

An Exploratory Analysis on the Use of AI Technology in predicting weather, climate modelling and Disaster forecasting

Aarav Singhal

St. Columbas School New Delhi

DOI: 10.46609/IJSSER.2026.v11i10.017 URL: <https://doi.org/10.46609/IJSSER.2026.v11i10.017>

Received: 20 September 2026 / Accepted: 5 October 2026 / Published: 12 October 2026

ABSTRACT

Weather and climate extremes are increasing in frequency, severity and duration, placing growing pressure on ecosystems, economies and human lives. Accurate prediction is therefore essential for preparing countries against climate-driven disasters. This paper presents an exploratory analysis of the use of Artificial Intelligence (AI) in weather prediction, climate modelling and disaster forecasting, and examines how nations can act on these forecasts to reduce adverse impacts. Using a mixed-method approach, the study combines quantitative comparison, presented in tables and graphs, with qualitative interpretation drawn from authentic secondary sources. It compares leading AI models, including GraphCast, Pangu-Weather, AIFS, FourCastNet, Aurora, FuXi and FengWu, with conventional numerical weather prediction systems such as the IFS, GFS, WRF and the Unified Model. It also reviews AI-based downscaling of climate projections over India and the role of AI in multi-hazard early warning systems. The findings show that AI models match or outperform traditional systems on many forecast variables while producing forecasts far faster and at lower computational cost. However, they tend to underestimate the frequency and severity of record-breaking extremes, where physics-based models still perform better. Challenges remain in data quality and bias, model explainability, energy consumption and unequal access to technology. The paper further finds that accurate forecasts reduce disaster impact only when integrated into trusted, community-centred early warning systems guided by principles of fairness, accountability, transparency, ethics and sustainability. The paper concludes that a hybrid approach, combining the physical grounding of traditional models with the speed and pattern-recognition ability of AI, offers the most reliable route to anticipating extreme events. It recommends stronger observation networks, explainable and ethical AI, regional capacity-building, sustained funding and people-centred system design. Ultimately, AI complements rather than replaces meteorological science, and its value depends on how well it is integrated with governance, local context and community needs.

Keywords: Artificial Intelligence, Weather Forecasting, Climate Modelling, Disaster Risk Reduction, Numerical Weather Prediction, Early Warning Systems, Extreme Weather Events

1. Introduction

Artificial intelligence is a broad field; this refers to the adoption of technology to build machines and computers that have the ability to follow instructions as well as cognitive functions akin to human intelligence. This involves the ability to see, understand, and respond to both spoken or written language. It can analyse data and make suggestions.

AI is categorized into three formats namely:

- **Artificial Narrow Intelligence (ANI)**, which is a specialized AI that is commonly used in our daily lives involving image recognition.
- **Artificial General Intelligence (AGI)**, is more sophisticated than ANI as it is capable of intellectual tasks.
- **Artificial Super Intelligence (ASI)**, is that level of technology that surpasses human intellect. Researchers and scientist are focusing on this technology.

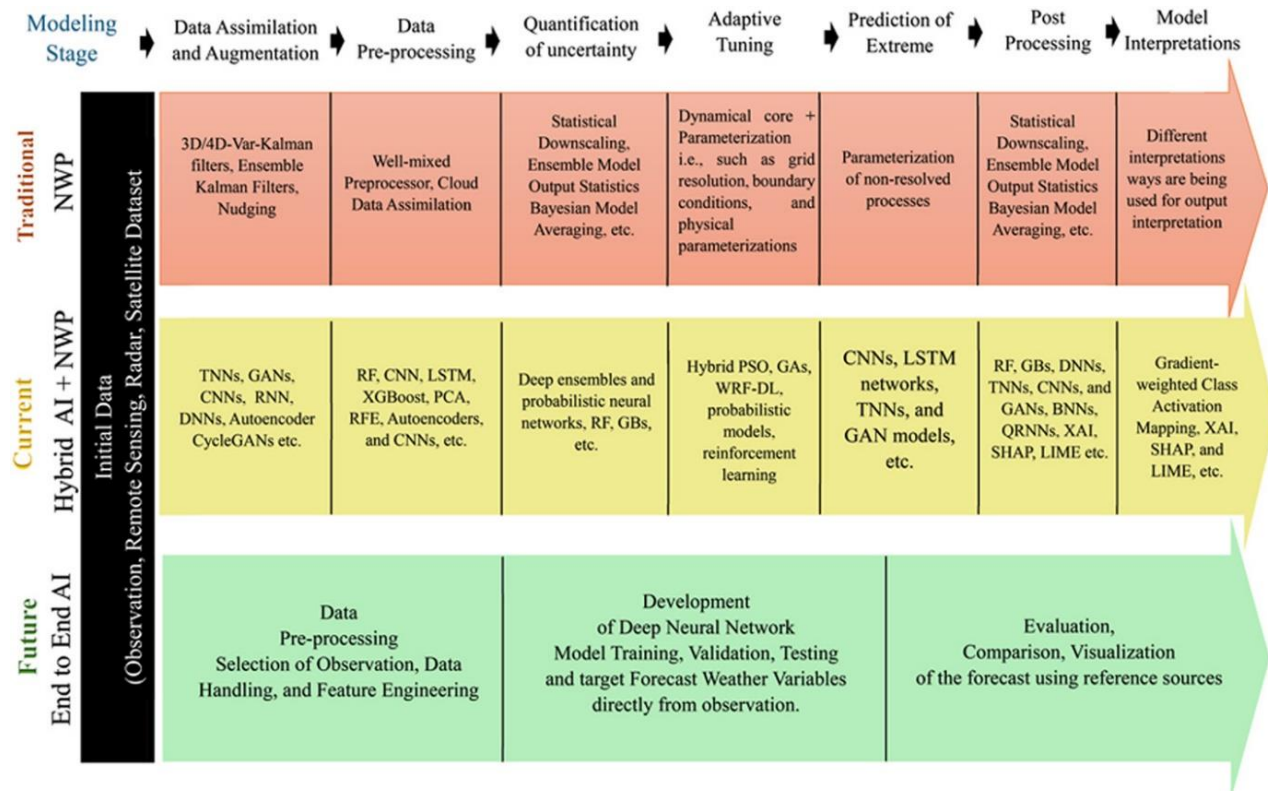
Machine Learning comes under AI. It helps machines or systems to learn and improve from experience these set of machines use algorithms that analyse large amount of data, learn form experience and then pronounce their decisions. These algorithms improve performance of the machines over time as and when they work with larger and larger amount of data.

The synthesis of AI, ML and Deep Learning (DL) are important for understanding climate modelling, extreme weather analysis, renewable energy optimisation, emission monitoring and climate adaption. Weather and climate change are important for a country as they impact socio-economic and environmental systems. Accurate weather forecasting and climate prediction are extremely essential to prepare the country for any hazards that might occur. These systems also help in preparing resource management and understanding long term climate changes. Before the advent of AI and ML weather forecasting relied on Numerical Prediction Models involving atmospheric dynamics. (Richardson,1922) The traditional models were based on calculations of atmospheric and oceanic conditions. All these are based on physical laws such as thermodynamics and conservation of mass.

Meteorological Physics over time has provided robust models that can accurately interpret and are reliable. Current advances have further improved on accuracy and predictability for example; the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecasting

System (IFS) achieved a mean error of just 63.3 km for 24-hour typhoon track forecasts over the Western North Pacific and the South China Sea in 2022(Yang et al., 2024)

Table 1: Analysis of various models and their stages



Source: (Yang et al., 2024)

The above table indicates a clear progression from traditional models to ones that are going to be completely dependent on AI. The use of AI is within the NWP models in data assimilation, augmentation, pre-processing, adaptive parameter tuning, optimization, uncertainty quantification, extreme event prediction, post-processing, and the interpretation of NWP outputs. The problem that arises is in preprocessing of data. The best for the moment would be the use of an AI based hybrid model.

Climate change poses scientific and societal challenges that require accurate prediction of extreme events and rigorous adaptation approaches. Classical methods such as numerical weather prediction (NWP) and general circulation (GCM) models are still currently essential for climate depictions. This indicates the imperative importance of synergies between traditional models and AI integration.

2. Background

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to address the use of AI in forecasting will draw attention to the dangers of utilizing AI for climate adaptation and forecasting. GraphCast(a forecasting model built using **Graph** Neural Networks to forecast global weather) outperforms ECMWF HRES in almost 90% of forecasting measures, GenCast("Generative" and "Cast" (as in forecasting), designed by [Google DeepMind](#) as an advanced AI weather model) outperforms ensemble means by 97%, and MetNet-2(Meteorological Neural Network 2, a deep learning AI model developed by [Google Research](#) for weather forecasting.) improves precipitation forecasting horizons to nine hours. AI has improved urban flood resilience with accuracy levels as high as 92%, predicted agricultural yield with up to 88% accuracy, warned farmers of impending drought two months in advance, and provided early warnings of dengue disease with a reported AUC (Area Under the Curve) of 0.89. *This paper highlights the limitations in AI applications, such as the dataset and the difficulty of weather explanation models, and focuses on both opportunities and problems.*

But despite these developments, problems still exist because of biased data, poor visibility into deep learning models, excessive energy use, and unequal access to technology. *The review proposes a three-pillar framework that incorporates sustainability, transparency, and equity to improve responsible use within climate adaptation and resilience.* It also evaluates opportunities and challenges from which AI might be applied to climate science and climate-related policy.

Recent years have seen an increase in the frequency, severity, and duration of climate extremes, creating previously unheard-of difficulties for ecological integrity, biodiversity loss, economic security, and societal stability. These occurrences, which can range from extreme storms and floods to droughts and heatwaves, have a significant impact on both the natural environment and human livelihoods, frequently with long-lasting and occasionally permanent effects. To advance mitigation and adaptation methods, it is essential to model, characterize, and comprehend extreme occurrences.

Google DeepMind unveiled GenCast, a new artificial intelligence weather forecast tool. GenCast is different from existing models, according to Google DeepMind, since it has "adapted to the spherical geometry of the Earth and learns to accurately generate the complex probability distribution of future weather scenarios when given the most recent state of the weather as input."

Google DeepMind claimed that GenCast offers more accurate forecasts than the "top operating system," citing the European Centre for Medium-Range Weather Forecasts and its ENS model, which forecasts up to 15 days ahead. The European centre's data was used to train GenCast,

which "consistently outperformed ENS" in predicting extreme heat, extreme cold, and high wind speeds.

Although the quality of climate predictions has increased in recent decades due to scientific and technological advancements in numerical modelling, forecasting skill is still limited in many areas. Due to their rarity, non-linear chaotic nature, and model limitations, extreme occurrences like heat and cold waves, droughts, heavy rain, and storms are extremely difficult to predict with accuracy. Recent research, however, has demonstrated that employing more advanced techniques can improve the prediction capacity of extremes, suggesting that systemic predictability may exist but is not being utilized. Recently, a lot of research has focused on using artificial intelligence (AI) to analyse and forecast weather and climate.

AI methods have demonstrated significant promise in enhancing the forecasting of extreme events and revealing their connections to both local and global factors. Some of the methods that have been tested to increase our comprehension of the mechanisms underpinning predictability and improving our capacity to forecast extreme events include explainable AI, machine and deep learning, and causal discovery. The results have been encouraging, particularly for hybrid projections that combine climate models, which offer the theoretical foundation and interpretability of the physical world, with artificial intelligence (AI), which can uncover and take advantage of unknown spatiotemporal relationships. However, there are numerous obstacles to overcome, ranging from data curation to model uncertainty and generalizability to method and workflow reproducibility. Future options for additional scientific advancement are envisioned, and a few best practices are identified to boost confidence in these innovative procedures.

Chaotic dynamics, high dimensionality, and interactions on a wide range of spatial and temporal dimensions dominate weather and climate prediction. Due to this, many of the field's challenges are extremely complicated, and even the most advanced numerical models are insufficient for many applications despite their high processing costs. Using cutting-edge new technologies like artificial intelligence to address these issues is intriguing. the possibility of *deep neural networks* that can replicate the dynamics of a highly simplified *general circulation model* that in turn would yield stable long-term climatic timeseries and accurate predictions several days in advance. This type of approach partially works with more intricate and realistic models, but it is limited to predicting the model's weather a few days in advance rather than generating climate runs, simulating long-term climate conditions over years or decades to study climate patterns and future changes. The networks may be trained with 50 to 100 years of data. The neural networks can produce probably accurate forecasts that combine neural network technology with singular value decomposition. The problem arises in the constraints that appear in these systems when they attempt to generalize new areas of the system in a basic dynamical systems context. The complications are not the same for every model and may differ depending on the type of

dynamical systems resulting in doubting their capability and their applicability to advanced complicated systems. Given sufficiently broad forcing regimes, neural networks can "learn" to some extent how slowly changing external forcings, external factors that influence the climate system, such as greenhouse gases, solar radiation, and volcanic activity, affect the system's dynamics. A neural network is used to predict the uncertainty in future forecasts. They use the initial field of the new forecast, the initial fields and the error of previous weather forecasts.

The demand for precise, high-resolution climate forecasts that can be examined in order to implement corrective measures and develop regional-scale policies is growing as the effects of climate change become more noticeable. In order to forecast future weather variables like temperature and precipitation, global climate models (GCMs), which are computationally costly models based on physics, simulate the atmosphere, land, and ocean. However, the coarse spatial resolution output that GCMs produce—typically larger than 100 km x 100 km grid boxes—is not helpful for understanding regional climates. Although dynamic downscaling models attempt to downscale this low resolution GCM output, they have limitations of their own, such as being non-generalizable and computationally costly. Instead of relying on intricate physics computations, statistical/machine learning-based downscaling models attempt to tackle this issue by learning the patterns through statistical associations in the data, which makes them significantly faster. **Ansari (2022)** attempted to develop machine learning-based models in this study that are capable of downscaling low-resolution temperatures to high resolution temperatures. The CMIP6 dataset provided the low-resolution training data, whereas the ERA5 dataset provided the high-resolution training data. The study was conducted across India with the ultimate goal of downscaling GCM data to produce future regional scale climate projections and then using it to analyse the effects of climate change over India. They came to the conclusion that when temperatures are downscaled from low resolution to high resolution, the modal temperature rises while the extremes decrease. While the publicly available low resolution CMIP6 projections indicate an average warming of 0.33°C across India over the next nine years, the ML-based downscaled estimate suggests a warming of 0.51°C. Ansari (2022) generated high resolution temperature data for India based on our predictions. Furthermore, compared to what the ML forecasts indicate, the temperature extremes indicated by CMIP6 estimates are less severe.

3. Research Gap and Methodology

The aim of this paper is the intensive and extensive use of artificial intelligence technology in the prediction of weather changes and how countries in the world can take cognisance of these warnings such that they are in a position to face climate change disasters and subsequently save humanity and avoid adverse conditions.

The methodology adopted is of the mixed method type where both quantitative and qualitative analysis from authentic sources would be adopted. The quantitative analysis would be shown in a tabular and graphical format making it easier and relevant for the reader to understand the impact of AI forecasting tools. The explanation would be of a qualitative nature based on the data presented in the paper.

4. Analysis

In predicting whether both normal and extreme it is important to study the impact of various AI models and compare them to the traditional onsets to envisage a better understanding on the optimum application of different models.

Table-2: A comparison of various AI models that predict weather impact

AI model	Developed By	Year	AI predicted weather impact	Reported Performance
Graph Cast	Google DeepMind	2023	*Temperature, precipitation, cyclones, atmospheric rivers, extreme heat, wind	*Outperformed ECMWF HRES on >90% of forecast variables; 99.7% in the troposphere
Pangu-Weather	Huawei Cloud	2023	**Global weather, typhoons, rainfall, temperature, pressure, wind	**Comparable to or better than leading numerical weather prediction models for medium-range forecasts
AIFS (Artificial Intelligence Forecasting System)	ECMWF	2024	****Global weather, storms, precipitation, wind, temperature, extreme weather	****Around 20% improvement over conventional forecasts in operational testing
FourCastNet / Earth-2	NVIDIA	2022	***Extreme weather, hurricanes, precipitation, wind, atmospheric rivers	***Approaches state-of-the-art numerical forecast accuracy while producing forecasts thousands of times faster
Aurora	Microsoft Research	2025	*****Hurricanes, typhoons, air quality, temperature, precipitation, ocean waves	*****Outperformed leading weather models on about 92% of evaluated variables
Fuxi & FengWu	(Fudan University and Shanghai	2023	*****Global weather, precipitation, temperature, wind, pressure	*****Comparable to GraphCast and Pangu-Weather with state-of-the-art medium-range forecasting skill

	teams			
HRES	ECMWF	2016	*Conventional numerical weather prediction for all weather variables	*Benchmark (reference model) against which AI models are compared

Source: * Lam, R., et al. (2023). *GraphCast: Learning Skilful Medium-Range Global Weather Forecasting*. Science. ([Google DeepMind](#)), **Bi, K., et al. (2023). *Accurate Medium-Range Global Weather Forecasting with 3D Neural Networks (Pangu-Weather)*. ([Wiley Online Library](#)), *** Kurth, T., et al. (2022). *FourCastNet: Accelerating Global High-Resolution Weather Forecasting using Adaptive Fourier Neural Operators*. ([arXiv](#)), ****ECMWF. *Artificial Intelligence Forecasting System (AIFS)*.([Financial Times](#)) , *****Bodnar, C., et al. (2025). *Aurora: A Foundation Model of the Atmosphere*. ([The Washington Post](#)), *****Aman Gupta., et al. (2025). *An Observations-focused assessment of Global AI Weather Prediction Models During the South Asian Monsoon*([arXiv](#))

Table-3: A comparison of various Traditional models that predict weather impact

Traditional Models	Developed By	Year	Weather prediction Impact	Reported Performance
IFS (Integrated Forecasting System)	ECMWF	1979	Global weather forecasting, temperature, precipitation, wind, storms, cyclones ¹	World-leading operational NWP model; highest medium-range forecast skill (≈90–95% for 5-day synoptic forecasts) ¹
GFS (Global Forecast System)	NOAA	1980 (major modernization in 2019)	Global weather forecasting, hurricanes, rainfall, temperature, wind ²	Highly accurate for short- and medium-range forecasts; generally, slightly less accurate than ECMWF IFS ²
WRF (Weather Research and Forecasting)	NCAR & NOAA	2000	Regional weather forecasting, severe storms, air quality, hurricanes, climate research ³	High regional forecast accuracy when initialized with quality observational data ³
UM (Unified Model)	UK Met Office	1990	Global and regional weather forecasting, climate prediction, tropical cyclones ⁴	Comparable to ECMWF for many forecast variables; widely used operationally in the UK and internationally ⁴

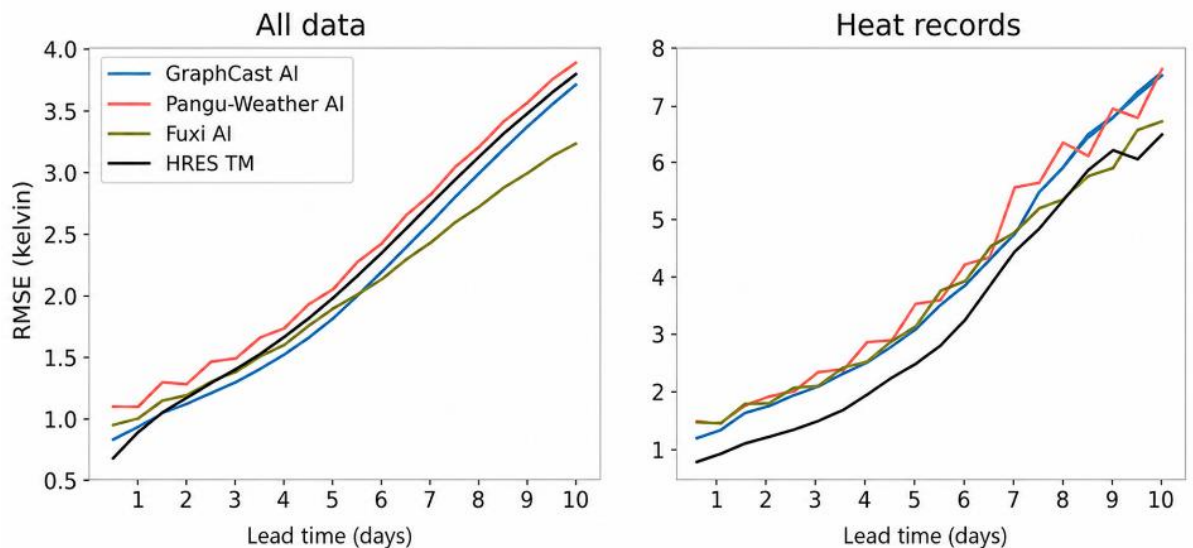
Source: ECMWF. *Integrated Forecasting System (IFS) Documentation*. <https://www.ecmwf.int/> , NOAA/NCEP. *Global Forecast System (GFS)*. <https://www.ncep.noaa.gov/> , NCAR. *Weather Research and Forecasting (WRF) Model*. <https://www.mmm.ucar.edu/weather-research-and-forecasting-model> , UK Met Office. *Unified Model Documentation*. <https://www.metoffice.gov.uk/>

Google DeepMind's GraphCast uses graph neural networks to produce 10-day forecasts in less than 60 seconds. **Pangu-Weather**: Created by Huawei Cloud, tracks cyclones and extreme weather conditions instantaneously by using a 3D deep-learning transformer architecture. The **ECMWF** developed the **AIFS (Artificial Intelligence Forecasting System)**, which is a standard AI model used by official weather agencies. They predict 90% accurate results. **FourCastNet/Earth-2**: Developed by **NVIDIA**, simulates high-resolution atmospheres using generative AI and Fourier neural operators. **Microsoft Research** created **Aurora**, a vast basic parameter model that predicts multiple variables like pollution and severe storms. **FuXi and FengWu**: Created by Chinese academic and research teams (Fudan University and Shanghai teams), routinely top regional and international performance rankings in their prediction.

The Integrated Forecasting System, or IFS: created by the European Centre for Medium-Range Weather Forecasts, or ECMWF, is often regarded as the gold standard for conventional modelling. It is well-known for its 4D-Var data assimilation, which means that before beginning the prediction, it computes how the weather data changed over a period of four to twelve hours. NOAA (United States) created the GFS (Global Forecast System), the world's most accessible conventional model. It calculates worldwide wind and temperature changes four times a day using a *spectral grid*, which is based on mathematical wave frequencies rather than rigid grid squares. Weather Research and Forecasting, or WRF, is a highly adaptable regional model that is utilized by organizations and colleges all around the world, including the Indian Meteorological Department. WRF is less accessible, in contrast to GFS or IFS, which examine the entire world. It is used by meteorologists to forecast high-impact, localized occurrences like in the Bay of Bengal cyclones or Himalayan cloudbursts. The National Centre for Atmospheric Research (NCAR) and the National Oceanic and Atmospheric Administration (NOAA) were the main partners in the development of the Weather Research and Forecasting (WRF) model. The UK Met Office created the UM (Unified Model). It is distinct because it makes use of the same fundamental physics formulas for both *long-term climate change projections spanning a century and short-term daily weather forecasts*.

According to a recent study, artificial intelligence (AI)-based computer models are unable to predict record-breaking weather as accurately as conventional climate models. For some areas of weather forecasting, it is generally known that AI climate models have outperformed conventional, physics-based climate models. AI models still "underperform" in predicting record-breaking extreme weather occurrences, according to recent research published in Science Advances. Thousands of record-breaking hot, cold, and windy events from 2018 and 2020 were simulated by the authors using both AI and conventional weather models. *They discover that the frequency and severity of record-breaking incidents are underestimated by AI models.*

Graph 1: A comparison between AI and traditional models in extreme weather conditions



AI: Artificial Intelligence; TM: Traditional Model

The models' accuracy in predicting all extreme occurrences (left) and heat extremes (right) under various lead times is displayed in the graphic above. "Root mean square error" is a measure of a model's correctness and is used to quantify this; a lower value denotes both lower error and more accuracy. The graph on the left illustrates how two AI models (blue and green) outperformed the physics-based traditional model (black) in terms of weather predicting for the entire year 2020. But when it came to predicting heat extremes, the physics-based traditional model (black) outperformed all three AI models (blue, red, and green), as shown in the chart on the right.

5. Use of AI in optimum climate modelling and mitigating disaster impact

This piece examines how integrated artificial intelligence modelling is changing the game in climate science and crisis management. AI isn't just analysing data anymore—it's helping create multi-hazard early warning systems (EWSs) that draw on both meteorological and geospatial foundation models to predict impacts more accurately. Central to this vision is putting users first. One need interface that feel intuitive, systems that encourage feedback from local communities, and tools that actually help people respond better when disaster strikes.

Addressing today's complex climate risks takes more than brute computational force. There is a need to push for causal AI models—designed to avoid misleading correlations—and insist on responsible practices. Trust doesn't come automatically, so we point to the FATES (Fairness, Accountability, Transparency, Ethics, and Sustainability) principles as non-negotiable for any

equitable, trustworthy AI-based EWS, and since adaptation is not just about the next storm, researchers are championing the development of decadal-scale warning systems, using climate ensembles and generative methods to give long-term, high-resolution predictions. This approach enables proactive responses, rather than scrambling after a crisis.

AI's influence in Earth system science keeps growing. It has sharpened weather forecasts, sped up model simulations, improved parameter estimation, and delivered new insights for predicting extreme events. Of course, working with noisy, sparse, and poorly labelled data remains a challenge—especially when dealing with rare climate extremes like floods, wildfires, and heatwaves. It is necessary review how recent advances are making sense of these difficulties, helping researchers sift out meaningful patterns from messy data.

The story of modern climate science is really about explosive growth—in computing power and in observations from space. Even more, causal machine learning can dig into whether certain variables really drive specific outcomes, often going beyond what traditional approaches can do. Paired with clever modelling experiments, ML speeds up computation, boosts accuracy, and allows scientists to run vast ensembles without breaking the bank.

This review traces ML's growing role in climate physics—from reconstructing spotty observations and representing small-scale phenomena to strengthening weather and climate forecasts. It is necessary to step back to weigh the benefits, the open questions, and the technical hurdles ahead.

For decades, weather and climate felt like separate universes: one about tomorrow, the other about the distant future. That division slowed both fields. Today, AI is starting to blur—and even erase—that line. Researchers are now using unified AI models to predict both next week's weather and next century's climate. This convergence is not just a technical feat; it is a new mindset. Weather and climate science can learn from each other, but challenges remain. There is a need to build trust, ensure transparency and fairness, reduce computation's energy footprint, and guard against global inequalities that technology could reinforce.

Realizing this vision means more than writing better code. It requires a culture shift—true collaboration connecting scientists, operational teams, and experts across disciplines. If this is achieved there will be a faster, sharper, and more useful predictions, equipping societies everywhere to meet the challenge of a warming world head-on.

6. Limitations

This report dives into how technology has shaped disaster risk reduction over the years—what worked, what's changing, and where things are headed next. The paper looks at real examples,

clear definitions, and stories from around the world to show how technology helps fill big gaps in things like data collection, processing, and disaster risk modelling. Different hazards, different places—technology's role keeps growing.

The challenges are messy data, the struggle to plug in real-time info, and the need to build models that people actually trust and understand. These are not side issues; they are crucial if results are to be obtained. AI can spot and explain extreme events better than ever before, making disaster response faster and clearer. This requires using consolidated efforts from different fields.

Over the years, technology has pulled off some impressive feats. Earth observation, early warning systems, and hazard analysis are more sophisticated now than ever. But the facts are clear: technology, even at its best, does not solve every problem in disaster risk reduction. AI and machine learning have pushed the field forward fast, but their real impact depends on how well technology is aligned to social realities, local cultures, and actual infrastructure on the ground.

To build more reliable, responsible, and well-integrated AI into early warning systems, the following priorities have to be considered:

There is a need for a solid, widespread observation networks, on the ground, in the sky, and everywhere in between more so for the world's most vulnerable countries like SIDS (Small Island Developing States), LDCs (Least Developed Countries), and LLDCs (Landlocked Developing Countries). Reliable data forms the backbone of every AI tool in this space.

AI cannot run on autopilot, there is a need for national leadership, strict oversight whenever lives are at stake, accountability is completely non-negotiable. Design of the model must put people first, it requires focusing on equity, weaving in humanitarian values, making sure systems work in any language and even where connectivity is unstable and requires the active participation of all affected communities at every stage of development. Early warning systems should be built to share and support risk models to forecasts to communication channels and preparedness plans. Modular design and smart feedback loops help strengthening the model and the system.

AI investment holds tremendous promise but needs consistent funding from pilot projects to large operational scale-ups. This requires partnership between governments businesses and researchers. Every push to add AI into early warning must start by bridging today's gaps and not by just adding flashy features. The challenge is big, but the potential benefits are even bigger.

7. Conclusions and the Way forward

This paper examined the manner in which AI is used to predict weather, climate modelling and disaster forecasting. Models such as GraphCast, Pangu-Weather, AIFS and Aurora now match or exceed traditional numerical weather prediction on many variables, and they do so at a faster and at a lower computational cost. AI-based downscaling, (Ansari's (2022)) study of India, gives the regional detail that global climate models lack. Global models should be the basis on which the country specific and regional models are based.

However, AI cannot yet replace physics-based models. It underestimates record-breaking extremes, and it still faces problems of biased data, poor explainability, high energy use and unequal access. Better forecasts also save lives only when they are fed into trusted, people-centric early warning systems. A hybrid approach that combines the interpretability of physical models with the speed and pattern recognition of AI is therefore the most reliable path forward.

The way ahead in ensuring adequate and accurate climate warning systems is to build hybrid physics-AI systems, with a focus on improving the prediction of rare and extreme events. Strengthen observation networks and data quality, especially in vulnerable countries. Ensure transparency and ethics through explainable AI, human oversight and the FATES (Fairness, Accountability, Transparency Ethics, and Safety) principles. Build regional capacity by combining AI with operational models such as WRF, and by extending AI downscaling for local adaptation planning in countries like India. Design early warning systems with communities, in local languages and for areas with limited connectivity. Secure sustained funding and adopt energy-efficient models to keep AI's carbon footprint low.

AI will never replace meteorological science, but if integrated with physical models, sound governance and community needs, it will make societies better prepared for a world that is progressively facing climate warming conditions.

Bibliography

- [1] Houssein, E. H., Dirar, M., Ali, A. A., Mohamed, W. M., & Hamed, K. (2026). Advances in artificial intelligence for climate science methods applications and evaluation challenges. *Discover Artificial Intelligence*, 6(1). <https://doi.org/10.1007/s44163-026-01262-8>
- [2] Yang, R. (2024). Interpretable Machine Learning for Weather and Climate Prediction: A review Ruyi Yang A , Jingyu Hu B , Zihao Li C , Jianli Mu A , Tingzhao Yu A , Jiangjiang Xia D , Xuhong Li E , Aritra Dasgupta F , Haoyi Xiong e. *Science Direct*.

- [3] Waqas, M. (2024). Artificial Intelligence and Numerical Weather Prediction Models: A Technical Survey Muhammad Waqas A , USA Wannasingha Humphries B, Bunthid Chueasa B , Angkool Wangwongchai B. *Science Direct*.
- [4] Derea, Z. (2025). Artificial Intelligence in Climate Science: A Review of Advances in Forecasting, Adaptation, and Future Directions Authors Zaid Derea College of Computer Science and Information Technology, Wasit University, Wasit 52001, Iraq Muhanad Mohammed Kadum College of Computer Science Mathematics, University of Thi Qar, Dhy Qar, 64001, Iraq. *University of Thi-Qar Journal*.
- [5] Camps-Valls, G., Fernández-Torres, M., Cohrs, K., Höhl, A., Castelletti, A., Pacal, A., Robin, C., Martinuzzi, F., Papoutsis, I., Prapas, I., Pérez-Aracil, J., Weigel, K., Gonzalez-Calabuig, M., Reichstein, M., Rabel, M., Giuliani, M., Mahecha, M. D., Popescu, O., Pellicer-Valero, O. J., . . . Williams, T. (2025). Artificial intelligence for modeling and understanding extreme weather and climate events. *Nature Communications*, 16(1), 1919. <https://doi.org/10.1038/s41467-025-56573-8>
- [6] Balevic, K. (2024, December 4). *Google DeepMind says its new AI weather prediction tool outperforms top forecasters*. Business Insider. <https://www.businessinsider.com/deepmind-google-ai-weather-forecast-tool-gencast-2024-12?>
- [7] Singh, A. (2025). Developing AI models to predict and mitigate the effects of climate change Ajit Singh. *SSRN*.
- [8] Kamble, R. (2024). Climate Change Prediction Using Artificial Intelligence Rutuja Kamble. *SSRN*.
- [9] Materia, S., García, L. P., Chiem, V. S., O, S., Mamalakis, A., Cavicchia, L., Coumou, D., Paolo, D. L., Kretschmer, M., & Donat, M. G. (2023, October 3). *Artificial Intelligence for Prediction of Climate Extremes: State of the art, challenges and future perspectives*. arXiv.org. <https://arxiv.org/abs/2310.01944?>
- [10] Nawaz Ansari, D. (2022). DEEP LEARNING BASED CLIMATE DATA DOWNSCALING OVER INDIA Danish Nawaz Ansari Altera Digital Health. *ResearchGate*.
- [11] Swepub | Kollar att du inte är en bot. (n.d.). <https://swepub.kb.se/bib/swepub%3Aoi%3ADiVA.org%3Asu-180877?language=en&tab2=abs>
- [12] Tandon, A. (2026, July 17). *Traditional models still 'outperform AI' for extreme weather forecasts*. Carbon Brief. <https://www.carbonbrief.org/traditional-models-still-outperform-ai-for-extreme-weather-forecasts>

- [13] Schneider, T., Behera, S., Boccaletti, G., Deser, C., Emanuel, K., Ferrari, R., Leung, L. R., Lin, N., Müller, T., Navarra, A., Ndiaye, O., Stuart, A., Tribbia, J., & Yamagata, T. (2023). Harnessing AI and computing to advance climate modelling and prediction. *Nature Climate Change*, 13(9), 887–889. <https://doi.org/10.1038/s41558-023-01769-3>
- [14] Eyring, V., Collins, W. D., Gentine, P., Barnes, E. A., Barreiro, M., Beucler, T., Bocquet, M., Bretherton, C. S., Christensen, H. M., Dagon, K., Gagne, D. J., Hall, D., Hammerling, D., Hoyer, S., Iglesias-Suarez, F., Lopez-Gomez, I., McGraw, M. C., Meehl, G. A., Molina, M. J., . . . Zanna, L. (2024). Pushing the frontiers in climate modelling and analysis with machine learning. *Nature Climate Change*, 14(9), 916–928. <https://doi.org/10.1038/s41558-024-02095-y>
- [15] Camps-Valls, G., Fernández-Torres, M., Cohrs, K., Höhl, A., Castelletti, A., Pacal, A., Robin, C., Martinuzzi, F., Papoutsis, I., Prapas, I., Pérez-Aracil, J., Weigel, K., Gonzalez-Calabuig, M., Reichstein, M., Rabel, M., Giuliani, M., Mahecha, M. D., Popescu, O., Pellicer-Valero, O. J., . . . Williams, T. (2025b). Artificial intelligence for modeling and understanding extreme weather and climate events. *Nature Communications*, 16(1), 1919. <https://doi.org/10.1038/s41467-025-56573-8>
- [16] Jones, A., Kuehnert, J., Fraccaro, P., Meuriot, O., Ishikawa, T., Edwards, B., Stoyanov, N., Remy, S. L., Weldemariam, K., & Assefa, S. (2023). AI for climate impacts: applications in flood risk. *Npj Climate and Atmospheric Science*, 6(1). <https://doi.org/10.1038/s41612-023-00388-1>
- [17] Reichstein, M., Benson, V., Blunk, J., Camps-Valls, G., Creutzig, F., Fearnley, C. J., Han, B., Kornhuber, K., Rahaman, N., Schölkopf, B., Tárraga, J. M., Vinuesa, R., Dall, K., Denzler, J., Frank, D., Martini, G., Nganga, N., Maddix, D. C., & Weldemariam, K. (2025). Early warning of complex climate risk with integrated artificial intelligence. *Nature Communications*, 16(1), 2564. <https://doi.org/10.1038/s41467-025-57640-w>
- [18] *Artificial Intelligence for Disaster Risk Reduction: Opportunities, challenges, and prospects.* (2026, September 8). World Meteorological Organization. <https://wmo.int/resources/wmo-bulletin/wmo-bulletin-vol-71-1-2022/artificial-intelligence-disaster-risk-reduction-opportunities-challenges-and-prospects>
- [19] Bracco, A., Brajard, J., Dijkstra, H. A., Hassanzadeh, P., Lessig, C., & Monteleoni, C. (2024). Machine learning for the physics of climate. *Nature Reviews Physics*, 7(1), 6–20. <https://doi.org/10.1038/s42254-024-00776-3>
- [20] Camps-Valls, G., Carrassi, A., De Melo Viríssimo, F., Debeire, K., Fernández-Torres, M., Hess, P., Heuer, H., Mankovich, N., Montero, D., Rodrigo-Bonet, E., Serva, F., Sitokonstantinou, V., White, A., Cohrs, K., Wider, J., Reimers, C., Bountos, N. I., Papoutsis, I., Gentine, P., &

Eyring, V. (2026). Bridging the weather and climate divide with artificial intelligence. *Nature Communications*, 17(1). <https://doi.org/10.1038/s41467-026-75787-y>