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From Mapping to Prediction: A Conceptual Framework for Digital Surveying in Disaster Management

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Abstract: ***Disasters caused by natural and human activities are increasing in frequency and complexity, requiring geospatial systems that go beyond post-event mapping to enable prediction and proactive measures. This paper discusses how digital surveying can become a predictive tool for disaster management by integrating technologies such as Geographic Information Systems, remote sensing, Global Navigation Satellite Systems, unmanned aerial vehicles, LiDAR, Internet of Things sensors, artificial intelligence, and digital twins. These advancements establish a continuous spatial-temporal process that converts raw data into valuable insights. The paper introduces a conceptual framework with six interconnected stages: data collection from various sources, data integration into unified platforms, analytics for identifying patterns, risk scenario prediction, decision support through visualizations, and feedback loops for system enhancement. Despite challenges like data interoperability, quality assurance, technical skill gaps, infrastructure limitations in developing regions, and privacy concerns, this predictive approach ultimately boosts disaster resilience through better situational awareness, informed decision-making, and timely risk mitigation across all phases of management.***

Keywords: Digital surveying, disaster management, predictive frameworks, geospatial technologies, disaster resilience.

1. Introduction

In recent decades, the world has seen a rise in both the number and severity of disasters caused by natural and human activities. Events such as floods, earthquakes, cyclones, landslides, droughts, and wildfires have affected communities, damaged infrastructure, and resulted in significant economic losses. Rapid urbanisation, environmental degradation, and changing climate patterns have further increased the frequency and complexity of these disasters (Haen & Hemrich, 2007; Schardong et al., 2019). In this context, reliable geospatial information has become essential for effective decision-making at all stages of disaster management. Traditionally, surveying has played a crucial role in documenting the impacts of disasters and supporting recovery efforts. Surveyors gathered field measurements, created maps, and identified affected areas (Bray et al., 2019; Ebrahim, 2025; Vučić et al., 2018). However, these methods were mostly static and typically depicted conditions only after a disaster had occurred.

The development of digital technologies has significantly transformed this role. With the integration of advanced sensors, computing systems, and data analysis tools, digital surveying now enables a more dynamic understanding of the Earth's surface (Bray et al., 2019; Ebrahim, 2025; Falcone & Dell'Annunziata, 2023). However, a gap remains between digital surveying as a data-collection activity and its potential as a predictive analytical system. Although geospatial tools such as Geographic Information Systems and Remote Sensing are widely used for post-disaster mapping, their application in prediction and early warning remains limited (Jain, 2024; Mitsova, 2018). This paper aims to address this gap by presenting a conceptual framework that explains how digital surveying can transition from simple mapping to a predictive role in disaster management. The proposed model describes a continuous process involving data collection, analysis, prediction, decision support, and feedback, demonstrating that geospatial systems can help anticipate disasters and mitigate their impacts rather than merely document them after they occur.

2. Digital surveying in disaster management

In its early stages, surveying was primarily used to document the physical environment after disasters. Surveyors measured damaged buildings, mapped flood areas, and identified landslides or fault lines. This information was compiled into maps and reports to assist governments and aid agencies in assessing damage and planning recovery. Although these records were valuable for documentation and compensation, they were mostly static and did not show how landscapes and hazards change over time (Fan et al., 2020; Scheip & Wegmann, 2021).

With digital technologies, surveying has extended beyond post-disaster documentation. Real-time data collection using satellites, drones, and ground sensors now allows for continuous monitoring of environmental changes (Kumar & Shankar, 2024; Perfetti et al., 2018). Dynamic mapping can track flood levels, land subsidence, vegetation stress, and soil moisture, which are key indicators of changing risk (Cozannet et al., 2020; McCallum et al., 2016). This development signifies a shift from static to more dynamic mapping, in which survey data can support prediction. Instead of solely recording past events, modern digital surveying combines data collection, analysis, and modelling with advanced tools like Machine Learning, Big Data, and Digital Twin (Döllner, 2020; Sagandykova et al., 2024; Xu & Diao, 2023). Consequently, surveying is becoming a continuous process that enhances understanding of disaster risks and aids in better planning and response.

3. Technological Foundations of Predictive Digital Surveying

Digital surveying depends on several interconnected technologies to support prediction and decision-making (Ebrahim, 2025). Geographic Information Systems (GIS) provide the main spatial framework for organising, visualising, and analysing geographically referenced data (Gwani et al., 2024). Modern GIS platforms support time-based layers, allowing the study of how spatial patterns change over time. Remote sensing enhances this by collecting data from satellites and airborne sensors, offering rapid coverage of large areas (Hostettler et al., 2018). Through multi-temporal analysis, remote sensing can identify changes in land cover, water levels, and temperature patterns that may signal early stages of disasters such as droughts, floods, or wildfires (Ahmadi et al., 2023; Kumar & Shankar, 2024; Westen, 2000). The Global Navigation Satellite System also plays a key role by providing accurate positioning and tracking of movement. Advanced techniques like Interferometric Synthetic Aperture Radar can measure very small ground movements, often detecting surface deformation months before visible damage occurs, aiding in predicting landslides, earthquakes, and land subsidence (Bernardi et al., 2021; Kamali et al., 2020; Milev et al., 2023; Sneed & Brandt, 2007).

Other technologies enhance local monitoring and real-time data collection. Unmanned Aerial Vehicles offer flexible, high-resolution imaging, especially useful in areas that are difficult or dangerous to access during disasters (Chen, 2024; Gomez & Purdie, 2016). LiDAR produces detailed three-dimensional models of terrain and infrastructure, which are vital for studying flood paths, debris flows, and structural risks (Twumasi et al., 2019). Simultaneously, the Internet of Things enables networks of sensors to continuously record data such as rainfall, soil moisture, river levels, and temperature (Bakhtiari et al., 2025; Fan et al., 2023). These real-time observations feed predictive models through cloud-based systems. Innovations like GeoAI and Digital Twin further enhance these capabilities by leveraging machine learning and simulations to analyse complex spatial patterns and evaluate potential disaster scenarios (Ghaffarian, 2025; Jain, 2024; Ma et al., 2024). Together, these technologies form an integrated system that transforms spatial data into predictive insights for disaster management.

4. Proposed conceptual framework for digital surveying in disaster management

The conceptual framework proposed envisions digital surveying as a continuous cycle with six interconnected components: data acquisition, data integration, data analytics, prediction, decision support, and feedback. The framework is illustrated in Figure 1.1.

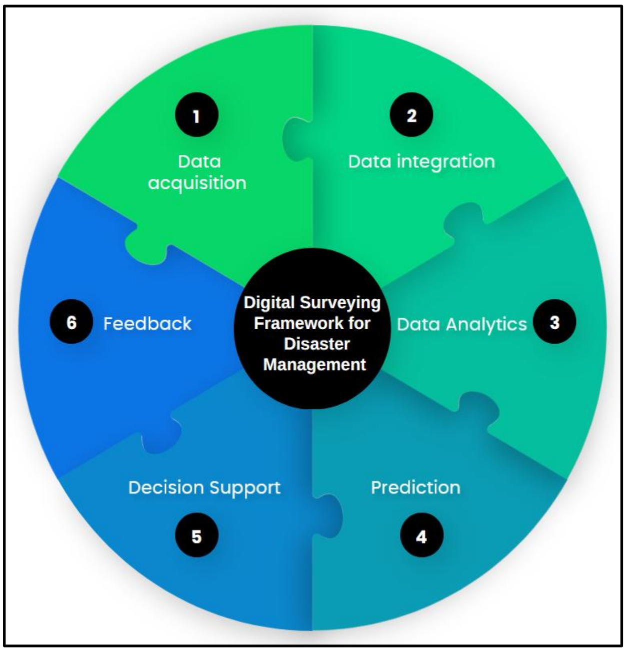

Figure 1.1: Digital Surveying Framework for Disaster Management

4.1 Data acquisition

It forms the foundation. The process begins with collecting raw spatial data from multiple sources, both terrestrial and remote. Survey-grade GNSS receivers, UAV photogrammetry, LiDAR scanning, and sensor networks gather information about terrain, infrastructure, and environmental conditions. Because each technology offers a unique scale, resolution, and frequency, integrating these data streams produces a comprehensive spatial-temporal picture.

4.2 Data integration

Data integration involves organising and harmonising information collected from diverse platforms into a unified digital environment. This requires careful attention to coordinate systems, data compatibility, and metadata standards. Cloud-based GIS and databases now enable linking real-time sensor feeds to archived spatial datasets, producing a dynamic map that reflects both historical records and current states (Vasilev et al., 2024).

4.3 Data Analytics

Data Analytics refers to the stage where data is processed and interpreted. It includes image classification, change detection, pattern recognition, and anomaly detection. The use of big data analytics and artificial intelligence greatly enhances this step by identifying correlations between environmental changes and hazard indicators (Kumar et al., 2024). For example, a combination of rainfall intensity, soil moisture indices, and slope angle extracted from LiDAR can be analysed to predict potential landslide initiation zones.

4.4 Prediction

Prediction occurs when analytical outputs are further modelled to simulate future conditions. Here, digital twins are particularly useful because they connect physical sensors to virtual models, allowing continuous collection of real-world data and updating projections. (Eramo et al., 2021; Mulder et al., 2022). Predictive analysis turns digital surveying into an anticipatory system that provides early warning signals and risk scenarios before disasters happen.

4.5 Decision Support

Decision support is the next stage, where information from predictive models is transformed into operational insights. Decision-makers can use these outputs to prioritise evacuation routes, allocate resources, or plan emergency responses (Domfeh & Dancy, 2025; Suárez et al., 2024). Visualisation tools, dashboards, and scenario-based simulations help make complex data understandable to non-technical users.

4.6 Feedback

Feedback completes the cycle. Once an event occurs, actual field observations and outcomes are compared with predicted results. This feedback process enhances model accuracy, updates parameters, and ensures that the system learns and adapts. The framework, therefore, represents a continuous loop from observation to decision, keeping digital surveying active and self-correcting.

5. Application across Disaster Management Phases

The proposed framework enhances each stage of the disaster management cycle: mitigation, preparedness, response, and recovery.

During the mitigation phase, predictive digital surveying helps identify risk zones and inform the development of land-use policies. By analysing hazards and population exposure through spatial analysis, authorities can steer development away from vulnerable areas (Raduszynski & Numada, 2023). For example, flood simulation models that incorporate long-term rainfall data can assist in designating buffer zones along riverbanks and prevent unplanned urban growth in floodplains.

In the preparedness phase, the framework supports early warning and scenario planning. Continuous monitoring of environmental indicators enables the timely issuing of alerts when thresholds are exceeded. Digital twins of urban areas can be used for simulated evacuations, helping local authorities test emergency plans before an actual crisis (Elsehrawy et al., 2021). Communities can also benefit from participatory mapping that incorporates local knowledge into predictive models, improving their accuracy and acceptance.

During the response phase, quick and precise situational awareness is essential. UAVs can rapidly survey affected areas, creating updated maps of accessibility, damage, and infrastructure condition. Sensor networks send real-time data on water levels or ground movement, enabling emergency teams to adapt their actions dynamically (Kedia et al., 2020). GIS-based dashboards combine these data streams into a unified operational picture, facilitating coordination and communication between agencies (Okem et al., 2024).

Finally, during the recovery phase, digital surveying continues to serve as a monitoring tool. Repeating LiDAR or photogrammetric surveys can assess reconstruction progress and identify structural vulnerabilities that may have appeared after the event (Giardina et al., 2023). Updated models also aid in risk reassessment and long-term planning. This way, the predictive framework ensures that lessons learned from each event are integrated to improve preparedness for future incidents.

6. Implementation Challenges

Implementing a predictive digital surveying framework at scale involves several practical and institutional challenges. One major issue is interoperability. The data collected by different organisations and instruments often use different formats and standards, making integration difficult. Developing common data standards and shared protocols is essential for effective collaboration (Snowden et al., 2019). Data quality is another concern, as predictive models depend on accurate, consistent, and high-resolution information. Errors in calibration, differences in time intervals, or missing data can affect prediction accuracy, so strong quality control and proper metadata documentation are necessary (Ijeh et al., 2024). Limited technical capacity and infrastructure also create barriers, especially in developing regions where cloud computing resources, high-speed internet, and advanced sensors may be unavailable or too expensive. Governance and ethical issues must also be considered, since spatial data may include personal or sensitive information, particularly when collected from mobile devices or social media. Protecting privacy, ensuring consent, and maintaining data security are therefore important. In addition, clear data sharing policies and international guidelines, such as those promoted by the United Nations Committee of Experts on Global Geospatial Information Management, can help balance data access with protection (Ghamisi et al., 2024). Finally, training and interdisciplinary collaboration among surveyors, computer scientists, disaster managers, and policymakers are necessary to realise the full predictive potential of digital surveying.

7. Future Directions

The future of predictive digital surveying is heading toward more autonomy, intelligence, and integration. As artificial intelligence advances, predictive models will automatically learn from new data and improve as environmental conditions change. Autonomous data collection systems, such as drones equipped with multiple sensors, can conduct surveys before, during, and after disasters using AI-based flight planning. In contrast, ground-based IoT sensor networks offer continuous monitoring across various scales (Domfeh & Dancy, 2025). Another key development is the concept of digital risk twins, which are dynamic models that represent not only physical infrastructure but also social and economic systems, helping simulate disaster impacts and enhance preparedness strategies. Future advancements will also rely on stronger collaboration between governments, academic institutions, and the private sector through shared cloud-based geospatial platforms that enable real-time data sharing and analysis. With the support of open-source platforms and common standards, predictive digital surveying can become more accessible and help build a global system to forecast and reduce disaster risks.

8. Conclusion

The shift from mapping to prediction signifies a key technological and conceptual change in disaster management. Digital surveying, once primarily used for static observation, has now evolved into an integrated predictive system that supports early warning, real-time monitoring, and post-disaster assessment. The framework outlined in this paper explains this transition through a continuous cycle of data collection, integration, analysis, prediction, decision-making, and feedback. By placing digital surveying in a predictive and participatory context, the framework underscores its value not only for scientists and engineers but also for planners, emergency services, and local communities. As digital technologies continue to advance, the combination of autonomous sensors, artificial intelligence, and digital twins will further enhance our ability to anticipate and respond to environmental challenges. In this way, predictive digital surveying can play a crucial role in building a resilient disaster management system that safeguards people, infrastructure, and ecosystems through timely and informed actions.

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