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COMMENTS

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Harnessing emerging technologies to address data gaps in natural disaster risk management: A conceptual framework and applications

Abstract Natural disasters have increasingly disrupted and devastated economic and social systems worldwide. Emerging technologies, such as artificial intelligence and machine learning have demonstrated significant potential for enhancing natural disaster risk management (DRM). However, existing studies predominantly emphasize practical technological applications, focusing narrowly on specific use cases. Only a limited number of conceptual frameworks have been proposed, each grounded in distinct thematic perspectives, such as principle-technology integration, life-cycle application, or operational reliability. Critically, there remains a notable gap regarding a comprehensive framework that systematically addresses data challenges inherent in DRM. This paper proposes a data-governance-oriented conceptual framework that classifies three major data challenges—insufficient data, poor data quality, and limited application, across both objective and subjective dimensions of risk management. By integrating practical case studies, the framework illustrates how emerging technologies can systematically mitigate these challenges. Furthermore, this paper identifies new data-related risks introduced by emerging technologies. By offering a closed-loop structure that aligns internal data governance with evolving DRM needs, this work contributes novel and actionable approaches to guiding the integration of emerging technologies into disaster risk management practice.

Keywords emerging technology, data challenge, natural disaster risk, objective risk, subjective risk

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1 Introduction

Natural disasters have emerged as an increasingly critical global challenge, demonstrating escalating frequency and severity that pose substantial threats to socioeconomic systems worldwide. In 2023, 326 major natural disasters were recorded, impacting over 93 million people and causing direct economic losses of USD 202.65 billion. Floods (46.63%), storms (26.99%), and earthquakes (8.28%) constituted the predominant disaster types (Academy of Disaster Reduction and Emergency Management et al., 2024). These high-impact events occurred across varied geographies and timescales, exposing key limitations of traditional monitoring and response systems, such as the inability to integrate real-time data from multi sources for higher spatio-temporal resolution, track cascading hazards, systematically predict impacts, and accurately model public behavioral responses (Baraldo and Di Giuseppantonio Di Franco, 2024). For example, operational hydrological forecasting systems typically function at coarse spatial resolutions ranging from 5 km in regional systems like EFAS to over 10 km in global systems like GloFAS, and require long-term historical records for individual watershed calibration (Najafi et al., 2024). With only a few percent of global watersheds gauged, and highly uneven distribution worldwide, high-quality forecasts remain challenging, particularly in the most flood-vulnerable regions (Nearing et al., 2024). Additionally, most systems provide hazard forecasts rather than impact-based warnings, limiting the effectiveness of timely emergency measures, as demonstrated by the 2021 German flood event, which resulted in 134 fatalities and over 40 billion EUR in economic losses (Najafi et al., 2024). Despite ongoing international efforts in climate change mitigation and adaptation, these disaster losses highlight that conventional approaches remain insufficient to fully address today's challenges. This is particularly evident in the unprecedented intensity of extreme weather events, including record-breaking heat conditions (Thompson et al., 2023), prolonged droughts (Dai, 2013), catastrophic wildfires (Bowman et al., 2017; Modaresi Rad et al., 2023), and devastating floods (Tellman et al., 2021; Rentschler et al., 2022). As such environmental risks are projected to dominate both short-term and long-term risk landscapes (World Economic Forum, 2024), there is an urgent need for emerging technologies that can support more adaptative, predictive, and integrated disaster risk management strategies to address persistent data and capacity gaps.

Disaster risk management (DRM) refers to the comprehensive approach to prevent new disaster risks, reduce existing disaster risks and manage residual risks through hazard identification, risk analysis and prediction, vulnerability and resilience assessment, as well as the understanding and regulation of public risk perception and behavioral responses (United Nations Office for Disaster Risk Reduction, 2017; Agrawal, 2018). Emerging technologies offer promising solutions to DRM through enhanced data acquisition and analysis capabilities. In data acquisition, these technologies enable the integration of diverse data sources, including high-resolution earth observation imagery, street-level imagery, Internet of Things (IoT) sensor networks, and volunteered geographic information (OECD/ADB, 2020). For example, artificial intelligence (AI) can synthesize real-time disaster-related data from satellites, drones, and social media, to generate event maps and disaster information. The high temporal and spatial resolution of these data enables rapid assessment of disaster impacts through pre- and post-event comparison, facilitating effective prioritization of response efforts (Sun et al., 2020).

In terms of data analysis, emerging technologies demonstrate superior capabilities in processing semi-structured or unstructured data and identifying nonlinear relationships, leading to more comprehensive, accurate, and timely disaster information analysis. A recent review by Byaruhanga et al. (2024) on the evolution of flood prediction and forecasting models highlights the increasing significance of emerging technologies in contemporary forecasting and warning systems, noting substantial improvements in both accuracy and reliability. Similar advancements are observed across other types of disaster management. For instance, Lin et al., (2021) developed an advanced earthquake warning model using deep learning to characterize crustal deformation patterns of large earthquakes with 99% accuracy, successfully predicting five real Chilean earthquakes and overcoming the magnitude underprediction common in traditional earthquake early warning systems.

Most research on emerging technologies in disaster risk management focuses on application-level case studies. These studies typically explore specific technological resolutions for hazard identification, detection, prediction and communication across diverse disaster scenarios (Yuan et al., 2016; Zhou et al., 2018; Najafi et al., 2024; Scorzini et al., 2024). In contrast, only a few conceptual frameworks have been proposed, each developed from distinct thematic perspectives, including principle-technology integration (Thekdi et al., 2023), life-cycle application (Khan et al., 2020; Munawar et al., 2022), operational reliability (Camps-Valls et al., 2025), and stakeholder coordination (Pang, 2022). However, a comprehensive framework that specifically addresses systematic data challenges within DRM remains lacking. As traditional monitoring and response systems cannot address fundamental challenges in data acquisition, integration and governance through incremental improvements alone, this study fills this gap by proposing a data-governance-oriented conceptual framework. This framework systematically classifies three typical data challenges-insufficient data, poor data quality, and limited data application- across both objective and subjective dimensions of risk management. By integrating practical case studies, the framework demonstrates how emerging technologies can be systematically applied to mitigate these challenges. Furthermore, this paper acknowledges and identifies potential new data-related risks introduced by these emerging technologies, such as data quality and reliability, data integration and standardization, and data sharing and security. This framework adopts a closed-loop structure that supports adaptive and responsive data governance aligned with the dynamic nature of both disaster risks and technological advancements. By incorporating subjective risk dimensions, such as public perception and behavioral response, alongside objective indicators, this framework enables a more comprehensive, human-centered approach to DRM, supporting more effective policy design, public engagement, and adaptive capacity building.

2 Conceptual framework

This section introduces a systematic conceptual framework (Fig. 1) illustrating how emerging technologies can address critical data challenges in natural disaster risk management. We begin by examining the data demands for both objective and subjective risks, focusing on the limitations of current data collection and utilization practices. Our analysis identifies three typical data-related barriers: insufficient data, poor data quality and limited data application, which significantly constrain effective risk management practices. To address these barriers, we propose three corresponding solutions and subsequently illustrate their implementation through empirical case studies. Finally, we discuss new complexities that may be introduced by the use of these technologies to offer a balanced perspective in leveraging emerging technologies for enhanced natural disaster risk management. Our framework incorporates a dynamic, iterative structure in which post-event data feed back into the DRM cycle. This process supports model improvement, facilitates continuous learning, and helps identify new data demands for future risk scenarios. This integrative framework not only enhances the understanding of the interplay between data challenges and emerging technologies in DRM, but also serves as a transferable tool for guiding the design of data-driven management strategies across diverse contexts.

2.1 Data demands and challenges in natural disaster risk management

Natural disaster risk management involves both objective and subjective risk dimensions. Objective risks arise directly from natural hazards' physical impacts, while subjective risks emerge from how stakeholders, such as the public, insurance companies and utility providers, perceive and respond to these hazards. Data are fundamental to both risk dimensions, facilitating evidence-based decision-making throughout the disaster management lifecycle. However, the data demands differ between objective and subjective risk management. This subsection examines these specific data demands and associated challenges, highlighting their interconnections and unique characteristics within natural disaster contexts.

2.1.1 Data demands and challenges for objective risk management

Objective risk management aims to understand and

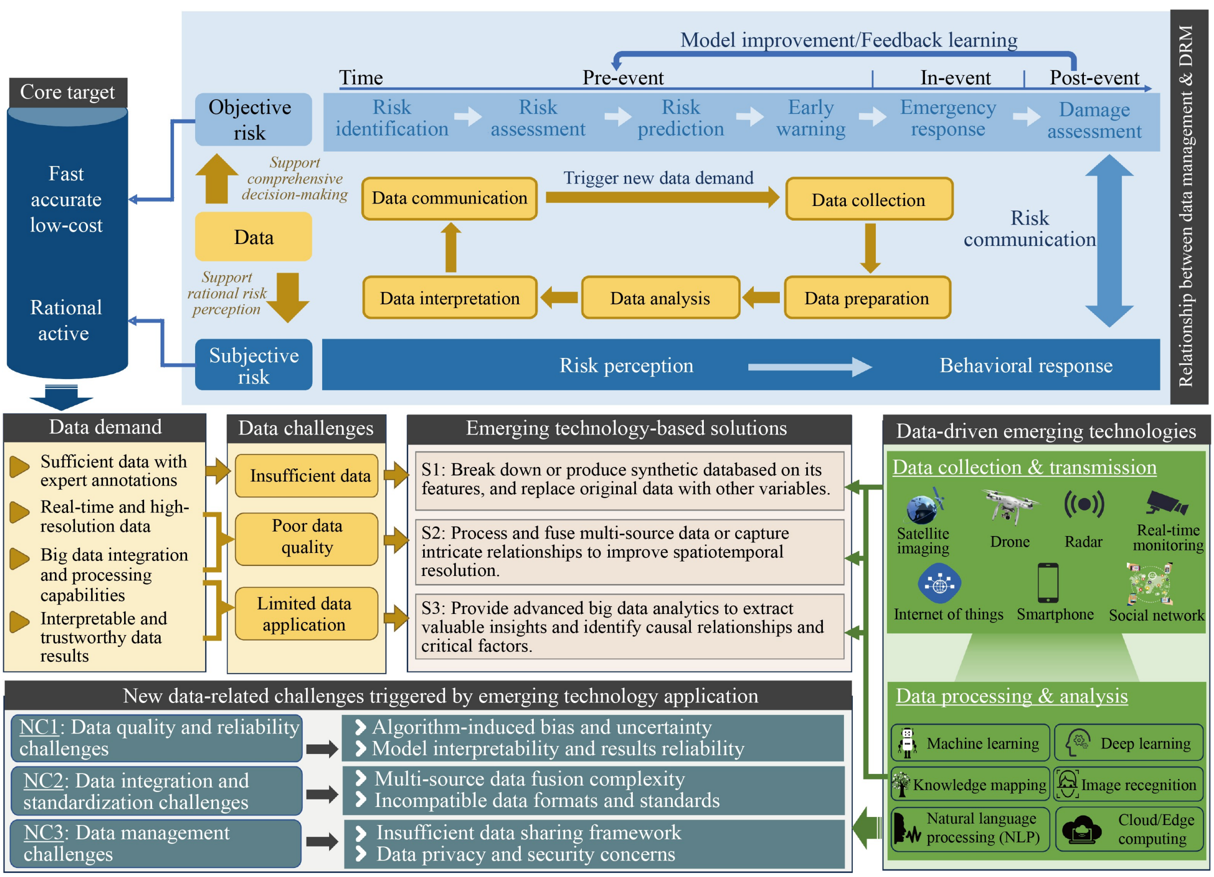

Fig. 1 Conceptual framework for harnessing emerging technologies to address data challenges in natural disaster risk management.

mitigate natural disasters' impacts through data-driven decision-making across different disaster stages. This approach requires specific types of data at each stage: pre-event management relies on high-resolution historical records and real-time monitoring data for risk detection, assessment and early warning; during-event response depends on rapid data collection and processing for emergency coordination; and post-event evaluation demands comprehensive damage assessments and recovery tracking data.

A fundamental challenge in objective risk management is the limited availability of empirical data. Natural disasters are low-probability events, making it difficult to collect comprehensive evidence across different scenarios. For example, landslides are typically only recorded when they cause substantial damages to infrastructure or human populations (Simpson et al., 2016).

Traditional natural disaster management primarily relies on two approaches for collecting risk information: monitoring systems and investigations. Monitoring networks collect risk-related parameters through an array of techniques, including ground-based sensors, satellite remote sensing, global navigation systems, and unmanned aerial vehicles. However, the coverage and capability of these networks vary significantly across different types of natural disasters and regions. Investigations complement monitoring by gathering information about historical records, vulnerable assets, mitigation capacities and potential hazards for further risk assessment. While these investigations can collect detailed data, they are resource-intensive and provide only periodic snapshots with limited temporal resolution. China's first national disaster census, launched in 2022, illustrates this challenge: it required more than two years and approximately five million professionals to investigate hazard elements across six major types of disasters such as earthquake disasters, geological disasters, meteorological disasters, water and drought disasters, marine disasters, and forest and grassland fires. The great variations in time and location accuracy of risk information collected through these traditional methods create data quality challenges. Furthermore, traditional statistical methods struggle to capture the complex spatial and temporal dynamics of natural disasters, which significantly compromises the accuracy of disaster forecasting and early warning systems (Yuan et al., 2016).

Recent technological advances have introduced diverse new data sources, including satellite imagery, social media information, mobile communication records, and IoT sensors, offering more real-time and comprehensive data for objective risk management. However, limited big data processing capabilities often render this valuable information inaccessible and unusable. As a result, decision-making in DRM continues to rely heavily on expert consultation, resulting in high labor costs, time consumption, limited transparency, and poor reproducibility of results (Thekdi et al., 2023).

2.1.2 Data demands and challenges for subjective risk management

Understanding and managing subjective risk perceptions is crucial for effective disaster risk management, as individuals often respond more strongly to perceived risks than to objective assessments. Due to bounded rationality-the cognitive limitations and incomplete information that constrain human decision-making - people tend to rely on mental shortcuts rather than conducting comprehensive cost-benefit analyses when making risk mitigation decisions. Their subjective perceptions of natural disasters are influenced by a variety of social, psychological and individual factors, including a sense of belonging, self-identity, socioeconomic status, social environment and culture (United Nations Office for Disaster Risk Reduction, 2022). These influential factors can lead to deviations from objective assessments, and these irrational perceptions subsequently shape public's protective behaviors toward natural disaster risks (Long et al., 2020). To better capture public perception levels, simulate decision-making behaviors, and guide these perceptions toward more rational evaluations, it is essential to obtain high-resolution, continuously updated risk perception data along with extensive decision-making data.

Traditional methods such as questionnaire surveys and interviews have been widely used to investigate public cognition, attitudes, and behavioral intentions regarding specific natural disaster risks (Ho et al., 2008). However, these methods typically suffer from limited sample coverage, low spatio-temporal resolution, and significant time lags due to the resources required for implementation. Additionally, survey responses may be influenced by recall bias and social desirability bias, potentially misrepresenting actual risk perceptions and behaviors (Lu et al., 2016).

The advent of social media and behavioral data offers real-time insights into public risk perceptions and behavioral patterns, overcoming many limitations of traditional surveys. For instance, Wang et al. (2020a) analyzed over 400 million social media posts from 43 million users to investigate the impact of extreme weather on people's emotions in China, revealing patterns that might otherwise remain undetected. These social media data enable the identification of disparities in risk perception across different demographic groups and geographic regions, facilitating more targeted and effective risk communication strategies. However, traditional statistical methods are inadequate for processing and extracting meaningful insights from vast amounts of unstructured texts and cannot interpret the initial decision-making processes, presenting significant challenges in data application.

Taken together, the data demands discussed across both objective and subjective risk management reveal several common priorities: the need for comprehensive and annotated data sets, real-time and high-resolution data, advanced integration and processing capabilities, and interpretable outputs that supports evidence-based decision making. However, in practice, these demands are often unmet due to persistent limitations in existing data systems, traditional collection methods, and analytical tools. We identified three typical categories of data-related challenges that commonly constrain effective DRM implementation: (1) insufficient data, referring to the lack of comprehensive, annotated, and high spatio-temporal coverage data sets required for accurate modeling and prediction; (2) poor data quality, stemming from limitations in accuracy, timeliness, consistency and high-resolution of available data; (3) limited data application, reflecting the underutilization of existing data resources in analysis, interpretation, knowledge extraction, and decision-support processes.

These three categories form the conceptual foundation of our framework and serve as key entry points for aligning emerging technologies with data governance needs in DRM.

2.2 Emerging technology-based solutions and real applications in natural disaster management

Emerging technologies have revolutionized the potential value of data in natural disaster risk management, especially through innovative data collection methods utilizing diverse big data resources. The integration of big data with emerging technologies, such as machine learning, deep learning, natural language processing, image recognition, and knowledge mapping, offers multi-dimensional solutions to effectively address the three typical data challenges (insufficient data, poor data quality and limited data application) in natural disaster risk management.

Each of these emerging technologies contributes distinct capabilities to data-driven disaster management. Machine learning encompasses a range of algorithms capable of detecting patterns and generating predictions from structured or semi-structured data, making it particularly effective in tasks involving risk modeling, classification, and regression (Yu et al., 2018). Deep learning, a subset of machine learning based on neural network architectures, excels at handling large volumes of unstructured data (e.g., imagery or sensor signals), and is well-suited for learning complex, nonlinear relationships across time and space (Linardos et al., 2022). Natural language processing (NLP) enables the extraction of meaningful insights from unstructured text sources such as news articles or social media, supporting real-time situational awareness and public sentiment analysis (Sun et al., 2020). Image recognition technologies allow for the automated classification and interpretation of visual data, including satellite and drone imagery, facilitating damage assessment and spatial mapping (Lefevre et al., 2017). Knowledge mapping focuses on linking disparate information sources and revealing latent relationships through semantic networks or expert-driven inference, thereby enhancing interpretability and filling data gaps (Cao et al., 2024). In addition, cloud and edge computing technologies provide the necessary infrastructure for real-time, distributed data processing (Byaruhanga et al., 2024).

While these technologies offer substantial potential, it is important to acknowledge that their practical implementation often requires substantial computational infrastructure (Basu et al., 2019), interdisciplinary technical expertise (Pang, 2022), and considerable economic investment in data acquisition, annotation, and system maintenance, which may limit scalability in resource-constrained settings (Konya and Nematzadeh, 2024).

2.2.1 Emerging technology-based solution for insufficient data challenges

To address the challenge of insufficient data due to the rarity of disaster risks, an effective solution involves extracting and decomposing available risk data into distinct components for targeted prediction. Emerging technologies, particularly machine learning and deep learning, support this approach by extracting latent structures and features from limited data sets, thereby generating more analyzable components to improve prediction accuracy. This strategy has shown promising results, especially in the context of landslides and earthquakes. For example, Zhou et al. (2018) applied wavelet transform to break down the total landslide displacement into frequency components, each of which was predicted using an artificial bee colony-optimized learning algorithm. This method significantly improved prediction accuracy for the Shuping landslide in the Three Gorges Reservoir Area (TGRA), China. Similarly, Wang et al. (2023) proposed a probabilistic forecasting framework combining double exponential smoothing for linear component prediction and Bayesian deep neural networks for nonlinear residuals prediction. Applied to the Baishuihe landslide, their framework not only enhanced prediction precision but also quantified both data-inherent and model-based uncertainties.

Another effective solution to data scarcity involves data augmentation through synthetic generation or transfer learning from well-explored related networks (Kuglitsch et al., 2022). Emerging machine learning and deep learning methods- such as transformer networks and transfer learning- enable this process by extracting generalizable patterns and applying them across domains. In seismic monitoring, Münchmeyer et al. (2021) developed an attention-based transformer network that processes waveforms from dynamic station combinations outperforming traditional fixed-network localization methods. This concept has also advanced flood management, particularly in regions lacking dense streamflow gauge networks. Nearing et al. (2024) developed a global-scale AI forecasting model trained on data from 5680 gauged watersheds, enabling generalization to ungauged basins across more than 80 countries with a five-day lead time.

A third potential solution is to identify proxy variables that offer broader spatial and temporal coverage to substitute direct monitoring data with limited availability. Emerging technologies support this strategy through both new data sources (e.g., satellite imagery, mobile phone data) and advanced analytical techniques (machine learning, natural language processing).

For example, nighttime light data can be used to monitor large-scale flood exposure and serve as a proxy to assess post-flood recovery (Mård et al., 2018). This method overcomes the limitations of optical remote sensing images affected by cloud cover, providing more stable monitoring results (Ayanu et al., 2012). Giardini et al. (2023) utilized aggregated call detail records to measure post-disaster displacement in four Italian regions affected by repeated earthquakes in 2016–2017, suggesting that changes in mobile phone presence can reliably indicate immediate and medium-term displacement due to the earthquake. These cases illustrate how emerging data sources can enhance spatial and temporal coverage, effectively supplementing traditional monitoring networks.

Meanwhile, advanced data analytics, particularly machine learning, can be used to derive synthetic proxy variables when direct measurements are unavailable. For instance, in a recent study of the 2011 Great East Japan tsunami, Scorzini et al. (2024) used machine learning to construct proxy indicators for building shielding and debris impact, achieving comparable predictive accuracy to direct water velocity measurements while improving practicality for rapid damage assessment.

2.2.2 Emerging technology-based solution for poor data quality challenges

The emergence of data-driven technologies has greatly enhanced our ability to integrate multi-source data, providing new solutions to data quality challenges in DRM (Zhu et al., 2017; Kato and Ben-Zion, 2021). Techniques such as machine learning, deep learning, image recognition and natural language processing, enable the fusion of heterogenous data sets, enhancing data resolution, consistency and reliability. For instance, Kato and Ben-Zion (2021) reviewed how combining seismic and geodetic data can reveal previously unobservable patterns in earthquake generation. In a different context, Tellman et al. (2021) utilized satellite imagery to estimate global flood exposure between 2000 and 2015, revealing a 20-24% increase in the flood-exposed population, nearly ten times higher than previously estimated.

Emerging technologies, such as machine learning and deep learning, also address poor data quality by capturing complex, nonlinear relationships between variables. This modeling capacity allows for more accurate and robust predictions in the face of noisy or incomplete data. For example, Long Short-Term Memory (LSTM) networks are employed to learn spatio-temporal relationships and provide more accurate predictions of dynamic changes associated with earthquakes (Wang et al., 2020b) or floods (Shi et al., 2015). The extra trees algorithm was employed to enhance the efficiency and accuracy of tsunami damage assessment, especially with limited velocity data (Scorzini et al., 2024). Hybrid models, which combine various machine learning algorithms, have demonstrated superior capability in capturing complex relationships between variables and improving estimation precision for natural disasters, such as super droughts events (Das et al., 2024). Taking advantage of these relationships, larger-scale data sets can be utilized to analyze the impact of specific variables on natural disaster risks more effectively, improving prediction extensibility and accuracy.

In addition, advanced technologies are increasingly applied to multi-hazard risks by capturing potential interrelationships among different types of natural hazards. For example, Yousefi et al. (2020) developed a machine learning framework that combined support vector machine (SVM), generalized linear model (GLM), and functional discriminant analysis (FDA) to assess five natural hazards (snow avalanches, landslides, wildfires, land subsidence, and floods) in mountainous regions. Their results showed that different machine learning models exceled at predicting different types of hazards and this integrated approach achieved high prediction accuracy (AUC > 0.8).

Rather than merely producing higher-resolution assessments or predictions, emerging technologies- particularly machine learning, have demonstrated strong potential for identifying and correcting systematic errors embedded in traditional monitoring methods (Xiong et al., 2023). By leveraging large volumes of historical data or addressing issues such as data loss and duplication in monitoring systems, these models can significantly improve accuracy (Liang et al., 2018).

2.2.3 Emerging technology-based solution for limited data application challenges

A key strategy for addressing limited data application challenges lies in the ability of emerging technologies to extract valuable information from large volumes of semi-structured and unstructured data. Recent advances in image recognition, natural language processing, and deep learning have significantly expanded our capacity to rapidly extract and interpret these previously underexploited data sources for disaster management. For instance, Rahnemoonfar et al. (2023) developed the RescueNet data set, which integrates unmanned aerial vehicles and computer vision techniques to process over 4,000 post-disaster aerial images. Through advanced deep learning models, the system successfully transforms unstructured visual data into structured information, achieving up to 98.47% accuracy in identifying and classifying critical disaster-related features such as building damage levels and road conditions.

Beyond information extraction, emerging technologies are also increasingly used to uncover causal mechanisms and identify key risk drivers. While machine learning algorithms are often perceived as 'black-box' models whose internal workings are not easily interpretable, recent advancements have focused on enhancing their interpretability and integrating them with domain-specific knowledge, such as physical or psychological models (Peterson et al., 2021; Cilli et al., 2022). For example, Peterson et al. (2021) integrated machine-learning models with psychological theory constraints to simulate public decision-making processes. Based on approximately 10000 choice problems, their hybrid framework revealed complex behavioral patterns and demonstrated superior prediction accuracy compared to traditional psychological models. Cilli et al. (2022) developed an explainable artificial intelligence framework that combines a random forest model with the Shapley values to explain the driving factors of wildfire events across Italy. Similarly, Choubin et al. (2023) applied a simulated annealing (SA) algorithm to identify the key variables affecting land subsidence based on radar-derived data sets.

To synthesize these findings, we constructed a mapping matrix (Table 1) that clearly illustrates how each data-driven emerging technologies address the above three kinds of data challenges. This matrix presents empirical and theoretical linkages between 14 technologies and 8 sub-solutions.

Notably, in practical DRM scenarios, data challenges such as insufficiency, poor quality and limited application often interact in complex ways, requiring integrative and collaborative solutions. Xu et al. (2022) provides a representative example of this approach, demonstrating how the application of emerging technologies can address multiple interrelated data issues in post-seismic assessments. Their system simultaneously mitigates data insufficiency using high-resolution remote sensing imagery derived from synthetic aperture radar (SAR), enhances interpretability through the construction of a causal Bayesian network, and improves spatial resolution by integrating these remote sensing data with lower-resolution geospatial data sets. This integrated methodology significantly enhances the effectiveness, robustness, and practical applicability of the DRM data governance framework.

2.2.4 Bridging objective and subjective risk data: Integration pathways enabled by emerging technologies

While emerging technologies offer promising solutions to the distinct challenges associated with either objective or subjective risk domains, they also serve as critical enablers for harmonizing data across both domains. This integration supports more comprehensive and adaptive disaster risk management. Specifically, we identify three primary pathways through which emerging technologies bridge these domains.

First, emerging technologies enable the use of subjective risk data, such as social media posts and crowdsourcing observations, to supplement and enhance conventional objective risk data from manual or sensor records. For example, Eyre et al. (2020) utilized social media activities from small businesses to estimate post-disaster recovery timelines following three natural hazard events in Nepal, Puerto Rico and Mexico. Similarly, Brouwer et al. (2017) used Twitter data to generate deterministic and probabilistic flood maps for the 2015 flood in York, UK, revealing that subjective inputs can enrich flood modeling where hydraulic models and remote sensing networks are lacking.

Second, high-resolution objective data, such as mobile phone signals, GPS trajectories, and app usage can be leveraged to provide crucial insights into population-level behavioral responses to disasters. For example, Lu et al. (2012) tracked the locations of 1.9 million mobile phone users 42 days before and 341 days after the Haiti earthquake, highlighting the predictive value of objective exposure data in understanding displacement and return patterns. More recently, Cai et al. (2024) analyzed 2.6 million mobile phone signal data to assess flood-related mobility changes in urban areas, helping to infer public perceived risk and behavioral adaptations.

Third, emerging technologies facilitate the fusion of subjective and objective data streams to support more robust decision-making in disaster preparedness and response. For example, Baranowski et al. (2020) integrated five years of flood records with crowdsourcing information from Twitter and local news reports to identify atmospheric triggers of floods, highlighting the potential for increased predictability of flood risk. Najafi et al. (2024) developed an impact-based flood early warning system that integrates radar-adjusted precipitation data, real-time meteorological observations, and OpenStreetMap infrastructure data. This system provided high-resolution (10-m) flood forecasts with up to 17 h of lead time, demonstrating the potential of integrated data to increase the accuracy and timeliness of disaster early warning.

2.3 New data-related challenges triggered by the implementation of emerging technologies

While emerging technologies offer promising solutions for natural disaster risk management, their implementation presents new data-related challenges that require systematic approaches to address.

The integration of emerging technologies in disaster

Table 1 Mapping between emerging technologies and solutions to data-related challenges in disaster risk management

	S1-Address insufficient data challenge			S2-Address poor data quality challenge			S3-Address limited data application challenge	
	Decompose risk data for targeted component-level prediction	Augment data through synthetic generation or transfer learning	Use proxy variables for roader spatio-temporal coverage	Integrate multi-source data to improve timeliness and resolution	Capture complex non-linear relationships among variables	Correct systematic errors in traditional monitoring data	Extract insights from large-scale semi-structured and unstructured data	Enable causal inference and identification of key drivers
Satellite imaging			√	√		√	√	
Drone		√	√	√		√	√	
Radar			√	√			√	
Real-time monitoring				√	√		√	
Internet of things			√	√				
Smartphone			√	√			√	
Social network			√	√			√	
Machine learning	√	√	√	√	√	√		√
Deep learning	√	√		√	√		√	√
Knowledge mapping	√	√						
Image recognition			√	√			√	
Natural language processing			√	√			√	
Cloud/Edge computing	√	√		√	√	√	√	√

Note: Each checkmark (√) indicates a demonstrated applicability of the corresponding technology to the specified solution pathway, based on theoretical alignment or empirical evidence.

management has raised significant concerns about data quality and reliability. A primary challenge lies in algorithmic bias, particularly when applying machine learning models to disaster management scenarios. This bias often stems from data quality issues, including non-representative or incomplete data sets. Various factors, such as sample size limitations, accurate critical parameters, and spatial-temporal variations can introduce significant uncertainty into prediction-based decision-making (Ma et al., 2021). For example, insufficient training data can to lead to unrealistic scenarios when simulating extreme disaster events (Camps-Valls et al., 2025), thereby diminishing trust in these technologies for high-stake decisions. Moreover, as algorithms become more sophisticated, ensuring their transparency and reliability becomes increasingly complex. Kuglitsch et al. (2022) highlighted the difficulties in assessing optimal model architectures due to the limited explainability of emerging technologies. The complexity of interpreting data outputs, especially under time-critical conditions, further complicates their operational use. Emergency managers face the demanding task of translating complex, sometimes conflicting, analytical outputs into rapid, actionable decisions.

To mitigate these challenges, hybrid modeling approaches that integrate physically based models with data-driven techniques have shown promise in increasing robustness and interpretability (Cheng et al., 2023). These models not only enhance the generalizability and reliability of model outputs but also reduce dependency on large training data sets (Tuia et al., 2024).

Meanwhile, while data integration can improve prediction accuracy and response capabilities in DRM, the proliferation of multi-source data has intensified integration and standardization challenges. Yu et al. (2018) highlighted that the synthesis of large volumes of heterogeneous data poses significant challenges for rapid and effective information processing. Data samples from different scales and resolutions require preprocessing for aggregation, which may result in the loss of critical information (Jiang, 2019). The incompatible data formats and a lack of standardization further hamper collaboration across stakeholders and prevent integration of diverse data sets. Disaster management agencies and researchers often collect and store data using different formats, without a unified framework for structuring or exchanging disaster-related information. Rüegg et al. (2014) highlighted that these challenges are exacerbated by the need for specialized domain knowledge and technical expertise in handling data conversion across incompatible formats.

To address these issues, future development of emerging technologies should focus on advanced feature extraction techniques that can capture hazard-specific characteristics across data sources (Camps-Valls et al., 2025). Moreover, the promotion and adoption of internationally recognized metadata standards (e.g., ISO 19115 for geospatial data) and alignment with global initiatives such as the Integrated Research on Disaster Risk (IRDR) and the Global Earthquake Model (GEM) can improve interoperability and facilitate cross-platform integration (Curt, 2021).

The third challenge involves effective data management in implementing emerging technologies, particularly regarding data sharing and data security concerns. The fragmented nature of data ownership across various agencies and departments significantly impedes coordinated disaster response efforts. For example, in China, natural disaster risk management data typically resides with emergency departments, while statistical departments maintain macroeconomic and social data, and telecommunications agencies control behavioral data such as mobile signal information. This institutional fragmentation, combined with legal constraints, hinders the formation of effective, real-time information-sharing mechanisms, especially during cross-regional or transboundary disasters. Moreover, concerns surrounding data privacy and security present great challenge for the application of emerging technologies. A fundamental tension exists between the need for rapid data access during emergencies and the imperative to protect sensitive information about infrastructure and vulnerable populations. Kyrkou et al. (2023) emphasized the critical importance of balancing data accessibility with security to maintain public trust while preventing the misuse of sensitive information, particularly from mobile devices and social media platforms. Fragmented storage systems and incomplete sharing protocols can cause critical delays in emergency decision-making and limit the effectiveness of technology-enabled disaster responses.

To address these challenges, we recommend establishing formalized data-sharing agreements that include built-in privacy safeguards and liability protections. Cross-sectoral legislation and inter-agency protocols, aligned with ethical data governance principles can facilitate secure but responsive data sharing during disasters.

Looking forward, future research should prioritize several key areas. First, more empirical studies are needed to evaluate the real-world performance and reliability of hybrid modeling approaches under different disaster scenarios. Second, further work is required to develop practical standards and evaluation frameworks that support data interoperability across institutions and platforms. Third, exploring ethical and legal mechanisms to balance data accessibility and privacy protection remains critical, especially in time-sensitive disaster contexts. Advancing these areas can help shape a more robust and inclusive data governance system that meets both operational and societal needs.

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