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Artificial Intelligence, Extreme Climate Events, and Disaster Risk Reduction: A Scientific Review

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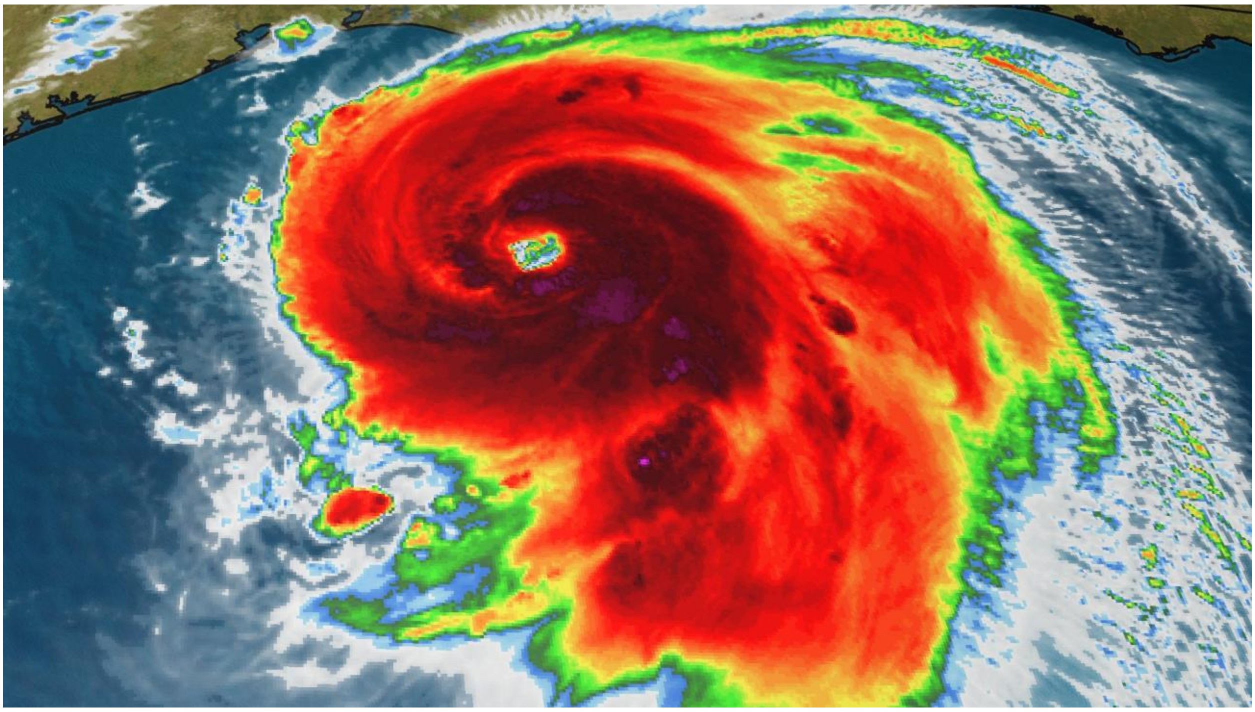
Abstract: ***Extreme climate events- heatwaves, floods, droughts, wildfires, and intensified tropical cyclones- are increasing in frequency and severity as anthropogenic climate change reshapes the statistical distribution of weather. Traditional numerical weather and climate prediction, built on physics-based equations solved on supercomputers, remains the backbone of forecasting but faces limits in computational cost, resolution, and speed. Over the past five years, artificial intelligence (AI), particularly deep learning, has emerged as a complementary and in some respects transformative tool across the full disaster management cycle: prediction, early warning, real-time monitoring, response coordination, and post-event damage assessment. This article reviews the scientific basis of AI-based weather and climate modeling, surveys applications across major hazard types, examines documented strengths and limitations (including the "blurring" problem in deterministic AI forecasts and the loss of physical interpretability), and discusses governance and equity challenges that will determine whether these tools reduce or exacerbate global disaster risk.***

Keywords: Artificial intelligence, Climate change, Weather forecasting, Disaster management, Early warning systems

1. Introduction

1.1 The changing climate risk landscape

The Intergovernmental Panel on Climate Change (IPCC) and national meteorological agencies have documented a robust upward trend in the frequency and intensity of several categories of extreme events since the mid-20th century: heatwaves and warm extremes, heavy precipitation events, agricultural and ecological droughts in some regions, and the proportion of tropical cyclones reaching high intensity categories. These shifts are consistent with the thermodynamic and dynamic responses expected from a warming atmosphere and ocean — a warmer atmosphere holds more moisture (following the Clausius–Clapeyron relation, roughly 7% more water vapor per degree Celsius of warming), which intensifies precipitation extremes and fuels convective storms, while shifting jet-stream and monsoon patterns alter the geography of drought and flood risk.



Disasters associated with these events already impose costs exceeding hundreds of billions of dollars annually and disproportionately affect low-income and geographically exposed populations. The urgency of improving forecasting lead time, spatial precision, and the translation of forecasts into effective action has made this one of the most active intersections of climate science and computer science.

1.2 Why AI, and why now

Three developments have converged to make AI newly relevant to climate and disaster science:

1) **Data availability**- decades of satellite reanalysis (e.g., ECMWF's ERA5), radar, in-situ sensor networks, and high-resolution Earth observation now provide the large, labeled, and physically consistent datasets that deep learning requires.

2) **Architectural advances-** graph neural networks, transformers, and diffusion models can represent the spatial and temporal structure of atmospheric and hydrological systems in ways that earlier machine learning methods could not.
3) **Computational economics**- a trained AI weather model can generate a 10-day global forecast in a fraction of the time and energy required by a physics-based numerical weather prediction (NWP) run on a supercomputer, since inference (unlike training) is comparatively cheap.

2. AI in weather and climate prediction

2.1 From numerical weather prediction to data-driven emulators

Operational forecasting has for decades relied on NWP: solving the primitive equations of fluid dynamics and thermodynamics on a three-dimensional grid, initialized through data assimilation of observations. This approach is physically grounded but computationally expensive and resolution-limited by available compute.

Since 2022–2023, a new generation of AI weather models trained on reanalysis data has matched or exceeded NWP skill on many verification metrics while running orders of magnitude faster:

- **Pangu-Weather** (Huawei), a 3D Earth-Specific Transformer, matched or outperformed the ECMWF high-resolution model (HRES) on a majority of evaluated metrics for medium-range forecasts, with particularly strong tropical cyclone track predictions at longer lead times.
- **GraphCast** (Google DeepMind), a graph neural network operating at 0.25° resolution, outperformed HRES on roughly 90% of more than a thousand verification targets and could produce a 10-day global forecast in under a minute on a single processor.
- **GenCast**, a diffusion-based ensemble model, generates dozens of stochastic forecast trajectories rather than one deterministic output, allowing probabilistic estimates of storm tracks and extreme rainfall; it has been reported to outperform ECMWF's full ensemble system on the large majority of evaluated targets. Its successor family (referred to in industry reporting as "WeatherNext 2") has continued this trajectory into 2026 operational use.
- **Aurora** (Microsoft), a large "foundation model" for the atmosphere, is pretrained on a heterogeneous mixture of reanalysis, climate simulation, and air-quality data before fine-tuning, extending the AI approach beyond weather into air quality and ocean-wave prediction.

National agencies have begun operationalizing these tools: NOAA, for example, has fine-tuned GraphCast-derived architectures on its own Global Data Assimilation System analyses to improve regional performance and integrate AI guidance into hurricane forecasting workflows.

2.2 Documented strengths

- **Speed and cost**: AI inference requires a small fraction of the energy and hardware of a full NWP run, enabling more frequent forecast updates and larger ensembles.
- **Track prediction**: For tropical cyclones, several AI models have shown track errors competitive with or better than official guidance beyond 48–120 hour lead times.
- **Ensemble/probabilistic skill**: Diffusion-based approaches like GenCast can generate large ensembles cheaply, improving the quantification of uncertainty — critical for evacuation and resource-allocation decisions.
- **Democratization**: Because inference is inexpensive relative to running an NWP center, national meteorological services in lower-resource countries can potentially access high-resolution guidance without building supercomputing infrastructure.

2.3 Documented limitations

- **Blurring / underestimation of extremes**: Deterministic AI models trained with mean-squared-error objectives tend to hedge toward smooth, averaged fields, which systematically underestimates the intensity of rare, sharp events. Independent verification has found that models such as GraphCast and Pangu-Weather underestimated the top one percent of precipitation intensities by roughly 20–35%, a larger underestimation than seen in physics-based HRES forecasts. This is a structural artifact of the training objective rather than a data problem, and it is only partially mitigated by ensemble/diffusion approaches.
- **Dependence on initial conditions**: AI models do not perform their own data assimilation; they still depend on physically-generated analyses (typically from NWP systems) as their starting point, which means they inherit any errors present in those initial fields and cannot yet function as fully independent forecasting pipelines.
- **Interpretability and the "black box" problem**: Physics-based models allow a forecaster to trace a predicted storm's evolution to specific physical mechanisms. AI models, in contrast, are largely inscrutable, which has generated debate within the World Meteorological Organization and national agencies about how forecasters should communicate and justify high-stakes warnings- such as evacuation orders- generated substantially by opaque models.
- **Training-data circularity**: Some evaluation studies rely on the same reanalysis products used in model training or fine-tuning, meaning reported skill may partly reflect consistency with the training target rather than fully independent validation against observations.

3. AI across the Disaster Management Cycle

Disaster management is commonly organized into four phases- mitigation, preparedness, response, and recovery- and AI applications now span all four.

3.1 Prediction and early warning systems (preparedness)

Early warning systems (EWS) increasingly combine satellite imagery, ground sensors, and AI pattern recognition:

- **Flood mapping**: Convolutional neural networks trained on historical flood imagery can distinguish river overflow from standing water and generate near-real-time flood extent maps from satellite data, supporting systems such as Google's flood forecasting initiative, which has extended coverage to river basins in dozens of countries.

- **Wildfire detection**: Specialized models identify smoke plumes and thermal anomalies from satellite or aerial imagery, in some cases even under partial cloud cover, enabling alerts before fire fronts expand; Microsoft and other technology providers have deployed similar capabilities for forest monitoring.
- **Heatwave and drought indices**: Machine learning models increasingly incorporate soil moisture, vegetation indices, and long-range atmospheric patterns to provide sub-seasonal to seasonal outlooks for heat and drought risk, complementing traditional statistical climate indices.
- **Explainable AI for hazard drivers**: Methods such as SHAP (SHapley Additive exPlanations) are being used in wildfire and flood-susceptibility models to identify which environmental and meteorological variables most strongly drive risk in a given region, partially addressing the interpretability gap.

International coordination on this front has accelerated: the World Meteorological Organization, together with the International Telecommunication Union and the European Commission's civil protection directorate, convened a Global Initiative on Resilience to Natural Hazards through AI Solutions in late 2025, aimed at developing shared standards and governance frameworks for trustworthy AI in hydrometeorological services.

3.2 Response coordination

- **Dynamic evacuation routing**: Reinforcement learning agents can process live data on road congestion, hazard spread, and shelter capacity to recommend adaptive evacuation routes and shelter allocation, updating recommendations as conditions change rather than relying on static evacuation plans.
- **Damage assessment**: Machine learning analysis of pre- and post-event satellite or aerial imagery can rapidly estimate the extent and severity of wildfire or flood damage to structures, accelerating insurance claims processing and the targeting of relief resources. Platforms used by organizations such as One Concern and Palantir combine such imagery analysis with real-time data feeds to support coordination across responding agencies.
- **Infrastructure monitoring**: Predictive-maintenance models that ingest flood-sensor and structural-stress data on bridges and levees can flag elevated failure risk before catastrophic infrastructure failure occurs.
- **Social media and crowd-sourced signals**: Natural language processing applied to social media posts can help identify emerging crises and public sentiment in near real time, supplementing official sensor networks, particularly in data-sparse regions.

3.3 Recovery and long-term resilience

Post-disaster recovery increasingly draws on AI-assisted damage mapping to prioritize rebuilding, on climate risk models to inform where and how reconstruction should occur to reduce future exposure, and on scenario simulation to stress-test infrastructure and land-use plans against a range of future climate trajectories.

4. Case-relevant Hazard Types

Hazard	Representative AI approaches	Key capability gains	Persistent challenges
Tropical cyclones	GraphCast, Pangu-Weather, GenCast ensembles	Improved track accuracy beyond 48h; probabilistic landfall cones	Intensity/rapid-intensification prediction remains harder than track prediction
Flash floods / river flooding	CNN-based flood mapping, hybrid hydrology-ML models	Near-real-time inundation maps; extended lead time for river basins	Underestimation of extreme rainfall intensities; data scarcity in ungauged basins
Wildfires	Satellite CNNs for smoke/heat detection, SHAP-based susceptibility models	Earlier ignition detection; identification of key risk drivers	False positives from non-fire heat sources; real-time data latency
Heatwaves	ML-enhanced sub-seasonal forecasting	Better anticipation of persistent heat domes	Compound risk (heat + humidity + power-grid stress) modeling still maturing
Droughts	ML integration of soil moisture, vegetation, precipitation history	Improved multi-month outlooks	Regional data gaps; slow-onset nature complicates "event" framing

5. Cross- Cutting Scientific and Ethical Challenges

5.1 The accuracy–interpretability trade-off

The same architectural properties (deep, nonlinear, high-dimensional networks) that give AI weather models their skill also make it difficult to explain individual predictions. This raises a governance question with direct human-safety stakes: how much explanatory justification should be required before an AI-derived forecast triggers a mandatory evacuation order.

5.2 Equity and access

Because AI inference is cheap relative to full NWP infrastructure, it has the potential to close forecasting gaps for lower-income countries. However, this potential depends on data-sharing arrangements, model licensing, and local capacity to interpret and act on AI guidance responsibly- none of which are guaranteed to keep pace with the technology itself. Concerns about data sovereignty (which entities control the observational data feeding these models) have become a recurring theme in international discussions.

5.3 Validation and trust

Because several leading AI models are trained and fine-tuned on the same reanalysis products used for evaluation, independent, out-of-sample validation against direct observations remains essential, and is not yet universal practice across the field.

5.4 Compounding and cascading risk

Real-world disasters increasingly involve compound and cascading hazards- for example, a heatwave stressing an

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electrical grid at the same time storms damage transmission infrastructure. Most current AI systems are specialized for single hazard types; integrating them into coupled, compound-risk models is an active area of research rather than a solved problem.

6. Outlook

The trajectory of the field suggests several near-term developments:

- **Hyper-local forecasting**: Industry roadmaps point toward neighborhood-scale, hourly predictions of phenomena such as urban heat islands, extending AI weather guidance well beyond the historical resolution of global models.
- **Hybrid physics–AI systems**: Rather than replacing NWP, the most promising operational path appears to be hybrid systems in which AI accelerates or emulates specific components (e.g., initial-condition generation, ensemble generation, or downscaling) while physics-based cores continue to anchor overall consistency and interpretability.
- **Standardization and governance**: Multilateral efforts led by the WMO and partner UN and standards bodies aim to establish shared benchmarks, verification protocols, and trust frameworks so that AI-based warnings can be integrated into official early warning systems without undermining public confidence.

7. Conclusion

Artificial intelligence has moved, within a few years, from an experimental technique to a component of operational weather and climate-hazard forecasting used by national agencies and international bodies. It offers genuine, measurable improvements in speed, cost, and- for several hazard types- accuracy, and it is reshaping every phase of the disaster management cycle, from prediction through response and recovery. At the same time, the scientific record is clear that current AI models systematically underrepresent the most extreme events precisely where forecasting matters most for life safety, and that the interpretability and validation of these systems lag behind their raw predictive performance. Realizing the technology's potential to reduce global disaster losses- rather than simply shifting where and how forecasting errors occur- will require continued attention to extreme-event calibration, independent validation, equitable access, and governance frameworks that keep pace with a rapidly moving field.

References

[1] Bi, K., et al. (2023). "Accurate medium-range global weather forecasting with 3D neural networks." *Nature*, 619.
[2] Lam, R., et al. (2023). "Learning skillful medium-range global weather forecasting." *Science*, 382(6677).
[3] Bodnar, C., et al. (2024/2025). "Aurora: A Foundation Model for the Earth System."
[4] Hamill, T., et al. (2024). Geophysical Research Letters (evaluation of AI model extreme-precipitation performance).
[5] World Meteorological Organization, meeting summaries on AI for early warning systems (2025–2026).
[6] NOAA news release, "NOAA deploys new generation of AI-driven global weather models" (2026).
[7] Otero, N., et al. (2026). "Advancing early warning systems: AI applications, challenges and emerging insights." *Environmental Research Letters*, 21(8).
[8] ScienceDirect / PMC review, "The role of artificial intelligence for early warning systems: Status, applicability, guardrails, and ways forward" (2025).

This article synthesizes peer-reviewed literature, agency releases, and industry reporting current as of mid-2026; given the pace of development in this field, readers should verify the latest model benchmarks and operational deployments before citing specific performance figures.