Research Article

Systematic Literature Review of Graph Neural Networks in Disaster Management: Methods, Applications, and Future Directions

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Abstract: The increasing frequency and complexity of natural disasters underscore the urgent need for intelligent systems that support timely and effective decision-making. Graph Neural Networks (GNNs) have emerged as a powerful deep-learning paradigm for modeling spatial and relational data, offering distinct advantages for disaster management. This study presents a Systematic Literature Review (SLR) of GNN-based approaches for disaster mitigation, emergency response, and post-disaster recovery, covering peer-reviewed publications from 2023 to 2024 and following PRISMA 2020 guidelines. A reproducible search strategy with explicit Boolean strings and database filters was applied across Scopus, IEEE Xplore, SpringerLink, and ACM Digital Library, yielding 50 primary studies after deduplication. Records were screened independently by two reviewers, disagreements were resolved by consensus, and the methodological quality of included studies was assessed using a predefined checklist. The findings show that GCN-based models were most widely applied (≈40%), particularly for flood mapping, landslide susceptibility, and infrastructure assessment. ST-GNNs (≈25%) supported dynamic hazard prediction, especially floods and wildfires, while Graph SAGE (≈10%) and GATs (≈8%) addressed sensor reliability, hazard monitoring, and evacuation planning. Hybrid architectures (≈12%) enabled multi-modal integration of satellite imagery, IoT sensor data, and social media, whereas ≈5% of studies explored transfer-learning or multi-task frameworks and explainable models such as GNN Explainer and GRAPHLIME. Common benchmark datasets included GFED, GHCN, LISFLOOD-FP, Sentinel, and OpenStreetMap, with evaluation metrics spanning RMSE/MAE for regression and Accuracy/F1/AUROC for classification. Key trends indicate a shift toward context-aware, real-time models and greater reliance on heterogeneous data sources. Despite these advances, challenges remain in interpretability, scalability, standardized benchmarking, and validation on real-world disaster datasets.

Keywords: Graph Neural Network, Disaster Management, Systematic, Evacuation, Prediction

Introduction

Disaster management is a strategic field that continues to evolve rapidly in response to the increasing intensity, frequency, and complexity of disasters worldwide. Phenomena such as global climate change, exponential population growth, uncontrolled urbanization, and excessive environmental exploitation have significantly heightened vulnerability to various natural disasters, including floods, earthquakes, forest fires, landslides, and tsunamis (Villagra et al., 2023; Romanello et al., 2024; Rezvani et al., 2023). In developing countries, including Indonesia, this vulnerability is further exacerbated by socio-economic disparities, a lack of resilient infrastructure, and weak early warning systems. Under these conditions, conventional approaches traditionally used in early warning systems, disaster prediction, and risk mitigation are proving increasingly inadequate in responding to dynamic and complex challenges (Agbehadji et al., 2023; Awah et al., 2024; Pu et al., 2025).

Disaster dynamics require not only rapid response but also accurate, data-driven decision-making. As such, digital transformation through the adoption of advanced technologies has become essential for improving the overall effectiveness of disaster management. One of the most rapidly advancing technologies being adopted in this field is Artificial Intelligence (AI), particularly through Machine Learning (ML) and Deep Learning (DL) approaches. These technologies have shown promise in processing large-scale disaster data, predicting affected areas, classifying risk levels, and developing real-time, data-driven early warning systems (Ghaffarian et al., 2023; Bajwa, 2025).

However, the application of AI models still faces several challenges; chief among them is their “black-box” nature. Models such as Convolutional Neural Networks (CNNS) and Long Short-Term Memory (LSTM) networks often produce outputs that are difficult for end users to interpret, especially within policymaking or emergency response contexts. The lack of interpretability and transparency in decision-making processes poses a significant barrier to the deployment of AI in disaster scenarios, where user trust is critical (Hassija et al., 2024).

To address these challenges, there is a need for approaches that are not only powerful in modeling complex data but also capable of providing intuitive and structured representations of relationships between entities in both space and time. One such emerging approach is Graph Neural Networks (GNN). GNNs belong to a family of deep learning models specifically designed to process graph-structured data composed of nodes and edges that represent relationships between entities (Zeghina et al., 2024; Khemani et al., 2024). The key strength of GNNs lies in their ability to leverage topological information from spatial and temporal data, which are often irregular and complex.

The disaster management domain is inherently compatible with graph structures, as disaster-related phenomena frequently involve interconnected infrastructures, interregional dependencies, logistics distribution, and evacuation routes. For example, the impact of an earthquake is not solely determined by the epicenter but also by the connectivity of road networks, the location of healthcare facilities, population density, and geographic conditions, factors that collectively form a dynamic risk network (Jana et al., 2023; Malama et al., 2025). GNNs enable models to absorb information from these relational structures, resulting in more holistic predictions and decisions.

Several studies have demonstrated the successful application of GNNs in disaster management scenarios. In flood prediction, for instance, a Multi-Source Water Elevation GNN (MSWE-GNN) model has improved the accuracy of water spread modeling and reduced computational requirements compared to conventional numerical methods (Bentivoglio et al., 2025; Oliveira Santos et al., 2023). Elsewhere, Graph Attention Networks (GATs) have been employed to generate optimal evacuation routes based on real-time traffic and road conditions (Xu et al., 2025). Another study utilized GNNs to predict post-earthquake infrastructure damage by leveraging satellite imagery and building network data (Rastiveis et al., 2023).

In the disaster recovery phase, GNNs have also been used to develop logistics distribution recommendation systems. These systems take into account damaged infrastructure, evacuation shelter locations, and storage capacity using the network of relationships between distribution points (Andrianarivony and Akhloufi, 2024). In the context of forest fires, GNNs have been applied to map fire spread risks by analyzing the vegetation network structure, wind direction, and land slope (Rösch et al., 2024).

Nonetheless, the literature on GNN applications in disaster management remains scattered and fragmented. Most existing studies are exploratory in nature, focused on specific case studies, or propose models without providing a comprehensive overview of the methodological and application landscape. To date, there has been no Systematic Literature Review (SLR) that thoroughly maps the use of GNNs across the full disaster management cycle, mitigation, preparedness, emergency response, and recovery, and explores future research directions.

This study addresses this gap by conducting a PRISMA-2020–compliant SLR of peer-reviewed publications from 2023 to 2024. A reproducible search strategy using explicit Boolean strings and database-specific filters was applied across Scopus, IEEE Xplore, SpringerLink, and ACM Digital Library. Two independent reviewers screened all records, resolved conflicts by consensus, and assessed the methodological quality of each study using a predefined checklist.

The review aims to answer three research questions:

(1) Which specific GNN methods have been applied to disaster management
(2) How are these methods used across different disaster phases and data types (satellite, IoT, social media)
(3) What research gaps and future directions emerge, particularly regarding scalability, interpretability, and transfer-learning or explainable AI (XAI) techniques such as GNNExplainer and Graph LIME

To facilitate comparison and reproducibility, the review provides structured tables summarizing GNN methods, disaster types, commonly used datasets (GFED, GHCN), and evaluation metrics (F1-score, AUC, RMSE).

By addressing these questions, this study contributes a systematic mapping of the literature, identifies key trends and challenges, and provides strategic recommendations for the development of GNN-based disaster management systems. The findings offer practical insights for policymakers and system developers and highlight how integrating heterogeneous data sources and advanced AI techniques can enable more adaptive, accurate, and transparent decision-support systems for future disaster scenarios (Aljurbua et al., 2025).

Materials and Methods

Materials

The materials in this study consisted of peer-reviewed scientific articles retrieved from four major academic databases: Scopus, IEEE Xplore, SpringerLink, and the ACM Digital Library. The retrieved records were managed using Mendeley reference management software, which enabled systematic screening, deduplication, and documentation of the selection process.

This study employs a Systematic Literature Review (SLR) methodology to identify, evaluate, and synthesize scholarly research on the application of Graph Neural Networks (GNNs) in disaster management. The SLR approach was selected for its ability to produce a comprehensive, transparent, and methodologically rigorous synthesis of existing literature. By applying predefined inclusion and exclusion criteria, the review ensures objectivity, reproducibility, and minimized selection bias. As emphasized in prior studies such as Aboualola et al. (2023) in Computers & Electrical Engineering and the review titled "Edge Technologies for Disaster Management: A Survey of Social Media and Artificial Intelligence Integration" the SLR methodology is instrumental in systematically mapping research trends, methodological approaches, real-world applications, and identifying critical gaps in knowledge within the domain of AI-based disaster response and management (Albahri et al., 2024).

This review adopts the PRISMA 2020 framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), utilizing its updated 27-item checklist and flow-diagram structure to ensure transparency, methodological rigor, and reproducibility throughout the review process. The relevance and utility of PRISMA 2020 have been reaffirmed in recent studies, including its application in nursing research (Carlo et al., 2024), which highlights its role in improving the completeness and clarity of systematic review reporting. Furthermore, the development of domain-specific extensions such as PRISMA-COSMIN for OMIs 2024 (Elsman et al., 2024) demonstrates its adaptability across specialized review contexts. In this study, PRISMA guidelines were systematically applied during the article selection phase, encompassing the definition of inclusion and exclusion criteria, critical appraisal of study quality, and transparent documentation of all review stages.

Research Design

This study is driven by three main research questions, formulated using the PICO framework (Population, Intervention, Comparison, Outcome, Context) (Ullah and Ali, 2025). The PICO framework was chosen because it offers a structured approach to defining the scope of the review, ensuring a focused and consistent process. It allows for a clear identification of the relevant studies by specifying the population, intervention, comparison, and outcomes, which helps in formulating precise research questions and guiding the literature selection process. The use of PICO in this context ensures that the review comprehensively addresses the core areas of interest in GNN applications for disaster management. The three research questions are as follows:

RQ1: What types of GNN methods have been used in the context of disaster management
RQ2: What are the primary applications of GNNs in various phases of disaster management, such as mitigation, emergency response, and recovery
RQ3: What research gaps remain, and what future research directions should be pursued

These questions provide a focused analytical framework for synthesizing the literature, ensuring that the review addresses all relevant aspects of GNN applications in disaster management.

Literature Search Strategy

The literature search in this study was conducted systematically and in a structured manner across four major academic databases: Scopus, IEEE Xplore, SpringerLink, and the ACM Digital Library. These databases were selected for their broad coverage of high-quality peer-reviewed publications in the fields of Graph Neural Networks (GNNs), artificial intelligence, and disaster management and mitigation (Alshehri et al., 2025). The search specifically focused on articles published within the timeframe of 2023 to 2024, to ensure that this review incorporates the latest developments and emerging trends in the relevant research domain. The initial inclusion criteria required that articles be written in English, have undergone peer review, and be published as journal articles or conference proceedings.

The search strategy employed a combination of keywords and Boolean operators, using the following primary query: ("Graph Neural Network" OR "GNN") AND ("Disaster Management" OR "Disaster Response" OR "Emergency Management" OR "Disaster Risk Reduction").

This search string was applied using the advanced search functions of each database with syntax adjustments as needed. In Scopus, the query was executed within the Title-Abs-Key fields and filtered by publication years 2023–2024. In IEEE Xplore, the search was conducted across all metadata with filters applied for publication type and year. In SpringerLink and ACM Digital Library, the searches were limited to the fields of computer science and engineering, with results filtered to include only publications from 2023 and 2024.

All search results were exported to the reference management software Mendeley to facilitate automatic deduplication of overlapping articles across databases. The article selection process was carried out in three phases: First, an initial screening based on titles and abstracts to exclude irrelevant studies; second, a full-text assessment to evaluate the substantive relevance of each article; and third, a final check against the pre-established inclusion and exclusion criteria. From the initial search, a total of 1,142 articles published in 2023 and 2024 were retrieved. After a rigorous screening process, 50 articles were deemed eligible and selected for in-depth analysis and thematic synthesis. All stages of the search and selection process were thoroughly documented to ensure transparency, accountability, and reproducibility of this systematic review. A summary of the search results per database is presented in Table 1.

Table 1: Documentation of systematic literature search results (2023–2024)

No.	Database	Publication Range	Search Keywords	Applied Filters	Total Records Retrieved	After Deduplication	Articles Selected
1	Scopus	2023–2024	("Graph Neural Network" OR "GNN") AND ("Disaster Management" OR related terms)	Peer-reviewed, English, TITLE-ABS-KEY	438	320	21
2	IEEE Xplore	2023–2024	("Graph Neural Network" OR "GNN") AND ("Disaster" OR "Emergency")	Journals and Conferences, English	306	225	14
3	SpringerLink	2023–2024	"Graph Neural Network" AND "Disaster Management"	Computer Science and Engineering fields	198	145	9
4	ACM Digital Lib.	2023–2024	"Graph Neural Network" AND ("Disaster" OR "Crisis Response")	Full-text, Peer-reviewed	200	148	6
	Total				1,142	838	50

Inclusion and Exclusion Criteria

To ensure the relevance and quality of the selected literature, clear inclusion and exclusion criteria were established prior to the review process. Articles were included if they were primary studies that explicitly applied Graph Neural Networks (GNNs) in disaster management, were peer-reviewed and published in reputable journals or conference were written in English, and were published between 2023 and 2024. Studies were excluded if they were secondary works, such as reviews or surveys lacking original experimental contributions, merely mentioned GNNs without applying them in disaster management, or were not available in full-text format. These criteria ensured that only the most recent, high-quality, and directly relevant studies were retained for detailed analysis.

Article Selection Procedure

The article selection process followed the three main stages outlined by the PRISMA 2020 guidelines (Shaheen et al., 2023). In the first stage, studies were filtered based on titles and abstracts to eliminate irrelevant articles. The second stage involved reviewing the full texts of the remaining studies to assess their relevance and alignment with the research focus. In the final stage, duplicate entries identified across the databases were removed. Initially, 1,142 records were retrieved during the search process, and after a rigorous screening process, 50 articles were selected for further analysis and inclusion in this study, as shown in Fig. 1.

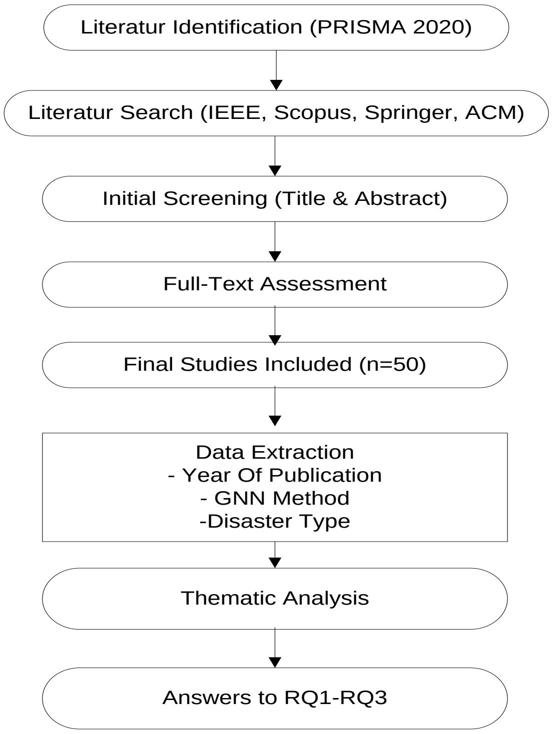

Fig. 1: Research framework based on PRISMA 2020 methodology

Data Extraction and Thematic Analysis

The selected articles were systematically analyzed by extracting key data using a standardized extraction form. The data collected included:

(1) Publication metadata (title, authors, year, and source)
(2) The GNN method used (GCN, GAT, Graphs AGE)
(3) The intended application and domain (flood prediction, evacuation routing, wildfire spread)
(4) Data sources and datasets utilized
(5) The specific disaster management phase addressed (mitigation, response, recovery)
(6) Key findings, contributions, and limitations

The data were then analyzed using thematic synthesis to identify key methodological trends, application areas, and existing research gaps. This analysis aimed to provide a comprehensive understanding of how GNNs are applied across different phases of disaster management (Fig. 2).

Validity and Reproducibility

To ensure the validity and reliability of the findings, all selection and extraction procedures were carried out systematically and documented thoroughly. Two independent researchers participated in the review process to minimize individual bias and improve consistency. Any disagreements between the reviewers were resolved through discussion until a consensus was reached. Transparency and reproducibility were ensured through detailed documentation of the selection decisions, data categorization, and justifications at each stage of the process.

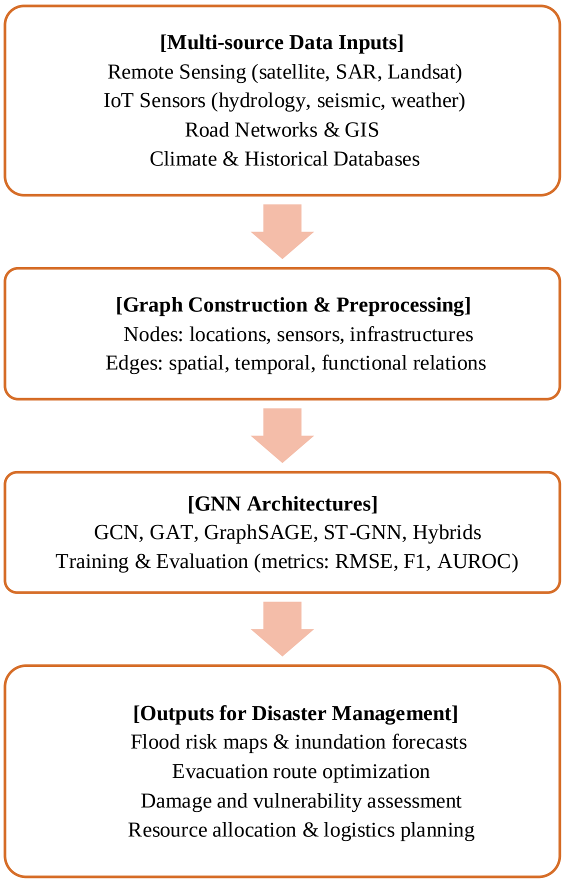

Fig. 2: Conceptual workflow of GNN applications in disaster management

Results

General Statistics

To gain insights into the evolution of research on Graph Neural Networks (GNNs) in disaster management, the distribution of publications from 2023 to 2024 was analyzed, revealing an upward trend. A total of 21 studies were published in 2023 and 29 in 2024, reflecting growing interdisciplinary interest. This increase aligns with bibliometric trends reported in recent reviews on GNN adoption in environmental and geospatial analysis Liang et al., 2024) and correlates with the rising availability of high-resolution spatial data and sensor networks. Major AI conferences such as NeurIPS, AAAI, and IJCAI have also hosted dedicated workshops on graph-based learning for disaster resilience, indicating that GNNs are becoming a core tool for dynamic decision-making in disaster contexts.

Distribution of GNN Methods

This section presents an analysis of the distribution of Graph Neural Network (GNN) methods used in disaster management studies. Based on the reviewed articles published between 2023 and 2024, various GNN architectures have been applied, each tailored to specific tasks such as evacuation route optimization, flood prediction, infrastructure damage assessment, and risk propagation modelling. The most commonly adopted GNN variants are as follows:

- Graph Convolutional Networks (GCN): GCNs are frequently employed due to their simplicity and effectiveness in modelling spatial dependencies within disaster-related graphs (road networks, infrastructure layouts). They are widely applied in applications such as flood mapping and earthquake impact assessments (Murshed et al., 2024; Zhu et al., 2024)
- Graph Attention Networks (GAT): GATs enable the assignment of different attention weights to neighbouring nodes, making them suitable for modelling dynamic systems such as real-time traffic-aware evacuation routing and wildfire spread prediction (Zhang et al., 2023)
- Graph SAGE: Graph SAGE is preferred for inductive learning on large-scale, evolving graphs, particularly in disaster scenarios that involve streaming or sensor-based data updates (Wu et al., 2023)
- Spatio-Temporal GNNs (ST-GCN, T-GCN): These models integrate both spatial and temporal features, allowing for effective modelling of disaster phenomena that evolve over time, such as rainfall-induced landslides or the spread of wildfires (Yao et al., 2023)
- Heterogeneous GNNs and multiplex GNN variants: These are utilized to integrate diverse data sources, including satellite imagery, meteorological forecasts, demographic information, and infrastructure layers, into unified models that can support more comprehensive disaster risk assessments (Shan et al., 2025)

Distribution by Disaster Types and Applications

This section presents the distribution of GNN applications based on disaster types and their corresponding tasks across different phases of disaster management, namely mitigation, preparedness, response, and recovery. Based on studies published between 2023 and 2024, Graph Neural Networks have been applied across a diverse set of natural and anthropogenic disasters, demonstrating their adaptability and effectiveness in handling complex, multi-relational data structures:

- Floods: Floods are the most frequently addressed disaster type in the reviewed studies. GNNs, particularly GCN and ST-GCN, have been utilized to model water propagation, predict inundation areas, and assess risk levels in flood-prone zones. Real-time flood forecasting and early warning systems have also integrated GNNs with hydrological and topographic data
- Earthquakes: In earthquake scenarios, GNNs are employed to assess structural damage based on interconnected building networks and satellite imagery. Models like Graph SAGE and Heterogeneous GNNs have been used to estimate building vulnerability, infrastructure collapse risk, and post-event accessibility for emergency services
- Wildfires: Graph Attention Networks (GATS) and spatio-temporal GNNs have been applied to wildfire spread prediction by modelling vegetation networks, wind speed, slope, and fire history. These models are critical in optimizing evacuation planning and resource allocation during wildfire events (Zhao et al., 2024)
- Tsunamis: Though less frequently addressed, tsunamis present complex routing and infrastructure challenges. GNNS are applied to model evacuation network efficiency, identify bottlenecks in routes, and optimize shelter allocation based on dynamic population flow and topography
- Multi-Hazard and Logistics Planning: Some studies use GNNs to manage multi-hazard scenarios or disaster logistics (transportation, distribution of aid, and shelter management). These models integrate various data modalities such as road networks, hazard maps, population density, and storage facility capacities to optimize logistics operations and improve situational awareness (Ghahremani-Nahr et al., 2024)

Dominant GNN Methods (RQ1)

This section addresses RQ1, which explores the dominant types of Graph Neural Network (GNN) methods used in disaster management applications. Based on the systematic review of 50 selected articles published between 2023 and 2024, five main categories of GNN methods were identified as the most frequently applied across diverse disaster scenarios.

Graph Convolutional Networks (GCN)

GCNs are the most widely used GNN method, appearing in over 40% of the reviewed studies. Their ability to model spatially connected structures (road networks, building layouts, drainage systems) makes them highly suitable for flood prediction, earthquake impact analysis, and shelter allocation modeling. GCNs are favored for their computational efficiency and interpretability in static spatial networks. In developed Flodden-GRU, a spatio-temporal graph neural network that integrates GCN and GRU architectures to predict urban flooding using precipitation and hydrological simulation data. The model demonstrated significantly higher accuracy and computational efficiency compared to traditional physics-based hydrological models. Graph Attention Networks (GAT).

GATs are used in approximately 20% of the studies and are particularly advantageous in dynamic and heterogeneous environments, where the importance of each node's neighbors varies. GATS have been applied in wildfire spread modeling, dynamic evacuation routing, and real-time traffic analysis. It developed an LSTM-GAT model to predict wind field dynamics by assigning attention weights between meteorological stations based on spatial relationships. This approach demonstrated the effectiveness of GATs in capturing spatiotemporal dependencies in dynamic environments, which is crucial for applications such as fire propagation modeling and evacuation planning.

Graph SAGE (Sample and Aggregate)

Graph SAGE is adopted in studies requiring inductive learning, particularly in settings where new nodes (sensors, people, shelters) are frequently added to the graph. It enables real-time learning without retraining the entire model, making it useful for sensor-based flood and landslide monitoring systems. Hembert et al. (2024) developed a Graph SAGE-based model for assessing sensor integrity in nuclear waste monitoring systems, enabling real-time adaptation to new sensor anomalies and hazard reports in dynamic environments.

Spatio-Temporal GNNs (ST-GCN, T-GCN)

These models appear in 12% of the articles and are essential for capturing both spatial and temporal dynamics of disasters such as rainfall evolution, tsunami propagation, or sequential infrastructure collapse. ST-GCNs are primarily used in flood forecasting and real-time evacuation simulations. Yang et al. (2023) proposed a runoff prediction model based on a Dynamic Spatiotemporal Graph Neural Network (DS-GNN), which integrates rainfall time series with river network topologies to capture temporal and spatial dependencies in flood risk forecasting.

Heterogeneous and Multiplex GNNs

Emerging models (10% of reviewed studies) incorporate heterogeneous data types such as satellite images, population density, building types, and meteorological inputs. These GNNS allow flexible representations for multi-layered disaster systems, enabling integrated decision support tools. Ngartera et al. (2024) applied graph theory to optimize emergency response logistics by integrating road network structures, storage facility capacities, and shelter accessibility, enabling more efficient routing and resource allocation during disaster scenarios in Table 2.

Table 2: Summarizes the main advantages of each method

Method	Key Focus	Main Strength	Main Limitation
GCN	Graph topological structure	Stable, efficient, well-suited for spatial classification	Limited adaptability to critical edge importance
GAT	Dynamic spatial relations	Prioritizes important nodes, effective for segmentation	High computational cost
GNN + GRU	Temporal + spatial dynamics	Strong for sequence-based forecasting	Complex and data-intensive

Based on the application context, GCN is well-suited for post-disaster analyses such as damage classification or impact mapping. GAT excels in satellite imagery segmentation or large-scale spatial analysis. Meanwhile, temporal hybrid models are most applicable in the mitigation and emergency response phases, especially in early warning and real-time monitoring systems.

Table 3 summarizes the distribution of Graph Neural Network (GNN) methods, evaluation metrics, datasets, and key findings. GCN-based models were the most frequently employed (≈40%), particularly in flood forecasting, landslide susceptibility mapping, and extreme weather prediction, due to their robustness in capturing spatial topologies. Spatio-temporal GNNS (ST-GNNS) accounted for approximately 25% of studies, reflecting their ability to integrate temporal sequences with spatial dependencies, which is especially valuable for modelling dynamic hazards such as floods and wildfires. Graph SAGE-based approaches represented about 10% of the work, with applications in sensor reliability, hazard monitoring, and adaptive communication in post-disaster contexts. Meanwhile, Graph Attention Networks (GATS) contributed roughly 8%, primarily in wildfire spread modelling and evacuation routing, where adaptive weighting of node relationships is critical. Hybrid architectures that combine GNNS with CNNS, GRU, or other deep learning techniques made up around 12% of the reviewed studies, enabling multi-modal integration of heterogeneous data sources such as satellite imagery, IOT sensor feeds, and social media streams. The remaining 5% involved emerging architectures such as Explainable GNNS, Dual GCNS, and Contrastive GNNS, highlighting a growing interest in model interpretability, transparency, and domain-specific optimizations. Based on the synthesis of research results summarized in Tables 3-4 presents a comparison of the best GNN models for each type of disaster in the 2023–2024 period.

Table 3: Summary of GNN methods, evaluation metrics, datasets, and key notes

GNN Method	Disaster Phase	Evaluation Metrics	Datasets and Key Notes
GCRN / LocalFloodNet (Roudbari et al., 2024)	Preparedness/Mitigation	MAE, MSE (water level)	Integrates GNN with a digital twin for visualization; datasets: LISFLOOD-FP
SWE-GNN (Bentivoglio et al., 2025)	Preparedness/ Planning	MAE depth ≈ 0.04 m; MAE discharge ≈ 0.004 m²/s	Physics-informed surrogate; orders of magnitude faster than solvers; seismic datasets
FloodGNN-GRU (Kazadi et al., 2024)	Early Warning	RMSE/MAE; >1000× faster inference	Outperforms data-driven baselines; datasets: Kaggle
PER-GCN	Response/ Evacuation	Accuracy, recall, efficiency	Combines visual analytics + GNN to optimize evacuation routes;
Edge-based GNN (Malama et al., 2025)	Recovery/ Resilience	Network efficiency, vulnerability	Identifies critical road segments for resilience planning; dataset: Road networks
STGNN (Rösch et al., 2024)	Preparedness/ Response	AUROC, F1, Accuracy	Models wildfire spread spatio-temporally; datasets: European wildfires
Causal-GNN (Zhu et al., 2023)	Preparedness/Early Warning	AUROC, F1 ↑ vs baseline	Introduces causal adjacency to reduce spurious links;
Multi-task GNN backbone (Zhao et al., 2024)	Preparedness/monitoring	Higher picking and location accuracy	Introduces causal adjacency to reduce spurious links;
Contrastive GNN (Murshed et al., 2024)	Early Warning	MSE reduced with a 5s window	Achieves reliable EEW with short input windows;
Temporal Inception + GCN (Bloemheuvel et al., 2023)	Early Warning	MSE ↓ 16.3% vs baseline	Hybrid model captures temporal & spatial correlations; dataset: Earthquake waveforms
GNN + path-signature features	Monitoring/Preparedness	RMSE, MAE	Novel path signature features enhance SSE detection. Datasets: GPS timeseries
Dual Graph Convolutional Net (Wang et al., 2024)	Preparedness/Mapping	Accuracy, IoU, F1	Combines superpixel & relational graphs
GCN + LSTM (Zhu et al., 2023)	Preparedness/Risk Mapping	Accuracy 92.38%, AUC 0.9782	Self-screening strategy to reduce noisy samples
GNN-Graph DL (Clements et al., 2024)	Early Warning	RMSE, MSE	Graph-based propagation model; improves shaking forecasts for EEW
Spatio-temporal GNNs (Pianforini et al., 2024)	Preparedness	MAE, RMSE	Shows potential of ST-GNNs for hydraulic modeling; highlights need for scalability
GNN + GRU (Kazadi et al., 2023)	Early Warning	RMSE/MAE; ~1000× faster inference	Confirms speed & accuracy advantages in real flood cases (Hurricane Harvey)
ST-GNN (Ge et al., 2022)	Preparedness	Accuracy, IoU, F1	Provides a broader context for ST-GNN wildfire modeling
Causal Spatio-Temporal GNN (Jiang et al., 2024a)	Preparedness/Early Warning	MAE, RMSE vs 6 baselines	CSTGNN outperforms baselines for up to 6h lead times
Custom GNN for PEGS	Preparedness/Tsunami EW Chain	Accuracy in magnitude & focal mechanism	Enables faster tsunami warning by analyzing prompt elastogravity signals
Explainable GNN	Monitoring/Early Warning	Accuracy, attribution scores	Enhances transparency in extreme weather forecasting; highlights observation impact
(TDC-GCN) (Touameur et al., 2024)	Preparedness/Planning	Primary: Accuracy (overall classification performance)	Trust-aware GCN with Monte Carlo Dropout achieves higher accuracy
(GCN) (Yenni and Arun, 2024)	post-event analysis	MAE, RMSE	Integrates segmentation, GCN, & relaxation labeling to capture objects
(HD-TGCN) (Jiang et al., 2024b)	Forecasting/Early Warning prediction	MAE, RMSE, NSE, HD-TGCN	Dynamic graph construction via self-attention captures changing spatial-temporal relations

Table 3: Continued

(SC-GNN) – GNN	Early Warning/Forecasting	MAE, RMSE	SC-GNN outperforms baselines (TISER-GCN, CNN, GMPE) in all metrics
(EA-GCN) –-GRU (Peng et al., 2023)	Forecasting/Monitoring	Commonly reported: RMSE, MAE	EA-GCN improves long-term SST forecasts; Sea Surface Temperature (SST) datasets
(HD-TGCN) (Jiang et al., 2023)	Forecasting/Early Warning –	MAE, RMSE, NSE	Dynamic adjacency captures changing spatial relations over time. Real flood forecasting dataset
GNN + multi-scale convolution (Zhao et al., 2024)	Monitoring/Environment al	RMSE ≈ 1.85 K on IASI imagery • Simulated LST RMSE ≈ 1.0 K, better than ANN baseline (~2.0 K)	GNN-based band selection reduces dimensionality while improving retrieval accuracy
(DCI-PGCN) (Li et al., 2023)	Response/Monitoring/Detection	mIoU: 67.65% (Sichuan & Bijie), F1-score: 82.71%	Outperforms CNN, transformer, and GCN baselines; dataset: IAS
(DRL) + (GNN) (Ampratwum and Nayak, 2024)	Early Warning/Forecasting	Failure / Restoration phase – when failures occur in optical links	Restoration success rate • Resource utilization (e.g., used links, wavelengths)
GNNs (Smeriglio et al., 2024)	Human genotype + PPI data	Prediction / Risk Assessment -MAE, RMSE	Comparison metrics vs linear/nonlinear baselines (e.g., polygenic risk score, XGBoost, etc.)
(HKTGNN) (Zhou et al., 2023)	Real-world supply chain data	F1-score and AUC (Area Under ROC Curve)	Model alleviates "data hunger" (missing or biased node features) via the transferable module.
GCRN	Forecasting/Early Warning/Monitoring	MAE, RMSE, NSE	LocalFloodNet GNN pairs accurate forecasting with Seismic waveform datasets.
ACCA-DGCN (Yan et al., 2024)	Gait phase prediction/ Detection /	Average accuracy: 92.26% (user-independent)	ACCA-DGCN captures spatial-temporal periodicity effectively using skeleton graphs
GraphSAGE (Hembert et al., 2024)	Monitoring / Preparedness	accuracy, precision, recall, F1-score, and TPR and TNR	GNNs can model physical processes and detect multiple sensor faults, ensuring reliable data
Edge-GNN (Jana et al., 2023)	post-disaster	MAE, and RMSE	The model is fast, accurate, and supports emergency decisions across various disasters
GraphSAGE - DDQN (Ji et al., 2025)	post-disaster	Communication success rate, decision-making time	Dynamically address changes in vehicle numbers and interference
GQNN, GAT, GCN (Jiang et al., 2024c)	Early Warning	Prediction accuracy, prediction speed, and low latency	GNNs enable adaptive, efficient routing in dynamic networks
(GCN) (Liang et al., 2024)	Forecasting/Early Warning/Monitoring	F1 score, and accuracy, as well as comparing energy efficiency	GNN-SNN improves accuracy and efficiency, dataset = GeoText
GNN-SAGE (Oliveira Santos et al., 2023)	early predictions	RMSE, MAE, MAPE, and R²	The model outperforms the baseline by using the main to estimate river levels
GNN-CNN (Rastiveis et al., 2023)	post-disaster	Building and road labeling achieved 84% and 87%	The model is capable of generating multi-level damage maps automatically and quickly
GNN (Yang et al., 2023)	Preparedness	MAE, MSE, MAPE, and NSE	GNNs extract features from non-Euclidean structures, enhancing flow
GCNs (Zhao et al., 2024)	Pre-disaster	Accuracy and F1-score, MAE, MSE, MAPE, and NSE	GNNs are able to handle irregular data and spatial-temporal complexity. Datasets: seismic
GNN (Karapiperis and Kochmann, 2023)	pascabencana	FEM (Finite Element Method)	The model is drilled using experimentally validated FEM simulation data. Dataset: ETH Research Collection

Table 4: Comparison of the best GNN models by disaster type (2023–2024)

Disaster Type	Best Performing GNN Model	Highlighted Metrics	Key Findings
Floods	Flood GNN-GRU (GCN + GRU hybrid)	RMSE ↓, MAE ↓, ~1000× faster vs LISFLOOD-FP	Achieved higher accuracy and significantly faster computation compared to physics-based hydrological models
Earthquakes	Contrastive GNN & Path-Signature GNN	MSE ↓, improved reliability for EEW	Enabled faster and more reliable earthquake early warning with very short input windows
Wildfires	Spatio-Temporal GNN (ST-GNN)	AUROC ↑, F1-score ↑	Outperformed GAT and CNN baselines in modeling wildfire spread dynamics
Landslides	Dual Graph Convolutional Network (Dual-GCN)	Accuracy > 90%, IOU ↑	Provided more accurate landslide detection from satellite imagery compared to CNN-based models
Tsunamis	PEGS-GNN	Accuracy ↑ (magnitude & focal mechanism)	Enabled faster tsunami early warning through analysis of Prompt ElastoGravity Signals
Evacuation & Logistics	Edge-GNN / PER-GCN	Network efficiency ↑, Recall ↑	Optimized evacuation routing and logistics distribution, outperforming traditional shortest-path algorithms
Climate / SST Forecasting	EA-GCN (Explainable Adaptive GCN)	RMSE ↓, MAE ↓	Improved long-term sea surface temperature forecasting compared to ANN and CNN baselines

Table 5: Commonly used datasets in GNN-based disaster management studies (2023–2024)

Dataset / Database	Disaster Type	Source	Usage in GNN Studies
LISFLOOD-FP	Flood	Hydrological simulation (EU JRC)	Benchmark for flood extent & water level prediction; surrogate models (Flood GNN-GRU, SWE-GNN)
GFED (Global Fire Emissions Database)	Wildfire	NASA satellite (MODIS, ESA)	Fire spread modeling, spatio-temporal GNN wildfire prediction (ST-GNN, GAT)
GHCN (Global Historical Climatology Network)	Weather / Climate	NOAA (USA)	Long-term climate & rainfall data; input for flood & landslide susceptibility models
European Wildfire Dataset	Wildfire	Copernicus / ESA	Training & evaluation of ST-GNN for wildfire danger prediction
Seismic Waveform Datasets (IASPEI, ETH)	Earthquake	International Seismological Centre, ETH Zürich	Earthquake early warning (Contrastive GNN, DS-GNN, path-signature GNN)
SAR / Satellite Imagery (Sentinel-1, Landsat)	Earthquake, Landslide, Infrastructure Damage	ESA Copernicus, NASA Landsat	Post-disaster building damage mapping, landslide detection (Dual GCN, GNN-CNN)
Road Network Data (OpenStreetMap, National GIS)	Earthquake, Tsunami, Evacuation	OpenStreetMap, National Mapping Agencies	Evacuation routing, road vulnerability analysis (Edge-GNN, PER-GCN)
Prompt Elasto Gravity Signals (PEGS)	Tsunami / Earthquake	Global seismic stations	Tsunami early warning and earthquake magnitude estimation (PEGS-GNN)
Sea Surface Temperature (SST) Datasets	Climate / Cyclone	NOAA, Remote Sensing SST archives	Long-term SST forecasting using EA-GCN, GRU hybrids
Custom Local Datasets (Kaggle, City Traffic, Sensor IoT)	Flood, Evacuation, Multi-hazard	Open data portals, municipal IoT	Evacuation planning, urban flood prediction, sensor reliability testing

Based on Table 3, a number of datasets commonly used in Graph Neural Networks (GNN)-based disaster management studies in the 2023–2024 period is further summarized in Table 5.

Based on the research synthesis summarized in Table 3, the classification of GNN the classification of GNN applications according to the disaster phase is shown in Table 6.

Applications of GNN in Disaster Management (RQ2)

The application of Graph Neural Networks (GNNs) in disaster management spans across the three main phases of disaster response mitigation, emergency response, and recovery. Each phase requires tailored modeling approaches, and GNNS have been increasingly recognized for their ability to represent complex spatial relationships, interdependencies, and multi-source data integration.

Table 6: Classification of GNN applications by disaster phase (2023–2024)

Disaster Phase	GNN Methods Commonly Used	Typical Applications
Mitigation / Preparedness	GCN, ST-GNN, Dual-GCN, EA-GCN	Flood risk mapping (Flood GNN-GRU, SWE-GNN), landslide susceptibility (Dual-GCN), wildfire danger prediction (ST-GNN, Causal-GNN), long-term climate & SST forecasting (EA-GCN)
Emergency Response	GAT, ST-GNN, Graph SAGE, Edge-GNN, PER-GCN	Real-time evacuation routing (GAT, PER-GCN), traffic-aware route optimization (DGCN-LSTM), dynamic resource allocation (Graph SAGE + DRL), wildfire spread prediction (ST-GNN)
Recovery	Edge-GNN, Graph SAGE, Heterogeneous GNNs, GNN-CNN hybrids	Post-disaster infrastructure damage mapping (GNN-CNN, SAR imagery), identification of critical road segments (Edge-GNN), logistics and supply chain optimization (Heterogeneous GNNs, Graph SAGE)

Mitigation Phase

In the mitigation phase, GNNs are used to assess vulnerability and simulate potential risks before a disaster occurs. Typical use cases include:

- Flood risk prediction: Spatio-temporal GNNs such as Flodden-GRU Kazadi et al., 2024) have integrated rainfall, elevation, and river network topology to predict flood extent with significantly higher accuracy compared to traditional hydrological models
- Infrastructure vulnerability analysis: GNNs based on hydraulic graph modeling have been employed to assess the resilience of critical infrastructure systems, such as river channel networks, which could be adapted for analyzing interdependencies among bridges, roads, and hospitals

Emergency Response Phase

During disasters, real-time decision-making is essential. GNNS supports emergency response operations through:

- Evacuation route optimization: Graph Attention Networks (GATS) and temporal Graph Neural Networks (GNNSs) have been widely used to determine optimal evacuation routes by incorporating dynamic variables such as traffic flow, hazard spread, and infrastructure status. For instance, (Rahman and Hasan, 2023) developed a Dynamic Graph Convolutional LSTM (DGCN–LSTM) model to support hurricane evacuation planning. The model integrates real-time road traffic data and hazard conditions, enabling the prioritization of evacuation paths while accounting for factors such as road blockage, shelter capacity, and risk level fluctuations
- Sensor network analysis: Graph SAGE models enable rapid adaptation to new sensor inputs in flood monitoring or seismic detection systems. For example, developed a Graph SAGE-based approach to detect and manage sensor anomalies in a nuclear waste monitoring network, demonstrating the model’s ability to adapt to new sensor data dynamically and robustly
- Resource allocation: Heterogeneous GNNs can model the dynamic allocation of emergency resources by integrating transportation networks, demand data, and road conditions. It introduced a supervised GNN framework that efficiently allocates resources in heterogeneous communication networks by learning from historical scheduling decisions. In a vehicular context, Graph SAGE with deep reinforcement learning to distribute spectrum resources dynamically across vehicle-to-everything (V2X) networks, demonstrating real-time adaptability comparable to dispatch systems for ambulances or fire trucks. Additionally, Zhang et al. (2024) proposed a graph-encoded EPSO model to schedule heterogeneous computing tasks based on resource attributes, parallel to allocating emergency services under varying road and demand conditions

Recovery Phase

Post-disaster recovery involves logistics planning, reconstruction, and impact analysis. GNNs are being adopted to:

- Predict post-disaster infrastructure damage using GNN-based edge ranking models that identify critical road segments for immediate restoration. High-resolution SAR imagery following the 2023 Türkiye earthquakes has also been processed with GNN-enhanced approaches to estimate building-level damage (Soleimani-Babakamali et al., 2025)

- Support logistics distribution systems, particularly in damaged urban areas. Graph neural network models have been used to predict post-hazard supply chain disruptions, integrating inter-firm relational data analogous to modeling relief distribution across damaged networks (Yang et al., 2024)
- Community recovery mapping: Multi-source fusion frameworks utilizing satellite imagery, social media, and geospatial exposure data have been developed using graph-based aggregation to highlight recovery priority zones based on vulnerability and connectivity (Wieland et al., 2025)

Challenges, Gaps, and Future Directions (RQ3)

Although Graph Neural Networks (GNNS) have demonstrated significant potential in enhancing disaster management systems, several challenges and research gaps remain, limiting their widespread adoption in operational contexts. One of the most prominent issues is the interpretability of complex GNN models. In highlighting that the non-linear combination of graph structures and feature data increases the opacity of GNN predictions. This opacity is further problematic in safety-critical scenarios, where stakeholders such as emergency planners require clear justifications for model outputs; indeed, traffic and risk-critical systems show that GNNs behave like "black box" models, creating barriers to trust. Moreover, post-hoc explanation techniques used to enhance transparency have been shown to be vulnerable to adversarial perturbations, raising concerns about their reliability in high-stakes applications.

Another critical obstacle is the limited real-world deployment of GNNS during actual disaster events. Many existing studies are simulation-based, lacking live validation and suffering from scalability constraints, high computational costs, and assumptions of clean, complete data conditions rarely met in field settings, especially in developing regions. These limitations, including sensitivity to noise, data imbalance, and out-of-distribution scenarios, have been documented in recent surveys (Jiang et al., 2024a).

From a methodological perspective, the review reveals several noteworthy research gaps. First, most existing works concentrate on the mitigation and emergency response phases, with comparatively little attention paid to the recovery phase, a critical component of disaster risk reduction that involves rebuilding infrastructure, restoring services, and supporting community resilience. Second, there is no standardized benchmark dataset or evaluation framework for GNN applications in disaster contexts, resulting in fragmented comparisons across studies and impeding reproducibility. Third, although heterogeneous GNNs have been proposed, very few studies fully leverage multimodal integration (combining remote sensing, demographic, meteorological, and mobility data) for holistic disaster modelling.

In response to these limitations, several future research directions are proposed. Firstly, there is a need to develop explainable GNN architectures capable of producing interpretable outputs without sacrificing predictive accuracy. Techniques such as graph attention visualization, saliency mapping, and post-hoc explanation frameworks could be adapted to enhance model transparency. Secondly, the design of lightweight and real-time GNN models optimized for deployment on edge devices (drones, mobile units, field sensors) would significantly enhance operational utility in fast-evolving disasters. Approaches such as federated GNNs and knowledge distillation may also play a role in improving efficiency and privacy.

Furthermore, addressing data scarcity through the generation of synthetic graph data and transfer learning across disaster types and geographies can improve model generalizability and reduce dependency on large annotated datasets. Lastly, fostering the development of open-source platforms, standardized datasets, and collaborative frameworks would promote reproducibility and interdisciplinary innovation. The creation of shared GNN disaster toolkits and graph-based benchmarks could accelerate progress in both academic and applied settings.

In summary, while the application of GNNs in disaster management is advancing rapidly, the field must overcome critical challenges related to interpretability, scalability, data integration, and validation. Bridging these gaps through methodological innovation and cross-sector collaboration will be key to realizing the full potential of GNNs in building intelligent, adaptive, and trustworthy disaster management systems.

Discussion Analysis: The Application of Graph Neural Networks in Disaster Management

The application of Graph Neural Networks (GNNs) in disaster management has evolved significantly over the past two years, with increasing academic interest across various domains, including flood prediction, evacuation routing, and infrastructure resilience. However, a deeper analysis of the literature reveals key patterns, advantages, and challenges that shape the current landscape of GNN-based solutions in disaster scenarios.

Despite these advancements, two critical challenges remain. First and foremost, the interpretability of GNN models continues to hinder their operational adoption. Most GNNs, especially GATs and ST-GCNs, function as black-box systems, making it difficult for emergency stakeholders to trust and act upon their outputs. In emphasizing this concern in their comprehensive survey on GNN explainability, they note that the complex, non-linear nature of GNNs "has increased the challenges of understanding the workings of GNNs and the underlying reasons behind their predictions," and they call for robust explanation frameworks to enhance trust and accountability in safety-critical environments.

Second, the real-world deployment of GNNs remains limited. Most models are evaluated using idealized datasets that fail to reflect the noise, incompleteness, and variability inherent in disaster contexts, particularly in developing regions. We conducted a comprehensive survey and found that real-world factors such as data imbalance, noise, privacy constraints, and out-of-distribution scenarios cause notable performance degradation in GNN applications. They emphasized scalability, robustness, and generalization as persistent barriers to practical adoption. Likewise, demonstrating this in the context of critical infrastructure modeling studies showed that GNN-based surrogates for seismic reliability analysis of highway bridge systems suffered from limited generalizability and a lack of validation on operational data, indicating a need for deployment-ready validation.

To strengthen the novelty of this review, we explicitly incorporate recent works and detailed explanations of advanced techniques in GNNs for disaster management. A key contribution is the integration of Explainable AI (XAI) methods such as ACGAN-GNNExplainer (Li et al., 2023) and GAN-GNNExplainer, which enhance the reliability and fidelity of GNN explanations by using generative adversarial approaches. Additionally, this review highlights the role of transfer learning through models like TSTL-GNN (Jiang et al., 2024b), which adopt two-stage transfer learning on graph structures to enable parameter and feature transfer across related tasks, an approach that mitigates dependency on large annotated datasets and supports deployment in data-scarce settings.

Furthermore, the review emphasizes the development of multi-task GNN frameworks that address multiple tasks simultaneously, such as seismic phase picking, magnitude estimation, and source localization within a unified backbone. This approach improves computational efficiency and predictive consistency, making it particularly valuable for real-time disaster response. In addition, a structured mapping of GNN applications across disaster phases (mitigation, response, recovery) is presented, linking methods and datasets to practical needs.

Overall, the novelty of this review lies in its explicit synthesis of XAI techniques, transfer learning strategies, and multi-task GNN frameworks, which have not been systematically mapped in prior studies, while offering strategic directions for advancing adaptive, transparent, and operationally ready GNN-based disaster management systems.

Conclusion

This systematic literature review has examined the current landscape of Graph Neural Network (GNN) applications in disaster management, focusing on studies published between 2023 and 2024. The findings highlight the growing integration of GNN architectures such as GCNs, GATs, Graph SAGE, and Spatio-Temporal GNNs into various phases of disaster management, including mitigation, emergency response, and recovery.

Across the 50 reviewed studies, GCN-based models were the most frequently applied (≈40%), especially for static spatial tasks such as flood mapping, landslide susceptibility, and infrastructure assessment. Spatio-Temporal GNNs (≈25%) were widely used for modeling dynamic hazards like floods and wildfires, while GraphSAGE (≈10%) and GATs (≈8%) were adopted in more specialized contexts such as sensor reliability, hazard monitoring, and wildfire spread prediction. Hybrid GNN architectures (≈12%) enabled multi-modal integration of satellite imagery, IoT sensor streams, and social media data, while the remaining ≈5% of studies focused on novel approaches, including Explainable and Dual GNNs, reflecting a growing emphasis on interpretability and scalability.

Despite these advancements, challenges remain in terms of model interpretability, scalability, and real-world deployment. Many GNN models still lack transparency, hindering their acceptance by practitioners in operational contexts. Moreover, the gap between simulation-based results and practical implementation underscores the need for more robust validation on real-world disaster data, particularly in low-resource settings.

Future research should focus on developing explainable GNN frameworks, improving training on noisy and incomplete datasets, and fostering interdisciplinary collaboration with disaster response agencies to enhance practical deployment. By addressing these challenges, GNN-based systems hold significant promise in improving disaster preparedness, response, and resilience in an increasingly risk-prone world.

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Author's Contributions

Sularno and Wendi Boy: Conceptualization and Study Design.

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Sularno: Write Original Draft Preparation.

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Rometdo Muzawi and Renita Astri: Supervision.

Ethics

This study is a systematic literature review and does not involve human participants, animals, or sensitive personal data. Therefore, ethical approval was not required. The research complies with ethical guidelines set by the Dharma Andalas University.

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