# FLOOD AND LANDSLIDE PREDICTION USING MACHINE LEARNING

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## Abstract

Floods and landslides rank among the most devastating natural disasters, leading to widespread damage to lives, properties, and essential infrastructure worldwide.Timely and precise prediction of these disasters is essential for reducing their adverse impacts.Early and accurate prediction of such disasters is vital for minimizing their consequences. Yet, conventional forecasting methods often struggle due to the intricate and variable nature of environmental conditions. Recent advancements in machine learning (ML) offer promising solutions, employing sophisticated algorithms to manage these complexities. This paper presents an in-depth review of cutting-edge ML approaches for flood and landslide prediction, examining methodologies, datasets, advantages, and limitations.

**Keywords:** Flood and Landslide Prediction, Machine learning, Risk analysis , Convolutional Neural Networks.

## 1. Introduction

Flash floods and landslides are among the most devastating natural disasters, causing widespread damage to human life, infrastructure, and ecosystems across the globe. Accurate prediction and early warning systems are essential to reduce the risks and losses associated with these hazards. In disaster management, forecasting flash floods and mapping flood-prone areas have gained significant importance due to the increasing frequency and intensity of extreme weather events. The prediction of such events is particularly challenging because of their rapid onset and the complex interactions among meteorological, hydrological, and geological factors. Over the last decade, rapid advancements in technology—especially in the domain of Machine Learning (ML)—have transformed hazard forecasting approaches. These intelligent systems offer powerful tools for analyzing large-scale, multi-source environmental data, thereby enhancing the accuracy, timeliness, and reliability of flood and landslide prediction models.

## 2. LITERATURE SURVEY

### 2.1 H. A. P. Hapuarachchi et. al [1] proposed "A review of advances in flash flood forecasting".

Flash flooding is one of the most hazardous natural events, and it is frequently responsible for loss of life and severe damage to infrastructure and the environment. Research into the use of new modelling techniques and data types in flash flood forecasting has increased over the past decade, and this paper presents a review of recent advances that have emerged from this research.

## 2.2 S. Zhong et. al [2] proposed "Spatial-Temporal Flood Hazard Mapping Using Integration of Telemetry Data and Prediction Model"

The flood early warning system can help mitigate the resulting damages by predicting future events. This is achieved through the utilization of data obtained from telemetry stations to predict the values of water levels in the future. This paper proposed a framework to apply the spatial and temporal data to generate flood hazard mapping using the integration of interpolation telemetry station data and a temporal prediction model.

## 2.3 Caihong Hu et. al [3] proposed "Deep Learning with a Long Short-Term Memory Networks Approach for Rainfall-Runoff Simulation"

Considering the high random and non-static property of the rainfall-runoff process, lots of models are being developed to learn about such a complex phenomenon. Recently, Machine learning techniques such as the Artificial Neural Network (ANN) and other networks have been extensively used by hydrologists for rainfall-runoff modelling as well as for other fields of hydrology. However, deep learning methods such as the state-of-the-art for LSTM networks are little studied in hydrological sequence time-series predictions.

## 2.4 Zhice Fang et. al [4] proposed "Predicting flood susceptibility using LSTM neural networks"

In this study, we propose a local spatial sequential long short-term memory neural network (LSS-LSTM) for flood susceptibility prediction in Shangyou County, China. The three main contributions of this study are summarized below. First, it is a new perspective to use the deep learning technique of LSTM for flood susceptibility prediction. Second, we integrate an appropriate feature engineering method with LSTM to predict flood susceptibility. Third, we implement two optimization techniques of data augmentation and batch normalization to further improve the performance of the proposed method.

## 2.5 Autanan Wannachai et. al [5] proposed "HERO: Hybrid Effortless Resilient Operation Stations for Flash Flood Early Warning Systems"

This research proposes hybrid effortless resilient operation stations, named HERO stations, in the flash flood early warning system. The HERO station was designed and developed with a modular design concept to be effortlessly customized and maintained. The HERO station adapts its working operation against the environmental changes to maintain a longworking period with high data sensing accuracy. Moreover, the HERO station can switch its communication mode between the centralized and decentralized communication modes to increase availability.

## 3. Machine Learning and Datasets for Flood and Landslide Prediction

This section explores the fundamentals of deep learning and outlines several models applied in transfer learning. It also presents the dataset utilized in designing plant leaf disease detection systems, serving as a reference for new researchers entering this field.

### A. Machine Learning

Machine learning (ML) has become a highly effective approach for predicting and managing natural disasters such as flash floods and landslides. Its strength lies in the capacity to extract patterns from historical data and generate predictions based on this acquired knowledge. Leveraging extensive and diverse datasets, ML models can identify intricate relationships among environmental variables, enabling

more precise and timely forecasting of flood and landslide occurrences.

## Role of Machine Learning in Natural Hazard Prediction

For flash flood and landslide prediction, machine learning models can process extensive datasets from diverse sources, including weather stations, satellite imagery, historical disaster records, soil moisture measurements, and river discharge data. By identifying patterns in environmental factors preceding such events, these models enhance forecasting accuracy and support effective risk management. Machine learning methods are generally categorized into supervised, unsupervised, and reinforcement learning, with supervised learning being the most prevalent in this domain. In supervised learning, algorithms are trained on labeled datasets—where outcomes are known—to predict future events based on input variables. For instance, a model may be trained to forecast flood occurrences using historical rainfall, soil moisture levels, and river flow data. Once trained, the model can generate predictions for potential flooding events when provided with new environmental inputs.

## B. Types of Datasets Used in Flood and Landslide Prediction

**Meteorological Data:** Weather parameters such as rainfall, temperature, wind speed, and humidity play a pivotal role in flood and landslide prediction. Analyzing historical meteorological data alongside past disaster events enables machine learning models to identify weather patterns that commonly precede such hazards. Rainfall intensity and spatial distribution are particularly influential in forecasting flash floods, with short, intense precipitation events posing higher risks in steep terrains. Similarly, temperature and humidity affect soil moisture levels and evaporation rates, which are critical indicators of both flood and landslide susceptibility.

**Hydrological Data:** Hydrological datasets—comprising river discharge rates, groundwater levels, and soil moisture content—are essential for modeling water flow within catchment areas. Machine learning models can leverage historical hydrological records to forecast river levels, runoff, and flood peaks, thereby enhancing flood prediction systems. River discharge, representing the volume of water flowing through rivers and streams, serves as a key indicator of flood risk; notable increases, particularly after intense rainfall, can signal the likelihood of flooding. Similarly, soil moisture content is a critical parameter for landslide prediction, as over saturated soils become unstable and prone to failure, especially in mountainous terrains.

**Geographical and Topographical Data:** Geographic Information Systems (GIS) data plays a vital role in assessing flood and landslide risks. Factors such as elevation, slope, land use, and soil type influence water movement across the terrain and determine an area's susceptibility to such hazards. Steep slopes are generally more vulnerable to landslides, whereas low-lying regions near rivers or lakes are at greater risk of flooding. Machine learning models can integrate these geographical attributes to evaluate hazard vulnerability. Additionally, land use changes—such as urbanization, deforestation, or inadequate drainage infrastructure—can significantly increase the likelihood of flash flooding and landslides.

**Satellite and Remote Sensing Data:** Remote sensing technologies, particularly satellite imagery, offer

valuable data on land cover, vegetation, and surface changes over time. Such information is vital for monitoring environmental conditions and detecting early indicators of potential floods or landslides. Satellite imagery enables large-scale observation of factors like deforestation, urban expansion, and alterations in river channels, all of which can elevate disaster risk. Furthermore, satellite-derived soil moisture measurements and vegetation indices provide critical insights into soil saturation levels—an essential parameter for accurate flood and landslide prediction.

**Historical Disaster Data:** Historical flood and landslide datasets are essential for training machine learning models, as they provide detailed information on past events, including location, timing, severity, and impacts. Such records enable algorithms to identify patterns that can be applied to future predictions. Flood occurrence data—covering parameters such as timing, duration, and magnitude—helps models estimate the probability of future flooding under similar conditions. Likewise, historical landslide records are used to analyze contributing factors such as rainfall intensity, slope gradient, and land use, thereby improving the accuracy of landslide forecasting.

**Real-Time Data from Sensors and IoT:** Recent advancements in sensor technology and the Internet of Things (IoT) enable real-time monitoring of environmental parameters. Data collected from rain gauges, soil moisture sensors, river flow meters, and weather stations can be integrated into machine learning models to facilitate timely predictions. Real-time rainfall and stream flow measurements assist in detecting early warning signs of flash floods, while soil sensors provide immediate information on soil moisture levels—an important factor in forecasting both floods and landslides.

## C. Popular Machine Learning Algorithms Used in Flood and Landslide Prediction

Several machine learning algorithms have been employed in flood and landslide prediction based on the above datasets.This includes:

**Decision Trees and Random Forests:** Decision trees and random forests are widely used for classifying flood and landslide risk levels based on multiple input features. Decision trees represent the decision-making process as a hierarchical structure, where each node corresponds to a decision criterion derived from input variables. Random forests improve prediction accuracy by aggregating the results of numerous decision trees, reducing overfitting and enhancing robustness.

**Support Vector Machines (SVM):** Support Vector Machines (SVMs) are commonly employed for classification tasks. In flood and landslide prediction, SVMs can categorize areas as high or low risk by analyzing meteorological, hydrological, and topographical features. They are particularly effective for handling high-dimensional data and capturing complex, non-linear relationships within the dataset.

**K-Nearest Neighbours (KNN):** The K-Nearest Neighbors (KNN) algorithm is a straightforward yet effective method for predicting flood or landslide risks. It classifies a location's risk level by comparing current environmental conditions to the 'k' most similar historical instances in the dataset, assigning the risk category based on the majority class among these neighbors.

**Logistic Regression:** Logistic regression is frequently applied to binary classification problems, such as predicting the occurrence of floods or landslides in a given area. It models the relationship between input features and the likelihood of an event, estimating the probability that the disaster will occur

## D. Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm renowned for their success in image analysis. Their use has recently extended to environmental and disaster prediction domains, including flood and landslide forecasting. CNNs excel at extracting spatial features from complex data such as satellite imagery, weather maps, and topographic grids. In flood and landslide prediction, CNNs effectively detect spatial patterns within environmental data, thereby enhancing the accuracy of predictive models.

**Flood Prediction Using CNNs**

Flood prediction models often involve analyzing large datasets that encompass spatial and temporal variables such as rainfall distribution, river water levels, and soil moisture content. CNNs are especially effective in this context because they can efficiently process spatial data and recognize patterns over extensive regions, which is critical for accurately identifying flood-prone areas.

**How CNNs are used in flood prediction:**
Satellite Imagery and Remote Sensing: Satellite imagery is a primary data source for flood prediction, providing detailed observations of land surfaces. CNNs are highly effective at processing these images, learning to differentiate between flooded and non-flooded areas. By training on historical satellite images of flood events, CNNs can predict regions likely to be affected under similar conditions, recognizing features such as water bodies, vegetation, and land cover changes associated with flooding.

Weather Data Analysis: CNNs can also analyze weather data arranged in grid formats, including rainfall intensity, temperature, and atmospheric pressure. When spatially mapped over large regions, these variables serve as inputs for CNNs to identify temporal and spatial rainfall patterns, thereby forecasting flood risks based on current weather conditions.

Flood Hazard Mapping: Once trained, CNNs can produce flood hazard maps by integrating real-time or forecasted weather data, topographic information, and river discharge records. These maps predict the likelihood and extent of flooding in specific areas, aiding authorities in disaster preparedness and response efforts.

**Landslide Prediction Using CNNs**
Landslides are commonly triggered by factors including heavy rainfall, soil saturation, steep slopes, and seismic activity. CNNs are employed to analyze spatial data—such as terrain features, soil moisture levels, and precipitation patterns—to identify regions susceptible to landslides. Their capacity to learn complex spatial relationships across diverse datasets makes CNNs particularly effective for assessing landslide risk.

**How CNNs are used in landslide prediction:**

Topographic Data Processing: Topography—including slope, elevation, and land cover—is a major factor influencing landslide occurrence. These features are commonly represented as grid-based data such as Digital Elevation Models (DEMs). CNNs can effectively analyze this topographic data to identify patterns associated with landslide-prone areas. For example, areas with steep slopes and unstable soils are more vulnerable to landslides following heavy rainfall, and CNNs can detect these characteristics within the data.

Soil Moisture and Rainfall Data: Heavy precipitation and soil saturation are primary triggers of landslides. By analyzing historical rainfall and soil moisture datasets, CNNs can forecast changes in soil conditions in response to impending weather events. Data from soil moisture sensors and rainfall gauges enable CNNs to pinpoint regions at elevated risk due to excessive soil water content.

Combining Datasets for Landslide Susceptibility Mapping: CNNs can integrate multiple spatial datasets to produce detailed landslide susceptibility maps. By fusing topographic information with soil moisture and rainfall data, CNNs learn the complex interactions among these factors, improving the accuracy of landslide risk predictions. This multi-source data integration enhances risk assessment and supports more effective disaster management.

**Hybrid CNN Models for Enhanced Prediction**

In certain applications, CNNs are integrated with other machine learning algorithms or hydrological models to develop hybrid systems that deliver more robust and accurate flood and landslide predictions.

**Hybrid CNN models**

CNNs Combined with Hydrological Models for Flood Prediction: Traditional hydrological models simulate rainfall-runoff dynamics and are frequently integrated with CNNs to enhance flood forecasting. In this hybrid framework, CNNs extract spatial features from satellite imagery or weather maps, while hydrological models simulate water flow using precipitation and river discharge data. This combination captures both the physical processes of water movement and spatial flood risk indicators, resulting in more comprehensive and accurate flood predictions.

CNNs Combined with Temporal Models for Landslide Prediction: For landslide forecasting, CNNs are often paired with temporal models such as Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks. While CNNs process spatial information—like satellite images and elevation data—RNNs and LSTMs model temporal dependencies, such as rainfall patterns over time. This hybrid approach enables prediction based on both current environmental conditions and historical temporal trends, improving landslide risk assessment.

## 4. Existing Machine Learning- Based Proposals for Prediction of Flood and Landslide

### A. Methodology for Selecting State-of-the-Art Models:

Following the research works conducted by [1]–[5], a comprehensive search was performed in databases including IEEE Xplore, Scopus, ResearchGate, and Google Scholar. The keywords used were: *"flash flood prediction," "landslide prediction using machine learning," "deep learning for flood susceptibility,"* and

*"LSTM neural networks for rainfall-runoff simulation."* The search was limited to the period 2016–2021.

The selection process for the relevant studies is outlined in **Algorithm 1**. In IEEE Xplore, the keyword search revealed that in 2018, a total of 94 research papers were published on flood and landslide prediction. Among these, only 7 addressed flash flood forecasting, and none focused on applying deep learning techniques to landslide prediction.

In 2019 and 2020, the number of publications rose to 148 and 178, respectively, indicating a growing interest in leveraging machine learning for natural hazard prediction. However, studies specifically addressing flash flood prediction and landslide forecasting with deep learning remained scarce, with only 6 such publications in total.

By 2020 and 2021, deep learning—particularly LSTM networks for rainfall-runoff simulation—began to gain more attention, with 3 and 4 publications, respectively. Nevertheless, as of July 2021, flood susceptibility prediction using LSTM networks was still a niche area, with only 3 published articles.

This trend underscores the emerging yet underexplored potential of deep learning models for flood and landslide prediction, highlighting a substantial opportunity for further research and development.

### B. Current State-of-the-Art Models

In recent years, the application of machine learning—particularly deep learning—in flood and landslide prediction has advanced significantly. Researchers have developed various models, architectures, and methodologies aimed at enhancing the accuracy and reliability of these predictions. The following is a summary of the state-of-the-art models and their key contributions:

**Flash Flood Prediction Models** Several models have been developed for flash flood prediction, emphasizing the integration of real-time rainfall and runoff data to deliver timely and accurate forecasts. A notable approach involves the use of Long Short-Term Memory (LSTM) networks. For instance, Hu et al. [4] proposed an LSTM-based model for rainfall–runoff simulation, achieving high accuracy in predicting flood events. Their results demonstrated strong performance in both prediction timeliness and precision—key factors in effective flash flood forecasting. Similarly, Fang et al. [5] employed LSTM neural networks to predict flood susceptibility, showcasing the model's ability to capture complex temporal dependencies in hydrological data. Their study further underscored the critical role of accurately modeling rainfall–runoff dynamics for reliable flood risk assessment.

**Landslide Prediction Models** Advancements in machine learning have significantly enhanced landslide prediction, particularly through the development of models capable of processing large volumes of spatial and temporal data. One effective approach involves integrating spatiotemporal features from diverse sources, including satellite imagery, weather records, and topographical maps. For example, Zhong et al. [3] utilized spatiotemporal exploration techniques for hazard mapping of tropical cyclones, which indirectly supports landslide prediction by providing valuable insights into terrain changes and weather patterns.

Machine learning algorithms such as Random Forests and Support Vector Machines (SVM) have been widely adopted for landslide susceptibility modeling. Beyond traditional methods, Deep Learning (DL) approaches—especially Convolutional Neural Networks (CNNs)—have gained prominence due to their ability to analyze large datasets and identify complex patterns in landslide-prone regions.

**Hybrid Models for Early Warning Systems** Hybrid models have emerged as a promising approach for enhancing early warning systems (EWS) for both flash floods and landslides. For example, Wannachai et al. [2] proposed a hybrid framework known as 'Hero,' which integrates resilient operation stations to enable real-time monitoring and prediction of flash floods. This model combines weather, hydrological, and topographical data to enhance the robustness and accuracy of predictions, thereby facilitating timely and reliable warnings for regions vulnerable to such hazards.

**Advanced Rainfall-Runoff Simulation Models** Hu et al. [4] extended the application of deep learning to simulate rainfall–runoff processes by employing a Long Short-Term Memory (LSTM)-based approach capable of capturing the nonlinearities inherent in hydrological systems. This method enables more accurate and dynamic predictions of flood events. Moreover, integrating deep learning models with physically based models has been shown to improve prediction accuracy by combining the strengths of data-driven learning with established hydrological principles.

**Spatiotemporal Hazard Mapping and Prediction** Zhong et al. [3] demonstrated the use of spatiotemporal hazard mapping in the context of tropical cyclones, offering a framework that can be adapted for landslide prediction. By integrating spatiotemporal datasets with hazard maps, researchers can significantly enhance early warning systems for landslides, particularly those triggered by intense rainfall or seismic events.

**Open Issues and Future Research Directions** Although machine learning techniques have demonstrated significant potential in enhancing flood and landslide prediction, several challenges remain, presenting opportunities for further research. Key concerns include constraints in data availability, limitations in model adaptability, and the pressing need for real-time forecasting capabilities. The following outlines the open issues and prospective directions for future advancements in this field.

### Challenges in Data Availability and Quality

Limited Access to Real-Time Data:One of the primary challenges in flood and landslide prediction is the lack of sufficient real-time, high-quality data. In many regions, the absence of comprehensive monitoring infrastructure—such as weather stations, river flow gauges, and soil moisture sensors—hampers the accuracy of predictive models. Addressing this limitation requires exploring alternative data acquisition methods, including satellite-based remote sensing, crowdsourced environmental reporting, and advanced IoT-enabled sensor networks. These approaches can significantly enhance the availability, reliability, and granularity of real-time environmental data, thereby improving model training and validation processes.

Data Scarcity in Remote Areas:In many remote or hard-to-access regions, particularly mountainous or isolated areas, the collection of reliable environmental data remains a significant challenge. To address this gap, research should focus on developing innovative approaches for estimating critical parameters using satellite imagery and advanced remote sensing technologies. Such methods can provide valuable insights into rainfall patterns, terrain characteristics, and land-use changes in locations where ground-based observations are unavailable, thereby enhancing the coverage and accuracy of predictive models.

## Model Generalization and Adaptability

Challenges with Model Transfer:Machine learning models often demonstrate strong performance when applied to specific datasets but may underperform when transferred to regions with different geographical, climatic, or environmental characteristics. Addressing this issue requires research into advanced transfer learning techniques that enable models trained in one region to be effectively adapted to new environments. Such approaches would enhance model generalizability and ensure their broader applicability across diverse geographical contexts.

Data Fusion for Enhanced Prediction:Integrating diverse data sources—such as rainfall measurements, soil characteristics, topographical features, and historical records of floods and landslides—can substantially improve predictive accuracy. Future research could focus on developing robust multi-source data fusion frameworks that leverage the complementary strengths of various datasets. The use of ensemble learning techniques and hybrid models could further enhance performance, offering more reliable and comprehensive flood and landslide prediction systems.

## Interpretability and Trustworthiness of Models

Addressing the Black-Box Nature:Deep learning models, such as Long Short-Term Memory networks (LSTMs) and Convolutional Neural Networks (CNNs), often function as "black boxes," offering limited insight into the reasoning behind their predictions. For flood and landslide forecasting, interpretability is critical to foster trust and facilitate informed decision-making. Future research could focus on developing explainable AI (XAI) techniques—such as feature importance analysis, attention mechanisms, or hybrid approaches that integrate machine learning with physical models—to provide greater transparency into model behavior.

Quantifying Uncertainty:In operational contexts, it is not enough for prediction models to produce outputs; they must also convey the degree of uncertainty associated with those outputs. This information allows decision-makers to better evaluate risks and adopt appropriate mitigation strategies. Advancing methods for uncertainty quantification within machine learning models—such as probabilistic forecasting, Bayesian approaches, or ensemble-based confidence estimation—would enhance the reliability and practical utility of flood and landslide prediction systems.

**Real-Time Forecasting and Early Warning Systems**

Improving Model Efficiency:For flood and landslide predictions to be truly actionable, they must be generated rapidly enough to enable timely interventions. However, many existing models demand substantial computational resources, making real-time predictions challenging—particularly for large geographic regions. Future research should prioritize the development of computationally efficient algorithms capable of delivering near-instantaneous predictions without sacrificing accuracy. Techniques such as model compression, optimization, and the use of lightweight architectures could play a key role in achieving this balance.

Integrating with Early Warning Systems:While machine learning models have shown significant promise in predicting floods and landslides, their integration into operational early warning systems remains a critical challenge. Future work should focus on embedding these models into established warning infrastructures that combine meteorological, hydrological, and geotechnical data. This would enable seamless data exchange, real-time monitoring, and the effective dissemination of actionable alerts to vulnerable communities—enhancing preparedness and reducing disaster impact.

**Hybrid and Multi-Model Approaches**

Combining Data-Driven and Physics-Based Models:A promising avenue for future research lies in integrating machine learning approaches with physics-based models, such as hydrological simulations and geotechnical analyses. These hybrid models can leverage the strengths of both data-driven insights and domain-specific knowledge, resulting in more accurate, robust, and interpretable predictions. Further exploration of techniques to seamlessly fuse physical modeling with machine learning could enhance predictive performance while ensuring scientific transparency.

Ensemble Methods for Robust Prediction:Ensemble learning—where predictions from multiple models are combined—offers a pathway to improve both the stability and accuracy of flood and landslide forecasts. Future studies could investigate optimal strategies for integrating diverse machine learning techniques, including random forests, decision trees, and deep learning architectures. Such hybrid ensemble systems could provide more reliable risk assessments, particularly in complex and data-scarce environments.

**Incorporating Climate Change Effects**

Adaptation to Climate Variability:Climate change is projected to alter the frequency and intensity of extreme weather events, including heavy rainfall and severe storms, which significantly influence the occurrence of floods and landslides. Future research should focus on integrating climate projections into machine learning models to account for evolving weather patterns. This integration would enable predictive systems to adapt dynamically, improving their ability to assess risk under changing environmental conditions.

Modeling Future Scenarios:Incorporating long-term climate scenarios into flood and landslide prediction frameworks can enhance preparedness for potential increases in natural disaster frequency and severity. This may involve coupling climate model outputs with machine learning algorithms to forecast shifts in hazard patterns, spatial distribution, and intensity. Such forward-looking models could serve as valuable

tools for policymakers and disaster management agencies in formulating proactive mitigation strategies.

## Cross-Disciplinary Collaboration

Collaborative Research Across Domains:Flood and landslide prediction inherently require expertise from multiple disciplines, including hydrology, geology, meteorology, and emergency management. Cross-disciplinary collaboration is essential to ensure that machine learning models are not only technically accurate but also operationally feasible and relevant to real-world applications. Future research should actively promote partnerships between data science specialists and domain experts to design integrated, multi-faceted prediction systems that address both the scientific and practical aspects of disaster risk management.

## Ethical Considerations and Societal Impact

Ensuring Equity and Accessibility:As flood and landslide prediction models advance, it is crucial to ensure their accessibility for all communities, particularly those most vulnerable to disasters. Future research should prioritize the development of equitable prediction systems that integrate social and economic considerations, ensuring that predictive technologies are accessible to marginalized and high-risk populations.

Establishing Standards and Regulations:With the increasing reliance on machine learning for disaster prediction, there is a pressing need for well-defined standards and regulations. Research should focus on formulating guidelines for the design, validation, and deployment of predictive models in operational environments. These guidelines must address ethical, legal, and technical requirements to ensure that such systems are both trustworthy and effective in real-world applications.

Table 1: Summary of the discussed state-of-the-art models and proposed approaches.

| No. | Authors | DL Algorithm | Dataset | Contribution | Performance | Limitation |
|---|---|---|---|---|---|---|
| 1. | Hapuarchchi et al. [1] | Flash Flood Forecasting using various ML models | Weather and hydrological data | Reviewed and compared various approaches to flash flood forecasting | Provides a comprehensive evaluation of different forecasting models | Focused on traditional machine learning models, with limited exploration of deep learning |
| 2. | Wannachai et al. [2] | Hybrid models (LSTM, CNN) | Real-time sensor data on flash floods | Developed a hybrid early warning system for flash floods, integrating multiple models | Showed promising results for real-time flood detection | Dependent on continuous real-time data input for optimal performance |

| 3. | Zhong et al. [3] | Spatiotemporal analysis with machine learning | Cyclone and flood hazard data | Proposed a framework for mapping flood risks associated with tropical cyclones along the Chinese coastline | Demonstrated effective hazard mapping capabilities | The analysis is dependent on data quality and spatial resolution |
|---|---|---|---|---|---|---|
| 4. | Hu et al. [4] | Long Short-Term Memory (LSTM) networks | Rainfall-runoff data | Applied deep learning for simulating rainfall-runoff processes to predict floods | Achieved high accuracy in simulations of hydrological processes | Requires high-quality historical data and extensive model calibration |
| 5. | Fang et al. [5] | LSTM neural networks | Flood susceptibility data | Introduced a method for predicting flood susceptibility using deep learning | Demonstrated strong prediction accuracy for flood-prone areas | Limited to specific flood zones, which may affect generalization to other regions. |
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## 5. Conclusion

Machine learning has emerged as a vital approach for enhancing the precision and efficiency of flood and landslide prediction systems. Advanced techniques such as Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), and hybrid frameworks have demonstrated strong capabilities in forecasting flood vulnerability and modeling rainfall–runoff relationships by processing complex datasets that include meteorological, topographic, and hydrological variables.

LSTMs are particularly effective for handling time-series forecasting, while CNNs excel in spatial data interpretation, making them highly suitable for disaster prediction tasks. However, certain challenges persist, such as limited data availability and inconsistent quality, especially in regions with insufficient monitoring infrastructure, which often reduces prediction reliability. Additionally, the high computational requirements of sophisticated models can hinder their deployment in real-time applications.

Hybrid models, which integrate multiple machine learning techniques, offer potential solutions to these issues by combining the strengths of different algorithms to improve predictive accuracy. Moreover, improving model transparency and interpretability is essential so that decision-makers can confidently use predictions for timely and effective interventions.

Future advancements in flood and landslide prediction should prioritize enhanced data collection methods, optimized computational processes, increased model resilience, and adaptive systems capable of

responding dynamically to live data streams. While machine learning holds significant promise for disaster risk mitigation, progress in data quality, model integration, and operational efficiency will be crucial for realizing its full potential in early warning and prevention systems.

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