate change is an international challenge that does not respect national boundaries and the solutions will in turn require cross-border collaboration. To address the climate crisis with the urgency it deserves there is a need to pool resources, data and emerging solutions and methodologies to accelerate the development of impactful AI-for-climate solutions.

In this section, we provide further recommendations on how such international initiatives should be taken forward and propose recommendations on how international collaboration at the intersection of AI and climate change should be structured. International collaboration between governments and industry from different countries can play an important role if well targeted, but can equally be ineffectual if poorly conceived. International collaboration on AI and climate change has similarities to other areas of international collaboration on technology, but some aspects are unique.

Bottlenecks

There are a wide range of climate-focused international initiatives that have yet to fully recognise the opportunities that AI presents. A range of governmental and non-governmental initiatives have been built up to support international climate collaboration, ranging from initiatives that support climate innovation and deployment at a high-level such as Mission Innovation,[50] the Mission Possible Partnership,[51] and the UNFCCC Climate Technology Centre and Network,[52] to more sector specific initiatives such as the Clean Energy Ministerial[53] process. As yet, many of these initiatives have yet to integrate AI into their work due to insufficient awareness about the potential, lack of capacity to harness it, or limited interaction with the AI community. If AI is integrated into such initiatives, it is important that it be done responsibly and effectively, with a recognition of the dangers of techno-solutionism.

International organizations and donor countries that play a role in delivering climate finance, programs and strategies across

[50] Mission Innovation: *http://mission-innovation.net*
[51] Mission Possible Partnership: *https://missionpossiblepartnership.org*
[52] UNFCCC Climate Technology Centre and Network: *https://www.ctc-n.org*
[53] Clean Energy Ministerial: *https://www.cleanenergyministerial.org*

the Global South would benefit from capacity building on data science and AI. The COP16 Accord agreed that developed countries under the UNFCCC are to deliver $100B per year in climate finance to developing countries. There are a range of organizations and governments that play a key role in delivering climate finance within the Global South, such as the UN Green Climate Fund, the Global Environment Facility (GEF), UNEP, UNDP, the Multilateral Development Banks (World Bank, Asian Development Bank, African Development Bank etc), and the Adaptation Fund. There are also a range of countries and regional donors (such as the EU) in the Global North that deliver climate finance directly. Many of these organizations and government departments are starting to appreciate the role that data and AI can have to support climate action. However, this has yet to be translated into significant funding provision to the Global South for data and AI approaches, where relevant, to climate challenges, or the integration of AI into wider climate finance programs. There is a need to support decision makers in these organizations to determine key areas where each international organization can best support impactful work applying AI to climate change.

Data are often national in focus, limiting the feasibility and effectiveness of international projects. There is currently insufficient international coordination on climate-relevant data collection, access and standards. This results in national siloes for data, often with incompatible standards. AI-for-climate solutions benefit from large and diverse datasets, meaning that pooling datasets gives much better results than using any one of the individual datasets. Even for well-resourced countries, therefore, there is a significant benefit to obtaining data and models from other countries, while for some countries in the Global South, data-sharing may be critical for some AI-for-climate applications to be remotely viable.

Digital infrastructure and models are not shared internationally. Beyond data, there are opportunities for international collaboration on the development of digital infrastructure for AI-for-climate solutions ranging from simulation environments, to international AI-for-climate challenge hubs to collate AI-for-climate challenges that data scientists can get involved in.

RECOMMENDATIONS

- **Support knowledge sharing on policy design, implementation, and evaluation between governments, industries, and key stakeholders in different countries.** While some AI-for-climate solutions need to be developed at a national level (e.g. energy markets are mostly country-specific), it is important for governments and industry to share relevant knowledge and best practices (e.g., about how to apply AI to support the decarbonization of energy systems). This knowledge sharing often needs to be supported at a range of levels, including the design of R&D support needed to accelerate the responsible development of applications, to the policies and incentive structures needed to support their development, to standards and best practices for project implementation and evaluation (see also: *Responsible AI*, *Assessing Overall Impacts*, and *Capacity Building*). GPAI could usefully work with a range of climate initiatives, including Mission Innovation, the Mission Possible Partnership, and the Climate Technology Centre and Network, to support knowledge sharing in this space.

- **Pool limited government RD&D resources.** Many national climate challenges where AI could be part of the solution are common across countries, but national resources are often limited and there would be a significant benefit to pooling and coordinating international R&D funding.

- **Specifically, governments should coordinate AI-for-climate funding or develop cross-functional consortium institutions with in-house RD&D capacity that multiple entities within a climate-relevant sector, and across the globe, can benefit from.** For instance, the Electric Power Research Institute (EPRI), a non-profit organization that conducts RD&D projects focused on the electric power sector, serves over 1,000 member organizations around the world, and includes a dedicated initiative on artificial intelligence.[54]

- **Bring together researchers and innovators to address common and cross-border AI-for-climate challenges.** Creating processes to bring together interdisciplinary research teams and innovators to address common and cross-border AI-for-climate challenges would accelerate the development of such solutions.

[54] AI.EPRI at the Electric Power Research Institute: *https://www.epri.com/thought-leadership/artificial-intelligence*

CASE STUDY

The ***Monitoring the Andean Amazon Project (MAAP)*** *uses AI and satellite imagery to detect illegal deforestation in the Amazon, and has been critical in shaping policy decisions across the region. Processes for international data-sharing are vital for such techniques to be effective. Full description on page 78.*

- **Support shared AI-for-climate capacity-building activities.** In the *Capacity Building* section we highlight the need for AI literacy and "upskilling" programs for policymakers, leaders in climate-relevant industries, and civil society. Given that the content for such programs will need to be similar across many countries, such programs could more efficiently be developed internationally.

- **Pool data for common or cross-border AI-for-climate challenges and agree on data standards internationally.** As discussed in the *Data and Digital Infrastructure* section, there is a need to facilitate data collection and access in climate-critical sectors. In instances where there are common or cross border challenges between countries, there is a strong case for data to be pooled internationally to allow for greater international collaboration and improve the process of applying common solutions across different countries. To deliver this, governments could consider coordinating international data task-forces in areas such as energy, land use, and climate science. Such data task-forces could usefully establish existing data availability, access, standards and sharing incentives, and e.g. seek to aggregate or facilitate the discovery of data portals that may already exist.

- **Coordinate on the development and use of specific physical and digital assets to support the development of AI-for-climate solutions.** There are a range of physical and digital assets that governments could consider collaborating on, whether it is sensor networks to measure permafrost methane release in the arctic, or digital simulations for electricity and transport systems.

- **Coordinate government support for the development and maintenance of non-commercial public interest applications.** Where there are no commercial incentives to support the development of AI for climate solutions, there is a need for governments and international organizations to support the development of specific applications. Further details on this recommendation, including application areas, can be found in the *Deployment and Systems Integration* section.

- **Existing international initiatives with the capacity to advance AI-for-climate applications should be supported.** There are many international organizations, such as the Climate Technology Centre and Network (CTCN), that facilitate tech transfer and development for climate solutions. Other organizations focus on specific areas of capability relevant to AI-for-climate, such as the Group on Earth Observations (GEO) and the EU Copernicus program, both focused on remote sensing, and Global Open Data for Agriculture and Nutrition (GODAN). These kinds of initiatives should be supported where they exist.

- **GPAI could champion the development of an international Responsible AI-for-Climate Partnership made up of governments, relevant international organizations, and a network of businesses and NGOs from both the climate and AI communities to support the coordination and delivery of international AI-for-climate work.** There are a wide range of organizations that are relevant for international AI-for-climate work that need to be brought together to integrate AI-for-climate work from both the AI and climate communities. Creating a partnership amongst these organizations would accelerate international work at the intersection of AI and climate.

CASE STUDIES

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Tracking global greenhouse gas emissions: **Climate TRACE**

CLIMATE TRACE USES AI TO RADICALLY IMPROVE ACCURACY AND TRANSPARENCY OF GLOBAL EMISSIONS INVENTORIES

Historically, emissions inventories have relied on unverified, self-reported country data that has been collected via a bottom-up approach. This lack of independently verified data, often collected in a varying range of formats, has created challenges in accurately assessing sectoral, national, and global emissions profiles. Existing bottom-up processes have also taken years to populate national emissions inventories, resulting in a significant time-lag between changes in sectoral and country emissions, and domestic and international awareness of these changes.

Climate TRACE is a coalition of organizations that have built an approach to emissions monitoring that combines data from more than 300 satellites and 11,000 sensors, together with AI algorithms, to identify and quantify emissions sources. Initially, WattTime and Transition Zero focused on measuring emissions from coal plants using satellite imagery. More recently they have come together with ten other organizations focused on other emissions sectors, to develop the world's first comprehensive accounting of GHG emissions based primarily on direct, independent observational data.[55] The inventory is particularly relevant to the more than 100 countries that lack access to comprehensive emissions data from the past five years. As a result, world leaders can inform their decisions with data that reflects accurate and up-to-date emissions trends.

[55] *Emissions Inventory*, Climate TRACE (2021).

Climate TRACE has scaled its approach to include a wide range of emission sources, including monitoring of emissions data associated with:

- Oil and gas production and refining, which Climate TRACE's work demonstrates may collectively be around double recent UNFCCC estimates
- Shipping and aviation, which Climate TRACE have demonstrated have together contributed nearly 11 billion tons of CO2e between 2015 and 2020
- Forest fires, which have more than doubled in Russia and the United States since 2015
- Rice-related emissions, which are significantly higher than previously thought in several areas.

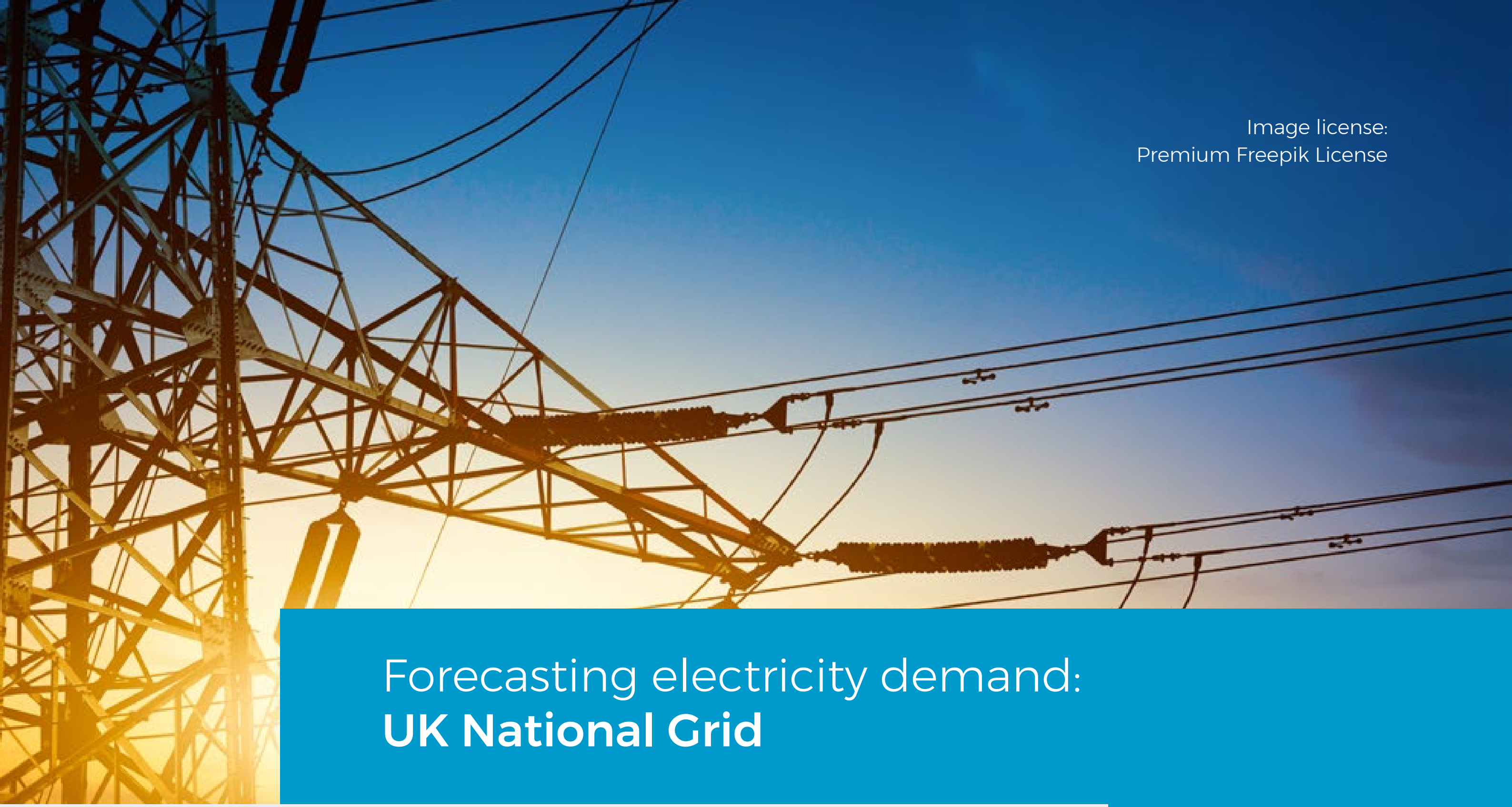
Coalition members include Blue Sky Analytics (India), CarbonPlan (US), Earthrise Alliance (US), Hudson Carbon (US), University of Malaysia (Malaysia), Hypervine (UK), Johns Hopkins Applied Physics Laboratory (US), OceanMind (UK), RMI (US), TransitionZero (UK), WattTime (US), former US Vice President Al Gore, and many other contributors and partners.

Bottlenecks to the wider adoption of AI to support remote monitoring use cases include:

Affordability of satellite imagery, despite reductions in costs, can still be prohibitive;

Access to high quality ground truth data to inform and corroborate satellite data;

Wider acceptance of the reliability of AI-based monitoring, particularly in the emissions monitoring community.



Forecasting electricity demand: **UK National Grid**

UK NATIONAL GRID USES AI TO DOUBLE THE ACCURACY OF DEMAND FORECASTING

Electricity system operators need to almost perfectly balance electricity supply and demand at every moment. As electricity grids incorporate greater percentages of variable solar and wind power generation, this challenge of balancing supply and demand becomes all the more challenging. This challenge is made harder by the fact there is often a delay of minutes or hours between electricity system operators requesting a balancing action and that action being taken, as generation capacity takes time to bring online and ramp up, requiring advanced planning. As a result, radically improving the forecasts of electricity demand and renewable supply will be a prerequisite for managing renewables-dominant grids.

Forecasting electricity demand is especially challenging because demand is largely driven by human behavior. Electricity consumption is influenced by the weather, the state of the economy, holidays, whether there is a COVID lockdown, and the timing of major sporting events. The best approach to forecasting the future is in analyzing trends in historical data, something AI is good at.

The UK National Grid Electricity System Operator (ESO) worked with Open Climate Fix to implement deep learning approaches to help optimize national electricity demand forecasts. After trying over five hundred variants of a Transformer model (a type of deep learning method, they found that they obtained best performance using a Temporal Fusion Transformer.[56]

[56] *Temporal Fusion Transformers for Interpretable Multi-horizon Time Series Forecasting*, Lim et al (2020)

IThis method achieved a mean absolute error of 200 MW for 30-minutes ahead forecasts, which is a third of the error of the previous forecasting system. For 48-hours ahead forecasts, the mean absolute error is 450 MW: half the error of the previous forecasting system.

This approach is now in use by the UK National Grid ESO control room.

Bottlenecks to the wider adoption of AI to support power system forecasting use cases include:

- Data quality and access for weather data and national demand data;
- Data and trends do not always generalize between countries, and the types of national and regional players involved also vary extensively, leading to potentially large discrepancies and inequities in adoption;
- Lack of recognition by regulators and government departments about the potential that advanced energy forecasting has to reduce bills and the potential that AI offers to improve forecasting;
- Lack of incentives for energy networks to improve electricity forecasts;
- A wariness by electricity system operators to support open sharing of electricity forecasting models and code, leading to fragmented and duplicated efforts.

Predicting locust outbreaks: **Kuzi**

KUZI HELPS FARMERS ADAPT TO CLIMATE CHANGE VIA EARLY WARNING OF POTENTIALLY DEVASTATING LOCUST OUTBREAKS

As the climate changes, locust outbreaks are becoming more severe and frequent, and traditional means of predicting them have become less reliable. In particular, droughts are becoming longer and more common, and extreme storms such as cyclones are becoming more frequent; prolonged drought followed by heavy rain creates ideal conditions for locust outbreaks. Like other agricultural pests, locusts cause significant crop damages, but they are unique in their scale and intensity — at full plague density, locust outbreaks can cover as much as 20% of Earth's landmass, and a single swarm of 40-80 million locusts consumes the same amount of crops as 35,000 people. The year 2020 saw an historic locust crisis (which has not entirely ended as of 2021), affecting 23 countries from Tanzania to Pakistan. Even with plague containment measures implemented so far exceeding US$138 million, the World Bank has estimated the costs in damages and losses reaching $9 billion in the coming years. These outbreaks primarily occur in regions that already face extreme food insecurity, further exacerbated by COVID-19.

The primary method of dealing with outbreaks once they occur is heavy use of pesticides, which are not completely effective and can be harmful to other beneficial insects, as well as to other small animals and birds (and, with prolonged exposure, humans). Predicting outbreaks before they are out of control or even before locust eggs have hatched can enable more targeted, lower-dose applications of pesticide, or bio-control interventions such as controlled introductions of insectivorous flocks of birds. Kuzi is the Swahili name for one such bird (the wattled starling).

Kuzi is a tool developed by the Kenya-based agri-social company Selina Wamucii in January 2021, to help the smallholder farmers whose wares they sell deal with the ongoing crisis. Kuzi aggregates many sources of data, including soil moisture, wind, humidity, and temperature sensors; vegetation indices; satellite images; and local weather, and uses AI to make predictions about locust breeding locations and migration routes. The predictions, with corresponding recommendations, are delivered to farmers as text alerts, currently available in several languages. These predictions can arrive up to 3 months in advance of an infestation, allowing time to prevent, contain, mitigate, and prepare for the outbreak.

Bottlenecks faced in this and related applications of AI for climate change adaptation include:

- Climate change effects, such as locust outbreaks, that primarily affect the Global South have often received less interest and funding from governmental entities, technologists, and VCs based in the Global North;
- Where such problems are considered, solutions are sometimes driven by teams that do not include experts from the regions that are affected, and therefore often lack important relevant knowledge;
- Cutting-edge innovations in ML are important in problems where multiple types and scales of data must be aggregated.

Designing better batteries: **Aionics**

AIONICS' SOFTWARE PROVIDES A 10X SPEEDUP IN THE PROCESS OF DESIGNING BETTER BATTERIES

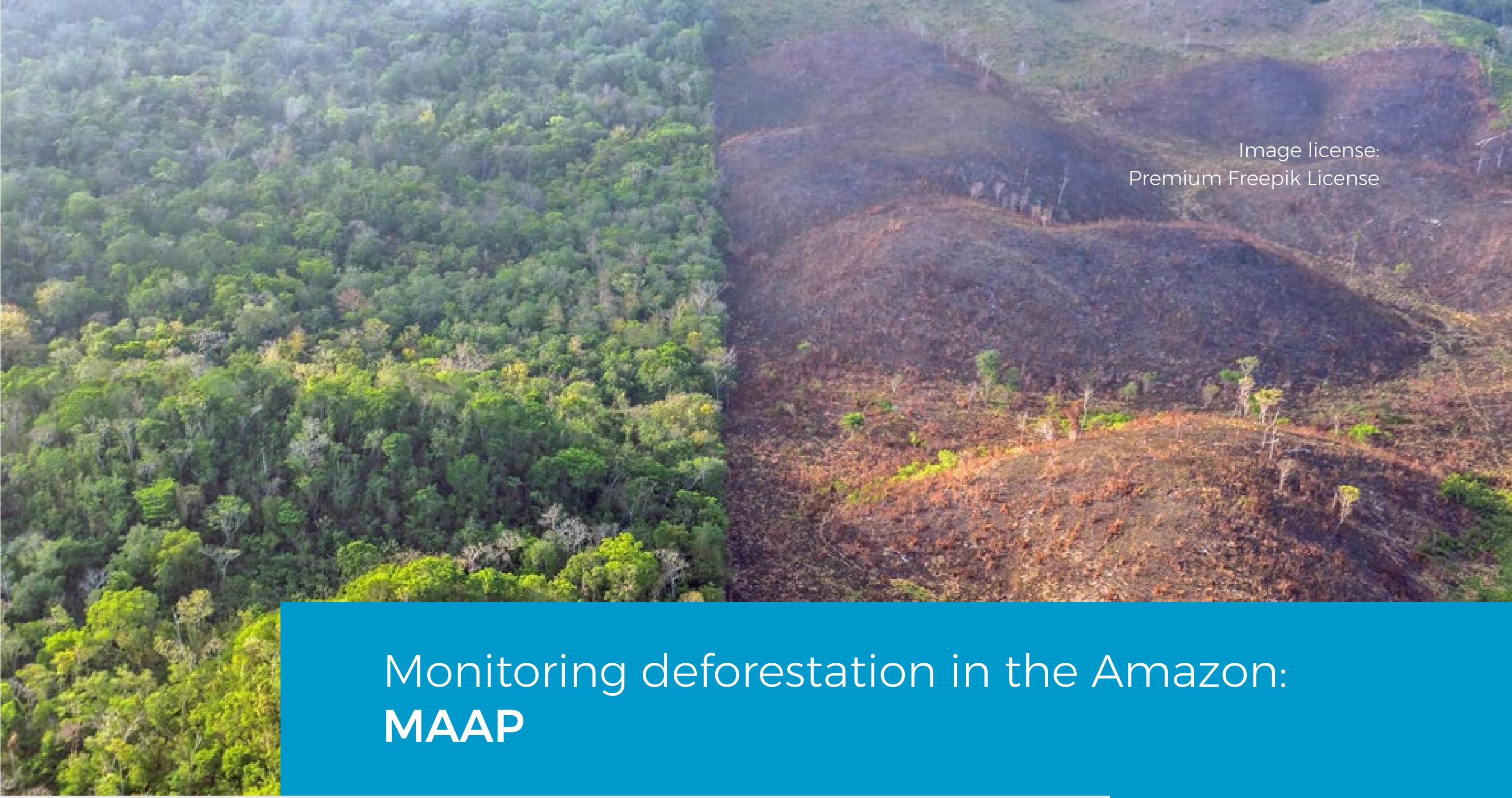
Developing better batteries will be critical to decarbonizing electricity and transport, but the R&D process can take immense amounts of time. For instance, for electric vehicles, it can take weeks to months to test out just one candidate battery design. Since manufacturers often need to test out dozens of designs before finding one that works well, the overall process of developing a battery can take on the order of years.

US-based startup Aionics aims to tackle this challenge by using machine learning to cut down on the number of designs that manufacturers need to try. Aionics' software works by using an approach called physics-constrained machine learning to analyze the outcomes of past experiments, and then recommend which designs are best to try out next. This approach works even when only small amounts of data are available, which is often the case for battery manufacturers who may have previously run only dozens of experiments.

Aionics' software has enabled, on average, a 10x reduction in the number of experiments their customers need to try, dramatically reducing the time and effort needed to design a better battery. Some of their customers include electric vehicle battery manufacturers Cuberg and Sepion, as well as grid energy storage manufacturer Form Energy.

Bottlenecks to developing and scaling the use of ML for the design of next-generation batteries include:

- Lack of third-party benchmarks for the demonstration of battery designs, whose presence could improve investor confidence in batteries designed via non-traditional routes;
- Low availability of data on previous battery design experiments and outcomes, as industrial manufacturers are not incentivized to share their data widely and academic labs are often more limited in the amount of data they can produce;
- Lack of translation from research to deployment of work in areas such as physics-informed AI;
- Uneven access to financing for ML innovations in deep tech, particularly for those innovations developed outside of traditional "tech hubs."



Monitoring deforestation in the Amazon: **MAAP**

MAAP USES SATELLITE IMAGERY TO PROVIDE A REAL-TIME LOOK AT WHERE DEFORESTATION IS HAPPENING

In addition to its immense benefits for biodiversity and ecosystem services, the Amazon rainforest stores the equivalent of 200 gigatons of carbon dioxide, about four times the world's annual greenhouse gas emissions. Nevertheless, the Amazon continues to be destroyed by human activity at the rate of over 10,000 sq km a year. The consequences of such deforestation compound, since it has been predicted that if even 20-25 percent of the Amazon is felled, the entire forest may cease to be self-sustaining and could rapidly degenerate into a grassland.[57] Much of this deforestation is illegal — the result of illicit agricultural, mining, and timbering operations — but such laws can be difficult to enforce in part due to the challenge of pinpointing deforestation over large, sparsely populated areas.

The Mapping the Andean Amazon Project (MAAP), an international nonprofit, is using remote sensing to track deforestation in real time. Satellite imagery makes it possible to pinpoint the smoke from fires across the region. Fires in the Amazon are not natural, but instead are typically set deliberately to burn felled trees, and are therefore an indicator of deforestation. MAAP uses highly scalable regression models for wide-area surveys, combined with ensemble methods (another type of AI algorithm) that detect large changes in the forest landscape.[58] MAAP then queries high-resolution imagery through Planet Labs (a commercial satellite provider) to detect more specific attributes such as mining camps that can help identify the driver of the deforestation.

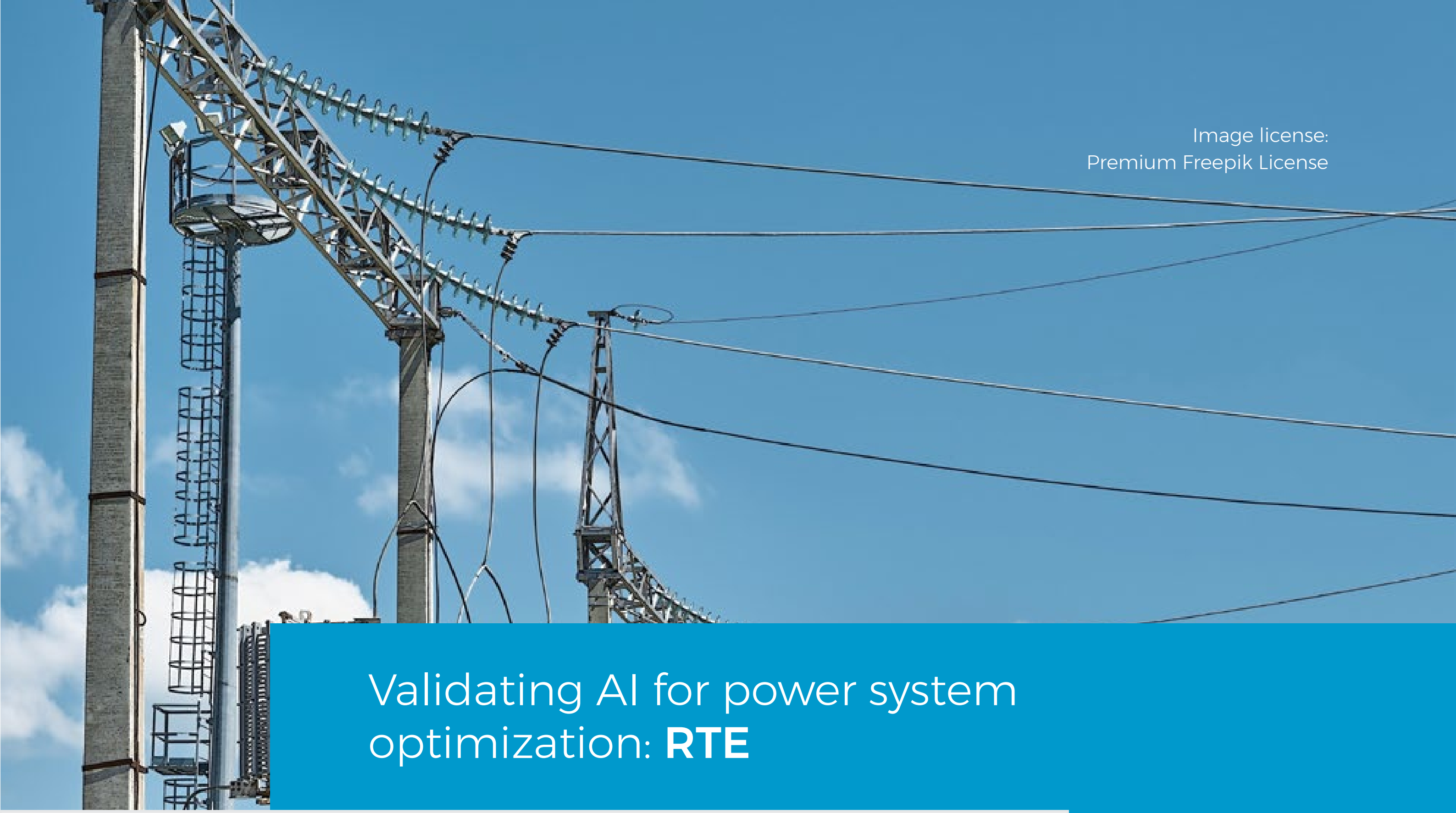
[57] *Amazon tipping point: Last chance for action,* Lovejoy and Nobre (2019).
[58] *High-Resolution Global Maps of 21st-Century Forest Cover Change*. Hansen et al. (2013).

MAAP's algorithm has been critical in shaping policy decisions in the region, and is deployed to monitor 83% of the Amazon in 5 countries: Peru, Brazil, Colombia, Ecuador, and Bolivia. Over the past years, MAAP's monitoring has been highly influential in detecting illegal deforestation, uncovering industrial-scale fraud and incentivizing anti-deforestation policy responses. For instance, in 2013, United Cacao infamously purchased thousands of hectares of Peruvian rainforest and established cacao plantations claiming no primary forests existed beforehand and their production was sustainable. MAAP's algorithms provided satellite-based evidence that challenged United Cacao's claims,[59] leading to the resignation of the company's CEO and several executives. As a result, the company was delisted from exchanges.

Bottlenecks for wider deployment of AI for deforestation monitoring include:

- Scarcity of Amazon-wide high-resolution imagery for detecting and understanding deforestation drivers and small-scale changes, such as selective mining;
- Missing data underneath the forest canopy, such as hidden roads and selective logging;
- Lack of technological pipelines and policy processes that incorporate the voices of Indigenous communities, which are often on the front lines of protecting forests under threat.

[59] *Science refutes United Cacao's claim it didn't deforest Peruvian Amazon,* Cannon (2021).



Validating AI for power system optimization: **RTE**

RTE'S COMPETITION SERIES PROVIDES AN INNOVATIVE PLATFORM TO VALIDATE THE POTENTIAL OF REINFORCEMENT LEARNING TO OPTIMIZE POWER GRIDS IN REAL TIME

Electric power systems must be operated more and more dynamically to accommodate large amounts of time-varying renewable energy (such as solar and wind). However, traditional power system monitoring, optimization, and control methods are proving inadequate for these purposes, prompting interest in using AI to optimize power grids in real time. While there has been some initial research in this area, there are very few opportunities to validate new methods on realistic power systems due to system reliability requirements, posing bottlenecks to development and deployment.

The Learning to Run a Power Network (L2RPN) competition series aims to address this issue by providing a platform for the development and testing of novel power system optimization methods based on reinforcement learning (a type of machine learning). Led by RTE, France's transmission system operator, installments of this competition series have featured iteratively larger and more complex power grid scenarios, building towards a realistic-scale system. The bedrock of this competition series is a novel power system simulation platform called Grid2Op, which provides an easy interface for machine learning and power systems researchers to test out new methods. This has allowed RTE to validate the efficacy of different reinforcement learning approaches for integration into its own systems.

The L2RPN team has led four challenges since 2019, drawing over 500 participants from around the globe. Competition winners have used a variety of reinforcement learning approaches, often combined with power system heuristics, with some methods obtaining "super-human" performance.[60]

The L2RPN competition team and sponsors include RTE (France), EPRI (USA), TenneT (Netherlands), State Grid (China), TU Delft (Netherlands), University College London (UK), Pacific Northwest National Labs (USA), Iowa State University (USA), IQT Labs (USA), Google Research (USA), V&R Energy (USA), and ChaLearn (USA). Past winners include KAIST (South Korea), Baidu (China), and China State Grid.

Bottlenecks to developing and scaling ML methods for power system optimization include:

- Building teams with skills and expertise spanning machine learning, power systems, data engineering, and software engineering to develop relevant testbeds;
- Procuring adequate capacity for ongoing maintenance and scaling of such testbeds;
- Access to scalable computational resources, both to facilitate the hosting of testbeds, and to enable a wide range of players to develop and test methods;
- Developing standards and frameworks for the validation of proposed methods;
- Integration challenges, given tight regulatory environments and legacy infrastructure.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[60] *Learning to Run a Power Network Challenge: A Retrospective Analysis*, Marot et al. (2021).

Mapping floods with AI:
The United Nations Satellite Centre

UNOSAT'S FLOODAI ENABLES HIGH-FREQUENCY FLOOD REPORTS THAT HAVE IMPROVED DISASTER RESPONSE IN ASIA AND AFRICA

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Climate change is making flooding events more frequent and severe, as a result of rising sea levels and more extreme weather. According to recent studies, the number of people exposed to floods is likely to continue to increase more quickly than the overall population in 59 countries, mostly in Asia and Africa. For instance, heavy rains and massive floods caused by the 2020 southwest monsoon season hit nearly 10 million people across South Asia, destroying crops and farmland, forcing evacuations, and killing at least 550 people in Bangladesh, India, and Nepal, according to the UN and the International Federation of Red Cross and Red Crescent Societies.[61]

The United Nations Satellite Centre (UNOSAT) Rapid Mapping Service provides satellite image analysis during humanitarian emergencies. UNOSAT typically responds to more than 20 flood events per year, with expert analysts providing maps of flooded regions for humanitarian agencies and flood response teams. However, with the number of incidents on the rise, UNOSAT has begun to leverage AI to automate and improve analytical workflows. The UNOSAT S-1 FloodAI pipeline uses fully convolutional neural networks, a type of deep learning method, to automatically predict flooded regions from Copernicus Sentinel-1 Synthetic Aperture Radar (SAR) imagery.

FloodAI is already deployed across UNOSAT's flood operations in countries such as Bangladesh, Cambodia, Mozambique, Myanmar, Nepal, Thailand, and Vietnam, and has allowed more numerous and granular predictions to guide disaster response. For example, during 2021 floods in Nepal and Myanmar, FloodAI made it possible to process over six times the images previously processed by other methods, giving daily updates on the evolution of the extent of flooding and the exposed population.

Bottlenecks to further deployment of flood-mapping AI algorithms in general include:

- Lack of availability of labeled data (annotated flood maps) across different regions, from which the algorithms can learn;
- Access to computational power and data storage servers;
- Technical capacity within relevant national and international organizations for implementing and working with AI algorithms.

[61] *South Asia floods: 9.6 million people swamped as humanitarian crisis deepens*, International Federation of Red Cross and Red Crescent Societies (2020).

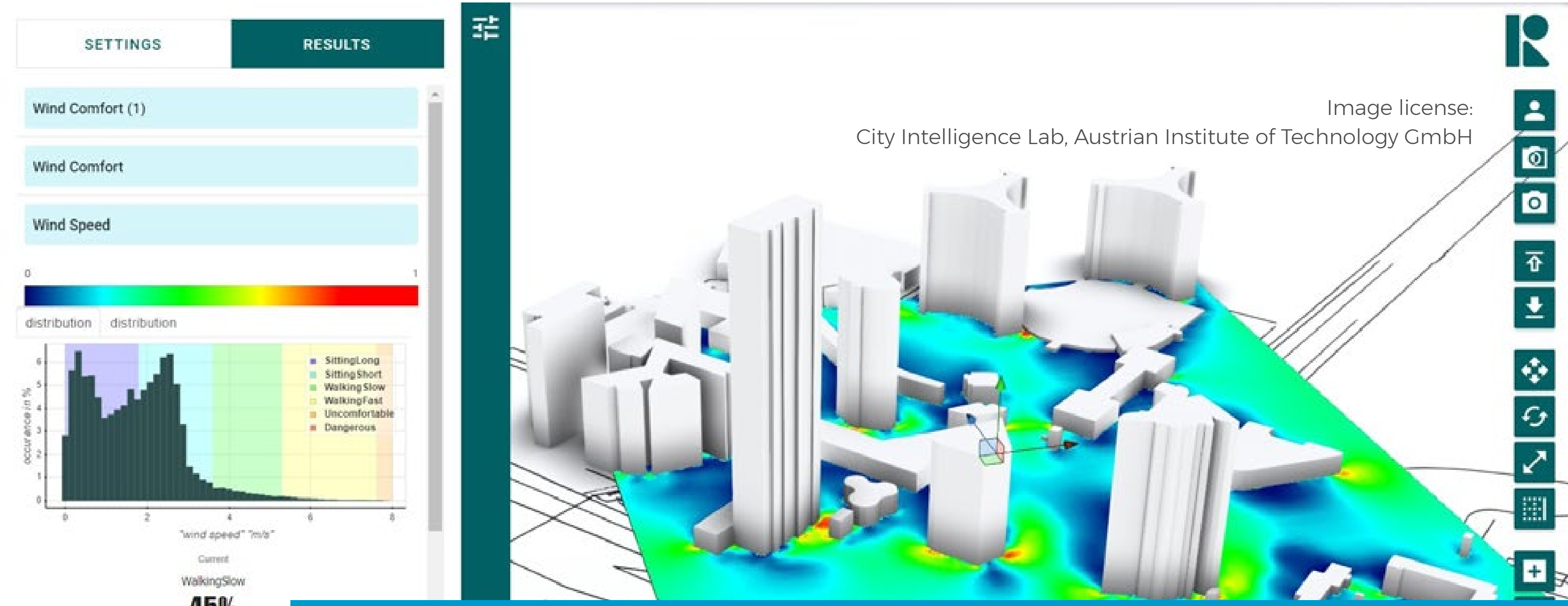


Image license:
City Intelligence Lab, Austrian Institute of Technology GmbH

Modeling urban microclimates: **InFraReD**

IMPROVING URBAN DESIGN BY SIMULATING THE URBAN MICROCLIMATE IN SECONDS, INSTEAD OF HOURS, THANKS TO AI

Urban areas are especially sensitive to heat waves, as the temperature inside a city is affected by the built infrastructure and can be several degrees warmer than outside. To adapt to climate change, buildings and other urban spaces must be designed with an understanding of how they influence the urban microclimate. This is also relevant for mitigation, as it affects the energy needed to ventilate, heat and cool buildings. Urban planners for example need to understand how wind flows through streets and around buildings and simulate the effects on wind chill, natural ventilation, and air quality. Such large-scale simulations are, however, computationally intensive and time-consuming to run, making them costly and impeding their real-time use, e.g. for evaluating and comparing designs.

InFraReD, developed by the City Intelligence Lab of the Austrian Institute of Technology (AIT)[62] in collaboration with the Bauhaus University, aims to make environmental simulations accessible to a wide range of stakeholders. It uses deep learning models to predict simulation results, allowing users to reduce the time and costs of running complex environmental simulations such as wind simulations that are normally based on time-consuming computational fluid dynamics.

By speeding up simulations, InFraReD allows architects, urban planners, policy makers, developers, and municipalities globally to access previously unattainable information on the climate effects of new and existing urban

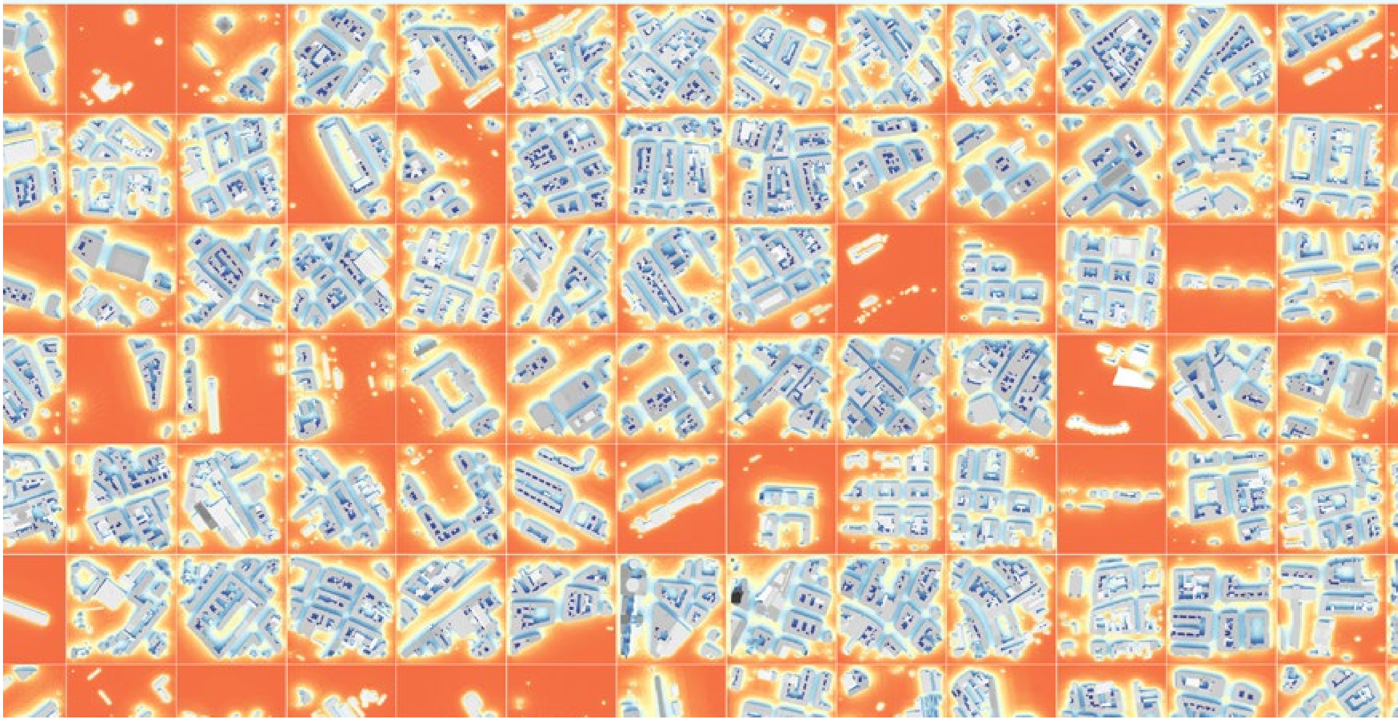
[62] *City Intelligence Lab at AIT* (accessed 2021).

plans. When the prediction models are integrated with governmental or municipal design and planning platforms, the speed and ease of use can allow users to quickly evaluate fundamental environmental effects of candidate designs. InFraReD has been deployed as a software integrated plugin, as a cloud application integrating with the the urban design platform Giraffe[63], as well as through an API, and interfaces with several other design platforms. It is already used by a number of researchers and companies (such as LINK Architektur), and it was recognized with the VCO mobility award.

Bottlenecks to the wider use of AI in aiding urban design are:

The availability of data, both real-world and from computationally intensive simulations, to train AI-based approaches. This could be alleviated by large-scale data and data-sharing protocols;

Standards for integration of AI-based simulation prediction models into design and planning workflows.



[63] *CIL & Giraffe: AI Wind Comfort on the cloud*, Austrian Institute of Technology (accessed 2021).

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Reducing the footprint of recycled steel: **Fero Labs**

FERO LABS USES AI TO HELP STEEL MANUFACTURERS REDUCE THE USE OF MINED INGREDIENTS BY UP TO 34%, PREVENTING AN ESTIMATED 450,000 TONS OF CO2 EMISSIONS PER YEAR.

Steel production accounts for over 20% of greenhouse gas emissions from manufacturing,[64] making it a prime target for emissions reduction. A core component of steel emissions is the mining and transportation of ingredients. Recycling steel reduces this burden by leveraging scrap steel, from sources like old vehicles — and thus is the most commonly employed method in the US.

However, recycling steel comes with a major challenge. Each batch of melted scrap steel has a unique chemical composition, affecting the strength and resilience of the new steel it will eventually turn into. To ensure that the final product meets quality standards, manufacturers must add freshly mined materials to each batch — these are called "alloys." Ideally, they would add only the precise amount of alloys needed to ensure a high-quality final product. In practice, however, the costliness of scrapping a batch and the complexity of determining quality motivate manufacturers to act conservatively and add more than they might need. This is a major source of preventable emissions.

To address this challenge, the US-based company Fero Labs has partnered with a major manufacturer of recycled steel to reduce the amount of new alloys they add during the production process. Using an explainable AI approach called Bayesian machine learning, Fero's software learns from historical data to recommend the minimum amount of additional

[64] *Emissions Inventory*, Climate TRACE (2021).

new material (if any) that needs to be added to a particular batch of molten recycled steel, thereby reducing the amount of freshly mined materials used. As recommendations are provided in real time, this approach also decreases the amount of time that the steel must be maintained in a molten state, reducing overall energy usage during production.

Over the last three years, Fero's AI-driven optimization software reduced alloy usage by 9-34% at 5 steel manufacturing plants. Avoiding mining, smelting, and transporting these alloys has prevented an estimated 450,000 tons of CO2 emissions per year. If scaled to the rest of steel production in the US, this approach could prevent 11.9 million tons of CO2 emissions per year — equivalent to a quarter of New York City's yearly CO2 emissions.[65]

Bottlenecks to the wider adoption of predictive methods in materials manufacturing include:

- Insufficient availability of high-quality industrial data to formulate predictive methods;
- Potential lack of trust among manufacturers in the quality or reliability of AI methods, due to, e.g., a lack of available standards;
- Lack of translation from research to deployment of work in areas such as explainable, interpretable, and robust AI.

Image license:
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[65] *Inventory of New York City Greenhouse Gas Emissions*, The City of New York (2016).

Optimizing energy consumption in smart buildings: **Arup**

ARUP'S SMART BUILDING OPTIMIZATION TOOLS SAVE 10-30% OF THE ENERGY USED IN A TYPICAL COMMERCIAL BUILDING

Image license:
Neuron - 2 - © Arup

Buildings account for 90% of the total electricity consumption in Hong Kong,[66] about a quarter of which comes from heating, ventilation and air-conditioning (HVAC) systems.[67] Optimizing these HVAC systems is therefore critical for saving energy and thereby reducing carbon emissions, as well as decreasing consumers' energy bills.

To tackle this challenge, Arup developed Neuron, an intuitive and fully customizable visualization tool that enhances buildings' energy savings, improves efficiency, and optimizes operational workflows. Neuron uses 5G and Internet of Things sensors to gather real-time data from building equipment and systems. It then uses AI to analyze this real-time building data in order to optimize and automate HVAC operations, and then provide insights on building performance to the building manager.

Arup's energy optimization modules have currently been adopted in 10 buildings in Hong Kong, delivering ~10-30% energy savings in each building. They are expected to expand to 100+ buildings in the next 12 months. They are also piloting the use of their technology beyond "traditional" commercial buildings. For instance, Arup has piloted the use of their building intelligence and analytics platform for Water Cube, one of the most iconic symbols of 2008 Beijing Olympic Games, with an eye towards expanding to additional sports venues.

Bottlenecks for wider use of AI for optimizing building energy use include:

- Lack of effective physics-informed and ML based building simulation models, which often are integral parts of such products;
- Lack of trust in the privacy mechanisms associated with data collection, processing and sharing of building data;
- Slow pace of building refurbishments to enable installation of smart devices and sensors.

[66] *Hong Kong's Climate Action Plan 2030+*, Government of Hong Kong (2017).
[67] *Hong Kong Energy End-use Data 2021*, Electrical and Mechanical Services Department of the Government of Hong Kong (2021).

Helping the trains run on time: **Deutsche Bahn**

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AI CAN ANALYZE DATA TO DETECT PROBLEMS EARLY OR EVEN BEFORE THEY HAPPEN, HELPING TO RUN VAST TRAIN INFRASTRUCTURE SYSTEMS MORE RELIABLY

Trains are a low-emissions option for passenger travel and freight, and therefore are key to decarbonizing transportation. The choice to use trains instead of planes or cars (for passenger travel) or trucks (for freight) can depend on the speed and reliability of rail, which makes preventing failures and overcoming irregularities in schedules a priority for railway companies.

Deutsche Bahn, Europe's largest railway company, uses AI to help optimize aspects of their freight and passenger operations. AI can analyze sensor, visual, and audio data at unprecedented scale and accuracy, capabilities that Deutsche Bahn has used to detect snow on the tracks, help inspect vehicles to speed up maintenance, and identify when railroad switches and other mechanical equipment may be at risk of failing.[68,69] Deutsche Bahn also uses AI to help with complex scheduling decisions when delays occur, in order to bring the large system back on track, and to increase the density of trains that can run simultaneously.[70] Many at Deutsche Bahn see AI as a key lever for ensuring that trains run on time.

Deutsche Bahn has worked on piloting and rolling out many of these AI approaches over the last several years. The technology is still new, and the railway company is working to integrate it into the decades-old processes and infrastructure. For this, not only the technical aspects are relevant, but also the integration with the workflows of the responsible personnel. When using AI-powered recommendations, Deutsche Bahn relies on human operators to make final decisions.[71]

Bottlenecks in this area more generally can include:

Integration of AI systems into existing processes that have humans in the loop, which requires trust of decision makers in the system;

Integration of AI systems into legacy software and infrastructure;

Lack of data sharing between entities, leading to small and siloed databases. Many predictive maintenance approaches could be greatly improved if more data were shared within and between entities.

[68] *Using computer intelligence to enhance human skills,* Deutsche Bahn (accessed 2021).
[69] *Artificial Intelligence at DB,* Deutsche Bahn (accessed 2021).
[70] *Künstliche Intelligenz macht die Bahn pünktlicher und zuverlässiger,* Deutsche Bahn (2021).
[71] *Bahn bringt Künstliche Intelligenz aufs Gleis,* Handelsblatt (2021).

Analyzing climate risk in financial disclosures

AI-BASED TEXT-PROCESSING TECHNIQUES CAN HELP ANALYZE AND QUANTIFY THE IMPACTS OF CLIMATE CHANGE ON FINANCIAL MARKETS AND INDIVIDUAL COMPANIES.

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In the coming years and decades, climate change will have an extensive impact on the global stock market, with damages estimated to be in the trillions of dollars.[72] However, without adequate data, it is difficult to predict exactly how and when climate change will impact financial assets. While qualitative data has historically been hard to come by, in recent years, fiscal legislation in both North America and Europe has obliged publicly traded companies to disclose climate-related risks and uncertainties. This, coupled with voluntary initiatives such as the Task Force on Climate-related Financial Disclosures (TCFD), has engendered a wealth of textual data from ESG (Environmental, Social and Corporate Governance) reports to more generic texts such as quarterly and annual disclosures.

Natural Language Processing (NLP) techniques allow AI algorithms to process large amounts of unstructured text and to identify relevant sentences and passages. They can be trained on data annotated by experts such as sustainability analysts, who currently carry out all analyses manually. Trained NLP models can be deployed either independently to extract relevant passages, or in tandem with human annotators to spare them from reading entire reports, which can span hundreds of pages.

Recent work[73,74] by researchers in Canada, Switzerland, and Germany has demonstrated the advantages of NLP approaches in pinpointing different

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[72] *Climate Value at Risk' of Global Financial Assets,* Dietz et al. (2016).
[73] *Automated Identification of Climate Risk Disclosures in Annual Corporate Reports,* Friederich et al. (2021)
[74] *Cheap Talk and Cherry-Picking: What ClimateBert has to say on Corporate Climate Risk Disclosures,* Bingler et al. (2021).

types of climate-related risks in annual corporate reports from companies in a variety of European countries, including both physical and transition risks. For example, such work shows that in recent years, disclosure of transition risks has grown more significantly than disclosure of physical risks, and that certain industries (notably, the energy industry) have much higher rates of climate-related risk disclosures than others.

Bottlenecks in developing and deploying NLP tools for analyzing climate risk in financial disclosures, and for large-scale analysis of policy-relevant documents in general, include:

Lack of annotated data, most of which is proprietary and/or not free to access;

Data formatting: When data is available, it is overwhelmingly in PDF format (rather than as machine-readable text, spreadsheets or CSV format), which renders it hard to extract and process automatically.

Heterogeneity in climate risk reporting policies, which vary between countries and markets, making it difficult to develop a single model or algorithm for risk identification.

Optimizing data center energy usage: **DeepMind**

DEEPMIND USES AI TO INCREASE DATA CENTER COOLING SYSTEM EFFICIENCY BY APPROXIMATELY 30-40%

As the ICT sector grows, the power used by industrial-scale data centers is growing. While much of the energy demand is from computation, over 40%[75] comes from data center cooling systems. There is significant scope for making these cooling systems more efficient, by optimally timing and coordinating cooling operations.

DeepMind, a UK-based subsidiary of Alphabet, has developed an AI approach to significantly reduce the energy required for cooling Google's data centers. DeepMind's approach uses reinforcement learning (RL), a branch of machine learning where the algorithm learns to control a system in order to maximize a "reward." This RL system can proactively explore safe configurations that have not been tried historically, leading to non-intuitive discoveries that can boost efficiency, such as spreading loads across more equipment. DeepMind uses different mechanisms to ensure the system will behave as intended, such as verifying optimal actions against an internal list of safety constraints defined by data center operators, who can also choose to exit the AI control mode at any time.

Compared to a baseline of standard data center cooling systems without optimization, the algorithm has reduced energy usage by approximately 30-40%. The amount of energy saved depends on various factors, such as the configuration of equipment in a facility. DeepMind and Google are looking to explore how the system could be deployed across other sectors and use cases.

Bottlenecks to the wider adoption of power-use optimization techniques by industrial facilities include:

- Potentially slow adaptation of AI techniques by some facilities, due to concerns about reliability;
- Potentially insufficient in-house AI capacity within some industrial facilities to integrate and operate such systems.

[75] *Cooling Energy Consumption Investigation of Data Center IT Room with Vertical Placed Server,* Zhang et al (2016).

Further reading

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