ARTIFICIAL INTELLIGENCE FOR CLIMATE CHANGE MITIGATION ROADMAP (SECOND EDITION)

CHAPTER 14:

EXTREME WEATHER RESPONSE

ALICE C. HILL AND COLIN MCCORMICK

November 2024

Innovation for Cool Earth Forum

CHAPTER 14:

EXTREME WEATHER RESPONSE

Alice C. Hill and Colin McCormick

In 2023, the Earth experienced its hottest year in recorded history, primarily due to the burning of fossil fuels and land-use change.[1] To reduce future heating, more than 190 nations have agreed on the necessity of reducing the greenhouse gas (GHG) pollution that causes climate change.[2] Yet that pollution—and temperatures—continue to rise. With higher temperatures have come more extreme weather events, such as deeper droughts, more intense storms, bigger wildfires and extended heat waves. Sea-level rise has also accelerated. These climate-worsened events have caused economic damage. Researchers estimate that from 2000 to 2019, 185 climate-worsened events caused $2.86 trillion in global damages, averaging $143 billion per year, a figure the researchers say likely underestimates the full harm.[3]

Even if nations succeed in aggressively cutting GHG emissions, accumulated atmospheric pollution will continue to drive new climate-worsened extremes for at least the next few decades. Those extremes require humans to adapt. Climate adaptation involves preparing for and building resilience to the current and looming impacts of climate change. Adaptation efforts can protect lives, livelihoods, infrastructure and ecosystems. They can also save money. According to the Global Commission on Adaptation, investments in adaptation carry a high rate of return: an estimated $2 to $10 or more for every $1 spent.[4]

Adaptation can take many forms, over many different timescales. On the scale of years to decades, the construction of climate-resilient physical infrastructure—such as power grids, roads, and flood and heat protection measures—can ensure continuity of critical services during extreme weather. On the scale of months, improved management of seasonal agriculture planting and harvesting can ensure food supplies. And on short timescales (days to weeks) improved forecasting and early warning serves as one of the most important adaptation measures to reduce economic damage and save lives. This chapter explores how artificial intelligence (AI) can enhance adaptation in the essential area of forecasting and early warning of extreme weather events, including wildfires and extreme flooding.

A. Forecasting and Early Warning

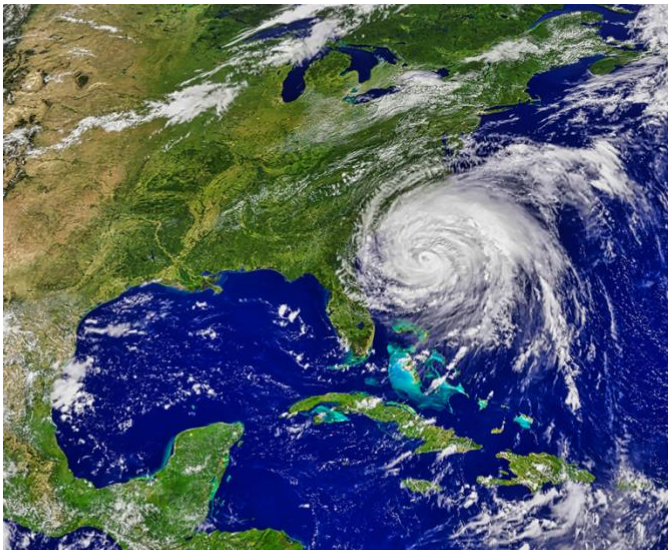
Accurate weather data and forecasting can assist people in adapting to climate change by giving them additional time to prepare for damaging events. For example, in the near term, storm forecasts can provide people time to seek shelter or evacuate and take resilience measures to reduce damage to structures, like removing flammable materials outside and protecting windows from high winds. Similarly, near-term forecasts can aid utilities in managing electricity production and transmission during extreme heat events. Seasonal forecasts can assist farmers in making better decisions as to when to irrigate, plant and harvest. They can also inform continuity planning for businesses worried about weather disruptions to supply chains. Multi-year forecasts can help building owners and city planners make informed decisions about where and how to build facilities that can withstand climate-worsened extremes.

In recent years, near-term forecasting has attracted significant attention. Improved forecasting of impending extreme events saves lives when coupled with early warning. These systems can also empower people to take action to reduce the risk of economic harm from worsening climate extremes. For example, people could move livestock to higher ground as storms approach or shut down electricity production as winds increase the risk of downed wires sparking wildfire.

The safety and economic benefits of improved weather forecasts are large. One World Bank analysis estimated that early warning systems could reduce annual deaths from weather events and cut economic losses from disasters by $35 billion per year.[5] In the US, forecasting improvements since 2007 have saved an average of $5 billion per hurricane.[6] However, about a third of the world's population lives in areas without early warning systems.[7] Countries that have limited or only modest weather forecasting and early warning coverage suffer disaster-related deaths at nearly six times the rate of countries with better coverage.[8]

In 2022, the United Nations called for a concerted global effort to improve early warnings for all by 2027.[9] The number of countries with early warning systems has increased since 2015 when the World Meteorological Organization (WMO) and other international groups launched the Climate Risk and Early Warning Systems initiative. This initiative aimed at increasing the capacity of least-developed and small-island nations to generate early warnings for seventeen hazards, ranging from flood to drought to sand and dust storms. In some places coverage includes seasonal outlooks.[10] But only about half of all nations currently have adequate systems, with many countries in Africa, the Caribbean, the Americas and the Pacific experiencing significant gaps in coverage.[8]

Weather forecasting has improved in recent years with the help of increased satellite data, better algorithms and evolving understanding of weather patterns.[8] However, climate change has made forecasting more complex because it is shifting traditional weather patterns and changing the frequency and intensity of extreme weather events.[11] There is considerable uncertainty about whether this shift will impact the accuracy of weather forecasting. Stanford University researchers found that for every Celsius degree of warning, the reliable forecast window may decrease in certain locations.[12] However, other researchers argue that a changing climate does not inherently lead to more difficulty in making predictions or less accurate weather predictions.[13] The introduction of AI-based weather forecasting models further complicates this picture.



B. Changing Risk Picture

Despite continuing improvements in forecasting, escalating risks and damage from climate-worsened events sharpens the need for improved forecasting and early warning. Damage from climate extremes has climbed in recent years and is predicted to continue to rise. In 2023 alone, the United States suffered almost $95 billion dollars in damages from 28 separate extreme events.[14] By 2050, "global annual damages are estimated to be at 38 trillion dollars

annually."[15] According to World Bank data, five health risks worsened by a warmer climate could lead to at least 21 million deaths by 2050.[16]

Consider the changing risk picture for wildfire. Climate change brings higher temperatures that can reduce humidity in the air, which in turn can dry out vegetation and lower soil moisture content. It also can produce intense winds. All these factors can lead to bigger and more intense wildfires. According to an analysis of satellite data, the frequency of extreme fires has more than doubled from 2003 to 2023. An explosion of extreme fires has occurred in Canada, the United States and Russia.[17] Some parts of the western United States experience two more months of wildfire weather than a century ago.[18] The UN Environment Programme estimates the number of wildfires will increase 50 percent by 2100.[19]

Climate change has similarly altered the risk picture for flooding. A warmer atmosphere can hold more moisture. This increase can lead to extreme rainfall, otherwise known as "rain bombs," that overwhelm existing flood infrastructure. Changing snowmelt patterns from higher temperatures can extend flood seasons in some areas. Higher ocean temperatures mean that storms can pull in more water vapor and heat, leading to stronger winds, higher storm surge and heavier rainfall. All of this can lead to more flooding when storms make land fall. Rising sea levels also add to tidal and coastal flood risk. Ocean warming can cause hurricanes to intensify more rapidly, leaving people less time to prepare. Scientists predict that climate change will drive greater flooding in the future. For example, according to the Human Climate Horizons platform, a collaboration between the Climate Impact Lab and the United Nations Development Programme (UNDP), in the past two decades, sea level rise alone has expanded the areas prone to flooding to places where over 14 million people live. By 2100, flood-prone areas will expand to places populated by over 73 million people.[19]

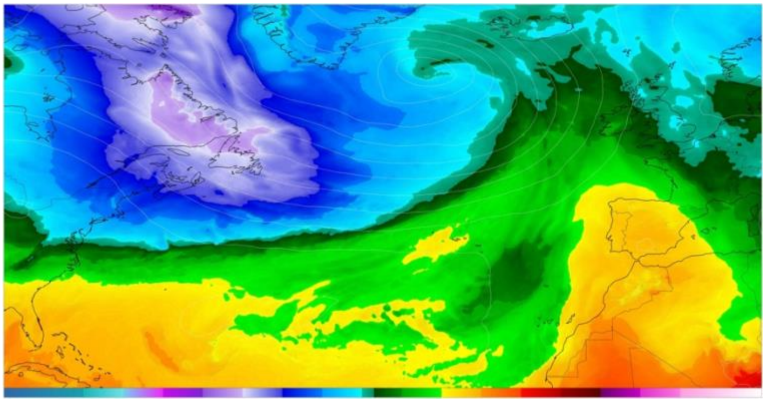
C. How Can AI Improve Forecasting?

AI can significantly enhance the accuracy of weather forecasting and reduce the cost and energy consumption of running forecasting computer models. Current state-of-the-art conventional medium-range weather forecasting models include the Global Forecast System (GFS) of the US National Oceanic and Atmospheric Administration (NOAA)[14] and the Integrated Forecasting System (IFS) of the European Centre for Medium-Range Weather Forecasts (ECMWF).[20] These numerical weather prediction (NWP) models solve complex physics-based equations for atmospheric, ocean and land behavior using best available science for the underlying interactions of heat, pressure, moisture and other fundamental physical and chemical parameters.

Typically, a single "run" of these models starts with the most recent observational data from satellites and weather stations and then calculates solutions for the equations at each hour in the future, up to 10–14 days in advance. Because weather systems are constantly changing, the error in the forecast grows dramatically at later times, using current models.[21] Spatially, the model calculates the solutions at each location on a global grid with horizontal spacing of ~13 km at the surface and roughly 100 vertical layers throughout the atmosphere. The solution outputs include temperature, pressure, wind speed, precipitation, soil moisture and many other variables.

National weather services, such as NOAA, run their primary medium-range weather model several times in a single day, using updated observational data each time, and continually release revised forecasts. Because of the size and complexity of these models, they require supercomputers and may take several hours to complete, consuming large amounts of energy in the process. (See Box 14-1.) These models could run faster if they used a sparser grid (e.g., only producing solutions every 20–30 km) or less frequent time intervals (e.g., only producing solutions for 2-hour intervals rather than hourly), but this would reduce the quality and value of the forecasts.

Many countries are unable to afford the supercomputing facilities and expert meteorology teams required to run these state-of-the-art weather models. The high cost and large energy consumption of conventional weather models has driven much of the interest in developing AI-based weather models. In general, these models run with vastly smaller computing power, meaning they could potentially use higher-resolution spatial grids and shorter time steps and/or be updated more frequently compared to conventional models. However, for this to be a widely accepted approach, AI-based weather models must demonstrate that they can achieve similar or better accuracy than conventional models, which use a full simulation of key atmospheric physics and chemistry equations.



In 2023, Huawei, a Chinese communications technology conglomerate, released the first AI-based weather model that not only matched the accuracy of conventional models, but significantly outperformed them.[22] Instead of using physics-based equations, Huawei's PanguWeather (PGW) is based on a deep neural network trained on almost 40 years of historical observed weather data (ERA5[23]). This enables it to emulate the statistical patterns hidden in that dataset. Compared to the ECMWF's IFS model, it has smaller error in most cases (i.e., the forecasted weather vs the actual weather). Given the need for accuracy in forecasts, this result helped galvanize interest in AI-based weather forecasting.

PGW also runs approximately 10,000 times faster than IFS, a huge reduction in cost and energy consumption. Ongoing studies of PGW (which is open source for noncommercial use) in an operational environment show that, for many tasks, its accuracy is comparable to IFS or better (still at vastly lower compute cost), although it underperforms in others.[24]

Since the release of PGW, several other companies have released AI-based weather forecasting models, including GraphCast by Google, an American technology company. GraphCast also performs very well compared to IFS in many contexts.[25] While private technology companies have largely driven the development of these models, government agencies have directly collaborated on their development in some cases. For example, the ECMWF worked with Google to develop GraphCast, and NASA is collaborating with IBM to release the Prithvi-weather-climate model.[26]

AI-based weather forecasting models can assist in a variety of adaptation-related tasks, including extreme weather forecasting coupled with early warnings. The low cost and improved accuracy of AI-based weather forecasting could potentially make the UN goal of "early warning for all by 2027" more achievable.

Box 14-1

Energy Consumption of AI-Based Weather Forecasting Models

AI-based weather models consume much less energy on a life-cycle basis than conventional weather models. Although they require large amounts of energy to train, they consume very little energy to use for weather forecasting (approximately 1000x less than conventional models). This dramatic energy benefit can translate into lower costs and can help improve access to weather forecasting globally.

AI models consume energy during two main phases of their life-cycle: *training* and *use* (or "inference"). During training, the parameters of an AI model (which may number in the billions) are gradually adjusted to make the model's output match patterns in a set of training data. In the case of weather forecasting, the training data are historic weather observations, and the goal of training is to "tune" the AI model to be able to output the weather patterns that were observed in the past. (In the case of LLMs, the training data are thousands to millions of documents spanning many types of writing.)

Training an AI weather model can consume large amounts of energy. For example, training Google's GraphCast model took approximately 4 weeks (28 days) of continuous processing on 32 TPU v4 devices (similar to GPUs).[25] Because these devices have an average power consumption of 200 W, the electricity consumed in training one version of the model was about 4.3 MWh.[27] If this electricity was supplied by average US grid power, it would have resulted in 1.7 tCO_2 of emissions.[28] The overall model creation process typically involves repeating this training process several times (at least four versions of GraphCast were trained, for comparison), so the total energy consumption could be an order of magnitude larger. However, Google (like many other data center operators) supplies some of its data center power using renewable energy, so the CO_2 emissions may have been substantially lower.[29] AI weather models will need to be retrained occasionally, consuming additional energy, but this is likely to be infrequent.

Using a trained AI weather model to make a single forecast consumes far less energy than the training phase. The GraphCast model can calculate a 10-day weather forecast in under 1 minute on a single TPU,[25] implying that the electricity consumption for making this forecast is only a few Watt-hours, or approximately 1 million times less than the training phase. Of course, under normal forecasting operations the model would run multiple times a day to update forecasts, repeated every day for the foreseeable future. Nevertheless, the cumulative electricity consumed during the use phase would likely be quite small.

By contrast, current leading medium-range weather models, such as the European Centre for Medium-Range Weather Forecasts' (ECMWF's) Integrated Forecast System (IFS), take multiple hours to run on a large supercomputer and consume tens of kWh per run.[30] These models do not require training, so the only energy consumption is during the use phase (although there are embedded CO_2 emissions from producing the dedicated supercomputing equipment). These comparisons must be viewed carefully because the models do not necessarily produce solutions at the same spatial resolution; however, the general comparison is broadly correct.

In addition to predicting extreme weather events, related AI-based models can increasingly provide early warning for river flooding and wildfires. For example, Google and ECMWF recently collaborated to demonstrate a flood prediction model based on a deep neural network that can predict river flood events with a five-day lead time and comparable accuracy to same-day lead time predictions from the conventional Global Flood Awareness System.[31,32] Google now makes predictions available for free and in real time to dozens of countries.[33]

Companies have also developed AI models to predict where wildfires are likely to ignite. For example, Athena Intelligence's model aims to identify the probability of a wildfire occurring within a specific geographic area, the potential severity and intensity of that wildfire, and the potential losses if such a wildfire were to happen. AI-driven prediction models primarily use remote sensing data, and recent results are quite promising in terms of both high accuracy and low computational cost.[20,34] Some emerging use cases of AI for wildfire focus more on early/rapid detection of new wildfires. This includes systems in several US states, including California and Oregon, that use networks of cameras and AI to automatically identify wildfires soon after they ignite. These systems aim to optimize allocation of scarce firefighting resources and potentially extinguish fires before they spread.[35,36] In Türkiye, the World Economic Forum (WEF) has worked to develop the FireAId program, which uses AI to create an interactive map of fire risk. That initiative has predicted wildfire outbreaks 24 hours in advance with high accuracy.[37]

Longer-term forecasts also help climate adaptation, including efforts to limit crop failures during droughts. The time horizon for useful predictions of these events runs from weeks to months since adaptation actions, such as food shipments or water conservation, take this long to implement. Application of AI to drought prediction has begun to make significant progress, although important challenges remain.[38-41] Several government-led projects focus on applying AI to prediction of drought, including the European Space Agency's AI for Drought project[42] and NASA's TERRAHydro software system.[43] The AI for Drought initiative has downscaled existing satellite-based drought prediction estimates to make them higher resolution and thus more geographically precise.[44]

D. Barriers

Despite the ability of AI to improve forecasting and early warnings, barriers to adoption remain. Those barriers include insufficient data and technical expertise and capacity, lack of confidence, lack of supporting infrastructure, and financial constraints.

i. Insufficient Data

AI systems are only as good as the data used to train them.[45] Limited or incomplete data for certain weather conditions can impair accuracy. Since AI models rely on historical data, they may struggle with the more extreme, record-breaking events that climate change brings.[46] This challenge becomes even more acute in developing countries that lack high-resolution observational data about atmospheric or other conditions. For example, India has close to 10,000 glaciers in the Himalayas, yet it has detailed *in situ* data on only 30 of those.[47] Inaccurate or incomplete data can degrade the quality of predictions.[48] While satellite-derived datasets on important parameters, such as land

surface temperature and vegetation, are globally available, other important input parameters for training data sets are far more available in developed countries than in developing ones.[49]

Although the WMO has pushed for greater standardization of observing practices and instrumentation, when it comes to weather forecasting, different countries use different technologies and have different hardware standards. Differences arise in the level of resolution, with some countries prioritizing high-resolution localized forecasts while others focus on broader forecasting. Countries also use different combinations of data sources, be it on-the-ground observations or satellite data. And of course, some countries lack sufficient resources and technology to support robust weather forecasting, with high-income countries enjoying more accurate forecasts as a result.

ii. Insufficient Technical Expertise and Capacity

Human expertise is essential for interpreting results and handling complexities that AI models may not be able to interpret. Currently only a limited pool of human capital and expertise exists. The lack of talent is particularly challenging for public agencies since they often cannot compete with private salaries. This will make it imperative for governments to invest in recruiting, training and retaining AI experts.

iii. Lack of Confidence

With AI weather-forecasting models, results are not easily traced back to the tens of millions of underlying assumptions upon which they rest.[46] These models are a "black box", often lacking transparency as to how conclusions are reached. Thus, some meteorologists may be hesitant to rely on AI-based predictions since, if they are wrong, it is difficult to understand why. This issue is the focus of substantial research, and more "interpretable" AI models may eventually be developed.[50] For example, in the United States, NOAA has taken a cautious approach to adopting recent technologies, including AI, although it is working to integrate AI and understand the opportunities and obstacles.[51]

iv. Lack of Supporting Infrastructure

Translating forecasts into actionable information requires supporting infrastructure. For example, ready access to the internet can speed dissemination and receipt of warnings based on a storm forecast. But some communities and individuals may lack internet access, or power failures may impede dissemination.[8] Currently only about 20 percent of poor nations have a plan to act on early warnings as compared to about half of the nations in the Asia-Pacific region.[52]

v. Financial Constraints

Lack of adequate funding will remain a challenge, both for research and development (R&D) of early warning systems and for their deployment and use. Establishing an early warning system takes money. So does maintenance of the system. Developing complex AI models requires significant computational resources (although they require far fewer to use operationally).[48] Because weather patterns and climate conditions are dynamic, AI models also need updating and retraining to capture the latest information.[48]

Government agencies will likely require additional funding to evaluate emerging technologies for accuracy and reliability. Given the speed with which these technologies are changing, the need for funding could increase over time.

E. Risks

While the accuracy of some flagship AI medium-term weather models is high, they do not currently perform as well as conventional models in some areas, such as forecasting tropical cyclone intensity.[24] They may need to be deployed in combination with conventional models, with the forecasts integrated or synthesized.

The relative ease and low cost of AI-based weather forecasting may undermine support for public meteorological agencies, as some policymakers may conclude that they are no longer necessary. Lack of adequate funding could undermine the ability of public meteorological agencies to assess and understand the performance of AI-based models and to collect the observational data on which these models are based. This in turn could increase dependency on private sector companies for the public service of weather forecasting.

While major private companies currently offer these flagship AI weather models as open source, that could change in the future. Legislators should carefully weigh the appropriate role of public funding as opposed to private development.

F. Recommendations

1. *National governments, international organizations, and the private sector should invest in AI models that increase accuracy, improve the timeliness and reduce the cost of extreme weather event forecasts. They should also collaborate on ways to evaluate accuracy and to develop frameworks that promote long-term sustainability.*
2. *National governments should:*
   - *continue collecting and publishing weather data as a foundational public service;*
   - *provide a base level of access for poorer communities and countries;*
   - *explore innovative programs to attract the necessary talent to lead public AI systems (this could include government-sponsored fellowships, additional compensation and opportunities for continued education);*
   - *integrate AI training into professional development programs for meteorologists and climate scientists working in public sector weather agencies;*
   - *ensure robust understanding of the limitations and opportunities of AI-assisted forecasting and early warning; and*
   - *promote and construct necessary infrastructure to disseminate forecasts and warnings effectively.*
3. *National governments and international organizations should develop the capacity to build and use cutting-edge AI-based weather models as those models improve in the years ahead. Public-private partnerships are important for equity. National governments and international organizations should also support the expansion of AI-based early warning systems for extreme weather to underserved regions, ensuring equitable access and bridging the gap in global forecasting capabilities.*
4. *National governments, international organizations, and the private sector should prioritize collection and integration of weather and climate data from the global south and provide technical support for adopting AI-based forecasting models to countries that have previously lacked advanced forecasting capabilities due to resource constraints.*
5. *Research institutions and AI developers should prioritize creating AI models that are transparent and interpretable to help meteorologists and emergency responders gain trust in AI-generated weather predictions.*
6. *Emergency management and humanitarian aid agencies should implement AI-driven decision support systems to optimize response strategies during extreme weather events, such as evacuations or resource allocation, based on real-time data and predictions.*

G. References

1 Angela Colbert & Sally Younger. *Five Factors to Explain the Record Heat in 2023;* NASA Earth Observatory, Greenbelt, Maryland, https://earthobservatory.nasa.gov/images/152313/five-factors-to-explain-the-record-heat-in-2023#:~:text=But%20what%20caused%202023%2C%20especially,gases%20is%20the%20primary%20driver (2023).

2 United Nations Framework Convention on Climate Change (UNFCCC). *The Paris Agreement;* Bonn, Germany, https://unfccc.int/process-and-meetings/the-paris-agreement (Accessed August 2024).

3 Rebecca Newman & Ilan Noy. The global costs of extreme weather that are attributable to climate change. *Nature Communications* 14, 6103 (2023). https://doi.org/10.1038/s41467-023-41888-1.

4 Susannah Fisher, Sophie Dicker & Georgina Kyriacou. *What is climate change adaptation?;* Grantham Research Institute on Climate Change and the Environment at the London School of Economics and Political Science (LSE) (republished from The Guardian), London, UK, https://www.lse.ac.uk/granthaminstitute/explainers/what-is-climate-change-adaptation/ (2021).

5 Stéphane Hallegatte. *Early Warning Weather Systems Have Very Real Benefits;* World Bank Blogs, Washington, D.C., https://blogs.worldbank.org/en/developmenttalk/early-warning-weather-systems-have-very-real-benefits (2012).

6 Renato Molina & Ivan Rudik. *The Social Value of Hurricane Forecasts;* National Bureau of Economic Research (NBER), Cambridge, Massachusetts, http://www.nber.org/papers/w32548; https://www.doi.org/10.3386/w32548 (2024).

7 Lara Loussert *et al. Scaling up early warning systems for communities in fragile and conflict zones;* World Bank Blogs, Washington, D.C., https://blogs.worldbank.org/en/dev4peace/scaling-early-warning-systems-communities-fragile-and-conflict-zones (2024).

8 United Nations Office for Disaster Risk Reduction and World Meteorological Organization. *Global status of multi-hazard early warning systems 2023;* Geneva, Switzerland, https://www.undrr.org/reports/global-status-MHEWS-2023 (2023).

9 Amina J. Mohammed. *Secretary-General's message on World Meteorological Day;* United Nations, New York, New York, https://www.un.org/sg/en/content/sg/statement/2022-03-23/secretary-generals-message-world-meteorological-day (2022).

10 Climate Risk & Early Warning Systems Initiative (CREWS). *Annual Report 7 - 2023;* Geneva, Switzerland, https://crews-initiative.org/wp-content/uploads/2024/06/20240605_CREWS_AR_2023_ENG_webspread.pdf (2024).

11 Rebecca Hersher. *FAQ: 5 things to know about weather forecasts and climate change;* National Public Radio (NPR), Washington, DC, https://www.wfae.org/energy-environment/2024-06-11/faq-5-things-to-know-about-weather-forecasts-and-climate-change (2024).

12 Josie Garthwaite. *Climate of chaos: Stanford researchers show why heat may make weather less predictable;* Stanford Report, Stanford, California, https://news.stanford.edu/stories/2021/12/warming-makes-weather-less-predictable (2021).

13 Andrew Moseman. *Will climate change make weather forecasting less accurate?;* Massachusetts Institution of Technology (MIT), Boston, Massachusetts, https://climate.mit.edu/ask-mit/will-climate-change-make-weather-forecasting-less-accurate (2023).

14 NOAA National Centers for Environmental Information (NCEI). *U.S. Billion-Dollar Weather and Climate Disasters;* Stennis Space Center, Mississippi, https://www.ncei.noaa.gov/access/billions/; https://www.doi.org/10.25921/stkw-7w73 (2024).

15 Potsdam Institute for Climate Impact Research (PIK). *38 trillion dollars in damages each year: World economy already committed to income reduction of 19 % due to climate change;* ScienceDaily, Rockville, Maryland, https://www.sciencedaily.com/releases/2024/04/240417131138.htm#:~:text=Overall%2C%20global%20annual%20damages%20are,in%20rainfall%20and%20temperature%20variability (2024).

16 World Bank Group. *Health and Climate Change;* Washington, D.C., https://www.worldbank.org/en/topic/health/brief/health-and-climate-change (2024).

17 Jeff Tollefson. You're not imagining it: extreme wildfires are now more common. *Nature News* (2024). https://www.nature.com/articles/d41586-024-02071-8.

18 Climate Central. *Longer, More Intense Fire Weather Seasons;* Princeton, New Jersey, https://www.climatecentral.org/climate-matters/longer-more-intense-fire-weather-seasons (2024).

19 United Nations Environment Programme. *Spreading like Wildfire: The Rising Threat of Extraordinary Landscape Fires;* A UNEP Rapid Response Assessment, Nairobi, Kenya, https://www.unep.org/resources/report/spreading-wildfire-rising-threat-extraordinary-landscape-fires (2022).

20 European Centre for Medium-Range Weather Forecasts (ECMWF). *Integrated Forecasting System;* Reading, UK, https://www.ecmwf.int/en/forecasts/documentation-and-support/changes-ecmwf-model (Accessed June 2024).

21 Rosella (Qian-Ze) Zhu. *A Sky Full of Data: Weather forecasting in the age of AI;* Harvard Graduate School of Arts and Sciences – Science in the News, Boston, Massachusetts, https://sitn.hms.harvard.edu/flash/2024/ai_weather_forecasting/ (2024).

22 Kaifeng Bi *et al.* Accurate medium-range global weather forecasting with 3D neural networks. *Nature* 619, 533-538 (2023). https://doi.org/10.1038/s41586-023-06185-3.

23 European Centre for Medium-Range Weather Forecasts (ECMWF). *ECMWF Reanalysis v5 (ERA5);* Reading, UK, https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5 (Accessed August 2024).

24 Zied Ben Bouallègue *et al.* The Rise of Data-Driven Weather Forecasting: A First Statistical Assessment of Machine Learning–Based Weather Forecasts in an Operational-Like Context. *Bulletin of the American Meteorological Society* 105, E864-E883 (2024). https://doi.org/10.1175/BAMS-D-23-0162.1.

25 Remi Lam *et al.* Learning skillful medium-range global weather forecasting. *Science* 382, 1416-1421 (2023). https://doi.org/10.1126/science.adi2336.

26 Josh Blumenfeld. *NASA and IBM Research Apply AI to Weather and Climate;* NASA: Earth Data, Washington, D.C., https://www.earthdata.nasa.gov/learn/blog/nasa-ibm-weather-climate-foundation-model (2024).

27 Norm Jouppi & David Patterson. *Google's Cloud TPU v4 provides exaFLOPS-scale ML with industry-leading efficiency;* Google Cloud, Mountain View, California, https://cloud.google.com/blog/topics/systems/tpu-v4-enables-performance-energy-and-co2e-efficiency-gains (2023).

28 US Energy Information Administration (EIA). *Frequently Asked Questions (FAQs): How much carbon dioxide is produced per kilowatthour of U.S. electricity generation?;* Washington, D.C., https://www.eia.gov/tools/faqs/faq.php?id=74&t=11 (Accessed August 2024).

29 Google. *2024 Environmental Report;* Mountain View, California, https://sustainability.google/reports/google-2024-environmental-report/ (2024).

30 Peter Bauer *et al. The ECMWF scalability programme: Progress and plans;* European Centre for Medium Range Weather Forecasts, https://doi.org/10.21957/gdit22ulm (2020).

31 Grey Nearing *et al.* Global prediction of extreme floods in ungauged watersheds. *Nature* 627, 559-563 (2024). https://doi.org/10.1038/s41586-024-07145-1.

32 Copernicus Programme. *Global Flood Awareness System;* European Union, Vincennes, France, https://global-flood.emergency.copernicus.eu/ (Accessed August 2024).

33 Google Research. *Flood Hub;* Mountain View, California, https://sites.research.google/floods/l/0/0/3 (Accessed August 2024).

34 Younes Oulad Sayad, Hajar Mousannif & Hassan Al Moatassime. Predictive modeling of wildfires: A new dataset and machine learning approach. *Fire Safety Journal* 104, 130-146 (2019). https://doi.org/10.1016/j.firesaf.2019.01.006.

35 Caitlin Scully. *ALERTCalifornia and CAL FIRE's Fire Detection AI Program Named One of TIME's Best Inventions of 2023;* UC Sand Diego Today, San Diego, California, https://today.ucsd.edu/story/alertcalifornia-and-cal-fires-fire-detection-ai-program-named-one-of-times-best-inventions-of-2023 (2023).

36 University of Oregon. *Wildfire Cameras: A 21st Century Firespotting System;* Eugene, Oregon, https://ohaz.uoregon.edu/wildfire-cameras/ (2024).

37 Marco Aguilar. *The power of AI in wildfire prediction and prevention;* World Economic Forum, Cologny, Switzerland, https://www.weforum.org/impact/artificial-intelligence-wildfire-prediction-and-prevention/ (2023 (Updated 2024)).

38 A. AghaKouchak *et al.* Status and prospects for drought forecasting: opportunities in artificial intelligence and hybrid physical–statistical forecasting. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 380, 20210288 (2022). https://doi.org/10.1098/rsta.2021.0288.

39 Lincoln Laboratory - Massachusetts Institute of Technology. *Artificial Intelligence–Based Drought Prediction;* Lexington, Massachusetts, https://www.ll.mit.edu/r-d/projects/artificial-intelligence-based-drought-prediction (Accessed August 2024).

40 Aldo Márquez-Grajales *et al.* Characterizing drought prediction with deep learning: A literature review. *MethodsX* 13, 102800 (2024). https://doi.org/10.1016/j.mex.2024.102800.

41 Neeta Nandgude *et al.* Drought Prediction: A Comprehensive Review of Different Drought Prediction Models and Adopted Technologies. *Sustainability* 15, 11684 (2023). https://doi.org/10.3390/su151511684.

42 AI for Drought. *Explainable AI and Earth Observation for seasonal drought prediction;* Eurpean Space Agency, Paris, France, https://www.ai4drought.com/ (Accessed August 2024).

43 Gage Taylor. *AI-powered TERRAHydro could help hydrologists better understand the water cycle;* NASA Earth Science Techbology Office (ESTO), Washington, D.C., https://esto.nasa.gov/ai-powered-terrahydro-could-help-hydrologists-better-understand-the-water-cycle/ (2023).

44 Nazanin Behfar *et al.* Drought index downscaling using AI-based ensemble technique and satellite data. *Theoretical and Applied Climatology* 155, 2379-2397 (2024). https://doi.org/10.1007/s00704-023-04822-5.

45 Rob Carey. *Trusted data is the heart of trustworthy AI;* NextGov/FCW (Washington Technology), Washington, D.C., https://www.nextgov.com/ideas/2024/02/trusted-data-heart-trustworthy-ai/394460/ (2024).

46 Lauren Leffer. *AI Weather Forecasting Can't Replace Humans—Yet;* Scientific American, New York, New York, https://www.scientificamerican.com/article/ai-weather-forecasting-cant-replace-humans-yet/ (2024).

47 Nidhi Jamwal. *Data drought: The challenge of AI weather forecasting in India;* Eco-Business, Rochester Commons, Singapore, https://www.eco-business.com/news/data-drought-the-challenge-of-ai-weather-forecasting-in-india/?t&utm_source=perplexity (2024).

48 Snezhanaszillat. *The Role of Artificial Intelligence in Modern Weather Prediction;* Enago Academy, Mumbai, India, https://www.enago.com/academy/guestposts/snezhanaszillat/the-role-of-artificial-intelligence-in-modern-weather-prediction/ (2024).

49 NOAA National Centers for Environmental Information (NCEI). *Integrated Global Radiosonde Archive (IGRA);* Stennis Space Center, Mississippi, https://www.ncei.noaa.gov/products/weather-balloon/integrated-global-radiosonde-archive (Accessed August 2024).

50 Ruyi Yang *et al.* Interpretable Machine Learning for Weather and Climate Prediction: A Survey. arXiv:2403.18864 (2024). https://ui.adsabs.harvard.edu/abs/2024arXiv240318864Y.

51 Sergey Frolov *et al.* Integration of emerging data-driven models into the NOAA research to operation pipeline for numerical weather prediction. *Bulletin of the American Meteorological Society* (2024). https://doi.org/10.1175/BAMS-D-24-0062.1.

52 Early Warnings for All. *Early Warnings for All Dashboard;* World Meteorological Organization (WMO), Geneva, Switzerland, https://earlywarningsforall.org/site/early-warnings-all/early-warnings-all-dashboard (Accessed August 2024).