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Artificial Intelligence in Disaster Management: A Structured Review from Forecasting to Anticipatory Action

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Abstract

The increasing complexity, interdependence, and unpredictability of hazards have created a growing need for advanced technologies to strengthen disaster risk reduction and management. This article reviews the applications of Artificial Intelligence (AI) and Machine Learning (ML) across the disaster-management cycle, including hazard forecasting, early warning, preparedness, emergency response, damage assessment, and recovery. It examines the use of neural networks, support vector machines, random forests, ensemble techniques, convolutional neural networks, and other deep-learning approaches in flood forecasting, landslide susceptibility and warning, wildfire detection, seismic monitoring, disaster mapping, and social-media-based information analysis. The review highlights the capacity of AI to integrate large and heterogeneous datasets from remote sensing, GIS, IoT sensors, and other digital sources and to identify complex nonlinear relationships that may be difficult to capture through conventional approaches. However, limitations related to data quality and bias, model transferability, uncertainty, interpretability, false alarms, interoperability, and last-mile communication remain significant. The study argues that the greatest value of AI lies not simply in improving predictive accuracy but in extending useful warning lead time and enabling timely anticipatory action. Future disaster management should therefore adopt impact-based forecasting and people-centred early-warning systems, with AI functioning as a decision-support tool integrated with scientific expertise, institutions, and community knowledge.

Keywords: *Artificial Intelligence, Machine Learning, Disaster Risk Reduction, Early Warning Systems, Anticipatory Action.*

Introduction

Disasters are not simply sudden hazardous events; disaster risk often accumulates over time through the interaction of hazards, exposure, vulnerability and inadequate preparedness. Rapid urbanisation, environmental degradation, poorly planned development, climate change and inadequate infrastructure can intensify the impacts of floods, landslides, cyclones, earthquakes and wildfires, creating severe human, social and economic consequences. Consequently, contemporary disaster risk reduction (DRR) increasingly requires a shift from reactive response towards risk anticipation, prevention, preparedness and timely action. Although conventional approaches based on historical observations, physical modelling, statistical analysis, expert judgement and field monitoring remain essential, the rapid expansion of digital technologies has generated unprecedented volumes of heterogeneous disaster-related information. Satellites, weather stations, river gauges, drones and digital communication platforms continuously produce environmental, spatial and human-generated data. The challenge is therefore to integrate and interpret these diverse sources rapidly enough to support effective decision-making. Artificial Intelligence (AI) and Machine Learning (ML) provide important opportunities by identifying complex patterns and nonlinear relationships within large and multidimensional datasets.

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AI encompasses computational systems capable of learning, reasoning, pattern recognition and decision support, while ML enables systems to learn relationships from data and deep learning uses multilayer neural networks to identify highly complex patterns. Their applications have expanded across different hazards and stages of disaster management, particularly flood prediction (Guha et al., 2022). However, AI should complement rather than replace conventional disaster science and human judgement. Historical data may not adequately represent emerging risks under changing climatic and socioeconomic conditions, and accurate predictions are useful only when they lead to timely and appropriate action. People-centred DRR therefore requires integration of scientific, technological and local knowledge with human oversight and community participation (Hermans et al., 2022). Against this background, the present review examines the role of AI and ML in risk identification, forecasting, early warning, preparedness, response, damage assessment and recovery, with particular emphasis on extending warning lead time and enabling anticipatory action.

Literature Review

The growing application of Artificial Intelligence (AI) and Machine Learning (ML) in disaster management has attracted substantial scholarly attention because of their ability to process large, complex and multidimensional datasets. Huang, Wang and Liu (2021) reviewed prediction methods for emergency management and observed that accurate prediction is fundamental to efficient resource allocation, evacuation and emergency response. Their review demonstrated the increasing importance of statistical, simulation-based and AI techniques for predicting disaster occurrence and impacts. Similarly, Tan et al. (2021), after reviewing 278 studies, found that AI models were increasingly applied across different stages of natural disaster management, particularly because of their capacity to handle nonlinear relationships and large datasets with greater efficiency. Chamola et al. (2021) further highlighted the usefulness of ML for disaster prediction, crowd evacuation, social-media analysis and post-disaster assessment, while also identifying data quality, model limitations and implementation challenges. Lu et al. (2022) reviewed AI and ML applications in disasters and public-health emergencies and concluded that their use had expanded rapidly, although contextual limitations and the need for appropriate implementation remained important concerns. These studies collectively suggest that AI is particularly valuable where conventional analytical approaches face difficulties in processing rapidly changing, heterogeneous and high-volume information.

More focused evidence demonstrates the potential of AI for specific hazards and disaster-management functions. Guha et al. (2022), in a review of 128 studies published during 2010–2021, found extensive application of artificial neural networks in disaster management, with flood prediction emerging as a particularly prominent area. Their findings indicate that neural-network techniques can effectively capture complex relationships that are difficult to represent through conventional models. Recent reviews also show applications of ML and deep learning in hazard prediction, risk and vulnerability assessment, detection, early warning, monitoring, damage assessment and post-disaster response (Kav et al., 2022). However, technological accuracy alone does not guarantee effective disaster-risk reduction. Hermans et al. (2022) emphasised that people-centred early-warning systems benefit from integrating scientific and local knowledge, while social dimensions influence whether warnings are understood, trusted and acted upon. In the authors' view, therefore, the literature indicates that AI and ML should be regarded as decision-support technologies rather than substitutes for established disaster science, expert judgement or community knowledge. Their greatest contribution lies in improving the speed, accuracy and lead time of risk information so that institutions and communities can undertake anticipatory action. The present review consequently adopts a broader perspective, evaluating AI not merely through prediction

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accuracy but through its practical contribution to forecasting, early warning, preparedness, response and overall disaster risk reduction.

Objectives

The present paper aims to critically examine the applications and potential of Artificial Intelligence (AI) and Machine Learning (ML) in disaster risk reduction and disaster management. Specifically, it seeks to: (i) review the use of AI/ML for risk identification, hazard detection, forecasting, early warning, preparedness, emergency response, damage assessment and recovery; (ii) examine major AI/ML techniques and their applications across floods, landslides, cyclones and extreme weather, earthquakes, wildfires and social-media-based disaster intelligence; (iii) assess the contribution of these technologies to improving prediction, mapping, warning, resource allocation and decision-making; and (iv) identify key limitations concerning data quality, model generalisation, changing climatic conditions, human oversight and community engagement. The review ultimately evaluates AI not merely by predictive accuracy but by its capacity to extend warning lead time and facilitate anticipatory action.

Materials and Methods

The study adopted a structured narrative review design to examine the applications of Artificial Intelligence (AI) and Machine Learning (ML) in disaster risk reduction and disaster management. A structured narrative approach was considered appropriate because the reviewed studies covered diverse hazards, datasets, algorithms, spatial scales and performance measures that were not directly comparable for meta-analysis. The literature search covered publications available up to 31 January 2023, using combinations of keywords including “artificial intelligence” and disaster risk reduction, “machine learning” and disaster management/early warning/landslide prediction, “deep learning” and disaster response/wildfire detection, “AI” and flood forecasting, and “social media” and machine learning/disaster response. Relevant peer-reviewed studies and authoritative institutional publications identified through Google Scholar and Semantic Scholar were included when they applied or reviewed AI/ML and provided empirical, methodological or conceptual evidence related to disaster management. The selected literature was analysed across four dimensions: hazard type (flood, landslide, cyclone/extreme weather, earthquake and wildfire), technology (neural networks, support vector machines, random forests, ensembles, CNNs and natural-language processing), disaster phase (mitigation, preparedness, response and recovery), and decision function (detection, prediction, forecasting, mapping, warning, resource allocation and assessment). The analysis emphasised practical disaster-management outcomes, particularly improved warning lead time and opportunities for anticipatory action.

Analysis and Results

Flood forecasting, early warning, and mapping - Flood forecasting is one of the most mature areas of ML application, since flood behaviour emerges from nonlinear relationships among rainfall, catchment response, discharge, soil moisture, land cover, and topography. Reviews of AI in hydrology indicate that ML has been especially useful for short-term forecasting and that hybridisation with other modelling approaches improves performance further (Piadeh et al., 2022). Operational deployments show its practical importance: Google's operational flood-warning system was used in India and Bangladesh during the 2021 monsoon season (Nevo et al., 2022), moving ML from the laboratory experiment to the operational disaster management. Deep learning has also broadened the capability to rapidly map flood extent because CNNs learn spatial patterns directly from imagery. A review of 58 studies on deep-learning flood mapping identified strong use of

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convolutional architectures and future research needs for physics-based and probabilistic deep learning (Bentivoglio et al., 2022). An estimate of flood extent provided shortly after a rapidly developing flood may be more operationally useful than a highly detailed model provided after the decision window has closed; therefore, model usefulness should be assessed based on accuracy with respect to decision time, not accuracy alone.

Table 1: Representative AI/ML applications by hazard type, with typical input data and disaster-risk-reduction function

Hazard	Typical input data	Representative methods	DRR application
Flood	Rainfall, river level, soil moisture, catchment and land-cover data, satellite imagery	Artificial neural networks (Guha et al., 2022); deep convolutional networks (Bentivoglio et al., 2022)	Stage forecasting, inundation mapping, operational early warning (Nevo et al., 2022)
Landslide	Slope, geology, rainfall intensity and antecedence, soil moisture, ground displacement, imagery	U-Net detection (Meena et al., 2022); hybrid ensembles (Kainthura & Sharma, 2022; Saha & Saha, 2022); attention-based temporal CNN with entropy weighting (Zhang et al., 2022)	Detection, susceptibility mapping, dynamic regional early warning (Liu et al., 2022)
Earthquake	Seismic waveforms, ground-motion records	ML for seismology (Mousavi & Beroza, 2022)	Event detection, waveform classification, hazard assessment
Wildfire	UAV and remote-sensing imagery	Deep-learning computer vision (Bouguettaya et al., 2021)	Early detection, smoke/flame and fire-boundary identification
Social media / disaster intelligence	Text posts, messages, images	NLP and BERT-based models (Ponce-López & Spataru, 2022; Zhou et al., 2022)	Rescue-request detection, situational awareness (Ogie et al., 2022)
Multimodal response	Text, imagery, sensor data combined	Deep-learning data fusion (Algiriyage et al., 2021)	Integrated situational picture for response

Landslide susceptibility, prediction, and warning - Landslide susceptibility is affected by interacting variables such as slope, geology, rainfall, soil properties, drainage, vegetation, and human modification, which ML methods can combine to identify areas of relatively high susceptibility. A review of ML in landslide research (Tehrani et al., 2022) noted that in 2022, ML was used for spatial and temporal forecasting, detection, and data-driven analysis. For example, work in the Himalayas has utilized machine-learning algorithms and U-Net architectures for landslide detection (Meena et al., 2022), while hybrid ML methods combining Bayesian networks, neural networks, bagging, XGBoost, and random forests for prediction have been used in Uttarakhand (Kainthura and Sharma, 2022), and ensemble approaches for susceptibility modelling have reported improvements in the Kurseong Himalayan region (Saha and Saha, 2022). An important distinction is that a susceptibility map indicates where conditions favor landsliding; it does not indicate when a specific landslide will

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happen. The progression from susceptibility mapping to early warning is particularly promising. A rainfall-induced landslide warning system can include rainfall intensity, cumulative and antecedent rainfall, soil moisture, slope, geology, ground displacement, vegetation, and historical occurrence, revising failure probability as conditions evolve (Zhang et al., 2022), suggesting a future architecture of static susceptibility + real-time observations + ML forecasting = dynamic landslide warning. Regional ML-based early-warning models, such as a 2022 case study in Fujian Province, China (Liu et al., 2022), illustrate this transition. The final serious caveat: landslide inventories are often not comprehensive, and an AI model inherits the weaknesses of the database from which it learns.

Earthquakes, wildfires, and social media - There is an important distinction in seismology between prediction (specifying when, where, and how large an event will be) and detection, monitoring, and forecasting seismic characteristics. A 2022 review noted that ML is becoming more central to seismic monitoring and related tasks (Mousavi and Beroza, 2022). Automated event detection, waveform classification, catalogue development, ground-motion analysis, hazard assessment, and post-earthquake image analysis are all defensible applications for DRR, but claiming reliable deterministic prediction of earthquakes would exceed the evidence (Mousavi and Beroza, 2022). Another area of active deep-learning application is in the detection of wildfires. In a 2021 review of computer-vision methods for early wildfire detection from UAV imagery, it was suggested that autonomous systems might be able to detect a fire before it becomes unmanageable (Bouguettaya et al., 2021). Deep learning can be used to analyze visual features such as smoke, flame, thermal anomalies, vegetation change, and fire boundaries; like flood forecasting, the central tension here is between accuracy and speed. Disasters also produce massive amounts of human-generated information, and NLP can sort messages into relevance and urgency, separating discussion from direct rescue requests. A 2022 framework used ML classifiers for social-media disaster-response information, noting the scarcity of benchmark datasets and generalisation issues (Ponce-López & Spataru, 2022); additional work, like VictimFinder, uses BERT-based NLP to identify rescue requests from social-media streams (Zhou et al., 2022), and systematic reviews of social media in disaster recovery also document the extent and limitations of these platforms (Ogie et al., 2022). Digital participation is not equal, however, and communities without connectivity can be lost in the digital data, the population most visible to AI is not always the population most at risk for disaster.

Multimodal AI for disaster response - Multimodal disaster information, including text, photographs, satellite and drone imagery, video, sensor readings, maps, and social-media messages, is becoming more prevalent. A review of 83 studies of multimodal data and deep learning for disaster response showed considerable research interest in combining modalities of data for emergency tasks, but that there was a gap between academic demonstration and operational deployment (Algiriyage et al., 2021). The possibilities are vast: one platform could combine satellite images of flooding, sensor readings of rivers, rainfall predictions, and messages from communities about trapped residents to paint a more complete picture than any one source alone.

Table 2. Synthesis of key studies reviewed, listing domain, method, and main contribution

Study	Year	Domain	Method	Contribution
Meena et al. (Meena et al., 2022)	2022	Landslide	Machine learning + U-Net	Landslide detection in the Himalayas
Guha et al. (Guha et al., 2022)	2022	Multi-disaster	Review of artificial neural networks	128 studies (2010–2021); strongest interest in flood prediction
Algiriyage et al.	2021	Disaster	Systematic review	83 studies; gap between

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(Algiriyage et al., 2021)		response	of multimodal deep learning	academic demonstration and operational deployment
Liu et al. (Liu et al., 2022)	2022	Landslide warning	Regional ML early-warning model	Case study, Fujian Province, China
Zhang et al. (Zhang et al., 2022)	2022	Landslide warning	Attention-based temporal CNN + entropy weights	Capture and prediction of rainfall-induced warning signals
Ogie et al. (Ogie et al., 2022)	2022	Disaster recovery	Systematic literature review	Social-media use across the recovery phase
Kainthura & Sharma (Kainthura & Sharma, 2022)	2022	Landslide	Hybrid ML	Landslide prediction, Uttarakhand, India
Mousavi & Beroza (Mousavi & Beroza, 2022)	2022	Seismology	Review of ML	ML increasingly central to seismic monitoring
Ponce-López & Spataru (Ponce-López & Spataru, 2022)	2022	Disaster response	Social-media ML framework	Response-information classification; limited benchmarks and generalisation
Zhou et al. (Zhou et al., 2022)	2022	Disaster response	BERT-based NLP	VictimFinder: harvesting rescue requests from social media
Nevo et al. (Nevo et al., 2022)	2022	Flood	Operational ML forecasting	River-stage forecasts during 2021 monsoon, India and Bangladesh
Hermans et al. (Hermans et al., 2022)	2022	Early warning	Review	Integration of local and scientific knowledge in EWS
Saha & Saha (Saha & Saha, 2022)	2022	Landslide	AI + hybrid ML ensembles	Susceptibility mapping, Kurseong Himalayan region
Piadeh et al. (Piadeh et al., 2022)	2022	Flood	Critical review	Real-time flood forecasting in urban drainage systems
Tehrani et al. (Tehrani et al., 2022)	2022	Landslide	Review of ML applications	Spatial and temporal forecasting, detection, data-driven analysis
Bouguettaya et al. (Bouguettaya et al., 2021)	2021	Wildfire	Review of deep-learning computer vision	Early detection from UAV imagery
Bentivoglio et al. (Bentivoglio et al., 2022)	2022	Flood mapping	Review of deep learning	58 studies; physics-based and probabilistic DL as future directions

Discussion

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From reactive response to anticipatory action - The deepest implication of AI for DRR is the potential for reordering the temporal logic of disaster management: the Hazard → Impact → Emergency response model can be converted into an Observation → Detection → Forecast → Warning → Anticipatory action → Reduced impact model, which is not just technological, but a philosophical change: the primary purpose of forecasting is to give society time to act. A flood forecast might allow for evacuation before roads are impassable, moving livestock to a safer location, protecting equipment, pre-positioning food and medicine, and dispatching rescue teams and opening shelters. This transition is no longer hypothetical; the 2021 monsoon experience in India and Bangladesh illustrates this (Nevo et al., 2022). Thus, lead time is a key metric of AI performance.

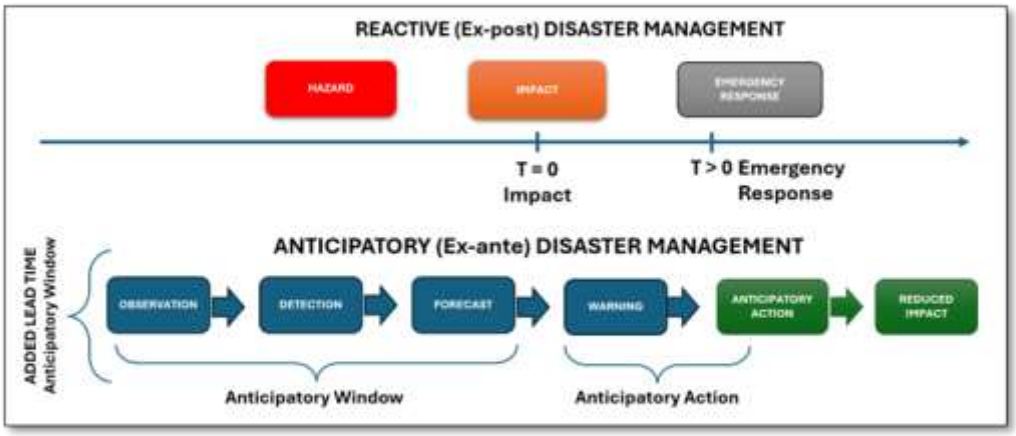

Figure 1: Two models of disaster management: reactive response (top) and AI-supported anticipatory action (bottom). The lower chain inserts lead time between hazard and impact

Future scope: forecasting and early warning - Looking forward from September 2023, AI-enabled DRR should focus on forecasting and early warning: 1) systems should transition from static prediction to dynamic forecasting, updating risk continuously as conditions evolve: for landslides, rainfall + soil moisture + slope movement + susceptibility → updated probability; for floods, rainfall + river level + soil moisture + catchment response → updated forecast; regional ML-based early-warning models already demonstrate this transition in practice (Liu et al., 2022); 2) systems should be evaluated not only by whether they predict an event, but also by how much useful time the forecast allowed: a forecast six hours in advance of a flood might allow for meaningful evacuation; the same forecast issued ten minutes before the flood would have little practical utility; research should therefore consider accuracy, lead time, false-alarm and missed-event frequency, spatial precision, computational speed, and decision usefulness, a multi-criteria view of performance.

Impact-based and multi-hazard forecasting - One major future direction is the transition from hazard forecasting to impact forecasting. Traditional forecasting asks, will flooding occur? impact-based forecasting asks, what will the flooding do? An emergency manager must know which villages will be inundated, which roads will be closed, which schools will be evacuated, and where shelters and supplies need to be placed. AI that combines hazard forecasts with exposure and vulnerability data can deliver precisely that: Hazard forecast × Exposure × Vulnerability × Infrastructure = Expected impact. This direction links prediction directly to the decisions that will determine whether a hazard becomes a disaster. Disasters also interconnect: heavy rainfall might cause flood → landslide → road blockage → isolation → disrupted response; a cyclone may generate high winds → storm surge → coastal flooding → power and communication failure. Because a single-hazard lens underestimates the burden on response systems, future AI systems

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should transition toward multi-hazard and cascading-risk analysis, and because AI is well-suited to modeling chains of consequence, it should do so.

Physics-informed AI, explainability, and uncertainty - A common drawback of data-driven models is their reliance on historic observations, which are often skewed in the case of extreme events: since extreme events are rare by definition, datasets may include hundreds of typical rainfall events, but only a few floods. AI coupled with physical understanding say for instance physical hydrological model + ML correction; slope-stability principles + ML classification, should be used in future research. The literature on flood mapping already indicates that physics-based deep learning will be useful because it retains the physical relationships while providing computational benefits (Bentivoglio et al., 2022). The hybridisation reflects the realization that data-driven pattern recognition and process-based understanding address distinct aspects of the forecasting problem. The AI systems that underpin disaster decisions cannot be black boxes: an emergency manager needs to be able to explain why an area was flagged as high risk, which factors played into this, how confident the model is, and what could cause the model to fail. Uncertainty must be communicated transparently: whereas a responsible system may say "there is a high likelihood of landslide occurrence given current rainfall and ground-movement conditions," instead of "there will be a landslide," uncertainty will be acknowledged while still allowing action to be taken, and institutional credibility will be maintained when probabilities do not translate to events.

Data quality, transferability, and last-mile delivery - AI performance is inherently data-driven. Incomplete historical records, inconsistent monitoring, insufficient sensor density, inaccurate inventories, spatial gaps, inconsistent formats, changing land-use conditions, and few records of extreme events are major limitations. Moreover, another challenge is geographical transferability; a model trained at one location may not work well at another due to geological, climatic, hydrological, and social conditions, which may vary across a country like India. Therefore, future studies should concentrate on regional benchmark datasets, open disaster inventories, cross-region validation, transfer learning, uncertainty quantification, and long-term operational validation. One of the biggest challenges is the last mile. An advanced AI system may predict a flood hour in advance, but the warning is useless if there is no connectivity, if messages are sent only in technical language, if communities do not understand them, if authorities have no means to evacuate, or if people do not trust the issuing institution. It is therefore necessary to have redundant pathways, AI forecast → disaster authority → local government → community leaders → households, combined with SMS, radio, public-address systems, sirens, volunteers, social media, and face-to-face communication. Resilience does not necessarily depend on technological sophistication: a warning is only useful if people receive it, understand it, trust it, and can respond. The body of early-warning literature overwhelmingly favors the integration of scientific and local knowledge, rather than technological solutions (Hermans et al., 2022), particularly in rural areas where communities identify environmental signals that never make it into a central database.

Ethical and governance issues - Disaster management also raises new governance questions for AI. Algorithmic bias can occur when populations are systematically underrepresented in datasets, resulting in less accurate predictions for those communities. Accountability remains both human and institutional: if a warning is generated and no one responds, no one can shift blame to software. Social-media and mobile-location data can raise privacy concerns because of the sensitive information they may hold. Decision-makers may also fall victim to automation bias, which is the tendency to believe algorithmic recommendations are accurate because they are complex, and technological dependency, which is the condition in which institutions become dependent on

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automated systems while human expertise atrophies. The implications for AI governance is that AI governance needs to be integrated into disaster-risk governance itself.

Table 3. Persistent limitations of AI in disaster risk reduction and corresponding mitigation strategies

Limitation	Mitigation
Incomplete and biased disaster inventories	Open regional benchmark datasets, community-contributed inventories
Poor model transferability across regions	Cross-region validation, transfer learning
Black-box behaviour	Explainable AI, feature-attribution reporting
False alarms and missed events	Multi-criteria evaluation (lead time, false-alarm rate, miss rate), probabilistic outputs
Dependence on scarce historical extreme-event data	Physics-informed and hybrid models
Last-mile warning failure	Redundant communication channels, community-based dissemination
Privacy and algorithmic bias	Governance frameworks, fairness audits
Institutional capacity gaps	Long-term operational validation, human-in-the-loop design

A human-centred AI framework for anticipatory action - Multi-source observations. Continuous streams from satellites, weather and river-gauge networks, seismic stations, UAVs, in-situ sensors, and digital platforms form the raw material for risk assessment; value in diversity, as no single source can capture the complexity of an evolving hazard. Data integration. Heterogeneous observations are standardized, georeferenced, quality-controlled, and fused into coherent, analysis-ready datasets, a prerequisite for any downstream model. AI/ML analytics. Predictive, classification, detection, and mapping models, from neural networks and ensembles to deep convolutional architectures and NLP, convert integrated data into hazard information: a flood forecast, a landslide probability, mapped inundation. Risk intelligence. When hazard information is combined with exposure, vulnerability, and infrastructure data, it becomes risk intelligence, producing estimates not only of what may happen, but also of what it would mean for people and assets, the impact-based logic. Human interpretation. Experts and communities interpret the intelligence, assess its uncertainty, and determine whether and how to act; this layer is intentionally not automated because accountability, judgement, and trust cannot be delegated to software, and local knowledge must be integrated with scientific output rather than displaced by it. Anticipatory action and resilience. Warnings are disseminated through redundant last-mile channels, and prepared institutions and communities convert them into protective actions evacuation, pre-positioning, shelter, livelihood protection that minimize impact and develop resilience. The principle that should guide this framework is that human judgement must be placed between prediction and action. The fundamental principle of the framework is the insertion of human judgment between prediction and action: an accurate forecast is useless without a communication channel, and a perfectly disseminated warning is meaningless if the forecast was too late. Therefore, AI-enabled disaster management is a socio-technical system, not a software issue.

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Figure 2: Six-layer human-centered AI framework

Conclusions

The review concludes that Artificial Intelligence (AI) and Machine Learning (ML) have considerable potential to strengthen disaster risk reduction by transforming disaster management from a predominantly reactive system into a more predictive, anticipatory and decision-oriented approach. Evidence across floods, landslides, cyclones and extreme weather, earthquakes, wildfires and disaster-response information demonstrates that AI can process large, heterogeneous and rapidly changing datasets from satellites, sensors, weather stations, drones, imagery and social-media platforms to improve hazard detection, susceptibility mapping, forecasting, early warning, damage assessment and resource allocation. Flood forecasting and mapping appear particularly advanced, while landslide monitoring, wildfire detection, seismic monitoring and natural-language processing are promising areas of application. However, the review emphasises that the effectiveness of AI should not be judged solely by conventional measures of prediction accuracy. Its real disaster-management value lies in whether it can provide earlier, reliable and actionable information that enables evacuation, protection of assets, pre-positioning of resources, rescue preparation and other anticipatory measures. Thus, lead time, false alarms, missed events, spatial precision, computational speed and decision usefulness should complement conventional model-performance indicators. At the same time, AI cannot replace conventional disaster science, expert judgement or community knowledge. Models trained on historical data may perform poorly when climatic, environmental and socioeconomic conditions change, while data limitations, poor generalisation, unequal digital connectivity, lack of benchmark datasets and the gap between experimental research and operational deployment remain significant challenges. Therefore, future development should prioritise dynamic rather than static forecasting, impact-based and multi-hazard prediction, integration of exposure and vulnerability information, and systems capable of analysing cascading risks. AI-supported warning systems should combine real-time observations with continuously updated forecasts and communicate information in ways that are understandable and actionable for affected communities. Ultimately, AI should be understood as a powerful decision-support technology, not an autonomous substitute for human responsibility. Scientifically robust models, human oversight, local knowledge, institutional capacity and meaningful community participation must operate together to ensure that improved prediction is translated into timely action and reduced disaster impacts.

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