Revue Internationale
de Géomatique

Tech Science Press

DOI: 10.32604/rig.2024.053857

REVIEW

Multi-Aspect Critical Assessment of Applying Digital Elevation Models in Environmental Hazard Mapping

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Received: 11 May 2024 Accepted: 08 July 2024 Published: 07 August 2024

ABSTRACT

Digital elevation models (DEMs) are essential tools in environmental science, particularly for hazard assessments and landscape analyses. However, their application across multiple environmental hazards simultaneously remains in need for a multi-aspect critical assessment to promote their effectiveness in comprehensive risk management. This paper aims to review and critically assess the application of DEMs in mapping and managing specific environmental hazards, namely floods, landslides, and coastal erosion. In this regard, it seeks to promote their utility of hazard maps as key tools in disaster risk reduction and environmental planning by employing high-resolution DEMs integrated with advanced geographic information systems. The findings offer valuable insights into optimizing DEM technology for environmental management, contributing to safer and more resilient communities. The paper addresses an important gap in the geospatial analysis of natural hazards and serves as a foundational reference for future advancements in the field, emphasizing its importance to academic researchers and practical stakeholders in environmental and disaster management.

KEYWORDS

Hazard mapping; flood risk assessment; DEM; geographic information systems (GIS); multi-hazard assessment; disaster risk reduction; landslide susceptibility; coastal erosion analysis

1 Introduction

Integrating digital elevation models (DEMs) into environmental hazard mapping represents a pivotal development in geospatial sciences [1–4]. DEMs are essential tools for accurately assessing and managing environmental hazards such as floods [5,6], landslides [7–9], and coastal erosion [10–13]. They are widely used in environmental-related studies, particularly in hydrological and hydraulic models, where the high resolution of these models significantly affects the accuracy of hazard assessments [13–16]. Their importance is underscored by the increased frequency of these hazards, driven by climate change and urban expansion. DEMs are fundamental in determining landscapes and analyzing topography and are instrumental in enhancing the precision and utility of hazard maps, which are vital tools in disaster risk reduction [17–20]. DEMs provide fundamental elevation data that enable researchers to identify regions susceptible to environmental hazards by determining watershed boundaries, identifying flood plains, highlighting seismic affected areas, and recognizing steep slopes that can predispose areas to landslides [21–23]. Recent studies have emphasized the role of DEM resolution in the performance of machine learning models for predicting flood probabilities, indicating that finer resolutions can substantially improve prediction accuracy [24–27]. In addition, the technological advancements in DEMs have expanded their application in environmental management [28–30]. This includes the fusion of multiple DEM sources to enhance model accuracy, which has proven essential in refining the precision of hazard maps crucial for disaster risk planning [31,32]. In addition, integrating DEMs with geographic information systems (GIS) has revolutionized environmental planning and hazard management, allowing for more detailed and accurate mapping and significantly enhancing disaster preparedness and response strategies [9, 33–35]. The use of LiDAR-derived DEMs has been highlighted for its effectiveness in flood applications, providing detailed and accurate topographical data that improve flood risk assessments [36,37]. Integrating UAV-derived DEMs demonstrates substantial potential, particularly in small-scale hazard mapping and monitoring geo-hazards in challenging terrains [38,39].

Although the utility of DEMs in hazard mapping is well-established, existing literature reveals several current problems. One significant issue is the gap in the simultaneous application across various types of environmental hazards. Most studies focus on a single type of hazard, leading to deficiency in comprehensive risk assessments that integrate high-resolution DEMs with other geospatial technologies across multiple hazard types. This lack of integration limits the ability to provide a holistic view of environmental risks, which is crucial for effective disaster preparedness. In addition, there is a gap in the application of machine learning techniques in enhancing DEM-based environmental hazard mapping. Machine learning methods can significantly improve the predictive accuracy of hazard maps by learning complex patterns from large and diverse datasets that traditional methods cannot capture. These techniques can refine the resolution and accuracy of DEMs, optimize hazard prediction models, and facilitate the development of more robust and comprehensive hazard assessment tools [40–42].

The potential for machine learning in this context is vast, as it can analyze the interactions between multiple hazard types and their environmental impacts more efficiently than conventional statistical methods. For instance, Su et al. [43] demonstrated the application of deep learning for assessing earthquake disaster chains, suggesting that similar methodologies can enhance multi-hazard models by integrating various data types and sources, including high-resolution DEMs. In addition, the integration of DEMs with other geospatial technologies, such as remote sensing and GIS, has been shown to effectively map hazards such as floods, landslides, and soil erosion, but the simultaneous use of these technologies across multiple hazard scenarios remains underexplored [44–47]. These gaps present significant opportunities for future research, where the development of integrated, multi-hazard assessment models can significantly increase the accuracy and efficiency of hazard maps, thus improving disaster risk management strategies. This study aims to review and critically assess the application of DEMs in mapping and managing specific environmental hazards, focusing on floods, landslides, and coastal erosion. The study seeks to enhance the accuracy and utility of hazard maps by employing high-resolution DEMs integrated with advanced GIS and innovative machine learning techniques. These improved maps are expected to provide more detailed and precise hazard assessments, crucial for effective disaster risk reduction and strategic environmental planning. In addition, the study aims to develop a robust framework that utilizes the combined capabilities of high-resolution DEMs, GIS, and machine learning to create a multi-hazard assessment tool, identifying potential hazard zones with greater precision and predicting the severity and probable impact of these hazards under various environmental scenarios. This approach intends to fill existing gaps in current hazard mapping practices, which often do not simultaneously consider multiple types of hazards or fully utilize the potential of modern technological advancements. The findings offer valuable insights into optimizing DEM technology for environmental management, contributing to safer and more resilient communities. This research addresses an important gap in the geospatial analysis of natural hazards and serves as a foundational reference for future advancements in the field, emphasizing its importance to academic researchers and practical stakeholders in environmental and disaster management.

2 Bibliometric Assessment

A bibliometric assessment was conducted to evaluate the existing literature on the application of DEMs in environmental hazard mapping. A search was performed on the Web of Science platform, yielding a total of 2110 documents relevant to the study. The temporal distribution of publications from 2000 to 2023 is illustrated in Fig. 1, showing a steady increase in research activity over the years, with growth after 2010. The analysis of keyword co-occurrence within these publications reveals the most frequently used terms, including "hazard," "GIS," "model," "LIDAR," "remote sensing," "uncertainty," "risk," "earthquake," "vulnerability," "climate change," "deformation," "landslide," "evolution," "susceptibility," and "logistic regression," as depicted in Fig. 2. These keywords highlight the multidisciplinary nature of the research and the integration of various technologies and methodologies in the field.

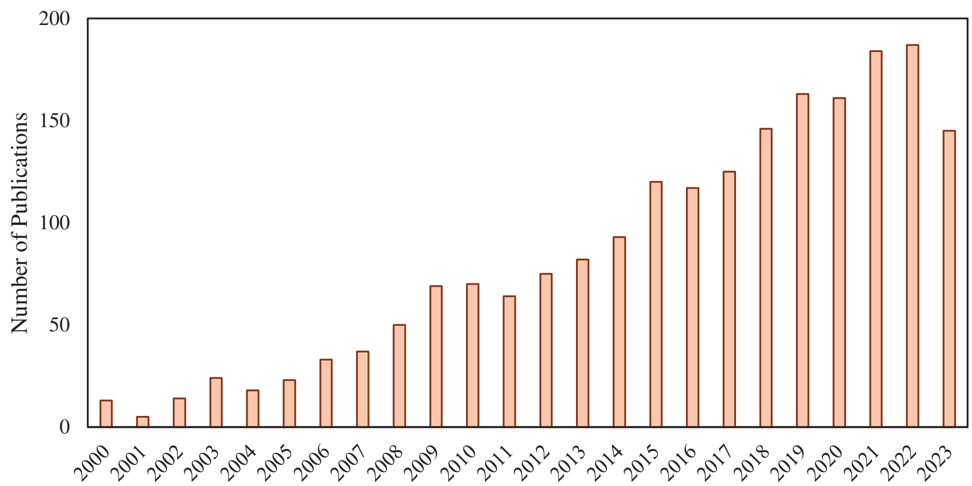


Figure 1: Number of publications related to DEM applications in environmental hazard mapping over the period between 2000 and 2023

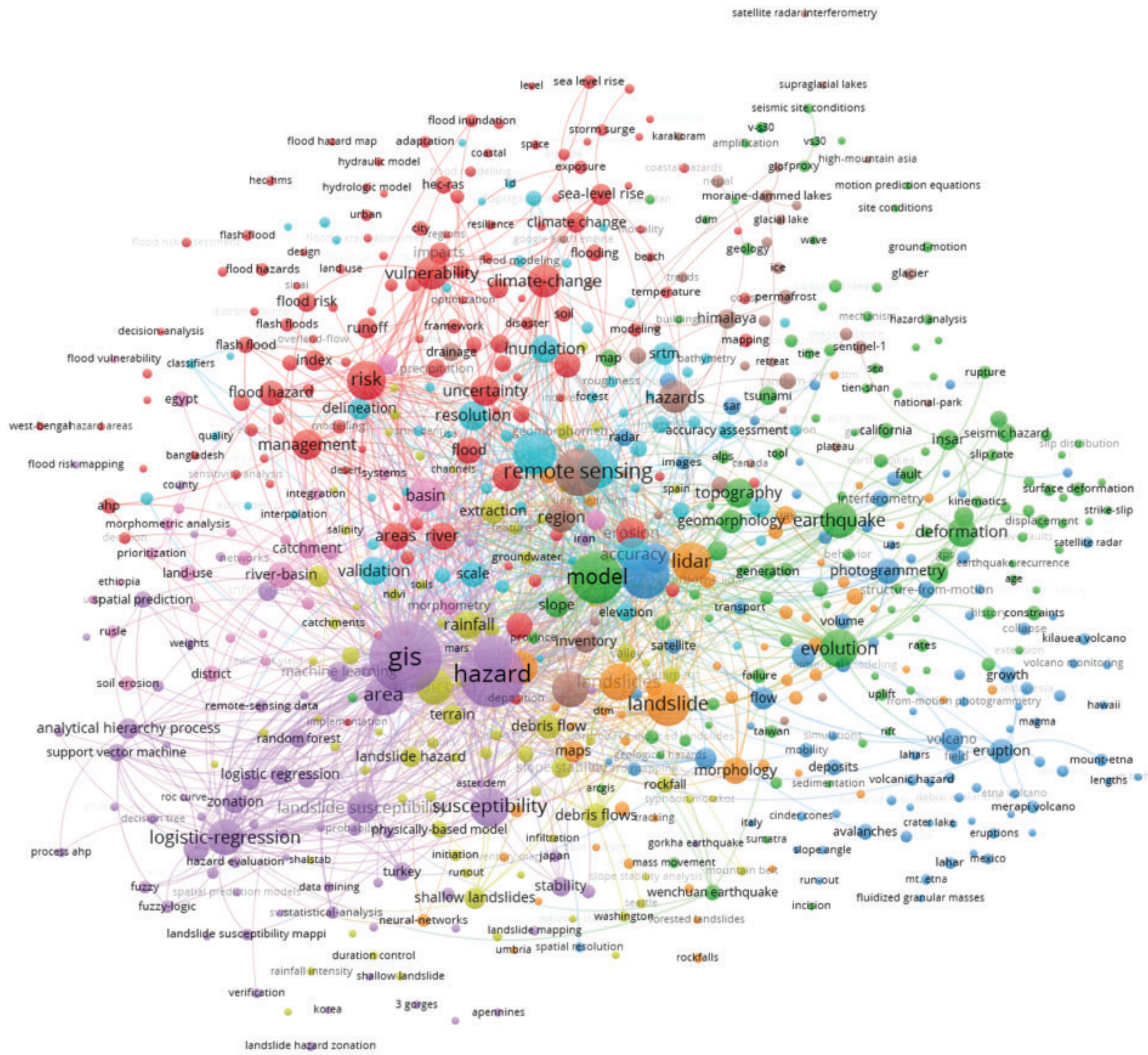


Figure 2: Co-occurrence of keywords in research related to DEM applications in environmental hazard mapping

Additionally, the assessment identified the journals that published the most research on DEM applications in environmental hazard mapping. The prominent journals include Natural Hazards and Earth System Sciences, Natural Hazards, Geomorphology, Remote Sensing, Landslides, Environmental Earth Sciences, Geomatics Natural Hazards and Risk, and ISPRS International Journal of Geo-Information, as shown in Fig. 3. These journals are pivotal in disseminating advancements and findings related to DEM applications in hazard mapping. Citation analysis by country, as presented in Fig. 4, indicates that China, the USA, Italy, Germany, England, France, India, and Switzerland are the leading contributors to this research domain. This geographical distribution underscores the global interest and collaboration in utilizing DEMs for environmental hazard assessment and management.

The bibliometric assessment demonstrates the evolving and expanding body of knowledge in the application of DEMs for environmental hazard mapping, emphasizing the importance of interdisciplinary approaches and international collaboration in advancing this critical field.

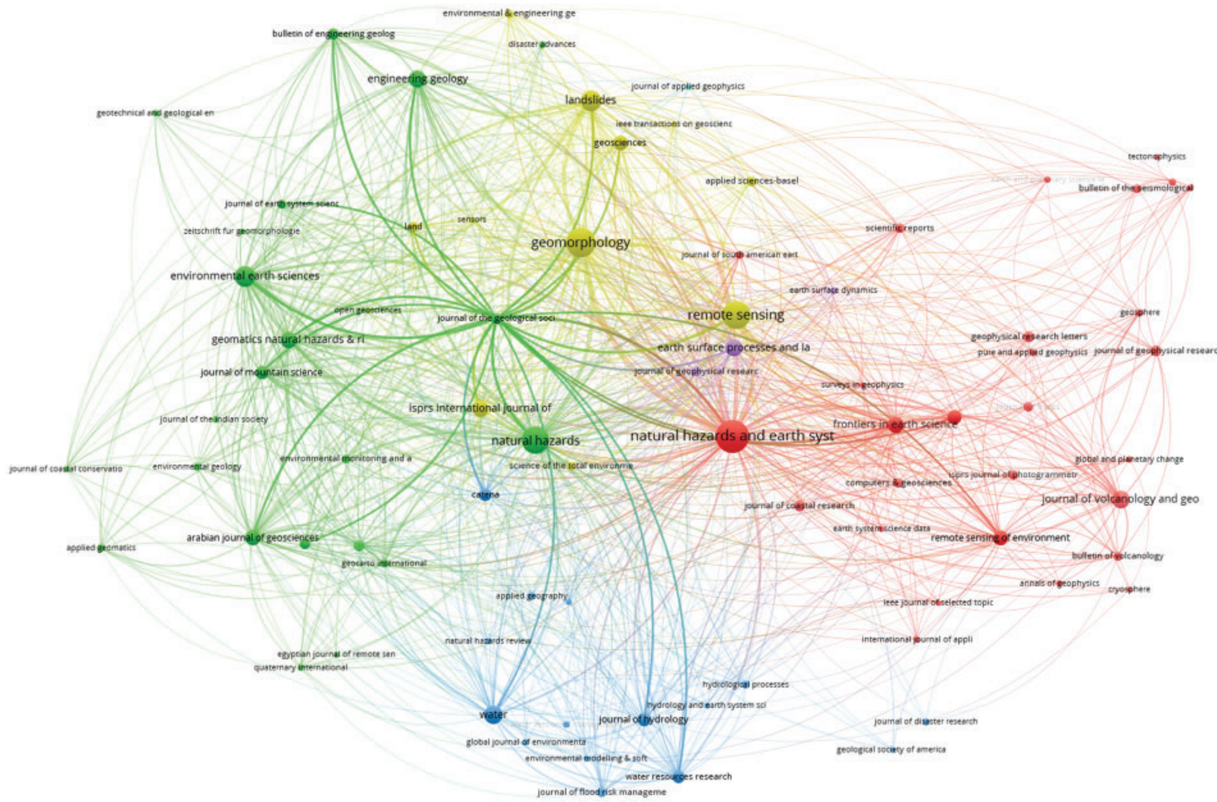


Figure 3: Journals with most publications of research related to DEM applications in environmental hazard mapping

3 Materials and Methods

This section outlines the materials and methods employed in the study to evaluate the effectiveness of DEMs in environmental hazard mapping. The methodology is designed to explore the integration of high-resolution DEMs with advanced GIS and machine learning techniques to enhance the accuracy and utility of hazard maps. Fig. 5a illustrates the integration process of DEMs, GIS, and machine learning in creating a comprehensive multi-hazard assessment tool. The framework is divided into several components, each representing a step in the process from data acquisition to hazard mitigation and planning. However, Fig. 5b describes the general approach applied in this study. This includes a step-by-step depiction of the operational workflow, which helps in understanding the systematic application of integrated technologies and methodologies to address the complexities of environmental hazard mapping and provides a clear roadmap for achieving the research objectives.

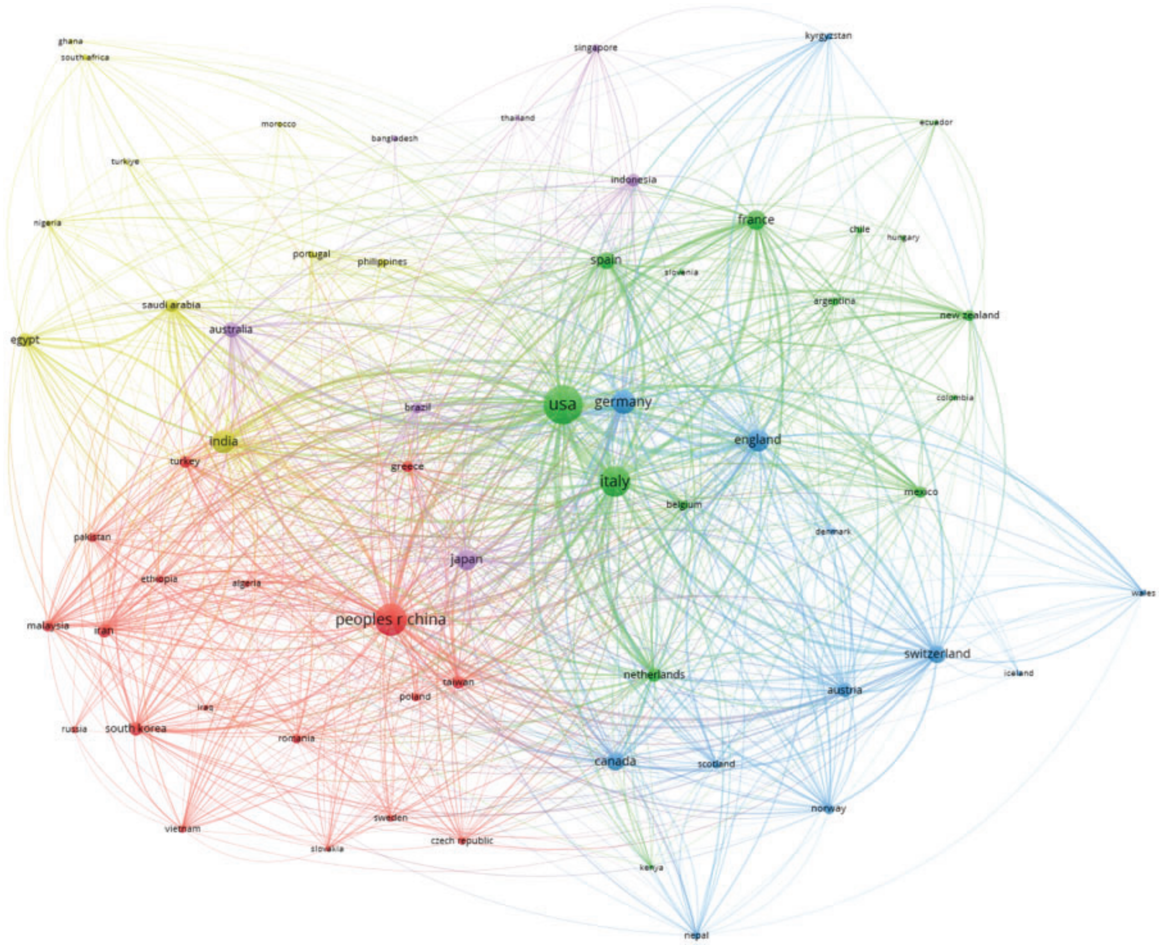
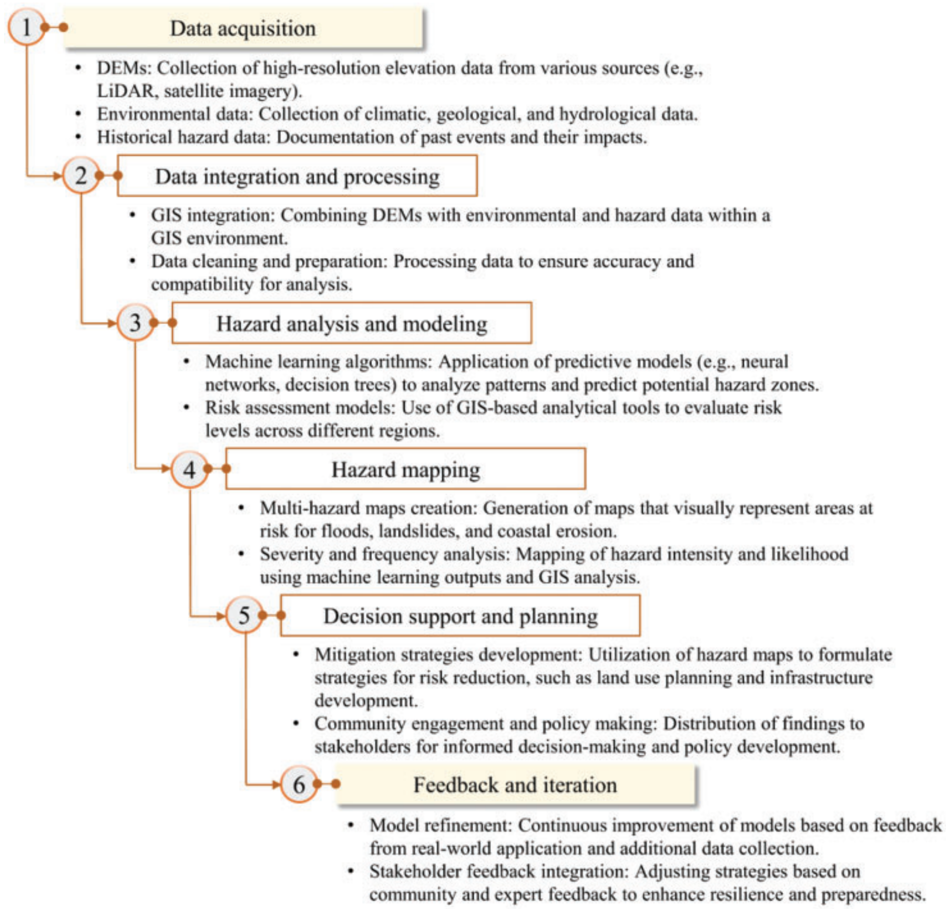


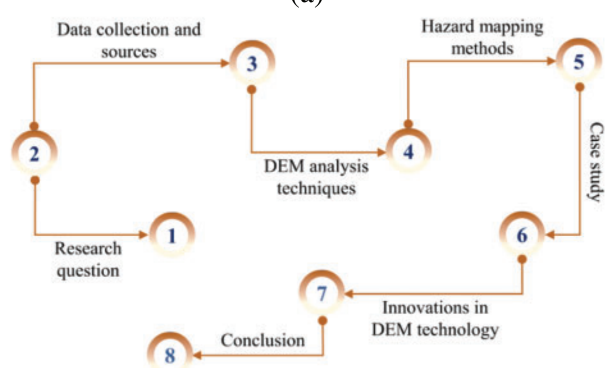
Figure 4: Citation analysis by country in research related to DEM applications in environmental hazard mapping

3.1 Data Collection and Sources

The successful application of DEMs in environmental hazard mapping fundamentally depends on the accuracy of the elevation data. DEMs are pivotal in the mapping process, providing detailed representations of surface terrains essential for identifying and analyzing various environmental hazards. The precision of these models is crucial; even minor inaccuracies in elevation data can lead to significant errors in hazard identification and subsequent mitigation strategies [48,49]. Therefore, selecting high-quality DEMs, characterized by their resolution, accuracy, and frequency of updates, is imperative for maintaining the integrity of hazard mapping efforts. This section investigates the diverse data sources used in hazard mapping, detailing their inherent characteristics such as spatial resolution, data collection methodologies, and both vertical and horizontal accuracy. It also examines the coverage of each dataset. The application of each DEM in multi-hazard assessments is discussed, indicating how their unique attributes meet the specific demands of different environmental hazards, including floods, landslides, and coastal erosion. This study aims to underscore the vital role of accurate and detailed elevation data in supporting the capacity for effective environmental and disaster management through refined hazard mapping techniques by exploring these aspects. Table 1 lists key factors in developing effective DEMs for environmental hazard mapping.



(a)



(b)

Figure 5: Comprehensive framework and methodology for multi-hazard assessment: (a) Conceptual framework and (b) Schematic illustration of the research methodology

Table 1: Critical considerations for building an influential DEM for hazard mapping

Consideration	Description	Purpose
Data source	Selecting high-quality, reliable sources of elevation data (e.g., satellite, aerial, LiDAR).	To ensure the elevation data is accurate and detailed enough for modeling hazards.
Resolution	Choosing the appropriate spatial resolution (e.g., 1, 10, 30 m) based on the scale of the area and the detail required.	Higher resolutions provide more detail but require more processing power and data storage.
Accuracy	Verification of elevation data accuracy through ground-truthing or comparison with known benchmarks.	To minimize errors in elevation that can affect hazard analysis outcomes.
Data processing	Processing raw data to remove noise and errors, including filtering and smoothing techniques.	To create a clean and reliable DEM that accurately represents the terrain.
Terrain analysis	Analyzing terrain features critical for hazard mapping, such as slopes, aspect, and elevation ranges.	To identify areas potentially at risk of hazards like landslides, floods, or avalanches.
Model update frequency	Determining how frequently the DEM should be updated to reflect changes in the terrain due to natural processes or human activities.	To maintain an up-to-date model that reflects current terrain conditions and potential hazard zones.
Interoperability	Ensuring the DEM is compatible with other GIS and hazard modeling tools.	To facilitate integration with other data layers and tools for comprehensive hazard assessment and mapping.
Scale and coverage	Defining the extent of the area covered by the DEM and the scale at which the data is presented.	To ensure the model covers all areas of interest and is suitable for the level of analysis required.
Data integration	Integrating the DEM with other datasets such as hydrological, geological, and land use data.	To enhance the model's capability to predict various types of hazards more accurately.
Validation and testing	Regularly testing the DEM with historical hazard events to validate its predictive capability.	To refine the model and improve its reliability and accuracy in hazard prediction.

Algorithm 1 depicts a pseudocode for applying DEMs in hazard analysis. The procedure begins with Data Acquisition, where elevation data is collected from various sources. Following the acquisition, the Data Preprocessing phase involves filtering and smoothing the data to eliminate noise and correct errors, which is vital for maintaining the DEM's accuracy and reliability. In the Construct DEM phase, a grid structure is created at the desired resolution, and elevation values are assigned to each grid cell. For cells lacking data, interpolation methods are employed to estimate values, ensuring a complete and continuous elevation model. Terrain Analysis follows, calculating essential terrain attributes crucial for assessing the terrain's susceptibility to hazards. Integrate Additional Datasets involves incorporating additional data such as hydrological, geological, and land use information into the DEM. Hazard-specific modeling then applies risk models based on the DEM and additional data to define hazard zones. Finally, Validation and Update tests the DEM against historical data to ensure accuracy.

The accuracy evaluation of DEMs is conducted by comparing the elevation data from the DEMs to ground control points (GCPs) collected using differential GPS. This process involves statistical measures such as root mean square error (RMSE) and mean absolute error (MAE) to quantify the differences [13,50]. High-resolution DEMs from sources such as satellite imagery and aerial surveys are pre-processed for spatial resolution and coordinate systems consistency. The resulting accuracy metrics provide a quantitative basis for assessing the reliability of the DEMs in representing the actual terrain, ensuring the precision required for effective environmental hazard mapping. The generated hazard maps are also validated using historical hazard event data and field observations. The spatial extent and severity of the hazards, as predicted by the DEMs, are compared to the actual events to assess the predictive capability of the models.

Algorithm 1: Pseudocode for DEM application in hazard analysis

```
Procedure Build DEM for Hazard Assessment
    Start
    Step 1: Data Acquisition
    Acquire elevation data from sources like satellite, aerial, LiDAR
    If no data available
      Exit "Elevation data required"
    End If
    Step 2: Data Preprocessing
    For each data point in elevation data
      Filter and smooth data to remove noise
      Correct any known data errors
    End For
    Step 3: Construct DEM
    Create grid structure based on desired resolution
    Assign elevation values to each grid cell
    If any grid cell lacks data
      Use interpolation methods to estimate values
    End If
    Step 4: Terrain Analysis
    For each cell in DEM
      Calculate terrain attributes (slope, aspect, elevation range)
    End For
```

(Continued)

Algorithm 1 (continued)

Step 5: Integrate Additional Datasets
Load additional data (hydrological, geological, land use)
For each dataset
Align dataset with DEM grid
Combine datasets with DEM to enhance the terrain model
End For
Step 6: Hazard-Specific Modeling
Define hazard types (e.g., flooding, landslides)
For each hazard type
Apply risk models to DEM considering relevant terrain and additional data
Determine hazard zones based on thresholds and criteria
End For
Step 7: Validation and Update
Test the DEM model with historical hazard data
If model predictions align with historical events
Validate model effectiveness
Else
Adjust model parameters and retest
End If
Determine update frequency based on terrain changes and data availability
End
End Procedure

Table 2 compares various DEMs, examining how their source, characteristics such as spatial resolution, and data collection methods impact the accuracy of hazard assessment. It highlights the trade-offs between high-resolution DEMs, such as those from LiDAR, which provide detailed data for precise modeling but may be costly and less available.

Table 2: Comparison of different types of DEMs and their effects on hazard assessment accuracy

Type of DEM	Source	Characteristics	Advantages	Disadvantages	Effect on hazard assessments accuracy	References
SRTM (Shuttle Radar Topography Mission)	Space Shuttle Endeavour (NASA/USGS)	Provides elevation data for the globe, covering latitudes between 60°N and 56°S.	Wide coverage, freely available, moderate resolution.	Lower resolution in vertical and spatial dimensions.	Suitable for regional scale studies; less effective for detailed local hazard analysis.	Farr et al. [51]
ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer)	Terra satellite (NASA/METI)	Provides global DEMs with a resolution of 30 meters.	High spatial resolution, global availability.	Susceptible to data noise and artifacts.	Good for medium-scale hazard mapping but may require validation for precision tasks.	Tachikawa et al. [52]

(Continued)

Table 2 (continued)

Type of DEM	Source	Characteristics	Advantages	Disadvantages	Effect on hazard assessments accuracy	References
LiDAR (Light Detection and Ranging)	Airborne and terrestrial sensors	High-resolution 3D representation of the Earth's surface.	Very high resolution, highly accurate, 3D data.	Expensive, limited to smaller, specific areas.	Excellent for detailed hazard analysis and mitigation planning in focused areas.	Hodgson et al. [53]
ALOS PALSAR (Advanced Land Observing Satellite, Phased Array type L-band Synthetic Aperture Radar)	ALOS Satellite (JAXA)	Provides 12.5-meter resolution DEMs, particularly useful in tropical and subtropical regions.	Good canopy penetration, useful in cloudy regions.	Less detailed than LiDAR.	Effective in vegetation-rich areas where optical sensors are less reliable.	Rosenqvist et al. [54]
Photogrammetric DEMs	Aerial photographs and high-resolution satellites	Derived from stereo pairs of images, allowing for detailed elevation models.	High accuracy and detail in developed regions.	Requires extensive processing, can be costly.	Highly accurate for local and detailed terrain analysis, crucial for urban hazard assessment.	Baltsavias [55]
UAV-derived DEMs	Unmanned Aerial Vehicles (Drones)	Customizable and very high-resolution DEMs tailored to specific project needs.	Flexible, high-resolution, cost-effective for small areas.	Limited by drone battery life and flying regulations.	Provides high precision for small-scale hazard evaluations, ideal for localized studies.	Nex et al. [56]

Table 3 categorizes different natural hazards, explains how DEMs are applied for each hazard type, outlines key methodologies used, and discusses the benefits and challenges of employing DEMs in these settings. It also emphasizes the practical significance of DEMs in enhancing hazard mapping and mitigation efforts. Fundamental DEM analysis techniques include slope stability analysis for identifying areas prone to landslides and hydrological modeling for delineating floodplains and analyzing water flow dynamics. DEMs are also instrumental in tsunami inundation mapping, providing detailed coastal elevation profiles to predict the inland travel of tsunami waves [57].

Table 3: Overview of DEM applications in hazard mapping

Hazard type	Application of DEM	Key methodologies	Benefits of using DEM	Key challenges	Practical importance
Flood	Flood risk assessment and inundation modeling	Hydrological modeling, surface runoff simulation	Accurate delineation of floodplains aids in flood response planning	Sensitivity to resolution and accuracy of elevation data	Essential for emergency planning and infrastructure protection
Landslide	Landslide susceptibility and risk mapping	Slope stability analysis, susceptibility indexing	Identification of potential landslide zones	Influenced by terrain accuracy and resolution	Crucial for urban planning and disaster risk reduction

(Continued)

Table 3 (continued)

Hazard type	Application of DEM	Key methodologies	Benefits of using DEM	Key challenges	Practical importance
Seismic	Seismic hazard mapping and risk assessment	Ground shaking and seismic hazard analysis	Enhances precision in seismic hazard assessments	Requires integration with geological data	Important for earthquake preparedness and building codes
Coastal erosion	Coastal erosion assessment and shoreline management	Coastal vulnerability assessments, erosion modeling	Provides insights into coastal dynamics and erosion risks	Needs high-resolution coastal and bathymetric data	Vital for coastal development and conservation strategies
Tsunami	Tsunami inundation mapping and evacuation planning	Tsunami modeling, evacuation route optimization	Supports effective evacuation strategies	Demands detailed bathymetric and topographic data	Critical for coastal city planning and safety measures
Avalanche	Avalanche prediction and risk management	Avalanche simulation models	Assists in identifying potential avalanche paths	Requires detailed snowpack and topographic data	Key for winter sport areas and mountain community safety
Volcanic hazards	Volcanic risk assessment and lava flow simulation	Lava flow modeling	Helps in planning evacuation and managing volcanic crises	Dependent on accurate DEMs and volcanic vent data	Essential for volcanic region monitoring and response planning

Probabilistic risk assessment (PRA) is a systematic and comprehensive methodology employed to evaluate risks associated with safety-critical systems [58,59]. It calculates the probability of adverse events and their potential impacts to enhance decision-making and boost safety and operational integrity. The process begins with hazard identification, utilizing tools such as failure mode and effects analysis (FMEA) or hazard and operability study (HAZOP) to systematically detect and categorize possible risks. Event tree analysis (ETA) is then employed to explore different accident scenarios. This technique starts with an initiating event and follows possible progression paths, incorporating system responses and safety measures. Each path represents events that can lead to a specific outcome. Simultaneously, fault tree analysis (FTA) analyzes the probability of a particular adverse event by constructing a logical diagram that lays out various mechanical or human failures that could lead to the undesired event. This helps identify root causes and system vulnerabilities. Probability determination is then performed, calculating the likelihood of different failure scenarios using statistical data, historical failure rates, and expert judgments. This phase often involves complex mathematical models. The results support risk quantification, combining the probability analysis with the potential consequences of each event, typically expressed as a risk index to prioritize risks and evaluate mitigation strategies. Based on the findings, mitigation and decision-support strategies are developed to reduce the likelihood or impact of hazardous events. PRA provides objective data crucial for making informed decisions on risk management. Finally, continuous review and update are essential as systems and environments evolve with regular monitoring and refinement of risk models to maintain the relevance and effectiveness of the assessment in risk management.

3.2 Case Studies

Applying DEMs in environmental hazard mapping has caused significant advances in managing and assessing various natural hazards. This section introduces a series of case studies that illustrate the practical application of DEMs in mapping various environmental hazards. Each case study focuses on a specific type of hazard, including seismic events, floods, landslides, and coastal erosion, and illustrates how integrating DEMs with GIS and machine learning techniques can enhance hazard assessment and planning [60,61]. This structured approach details the methodology and findings from each case study and connects them under the broader theme of improving hazard preparedness through technological innovation. The following case studies underline the versatility and effectiveness of DEMs in environmental hazard assessment across different contexts.

Manfreda et al. [62] developed a DEM-based method to estimate flood inundation depth. Al-Areeq et al. [63] demonstrated using DEMs for flood hazard analysis in complex terrains such as Jeddah, Saudi Arabia, enhancing the understanding of flood dynamics in urban settings. Sulaiman et al. [64] explored the extraction of DEMs using remote sensing and GIS for flood risk assessment, providing insights into the practical applications of these technologies in urban planning. Niyongabire et al. [65] indicated that DEMs in GIS are used for flood susceptibility mapping in Bujumbura City, highlighting the critical role of geospatial technologies in urban disaster risk management. Meena et al. [66] highlighted the effect of spatial resolution of DEMs on the accuracy of landslide susceptibility maps. Rabby et al. [8] evaluated DEM effects in landslide mapping in Rangamati District, Bangladesh. Brock et al. [9] investigated the impact of the resolution and quality of DEMs on the performance of landslide susceptibility models and indicated that it heavily relies on the quality of the underlying DEMs.

Jibson et al. [67,68] developed methodologies for digital probabilistic seismic landslide hazard mapping, enhancing risk management strategies in seismically active regions. In addition, Li et al. [69] employed Monte Carlo simulations for probabilistic seismic landslide hazard mapping. They reported that advancements in computational techniques with reliable DEM data can significantly improve hazard prediction and risk assessment. Haneberg [70] discussed the effects of DEM errors on seismic slope stability calculations, marking a pivotal study in understanding the impact of DEM errors on seismic hazard assessments. Ahmad et al. [71] conducted a comprehensive seismic hazard assessment of Syria, incorporating seismicity, DEMs, slope data, active faults, and GIS. They illustrated the comprehensive approach required to assess seismic risks effectively. Theilen-Willige et al. [72] performed seismic hazard analysis along the Koyna Dam area in India, exhibiting the effective integration of remote sensing and GIS with DEMs to understand and mitigate seismic hazards. Marfai et al. [73] utilized high-resolution UAV-derived DEMs to plan tsunami vertical evacuation routes in Indonesia, demonstrating the importance of precise elevation data in coastal hazard planning. Demirkesen et al. [74] conducted a coastal flood risk analysis in Izmir, Turkey, utilizing Landsat-7 ETM+ imagery and SRTM DEM. They demonstrated the enhancement of hazard analysis by integrating DEMs with other geospatial data.

These case studies collectively illustrate the critical role of DEMs in environmental hazard mapping. They underscore the necessity for high-resolution and accurate DEMs and demonstrate the diverse applications of this technology across various types of environmental hazards. Each study contributes to a broader understanding and application of DEMs in risk reduction, emphasizing their importance to academic researchers and practical stakeholders in environmental and disaster management.

4 Critical Analysis of DEM Applications in Hazard Mapping

This section presents a critical analysis to explore the applications, benefits, challenges, and practical implications of using DEMs in environmental hazard mapping, highlighting critical areas for improvement and future research. The case studies highlighted numerous applications of DEMs across different environmental hazards [21,63]. Each case study demonstrated the specific capabilities of DEMs in hazard mapping and revealed the improvements in hazard preparedness enabled by technological advancements. The effectiveness of DEMs can vary significantly based on the resolution, quality, and the specific environmental hazard being assessed [75]. Although high-resolution DEMs offer greater detail and accuracy, they require substantial computational resources and are more expensive. Lower-resolution DEMs, while less costly and computationally demanding, cannot provide sufficient detail for all types of hazard assessments, particularly in complex urban or densely vegetated areas. Table 4 categorizes strategic measures to enhance the application of DEMs in environmental hazard mapping. Each category addresses specific aspects, from technical challenges and operational needs to capacity building and policy support, ensuring a comprehensive strategy for implementing DEM technology in hazard assessments.

Table 4: Measures for DEM applications in hazard mapping

Category	Consideration	Measure
Technical	High resolution & accuracy	Invest in acquiring high-resolution DEMs and enhance them using data fusion techniques.
	Dynamic updates	Utilize real-time data integration and adaptive models to account for landscape changes.
	Computational resources	Develop local computational infrastructure and employ cloud computing solutions.
Operational	Data integration	Implement advanced GIS platforms that facilitate DEM integration with other relevant spatial data.
	Accessibility & coverage	Expand the use of drones and satellite-based LiDAR to improve data coverage and accessibility.
	Cost efficiency	Seek partnerships and grants to fund DEM acquisition and processing; promote shared data initiatives.
Human Capacity	Expertise & training	Enhance training programs in GIS and remote sensing technologies, focusing on hazard mapping applications.
	Collaboration & sharing	Foster international collaborations for data sharing and joint projects on hazard mapping.
Policy and Governance	Policy support	Advocate for governmental support and policies that prioritize hazard mapping and DEM application.
	Intersectoral collaboration	Encourage collaborations across governmental, academic, and private sectors to leverage diverse expertise.

The critical role of DEMs in environmental hazard mapping carries significant implications for environmental management. Initially, the ability of DEMs to provide detailed topographical data aids decision-makers in planning and implementing effective mitigation strategies, such as flood barriers or landslide warning systems [76,77]. These tools are essential for reducing the potential impact of natural disasters on vulnerable communities and infrastructures. In addition, integrating DEMs with GIS and machine learning opens up new methods for predictive hazard modeling, allowing for more proactive management strategies. This approach helps in immediate hazard response and long-term planning for climate change impacts, such as sea-level rise and increased frequency of extreme weather events.

DEMs are crucial in hydrological modeling, particularly in flood simulation and management. They provide detailed information about land surface and riverbed elevations, essential for modeling water flow paths and accumulation zones [5,6]. High-resolution DEMs enable accurate delineation of floodplains and identification of flood-prone areas, facilitating effective emergency planning and community alerts. For example, integrating DEMs with GIS and real-time meteorological data can enhance predictive models, allowing for dynamic flood risk assessments that support timely and targeted responses [78]. The role of DEMs in landslide risk assessment is primarily related to their ability to provide detailed data on terrain slope, aspect, and elevation, all critical factors in determining landslide susceptibility. Scientists can predict potential landslide hotspots by analyzing these terrain parameters, especially in mountainous regions where natural disasters frequently occur. This predictive capability supports land use planning and infrastructure development, aiming to mitigate the impacts of landslides on human settlements and critical transport routes. In seismic hazard assessment, DEMs are employed to model ground shaking and to identify fault zones where earthquakes are likely to occur. Elevation data contribute to the understanding of tectonic settings and the mapping of seismic risk areas [69,79]. This information is vital for urban planning and the design of earthquake-resistant structures, which are critical in minimizing human and economic losses during seismic events. DEMs facilitate the monitoring and prediction of coastal erosion, providing essential data that helps understand how waves and tidal patterns affect shoreline changes [80,81]. This application is critical in the context of rising sea levels and increased storm activity associated with climate change. Coastal managers use DEMs to plan protective measures, such as sea walls and restored habitats, to prevent loss of land and protect coastal communities.

Despite their advantages, the application of DEMs in environmental hazard mapping is limited by several factors. The resolution and coverage of DEM data cannot adequately capture detailed terrain features crucial for accurate analyses. In addition, the static nature of DEMs means they can quickly become outdated as landscapes change. Low-resolution DEMs struggle to capture essential landform details that impact water flow, slope stability, or seismic wave propagation. High-resolution DEMs are often inaccessible in many parts of the world, particularly in developing countries, due to the prohibitive data acquisition and processing costs. Environmental conditions are inherently dynamic; thus, landscapes evolve due to natural processes and human activities, necessitating frequent DEM updates that are impossible due to logistical and financial constraints. Although DEMs are valuable tools, their effectiveness is enhanced when integrated with other geographic and environmental data [82]. This process can be complex and resource-intensive, requiring sophisticated GIS and computational modeling skills. In addition, managing and processing high-resolution DEM demands considerable computational power and technical expertise, which can be challenging, especially in resource-limited environments. However, as natural disasters become more frequent and intense, incorporating climate variables into DEM analyses is essential for accurate hazard assessments. Climate change affects temperature, precipitation, sea level rise, and extreme weather events, altering landscapes and natural hazards such as floods, landslides, and coastal erosion [83,84]. Integrating climate change projections with DEM data can assess future scenarios and regional impacts. Table 5 provides a comprehensive view of the advantages, challenges, opportunities for improvement, and potential risks associated with DEM applications in hazard mapping.

Table 5: Considerations for using DEM in hazard mapping

Advantages	Challenges
High accuracy: Precise elevation data is crucial for modeling environmental hazards.	High cost: Production, especially with technologies like LiDAR, is expensive.
Versatility: Applicable to a wide range of hazards, including floods, landslides, and earthquakes.	Data handling: Large datasets demand substantial computational resources.
Technological integration: Seamless integration with GIS, remote sensing, and machine learning.	Technical skill requirements: Effective use requires high expertise in GIS and related technologies.
Opportunities for improvement	**Potential risks**
Technological advancements: Improvements in remote sensing and aerial surveys enhance data quality.	Rapid environmental changes: Dynamic landscapes require frequent DEM updates.
Collaborative data sharing: Global cooperation can improve access to high-quality DEMs.	Data accessibility and privacy: Concerns over the sharing and privacy of geospatial data.
Climate change adaptation: Growing demand for accurate hazard mapping tools due to climate change impacts.	Competing technologies: Development of alternative hazard assessment methods may challenge DEMs' dominance.

However, addressing these challenges involves several practical implications crucial for maximizing the accuracy and effectiveness of DEMs in environmental hazard mapping and ensuring they remain relevant over time. Enhanced data acquisition and sharing through advanced remote sensing and aerial survey technologies such as drones and satellite-based LiDAR are essential. These technologies provide more frequent updates and higher resolutions, and fostering global cooperation in data sharing can help overcome data availability limitations, especially in under-resourced regions. Developing adaptive models incorporating real-time data and feedback mechanisms can maintain the relevance of DEMs as landscapes change. Integrating DEMs with other environmental and social data through comprehensive GIS platforms can offer a more holistic view of hazard risks. Significant investment in technology and training is necessary to enhance the potential of DEMs. This includes building computational infrastructure and training local experts in advanced GIS and modeling techniques. In addition, continued research and development into new methodologies, including machine learning and artificial intelligence, can improve the accuracy and utility of DEMs, enhancing their predictive power in hazard management. Fig. 6 shows the interaction between the various factors influencing DEM application in environmental hazard mapping.

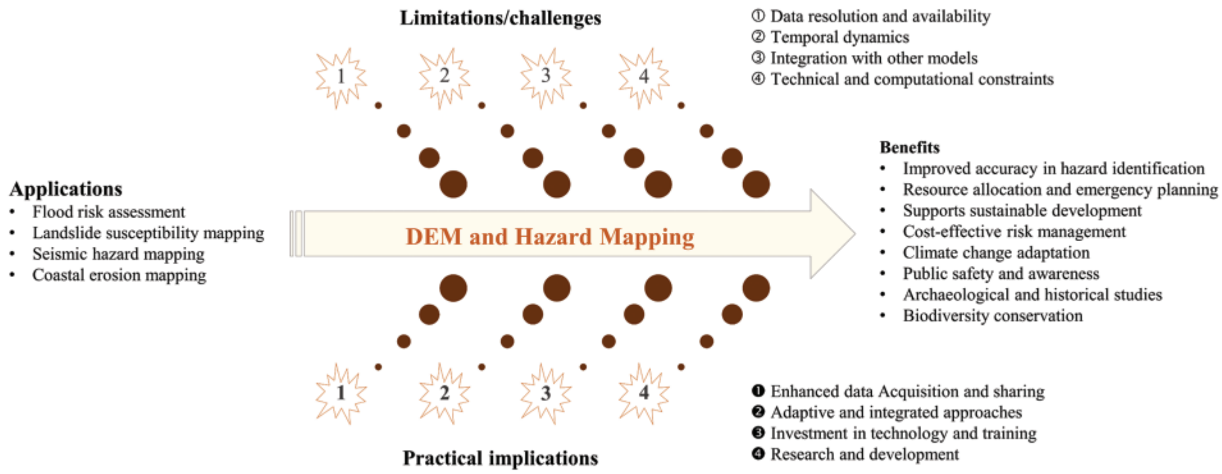


Figure 6: Critical analysis of DEM applications in environmental hazard mapping

Accordingly, DEMs have limitations that affect hazard mapping despite their significant utility. The quality and availability of high-resolution DEMs are often restricted by costs and logistical challenges, compromising accuracy in data-scarce regions. In addition, DEMs are static, necessitating frequent updates to capture recent changes due to natural events or human activities. Integrating DEMs with other geospatial data is complex and resource-intensive, requiring advanced computational resources and specialized technical expertise. To overcome these limitations, future work should focus on improving data acquisition through technologies such as drones and satellite-based LiDAR and developing adaptive models that integrate real-time data. Enhancing machine learning applications can also increase predictive accuracy.

5 Soft Computing Techniques for Multi-Hazard Mapping

Soft computing encompasses a variety of methodologies, including fuzzy logic, neural networks, genetic algorithms, and machine learning, which are particularly effective in enhancing the precision of hazard management [85,86]. These techniques integrate diverse data types such as experimental, remote sensing, topographic maps, and socio-economic datasets [24,87]. Such integration is essential for comprehensive hazard analysis, facilitating the management of the inherent uncertainty and variability of hazards due to changing climatic conditions and geographical transformations [88,89]. Fig. 7 highlights the benefits of integrating soft computing techniques into hazard analysis. These methods improve the accuracy and efficiency of solutions across various hazard mapping applications. Fig. 8 illustrates two problem-solving strategies in computer science and artificial intelligence: hard and soft computing techniques. Each approach has benefits and usages, frequently combined to achieve the best results. Hard computing relies on mathematical logic and accurate and deterministic techniques, which need well-defined issues and yield exact and reliable solutions. However, soft computing offers a more adaptable method that assumes the nuances of imprecision and uncertainty. This adaptability makes it well-suited for addressing complex issues in real-world scenarios.

Explainability in artificial intelligence (AI) models is crucial for their acceptance and effectiveness in multi-hazard mapping. Techniques such as shapley additive explanations (SHAP) and LIME (local interpretable model-agnostic explanations) provide insights into the variables influencing model predictions, enhancing trust and decision-making in hazard mitigation [85,90,91].

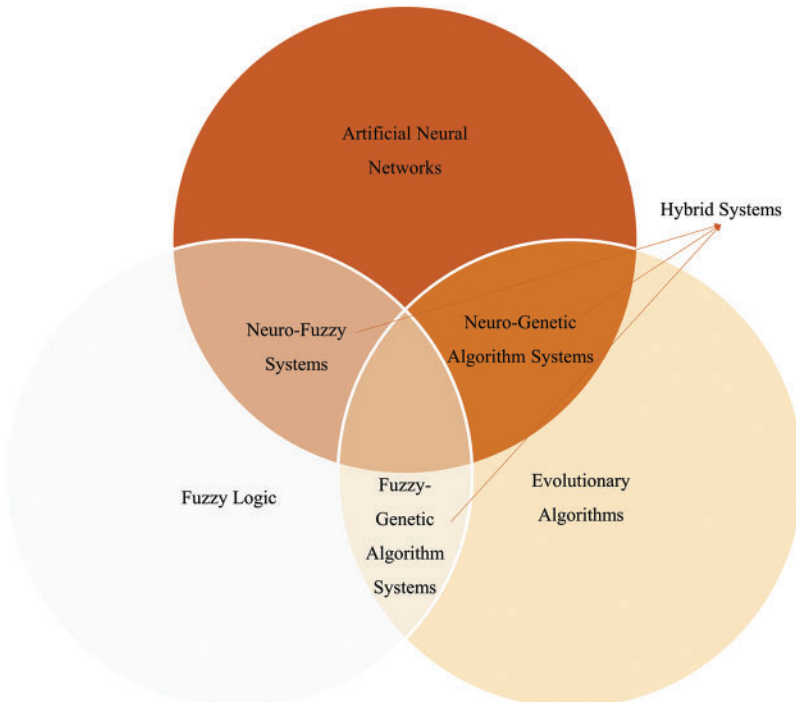


Figure 7: Various soft computing methods

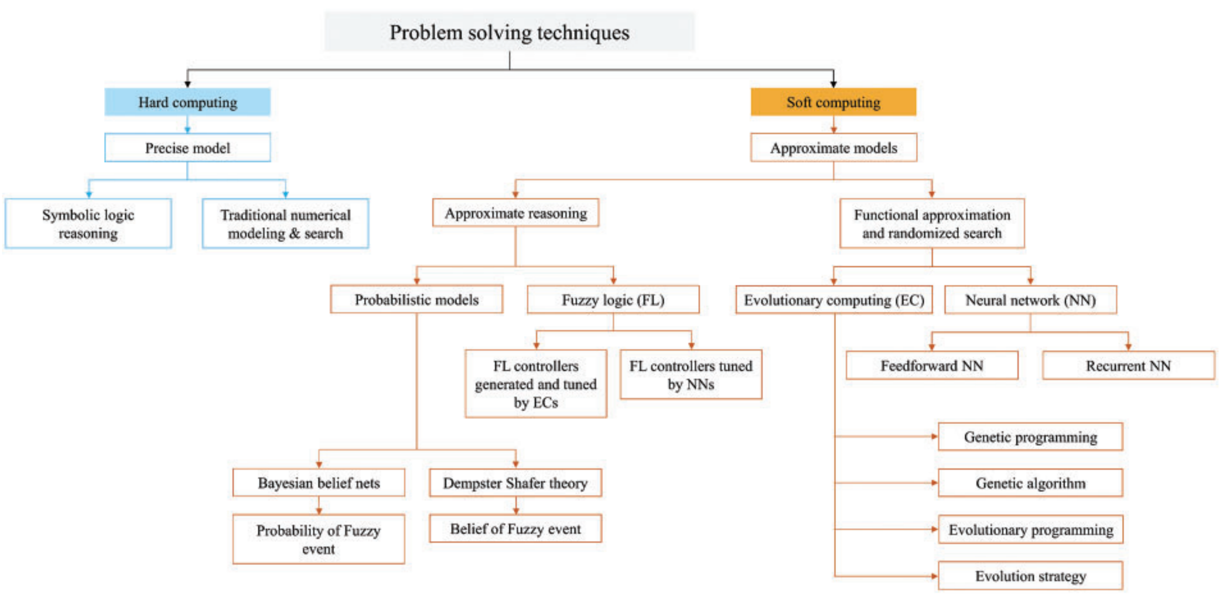


Figure 8: Hard and soft computing methods

Previous studies have developed various methodologies for integrating machine learning in the process of multi-hazard mapping, such as the one given in Fig. 9 by Nachappa et al. [92]. One of the main benefits comes from the adaptability of neural networks and machine learning models that allows for continual learning from new data, improving hazard prediction models [93,94]. As a result, using soft computing in multi-hazard mapping improves the accuracy and reliability of hazard assessments and significantly contributes to developing informed and effective disaster risk reduction strategies. Previously, Kariminejad et al. [95–97] emphasized the role of geo-environmental modeling and deep learning methods in improving hazard mapping and management. Ullah et al. [98–100] further underscored the potential of machine learning techniques in multi-hazard susceptibility mapping, presenting substantial advancements in the field. Rahmati et al. [24] and Nachappa et al. [92] highlighted using machine learning in multi-hazard exposure mapping, providing a practical framework for assessing risks associated with various natural hazards. Despite these advantages, soft computing faces challenges such as computational complexity, the necessity for extensive training datasets, and difficulties in interpreting complex model outputs. However, future advancements in computational power and algorithm efficiency, along with improved data collection methods, are expected to enhance the applicability of soft computing in hazard management.

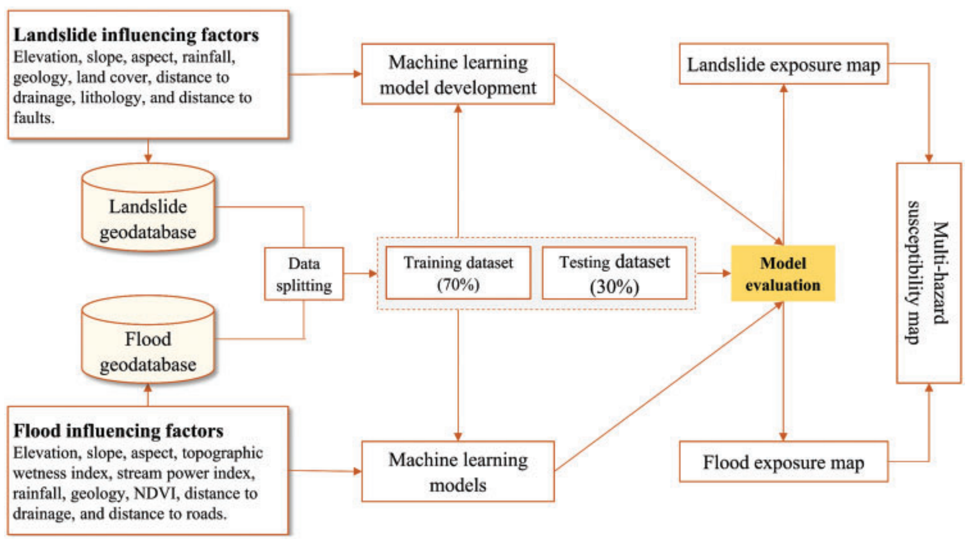


Figure 9: General procedure for multi-hazard mapping using DEM models integrated with machine learning techniques

6 Conclusion

This paper attempts to review and critically analyze existing literature on applying DEMs in multi-hazard assessments. It highlights the need for broader application of DEMs in multi-hazard assessments by integrating high-resolution DEMs with advanced methods such as machine learning techniques to enhance the precision and utility of hazard maps, which are essential for effective disaster risk reduction and strategic environmental planning. Based on the statements above, the following conclusions are drawn:

- Integrating DEMs across multiple hazard types, including floods, landslides, and coastal erosion, enables more comprehensive environmental risk assessments.
- Using high-resolution DEMs significantly improves the precision of hazard assessments, proving essential in accurately identifying and managing environmental risks.

- Machine learning techniques enhance hazard maps' predictive accuracy by identifying complex patterns and interactions between various hazard types and environmental factors.
- Utilizing DEMs with GIS technology helps with environmental planning and hazard management, which allows for detailed and dynamic hazard mapping.
- The enhanced DEMs could facilitate better preparedness and response strategies in disaster management.

The review outlines several limitations in the current applications of DEMs, such as the challenges related to data resolution, update frequency, and the accessibility of high-resolution models, particularly in resource-limited areas. In order to address these limitations, it is recommended that DEMs be enhanced in resolution and accessibility to ensure they provide accurate and current data for hazard assessments. In addition, it recommends developing innovative methods to integrate real-time environmental data into DEMs to capture dynamic changes more effectively and improve the models' predictive accuracy. Further exploration into expanding machine learning algorithms in conjunction with DEMs is also advised to bolster multi-hazard assessment capabilities. This critical review lays the foundation for future advancements in the field and underscores the importance of bridging these gaps to enhance DEM applications in environmental hazard mapping.

Acknowledgement: The authors would like to thank the editors and reviewers for their review and recommendations.

Funding Statement: The authors received no specific funding for this study.

Author Contributions: The authors confirm their contribution to the paper as follows: study conception and design: Maan Habib and Ahed Habib; data collection: Mohammad Abboud; analysis and interpretation of results: Maan Habib, Mohammad Abboud and Ahed Habib; draft manuscript preparation: Maan Habib. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: The authors confirm that the data supporting the findings of this study are available within the article and supplementary material.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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