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A Review of Flood Hazard Assessment and Risk Zone Identification Using Conventional Physical Models and Machine Learning Algorithms: A Study of the Kalu River Basin

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Abstract — The Kalu River Basin in southwestern Sri Lanka has experienced significant flooding, primarily from monsoonal and cyclonic rainfall. Steep topography, rapid land-use changes, and climate change exacerbate flood risk. Notable flood events in this region occurred in 2003, 2008, 2012, 2014, 2017, 2018, and 2021, causing substantial economic losses and social impacts. Traditional forecasting methods have relied on physically based hydrological and hydrodynamic models to simulate rainfall–runoff relationships, particularly in well-instrumented catchments. However, these conventional models often require extensive data, presenting challenges in data-limited environments such as Sri Lanka. Machine learning (ML) models offer an alternative by learning flood-generating patterns directly from hydrological and environmental data, achieving high forecasting accuracy with limited information.

In contrast, process-based models encounter challenges such as inflexibility, nonlinear dynamics, and residual biases. This paper reviews global and regional research focusing on hybrid approaches that integrate physical models with ML techniques and assesses their potential application in the Kalu River Basin. The review emphasizes the significance of combining physical and ML models, demonstrating that hybrid methods generally outperform standalone models in estimating peak flows and predicting extreme events, even under data-limited conditions. In summary, this review advocates adopting integrated modeling systems as robust and adaptable solutions for flood forecasting.

Keywords — Kalu River Basin, Flood Hazard Assessment, Integrated Modeling, Hydrological Modeling, Hydrodynamic Modeling, Machine Learning

I. INTRODUCTION

Kalu River Basin, located in the vibrant southwestern region of Sri Lanka, frequently experiences intense monsoon rainfall [1]. Historical records show that catastrophic floods in this basin primarily stem from extreme convective precipitation, creating a cycle of destruction and regeneration [2]. The basin's unique topography, characterized by varied elevations and valleys, coupled with shifting land-use patterns, further increases flood risk [3].

A particularly devastating incident occurred in May 2003, when approximately 432.2 mm of precipitation was recorded over three consecutive days. This event, with a 15-year return period, resulted in estimated damages of LKR 73 million [4]. A similar meteorological event occurred in late April 2008, when 473 mm of rainfall was recorded over three days, causing significant flooding in Kukulegama with a 20-year return period [5].

In recent decades, the basin has experienced recurrent severe flooding, particularly in 2012, 2014, 2017, 2018, and 2021 [6]. For example, flash floods in the Ratnapura area during the 2003 event caused damage estimated at approximately LKR 50.6 million [4]. These events underscore the Kalu River Basin's vulnerability to monsoonal and cyclonic rainfall.

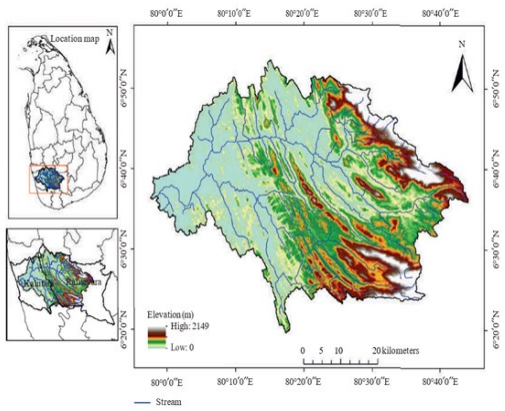


Figure 1. Geographical location and digital elevation model (DEM) of the Kalu River Basin (adapted from [7]).

Historically, flood forecasting has relied heavily on traditional physical hydrological and hydrodynamic models. However, these approaches often require

substantial data and can struggle to capture the complex interactions typical of data-scarce environments [8]. In light of these challenges, recent research has highlighted ML as a promising alternative. ML models can identify flood-generating patterns from a variety of sources, such as rainfall intensity, slope variations, and land use, without explicitly representing the underlying physical processes [9]. These models require less calibration and fewer input data, making them particularly suitable for data-limited regions. Notably, ML methodologies have shown high predictive accuracy for both short- and long-term flood forecasting [10].

Given the ongoing challenges posed by flooding and climate change, there is a pressing need to reevaluate traditional modeling techniques and develop hybrid models [11]. Conventional process-based models, including hydrological and hydrodynamic frameworks, often struggle to capture the full range of nonlinear flood processes and may not adequately address data biases. Furthermore, purely data-driven approaches require domain expertise and frequently lack physical interpretability. Recent reviews show a strong global trend toward integrating physical models with ML algorithms, emphasizing the strengths of each approach. For example, Liu et al. [12] argued that ML excels at handling large, complex flood datasets and that integrating ML with traditional modeling significantly improves flood depth and peak discharge predictions. Similarly, Du and Pechlivanidis [13] showed that hybrid frameworks substantially improve local-scale streamflow and flood forecasting, yielding greater accuracy in predicting extreme events than standalone physical models. This growing body of evidence has encouraged researchers in Sri Lanka to explore integrated modeling strategies to improve flood forecasting and early warning systems [14].

However, the application of such integrated approaches to the Kalu River Basin remains limited, particularly in representing the combined effects of hydrological, spatial, and anthropogenic factors under data constraints. Conventional physical models primarily represent rainfall-runoff processes, whereas ML approaches can incorporate multiple spatial variables but may offer limited physical interpretability. Therefore, this review focuses on integrated approaches that combine physical modeling, ML techniques, and relevant spatial factors, including rainfall, terrain characteristics, land use, and proximity to roads, for flood hazard assessment and risk zone identification in the Kalu River Basin.

II. METHODOLOGY

This study used a structured literature review to examine conventional physical models, ML methods, and integrated modeling approaches for flood hazard assessment, forecasting, and risk zone identification. This study placed particular emphasis on assessing the applicability of these approaches to the Kalu River Basin, Sri Lanka.

A. Literature Search and Sources

Relevant journal articles, conference papers, technical reports, academic studies, and institutional publications were reviewed. The literature search focused on hydrological and hydrodynamic modeling, ML-based flood forecasting, Geographic Information Systems (GIS)-based flood susceptibility mapping, and integrated physical-ML modeling approaches. The review paid particular attention to studies conducted in Sri Lanka, particularly those focusing on the Kalu River Basin. The review also examined relevant international studies to identify recent methodological developments and broader advances in flood assessment and modeling.

B. Study Selection

We selected studies based on their relevance to flood hazard assessment, flood forecasting, flood susceptibility assessment, risk mapping, and the application of conventional physical, ML, GIS-based, and integrated modeling techniques. We excluded studies with limited relevance to these themes. The review considered both earlier studies that contributed to flood assessment and modeling in the Kalu River Basin and recent studies demonstrating advances in ML and integrated modeling approaches.

C. Literature Analysis and Synthesis

The review comparatively evaluated the selected studies based on their modeling approaches, data requirements, applications, outputs, advantages, and limitations. The review first examined conventional physical models and ML methods separately, then assessed integrated modeling approaches, including one-way and two-way coupling strategies. The review also considered the application of rainfall, DEM, land-use and land-cover (LULC), soil, drainage, and river-related data in flood assessment and modeling. The study then synthesized findings from Sri Lankan and international studies to identify methodological gaps and assess the potential applicability of integrated physical and ML approaches for flood hazard assessment and risk zone identification in the Kalu River Basin.

III. OVERVIEW OF CONVENTIONAL AND ML FLOOD MODELING

A. Hydrological and Hydrodynamic Modeling

Hydrological and hydrodynamic modeling are well-established tools for flood hazard analysis and risk prediction, enabling accurate analysis of the spatial and temporal variations of floods [15, 16]. Current studies indicate that researchers use various physical modeling tools, each serving distinct research and practical objectives. Primary criteria for model selection include model objectives, prevalence, availability of user manuals, input and output characteristics, historical data requirements, potential for distributed applications, data availability, acquisition cost, and the human resources required for implementation [17].

A wide range of hydrological and hydrodynamic models is available for different applications. The Hydrologic Engineering Centre–Hydrologic Modeling System (HEC-HMS) is widely used for rainfall–runoff simulation [18]. At the same time, the Soil and Water Assessment Tool (SWAT) is commonly used for watershed hydrological modeling [19]. The Storm Water Management Model (SWMM) is extensively used for urban runoff modeling [20]. Among hydrodynamic models, the Hydrologic Engineering Center–River Analysis System (HEC-RAS) is one of the most widely used. It supports both one-dimensional (1D) and two-dimensional (2D) hydraulic simulations of open-channel flow [21]. Similarly, MIKE FLOOD is widely used for flood inundation modeling across different flood scenarios [22].

Among these models, HEC-HMS is the most commonly used in Sri Lanka due to its availability, robustness, and widespread adoption by water-related agencies.

Conventional hydrological and hydrodynamic models (e.g., HEC-HMS, MIKE 11/21, and SWAT) require detailed input data and extensive calibration. In Sri Lanka, intense convective storms and highly variable terrain generate complex nonlinear runoff processes that conventional models struggle to represent accurately. Moreover, sparse or incomplete hydrometric networks and rapid land-use changes, particularly on steep deforested slopes, further increase modeling uncertainty. For example, Sampurno et al. [23] noted that developing a standalone hydrodynamic model for a developing-country basin is challenging due to limited computational resources and scarce observational data. Consequently, Sri Lankan flood studies commonly adopt simplified 1D or conceptual models. However, these approaches may not accurately represent flood inundation unless they are carefully calibrated and supported by sufficient field data.

Internationally, modern flood studies increasingly employ fully 2D or coupled 1D/2D hydrodynamic models integrated with hydrological components. Recent studies have also adopted integrated 1D/2D modeling frameworks supported by high-resolution DEMs and satellite-derived data for urban and coastal flood simulations. In contrast, such applications remain limited in Sri Lanka. Most flood simulations continue to rely on HEC-HMS coupled with 1D HEC-RAS, often integrated with ArcGIS and empirical rating curves. Only a few studies have applied fully 2D models or multiple-model frameworks. Overall, flood modeling practice in Sri Lanka remains largely based on conventional one-way workflows (e.g., HEC-HMS → HEC-RAS) because of data and resource limitations. In contrast, international research increasingly favors coupled modeling approaches and data assimilation techniques.

B. ML Algorithms in Flood Modeling

ML models can analyze complex datasets to predict flood occurrence and identify areas vulnerable to flooding [24, 25]. Traditionally, physical modeling approaches require substantial amounts of data, while developing countries often experience limitations due to long-term data gaps [10]. Moreover, these models can involve considerable computational costs, and conventional modeling approaches may require extended processing time. To address these limitations, ML approaches have emerged as a promising alternative for flood hazard assessment. Several ML algorithms have been applied for flood susceptibility mapping, including Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and Extreme Gradient Boosting (XGBoost) [16, 24, 26, 27].

Developing a reliable ML model requires proper preparation and quality control of input datasets. Rainfall and hydrological datasets commonly contain outliers, biases, and missing records, which can affect model performance [28]. For example, Saubhagya *et al*. [29] addressed missing rainfall records in the Ratnapura Basin using a hybrid Multi-Layer Perceptron (MLP)-kriging algorithm for bias correction. Similarly, bias correction of satellite-derived rainfall products is widely applied, in which local gauge observations are integrated with the Global Satellite Mapping of Precipitation (GSMaP) products to improve heavy rainfall estimation in the Kalu River Basin [6]. In many applications, satellite rainfall data are corrected using ground observations, while input variables are normalized or standardized before ML training. Data quality control techniques, including removal of abnormal values and spatial interpolation for gap filling, are commonly adopted to improve dataset reliability.

The selection of appropriate predictor variables is another critical factor influencing ML model performance. Common approaches include statistical filter methods, such as Pearson correlation analysis and variance inflation factor (VIF), to identify relationships and reduce multicollinearity among variables. Dimensionality reduction techniques, such as Principal Component Analysis (PCA), and feature selection approaches, including wrapper and embedded methods, are also widely applied. Some studies have used PCA to reduce the dimensionality of complex topographical and climatic variables. At the same time, techniques such as backward elimination and Least Absolute Shrinkage and Selection Operator (LASSO) have been applied to remove less influential predictors. Therefore, ML-based flood hazard models in Sri Lanka can benefit from combining domain knowledge with statistical feature selection methods, considering key variables such as rainfall, slope, distance to rivers, and soil characteristics, followed by ML-based feature-importance analysis for further refinement.

C. Integrated Modeling Approaches in Flood Hazard Assessment

Models and data-driven approaches to improve flood prediction and risk assessment. In a one-way coupling framework, outputs from physical models, such as hydraulic water levels or simulated flood characteristics, are used as input data for training or calibrating ML models. In contrast, two-way coupling involves an iterative exchange of information between the two components, in which ML-derived parameters or corrections can update the physical model, and the physical model outputs can further improve ML predictions. Most existing hybrid modeling studies have adopted one-way coupling approaches, in which hydrological or hydraulic simulations are conducted under different scenarios and ML models are trained as surrogates. Although two-way coupling frameworks are emerging, their application remains limited because of the complexity of model development and calibration.

When integrated with hydrodynamic models, ML approaches can improve flood prediction accuracy and efficiency [30]. Recent studies on flood forecasting and risk assessment have demonstrated the potential of combining ML techniques with conventional modeling approaches. Tamiru and Wagari [31] integrated an ANN with the HEC-RAS model in Ethiopia and achieved high predictive performance, with a Nash–Sutcliffe Efficiency (NSE) of 0.88. Similarly, Sampurno *et al*. [23] developed an integrated flood prediction approach in Pontianak using RF, achieving a Root Mean Square Error (RMSE) of 0.11 m, demonstrating its suitability for data-scarce regions.

Koutsovili *et al*. [32] developed an early monitoring and forecasting system for an urban basin in Greece by integrating HEC-HMS for runoff simulation with a Long Short-Term Memory (LSTM) neural network for short-term forecasting. The coupled approach improved flash flood prediction performance. In Vietnam, Huu Duy *et al*. [33] proposed a framework that combines ML, hydrodynamic modeling, and the Analytic Hierarchy Process (AHP) for flood risk mapping in the Ba River Basin, Phu Yen. Furthermore, Nguyen *et al*. [16] combined MIKE FLOOD with ML algorithms, including SVM-SGD, Decision Tree (DT), and Dagging, achieving an Area Under the Curve (AUC) value of 0.98 for the Vu Gia–Thu Bon Basin. For urban flood applications, Khoshkonesh *et al*. [34] integrated 1D and 2D hydrological modeling with Ensemble Transformed Principal Component Analysis (ETPCA) and demonstrated improved flood-dynamics prediction. Additionally, Ahmad *et al*. [30] combined hydrological modeling, ML, and remote sensing techniques for comprehensive flood hazard assessment in the Hunza-Nagar Division of Pakistan.

These studies show that integrating ML with conventional physical models can improve prediction accuracy, enhance computational efficiency, and address limitations of traditional modeling approaches. Hybrid approaches also have potential applications in real-time flood management systems [24, 31, 35, 36]. Du and Pechlivanidis [13] reported that combining ML with process-based models can reduce prediction errors and improve model robustness under extreme events. Liu *et al*. [12] further highlighted that ML-based surrogate models can improve flood-depth prediction accuracy and computational efficiency by capturing nonlinear relationships that conventional models may not represent effectively.

A major advantage of hybrid modeling is reduced computational time after model training. For example, an ANN-based model required approximately 5 seconds to predict flood depths, whereas a full hydrodynamic simulation required approximately 5 minutes [37]. However, hybrid approaches also introduce challenges, including complex coupling design, additional computational requirements for ML training, reliance on high-quality datasets, and reduced interpretability because some ML algorithms are black-box. Fully coupled two-way frameworks are particularly challenging because they require more complex development and calibration.

In Sri Lanka, applications of hybrid flood modeling remain limited. Although interest in integrating hydrological/hydraulic models, such as SWAT or HEC-RAS, with ML approaches is increasing, published studies applying these frameworks specifically to the Kalu River Basin remain scarce. Therefore, international

developments in hybrid modeling offer valuable guidance for adapting integrated ML and physical modeling approaches to improve flood hazard assessment and risk prediction in the Kalu River Basin.

D. Computational Advancements in Flood Susceptibility Mapping

Flood Susceptibility Maps (FSMs) play an important role in flood prediction, risk assessment, and disaster mitigation [38]. Well-developed flood susceptibility maps can support early warning systems, helping to reduce human casualties and minimize economic losses [39]. However, because geographic characteristics and interactions between natural and anthropogenic factors vary, developing location-specific flood models remains challenging [16]. Researchers have applied various approaches for flood susceptibility assessment, including ML, deep learning (DL), and Multi-Criteria Decision Analysis (MCDA). In recent years, integrating GIS with ML techniques has become an effective approach for developing FSMs.

FSM development requires integrating multiple spatial datasets that represent hydrological, topographical, environmental, and anthropogenic conditions. These datasets commonly include DEMs for deriving topographic parameters such as slope, aspect, and flow accumulation; Land Use/Land Cover (LULC) maps for representing land use patterns, vegetation characteristics, and land cover changes; rainfall data for capturing spatial rainfall variability; soil and geological information for assessing infiltration and runoff characteristics; and proximity-based factors such as distance to rivers and drainage networks [40].

Many studies have applied DEMs with an approximate 30 m spatial resolution to flood susceptibility analysis [41]. Higher-resolution DEM products, including 10–30 m Shuttle Radar Topography Mission (SRTM), Advanced Land Observing Satellite (ALOS), and Light Detection and Ranging (LiDAR) datasets, can improve the derivation of terrain-related indices such as slope, curvature, and Topographic Wetness Index (TWI). Similarly, LULC information is essential for identifying developed and vegetated areas, as increased impervious surfaces can significantly influence flood generation processes [40]. Rainfall information is commonly incorporated as spatial raster data, derived from satellite-based rainfall products or interpolated gauge observations, to represent variations in rainfall intensity.

Previous studies have typically incorporated approximately 10–15 conditioning factors, including elevation, slope, curvature, rainfall, LULC, drainage density, soil characteristics, and proximity-related variables, within GIS-based flood susceptibility frameworks [9, 24, 25, 27]. Therefore, integrating GIS, remote sensing, and ML approaches provides a promising framework for developing location-specific flood susceptibility assessments that account for the combined influence of environmental and anthropogenic factors.

IV. HISTORICAL DEVELOPMENTS IN THE KALU RIVER BASIN

A. Forecasting and Institutional Framework

Several sector-specific agencies traditionally manage flood forecasting and warning activities in Sri Lanka. The Irrigation Department (ID) plays a major role in river and reservoir monitoring, managing 91 out of 122 stations within the national flood monitoring network, with warnings primarily focused on reservoir operations and flood releases [42]. The Mahaweli Authority of Sri Lanka (MASL) monitors flow conditions mainly for dam safety and water resource management within the Mahaweli and associated basins. Meanwhile, the Department of Meteorology is responsible for weather forecasting and issuing monsoon-related advisories.

Following the 2004 tsunami, Sri Lanka established the Disaster Management Center (DMC) to coordinate disaster preparedness and warning activities. Currently, DMC serves as the national coordinating agency for issuing multi-hazard advisories and for receiving information from several institutions, including ID, MASL, and the Ceylon Electricity Board (CEB). However, effective coordination, data integration, and information sharing among these agencies remain challenging. A recent review highlighted that despite institutional development, “data acquisition and data management for integrated flood risk management … is still unsuccessful” and that “coordination and information sharing among stakeholders is still a gap” [43].

Therefore, although multiple agencies contribute hydrological and meteorological data through conventional and telemetry-based monitoring systems, Sri Lanka still lacks a fully integrated national platform with advanced modeling capabilities for real-time flood prediction and early warning. Developing such integrated systems could improve data utilization, forecasting accuracy, and disaster response capacity.

B. Evolution of Flood Forecasting Methods in the Kalu River Basin

Flood forecasting research in the Kalu River Basin has gradually shifted from conventional hydrological and hydrodynamic modeling approaches to data-driven ML techniques. Nandalal [4] initially applied the HEC-RAS model to hydrodynamic flood modeling between Ratnapura and Kalutara, laying the foundation for flood analysis in the basin. Subsequent studies expanded

these modeling approaches by incorporating hydrological simulation and ML-based forecasting techniques.

Kanchanamala *et al*. [44] improved flood modeling performance by dividing the catchment into sub-basins using HEC-HMS. Hettiwaththa and Abeygunawardana [45] applied Autoregressive Integrated Moving Average with Generalised Autoregressive Conditional Heteroscedasticity (ARIMAX-GARCH) models for water level forecasting. Furthermore, Gamage and Ilmini [46] employed ANNs for flood forecasting across four sub-basins while addressing data class imbalance.

Other studies have applied physically based hydrological models, including SWAT and SWMM, for rainfall-runoff simulation and hydrological modeling, as reported by Madushanka *et al*. [47] and Thakuri and Wijesekera [48], respectively. Mahaganapathy *et al*. [49] further investigated ensemble ML approaches, combining a bagging classifier with backward feature selection. More recently, Sudasingha and Koswatte [50] developed an ML-based real-time flood forecasting approach using 10 months of observed data.

Overall, these studies show the progressive shift in flood forecasting research in the Kalu River Basin from conventional hydrological modeling to ML-based methods, highlighting the growing adoption of data-driven techniques to improve flood prediction.

C. Socioeconomic Dynamics

Satellite observations indicate significant LULC changes in the Kalu River Basin over the past two decades. According to a GIS-based analysis by Amarakoon [51], natural vegetation cover decreased by about 14.2%, while built-up areas increased by about 8.6% between 2000 and 2020. These changes were particularly prominent in the lower basin, including the Kalutara and Ratnapura districts, where floods occur more frequently. The expansion of tea and rubber plantations, along with rapid urbanization around Ratnapura town and downstream areas, has contributed to converting forested and agricultural lands into more impervious surfaces.

Local observations also suggest that recent increases in flood impacts may be associated with deforestation, river channel encroachment, and population growth, particularly in highly exposed areas of Kalutara District. Increased development in flood-prone areas, modifications to natural drainage pathways, and restrictions due to floodplain encroachment may reduce the basin's capacity to accommodate intense rainfall events, resulting in higher flood peaks.

Therefore, rapid LULC changes are considered a significant factor contributing to increasing flood risk in the Kalu River Basin. However, existing studies have paid limited attention to how socioeconomic dynamics influence flood vulnerability, highlighting a research gap in understanding the combined effects of environmental and social factors on flood risk assessment.

D. Progression of Flood Risk Mapping Technologies in the Kalu River Basin

A detailed analysis of flood risk mapping in the Kalu River Basin has been initiated using geospatial techniques. Fowze *et al*. [52] first reported using ALOS/Phased Array type L-band Synthetic Aperture Radar (PALSAR) data to delineate flood extent and calibrate the HEC-RAS model in Sri Lanka. Subsequently, Samarasinghe *et al*. [53], through remote sensing and GIS-based analysis, identified that approximately 11.5 km² and 5.41 km² of the basin are exposed to high-risk areas under a 100-year flood event, with nearly 19% of the population classified as highly vulnerable. Nandalal and Ratnayake [54] further investigated flood risk mapping using conventional and fuzzy modeling approaches. Moreover, Wickramasooriya and Walpita [55] assessed flood impacts in the Kalutara District using MCDA, incorporating pairwise comparison and weighted overlay techniques.

These studies show the growing use of advanced geospatial technologies for flood risk assessment and mapping in the Kalu River Basin. However, a comprehensive and validated FSM that integrates multiple influencing factors has not yet been fully established.

V. SYNTHESIS AND ANALYSIS OF EXISTING RESULTS

The reviewed studies demonstrate a methodological progression in flood assessment within the Kalu River Basin, from conventional hydrological and hydrodynamic modeling to ML-based flood forecasting and geospatial risk assessment. Conventional models provide physically based representations of rainfall-runoff and hydrodynamic processes, while ML approaches improve data-driven prediction by capturing complex relationships in available datasets. In addition, GIS and remote sensing techniques support identifying, analyzing, and mapping flood-prone areas.

However, the literature indicates that these methodologies are predominantly applied independently, resulting in limited integration among physical models, ML algorithms, spatial factors, and socioeconomic conditions. The reviewed findings demonstrate the potential of integrated modeling approaches while highlighting persistent challenges related to data availability, model calibration, validation, and cross-domain integration.

Furthermore, the application of such integrated approaches to the Kalu River Basin remains limited, particularly in representing the combined effects of hydrological, spatial, and anthropogenic factors under data constraints. Conventional physical models primarily represent rainfall-runoff processes, whereas ML approaches can incorporate multiple spatial variables but may offer limited physical.

VI. CONCLUSIONS

The review indicates the growing application of ML and physical models in flood hazard assessment. Physical models are primarily developed based on the relationship between rainfall and runoff; however, they often fail to adequately account for the influence of geomorphological and anthropogenic factors. Therefore, integrating ML approaches with conventional physical models can improve flood hazard estimation accuracy while addressing the limitations of traditional modeling.

The complex interactions among meteorological, geomorphological, and anthropogenic conditions significantly influence flood hazards in the Kalu River Basin. However, current flood risk assessments in the region largely rely on conventional physical models, which may struggle to represent the combined factors influencing floods. An integrated framework that combines physical and ML models offers a promising approach to more comprehensively evaluating these factors. Such an approach can help policymakers and local disaster management agencies improve flood preparedness and decision-making.

Future research should focus on developing explainable artificial intelligence (XAI) approaches for flood forecasting to enable better interpretation and acceptance of ML-based predictions among decision-makers. Furthermore, integrating Internet of Things (IoT) networks can provide near-real-time hydrological and meteorological data, improving model performance and increasing flood-forecasting lead time. The impacts of climate change on monsoon patterns should also be continuously incorporated into basin-scale modeling frameworks. Ultimately, combining advanced modeling techniques with effective community participation can help improve flood resilience in Sri Lanka.

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