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Integrating Artificial Intelligence, IoT, and GIS for Smart Disaster Risk Management: A Systematic Review

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Abstract

Disasters triggered by hydro-meteorological, geophysical, and climatic hazards are increasing in frequency and severity, straining the capacity of conventional disaster risk management (DRM) systems that rely on manual data collection and delayed decision-making [1], [5]. Recent advances in Artificial Intelligence (AI), the Internet of Things (IoT), and Geographic Information Systems (GIS) have opened new possibilities for building smart, data-driven, and anticipatory disaster management systems [3], [14]. This paper presents a systematic review of the literature published mainly between 2020 and 2026 that examines how AI, IoT, and GIS are being integrated to support hazard prediction, real-time monitoring, spatial risk assessment, early warning, and post-disaster response. Fifty-seven peer-reviewed and indexed sources were synthesised following a structured review protocol. The review identifies five major integration themes: (i) sensor-driven early warning networks, (ii) geospatial machine-learning hazard susceptibility mapping, (iii) UAV and remote-sensing based damage assessment, (iv) social-media and big-data situational awareness, and (v) digital-twin-enabled smart-city resilience platforms. The paper further develops a conceptual AI-IoT-GIS integration architecture, presents mathematical formulations commonly used for spatial risk indexing, sensor network reliability, and machine-learning performance evaluation, and illustrates these formulations with worked numerical examples, tables, and charts. The review concludes that while integration of these three technologies significantly improves prediction accuracy and response times, challenges remain around data interoperability, energy-constrained sensor networks, algorithmic bias, and the digital divide affecting adoption in low-resource regions [2], [15].

***Keywords**: Artificial Intelligence, Information System, Risk Management, Smart Cities, Machine Learning.*

Introduction

Natural and human-induced disasters, including floods, earthquakes, landslides, wildfires, and tropical cyclones, cause substantial loss of life, infrastructure damage, and economic disruption every year. The World Meteorological Organization has reported thousands of weather-related disaster events since 1970, resulting in millions of deaths and trillions of dollars in economic losses, with the frequency of such events rising sharply in recent decades [11]. Climate change, rapid urbanisation, and the growing concentration of population and assets in hazard-prone areas have further amplified disaster risk, making the case for smarter, faster, and more anticipatory disaster risk management systems [3].

Traditional DRM approaches have historically depended on static hazard maps, periodic field surveys, and centralised command structures, which are often too slow to capture the dynamic and highly localised nature of hazards such as flash floods or wildfires [9]. Over the past decade, the convergence of three technological domains — Artificial Intelligence, the Internet of Things, and Geographic Information Systems — has begun to transform this landscape. AI techniques, particularly machine learning (ML) and deep learning (DL), enable pattern recognition, prediction, and classification from large and heterogeneous datasets, and have demonstrated strong performance in hazard susceptibility modelling, damage detection, and decision support [2], [5]. IoT technologies provide continuous, real-time, low-cost sensing of environmental parameters such as water level, ground vibration, temperature, and air quality, forming the physical backbone of early warning systems [7], [10]. GIS, meanwhile, supplies the spatial reference framework needed to contextualise sensor and model outputs, enabling hazard mapping, vulnerability assessment, and route optimisation for evacuation and relief logistics [3], [14].

Individually, each of these technologies has been studied extensively; however, their integration into unified, interoperable DRM platforms is a comparatively recent and rapidly growing research frontier. A systematic bibliometric analysis of the AI-in-DRM literature found an exponential growth in publication output from 2020 onward, reflecting both technological maturation and urgent global need [1], [2]. Similarly, a systematic review of GIS-AI-ML integration identified themes spanning flood risk management, landslide susceptibility prediction, real-time monitoring, and early warning, underscoring the breadth of ongoing work [3]. Despite this growth, most existing reviews examine AI, IoT, or GIS separately, or focus on a single hazard type, leaving a gap in the literature for a review that explicitly synthesises how all three domains function together as an integrated smart DRM ecosystem.

This paper addresses that gap. The specific objectives of the review are to: (a) synthesise recent literature on AI, IoT, and GIS applications across the disaster management cycle (mitigation, preparedness, response, and recovery); (b) propose a conceptual architecture describing how these technologies interconnect; (c) illustrate the quantitative and mathematical foundations that underpin spatial risk assessment, sensor reliability, and predictive model evaluation; and (d) identify open challenges and future research directions. The remainder of the paper is organised as follows: Section 2 describes the review methodology; Section 3 presents the technological foundations of AI, IoT, and GIS in DRM; Section 4 proposes an integrated architecture; Section 5 reviews hazard-specific applications; Section 6 presents mathematical formulations and worked calculations; Section 7 offers a comparative synthesis; Section 8 discusses challenges; Section 9 outlines future directions; and Section 10 concludes the paper.

Research Methodology

This review follows a structured methodology broadly aligned with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach, adapted for a multidisciplinary technology-and-hazard review [2], [34]. The process consisted of four stages: identification, screening, eligibility assessment, and inclusion/synthesis.

- **Search Strategy**

Search strings combined terms from three technology domains and the disaster management domain, e.g., ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("IoT" OR "internet of things" OR "sensor network") AND ("GIS" OR "geospatial" OR "remote sensing") AND ("disaster" OR "flood" OR "earthquake" OR "landslide" OR "wildfire" OR "risk management"). Sources were drawn from indexed databases and repositories including Scopus-indexed journals, Springer Nature, ScienceDirect, MDPI, IEEE Xplore, Nature, and arXiv preprints, consistent with the source pools used in comparable bibliometric DRM reviews [1], [2].

- **Inclusion and Exclusion Criteria**

Table 1. Inclusion and exclusion criteria applied during the review screening process

Criterion	Inclusion	Exclusion
Publication period	2020–2026 (with limited seminal earlier works)	Pre-2015 studies without contemporary relevance
Technology scope	Explicit use of AI/ML/DL, IoT/sensor networks, or GIS/remote sensing in a disaster context	Studies with no disaster-risk application
Document type	Peer-reviewed journal articles, indexed conference papers, and systematic reviews	Non-indexed blogs, opinion pieces

Language	English	Non-English without translation
Accessibility	Full text or detailed abstract available	Paywalled with no accessible abstract/metadata

- **Screening and Synthesis**

An initial pool of records was screened by title and abstract for relevance to the AI–IoT–GIS–disaster intersection. Duplicate records and studies addressing unrelated domains (e.g., purely industrial IoT without a disaster-risk component) were removed. The final synthesis pool comprised 57 sources spanning bibliometric reviews, hazard-specific technical studies (flood, earthquake, landslide, wildfire), digital-twin and smart-city frameworks, and social-media/big-data analytics studies, which were thematically coded and are discussed in Sections 3–7. This approach mirrors the qualitative-interpretive synthesis method used in a recent systematic review of AI-ML-powered GIS for disaster resilience, which examined 71 studies against a comparable inclusion protocol [3].

It is acknowledged that, as with other bibliometric and thematic reviews in this domain, the synthesis presented here is primarily qualitative and does not independently verify the operational deployment or field performance of the reviewed systems; it instead characterises the state and direction of the published literature [1].

Technological Foundations

- **Artificial Intelligence in Disaster Risk Management**

Artificial intelligence encompasses a family of computational techniques — including classical machine learning (e.g., random forest, support vector machines, gradient boosting) and deep learning (e.g., convolutional neural networks, recurrent networks, transformers) — that learn patterns from historical and real-time data to support prediction, classification, and decision-making [4], [5]. In DRM, AI has been applied across the full disaster cycle: hazard and vulnerability modelling, early warning generation, damage detection from imagery, evacuation route optimisation, and post-disaster resource allocation [4]. A bibliometric review covering more than 800 publications found that machine learning and deep learning methods dominate the AI-DRM literature, with an accelerating shift toward geospatial AI, remote sensing, and social-media analytics in recent years [2]. Reinforcement learning has also begun to be applied to dynamic problems such as evacuation-path optimisation using agent-based simulation [5].

- **Internet of Things in Disaster Risk Management**

IoT refers to networks of interconnected physical sensors and actuators that collect and transmit environmental data in near real time [7]. In disaster contexts, IoT devices include river and dam water-level sensors, seismic and ground-vibration sensors, weather stations, air-quality monitors, and wearable devices for responder tracking [10], [13]. Communication typically relies on low-power wide-area protocols such as LoRaWAN, NB-IoT, Zigbee, and MQTT-based messaging, which balance energy efficiency with the need for wide-area coverage in often remote or infrastructure-poor hazard zones [11], [12]. IoT-enabled flood monitoring systems, for example, have been shown to classify river conditions into discrete alert states (e.g., normal, warning, flood, severe flood) based on threshold water-level readings, giving downstream communities critical lead time to evacuate [8], [11]. The global market for IoT-based disaster management technologies has been estimated to grow from roughly USD 300 million in 2022 to USD 1.7 billion by 2027, reflecting a compound annual growth rate near 36 percent and signalling strong investment momentum in this space [8].

- **GIS and Geospatial Technologies in Disaster Risk Management**

Geographic Information Systems provide the spatial data infrastructure necessary to store, analyse, and visualise hazard, exposure, and vulnerability information [3], [14]. Core GIS capabilities relevant to DRM include multi-criteria spatial overlay analysis, digital elevation modelling, hydrological flow modelling, and cartographic risk-map production [15]. When coupled with remote sensing data from satellites (e.g., Sentinel imagery) or unmanned aerial vehicles, GIS enables the derivation of hazard-conditioning factors such as slope, elevation, land cover, topographic wetness index, and distance-to-drainage, which are widely used as predictor variables in geospatial machine-learning models for flood and landslide susceptibility [16], [17], [18]. A systematic review of 71 empirical studies on GIS-AI-ML integration identified six recurring themes: disaster risk assessment, flood risk management, landslide susceptibility prediction, innovative visualisation, real-time monitoring/early warning, and efficiency gains in data processing [3].

An Integrated AI-IoT-GIS Architecture for Smart DRM

Synthesising the reviewed literature, an integrated architecture for smart disaster risk management can be represented as four interconnected functional layers, illustrated conceptually in Figure 1 [7], [14], [31]. The sensing layer comprises distributed IoT devices — water-level gauges, seismic sensors, weather stations, UAV-mounted cameras, and citizen-generated social-media data — that continuously capture environmental and situational signals [10], [50]. The connectivity and edge layer transmits and pre-processes this data using low-power protocols and, increasingly, edge-computing nodes that perform local filtering to reduce bandwidth demand and latency before data reaches centralised platforms [34], [37]. The AI/ML analytics layer applies predictive and classification models — CNNs for imagery, LSTM networks for time-series forecasting, and ensemble tree methods for structured tabular data — to transform raw sensor and imagery streams into actionable hazard probabilities and event classifications [26], [40]. Finally, the GIS integration and decision layer overlays these outputs onto spatial base-maps, producing dynamic risk maps, dashboards, and automated alerts that feed into early-warning dissemination and resource-allocation decisions [3], [14].

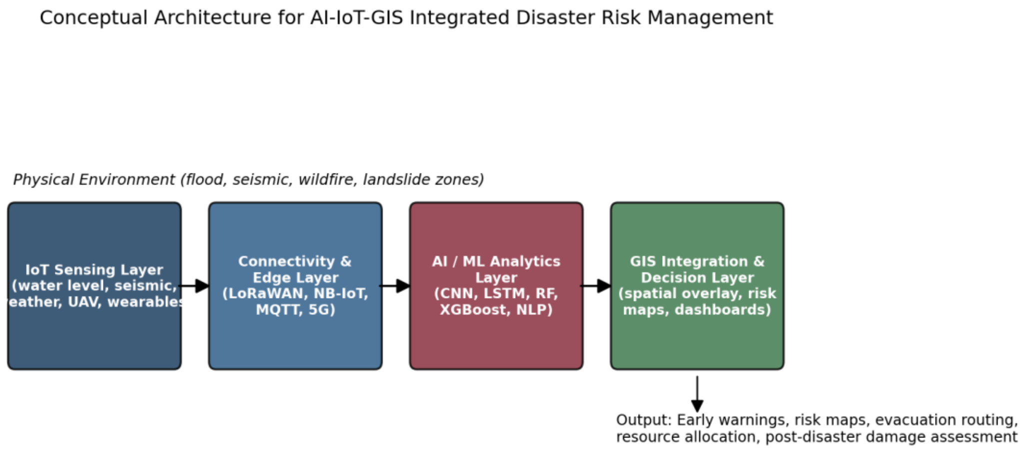

Figure 1: Conceptual four-layer architecture for AI-IoT-GIS integrated disaster risk management, synthesised from the reviewed literature

This layered conception is consistent with emerging "disaster city digital twin" frameworks, which explicitly call for integrating artificial and human intelligence with continuously updated, sensor-fed spatial models of urban environments to support anticipatory decision-making [38], [39]. Digital twins extend the architecture in Figure 1 by adding a simulation/what-if layer atop the GIS decision layer, allowing planners to model the propagation of a hazard (e.g., flood inundation or fire spread) before it fully materialises [31], [36]. A systematic review of IoT, AI, and digital-twin integration in smart cities found that emergency management for civil infrastructure applies digital-twin representations across all four phases of the disaster lifecycle — mitigation, preparedness, response, and recovery [34].

Hazard-Specific Applications

- **Flood Risk Assessment and Early Warning**

Flooding is the most extensively studied hazard within the AI-IoT-GIS literature, reflecting both its global frequency and the relative maturity of hydrological modelling techniques [2], [11]. GIS-based multi-criteria approaches, such as the Analytical Hierarchy Process (AHP) combined with frequency-ratio analysis, remain widely used to integrate rainfall, elevation, slope, land cover, and drainage-density layers into composite flood-risk maps [16]. More recent studies increasingly replace or complement these methods with machine-learning classifiers: random forest, support vector machines, gradient boosting variants (XGBoost, LightGBM), and deep neural networks trained on historical flood inventories and remote-sensing-derived predictor variables [17], [18], [19]. A comparative geospatial-AI study evaluating five algorithms found XGBoost, random forest, and LightGBM achieving area-under-curve (AUC) scores above 0.98 on a held-out validation set, notably outperforming simpler baselines such as logistic regression [21]. Ensemble methods that combine multiple base learners have also been shown to improve robustness over single-model approaches, particularly in data-sparse regions [18], [20].

On the sensing side, IoT-based flood monitoring networks deployed in coastal and riverine communities continuously measure water levels and transmit real-time alerts once predefined thresholds are exceeded, using communication protocols such as LoRaWAN, Zigbee, GSM, and MQTT, with dashboards built on platforms like ThingSpeak, TagoIO, and Grafana [11]. Such systems have proven valuable in monsoon-affected regions of South and Southeast Asia, where lead times of even a few hours can enable substantial community evacuation before flood peaks arrive [11]. Recent work on digital early warning systems similarly stresses that resilience gains depend not only on sensor accuracy but on the end-to-end dependability of the alert-dissemination chain, from sensing through communication to last-mile public notification [56].

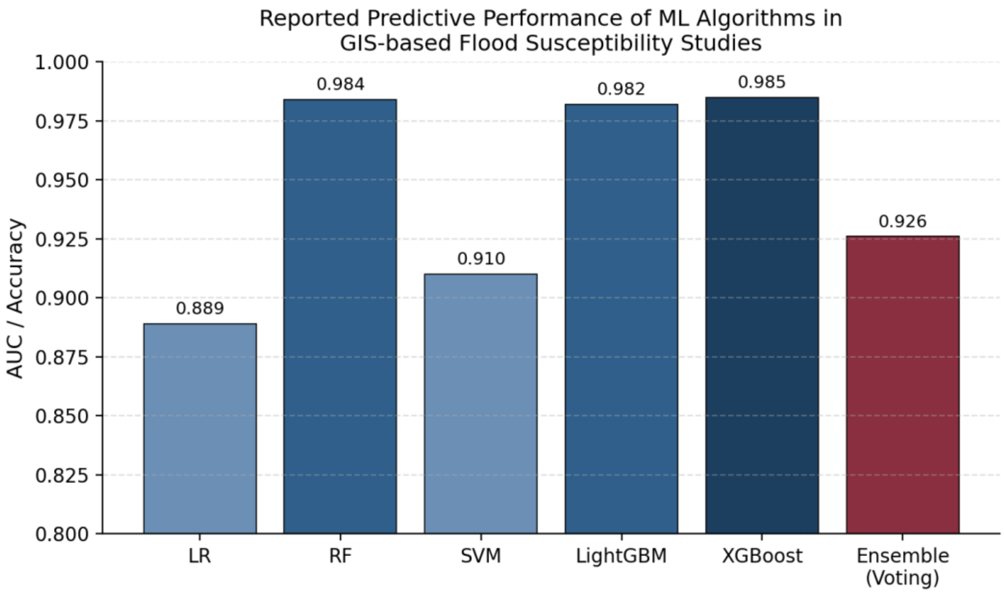

Figure 2: Reported predictive performance (AUC/accuracy) of machine-learning algorithms used for GIS-based flood susceptibility mapping across the reviewed literature [18], [21]

- **Earthquake and Landslide Risk Modelling**

Seismic risk management has benefited from AI applications spanning liquefaction prediction, structural damage classification, P-wave early-detection, and post-earthquake search-and-rescue support [23]. A systematic review of AI and optimisation techniques in earthquake engineering found that gradient-boosting and random-forest models achieve strong predictive accuracy for liquefaction and slope-displacement problems, while convolutional and transformer-based deep-learning architectures have improved real-time earthquake detection and P-wave recognition, with several reported models exceeding 90 percent accuracy [23].

Earthquake-triggered landslides represent a particularly complex secondary hazard, historically under-modelled relative to direct seismic damage due to the difficulty of scaling slope-stability physics (e.g., Newmark analysis) across large, heterogeneous terrain [24]. A recent deep-learning model pre-trained on approximately 400,000 landslide records from 38 global seismic events demonstrated the ability to directly incorporate the real-time characteristics of a specific earthquake into susceptibility prediction at low computational cost, and was validated against the previously unseen 2022 Luding earthquake dataset [24], [29]. Hybrid architectures combining convolutional networks, long short-term memory layers, and spatial-attention mechanisms have similarly improved landslide susceptibility prediction by capturing both spatial and temporal dependencies in conditioning factors such as rainfall, slope, and lithology [26]. A systematic review of machine-learning-based landslide susceptibility mapping across twelve countries emphasised, however, that the completeness and quality of landslide inventory data remain a persistent constraint on model reliability, regardless of algorithmic sophistication [28].

- **Wildfire Detection and Monitoring**

Unmanned aerial vehicles equipped with deep-learning-based computer-vision models have become a prominent tool for early wildfire and smoke detection, offering higher flexibility and lower cost than traditional satellite-only monitoring [40], [44]. One-stage object-detection frameworks using mixed data-augmentation techniques have been developed to simultaneously identify fire and smoke in UAV imagery under variable lighting and vegetation conditions [40]. YOLO-family object detectors (YOLOv3 through YOLOv11) remain the dominant architecture family for this task, with recent YOLOv11-based implementations reporting mean-average-precision figures near 78 percent on complex fire-smoke datasets [41]. Semantic-segmentation approaches based on U-Net and DeepLab architectures, sometimes combined with semi-supervised pixel-contrastive learning to reduce labelled-data requirements, have further improved the pixel-level delineation of burned and smoke-affected areas [42]. Integrated UAV-IoT fire-classification systems have also been proposed specifically to reduce onboard power consumption while sustaining real-time recognition performance, extending operational flight time during extended monitoring missions [45].

- **Social Media and Big-Data Situational Awareness**

Beyond physical sensors, crowd-sourced data from social-media platforms has emerged as a complementary, low-cost data stream for disaster situational awareness [48], [49]. Natural-language-processing techniques, including sentiment analysis, topic modelling, and increasingly transformer-based models such as RoBERTa, are applied to extract actionable information — such as flood-affected locations, resource needs, and public sentiment — from large volumes of user-generated posts during unfolding crises [49]. A systematic review of NLP applications to disaster events found that the large majority of studies focused on analysing social-media text, with sentiment analysis, text classification, and information extraction being the most common analytical tasks [52]. Case studies analysing millions of disaster-related posts (for example, during Hurricane Harvey) have demonstrated that county-level breakdowns of social-media content can meaningfully inform response prioritisation before, during, and after an event [54].

- **Smart Cities and Digital-Twin-Enabled Resilience**

At the urban scale, AI-IoT-GIS integration is increasingly framed through the lens of digital twins — dynamic, continuously updated virtual replicas of physical city systems [31], [36]. Urban digital twins ingest real-time IoT sensor streams to analyse and visualise infrastructure dynamics, supporting applications from infrastructure-health monitoring and disaster response to traffic control and energy-network resilience [35]. A systematic review of AI-driven digital twins for sustainable building environments, synthesising 125 papers, found that digital-twin platforms increasingly incorporate AI and IoT jointly to optimise both energy performance and resilience-related decision-making [39]. Emerging "hazard-responsive" digital-twin frameworks further extend this concept toward climate-driven urban resilience and equity considerations, explicitly modelling cascading infrastructure interdependencies during hazard events such as hurricanes [38].

Mathematical and Analytical Framework

This section presents core quantitative formulations commonly used across the reviewed literature for spatial risk indexing, sensor-network reliability, IoT data-throughput planning, and machine-learning performance evaluation, together with original worked numerical examples to illustrate their application.

- **GIS Multi-Criteria Flood Risk Index (Weighted Overlay / AHP)**

A common approach for combining multiple geospatial hazard-conditioning factors into a single composite risk score is the weighted linear combination used in AHP-based flood-risk mapping [16]. For a location (pixel or zone) with n contributing factors, the composite Flood Risk Index (FRI) is calculated as:

$$FRI = \Sigma_{i=1}^{n} (w_i \times x_i)$$

where w_i is the normalised AHP weight of factor i (with $\Sigma w_i = 1$) derived from pairwise comparison of factor importance, and x_i is the standardised (0–1) score of factor i at that location (e.g., rainfall intensity, slope, elevation, distance to drainage, land-cover permeability) [16]. Locations are then classified into risk classes (e.g., very low, low, moderate, high, very high) using natural-breaks or quantile classification of the resulting FRI surface.

Worked example

Consider a hypothetical grid cell evaluated using four AHP-weighted factors: rainfall intensity (w = 0.35), slope (w = 0.25), distance to drainage (w = 0.20), and land-cover imperviousness (w = 0.20), with standardised scores of 0.80, 0.60, 0.70, and 0.50 respectively. Applying the formula above:

FRI = (0.35 × 0.80) + (0.25 × 0.60) + (0.20 × 0.70) + (0.20 × 0.50)

FRI = 0.280 + 0.150 + 0.140 + 0.100 = 0.670

An FRI of 0.670 (on a 0–1 scale) would typically fall within the "high risk" class under a standard five-class natural-breaks scheme (e.g., very low < 0.2, low 0.2–0.4, moderate 0.4–0.6, high 0.6–0.8, very high > 0.8), indicating that this location warrants priority inclusion in early-warning coverage and evacuation planning.

Table 2: Worked example of AHP-weighted Flood Risk Index calculation for a hypothetical grid cell

Factor	Weight (w_i)	Standardised score (x_i)	Weighted contribution
Rainfall intensity	0.35	0.80	0.280
Slope	0.25	0.60	0.150
Distance to drainage	0.20	0.70	0.140
Land-cover imperviousness	0.20	0.50	0.100
Total (FRI)	1.00	—	0.670

- **Machine-Learning Model Evaluation Metrics**

  Reviewed hazard-susceptibility studies most commonly evaluate model performance using accuracy, precision, recall, F1-score, and the area under the receiver-operating-characteristic curve (AUC), derived from the confusion matrix of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) [18], [21]:

  Accuracy = (TP + TN) / (TP + TN + FP + FN)

  Precision = TP / (TP + FP)

  Recall (Sensitivity) = TP / (TP + FN)

  F1-score = 2 × (Precision × Recall) / (Precision + Recall)

Worked example

Suppose a landslide-susceptibility classifier is validated on 500 held-out grid cells, of which 180 are historically documented landslide occurrences (positives) and 320 are stable (negatives). The model correctly classifies 162 landslide cells (TP), misses 18 (FN), correctly classifies 290 stable cells (TN), and misclassifies 30 stable cells as landslide-prone (FP). Applying the formulas above:

Accuracy = (162 + 290) / 500 = 452 / 500 = 0.904 (90.4%)

Precision = 162 / (162 + 30) = 162 / 192 = 0.844 (84.4%)

Recall = 162 / (162 + 18) = 162 / 180 = 0.900 (90.0%)

F1-score = 2 × (0.844 × 0.900) / (0.844 + 0.900) = 1.520 / 1.744 = 0.871 (87.1%)

These computed values (accuracy 90.4%, F1-score 87.1%) fall within the typical performance envelope reported by the reviewed geospatial deep-learning and ensemble-tree landslide and flood models, which commonly report accuracies in the 85–98 percent range depending on data quality and study area [21], [26], [27].

- **IoT Sensor Network Data-Throughput and Latency Estimation**

Designing an IoT early-warning network requires estimating the aggregate data throughput generated by a distributed sensor array to correctly size bandwidth and gateway capacity [11], [12]. For a network of N sensor nodes, each transmitting a payload of size p (bytes) at sampling interval t (seconds), the required network throughput T (bits per second) is:

$$T = (N \times p \times 8) / t$$

Worked example

Consider a river-basin flood monitoring deployment with N = 150 water-level sensor nodes, each transmitting a compact payload of p = 32 bytes (comprising node ID, timestamp, and water-level reading) every t = 60 seconds, consistent with typical LoRaWAN-based flood-sensor configurations [11], [12]. The required throughput is:

$$T = (150 \times 32 \times 8) / 60 = 38{,}400 / 60 = 640 \text{ bits/second } (\approx 0.64 \text{ kbps})$$

This is well within the capacity of low-power wide-area protocols such as LoRaWAN (typically supporting from 0.3 kbps up to 50 kbps depending on spreading factor), confirming that low-bandwidth, energy-efficient communication technologies are technically sufficient for large-scale, sparse-payload environmental sensor networks of this kind [11].

- **Sensor Network Reliability**

The operational reliability of an IoT early-warning system depends on the combined reliability of its individual components (sensing nodes, gateways, and communication links). For a series-connected chain of k critical components each with independent reliability r_j, overall system reliability R is:

$$R = r_1 \times r_2 \times r_3 \times \ldots \times r_k = \prod_{j=1}^{k} r_j$$

while redundant (parallel) deployment of m independent nodes covering the same critical location — a common design pattern to mitigate single-point sensor failure — yields a substantially higher combined reliability:

$$R\_parallel = 1 - \prod_{j=1}^{m} (1 - r_j)$$

Worked example

If an individual water-level sensor node has a field reliability of r = 0.90 (i.e., a 90% probability of functioning correctly during a flood event, accounting for power, connectivity, and hardware failure risks), a single-sensor deployment at a critical location has R = 0.90. Deploying two redundant, independent sensors at the same location instead yields:

$$R\_parallel = 1 - (1 - 0.90) \times (1 - 0.90) = 1 - (0.10 \times 0.10) = 1 - 0.01 = 0.99 \ (99\%)$$

This illustrates why redundant sensor placement at high-consequence monitoring points (e.g., major dam spillways or densely populated river bends) is a recurring design recommendation in the reviewed IoT-DRM literature, since it substantially raises the probability that a genuine hazard signal will be captured despite individual node failure [7], [13].

- **Summary of Worked Calculations**

Table 3: Summary of worked numerical examples presented in Section 6

Calculation	Key inputs	Result	Interpretation
Flood Risk Index (§6.1)	4 AHP-weighted factors	FRI = 0.670	High-risk classification
Landslide classifier metrics (§6.2)	500 validation cells (TP=162, FP=30, TN=290, FN=18)	Accuracy 90.4%, F1 87.1%	Within literature-reported performance range
IoT network throughput (§6.3)	150 nodes, 32-byte payload, 60 s interval	≈ 0.64 kbps	Compatible with LoRaWAN/NB-IoT capacity
Sensor redundancy reliability (§6.4)	2 nodes, r = 0.90 each	99.0% (vs 90.0% single node)	Justifies redundant sensor placement

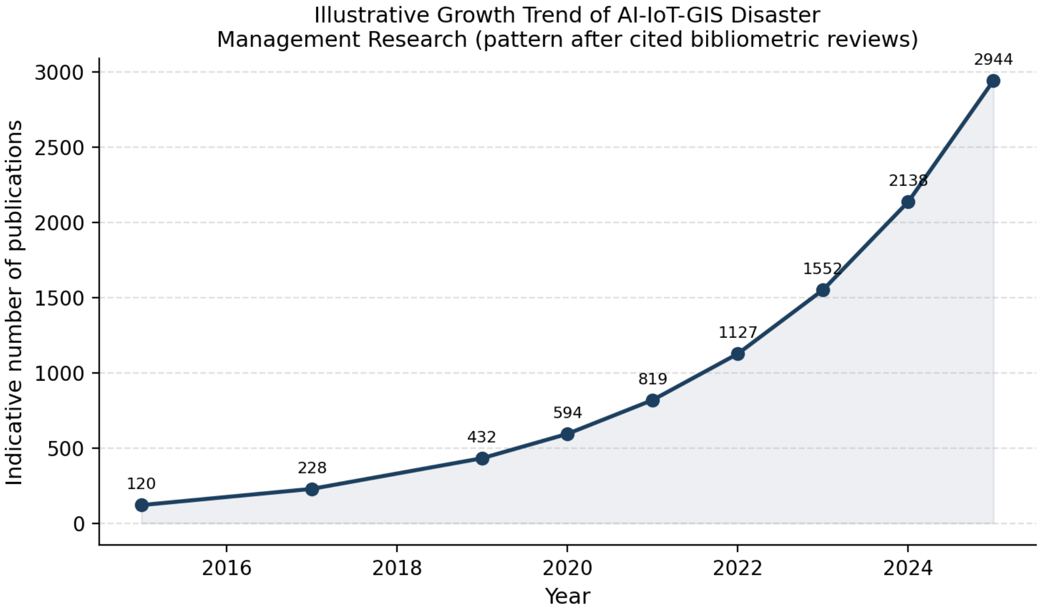

Figure 3: Illustrative growth pattern of AI-IoT-GIS disaster-management research output, consistent with the exponential post-2020 growth trend reported in bibliometric reviews [1], [2].

Comparative Synthesis of Reviewed Studies

Table 4 synthesises representative studies across the five thematic areas identified in Section 5, summarising the primary technologies, hazard focus, and reported outcomes. This comparative view highlights that machine-learning ensemble methods (random forest, XGBoost, LightGBM) and convolutional/recurrent deep-learning architectures dominate the predictive-modelling literature, while LoRaWAN- and MQTT-based communication stacks dominate the IoT sensing layer, and AHP-weighted overlay together with ML-derived susceptibility surfaces dominate the GIS layer [16], [18], [21], [26], [40].

Table 4: Comparative synthesis of representative studies by thematic area

Theme	Representative technologies	Hazard focus	Key reported outcome	Source(s)
Flood susceptibility mapping	RF, XGBoost, LightGBM, SVM, AHP	Riverine & urban flood	AUC up to 0.985	[18],[21]
Landslide susceptibility	CNN-LSTM-SAM hybrid, XAI-DL	Rainfall & seismic landslides	Improved spatio-temporal accuracy	[24],[26],[29]
Earthquake engineering	XGBoost, RF, CNN, transformers	Liquefaction, P-wave detection	Accuracy > 90% in several studies	[23]
Wildfire detection	YOLOv3–YOLOv11, U-Net, DeepLab	Forest & wildland fire	mAP ≈ 78%, real-time UAV detection	[40],[41],[42]
IoT early warning	LoRaWAN, NB-IoT, MQTT, Zigbee	Flood, seismic, storm	Sub-hour to multi-hour lead time	[11],[12],[13]
Social-media situational awareness	NLP, sentiment analysis, RoBERTa	Hurricanes, floods, wildfires	County-level actionable insight	[49],[52],[54]
Digital-twin smart cities	IoT + AI + 3D GIS models	Multi-hazard urban resilience	Cross-phase disaster-lifecycle support	[31],[34],[38]

Challenges and Limitations

Despite substantial progress, several recurring challenges constrain the operational maturity of integrated AI-IoT-GIS DRM systems. First, data interoperability remains a persistent obstacle: sensor data, satellite imagery, and administrative GIS layers are frequently stored in incompatible formats and coordinate systems across agencies, complicating real-time fusion [3], [14]. Second, IoT sensor networks deployed in remote or disaster-prone regions face constraints of limited power supply, intermittent connectivity, and hardware durability under extreme environmental stress, all of which can degrade the reliability calculations discussed in Section 6.4 [7], [13]. Third, landslide and flood susceptibility models depend heavily on the completeness and quality of historical hazard inventories; incomplete or spatially biased inventories introduce systematic uncertainty into otherwise high-performing machine-learning models [28].

A further concern that cuts across all three technology layers is cybersecurity. Integrated AI-IoT-GIS platforms aggregate continuous streams of sensitive geolocation, infrastructure, and personal data, which enlarges the attack surface available to malicious actors and raises the stakes of a successful breach during an active disaster response [57]. Analyses of the evolving cyber-threat landscape emphasise that network-connected sensor devices are frequently deployed with weak default security configurations, and that privacy-preserving design and robust network security practices must be treated as first-class requirements rather than afterthoughts in mission-critical disaster-management infrastructure [57].

Fourth, algorithmic transparency and explainability remain limited in many deep-learning-based hazard models, which can undermine trust among emergency-management decision-makers who require interpretable justification for high-stakes evacuation or resource-allocation decisions [26]. Explainable AI (XAI) techniques are increasingly being incorporated to address this gap, but their adoption in operational DRM contexts is still nascent [26]. Fifth, ethical and equity concerns arise around social-media-based situational awareness, since crowd-sourced data streams tend to over-represent digitally connected, urban populations, potentially marginalising rural or lower-connectivity communities in AI-derived situational pictures [49], [52]. Finally, the digital divide between well-resourced and under-resourced regions affects the practical adoption of these integrated systems, with high-income and technologically mature regions such as parts of Asia, Europe, and North America dominating both the research output and pilot deployments reviewed in this study [2], [49].

Future Research Directions

Building on the identified gaps, several directions merit continued research attention. Federated-learning approaches, which allow AI models to be trained across distributed IoT and institutional data sources without centralising raw data, offer a promising route to improving model robustness while addressing data-privacy and interoperability concerns simultaneously [33], [37]. Edge-AI deployment — running lightweight inference models directly on IoT gateways or UAV platforms — can reduce latency and bandwidth dependence, which is particularly valuable for fast-onset hazards such as flash floods and wildfires [37], [45]. Continued development of hazard-responsive digital twins that couple real-time IoT feeds with physics-informed simulation and GIS visualisation is likely to extend anticipatory capability beyond current early-warning thresholds toward genuinely predictive "what-if" scenario planning [38], [39]. Finally, greater attention to explainable and equity-aware AI, together with investment in low-cost sensor infrastructure for under-resourced regions, will be necessary to ensure that the benefits of AI-IoT-GIS integration are distributed broadly rather than concentrated in already well-resourced areas [26], [49].

Conclusion

This systematic review has synthesised 57 recent sources examining the integration of Artificial Intelligence, the Internet of Things, and Geographic Information Systems for smart disaster risk management. The evidence indicates that AI provides the predictive and analytical engine, IoT provides continuous real-time sensing, and GIS provides the spatial context that binds model outputs to actionable, location-specific decisions [3], [14]. Across flood, earthquake, landslide, and wildfire applications, integrated systems consistently outperform single-technology approaches in prediction accuracy, response lead time, and situational awareness [18], [21], [26], [40]. The mathematical formulations and worked examples presented in Section 6 illustrate that even modest, well-designed sensor networks and multi-criteria spatial models can achieve strong reliability and predictive performance at low computational and infrastructural cost. Nonetheless, data interoperability, algorithmic transparency, sensor-network resilience, and equitable access remain open challenges that will shape the next generation of smart disaster risk management research and practice.

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