ARTIFICIAL INTELLIGENCE FOR CLIMATE SECURITY

Possibilities and Challenges

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STOCKHOLM INTERNATIONAL PEACE RESEARCH INSTITUTE

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Preface

As the world grapples with the intensifying impacts of climate change, the peace and security landscape is undergoing a transformation. The impacts of climate change range from extreme weather events to rising sea levels, biodiversity loss and ill health. These are not merely environmental challenges; evidence shows they pose a significant risk to national and international security.

Artificial intelligence (AI) can play a critical role in addressing the security challenges posed by climate change. This report provides an overview of opportunities that AI offers in tackling these emerging and urgent challenges, with concrete examples of existing initiatives. AI can help us deepen our understanding of climate hazards and risks, develop more effective climate change adaptation strategies, and enhance the social and community resilience that we need in the face of insecurity induced by climate change.

As this report shows, these actions must be accompanied by caution in safeguarding diversity and equity, and by attention to the accountability of AI-generated or -assisted insights. Indeed, the secretary-general of the United Nations has recently announced the formation of a high-level advisory body to consider the risks, opportunities and international governance of AI. To harness the potential of AI for good, a global, multidisciplinary and multistakeholder conversation is essential.

Research such as this SIPRI Policy Report, which critically reflects on the challenges that AI harbours, can contribute to and guide such conversations, promoting the potential for AI to play an even greater role in ensuring a secure and sustainable future. It is an essential resource for anyone seeking to understand the role of AI in addressing climate-related security risks, and for those who are committed to finding solutions to this pressing global challenge.

Dan Smith
SIPRI Director
Stockholm, December 2023

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Summary

Recent advances in artificial intelligence (AI)—largely based on machine learning—offer possibilities for addressing climate-related security risks.

They are particularly useful for addressing risks related to climate hazards and risks related to climate vulnerabilities and exposure. Indeed, AI can make disaster early-warning systems and long-term climate hazard modelling more efficient. These improvements can reduce the risk that the impacts of climate change will lead to insecurity and conflict. These tools can also be used to optimize food production and the management of natural resources (e.g. in the form of precision agriculture) in countries where livelihood conditions have deteriorated as a result of climate change; or could facilitate the use of autonomous robots for delivery of humanitarian assistance during climate disasters. There are already ongoing projects that demonstrate these possibilities.

In the case of a third type of risk—climate change-related grievances and tensions—the picture needs to be more nuanced. In theory, AI data-processing capabilities can be used to track grievances and social tensions stemming from exposure to climate change. In practice, however, there are many challenges with using AI to monitor and track the political views and behaviours of a population.

AI presents particular opportunities to address the lack of climate-related data in conflict-affected and fragile countries. These countries are typically among those that are the most exposed to climate hazards and already suffer from environmental degradation exacerbated by climate change. The availability of data in such countries is one of the main obstacles that national governments and international organizations need to tackle head-on when seeking to reduce the risks posed by climate change to peace and security. AI can help policy actors overcome the data problem by enabling efficient use of remote sensing systems, especially satellite imagery, as well as social media.

At the same time, the use of AI for climate security presents technical and ethical challenges. Machine learning, one of the main areas of AI application discussed here, is a powerful technology, but it has important shortcomings. Machine learning algorithms can be opaque and may not explain why and how certain outcomes resulted from a calculation. AI systems powered by machine learning demand a lot of computer resources and can be costly. Their viability and usefulness are likely to depend on the volume and the quality of the data on which they are trained.

For researchers who wish to develop AI tools to empirically study climate-related security risks, these challenges raise difficult methodological questions around the verifiability of outputs, the scalability of the model and, most importantly, decisions about the curation of input data. Ensuring that the system is trained on representative and reliable data is critical to ensuring the usefulness of the system and to minimizing the risk of bias.

Actors who see a great potential in using AI to gather and analyse data related to climate change adaptation and climate change-related grievance monitoring also need to consider associated ethical concerns. These include the need to bear in mind that an over-reliance on such systems may lead to policy interventions that discriminate against certain social groups—particularly those that do not engage with social media for economic, social or political reasons. The possibility that automated social monitoring tools could be misused by authoritarian regimes must also be acknowledged. More generally, the use of such tools could undermine human rights, not least people's rights to privacy and the right not to be discriminated against.

Based on these key findings, policymakers interested in further exploring the potential of AI for climate security should support critical research on AI and climate security.

They should also support access to digital infrastructure and digital literacy, and the development of an open-access AI tool for the collection of climate security-related data in conflict-affected and fragile countries.

Researchers who wish to make use of AI to better understand the nexus between climate change and security should conduct empirical research and explore methodological questions. They should also consider ethical and political risks associated with the use of AI methods to monitor climate change-related tensions and political grievances. In all this, they should maintain close links with affected communities.

Abbreviations

AI	Artificial intelligence
CEWS	Conflict early-warning system
EU	European Union
FEWS NET	Famine Early Warning Systems Network
ICT	Information and communications technology
ITU	International Telecommunication Union
UN	United Nations
UNEP	United Nations Environment Programme
UAV	Unmanned aerial vehicle
WFP	World Food Programme
WPS	Water, Peace and Security (partnership)

1. Introduction

Climate security is a field of research and an area of policy that focuses on the impact of climate change on peace and security. Research to date has established that the current climate crisis has significant implications for peace and security—especially in conflict-affected and fragile countries.[1] Climate change increases the intensity and frequency of extreme weather events, affects long-term climate trends, and accelerates environmental degradation. These physical changes can, in turn, be the source of dramatic societal disruptions and insecurity at various scales. For example, they can cause livelihood conditions to deteriorate and expose vulnerable populations to food insecurity. As well as triggering mass migration, the adverse impacts of climate change on livelihood and food security can generate or amplify sociopolitical grievances, which can be exploited by political elites or armed groups.[2] This set of interconnected challenges is captured in the term 'climate-related security risks' (see box 1.1 for this and other definitions).

The relationship between climate change and peace and security is now almost beyond dispute in international policy circles. National governments, United Nations political and peace missions, and regional and international organizations face mounting pressure to effectively manage climate-related security risks.[3] However, these policy actors are not equally equipped to deal with these challenges. Many of them, particularly states in the Global South, have limited resources at their disposal to monitor these risks and to deploy adequate policy interventions.

In this context, advances in science and technology are often regarded as a source of opportunity for efficient and cost-effective policy interventions.[4] Artificial intelligence (AI) has attracted a lot of attention in policy circles in recent years, not least because of hype around the advances in machine learning and, more recently, generative AI.[5] This report starts from the premise that AI is likely to both present possibilities for understanding and responding to climate-related security risks, and also carry potential risks. These risks mean that the possibilities offered by AI warrant careful review. This is the purpose of this report. It seeks to provide interested policy actors and researchers with a nuanced overview of what AI could bring to the field of climate security.

This report is based on desk research and expert interviews. It continues in chapter 2 with a presentation of the opportunities that AI presents for managing climate-related security risks. Chapter 3 then gives examples of the use of AI in the field, while chapter 4 delves into the problems—notably methodological and ethical—associated with the use of AI for climate security. Chapter 5 concludes the report by presenting recommendations for policymakers and researchers who are active in the field of climate security or who use AI for sustainability. Appendix A lists examples of AI tools relevant for climate security interventions.

[1] Kim, K. and Garcia, T. F., 'Climate change and violent conflict in the Middle East and North Africa', *International Studies Review*, vol. 25, no. 4 (Dec. 2023); von Uexkull, N. and Buhaug, H., 'Security implications of climate change: A decade of scientific progress', *Journal of Peace Research*, vol. 58, no. 1 (Jan. 2021); and Busby, J., 'Taking stock: The field of climate and security', *Current Climate Change Reports*, vol. 4, no. 4 (Dec. 2018).

[2] Mobjörk, M., Krampe, F. and Tarif, K., 'Pathways of climate insecurity: Guidance for policymakers', SIPRI Policy Brief, Nov. 2020. See also the Climate, Peace and Security Fact Sheet series by SIPRI and the Norwegian Institute of International Affairs (NUPI).

[3] Hegazi, F., Krampe, F. and Smith, E. S., *Climate-related Security Risks and Peacebuilding in Mali*, SIPRI Policy Paper no. 60 (SIPRI: Stockholm, Apr. 2021).

[4] Sætra, H. S., *AI for the Sustainable Development Goals*, AI for Everything (CRC Press: Boca Raton, FL, 2022).

[5] Maher, H. et al., 'AI is essential for solving the climate crisis', Boston Consulting Group, 7 July 2022; and Mastrola, M., 'How AI can help combat climate change', The Hub, Johns Hopkins University, 7 Mar. 2023.

Box 1.1. Key concepts related to climate change and security

Climate change refers to 'a statistically significant variation in either the mean state of the climate or in its variability, persisting for an extended period (typically decades or longer). Climate change may be due to natural internal processes or external factors such as persistent changes to the atmosphere or changes in land use'.[a]

Climate variability is defined as 'variations in the mean state and other statistics of the climate on all temporal and spatial scales, beyond individual weather events'.[b] In essence, climate variability looks at changes that occur within smaller time frames (e.g. a month, a season or a year) and climate change considers changes that occur over a longer period of time (typically decades or longer). A key difference between climate variability and climate change is in persistence of 'anomalous' conditions—when events that used to be rare occur more frequently, or vice versa.[c]

Climate hazard is the potential occurrence of a natural or human-induced physical climate-related event or trend that may cause loss of life, injury or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems or environmental resources.

Climate-related security risks refer to risks to people's well-being and livelihoods that emerge from climate change and that may have implications for societal, economic or political stability at local, national, regional or international levels.[d]

Climate security is a field of research and an area of policy debate that provides foundations for evaluating, managing and reducing the risks to peace and stability brought on by the climate crisis. Climate security is anchored in a comprehensive approach to security that includes human, societal, state and international security. Such an approach allows consideration of various dimensions of security that are relevant for multifaceted risks derived from climate change.[e]

Climate change adaptation refers to the process of adjustment to actual or expected climate change and its effects on human systems in order to moderate harm or exploit beneficial opportunities.[f]

Climate change mitigation is a human intervention to reduce emissions or enhance the sinks of greenhouse gases.[g]

Climate resilience refers to the ability of a social or ecological system to absorb disturbances while retaining the same basic structure and ways of functioning, the capacity for self-organization, and the capacity to adapt to stress and change.[h]

[a] World Meteorological Organization (WMO), 'FAQs—Climate', [n.d.].

[b] World Meteorological Organization (note a).

[c] World Meteorological Organization (note a).

[d] Remling, E. and Causevic, A., 'Climate-related security risks in the 2020 updated nationally determined contributions', SIPRI Insights on Peace and Security no. 2021/1, Jan. 2021.

[e] Krampe, F. and Mobjörk, M., 'Responding to climate-related security risks: Reviewing regional organizations in Asia and Africa', *Current Climate Change Reports*, vol. 4, no. 4 (Dec. 2018), p. 331.

[f] Robins, J. B. R. (ed.), 'Glossary', annex I of eds V. Masson-Delmotte et al., *Global Warming of 1.5°C*, Intergovernmental Panel on Climate Change (IPCC) Special Report (Cambridge University Press: Cambridge, 2018).

[g] ed. Robins (note f).

[h] UN Framework Convention on Climate Change (UNFCCC), 'Glossary of key terms', NAP Central, [n.d.].

2. The possibilities that AI presents for addressing climate-related security risks

As noted above, mounting evidence showing both the direct and the indirect impacts of climate change on peace and security has prompted international and national authorities to respond to climate-related security risks more effectively.[6] This chapter provides an overview of the opportunities for addressing climate-related security risks that are offered by artificial intelligence. It starts with a short primer on what makes AI a potentially useful technology. It then reviews the possibilities that AI brings for addressing three types of climate-related security risk: climate hazards; climate vulnerabilities and exposure; and climate change-related grievances and tensions.

AI and its possibilities

AI is a 'catch-all term that refers to a wide set of computational techniques that allow computers and robots to solve complex, seemingly abstract problems that had previously yielded only to human cognition'.[7] These problems include, for example, recognizing people, objects or patterns in pictures and video; translating languages; and generating original text and images.

State-of-the-art AI typically relies on a suite of computational techniques called machine learning.[8] Machine learning contrasts with 'traditional' AI software techniques in that it does not require the programmer to explicitly define for the system how to solve a given problem: a machine learning system learns how to solve a problem on its own, based on different teaching methods and a lot of data. Machine learning has outpaced traditional AI programming techniques in many, if not most, AI application areas: computer vision, natural language processing, robotics and process optimization, to name a few. Thus, while traditional AI methods are still in use, machine learning has emerged in the past 10–15 years as the dominant approach to AI programming.

What makes machine learning so powerful is its ability to find statistical relationships within data—that is, to recognize patterns in data. That ability makes machine learning particularly useful for four types of task: sensing; data curation and analysis; prediction; and resource optimization. First, machine learning has made machines better at perceiving the world. Over the past 15 years machine learning has drastically improved the ability of computer systems to detect and identify objects and other patterns in sensory data. That has led to the development of more accurate detection and monitoring systems, and also smarter and more autonomous robot systems, which may, for instance, be used for remote sensing. In the case of data curation and analysis, machine learning's pattern-recognition capabilities can be used to classify and make use of virtually any type of digitalized data. This, in turn, enables the third type of task, prediction: the ability of machine learning to make sense of data can provide a basis for predictive models and offer future-oriented insights. Machine learning is, for instance, routinely used in the commercial sector to predict consumer preferences. Finally, the data-processing capability of machine learning can be leveraged for resource optimization. It facilitates

[6] Vogler, A., 'Barking up the tree wrongly? How national security strategies frame climate and other environmental change as security issues', *Political Geography*, vol. 105 (Aug. 2023); and Krampe, F. and Mobjörk, M., 'Responding to climate-related security risks: Reviewing regional organizations in Asia and Africa', *Current Climate Change Reports*, vol. 4, no. 4 (Dec. 2018).

[7] See the detailed definition in Boulanin, V., 'Artificial intelligence: A primer', ed. V. Boulanin, *The Impact of Artificial Intelligence on Strategic Stability and Nuclear Risk*, vol. I, *Euro-Atlantic Perspectives* (SIPRI: Stockholm, May 2019).

[8] Somers, J., 'Is AI riding a one-trick pony', *MIT Technology Review*, 29 Sep. 2017.

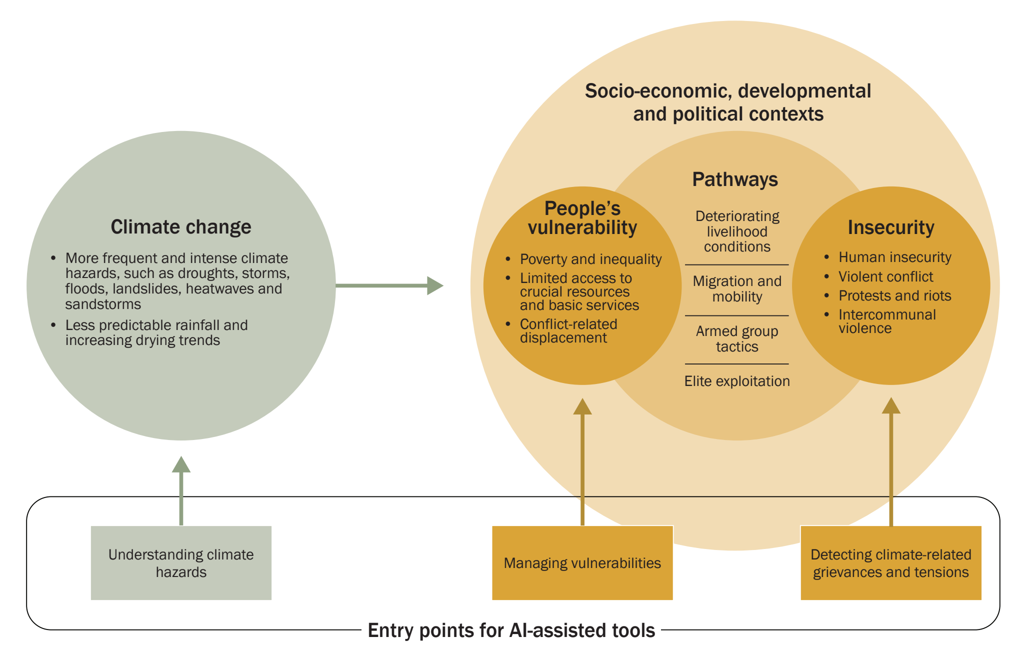

Figure 2.1. Entry points for artificial intelligence to respond to climate-related security risks

the processes of identifying patterns of resource consumption, and the calculation of alternative models that could generate efficiencies.

It is not hard to imagine how the possibilities that machine learning offer for these four types of task could have some utility for the mitigation of climate-related security risks. These can be summarized as follows.

Sensing. Collecting data on climate and environmental changes and on peace and security is costly. It requires extensive physical infrastructure and human resources on the ground. Progress in machine learning allows for the deployment of more accurate and more versatile remote sensing systems. Computer vision systems and autonomous remote sensing platforms (e.g. unmanned aerial vehicles (UAVs), which could be deployed in swarms) can be used to facilitate the collection of data on water resources or on land and forest over large areas in remote or hard-to-reach environments.[9] Machine learning can also speed up the collection of data on social outcomes linked to environmental changes, from livelihood conditions and food security, via migration and transhumance (i.e. the seasonal movement of livestock to new pastures), to trafficking.

Data curation and analysis. Machine learning's data-processing capability offers researchers new ways to analyse data on environmental changes as well as on the human activities related to environmental changes. For instance, classification and detection algorithms can automatically identify and locate objects and compare changes with historical earth observation images. Machine learning can also integrate and find linkages between data from different sources (e.g. social media, weather stations and satellite images).[10] This could help researchers to detect patterns or feedback loops

[9] Albuquerque, R. W. et al., 'Mapping key indicators of forest restoration in the Amazon using a low-cost drone and artificial intelligence', *Remote Sensing*, vol. 14, no. 4 (Feb. 2022); Ampatzidis, Y. and Partel, V., 'UAV-based high throughput phenotyping in citrus utilizing multispectral imaging and artificial intelligence', *Remote Sensing*, vol. 11, no. 4 (Feb. 2019); and Dauvergne, P., *AI in the Wild: Sustainability in the Age of Artificial Intelligence* (MIT Press: Cambridge, MA, 2020).

[10] Anyamba, A., Tucker, C. J. and Eastman, J. R., 'NDVI anomaly patterns over Africa during the 1997/98 ENSO warm event', *International Journal of Remote Sensing*, vol. 22, no. 10 (2001).

involving environmental systems, society and conflict dynamics that may otherwise be invisible.

Prediction. The above-mentioned possibilities can in turn be used to develop new early-warning and forecasting tools for phenomena such as climate hazards, insecurity, forced migration and political unrest, or to improve existing tools.

Resource optimization. Mitigating climate-related security risks requires long-term investment in reducing vulnerability to climate change and enhancing resilience at all levels. Using AI for resource optimization is highly valuable in that context.[11] AI can facilitate the identification of resource consumption patterns and the development of alternative, more efficient models. For instance, near real-time monitoring systems for managing urban water management, transportation, agriculture and livestock can be set up cost-effectively with the deployment of AI. AI-powered systems can also help humanitarian and development actors become more resilient to weather shocks and adverse impacts of climate change on ecosystems and nature-based livelihoods. Moreover, AI-assisted models can contribute to resource allocation for climate change-adaptation efforts.

The remainder of this chapter explores these opportunities in greater detail. Rather than focusing on the four types of task that AI can help with, it proceeds by outlining the impact of climate change on society and then describing how AI can help (see figure 2.1). The next section delves into the possibilities that AI offers for understanding and addressing a set of environmental changes that present security risks. These include extreme weather events, water scarcity and warmer temperatures, which can harm human life and health and have adverse impacts on livelihood conditions, property, infrastructure, service provision and ecosystems, and which can exacerbate existing vulnerabilities. These phenomena are captured here under the label 'climate hazards' (see also box 1.1 above). The following section focuses on how AI can help understand and manage societies' vulnerabilities and exposure to climate change-induced environmental changes. This is followed by a section that zooms in on the linkage between climate hazards and sociopolitical grievances and discusses how AI could help better detect climate change-related grievances and tensions between social groups.

Understanding and predicting the impact of climate hazards

Climate change will increase the frequency and intensity of natural disasters, with their consequent political, economic and social impacts. These impacts could exacerbate existing conflict risks and escalate social tensions, potentially leading to an increased likelihood of conflict and violence. Modelling climate hazards and forecasting climate change-related disasters and climate variability are, therefore, crucial steps for effectively managing climate-related security risks. In this context, AI holds great potential, as it is able not only to help predict climate hazards but also to assist humanitarian responders to plan timely interventions either in the form of preventive measures or humanitarian relief. This section covers these two aspects, starting with how AI can help with early warning of near-term hazards, then looking at forecasting long-term climate trends.

[11] Sætra (note 4).

Early-warning systems for near-term hazards

Extreme weather events such as tropical storms and heatwaves are bound to become more frequent and intense due to the changing climate. The impacts they have on livelihood systems can have various socio-economic consequences, contributing to political instability and insecurity.[12] For instance, floods and droughts may exacerbate the risk of food insecurity for the most vulnerable populations and marginalized groups. In some cases, such events could force them to migrate to areas under stress from resource scarcity and a lack of infrastructure.[13] In conflict-affected and fragile settings, food insecurity and the influx of people in the aftermath of climate change-related disasters can be particularly critical. These climate disasters can exacerbate the risk of mass displacement, social unrest and intercommunal tensions and clashes. In addition, armed groups can exploit the devastation to increase recruitment.[14] Examples of precarious situations can be observed in instances of prolonged droughts in Somalia and Afghanistan that are linked to increased competition over water and land between communities, on which central elites and armed groups have capitalized.[15]

In that context, early-warning systems for near-term prediction of extreme weather events are a crucial risk-mitigation tool. In conflict-affected and fragile countries, preventive measures and anticipatory action can protect the population from climate hazards and contribute to stability and peace. According to the Global Commission on Adaptation, giving just 24 hours' notice of a storm or heatwave can reduce damage by 30 per cent and investing just US$800 million on early-warning systems in the Global South would avoid losses of $3–16 billion per year.[16] These statistics highlight the value of improved early-warning systems in minimizing the impacts of climate change-related hazards and their associated socio-economic consequences.

However, many countries in the Global South lack the resources and capacities to establish such systems.[17] Developing early-warning systems requires substantial computing and communication capacities to integrate and transmit data. Many of these countries lack the financial resources to develop or maintain such capacities, which is particularly concerning since they are typically the countries most exposed to the adverse impacts of climate change.[18]

The question, in that context, is how AI may help. At least three opportunities can be identified.

First, AI can contribute to cost-efficient sensing and data collection for early-warning systems in countries that lack sufficient infrastructure and capacity for traditional climate information systems. AI allows governments and organizations that work on humanitarian, development and climate change adaptation efforts to make efficient use of remote sensing data, notably satellite imagery, which is useful for detection of extreme weather in areas without weather stations.[19] Making use of early warning

[12] Moseley, W. G., 'Recovering from livelihood insecurity and political instability in northern Mali: Bouncing back', *International Journal: Canada's Journal of Global Policy Analysis*, vol. 68, no. 3 (Sep. 2013).

[13] Sitati, A. et al., 'Climate change adaptation in conflict-affected countries: A systematic assessment of evidence', *Discover Sustainability*, vol. 2, article no. 42 (27 Sep. 2021).

[14] Walch, C., 'Weakened by the storm: Rebel group recruitment in the wake of natural disasters in the Philippines', *Journal of Peace Research*, vol. 55, no. 3 (May 2018).

[15] See the SIPRI and NUPI Climate, Peace and Security Fact Sheet series (note 2).

[16] Global Commission on Adaptation, *Adapt Now: A Global Call for Leadership on Climate Resilience* (Global Center on Adaptation: The Hague, Sep. 2019), p. 5.

[17] World Meteorological Organization (WMO), 'Early Warnings For All initiative scaled up into action on the ground', Press release, 21 Mar. 2023.

[18] Gavin, M., 'From climate change to regional security, the DRC looms large', Council on Foreign Relations, 13 July 2022.

[19] World Meteorological Organization (WMO), 'Least Developed Countries programme', [n.d.]; and Bhaga, T. D. et al., 'Impacts of climate variability and drought on surface water resources in Sub-Saharan Africa using remote

requires availability of reliable weather data. AI analysis of satellite imagery could be particularly helpful for conflict-affected and fragile countries where weather stations may have been destroyed or are difficult to maintain.[20] Such countries typically have limited resources to rehabilitate and upgrade facilities.[21] Using satellite images can be much safer and cheaper than installing and maintaining facilities in conflict zones. Conflict-affected and fragile countries may require support from external organizations and development cooperation partners in the Global North for additional technical and financial resources. AI systems also have financial costs and considerable environmental impacts, but AI-based solutions may overall still be cheaper options. While AI cannot replace the enormous needs for climate information capacity building in these countries, it can help address the problem of data availability in the short and medium terms. The usefulness of AI has already been demonstrated by several research projects that have shown how machine learning-trained models can improve the accuracy of weather-monitoring systems.[22]

Second, AI developed from quality input data can enhance the accuracy of prediction by early-warning systems. Early-warning systems make predictions based on mathematical models. The progress of machine learning plays a role here in the sense that it allows the designers of such systems to develop more complex models, which draw on larger and more heterogenous sets of data. This capability represents a major opportunity for climate hazards prediction because it can make it easier to account for the complexities of phenomena and the interactions of factors that determine the likely impact of extreme weather events. In the case of droughts, for example, machine learning can help take into account the multitude of meteorological and local conditions that influence water availability and their impact on agriculture.[23] Some researchers have shown that models trained on machine learning can predict drought with more accuracy even in areas where access to ground data is limited (thanks to satellite data).[24] Similar methods could be used to predict other types of hazard such as floods, heatwaves and tropical storms.[25]

Third, AI can make early-warning systems more comprehensive in their impact assessment as it enables the integration of not just environmental data but also socioeconomic data. State-of-the-art early-warning systems focus on predicting the magnitude, location and timing of climate hazards but may not provide a comprehensive evaluation of the expected physical damage, humanitarian consequences, service

sensing: A review', *Remote Sensing*, vol. 12, no. 24 (Dec. 2020).

[20] See the examples of international support for climate information capacity building in conflict-affected and fragile countries in United Nations, Climate Action, 'Early warning systems', [n.d.].

[21] SIPRI and NUPI, 'South Sudan', Climate, Peace and Security Fact Sheet, Mar. 2022.

[22] Han, H. et al., 'A combined drought monitoring index based on multi-sensor remote sensing data and machine learning', *Geocarto International*, vol. 36, no. 10 (2021); Feng, P. et al., 'Machine learning-based integration of remotely-sensed drought factors can improve the estimation of agricultural drought in south-eastern Australia', *Agricultural Systems*, vol. 173 (July 2019); Neeti, N. et al., 'Integrated meteorological drought monitoring framework using multi-sensor and multi-temporal earth observation datasets and machine learning algorithms: A case study of central India', *Journal of Hydrology*, vol. 601 (Oct. 2021); Prodhan, F. A. et al., 'A review of machine learning methods for drought hazard monitoring and forecasting: Current research trends, challenges, and future research directions', *Environmental Modelling & Software*, vol. 149 (Mar. 2022); and Dewitte, S. et al., 'Artificial intelligence revolutionises weather forecast, climate monitoring and decadal prediction', *Remote Sensing*, vol. 13, no. 16 (Aug. 2021).

[23] Crane-Droesch, A., 'Machine learning methods for crop yield prediction and climate change impact assessment in agriculture', *Environmental Research Letters*, vol. 13, no. 11 (Nov. 2018).

[24] Han et al. (note 22), p. 1162.

[25] Hosseini, F. S. et al., 'Flash-flood hazard assessment using ensembles and Bayesian-based machine learning models: Application of the simulated annealing feature selection method', *Science of the Total Environment*, vol. 711 (1 Apr. 2020); and Munawar, H. S. et al., 'UAVs in disaster management: Application of integrated aerial imagery and convolutional neural network for flood detection', *Sustainability*, vol. 13, no. 14 (July 2021).

disruptions and financial losses.[26] In order to produce a more comprehensive impact estimation, early-warning systems require the capacity to process large volumes of data from multiple sources and conduct integrative analyses. AI can significantly enhance such tasks.

Forecasting long-term climate trends and their impacts on livelihood systems

Climate change is generating long-term regionalized environmental trends, such as rising sea levels, changing temperatures and shifting rainfall patterns. These long-term trends affect the primary sector such as agriculture, fisheries and forestry. These nature-based livelihood systems serve as essential sources of income for populations living in many conflict-affected and fragile countries. Changing climate conditions can have substantial consequences for livelihood and food security of these populations. It has been estimated that a 1°C increase in global temperature would lead to a 3–7 per cent reduction in crop yields of soya beans, rice, wheat and corn worldwide.[27] The adverse impact of the decreased agricultural yield would disproportionately affect the most vulnerable populations in conflict-affected and fragile countries.

These long-term trends also affect the secondary and tertiary sectors that are dependent on climate conditions such as construction, oil and gas exploration, and tourism. For example, countries whose economies rely heavily on tourism can be negatively impacted by more frequent and intense heatwaves and tropical storms.

The projection of long-term regionalized trends in environmental changes linked to climate change is, in that context, crucial to the planning of long-term climate change-adaptation strategies. Long-term climate hazard forecasting involves integrating data from various sources, applying quantitative techniques and maintaining up-to-date monitoring efforts. For instance, agronomists can find drought-resilient seeds more efficiently by deploying AI-based simulations.[28] AI offers numerous opportunities in this regard.

As for monitoring and prediction of climate hazards, AI opens up new possibilities for collection of data on environmental changes (as noted above). Machine learning's data-processing capabilities are particularly well suited for developing comprehensive models for long-term and localized prediction. These models can integrate 'big data' from various sources, including historical climate records, land-use changes, ocean topography and parameters, and moisture content.[29] AI-powered models can assist local authorities, and development organizations can be better informed in their support for livelihood adaptation in climate change-exposed regions.[30]

By using precise and enhanced models, these entities can identify populations at risk of displacement or in needs of livelihood adjustments due to changing long-term climate conditions. More comprehensive climate change-vulnerability assessments can be done by employing machine learning-based models.[31] This knowledge can also

[26] Merz, B. et al., 'Impact forecasting to support emergency management of natural hazards', *Reviews of Geophysics*, vol. 58, no. 4 (Dec. 2020).

[27] Zhao, C. et al., 'Temperature increase reduces global yields of major crops in four independent estimates', *Proceedings of the National Academy of Sciences*, vol. 114, no. 35 (29 Aug. 2017).

[28] Etminan, A. et al., 'Determining the best drought tolerance indices using Artificial Neural Network (ANN): Insight into application of intelligent agriculture in agronomy and plant breeding', *Cereal Research Communications*, vol. 47, no. 1 (Mar. 2019).

[29] Merz et al. (note 26); and Mhanna, S. et al., 'Using machine learning and remote sensing to track land use/land cover changes due to armed conflict', *Science of the Total Environment*, vol. 898 (10 Nov. 2023).

[30] Talukdar, S., Pal, S. and Singha, P., 'Proposing artificial intelligence based livelihood vulnerability index in river islands', *Journal of Cleaner Production*, vol. 284 (15 Feb. 2021); and Jakariya, M. et al., 'Assessing climate-induced agricultural vulnerable coastal communities of Bangladesh using machine learning techniques', *Science of the Total Environment*, vol. 742 (Nov. 2020).

[31] Jakariya et al. (note 30).

inform urban planning, climate change-resilient agricultural practices and coastal management, thereby strengthening the resilience of societies to climate change. AI has already been used in crop and livestock farming to enhance resource efficiency and sustainability (known as precision agriculture) in the United States, China, the European Union (EU) and other advanced economies, but much less so in countries in the Global South.[32]

Managing vulnerabilities and exposure to climate change

Reducing the vulnerabilities and exposure to climate change is one of the key objectives of climate change adaptation. The risk of social tensions and conflict can be addressed if adaptation efforts are designed with considerations for inclusivity and justice.[33] AI-powered information systems and tools can assist governments, civil society and international actors with designing climate change-adaptation efforts to address context-specific and targeted climate-related security risks. Areas that might exacerbate climate-related security risks and where AI can support adaptation policies include climate change-related crises, climate change-induced migration, and infrastructure and urban space.

Enhancing management of climate change-related crises

Enhancing responses to climate disasters is a critical aspect of climate change adaptation. More frequent and intense climate change-induced disasters have adverse impacts on society and disproportionately affect marginalized populations.[34] Disaster-affected people who are dispossessed and displaced can be politically radicalized, and these individuals can be targeted for armed group recruitment in conflict-affected and fragile contexts.[35] Improving the responses to climate change-related crises is a key measure to reduce climate-related security risks. The application of AI technologies can greatly contribute to this endeavour, particularly in rapid mapping of affected regions, real-time dashboards, risk assessment, identifying populations in need and disaster communication.

A major challenge faced by humanitarian responders is the absence of accurate maps of disaster-stricken areas, including buildings and infrastructure. To address this, experts recommend using AI to convert satellite imagery into maps of informal settlements, significantly expediting the mapping process.[36] Completing such tasks manually can take several days, hindering the ability of humanitarian responders to reach affected populations swiftly. Machine learning techniques can expedite the mapping process dramatically, enabling humanitarian organizations to promptly initiate rescue and relief operations.[37] In disaster-prone areas, community-based organizations can

[32] Galaz, V. et al., 'Artificial intelligence, systemic risks, and sustainability', *Technology in Society*, vol. 67 (Nov. 2021); and Stock, R. and Gardezi, M., 'Arrays and algorithms: Emerging regimes of dispossession at the frontiers of agrarian technological governance', *Earth System Governance*, vol. 12 (Apr. 2022).

[33] Leonardsson, H. et al., 'Achieving peaceful climate change adaptation through transformative governance', *World Development*, vol. 147 (Nov. 2021).

[34] Lindersson, S. et al., 'The wider the gap between rich and poor the higher the flood mortality', *Nature Sustainability*, vol. 6, no. 4 (Aug. 2023).

[35] Cárdenas, J., Downing, C. and Vélez, J., *Climate-driven Recruitment and Other Conflict Dynamics in Colombia*, Managing Exits from Armed Conflict (MEAC) Findings Report no. 8 (UN University: Tokyo, Oct. 2021).

[36] O'Malley, J., 'Urban planning to disaster relief: How AI-generated maps are helping to improve lives', *The Guardian*, 14 June 2023.

[37] See Humanitarian OpenStreetMap Team.

use these AI-generated maps to improve disaster preparedness of neighbourhoods and communities.[38]

AI can be employed for near real-time crisis monitoring. For instance, AI-powered dashboards can be used for crisis management in urban community settings where the impacts of flooding on property and infrastructure are typically intense.[39] Relief workers can quickly navigate, find resources and reach people in need. On the prevention side, governments and communities in flood-prone regions can use these AI-powered tools to reduce the risk and harm from floods and better protect vulnerable populations and their property and livelihoods.[40]

Aerial imagery by UAVs can be used for disaster monitoring. This is particularly effective in identifying damage to local infrastructure during floods.[41] AI provides the ability to deploy UAVs with enhanced autonomous navigation capabilities, which may rely for instance on vision-based guidance rather than GPS coordinates. This can be helpful in environments where the communications infrastructure is limited and when non-intrusive monitoring is required. AI could also enable the use of autonomous robots and UAVs for humanitarian aid delivery during climate disasters.[42]

AI also holds great potential for supporting decision making during disaster responses by providing real-time information. The availability of analytics and timely updates aids government decision-making processes in times of disaster, thereby enhancing the government's capacity to respond effectively. Collaboration between international organizations, such as the UN, and national governments in the Global South has led to the development of integrated information platforms for disaster monitoring and management, incorporating AI components.[43] In terms of resource allocation during crises, the World Food Programme (WFP)—the largest food relief provider—has started implementing AI-assisted tools for needs assessment to accurately calculate relief packages.[44] The private sector also has cooperated with humanitarian responders in developing a real-time visualization platform using AI, natural language processing and an application programming interface (API) to process data from various sources, including social media networks.[45] Such a platform enables humanitarian organizations to benefit from visualized real-time information regarding the severity of disasters, hospital locations and weather reports during events such as a hurricane.[46]

AI can play a crucial role in processing big data during disasters, enabling the detection of affected areas, identifying populations in need and assessing the scale of the disaster. It can also provide timely and accurate information regarding population

[38] The Humanitarian OpenStreetMap Team (note 37) works with communities in disaster-prone regions and relies on volunteers to map their own neighbourhoods and local communities. Fathi, R. et al., 'VOST: A case study in voluntary digital participation for collaborative emergency management', *Information Processing & Management*, vol. 57, no. 4 (July 2020).

[39] Zahura, F. T. et al., 'Training machine learning surrogate models from a high-fidelity physics-based model: Application for real-time street-scale flood prediction in an urban coastal community', *Water Resources Research*, vol. 56, no. 10 (Oct. 2020).

[40] Zahura et al. (note 39).

[41] Munawar et al. (note 25).

[42] Azmat, M. and Kummer, S., 'Potential applications of unmanned ground and aerial vehicles to mitigate challenges of transport and logistics-related critical success factors in the humanitarian supply chain', *Asian Journal of Sustainability and Social Responsibility*, vol. 5 (2020).

[43] Hidalgo-Sanchis, P., 'UN Global Pulse: A UN innovation initiative with a multiplier effect', eds M. Lapucci and C. Cattuto, *Data Science for Social Good: Philanthropy and Social Impact in a Complex World* (Springer: Cham, 2021), pp. 34–35.

[44] Omdena, 'AI for disaster response: World Food Programme project', 17 May 2020.

[45] Kuglitsch, M. M. et al., 'Facilitating adoption of AI in natural disaster management through collaboration', *Nature Communications*, vol. 13, article no. 1579 (24 Mar. 2022).

[46] Kuglitsch et al. (note 45).

movements following a natural disaster.[47] While social media platforms can serve as a valuable complementary source during disasters, providing eyewitness reports and other relevant information, the sheer volume of social media data makes it hard for disaster responders to collect and analyse it without the assistance of automated data processing.[48] Employing machine learning techniques makes it possible to overlay satellite images with data from X (formerly Twitter), allowing for their use to be combined, particularly during floods.[49] Additionally, there are specific applications such as Artificial Intelligence for Digital Response (AIDR), open-source software that collects and categorizes tweets posted during humanitarian crises.[50] Large language models have been used in disaster management. For instance, an AI chatbot developed by the UN Educational, Scientific and Cultural Organization (UNESCO) aims to enhance preparedness for and response to climate change-induced disasters in Uganda.[51]

The existing applications of AI demonstrate a wide range of potential benefits in reducing vulnerabilities among disaster-affected populations in various contexts.

Managing climate change-induced migration and changes in mobility patterns

Climate change is likely to influence people's decisions on migration and to change mobility patterns.[52] While the exact role of climate change in moving people out from impoverished and conflict-affected regions is disputed, climate hazards have undoubtedly worsened people's livelihoods and food security, especially in the absence of alternative livelihoods and sources of food.[53] AI-powered tools can aid understanding of climate change-induced migration and changing mobility patterns. Two opportunities are identified here: managing transhumance conflict; and better understanding the complex drivers of climate change-induced migration.

Managing transhumance migration is a crucial area that can help reduce climate change-related conflict risks, and AI-assisted tools can complement existing initiatives. Another aspect of climate change-related mobility linked to conflict is the effect of climate change on communities whose migratory paths have been affected by changing water availability and vegetation.[54] This leads to increasing tensions between different livelihood groups over land and water access. Declining availability of grassland and water has a direct impact on these groups' livelihoods, as livestock rearing is integral to their identity and culture. Changes in grazing land and water access have altered the migratory paths of these communities, leading to an increased risk of clashes with farming communities. Early warning of droughts and of anticipating migration can help

[47] Lu, X. et al., 'Unveiling hidden migration and mobility patterns in climate stressed regions: A longitudinal study of six million anonymous mobile phone users in Bangladesh', *Global Environmental Change*, vol. 38 (May 2016).

[48] Smith, L. et al., 'Assessing the utility of social media as a data source for flood risk management using a real-time modelling framework', *Journal of Flood Risk Management*, vol. 10, no. 3 (Sep. 2017); Kaufhold, M.-A., Bayer, M. and Reuter, C., 'Rapid relevance classification of social media posts in disasters and emergencies: A system and evaluation featuring active, incremental and online learning', *Information Processing & Management*, vol. 57, no. 1 (Jan. 2020); and Zahra, K., Imran, M. and Ostermann, F. O., 'Automatic identification of eyewitness messages on twitter during disasters', *Information Processing & Management*, vol. 57, no. 1 (Jan. 2020).

[49] Sadiq, R. et al., 'Integrating remote sensing and social sensing for flood mapping', *Remote Sensing Applications: Society and Environment*, vol. 25 (Jan. 2022).

[50] Artificial Intelligence for Digital Response (AIDR), 'AIDR overview', 23 Oct. 2016.

[51] UN Educational, Scientific and Cultural Organization (UNESCO), 'AI chatbot training for managing disasters in Uganda', 20 Apr. 2023.

[52] Lu et al. (note 47).

[53] Cottier, F. and Salehyan, I., 'Climate variability and irregular migration to the European Union', *Global Environmental Change*, vol. 69 (July 2021). See also the SIPRI and NUPI Climate, Peace and Security Fact Sheet series (note 2).

[54] Muricho, D. N. et al., 'Building pastoralists' resilience to shocks for sustainable disaster risk mitigation: Lessons from West Pokot County, Kenya', *International Journal of Disaster Risk Reduction*, vol. 34 (Mar. 2019).

regional organizations and conflict-mediation actors as they set up conflict-prevention measures and strategies to prevent clashes between communities.[55]

Information and mapping tools are crucial to reducing conflict risk, and AI-powered sensors and analytics can complement existing tools. The International Organization for Migration (IOM) operates the Transhumance Tracking Tool, which involves collecting data to identify transhumance movement and to assess the risk of inter-communal conflict.[56] Enumerators and key informants conduct interviews to gather information on access to grazing land, water points and markets along migratory paths.[57] AI-assisted remote sensing data can complement these efforts, particularly in areas where accessing data becomes difficult or dangerous due to security risks. For instance, the US Geological Survey provides estimated data on water and grassland availability.[58] High-resolution and high-frequency satellite images can be used to build a real-time tracking platform for livestock and herder movement.[59] The data generated from satellite imagery can inform discussion between pastoralist and farming communities, allowing them to engage in collective management practices for shared resources.[60]

Enhancing understanding of the drivers of migration would provide a crucial input for efforts to reduce conflict related to climate change-induced migration. Migration is a complex phenomenon, and understanding and predicting climate change-related migration patterns can be hard. AI can play a significant role in identifying, assessing and even predicting such migration. The increasing availability of digitally traceable data, including mobile phones and social media, provides new opportunities for migration research. Machine learning models can process large volumes of data and identify migration and mobility patterns in climate change-exposed areas.[61] To understand the linkages between water scarcity and migration at regional or global scales, factors such as water availability, income, education, ethnicity, gender, household size and other demographic information need to be evaluated. Developing a model that can process vast amounts of data can help reveal these relationships.

Recent research by the World Bank serves as an example of the use of AI in migration research. The project used machine learning to analyse data from over 442 million individuals from 189 different population censuses in 64 countries between 1960 and 2015.[62] The AI-powered model can classify variables, evaluate their importance in various migration scenarios and generate forecasting models for future migration projections.[63] Fully understanding such complexity is nearly impossible without the

[55] Kasaija, P. A., 'The Intergovernmental Authority on Development's Conflict Early Warning and Response Mechanism: Can it go beyond pastoral conflicts?', *African Security Review*, vol. 22, no. 2 (June 2013).

[56] Jusselme, D., 'Transhumance Tracking Tool—A regional perspective of mobility in West Africa', eds P. Fargues et al., *Migration in West and North Africa and across the Mediterranean: Trends, Risks, Development and Governance* (International Organization for Migration: Geneva, 2020).

[57] International Organization for Migration (IOM) Displacement Tracking Matrix, 'Mapping of herders stranded along the central transhumance corridor', Transhumance Tracking Tool Dashboard no. 1, Feb. 2021.

[58] US Geological Survey (USGS), 'RFE Waterpoint', USGS FEWS NET Data Portal.

[59] Schwarz, M. et al., 'Assessing the environmental suitability for transhumance in support of conflict prevention in the Sahel', *Remote Sensing*, vol. 14, no. 5 (Mar. 2022); Oyekan, A. O., 'Technology and social cohesion: Deploying artificial intelligence in mediating herder–farmer conflicts in Nigeria', *Filosofia Theoretica: Journal of African Philosophy, Culture and Religions*, vol. 9, no. 3 (Sep./Dec. 2020); and Collignon, B., 'A new tool for the remote sensing of groundwater tables: Satellite images of pastoral wells', *Open Geospatial Data, Software and Standards*, vol. 5, no. 4 (30 Sep. 2020).

[60] Ostrom, E., *Governing the Commons: The Evolution of Institutions for Collective Action* (Cambridge University Press: Cambridge, 1990); and Ntumva, M. E., 'Farmer–pastoralist conflicts management approaches in Sub-Saharan Africa: Insights into their strengths and pitfalls', *Journal of African Studies and Development*, vol. 14, no. 1 (Jan. 2022).

[61] Chi, G. et al., 'A general approach to detecting migration events in digital trace data', *PLOS One*, vol. 15, no. 10 (Oct. 2020).

[62] Zaveri, E. et al., *Ebb and Flow*, vol. 1, *Water, Migration, and Development* (World Bank: Washington, DC, 2021).

[63] Zaveri et al. (note 62).

application of machine learning techniques. The use of AI in this way can inform climate change adaptation measures that aim to reduce the risk of displacement and to improve urban space and infrastructure amid rapid urbanization.

Strengthening infrastructure and improving urban space

Climate change-induced migration can contribute to the increasing pressure in urban and peri-urban areas in the Global South that are struggling to accommodate sprawling informal settlements and inadequate public infrastructure.[64] Climate change is also likely to adversely affect infrastructure and cities, particularly through rising sea levels that pose serious threats to densely populated coastal cities: about 40 per cent of the world's population lives within 100 kilometres of the coast.[65] Enhancing the climate resilience of infrastructure and urban areas is thus vital for effective climate change adaptation. AI can be used to strengthen urban infrastructure and for better urban planning mostly through enhanced information tools for planning and risk assessment.

Improving urban spaces is not just relevant to conflict-affected and fragile countries; it is crucial for enhancing living standards and livelihood conditions in urban settings to mitigate the risk of social unrest and intercommunal conflicts. There are several ways that advanced modelling and real-time information can contribute to better urban space.[66] Social media data, for example, can serve as a valuable resource for urban planners.[67] Machine learning and geolocation techniques have been used to generate traffic crash reports in urban settings from social media data, which can be used to enhance urban planning for traffic safety in data-scarce countries in the Global South.[68] Analysing big data derived from open-source social media can provide insights into public perceptions of large-scale urban projects.[69]

It remains unclear how relevant authorities will effectively use the 'new' information provided by AI in urban planning. Countries with limited capacity and resources for monitoring and data collection can particularly benefit from this information. It can be especially useful in post-conflict settings where urban areas face increasing pressure from environmental scarcities and insecurity from inadequate infrastructure. (Issues related to human agency in response to AI-generated information and in developing AI systems are further discussed in chapter 4.)

Another area of potential AI deployment is in improved climate risk assessment for both existing and new infrastructure. By considering geographical factors and climate variables, AI models can identify areas most susceptible to climate impacts such as flooding or landslides. This valuable information can guide decision makers in prioritizing adaptation measures and effectively allocating resources for better disaster preparedness and recovery. Infrastructure management can be done more effectively with near real-time monitoring by AI-powered sensors and models. Machine learning has been used for decision-support tools for water management for cities by providing

[64] World Bank, 'Climate change could force 216 million people to migrate within their own countries by 2050', Press release, 13 Sep. 2021; and Adger, W. N. et al., 'Human security of urban migrant populations affected by length of residence and environmental hazards', *Journal of Peace Research*, vol. 58, no. 1 (Jan. 2021).

[65] UN Framework Convention on Climate Change (UNFCCC), Subsidiary Body for Scientific and Technological Advice, 'Initiatives in the area of human settlements and adaptation', Summary report by the secretariat, FCCC/SBSTA/2017/INF.3, 25 Apr. 2017.

[66] Chaturvedi, V., Kuffer, M. and Kohli, D., 'Analysing urban development patterns in a conflict zone: A case study of Kabul', *Remote Sensing*, vol. 12, no. 21 (Nov. 2020).

[67] Milusheva, S. et al., 'Applying machine learning and geolocation techniques to social media data (Twitter) to develop a resource for urban planning', *PLOS One*, vol. 16, no. 2 (Feb. 2021); and Batty, M., 'Big data, smart cities and city planning', *Dialogues in Human Geography*, vol. 3, no. 3 (Nov. 2013).

[68] Milusheva et al. (note 67).

[69] Gabdrakhmanova, N. and Pilgun, M., 'Intelligent control systems in urban planning conflicts: Social media users' perception', *Applied Sciences*, vol. 11, no. 14 (July. 2021).

near real-time updates on leakage, flows and storm water management.[70] As the example of 'smart' water-management systems demonstrates, AI systems can help with infrastructure management for enhancing climate resilience in various contexts.

Detecting climate change-related grievances and tensions

Climate change and variability can affect vulnerable and marginalized groups and deepen existing grievances, which can lead to heightened tensions between communities and social groups.[71] Individual grievances can be triggered by the effects of climate shocks on livelihoods as well as inadequate service provision during extreme weather events. When people collectively perceive water and food insecurity in their daily lives, it can be a major source of grievance, which can spark collective resistance and other action.[72] Researchers can use AI to enhance knowledge on the social psychological impacts of climate change that can lead to increased tensions and risks of conflict. Detecting social grievances that stem from the adverse impact of climate change can be achieved by big data analysis, which AI can enhance substantially.

Better understanding of grievances can inform socially inclusive and conflict-sensitive climate change adaptation policies. Understanding social grievances and tensions would help policy actors develop interventions to mitigate conflict risks, but researching social grievances related to adverse climate impacts can be difficult without reliable and sufficient data at the individual level. Social media can be a particularly useful source of such data. Extreme weather events, for instance, can trigger a trend in social media that in that given context can be understood as expression of grievances. In the future, AI may be able to track different related keywords in social media in real time, which can be a basis for a real-time monitoring system that can detect new trends and sense public opinion.

Such context-specific dissent is difficult to capture without intimate knowledge of local contexts. If machine learning develops further, with advanced capacities to capture slight nuances in different languages, these models may spot subtle expressions of grievance that are not obvious.[73] However, how representative social media data is should always be questioned since access to social media platforms varies depending on levels of digital literacy, internet access and government restrictions (see the discussion in chapter 4).

Large language models can also facilitate stakeholder consultations that can feed into need assessments for climate change adaptation. Conducting public consultations is generally costly and risky in conflict-affected and fragile countries, but using AI can reduce the financial costs and security risks. Large language models and natural language processing applications can assist consultation by enabling simultaneous interaction with many participants during a single session. For instance, the UN country teams in Libya and Yemen conducted rounds of public consultation assisted by AI that enabled consultation with 1000 participants from multiple locations in a single session.[74] While, as noted above, how representative a stakeholder consultation is

[70] Krishnan, S. R. et al., 'Smart water resource management using artificial intelligence—A review', *Sustainability*, vol. 14, no. 20 (Oct. 2022).

[71] Döring, S. and Hall, J., 'Drought exposure decreases altruism with salient group identities as key moderator', *Nature Climate Change*, vol. 13, no. 8 (Aug. 2023).

[72] Koren, O., Bagozzi, B. E. and Benson, T. S., 'Food and water insecurity as causes of social unrest: Evidence from geolocated Twitter data', *Journal of Peace Research*, vol. 58, no. 1 (Jan. 2021).

[73] Koren et al. (note 72).

[74] Brown, D., 'The United Nations is turning to artificial intelligence in search for peace in war zones', *Washington Post*, 23 Apr. 2021.

should be critically questioned, the input from AI-facilitated consultations can serve as part of a diverse set of sources of information.

Tensions between communities and social groups over water and land resources and unemployment and low wages in urban areas that are affected by climate change-induced migration and disrupted trade patterns are likely to intensify due to climate change and increased climate variability. Using a combination of social media data and satellite images, AI-powered systems can enhance the monitoring of intercommunal tensions that stem from climate shocks. Detecting communal tensions over natural resources can lead to timely deployment of resources, contributing to dispute resolution and conflict de-escalation.

AI seems to be particularly promising in the field of early-warning systems and models that provide accurate and timely insights on the impact of climate hazards and potential adaptation measures. Such insights also allow governments and authorities to prepare proactive measures to mitigate risks and protect vulnerable communities. Moreover, AI technologies can assist in crisis management, migration-related issues, and enhancing infrastructure and urban spaces, which can inform targeted interventions. Social grievances and tensions stemming from adverse climate impacts can be detected in a timely manner and managed if AI can be deployed to catch the early signs. The ongoing development and application of AI in this domain offers various possibilities for future development. Materializing these opportunities requires cooperation among a diverse set of actors, from the private and public sectors and civil society, including members of the affected communities.

3. Examples of AI for climate security

This chapter reviews some current climate security interventions that integrate the methods outlined in chapter 2. The case study interventions are primarily led by external actors such as international humanitarian actors and UN agencies. These examples demonstrate specific entry points for the use of artificial intelligence for climate security. Assessing existing policy initiatives and programmes allows identification of areas where AI technologies can be effectively integrated.

Climate hazards and socio-economic stressor mapping tools

For evidence-based policymaking and intervention design, policymakers should be able to access and use information about hazards, climate change exposure and vulnerability via accessible tools. However, many organizations lack the required training and technical capacity to use advanced tools. It would therefore be desirable to make dashboards and mapping tools user-friendly and accessible. Several online mapping tools have been developed for this purpose. For instance, the World Bank's Climate Change Knowledge Portal offers visualized climate data and historical and future climate trends at national and subnational scales.[75] The UN Environment Programme (UNEP) has developed a mapping tool, the World Environment Situation Room, which offers 'near real-time analysis and future predictions' of environmental and climate hazards.[76] The tool sets include a range of environmental risks, including mangrove deforestation, air quality, floods and tropical storms.[77] AI technologies are used in curating, aggregating and visualizing the most suitable earth-observation data for the mapping platform.[78] These environment and climate analytic tools can be further developed into mapping tools that can incorporate socio-economic and conflict-related variables. Existing mapping tools include the Aqueduct Water Risk Atlas, Anomaly Hot Spots of Agricultural Production and the Global Drought Observatory.[79]

UNEP's Strata platform is envisioned as a decision-support tool that can be used to visualize conflict and insecurity hotspots in climate change-exposed regions (see table 3.1 for a summary). Strata is based on the 'convergence of evidence' approach, which identifies geographical locations of concern from relevant indicators and predetermined thresholds.[80] The Strata dashboard offers a hotspot map based on a combination of environmental, climate and security stressor scores. Environmental and climate stressors include meteorological and agricultural droughts, heatwaves, floods, coastal inundations, deforestation and land degradation. When data is not available, modelled probabilities of hazards are used.[81] Data availability is often a problem in conflict-affected countries (see chapter 4). AI can be used to model hazard probabilities or process earth-observation data to fill the data gap. With the inclusion of AI technology, Strata can support near real-time analysis of climate-related security risks.

[75] See the World Bank's Climate Change Knowledge Portal.

[76] UN Environment Programme (UNEP), 'How artificial intelligence is helping tackle environmental challenges', 2 Nov. 2022.

[77] UN Environment Programme (UNEP), World Environment Situation Room, 'Global environment monitoring', [n.d.].

[78] UN Environment Programme (note 76).

[79] Aqueduct Water Risk Atlas; Anomaly Hot Spots of Agricultural Production (ASAP); and Global Drought Observatory.

[80] Young, H. R. et al., 'Strata: Mapping climate, environmental and security vulnerability hotspots', *Political Geography*, vol. 100 (Jan. 2023), p. 5.

[81] Young et al. (note 80).

Table 3.1. Examples of policy interventions addressing climate-related security risks

Intervention	Type	Input data	Outputs	Methods
UNEP Strata	Climate hazards and socio-economic stressor mapping tools	Climate, violence and conflict events, demographic and socio-economic data	Hotspot maps of climate-related security risks	Convergence of evidence approach
WFP World Hunger Map	Climate change-related disaster risk management	Rainfall, price projections, household income sources, household food sources, market trends	Monitoring and forecasting food (in)security	Quantitative, qualitative, integrative approach with expert inputs
Water, Peace and Security partnership	Conflict early-warning systems	Water, community violence and conflict events, socio-economic data, food	Monthly and annual forecast of conflict	Random forest and long-short term memory neural network

UNEP = United Nations Environment Programme; WFP = World Food Programme.

UNEP and partner organizations have developed Strata with strong emphasis on co-production, to make the platform easy to use and customizable for users' needs.[82] This co-production method is intended to reduce the barriers to accessing data and information when users lack technical capacities. Compared to other mapping tools, Strata allows each user to choose relevant stressors to generate a hotspot map that is relevant for their needs. This customizability is a unique selling point of Strata for its potential users, who may use the dashboard for their day-to-day risk analyses. The first phase of Strata focused on developing relevant indicators and generating hotspot maps for Somalia. Several other initiatives focus on Somalia and the Horn of Africa for climate change-related human insecurity. The Food Security and Nutrition Analysis Unit in Somalia of the UN Food and Agriculture Organization (FAO) has developed mapping tools for acute food insecurity and situation maps.[83] The Climate Prediction and Application Centre of the Intergovernmental Authority on Development (IGAD) operates the East Africa Hazards Watch, which focuses on the mapping of climate change-related emergencies in East Africa.[84] These mapping tools can complement different aspects of climate-related security risk assessment that can be used for crisis prevention and provision of humanitarian relief.

However, there are risks associated with the use of these sophisticated dashboards (see chapter 4) and the insights generated from mapping tools may go under-used by policy actors. The questions are how information on climate insecurity can be used by users at different levels, how it can reach policymakers, and how policy interventions can be enhanced by more accurate and up-to-date information. Discussing the potential use of information for policy intervention is highly important. Such outreach activities can be accompanied by communication and training activities that target end users

[82] Young et al. (note 80).

[83] Food and Agriculture Organization of the UN (FAO), Food Security and Nutrition Analysis Unit Somalia, 'Early Warning Early Action Dashboard'.

[84] Intergovernmental Authority on Development (IGAD) Climate Prediction & Applications Centre (ICPAC), 'East Africa Hazards Watch'.

such as national and local governments and civil society actors in conflict-affected and fragile countries that are exposed to climate hazards.

Risk management of climate change-related disasters

Climate change-related disaster risk management has been a major measure of climate change adaptation, including a range of interventions focusing on anticipatory action. Early-warning systems for climate change-induced disasters are particularly important for reducing humanitarian impacts of climate change in conflict-affected countries (as discussed in chapter 2). Extreme weather events such as droughts and flooding can lead to mass displacement. This exposes the displaced population to a greater risk of armed group recruitment; such recruitment can, in turn, alter existing conflict dynamics. Reducing the harm from climate change-induced disasters can thus be an effective measure for curtailing recruitment by armed groups and preventing violent extremism. Timely responses to climate change-induced disasters and anticipatory actions are the best preventative measures to avoid escalating conflict risks and complicating existing conflict dynamics.

It is hard to predict severe food insecurity because multiple factors contribute to the risk, including weather shocks and changing climate conditions, conflict-related violence, and displacement. Early-warning systems for food insecurity require comprehensive and integrated approaches with serious consideration of climate hazards and the environmental conditions affected by climate change. Predictive analysis is one of the tasks for which AI is best suited. Its ability to analyse big data is useful for unpacking complexity around food insecurity.

The WFP's World Hunger Map is a mapping tool that provides near real-time monitoring of food insecurity in 94 countries (see table 3.1 for a summary). The platform uses machine learning-based predictive models to estimate the food security situation in areas with insufficient data. Predictive models feed into risk management by providing inputs for resource allocation for humanitarian organizations such as the WFP. These international humanitarian relief agencies operate globally and require a global overview of humanitarian crises. Forecasting models can assist these humanitarian actors to manage risks in a more comprehensive manner. The World Hunger Map also offers near real-time visualized overviews of multiple drivers of food insecurity such as climate hazards, conflict, vegetation coverage and rainfall. Having a comprehensive overview and up-to-date information can help the WFP to optimize its limited resources.

The Famine Early Warning Systems Network (FEWS NET) is another primary example of an early-warning system for climate change-induced disasters, but one that relies solely on traditional methods that are not machine learning based. With support from a network of global research institutions and local organizations, FEWS NET provides regional- and national-level warnings and analysis on food insecurity and offers monthly situation updates and scenario-based analyses informed by agroclimatic, livelihood, market and nutrition data.[85] Monthly reports include the population in need of urgent food assistance during the forthcoming 6 months and an analysis of new trends in food prices in relation to climate and market conditions. Currently, FEWS NET's focal regions include countries that are experiencing civil war, communal conflict involving pastoralists and high levels of political instability. These include the Sahel region including Somalia and Ethiopia; key pastoralist corridors in northern Uganda and Kenya and in Mali and Niger; and El Salvador, Guatemala, Haiti, Honduras, and

[85] Famine Early Warning Systems Network (FEWS NET), 'About FEWS NET', [n.d.].

Nicaragua in Central America and the Caribbean. FEWS NET also focuses on Yemen and Afghanistan.

Traditional methods have the advantage over machine learning-generated predictive models in that they are more explainable and are easier to translate into policy action. Food security is highly contextual, and machine learning models may struggle to capture the intricacies and nuances of these contextual elements. Oversimplification of such complex systems may lead to oversights or inaccurate predictions. AI can be used to further optimize resources, but AI may not be explainable. These trade-offs in the use of AI need to be carefully considered in designing early-warning systems for climate change-related disasters.

Conflict early-warning systems with a focus on climate-related security risks

In recent years several conflict early-warning systems (CEWS) have been developed by researchers and policy actors.[86] This is a growing field in the application of AI. Machine learning allows the user to build predictive models from historic data, which can be useful for generating future-oriented insights on climate–conflict linkages. CEWS focus on forecasting different types of political violence and assessing future risks of political fragility and conflict. CEWS forecasts rely on advanced quantitative methods, including machine learning techniques. Advances in AI technologies have been influential in the fast-developing field of CEWS. This section discusses how each CEWS models climate-related security risks. These models include different climate indicators that capture climate change-related disasters, climate variability, freshwater availability and macro-climate trends such as El Niño.[87]

National governments and international organizations are increasingly cooperating with CEWS programmes developed by academic institutions or are developing their own CEWS. The UN High Commissioner for Refugees (UNHCR) works closely with the Violence Early-Warning System (ViEWS) developed by Uppsala University and Peace Research Institute Oslo (PRIO). This is one of the leading CEWS, with a focus on the Sahel region.[88] Other CEWS developed by academic institutions include Patterns of Conflict Emergence (PaCE) at Trinity College Dublin, the Conflict Forecast project of the Barcelona School of Economics, and the Political Instability Task Force (PITF).[89] For governments and international organizations, insights produced by CEWS can be used for enhancing institutional understanding of conflict risks and the capacities for conflict prevention and response. The EU's Disaster Risk Management Knowledge Centre produces the in-house Global Conflict Risk Index (GCRI), which forecasts the risk of violent conflict in a country 1–4 years into the future. The German Federal Foreign Office operates the Preview project to provide decision support to German government officials. It identifies countries and regions at risk of political fragility and violent conflict.[90]

Some CEWS have incorporated environmental and climate change-related factors as inputs for forecasting. The Water, Peace and Security (WPS) partnership, for instance, has its primary focus on addressing water-related conflict risk by generating conflict forecasts (see table 3.1 for a summary). It offers a dashboard as a global tool that predicts conflict events based on a range of variables related to water, community,

[86] Rød, E. G., Gåsste, T. and Hegre, H., 'A review and comparison of conflict early warning systems', *International Journal of Forecasting*, vol. 40, no. 1 (Jan.–Mar. 2024).

[87] Rød et al. (note 86).

[88] Hegre, H. et al., 'ViEWS2020: Revising and evaluating the ViEWS political Violence Early-Warning System', *Journal of Peace Research*, vol. 58, no. 3 (May 2021).

[89] Rød et al. (note 86).

[90] Rød et al. (note 86).

conflict, economy, food and governance.[91] Compared to other CEWS, the WPS model incorporates an extensive list of water-related variables, including precipitation, evapotranspiration, water stress, flood risks, and seasonal and interannual water variability.[92]

WPS is transparent in terms of its methodology and data sources, but the data set and codes are not available to the public. WPS uses a machine learning technique for its predictive modelling. Its authors acknowledge that the aggregate model remains 'somewhat opaque', but the method is 'more apprehensible to a general audience than many alternatives'.[93] As addressed in chapter 4, transparency, accessibility and legibility are important for the credibility of forecasts and the usefulness to potential users.[94] CEWS would be more relevant as a decision-support tool if the forecast outputs could be explained by unpacking the complex interplay between relevant actors and the multiple factors at play.

It is not yet clear to what extent decision makers use AI-driven insights such as forecast reports produced by CEWS. In international policy forums, the narrative clearly advocates for better information and foresights for responding to climate-related security risks.[95] The WPS partnership, for instance, has close links to policymakers, but there are limited testimonies and impact reports on how analytic insights produced by WPS have fed into a decision-making process. It is unclear whether this gap between information and policy action is linked to the inherent complexity of decision-making processes or to the distrust in AI technology in decision-support tools. More transparency and accessibility would help policymakers make better use of future-oriented insights from CEWS. One way to narrow the information-to-policy gap is to enhance communication about the real-world implications of forecast reports. Such communication efforts can encourage policy–research conversations about potential interventions informed by foresights.

[91] Kuzma, S. et al., 'Leveraging water data in machine learning-based model for forecasting violent conflict', Technical note, World Resources Institute, Feb. 2020.

[92] Kuzma et al. (note 91).

[93] Kuzma et al. (note 91), p. 4.

[94] Rød et al. (note 86).

[95] E.g. the need for foresight capacities was one of the main themes of the international ministerial conference 'Sustaining Peace Amidst the Climate Crisis: The Role of Data Science, Technology & Innovation', Berlin, 2–3 May 2022, organized by the Preview department of the German Federal Foreign Office.

4. The challenges associated with AI

While artificial intelligence offers immense potential for enhancing responses to climate-related security risks, realizing its potential is not without its challenges. The development and use of AI systems based on machine learning is typically associated with design challenges and social and ethical problems that deserve careful review. After discussing these problems, this chapter discusses how they could affect the utility of AI for climate security.

Design challenges

The promise of AI is grounded in the ability of machine learning to make sense of big data. With that ability comes important shortcomings: potential biases, dependence on data availability and opacity.[96]

Biases

Machine learning systems are trained with past data, which forms the basis of AI's assumptions. The quality and diversity of the data on which AI systems are trained determine their performance—especially for such tasks as pattern recognition or prediction.[97] If the training data is not representative of the reality with which the system is supposed to interact, then the system may not only fail at the task (e.g. recognizing an object or predicting an event), but may also perpetuate or create new social biases.[98] For example, machine learning systems used for facial recognition and risk assessment in criminal justice have been reported to be positively biased towards certain social groups and negatively biased against others.[99] Gender bias is another concern in AI development.[100] This shortcoming—designated in the machine community as 'data bias'—has concrete implications for the design of AI systems for climate security.[101]

First, the reliability of machine learning-based prediction must be assessed with caution. Machine learning systems are in practice statistical mirrors that reflect data of the past. If the training data set is large and representative, then the prediction may be robust. In contrast, if the data set fails to reflect variations over time, is inconsistent or is too specific to a particular geographical context, then the predictive value of a machine learning system may be limited.

The second implication is that the data bias problem demands rigorous curation of the training data. Outdated or unrepresentative data can make an AI system deliver outcomes that are not only inaccurate but also potentially discriminatory.[102] In the context of climate security, data biases could lead to misguided climate resilience

[96] Soden, R., Wagenaar, D. and Tijssen, A., *Responsible AI for Disaster Risk Management*, Working Group Summary (Global Facility for Disaster Reduction and Recovery: 2021).

[97] Gershgorn, D., 'The data that transformed AI research—and possibly the world', Quartz, 26 July 2017.

[98] Hao, K., 'This is how AI bias really happens—and why it's so hard to fix', *MIT Technology Review*, 4 Feb. 2019; and Christian, B., *The Alignment Problem: Machine Learning and Human Values* (Norton & Co.: New York, 2021), pp. 17–51.

[99] Birhane, A., 'Algorithmic injustice: A relational ethics approach', *Patterns*, vol. 2, no. 2 (Feb. 2021); and Simonite, T., 'When it comes to gorillas, Google Photos remains blind', Wired, 11 Jan. 2018.

[100] Sutko, D. M., 'Theorizing femininity in artificial intelligence: A framework for undoing technology's gender troubles', *Cultural Studies*, vol. 34, no. 4 (2020); and Costa, P. and Ribas, L., 'AI becomes her: Discussing gender and artificial intelligence', *Technoetic Arts*, vol. 17, nos 1–2 (June 2019).

[101] Friedman, T. and Nissembaum, H., 'Bias in computer systems', *ACM Transaction in Information Systems*, vol. 14. no. 3 (July 1996).

[102] Benjamin, R., *Race after Technology: Abolitionist Tools for the New Jim Code* (Polity: Medford, MA, 2019); and Buolamwini, J. and Gebru, T., 'Gender shades: Intersectional accuracy disparities in commercial gender classification', *Proceedings of Machine Learning Research*, vol. 81 (2018).

efforts and even climate maladaptation.[103] To address these biases, several mitigation strategies can be considered. These strategies include acquiring more appropriate data, pre-processing the data by adjusting selection criteria for groups that are presumed to be marginalized or under-represented, increasing the model's complexity to account for differences between groups, and taking special measures to redress historical biases.[104] Each mitigation strategy carries its own risks that need careful handling.[105]

Data availability

The representativeness of the training data set is critical to ensuring the reliability—and hence the value—of an AI system. The problem is that representativeness is dependent on data availability. When it comes to data relevant to climate-related security risks, it can be hard to find accurate and representative data sets. This is true for risk-associated physical phenomena such as climate hazards and climate vulnerabilities, but also—and more acutely—for climate change-related risks in the social domains such as climate change-related grievances.

Collecting precise climate data remains difficult. Many countries lack a proper network of ground meteorological and hydrological stations.[106] In fact, the situation is worsening: the number of functioning weather stations is declining in countries in the Global South due to limited financial resources.[107] The challenge is even more severe in conflict-affected and fragile countries, which face difficulties with upgrading and maintaining physical weather stations due to security concerns. Additionally, meteorological stations in some countries have been destroyed during wartime. For example, South Sudan has only five functioning weather stations, which is inadequate to provide relevant climate information for its agriculture- and livestock-dependent population.[108] For instance, this does not provide sufficiently comprehensive information for assessing the risk of floods and drought.

As discussed in chapter 2, remote sensing technology, with the help of AI, could help address the shortage of measurement stations.[109] However, not every country is in a position to use this technology and the countries that have access to it may be protective of the data collected by such systems. Even though environmental and climatic data appear to be fairly neutral and uncontested, some governments are known to be unwilling to share the climate and environmental data collected by their agencies with other countries.[110] For instance, some governments in water-scarce regions in the Middle East and South Asia have withheld water data on transboundary rivers due to potential negative consequences for the respective country's share of water.[111] Typically, they were hesitant to share water data and to cooperate with neighbouring

[103] Schipper, E. L. F., 'Maladaptation: When adaptation to climate change goes very wrong', *One Earth*, vol. 3, no. 4 (Oct. 2020).

[104] Lattimore, F. et al., *Using Artificial Intelligence to Make Decisions: Addressing the Problem of Algorithmic Bias*, Technical paper (Australian Human Rights Commission: Sydney, 2020), pp. 24–30.

[105] Lattimore et al. (note 104), pp. 24–30.

[106] Karimi, P. and Bastiaanssen, W. G. M., 'Spatial evapotranspiration, rainfall and land use data in water accounting—Part 1: Review of the accuracy of the remote sensing data', *Hydrology and Earth System Sciences*, vol. 19, no. 1 (Jan. 2015).

[107] Teixeira de Aguiar, J. and Lobo, M., 'Reliability and discrepancies of rainfall and temperatures from remote sensing and Brazilian ground weather stations', *Remote Sensing Applications: Society and Environment*, vol. 18 (Apr. 2020).

[108] Toby, H., 'Forecasting trouble: How South Sudan's weather service is failing farmers', Reuters, 3 Dec. 2018.

[109] Karimi and Bastiaanssen (note 106).

[110] Gao, J. et al., 'Soft-cooperation via data sharing eases transboundary conflicts in the Lancang-Mekong River Basin', *Journal of Hydrology*, vol. 606 (Mar. 2022).

[111] Prasai, S. and Surie, M. D., 'Water and climate data in the Ganges basin: Assessing access to information regimes and implications for cooperation on transboundary rivers', *Water Alternatives*, vol. 8, no. 2 (June 2015).

countries due to existing tensions.[112] This problem is not unique to countries from the Global South: members of the Arctic Council stopped sharing data and research on the Arctic with Russia following its invasion of Ukraine.[113] AI can help with data sharing and can further promote transparency between countries that share resources.

The availability of data on climate change-related social phenomena is even more problematic. Obtaining up-to-date and high-quality data on socio-economic indicators, political perceptions and social grievances is already notoriously difficult. Research on climate-related security risks relies on data on migration, social unrest and violent conflict. Collecting such data is resource-intensive and time-consuming and demands rigorous verification procedures. Moreover, the nature of this data can be contentious, and different measurement methods and data-collection processes can hinder comparisons across different contexts.

A complicating factor is that the data would need to account for social complexities associated with climate-related security risks. Individuals can subscribe to multiple social identities that shape differentiated vulnerabilities depending on social, political, economic, geographical and temporal contexts.[114] Capturing such complexity is essential for generating policy-relevant insights.[115] Policy interventions target the most vulnerable groups and the populations at risk, but if these interventions are based on incomplete and simplistic analysis that overlooks social complexities and different vulnerabilities, then the interventions may not target the right individuals and groups and may even complicate existing local politics and conflict dynamics. Yet, it can be difficult to make full sense of social dynamics using only hard metrics. Typically, accounting for such complexity requires insights from qualitative research, including anthropology.[116]

Compounding problems in many conflict-affected and fragile countries stem from the lack of digital data. This is simply due to the fact that a large part of the population is disconnected from the internet. International entities such as the International Telecommunication Union (ITU) have been working to enhance internet connectivity and fundamental digital skills in the Global South. However, further progress is still needed: in 2021, 63 per cent of the world's population had internet access, but the figure for conflict-affected and fragile countries was only 38 per cent, and for sub-Saharan Africa it was 36 per cent.[117] Lack of internet access limits the ability to engage in social media platforms and other internet-based platform that are typically used for collecting data on people's behaviours and perceptions. Their views are therefore either absent or under-represented on these platforms. This reality warrants a caution against only relying on insights from AI systems developed from social media data or AI-assisted public consultations. The use of AI or any internet-based tools in countries with unequal and limited internet access entails the risk of over- or under-representing segments of the population, which could lead to misguided policy interventions.

Overcoming challenges related to collection of and access to data is essential to ensuring the reliability and effectiveness of AI-powered systems in this domain. The World Bank's Global Data Facility is one attempt to tackle these data challenges and

[112] Sümer, V., 'A chance for a pax aquarum in the Middle-East? Transcending the six obstacles for transboundary water cooperation', *Journal of Peacebuilding & Development*, vol. 9, no. 2 (Aug. 2014).

[113] Tingstad, A. and Pezard, S., 'What is next for the Arctic Council in the wake of Russian rule?', The Hill, 14 May 2023.

[114] Thomas, K. et al., 'Explaining differential vulnerability to climate change: A social science review', *WIREs Climate Change*, vol. 10, no. 2 (Mar./Apr. 2019).

[115] Muñoz, H. M., 'The power of real-world qualitative assessments for addressing climate security risks', Climate Diplomacy, 19 July 2023.

[116] Muñoz (note 115).

[117] World Bank, Data, 'Individuals using the internet (% of population)', accessed 10 May 2022.

enhance governments' information systems.[118] Comprehensive strategies are necessary to address these challenges. Policy interventions that seek to support access to digital infrastructure and digital literacy can be viewed as a prerequisite in this regard. Cooperation between governments but also between researchers and policy actors can contribute to the generation of more comprehensive and accurate data. This is a first step towards closing data gaps in conflict-affected and fragile countries and enhancing data-verification and validation processes, which can help establish the credibility and reliability of the collected data and the AI systems trained on the data.

Opacity

The inherent opacity of machine learning-based AI systems is another problem that deserves to be acknowledged and that needs to be addressed.

Transparency and explainability of an AI system is vital for its credibility. For the outcome of an AI-based model to be considered seriously, decision makers should be able to understand and evaluate how and why the model produced such an outcome. Public buy-in and understanding can be crucial for improving the likelihood of insights generated by AI systems being effective in public sector decision making.[119] Such logic is similar to that of scientific research, which requires a level of transparency that allows for the verification of research procedures and outcomes. At all stages of scientific research—including data collection, modelling and analysis—a risk of errors can occur with implications of various degrees. This is why transparency is needed in order to make all decisions at each step available for evaluation.

The primary problem in this context is related to the inner working of machine learning-based systems. By design, these systems are opaque and operate like 'black boxes'.[120] Human engineers who have designed the model can monitor the list of input variables, set up the perimeters and follow up with the output, but how the variables are connected to one another can be elusive and cannot be explained.[121] Black box-like models are therefore inherently uninterpretable, limiting the in-depth understanding of mechanisms necessary for effective policy interventions.[122] If they do not precisely explain the *how* and the *why*, insights derived from AI systems are not as useful for policymaking as they could be.[123]

The fact that the functioning of these systems cannot be properly explained is doubly challenging. First, it prevents the system designers and the end users from properly verifying their reliability. Second, it limits the value of the systems for the end users who need to understand why and how the systems came to specific recommendations.[124] This is particularly problematic in the context of conflict early warning, where it is paramount that researchers and policymakers can question the basis on which a system makes its prediction.[125] Numerous AI systems for conflict early warning are trained on data that is either not publicly available or of a sensitive nature.[126] The lack of data accessibility hinders other researchers from replicating and learning from existing models, hindering knowledge accumulation. These problems fundamentally limit

[118] World Bank, 'The Global Data Facility at a glance', [n.d.].

[119] Kuziemski, M. and Misuraca, G., 'AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings', *Telecommunications Policy*, vol. 44, no. 6 (July 2020).

[120] Rudin, C. and Radin, J., 'Why are we using black box models in AI when we don't need to? A lesson from an explainable AI competition', *Harvard Data Science Review*, vol. 1, no. 2 (fall 2019).

[121] Rudin and Radin (note 120).

[122] Rudin and Radin (note 120).

[123] Cederman, L.-E. and Weidmann, N. B., 'Predicting armed conflict: Time to adjust our expectations?', *Science*, 3 Feb. 2017.

[124] Cederman and Weidmann (note 123).

[125] Rød et al. (note 86). See also the section on conflict early-warning systems in chapter 3.

[126] Rød et al. (note 86).

the value of machine learning compared with more traditional AI programming techniques, which, while they may be less efficient, remain verifiable.[127]

Social and ethical challenges: Who has access, who is affected, and who should respond and when?

The development and use of AI systems based on machine learning is associated with social problems, notably in terms of equity.[128] This section examines the key issues around who can develop AI technology, who is affected by its design and use, and who can effectively make use of AI-generated insights. Addressing these questions is crucial for ensuring equitable and responsible development and deployment of AI systems in the context of climate-related security risks.

Who can develop AI for climate security?

Currently, the resources necessary to develop powerful machine learning-based AI systems are concentrated in the hands of only a few countries and companies. These entities have the capacity to mobilize resources that include computing power, data and the expertise of trained data scientists and AI engineers.

There are significant disparities in the global distribution of AI technologies and investment.[129] One study identified a total of 1296 companies with AI technology, 36 per cent registered in North America, 26 per cent in Europe, 16 per cent in East Asia, 12 per cent in South America and 4 per cent in Africa.[130] The disparity per capita is significant: in North America, Europe and South America there are, respectively, 7, 4 and 3 companies per 10 million people, while in Africa and Asia there are, respectively, 0.3 and 0.4 companies.[131] These companies have varying access to public and private sources of funding. Companies registered in China received $5.4 billion during 2007–20 and USA-based companies obtained $1.5 billion during the same period.[132] These amounts are significantly larger than the investment made in companies located in South America and Africa, which received $84 million and $73 million, respectively.[133] One technology journalist remarked that a few technology giants 'have all the computational power [and] they have all the power of decision making for how this technology can be developed and deployed'.[134]

The unequal distribution of AI power is a well-established concern in the conversation on the governance of the AI sector. This disparity carries problematic implications for the use of AI to respond to climate-related security risks. The countries that are most severely exposed to climate-related security risks are in the Global South and often lack the financial, technical and human resources to develop their own AI systems. Consequently, they find themselves relying on external actors such as international organizations, foreign donors, research institutions and companies for funding or technical solutions.

This creates problems at the general and practical levels. At the general level, it reinforces a situation in which countries affected by climate-related security risks

[127] Russel, S., *Human Compatible: Artificial Intelligence and the Problem of Control* (Penguin: London, 2020); and Christian (note 98), pp. 83–117.

[128] Crawford, K., *Atlas of AI* (Yale University Press: New Haven, CT, 2021).

[129] Here the sustainability science includes agriculture, forestry, and the marine and aquaculture sectors. Galaz et al. (note 32), p. 3.

[130] Galaz et al. (note 32).

[131] The assessment is based on appendix A of Galaz et al. (note 32).

[132] The assessment is based on appendix A of Galaz et al. (note 32).

[133] Galaz et al. (note 32), p. 3.

[134] Karen Hao, senior AI editor, *MIT Technology Review*, speaking in the session 'Artificial Intelligence: Opportunities and risks for development', Stockholm Forum on Peace and Development 2021, 5 May 2021, 17:45–17:53.

depend on foreign aid and technology. Affected people may not be able to influence decision making during the development of AI-powered systems. This reliance limits the agency and local ownership of affected communities.[135]

At a more practical level, there are questions of ownership and governance. The private companies and decision makers with the means to develop powerful AI systems may not have a sufficient contextual understanding of conflict-affected and fragile countries to design truly effective AI solutions for their specific needs and contexts. While developed with good intentions, AI systems for the analysis and prediction of resource requirements that are designed without strong knowledge or engagement with local communities may end up omitting key variables, developing inadequate models, addressing the wrong problem or having negative unintended consequences. Leading scholars have explained that

> an AI system that uses imaging data to determine carbon sequestration potential could optimize climate change goals in a narrow sense, but fail to account for social-ecological aspects of the land important to indigenous groups, or ignore endangered species important to conservationists. This could engender a lack of coordination and collaboration among stakeholders and lead to costly delays and conflict, as parties are unwilling to accept afforestation efforts or even work actively against them.[136]

Stakeholders from countries severely affected by climate-related security risks have a critical role to play in the development of AI systems for their own climate security. Authorities, civil society and populations in climate change-exposed and conflict-affected countries can benefit from enhanced climate information systems with AI components and information tools for their climate change adaptation efforts. Providing these actors with greater access to computing resources may not be the most efficient and viable solution, not least because (as discussed above) many of these countries lack basic access to information and communications technology (ICT) and associated infrastructure. Access to and sharing of computer resources is also a vexed issue in the current geopolitical landscape.[137] Another option is to allow such actors to be involved, through participatory mechanisms, in the design of the systems.[138] Ensuring diversity is critical to ensuring that the systems are useful and do not have unforeseen negative impacts.[139]

Who is affected?

The way in which the training data for machine learning systems is collected matters not just for the reliability and efficiency of such systems; the way in which the data is gathered, stored, shared and used can also have societal implications. The process should therefore be done in an ethical way.[140] This is true for all AI systems, but especially for the application of AI for climate security. This requires two types of concern to be weighed: (*a*) data privacy and (*b*) unintended negative effects that could stem from design bias or possible misuse of the AI.

Many of the applications of AI for climate security require collecting, storing and sharing data related to human activities. This is particularly true for systems that seek to

[135] Sultana, F., 'The unbearable heaviness of climate coloniality', *Political Geography*, vol. 99 (Nov. 2022).

[136] Schiff, D. et al., 'Principles to practices for responsible AI: Closing the gap', ArXiv 2006.04.70v1, 8 June 2020.

[137] Ye, J., 'China targets 50% growth in computer power race against US', Reuters, 9 Oct. 2023; and Vipra, J. and Myert West, S., 'Computer power and AI', AI Now Institute, 27 Sep. 2023.

[138] Institute of Electrical and Electronics Engineers (IEEE), 'IEEE recommended practice for assessing the impact of autonomous and intelligent systems on human well-being', IEEE Standard 7010-2020, 1 May 2020.

[139] Alex Tsado, co-founder, Alliance for AI, remark at the session 'Artificial Intelligence: Opportunities and risks for development', Stockholm Forum on Peace and Development 2021, 5 May 2021, 50:00–52:00; Institute of Electrical and Electronics Engineers (note 138); and Soden et al. (note 96).

[140] Dignum, V., *Responsible Artificial Intelligence: How to Develop and Use AI in a Responsible Way* (Springer: Cham, 2019).

collect, analyse or predict such climate change-related phenomena as migration, food security and political grievance. These may rely on satellite images of populated areas, social media data, mobile phone metadata, and data on purchases and consumption. In this context, it is critical to ensure that the data-collection process preserves individuals' right to privacy.

Discussions within the AI community are already under way to address these concerns.[141] Civil society groups have advocated for AI governance and regulatory frameworks that protect the individual rights of those affected by AI systems.[142] Some steps have already been taken; in the EU these include the 2016 General Data Protection Regulation (GDPR), one of the most significant regulations to protect people's personal data, and the proposed AI Act to regulate the use of AI in the EU and ensure the integrity of individuals whose data is processed by AI systems.[143] Additional measures, such as establishing ethical review procedures and conducting technology impact assessments, can also mitigate potential negative effects on privacy and integrity resulting from the development and use of certain technologies.

Another concern related to the use of AI systems for climate security is the possibility of unintended harm for the underprivileged, the less educated, minorities, women, those who are homeless, residents of informal communities and newly arrived rural-to-urban migrants, among others. These negative consequences could stem from design biases within AI systems that can lead to discrimination.[144] For instance, risks of conflict between pastoralist and farming communities have worsened due to climate change, with the historical root of the conflict often related to government policies that discriminate against pastoralist communities.[145] AI-assisted conflict-prediction and -management tools can be used to justify government policies to resettle pastoralists and reinforce existing discrimination. Such a risk can be manifested as AI systems directing disproportionate funding to one community, which can be perceived as discrimination by other groups. Additionally, some actors might misuse the information generated by these systems. For instance, systems intended to detect grievance could be misused by authoritarian regimes to identify and repress certain politically active groups.

To address these risks, it is essential for those involved in the design of AI systems for climate security to critically consider the potential harm, considering not only immediate but also secondary and tertiary effects. In this regard, they can rely on an increasing number of risk-assessment methodologies stemming from discussion on responsible innovation in the AI field.[146]

Who can or should act?

A third, non-trivial challenge pertains to who can or should make use of AI-generated insights for climate security. Multiple actors are engaged in mitigating climate-related security risks: states, international organizations and civil society organizations. As discussed above, not all of them are in a position to develop their own AI systems or to use AI-assisted services due to a lack of required resources. This creates a mismatch

[141] One example of policy work on governance of AI is the High-level Expert Group on Artificial Intelligence, *Ethics Guidelines for Trustworthy AI* (European Commission: Brussels, 8 Apr. 2019).

[142] European Digital Rights (EDRi), 'The EU's Artificial Intelligence Act: Civil society amendments', 3 May 2021.

[143] Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data (General Data Protection Regulation), *Official Journal of the European Union*, L 119, 4 May 2016; and European Parliament, 'EU AI Act: First regulation on artificial intelligence', 14 June 2023.

[144] Kuziemski and Misuraca (note 119).

[145] Benjaminsen, T. A. and Ba, B., 'Why do pastoralists in Mali join jihadist groups? A political ecological explanation', *Journal of Peasant Studies*, vol. 46, no. 1 (2019).

[146] Boulanin, V., Brockmann, K. and Richards, L., *Responsible Artificial Intelligence Research and Innovation for International Peace and Security* (SIPRI: Stockholm, Nov. 2020).

between the actors that can generate relevant insights from AI systems and those that need the information the most—typically states in conflict-affected and fragile countries.

As alluded to in the above sections, this problem can only be solved through greater cooperation, including information sharing between relevant actors. International organizations engaged in peacebuilding, humanitarian and development efforts have a critical role to play here. They are well placed to support—or coordinate—the production and distribution of AI-generated insights. They can contribute to ensuring the quality of AI outputs, from the perspective of both reliability and verifiability. They are also well suited to connecting with local actors who hold crucial knowledge about on-the-ground trends.[147] Such connections with local actors are essential to ensuring that AI systems for early warning can properly fulfil their objectives and do not lead to misguided policy interventions.[148]

Having international organizations as key brokers of AI-generated insight can also help with dissemination of climate security-related information, especially during crises. They can gather relevant actors and mobilize attention and further help ensure that information about potential climate change-related disasters or conflicts is followed up with adequate action when national institutions and governance are weak.[149] Conflict early warning is an example of a field where international organizations can play this role as there is limited evidence that the growing body of research conducted since 2010 has had major policy impacts. The limited policy impacts can be related to the 'warning–response gap', which refers to inefficient dissemination mechanisms that lag behind advances in analytical power.[150] An international organization acting as a trusted broker of AI generated insights can communicate with relevant national authorities to effectively take preventive harm-reduction measures, such as in the cases of the 2010 earthquake in Haiti, the civil war in Syria and Hurricane Katrina in New Orleans in the USA.[151]

When to act

A related challenge concerns determining the timing of when actors involved in mitigating climate-related security risk should act on AI-generated insights. This question deals with issues beyond the scope of this report given the multiplicity and complexity of decision-making processes in general.[152] What can be flagged here is that the design challenges discussed above provide grounds for policymakers to take predictive analysis as an input to their policymaking.[153] While some physical phenomena (e.g. the risk of climate hazards) can be predicted with a degree of certainty, climate change-induced social tensions and violent conflicts are compounded with other sociopolitical factors and so are difficult to predict.

[147] Andrew Harper, special advisor on climate action, UN High Commissioner for Refugees (UNHCR), during the panel discussion 'The future of sustaining peace amidst the climate-crisis I: The strategic approaches' at the ministerial conference 'Sustaining Peace Amidst the Climate Crisis' (note 95), 2 May 2022, 24:51.

[148] Panel discussion 'The future of sustaining peace amidst the climate-crisis I' (note 147), 24:51; and Soden et al. (note 96).

[149] Stanton, G., 'The Rwandan genocide: Why early warning failed', *Journal of African Conflicts and Peace Studies*, vol. 1, no. 2 (Sep. 2009); and Adelman, H. and Suhrke, A., 'Early warning and response: Why the international community failed to prevent the genocide', *Disasters*, vol. 20, no. 4 (Dec. 1996).

[150] Meyer, C. O., De Franco, C. and Otto, F., *Warning about War: Conflict, Persuasion and Foreign Policy* (Cambridge University Press: Cambridge, 2019), chapter 2.

[151] Meyer et al. (note 150).

[152] Hernandez, K. and Roberts, T., *Predictive Analytics in Humanitarian Action: A Preliminary Mapping and Analysis*, K4D Emerging Issues Report no. 33 (Institute of Development Studies: Brighton, June 2020).

[153] Soden et al. (note 96); and Enenkel, M. et al, 'Why predict climate hazards if we need to understand impacts? Putting humans back into the drought equation', *Climate Change*, vol. 162, no. 3 (Oct. 2020).

Moreover, there is no obvious guidance for determining the threshold for taking action because it is always highly context-dependent.[154] For instance, a 60 per cent probability that an event will occur may be enough for taking action in some cases but not in others. Some policy actors may not be comfortable acting on information with an 80 per cent probability, while others would consider deploying resources with a 70 per cent probability. Those who produce and disseminate AI-assisted predictive tools and forecast reports have an important responsibility to ensure that policymakers can understand and contextualize the AI-generated insights. To that end, they could consider noting in their dissemination material the need to weigh in the implications of different thresholds for policy interventions. This would enable policymakers to clearly understand the risks associated both with taking action and with inaction.[155]

[154] Paola Vesco, researcher working with CEWS, Interview with author, 5 Apr. 2022.
[155] Vesco (note 154).

5. Key findings and recommendations

This report explores how recent advances in artificial intelligence can be useful for climate security. It focuses on the possibilities that AI offers for addressing three types of climate-related security risk: climate hazards, climate vulnerabilities and exposure, and climate change-related grievances and tensions.

Recent advances in AI—largely based on machine learning—are particularly useful for addressing the first two types of risk. The use of AI can make disaster early-warning systems and long-term climate hazard modelling more efficient. These tools can be used to optimize food production and the management of natural resources (e.g. in the form of precision agriculture) in countries where livelihood conditions have deteriorated as a result of climate change. Or they could facilitate the use of autonomous robots for delivery of humanitarian assistance during climate disasters. There are already ongoing projects that demonstrate these possibilities. In the case of monitoring climate change-related grievances and tensions, the picture needs to be more nuanced. In theory, AI data-processing capabilities can be used to track grievances and social tensions that stem from exposure to climate change. In practice, however, there are many challenges with using AI to monitor and track the political views and behaviours of a population. Overall, recent advances in AI primarily offer promise in understanding the physical impacts of climate change but not the social impacts that have implications for human security.

AI presents particular opportunities to address the lack of climate-related data in conflict-affected and fragile countries. These countries are typically among those that are the most exposed to climate hazards and already suffer from environmental degradation exacerbated by climate change. The availability of data in such countries is one of the main obstacles that national governments and international organizations need to tackle head-on when seeking to reduce the risks to peace and security of climate change. AI can help policy actors overcome the data problem by enabling efficient use of remote sensing systems, especially satellite imagery, as well as social media. (A range of relevant AI tools can be found in appendix A.)

At the same time, the use of AI for climate security presents technical and ethical challenges. Machine learning, one of the main areas of AI application discussed here, is a powerful technology, but it has important shortcomings. Machine learning algorithms can be opaque and may not explain why and how certain outcomes resulted from a calculation. AI systems powered by machine learning demand a lot of computer resources and can be costly. Their viability and usefulness are likely to depend on the volume and the quality of the data on which they are trained.

For researchers who wish to develop AI tools to empirically study climate-related security risks, these challenges raise difficult methodological questions around the verifiability of outputs, the scalability of the model and, most importantly, decisions about the curation of input data. Ensuring that the system is trained on representative and reliable data is critical to ensuring the usefulness of the system and to minimizing the risk of bias. Actors who see a great potential in using AI to gather and analyse data related to climate change adaptation and climate change-related grievance monitoring also need to consider associated policy and ethical concerns.

From a policy perspective, it is critical to bear in mind that the output of AI systems—particularly those trained on certain social media data—may not be representative. An over-reliance on such systems may lead to policy interventions that discriminate against certain social groups, particularly those that do not engage with social media for economic, social or political reasons (e.g. a lack of internet access or digital literacy, or a fear of censorship and political reprisal).[156] From an ethical standpoint, it is important to acknowledge that an automated social monitoring tool could, in some contexts, intentionally or unintentionally undermine people's human rights, not least the right to privacy and the right not to be discriminated against.[157]

These policy and ethical concerns are not unique to the field of climate security, but they are particularly acute in this case because of the potential use in AI tools of data on human behaviour in conflict-affected and fragile countries. Stakeholders that seek to make use of AI for climate security—be they application developers, researchers or policy actors—should therefore take measures to ensure its responsible development and use. Such measures should seek to prevent harm—both intended and unintended—especially harm that may stem from the misuse of information and AI tools by authoritarian regimes.

Based on these key findings, the final sections offer recommendations for policymakers and researchers who may wish to further explore the potential of AI for climate security.

Recommendations for policymakers

Policy actors who wish to accelerate the response to climate security with AI at the national and international levels should consider the following interventions.

Support access to digital infrastructure and capacity building

Countries and communities around the globe are unequally equipped to take advantage of the recent advances in AI. There is still a major digital divide between and within countries, with significant numbers of people having limited access to and capacity to use the digital infrastructure necessary to employ AI tools and services. Conflict-affected and fragile countries are on the wrong side of the digital divide. The lack of climate-related data in these countries is worsened by their lack of digital infrastructure.

Policy interventions that seek to support access to digital infrastructure and digital literacy can, in that regard, be viewed as a prerequisite for the development of viable AI-powered climate information systems in these countries. Such investments in basic ICT infrastructure are typically outside the scope of climate financing (i.e. financial support for climate change mitigation and adaptation). However, these baseline investments are necessary if AI-driven solutions are to be seriously considered for reducing the risks of climate change-driven insecurity and conflict. Climate financing institutions can complement the efforts made by other international organizations (e.g. the ITU among others) and support targeted capacity building for the potential users of existing climate information systems. Capacity-building efforts should be inclusive and should benefit both governments and civil society.[158]

Support the development of an open-access AI tool for the collection of climate security-related data in conflict-affected and fragile countries

Climate information systems and climate data are scarce in countries affected by conflict and fragility, usually because it can be extremely difficult to obtain climate data on the ground. Governments and international organizations that seek to support the building of climate resilience in these countries could—in addition to supporting

[156] Tai, Y. and Fu, K., 'Specificity, conflict, and focal point: A systematic investigation into social media censorship in China', *Journal of Communication*, vol. 70, no. 6 (Dec. 2020); and Earl, J., Maher, T. V. and Pan, J., 'The digital repression of social movements, protest, and activism: A synthetic review', *Science Advances*, 11 Mar. 2022.

[157] Lovari, A. and Bowen, S. A., 'Social media in disaster communication: A case study of strategies, barriers, and ethical implications', *Journal of Public Affairs*, vol. 20, no. 1 (2020).

[158] World Meteorological Organization (note 17).

the development of basic infrastructure such as electricity—provide funding for the development or improvement of open-access AI tools that could enhance the use of remote sensing data.

Such tools should be easy to use and should be accessible to civil society and other actors who operate on the ground (e.g. via mobile browsers and smartphone applications). Open-access and easy-to-use interfaces are essential for reducing technical barriers. In turn, these open-access and user-friendly AI tools can be used by all relevant stakeholders, from public authorities to civil society and community actors.

Support critical research on AI and climate security

Advances in AI could unlock many possibilities for promoting climate security, but important questions remain as to how such technology can be used in meaningful, reliable and ethical ways. Relevant governments and international organizations should thus invest in risk mitigation.

This investment could take the form of funding for critical research on the viability, shortcomings and policy issues associated with the use of AI for climate security. Such a step is meant to encourage serious engagement in considering and using AI as a tool, not to scare away policymakers from new, exciting opportunities.

Recommendations for researchers

Researchers who wish to make use of AI to better understand the nexus between climate change and security should focus in particular on the following.

Conduct empirical research and explore methodological solutions

This report maps out in broad strokes what AI could offer for the field of climate security. Further research should assess in greater detail the potential and limitations of AI in this field.

Such research could take the form of case studies and theory-oriented papers that discuss methodological issues associated with the use of machine learning methods. These efforts could generate actionable policy insights or could help forge novel methodologies and empirical techniques. The results could, in turn, contribute significantly to the development of strategies that mitigate the risks posed by climate change and foster a more secure and peaceful world.

Consider ethical and political risks associated with the use of AI methods to monitor climate change-related tensions and political grievances

Researchers should be mindful of the ethical and political risks associated with using AI tools to monitor climate change-related social phenomena, especially tensions and political grievances. They should share data responsibly.

This includes looking for ways to ensure that AI technology is not repurposed by some actors—be it an authoritarian regime or a political group—for mass surveillance or digitally fuelled repression. There have already been cases in which social media monitoring and social tracking have been used to target politically active individuals. One way to avoid this is to ensure that risk assessments (i.e. algorithmic-impact assessments) are conducted as part of the development process and that proactive risk-mitigation measures are taken so that the information generated by AI systems may not be used to violate an individual's right to privacy or fundamental rights (e.g. freedom of expression, right to life, freedom from torture, and freedom from degrading treatment).

Maintain close links with affected communities

Researchers should collaborate with relevant stakeholders in conflict-affected and fragile countries in the development of AI-powered tools and research products.[159] This is particularly important in ensuring that the data they collect can serve the communities that are directly affected by climate-related security risks.

Such engagement may provide representatives of the affected communities with opportunities to offer feedback and critical inputs. Researcher–community engagement is also useful for data verification and accuracy. It can enhance data representativeness and help avoid the bias that may be inherent in remote sensing data and secondary sources. More broadly, engaging with these important local stakeholders is essential to gaining or maintaining a nuanced understanding of the sociopolitical dynamics connected to climate change and climate variability.

[159] This echoes remarks by Andrew Harper, UNHCR, during the panel 'The future of cooperation: Advancing communication practices and creating new partnerships', at the ministerial conference 'Sustaining Peace Amidst the Climate Crisis' (note 95), 24:51.

Appendix A. A list of AI tools for climate security interventions

The following table presents examples of the use of artificial intelligence in areas relevant for addressing climate-related security risks and outlines the potential benefits.

Intervention opportunity	Artificial intelligence (AI) tools	Benefits
Gathering weather data in conflict-affected and fragile countries	Machine learning used for satellite image analysis [a]	Supplying data for data-scarce locations including conflict-affected regions; laying foundations for other AI applications
Modelling and predicting hazards	Machine learning used for improved hazard modelling [b]	Enabling preventive measures and anticipatory actions; reducing harm of climate disasters
Assessing disaster impact	Machine learning models taking in multisource inputs for multisector and multidimensional disaster assessment; unmanned aerial vehicles (UAVs) in damage detection; machine learning to analyse social media data for disaster impact monitoring [c]	Informing humanitarian responders to enhance relief provision and reconstruction efforts; aiding disaster recovery and resilience building
Disaster early-warning systems	Machine learning used for forecasting models [d]	Enabling cost-effective early warning of extreme weather events and disasters; reducing the risk of population displacement and livelihood disruption
Assessing climate impact on livelihoods such as agriculture, fisheries and forestry	Machine learning used for improved modelling of regionalized environmental changes to livelihood systems [e]	Enhancing climate-adaptation decision making; reducing climate vulnerability
Assessing climate impact on coastal urban areas	Machine learning used for improved modelling of sea level rise on urban infrastructure [f]	Informing urban planning; reducing climate vulnerability
Monitoring and managing disasters	Near real-time dashboard, rapid mapping, large language models (chatbots), UAVs [g]	Assisting humanitarian responders and populations in need; reducing harm from climate disasters
Tracking climate change-related grievance	Machine learning used for social media analysis, public consultation using large language model [h]	Informing policymakers of priorities for service provision and climate-adaptation initiatives
Monitoring communal tensions and conflict	Machine learning used for monitoring pressure on shared resources [i]	Preventing conflict and mediating
Mapping surface water and ground-water resources	Machine learning used for enhancing remote sensing systems [j]	Managing water resources to be climate resilient; reducing the risk of water-related conflicts
Monitoring land-use change and vegetation coverage including deforestation	Machine learning used for enhancing remote sensing systems [k]	Tracking forest coverage for climate mitigation

[a] Anyamba, A., Tucker, C. J. and Eastman, J. R., 'NDVI anomaly patterns over Africa during the 1997/98 ENSO warm event', *International Journal of Remote Sensing*, vol. 22, no. 10 (2001); and Bhaga, T. D. et al., 'Impacts of climate variability and drought on surface water resources in Sub-Saharan Africa using remote sensing: A review', *Remote Sensing*, vol. 12, no. 24 (Dec. 2020).

[b] Hosseini, F. S. et al., 'Flash-flood hazard assessment using ensembles and Bayesian-based machine learning models: Application of the simulated annealing feature selection method', *Science of the Total Environment*, vol. 711 (1 Apr. 2020); and Neeti, N. et al., 'Integrated meteorological drought monitoring framework using multi-sensor and multi-temporal earth observation datasets and machine learning algorithms: A case study of central India', *Journal of Hydrology*, vol. 601 (Oct. 2021).

[c] Kaufhold, M.-A., Bayer, M. and Reuter, C., 'Rapid relevance classification of social media posts in disasters and emergencies: A system and evaluation featuring active, incremental and online learning', *Information Processing & Management*, vol. 57, no. 1 (Jan. 2020); Munawar, H. S. et al., 'UAVs in disaster management: Application of integrated aerial imagery and convolutional neural network for flood detection', *Sustainability*, vol. 13, no. 14 (July 2021); and Zahra, K., Imran, M. and Ostermann, F. O., 'Automatic identification of eyewitness messages on twitter during disasters', *Information Processing & Management*, vol. 57, no. 1 (Jan. 2020).

[d] Dewitte, S. et al., 'Artificial intelligence revolutionises weather forecast, climate monitoring and decadal prediction', *Remote Sensing*, vol. 13, no. 16 (Aug. 2021).

[e] Collignon, B., 'A new tool for the remote sensing of groundwater tables: satellite images of pastoral wells', *Open Geospatial Data, Software and Standards*, vol. 5, article no. 4 (30 Sep. 2020); Crane-Droesch, A., 'Machine learning methods for crop yield prediction and climate change impact assessment in agriculture', *Environmental Research Letters*, vol. 13, no. 11 (Nov. 2018); and Etminan, A. et al., 'Determining the best drought tolerance indices using Artificial Neural Network (ANN): Insight into application of intelligent agriculture in agronomy and plant breeding', *Cereal Research Communications*, vol. 47, no. 1 (Mar. 2019).

[f] Jakariya, M. et al., 'Assessing climate-induced agricultural vulnerable coastal communities of Bangladesh using machine learning techniques', *Science of the Total Environment*, vol. 742 (Nov. 2020); and Zahura, F. T. et al., 'Training machine learning surrogate models from a high-fidelity physics-based model: Application for real-time street-scale flood prediction in an urban coastal community', *Water Resources Research*, vol. 56, no. 10 (Oct. 2020).

[g] Kuglitsch, M. M. et al., 'Facilitating adoption of AI in natural disaster management through collaboration', *Nature Communications*, vol. 13, article no. 1579 (24 Mar. 2022).

[h] Koren, O., Bagozzi, B. E. and Benson, T. S., 'Food and water insecurity as causes of social unrest: Evidence from geolocated Twitter data', *Journal of Peace Research,* vol. 58, no. 1 (Jan. 2021).

[i] Schwarz, M. et al., 'Assessing the environmental suitability for transhumance in support of conflict prevention in the Sahel', *Remote Sensing*, vol. 14, no. 5 (Mar. 2022).

[j] Collignon (note e); and Krishnan, S. R. et al., 'Smart water resource management using artificial intelligence—A review', *Sustainability*, vol. 14, no. 20 (Oct. 2022).

[k] Albuquerque, R. W. et al., 'Mapping key indicators of forest restoration in the Amazon using a low-cost drone and artificial intelligence', *Remote Sensing*, vol. 14, no. 4 (Feb. 2022); Ampatzidis, Y. and Partel, V., 'UAV-based high throughput phenotyping in citrus utilizing multispectral imaging and artificial intelligence', *Remote Sensing,* vol. 11, no. 4 (Feb. 2019); and Mhanna, S. et al., 'Using machine learning and remote sensing to track land use/land cover changes due to armed conflict', *Science of the Total Environment*, vol. 898 (10 Nov. 2023).

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