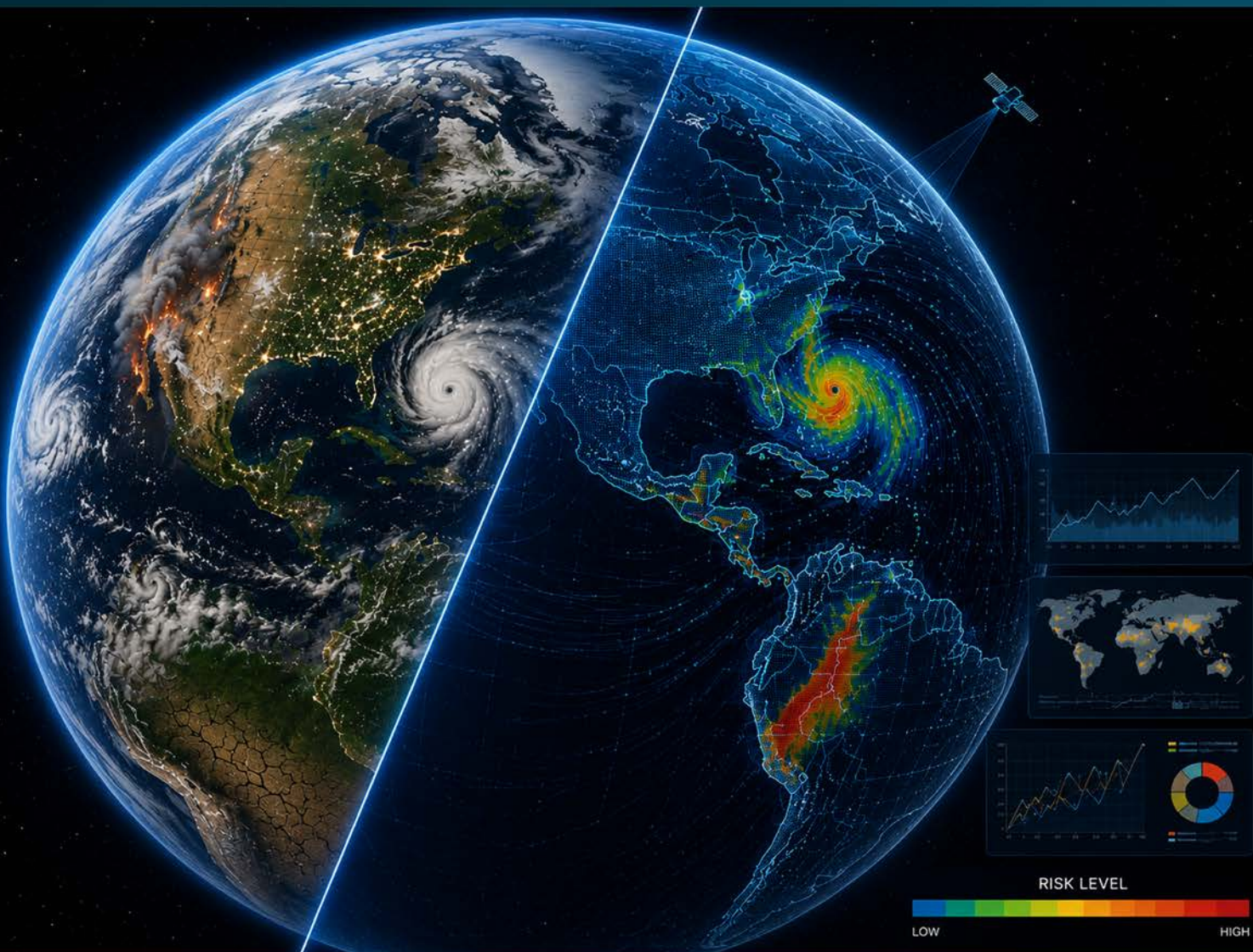


ARTIFICIAL INTELLIGENCE FOR CLIMATE RISK PREDICTION AND ADAPTATION



Report writers

Thomas Chandler, PhD, Richard Hendra, PhD, Joshua L. DeVincenzo, EdD, Shuyang Huang, MS, March
Part of the "AI and Future of Work" Initiative
Under the leadership of Professor **Yanis Ben Amor**
Center for Sustainable Development,
Columbia University

Executive Summary

Many types of disasters are becoming more frequent and intense due to climate change, putting a previously unheard-of strain on governmental institutions, emergency management systems, and vital infrastructure. In a world where climate threats are cascading, traditional forecasting and disaster-response models, which frequently rely on past patterns and reactive tactics, are becoming less effective. This report examines how artificial intelligence (AI) can assist emergency managers, governments, and the private sector in moving away from passive disaster management and toward more proactive and resilience-focused strategies. AI presents new opportunities to enhance disaster preparedness, response, and long-term recovery by quickly evaluating vast amounts of environmental, infrastructure, and socioeconomic data, much of which can now be analyzed in real-time.

Numerous instances in which AI is already showing practical benefit are highlighted in this report. Flood forecasting, wildfire detection, housing damage assessments, humanitarian aid targeting, and real-time situational awareness are all being improved by machine learning algorithms. While operating at lower computational costs, advances in AI weather prediction are increasingly competing with conventional forecasting techniques. That said, this report does stress that technological capability is not enough on its own. High-quality data, reliable validation procedures, and human supervision

are all critical components of AI systems. To ensure that technology enhances rather than replaces expert judgment and local knowledge, emergency managers must be able to comprehend, assess, and operationalize AI-generated insights.

The report's main conclusion is that the data infrastructure needed to assess, regulate, and expand AI models responsibly may present the biggest long-term opportunity for return on investment. Climate AI solutions are receiving substantial funding, but data provenance, administrative data linking, outcome measurement, and performance verification have received far less attention. Governments and investors cannot accurately assess whether AI systems enhance public outcomes, lessen vulnerability, or distribute resources fairly without these fundamental capabilities. Governments, business, academia, and civil society must make investments in open data platforms, workforce development, transparent governance frameworks, and locally appropriate implementation strategies to ensure that AI does not exacerbate already-existing disparities. The report concludes that while AI has the potential to revolutionize climate resilience, its long-term worth will ultimately depend on how well it supports equitable adaptation outcomes, produces quantifiable societal benefits, and stays firmly guided by human judgment and public accountability.

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Introduction

The operating environment of emergency management agencies worldwide is being increasingly altered by climate change. Rising temperatures and sea levels, and the increasing frequency and intensity of extreme weather events, are placing ever greater strain on physical infrastructure and the ability of agencies to respond. Traditional models for forecasting and disaster response, largely developed around historical baselines and discrete hazard events, are increasingly ineffective in the face of simultaneous cascading climatological disasters and rapidly changing environmental and risk conditions. Consequently, governments and emergency management agencies are under growing pressure to adopt more adaptive and anticipatory approaches to climate risk governance.¹ This report explores the application of artificial intelligence (AI) for predicting and responding to climate risks, its potential and limitations, the strategic implications for emergency management, and considerations for achieving a more effective return on investment in this sector.

AI, particularly machine learning, provides new opportunities for emergency managers to anticipate and act upon a plethora of hazards and threats, including wildfires, extreme flooding, typhoons and hurricanes, droughts, and heatwaves. AI developers are continually upgrading models for forecasting, improving decision-making, and assisting in resilience-building processes by instantaneously analyzing massive datasets and providing insights on emerging trends.² Furthermore, AI use supports climate risk management in moving from reactive to anticipatory governance. As humanity experiences rapidly changing meteorological events, traditional disaster management techniques—which often rely on historical trends, unstructured data sets, and post-event evaluations—become increasingly cumbersome and inefficient. In contrast, emergency managers can now simulate solutions before a disaster strikes by using AI-driven models that often predict future scenarios under an array of weather conditions.³ By encouraging greater proactive investments in infrastructure, land-use planning, and community readiness, this forward-looking capability has the potential to eventually lower long-term social and economic costs.

At the same time, the rise of AI in climate risk prediction poses major questions around uncertainty, data quality, adequate guardrails, and public trust. The climate system is itself highly nonlinear and difficult to predict over long time horizons, and AI systems fundamentally depend on the quality and representativeness of the data on which they are trained. A popular analogy about the challenges of predicting weather phenomena is the “butterfly effect” from the early work of the meteorologist Edward Lorenz, which addresses how small differences in initial conditions can lead to extremely divergent long-term outcomes.⁴ In practice, predictive reliability of AI for weather prediction may also be undermined by incomplete monitoring systems, uneven global data coverage, and historically biased datasets, particularly in vulnerable regions with limited technical infrastructure. As such, AI-generated forecasts cannot be considered purely technical outputs detached from institutional and local context. In the upcoming years, effective climate adaptation will increasingly depend on the successful integration of AI systems into the work of climate scientists, emergency managers, private sector stakeholders, and local communities who can interpret and operationalize those insights into real-world decision environments.⁵

Likewise, the larger relevance of AI for climate adaptation needs to be understood within economic, political, and societal frameworks rather than simply through the lens of technological capacity. The success of AI-enabled climate governance will hinge on whether these systems are embedded in institutions that prioritize accountability, transparency, and equitable access to information and resources. The latter challenge is especially critical, as those most vulnerable to climate-related disasters are often those with the least access to advanced technological infrastructure and decision-making capacity. Accordingly, the value of AI for climate adaptation will depend not only on predictive performance but also on its ability to improve institutional coordination, foster public trust, and promote more equitable resilience outcomes across communities and regions.



“When considering return on investment, firms specializing in data provenance, linkage, verification, and monitoring infrastructure may represent some of the most durable opportunities within the climate AI ecosystem.”

Current Issues Regarding Climate Change and Emergency Management

The stages of preparedness, response, and recovery remain the guiding framework for emergency management systems globally. But as communities attempt to build back better and recover economically, many institutions are still structured to respond in the short term rather than to anticipate risk and plan for resilience. In practice, limited forecasting capabilities, fragmented data systems, and uneven resource distribution still constrain effective disaster management efforts. Recovery processes also tend to focus on a return to pre-disaster conditions, rather than addressing the structural vulnerabilities that contributed to the severity of impacts in the first place. This reactive stance is increasingly difficult to sustain in the face of mounting climate risks.⁶

Another challenge is the growing mismatch between the scale of new climate risks and institutions’ ability to respond. Many emergency management organizations have focused on discrete, localized disaster events rather than cascading or compounding crises (e.g., simultaneous heatwaves and droughts, sequential storms on already-damaged infrastructure, or wildfire particulate matter reducing air quality in major urban areas). These linkages create operational demands that go beyond traditional sector-based coordination models and highlight deficiencies in logistics, communication, and intergovernmental planning.⁷ The growing frequency of such disasters also means that emergency management systems may need to rely more on integrated, systems-oriented approaches that can work across multiple hazards, jurisdictions, and infrastructure networks simultaneously.

Emergency response activities are further complicated by the growing vulnerability of vital infrastructure systems to the effects of climate change. During extreme disasters, energy grids, transportation networks, water systems, and healthcare facilities can all be disrupted. Failure of these systems has repercussions that go beyond the

immediate danger, severely increasing societal and financial damages. Prolonged power outages during heatwaves, for instance, can increase the risk of death, and damaged transportation networks can delay the delivery of supplies and emergency services. Because infrastructure systems are interdependent, a single point of failure can have a domino effect, underscoring the need for resilience-oriented planning. Disasters can also trigger a downward economic spiral for more than a decade: population loss and business closures can erode the local tax base, rising risk can increase insurance costs or reduce coverage availability, and weakened public finances can make recovery and future resilience harder to sustain.^{8,9}

Artificial Intelligence in Emergency Management

AI can be most useful in emergency management through utilization of AI to provide a set of analytic tools. Computer vision, forecasting, natural-language processing, optimization, and anomaly detection can each help translate complex hazard data into signals that support operational decisions. Reviews of AI applications by the European Resilience Management Guideline and the Sendai Framework for Disaster Resilience Network have identified use cases across hazard prediction, risk and vulnerability assessment, early warning, event detection, damage assessment, search and rescue, and resource allocation.¹⁰

For imagery-heavy tasks, object-detection models such as You Only Look Once (YOLO) are useful because they can rapidly scan streaming video or large image collections and flag operationally relevant features, including damaged buildings, blocked roads, vehicles, smoke, flood extent, or other visible indicators of hazard impact.¹¹ This capability is especially important when satellite images or unmanned aerial vehicle (UAV) imagery must be reviewed quickly after



xBD Dataset Sample: (top) Pre- and (bottom) Post-Disaster Images.

a disaster. A related post-disaster damage-assessment use case is the xView2 challenge and xBD dataset, developed by the U.S. Defense Innovation Unit (DIU) in collaboration with Carnegie Mellon University's Software Engineering Institute (SEI), which helps automate building-damage assessment from pre- and post-disaster satellite imagery across hazards such as floods, wildfires, earthquakes, tsunamis, storms, and volcanic eruptions. This type of computer vision can triage large areas rapidly, identify where human assessment should begin, and reduce first responders' exposure to unsafe structures. The main caveat is that models trained on one geography or hazard may generalize poorly elsewhere unless they are validated against local ground truth.¹² More broadly, deep neural networks can learn complex relationships across satellite imagery, UAV feeds, sensor measurements, weather records, and socioeconomic data.¹³ This allows emergency managers to connect physical damage, environmental conditions, and population vulnerability in a more integrated way.

This matters because emergency managers do not make decisions from forecasts alone. They must combine hazard predictions with what the infrastructure condition is, how vulnerable the population is, how the field reports are generated, and how available the resources are. In mitigation, AI can help identify high-risk areas of the built environment and detect immediate maintenance needs. In preparedness, it can support early warning systems and training programs, where learners can practice key concepts and participate more meaningfully in planning scenarios. During response, it can help optimize logistics and resource allocation, while also identifying vulnerable populations in immediate need of assistance. In recovery, it can support rapid damage assessment and help agencies target inspections, debris removal, and guide rebuilding efforts. Across these phases, AI can assist agencies in moving from scattered information to faster, more targeted action.

Across all phases of disaster management of extreme weather, AI can assist agencies in moving from scattered information to faster, more targeted action.

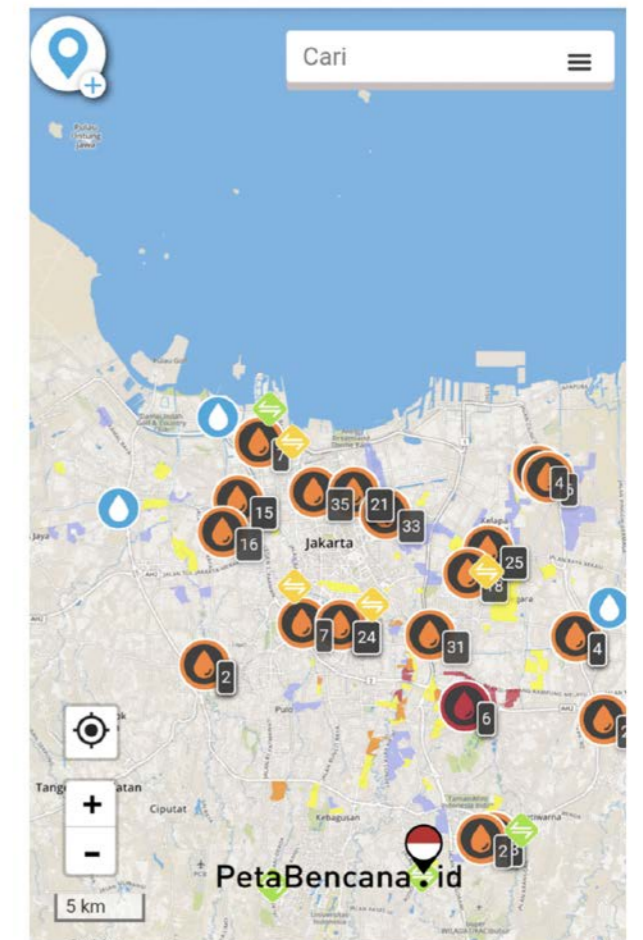
MITIGATION	PREPAREDNESS	RESPONSE	RECOVERY
Identify high-risk areas of the built environment and detect immediate maintenance needs.	Conduct scenario planning, evacuation modeling with digital twins, resource allocation, and training exercises.	Optimize logistics and resource allocation, while also identifying vulnerable populations in immediate need of assistance.	Support rapid damage assessment and help agencies target inspections, debris removal, and guide rebuilding efforts.

Flood forecasting is an example which shows how AI can turn environmental data into more immediate and localized warnings. Google's AI-based flood forecasting work has shown that machine-learning models can produce reliable riverine flood forecasts for ungauged basins up to five days ahead, with the operational Flood Hub providing free forecasts in dozens of countries. For emergency managers, the value of this modeling is immediately practical. Earlier and more spatially specific warnings can enable pre-positioning of supplies, evacuation messaging, school closures, and anticipatory cash or relief actions before rivers peak.¹⁴

Wildfire management is another example that shows how AI can support both early detection and real-time fire-spread modeling. Developed with CAL FIRE and UC San Diego partners, ALERTCalifornia uses AI to scan images from a statewide camera network and alert trained staff when it detects signs of a possible new fire. Since September 2023, the tool has been available to all twenty-one CAL FIRE 911 dispatch centers. A 2025 report found that in 2024, ALERTCalifornia cameras detected 1,668 fires, 38% of which were detected before any 911 call. One reported case near the city of Auburn, California shows the value of this early-warning system: on July 6, 2024, an AI camera posted an alert at 2:33 a.m. before anyone had called 911. CAL FIRE verified the alert, sent engines, and crews put the fire out before it spread beyond a 30-by-30-foot area.¹⁵

AI can also improve real-time situational awareness during cascading events, when conditions change quickly and information comes from many places at once. Crisis-informatics tools are a prime example, helping agencies sort these fast-moving information streams and detect emerging needs, infrastructure disruption, evacuation bottlenecks, or misinformation. Research datasets such as CrisisMMD show how disaster-related posts can be classified into categories

such as infrastructure damage, injuries, missing persons, and requests for assistance.¹⁶ PetaBencana.id in Indonesia shows how this approach can be used operationally. Its BencanaBot collects resident reports of hazards through social media and messaging platforms, maps those reports in real time, and shares the information with communities and government responders.¹⁷



A cellphone screenshot of reported flood waters rising in Jakarta, Indonesia, from the PetaBencana.id platform.



AI can also help agencies target emergency humanitarian relief when response time matters. After Hurricane Ian devastated the U.S. state of Florida in 2022, GiveDirectly and Google.org used the Delphi tool to combine AI-derived building damage estimates from aerial imagery with poverty and population data. This allowed staff to identify census block groups with both severe damage and high poverty and to prioritize them for emergency cash transfers. GiveDirectly reported work that previously required weeks of block-by-block assessment could be completed in hours. Remote enrollment and payment through a benefits app also allowed many recipients to receive funds within a day.¹⁸ This example strengthens the emergency-management argument because it shows how AI outputs can inform a concrete humanitarian decision: who should receive scarce assistance first.

AI can also support cooperation across agencies and jurisdictions, especially during multi-hazard incidents where local, regional, and national authorities and international NGOs need to work with the same information. Shared AI-enabled platforms can bring together weather data, infrastructure conditions, field reports, resource locations, and hazard models in one place. It reduces the risk that different agencies act on incomplete or conflicting information. A concrete example is UC San Diego's WIFIRE Firemap, a wildfire decision-support platform that integrates data on weather, topography, vegetation and fuels, fire ignitions, and real-time conditions to model fire spread and visualize risks for emergency decision-makers.¹⁹ It gives responders a shared operating picture that can guide evacuation planning, resource deployment, and cross-agency coordination during fast-moving wildfire events.

The value of AI in emergency management depends on whether the tools fit the way agencies actually work. Models need to be simple enough to use in emergency settings and accessible enough for incident commanders and emergency managers to understand their recommendations. This is the basic idea behind explainable AI: users should be able to question the output, compare it with local knowledge, and decide whether it makes sense. AI tools also need clear interfaces, staff training, and procedures for when model outputs should inform decisions. Even a technically strong system can fail if it feels disconnected from real emergency work. AI can help agencies move faster, but people still need to decide what action should follow.

Challenges Between the Global North and Global South

Although AI technologies have evolved at reduced cost and are showing promise in the emergency management sector internationally, access has not always been equitable across Global South countries. Due to insufficient funding or limited educational initiatives to promote AI innovation, many nations that could benefit from it in disaster preparedness, response, and recovery for climatological disasters are still heavily reliant on analog systems that are extremely labor-intensive.

The issue of data inequality poses another serious challenge. Huge amounts of data are required to train contemporary AI systems, yet they can either be nonexistent or insufficiently available in many developing countries. Further, models developed in the Global North may not be suitable for other regions, leading to distorted directives and recommendations. An additional barrier relates to external control and dependence on technology. A considerable number of AI technologies utilized in the Global South are developed, managed, and owned by private or institutional enterprises from the Global North. In such cases, decision making can become externally controlled, thereby increasing concerns of foreign influence.²⁰

Additionally, there is a discrepancy between the conventional methods frequently incorporated into AI systems and locally relevant knowledge. AI models may miss important context or make disaster-response recommendations that are unworkable or culturally insensitive if they do not account for a multitude of cultural nuances. Participatory methods that incorporate local knowledge into the development, training, and deployment of AI systems are sorely needed to close this gap.^{21,22}

AI companies' development of open and interoperable AI systems should be prioritized alongside these actions. Shared platforms, robust climate data, and accessible decision-support tools can improve knowledge-sharing, reduce fragmentation, and support more effective adaptation planning, especially where technical capacity is limited. Evaluations of disaster relief efforts are often a good starting point, due to their wide accessibility.²³ Moreover, AI coding tools such as OpenAI Codex and Anthropic's Claude Code may lower the technical barriers to developing and adapting open-source emergency-management tools by helping local teams write, review, debug, and modify their own code more efficiently.

Similarly, it is important for policymakers to foster the institutionalization of AI education and training programs to build the required expertise as climate risks grow more pronounced. While training the next generation on data science and machine learning algorithms is an imperative, it is also necessary to develop the competency of emergency managers, legislators, and community leaders in applying the latest skills and concepts for successfully using AI tools.²⁴ This would ensure the proper use of such tools by integrating AI literacy into professional degree and workforce development programs.

Fostering Return on Investment

Even when investments in climate tools incorporating artificial intelligence are made, without additional mechanisms to ensure proper monitoring, evaluation, and accountability, these efforts may not be effective. The ability to measure results is necessary not only to determine the return on investment but also to ensure that, over time, these systems remain focused on their primary public goals. An adaptive evaluation strategy, such as formative assessment techniques, enables governments and organizations to detect emerging issues. This is especially crucial given that AI solutions can have unforeseen consequences, one of which is the exacerbation of inherent biases in data sets and processes within organizational structures. In due course, the measurement of results cannot be limited to technical measures of success alone. Instead, an organization will have to ensure its alignment with verified data by human managers collected during onsite damage assessments.

The next major return-on-investment frontier is therefore not only the AI models themselves, but also the measurement and data infrastructure required to transform model outputs into accountable, financeable, and operationally credible decisions. The financial stakes are substantial. Munich Re estimated that global natural catastrophe losses reached approximately US\$320 billion in 2024, including US\$140 billion in insured losses, making 2024 the third-costliest year for insurers since 1980. Meanwhile, Swiss Re projected that insured catastrophe losses would again exceed US\$100 billion in 2025, continuing a multi-year trend of escalating disaster costs.²⁵ Large portions of these losses remain uninsured, underscoring the scale of the global protection gap and increasing pressure on governments and financial institutions to improve risk prediction, preparedness, and recovery systems.

Pilot projects across the world already demonstrate that AI can improve disaster response capabilities, wildfire detection, and post-disaster targeting of assistance. However, these deployments do not yet consistently demonstrate whether AI systems improve population-level outcomes, distribute aid equitably at scale, or materially reduce long-term vulnerability. Capability alone is insufficient without accountability. Increasingly, the core challenge is not whether AI systems can generate forecasts or automate decisions, but whether governments and investors have the institutional capacity to verify that these systems produce measurable public benefit.

This challenge is fundamentally a capital allocation issue rather than a purely academic one. Public investment in administrative data systems, exposure-outcome linkage, audit capacity, and longitudinal monitoring of infrastructure is becoming a prerequisite for large-scale private investment in climate AI markets. While capital is rapidly flowing toward AI-enabled climate forecasting, resilience analytics, and disaster-risk products, the infrastructure needed to independently verify performance and fairness remains significantly underdeveloped. As a result, governments are increasingly being asked to procure systems, and investors are being asked to finance technologies, whose real-world societal impacts cannot always be comprehensively measured.

Recent advances in AI weather forecasting nevertheless demonstrate that the technical capabilities of these systems are improving rapidly. Models such as GraphCast²⁶ and Pangu-Weather²⁷ have shown that data-driven forecasting systems can rival or exceed traditional numerical weather prediction methods at medium-range forecasting while operating at substantially lower computational cost. Benchmarking initiatives such as WeatherBench 2²⁸ have also improved the ability to evaluate forecasting accuracy across models. At the same time, recent comparative studies show that performance still varies considerably by geography, lead time, and hazard type, especially during extreme weather events.²⁹ This suggests that while forecasting capability is becoming increasingly mature in data-rich regions, the surrounding infrastructure required for integration, operational decision-making, and outcome evaluation remains unevenly developed.

The investment imbalance is increasingly clear. Most current capital targets the model-development layer, where competition is intensifying, and technical advantages may erode relatively quickly. By contrast, the data infrastructure layer, including data provenance, curation, linkage, verification, and ground-truth monitoring, often offers more durable and defensible long-term value. Administrative data infrastructure is especially important because it determines whether climate exposures can be connected to measurable social and economic outcomes, including employment disruption, health impacts, housing displacement, and business continuity. Jurisdictions capable of linking these datasets become environments where climate AI systems can be properly evaluated, refined, financed, and scaled.

→ **Investors and governments should treat data linkage infrastructure as a foundational asset class.**

CAREs is a working demonstration that exposure data (from NOAA and DOE) can be linked to disaster assistance data (from FEMA) and population characteristics (from the U.S. Census), enabling direct measurement of how disaster impacts translate into recovery needs at the household level.

Jurisdictions lacking such infrastructure risk becoming locations where pilot projects remain isolated experiments without long-term institutional adoption.

The United States has already begun demonstrating what this type of integrated infrastructure can look like in practice. In 2025, the United States Census Bureau released the Assessment, Recovery, and Evaluation Datasets (CAREs), which links administrative data from agencies including the U.S. Federal Emergency Management Agency, National Oceanic and Atmospheric Administration, Department of Energy, and Bureau of Labor Statistics to support disaster impact analysis. By connecting climate exposure data with assistance programs and demographic information, CAREs demonstrate how governments can directly evaluate how disasters affect households and communities, while improving targeting and recovery planning. This type of integrated administrative data architecture may become foundational for future climate resilience investment strategies.³⁰

This matters for the investment case. Investors and governments should treat data linkage infrastructure as a foundational asset class. CAREs is a working demonstration that exposure data (from NOAA and DOE) can be linked to disaster assistance data (from FEMA) and population characteristics (from the U.S. Census), enabling direct measurement of how disaster impacts translate into recovery needs at the household level. The methodological literature on administrative data linkage, going back to Harron et al. (2017),³¹ is well established, but its application to climate disaster outcomes remains the exception rather than the rule.

The European Union has several of the same capabilities. The EU's Copernicus program provides continental Earth observation through the Sentinel missions on an open data policy. The governance is present: the EU AI Act sets data quality and oversight requirements for high-risk systems. What is currently missing is the integration layer and the ability to link member-state administrative data (benefits, health, employment) to environmental monitoring.³² Without this, it is difficult to determine whether forecasts will reach the people who need them.

These disparities also expose an important structural challenge for inclusive climate resilience. AI model performance is often weakest in regions where vulnerability is highest because training data reflects historical underinvestment in monitoring systems and administrative infrastructure. Research on satellite-based damage assessment datasets has shown that models frequently perform less accurately in non-Western or underrepresented regions, particularly in identifying isolated or rural damage patterns. As a result, transferring AI systems from data-rich countries to data-poor regions without investing in underlying monitoring and validation infrastructure can unintentionally reinforce existing inequalities. Inclusive climate AI development, therefore, depends as much on investment in foundational data systems as on advances in algorithmic sophistication. The European Union has already invested heavily in satellite-based disaster monitoring through its Copernicus Programme, with climate adaptation and early warning projects across Africa, the Caribbean, and Pacific Island nations. Capacity building for national meteorological agencies also has seen renewed emphasis in 2026.

For governments, this implies that longitudinal exposure-outcome data systems should be funded alongside AI model development itself. When considering return on investment, firms specializing in data provenance, linkage, verification, and monitoring infrastructure may represent some of the most durable opportunities within the climate AI ecosystem. Public-private partnerships will also become increasingly important, particularly when structured to preserve data sovereignty while supporting capability transfer across jurisdictions. Ultimately, the AI-for-climate market is unlikely to scale sustainably until its outcomes can be systematically measured and verified. The jurisdictions

that build this measurement capacity first are likely to shape the standards, governance models, and investment flows that define the next phase of AI-enabled climate resilience.

Return on Investment Strategies

Investments in AI for climate risk reduction and response are likely to increase over the next five years. Uncovered losses are rising, and both public- and private-sector leaders have identified this gap internationally. The needed investments span (1) climate data infrastructure, (2) predictive analytics, (3) insurance technology, and (4) resilient infrastructure. Returns are plausible across all four areas, and the work aligns with ESG mandates without requiring a values argument.

The fast-growing AI markets have created investment conditions that in some ways are similar to earlier speculative technology cycles, such as the dot-com era. With increasing investor demand for AI-related products and services, many firms have sought to position themselves in the sector regardless of the maturity or credibility of their underlying capabilities. This environment makes thorough due diligence all the more important. The quality of a company's data infrastructure is one of the most important measures of long-term viability and is a competitive advantage, particularly for data sets that are found to be timely, geographically relevant, interoperable, and operationally reliable, rather than simply large in volume. Thus, investors should distinguish between companies with robust data integration and validation processes and those that cannot document such capabilities.

A major consideration is scalability across geographies and use cases. Climate risks differ by region, and AI solutions need to be flexible to different environmental, regulatory, and economic contexts. Investors should assess whether a company's technology can address different hazard types, such as floods, wildfires, and extreme heat, without requiring a complete system redesign. Such systems are usually built on Amazon Web Services or Microsoft Azure infrastructure and feature modular architectures or cloud-based delivery models, enabling more efficient scaling and broader market reach.

Investment decisions must also be based on risk management and transparency. AI models are increasingly being used for climate forecasting and adaptation planning, but they need to be interpretable and auditable, especially when used to support government-led financial or policy decisions. Investors should look for companies that are working on robust validation processes, and compliance with new regulatory standards. Participation in international standards such as those promoted by the Task Force on Climate-related Financial Disclosures can serve as a signal of a company's commitment to transparency and preparedness for new disclosure standards.³³

Recent industry analysis suggests that infrastructure resilience itself is becoming a major global investment category as the economic value of infrastructure assets continues to expand worldwide. Deloitte estimates that global infrastructure value could approach US\$390 trillion by 2050, while annual losses from natural hazards may rise to approximately US\$460 billion per year.³⁴ These trends are driving increased demand for AI-enabled technologies capable of improving prevention, response, and recovery capabilities across infrastructure systems. As governments and industries seek to protect increasingly interconnected physical and digital assets, AI applications such as predictive maintenance, digital twins, and intelligent early warning systems are emerging as attractive long-term infrastructure investment opportunities.

There is also growing investment interest in AI systems that can reduce infrastructure downtime and operational losses using predictive maintenance capabilities, thus reducing repair costs and improving operational continuity. In sectors such as offshore wind energy, AI-enabled maintenance systems have shown the ability to reduce downtime, boost annual revenue and increase long-term asset reliability.³⁵ Similar strategies are being applied to power grids, water systems and transportation infrastructure, where investors are increasingly viewing resilient technologies as a way to reduce risk and improve operational efficiency.

Digital twin technologies are similarly gaining attention for their ability to simulate infrastructure performance under future climate conditions and stress-test resilience strategies before physical investments are made. The literature has noted instances from Portugal, Singapore, India, and

the United States, where digital twins have been used to enhance flood resilience, optimize waste management systems, and model urban heat adaptation strategies.³⁶ This technology not only increases the efficiency of planning, but can also provide measurable economic benefits through avoided damages, reduced emissions, and more efficient infrastructure operations. For investors, digital twins offer an AI-powered platform that can be scaled and deployed in urban planning, utilities, transportation, and emergency management.

Financial institutions and insurers are also expected to play an increasing role in accelerating investment in AI-enabled resilience. Innovative financing mechanisms, such as resilience bonds and AI-linked credit instruments, as well as public-private partnerships, can help move beyond the long payback periods of traditional infrastructure modernization projects. Insurers are also incorporating AI for underwriting, risk modeling and resilience incentive programs, such as premium discounts for infrastructure systems that employ trusted resilience technologies. With financial markets increasingly incorporating climate and infrastructure risk into their investment decisions, AI-enabled resilience capabilities could be a key differentiator for infrastructure operators and investors alike.

Finally, investors should evaluate the long-term adaptability of AI solutions to a rapidly changing climate landscape. The most effective platforms will be those that continually learn from new data and improve their predictive accuracy over time. This iterative capability enhances not just performance but also defensible competitive advantages. The companies that invest in continuous model training, feedback loops, and integration with real-time monitoring systems are more likely to remain relevant as climate conditions evolve. Innovation, scalability, and governance are the keys to unlocking both the financial upside and the broader societal impact of AI-driven climate resilience.³⁷

Conclusion

The scale and complexity of climate-related disasters are outstripping the current capabilities of many emergency management systems. More extreme climatological disasters are increasing pressure on institutions tasked with preparedness, response, and recovery.³⁸ At the same time, climate risk is shaped not only by environmental hazards themselves, but also by underlying social, economic, and political vulnerabilities that determine the severity of impact on different populations. Communities with poor infrastructure, limited access to resources, or histories of institutional neglect often face disproportionate impacts for several years after a disaster, underscoring the growing interconnectedness of climate exposure and societal vulnerability.³⁹ AI has the potential to transform climate risk prediction and emergency management. However, its benefits depend on equitable access, ethical governance, and effective integration into existing systems. By addressing current challenges and investing in necessary solutions, AI can play a critical role in building resilience and adapting to the impacts of climate change.⁴⁰

Looking ahead, continued cross-industry and cross-scale cooperation will be necessary for the effective integration of AI into climate risk management. To co-develop technologically sound and socially responsive tools, governments, academic institutions, the private sector, and civil society must collaborate. Such cooperation can better ensure that AI systems are grounded in practical requirements, informed by a variety of viewpoints, and flexible enough to adapt to diverse institutional and geographic settings. AI risks being dispersed or underutilized in tackling complex climate challenges in the absence of this coordinated effort.

Human society is currently in the early stages of AI development, but the emerging pattern is clear. AI is most powerful combined with human judgment. Emergency managers and the communities they serve hold knowledge that does not appear in any training set: which intersections flood first, which households need help evacuating, which past projections from outside experts didn't pan out. Hybrid approaches that keep humans driving the technology, not just "in the loop," produce better results everywhere and are nonnegotiable in communities with good reason to distrust technological solutions. Community engagement produces better forecasts. Adoption follows from that.

Climate change is an unprecedented risk, and AI is an unprecedented technology. If we want AI's benefits to mitigate climate-driven disasters, we need to ensure it narrows inequities rather than widens them. So far, the benefits have mostly gone to wealthy countries in the Global North. The next five years will show whether AI's benefits reach all countries or stay concentrated where they are now. Expanding access requires three things: goals that specify who benefits, investment that flows to the countries currently outside the AI economy, and measurement that tracks distribution alongside performance.

Appendix: Recommended Public Data Sources for AI Weather Prediction

Reliable observational data is abundant for AI weather prediction, and modern forecasting systems depend on it. The publicly available datasets listed below are very useful,

as they allow researchers, governments and startups to validate AI models, replicate results, and reduce reliance on proprietary sources.

SYSTEM	ORGANIZATION	BEST USE	WHY IMPORTANT FOR AI
ERA5	European Centre for Medium-Range Weather Forecasts	Global weather and climate reanalysis	Considered the gold standard training dataset for many AI weather models. Provides consistent historical atmospheric conditions worldwide.
Copernicus Climate Data Store	European Commission and European Centre for Medium-Range Weather Forecasts	Climate and environmental data	Provides open access to petabytes of atmospheric, oceanic, and land-surface data for AI model development.
Global Forecast System (GFS)	National Oceanic and Atmospheric Administration	Operational global forecasting	One of the world's most widely used public forecast datasets and benchmark sources for AI forecasting comparisons.
National Centers for Environmental Prediction Reanalysis	National Oceanic and Atmospheric Administration	Long-term weather archives	Valuable for training AI systems on historical weather patterns and extreme events.
GOES-R Satellite Program	National Oceanic and Atmospheric Administration	Real-time storm monitoring	Provides high-frequency satellite imagery crucial for deep-learning-based severe weather prediction.
JPSS	National Oceanic and Atmospheric Administration and National Aeronautics and Space Administration	Global atmospheric observations	Supplies temperature, moisture, cloud, and ocean measurements used in AI forecasting systems.

SYSTEM	ORGANIZATION	BEST USE	WHY IMPORTANT FOR AI
EUMETSAT Satellite Network	EUMETSAT	Europe, Africa, Middle East satellite coverage	Critical source of cloud, storm, and atmospheric observations over regions often underrepresented in datasets.
Meteosat Third Generation	EUMETSAT	Rapid-update severe weather monitoring	Provides advanced imagery supporting AI nowcasting and storm prediction.
NASA EarthData	National Aeronautics and Space Administration	Earth system observations	Offers open access to atmospheric, ocean, cryosphere, and land data used in AI climate-weather models.
MODIS	National Aeronautics and Space Administration	Land surface, vegetation, wildfire monitoring	Important for integrating weather prediction with drought, wildfire, and climate risk forecasting.
Sentinel Missions	European Space Agency	Earth observation and environmental monitoring	High-resolution imagery improves AI models for floods, droughts, and severe weather impacts.
Global Precipitation Measurement	National Aeronautics and Space Administration and Japan Aerospace Exploration Agency	Rainfall estimation	Essential for flood forecasting and precipitation-focused AI systems.
Integrated Multi-satellite Retrievals for GPM	National Aeronautics and Space Administration	Global precipitation archives	Frequently used to train machine-learning flood prediction models.
World Meteorological Organization Information System	World Meteorological Organization	International weather exchange	Enables standardized global sharing of meteorological observations needed for robust AI training.
Global Telecommunications System	World Meteorological Organization	Real-time observations	Provides worldwide weather station, buoy, aircraft, and upper-air data feeding forecasting systems.

SYSTEM	ORGANIZATION	BEST USE	WHY IMPORTANT FOR AI
Integrated Surface Database	National Centers for Environmental Information	Ground weather observations	Supplies decades of station observations for model validation and bias correction.
Argo Program	Argo Program	Ocean temperature and salinity	Ocean conditions drive weather prediction; Argo is indispensable for coupled AI weather-ocean models.
Copernicus Marine Service	European Commission	Ocean forecasting	Supports AI prediction of hurricanes, marine heatwaves, and coastal hazards.
MERRA-2	National Aeronautics and Space Administration	Climate and atmospheric reanalysis	Widely used for climate-risk AI and long-term forecasting applications.
Open-METEO Data Hub	Multiple public sources	Data integration and APIs	Simplifies AI model development by aggregating numerous public meteorological datasets.

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