AI & Climate Action in Asia

An Overview of Emerging Opportunity Areas and Socio-technical Challenges

AI + Climate Futures in Asia

Report by

digital futures lab

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Any errors or omissions are our own.

Foreword

Asia stands on the precipice of a monumental shift. As home to the majority of humanity, the decisions we make now for this region have the power to reshape our very existence. The brutal impacts of climate change bear down upon us relentlessly – floods ravage our cities, droughts leave our lands desolate, and extreme weather events impact large populations in the region. These events require urgent action.

But amidst this chaos, Asia is undergoing a profound digital transformation. Emerging technologies such as AI are heralded as potential mitigation and adaptation tools that can help cut down on emissions, build resilience and better prepare for the impacts of climate change.

Recognising the complexity of this intersection, The Rockefeller Foundation has created this space to convene a variety of voices, offering a breadth of perspectives on climate transitions and technologies. We initiated this discussion with the objective to understand our own blind spots. And through this journey, we have learnt from different viewpoints – some that are aligned with ours, others that present a different reality. The intent was never to arrive at a single unified view, rather explore the various futures that can potentially unfold. I am grateful to everyone who participated in the process and engaged in conversations that were a step outside their comfort zone sometimes. The nuance of this conversation indicates that these are ongoing discussions and we hope this initiative serves as a platform to synergise different views on the subject. You will read many diverse views presented across the compendium and I would encourage you to connect with the experts to understand their individual perspectives better.

Now more than ever, we stand at a critical juncture in the fight against climate change. It is a fight that demands intentional and thoughtful interventions, ones that account for the digital divide and financial disparities that plague the region. Only through an inclusive and equitable approach to thinking of problems and designing solutions can we hope to forge a path forward, one that promises a brighter future for our people and our planet.

Deepali Khanna
Vice-President, Asia Regional Office
The Rockefeller Foundation

List of Abbreviations

AI	Artificial Intelligence
AIIB	Asian Infrastructure Investment Bank
ASEAN	Association of Southeast Asian Nations
API	Application Programming Interface
CCTV	Closed Circuit Television
EO	Earth Observation
ESA	European Space Agency
ESG	Environmental, Social & Corporate Governance
EU	European Union
FM	Foundational Model
GDP	Gross Domestic Product
GDPR	General Data Protection Regulation
GHG	Greenhouse Gases
GIS	Geographic Information System
GPAI	Global Partnership on Artificial Intelligence
GPS	Global Positioning System
GPT	Generative Pre-trained Transformer
IPCC	Intergovernmental Panel on Climate Change
LEO	Low Earth Orbit
LLM	Large Language Model
ML	Machine Learning
MSME	Micro, Small & Medium Enterprises
NASA	National Aeronautics & Space Administration
NASSCOM	National Association of Software & Service Companies
NEC	Nippon Electric Company
NGO	Non-government Organization
NOAA	National Oceanic & Atmospheric Administration
OECD	Organisation for Economic Co-operation & Development
R&D	Research & Development
SEEDS	Sustainable Environment & Ecological Development Society
SGD	Singapore Dollar
SoI	Survey of India
UN	United Nations
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme
US	United States
USD	United States Dollar

Executive Summary

Introduction

Climate change and digital transformation are two of the most significant drivers shaping the future of Asia. However, the interaction between these two drivers and their future trajectories needs to be better understood.

This report provides an overview of the opportunities, challenges, and risks of using AI for climate action in nine Asian countries - Bangladesh, China, Indonesia, Malaysia, Philippines, Singapore, Thailand and Vietnam. It covers three critical sectors in the region—agriculture and food systems, power and energy transitions and disaster response.

We need to develop localised and context-specific knowledge about the interaction between climate action and AI. The severity of the climate crisis in Asia makes this an urgent priority.

Many studies have a product-oriented view of the space, highlighting, for example, the gains expected from specific interventions. This can obscure broader system dynamics and structural impacts, such as impacts on livelihoods and marginalised social groups.

The use of AI for climate action is still nascent in the region. Developing a context-specific understanding of the opportunities, challenges and risks can help avoid harmful technological and policy lock-ins, and identify the steps needed to steer AI trajectories toward equitable and sustainable climate action.

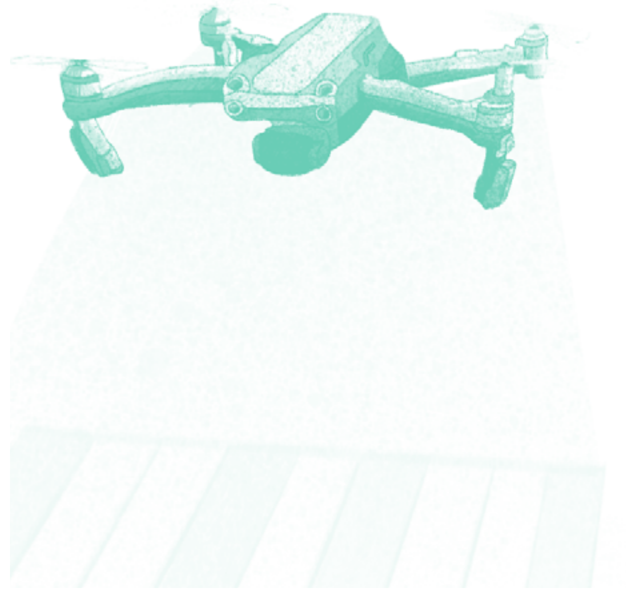
Assessing the Ecosystem

Developing AI applications for climate action requires appropriate data and digital infrastructure, targeted policy frameworks, and sustained investments in research and innovation. AI readiness across countries varies considerably, but most face a set of common challenges.

Countries in the region are enthusiastic about the use of digital technologies and AI for climate action, but there are considerable gaps between policy and practice. Some of the key reasons for this gap are siloed policy agendas, weak institutional capacities, limited investments in R&D, a lack of climate financing, and the absence of multidisciplinary capacities. There are also considerable differences across countries. The institutional landscape, as well as the use of AI, is far more mature in countries like China, Singapore and India compared with a country like Bangladesh. Most countries have yet to develop enforceable frameworks for responsible AI; frameworks for equitable data sharing between public and private actors are also absent.

A common challenge for building AI applications is the lack of climate data and the poor usability of existing data infrastructures. Existing public data sets are fragmented and collected using differing standards. While many countries have invested in open data portals, uptake and usage are limited. Satellite coverage is unequal across the globe, and the resolution of satellite data varies across topographies and areas with differing population densities. Satellite data needs to be combined with ground-truthing, which is an expensive and laborious process. Areas most vulnerable to climate action tend to have limited data collection infrastructures and capacities.

The lack of a sustainable revenue model and the absence of community consultation impedes the development of applications for vulnerable populations. Private-sector investment in climate tech is growing across the region, but it tends to be concentrated in solutions for urban areas or more financially lucrative sectors such as mobility and transport. The costs associated with collecting and processing data incentivise organisations to prioritise commercially viable applications. Global technology giants such as Microsoft and Google are leading investors in this space, often working in partnership with national or state governments—publicly available information about the nature and outcome of these partnerships is limited. Investments in AI for climate may grow as companies look for ways to demonstrate compliance with ESG targets, but an inability to measure impact is a deterrent to further investment.



Opportunities, Challenges and Risks

The use of Machine Learning for climate action is still nascent in most countries in Asia, and many initiatives are at the research or pilot stage. Sociotechnical challenges and risks can be extrapolated from earlier studies on digital technologies for climate action and the use of AI in other geographies.

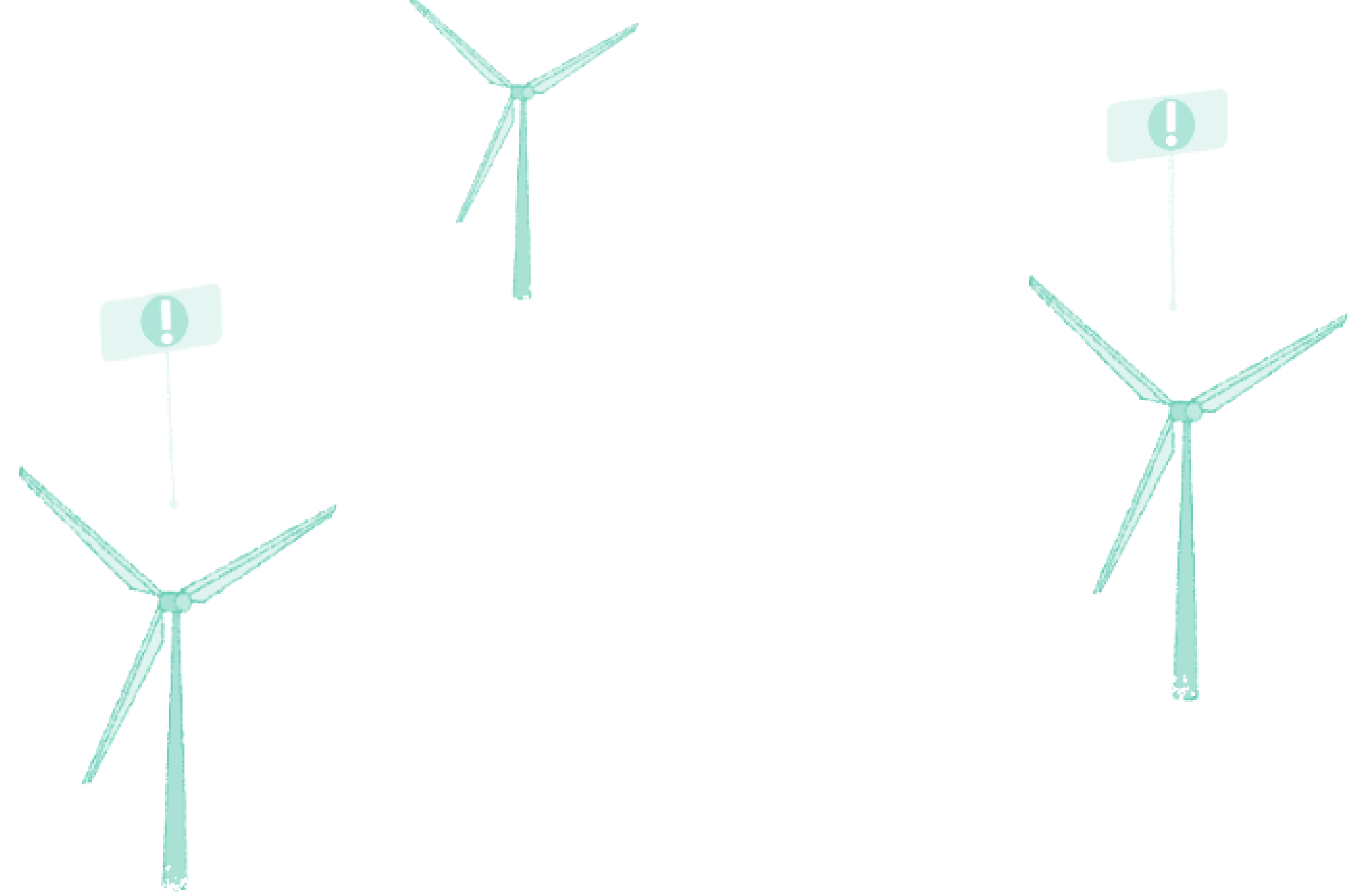
1

Agriculture and Food Systems

Within agriculture and food systems, a bulk of applications involve weather forecasting and crop advisories for farmers. However, large variances across agroclimatic zones and the resources required to capture accurate data make it difficult to develop accurate, context-specific, advisories.

Of concern is the unequal digital access and a lack of financing for farmers to sustain the use of ML applications. In the absence of enforceable regulations for data sharing and use, there is a risk that these applications could contribute to the commercialisation of farm data at the expense of farmer livelihoods and rights.

A promising area of intervention may be the use of ML for foundational research on new food and seed varieties. Such initiatives must prioritise a public benefit goal and not lead to private monopolies that impinge on the food sovereignty of communities and countries.



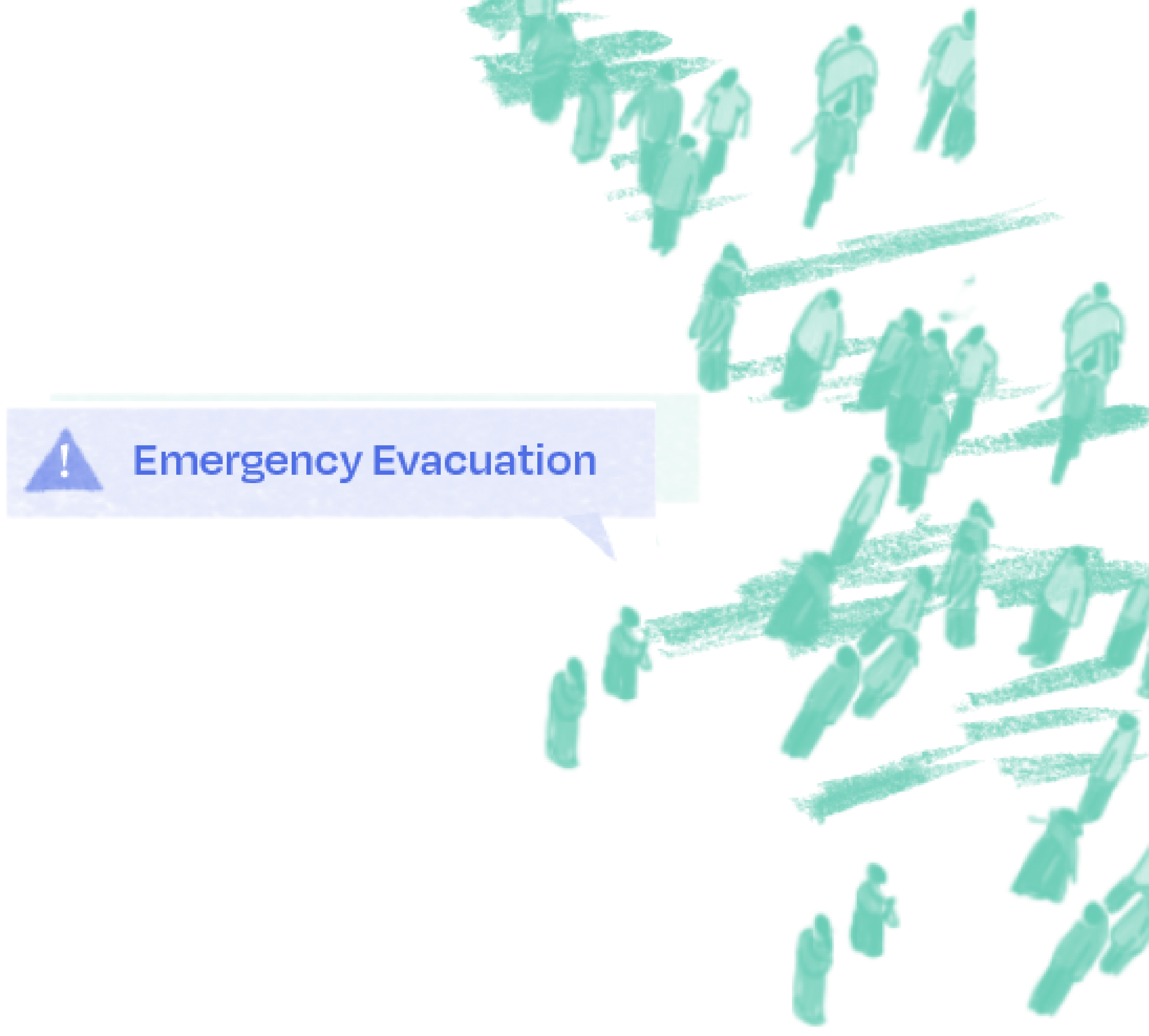
2

Power and Energy Transitions

ML is being used to forecast demand and supply of power and improve planning, as well as identify and monitor renewable sources of energy. However, the uptake is slow and incremental due to high costs and the potential risks associated with errors.

Interdisciplinary technical expertise that combines an understanding of data science ML, and energy grids, is limited, posing an impediment to innovation and adoption. Cybersecurity and privacy risks need to be considered, especially given the nascency of data infrastructure and regulation.

Using ML to advance scientific research and innovation on climate mitigation is a potential area. An example of this is the acceleration and optimization of scientific discoveries related to new materials, aiming to decrease carbon emissions from construction activities.



3

Disaster Response

The application of ML for disaster response and preparedness is growing with several tools for early warning, disease surveillance, environmental monitoring, and crisis response. There are several examples of successful civil society initiatives, alongside applications targeted at private sector companies to help them climate-proof their investments and supply chains.

Weather prediction models based on ML may produce errors as these algorithmic models are not constrained by laws of physics. Based on historical data, they are also not good at predicting sudden or unexpected climate events.

Crowdsourced data will reflect a digital divide and risk contributing to exclusionary relief initiatives.

The use of large language models (LLMs) for climate modelling is a promising area for research. LLMs can improve access to information across languages and differing levels of digital competence, while also helping build more complex system models. A note of caution is the potential to misuse LLMs for spreading false or misleading climate information.

Structural Considerations

In addition to specific AI applications for climate action, we must also consider the broader system-level impacts and structural transformations that may result from the use of AI for climate action.

Training, building and running AI models requires an enormous amount of energy and water resources, contributing to considerable environmental costs. The emissions from training a single AI model is equivalent to nearly five times the emissions of an average car in America. Improving the accuracy and size of the models consumes even more energy. Water consumption for cooling data centres is likely to be higher in Asia's warmer climates. Much of global e-waste is disposed of in developing countries, exposing populations to a range of health risks.

The use of AI can accentuate global climate injustice, contributing to an unequal distribution of benefits and harm. Industrialised economies are better positioned to develop and leverage new digital technologies, because of better digital infrastructure, talent, data, and financing. Populations most vulnerable to climate action are likely to be underrepresented in climate data and may not have the resources to adopt emerging applications.

Many existing applications prioritise commercial gain over meaningful climate action, and risk contributing to greenwashing by private companies.

AI could displace traditional knowledge systems and local capacities while contributing to further entrenchment of power with leading technology companies. Top-down AI-based interventions risk displacing or delegitimizing traditional or indigenous knowledge systems. The hype around AI risks elevating techno-solutionist approaches, at the expense of more crucial policy interventions. A handful of technology companies dominate critical social sectors; policy approaches that rely on AI applications for climate action risk further entrenching their power.

1 Introduction

Asia is one of the most vulnerable regions to climate change in the world. Climate-related risks to agriculture and food systems in Asia are expected to escalate with the changing climate, as are incidences of disease and illness with hazards such as heatwaves, flooding, and drought becoming more frequent.

Thirteen of the twenty most vulnerable countries to climate impacts are in the East Asia-Pacific Region and 7.5 million people in the region could fall into poverty due to climate impacts by 2030.[1] Addressing climate change is an urgent priority, and interventions to help mitigate and rapidly adapt to climate change at scale are needed.

Technological innovation is posited to be a key component in strategies for addressing climate action. The market for climate tech[2] is growing rapidly in Asia, with increasing attention on the uses of artificial intelligence (AI).

Southeast Asia saw investments amounting to USD 1.1 billion in climate tech in 2022.[3] Overall, Asia Pacific witnessed a surge in climate-tech investments, with start-ups receiving USD 4.5 billion and venture funding reaching USD 7.7 billion in 2022.[4]

The use of AI is expected to accelerate climate action in multiple ways – distilling raw data into actionable information, improving predictions, optimizing complex systems, and accelerating scientific modeling and discovery.[5] A recent study by Climate Change AI, a pioneering organization in this space, points to 37 potential use cases of AI in 13 domains. These include gathering and processing data on temperature change, improving the management of energy demand and supply, supporting precision agriculture, and facilitating scientific discovery.[6]

The development and deployment of AI can also have harmful outcomes for climate and sustainability.[7] For example, a recent report by the Organisation for Economic Co-operation & Development (OECD) highlights how AI can contribute to increased emissions and energy and water consumption.[8] AI can also be used to augment or accelerate activities that have negative environmental consequences, such as the use of AI for drilling optimization and anomaly detection in the high GHG-emitting oil and gas sectors.[9] The use of AI in climate action also raises a broader set of issues around the unequal distribution of harms and gains, data sovereignty, privacy, and community rights.[10]

Research and applications of the use of machine learning (ML)[11] and AI are still nascent, and the impacts are yet to be determined. This creates an opportune moment to consider the likely future trajectories of AI and climate action. This can help avoid harmful technological lock-ins and identify the policy pathways needed to steer AI trajectories toward positive climate action.

Much of the literature highlighting the potential of AI originates from a few industrialized economies, primarily the United States (US) and Europe.[12] However, technology trajectories and their impacts will not be the same all over the world, as they are refracted through diverse social contexts. As we advance the debate on the opportunities and challenges around the use of AI for climate action, it is important to base it on context-specific knowledge and capacities.

Research Query and Scope

This report provides an overview of how ML and AI are being used to target climate change in Asia, the potential opportunity areas, and the challenges and risks that might arise. It covers nine countries – Bangladesh, China, India, Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam.

Can AI support climate policy and climate mitigation and adaptation efforts?

What are the enablers, challenges, and risks?

How might the development and deployment of AI exacerbate climate-related risks?

Chapter 2 examines the broader ecosystem for AI development and use in terms of data infrastructure, policy and regulation, and research and innovation.

Chapter 3 identifies potential opportunity areas, challenges, and risks across three domains – agriculture and food systems, power and energy transitions, and disaster response and preparedness.

Chapter 4 looks beyond specific applications to evaluate the broader structural impacts of the use of AI.

This report is based on five months of desk research, including secondary literature and media analysis, and 30+ expert interviews. A formal expert network was also established for this project, consisting of an expert from each of the mentioned countries.

The vastness of the subject matter combined with the time available has meant that this report sacrifices depth for breadth – the aim is to provide an overview of the activity and issues in the region.

Moreover, the use of ML applications for mitigating and adapting to climate change is still at a nascent stage in most countries in Asia. Many initiatives are at a research or pilot stage and there is limited information available on their outcomes and impacts.

Most of the publicly available information is from companies themselves or media reports. Further longitudinal research and evidence are required to understand the impacts of AI on climate action.

Expert Network

Name	Country	Institution
Aaditeshwar Seth	India	Professor, IIT Delhi
ChengHe Guan	China	Assistant Professor, NYU Shanghai
Cindy Lin	Indonesia	Assistant Professor, Pennsylvania State University
Elenita Daño	The Philippines	Asia Director, ETC Group
Elina Noor	Malaysia/ South-East Asia	Senior Fellow, Carnegie Endowment for International Peace
Gaurav Sharma	India	Advisor, AI, GIZ
Md. Golam Rabbani	Bangladesh	Head, Climate Bridge Fund
Pyrou Chung	Thailand/Lower Mekong Delta	Director, Open Development Initiative
Tien Nguyen	Vietnam	Founder Partner, Earth Venture Capital
Veerappan Swaminathan	Singapore	Founder, Sustainable Living Lab

The Potential and Limits of Machine Learning

AI refers to the broader concept of machines being able to carry out tasks that normally require human intelligence. At a high level, key cognitive capabilities displayed by "intelligent" machine systems include a combination of classification, prediction, and decision-making tasks. Most references to AI relate to the more popular and prevalent application of AI in the global market, i.e., machine learning.[13] ML learns by example, i.e., it draws patterns and rules from the data, which it then applies to future cases.

Two types of tasks are most common in machine-learning applications: classification (e.g., is this a wildfire or not?) and prediction (e.g., how much fertilizer should be applied to improve yield outcomes?). Newer forms of ML, such as generative AI,[14] also create or generate new content.

AI is often confused with automation, but the two are distinct (albeit related) – automated systems perform repetitive tasks following a programmed set of rules, while AI identifies patterns and insights in data and "learns" to do this more accurately and effectively over time. This is significant because the outcomes produced by AI systems cannot always be known beforehand – how the system behaves in a lab setting may be different from real-world settings and the nature of these differences cannot always be foreseen, even by the developers of these applications.

The use of ML also poses a range of limitations and risks. Machine learning applications are only as good as the data they are trained on—applications built on incomplete, fragmented or unrepresentative data are likely to produce incorrect, biased or exclusionary outcomes. ML models are also not neutral; they are optimized for certain ends or goals, based on decisions made by developers, programmers, or companies, often shaped by reasons beyond just technical preference[15] Generative AI models can also extrapolate outside of the domain of the training data in unusual or undesirable ways.

ML must thus be used judiciously, fully cognizant of its limitations. Not all problems exist because of a lack of information and understanding, but rather they exist because of a combination of social, political, economic, cultural, legal, and historical factors. These are not easily modellable, and even if they were, modelling these requires making complex decisions about how these factors relate to each other and their relative significance specific to diverse local contexts.

Machine learning applications are only as good as the data they are trained on—applications built on incomplete, fragmented or unrepresentative data are likely to produce incorrect, biased or exclusionary outcomes.

A Note on Climate Data

Climate data is typically of two types—data regarding the physical environment (e.g., land use, precipitation levels, etc.) and data regarding human activities (e.g., energy consumption, mobility, etc.).

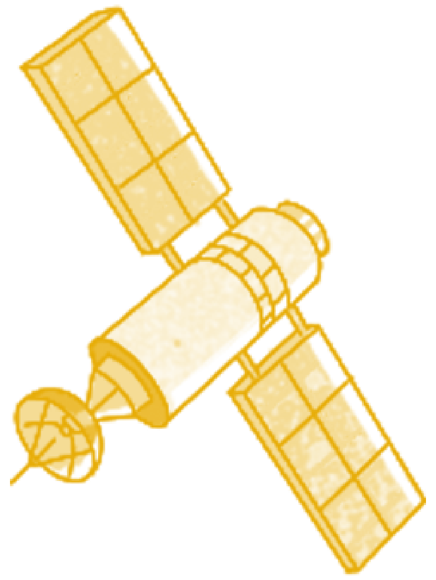
Data regarding the physical environment is typically collected through a combination of satellite imagery and remote sensing equipment; in recent years, drones and unmanned aerial vehicles have also been used. Satellite imagery, however, tends not to be of high enough resolution by itself. Satellite coverage is also not equal – some parts of the globe are mapped far more extensively than others, which is often reflective of colonial legacies.[16]

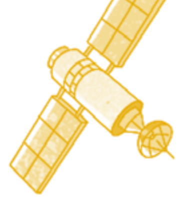
Satellite data thus needs to be corroborated by ground truthing, i.e., by physical data collection at localized sites through sensors and manual forms of data collection. This requires establishing extensive sensor equipment along with adequate digital transmission and connectivity infrastructure to allow for real-time processing and monitoring.

Collecting such data is an expensive and laborious activity, and there are significant data gaps, which reflect existing socio-economic inequities and digital divides. For example, even in an advanced economy like the US, air quality monitoring meters are concentrated in wealthier urban areas.[17] These inequities in data representation are magnified in other parts of the majority world, including Asia. Many areas that are most vulnerable to climate disasters are excluded from dominant data sets because of limited resources and institutional capacity.

Some experts have also noted that the ground-truthing process is insufficient to validate the "truth" behind data. It reflects a particular view of what counts as relevant data. While data might be collected on the ground, the epistemic categories are constructed top-down and often without community consultation.

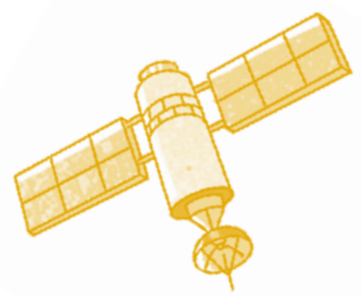
The quality of satellite data also varies based on factors such as geography and cloud cover. Satellites are better at capturing certain types of topographic data. For example, data on landslides are easier to capture compared to data on air precipitation levels. Similarly, the detection of peatland fires (very common in Indonesia) by satellites is challenging since these fires burn underground.[18]





Most active satellites in orbit are optical satellites. They rely heavily on reflected sunlight to capture images, which can be compromised by cloud cover. Shadows, reduced contrast, and colour distortion in the captured images can make obtaining detailed observations extremely challenging.[19]

Advancements in low-Earth orbit (LEO) satellites are improving the quality of available data, but these have a far more limited coverage area. Private investments in satellites have been central to spurring innovation in LEO satellites and have helped diversify the services provided and enabled through this imagery.[20] Google, for example, has backed a collaboration between non-profit organizations (NGOs) WattTime, Carbon Tracker, and the World Resources Institute to operate a global network of satellites to monitor the greenhouse gas emissions (GHGs) of large power plants.[21]



Policy support is provided to private players in some countries to help augment the state's data collection capacities. For example, a government consultation paper on Earth orbit (EO) missions in India advocates for the involvement of the private sector to meet increasing demands for frequent high-resolution satellite data.[22] Some civil society groups have, however, voiced concerns about the growing privatization of this space, highlighting issues of data sovereignty and the commercialization of climate data.[23]

The enormous costs associated with cleaning and processing data have also meant that many start-ups and private companies working in this space orient their product development to sectors that are most commercially lucrative, such as supporting banking and insurance services rather than those most vulnerable to climate disaster.[24]

For example, data on precipitation and temperature is publicly available, but in a raw format, which needs a lot of resources for processing. AI companies using this data are incentivized to build products for insurance companies or other commercial ventures, as that would help them cover these costs. They are not incentivized to use these data sets for "public good" initiatives because of a lack of financing or a sustainable business model.[25]

The second type of climate data, i.e., data about human activity, is growing alongside the increasing digitalization and datafication in the region. However, much of this data is often proprietary and held by private companies. Private entities hold sector-specific data, such as mobility data owned by ride-hailing businesses, agriculture data by agri-tech companies, or energy consumption data by private companies.

Advancements in low-Earth orbit (LEO) satellites are improving the quality of available data, but these have a far more limited coverage area.

While data might be collected on the ground, the epistemic categories are constructed top-down and often without community consultation.

A lot of climate data also relies on self-reporting by companies, but companies often fail to disclose data. The lack of unified standards for reporting GHG emissions also makes it easier for companies to selectively report or conceal their emission levels.[26] Certain types of data are also persistently under-reported – for example, there is limited data on land-use change. Land-use change strongly affects carbon sources and sinks and can lead to habitat loss.[27]

As a result of these issues, climate-relevant data is often not available equally across the world, and even where it is available, the quality is too poor for ML. This means that certain parts of the world with better data coverage and quality will have comparatively more accurate AI tools built on those datasets. Because of regional variations in climatic conditions, global forecasting models cannot be applied as is in local contexts.

Some partnerships have emerged in this space, but these are far and few in between. For example, in Bangladesh, local experts rely on global forecasts produced in Europe for the country's disaster-management protocol. These forecasts are sent to the United States and turned into flood forecasts which, within six hours, can be integrated into Bangladesh's disaster-management protocol.[28] Models like this also create dependencies on external actors.

1 World Bank. (2023). *Climate and development in East Asia and Pacific Region.* www.worldbank.org

2 Technologies that focus specifically on reducing GHG emissions, or, more broadly, are geared towards mitigating or adapting to climate change.

3 Gideon, N.G. (2023, April 14). *5 takeaways from Venturra's report on the state of climate tech in Southeast Asia*. KrAsia. https://kr-asia.com

4 Kuo, I. (2023, June 2). *Q&A: Decarbonising Asia Pacific: Challenges and opportunities. The Climate Group.* www.theclimategroup.org

5 Clutton-Brock, P., Rolnick, D., Donti, P. L., & Kaack, L. H. (2021, November). *Climate change & AI: Recommendations for government action.* Global Partnership on AI. www.gpai.ai

6 Rolnick, D. (2022). *Tackling climate change with machine learning. ACM Computing Surveys*, 55(2), 1–96. https://dl.acm.org

7 Organisation for Economic Co-operation and Development. (2022). *Measuring the environmental impacts of artificial intelligence compute and applications: The AI footprint.* OECD Digital Economy Papers. https://doi.org

8 Organisation for Economic Co-operation and Development. (2022). *Measuring the environmental impacts of artificial intelligence compute and applications: The AI footprint.* OECD Digital Economy Papers. https://doi.org

9 Clutton-Brock, P. Rolnick, D., Donti, P.L., & Kaack, L.H. (2021, November). *Climate change & AI: Recommendations for government action. Global Partnership on AI.* www.gpai.ai

10 Coeckelbergh, M. (2021). *AI for climate: Freedom, justice, and other ethical and political challenges.* AI Ethics, 1, 67–72. https://doi.org

11 Machine learning is a technique that learns by drawing inferences from datasets, i.e., it draws patterns and rules from the data, which it then applies to future cases. Elaborated further at p._.

12 Clutton-Brock, P. Rolnick, D., Donti, P.L., & Kaack, L.H. (2021, November). *Climate change & AI: Recommendations for government action. Global Partnership on AI.* www.gpai.ai; University of Cambridge. (n.d.). *Is data justice key to climate justice?* www.cam.ac.uk

13 Supervised machine learning uses labelled datasets to train the system to carry out tasks of regression (e.g., calculating the rent in particular area given previous years' data) or classification (e.g., is this a spam email or not)

14 Generative AI refers to AI systems that can generate content based on user inputs such as text prompts. They can be unimodal (receiving input and generating outputs based on just one content input type) or multimodal (i.e., able to receive input and generate content in multiple modes; e.g., text, images, and video). Jones, E. (2023). Explainer: What is a foundation model? Ada Lovelace Institute. www.adalovelaceinstitute.org

15 Digital Futures Lab. (2022, July). A framework for artificial intelligence procurement in the public sector (Unpublished).

16 Bronnimann, S. Climate data empathy. Wiley Interdisciplinary Reviews. www.geography.unibe.ch

17 For example, commercially available low-cost sensors are more widely used in affluent neighbourhoods in San Francisco. Jung, Y. & Echeverria, D. (2021, October 11). *The number of air monitors in the Bay Area has exploded. Where are they?* San Francisco Chronicle. www.sfchronicle.com

18 Ekin, A. (2019, October 31). *In a picture: 'Not enough people are aware of this monster'. Horizon.* European Union. https://ec.europa.eu

19 SatSure. (2023). *The Earth observation industry: A glimpse into the future and solutions for cloud cover challenges.* www.blog.satsure.co

20 Coykendall, J et al. (2023, March 22). *Riding the exponential growth in space.* Deloitte. www2.deloitte.com

21 WattTime. (2019, May 7). *WattTime will measure world's power plant emissions from space with support from Google.org.* www.watttime.org

22 In-SPACE and ISRO, Status of Indian EO Missions and Opportunities for participation for Indian Industries.

23 Eijk, C.V. (2023). *Symposium on fairness, equality, and diversity in open source investigations: Earth imagery's colonial legacy.* OpinioJuris. http://opiniojuris.org

24 Interview with representative from Environmental Data Analytics Company, April 12, 2023.

25 Ibid.

26 Kaplan, R. & Ramanna, K. (2021, November–December). *Accounting for climate change.* Harvard Business Review. https://hbr.org

27 Winkler, K., Fuchs, R., Rounsevell, M., & Herold, M. (2021, May 11). *Global land use changes are four times greater than previously estimated.* Nature, 12, 2501. www.nature.com

28 Webster, P. (2013). *Improve weather forecasts for the developing world.* Nature, 493, 17–19. www.nature.com

2 Assessing the Ecosystem

If countries are to responsibly build and use ML tools for climate change, several foundational infrastructures and capacities need to be established.

This chapter provides an overview of three key pillars in the Asian context—data and digital infrastructure, policy frameworks and initiatives, and research and innovation funding.

A few common themes can be observed

- Common across all countries is a great deal of policy enthusiasm around the use of digital technologies and AI for economic growth and innovation, as well as for various climate-relevant sectors and domains. Open-data initiatives are also common across the region, and investments in cloud and data infrastructure are growing.
- However, there is a gap in translating policy into action. Climate-specific data is not easily available and many countries in the region lack the technical and financial capacity to collect and process this data. Existing open-data initiatives have seen limited use, and most do not include climate-specific datasets.
- Countries also vary in their institutional and research capacities – countries like China and Singapore have a more mature ecosystem in terms of digital infrastructure, government policy and investments, and R&D capacity, whereas others such as Bangladesh are in the process of investing in digital infrastructure and setting up roadmaps for the adoption of Artificial Intelligencel.
- Private-sector investment is growing, particularly as companies look to meet environmental, social, and governance (ESG) requirements, but an inability to measure impact is a deterrent to further investment. A notable feature of the "AI for climate" landscape in Asia is the dominance of large global and regional technology companies. They operate as both funders and developers of new applications, often in partnership with local governments and/or academic institutions.
- Gaps in privacy and data protection regulation, with wide exceptions given to government agencies and private players, are causes for concern for civil society organizations across the region. The primacy given to economic imperatives over rights and safety in digital transformation agendas in the region has also contributed to an unregulated environment in terms of private companies' access to personal data in many countries.
- Enforceable frameworks for the responsible use and adoption of AI are also underdeveloped in the region, though countries like China and Singapore have introduced a few initiatives. The lack of civil society participation in rule-making processes is also common in many countries in the region. This contributes to what one expert has termed a "vicious cycle of bad laws" that neglect rights-based considerations.

Data & Digital Infrastructures

The countries reviewed for this study all have a digital transformation agenda; data-driven policymaking and innovation are seen as necessary catalysts for economic growth, development, and innovation. This enthusiasm is reflected in emerging policy and regulatory frameworks.

Open data portals, for example, are common across the region and countries have set targets for further opening up data and facilitating data exchange. Indonesia, for example, is a founding member of the Open Government Partnership and launched the One Data Policy in 2019 to support data sharing between central and regional agencies.[29] Vietnam has set a target of developing 50 open and linked data sets in different economic sectors to support AI development by 2030.[30]

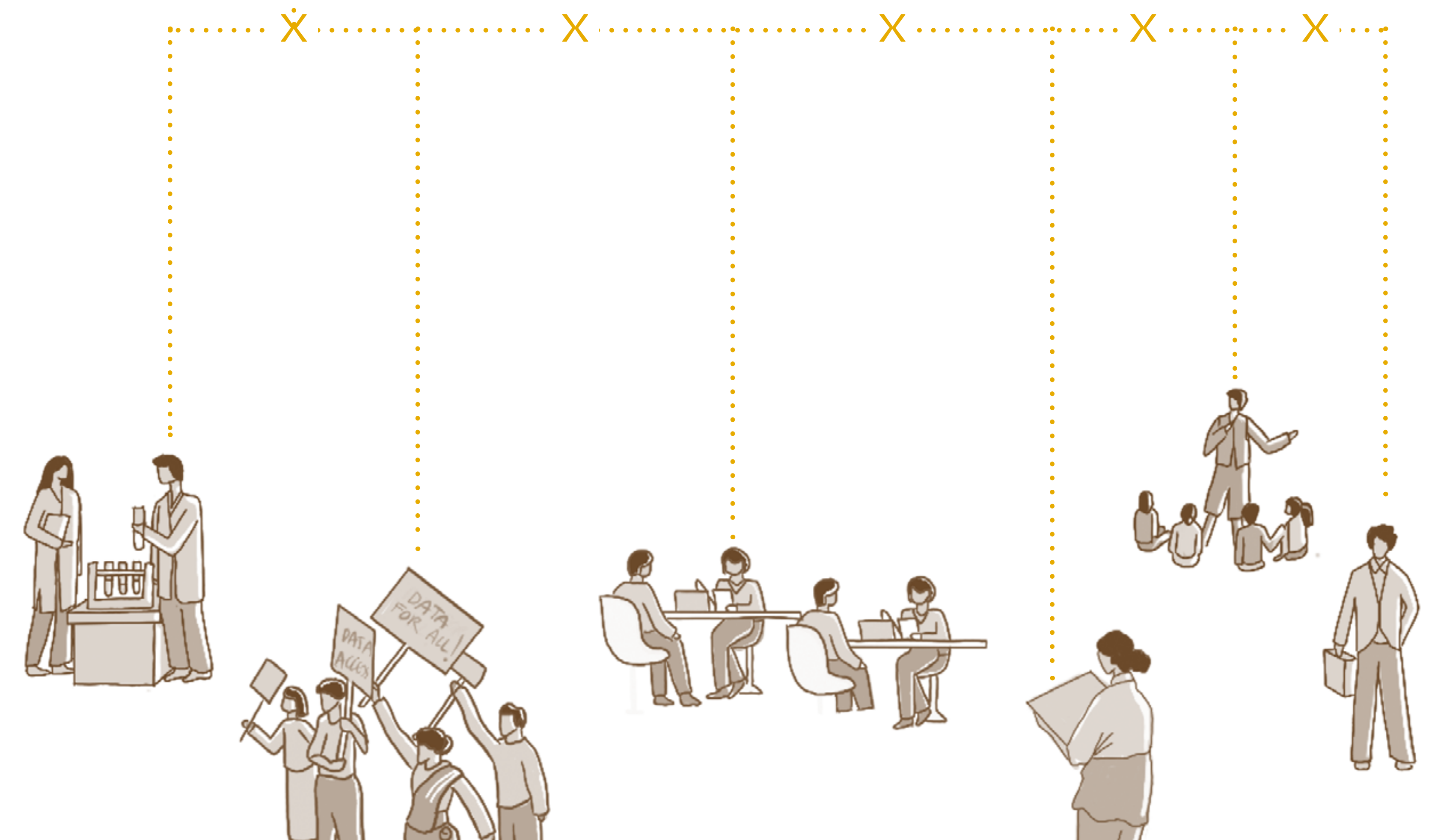
Many countries are also investing in digital platforms and identity systems to support public service delivery, contributing to further data generation and availability. Countries like Indonesia, Malaysia, Thailand, and Singapore have digitalized their foundational identity systems.[31] In the Philippines, a digital national ID system is in the works and is intended to deliver social protection schemes to intended beneficiaries.[32]

Countries like Singapore use real-time data to design and evaluate public policy; Pulse of the Economy, for example, uses data from public utilities, social media, and online apps to develop new indicators for economic and urban planning.[33]

Responding to the growth of the tech sector, countries are also investing in cloud and data infrastructure. In the Asia Pacific region, Singapore is the top destination for data centre markets.[34] Following a four-year moratorium on data centres, the Singapore government granted rights to four companies to build data centres in the country in 2022.[35] In Thailand, particularly Bangkok, both small and large operators have shown interest in setting up data centres. For example, investments of up to USD 1 billion towards the data centre market are expected in Thailand by 2026.[36]

However, these countries also share a number of common challenges. Digitalization has been uneven, and meaningful digital access varies greatly across geographies and social groups. China's urban–rural disparities in internet coverage and broadband speeds, despite its prominence in frontier technologies, speak to variations in network access even within countries.

Within countries, multiple agencies are involved in the collection of data, each with its own standards and parameters; coordination and data sharing between them are often poor.



In Bangladesh, despite the increase in the number of internet users, only 53.7% of the urban population has internet access; this figure goes down to 37.1% for rural populations.[37]

For many countries in the region, micro, small, and medium enterprises (MSMEs) form the backbone of the economy but the level of digitalization remains low.[38] The majority of MSMEs in Southeast Asia operate in rural areas, where broadband acess and electricity would be most likely absent or inadequate.[39]

Privacy and data protection legislation and their implementation are at different stages in the region. Of the countries in focus, all except Bangladesh have data protection laws in place. However, civil society groups across the region have called attention to the wide exceptions granted in many of these laws to government bodies and private actors for collecting and using data.[40]

A consistent observation in the literature and among experts and government officials concerns the limited use of open data portals due to the poor quality and limited usability of data. The reasons include a lack of awareness among the broader research and product development ecosystem, poor quality including a lack of standardization, and a lack of resources and skills to update and maintain these portals within the government.[41]

For example, Malaysia is part of the Open Data Initiative, but reports suggest that data is not presented in a user-friendly manner, and hence, the use and uptake of the platform is limited. Similarly, the Open Data Policy in the Philippines had limited impact because government officials lacked resources and data management capacities, and demand for the data among the general public was low.[42]

That being said, there have been instances where open data initiatives in the region have helped indigenous communities reclaim their land rights[43] by catalysing mapping activities to fill gaps in official data. For example, in Indonesia, independent mapping initiatives are helping indigenous communities establish claims[44] in the absence of funding and qualified government cartographers who can map these lands.[45]

A 2022 study on open data in the region also found that climate data is not available in most government portals despite the region facing tremendous challenges related to climate change.[46]

Within countries, multiple agencies are involved in the collection of data, each with its own standards and parameters; coordination and data sharing between them are often poor. This is owing to issues of capacity as well as reputational concerns or competition with other government agencies for state resources. Inter-ministerial data sharing is also hindered by conflicting interests.

Processing and cleaning satellite data is also expensive, time-consuming, and requires specialized skills. The higher the resolution of the data and larger geographical area it captures, bigger storage capacities are required, along with longer processing times.[47] In Europe, a dedicated agency is tasked with processing this data and making it available for public use, but such institutional capacities are yet to be established in the region.[48] In Asia, we see a few early attempts, but there is no designated agency at either the regional or country level. For example, in China, state-level remote sensing labs have now started processing satellite data.[49] India's new National Geospatial Policy 2022 makes geospatial data[50] available for research and commercial purposes

Ease of access to satellite data from European and American space agencies has promoted more research on this data, creating a streetlight effect.

Climate-relevant data that is usable for ML is difficult to access across the region, although differences exist across countries. As mentioned in Chapter 1, the coverage and quality of satellite imagery vary considerably across the globe. Many parts of Asia and Africa are poorly covered, often reflecting older colonial legacies.[51] The resolution of satellite imagery is also not high enough to adequately map high population density areas, which are common across the region.[52]

For the most part, AI-based interventions rely on satellite imagery and data sets from European or American satellites due to their relative ease of access.

As one expert notes, ESA has clear guidelines on how to access earth observation data and portals for private actors to communicate with the agency for accessing different kinds of data.[53] Because of the ease of access to this data, researchers often rely on them, leading to more scientific research based on these datasets.

The implication of this is that satellite data from countries like India do not feature often in peer-reviewed publications. As a result, research and product teams may be reluctant to use it, continuing to rely on data from American and European satellites,[54] invariably leading to a streetlight effect where research is guided by the ease of availability of data.[55]

However, countries in the region are working towards enhancing the sharing and visibility of satellite imagery. For example, satellite data from China and Brazil's Earth Resources Satellite, which captures topographical images, is freely available to anyone in the world.[56] India's National Remote Sensing Centre is tasked with the dissemination of satellite data with end users and hosts data of up to a resolution of 1 metre on the Bhuvan platform.[57]

Policy Frameworks and Initiatives

All the countries in focus have had a national AI strategy or roadmap in place since the late 2010s and numerous initiatives are underway to grow domestic AI capacities across the region.

In Indonesia, for example, the government has built a special economic zone called Bukit Algoritma, a technology and research centre inspired by Silicon Valley. In Vietnam, the government plans to set up a national centre for big data storage and high-performance computing along with national innovation centres for AI. In Thailand, there is a long history of government promotion of AI; in the early 2000s, the National Electronics and Computer Technology Center helped drive AI research among Thai universities.[58]

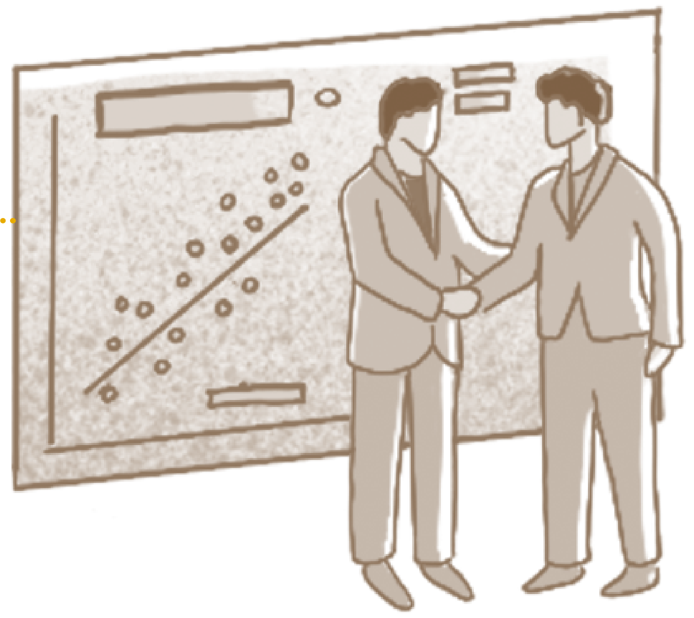
However, the core focus of these strategies is to leverage AI for economic growth and establish the enabling conditions for domestic innovation rather than climate-related issues. For example, a 2018 study by the International Data Corporation found that Indonesia had the highest AI adoption rate in Southeast Asia at 24.6%, followed by Thailand (17.1%), Singapore (9.9%), and Malaysia (8.1%), but most of this was concentrated in e-commerce and other urban services.[59]

The dominant policy narrative, particularly in larger economies like India, Indonesia, and Thailand, is that developing domestic AI capacities is essential for remaining competitive in the Fourth Industrial Revolution.

Countries also vary considerably in their level of AI readiness. In its Government AI Readiness Index, Oxford Insights identifies three pillars for AI adoption readiness – government (governance, ethics, and capacity), technology (innovation capacity and human capital) and data and infrastructure (data availability, data representativeness, and necessary infrastructure for powering AI).[60] For example, Bangladesh ranks 80 out of 181 countries in the index, while China ranks 17.[61]

Vietnam's ranking improved significantly in 2022, climbing seven positions to rank 6th among ASEAN countries and 55th globally.[62] This difference in performance is attributed to the government's increasing investment in

The institutional landscape for addressing harms and establishing guardrails around AI use is fairly nascent in most countries



AI technologies, an uptick in the number of digital technology enterprises, and the addition of a unicorn company (valued at more than USD 1 billion) in the country.[63]

Singapore has emerged as a global AI hub, owing to initiatives such as fast-tracking patent approval, incentivizing private investment, and addressing talent shortages.[64] Since 2018, it has invested SGD 500 million in AI research and development.[65] As a percentage of GDP, Singapore's government-supported AI R&D spending is eighteen times larger than the US R&D spending.[66]

Thailand has been an early adopter of AI technology, driven by the need to meet the demands of the global supply chain; it has the highest number of industrial robots in ASEAN and accounts for 1% of the robots globally in operation.[67]

With a focus on the potential of data and AI for economic growth, the institutional landscape for addressing harms and establishing guardrails around AI use is fairly nascent in most countries. China and Singapore have a relatively more mature ecosystem in terms of policies and initiatives that establish guardrails around AI development and use. China has introduced several legislative and policy frameworks to promote trustworthy AI.[68] India has participated in and promoted initiatives for the responsible use of AI, such as the presidency of the GPAI and various sector-level regulations.

However, the efficacy of many of these initiatives is yet to be seen. For example, even though Thailand has a comprehensive set of ethical guidelines for AI, a recent analysis shows a glaring bias towards the private sector; the top priority of the guidelines is to ensure the industry's compliance with international standards at the expense of public safety and protection.[69]

While climate is not an explicit focus of the AI strategies for any of these countries, climate-relevant areas such as agriculture, smart cities, mobility, disaster risk, and national resource management appear in AI policy documents.

For example, India and Bangladesh's AI policy frameworks emphasize smart agriculture, and Vietnam's AI policy includes a mention of managing natural resources and the environment. China's AI policy also highlights "intelligent environmental protection" for continuous monitoring of land, atmosphere, soil, and energy. Japan's 2022 AI Strategy prioritizes the use of AI for managing and responding to large-scale disasters.

The Aeronautics and Space Research Organisation in Indonesia is also developing an AI-enabled platform for remote sensing to monitor natural resources and the environment, and other government agencies are reported to be using AI technology to monitor and anticipate forest fires. Similarly, in Thailand, six major cities have committed to Smart City Development plans that seek to leverage advances in ML.

International agencies like UN organizations and multilateral banks also support governments in setting up climate-monitoring systems. These initiatives curate climate-relevant data, which is then available for informing decision-making on climate action. For example, the International Methane Emissions Observatory set up by the United Nations Environment Program (UNEP) reconciles methane data from scientific measurement studies, satellites through the Methane Alert and Response System (MARS), rigorous industry reporting through the Oil and Gas Methane Partnership 2.0 (OGMP 2.0), and national inventories.[70]

A few traditional conservation groups have also begun to use AI technologies to support their work and influence policy[71] CI's Wildlife Insights, an AI-driven platform, is the world's largest camera-trap database, currently hosting more than 16 million images. Built in partnership with Google, the Wildlife Conservation Society, World Wildlife Fund, Smithsonian, and others, it provides up-to-date information on myriad species and enables faster identification and tagging of species. According to CI, this data can be used by governments to make policies on wildlife protection.[72]

Overall, the ecosystems for AI and climate are quite distinct. While in countries like India, there are many pilots underway for the use of AI, these are not tied together by a comprehensive strategic or policy plan. Similarly, in Bangladesh, different ministries lead conversations around AI and climate and are yet to coordinate their strategic plans. Even in Singapore, which is perhaps the most advanced in the region concerning the use of emerging technologies and AI for climate, the AI and climate portfolios are held by different ministries that tend to operate in silos.

In larger economies like India, Indonesia, and Thailand, the dominant policy narrative is that developing domestic AI capacities is essential for remaining competitive in the Fourth Industrial Revolution.

Research and Innovation Investment

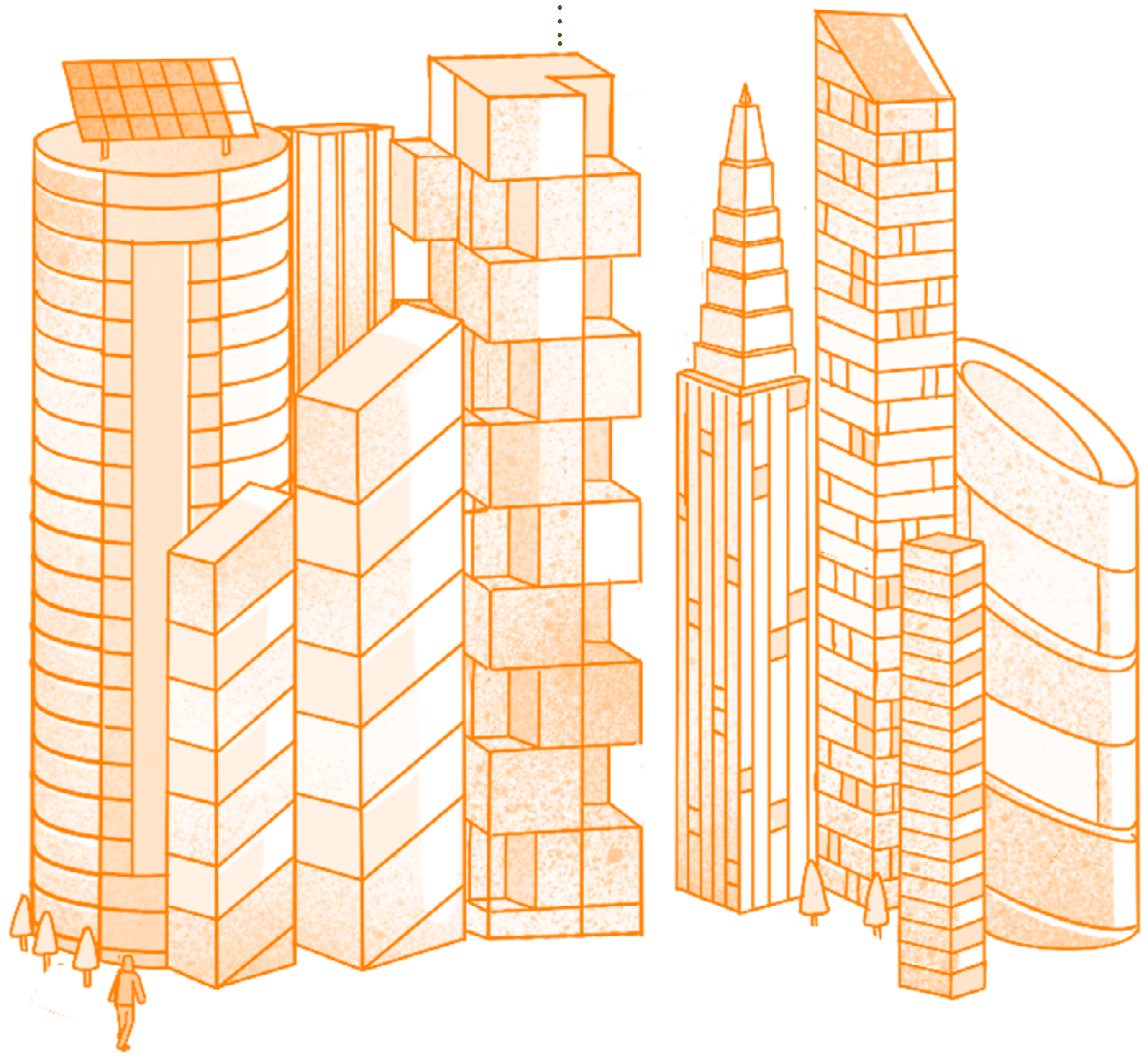
Countries in the region vary in the level of government investment in foundational and applied AI research, and, for the most part, existing government funding is not directly related to AI and climate.

Countries such as India and Vietnam have established AI centres of excellence or AI innovation as well as educational and skilling programmes for students. Singapore and China stand apart in terms of government investments in AI. As a percentage of GDP, the Singapore government's R&D spend is 18 times more than that of the US.[73] China's 14th Five-year Plan (2021-25) focused on the promotion of AI R&D – the plan stipulates an increase in R&D spending by up to 7% per year.[74] Local governments are also incentivized to promote the local AI economy through instruments such as the Shanghai AI Industry Investment Fund and the Shenzen New Generation AI Development Action Plan.[75]

There is a considerable talent deficit in the region, particularly for data scientists with multi-disciplinary expertise.[76] Even in a country like China which is on top of the Asian leaderboard in terms of the number of data scientists and ML experts, there is a mismatch between the talent being supplied and industry requirements for specialized and multi-disciplinary expertise.[77] China is the largest source of top-tier AI researchers in the world, with 29% of these researchers having received undergraduate degrees in China, but the majority of those Chinese researchers (56%) go on to study, work, and live in the US.[78]

Countries like Vietnam are now beginning to invest in nurturing local AI talent, and have set targets for increasing research and innovation centres and AI researchers in the country.[79] Companies like Samsung have invested in nurturing local talent in Vietnam, and in 2023, the Prime Minister of Vietnam urged Samsung in skill-building to lead their factories in the country.[80] In India, similar initiatives are underway to build domestic AI talent and capacities for applied and foundational research. The Ministry of Electronics & Information Technology, in partnership with NASSCOM, set up FutureSkills Prime, a digital skilling initiative, providing certificate courses in AI and big data analytics.[81]

Southeast Asia has experienced a boom in climate tech investments, amounting to USD 1.1 billion in the first 11 months of 2022.



A bulk of the investment and innovation in the region pertaining to the use of AI for climate action is led by the private sector. Southeast Asia has experienced a boom in climate tech investments, amounting to USD 1.1 billion in the first 11 months of 2022. The bulk of this funding was received by Singapore-based start-ups, followed by Indonesia and Vietnam.[82]

Most climate-tech investments have been made in mobility and transportation companies, with other areas such as wind power, food waste technology, and solar power receiving a smaller share. In India, for example, in 2021, USD 7 billion was raised by Indian climate-tech start-ups through private market and venture funding, mostly for energy management and electric vehicles. Funding is also growing for alternative fuel technologies and agri-tech in India.[83]

The number of climate-oriented start-ups working in this space is growing, but this also varies across the region. For example, a country like Bangladesh will have far fewer AI start-ups based on agriculture[84] compared to India, which has several.[85] A significant constraint is the lack of a viable business model and end-users for applications in sectors such as agriculture or disaster response. Many climate-specific products such as early warning systems are thus directed towards the banking and insurance sectors.[86]

Large technology companies also dominate investments in this space. For example, Microsoft signed an agreement with the Thai government to establish an AI laboratory that will create advanced solutions for Thai farmers and the Kingdom's smart city programme.[87] In Singapore, Microsoft launched a GreenTech challenge to accelerate the development and use of innovative sustainability solutions in the country.[88] Similarly, Huawei is an active player in exploring green technology such as solar power and electric vehicles in Thailand. In India, Google has been working with state governments to map India's agricultural landscape. It also launched a new USD 1 million grant for applications using advanced technology for better agricultural outcomes. Microsoft, in collaboration with ICRISAT (International Crop Research Institute for the Semi-Arid Tropics), has developed an AI Sowing App, which sends advisories on the optimal date to sow.[89]

In countries like Indonesia and China, this landscape is also dominated by domestic technology giants. For example, Indonesian AI companies have begun to invest in domestic universities and AI research centres to cultivate talent. The Tokopedia-UI AI Center of Excellence hopes to develop digital talent by advancing deep learning technologies for academics and researchers. Bukalapak, an Indonesian e-commerce company, also partnered with the Bandung Institute of Technology to launch the Artificial Intelligence and Cloud Computing Innovation Center to train Indonesian students, educators, and researchers. Both Amazon Web Services and Alibaba Cloud Indonesia, a subsidiary of the Alibaba Group, are also competing to roll out cloud training programmes targeting Indonesian students.[90]

Financing and investments in deploying AI for climate may also grow as companies look for ways to meet their Environmental, Social and Goverance (ESG) commitments. Some experts note that corporate ESG goals can also lead to greenwashing.[91] As ESG standards continue to be adopted in Asia, countries like Singapore are institutionalizing mechanisms to reduce greenwashing risks, and creating awareness among investors to better understand the ESG funds they invest in.[92] However, these measures may not be enough to disincentivize greenwashing, given the absence of adequate impact metrics to evaluate whether a particular investment or intervention is actually addressing climate change.

As companies look for ways to meet their ESG commitments, investments in deploying AI for climate may grow.

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3 Opportunities, Challenges and Risks

This chapter maps the emerging use cases and opportunity areas for climate action in three domains—agriculture and food systems, power and energy transitions, and disaster response and preparedness. It identifies the key socio-technical issues that must be taken into consideration in evaluating the use of AI in these sectors.

This is not an exhaustive list of the various ways in which ML can be used, but a representation of the current dominant applications of AI in the selected Asian countries.

The key takeaways from this chapter include:

- The use of ML applications for mitigating and adapting to climate change is still at a nascent stage in most countries in Asia. Many initiatives are at a research or pilot stage and information about their outcome and impacts is limited. Most of the publicly available information is from companies themselves or media reports. The use of AI is also unevenly spread across geographies; there are many more applications in more mature economies like Singapore, China, and India, and far fewer applications in countries such as Bangladesh.
- Within agriculture and food systems, a bulk of applications involve weather forecasting and crop advisories for farmers. However, large variances across agro-climatic zones and the resources required to capture accurate data make it difficult to develop accurate advisories. The lack of financing for farmers to sustain the use of these advisories is another concern. In the absence of enforceable regulations for data sharing and use, there are concerns that these applications could contribute to the commercialization of farm data at the expense of the farmers. A more promising area of intervention may be the use of ML for foundational research on new food and seed varieties, but implications for food sovereignty need to be considered.
- The use of ML is being used to forecast power demand and plan, as well as identify and monitor renewable sources of energy. However, the uptake of ML is slow and incremental, particularly because of a broader culture of risk aversion in the sector. Using ML to advance scientific research and innovation is a particularly promising area – one such example is the acceleration and optimization of the scientific discovery of new materials that can reduce the carbon emissions of construction activities. Threats to privacy and data security also need to be considered, especially given the state of data protection regulation and infrastructure in the region.
- The application of ML for disaster response and preparedness is also growing, with applications for early warning, disease surveillance, environmental monitoring, and crowd-sourced information processing and real-time response. Successful examples of crowd-sourced information platforms are already available in the region and can be scaled up further, but issues around uneven digital access and misinformation deserve sustained attention.

3.1 Agriculture and Food Systems

Agriculture and Food Systems

The Asia-Pacific region accounts for almost 60% of the global agricultural population. Asia contributes significantly to GHG emissions from agriculture, which have increased by 144% over the last five decades.[93] AI is expected to support both mitigation and adaptation efforts in agriculture. This section maps the emerging use cases and applications, along with the key challenges and risks from a socio-technical perspective.

A bulk of the applications are focused on helping farmers develop adaptive strategies for climate change. These include estimating yield variability, detecting pests, and recommendations on fertilizer use.

However, the reliability and utility of these applications remains to be established. Large variances across agro-climatic zones and the resources required to capture precise data make it difficult to develop accurate advisories.

Uneven digital access across geographies and social groups, combined with a lack of finance to adapt farming practices, further skews the adoption and utility of these tools.

Concerns around the commercialization of farm data by private players, particularly large technology companies, are commonly voiced by civil society actors.

A more promising area for the use of ML may lie in scientific research and the development of new seed and food varieties. Such work is already underway in countries like China and Singapore.

However, it is important that such initiatives are directed towards public benefit and do not lead to private monopolies that impinge on the food sovereignty of communities and countries. Dispersal of new seed varieties can also disrupt ecological ecosystems by affecting biodiversity and the functioning of plant communities.[94]

Dominant Use Cases
Farm Advisories

Several companies are building ML applications to help farmers prepare for climate variability. These include products to support crop health management, yield forecasting, and pest management. Research is required to understand the uptake and impact of these various products, including the relative capabilities and limitations of varying products.

In Bangladesh, for example, an AI-based seasonal forecasting tool has been launched to help farmers plan their planting and production. Currently, farmers get weather forecasts that span from one to five days, but this doesn't give them enough time to plan. The AI-based system promises to provide information four weeks to three months in advance.[95]

Open source tools and platforms, such as DICRA, have been developed to give farmers and policy makers information on cropping practices, soil health, crop health, monitoring of inputs, weather forecasts and potential pest attacks. These tools provide recommendations on crop-specific farming practices and measures to alleviate negative yield variability.[96]

Similar products are also being used to manage aquaculture. For example, an AI-based system in the Philippines has been developed to help farmers measure, predict, and mitigate weather-related changes – farmers are provided with information on parameters such as wave height, water temperature, dissolved oxygen, and salinity, to help them anticipate and respond to such climatic variability.[97]

Pilots are also underway to use robotics and ML to support climate-resilient agriculture. China has introduced the world's first AI robot to monitor fruit and vegetable planting and growth. The project has moved from the R&D phase to the application phase, though it is yet to be scaled up.[98]

Dominant Use Cases
Food R&D

With threats to food security due to climate change, countries are experimenting with different forms of proteins and cultivated meats.

In 2020, Singapore became the first country to permit the commercial sale of lab-grown meat.[99]

AI algorithms can analyse vast amounts of data on cell growth, nutrient composition, and other factors, to identify the optimal conditions for cultivating meat cells. This information can then be used to finetune the production process, reducing the time and resources required to produce lab-grown meat.

Advocates of cultivated meat claim it could be an answer to soaring agricultural emissions, deteriorating biodiversity, and alarming food insecurity, while critics worry that the high cost of cultivated meat, alongside its regulatory hurdles and unproven scalability, make it mostly hype for now.[100]

Research is also underway to develop crop varieties resilient to climate change. Large seed companies have been using components of AI for more than a decade.[101] Big data from a variety of seeds can be used to check their quality, identifying patterns, and features that make a seed resilient to various climatic factors. For example, a Singapore-based agri-genomics firm has developed a proprietary genomics technology platform and created the world's first climate-resilient strawberry.

AI algorithms can analyse vast amounts of data on cell growth, nutrient composition, and other factors, to identify the optimal conditions for cultivating meat cells.

3 Assessing Opportunity Areas

Dominant Use Cases Estimating Biological Sequestration

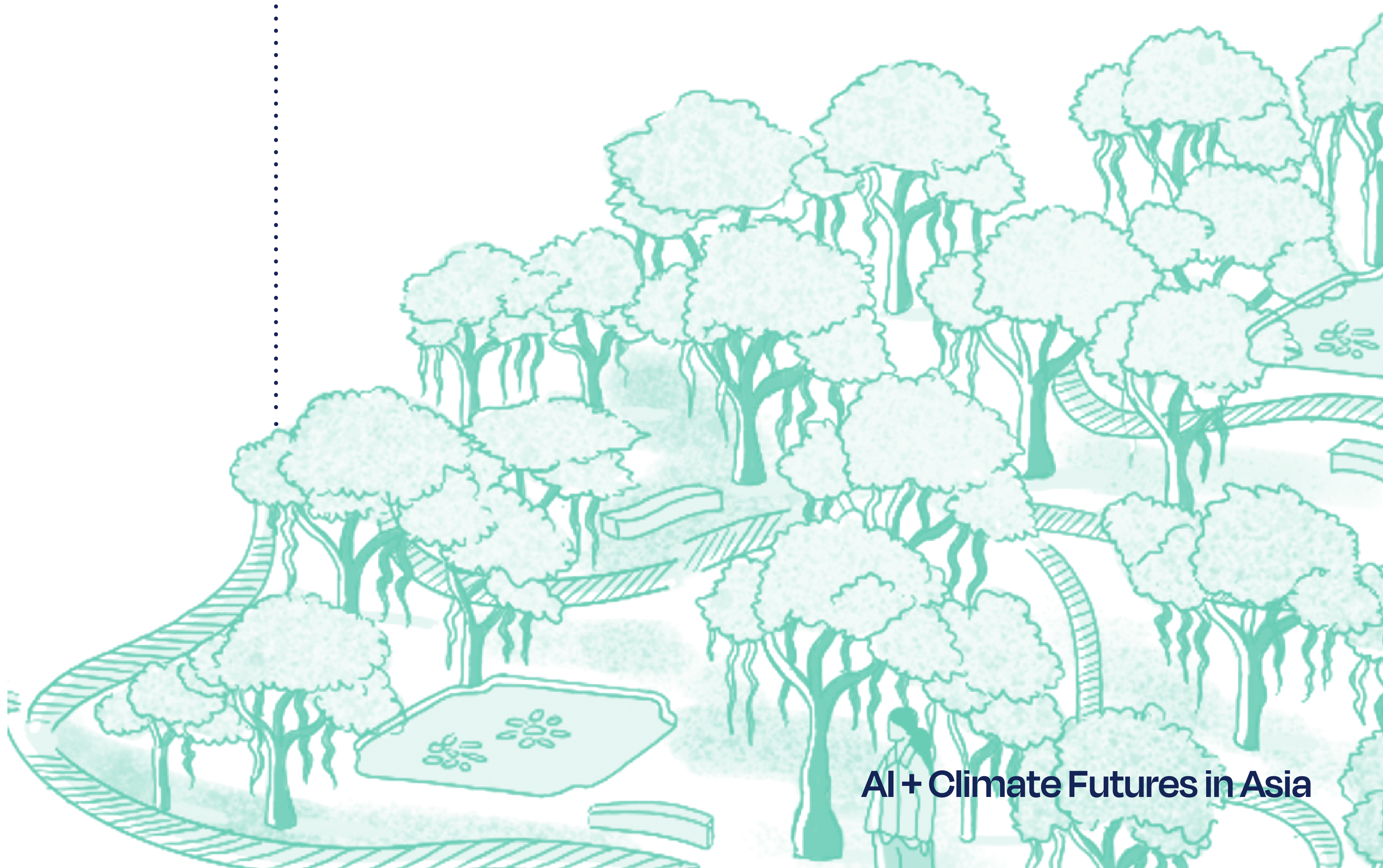
A few ML-based solutions are being piloted to improve measurements of soil and tree carbon sequestration.

With the use of ML and computer vision, hyperspectral imaging can be improved, and real-time assessments provided. For example, the use of ML means that farmers can provide a single round of soil samples rather than having to provide ongoing or repeat samples.

Improvements in imaging technology also enable the visibility of more bands across the spectrum of light. Given that the carbon in soil has a unique chemical property that reflects certain wavelengths of light, this is believed to improve the accuracy of these calculations.

Research initiatives are also underway to use AI to estimate the carbon sequestration capacity of forests. An international team is measuring forest carbon capacity in Northeast Asia using remote sensing, fieldwork, and ML. Their research provides current estimates for carbon capture potential in North Korea and highlights the benefits of reforestation in China and South Korea over the last two decades.[102] C-Tree is also a new global platform that seeks to capture, in real-time, the carbon stored and emitted in the world's forests.[103]

Research initiatives are underway to use AI to estimate the carbon sequestration capacity of forests.



Challenges and Risks

Accuracy, Reliability, and Suitability

Agro-climatic zones vary considerably, even within countries and across short distances within the same geographical area. Applications based on data and models from one zone or off-the-shelf products may lead to inaccurate results when applied in a different climatic zone.

Satellite data is typically not of high enough resolution for applications in agriculture and will need to be combined with on-ground data collection. This is an expensive and laborious process that can often involve installing a huge number of sensors or manually collecting and labelling a huge amount of plant-related data across various regions and climatic zones. Satellite data on farms also need to be accurately labelled to be useful for farm management.

There is also scepticism regarding the science around carbon sequestration. For example, the scientific community is uncertain about how long carbon can be stored in soil, how much carbon can be sequestered by different practices, and how to effectively measure and track the carbon that is sequestered.[104] Even if carbon sequestration is effective, it is unlikely to be of a large enough magnitude to make a significant impact on climate action.

The assumption that farmers lack appropriate or relevant information also needs to be re-examined. Many farmers already rely on traditional knowledge and practices; the larger issue for many farmers is the unequal distribution of value across agricultural value chains.

Moreover, farmers are not a monolithic category and have different requirements. In India, for example, subsistence farmers will be affected by increasing heat stress, leading to depletion of ground water[105]; but issues such as these are not well-covered in existing applications that are optimized to improve and increase yield variability.

Farmers are not a monolithic category and have different requirements.

Challenges and Risks

Unequal Digital and Financial Access

Varying levels of digital access and skills can limit the ability of farmers in specific geographies or from certain social groups to access and use these applications.

Globally, only 37% and 24% of farms less than 1 hectare receive 3G and 4G services, respectively.[106] In Asia, network coverage on cropland is only 46% for 3G and 29% for 4G services. However, coverage in Asia varies by country. For example, the majority of India and Thailand are covered by 3G and 4G services, whereas large gaps exist in China, Vietnam, and Mongolia. Poorer and more remote communities in rural Asia have limited access to ICT because of high costs and a general lack of reliable electricity and other infrastructure.

Narratives on the potential benefits of technological progress in the agricultural sector must also account for the costs associated with their continued use. Many farmers in Asia work as contract labour and often do not have the resources to afford technological upgradation. It is usually larger farmholders who can afford to devote part of their land to try new technology compared with those with smaller farm holdings.[107] The small land holdings of most farmers in Asia are often not suitable for such smart farming and precision agriculture practices, as these methods require economies of scale.

For farmers to adopt practices based on farm advisories, they must invest in new seeds and equipment; the financing to support such uptake is typically very little or is absent, thereby reducing the uptake of these advisory-style interventions.

Another key consideration in scaling such solutions should be the impact on livelihoods, a particularly important question in the region because of the dependence of vast segments of the population on agriculture for income generation. As farmers adopt automation to reduce labour input costs, this can displace traditional livelihoods dependent on farming.

For farmers to adopt practices based on farm advisories, they must invest in new seeds and equipment; the financing to support such uptake is typically very little or is absent.

Challenges and Risks

Commercialization of Climate Data

There is a risk that the commercialization of climate data could primarily benefit private companies while doing little to address climate change.

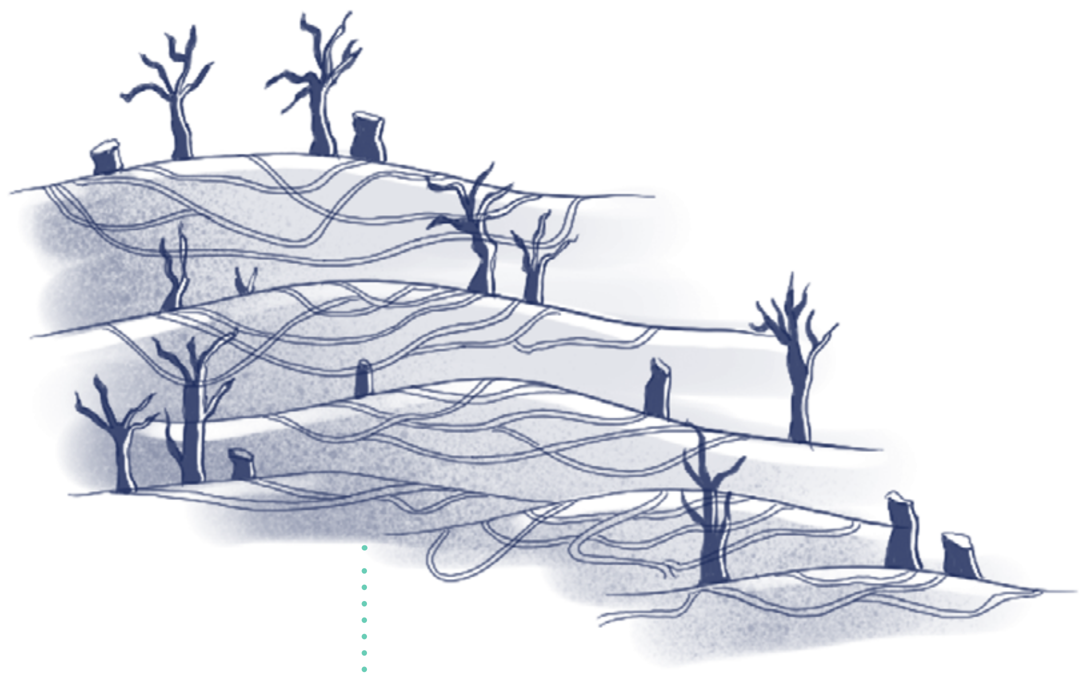
For example, as data around land use and agricultural practices get more sophisticated, this could contribute to speculative commodity pricing and trading. Agricultural data is used for crop insurance/financing tools because that is a more reliable way for start-ups working in this space to generate revenue from the use of these datasets.[108]

Considerable computing and storage capacity is also required to maintain and process agricultural farm databases. Advanced computing capacities are held by large technology companies, increasing the reliance on these companies by the government and smaller technology companies and start-ups.[109]

The use of ML for developing climate-resilient seeds can also undermine seed and food sovereignty for farming communities.

As technology advances and companies invest in developing climate-resilient seeds, often using AI to identify seeds with the estimated best yield, there is a risk of creating dependencies on climate-smart seeds that may be more expensive than traditional seeds. Globally, research indicates that the seed industry has been consolidated in the hands of four transnational companies that are also entering partnerships to promote digital agriculture.[110]

Commercial interests can also drive a further shift towards monoculture, which, in turn, can contribute to a loss of biodiversity and degradation of the natural resource base.[111] A lack of crop diversity can also have negative health outcomes. Furthermore, the nutrient quality of food has been declining with the increased use of fertilizers and antibiotics.[112] India is already among the highest antibiotic-resistant countries.[113]



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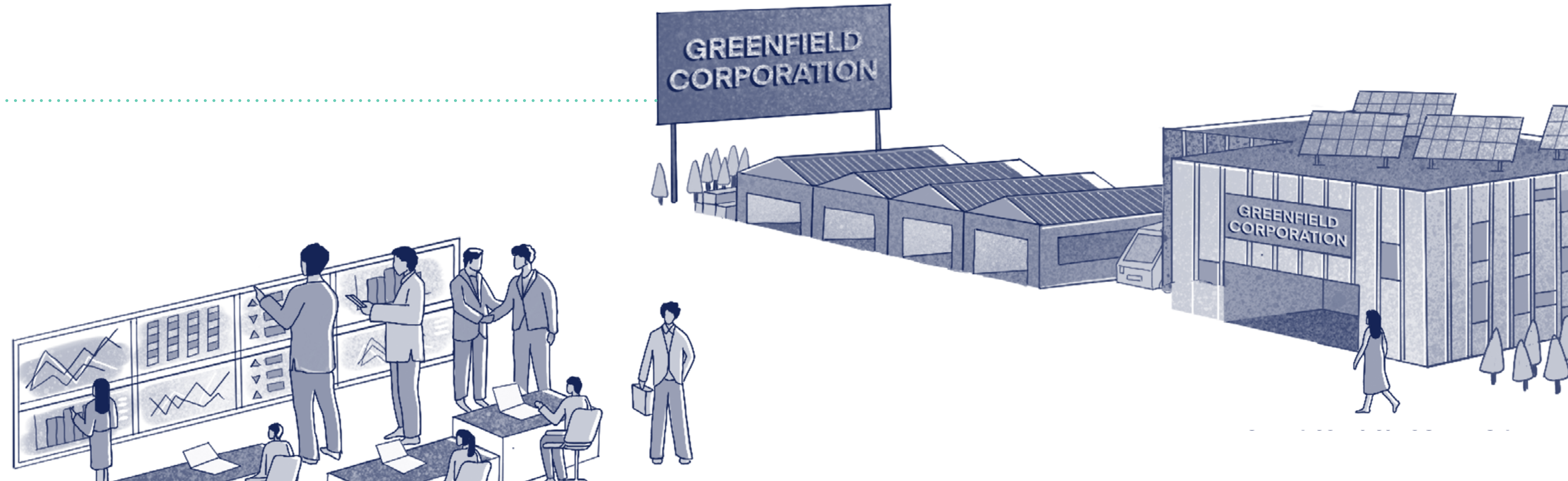

Conclusion

Several AI-based interventions for agriculture exist. If implemented properly, they can be potentially useful in mitigation and adaptation strategies. However, in their current form, their potential benefits need to be weighed against the challenges and risks these systems pose to farmers' agency, rights and livelihoods.

AI has the potential to support climate adaptation strategies for agriculture by providing farmers with advisories on climate variability and how to adapt cropping practices to such changes. However, for this to be effective, it is important that the advisories are based on accurate data and that farmers have the resources required to shift their cropping practices. It is also important that these advisories are based on a holistic understanding of agricultural ecosystems. For example, advisories that optimize for yield increase alone could contribute to a depletion of natural resources and thereby be harmful to continued agricultural practices and to the climate.

AI can also be used to support adaptation in terms of discoveries and innovation around climate-resilient seeds. However, this requires a critical lens to see who is building these solutions and how these benefits are distributed. ML-based investments by large agro-tech companies could lock in their monopoly over the food chain and contribute to a loss of food sovereignty for farmers. Even if this is effective in the short to medium term, from the perspective of adapting to climate action, it comes at a heavy cost for farmers and could create new forms of climate injustice and inequity.

It might be possible to develop AI-based models that evaluate various parameters (soil health, fertilizer use, livelihood impacts, GHG emissions, etc.) that can support more regenerative or carbon-neutral practices, but this requires engagement with domain experts, the building of appropriate models or frameworks, and thinking through the adoption pipeline (i.e., what would be required to change farming practices and sustain that change). Such conversations need to be localized to the Asian context where factors such as lack of data and the digital divide remain persistent issues. The adoption of AI for agriculture, therefore, must solve these issues first instead of trying to solve problems in siloes.

Without a holistic approach, AI for agriculture can risk perpetuating injustices at three levels – data injustice where AI solutions are built on incomplete or biased datasets, epistemic injustice where certain kinds of knowledge are prioritized over indigenous or local knowledge, and climate injustice where farmers are not supported to withstand the effects of climate change.

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It is important to note that the region's agricultural contribution to GHG emissions must be read in the context of global food chains. For example, more than 40% of the rice imported to the EU comes from countries such as Vietnam, Thailand, Myanmar, or Cambodia. Therefore, GHG emissions from agricultural practices in Asia are tied to consumers across this production cycle, a fact which is often overlooked in global conversations on reducing Asia's contributions to GHG emissions.
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108 Interview with representative of an environmental data analytics firm, dated April 12, 2023.
109 Interview with an ethnographer, dated May 22, 2023.
110 Gliessman, S. (2023). *The stories of seed sovereignty. Agroecology and Sustainable Food Systems*, 47(5), 643–645. www.tandfonline.com
111 Gallant (2022, May 25). *Environmental impacts of monoculture.* Gallant. www.gallantintl.com
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3.2 Power and Energy Transitions

Power and Energy Transitions

While the demand for coal is set to decline in Europe and the US from 2024, transitioning away from coal will be more complex for countries in Asia.[114]

In China and India, increasing energy demands have furthered the dependence on coal. Together, they account for 70% of global coal demand.[115] In 2021, five countries in Asia – China, India, Indonesia, Japan, and Vietnam – were responsible for 80% of new coal power investment.[116] Asia already accounts for almost 50% of global CO_2 emissions, with half of these emissions coming from the coal-reliant power sector.[117]

To reduce emissions from electricity systems, society must transition to low-carbon electricity sources (such as solar, wind, hydro, and nuclear) and phase out carbon-emitting sources (such as coal, natural gas, and other fossil fuels). Besides, these transitions to low-carbon power will not happen overnight – reducing GHG emissions associated with existing fossil fuel and electricity infrastructure is necessary.

ML can contribute by accelerating the development of clean energy technologies and materials, improving forecasts of energy demand, improving electricity system optimization and storage, and enhancing system monitoring.[118]

ML can improve power demand and supply forecasting and support the integration of renewable sources. Another promising area is materials R&D and research and innovation for low-data settings.

However, the adoption of ML is slow and incremental due to the high costs of error and the likely population-scale impacts.

For example, under the General Data Protection Regulation, 2016, AI systems that are intended to be used as safety components in the management and operation of critical infrastructure are considered high-risk as their failure could have population-scale impacts on human life and health. Further, privacy and surveillance concerns also arise with the use of smart meters.

Dominant Use Cases
Forecasting Demand and Supply

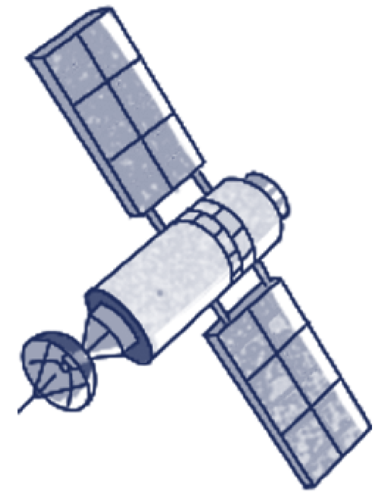
Supply and demand power forecasts help inform electricity planning and scheduling. ML can help in optimizing the distribution of electricity and in predicting and managing the behaviour of large power systems by leveraging the volumes of data available from various sources.[119]

For example, in India, Tata Power has developed an ML-enabled smart energy management system that forecasts energy demand across its residential, commercial, and industrial customer segments in Mumbai.

More complex systems are also being developed.[120] In Singapore, for example, an AI solution is being trialled to curb energy consumption while keeping temperatures cool at two underground train stations. This is expected to reduce energy consumption at train stations by over 7,000-megawatt hours a year.

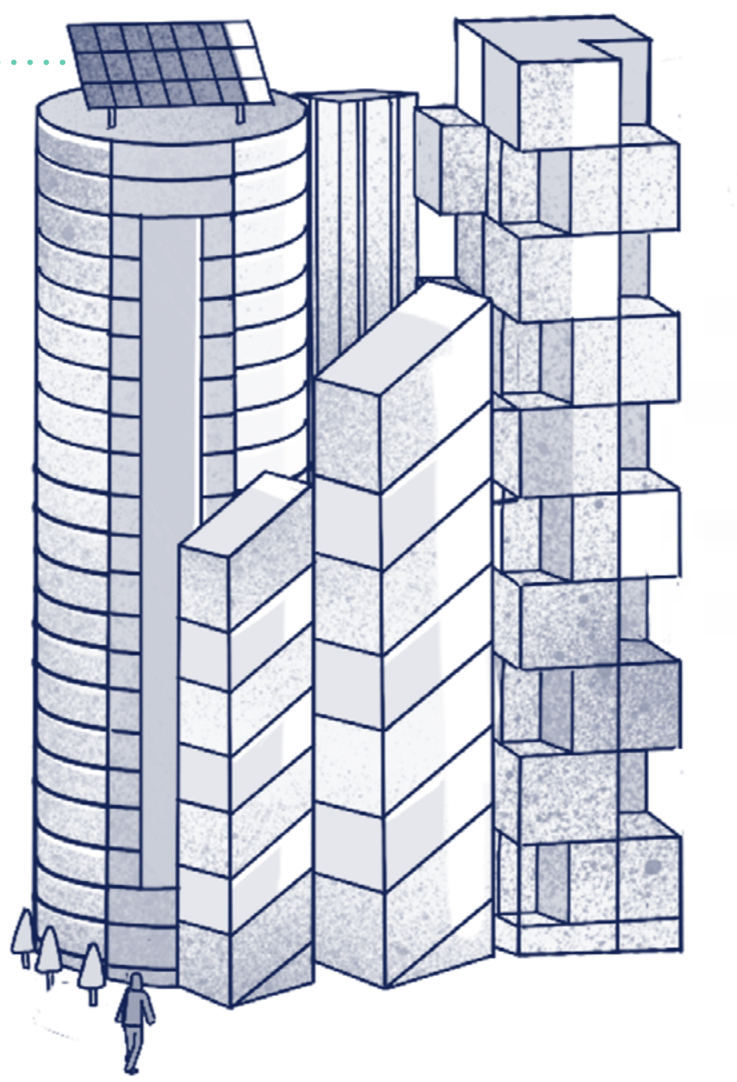
The system uses data such as weather conditions and the number of commuters to predict conditions such as the amount of heat expected in a train station for the next hour. The data is then used to automatically adjust the air-conditioning system to maintain an optimal temperature of approximately 26°C using the right amount of energy.[121]

Data about weather conditions and footfall is analysed to predict the temperature in a given place, and this insight is used to adjust centralised heating and cooling systems.



Dominant Use Cases
Planning and Monitoring Renewables

Solar AI in Singapore utilizes geospatial analysis, big data, and ML to assess rooftop solar potential and project future savings from transitioning to solar energy.



AI tools are being used to identify optimal geographies for positioning renewable energy sources. Locating the best place for these requires identifying favourable geographical locations with appropriate climate conditions for renewable power generation.

Solar AI in Singapore utilizes geospatial analysis, big data, and ML to assess rooftop solar potential and project future savings from transitioning to solar energy. Customers receive a satellite image of their rooftop, accompanied by a heat map depicting the solar potential measured in MWh per year.[122] In northwest India, remote sensing and geographic information system (GIS) techniques were applied to identify the optimal location for solar energy. For accurately calculating amount of radiation, multiple factors such as latitude and time of year have to be considered.[123]

AI technologies are also being used to monitor solar power systems and detect anomalies and errors in solar energy systems. Anomalies represent a major challenge in grid integration, as power planning and intelligent monitoring are required to ensure that anomalous output does not propagate through the grid.[124] Research across the world indicates the potential for using neural networks to detect anomalies in photovoltaic systems.[125] Many of these studies are at an experimental stage and are being undertaken in controlled environments. For instance, scientists are experimenting with edge computing to aid anomaly detection in solar panels.[126]

Another emerging use of AI tools is in forecasting output from renewable sources of energy. For example, in Vietnam, a tool is being used to calculate the power generated by rooftop solar systems using satellite image radiation data and forecast capacity. In Singapore, solar panels line roofs at the Sembcorp Marine shipyard. The panels are monitored by ML software, which recommends the best time to use equipment to lower energy bills. During peak periods, it is cheaper to use solar power stored in batteries than to draw power from the national grid. This tech is expected to reduce power drawn from the grid by 30% during peak production periods.[127]

Dominant Use Cases Management of Energy Demand

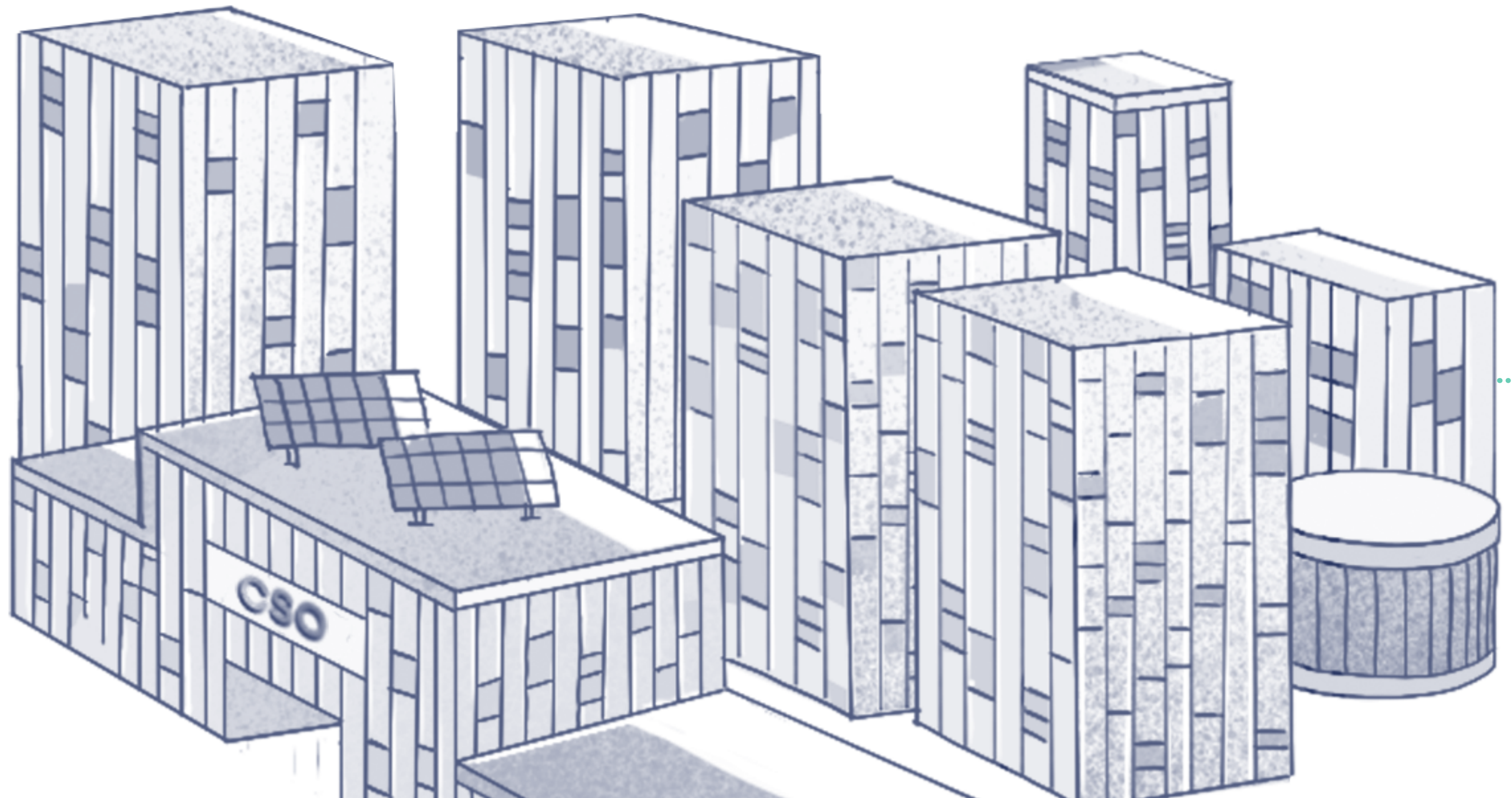
ML-based tools are also being developed to manage energy demand by nudging consumers to rationalize consumption.

For example, from 2017 to 2021, the Japanese Ministry of the Environment enlisted the Oracle Corporation (Japan) and Jyukankyo Research Institute to provide approximately 300,000 households with personalized information and advice on how to reduce their energy use and CO_2 emissions over four years.[128]

In 2019, Singapore announced that over the following five years, advanced meters would be provided in all residential premises. Advanced meters[129] were to be installed in new residential premises, while analogue meters at existing premises were to be replaced with advanced meters when they reached end-of-life.

Non-residential premises, including schools, would have advanced meters installed when they switch to buying electricity from retailers. Users can track their usage using an app. The app provides detailed consumption data as well as energy-saving tips and includes features such as nudging households to be more energy efficient.[130]

Advanced meters were to be installed in new residential premises, while analogue meters at existing premises were to be replaced with advanced meters when they reached end-of-life.



Dominant Use Cases
New Materials

Designing new materials is important for many climate applications, including energy storage via fuels and batteries.

ML can expedite the materials discovery process by analyzing vast datasets, identifying patterns, and predicting potential materials with desired properties. Scientists are working to develop new materials that can better store or otherwise harness energy from various natural resources.

Rapid urbanization and economic development in regions such as Southeast Asia and sub-Saharan Africa will increase demand for new buildings and, thus, for concrete and cement.[131] The construction industry globally is a leading carbon emitter.[132] The production of cement is one of the largest contributors to global CO_2 emissions.[133] The use of sustainable building materials can help minimise the impact of construction activities on the environment.[134] For example, a ML tool, Autopilot, is being developed to reduce fuel consumption and emissions during cement manufacture.[135]

As these processes can be slow and imprecise, ML can be used to automate this process and test different models. Moreover, as the use of these new products is still at an experimental stage, ML-based models can be built to anticipate likely outcomes and defects. Previous models were able to reproduce the stabilities of known materials, but they could not predict materials with unknown crystal structures – the way atoms, ions and molecules are arranged in a material, an essential factor in determining its physical properties. By training a new model on 'distorted structures', ML provides insights into how new materials will perform under strain and allows the model to relax a crystal structure to its more stable configuration.[136]

ML techniques can also be used to translate insights from high-data to low-data settings since all electric grids share the same underlying system physics.[137]

ML can help discover new materials, speeding up the materials discovery process.

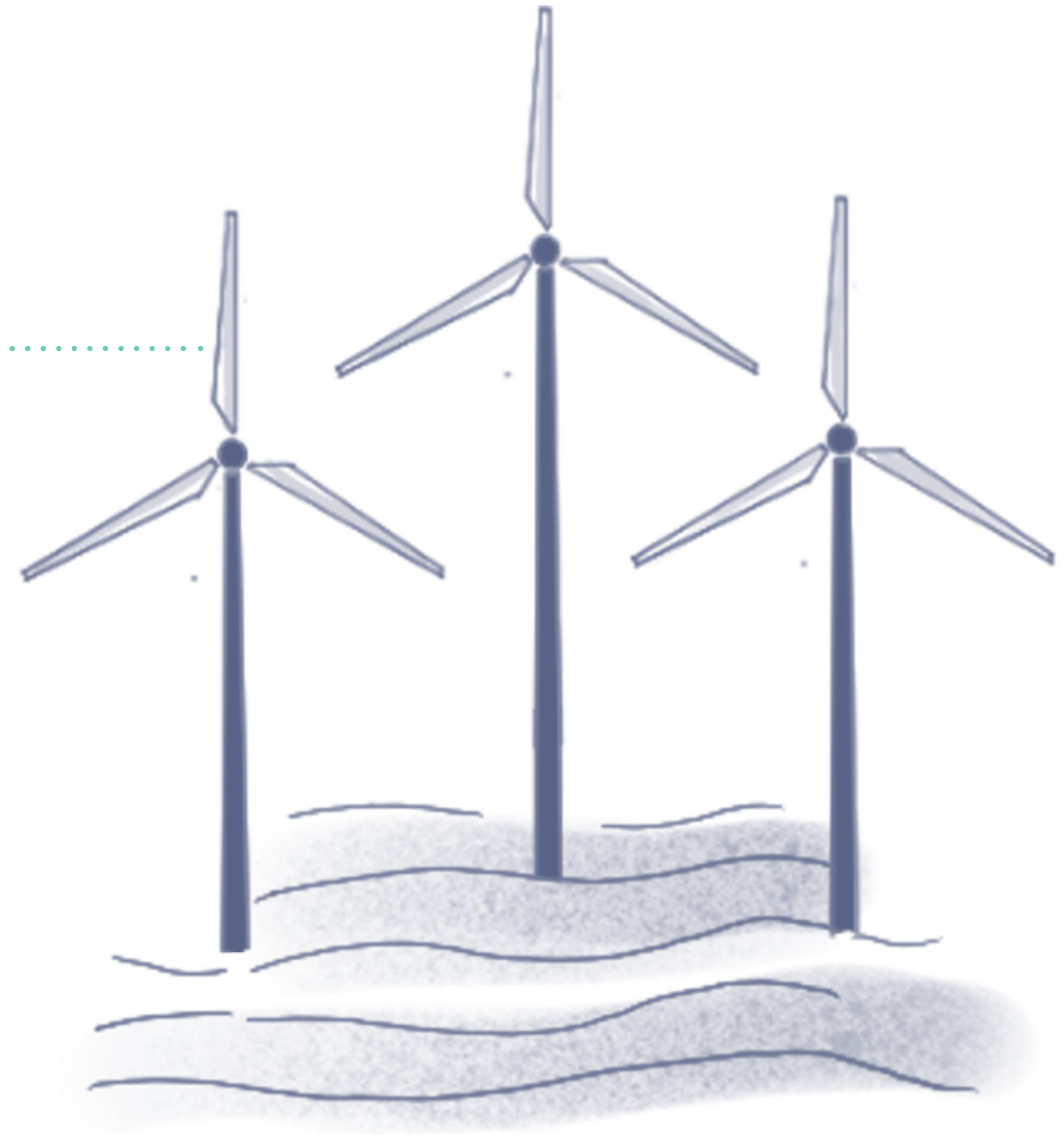
Challenges and Risks
Performance Uncertainty and High Costs of Error

Because the cost of error in the energy sector is high, many companies are reluctant to consider trying new strategies with little evidence of proven outcomes.

As it is a critical infrastructure, the power system can never be taken out of service to be tested. To study the system under a broad range of conditions, researchers need to work with well-developed models and simulators, but discrepancies may exist in simulations.

There are many uncertainties in renewable energy generation systems (for example, the output of wind energy generation across time is difficult to predict). This also leads to performance uncertainty about renewable energy systems.[138]

The energy sector's software architecture is much older than that of other sectors, such as finance.[139] Additionally, the energy industry needs to ensure that any change is compatible with on-the-ground infrastructure located across great distances. This makes the implementation of modern technology more costly and difficult, especially for smaller companies.[140]



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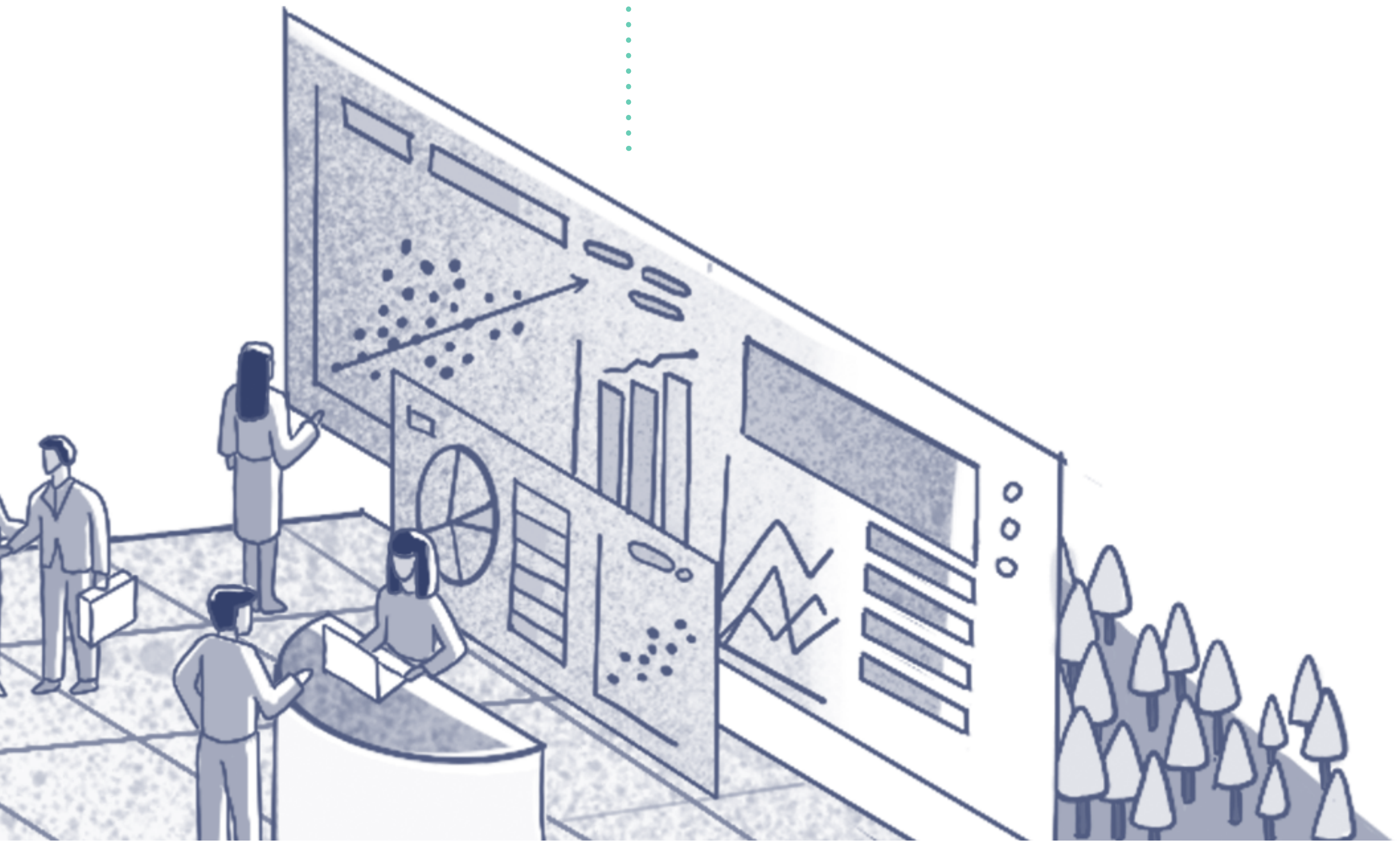

Challenges and Risks

Absence of Regulatory Frameworks and High Cost of Investments

Regulations around building materials and safety testing also lead to a reluctance to adopt new materials.

This prevents many start-ups from investing in this space. Dependent on venture capital funding, start-ups are under pressure to demonstrate results quicker than is often possible. Navigating complex regulations and compliance with different environmental standards can be time-consuming and expensive.[141]

Clear guidelines and policies are necessary to address data privacy, cybersecurity, and ethical considerations in order to build trust and ensure responsible AI implementation. The absence of a comprehensive regulatory framework specifically tailored to AI in the renewable energy context creates uncertainty and hampers adoption in the industry.[142]

Deploying AI infrastructure and systems often involves significant upfront costs, including expenses associated with hardware, software, and data storage. This financial burden can be particularly challenging for smaller companies and start-ups in the renewable energy sector to bear.[143]

The use of ML also requires the installation of a wide system of sensors that can collect high-quality data. While sensors may be available, system operators are reluctant to share this data because of competition reasons. Long seen as a natural monopoly, the energy sector has always been disinclined to share data,[144] which may prove to be a barrier to the pace of AI adoption in the sector.

Clear guidelines and policies are necessary to address data privacy, cybersecurity, and ethical considerations in order to build trust and ensure responsible AI implementation.

Challenges and Risks

Lack of Technical Expertise

Integrating AI technologies into the sector not only requires specialized data science and ML skills but also a good understanding of energy grids and how they function.[145]

Integrating AI technologies with existing infrastructure requires considerable amounts of high-quality data. This is a complex process and requires human expertise to make sure that individuals can understand and trust the outputs of these techniques.

Energy systems management also operates with a high degree of agility, where quick decisions need to be made with a very short turnaround time. Integrating AI into such systems will then need more human involvement to ensure optimum results.[146]

Challenges and Risks
Privacy and Security

Privacy concerns around smart grid technology can arise during the collection, retention, sharing, or reuse of electricity consumption information from homes or offices.

Potential privacy implications include real-time profiling and surveillance, identity theft, and targeted home invasions.[147] While these risks are not new, the use of AI can enable more granular insights based on inferred data and the combination of multiple data sources; techniques such as anonymization are also more vulnerable as AI systems combine multiple data sources.[148]

The digitalization of the sector with a system that is increasingly connected also exposes it to cyber threats. Vulnerable points on the grid, that are ageing or not adequately protected can be used as entry points into the entire network. An MIT study found the energy sector to be particularly vulnerable to cyber threats, with each average 2020 attack costing about USD 6.4 million in damages.[149]

Reports also indicate an increase in the frequency and sophistication of these attacks, with states sponsoring skilled operations in identifying vulnerabilities in power systems.[150] Consequently, the implementation of new technologies in the energy sector raises significant national security implications.[151]

Challenges and Risks
Equity Considerations

The conversation on adopting AI for the energy sector also overlooks geographical variations in electrification.

Energy poverty[152] is widespread in developing countries. Approximately 736 million people (10% of the world population) do not have access to electricity,[153] of which 200 million reside in Asia and the Pacific.[154] Bangladesh is home to almost 10% of those without access to electricity in Asia.[155] Only 2% of China's population is in the top 5% of energy consumers, while in India this drops to 0.02%.[156]

Access to electricity also varies between urban and rural areas. In 2020, about 80% of the world's population without access to electricity lived in rural areas.[157] Research also indicates that the overall positive impact of electrification is higher in urban areas compared to rural areas.

Adopting ML models for optimising grids and forecasting supply and demand risks prioritising the demands of certain populations, such as city dwellers and industrial units, without getting into the complexity of global energy poverty.

Conclusion

Unlike the agriculture sector, power and energy systems have been comparatively slower in adopting emerging technologies. This is owing to the critical nature of the infrastructure, which makes experimentation difficult.

AI has found some consistent applications in monitoring energy consumption, employing AI-driven data analytics to understand peaks in consumption, and nudging consumers towards lower consumption.

While there is interest in expanding the use of AI in mitigation strategies to reduce emissions from energy use through the timely detection of anomalies, by forecasting demand and supply for grid optimization, and even R&D, there are some big gaps in this conversation. They tend towards developing solutions for those who already have access to electricity or energy sources, which are mostly urban areas or industries.

Other mitigation strategies to reduce emissions include switching to renewable sources of energy. AI is being used to identify the best location for renewable energy generation sites. However, this puts communities at risk of displacement due to land acquisition for such projects. For example, India's solar farms are fuelling land conflicts due to rapid land acquisition projects.[158]

Therefore, switching to renewable energy sources or adopting green materials are not value-neutral climate actions. They have implications, particularly for communities that have no say in how these energy transitions affect their lives and livelihoods.

The transition to cleaner sources of energy, and by default, the use of AI to reduce emissions, is informed by net-zero goals. But as scholars note, while net zero is an important target in the drive toward limiting climate change to manageable levels, it will not solve all our climate problems. Research shows that an overreliance on yet-to-be proven technology solutions, such as carbon removal technologies, has deferred serious mitigation efforts, like a full transition away from fossil fuels. This is because collective political will is directed towards the promise of technological innovation, instead of making harder decisions that are most likely detrimental to dominant interests.[159]

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3.3 Disaster Preparedness and Response

Disaster Preparedness and Response

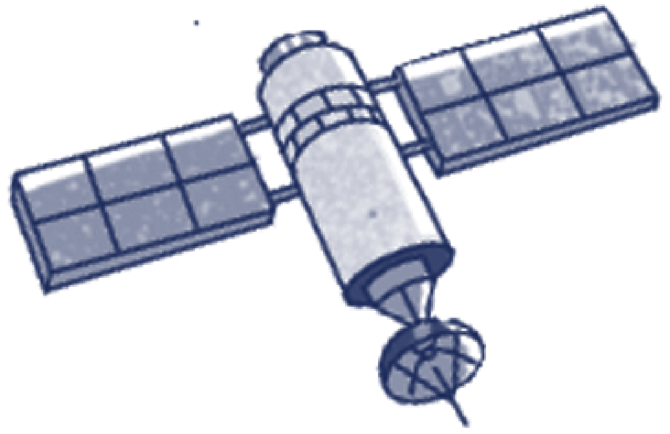
In Asia, climate-related disasters have become more recurrent and destructive in terms of social and economic impacts.[160]

More than half of South Asians, or 750 million people, have been affected by one or more climate-related disasters over the past two decades.[161] Extreme temperatures, storms, wildfires, floods, droughts, and pest infestations have led to financial losses of USD 35.6 billion in Asia in 2021,[162] along with a significant reduction in agricultural productivity.

Many pilots and products are already available, particularly for crisis analysis and response. AI systems could be helpful in aggregating a wide range of data points and inputs to provide early warnings and support disease surveillance.

However, these systems are still in the pilot and testing stages. Their efficacy will depend on the quality of data and the accuracy of the models, particularly, which variables are included and how weights are assigned to these variables.

Other concerns include unequal digital access, reliance on private technology providers for emergency services, and the spread of misinformation.



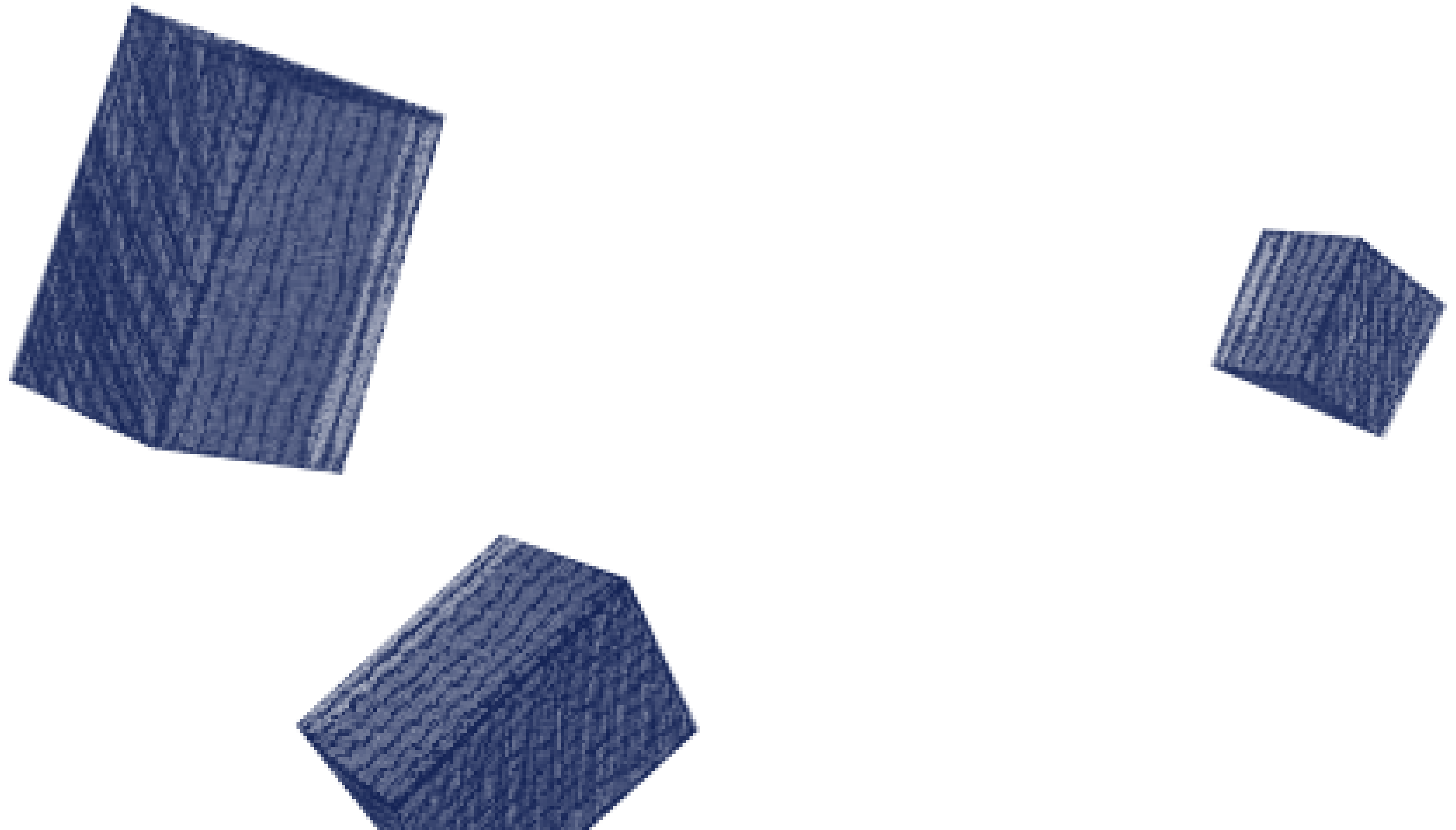
Dominant Use Cases
Weather Forecasting and Early Warning Systems

AI and Internet of Things (IoT) tools are being used to develop early warning systems, including for wildfire detection.

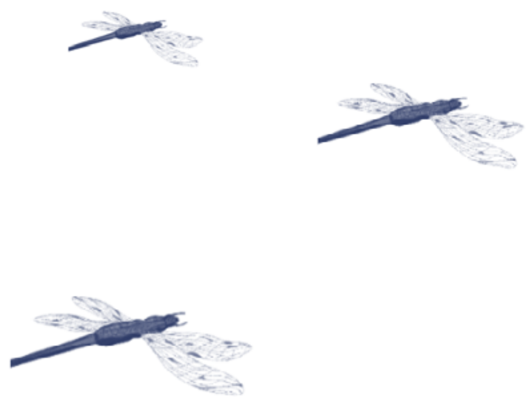
Firecast is a near-real-time (NRT) fire monitoring and alert system for the tropics. It uses EO satellite data to track fires and protected area encroachment, delivering time sensitive information to decision-makers.[163] In India, high-resolution satellite imagery and ML are being used to create heat vulnerability maps and provide early warnings to vulnerable communities.[164] Such interventions have also been used previously for cyclone and flood warnings in other parts of India.

In 2021, the Sustainable Environment and Ecological Development Society put its cyclone warning system into effective use during Cyclone *Yaas* in Odisha, a state in eastern India, warning communities at risk before the cyclone hit. The AI model uses high-resolution satellite images to spot houses on the path of a cyclone and charts a risk score for these houses.[165]

AI systems are being used for weather forecasting, and particularly, precision forecasting, in countries such as Thailand and Vietnam. Japan's Weathernews uses AI to collect and analyse data for real-time hyperlocal forecasts. It warns clients of potential squalls and floods, letting them put up barriers or move equipment to prevent damage.[166] Weathernews is also set to be piloted in squall and flood-prone Thailand and Vietnam.[167] Researchers at Huawei recently developed an AI-based forecasting system that is claimed to be more precise and have faster prediction speeds than traditional numerical weather prediction models.[168]



Dominant Use Cases
Disease Surveillance



AI tools are also in use to provide early warnings for the detection of infectious diseases in the population.

In Vietnam, researchers funded by the UK Space Agency are developing an early warning system to forecast the probability of dengue outbreaks up to six months in advance. This work builds on previous studies using seasonal climate forecasts to provide early warnings of dengue risk in Brazil and Ecuador. The Dengue Forecasting Model Satellite-based System uses historical and real-time meteorological data from satellite observations to produce forecasts predicting the likelihood of exceeding predefined epidemic thresholds in each province.[169]

However, early versions of such tools have seen mixed results. For instance, in 2014, an early warning system flagged visitors to Brazil for the World Cup as being at high risk of contracting dengue. However, a later study established that the model failed to account for seasonal highs in dengue spread and that visitors were not actually at risk of catching the fever.[170]

Another research team in Japan has combined AI with remote sensing data to predict the spatiotemporal distribution of dengue outbreaks in Taiwan.[171]

In India, Wadhwani AI has developed an AI-powered event-based surveillance system for early detection of infectious disease outbreaks. Instead of manually tracking disease incidences reported in local news, a deep learning approach was implemented to extract relevant information from the web.[172] This was used to automate the Government of India's disease surveillance system, which is used to detect and respond to disease outbreaks by generating early warning signals and ensuring that an effective and timely response to contain outbreaks can be initiated.[173]

In Vietnam, researchers are developing an early warning system to forecast the probability of dengue outbreaks up to six months in advance.

Dominant Use Cases Environmental Monitoring

ML-based tools are being used to monitor pollution levels in the air and in water sources.

For example, Vietnam University, in partnership with Ireland's CeADAR, has installed air quality monitoring systems around the city, [174] which are used to track changes in pollution levels across the city and predict air quality a day or two in advance. This data is then made available to the population with different colour codes – red, amber, and green – to help people decide if they should travel to parts of the city based on its air pollution.

In Indonesia, as of 2021, the Research Organization for Aeronautics and Space of the National Research and Innovation Agency was developing a platform that uses AI to monitor natural resources and the environment.[175] Further, AI will also be used to process remote sensing data.[176]

Monitoring tools using AI are also being developed at a global level by inter-governmental agencies and technology companies. UNEP has co-founded, in partnership with IQAir, the Geostationary Environment Monitoring Spectrometer Air Pollution Monitoring platform. It is the largest global air quality information network in the world. IQAir aggregates data from over 25,000 air quality monitoring stations from more than 140 countries and leverages AI to offer insights on the impact of real-time air quality on populations and help inform health protection measures.[177]

Microsoft's Clean Water AI proposes to use AI and high-definition cameras to detect bacteria and particles in a water source. Clean Water AI trains a neural network model and then deploys it to edge devices that classify and detect harmful bacteria and particles. Cities can install IoT devices across water sources to monitor quality in real time.[178] However, information on the deployment or piloting of this tool is unavailable.

Dominant Use Cases

Crisis Analysis and Response

Several nations, including Japan, India, Indonesia, and Mexico, have already employed ML to aid in disaster recovery and rehabilitation.

In Japan, the NEC Corporation has developed a tool for disaster damage assessment using LLMs[179] and image analysis.[180] The images collected include pictures from social media and images captured by CCTVs in an area. LLMs are used to identify the images useful for first responders using keywords and image analysis. Then the tool extracts information on roads and buildings and matches the field image to a map layout to get the estimated location.[181] The NEC hopes the tool can lead to the acceleration of evacuation guidance, rescue efforts, and other initial response activities in the event of a disaster.

In India, a start-up used an AI platform to convert physical locations into GPS coordinates and compiled the GPS locations and phone numbers of people who needed to be rescued or materials. The coordinates were then plotted on Google Maps. To speed up rescue operations, locations were colour-coded based on rescue, food, water, and medicine requirements. In three days, the platform processed 100,000 requests for help. After eliminating duplicate requests, it accurately pinned GPS locations of more than 35,000 people and saved thousands of lives.[182]

PetaBencana, which translates as Disaster Map, produces real-time, crowdsourced maps of emerging disasters from social media users.[183] The system feeds directly into national disaster management agency information management systems for immediate use.

Government ministries in Indonesia have also collaborated with the UN-led Global Pulse Lab to develop a prototype platform called Haze Gazer, a crisis analysis tool which combines satellite imagery of hotspots, census data, and real-time information captured from social media for disaster management efforts.[184] While the tool was built on feasibility studies conducted in 2014 and 2015,[185] the extent of its uptake is unknown.[186]


Emergency Evacuation

Challenges and Risks
Accuracy and Reliability

ML-based forecast systems face challenges in predicting extreme weather events that deviate from existing patterns in available data.

It is, therefore, possible that they could produce unrealistic results – for example, forecasting temperature extremes beyond the bounds of nature.

Satellite data is also not adequate to measure micro-climatic conditions and variations below a certain cloud level. To get accurate predictions, an extensive network of remote sensing equipment will be required. This is expensive and difficult to install and maintain, particularly in areas that are most vulnerable to climate disasters. The resolution of satellite imagery is also less accurate in more clustered settlements in Asia – for example, in densely populated areas, it may be difficult to distinguish between different types of buildings.

Existing infrastructure could also be at risk from the rollout of 5G. Electronic noise from 5G communications can distort computer models for forecasting.[187] Radio interference could degrade the quality of satellite observations.

Developers rely on proxies for their early warning assessments and prediction models and set the relative weight of these parameters. This is a complex process, which, without the correct domain expertise and technical infrastructure, can result in an over-simplified, reductive, or inaccurate model. For example, to build a model that classifies and predicts a household's vulnerability to extreme heat, developers will have to make a few assumptions around indicators of heat vulnerability. This decision will also be shaped by the data that is available or capturable in machine-readable format. or tools relying on inputs from the ground on the severity of a crisis, developers also need to bridge colloquial usage with scientific language to ensure accurate outputs.

For example, one of the biggest challenges that PetaBencana (Indonesia) faces as it scales up to cover more hazards is the disconnect between how relief agencies see a disaster from a distance and how it is experienced on the ground. For people reporting haze — the choking smoke that comes from peatland fires in Indonesia's rainforests — air quality indexes might not have any real resonance. Instead, people talk about haze based on their symptoms, such as watering of the eyes.[188]

To accommodate geographical and climate variability, a huge amount of data processing and pre-processing will also be required. The absence of this can lead to faulty results; for example, a wildfire detection tool built on images of wildfires in North America made inaccurate estimates of wildfires originating in Indonesia.

Challenges and Risks
Digital Divide

The crowd-sourced nature of certain interventions may yield unreliable results. It can also exacerbate the marginalization of already disadvantaged groups, stemming from differential access to and usage of digital technologies.

Studies on disaster politics show that disaster data-collection practices are competitive tools deeply shaped by political forces that might not account for the voices of the most disadvantaged social groups.[189] For example, information will tend to be mostly from areas with high digital connectivity, but these may not be the most affected areas.

Similarly, certain groups, such as women, may not have easy access to digital devices or may struggle with using them. Likewise, air monitoring stations tend to be clustered in wealthier geographies, particularly in urban areas; even if they are spread across geographies, the sensor equipment is not of consistently high quality, often reflecting geography-based income differences.

Poor application interface, lack of inclusivity because of language limitations or oversight of gender considerations and lack of digital infrastructure can also hinder the uptake of disaster-related apps at a large scale. A 2020 study found that the penetration of disaster-related mobile apps in India was almost negligible.[190]

The implication of this is that crowd-sourced information will not be representative, concentrating in areas which have access to these apps. Moreover, from an ethical perspective, individuals generating data points during disasters are unaware that their data is being collected and used for disaster response.[191]

Geographic inequalities, such as missing data from low and middle-income contexts, or inadequate infrastructure and human capital to maintain event-based disease surveillance systems, can hinder the accurate detection of outbreaks in certain regions.[192]

Moreover, improvements in forecasting primarily led by private companies193 or developed nations will not automatically percolate to developing countries unless systems are put in place for sharing this data effectively. Data from global forecasting systems such as the US National Center for Environmental Prediction are available on the internet. But downloading these large data sets requires fast data-transfer rates, which can be expensive and, in some areas, just not available.[194] Downloading these large data sets also requires fast data-transfer rates, which can be expensive and, in some areas, just not available.

The meaningful adoption of AI-based prediction tools is also dependent on local capacities and resources. For instance, the full adoption of Firecast in government fire response services has been limited because of inadequate technical capacity to integrate the near-real time data into their daily work. There is a lack of sufficient resources to support field staff such as forest patrols and trainers to use the system. Where data is available, limited budgets often lead to insufficient patrol staff needed to respond to forest threats.[195]

Challenges and Risks
Privatization of disaster response services

The growing reliance on the private sector and technology for disaster risk reduction and emergency response[196] is symptomatic of a wider trend to rely on third parties to make up for state capacity issues.

However, the role of the private sector raises concerns about the proprietary nature of emergency services offered through privately owned technology. If the access and availability of timely and accurate information is monetised, there is a risk of exclusion for communities who cannot afford these services.'

There is also a growing trend in packaging these forecasting applications as products that help the private sector climate-proof their investments – this has been described as 'resilience as a service' by some commentators.[197] The largest market for some of these early warning systems appears to be the banking and insurance sector – there are fewer incentives for companies to develop systems for the benefit of the larger public.

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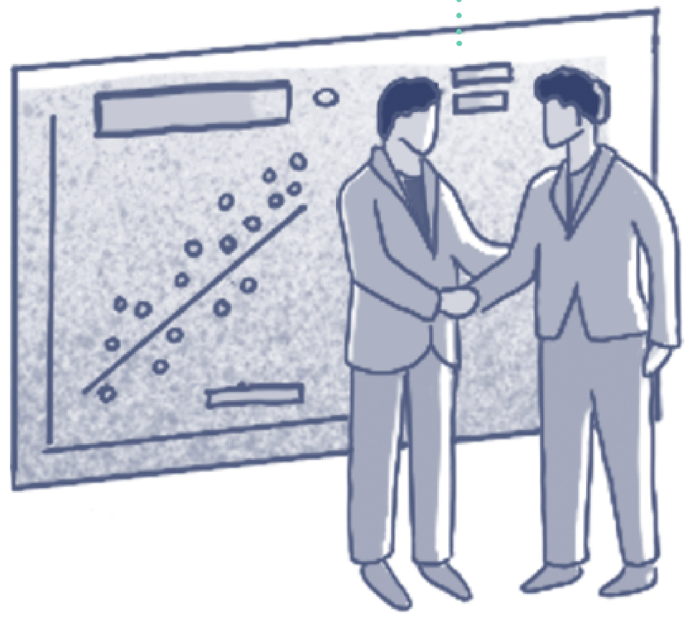


Challenges and Risks
Privacy and Surveillance

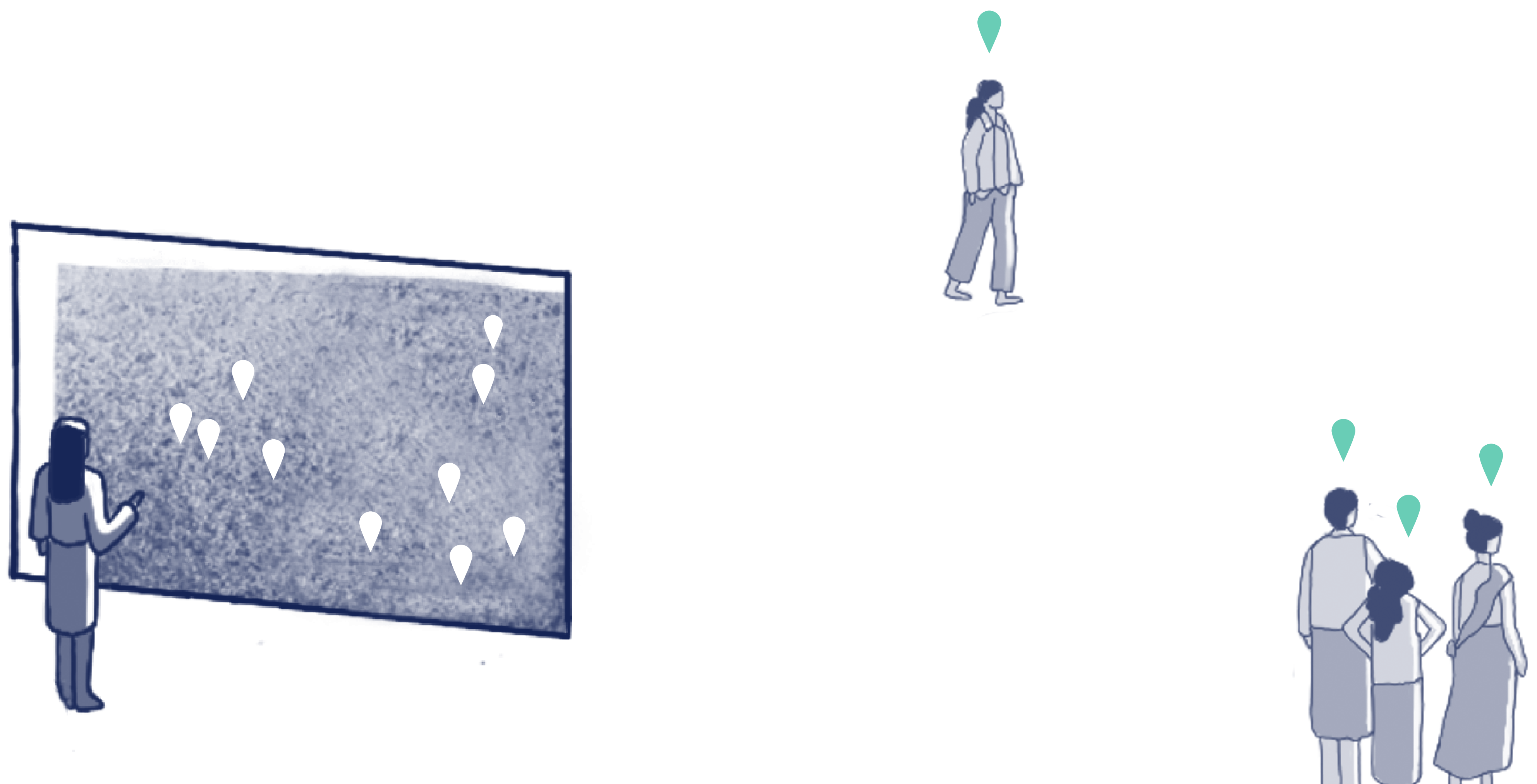
Event-based surveillance systems for disease outbreaks have the potential to normalize monitoring of individuals and communities.

Contact-tracing apps used during the pandemic became so entrenched in efforts to contain the spread of COVID-19 that rights activists warned that the long-term price of these applications would bet personal privacy.[198]

In India, data from a contact tracing app for COVID-19 was shared with the local police. Likewise, as noted earlier, Singapore also shared data from a COVID-19 tracing app with law enforcement agencies. Several Indian cities made it mandatory for municipal workers to wear tracking devices.[199]

This kind of 'opportunistic surveillance' [200] has risen post-pandemic because state agencies have access to public health surveillance data including location data and travel information.

While the potential benefits of AI-enabled disease surveillance are many from a public health perspective, this collection of data and its use must also be weighed against the potential for misuse.



Challenges and Risks
Misinformation

Conversational AI models can also be sources of misinformation, particularly in the climate context, where there are already a lot of competing narratives on the reality of climate change.

Experts warn that generative AI models can be used to fabricate knowledge and sources to deliberately spread incorrect information about science.[201] This also risks leading to an erosion of epistemic trust, when consumers of information have to constantly debate what information to trust and what to dismiss.[202]

These models are also prone to bias and inaccurate information. Most of them are built on English language text and then fine-tuned for other languages, but this is fraught with issues of accuracy, reliability, and bias.[203] By scraping the internet for content, they also rely on social media and non-authoritative data sources. This can contribute to the spread of incorrect information and even lead to the risk of language extinction, when the nuances of a particular language are not captured in its English translation.

The crowd-sourced nature of disaster-response services analysing data from social media platforms also increases the risk of false reports. For example, disaster management officials in Indonesia using information from disaster bots worry about the potential for misuse and hoaxes, such as through false reports of fire. Responding to such reports can strain economic capacities of government departments.

Data-driven disease surveillance systems often generate false alarms because it is difficult to distinguish natural variations in the data from real outbreaks.[204] Therefore, for accuracy, these systems need to be verified by human actors, which is time-consuming and costly.[205]

Moreover, the lack of transparency on how a particular output was achieved in these models also resurfaces issues around trust and reliability. False detection and an inability to explain these indistinguishable outcomes can erode public trust in these surveillance systems, and such misinformation could weaken an agency's or individual's power to effectively make decisions.[206]

Conclusion

The potential for harnessing AI for disaster management is quite high, primarily as an adaptation and planning tool in the event of extreme climate-related events.

Monitoring and forecasting applications can help authorities prepare for climate disasters, while crowd-sourced data can help shape decision-making during rescue activities. This is one domain where start-ups and civil society organisations have proven successful during disasters, particularly by pursuing the crowd-sourcing method.

But this is also a heavily contested space. Emergency response services have always been the domain of the government. To now have private parties participate in providing these services raises concerns relating to accountability and equity. Who will be liable if a crowd-sourced emergency alert is incorrect? Moreover, there is potential for commercial interests to drive these solutions. For example, if good-quality emergency alerts (built on large amounts of data and using massive processing power, which is resource-intensive) are based on a subscription model, the availability of critical life-saving information would be determined by an individual's ability to afford that information.

Tools for mitigating and adapting to climate-induced disasters are set in contexts with extreme disparities in access to finance, digital infrastructure, and technical capacities. And sometimes, providing information alone is not useful. For example, informing a citizen that the temperature will rise by 2°C is not useful unless it is accompanied by relevant information regarding the implications of these temperature variations.

Acting on this information requires additional resources for adapting to new practices. In a region with high heat stress and a population dependent on agriculture, especially daily wages from agricultural labour, an extreme heat warning is inadequate without income guarantee or food security.

Mitigation tools such as early warning systems and disease surveillance are potentially useful applications if deployed keeping in mind implications on vulnerable and marginalized populations and the risk for misuse or malfunction. All these systems also operate in complex socio-economic contexts, and recognizing that technology will not solve all humanitarian crises is key to pivoting to better, well-thought-out climate solutions.

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4 Structural Considerations

In assessing the use of AI for climate action, it is essential to look beyond the possibilities of specific applications to consider the broader system impacts and structural transformations that the use of AI may facilitate.

Direct environmental harms are already associated with the production and development of AI technologies. These are likely to increase if the current trajectory of building larger and larger models continues.

Benefits and harms are also not equitably distributed. For example, industrialized economies may be better positioned to leverage the benefits of AI due to the readiness of digital infrastructure and availability of local talent, but the harmful effects of unbridled natural resource extraction and excessive energy and water consumption might be disproportionately experienced by already vulnerable communities.

Further, the dominance of AI-centric models for addressing climate change could privilege and entrench the role of big tech companies at the expense of the agency of local communities and knowledge systems.

This concluding chapter highlights some of these broader and structural impacts of the use of AI for climate action. Given that an increasing share of development finance is being directed towards building AI-based solutions for climate action, these considerations must be kept in mind.

Environmental Costs of AI

Building and deploying AI systems requires significant planetary resources, such as rare metals for manufacturing GPUs, water to cool massive data centres, and energy to keep those data centres running.

Training just one AI model can emit more than 284 tonnes of CO_2, which is equivalent to nearly five times the lifetime emissions of an average American car.[207] A recent study similarly estimated that training GPT-3 consumes 1287 MWh of electricity and results in 502 metric tonnes of CO2 emissions, equivalent to driving 112 gasoline-powered cars for a year.[208] Improving the accuracy of models consumes even more energy. A study quoted by the Harvard Business Review found that the last 0.08% incremental increase in accuracy of an AI model took nearly 400% more energy than the first stage.[209]

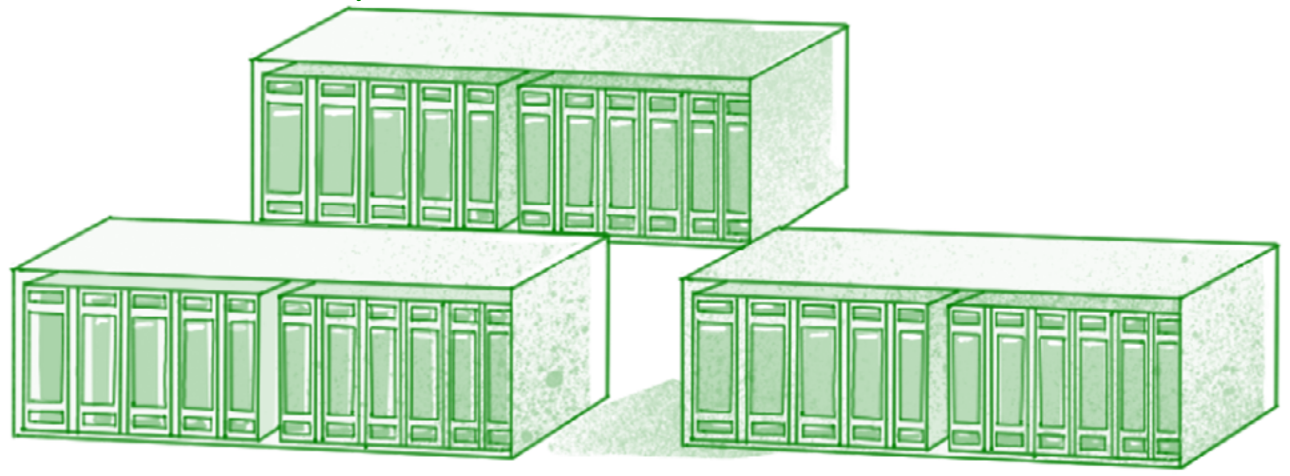
Studies also suggest that while training GPT-3 alone, Microsoft may have consumed 700,000 litres of water, which is equivalent to the amount of water needed to cool a nuclear reactor.[210] Water consumption for cooling data centres is likely to be even higher in warmer climates – by some estimates, it is likely to be triple in Asia.[211] The heat generated by data centres is a bigger cause of concern in Asia because of already rising temperatures.[212]

The resource lifecycle of AI compute[213] ends with recycling or disposing electronic waste (e-waste). As noted in an OECD paper, the collection, shipping, recovery, and disposal of AI compute has negative environmental impacts, such as the production of air and groundwater pollution and radioactive waste.

Much of global e-waste disposal is conducted in developing countries, adding to their environmental and social challenges.[214] Exposure to polybrominated diphenyl ethers, a group of chemical fire retardants commonly associated with the disposal of electronic waste, is likely to cause thyroid problems, neurodevelopmental deficits, and cancer. These ether emissions are highest in parts of China, India, Bangladesh, and western Africa.[215]

Improving the accuracy of models consumes even more energy.

Studies suggest that about 90% of data that is collected and stored is never used.



Research is underway to make computing more efficient and less energy-intensive, and many companies are experimenting with alternative sources of energy. However, it should not be assumed that greening digital infrastructure is straightforward and without challenges. For example, mining activities required to support the switch to rechargeable lithium batteries have a high environmental cost. In Chile's Salar de Atacama, for example, lithium and other mining activities consumed 65% of the water, resulting in groundwater depletion, soil contamination, and other forms of environmental degradation. The impacts of such activities are experienced most severely by local communities that have been forced to abandon their ancestral settlements.[216]

Admittedly, this issue is not specific to AI; the 120 trillion spam emails sent every year contribute to 36 million tonnes of CO_2 emissions.[217] Conversely, the issue at hand is the current trajectory of AI development, which is often rooted in Silicon Valley's "permission-less innovation" and "moving fast and breaking things" approach. This approach tends to completely overlook the materiality of AI production and the very real harms that arise from the current innovation paradigm.

The allure of building AI products and services is also contributing to data collection and storage without a clear purpose other than its future potential for AI. Some studies suggest that about 90% of data that is collected and stored is never used.[218] The very logic of such an innovation paradigm risks being contradictory to the logic of sustainability.

Climate Justice

The harms of climate change are unevenly distributed, often hitting the poorest the hardest.

In poorer economies, a large part of the population is directly dependent on activities vulnerable to climate risks, such as agriculture and forestry, and are dependent on natural resources for their livelihoods.[219] Rising temperatures and extreme weather events affect these populations more, while their contribution to greenhouse gas emissions is comparatively lower.

The use of AI in mitigation efforts may further entrench these inequalities, as those with the maximum resources (e.g., technical knowledge, computing capacity, and infrastructure) are able to develop and deploy AI.[220] As Korinek et al. note, AI and automation can encourage a "winner-takes-all" dynamic that benefits highly skilled individuals and countries that are leading technological progress.[221] The top ten in Oxford Insights' Government AI Readiness Index (2022) include only three countries outside of North America and Europe, reflecting "a persistent inequality in government AI readiness."[222] Data-poor regions and populations with limited digital access are also likely to remain illegible to new ML applications, creating risks of bias and exclusion.

The social, economic, and ecological impacts of climate change mitigation technologies are also likely to be disproportionately borne by marginalized sections across and within communities, following patterns of place-based structural inequalities.[223] For example, in Indonesia, nickel mining (nickel being a key component for electric vehicle batteries) has caused flooding of rice fields with laterite waste, resulting in soil erosion. This has led to longer harvest cycles and reduced productivity.[224] Mining has also contaminated the coastal ecosystem, leading to the degradation of mangroves and the decline of local fish populations.[225] This invariably affects marginalized communities reliant on rice cultivation and living closer to the coast.

Scholars also point to how green solutions often rely on dispossessing people from their homes, which exacerbates inequalities along the lines of class, gender, or ethnicity.[226]

As AI systems optimize and improve the efficiency of systems, they can also lock in and perpetuate contentious climate solutions or those with harmful social impacts. For example, AI is being used to optimize the discovery of sites for setting up renewable energy sources. However, these calculations, which are based on satellite imagery and remote sensing data, may capture the physical characteristics of the environment but

In parts of the world, carbon offsetting projects are displacing people from lands and their traditional livelihoods.

disregard its social dimensions or interpret them in a highly reductive manner. For instance, in Kutch (western India), which is being developed as a wind energy exploitation zone, farmers and herders have been protesting because wind energy turbines restrict their access to forests and the resources on which these communities depend.[227]

In other parts of the world, carbon offsetting projects are displacing people from lands and their traditional livelihoods. In Congo, an oil company, TotalEnergies, has started a major carbon offsetting project with the goal of planting Acacia trees across 40,000 hectares of land. This is expected to sequester about 10 million tonnes of CO_2 over 20 years. While the project will generate carbon credits, it has displaced families who have lived off the Batéké Plateaux for generations.[228]

These paradoxical interventions – where high-carbon emitting and resource-extracting oil companies plant trees to offset their carbon footprints – are being called out for being false climate solutions.[229] But as governments and big companies work in tandem, with acquiescence from international development agencies,[230] long-term impacts such as the loss of access to ancestral land and erosion of traditional knowledge practices are borne solely by indigenous communities who have for generations been closest to the land.

Similarly, AI systems are optimized for a particular goal and thus are not neutral in their objectives or functions. Policy agendas, for example, tend to elevate mitigation options with positive economic value, and optimising for this goal might exacerbate social inequities. For instance, experts in China are warning that the announcement of China's net-zero target by 2060, though a very significant achievement for its climate strategy, may bear the risk of shifting the focus from curbing emissions from fossil fuel industries to promoting reforestation, particularly with mixed crops plantations, to generate economic profits.

In the past decades, such massive reforestation programmes are suspected to have contributed to the loss of biodiversity and animal habitat within China, leading to unprecedented elephant migration in its Yunnan province in 2021.[231]

Erosion of traditional knowledge practices are borne solely by indigenous communities.

Concentration of Power and Knowledge

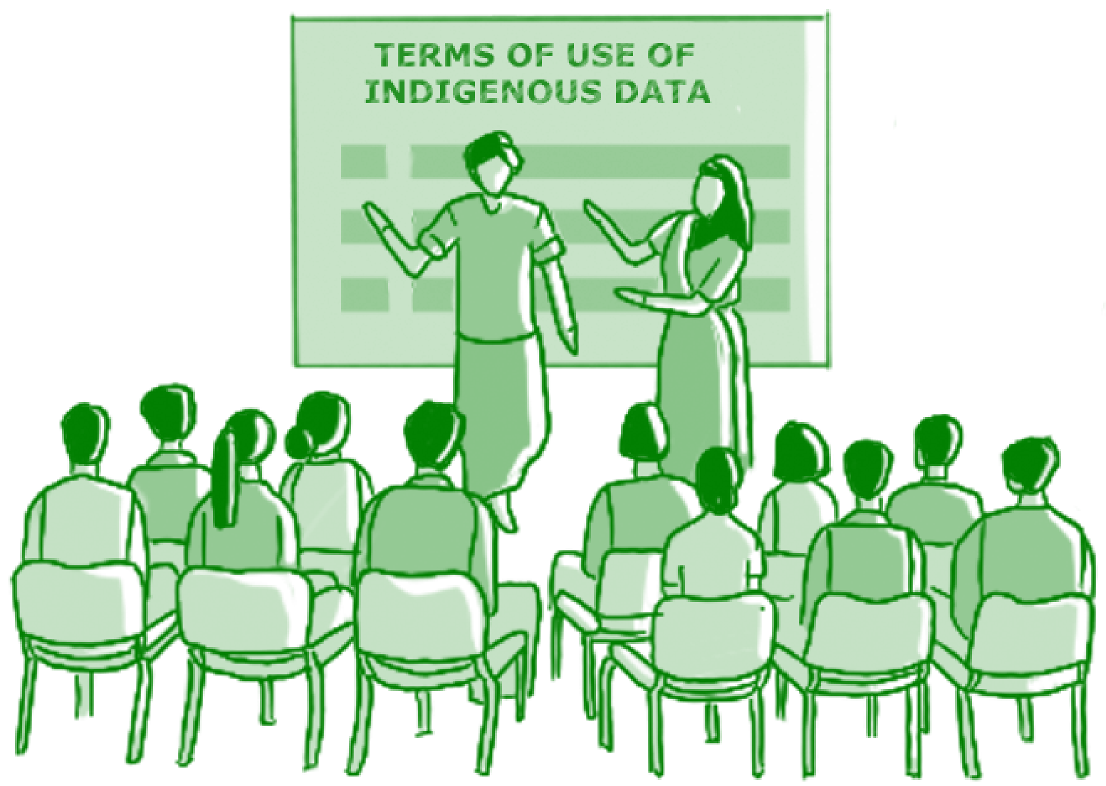
A handful of technology companies—popularly known as Big Tech—dominate the digital transformation of critical social sectors such as health and finance. This trend appears to be extending to climate action as well.

Companies such as Microsoft and Google are investing heavily in AI for climate action, including in extensively mapping geographies and landscapes around the globe. While opening this data to a broader community creates new opportunities for localized solutions and innovation, Big Tech's commitment to addressing climate action rings hollow in light of evidence that their platforms intentionally promote climate misinformation in support of fossil fuel companies. Even UN Secretary General António Guterres recently remarked that Big Tech are an overlooked piece of the "public relations machine" of fossil fuel industry greenwashing.[232]

Building AI systems is expensive, particularly as models are getting bigger. For instance, the number of parameters in language models has increased from approximately 100 million in 2018 to 500 billion in 2023. Bigger models typically take longer to train, require more GPUs, and cost more money, so only a select few organizations can train them. Training GPT-3, which has a massive 175 billion parameters, is estimated to cost USD 4.6 million, which is prohibitively high for most companies and organizations.[233] If this trend continues, there is a risk that only a select few technology companies will have the resources to be able to build and train these large models.

While many companies are making much of their data publicly available, only a few have the resources to most effectively make use of and leverage these systems. This is concerning given that many countries are creating or investing in open-data systems, but they typically do not have the resources within the government (or within civil society) to use these systems as quickly or effectively. Conversely, Big Tech companies have access to multiple other sources of data, augmenting the amount of intelligence they can leverage from this data.

Creating open-source systems also comes with its own risks, particularly pertaining to privacy, security, and misuse. Research on the open-data movement reveals that the manner in which state agencies collect, store, analyse, and disseminate information can reinforce colonial harms against indigenous and local community interests.[234] For example, a report by The Engine Room shows how open map data that was used by the local community to find clean drinking water was used by corporations to buy land and water rights in this area. [235]



Top-down AI-based interventions risk displacing local knowledge systems and ways of knowing.

Top-down AI-based interventions also risk displacing local knowledge systems and ways of knowing. Climate-relevant data and knowledge are reduced to that which can be enumerated and calibrated for ML. This can result in the deprioritization of community traditions and adaptive strategies and the imposition of top-down solutions that are not in tune with local contexts. It can contribute to what Miranda Fricker calls "epistemic injustice".[236]

Analysts from developing countries also point to the "parachute science"[237] that climate change research often involves. Researchers from developed economies gather data from developing countries but without making any apparent contribution to the development of local science capacity. For example, a review of coral reef biodiversity publications featuring fieldwork in Indonesia and the Philippines found that 40% of the publications were not authored by a scientist from the host nation. Practices such as these create dependencies on external expertise, ignore local research priorities, and hinder local research efforts.[238]

Mapping itself is a highly politicized activity. Aerial and satellite imagery–based mapping tell a particular story about communities and climate change. The challenges and initiatives of communities are reduced to what can be visually mapped in pixels, flattening or obfuscating the complex social dynamics and human interactions that shape how communities experience and respond to climate change. For example, the focus on using satellites to map forest cover and estimate carbon sequestration reduces forests to mere carbon sinks and glosses over the ways in which forests are integral to the livelihoods and medicinal traditions of communities.

In this context, it is important to note that even the IPCC recognizes that indigenous knowledge and local knowledge play an important role in the formulation of adaptation governance and related strategies.[239] The question is whether AI supports or undermines such local knowledge systems. In its current form, with the dominance of Big Tech players and advanced technology, the risk of displacement of local knowledge systems is very high.

Conclusion

Matteo Pasquinelli argues that ML, as a form of computational statistics, represents a form of "information compression", which goes together with "information silences". Information compression is what enables profit for companies, but information loss "often means a loss of the world's cultural diversity".[240]

Data are also never neutral and always partial and representative. Since ML systems are based on generating inferences from historical data, the patterns or predictions produced by these systems will tend to reproduce and amplify existing socio-economic inequities. The data-intensive nature of ML is also fuelling today's extractive information or data economy at the expense of individual rights and privacy.

If AI is seen in these terms – as computational statistics that, Cathy O'Neil argues, "reproduce the future based on the past"[241] – then it must force us to temper our expectations about "AI for development" or "AI for social good".

Statistical models are certainly useful as they can help identify trends, provide informational support, aid decision-making, plan resources, and automate certain processes. However, we need to recognize the limitations and gaps of these systems as well as the commercial interests driving current innovation and use trajectories. This is particularly important for developing countries, where AI is being positioned as a solution for complex development problems such as climate action.

As new computational techniques are being developed for machine intelligence, we should consider other types of personhood, intelligence, and ethics to chart alternative AI futures. Indigenous knowledge systems, for example, do not position humans as outside or above natural systems.

Relational paradigms based on social and environmental sustainability have long informed technology development in indigenous cultures. Such relational ethics are a core tenet in many cultural traditions across the world, which emphasize a communal duty of care towards people and the environment.

Undergirding emerging climate tech solutions, including AI, with these value systems and knowledge frameworks is critical to making technology work for climate justice. For our view on how these challenges can be addressed and Responsible AI practices fostered, please see our brief for Responsible AI for Climate Action.

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About the Project

About DFL

Digital Futures Lab is an interdisciplinary research collective that interrogates the complex interaction between technology and society in the global South. Through evidence-based research, public engagement and participatory foresight, we seek to realise pathways toward equitable, safe and just digital futures.

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About the Project

Commissioned in early 2023 by The Rockefeller Foundation, this project explores the intersection of Artificial Intelligence and Climate Action in Asia. It examines opportunities, challenges and risks across three domains – agriculture and food systems, energy transitions, and disaster response in nine countries - Bangladesh, China, India, Indonesia, Malaysia, Singapore, Thailand, The Philippines and Vietnam.

We assembled a network of regional experts to help guide our investigation and provide context specific insights.

Aaditeshwar Seth (India)
ChengHe Guan (China)
Cindy Lin (Indonesia)
Elenita Daño (The Philippines)
Elina Noor (Malaysia)
Gaurav Sharma (India)
Md. Golam Rabbani (Bangladesh)
Pyrou Chung (Thailand)
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