Governing Generative AI in Disaster Risk Management

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Abstract

The increasing frequency and severity of climate-related disasters, as well as scarcity of resources to counter them, highlight the urgent need for advanced tools in assessing and managing natural hazards. Recent developments in generative artificial intelligence offer new avenues to enhance disaster risk management. Among these advancements, large language models (LLMs) hold potential for improving situational awareness, risk management, and the communication of early warnings and forecasts. Additionally, new forms of agentic AI expand these capabilities by combining LLMs with memory, planning, and tool use, enabling them to support operational decisions even more effectively. While AI's role in forecasting and risk modeling is well-explored, GenAI brings new urgent challenges concerning bias, explainability, fair access, and trust. In this perspective piece, we critically examine both the operational potential and the ethical challenges of integrating GenAI into disaster risk workflows, focusing on how these technologies can support practitioners and policymakers. Drawing on recent literature, expert discussions, and a dedicated survey that was distributed during a disaster-related event from the European Commission, we underline the necessity of embedding human oversight, transparency, and cultural sensitivity into such systems. We stress that realizing the advantages of GenAI will require coordinated collaboration across different fields, improved interdisciplinary capacity building, and policy frameworks that ensure reliability, fairness, and practical usefulness from design to deployment.

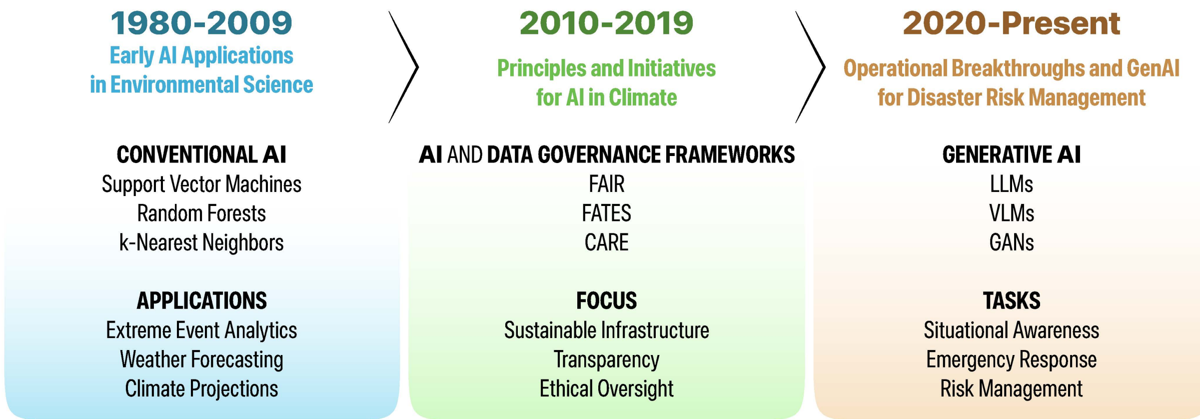

Figure 1: The evolution of AI in climate-related extremes emerged in the 1980s and 1990s, when environmental scientists first applied expert systems and shallow neural networks to forecast weather and climate extremes, marking some of the earliest data-driven approaches [13]. In the 2010s, foundational ethical frameworks emerged to guide responsible AI development. These included FAIR [14], which promotes open, machine-readable scientific data; FATES, which emphasizes the ethical design and governance of AI systems [5]; and CARE, which centers indigenous data sovereignty and equitable data governance [15]. From 2020 to 2025, operational AI and GenAI tools for natural hazard applications, enhancing short-range nowcasting, real-time flood and wildfire prediction, and multilingual early warning communication. These developments were further shaped by global initiatives such as the Climate Change AI initiative, which brings together researchers and practitioners to ensure AI for climate applications is socially beneficial, inclusive, and aligned with climate resilience goals. Together, these efforts reflect a growing commitment to embedding transparency, equity, and accountability into the use of AI for managing climate-related extremes [16, 5, 17].

The Emergence of Generative AI in Disaster Risk Management

Climate-related hazards (e.g., heat waves, droughts, and floods) are becoming less predictable, more complex, and more severe, with least developed and landlocked developing countries, as well as small island developing states, bearing the brunt of human and economic costs [1, 2, 3, 4]. To better prepare for and respond to such events, reliable systems must be in place to monitor, assess, forecast, and communicate disaster risk information so that informed and timely decisions can be made. For this, the integration of artificial intelligence (AI) applications within natural hazard assessment and management is increasingly being proposed [5, 6].

Currently, AI (e.g., conventional machine learning, generative AI (GenAI)), refers to engineered systems capable of learning from data and generating outputs to achieve human-defined objectives [7]. In the context of disaster risk management (DRM), academic literature provides many examples of how AI is being applied by the research community. Some of these studies are applying AI to: (i) process large volumes of observational data in near real time to detect relevant features, such as an earthquake in seismic data (e.g., Earthquake transformer [8]) or a flood in precipitation and runoff data (e.g., Asif et al., (2025) [9]); (ii) optimize numerical weather predictions (e.g., NowcastNet [10]) or physics-based models (e.g., MaxFloodCast [11]); (iii) integrate different sources and modalities of data (e.g., real-time observational data, social media data) to acquire situational awareness (e.g., Fan et al., (2020) [12]) and support decision-making; and (iv) support communication efforts (e.g., through automated translation systems or chatbots). An example of the latter is the drought advisory system recently released by the International Water Management Institute, which is equipped with AI that issues predictive, personalized advice in over 20 Indian languages[1].

In academic literature, machine learning (ML) and deep learning (DL) techniques remain the dominant AI methodologies for natural hazard assessment and management. While, the application of GenAI to produce original text, images, speech, or code remains relatively underexplored. However, several recent studies have begun to explore the potential of GenAI in disaster risk contexts. In this direction, several lines of research have focused on streamlining strategic operations and reporting. For instance, Goecks and Waytowich (2023) [18] developed DisasterResponseGPT, a system designed to accelerate the creation of action plans for disaster response. A primary advantage of this approach is its interactive design, which allows users to engage with and refine plans in real time. Similarly, Colverd et al. (2023) [19] introduced FloodBrain, a customized pipeline for flood disaster impact reporting that demonstrates how large language

[1]https://www.iwmi.org/blogs/india-to-get-its-first-ai-based-chatbot-to-tackle-drought/

models (LLMs) can enhance planning humanitarian assistance. Other applications focus on specialized communication and information retrieval. For instance, Luccioni et al. (2021) [20] utilized GenAI to generate visual representations of climate impacts, while Zhao et al. (2025) [21] developed a linguistically and culturally agile chatbot to improve outreach. Xie et al. (2024) [22] proposed WildfireGPT, an LLM agent that represents a significant step in applying generative models to specialized scientific domains, specifically wildfire risks. Vaghefi et al. (2023) [23] proposed a specialized chatbot capable of navigating and answering complex questions based on the IPCC AR6 climate reports, highlighting the utility of LLMs in distilling dense scientific data.

These instances, alongside the broader historical trajectory of AI in climate extremes and natural hazards, point toward a fundamental paradigm shift in DRM. Since the 1980s, AI has been evolving from early expert systems into modern tools for operational forecasting and decision-support tools (Fig. 1). Presently, GenAI is moving beyond restrictive, task-specific predictive models toward a future of flexible, human-centered support systems. This expansion of function brings new opportunities, but also introduces a distinct constellation of operational, technical, social, and policy challenges [16, 13, 24]. Although GenAI is currently in its early stages compared to traditional AI, its rapid evolution and inherent adaptability suggest it will soon become a cornerstone of hazard resilience. This is evident as researchers increasingly unlock its versatility to close the existing gap in adoption and pave the way for more intuitive and collaborative disaster response frameworks. However, as this technology matures, the field must proactively address emerging challenges (e.g., high computational demands, the transparency of model architectures, and responsibility and ethics) to ensure that the next generation of DRM tools remains accurate, inclusive, sustainable, and reliable under human oversight as well as actionable and explainable to the end users [25, 26, 27].

This perspective is motivated by the dual role of GenAI in DRM, presenting both opportunities and challenges. Situating GenAI within the broader landscape of AI-enabled DRM, the article calls for a systematic, critical assessment of its applications, limitations, and governance implications. It argues that the rapid uptake of GenAI is reshaping the relationship between technical capability, decision-making authority, and accountability in high-stakes hazard contexts, rendering existing governance approaches insufficient and highlighting the need for more operationally grounded principles to guide deployment [7, 28].

Challenges of GenAI Applications in DRM

Unlike traditional ML approaches, GenAI systems are resource-intensive and often seen as "black-box" systems. Their outputs are frequently narrative-driven and context-dependent, making them difficult to validate, audit, and regulate. This aspect becomes particularly relevant within high-stakes hazard contexts where decisions affect lives, livelihoods, and public trust. Existing AI and data governance frameworks, such as FAIR (findable, accessible, interoperable, and reusable) [14], CARE (collective benefit, authority to control, responsibility, and ethics) [15], and FATES (fairness, accountability, transparency, ethics, and sustainability) [5], provide essential principles for ethical data use and responsible AI development, yet they do not fully capture the epistemic and operational risks associated with generative systems whose outputs may appear authoritative without being verifiable. These challenges emerge mostly when GenAI is embedded into real-world operational workflows. Beyond technical performance, deployment raises operational, social, and policy concerns that are amplified in data-scarce and marginalized settings. For instance, populations living in informal settlements, undocumented communities, or structurally disadvantaged contexts are often both the most exposed to hazards and the least represented in training data; this disparity leads to poor GenAI performance within this imperative context. Furthermore, such models are not well suited for highly heterogeneous contexts and are challenged by life-and-death decisions under the extreme time pressure of acute crisis phases [28].

At the same time, the computational and environmental costs of large-scale GenAI models are coupled with increasing reliance on closed-source systems that have no clear overview on data provenance, validation, accountability and regulatory oversight. Moreover, reliability issues intrinsic to probabilistic generation (e.g., hallucinations and confidently incorrect outputs) further undermine trust, particularly where censuses, surveys, and situational data are incomplete or outdated [29, 30]. If left unaddressed, these limitations risk misrepresenting vulnerability, introducing new security threats, and reproducing or amplifying existing inequities in risk assessment and resource allocation [31, 32]. To further reflect on these issues, we explore operational and technical challenges in the following sections.

The Adoption Paradox in Operational Disaster Management

The operational deployment of GenAI in DRM remains at an early stage, particularly in high-stakes decision contexts where accountability, trust, and liability are central concerns [17]. Although mature case studies are still lacking, early deployment examples already highlight important governance challenges. Systems such as DisasterResponseGPT, which supports plan-of-action development, and FloodBrain, which uses retrieval-augmented generation to synthesize flood-related information for humanitarian reporting, illustrate how GenAI can shape planning processes and decision

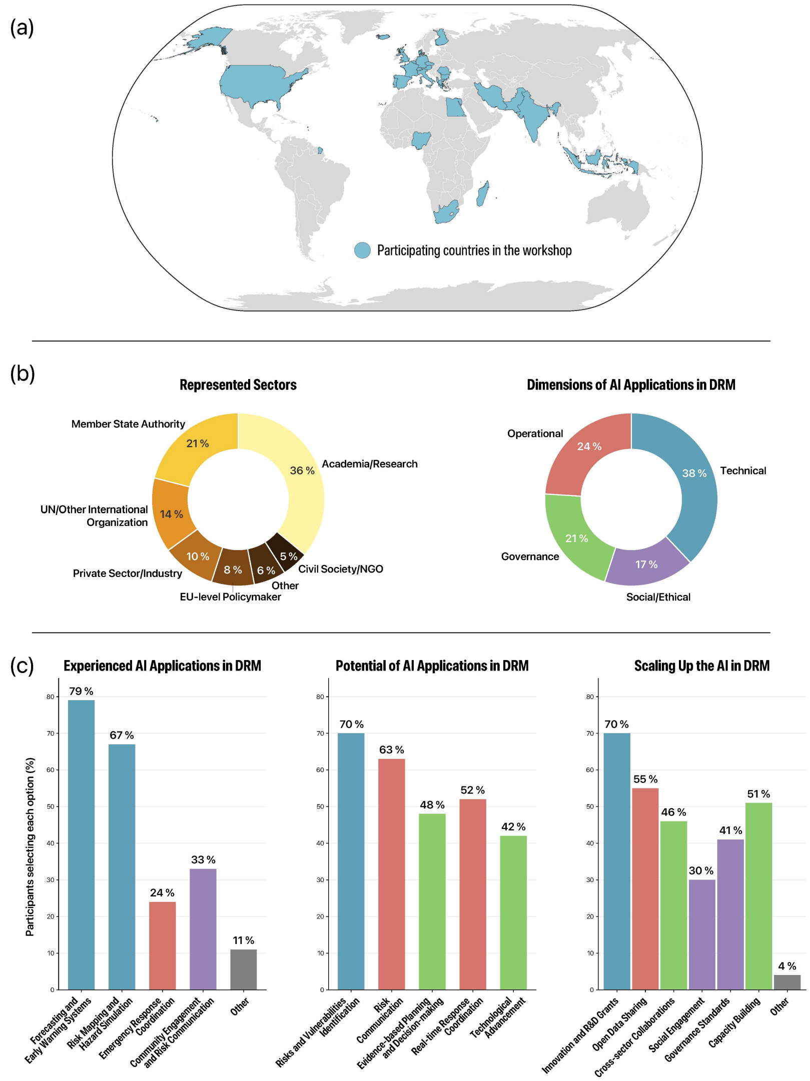

Figure 2: Hopes and concerns regarding the AI adoption in DRM. The figure provides an overview of the survey conducted at the workshop " Building Capacity on AI for Disaster Preparedness" organized by the European Commission [33]. Panel (a) shows the 33 countries represented by the workshop participants; pane (b) demonstrates the sectors represented by participants, as well as different dimensions of AI applications relevant to their fields in DRM; panel (c) illustrates three main deep-dive aspects that were surveyed among the participants: (left) experience with AI tools, where almost 80 % of the participants highlighted the AI application in forecasting and early warning systems, while approximately 55 % reported on the role and experience with AI in emergency response coordination, community engagement and risk communication; (center) expectation from the AI applications in DRM, where almost 48 % and 52 % see the potential of such tools in evidence-based planning and decision-making as well as real-time response coordination and resource allocation; (right) recommendations to scale up the AI in DRM, where by 70 % innovation and R&D funding has the highest percentage, while 30 % emphasizes on the local and community engagement (labeled as social engagement). Please note that the colors in panel (b), representing the dimensions of AI applications in DRM, correspond to the bars shown in panel (c).

structuring under uncertainty [18, 19]. In parallel, evaluations from EU civil protection-led workshops and prototype testing exercises indicate that practitioners remain concerned about transparency, accountability, and liability when such tools are used to inform real operational decisions [34, 33]. Thus, compared to ML and DL which are already embedded in forecasting and remote sensing data analysis [35, 36], GenAI applications, often framed as decision-support "copilots", largely remain at pilot or prototype stages.

A recent survey evidence points to a pronounced "humanitarian AI paradox", with 93% of more than 2,500 practitioners reporting individual use of AI tools, only 10% of organizations had formally integrated AI into workflows, and only 22% had dedicated AI policies. Notably, just 38% of respondents believed AI projects had improved decision-making. These findings reveal a gap between individual experimentation and institutional maturity, as well as between technological promise and perceived operational value [37].

While the potential of AI is recognized, the European Commission has noted three major challenges in operationalization of AI into DRM: (i) technological challenges; (ii) ethical standards and trustworthiness; (iii) and institutional capacity and financing [6]. As demonstrated in Fig. 2, comparable lines of findings were emerged from a survey undertaken at the workshop on "Building Capacity on AI for Disaster Preparedness" [33] organized by the European Commission in 2025. The survey results reflect both strong optimism and the clear need of both operational and governing guardrails regarding AI adoption in DRM. Participants from a wide range of countries and sectors highlighted that AI is already most mature in forecasting and early warning, with many also recognizing its growing role in emergency response coordination, risk communication, and community engagement. Looking ahead, respondents expressed high expectations for AI to enhance evidence-based planning, decision-making, and real-time response through improved coordination and resource allocation. At the same time, scaling up AI in DRM was seen to depend primarily on sustained innovation and research funding, complemented by the need to better anchor AI solutions in local contexts through meaningful community engagement.

Aligned dynamics were observed in a tailored session focused on interviews and prototype testing of GenAI tools during the European Commission's "AI for Preparedness" workshop [34]. Civil protection professionals judged GenAI-generated disaster storylines to be plausible and relevant, yet expressed strong reservations regarding transparency, interpretability, and accuracy. Across a diverse group of practitioners and policymakers, three obstacles to adoption were consistently identified: (a) limited trust in model outputs; (b) concerns about bias in underlying data; and (c) difficulties in integrating GenAI into established DRM procedures. Targeted interviews with decision-makers from the Italian Red Cross and regional emergency centers confirmed simialr findings, where GenAI use remains largely informal and individual, with attitudes ranging from recognizing its potential to viewing the technology as premature. Such concerns echo a recurring accountability issue, where despite highly capable GenAI systems offering comprehensive situational awareness, responsibility for poor decisions does and should remain with human operators, potentially increasing rather than reducing perceived liability.

Technical Risks in Disaster Settings

As illustrated by similar results in Fig. 2, at the core of these adoption challenges lie fundamental limitations of current GenAI architectures. As next-token prediction systems, LLMs generate statistically likely sequences without intrinsic semantic or physical understanding [38]. Alignment techniques such as reinforcement learning from human feedback reduce unsafe outputs but do not eliminate hallucinations or confidently incorrect responses [39]. In disaster contexts, where uncertainty must be explicitly communicated, such failures can have disproportionate consequences [24].

Bias is a persistent and systemic challenge. Training data may reflect uneven observational coverage, outdated or degraded instruments, annotation errors, or preprocessing artifacts [40, 41]. Because GenAI systems are trained on large, heterogeneous, and weakly curated datasets spanning regions and timescales, these biases can propagate through probabilistic generation in subtle and difficult-to-audit ways [42, 43]. Addressing such risks requires explicit attention to fairness, accountability, ethics, and sustainability, as also articulated in the FATES framework [5].

Technical reliability is another challenge, which is further linked to scale. Model performance depends on balancing the number of trainable parameters against available high-quality data to avoid underfitting or overfitting [44]. These concerns intersect directly with computational and environmental costs, where large-scale GenAI deployment demands substantial energy and water resources, yet environmental impacts remain difficult to quantify due to coarse reporting and limited transparency [45, 46]. Estimates suggest AI-related computing could contribute tens of millions of tons of CO_2 annually and water demands comparable to those of major cities, though uncertainty in the estimations remains high due to inconsistent disclosure [47, 48].

Structural risks compound these technical challenges. Increasing reliance on closed-source, proprietary models complicates validation, auditing, and regulatory oversight in public-sector and humanitarian settings. The reliance on closed-source APIs also introduces the risk of "model version drift", where unannounced updates can unpredictably alter system behavior and compromise the reliability of established disaster response workflows. GenAI systems also introduce new cybersecurity vulnerabilities, including prompt injection, data poisoning, and model inversion. In disaster response scenarios that ingest real-time reports and situational data, such vulnerabilities threaten not only system integrity but also confidentiality, operational safety, and trust. These risks highlight the need for standardized evaluation frameworks and benchmark datasets grounded in real disaster workflows; without them, GenAI adoption remains

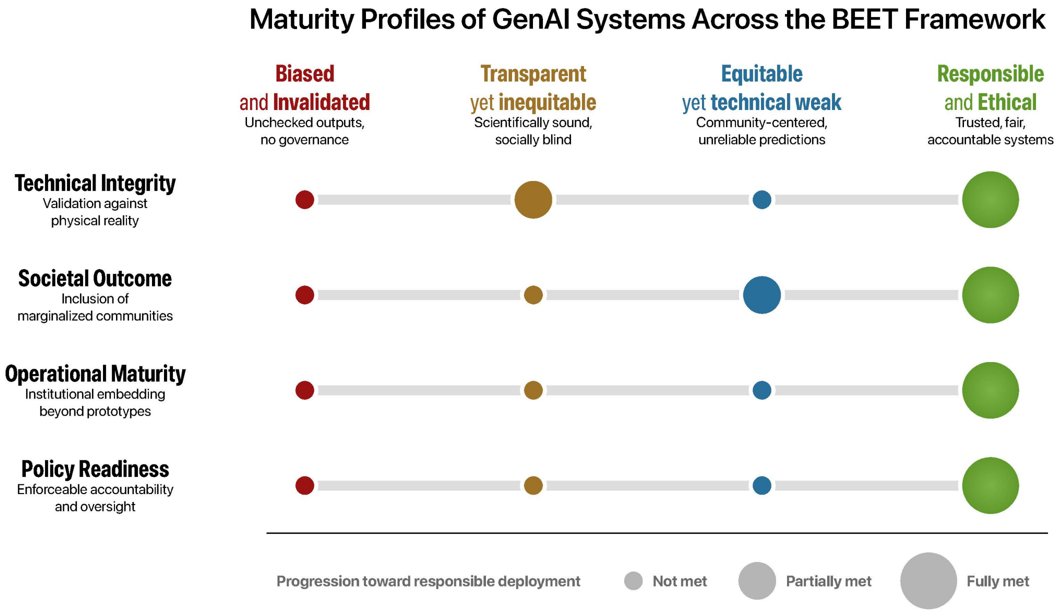

Figure 3: The figure depicts the progression across intersecting dimensions and associated critical BEET zones, moving from a biased and invalidated state toward responsible and ethical deployment, which is the target state. The figure organizes GenAI across four intersecting dimensions as follows: technical integrity (moving from high biased to high explainability), societal outcomes (moving from fragile or misplaced trust to equitable and inclusive impacts), operational maturity (from experimental deployment to monitored and adaptive use in the field), and policy readiness (from ad hoc oversight to accountable and aligned governance). These dimensions define distinct zones with corresponding implications for DRM: (i) biased and invalidated systems, where risks of misleading forecasts, inequitable risk communication, and erosion of public confidence could occur; (ii) transparent yet inequitable systems, which are scientifically robust tools yet fail to serve vulnerable or marginalized populations; (iii) equitable yet technically weak systems that are well-intentioned decisions, however, may lack the expected predictive accuracy or consistency; and (iv) responsible and ethical designs that are trusted, fair, and accountable GenAI systems that supports effective hazard preparedness, response, and recovery. Progress toward the target state reflects advancement toward responsible and ethical GenAI that aligns operational functionality, technical performance, societal benefit, and institutional governance in DRM.

difficult to validate. As an example in this direction, we cite PromptAId Arena [49] which illustrates how scalable, scenario-based benchmarking for disaster management tasks can enable systematic model evaluation and support more responsible, evidence-based adoption at scale.

Responsible GenAI for Natural Hazard Assessment and Disaster Management: Social and Policy

As GenAI reshapes how information is produced and interpreted in disaster contexts, the critical question is whether existing governance approaches can manage these new forms of influence. Addressing this challenge requires a shift from experimental innovation toward responsible, trusted public infrastructure. Technical performance alone is insufficient. GenAI systems used in DRM must be evaluated and governed as socio-technical systems embedded within institutional, legal, and cultural contexts. This section argues that current frameworks, while necessary, remain insufficiently grounded in operational decision-making, motivating the need for more practice-oriented principles. To address this gap, we frame responsible deployment of GenAI around the bias, explainability, equitability, and trust (henceforth referred to as BEET) principles. These principles extend beyond conventional metrics, such as accuracy or loss functions, to address the essential qualitative dimensions of high-stakes decision-making.

Bias and Explainability

Fig. 3 synthesizes the BEET principles into a practical framework for guiding the responsible and ethical development and deployment of GenAI in DRM. By organizing GenAI applications across intersecting operational, technical, social, and policy dimensions, the framework highlights critical zones of risks and opportunities, illustrating how different combinations of system maturity and governance can either undermine or strengthen effective, fair, and trustworthy DRM outcomes. From a technical integrity perspective, bias mitigation emerges as a foundational requirement. Addressing bias requires rigorous validation of GenAI systems used in DRM to ensure that generated situation reports, sensor summaries, social media analyses, and policy-relevant outputs are consistent with established scientific knowledge and physical laws. This need is particularly pronounced when GenAI systems analyze geospatial data (e.g., satellite imagery and in-situ observations). In such cases, validation is further complicated by sharp regional disparities in observational infrastructure. For instance, the state of Hawaii operates approximately 100 ground-shaking sensors, whereas Haiti's national seismic network consists of only seven stations [50, 51]. Even within data-rich countries, hurricane-prone regions of the United States continue to face Doppler radar coverage gaps [52]. To compensate for limited in-situ observations, practitioners often rely on remote sensing, but constraints related to spatial resolution, revisit frequency, and cost can introduce additional sources of bias [53]. In high-stakes hazard applications, fairness and trustworthiness depend critically on how these data limitations are acknowledged and managed.

In such contexts, validation must extend beyond conventional performance metrics to include spatial, temporal, energy efficiency, and physical consistency checks. Geospatial foundation models (i.e., large-scale pretrained geospatial models), which integrate satellite imagery, climate fields, and in-situ sensor data, require careful assessment of how learned representations generalize across regions, hazard types, and data-sparse environments. Coupled with LLMs, these systems could generate narratives, summaries, or decision-support insights, but could introduce additional risks of misinterpretation or overgeneralization if underlying geospatial outputs are uncertain or biased. Ensuring transparency in data provenance, model assumptions, and uncertainty communication is therefore essential to prevent the amplification of technical biases into operational and policy decisions, particularly in high-stakes DRM settings. In addition, model designs must maintain an appropriate balance between the number of trainable parameters and the volume of high-quality training data. Scaling laws suggest that data-to-parameter ratios on the order of 5:1 to 20:1 are necessary to reduce the risks of underfitting or overfitting [44].

Transitioning from bias toward explainability, we cite Schneider et al. [54] who emphasize that explainability is particularly critical for GenAI models because their architectural complexity, heterogeneous training data, and high-impact applications make them difficult to evaluate and raise concerns related to safety and security. As model complexity increases, decision pathways become harder to trace, complicating the identification of errors or latent biases. This has led some researchers to advocate for simpler, more interpretable models in high-stakes settings [55]. Where complex architectures are unavoidable, explainable AI (XAI) methods provide essential tools for probing internal mechanisms and diagnosing model behavior [56]. Established approaches include SHAP [57], which attributes importance to input features, and LIME [58], which explains predictions through local surrogate models. More recent techniques, such as Concept Relevance Propagation, extend these capabilities by identifying where salient features appear in attribution maps and clarifying their semantic meaning [59]. Nevertheless, XAI methods must be tailored to the geospatial domain to account for spatial autocorrelation, ensuring that hazard mapping attributions remain geographically and physically coherent. Alongside explainability, uncertainty quantification remains a persistent challenge for generative models. In hazard contexts, GenAI systems (and AI in general) must explicitly communicate uncertainty (through confidence intervals or probabilistic ranges) rather than conveying unwarranted precision. Given the inherent unpredictability of extreme events, rigorous uncertainty representation is essential for scientific integrity and user trust [60, 5]. Equally fundamental is the challenge of ensuring that AI-generated outputs conform to established scientific and physical constraints. GenAI-generated scenarios may appear plausible while still violating geophysical principles, underscoring the necessity of human oversight. Researchers emphasize the importance of validating outputs against domain knowledge and physical laws (e.g., verifying that synthetic weather patterns are consistent with known atmospheric dynamics) thereby maintaining a robust human-in-the-loop feedback process. While human-in-the-loop remains the gold standard for ethical accountability, we must also acknowledge an inherent contradiction, which oversight does not scale. As GenAI systems ingest petabytes of real-time data, human verification becomes a bottleneck that introduces unacceptable latency. To address this, we argue that the role of humans must evolve from direct intervention to "human-setting-the-loop", where experts define governance guardrails that are enforced by automated auditing agents. To rigorously implement this at a technical level, we advocate for the adoption of neuro-symbolic architectures and physics-informed machine learning [61]. Such a strategy allows GenAI system to function as an orchestrator, rather than a simulator; it parses unstructured data and feeds parameters into deterministic, physics-based models to generate predictions. This helps keep outputs grounded in physical laws, satisfying the BEET framework's "Technical Integrity" requirement while reducing the risk of plausible-sounding hallucinations. Furthermore, advancing responsible AI in natural hazard assessment requires integrated practices across data governance, model design, and validation to ensure integrity, fairness, and sustainability. In line with BEET principles, efforts should prioritize rigorous metadata documentation and bias evaluation, supported by techniques such as balanced sampling, weighted loss functions, and uncertainty-aware data augmentation to address representation gaps [62, 63]. At the model level, benchmarking must extend beyond predictive accuracy to include computational efficiency, energy consumption, and carbon footprint, which highlights the essential metrics for responsible, scalable deployment. Furthermore, we stress on the interdisciplinary collaboration among researchers, hazard experts, and decision-makers, as it remains vital throughout the GenAI lifecycle.

Social Equity and Trust

The deployment of GenAI in natural hazard management must be recognized as both a technical undertaking and a societal responsibility. Within the BEET framework, this corresponds to the societal outcomes dimension, which should transition from low equitability and fragile trust to inclusive, trusted, and socially legitimate systems. In marginalized contexts, these principles address the critical intersection of high hazard vulnerability and systemic data under-representation. Without deliberate design and governance choices, GenAI systems risk reinforcing or amplifying existing inequities [29, 30]. Data scarcity and bias can undermine model reliability and lead to the systematic underestimation of vulnerability, resulting in inequitable resource allocation.

To move toward higher equitability, the literature increasingly emphasizes data justice approaches, including participatory mapping, community-based data collection, and the integration of local and indigenous knowledge [64, 65, 66]. These strategies expand data coverage while grounding risk assessments in local context. However, advancing societal outcomes requires more than augmenting datasets. Structural mechanisms are needed to enable marginalized communities to shape how hazards are defined, how priorities are set, and how risk is communicated. In this sense, GenAI should be embedded within governance frameworks that recognize cultural pluralism and local agency, rather than deployed as a purely technical upgrade. As a promising technical avenue to address this representation gap is the use of privacy-preserving synthetic data generation [67]. By training GenAI models on statistical distributions of marginalized populations rather than raw personal data, researchers can create "digital twins" of under-represented communities. This approach actively converts the generative capability of AI from a source of bias into a tool for inclusive visibility.

A persistent barrier to positive societal outcomes is the gap between forecast accuracy and effective action. Even highly accurate models fail to reduce risk if individuals are unable or constrained from responding to warnings [5, 68]. Empirical evidence highlights barriers such as caregiving responsibilities, mobility limitations, lack of transportation, and economic constraints [5, 69]. GenAI offers pathways to improve compliance by enabling tailored, multilingual, and context-aware alerts that account for different social roles and constraints. Geo-located and situational specific guidance can further enhance practical relevance. Crucially, compliance should be understood not as passive adherence but as informed, feasible, and safe action aligned with lived realities, thereby supporting a transition from fragile trust toward meaningful engagement.

Trust, as the upper end of the societal outcomes dimension in the BEET framework, ultimately determines whether AI-enabled recommendations are accepted and acted upon. Communities with histories of neglect or inconsistent emergency responses often approach new technologies with skepticism. Trust is strengthened when GenAI systems are positioned as augmenting human judgment rather than replacing it, when uncertainties and limitations are communicated transparently, and when users are supported in developing risk literacy to interpret probabilistic information [70, 71, 72, 73]. Participatory approaches (e.g., co-design workshops, feedback mechanisms, and inclusive digital platforms) further enhance legitimacy by allowing affected groups to contest, refine, and co-own AI-supported interventions [74, 75]. A potential model for this integration is the "AI co-scientist" framework [76, 77], which fosters transdisciplinary collaboration between AI systems and domain experts under the technical guidance of AI experts. At present, these co-development schemes are primarily tailored to assist researchers in accelerating literature synthesis, generating novel insights, and formulating hypotheses, all while maintaining scientific rigor through expert oversight. However, looking ahead, this capacity could be extended further; by translating such collaborative frameworks into the DRM context and incorporating broader community perspectives, these systems can uphold more inclusive AI-assisted knowledge generation and empower evidence-based decision-making.

At the policy level, these societal concerns are increasingly reflected in regulatory frameworks. For instance, the European Commission's Ethics Guidelines for Trustworthy AI, prioritize fairness, transparency, accountability, and a respect for diversity [78]. These principles directly inform the European Union's AI Act [79]. Under this Act, specific guidelines for high-risk AI systems are expected in 2026; these will provide essential clarity for disaster management systems, which may be classified as "high-risk" depending on their specific scope. Once released, these guidelines will establish clear obligations for human oversight, risk management, and post-market monitoring [79]. Internationally, UNESCO's Recommendation on the Ethics of Artificial Intelligence and the United Nations' White Paper on AI Governance advance rights-based approaches that stress inclusion, protection of marginalized groups, and

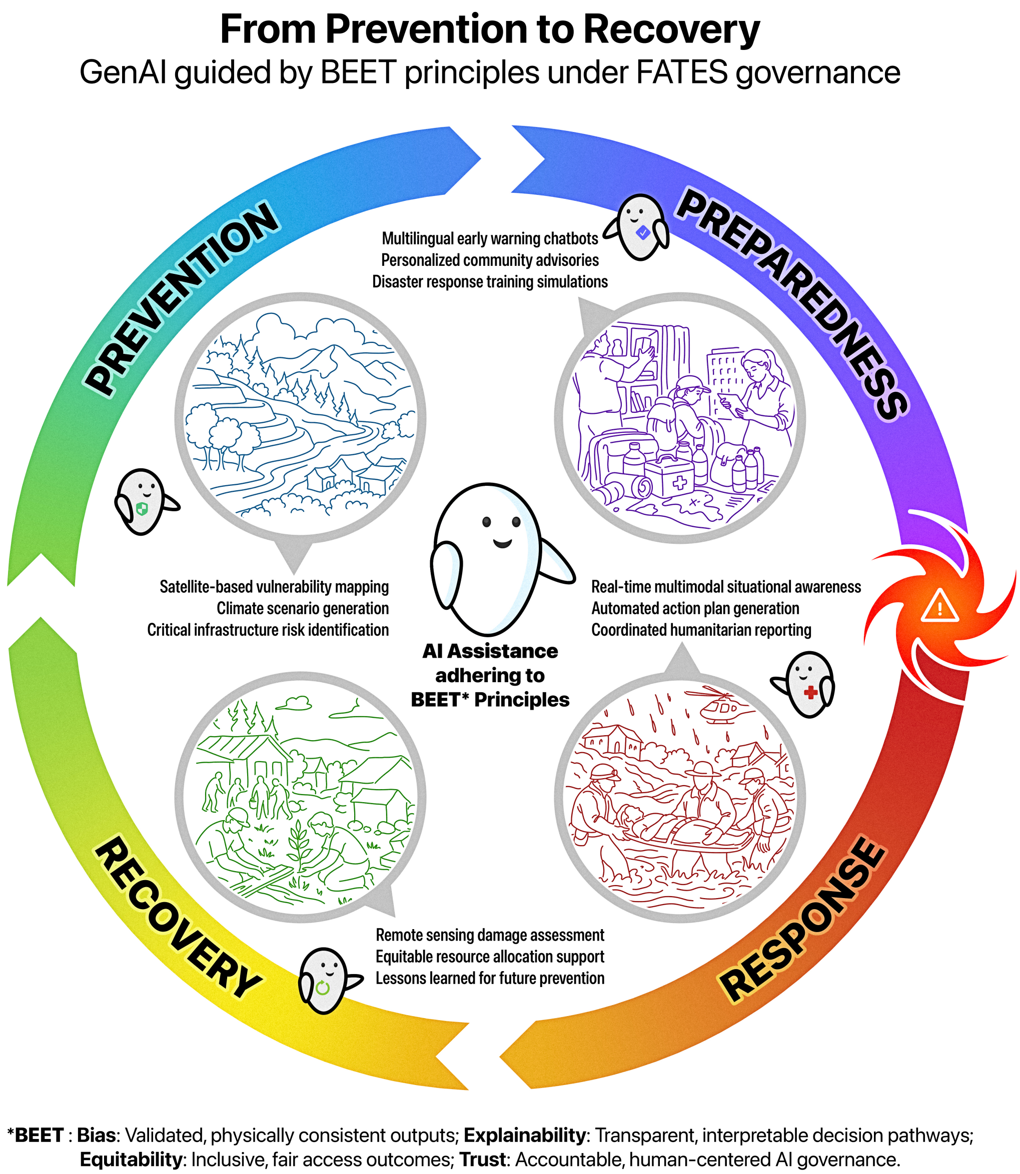

Figure 4: This diagram illustrates the potential role of GenAI within the full natural-hazard cycle, from prevention and preparedness to response and recovery. While broad governance frameworks such as FATES provide essential guidance on responsible AI deployment, operationalizing GenAI within this workflow requires a more socio-technical perspective. The proposed BEET principles offer this practical lens. By addressing data and model bias, ensuring transparent and interpretable system behavior, promoting equitable access and benefits across communities, and fostering user trust, BEET helps ensure that GenAI systems function reliably in high-stakes natural hazard contexts. Applying BEET alongside existing governance frameworks strengthens each phase of the hazard management continuum, improving the accuracy and fairness of impact assessments, supporting informed and trustworthy emergency response decisions, enhancing equitable recovery strategies, and enabling transparent, user-centered preparedness and risk-reduction planning.

accountability [80, 81]. These efforts, including ongoing work within the Global Initiative on Resilience to Natural Hazards through AI Solutions, underscore that equity and trust are not only ethical aspirations but also emerging legal and policy requirements.

Nevertheless, regulation alone cannot ensure ethical outcomes. In resource-constrained scenarios, ethical dilemmas (e.g., prioritizing evacuations or allocating scarce resources) inevitably arise, echoing triage challenges observed in healthcare during the COVID-19 pandemic [73]. In such contexts, GenAI should function strictly as a decision-support tool, offering structured input while preserving human authority and accountability. Transparent, collectively defined criteria and continuous evaluation are essential to avoid arbitrary or inequitable outcomes, particularly as models degrade and social conditions evolve [82, 83].

Ultimately, the societal value of GenAI in DRM cannot be measured solely by technical accuracy or computational performance. Progress toward the high-trust, high-equitability zone of the BEET framework depends on embedding inclusion, fairness, and cultural sensitivity throughout design, deployment, and governance. When developed under these conditions, GenAI can serve not only as a predictive capability but also as a mechanism for strengthening resilience, distributive justice, and public trust in disaster risk governance.

Operational and Governing Frameworks

These technical and societal insights naturally extend into the policy and operational dimensions of the BEET framework, where governance readiness and institutional capacity become decisive factors for responsible GenAI deployment in DRM. In recent years, policy and operational stakeholders have increasingly recognized the potential value of AI in supporting daily decision-making as profoundly exemplified in "The Adoption Paradox in Operational Disaster Management". Nevertheless, a substantial gap persists between the development of AI in general (including GenAI) solutions and their sustained integration into operational systems. This gap reflects the complexity of large-scale adoption, which depends not only on technical maturity but also on alignment with legal mandates, the translation of research outputs into actionable tools, and the organizational capacity of DRM authorities to deploy and maintain them [34, 84]. As a result, many AI applications remain experimental rather than operationally embedded.

From a policy perspective, the European Union's AI Act [79] provides a comprehensive, risk-based regulatory framework that clarifies obligations for AI systems based on their potential impact on health, safety, and fundamental rights. Entering into force gradually from August 2024, the Act is supported by complementary mechanisms such as the General-Purpose AI (GPAI) Code of Practice [85] and the AI Act Service Desk launched in October 2025, which together aim to facilitate compliance and implementation. For DRM authorities, this regulatory clarity represents a critical step toward strengthening institutional trust in AI-enabled systems with first guidelines on interpreting high-risk AI systems in emergency services to be released in 2026. More broadly, EU initiatives such as the "Apply AI Strategy" and the "European Strategy for AI in Science" signal a policy commitment to accelerating responsible AI uptake in domains including climate services and disaster preparedness [6].

In this context, progress toward higher policy readiness and operational maturity requires a shift in focus from developing ever more complex models toward ensuring that existing systems comply with regulatory requirements and are usable in real-world settings. Adherence to clear and enforceable rules improves predictability for public authorities and increases confidence in third-party AI (including emerging GenAI) solutions. Industry adoption of the GPAI Code of Practice by major developers illustrates growing alignment with these expectations, while standardization efforts can further support interoperability across jurisdictions. This is particularly important given the heterogeneity of DRM legislation and procedures across European countries, which complicates cross-border coordination.

Operational maturity is further constrained by limited AI literacy within public institutions. While policy frameworks and interdisciplinary training initiatives partially address this gap [86], the research community plays a critical role in developing solutions that are explainable, fit for purpose, and appropriately balanced in complexity and usability. XAI is therefore central to bridging policy and operational needs. Evidence from an EU scoping workshop in 2024, involving more than 150 primarily governmental participants, identified perceived shortcomings in ethical conformity and trustworthiness as key barriers to AI adoption [84]. Trust in AI systems is closely linked to their explainability and transparency [87, 88]. However, explainability is often underemphasized in academic development unless explicitly required [89], which significantly reducing the likelihood that otherwise high-performing models will be integrated into governance and operational workflows [6].

As shown in Fig. 4, GenAI could be situated within each step in the natural-hazard assessment and management cycle. It further highlights how socio-technical principles complement existing governance frameworks. Therefore, advancing GenAI toward the high-governance-readiness and high-operational-maturity zones of the BEET framework requires coordinated progress across regulation, institutional capacity, and model design. When policy clarity, explainability, and operational usability are addressed together, GenAI can transition from experimental applications to trusted components of disaster risk governance.

Actionable Recommendations

In conclusion, the governance challenge posed by GenAI in DRM is no longer prospective but immediate. Systems are already being tested, piloted, and in some cases informally adopted in operational settings, often ahead of clear accountability structures or shared standards. Decisions made in the near term will shape not only technical practice but also public trust in hazard information for years to come. Without deliberate, practice-oriented governance, there is a real risk that GenAI will amplify existing inequities and decision failures rather than enhance resilience. Addressing this gap now is therefore not optional, but central to the responsible use of GenAI in managing disaster risk. As articulated through the BEET principles, responsible GenAI adoption in DRM represents a fundamentally socio-technical challenge, requiring coordinated attention, across the full system cycle, to technical integrity, societal outcomes, operational maturity, and policy readiness.

First, sustained inter- and trans-disciplinary collaborations are essential for translating GenAI capabilities into operationally reliable and ethically sound applications. Engagement among AI developers, hazard scientists, operational practitioners, and decision-makers enables the co-design of systems that reflect real-world constraints while supporting continuous oversight and evaluation. Such a collaboration is particularly important given emerging evidence that GenAI- and LLM-enabled systems may exhibit delicate behavior or unexpected failure modes in complex disaster scenarios. Human-in-the-loop governance and ongoing performance assessment are therefore critical to maintain technical validity, accountability, and trust.

Second, capacity building and public engagement should be treated as core enabling conditions rather than ancillary activities. Advancing operational maturity requires sustained investment in applied training and AI literacy, ensuring that practitioners can interpret outputs, assess uncertainty, and recognize appropriate use cases. Developing hybrid, "T-shaped" skillsets (i.e., combining domain expertise with functional understanding of GenAI) supports informed decision-making and reinforces explainability as a practical requirement of responsible deployment. Transparent and accessible communication with affected communities is equally essential to ensure that AI-supported decisions are understandable, contestable, and aligned with lived realities, thereby advancing societal outcomes from low equitability toward high trust.

Third, coherent and adaptive policy frameworks are necessary to operationalize the BEET principles in rapidly evolving technological environments. Clear accountability structures, enforceable standards for data governance and model validation, and explicit requirements for transparency and equity are central to increasing policy readiness and institutional confidence. When aligned with operational needs, such frameworks help ensure that GenAI systems are not only technically accurate, but also inclusive, auditable, and socially legitimate. As a further step, such systems will have to move from principles and frameworks to adhering to legislation, such as the AI Act.

Taken together, these recommendations emphasize that GenAI should not be viewed as an autonomous decision-maker, but as an integrated socio-technical component of DRM systems. Its contribution to resilience ultimately depends on sustained collaboration, institutional capacity, and governance mechanisms that align technological innovation with societal values and BEET principles throughout the GenAI lifecycle.

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Author contributions
K. RS. and H. K. developed the initial concept, and together with M. V. G. organized the EGU discussions. K. RS. conceived the study, created an initial outline, main storyline and visualization, contributed to all sections, and wrote the original draft; M. M. K. contributed several sections of the manuscript, notably on the emergence of generative AI (GenAI) in disaster risk management; J-B. B. and M. R. contributed to sections related to the GenAI applications in operational disaster management; P. G. and Y. S. contributed to the technical sections; G. D. and M. V. G. contributed to the social, equity, and trust-related sections; J-P. J. and A. B. contributed to the governance, operational uptake, and

policy-related sections. F. P-D. contributed in the visualization. All authors contributed to editing and review process.

Competing interests
J-B.B. is a developer of the PromptAId Arena platform mentioned in this manuscript, which was developed as part of his PhD research at CIMA Research Foundation and the Italian Red Cross. J-B.B. declares no commercial or financial competing interests related to this work. The other authors declare no competing interests.

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