International Journal of Disaster Risk Management • Vol. 7, No. 1 • https://doi.org/10.18485/ijdrm.2025.7.1.13

Publisher: Scientific-Professional Society for Disaster Risk Management

International Journal of Disaster Risk Management

Review Article

Leveraging Artificial Intelligence for Enhanced Disaster Response Coordination

Fikret Emre Öcal[1*], Salih Torun[2]

[1] École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland; fikret.ocal@epfl.ch

[2] Ankara Hacı Bayram Veli University, Ankara, Turkey; salih.torun@hbv.edu.tr.

[*] Correspondence: fikret.ocal@epfl.ch.

Received: 1 January 2025; Revised: 5 March 2025; Accepted: 12 May 2025; Published: 30 June 2025.

ABSTRACT

This review critically examines the transformative role of artificial intelligence (AI) in coordinating the core phases of disaster response: preparedness, response, recovery, and mitigation. Drawing on illustrative case studies such as AI-driven flood forecasting with Delft-FEWS, post-disaster damage mapping via DroneDeploy, and optimised emergency dispatch through RescueME. It synthesises evidence on five core AI capabilities (machine learning, deep learning, computer vision, natural language processing, and optimisation algorithms). We find that AI can substantially improve predictive accuracy, real-time situational awareness, rapid decision-making, resource allocation, and inter-agency collaboration, thereby addressing the speed and complexity challenges of traditional disaster management. However, adoption is hindered by fragmented data ecosystems, opaque "black box" models, interoperability gaps, cybersecurity vulnerabilities, ethical and equity concerns, and limited accessibility in low-resource settings. To overcome these barriers, we argue for the development of interoperable data standards, explainable AI frameworks, robust cyber governance protocols, and inclusive stakeholder engagement. Emerging trends, such as the convergence of AI with IoT and edge computing, enhanced human-AI decision support, and the democratisation of AI tools, offer promising pathways for building more resilient, scalable, and ethically grounded disaster response systems. By aligning technological innovation with human oversight and participatory governance, strategic integration of AI can enhance preparedness, response effectiveness, and recovery efficiency, fostering safer and more resilient communities worldwide.

KEYWORDS

Artificial intelligence; disaster management; machine learning; computer vision; explainable AI; situational awareness; human–AI collaboration.

1. Introduction

In an era of increasing climate volatility and complex emergencies, the global community faces unprecedented challenges in managing natural and human-made disasters. Recent years have seen hundreds of catastrophic events annually, leading to significant human and economic losses (Gupta

Ocal, F. E., & Torun, S. (2025). Leveraging Artificial Intelligence for Enhanced Disaster Response Coordination. *International Journal of Disaster Risk Management, 7*(1), 235–246.

& Roy, 2024; Munich Re, 2023; Aon, 2024). Traditional disaster response practices, which rely on manual data collection, field surveys, and fragmented communication networks, often struggle to keep pace with rapidly evolving emergencies (NCDP, 2025). Decisions must be made rapidly under conditions of uncertainty. However, preliminary damage assessments can take days when done by teams physically inspecting sites, a process described as "time-consuming, potentially dangerous, and subject to human error". Likewise, coordinating multiple responding organisations (government, NGOs, private sector, community groups) is notoriously difficult, hampered by differing protocols and data systems. These challenges underscore the urgent need for more effective, data-driven, and coordinated approaches to disaster response. Integrated systems that combine traditional risk management with AI-enhanced monitoring (Cvetković et al., 2024; Cvetkovic & Martinovic, 2021) exemplify this coordinated approach. The growing complexity of industrial operations, as demonstrated by past catastrophes such as Bhopal and Fukushima, highlights how technological errors, human misjudgments, and organisational lapses converge to amplify the impacts of disasters. The incorporation of predictive models and real-time diagnostics has thus become central to disaster resilience planning in high-risk industries.

Natural disasters, including floods, earthquakes, and wildfires, are becoming more complex and interdependent. This necessitates a paradigm shift in how emergencies are anticipated and managed. Effective coordination among diverse stakeholders (government bodies, NGOs, private-sector responders, and community groups) is necessary and depends on a shared, up-to-date operational picture. However, disasters generate vast, heterogeneous data streams—from satellite imagery and sensor networks to social media feeds—that are typically siloed across agencies and formats. This fragmentation slows decision-making and leads to duplicated efforts or overlooked needs during critical windows of response. Artificial intelligence (AI) emerges as a critical innovation, promising not only efficiency but also strategic foresight in mitigating the impacts of disasters. AI enables the real-time analysis of vast datasets, such as satellite imagery, sensor outputs, and social media content, which are pivotal for disaster prediction, situational awareness, and coordinated response (Beeravelly, 2024). Systems like Delft-FEWS and DroneDeploy exemplify how AI is currently applied to predict floods and assess post-disaster damage, respectively. Moreover, AI-based decision support systems assist in resource allocation and emergency planning by simulating multiple scenarios (Schofield, 2022; Simões-Marques & Figueira, 2018).

However, this technological transformation is not without challenges. The deployment of AI in disaster contexts must navigate data privacy, algorithmic bias, and the risk of excluding marginalised communities from decision-making processes (Gevaert et al., 2021). There is also a need to harmonise AI applications with existing governance structures and disaster management protocols (Dean & Payne, 2013). Therefore, ethical frameworks and participatory models are essential for ensuring equitable and effective implementation.

This article reviews the theoretical frameworks and current implementations of AI in disaster response, analyses their benefits and limitations, and discusses future directions for research and policy.

2. Theoretical Framework and Background

Disaster management is commonly conceptualised as a continuous cycle with four phases: preparedness, mitigation, response, and recovery. During the preparedness phase, stakeholders develop plans, train personnel, and install early warning systems to prepare for potential emergencies. In preparedness, predictive models forecast risks; during response, AI facilitates real-time situational awareness; in recovery, it aids damage assessment and resource planning. This framework underscores AI's role as both a reactive and proactive tool, aligning technical capabilities with operational needs in disaster contexts (Simões-Marques & Figueira, 2018). Mitigation involves long-term measures to prevent disasters or reduce their impact (e.g. building codes, land-use planning, public education). The response phase encompasses immediate actions taken after a disaster strikes, including search and rescue, emergency medical care, shelter provision, and restoration of critical services.

Finally, recovery entails the longer-term process of rebuilding infrastructure, restoring livelihoods, and learning lessons to inform future preparedness. Each phase is interconnected; practical actions in one stage influence outcomes in the next, reinforcing a cycle of improved resilience. For instance, thorough recovery and documentation after an event can enhance preparedness for similar events in the future. (Gupta & Roy, 2024). In practice, implementing this ideal cycle presents significant challenges. Disasters often create chaotic environments with information overload and data gaps – vast amounts of data are generated (from sensors, satellites, social media, etc.), but they are fragmented among various entities. Responders struggle to assemble a coherent real-time picture (Cvetković, Renner, & Jakovljević, 2024).

Figure 1. Four phases of Disaster Management (AkitaBox, 2023)

Over the past few decades, emergency management has evolved from basic GIS mapping and statistical modelling toward sophisticated, data-driven approaches. Big data analytics and remote sensing technologies paved the way for AI by providing large volumes of data for analysis (Öcal & Torun, 2024). Today, AI systems not only analyse these vast datasets but also predict hazards, recommend actions, and enable real-time operational adjustments. Techniques such as machine learning and deep learning offer improved accuracy in forecasting disasters and damage assessments by identifying subtle patterns that traditional methods might miss (Odubola et al., 2025; NASA, 2024). Critical decisions (such as evacuation orders or resource deployments) must be made quickly, sometimes with incomplete or unreliable information. Moreover, the manual methods used for damage assessment and resource allocation are inherently slow and prone to human error (NCDP, 2025). Limited situational awareness impairs the ability to prioritise needs and allocate resources effectively. Moreover, large-scale disasters often involve numerous agencies and organisations. Inter-agency coordination is challenging when communication systems are incompatible, and each group operates with its data, resulting in siloed operations. These challenges are compounded by coordination difficulties among diverse response teams, which can lead to duplication of efforts or the overlooking of needs (APWA, 2025).

Several key attributes give AI an edge in disaster scenarios. First is sheer speed and scalability: AI can continuously ingest and analyse multi-source data in real time, which is invaluable during fast-moving crises. For example, during Hurricane Ida (2021), NASA's disaster program employed AI-driven analysis of satellite and aerial imagery to pinpoint flooded areas, power outages, and infrastructure damage shortly after landfall. This provided responders with near-real-time maps of impacted zones well before ground teams could survey those areas (NASA, 2024). Second, AI excels at pattern recognition. Machine learning models can be trained on historical disaster data to identify early warning signals. It can detect subtle environmental cues or precursor events that might foreshadow a disaster. Research demonstrates that AI-based techniques (e.g. image processing and agent-based simulations) can offer critical lead time in disaster prediction and early alerts, potentially enabling preemptive actions that save lives (Deekshith, 2022; Reichstein et al., 2023). Third, AI can automate routine and labour-intensive tasks, freeing human responders to focus on complex decision-making. For instance, image classification algorithms can scour thousands of drone photographs for signs of damage in a fraction of the time it would take a human analyst; similarly, AI chatbots can handle surges in emergency calls or social media inquiries by triaging requests and providing vetted information to the public, thus reducing the burden on call centres. In short, AI brings speed, precision, and efficiency to emergency management processes that have historically been slow and manual.

Another critical advancement is the use of AI to analyse the socio-economic consequences of disaster displacement. As highlighted by the Internal Displacement Monitoring Centre (IDMC), AI technologies are enabling the integration of non-traditional data, such as mobile signals and social media patterns, with geospatial and demographic datasets to model human displacement more effectively. These models offer insights into the duration, location, and vulnerabilities associated with disaster-driven migrations, enabling more effective planning and response mechanisms at both local and international levels (IDMC, 2024). Several studies have reinforced the importance of integrating AI as a dynamic feedback mechanism across the disaster cycle. For instance, Schofield (2022) describes AI-driven platforms that continuously update models using new field data to enhance preparedness and adapt response strategies in real-time. In another example, Abdul et al. (2024) propose an AI framework tailored for healthcare coordination during disasters, illustrating how domain-specific adaptations can optimise outcomes. Beeravelly (2024) also emphasises that cloud-based AI platforms enable continuous monitoring and prediction by analysing multi-source data, highlighting their scalability and resilience.

Moreover, Gevaert et al. (2021) argue for a conceptual expansion of AI's role, advocating that it be seen not just as a tool for automation but as an actor shaping decision pathways and ethical priorities. The goal is not just to react faster but to anticipate and mitigate impacts whenever possible. This perspective invites a reconsideration of AI systems as participatory infrastructures that mediate between technology, policy, and community resilience. Therefore, AI's conceptual integration must go beyond technical functions to encompass sociotechnical governance, stakeholder input, and adaptive policy alignment. As AI becomes more deeply embedded in disaster management institutions, it has the potential to improve how we handle crises fundamentally – but realising this potential will require addressing various challenges (technical, ethical, organisational) discussed later in this article. The following sections outline the current state of AI technologies in disaster response and their applications across various disaster phases.

3. AI Technologies in Disaster Response

Building on the theoretical framework established in Section II, we now turn to the core AI technologies that power modern disaster response systems. In this section, we examine four key categories: machine learning and deep learning for hazard prediction, computer vision for rapid damage assessment, natural language processing for extracting actionable insights from textual data, and optimisation algorithms for efficient resource allocation. For each technology, we outline its fundamental principles and typical applications in disaster scenarios and provide illustrative case studies that demonstrate its real-world impact.

3.1. Core AI Technologies in Disaster Response

Machine learning (ML) algorithms can analyse historical disaster data to predict future hazards. For instance, models such as Random Forests and neural networks have been applied to forecast earthquake characteristics (Asma & Aranas, 2024). These models often outperform traditional statistical methods by providing earlier and more reliable warnings. Deep learning, particularly using architectures like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks

(CNNs), further extends AI's capabilities. LSTM networks can recognise temporal patterns in seismic data, thereby enhancing earthquake prediction (Bhargava et al., 2022). Such image-based AI models can rapidly classify damage levels, significantly accelerating the traditionally laborious process of damage assessment. Early warning systems form the backbone of disaster preparedness and response. AI-enhanced systems can predict hazardous events by analysing sensor data, historical trends, and environmental indicators to identify potential risks. For example, machine learning has been applied to forecast earthquake likelihood and provide crucial seconds of warning that can trigger protective measures (Al-banna et al., 2023).

Natural Language Processing (NLP) enables emergency managers to sift through vast amounts of text data—from social media posts to official reports—in real time. Platforms like AIDR (Artificial Intelligence for Disaster Response) use NLP to categorise and filter relevant information, distinguishing urgent reports from background noise (Odubola et al., 2025). Advanced language models (e.g., GPT-4) further support crisis communication by summarising reports and translating content for multilingual audiences. Computer vision (CV) empowers AI to extract critical information from imagery. Drones and satellites collect high-resolution images of disaster zones, which AI-powered computer vision (CV) systems then analyse to detect damaged structures, obstructed roads, and other vital indicators of disaster impact (NCDP, 2025). For example, during Hurricane Ida, NASA's AI-assisted imaging was able to quickly identify areas affected by flooding and infrastructure damage (NASA, 2024). CV also supports search-and-rescue operations by processing thermal or infrared imagery to locate survivors in areas that are otherwise inaccessible. In wildfire management, the integration of AI-based risk mapping systems has improved both preparedness and response. In Colorado, AI tools that analyse weather data, vegetation health, and historical fire patterns have been used to pre-position firefighting resources in high-risk areas, thereby reducing response times and enhancing safety (APWA, 2025). Post-fire, drone imagery combined with computer vision has accelerated damage assessments that once took days to complete. In Yangbi, China, researchers have developed a computer vision model to detect earthquake damage from aerial images, enabling local authorities to prioritise relief efforts quickly (Jing et al., 2022).

3.2. How AI Technologies Are Transforming Disaster Response and Human Welfare

Long-term recovery strategies are also another key discussion in disaster resilience. Đorđević & Gačić (2024) highlight that integrating sustainability into disaster response planning, particularly by leveraging local knowledge and governance, yields higher community resilience. This approach aligns with AI's capacity for systems-level adaptation and supports policies that embed environmental, economic, and social dimensions into preparedness frameworks. Similarly, Ogunleye and Arohunsoro (2024) provide an empirical assessment of the socio-economic impacts of rainstorms in Nigeria, underlining the role of local governance and planning failures in exacerbating disaster vulnerability. In Algeria, Tout et al. (2024) demonstrate how improved forest road networks and drone technologies can aid fire prevention and emergency response. From a resilience measurement perspective, Milenković et al. (2024) advocate for context-specific adaptation of the BRIC (Baseline Resilience Indicators for Communities) indicators, suggesting that resilience must account for socio-economic and infrastructural variability. These insights emphasise the importance of integrating AI analytics with on-the-ground needs assessments to enhance responsiveness and resource targeting, particularly in low-income and high-risk regions.

Machine learning (ML) models have significantly enhanced the prediction of natural hazards, including earthquakes, floods, and wildfires. Techniques such as support vector machines, neural networks, and ensemble models are employed to identify patterns in historical and real-time sensor data. Integration with IoT networks enhances spatial and temporal resolution, as well as system responsiveness. Studies highlight AI's early warning contributions via platforms like Delft-FEWS, which combine real-time hydrological data with predictive analytics for flood forecasting in regions such as Bangladesh and Vietnam (Sun et al., 2020; Andrae, 2025). A case study by Sharma et al. (2025) examines how IBM's PAIRS geospatial analytics platform utilises satellite images to predict flood-prone zones, thereby enhancing response lead times and community preparedness. However, challenges include imbalanced data—such as an overrepresentation of high-income countries and more frequent disaster types like floods, compared to underrepresented hazards like droughts in arid regions or data-scarce locations in Sub-Saharan Africa. Other issues include the limited availability of labelled datasets and the difficulty of generalising models across diverse geographical regions. Few studies have explored deployment in low-resource settings, highlighting a gap in the equitable dissemination of technology.

AI enhances situational awareness through image analysis and natural language processing (NLP). Computer vision algorithms analyse satellite and drone imagery to assess damage and identify affected areas. NLP techniques process social media and emergency call transcripts to extract actionable information. Platforms like DroneDeploy facilitate rapid damage mapping using AI-processed aerial imagery (Bohland et al., 2024; Raut, 2024). Rescue Me, an AI emergency system, further illustrates the real-time analysis of emergency calls and social data to prioritise response actions and resource dispatch (Sreeketh et al., 2024). To handle multilingual contexts, recent NLP models, such as mBERT (multilingual BERT) and XLM-RoBERTa, are trained on diverse language corpora, enabling improved understanding and classification of multilingual texts in disaster communications. Datasets such as CrisisNLP and multilingual emergency tweets are increasingly used to fine-tune these models for low-resource languages. Despite these advancements, issues with data noise, language ambiguity, and dialectal variation persist. Research is needed on the trust and usability of these systems in multilingual and culturally diverse contexts, particularly in regions where training data is limited or linguistic diversity is high.

Optimisation algorithms and AI planning tools support real-time logistics, including route planning for emergency vehicles and allocation of supplies. Multi-agent systems facilitate coordination among different agencies and platforms, promoting interoperability. Examples include the use of decision support systems that recommend optimal resource allocation and evacuation planning based on evolving disaster scenarios (Schofield, 2022; Kumar, 2024). However, system complexity and data latency remain barriers to widespread adoption. Few models integrate ethical considerations or support human-in-the-loop decision-making, which limits trust and accountability in critical moments.

Post-disaster recovery benefits from AI-driven tools for damage assessment and resilience modelling. Deep learning models interpret aerial imagery to quantify damage, while agent-based simulations model recovery scenarios. AI can also inform infrastructure redesign and community resilience planning. In healthcare contexts, AI systems have been proposed to triage patients and optimise hospital resource distribution during large-scale emergencies (Abdul et al., 2024). Despite advancements, limited longitudinal studies and a lack of integration with socioeconomic data hinder comprehensive insights into recovery. There is a need for frameworks that align AI outputs with community-driven recovery goals (Abid et al., 2021; Singh & Agnihotri, 2024).

4. Ethical Concerns and Policy Integration

4.1. Ethical Concerns and Challenges

Emerging studies reinforce the transformative potential of AI in addressing ethical and operational dilemmas in disaster contexts. For instance, Harika et al. (2024) highlight how AI systems, such as DisasterAI-Net and ResQOptimize, enhance disaster detection and resource optimisation by utilising real-time data from social media, drones, and satellite imagery. These systems demonstrate superior responsiveness and adaptability, particularly when manual bottlenecks hinder traditional methods.

The complexity and opacity of AI models—intense learning systems, pose significant challenges to disaster risk management. Ghaffarian et al. (2023) underscore the urgent need for Explainable AI (XAI) to promote transparency and trust, especially as AI-driven decisions increasingly influence emergency protocols and resource allocation. Their review highlights the growing trend toward using SHAP and LIME techniques to interpret black-box models in flood prediction, wildfire susceptibility, and damage mapping. These methods help illuminate model logic but often add significant computational overhead, which can limit real-time applicability in resource-constrained settings. Moreover, current applications of XAI are disproportionately focused on response, with limited attention to preparedness or recovery phases.

Bari et al. (2023) provide a nuanced overview of how AI technologies, ranging from ANN for flood prediction in Ethiopia to sentiment analysis for mental health triage, are becoming cornerstones in disaster health management. These tools not only assist in immediate response but also support long-term psychological recovery. Despite these advancements, issues surrounding algorithmic transparency, data standardisation, and cross-border legal harmonisation remain unresolved. AI systems risk reinforcing existing social biases, compromising user privacy, and excluding marginalised groups from the decision-making process. For example, NLP models trained on limited language corpora may fail to capture emergency calls from speakers of minority languages, potentially delaying critical responses (Gevaert et al., 2021).

Despite the transformative potential of AI in disaster response, significant barriers exist in low-resource environments. Many regions lack the necessary technological infrastructure, including reliable broadband internet, edge computing devices, and trained personnel to operate advanced AI systems. Studies have highlighted that most AI models are trained on datasets from high-income countries, which limits their effectiveness when applied to diverse contexts, such as rural Africa or Southeast Asia. Organisational challenges, including limited governance capacity and fragmented disaster protocols, further complicate deployment efforts. To overcome these barriers, future efforts should prioritise the development of offline-capable AI models that can operate on solar-powered edge devices, reducing dependency on stable internet connections. Open-source, low-code AI platforms tailored for local agencies can democratise access to technology, while partnerships with NGOs and academic institutions can build long-term capacity. The equitable deployment of AI technologies must address both technological and organisational gaps to ensure that the benefits of innovation reach vulnerable communities worldwide.

An important yet underexplored challenge in AI-driven disaster response is the effective deployment of technologies in multicultural and multilingual environments (Behravan et al., 2024). While AI models, particularly in natural language processing (NLP), have made strides in multilingual understanding, significant gaps remain. Many AI systems are primarily trained on high-resource languages, leaving minority languages and dialects underrepresented, which can result in delayed or distorted emergency communications (Jiao, Lewis, Xu, Sussman, & Atkinson, 2024). Cultural differences also influence risk perception, communication styles, and trust in automated systems, which AI models often overlook—failure to incorporate cultural and linguistic diversity risks excluding vulnerable groups from critical response efforts. Inclusive AI design must prioritise diverse language datasets, dialect-specific fine-tuning, culturally sensitive user interfaces, and community engagement throughout model development and deployment. Future disaster AI systems should integrate continuous learning from localised data and support multilingual, culturally adaptive communication strategies to ensure equitable access to life-saving information.

Governance gaps further exacerbate these issues, including the lack of international standards for AI deployment in disaster contexts, unclear liability when automated decisions lead to harm, and fragmented data-sharing protocols across jurisdictions. Several studies stress the importance of participatory governance and human-in-the-loop approaches to ensure inclusivity and accountability (Dean & Payne, 2013; Andrae, 2025). Integrating AI into disaster policy and field operations requires not only ethical foresight but also technical adaptability. Systems must be interoperable with legacy infrastructure while maintaining real-time capabilities. Building ethical AI ecosystems for disaster management also involves educating stakeholders, continuous monitoring, and establishing adaptable standards that reflect diverse cultural and regional needs.

The convergence of these technical, ethical, and policy challenges underscores that effective disaster AI is as much a social endeavour as it is a technological one.

4.2. Policy Integration & Stakeholder Collaboration

A crucial yet often underrepresented dimension of AI in disaster management is the role of policy integration and stakeholder collaboration. Effective AI deployment depends not only on technological robustness but also on institutional readiness and community acceptance. Many AI systems struggle to gain traction due to misalignment with local disaster protocols or a lack of awareness among responders. Policies must be adapted to accommodate AI's rapid evolution while ensuring interoperability, accountability, and inclusivity. For instance, local governments need guidance on procurement, training, and oversight of AI tools. Meanwhile, cross-sector partnerships—with academia, tech firms, NGOs, and emergency services—can co-develop tailored solutions and support knowledge exchange.

One compelling example is the Rescue Me system, which relies on real-time data integration from sensors, calls, and social media to coordinate emergency services more efficiently (Sreeketh et al., 2024). Another example is the implementation of AI analytics in regional flood forecasting by the IBM PAIRS system, which supports proactive decision-making at the municipal level (Sharma et al., 2025). These platforms highlight the need for regulatory frameworks that strike a balance between innovation, data privacy, and operational resilience.

Embedding AI into national disaster strategies and harmonising standards at the international level is crucial for maximising AI's global impact. Beeravelly (2024) highlights the benefits of cloud-based platforms in enhancing scalability and facilitating data sharing among agencies, while Gevaert et al. (2021) advocate for the implementation of AI accountability mechanisms to ensure equitable representation. Only through multi-level collaboration and aligned incentives can AI systems move from pilots to scalable solutions that truly enhance disaster resilience.

5. Conclusion and Future Work

The integration of artificial intelligence into disaster management has demonstrated clear benefits, including rapid, real-time analysis of heterogeneous data streams (such as satellite imagery and sensor outputs), enhanced early warning through predictive modelling, improved situational awareness via computer vision and natural language processing (NLP), and optimised response coordination and resource allocation. Case studies such as Delft FEWS, DroneDeploy, and Rescue Me exemplify how AI-driven platforms can accelerate damage assessment and streamline multi-agency collaboration, making disaster response both more proactive and scalable.

Looking ahead, three priority areas emerge for future research and development:

• ***Multi-Modal AI–IoT Convergence: Future systems must fuse diverse data sources, such as IoT sensor networks, drone and satellite imagery, and text reports, into unified, edge-enabled*** platforms that remain operational even when central infrastructure fails. By deploying AI models at the edge (e.g., on-device ML for seismic sensors or onboard drone chips), disaster response tools can sustain low-latency hazard detection and decision support under austere conditions (Sharma et al., 2024).

Table 1. Comparison of Edge Computing and Cloud AI for Disaster Response (Moon Technolabs, 2023)

Feature	Edge Computing	Cloud AI
Latency	< 100 ms	> 500 ms
Connectivity	Works offline	Requires broadband
Compute Cost	Low per node (cheap devices)	High aggregated (expensive servers)
Data Privacy	Data stays local (so more secure)	Centralised storage (Data sent to the cloud)
Examples	Onboard drone damage detection	Centralised flood prediction

• Another emerging priority is ***human collaborative Decision Support:*** Rather than supplanting expert judgment, AI should serve as an explainable, interactive aid to human responders. Human–AI collaborative decision support systems enhance the capabilities of emergency managers by providing actionable recommendations while preserving human oversight. Advances in XAI (e.g., SHAP, LIME) will be crucial in building trust, enabling emergency managers to identify which factors drive AI recommendations, such as evacuation routing based on predicted fire spread, and to integrate those insights with local contextual knowledge (Matin & Pradhan, 2023). For example, the IBM Intelligent Operations Centre for Emergency Management integrates real-time data streams, including weather reports, emergency calls, and infrastructure status, into an interactive dashboard. This system allows human users to run scenario simulations (e.g., predicting the cascading impacts of a significant flood) and evaluate AI-recommended actions, combining automated insights with human expertise.

Similarly, the FEMA Planning Assistant for Resilient Communities (PARC) utilises AI-powered dialogue interfaces to support local governments in developing hazard mitigation plans. Rather than replacing human planners, it suggests customised strategies and explains regulatory frameworks, which users then review and modify based on local knowledge and priorities. Emerging multi-agent AI frameworks, like EvoTaskTree, are also promising. These systems autonomously develop decision trees for emergency actions yet require human supervisors to validate critical steps. This collaborative model enhances transparency and accountability, ensuring that AI acts as a partner, not a replacement, in complex disaster management decisions. Future training programs for emergency responders should integrate modules on AI interpretation, much like today's GIS or radio communication certifications. Only by fostering intuitive, explainable, and collaborative AI systems can disaster response truly leverage the combined strength of human and machine intelligence.

• Democratisation and Global Standards: To ensure equitable access, open-source AI toolkits and low-code platforms should be developed, allowing smaller agencies and NGOs to customise risk mapping and simulation models without specialised expertise. International collaboration—through shared disaster data repositories, interoperable model formats, and mutual aid agreements for AI analysis—will help lower-resource regions adopt lifesaving technologies, thereby narrowing resilience disparities worldwide (Jing et al., 2022).

AI's integration into disaster response delivers demonstrable gains in speed and accuracy, yet its full potential depends on overcoming data-sharing barriers and ensuring transparent, human-centred implementations. By advancing multi-modal edge computing, fostering transparent human-–AI partnerships, and establishing global cooperative frameworks, the field can transition from isolated pilots toward scalable, resilient solutions that protect vulnerable communities in the face of escalating climate and industrial hazards.

To translate these insights into actionable strategies, we offer the following recommendations for local authorities, humanitarian organisations, and emergency services:

- **Invest in Multilingual AI Tools:** Deploy NLP models trained in local languages and dialects to ensure inclusive communication during emergencies.
- **Prioritise Explainable AI Systems: Select decision-support tools that provide transparent reasoning, allowing** responders to understand and adapt AI recommendations.
- **Develop Offline-Capable Solutions:** Utilise edge computing technologies that operate independently of continuous internet access to ensure operational resilience.
- **Foster Cross-Sector Collaboration:** Partner with academic institutions, tech companies, and community organisations to co-develop and adapt AI tools for local contexts.
- **Incorporate Cultural Sensitivity:** Integrate cultural knowledge into AI training and decision processes to enhance trust and effectiveness in diverse communities.

Implementing these strategies can enhance the inclusivity, trustworthiness, and operational effectiveness of AI systems in disaster response.

Funding: This study does not have a financial fund.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Asma, A. B., & Aranas, P. J. B. (2024). Forecasting earthquakes using machine learning. Journal of Artificial Intelligence, Machine Learning and Neural Network, 4(3), 31–40. https://doi.org/10.55529/jaimlnn.43.31.40
2. Abdul, S., Adeghe, E. P., Adegoke, B. O., Adegoke, A. A., & Udedeh, E. H. (2024). AI-enhanced healthcare management during natural disasters: Conceptual insights. Emerging Science and Technology Journal, 5(5), Article 1155. https://doi.org/10.51594/estj.v5i5.1155
3. Abid, S. K., Sulaiman, N., Chan, S. W., Nazir, U., Abid, M., Han, H., Ariza-Montes, A., & Vega-Muñoz, A. (2021). Toward an integrated disaster management approach: How artificial intelligence can boost disaster management. Sustainability, 13(22), 12560. https://doi.org/10.3390/su132212560
4. Al-Banna, A., Rana, Z. A., Yaqot, M., & Menezes, B. C. (2023). Supply Chain Resilience, Industry 4.0, and Investment Interplays: A Review. Production& Manufacturing Research, 11(1). https://doi.org/10.1080/21693277.2023.2227881
5. Andrae, S. (2025). Artificial intelligence in disaster management. In Advances in Environmental Engineering and Green Technologies (pp. 75–98). IGI Global. https://doi.org/10.4018/979-8-3693-7483-2.ch004
6. Aon. (2024). Q1 2024 Global Insurance Market Insights Report. https://assets.aon.com/-/media/files/aon/reports/2024/aon---q1-2024-global-insurance-market-insights-report.pdf
7. APWA. (2025). Artificial Intelligence and the Emergency Services Sector – Benefits and Challenges. American Public Works Association. Retrieved from https://www.apwa.org/wp-content/uploads/Artificial-Intelligence-and-the-Emergency-Services-Sector-Case-Studies-Benefits-and-Challenges.pdf
8. Balanggoy, H. K. (2024). Implementation of disaster risk reduction and management. International Journal of Disaster Risk Management, 6(2), 45–59. https://doi.org/10.18485/ijdrm.2024.6.2.8
9. Bari, L. F., Ahmed, I., Ahamed, R., Zihan, T. A., Sharmin, S., Pranto, A. H., & Islam, M. R. (2023). Potential use of artificial intelligence (AI) in disaster risk and emergency health management: A critical appraisal on environmental health. Environmental Health Insights, 17, 1–5. https://doi.org/10.1177/11786302231217808
10. Beeravelly, S. R. (2024). Smart response: Leveraging AI analytics for enhanced disaster resilience. International Journal for Multidisciplinary Research, 6(6), 321–338. https://doi.org/10.36948/ijfmr.2024.v06i06.32137
11. Behravan, M., Mohammadrezaei, E., Azab, M., & Gracanin, D. (2024). Multilingual standalone trustworthy voice-based social network for disaster situations. arXiv. https://doi.org/10.48550/arXiv.2411.08889
12. Beriša, H., Cvetković, V. M., & Pavić, A. (2024). Implications of artificial intelligence and cyberspace on risk management capabilities. International Journal of Disaster Risk Management, 6(2), 101–118. https://doi.org/10.18485/ijdrm.2024.6.2.18
13. Bohland, J., Rechkemmer, A., & Rogers, P. H. (2024). Artificial intelligence. In The Oxford Handbook of AI for Decision Making (pp. 213–229). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190466145.013.13
14. CentralSquare. (2024, May 17). The role of AI in disaster management. https://www.centralsquare.com/resources/articles/the-role-of-ai-in-disaster-management
15. Cvetković, V. M., Renner, R., & Jakovljević, V. (2024). Industrial disasters and hazards: From causes to consequences—a holistic approach to resilience. International Journal of Disaster Risk Management, 6(2), 149–168. https://doi.org/10.18485/ijdrm.2024.6.2.10
16. Dean, M. D., & Payne, D. (2013). Disaster management: An ethical review and approach. International Journal of Emergency Management, 9(4), 327–339. https://doi.org/10.1504/ijem.2013.055157

17. Deekshith, A. (2022). AI-driven early warning systems for natural disaster prediction. International Journal of Sustainable Development in Computing Science, 4(4), 18–25. Retrieved from https://ijsdcs.com/index.php/ijsdcs/article/view/628
18. Đorđević, I., & Gačić, J. (2024). Sustainable recovery: The link between development and response to disasters. International Journal of Disaster Risk Management, 6(2), 86–100. https://doi.org/10.18485/ijdrm.2024.6.2.15
19. Gevaert, C. M., Carman, M., Rosman, B., Georgiadou, Y., & Soden, R. (2021). Fairness and accountability of AI in disaster risk management: Opportunities and challenges. Patterns, 2(10), Article 100363. https://doi.org/10.1016/j.patter.2021.100363
20. Ghaffarian, S., Taghikhah, F. R., & Maier, H. R. (2023). Explainable artificial intelligence in disaster risk management: Achievements and prospective futures. International Journal of Disaster Risk Reduction, 98, Article 104123. https://doi.org/10.1016/j.ijdrr.2023.104123
21. Gupta, T., & Roy, S. (2024). Applications of Artificial Intelligence in Disaster Management. In 2024 10th International Conference on Computing and Artificial Intelligence (ICCAI 2024), April 26–29, 2024, Bali Island, Indonesia. ACM, New York, NY, USA. https://doi.org/10.1145/3669754.3669802
22. Harika, A., Balan, G., Thethi, H. P., Rana, A., Rajkumar, K. V., & Al-Allak, M. A. (2024). Harnessing the power of artificial intelligence for disaster response and crisis management. In Proceedings of the 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE) (pp. 1–8). IEEE. https://doi.org/10.1109/IC3SE62002.2024.10593506
23. Internal Displacement Monitoring Centre. (2024). How AI is advancing socioeconomic insights into disaster displacement. https://www.internal-displacement.org/expert-analysis/how-ai-is-advancing-socioeconomic-insights-into-disaster-displacement/
24. Jiao, J., Lewis, S. H., Xu, Y., Sussman, K., & Atkinson, L. (2024). Multilingual AI-assisted emergency preparedness [Poster presentation]. Bridging Barriers, The University of Texas at Austin. http://bridgingbarriers.utexas.edu/sites/default/files/documents/multilingual-ai-assisted-emergency-preparedness_48x35.pdf
25. Jing, Y., Ren, Y., Liu, Y., Wang, D., & Yu, L. (2022). Automatic extraction of damaged houses by earthquake based on improved YOLOv5: A case study in Yangbi. Remote Sensing, 14(2), 382. https://doi.org/10.3390/rs14020382
26. Kumar, M. V. K. S. (2024). Leveraging AI in disaster management: Enhancing response and recovery for natural and man-made disasters. International Journal for Multidisciplinary Research, 6(2), 42–59. https://doi.org/10.36948/ijfmr.2024.v06i02.26729
27. Matin SS, Pradhan B. Earthquake-Induced Building-Damage Mapping Using Explainable AI (XAI). Sensors (Basel). 2021 Jun 30;21(13):4489. doi: 10.3390/s21134489. PMID: 34209169; PMCID: PMC8271973.
28. Milenković, D., Cvetković, V. M., & Renner, R. (2024). A systematic literary review on community resilience indicators: Adaptation and application of the BRIC method for measuring disaster resilience. International Journal of Disaster Risk Management, 6(2), 6–24. https://doi.org/10.18485/ijdrm.2024.6.2.6.
29. Cvetkovic, V. M., & Martinović, J. (2021). Innovative solutions for flood risk management. International Journal of Disaster Risk Management, 2(2), 71–100. https://doi.org/10.18485/ijdrm.2020.2.2.5
30. Moon Technolabs. (2023). Edge AI vs Cloud AI: Use Cases and Benefits. Retrieved from https://www.moontechnolabs.com/blog/edge-ai-vs-cloud-ai/
31. Munich Re. (2023). Munich Re Group Annual Report 2023. https://www.munichre.com/content/dam/munichre/mrwebsiteslaunches/2023-annual-report/MunichRe-Group-Annual-Report-2023-en.pdf/_jcr_content/renditions/original./MunichRe-Group-Annual-Report-2023-en.pdf
32. NASA. (2024). NASA AI, Open Science Advance Disaster Research and Recovery. NASA Science. Retrieved from https://science.nasa.gov/open-science/artificial-intelligence-hurricane-response/

33. NCDP. (2025). The Promise and Challenges of AI in Wildfire Damage Assessment. National Center for Disaster Preparedness, Columbia University. Retrieved from https://ncdp.columbia.edu/ncdp-perspectives/transforming-disaster-management-the-promise-and-challenges-of-ai-in-wildfire-damage-assessment/
34. Odubola, O., Adeyemi, T. S., Olajuwon, O. O., Iduwet, N. P., Aniekan, A. I., & Odubola, T. (2025). AI in Social Good: LLM Powered Interventions in Crisis Management and Disaster Response. Journal of Artificial Intelligence, Machine Learning and Data Science, 3(1), 3353–3360. https://doi.org/10.51219/JAIMLD/Oluwatimilehin-Odubola/510
35. Ogunleye, O. I., & Arohunsoro, S. J. (2024). An assessment of socio-economic impacts of rainstorm disaster on the livelihood of the residents of Ikole Local Government Area in Ekiti State, Nigeria. International Journal of Disaster Risk Management, 6(2), 14–31. https://doi.org/10.18485/ijdrm.2024.6.2.14
36. Öcal, F. E., & Torun, S. (2024). An inevitable technological disaster type: Space debris. International Journal of Disaster Risk Management, 6(2), 62–76. https://doi.org/10.18485/ijdrm.2024.6.2.5
37. Raut, S. V. (2024). Artificial intelligence use in disaster management. International Journal of Innovative Science and Research Technology, 9(5), 101–109. https://doi.org/10.38124/ijisrt/IJISRT24MAY1679
38. Reichstein, M., Benson, V., Blunk, J., Camps-Valls, G., Creutzig, F., Fearnley, C. J., Han, B., Kornhuber, K., Rahaman, N., Schölkopf, B., Tárraga, J. M., Vinuesa, R., Dall, K., Denzler, J., Frank, D., Martini, G., Nganga, N., Maddix, D. C., & Weldemariam, K. (2025). Early warning of complex climate risk with integrated artificial intelligence. Nature Communications, 16(1), e2564. https://doi.org/10.1038/s41467-025-57640-w
39. Schofield, M. (2022). An artificial intelligence (AI) approach to controlling disaster scenarios. In Advances in Electronic Government, Digital Divide, and Regional Development (pp. 45–62). IGI Global. https://doi.org/10.4018/978-1-7998-9815-3.ch003
40. Sharma, A., Rawal, T., Agarwal, S., & Aditaya, A. (2025). The application of support vector machine (SVM) and AI in enhancing disaster management. Social Science Research Network. https://doi.org/10.2139/ssrn.5076167
41. Simões-Marques, M., & Figueira, J. R. (2018). How can AI help reduce the burden of disaster management decision-making? In F.-Y. Wang (Ed.), Multicriteria Decision Aid and Artificial Intelligence (pp. 271–284). Springer. https://doi.org/10.1007/978-3-319-94334-3_14
42. Singh, V. A., & Agnihotri, A. (2024). Addressing environmental challenges through AI-powered natural disaster management. International Journal of Applied and Scientific Research, 2(5), 88–99. https://doi.org/10.59890/ijasr.v2i5.1413
43. Sun, W., Bocchini, P., & Davison, B. D. (2020). Applications of artificial intelligence for disaster management. Natural Hazards, 104, 2435–2460. https://doi.org/10.1007/s11069-020-04124-3
44. Tout, F., Rebouh, N., Dinar, H., Benzid, Y., & Zouak, Z. (2024). The contribution of roads to forest fire protection in Tamza Municipality, Northeast Algeria. International Journal of Disaster Risk Management, 6(2), 3–13. https://doi.org/10.18485/ijdrm.2024.6.2.3.