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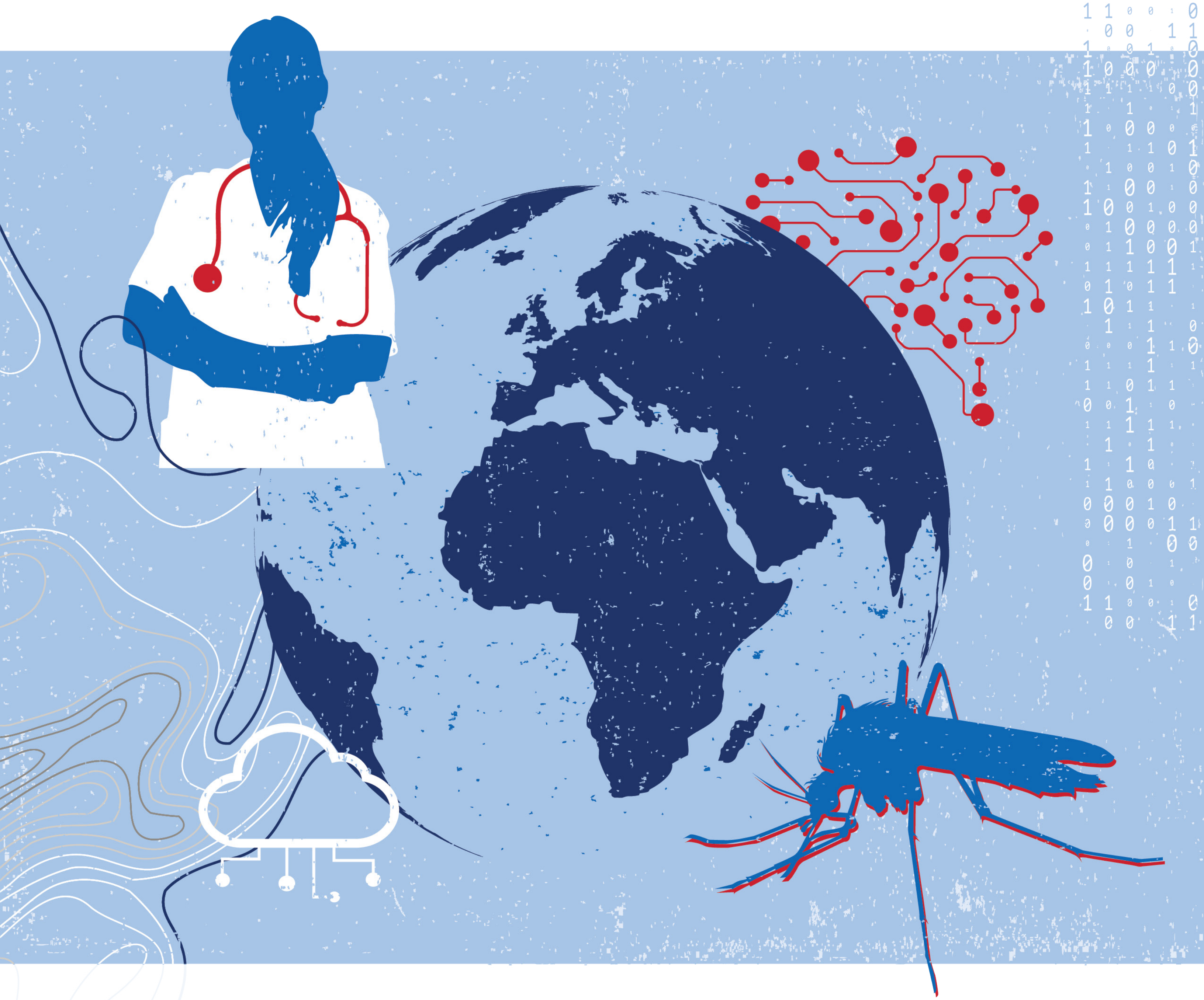

Finding the Signal:

Harnessing Artificial Intelligence and Advanced Analytics at the Intersection of Climate and Global Health

The lead authors of this report are the Center for Innovation and Impact (CII) at the United States Agency for International Development (USAID) and the Boston Consulting Group (BCG). This report could not have been written without the support and invaluable contributions of the USAID team, program partners, industry experts, and all who contributed their time, insights, and experience.

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1. Foreword

Climate change has become one of the most pressing crises of our time. Temperatures are reaching untenable heights in many parts of the world, patterns of rainfall are shifting to drive deadly droughts and flooding, and glaciers are melting leading to dangerous sea level rise. Although limiting global warming to 1.5 degrees Celsius in this century was a key climate goal of the Paris climate agreement in 2015, the World Meteorological Organization has indicated the world may warm 1.5 degrees Celsius by 2027, leading to even more catastrophic consequences than those we are already facing.[1] The climate crisis affects health and safety everywhere, but the consequences disproportionately fall on the most vulnerable in low- and middle-income countries (LMICs) where USAID works.[2] By launching the Emergency Plan for Adaptation and Resilience, President Biden issued a call to action with USAID's commitment to increasing the climate resilience of 500 million people worldwide as a centerpiece. USAID has also launched its ambitious Climate Strategy 2022–2030, which calls for a whole of Agency response to the crisis and guides our related development and humanitarian work through 2030.

While the impacts of the climate crisis are coming fast and furious, artificial intelligence and advanced analytics (AI/AA) offer a light at the end of the tunnel as they can help us make sense of how the complex, interwoven systems of climate and global health interact. As this report demonstrates, AI/AA has the potential to describe and predict global health consequences from climate change as well as identify courses of action for global health practitioners to adapt and improve decision-making and related health outcomes. To seize this opportunity, USAID has published this important Artificial Intelligence Action Plan outlining how development stakeholders can engage and align efforts in machine learning to strengthen development outcomes. However emerging technologies are used, it is critical to explore and act upon any machine learning biases that can lead to unintended consequences.[3] To mitigate machine learning bias that could arise, algorithms must rely on representative datasets and be designed with and by our partner countries.

Still a nascent field with scarce data especially in LMICs,[4] with concerted effort we can leverage the opportunities embedded in the intersection of AI/AA, climate, and global health. By investing in and building the capabilities and data requirements to scale the intersection between climate change, global health, and machine learning, USAID positions ourselves and the field with knowledge, facts, and data that allow for more agility and adaptability in our decision-making. It will take all of us working together and across sectors to confront the enormous global climate crisis, and I'm excited that this report maps initial opportunities for how AI/AA can serve as a support in this endeavor.

Gillian Caldwell
Chief Climate Officer and Deputy Assistant Director, USAID

1 Kasha Patel, "Earth could soon briefly hit threatening climate threshold," *The Washington Post*, May 10, 2022.
2 Nicolas Taconet, Aurélie Méjean, Céline Guivarch, "Influence of climate change impacts and mitigation costs on inequality between countries," *Climate Change* 160 (2020): 15–34.
3 *Artificial Intelligence in Global Health: Defining a Collective Path Forward*, The Rockefeller Foundation and CII, April 2019.
4 Raymond Zhong, "How Extreme Heat Kills, Sickens, Strains and Ages Us," *The New York Times*, June 13, 2022.

2. Executive Summary

Problem statement. **The increasingly erratic and intense nature of climate factors such as precipitation, temperature, and wind present unprecedented risks to human health.** The World Health Organization outlines nine climate-sensitive health risks, ranging from vector-borne diseases to heat-related illnesses. Addressing these climate-sensitive health risks requires the capability to **describe** complex and often non-obvious relationships, to **predict** scenarios accurately over different time horizons, and to **recommend** interventions, so that targeted, decisive action can be taken to prevent or respond to health impacts.

Opportunity. **Artificial intelligence and advanced analytics (AI/AA) methods offer the potential to augment our current capabilities to describe, predict, and recommend.** These methods can process data and make inferences more rapidly, continuously, and accurately than the human mind alone, thereby complementing, not replacing, human judgment and decision-making.

There are technical experts on AI/AA, climate, and health—many of whom were consulted during this effort—but relatively few with deep expertise at the intersection of all three. This report shares AI/AA use cases for climate and health that are already adding value in real-world settings while also recommending pathways to deploy more, allowing decision-makers at Ministries of Health and their development partners to realize the full potential of these novel methods.

Current state. **Despite its potential, AI/AA use cases at the intersection of climate and health remain nascent, particularly in low- and middle-income countries (LMICs)** where the requisite data, analytical, and ecosystem conditions may not yet exist. Currently deployed use cases tend to **describe** and **predict** vector- and water-borne diseases, where local stakeholders can make credible decisions using the available climate and health data. For example, the Epidemic Prognosis Incorporating Disease and Environmental Monitoring for Integrated Assessment machine learning model uses climatic variables (i.e., rainfall, land surface temperature, vegetation index) from Google Earth Engine and disease surveillance data to create a malaria early warning system that health partners in the Amhara region of Ethiopia piloted to inform resource allocation decisions weeks in advance. The D-MOSS machine learning model uses Earth Observation data on seasonal forecasts of water availability to predict dengue outbreaks several months in advance. It is being used as an early warning system in Vietnam and being scaled across seven South and Southeast Asian countries.

Why now. **Given the recent confluence of global attention on data, climate, and health topics, now is the time to deploy more of these value-adding use cases.** On data, as it continues to proliferate, new analytical methods are being developed in academic and applied settings. On climate, recent global commitments to address climate change have resulted in new funding, such as the pledges made by public and private sector actors at COP26. In addition, the U.S. government announced ambitious targets to advance the President's Emergency Plan for Adaptation and Resilience, reinforced by the United States Agency for International Development 2022–2030 Climate Strategy. On health, the COVID-19 pandemic reinforced the importance of global health security and equity, including the need for more data-informed decision-making in complex, evolving scenarios.

Recommendation. The problem is existential—AI/AA methods present an opportunity, current uses cases offer learnings, and the time to act is now. Given the nascence of this intersection, there is unlikely to be one "right" action. **To that end, this report recommends two complementary action pathways to deploy AI/AA use cases at the intersection of climate and health;** stakeholders can invest in either or both according to their organizations' strategic goals and comparative advantages. The methodology and detailed case studies are described in Section 6 and the Appendix.

Pathway I: Invest in enablers for data, analytical, and ecosystem conditions that are applicable across climate-sensitive health risks

- Increase usable climate and health datasets required for AI/AA methods
  - Support data collection tools and programs to improve data availability, quality, and granularity
  - Advocate and provide technical assistance for data interoperability and sharing across stakeholders
- Strengthen capabilities of local decision-makers to use and interpret outputs from AI/AA use cases for health decision-making
  - Invest in practical, user-friendly analytical tools
  - Build AI/AA capacity of relevant in-country users
  - Cultivate cross-functional expertise in decision-making
- Foster continuous engagement between the ecosystem of AI/AA, climate, and health stakeholders
  - Make funding available to pilot high-potential AI/AA use cases
  - Convene AI, climate, and health leaders
  - Track efforts across stakeholders

Pathway II: Take action on a specific climate-sensitive health risk based on a high-level assessment of the health problem, the current capabilities to describe, predict, and recommend, and near-term AI potential

- **Adapt and expand** AI/AA use cases where the climate-health linkages are better understood and where there are examples of AI/AA models effectively deployed in LMICs—such as for vector-borne diseases like malaria and dengue and water-borne diseases like cholera
- **Explore modification** where the climate-health linkages are somewhat understood and experts believe that existing AI/AA models deployed in similar contexts have the potential to be modified—such as from one vector-borne disease model to another (Chikungunya) or water-borne disease model to another (typhoid)
- **Shape understanding** where climate-health linkages are poorly understood and where there are few or no examples of AI/AA models deployed in LMICs but where experts believe that AI/AA methods can potentially augment capabilities to describe, predict, and recommend—such as for heat-related illnesses, extreme weather-induced injury, and zoonoses

Path forward. **Early investments in these action pathways can create trust and demonstrate value-add of AI/AA methods, or risk the opposite.** This report offers shared principles to guide next actions on AI/AA use cases for climate and health: (1) be demand-driven, focusing on areas of high health impact and clear value from AI/AA methods—which may not be the right solution for all climate-sensitive health risks; (2) enhance equity and fairness through responsible data management; (3) build capacity and contribute to a continuous learning ecosystem.

The hope is that this report contributes to thought leadership and sparks action. **This decade will be decisive for the future of our planet, and harnessing AI/AA use cases at the intersection of climate and health can contribute to a more resilient, prosperous, and equitable world.**

3. Introduction

Context for this effort. Climate factors present substantial risks to human health,[5] yet the global community has limited capabilities to **describe** these relationships, to **predict** what scenarios will happen with accuracy, and to **recommend** what decisions to take. Artificial intelligence and advanced analytics (AI/AA) methods offer the potential to augment current capabilities, but understanding and implementing at the intersection of AI/AA, climate, and health remains nascent today, particularly in low- and middle-income countries (LMICs). **This report shares AI/AA use cases for climate and health that are already adding value in real-world settings while recommending pathways to deploy more so that decision-makers can realize the full potential of these novel methods.**

Scope of this effort. **This effort aims to align with relatively consistent overall definitions and categorizations of artificial intelligence**—recognizing the variance that exists—and intends to focus on the subset of AI approaches that tend to be most relevant to climate and global health topics. AI is defined as the use of computers for automated decision-making to perform tasks that normally require human intelligence, including a focused subset of supervised and unsupervised machine learning methods (e.g., data mining, predictive modeling, deep learning). This definition builds on and is consistent with the recent United States Agency for International Development (USAID) guidance, AI Action Plan, and study, AI in Global Health. **In addition, this effort includes optimization and geo-analytics as advanced analytics (AA) approaches are in scope,** building on and consistent with the recent USAID study, Data and Advanced Analytics in HIV Service Delivery: Use Cases to Help Reach 95-95-95.

This effort considers climate factors such as precipitation, temperature, and wind across different time horizons—from hourly, to seasonal, to multi-decadal—based on underlying Earth systems.[6] These climate factors impact human health both directly and indirectly. Directly, changes in rainfall and temperature may impact endemic ranges of vectors carrying disease while extreme temperatures can cause physiological stress in the near-term and make certain geographies "unlivable" in the longer-term. Indirectly, extreme weather events can disrupt health facility operations or other related sectors such as agricultural systems or waste management infrastructure. **This effort considers health at the individual and population level, particularly those areas most relevant to LMIC settings,** recognizing the interdependencies between individual and population health, health facilities, and other sectors that impact health.

This effort recognizes that effective climate policy requires a portfolio of complementary adaptation and mitigation actions, while focusing its scope more on climate adaptation actions. Climate adaptation is defined by the Intergovernmental Panel on Climate Change (IPCC) as adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities.[7] Harnessing AI/AA methods present opportunities to address climate-sensitive health risks.

5 *Climate Change 2022: Impacts, Adaptation and Vulnerability*, IPCC, 2022; "Climate change and health," *WHO*, October 30, 2021; Marina Romanello, Alice McGushin, Claudia Di Napoli, et al, "The 2021 report of the Lancet Countdown on health and climate change: code red for a healthy future," *The Lancet* 398, no. 10311 (October 2021): 1619–1662.

6 *Climate Information for Public Health Action*, Routledge, 2018; National Geographic webpage; NASA webpage.

7 R.J.T. Klein, S. Huq, F. Denton, et al, "Inter-relationships between adaptation and mitigation," *Climate Change 2007: Impacts, Adaptation and Vulnerability, Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press (2007): 745–777.

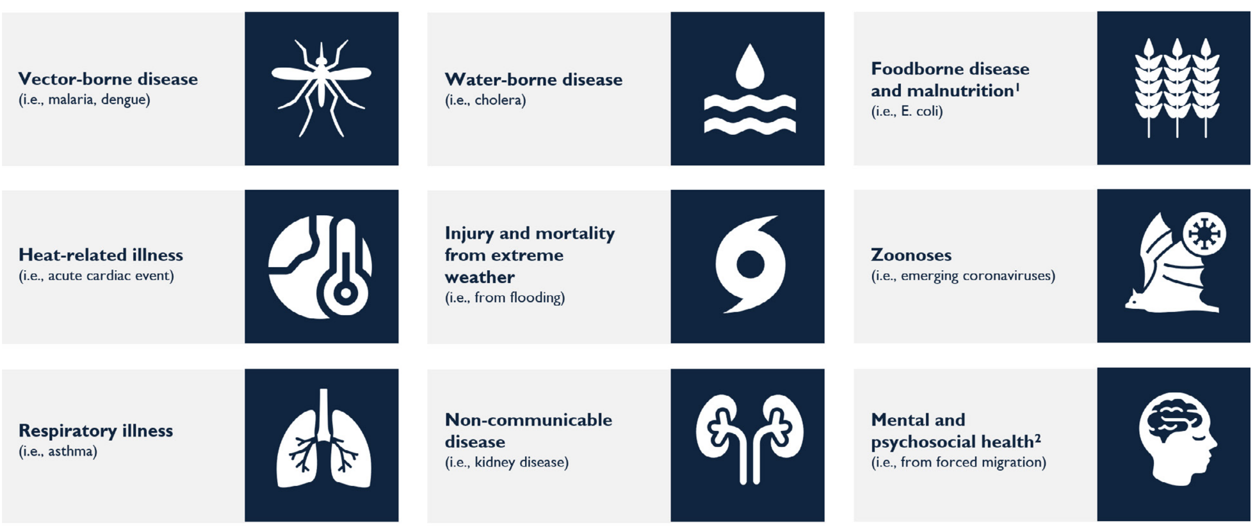
Methodology and approach. **This report synthesizes findings from a focused research and analysis effort that was completed in early 2022.** This included recurrent interviews with more than thirty AI/AA, climate, and/or global health experts, with a deliberate focus on experts potentially able to speak to at least two of the three domains. These expert inputs were supplemented with extensive secondary research and analysis, including a catalog of two hundred relevant academic papers, white papers, and articles on AI/AA, climate, and/or global health. This report does not target recommendations to a specific stakeholder group, but rather synthesizes information on a relatively nascent intersection of topics in order to offer pathways for stakeholders across geographies and sectors to collaborate at this intersection going forward.

4. Making the case for AI/AA, climate, and health

4.1 Problem Statement

Climate factors present a substantial health risk, with some existing health threats expected to intensify and new health threats expected to emerge, according to the World Health Organization (WHO) and the United States Centers for Disease Control and Prevention.[8] The WHO outlines nine climate-sensitive health risks that are exposed and vulnerable to the increasing frequency and intensity of extreme weather events, heat stress, air quality, water quality, and more (see Figure 1). For example, the number of dengue cases reported to the WHO increased over eight-fold in the last two decades, and dengue transmission risk will only increase with longer seasons and a wider band of impacted geographies across the world, potentially putting billions of additional people at risk by the end of the century.[9] Moreover, the higher frequency and longer duration of extreme heat events will impact morbidity and mortality, yet heat has not historically been considered in health policy and programs.[10]

Figure 1: Nine climate-sensitive health risks where climate factors impact health outcomes



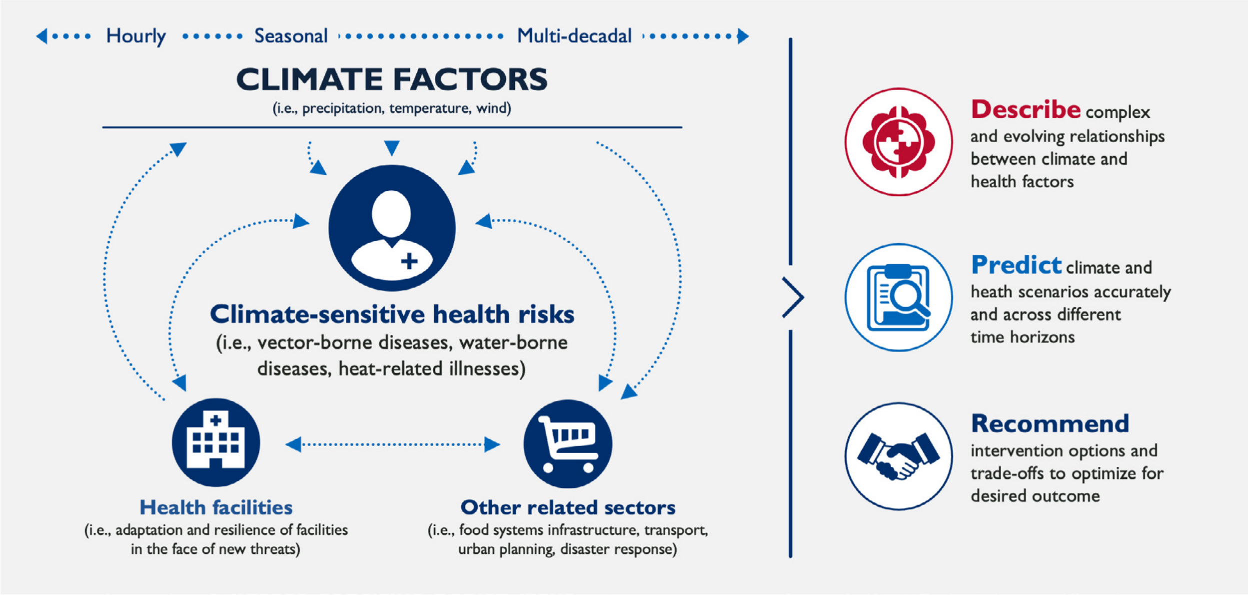
1. Focus of our effort on foodborne illness, not malnutrition more broadly; 2. WHO includes substance abuse disorders in this health risk
Source: Climate change and health (WHO, 2021)

8 "Climate Effects on Health," *CDC*, 2021; WHO, 2021.
9 "Dengue and severe dengue," WHO, January 10, 2022; IPCC, 2022; Tran BL, Tseng WC, Chen CC, et al, "Estimating the Threshold Effects of Climate on Dengue: A Case Study of Taiwan," *Int J Environ Res Public Health* 17, no. 4 (Feb 2020).
10 IPCC, 2022; Lancet, 2021.

4.2 Opportunity

Addressing climate-sensitive health risks requires the capability to **describe** complex and often non-obvious relationships, **predict** scenarios accurately over different time horizons, and **recommend** interventions, allowing for targeted, decisive action to prevent or respond to health impacts. **AI/AA methods have the potential to augment each of these capabilities at the intersection of climate and health** (see Figure 2).

Figure 2: AI/AA methods offer unique value-add across time horizons for the three capabilities required to address climate-sensitive health risks



- **Describing** ***complex relationships between climate and health risks.*** AI/AA methods can learn and discover non-obvious relationships by recognizing patterns across dimensions (i.e., space, time horizons), even if causal relationships between factors are not fully understood. For example, health experts did not understand why Chikungunya emerged and spread in the Western Hemisphere in 2013, so they developed a random forest model (i.e., supervised machine learning algorithms) using climate (i.e., precipitation, temperature), health (i.e., disease transmission), and mobility (i.e., aircraft route, passenger flow) data streams to generate descriptive and predictive information with greater accuracy than conventional analytical methods.[11]

- **Predicting** ***scenarios accurately, across different time horizons.*** AI/AA methods can increase the accuracy and granularity of predictions across time horizons (i.e., from near-term to seasonal to decadal) through continuous learning, even when relationships are not completely understood. For example, one challenge on the climate side of the equation is how to combine or compare projections from different global climate models. To address this, machine learning techniques were used to identify which model gave the more accurate prediction at a given time by assessing twenty IPCC global climate models and over one hundred years of historical temperature data.[12]

11 L.E. Escobar, H. Qiao, A.T. Peterson, "Forecasting Chikungunya spread in the Americas via data-driven empirical approaches," *Parasites Vectors* 9, no. 112 (2016).
12 C. Monteleoni, "Machine Learning Techniques for Combining Multi-Model Climate Projections," *AGU Fall Meeting Abstracts* (December 2013).

- **Recommending *intervention options and trade-offs to optimize for the desired outcome.*** AI/AA methods can perform optimization against desired outcomes by rapidly evaluating both existing and novel intervention approaches or scenarios when outcomes and constraints are quantifiable. For example, early and accurate tuberculosis diagnosis remains challenging in lower-resource settings, where radiographs may be cost-prohibitive, and radiologists are few. One application of deep learning—part of a broader family of machine learning methods—is using pre-trained convolutional neural networks (CNN or ConvNet) to read medical imaging, which has demonstrated accurate and fast results using data from both higher and lower-middle income countries.[13]

Despite their unique value proposition, AI/AA methods should supplement but not replace human judgment on health decision-making. AI/AA methods can process data and make inferences more rapidly, continuously, and accurately than the human mind can alone. But human judgment is required to determine what decisions need to be made (i.e., where and how much to invest), how valuable it can be to make better decisions (i.e., U.S. dollar per DALYs averted for a high-burden disease), what the logical reasoning and set of assumptions are (i.e., empirical evidence of changing rainfall patterns can lead to more vector- and water-borne diseases), and how to interpret and apply data insights to real-world settings where human lives may be on the line (i.e., change implementation strategy). As one expert noted, "AI can be a powerful new tool in the toolbox" for climate and health, but it is not the only tool and requires principled and deliberate implementation.

13 U.K. Lopes, J.F. Valiati, "Pre-trained convolutional neural networks as feature extractors for tuberculosis detection," *Computers in Biology and Medicine* 89 (October 2017): 135–143.

5. Current state of AI/AA use cases for climate and health

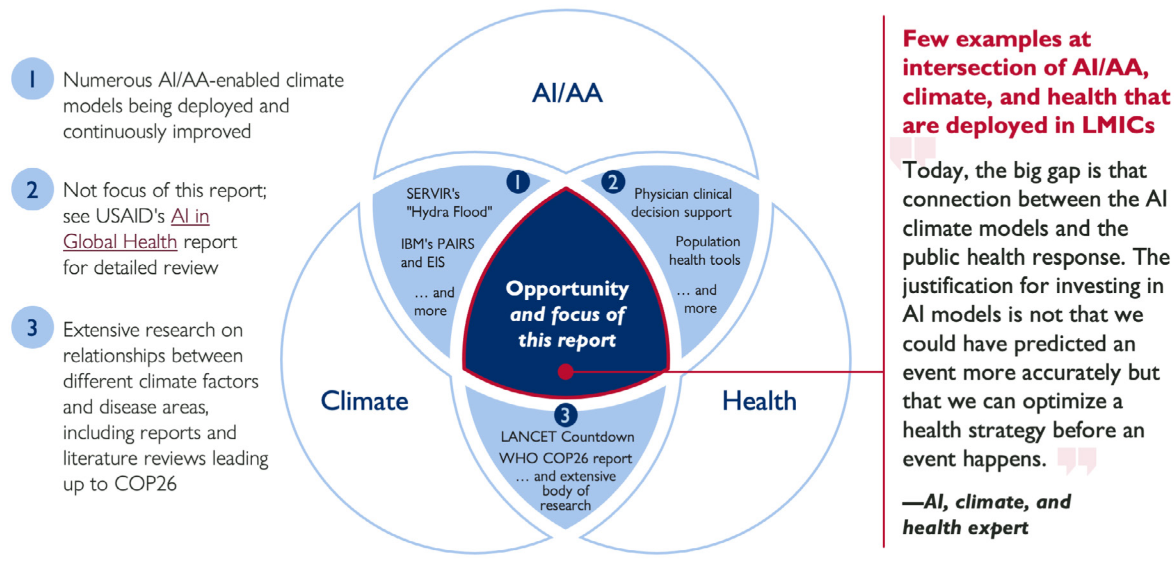
5.1 Challenging Conditions for Deployment, Particularly in LMICs

There are examples of AI/AA-enabled models that have been implemented to monitor climate factors. Climate factors such as precipitation, air and land surface temperature, and wind can be observed across different time horizons that are based on underlying Earth systems. The availability and quality of data varies significantly and is generally higher to lower as you move from weather (hours to two weeks), to sub-seasonal (about one to four weeks), to seasonal (about one to twelve months), to multi-annual (about one to ten years), to multi-decadal (about ten to thirty years), to long-term (greater than thirty years) patterns.[14] There are many examples of AI/AA-enabled data collection and modeling methods that **describe** and **predict** climate phenomena in order to **recommend** stakeholder action, such as in the context of disaster response, supply chain optimization, or food security. Select examples follow.

- SERVIR is a joint initiative of the National Aeronautics and Space Administration (NASA), USAID, and geospatial organizations in Asia, Africa, and Latin America to leverage Earth-observing satellite data and geospatial technology for different applications. One such application is the HYDRAFlood model, which uses neural networks (an AI/AA method) to create near real-time flood mapping that national government and community organizations use to issue flood alerts in a more timely and accurate manner.[15]

Figure 3: Use cases at the intersection of AI/AA, climate, and health are limited to-date

Illustrative, non-exhaustive



14 Routledge, 2018; National Geographic webpage; NASA webpage.
15 Jake Ramthun, "SERVIR Flood Mapping Service Brings Speed to Cambodia Disaster Management," *ClimateLinks,* January 14, 2021.

- IBM's Physical Analytics Integrated Data and Repository Services aggregates and analyzes climate data to predict the potential impact of upcoming weather events. When paired with IBM's AI-enabled Environmental Intelligence Suite, the use case helps companies plan for and adequately respond to potential supply chain challenges.[16]
- Google's DeepMind uses machine learning and weather data to predict wind patterns up to thirty-six hours in advance to optimize its own wind turbine performance; moving from days to multidecadal, the movement of the westerly winds have huge implications for precipitation patterns and potentially disruptive storm systems.[17]
- ClimateAI is a US-based start-up that developed an AI-enabled platform to monitor increasingly volatile climate factors such as heat and to predict the impact on agricultural yields, and in turn profitability, for food and agriculture businesses that often need to make production decisions at least one year in advance.[18]

These AI-enabled climate models, along with others available, can serve as the foundation for potential new use cases if health datasets and algorithms can be feasibly layered.

Extensive academic and applied research also exists at the intersection of climate and health. As part of this effort, two hundred relevant academic papers, white papers, and articles were reviewed—the majority of which explored the relationship between climate factors and specific health areas using conventional analytical methods. For example, there is a large body of research that explores the impact of climate change on future vector and pathogen risk, which is historically assessed using statistical models that produce static maps or by mechanistic models that are validated by their capability to accurately reproduce past outbreaks.[19] In the lead-up to COP26, many reports and literature reviews were published on the relationship between climate factors and health-related concerns. Two examples are the 2021 LANCET Countdown report[20] and the WHO COP26 report,[21] both of which discuss the relationships between climate and numerous health areas while emphasizing the importance of greater understanding and action. The existing body of research on climate and health has the potential to be further augmented by AI/AA methods.

To avoid duplicate efforts, this report builds on the comprehensive findings in the USAID reports AI in Global Health and Data and Advanced Analytics in HIV Service Delivery: Use Cases to Help Reach 95-95-95, both of which explore the intersection of AI/AA and health in detail.

Despite its potential, the intersection of AI/AA, climate, and health—the center of the diagram in Figure 3—remains quite nascent because the requisite data, analytical, and ecosystem conditions may not yet exist, particularly in LMICs. These conditions are thematically aligned with many of the challenges identified in prior USAID efforts, including the aforementioned AI in Global Health report, and are detailed below and in Figure 4.

Data conditions. AI/AA methods generally require data availability in large volumes over time to learn and discover non-obvious relationships. The quality and granularity of this data needs to be high to increase confidence that any insights generated can credibly inform decision-making.

On climate, global climate datasets such as World Meteorological Organization Data Processing and Forecasting System or National Oceanic and Atmospheric Administration tend to have less data from lower resource settings. For example, the Emergency Events Database reports two heatwaves in the last 120 years for sub-Saharan Africa—compared to 83 in Europe in the last 40 years alone—despite the latest empirical evidence and predictions for heatwaves in sub-Saharan Africa that certainly total more than two.[22] Moreover, global climate datasets are often re-analysis products that are difficult to reliably downscale to local contexts.

On health, despite concerted efforts in recent years to improve data collection (i.e., tools, processes, systems)

16 Katia Moskvitch, Larry Greenemeier, "IBM Research's AI-driven risk and impact predictions help businesses adapt to climate change," *IBM*, November 23, 2021.
17 Bernard Marr, "How Artificial Intelligence Can Power Climate Change Strategy," *Forbes*, January 4, 2021; Jordan Abell, Gisela Winckler, Robert Anderson, et al, "Poleward and weakened westerlies during Pliocene warmth," *Nature* 589 (2021): 70–75.
18 ClimateAI, webpage, accessed February 2022.
19 C. Caminade, K.M. McIntyre, A.E. Jones, "Impact of recent and future climate change on vector-borne diseases," *Animals of the New York Academy of Sciences* 1436, no.1 (2019): 157–173.
20 Lancet, 2021.
21 WHO, 2021.
22 Marlowe Hood, "Deadly under-the-radar heatwaves ravaging Africa," *Phys*, July 13 2020

and some convergence among global health stakeholders on priorities for digital initiatives in health (i.e., The Principles of Donor Alignment for Digital Health),[23] challenges persist on health data availability, quality, and granularity. Some health datasets in LMICs are available at the district level; achieving district-level granularity—or granularity at a household or 1km-by-1km level in order to credibly target interventions—will likely remain a significant barrier.

Analytical conditions. AI/AA methods require a foundational literacy in the relevant terminology and a proficiency in reading and translating outputs to decision-making in real-world settings—otherwise, the value-add is just theoretical. Current analytical capabilities for AI/AA methods remain concentrated in higher-income countries and organizations therein, though some initiatives are emerging to address this gap. For example, the National Institutes of Health (NIH) recently invested approximately $75 million for public health data science research and training focused on Africa.[24]

Moreover, this effort found that there are relatively few experts anywhere in the world at the intersection of AI/AA, health, and climate. As one expert observed, *"The AI, climate, and global health worlds are so far apart that bridging understanding between them would be a huge first step forward."*

Ecosystem conditions. To develop AI/AA use cases for climate and health, an increased awareness of examples of AI/AA use cases for climate and health that created tangible value is needed—which this report synthesizes in the next section.

To raise this awareness and drive future action, forums for continuous engagement are required to bring together disparate AI/AA, climate, and health stakeholders. Recent convening, such as the United Nation's AI for Good Global Summit, which included academic researchers, policymakers, and business leaders, have sparked early conversations about AI/AA, climate, and health, potentially resulting in one-off initiatives or grants.[25] The aforementioned NIH investment also includes the establishment of a consortium between public, private, and social sector actors led by African institutions. But, as one expert emphasized, *"Today, the big gap is that connection between the AI climate models and the public health response. The justification for investing in AI models is not that we could have predicted an event more accurately but that we can optimize a health strategy before an event happens."* Achieving that outcome and at scale will require recurring and sustained engagement across an ecosystem of currently disparate stakeholders.

Figure 4: Conditions for AI/AA methods in climate and health remain challenging

Conditions for AI/AA methods		What we heard from expert interviews
Data	Data availability in large volumes over time Data quality and granularity	• "Most climate models rely on re-analyzed data rather than continuous data feeds from local weather stations, which provides misleading results when downscaled and not well calibrated" • "You need large-scale, biomedical datasets for AI to work, which may not exist especially going back in time, or cannot be shared given privacy considerations" • "Quality of climate and health datasets varies, and at times, the data we have is mismatched with policy timelines, which limits what decisions any AI model can credibly inform"
Analytical	Foundational literacy of AI/AA methods Proficiency in reading and translating outputs	• "There is a push for more data-informed decision-making in global health and development, but very basic analytical skills are still fairly limited in many contexts" • "Important to explain what AI is and can or cannot do, so that it is not a 'black box'" • "The AI, climate, and global health worlds are so far apart that bridging understanding between them would be a huge first step forward"
Ecosystem	Awareness of tangible AI/AA use cases that add value Forum for continuous stakeholder engagement	• "The math is advanced enough to build useful models, and a lot of climate and health applications are low-hanging fruit; we need to get better at explaining this to policymakers" • "A lot of work must be done to gain buy-in from in-country stakeholders before AI models will be trusted to inform decisions that impact human health" • "AI, climate, and health topics can and have all been politicized, so it is particularly important to keep talking about issues of transparency, sovereignty, and equity"

23 Digital Investment Principles webpage, accessed January 2022.
24 "NIH awards nearly $75M to catalyze data science research in Africa," *NIH*, October 26, 2021.
25 NIH, 2021.

5.2 Existing Use Cases Largely Focus on Vector- and Water-Borne Diseases

Examples of AI/AA use cases for climate and health successfully deployed in LMICs tend to fall into the scope of describing and predicting vector- and water-borne diseases (see Figure 5).[26] In some instances, AI/AA methods may **recommend** interventions by simulating the outcome of different intervention scenarios, though human judgment determines the final action taken.

- Epidemic Prognosis Incorporating Disease and Environmental Monitoring for Integrated Assessment (EPIDEMIA) is a machine learning model that uses climatic variables (i.e., rainfall, land surface temperature, vegetation index) from Google Earth Engine and disease surveillance data to create a malaria early warning system. Health partners in the Amhara region of Ethiopia piloted this system to inform resource allocation decisions several weeks in advance. For further details, refer to USAID's technical report, Malaria Early Warning in Ethiopia: A Roadmap for Scaling to the National Level.[27]
- The Ministry of Health in Peru, in collaboration with NASA and other partners, uses AI-enabled models to predict malaria outbreaks 12 weeks in advance and down to the household level by leveraging the Land Data Assimilation System (LDAS) that incorporates precipitation, temperature, soil moisture, and vegetation data. These models also simulate different intervention scenarios—such as deploying long-lasting insecticidal nets, conducting indoor residual spraying, and administering anti-malarial treatments—that inform the Ministry of Health's decision-making.[28]
- Dengue forecasting MOdel Satellite-based System (D-MOSS) is a machine learning model that uses Earth Observation data on seasonal forecasts of water availability at a catchment scale to predict dengue outbreaks several months in advance. It is used as a dengue early warning system in Vietnam and being scaled to seven countries across South and Southeast Asia.[29]
- Following the 2016 hurricane in Haiti, Médecins Sans Frontières and École Polytechnique Fédérale de Lausanne developed an AI-enabled model to predict cholera cases in Haiti using a broad range of data including rain forecasts, the latest recorded cases, and people flows. This model helped inform the WHO's decision to run a vaccination campaign in southern Haiti.[30]

These use cases exist because the requisite data, analytical, and ecosystem conditions are in place in some geographies. The relationship between precipitation and vector- and water-borne diseases is relatively well-studied compared to other climate-sensitive health risks. For climate data, Earth-observing satellite data includes precipitation, which can be verified relatively easily. For health data, many governments and partners have invested in disease surveillance systems, such as for malaria case data. On analytics, academic and applied research on vector- and water-borne diseases have built global and in-country capacity for conventional methods—like regression analysis—and increasingly advanced ones—like Oxford Humbug using acoustic monitoring of mosquito flight tones, an AI/AA method, to determine the number and species of mosquitos, currently being piloted in the DRC and Tanzania. Finally, some vector- or water-borne diseases, such as malaria, have a well-developed ecosystem of committed stakeholders that continuously engage with new evidence and interventions—including those enabled by AI/AA methods.

By contrast, relatively few examples of AI/AA use cases for other climate-sensitive health risks—such as heat-related illnesses—have been deployed in LMICs, where the climate-health linkages remain poorly understood. In high-income countries, there are some early examples that leverage AI/AA methods to better **describe** and **predict** those linkages. For example, NASA's Earth Science division developed a machine learning model to understand the relationship between extreme heat and illness in New York, based on retroactive data, which led to lowering a heat advisory threshold as a policy change.[31] Similarly, researchers in Korea developed a random forest model (i.e., supervised machine learning algorithms) that predicted past heat-related morbidity more accurately than conventional analytical models.[32]

26 "Landscape mapping of software tools for climate-sensitive infectious disease modelling," *Wellcome Trust*, January 24, 2022.
27 *Malaria Early Warning in Ethiopia: A Roadmap for Scaling to the National Level*, USAID, May 2021.
28 "Using NASA Satellite Data to Predict Malaria Outbreaks," *NASA*, 2017.
29 "D-MOSS: Dengue forecasting Model Satellite-based System," HR Wallingford webpage, accessed February 2022.
30 Sandrine Perroud, "Fighting cholera by predicting how it spreads," *EPFL News*, October 2016.
31 "NASA Helps New Yorkers Cope with Summer Swelter," *NASA*, August 13, 2020.
32 Minsoo Park, Daekyo Jung, Seungsoo Lee, et al, "Heatwave Damage Prediction Using Random Forest Model in Korea," *Applied Sciences* 10, no. 22 (2020): 8237.

Figure 5: Existing AI/AA use cases at the intersection of climate and health

Illustrative, non-exhaustive

WHO climate-sensitive health risk	Selected example	Describe	Predict	Recommend
Vector-borne disease: malaria	EPIDEMIA: Malaria prediction model currently being used in Amhara, Ethiopia	✓	✓	✓
	MEWS: Malaria prediction model currently being used in Peru	✓	✓ → *Future iterations may help to recommend*	✓
	SCOPIC: Malaria prediction model currently being used in North Guadalcanal, Solomon Islands	✓	✓	✓
	Malaria Prediction and Planning Tool: Malaria prediction model currently being implemented in Odisha, India	✓	✓ → *Future iterations may help to recommend*	✓
	VECTRI: Malaria prediction model currently being piloted in Africa	✓	✓	
	Imperial College, London: Maps quantifying geographic spread of insecticide resistance	✓	✓	
	HumBug: Acoustic monitoring of mosquito flight tones to determine number and species, currently being piloted in the DRC and Tanzania	✓ → *Future iterations of model may help to predict and recommend*		
	Abuzz: Citizen-based mosquito monitoring system to determine geographic distribution of disease-carrying mosquitoes	✓		
Vector-borne disease: dengue	D-MOSS: Dengue prediction model currently being used in Vietnam and scaled across seven countries in South and Southeast Asia	✓	✓	✓
Vector-borne disease: multiple	AeDES: Forecasting transmission of diseases carried by Aedes mosquitoes (i.e., dengue, Chikungunya, Zika) across the Americas	✓	✓	
	BlueDot: Using travel and mobility data to sound early alarm for COVID-19 and Zika and identify future epicenters; used by policymakers in Taiwan to inform response	✓	✓	✓
Water-borne disease: cholera	Forecasting cholera outbreak in Yemen; being used by UNICEF and DFID to inform allocation of preparedness and support measures	✓	✓	✓
	Médecins Sans Frontières and École Polytechnique Fédérale de Lausanne forecasting cholera cases in Haiti; used by WHO to inform response	✓	✓	✓
Foodborne disease	Foodborne Disease Monitoring and Reporting System: Predicting risk of foodborne disease outbreaks in China	✓	✓	
Heat	NASA's Earth Science division: Model to understand the relationship between extreme heat and illness in New York, based on retroactive data; led to the heat advisory threshold being lowered	✓		✓
Respiratory illness	Air Pollution Health Effects: Tool to examine how climate factors (i.e., temperature, humidity) impact the relationship between air pollution and respiratory illnesses in India	✓		

Current state[1] ✓ *Involves AI/AA method* ✓ *Involves other analytical approaches* ✓ *Actions determined by human judgement*

1. Based on publicly available data; Source: Ecograph research group website: EPIDEMIA model; Duke Newsroom; Solomon Islands Govt Newsroom; Malaria NoMore website; Alekh report (Dec 2021)

5.3 Why Now

Stakeholders across sectors have recently been engaging more on AI/AA, climate, and health topics.

- On AI/AA, as data from all industries and geographies continues to proliferate in a hockey stick shape, new analytical methods are being developed in academic and applied settings. USAID recently released its first ever Artificial Intelligence Action Plan, noting the potential for AI methods to help address the United Nations (UN) Sustainable Development Goals.[33]
- On climate, recent global commitments to understanding and addressing the impacts of climate change have resulted in new funding, such as the pledges made at COP26 from public and private sector sources to reduce emissions and finance adaptation and mitigation efforts.[34] In addition, the U.S. government announced an ambitious set of targets to advance the President's Emergency Plan for Adaptation and Resilience—the largest United States commitment ever made to reduce the global impacts of climate change on the most vulnerable—reinforced by USAID's 2022–2030 Climate Strategy.
- On health, more than 70 countries have developed or are developing national e-health or digital health strategies as of 2015, while USAID's recently released 2020–2024 Vision for Action in Digital Health charts a course to sharpen the agency's investments in health-sector digital technologies.[35] If there was doubt before, the COVID-19 pandemic has reinforced the importance of global health security and equity and the need for more targeted and adaptive decision-making informed by data.[36]

Given this recent confluence of global attention, now is the time to deploy value-adding AI/AA use cases at the intersection of climate and health. According to one expert, *"We should be exploring the huge interconnection between climate and health in much greater depth with all the tools that we have at our disposal."* Improved capabilities to **describe**, **predict**, and **recommend** can contribute to more effective climate adaptation actions that address global health security and equity. This principle is a strategic objective outlined in USAID's 2022–2030 Climate Strategy and further detailed in its accompanying Guidance for Mainstreaming Climate Change Considerations into Global Health Programming. As described in the recent IPCC report and reiterated by one expert, *"Things are already happening now [in climate and health] that we didn't think would, so we need to develop practical models to help us understand and act fast."* This report believes, moving forward, there is value in implementing more AI/AA use cases for climate and health and in having more experts at the intersection of the three domains.

33 *Artificial Intelligence Action Plan,* USAID, May 3, 2022.
34 Lindsay Maizland, "COP26: Here's What Countries Pledged," *Council on Foreign Relations*, November 15, 2021.
35 "Health Systems and Innovation: Data," USAID, accessed February 2022; *A Vision for Action in Digital Health 2020–2024*, USAID, 2020.
36 "Spending for COVID-19 drove largest recorded increase in development assistance for health, but more is needed," *IHME*, September 22, 2021.

6. Recommendations to deploy AI/AA use cases for climate and health

6.1 Two Complementary Action Pathways for Stakeholders

As described in Section 4, AI/AA methods present opportunities to augment the global community's current capabilities to address the existential problems posed by climate-sensitive health risks. Section 5 details the data, analytical, and ecosystem conditions required to deploy AI/AA uses cases for climate and health and highlights examples of successful implementation in LMICs.

The time to act is now, but there is no single correct action given the nascent intersection of these domains. **To that end, this report recommends two action pathways to deploy AI/AA use cases at the intersection of climate and health, particularly in LMICs, drawing inspiration from detailed case studies.**

- Pathway I: Invest in enablers for data, analytical, and ecosystem conditions that are applicable across climate-sensitive health risks
- Pathway II: Take action on a specific climate-sensitive health risk based on a high-level maturity assessment

These pathways are intended to be complementary, not mutually exclusive. Stakeholders may be interested in exploring investments in one or both, depending on their organizations' mandate, strategic objectives, and areas of expertise. They were developed based on the aggregate input of technical experts from across sectors and geographies, supplemented by extensive secondary research.

6.1.1 Pathway I: Enablers Applicable Across Climate-Sensitive Health Risks

This action pathway focuses on enabling investments that improve the data, analytical, and ecosystem conditions required to deploy AI/AA use cases across climate-sensitive health risks (see Section 5.1). This pathway is sometimes referred to as a "platform approach"—focusing on AI/AA methods as a platform to improve health outcomes rather than focusing on a specific disease area. Enablers are detailed below and in Section 6.1.1.1.

Increase the usable climate and health datasets required for AI/AA methods

- Support data collection tools and programs that improve data availability, quality, and granularity (e.g., develop and install remote sensors for climate data, install voice-driven AI phone feature for health workers)
- Advocate and provide technical assistance for data interoperability and sharing across stakeholders (e.g., establish open API data platforms, define standards and processes)

Build capabilities to develop and translate the outputs from AI/AA use cases for health decision-making

- Invest in practical, user-friendly analytical tools that can be used by those with varying levels of technical expertise (e.g., that use freely available software, accessible language, and visualizations)
- Build AI/AA capacity of relevant in-country users (e.g., establish AI-climate-health "academy", fund PhD and postdoc programs on AI-climate-heath)

- Encourage cross-functional expertise in decision-making (e.g., embed AI/AA experts from academia or the private sector in government)

Foster continuous engagement between the ecosystem of AI/AA, climate, and health stakeholders

- Make funding available to pilot high-potential AI/AA use cases for climate and health
- Convene AI, climate, and health leaders on an ongoing basis to establish an active and collaborative community of practice
- Track ongoing efforts across stakeholders with potential to share learnings and make targeted introductions

If a stakeholder believes in harnessing the broad potential of AI/AA methods, then their investments may fall in this pathway. For example, some funding organizations believe that improving data, building capacity, and convening the stakeholder ecosystem will improve health decision-making and can allocate funding accordingly without a specific disease or programmatic focus. This may also be the case for AI/AA experts at academic research institutions and private sector companies who invest their time and organizational budgets in proving the value of AI/AA methods for any or many climate-sensitive health risks. Moreover, in some LMICs, there are government entities that focus on improving the conditions for evidence-based decision-making (i.e., information management or M&E teams under the Ministry of Health, data analytics team under the Ministry of ICT, Central Delivery Unit).

CASE STUDIES

6.1.1.1 Enabling Data, Analytical, and Ecosystem Conditions

Given the nascence of the intersection between AI/AA, climate, and health, there are limited examples of initiatives that improve the data, analytical, and ecosystem conditions outlined in Figure 4, though we can draw inspiration from initiatives in non-health sectors. For example, the Consultative Group for International Agricultural Research (CGIAR)—a global research partnership for a food secure future—launched a Platform for Big Data in Agriculture where disparate stakeholders could work toward a shared goal of equitable rural development through cross-cutting investments in open data and big data analytics between 2017 and 2022.[37]

- Aims to organize a platform for consistent open data, convene stakeholders to produce innovative solutions, and inspire the broader ecosystem by demonstrating the power of big data analytics through pilots and scaled solutions
- Leverages the 15 CGIAR Research Centers with strong footprints in LMICs, 12 relevant Research Programs, and nearly 50 external partners from academic research institutes (i.e., Columbia University), multilateral organizations (i.e., the World Bank group), and private sector companies (i.e., Google, IBM, Novogene)
- Improves data conditions by creating a "data harvester" function that encourages stakeholders to discover publications from across all CGIAR Centers and offers a data science platform for researchers to work on securely transferred datasets, among other initiatives
- Improves analytical conditions by providing educational webinars, resources, and templates to improve data management and interoperability, among other initiatives
- Improves ecosystem conditions by launching an innovation challenge with initial seed funding for pilots and follow-on funding for scale-up, as well as hosting an annual convention for big data practitioners and food security stakeholders who may not otherwise meet, among other initiatives

Specific to AI/AA, climate, and health, initiatives are emerging in higher-income countries to invest in cross-cutting enablers that improve data, analytics, and ecosystem conditions.

- For example, the European Climate and Health Observatory is a partnership between the European Commission, the European Environment Agency, and other organizations. It aims to prepare for and adapt to the impacts of climate change on human health in Europe by consolidating existing datasets,

37 CGIAR webpage, accessed January 2022.

publications, and tools while fostering engagement across relevant global, European, national, and non-state actors (i.e., ecosystem conditions). It is in its pilot stage and focused on compiling cross-cutting resources from partner organizations, with the eventual goal of developing new tools to contribute to the ecosystem.[38]

- Another example is NIH's Climate Change and Health Initiative, a cross-cutting effort to reduce health threats from climate change. While still in its early stages, the initiative's strategic framework for designing testable interventions for climate and health emphasizes data analytics as a core tenant. It also invests in data, analytical, and ecosystem conditions by consolidating a data and literature portal, launching a transdisciplinary seminar series, and involving participating institutes and centers, respectively.[39]

Furthermore, there are emerging initiatives for cross-cutting enablers that are more oriented toward stakeholders in LMICs.

- For example, the Lacuna Fund is a collaborative, local-first initiative to provide data scientists, researchers, and social entrepreneurs in low- and middle-income contexts with the enabling resources to produce labeled datasets that solve problems in their respective communities. In April 2022, it launched a request for proposals for open dataset creation, aggregation, maintenance, and analytics by and for local communities to understand and address the impacts of climate change on health outcomes. These proposals will be supported by a consortium of funders, including The Rockefeller Foundation, the Wellcome Trust, the German Federal Ministry for Economic Cooperation and Development (BMZ), FAIR Forward (a German Development Cooperation initiative), and Google.org.[40]
- Another encouraging example is the Wellcome Trust's pledge in 2021 of more than $100 million in initiatives. These include the creation and improvement of longitudinal population studies in the United Kingdom and across LMICs to enable integration between climate and health datasets, as well as the landscaping of 37 software tools for climate-sensitive infectious disease modelling and recommendations for funders to continue investing in tools, capacity building, communication between modelers and decision-makers, and policies that encourage data sharing and collaboration.[41]

38 European Climate and Health Observatory webpage, accessed April 18, 2022.
39 *Climate Change and Health Initiative Strategic Framework*, NIH, February 2022.
40 Lacuna Fund webpage, accessed February 2022.
41 "Longitudinal Population Studies Strategy," *Wellcome Trust*, July 2017; Wellcome Trust, 2022.

6.1.2 Pathway II: Action for a Specific Climate-Sensitive Health Risk

This action pathway identifies the most appropriate next action for each specific climate-sensitive health risk. If a stakeholder is programmatically-oriented then their investments may fall in this pathway. For example, some funding organizations have a specific disease focus and they are testing whether AI/AA methods can be a new tool in the toolkit to implement as part of a disease program. This may also be the case for researchers and policymakers focused on a specific disease area—such as an epidemiologist on a Neglected Tropical Disease research team focused on Chikungunya virus or a National Malaria Control Program within a Ministry of Health.

The appropriate next action may differ from one climate-sensitive health risk to another. **This report outlines a high-level assessment to determine the most appropriate next action for each of the nine WHO climate-sensitive health risks, based on the health problem, current capabilities, and near-term AI potential.** The methodology is described below and in further detail in the Appendix, which includes data sources used.

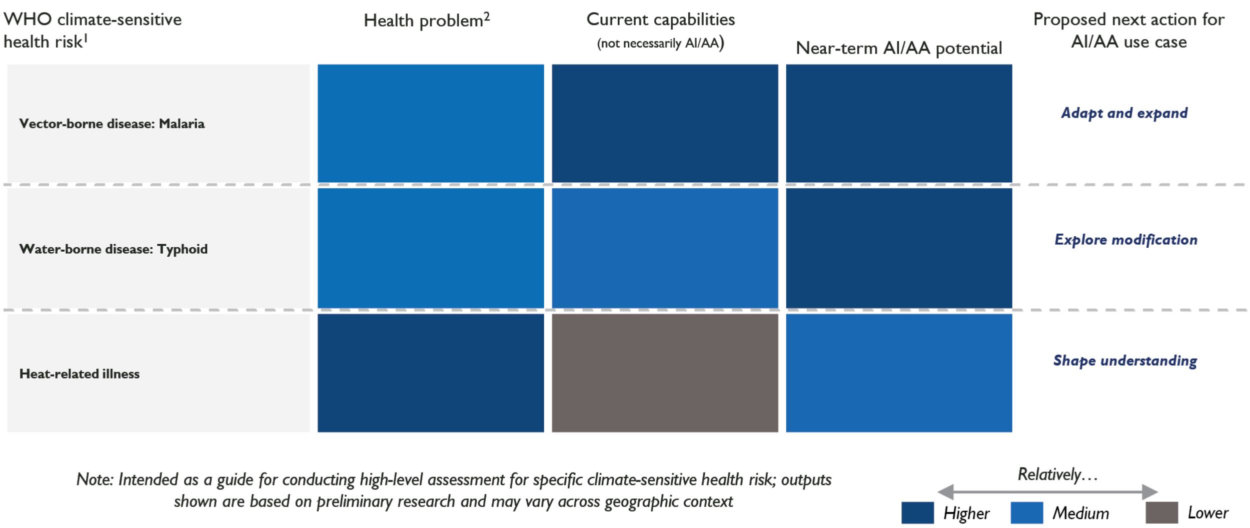
- **Health problem** is the scope of the problem of a climate-sensitive health risk relative to others. This considers the burden of disease (i.e., DALYs in LMICs and whether these DALYs disproportionately impact vulnerable groups), future trajectory (i.e., whether the disease burden will increase according to the latest IPCC reports), and secondary effects (i.e., how disruptive the impacts are). Taken together, the problem is rated as relatively higher (darker blue), medium (medium blue), or lower (grey). AI/AA use cases are likely more appropriate to deploy for climate-sensitive health risks that pose a relatively greater problem.
- **Current capabilities** are any analytical methods—not necessarily AA/AI—currently used to describe the climate-health linkages, predict scenarios accurately, and recommend interventions for a climate-sensitive health risk relative to others. It is rated as relatively higher (darker blue), medium (medium blue), or lower (grey) to help determine the most appropriate AI/AA use cases—for example, if almost no understanding exists of how climate impacts a disease, then the AI/AA method might focus on learning and looking for patterns across disparate datasets.
- **Near-term AI potential** is the likelihood that an AI/AA method can add value in a real-world setting in the near-term for a climate-sensitive health risk relative to others. It is rated as relatively higher (darker blue), medium (medium blue), or lower (grey). To illustrate, relatively higher looks like a climate-sensitive health risk that already has examples of AI/AA models deployed by policymakers in LMICs.
- The high-level assessment intends to provide practical, directional guidance. Details may vary depending on the specific disease, geography, or operating context, and further analyses may need to take place building on the high-level assessment before successfully deploying an AI/AA use case.

Based on this high-level assessment, the appropriate next action for each specific climate-sensitive health risk is one of the actions described below. Further detail is in Section 6.1.2.1 and the Appendix of this report.

- **Adapt and expand** AI/AA use cases where the climate-health linkages are better understood and where there are examples of AI/AA models effectively deployed in LMICs—such as for vector-borne diseases like malaria and dengue and water-borne diseases like cholera. The high-level assessment results here are at least medium (medium to darker blue) for health problem, higher (darker blue) for current capabilities, and higher (darker blue) for near-term AI potential.
- **Explore modification** where the climate-health linkages are at least somewhat understood and where experts believe that existing AI/AA models deployed in similar contexts have the potential be to modified—such as from one vector-borne disease model to another (Chikungunya) or water-borne disease model to another (typhoid). The high-level assessment results here are at least medium (medium to darker blue) for health problem, medium (medium blue) for current capabilities, and higher (darker blue) for near-term AI potential.
- **Shape understanding** where climate-health linkages are poorly understood, or there are few or no known examples of AI/AA models deployed in LMICs, but where experts believe that AI/AA methods have the potential to augment capabilities to describe, predict, and recommend—such as for heat-related illnesses, extreme weather-induced injury, and zoonoses. The high-level assessment results here are at least medium (medium to darker blue) for health problem, lower (grey) for current capabilities, and medium (medium blue) for near-term AI potential.
- For some climate-sensitive health risks, propose no immediate next action for AI/AA use cases, especially if the health problem is relatively less pressing for LMICs or the near-term potential AI is unclear and may benefit from seeing how the field evolves to make a more targeted investment.

Recall that investments in this pathway—while more specific and targeted to each climate-sensitive health risk—can complement those in Pathway I. Deploying an AI/AA use case for a specific climate-sensitive health risk can, in turn, improve the overall data, analytical, and ecosystem conditions that may allow for more AI/AA methods to work in general.

Figure 6: High-level assessment for <u>specific</u> climate-sensitive health risks to determine the appropriate next action for AI/AA use cases



1. Classification of health risks developed by WHO; in some instances health risks may be related or overlap; 2. As associated to changes in climate factors
Source: IHME Global Burden of Disease Database (2019); IPCC Human Health Report; Climate change and health (WHO, 2021); Stakeholder interviews (Dec 2021, Jan 2022); BCG analysis

CASE STUDIES

6.1.2.1 Adapt and Expand, Explore Modification, Shape Understanding

Adapt and Expand: Malaria

Health problem: Medium. Malaria remains a significant health problem. It is still a leading cause of death in sub-Saharan Africa, with the burden disproportionately impacting pregnant women, infants, and other vulnerable populations.[42] While the latest long-term forecasts do not predict a significant increase in malaria incidence, climate change may result in a different map of endemic regions or mosquito types and put communities at risk, including those that may not be as prepared for malaria control activities or where existing interventions may not be as effective.[43]

Current capabilities: Relatively higher. The global health community is currently able to describe, predict, and recommend interventions for malaria reasonably well using more conventional and AI/AA methods, as compared to other climate-sensitive health risks. The correlation between climate factors and malaria transmission is well-studied—for example, how precipitation can result in standing water in which mosquitoes breed—though there is potential to deepen understanding, such as precipitation thresholds on larval habitats.[44] There is capability to predict at least the seasonality of malaria transmission through the timing of the rainy season, though there is potential to improve the accuracy of predictions across different time horizons to recommend interventions. Current interventions to prevent, diagnose, and treat malaria exist, with potential for improvement given the threat of drug and insecticide resistance and the constraints of malaria decision-making timeframes—for example, procurement often occurs annually rather than dynamically in more real-time.[45]

42 "Malaria Fact Sheet," *WHO*, April 6, 2022.
43 IPCC, 2018.
44 IPCC, 2018.
45 "Global Malaria Programme," WHO, accessed February 2022.

Near-term AI potential: Relatively higher. Policymakers in LMICs are already using AI/AA models to inform decision-making. Refer to Section 5.2.

Summary. **For malaria as a specific vector-borne disease, the appropriate next action is to adapt and expand AI/AA use cases, especially compared to other climate-sensitive health risks.** It is important to stress the need to adapt because adjustments are required to continuously improve models used to inform decisions in real-world settings, especially at scale. Recalibration, reparameterization, or model restructuring may be required to adapt existing climate-based malaria risk models to the intended disease transmission settings, population/demographics, and ecoclimatic conditions.

Explore Modification: Typhoid

Health problem: Medium. Typhoid presents a notable health problem. The 11 million to 20 million annually confirmed cases disproportionately impact children and other vulnerable populations, such as those living in informal urban settlements and areas with limited access to clean water and sanitation systems.[46] The latest long-term forecasts predict an increase in typhoid, in part due to climate change-related extreme weather events. These events may result in more typhoid and further strain the health and related systems—like sanitation—required to address patients with typhoid.

Current capabilities: Medium. The global health community can describe, predict, and recommend interventions for typhoid reasonably well using more conventional and AI/AA methods compared to other climate-sensitive health risks. The correlation between climate factors and the transmission of Salmonella typhi bacteria is relatively well understood. There is capability to predict the seasonality of extreme weather events that often precede outbreaks, such as flooding. Current interventions for typhoid exist, including vaccines and antibiotics, though resistance to examples of the latter, such as fluoroquinolones, is increasing.[47]

Near-term AI potential: Relatively higher. Policymakers in LMICs are already using AI/AA models for other water-borne diseases such as cholera to predict and plan for outbreaks.[48] Experts with knowledge of AI, climate, and health believe that typhoid may have similar climate-health linkages and that it would be worthwhile to explore whether modification to existing AI/AA models such as those used for cholera can be credibly applied to inform decision-making for typhoid.

Summary. **For typhoid as a specific water-borne disease, the appropriate next action is to explore modification of AI/AA models that have been deployed in similar contexts.** As one expert said, *"The AI algorithm part of the model is not uncommon in climate and epidemiological research and can be tweaked for other diseases in the same geographic setting."*

Shape Understanding: Heat-Related Illnesses

Health problem: Relatively higher. Heat is a serious and growing health threat with potentially disruptive impacts beyond health. The current burden of heat-related illnesses is difficult to ascertain as health outcomes are not consistently attributed to heat. For example, while excess mortalities and increased emergency department visits were observed during the 2021 Seattle heatwave, the full impact was likely underestimated given that ICD codes and clinical guidelines have not been designed to systematically capture this information.[49] Long-term forecasts predict a substantial increase in extreme heat events, with empirical evidence suggesting that extreme heat disproportionately impacts the elderly, the young, pregnant women, comorbid populations, and agricultural workers.[50] According to a recent UN report focused on Latin America, low-income urban dwellers living in informal houses are highly susceptible to heatwaves yet have the least access to health services across many cities such as Bogota, Mexico City, and Santiago.[51] Heat may also present disruptive secondary effects on health given its impacts on agriculture, infrastructure, energy, and cross-border migration. The World Meteorological Organization estimates that Africa's GDP may risk a 2% to 12% decrease depending on the extent to which temperatures rise.[52]

46 "Typhoid Fact Sheet," *WHO*, January 31, 2018.
47 WHO, 2018.
48 EPFL, 2016.
49 Rebecca Falconer, "Study: Pacific Northwest heat wave 'virtually impossible' without climate change," *Axios*, July 8, 2021.
50 Lancet, 2021; IPCC, 2018.
51 UN ECLAC and Government of the Republic of Korea, 2021.
52 Peter Yeung, "Africa's First Heat Officer Faces a Daunting Task," *Bloomberg*, January 21, 2022.

Current capabilities: **Relatively lower.** The causal pathways and compound impacts between heat and human health are not yet well understood. Current capabilities to even describe this climate-sensitive health risk are limited, much less to predict scenarios accurately or to recommend interventions. Some early warning systems have been used to predict heat waves in higher-income countries. For example, policymakers in France used a heat wave early warning system to issue public notices and to give lead time for health facilities to prepare for a 2006 heatwave, which is attributed to the prevention of about 4000 deaths.[53] Still, one challenge for heat is that there are few existing interventions. For example, air conditioning units may be inaccessible in many LMIC contexts and exacerbate heat concerns if not powered by clean energy; and sleeping outdoors at night may not be a viable alternative as cooling periods shorten, as has already been observed in parts of India and Pakistan—especially given this can increase exposure to other health risks such as vector-borne diseases.[54]

Near-term AI potential: **Medium.** Policymakers are starting to recognize the unique value proposition of AI/AA methods for heat, at least in higher-income countries. For example, a NASA machine learning model correlated temperature data with emergency department visits in New York to understand the impact of heat on various illnesses. This led policymakers to lower the temperature threshold for a heat advisory warning.[55]

Summary. **For heat-related illnesses, the appropriate next action is to develop and deploy AI/AA use cases to shape understanding of heat, which presents too much of a health threat to remain poorly understood, particularly in LMICs.** AI/AA methods can build on existing academic research on heat-related illnesses—for example, acute cardiac events, kidney disease, or premature birth and birth defects—to discover non-obvious relationships and identify surrogate markers for heat injury. While data availability, accuracy, and granularity will be a significant barrier, especially in LMICs, this report aims to shine a light on this topic and to catalyze initial engagement on describing, predicting, and recommending better interventions.

53 IPCC, 2018.
54 "Heatwave across India," *European Space Agency*, April 29, 2022.
55 NASA, 2020.

7. Path forward

7.1 Shared Principles to Guide Action

Early investments in the aforementioned action pathways can create trust in and demonstrate the value-add of AI/AA methods or risk the opposite. As one expert noted, there is *"a lot of work to be done to gain buy-in from in-country stakeholders before AI models will be trusted to inform decisions that impact human health."* To that end, this report offers shared principles to guide future actions on AI/AA use cases for climate and health.

1. *Be demand-driven, focusing on areas of high health impact and clear value from AI/AA methods.* Stakeholders should focus on AI/AA use cases that can drive impact, particularly for underserved or vulnerable groups. Being demand-driven involves clearly communicating the benefits and limitations of AI/AA to relevant stakeholders, such as what decisions can or cannot be credibly informed by a specific model, and co-creating AI/AA use cases with local stakeholders that are value-adding and user-friendly, like being in the required language or using accessible software. In accordance with this principle, stakeholders should opt for non-AI/AA methods when they provide a comparable benefit at a lower cost—being thoughtful about when not to use AI can also contribute to trust.
2. *Enhance equity and fairness through responsible data management.* Stakeholders should be transparent about data collection and ownership of data and models across all relevant parties, manage data and models with the utmost integrity, and strive to mitigate bias and improve accuracy with representative datasets where possible. It is important for stakeholders to align with and contribute to responsible AI/AA standards and best practices, acting in accordance with existing relevant standards for data usage in global health (i.e., Principles of Donor Alignment for Digital Health),[56] climate (i.e., USAID's 2022–2030 Climate Strategy), and responsible AI (i.e., USAID's AI Action Plan) while acknowledging that specific principles may become more relevant as the space evolves.
3. *Build capacity and contribute to a continuous learning ecosystem.* As climate and health research grow, stakeholders should do what they can to leverage and improve upon existing tools while embedding continuous learning into new tools and processes. Local capacity building occurs throughout, whether it be through upskilling local teams on AI/AA terminology in the near-term, designing feedback loops in AI/AA models for local users to provide ongoing input, or funding use cases with more end-to-end local management. Sometimes, even a seemingly small design choice can build capacity—for example, incorporating a feedback loop within an AI/AA model that asks local users to answer yes/no on whether a predicted climate event (i.e., rainfall) or health event (i.e., dengue case) actually took place.

7.2 Looking Ahead

Without deliberate efforts against these action pathways, there is a risk that AI/AA use cases for climate and health will not be developed at all, which would be a missed opportunity. It is unlikely that the AI/AA use cases described throughout this report will emerge spontaneously. AI/AA, climate, and health stakeholders have not historically worked together, and there are only two experts with deep, technical knowledge across all three domains. **But if technological advancements are taking place, they**

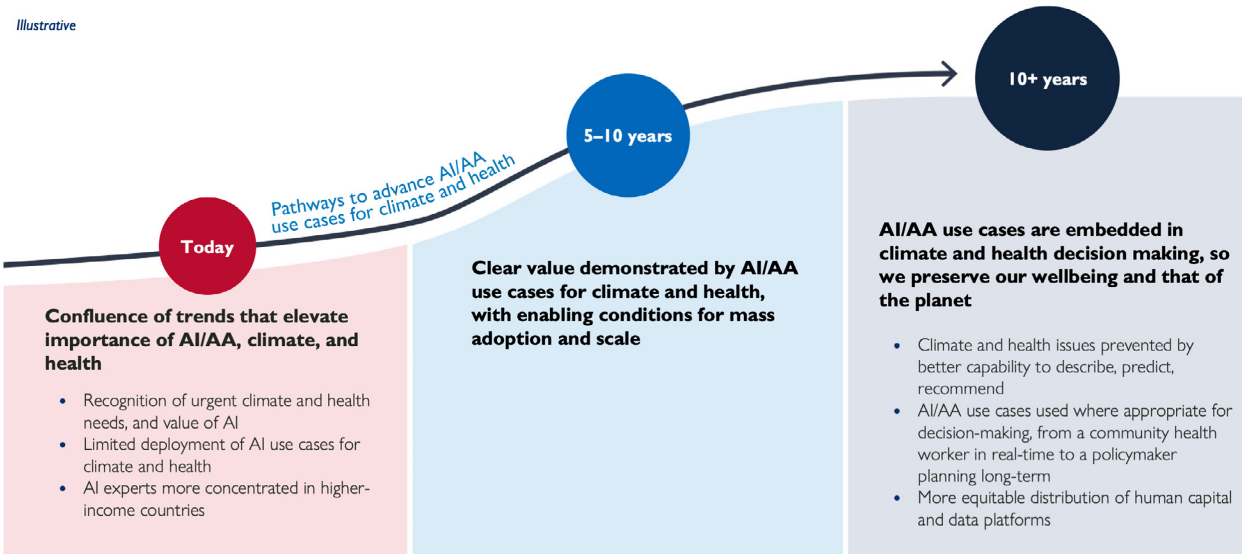
56 Digital Investment Principles, accessed February 2022.

should be applied to existential threats that impact all of us, especially the most vulnerable. As one expert observes, *"The field of global health is transforming, particularly when considering climate factors, and AI offers the potential to help us learn and act with intention."*

Going forward, AI/AA use cases for climate and health are likely to become more accessible and value-adding through principled and sustained efforts. Multi-sector efforts may be required to consolidate and coordinate the necessary expertise, data, tools, and funding to bring these AI/AA use cases to life in LMICs. Fortunately, as one expert notes, *"Today, there already are stakeholders with data that they want to use, stakeholders with tools that they want to apply for good, and stakeholders with funding that they want to deploy effectively—getting people in the same room could lead to a huge step forward, and then even more will come."*

The hope is that this report creates awareness of existing examples of AI/AA use cases and sparks engagement among disparate stakeholders to deploy more. **This decade will be decisive for the future of our planet, and harnessing AI/AA use cases at the intersection of climate and health can contribute to a more resilient, prosperous, and equitable world.**

Figure 7: AI/AA use cases for climate and health are likely to become more accessible and add more value over time



Source: Stakeholder interviews (Dec 2021, Jan 2022); BCG analysis

8. Glossary

AA	Advanced analytics
AI	Artificial intelligence
AI/AA	Artificial intelligence and advanced analytics
BCG	Boston Consulting Group
CII	Center for Accelerating Innovation and Impact
CNN	Convolutional neural networks
COP26	UN Climate Change Conference in Glasgow
COVID-19	Coronavirus disease of 2019
D-MOSS	Dengue forecasting MOdel Satellite-based System
DALY	Disability-adjusted life year
EPIDEMIA	Epidemic Prognosis Incorporating Disease and Environmental Monitoring for Integrated Assessment
EWS	Early warning system
IBM	International Business Machines Corporation
IPCC	Intergovernmental Panel on Climate Change
LDAS	Land Data Assimilation System
LMIC	Low- and middle-income country
M&E	Monitoring and evaluation
NASA	National Aeronautics and Space Administration
NIH	National Institutes of Health
SERVIR	Full stylized name of the NASA program, not an acronym
UN	United Nations
USAID	United States Agency for International Development
WHO	World Health Organization

9. Appendix

9.1 Criteria for High-Level Maturity Assessment in Pathway II

This report outlines a high-level assessment to determine the most appropriate next action for each of the nine WHO climate-sensitive health risks based on the health problem, current capabilities, and near-term AI potential. The methodology is described in Section 6.1.2 and Figure 8.

Figure 8: High-level assessment considers high, medium, or low for each criteria, relative to other climate-sensitive health risks

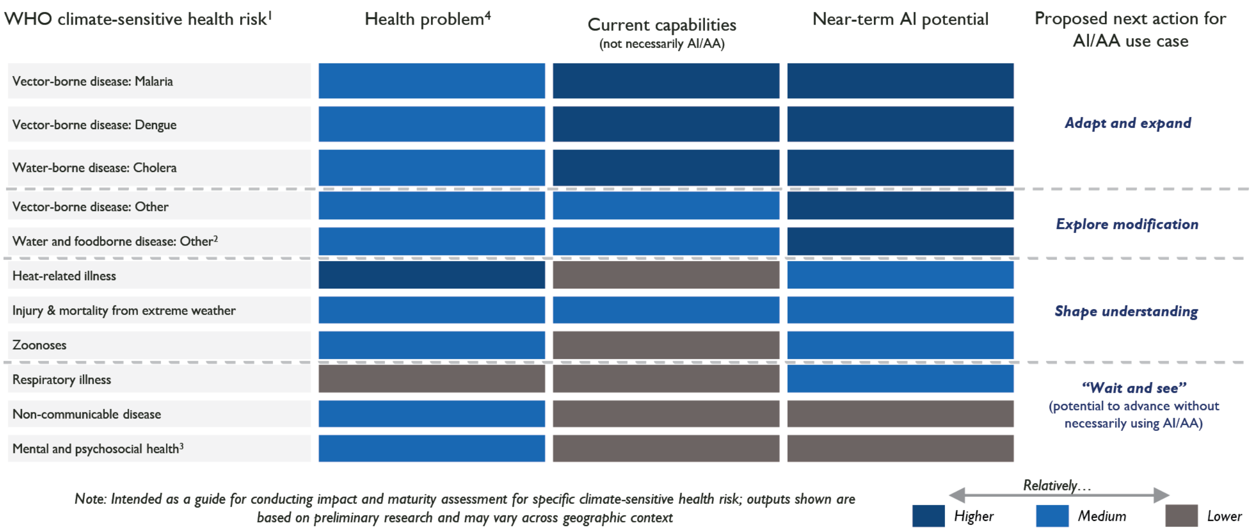
	Health problem			Current capabilities (not necessarily AI/AA)			Near-term AI potential
WHO Climate-sensitive health risk	Current burden[1] and equity considerations	Future trajectory[2]	Secondary effects	Describe	Predict	Recommend	
Low	DALYs <10M and not necessarily impacting the most vulnerable populations	Some increases in risk due to climate change, but largely addressable via mitigation efforts	Impacts are concentrated at individual- or household-level	Limited understanding of causal pathway between climate change and health	Limited ability to predict future outbreaks or events	Few policy interventions to mitigate impact (i.e., no choice but to migrate)	Few existing AI/AA models, have not been tested by policymakers in LMICs
Medium	10M ≥ DALYs ≥ 100M, or DALYs are "low" but largely impact vulnerable populations	Some increases in risk due to climate change, some of which may be addressable via mitigation efforts	Directly or indirectly impacts some sectors and systems	Understanding of some causal pathways of how climate impacts health, but not all	Some ability to predict future outbreaks or events (i.e., in HICs only), with varying accuracy	Some effective policy interventions, but not all issues are addressable with current funding/ capabilities	AI/AA models not currently used by LMIC policymakers, but promising (i.e., used in HICs, have EWS for event itself)
High	DALYs ≥ 100M, or DALYs are "medium" but largely impact vulnerable populations	Large increases in risk across the globe due to climate change, difficult to address via mitigation	Directly or indirectly impacts almost all sectors and systems	Understanding of how specific changes in climate impact health, and most causal pathways	Have predicted some outbreaks or events in real-world settings for LMICs, with improved accuracy	Multiple effective policy interventions to address almost all aspects of issue	AI/AA models of health impact for this or similar health risks in use by policymakers in LMICs

1. Using 2019 DALYs in low or lower middle income countries for disease areas in WHO summary tables (https://www.who.int/data/gho/data/themes/mortality-and-global-health-estimates) that can be readily mapped against the corresponding nine climate-sensitive health risks defined by the WHO (https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health); intended for comparison purposes between climate-sensitive health risks; 2. Relative future trajectory as assessed by the IPCC Human Health Report, supplemented with other sources
Source: IHME Global Burden of Disease Database (2019); IPCC Human Health Report; Climate change and health (WHO, 2021); Stakeholder interviews (Dec 2021, Jan 2022); BCG analysis

9.2 Pathway II Deep Dives

Based on this high-level assessment, the appropriate next action for each specific climate-sensitive health risk is one of the actions described in Section 6.1.2, Figure 9, and below.

Figure 9: Detailed impact and maturity assessment for <u>specific</u> climate-sensitive health risks



1. Classification of health risks developed by WHO; in some instances health risks may be related or overlap; 2. Foodborne illness excludes malnutrition for purposes of this effort; 3. WHO includes substance abuse disorders in this health risk; 4. As associated to changes in climate factors
Source: IHME Global Burden of Disease Database (2019); IPCC Human Health Report; Climate change and health (WHO, 2021); Stakeholder interviews (Dec 2021, Jan 2022); BCG analysis

9.2.1 Adapt and Expand

9.2.1.1 Malaria

- See Section 6.1.2 and Case Studies for a detailed discussion on malaria

9.2.1.2 Dengue

- Rapidly expanding in terms of geography and incidence, with 30-fold increase in global incidence over the past 50 years[57]
- Currently able to **describe** how climate factors are associated with the transmission, **predict** outbreaks based on seasonality, and **recommend** interventions such as insecticide control programs reasonably well[58]
- AI/AA models (i.e., "D-MOSS") have already been used by policymakers in Vietnam to predict outbreaks and inform response, with efforts underway to scale these to other countries in South and Southeast Asia[59]
- Next action is to adapt and expand existing models, such as by adjusting to specific country context and decision-maker needs (e.g., accuracy, granularity, time horizon), and scale usage

9.2.1.3 Cholera

- Approximately 1.3 million to 4 million cases a year, disproportionately impacting children, refugees, and urban residents of informal settlements,[60] with forecasts predicting increase in incidence[61]

57 IPCC, 2018.
58 WHO, 2022.
59 HR Wallingford, 2022.
60 WHO, 2021.
61 IPCC, 2018.

- Currently able to **describe** how climate factors are associated with transmission,[62] **predict** based on occurrence of extreme weather events that often precede outbreaks (e.g., flooding), and **recommend** short-term interventions such as oral rehydration solutions, reasonably well[63]
- AI/AA models have already been used by humanitarian organizations to predict outbreaks and inform response. For example, the MSF/EPFL model that predicted cholera following the 2016 Haiti hurricane informed the WHO's decision to run a vaccination campaign in southern Haiti[64]
- Next action would be to adapt and expand existing models. For example, adjust to specific country context and decision-maker needs (e.g., accuracy, granularity, and time horizon) and scale usage

9.2.2 Explore Modification

9.2.2.1 Other Vector-Borne Disease: Chikungunya

- Rapid increase in incidence, with forecasts **predicting** continued geographic expansion; while previously endemic to tropical climates, it has now been identified in 60+ countries[65]
- Currently able to **describe** how climate factors are associated with transmission (particularly as transmitted by the same mosquito that transmits dengue); some epidemiological models to **predict** incidence and **recommend** interventions such as insecticide control programs reasonably well[66]
- AI/AA models for other similar climate-sensitive health risks (e.g., malaria, dengue) have been used by policymakers to predict outbreaks and inform response, with interest expressed from experts and policymakers to adapt these models to Chikungunya
- Next action would be to explore potential modifications to the most relevant existing models. For example, prepare relevant climate and health data and adjust model parameters based on climate factors and health need specific to decision-making for Chikungunya

9.2.2.2 Other Water and Foodborne[67] Illness: Typhoid

- See Section 6.1.2 and Case Studies for detailed discussion on typhoid

9.2.3 Shape Understanding

9.2.3.1 Heat

- See Section 6.1.2 and Case Studies for detailed discussion on heat

9.2.3.2 Injury & Mortality from Extreme Weather

- Long-term forecasts **predict** substantial increase in frequency and intensity of impact, but current burden underreported as outcomes beyond mortalities are often not attributed (and even then, usually only immediate deaths)[68]
- Currently able to **describe** immediate health impacts of an event, but medium- and longer-term health impacts are less understood, despite the evidence (examples include cholera outbreaks following floods, diarrheal

62 IPCC, 2018.
63 WHO, 2021.
64 EPFL, 2016.
65 "Chikungunya Fact Sheet," *WHO*, September 15, 2020.
66 WHO, 2020.
67 Focus of effort is on foodborne illness, not malnutrition more broadly.
68 IPCC, 2018.

disease outbreaks and respiratory illnesses following volcanic eruptions,[69] and mental health impacts years after extreme weather events).[70] Early Warning Systems (EWS) to **predict** events have greatly improved, however the ability to **recommend** interventions in response are limited to mitigation. The event itself remains hard to prevent entirely

- EWS have improved greatly in recent decades and are being used by policymakers, for example, to predict tsunamis in the Indian Ocean. However, there is limited ability to predict medium- and longer-term health impacts beyond the event itself
- Next action would be to shape understanding. For example, leverage AI/AA for foundational research and data collection to understand health impacts beyond the immediate event and utilize this understanding to extend EWS to predict medium- and longer-term health impacts

9.2.3.3 Zoonoses

- Long-term forecasts **predict** geographic expansion and severity—though burden varies depending on disease, potential to evolve into epidemic/pandemic and inflict disruption on multiple sectors
- Limited ability to **describe** how climate impacts animal-to-vector spillover, as well as confounding factors (e.g., trade/travel, urbanization). Some EWS to **predict** spillover risk using non-AI/AA methods (e.g., expert opinions) but limited ability to **recommend** interventions to prevent spillover risk itself as most interventions are post-outbreak and costly (e.g., quarantine, drug R&D)
- Some non-AI/AA tools used by policymakers to assess animal-human spillover risk. For example, Global Early Warning System for Major Animal Diseases including Zoonoses (GLEWS)[71] and SpillOver,[72] as well as some AI/AA academic models to assess spillover risk (e.g., through using genomics)
- Next action would be to shape understanding. For example, leverage AI/AA for foundational research to understand how climate factors impact zoonotic spillovers, building off recent investments in zoonotic spillover research following COVID-19,[73] and leverage this understanding to develop AI/AA models to predict spillover risk

9.2.4 Wait and See

For climate-sensitive health risks where climate linkages and near-term AI/AA potential are unclear, we propose "wait and see" before taking next action on AI/AA use cases. While these climate-sensitive health risks are undeniably important and can pose great risks to communities, it may be more appropriate to pursue non-AI/AA methods while monitoring advances in AI/AA methods (i.e., should any become appropriate to deploy). This is consistent with the shared principles outlined in Section 7 to be thoughtful about when AI/AA methods are most appropriate and necessary (i.e., cost benefit).

9.2.4.1 Respiratory Illness

- There are some specific respiratory illnesses (i.e., influenza) where AI/AA models are being used in academic settings to predict incidence;[74] continue to monitor whether these models are tested in real-world settings
- For many respiratory illnesses, climate linkages are relatively less understood and will likely benefit from more data collection and foundational research, especially in LMICs that do not necessarily require AI/AA methods

69 Amruta Byatnal, Jenny Lei Ravelo, "Devex CheckUp: Tonga can't afford another crisis—especially COVID-19," *Devex*, January 27, 2022.
70 IPCC, 2018.
71 GLEWS+ webpage, accessed February 3, 2022.
72 Global Virome Project webpage, accessed February 3, 2022.
73 "USAID Announces New $125 Million Project to Detect Unknown Viruses with Pandemic Potential," *USAID*, October 5, 2021; "Stop Spillover," USAID, 2020.
74 "FluSight: Flu Forecasting," CDC, accessed February 2022.

9.2.4.2 Non-Communicable Diseases (NCDs)

- Some specific NCDs are linked to climate factors (i.e., extreme heat may increase incidence of acute cardiac events),[75] but data availability and understanding are relatively limited, especially in LMICs; continue to monitor research in academic and real-world settings
- For many NCDs, climate linkages are relatively less understood and would likely benefit from more data collection and foundational research, especially in LMICs that do not necessarily require AI/AA methods

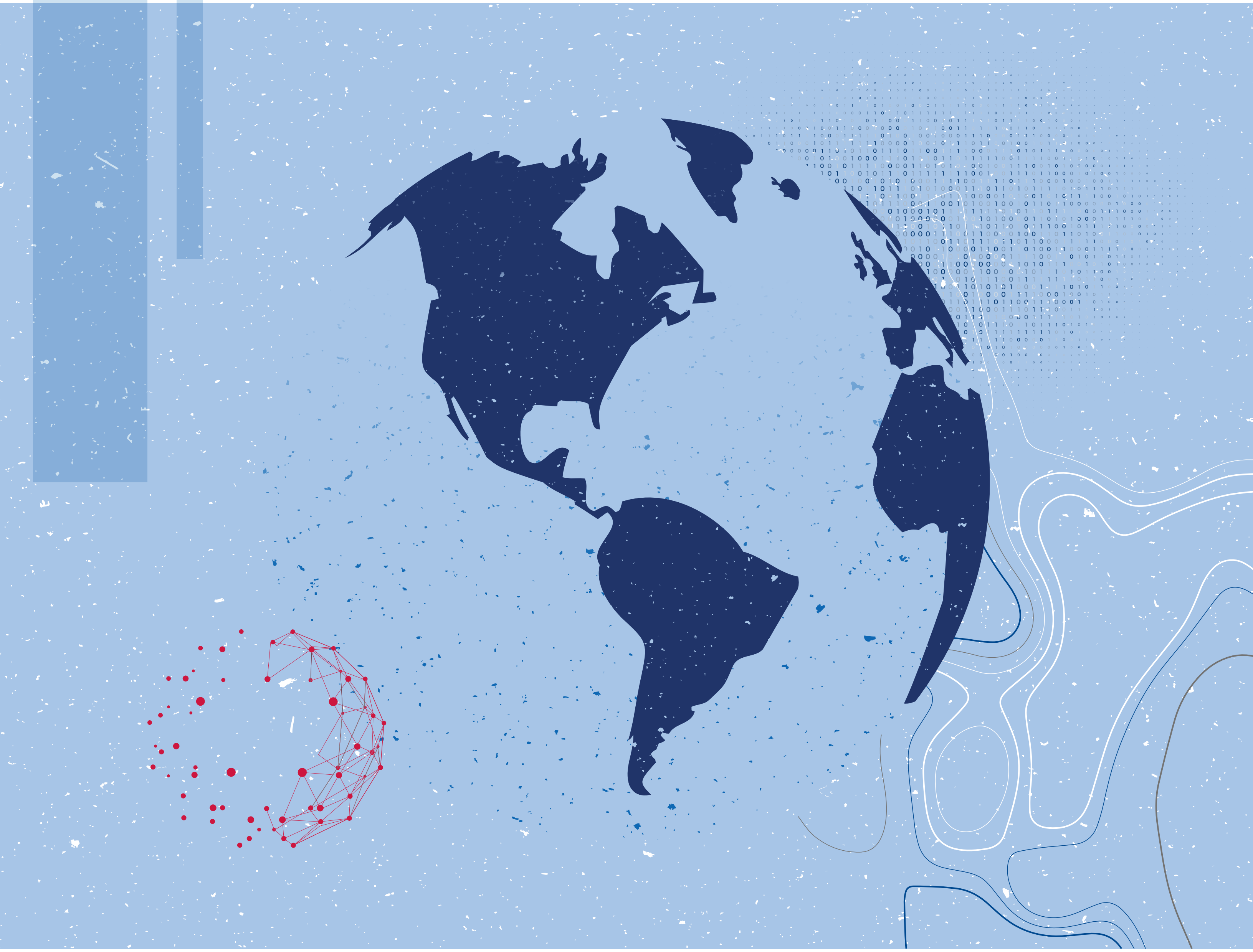
9.2.4.3 Mental and Psychosocial Health[76]

- Emerging evidence suggests that climate factors such as extreme weather events have profound impacts on physiological and psychological stress,[77] but mental and psychosocial health is an evolving field with significant sociocultural and geographic nuances
- Likely to benefit from more data collection and foundational research, especially in LMICs that do not necessarily require AI/AA method

75 Harikrishna Halaharvi, Paul Schramm, Ambarish Vaidyanathan, Heat Exposure and Cardiovascular Health: A Summary for Health Departments, CDC, July 2020.

76 WHO includes substance abuse disorders in this risk.

77 IPCC, 2018.



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