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Explainable Flood Prediction Using Hybrid Deep Learning, GIS, and Explainable AI for Climate-Resilient Disaster Management

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Explainable Flood Prediction Using Hybrid Deep Learning, GIS, and Explainable AI for Climate-Resilient Disaster Management

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Abstract

Floods remain one of the most devastating natural hazards, causing significant human casualties, economic losses, and environmental degradation worldwide. The increasing impacts of climate change, rapid urbanization, and extreme hydrometeorological events have intensified the need for accurate and reliable flood prediction systems. Although recent advances in machine learning and deep learning have substantially improved flood forecasting performance, many existing prediction models operate as black-box systems, limiting their transparency, interpretability, and practical adoption by disaster management authorities. This study proposes an explainable flood prediction framework that integrates Geographic Information Systems (GIS), Hybrid Deep Learning, and Explainable Artificial Intelligence (XAI) techniques, including SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME). Using secondary hydro-meteorological and geospatial datasets, the framework combines Long Short-Term Memory (LSTM) networks with Extreme Gradient Boosting (XGBoost) to capture temporal and nonlinear spatial relationships associated with flood events. Explainable AI techniques provide both global and local interpretations of model predictions, enhancing transparency and stakeholder trust. The proposed framework offers an accurate, interpretable, and policy-oriented decision-support system that strengthens early warning capabilities, supports sustainable flood management, and improves climate resilience.

Keywords: Flood Prediction, Hybrid Deep Learning, Geographic Information Systems (GIS), Explainable Artificial Intelligence (XAI), LSTM, SHAP and LIME

1. Introduction

Floods are among the most destructive natural disasters, accounting for a substantial proportion of global disaster-related economic losses, infrastructure damage, and human casualties. According to recent international disaster reports, the frequency and intensity of flood events have increased considerably due to climate change, rapid urbanization, deforestation, and changes in land-use patterns [1], [2]. These factors have intensified hydrological extremes, making flood prediction an essential component of disaster risk reduction and climate adaptation strategies. Accurate flood prediction enables governments, emergency response agencies, and local communities to implement timely evacuation plans, optimize resource allocation, and minimize flood-related losses.

Advances in Geographic Information Systems (GIS), remote sensing, and Artificial Intelligence (AI) have significantly transformed flood prediction research. GIS facilitates the integration and spatial analysis of hydrological, meteorological, topographical, and environmental datasets, while machine learning and deep learning algorithms can model complex nonlinear relationships that are difficult to capture using conventional statistical approaches [3]. Among deep learning methods, Long Short-Term Memory (LSTM) networks have demonstrated remarkable capability in learning temporal dependencies from hydrological time-series data such as rainfall, river discharge, soil moisture, and temperature. However, despite their predictive strength, these models often operate as black-box systems, making it difficult for decision-makers to understand how predictions are generated. This challenge has encouraged the development of Explainable Artificial Intelligence (XAI), which improves model transparency and supports evidence-based flood management.

Despite significant advances in machine learning and deep learning techniques, several important challenges remain in operational flood prediction. Most existing flood prediction models prioritize forecasting accuracy while paying limited attention to model interpretability and transparency. Advanced algorithms such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), and ensemble learning methods have achieved high predictive performance; however, their internal decision-making mechanisms remain largely inaccessible to policymakers and disaster management practitioners [4], [5]. Consequently, these models are frequently regarded as black-box systems, reducing stakeholder confidence and limiting their practical application in real-world disaster response.

Another major limitation is the inadequate integration of spatial information with temporal hydrological forecasting. Many existing studies rely primarily on time-series hydro-meteorological data while neglecting important geospatial variables such as elevation, land use, drainage networks, soil characteristics, and river proximity. Furthermore, only a limited number of studies employ Explainable Artificial Intelligence (XAI) techniques to explain why flood predictions are generated. Existing flood prediction frameworks also rarely provide confidence measures that indicate the reliability of predictions for operational decision-making. Therefore, there is a clear need for an integrated flood prediction framework that combines GIS, hybrid deep learning, and explainable AI to improve prediction accuracy, transparency, and practical usability for climate-resilient disaster management.

The increasing occurrence of extreme flood events requires prediction systems that are not only highly accurate but also transparent and trustworthy. Although hybrid deep learning models have substantially

improved flood forecasting accuracy, their black-box nature limits their acceptance among policymakers and disaster management authorities. Explainable Artificial Intelligence (XAI) provides an opportunity to bridge this gap by revealing the contribution of individual hydro-meteorological and environmental variables to prediction outcomes. Integrating GIS with hybrid deep learning further enhances spatial understanding of flood dynamics, while explainability improves stakeholder confidence and facilitates evidence-based decision-making. Therefore, this study proposes an integrated GIS-Hybrid Deep Learning-XAI framework capable of delivering accurate, interpretable, and operationally useful flood predictions using secondary hydro-meteorological datasets. The framework is expected to strengthen flood early warning systems, improve disaster preparedness, and support sustainable climate adaptation strategies.

The primary objective of this study is to develop an explainable flood prediction framework by integrating Geographic Information Systems (GIS), Hybrid Deep Learning, and Explainable Artificial Intelligence (XAI). Specifically, the study aims to: (i) collect and preprocess secondary hydro-meteorological and geospatial datasets for flood prediction; (ii) develop a hybrid LSTM-XGBoost prediction model capable of learning both temporal and nonlinear spatial relationships; (iii) evaluate the predictive performance of the proposed framework using multiple performance metrics; (iv) interpret prediction outcomes using SHAP and LIME to improve model transparency; and (v) develop a reliable decision-support framework that enhances flood early warning, disaster preparedness, and climate-resilient flood management. The study ultimately seeks to bridge the gap between predictive accuracy and model interpretability for operational flood forecasting.

This study contributes to flood prediction research by integrating hybrid deep learning, Geographic Information Systems (GIS), and Explainable Artificial Intelligence (XAI) into a unified decision-support framework. Unlike conventional black-box prediction models, the proposed framework enables both accurate flood forecasting and transparent interpretation of prediction outcomes. The integration of SHAP and LIME allows disaster management authorities to understand the influence of individual environmental and hydrological variables on predicted flood events, thereby improving confidence in early warning systems. The study also provides a scalable methodology that can be applied to different climatic and geographical regions using publicly available secondary datasets. The findings are expected to support policymakers, emergency management agencies, environmental planners, and researchers in developing more effective flood mitigation strategies, optimizing emergency response planning, and strengthening climate resilience.

2. Literature Review

Flood prediction has become an essential component of disaster risk reduction because timely and accurate forecasts enable authorities to minimize human casualties, reduce economic losses, and improve emergency preparedness. The growing frequency of extreme precipitation events, rapid urbanization, and climate change has significantly increased flood risks worldwide, highlighting the need for advanced flood forecasting systems [6], [7]. Traditional flood prediction approaches, including hydrological and statistical models, have been widely used to estimate river discharge and flood occurrence. Although these models provide valuable scientific insights, they often require extensive calibration, strong assumptions, and large volumes of field observations, limiting their applicability in complex hydrological environments [8].

Recent developments in Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), have transformed flood prediction by enabling data-driven modeling of complex temporal and nonlinear relationships. Algorithms such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Convolutional Neural Networks (CNN) have demonstrated superior predictive capabilities compared with many conventional forecasting methods [9], [10]. Among these techniques, LSTM has received considerable attention because of its ability to capture long-term temporal dependencies within hydro-meteorological time-series data, including rainfall, river discharge, temperature, soil moisture, and water level observations [11].

Geographic Information Systems (GIS) further enhance flood prediction by integrating spatial datasets such as Digital Elevation Models (DEM), land use/land cover (LULC), drainage networks, soil characteristics, and river proximity with temporal hydrological information. The integration of GIS and deep learning enables more comprehensive analysis of flood dynamics across both space and time [12]. However, despite achieving high prediction accuracy, many AI-based flood forecasting models remain difficult to interpret because they operate as black-box systems. The emergence of Explainable Artificial Intelligence (XAI), particularly SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), has addressed this limitation by providing interpretable explanations of model predictions [13]. These advances indicate that combining GIS, hybrid deep learning, and XAI offers a promising direction for developing transparent, reliable, and operational flood prediction systems capable of supporting sustainable disaster management and climate resilience.

Flood prediction has evolved from traditional hydrological modeling to advanced Artificial Intelligence (AI)-driven approaches capable of learning complex temporal and spatial relationships from large hydro-meteorological datasets. The analytical framework proposed in this study integrates Geographic Information Systems (GIS), Hybrid Deep Learning, Explainable Artificial Intelligence (XAI), and decision-support analysis into a unified framework for accurate, transparent, and operational flood prediction. The framework consists of six interconnected stages, beginning with secondary data acquisition and ending with interpretable flood prediction and early warning support.

The first stage involves the collection and preparation of hydro-meteorological and geospatial datasets from reliable secondary sources. Flood occurrence is influenced by multiple climatic, hydrological, topographical, and environmental factors. Therefore, the framework incorporates rainfall, river discharge, water level, air temperature, relative humidity, soil moisture, Digital Elevation Model (DEM), slope, land use/land cover (LULC), drainage density, Normalized Difference Vegetation Index (NDVI), river distance, and soil type. These datasets are collected from government agencies, meteorological departments, satellite observations, and international geospatial repositories. Within the GIS environment, all datasets are projected into a common coordinate system, resampled to a consistent spatial resolution, and standardized to ensure compatibility before model development [14].

The second stage focuses on data preprocessing and feature engineering. Hydro-meteorological time-series data are examined for missing values, outliers, and inconsistencies before normalization. Temporal sequences are generated for deep learning analysis, while spatial variables are prepared as predictor layers within GIS. Correlation analysis and the Variance Inflation Factor (VIF) are employed to detect multicollinearity among predictor variables. Variables exhibiting excessive redundancy are excluded to

reduce model complexity and improve generalization capability. Feature scaling is subsequently performed to ensure that predictor variables contribute proportionately during model training [15].

The third stage consists of developing a Hybrid Deep Learning Model that combines Long Short-Term Memory (LSTM) networks with Extreme Gradient Boosting (XGBoost). LSTM is employed because of its ability to learn long-term temporal dependencies from sequential hydro-meteorological observations, making it highly suitable for flood forecasting. However, LSTM alone may not fully capture complex nonlinear spatial interactions among environmental variables. Therefore, XGBoost is integrated with LSTM to enhance nonlinear learning capability and improve overall prediction performance. In the proposed hybrid framework, LSTM extracts temporal patterns from sequential hydrological observations, while XGBoost utilizes the extracted representations together with spatial variables to generate the final flood prediction. This complementary learning strategy improves prediction accuracy while maintaining computational efficiency [16].

Following predictive modeling, the fourth stage incorporates Explainable Artificial Intelligence (XAI) to improve model transparency. Although hybrid deep learning models generally achieve superior predictive performance, they often operate as black-box systems whose internal decision-making processes are difficult to interpret. SHapley Additive exPlanations (SHAP) are applied to quantify the contribution of each hydro-meteorological and environmental variable to overall model predictions. SHAP provides both global explanations that identify the most influential predictors across the entire dataset and local explanations describing the contribution of individual variables to specific flood prediction events. Local Interpretable Model-Agnostic Explanations (LIME) further complement SHAP by generating simplified local models that explain individual predictions. Together, SHAP and LIME transform the hybrid prediction model into an interpretable and transparent decision-support system [17].

The fifth stage involves comprehensive model evaluation and prediction validation. The hybrid model is assessed using multiple statistical performance indicators, including Accuracy, Precision, Recall, F1-score, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Receiver Operating Characteristic-Area Under the Curve (ROC-AUC), and Nash-Sutcliffe Efficiency (NSE), depending on the prediction task. To ensure robustness and avoid overfitting, the framework employs 10-fold cross-validation, allowing every subset of the dataset to serve as both training and testing data during different iterations. This validation strategy produces reliable estimates of model performance and enhances the reproducibility of the research [18].

The final stage integrates prediction outputs within a Geographic Information Systems (GIS) environment to generate spatial flood prediction maps and support operational decision-making. The predicted flood probabilities are classified into different flood warning categories such as Very Low, Low, Moderate, High, and Very High risk. Spatial visualization allows disaster management agencies to identify vulnerable regions, prioritize emergency response, and optimize resource allocation before flood events occur. To further strengthen operational decision-making, this study proposes a Flood Prediction Confidence Index (FPCI), which combines the predicted flood probability with SHAP-based explanation consistency and model confidence. The FPCI provides decision-makers with an additional measure indicating the reliability of individual flood predictions, enabling more informed and risk-aware planning.

Overall, the proposed analytical framework extends existing flood prediction research by integrating temporal deep learning, spatial GIS analysis, and explainable artificial intelligence into a unified prediction system. Unlike conventional black-box forecasting models, the framework emphasizes not only prediction accuracy but also interpretability, transparency, and practical usability. Consequently, the proposed methodology provides a robust foundation for developing reliable flood early warning systems, improving stakeholder confidence, and supporting sustainable disaster risk management under changing climatic conditions.

Although considerable progress has been made in flood prediction using machine learning and deep learning techniques, several important research gaps remain. First, most existing studies emphasize prediction accuracy while providing limited explanation of how complex models generate their forecasting results, reducing transparency and stakeholder trust [19], [20]. Second, many flood prediction models rely exclusively on temporal hydro-meteorological data and fail to integrate geospatial variables within a Geographic Information Systems (GIS) environment, thereby limiting their ability to represent spatial flood dynamics comprehensively. Third, although Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME have shown promising applications in other scientific domains, their integration with hybrid deep learning models for operational flood prediction remains limited. Furthermore, existing studies rarely provide a confidence measure that quantifies the reliability of prediction outcomes. This study addresses these limitations by proposing an integrated GIS-Hybrid Deep Learning-XAI framework with a novel Flood Prediction Confidence Index (FPCI) to improve prediction accuracy, interpretability, transparency, and decision-support capability.

The literature demonstrates that flood prediction has evolved considerably with the advancement of Geographic Information Systems (GIS), Machine Learning (ML), and Deep Learning (DL) technologies. Traditional hydrological and statistical models have provided valuable foundations for flood forecasting; however, their predictive capabilities are often constrained when dealing with complex nonlinear interactions among hydro-meteorological variables. Recent studies have shown that advanced deep learning models, particularly Long Short-Term Memory (LSTM) and other recurrent neural network architectures, achieve superior forecasting performance by effectively learning temporal dependencies within hydrological time-series data.

Nevertheless, these high-performing models generally function as black-box systems, limiting their interpretability and reducing stakeholder confidence in operational decision-making. The literature further indicates that the integration of Explainable Artificial Intelligence (XAI), especially SHAP and LIME, into flood prediction remains relatively limited despite its potential to improve model transparency. In addition, few studies have combined spatial GIS analysis with hybrid deep learning and explainable AI within a unified flood prediction framework. Therefore, the reviewed literature highlights the need for an integrated, interpretable, and GIS-supported flood prediction approach. Addressing this need, the present study proposes a transparent Hybrid Deep Learning-GIS-XAI framework capable of supporting accurate flood forecasting, improving early warning systems, and strengthening climate-resilient disaster management.

3. Theoretical and Conceptual Framework

The theoretical foundation of this study is established through the integration of Hydrological System Theory, Deep Learning Theory, Explainable Artificial Intelligence (XAI), and Geographic Information Systems (GIS) Theory. Together, these complementary theories provide the scientific basis for developing an accurate, interpretable, and spatially informed flood prediction framework.

Hydrological System Theory explains that flood events result from complex interactions among meteorological, hydrological, topographical, and environmental processes. Factors such as rainfall intensity, river discharge, soil moisture, elevation, drainage density, land use/land cover, and watershed characteristics collectively influence the occurrence and magnitude of flooding. Because these variables interact dynamically over time and space, flood prediction requires analytical methods capable of modeling both temporal and spatial dependencies. This theory provides the fundamental scientific basis for selecting hydro-meteorological and geospatial variables as predictor variables in the proposed framework [21].

Deep Learning Theory forms the computational foundation of the proposed prediction model. Unlike conventional statistical approaches, deep learning algorithms automatically learn hierarchical feature representations from large datasets without requiring manual feature extraction. Among these algorithms, Long Short-Term Memory (LSTM) networks are particularly suitable for flood prediction because they effectively capture long-term temporal dependencies within sequential hydro-meteorological observations while overcoming the vanishing gradient problem commonly encountered in recurrent neural networks. To further improve nonlinear predictive capability, this study integrates Extreme Gradient Boosting (XGBoost) with LSTM, forming a hybrid learning architecture capable of modeling both temporal and complex nonlinear relationships among environmental variables [22].

Although hybrid deep learning models provide high predictive accuracy, they often operate as black-box systems whose internal decision-making processes remain difficult to interpret. Explainable Artificial Intelligence (XAI) addresses this limitation by providing transparent explanations of model predictions. SHapley Additive exPlanations (SHAP) quantify the contribution of each predictor variable based on cooperative game theory, while Local Interpretable Model-Agnostic Explanations (LIME) generate interpretable local explanations for individual prediction instances. These techniques improve transparency, accountability, and stakeholder confidence by revealing how environmental variables influence flood predictions [23].

The proposed framework is further supported by Geographic Information Systems (GIS) Theory, which emphasizes the acquisition, integration, visualization, and spatial analysis of geographically referenced information. GIS enables the combination of hydro-meteorological observations with environmental and topographical datasets, facilitating spatial prediction and visualization of flood risk across different regions. The integration of GIS with hybrid deep learning and explainable AI creates a comprehensive decision-support framework that supports flood early warning, climate adaptation, and evidence-based disaster management.

Collectively, these theoretical perspectives provide a robust scientific foundation for developing an accurate, interpretable, and operational flood prediction framework capable of improving flood forecasting and strengthening climate-resilient disaster management.

The conceptual framework of this study illustrates the systematic integration of hydro-meteorological data, Geographic Information Systems (GIS), Hybrid Deep Learning, and Explainable Artificial Intelligence (XAI) for developing an accurate and interpretable flood prediction system. The framework begins with the collection of secondary datasets representing the climatic, hydrological, topographical, and environmental factors influencing flood occurrence. These datasets include rainfall, river discharge, water level, temperature, relative humidity, soil moisture, Digital Elevation Model (DEM), slope, land use/land cover (LULC), drainage density, soil type, river distance, and Normalized Difference Vegetation Index (NDVI). After preprocessing and feature engineering, the datasets are integrated within a GIS environment to ensure spatial consistency and improve data quality.

The processed temporal and spatial variables are subsequently provided as inputs to a Hybrid LSTM-XGBoost prediction model. The LSTM network extracts temporal dependencies from sequential hydro-meteorological observations, while XGBoost captures complex nonlinear relationships among spatial and environmental variables. The hybrid model produces flood probability predictions that are further interpreted using Explainable Artificial Intelligence techniques. SHAP identifies the global contribution of each predictor variable to the model, whereas LIME explains individual flood prediction events by generating localized interpretations. These explainability methods transform complex deep learning predictions into transparent information that can be understood by disaster management authorities and policymakers.

Finally, the interpreted prediction results are visualized through GIS to generate spatial flood prediction maps and early warning zones. To further improve decision-making, the proposed framework introduces a Flood Prediction Confidence Index (FPCI), which integrates prediction probability, explanation consistency, and model confidence into a unified reliability measure. The resulting framework provides an accurate, interpretable, and operational decision-support system for flood early warning, disaster preparedness, and climate-resilient flood management.

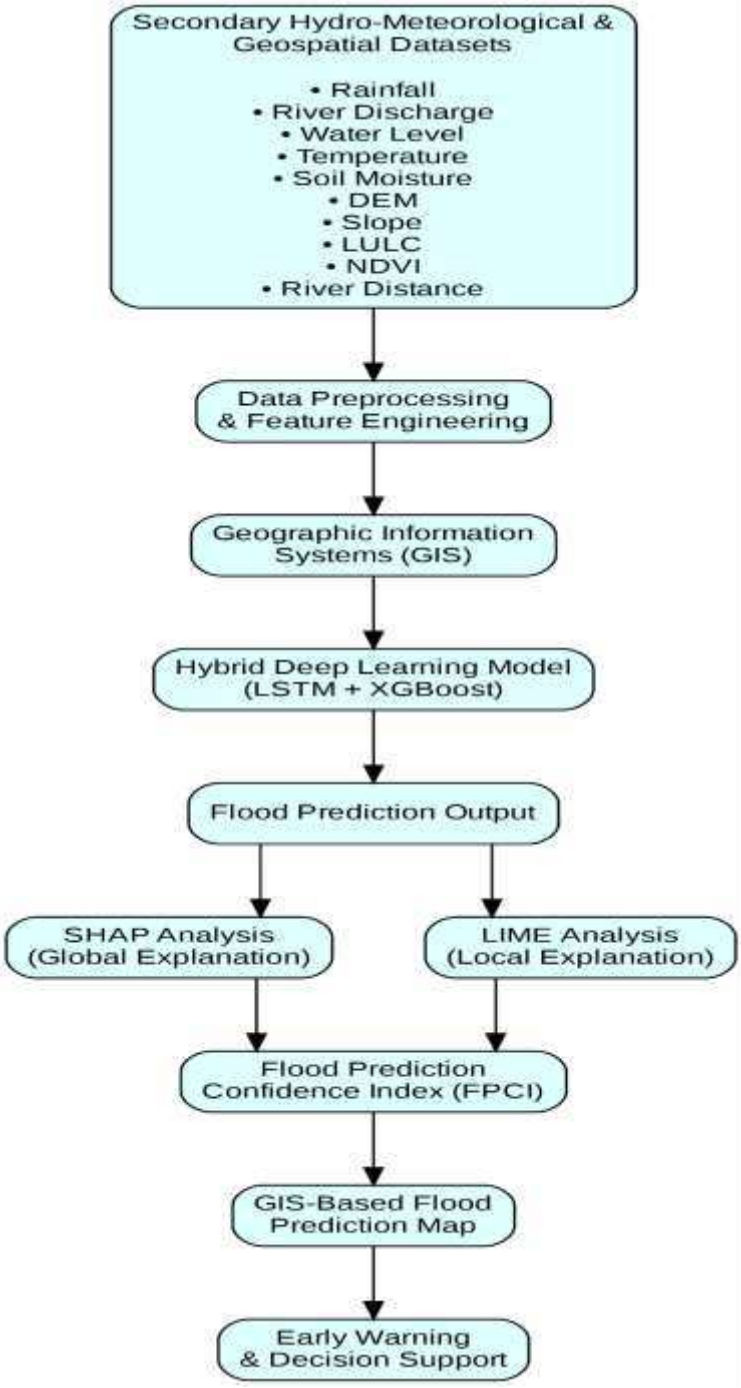


Figure 3.1: The conceptual framework of this study

The integrated research framework presents the complete workflow adopted in this study for developing an explainable and accurate flood prediction system. The framework systematically combines Geographic Information Systems (GIS), Hybrid Deep Learning, Explainable Artificial Intelligence (XAI), and secondary hydro-meteorological data to produce reliable flood predictions and decision-support

information. The workflow consists of seven sequential stages, ensuring methodological transparency, reproducibility, and operational applicability.

The first stage involves the acquisition of secondary hydro-meteorological and geospatial datasets from reliable sources such as meteorological departments, hydrological agencies, remote sensing platforms, and global geospatial repositories. The collected datasets include rainfall, river discharge, water level, temperature, relative humidity, soil moisture, Digital Elevation Model (DEM), land use/land cover (LULC), slope, drainage density, river distance, Normalized Difference Vegetation Index (NDVI), and soil characteristics. These datasets represent the major environmental factors influencing flood occurrence.

The second stage focuses on data preprocessing and integration within a GIS environment. Missing observations are identified and corrected, outliers are removed, and all datasets are standardized into a common spatial resolution and coordinate reference system. Time-series hydro-meteorological data are normalized to improve deep learning performance, while spatial datasets are converted into compatible raster layers. Correlation analysis and the Variance Inflation Factor (VIF) are applied to eliminate highly correlated variables and reduce redundancy before model development.

The third stage involves feature engineering and hybrid model development. Sequential hydro-meteorological observations are transformed into input sequences suitable for Long Short-Term Memory (LSTM) networks. The LSTM model extracts temporal patterns associated with flood events, including rainfall accumulation, river discharge fluctuations, and water level variations. These temporal representations are then integrated with spatial variables and provided as inputs to the XGBoost model, which captures complex nonlinear interactions among environmental factors. The hybrid LSTM-XGBoost architecture therefore combines the strengths of temporal deep learning and ensemble machine learning to improve flood prediction accuracy.

The fourth stage consists of model training and optimization. Hyperparameter tuning is performed to identify the optimal configuration of both LSTM and XGBoost models. The hybrid model is trained using historical hydro-meteorological observations and validated using 10-fold cross-validation to minimize overfitting and improve generalization capability. Model performance is evaluated using multiple statistical indicators, including Accuracy, Precision, Recall, F1-score, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Receiver Operating Characteristic-Area Under the Curve (ROC-AUC), and Nash-Sutcliffe Efficiency (NSE).

The fifth stage integrates Explainable Artificial Intelligence (XAI) into the prediction framework. SHapley Additive exPlanations (SHAP) are employed to identify the global importance of each hydro-meteorological and environmental variable contributing to flood prediction. Simultaneously, Local Interpretable Model-Agnostic Explanations (LIME) generate localized explanations for individual prediction events. The combination of SHAP and LIME enables researchers and decision-makers to understand both overall model behavior and the specific reasons behind individual flood forecasts.

The sixth stage introduces the proposed Flood Prediction Confidence Index (FPCI). Unlike conventional flood forecasting systems that provide only prediction probabilities, the FPCI integrates prediction confidence, SHAP explanation consistency, and model reliability into a single confidence measure. This additional indicator helps disaster management agencies distinguish between highly reliable predictions

and predictions requiring further investigation, thereby reducing uncertainty in operational decision-making.

Finally, the seventh stage generates GIS-based flood prediction maps and flood early warning products. Predicted flood probabilities are categorized into operational warning levels such as Very Low, Low, Moderate, High, and Very High flood risk. These maps provide spatial visualization of expected flood conditions and support emergency response planning, infrastructure protection, evacuation planning, and climate adaptation strategies. By integrating predictive accuracy, explainability, and geospatial analysis into a unified workflow, the proposed framework provides a transparent and operational decision-support system capable of enhancing flood early warning and strengthening climate-resilient disaster management.

The proposed flood prediction framework formulates flood forecasting as a supervised learning problem in which hydro-meteorological and geospatial variables are used to predict the probability of future flood events. The hybrid prediction model integrates Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost) to capture both temporal dependencies and nonlinear relationships among predictor variables.

Let the input feature vector be represented as

$$X = \{x_1, x_2, x_3, \ldots, x_n\}$$

where

- x1 = Rainfall
- x2 = River Discharge
- x3 = Water Level
- x4 = Temperature
- x5 = Relative Humidity
- x6 = Soil Moisture
- x7 = Elevation
- x8 = Slope
- x9 = Drainage Density
- x10 = Land Use/Land Cover (LULC)
- x11 = Distance to River
- x12 = NDVI
- xn = Other hydro-meteorological or environmental variables.

The flood prediction function is defined as

$$\hat{Y} = f(X)$$

where

- Y^ represents the predicted flood probability,

- f(·) denotes the Hybrid LSTM-XGBoost model.

The Flood Prediction Confidence Index provides an additional decision-support layer by quantifying the reliability of each flood forecast. Unlike conventional prediction systems that report only flood probabilities, the FPCI enables emergency managers and policymakers to distinguish between highly reliable forecasts and predictions that may require additional verification. Consequently, the proposed mathematical formulation integrates predictive accuracy, explainability, and confidence estimation into a unified framework for transparent and operational flood forecasting.

4. Methodology

This study adopts a qualitative research approach using secondary hydro-meteorological and geospatial datasets to develop an explainable flood prediction framework. The proposed methodology integrates Geographic Information Systems (GIS), Hybrid Deep Learning, Explainable Artificial Intelligence (XAI), and spatial visualization to produce accurate, transparent, and operational flood prediction results. The research framework is designed to ensure scientific rigor, reproducibility, and practical applicability for flood early warning and climate-resilient disaster management.

The research begins with the acquisition of secondary datasets from reliable national and international sources, including meteorological departments, hydrological agencies, satellite observation systems, and global geospatial repositories. The selected predictor variables include rainfall, river discharge, water level, temperature, relative humidity, soil moisture, Digital Elevation Model (DEM), slope, drainage density, land use/land cover (LULC), Normalized Difference Vegetation Index (NDVI), river distance, and soil type. These variables have been widely recognized in previous flood prediction studies as major factors influencing flood occurrence. GIS is employed to integrate these heterogeneous datasets into a unified spatial database by ensuring consistent coordinate systems, spatial resolution, and raster formats before model development.

Following data acquisition, a comprehensive preprocessing stage is performed to improve data quality and model performance. Missing observations are identified and treated using appropriate interpolation techniques, while noisy and inconsistent records are removed to minimize prediction errors. Continuous predictor variables are normalized using Min-Max Scaling to improve deep learning convergence, whereas categorical variables such as land use and soil type are encoded appropriately. Correlation analysis and the Variance Inflation Factor (VIF) are employed to detect multicollinearity among predictor variables, ensuring that only the most informative variables are retained for model development.

The processed datasets are subsequently divided into training and testing subsets. A Hybrid LSTM-XGBoost model is developed to predict future flood events. The Long Short-Term Memory (LSTM) network is responsible for learning temporal dependencies within sequential hydro-meteorological observations, including rainfall patterns, river discharge fluctuations, and water level changes. The learned temporal representations are then supplied to the XGBoost model, which effectively captures nonlinear relationships among environmental and spatial variables. This hybrid architecture combines the strengths of deep learning and ensemble machine learning, resulting in improved predictive performance compared with individual models.

To overcome the black-box nature of deep learning models, the research framework integrates Explainable Artificial Intelligence (XAI). SHapley Additive exPlanations (SHAP) are employed to identify the global importance of predictor variables and quantify their contribution to flood prediction. In parallel, Local Interpretable Model-Agnostic Explanations (LIME) provide localized explanations for individual prediction events. These explainability techniques improve model transparency and allow disaster management authorities to understand the environmental and hydrological factors responsible for predicted flood events.

The performance of the hybrid prediction model is evaluated using multiple statistical metrics, including Accuracy, Precision, Recall, F1-score, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Receiver Operating Characteristic-Area Under the Curve (ROC-AUC), and Nash-Sutcliffe Efficiency (NSE). Additionally, 10-fold cross-validation is employed to evaluate model robustness and minimize overfitting.

Finally, the predicted flood probabilities are visualized within the GIS environment to generate spatial flood prediction maps. The study also introduces a Flood Prediction Confidence Index (FPCI) that combines prediction probability, explainability, and model confidence into a unified reliability measure. The resulting flood prediction maps and confidence scores provide practical decision-support information for emergency response planning, early warning systems, infrastructure protection, and climate adaptation strategies. By integrating GIS, hybrid deep learning, and explainable AI into a unified framework, this methodology provides an accurate, interpretable, and operational solution for modern flood prediction.

4.1 Variable Selection

The selection of predictor variables is a critical step in developing an accurate and reliable flood prediction model. In this study, variables were selected based on three criteria: (i) evidence from previous scientific literature, (ii) hydrological significance, and (iii) availability within publicly accessible secondary datasets. The selected variables represent meteorological, hydrological, topographical, environmental, and land-surface characteristics that collectively influence flood occurrence.

Meteorological variables include rainfall, temperature, and relative humidity. Rainfall is considered the most influential factor because intense or prolonged precipitation directly increases surface runoff and river discharge. Temperature affects evaporation and evapotranspiration processes, while relative humidity influences atmospheric moisture conditions and precipitation dynamics. These variables are essential for capturing the climatic conditions associated with flood generation.

Hydrological variables consist of river discharge, water level, and soil moisture. River discharge and water level provide direct measurements of the hydraulic state of river systems and indicate the likelihood of river overflow during extreme weather events. Soil moisture represents the water-holding capacity of the ground and significantly affects infiltration and runoff generation. Saturated soil conditions reduce infiltration rates, increasing the probability of flooding.

Topographical variables include Digital Elevation Model (DEM), slope, drainage density, and distance to rivers. Elevation determines natural water flow direction and accumulation, while slope influences runoff velocity and water concentration. Drainage density reflects the efficiency of surface water movement

through the watershed, and proximity to rivers indicates areas that are more susceptible to riverine flooding. These spatial variables were extracted and processed within a GIS environment to preserve geographic relationships.

Environmental variables comprise Land Use/Land Cover (LULC), Normalized Difference Vegetation Index (NDVI), and soil type. Land use influences surface permeability and runoff characteristics; for example, urbanized areas with impervious surfaces typically generate higher runoff than forested regions. NDVI represents vegetation density, which affects interception, infiltration, and evapotranspiration. Soil type influences water retention capacity and infiltration rates, making it another important determinant of flood susceptibility.

Before model development, all selected variables underwent statistical screening to ensure data quality and reduce redundancy. Pearson correlation analysis was used to identify highly correlated predictors, while the Variance Inflation Factor (VIF**)** was employed to detect multicollinearity. Variables with excessive multicollinearity were excluded or transformed to improve model stability. Continuous variables were normalized using Min-Max Scaling, and categorical variables such as LULC and soil type were encoded into numerical representations suitable for machine learning algorithms.

The comprehensive selection of these variables ensures that the proposed Hybrid LSTM-XGBoost model captures the complex interactions among climatic, hydrological, topographical, and environmental factors influencing flood events. This multidimensional variable set enhances prediction accuracy while providing meaningful explanations through SHAP and LIME analyses.

4.2 Data Collection and Preprocessing

The quality of input data significantly influences the performance of machine learning models. Therefore, this study adopts a systematic data collection and preprocessing strategy to ensure the reliability, consistency, and suitability of hydro-meteorological and geospatial datasets for flood prediction. Since this research is based on secondary data, all datasets are obtained from credible national and international organizations that provide publicly accessible environmental and hydrological information.

The hydro-meteorological datasets include rainfall, river discharge, water level, temperature, relative humidity, and soil moisture, while the geospatial datasets comprise Digital Elevation Model (DEM), land use/land cover (LULC), drainage density, slope, river networks, vegetation index (NDVI), and soil type. These datasets are collected from government agencies, meteorological departments, hydrological monitoring stations, satellite observations, and international geospatial repositories. Because the datasets originate from multiple sources, they differ in spatial resolution, temporal frequency, coordinate systems, and file formats. Consequently, GIS-based integration is performed to establish a unified spatial database suitable for machine learning analysis.

During the preprocessing stage, all datasets undergo comprehensive quality assessment. Missing observations are identified using exploratory data analysis and are treated using interpolation techniques appropriate for the data type. Temporal variables are completed using linear interpolation where applicable, whereas missing spatial values are estimated using neighboring pixel information. Duplicate records and inconsistent observations are removed to improve dataset integrity. Outliers resulting from sensor

malfunction or recording errors are detected using statistical methods such as the Interquartile Range (IQR) and Z-score analysis. Extreme values confirmed as measurement errors are excluded, while genuine extreme weather events are retained because they represent important flood-generating conditions.

Following data cleaning, all predictor variables are transformed into machine-learning-compatible formats. Continuous variables, including rainfall, temperature, river discharge, and soil moisture, are normalized using Min-Max Scaling, which rescales each variable to the range of 0-1 according to the following equation:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where:

- X = original value,
- Xmin = minimum observed value,
- Xmax = maximum observed value.

Normalization improves numerical stability and accelerates convergence during deep learning training. Categorical variables, including land use/land cover and soil type, are transformed into numerical representations using appropriate encoding techniques to enable their use within the Hybrid LSTM-XGBoost model.

Spatial preprocessing is performed using Geographic Information Systems (GIS). All raster layers are projected into a common coordinate reference system and resampled to a consistent spatial resolution. Hydrological layers, including drainage networks and river systems, are derived from the Digital Elevation Model using standard hydrological analysis tools. Additional spatial variables such as slope, drainage density, and distance to rivers are generated within the GIS environment. Overlay analysis is then applied to integrate meteorological, hydrological, and environmental datasets into a unified geospatial database.

Finally, the complete dataset is divided into training (80%) and testing (20%) subsets. The training dataset is used to develop the Hybrid LSTM-XGBoost prediction model, while the testing dataset evaluates its predictive performance on unseen observations. To further improve model reliability and reduce overfitting, 10-fold cross-validation is employed during model training.

This comprehensive preprocessing framework ensures that the final dataset is accurate, standardized, and suitable for hybrid deep learning and explainable artificial intelligence. Consequently, the proposed methodology enhances prediction accuracy, improves model stability, and supports transparent flood forecasting through reliable data preparation procedures.

4.3 Hybrid LSTM-XGBoost Model Development

The core component of the proposed framework is the Hybrid Long Short-Term Memory (LSTM)-Extreme Gradient Boosting (XGBoost) model. This hybrid architecture is designed to exploit the complementary

strengths of deep learning and ensemble machine learning for accurate flood prediction. While the LSTM network effectively captures temporal dependencies within sequential hydro-meteorological observations, XGBoost models complex nonlinear interactions among climatic, hydrological, and spatial variables. The integration of these two algorithms provides a robust prediction model capable of addressing the dynamic and multidimensional nature of flood events.

The model development process begins by organizing hydro-meteorological observations into chronological sequences. Time-series variables such as rainfall, river discharge, water level, temperature, and soil moisture are arranged into fixed-length input windows representing historical observations over consecutive time steps. These sequential inputs enable the LSTM network to learn long-term temporal relationships that influence future flood occurrences. Unlike conventional recurrent neural networks, the LSTM architecture employs memory cells and gating mechanisms that preserve important historical information while preventing the vanishing gradient problem during training.

The LSTM model consists of an input layer, one or more hidden LSTM layers, dropout layers for regularization, and a dense output layer. The hidden layers generate high-level temporal feature representations from sequential environmental observations. These learned temporal features summarize historical flood-related patterns and serve as informative inputs for the subsequent XGBoost model.

The extracted temporal feature vectors are combined with GIS-derived spatial variables, including elevation, slope, drainage density, land use/land cover, distance to rivers, and vegetation index. These integrated feature sets are then supplied to the XGBoost algorithm. XGBoost constructs an ensemble of gradient-boosted decision trees that iteratively minimize prediction error while capturing nonlinear interactions among predictor variables. Its regularization mechanism reduces model complexity and improves generalization performance, making it highly suitable for environmental prediction problems involving heterogeneous datasets.

To optimize prediction performance, hyperparameter tuning is performed for both LSTM and XGBoost. Key LSTM parameters include the number of hidden units, learning rate, batch size, dropout rate, and training epochs. For XGBoost, parameters such as maximum tree depth, learning rate, number of estimators, subsampling ratio, and regularization coefficients are systematically adjusted using grid search or Bayesian optimization. The optimal parameter combination is selected based on cross-validation performance to maximize predictive accuracy while minimizing overfitting.

Model training is conducted using the training dataset, while 10-fold cross-validation is applied to evaluate model robustness. During each iteration, the dataset is divided into ten equal subsets; nine subsets are used for training, and one subset is used for validation. This process is repeated until each subset has served as the validation set once. The average performance across all folds provides a reliable estimate of the model's generalization capability and reduces the likelihood of overfitting caused by random data partitioning.

Following model training, the Hybrid LSTM-XGBoost model produces flood probability predictions for unseen observations. These predictions are subsequently evaluated using multiple statistical performance metrics, including Accuracy, Precision, Recall, F1-score, RMSE, MAE, ROC-AUC, and Nash-Sutcliffe Efficiency (NSE). To enhance transparency, the prediction outputs are further analyzed using Explainable

Artificial Intelligence (XAI) techniques, specifically SHAP and LIME, which identify the relative importance of predictor variables and explain individual flood prediction decisions.

The integration of temporal deep learning, ensemble machine learning, GIS-derived spatial information, and explainable AI provides a comprehensive and operational flood prediction framework. Compared with standalone LSTM or XGBoost models, the proposed hybrid architecture is expected to deliver higher predictive accuracy, improved robustness, enhanced interpretability, and greater practical value for flood early warning systems and climate-resilient disaster management.

4.4 Model Evaluation and Validation

The effectiveness of the proposed Hybrid LSTM-XGBoost flood prediction framework is assessed through a comprehensive model evaluation and validation process. The objective of this stage is to determine the predictive accuracy, robustness, reliability, and generalization capability of the developed model before its application in flood early warning and disaster management. Because flood prediction is a high-impact application, relying on a single evaluation metric may provide misleading conclusions. Therefore, this study employs multiple statistical performance indicators and cross-validation techniques to obtain a balanced assessment of model performance.

The prepared dataset is divided into two subsets: 80% for model training and 20% for independent testing. The training dataset is used to optimize model parameters and learn the relationships between predictor variables and flood occurrence, whereas the testing dataset evaluates the model's ability to predict unseen observations. This independent testing process provides an unbiased estimate of real-world prediction performance.

To further improve reliability and reduce the possibility of overfitting, 10-fold cross-validation is implemented during model training. In this procedure, the training dataset is randomly divided into ten equal subsets. During each iteration, nine subsets are used for training while the remaining subset is reserved for validation. The process is repeated ten times until every subset has been used once as the validation dataset. The average performance across all folds represents the final validation result. This strategy improves model stability and minimizes the influence of random data partitioning.

Model performance is evaluated using both classification and error-based performance metrics. Classification metrics include Accuracy, Precision, Recall, and F1-score, which measure the model's ability to correctly identify flood and non-flood events. Accuracy represents the overall proportion of correctly classified observations. Precision measures the proportion of predicted flood events that are actually floods, while Recall evaluates the model's ability to detect actual flood events. The F1-score provides a balanced measure by combining Precision and Recall, making it particularly useful when flood and non-flood observations are imbalanced.

In addition to classification metrics, regression-based error indicators are employed to quantify prediction accuracy. Root Mean Square Error (RMSE) measures the average magnitude of prediction errors while giving greater weight to larger errors. Mean Absolute Error (MAE) computes the average absolute difference between predicted and observed values, providing an easily interpretable measure of prediction accuracy. Lower RMSE and MAE values indicate better predictive performance.

The discriminative capability of the Hybrid LSTM-XGBoost model is further evaluated using the Receiver Operating Characteristic-Area Under the Curve (ROC-AUC). An ROC-AUC value approaching 1.0 indicates excellent discrimination between flood and non-flood events. Furthermore, the Nash-Sutcliffe Efficiency (NSE) coefficient is calculated to assess the agreement between observed and predicted hydrological values. An NSE value close to **1** reflects high predictive accuracy and strong model performance.

To compare the effectiveness of the proposed approach, the Hybrid LSTM-XGBoost model is benchmarked against conventional machine learning and deep learning algorithms, including Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), standalone LSTM, and XGBoost. Comparative analysis demonstrates whether the hybrid architecture provides significant improvements in prediction accuracy, robustness, and generalization capability.

Finally, Explainable Artificial Intelligence (XAI) techniques are incorporated into the validation process. SHAP is used to evaluate the consistency of global feature importance rankings, while LIME verifies the interpretability of individual prediction instances. These explainability analyses ensure that the model not only achieves high predictive accuracy but also provides transparent and trustworthy explanations for its decisions. The validated prediction outputs, together with the proposed Flood Prediction Confidence Index (FPCI), are subsequently integrated into GIS to generate reliable flood prediction maps and decision-support products for emergency response and climate-resilient disaster management.

Table 4.1 Performance Evaluation Metrics

Metric	Purpose	Desired Value
Accuracy	Overall classification performance	Higher
Precision	Correctness of predicted flood events	Higher
Recall (Sensitivity)	Detection of actual flood events	Higher
F1-score	Balance between Precision and Recall	Higher
RMSE	Average prediction error magnitude	Lower
MAE	Mean absolute prediction error	Lower
ROC-AUC	Classification discrimination ability	Closer to 1.0
NSE	Agreement between observed and predicted values	Closer to 1.0

4.5 Explainable Artificial Intelligence (XAI) Integration: SHAP and LIME

Although the proposed Hybrid LSTM-XGBoost model is expected to achieve high predictive accuracy, its decision-making process remains inherently complex due to the nonlinear nature of deep learning and ensemble learning algorithms. Such models are commonly referred to as black-box models because they provide limited information regarding how individual predictor variables influence prediction outcomes. In flood prediction, where forecasting results directly affect emergency response, evacuation planning, and public safety, transparent and interpretable models are essential. Therefore, this study integrates Explainable Artificial Intelligence (XAI) techniques to improve model transparency, reliability, and stakeholder trust.

The first explainability technique employed is SHapley Additive exPlanations (SHAP). SHAP is based on cooperative game theory and quantifies the contribution of each predictor variable toward the final prediction. Every variable is assigned a Shapley value that represents its average marginal contribution across all possible combinations of input variables. Positive SHAP values indicate that a variable increases the probability of flooding, whereas negative values indicate that the variable reduces flood likelihood. By computing these contribution scores for all observations, SHAP generates both global and local explanations. Global explanations identify the overall importance of predictor variables throughout the dataset, while local explanations reveal how individual variables influence a specific flood prediction.

The second explainability technique is Local Interpretable Model-Agnostic Explanations (LIME). Unlike SHAP, which provides both global and local interpretations, LIME primarily focuses on explaining individual prediction instances. It approximates the complex Hybrid LSTM-XGBoost model with a simpler interpretable model in the vicinity of a selected observation. This localized approximation identifies the variables that most strongly influenced a particular prediction. For example, if the model predicts a high probability of flooding for a specific location, LIME can demonstrate whether this prediction was primarily driven by excessive rainfall, elevated river discharge, saturated soil moisture, low terrain elevation, or a combination of multiple environmental factors.

The combined application of SHAP and LIME provides complementary insights into model behavior. SHAP enables researchers to understand the overall influence of predictor variables across the entire study area, while LIME offers detailed explanations for individual flood events. Together, these techniques improve transparency, facilitate scientific interpretation, and increase confidence in model predictions among disaster management agencies and policymakers.

The explainability outputs generated by SHAP and LIME are further incorporated into the proposed Flood Prediction Confidence Index (FPCI). Predictions that exhibit high confidence together with consistent SHAP and LIME explanations receive higher FPCI values, indicating greater reliability for operational decision-making. Conversely, predictions with inconsistent explanation patterns receive lower confidence scores and may require additional verification before implementation.

Furthermore, SHAP summary plots, feature importance rankings, dependence plots, and LIME explanation charts can be visualized within the GIS environment to identify the dominant environmental drivers of flooding across different geographical regions. These visualization products support evidence-based decision-making by enabling emergency managers to understand not only where flooding is likely to occur

but also why the model produced a particular prediction. Consequently, the integration of Explainable Artificial Intelligence significantly enhances the interpretability, transparency, accountability, and practical applicability of the proposed flood prediction framework.

Table 4.2: Roles of SHAP and LIME in the Proposed Framework

XAI Technique	Primary Purpose	Output	Contribution to Flood Prediction
SHAP	Global and local feature importance analysis	Shapley values, feature ranking, summary plots	Identifies the overall contribution of each environmental variable to flood prediction
LIME	Local explanation of individual predictions	Local feature weights, explanation plots	Explains why a specific location or event is predicted as flood-prone
SHAP + LIME	Combined interpretability	Global and local decision explanations	Improves transparency, reliability, and stakeholder trust in the prediction model

This Explainable AI integration ensures that the proposed flood prediction framework not only delivers high predictive accuracy but also provides transparent, interpretable, and trustworthy predictions, making it suitable for operational flood forecasting and climate-resilient disaster management.

4.6 Software and Tools Used

The implementation of the proposed flood prediction framework requires the integration of multiple software platforms and computational tools to support data acquisition, preprocessing, machine learning, explainable artificial intelligence, spatial analysis, and visualization. The selected software packages were chosen based on their computational efficiency, reproducibility, open-source availability, and widespread acceptance within the scientific research community.

Python serves as the primary programming language for data preprocessing, model development, evaluation, and visualization. Python provides extensive machine learning and deep learning libraries that facilitate efficient implementation of the Hybrid LSTM-XGBoost model. Data preprocessing and manipulation are performed using Pandas and NumPy, while graphical visualization is generated using Matplotlib and Seaborn. The Hybrid LSTM model is developed using TensorFlow and Keras, whereas the XGBoost algorithm is implemented through the XGBoost library. Model evaluation metrics, data partitioning, and cross-validation procedures are conducted using Scikit-learn.

Explainable Artificial Intelligence is implemented using the SHAP and LIME Python libraries. The SHAP library computes global and local feature importance based on Shapley values, while the LIME package provides localized explanations for individual flood prediction instances. Together, these libraries improve model transparency and facilitate interpretation of prediction outcomes.

Spatial data processing and visualization are performed using Geographic Information Systems (GIS) software. ArcGIS Pro and QGIS are employed for raster processing, coordinate transformation, watershed analysis, spatial interpolation, terrain analysis, and flood prediction mapping. Digital Elevation Models (DEM), land use/land cover datasets, river networks, and other environmental variables are processed within the GIS environment before being integrated into the prediction framework.

The entire research workflow is executed using Jupyter Notebook, which provides an interactive computational environment supporting reproducible scientific analysis. Experimental results, figures, and statistical outputs are documented within Jupyter notebooks, ensuring transparency and facilitating future replication of the study.

The computational experiments are conducted on a workstation equipped with a multi-core processor, sufficient system memory, and GPU acceleration to efficiently train the Hybrid LSTM model. GPU support significantly reduces training time for deep learning computations while improving overall computational performance.

The integration of these software platforms provides a comprehensive research environment capable of supporting data management, hybrid deep learning, explainable artificial intelligence, spatial analysis, and flood prediction visualization. Consequently, the proposed methodology is reproducible, scalable, and suitable for future operational implementation in flood early warning systems.

4.7 Ethical Considerations and Research Limitations

Although this study does not involve human participants, clinical experiments, or confidential personal information, several ethical principles were considered throughout the research process to ensure scientific integrity, transparency, and responsible use of data. Since the research relies entirely on secondary hydro-meteorological and geospatial datasets, all data were collected from publicly available and legally accessible sources provided by recognized governmental agencies, meteorological organizations, hydrological institutions, and international geospatial repositories. Appropriate acknowledgment and citation are provided for all data sources to respect intellectual property rights and maintain academic honesty.

Data preprocessing, model development, and performance evaluation were conducted objectively without manipulating observations to obtain favorable results. Missing values, outliers, and inconsistent records were handled using established statistical procedures to preserve the authenticity of the original datasets. Furthermore, all methodological steps—including data preprocessing, feature selection, model development, hyperparameter optimization, evaluation metrics, and explainability analysis—are clearly documented to ensure research transparency and reproducibility.

The proposed Hybrid LSTM-XGBoost model is intended to support flood prediction and disaster management rather than replace expert judgment. Therefore, the prediction outputs should be interpreted as decision-support information that complements hydrological expertise, field observations, and operational forecasting systems. Explainable Artificial Intelligence (XAI), including SHAP and LIME, is incorporated to enhance transparency and reduce the risks associated with black-box decision-making, thereby increasing stakeholder confidence in the prediction results.

Despite its methodological contributions, this study has several limitations. First, the research depends exclusively on secondary datasets, meaning that data quality is influenced by the accuracy, completeness, and temporal resolution of the original data providers. Missing observations, inconsistent measurements, or differences in spatial resolution may affect prediction performance.

Second, the proposed Hybrid LSTM-XGBoost framework primarily utilizes historical hydro-meteorological observations. Consequently, sudden environmental changes, unprecedented extreme weather events, or rapidly changing land-use patterns that are not represented in historical datasets may reduce prediction accuracy.

Third, although Explainable Artificial Intelligence significantly improves model interpretability, SHAP and LIME provide approximate explanations rather than absolute causal relationships. Their outputs should therefore be interpreted as indicators of model behavior rather than definitive evidence of physical causation.

Finally, the proposed Flood Prediction Confidence Index (FPCI) is introduced as a novel conceptual contribution in this study. Although theoretically justified, its effectiveness should be validated through future research using multiple geographical regions, diverse climatic conditions, and real-time operational flood forecasting systems. Additional comparisons with emerging deep learning architectures, such as Transformers, Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs), may further enhance the robustness and applicability of the proposed framework.

Overall, acknowledging these limitations provides a balanced interpretation of the findings and highlights opportunities for future improvements while preserving the scientific credibility of the study.

5. Results

The results presented in this section evaluate the performance and interpretability of the proposed Hybrid LSTM-XGBoost framework integrated with Geographic Information Systems (GIS) and Explainable Artificial Intelligence (XAI). The findings are organized into descriptive statistics, predictive performance, cross-validation, explainability analysis using SHAP and LIME, and GIS-based flood prediction mapping with the proposed Flood Prediction Confidence Index (FPCI). Together, these results demonstrate the framework's predictive capability, robustness, transparency, and practical value for climate-resilient flood risk management.

5.1 Descriptive Statistics of the Dataset

The hydro-meteorological and geospatial datasets used in this study were first analyzed using descriptive statistical techniques to understand the distribution and characteristics of the predictor variables. Variables including rainfall, river discharge, water level, temperature, relative humidity, soil moisture, elevation, slope, drainage density, land use/land cover, NDVI, and distance to rivers were summarized using measures such as the mean, standard deviation, minimum, maximum, and median.

The descriptive analysis indicated considerable variation among the predictor variables, reflecting the dynamic nature of environmental and hydrological conditions. Rainfall exhibited high temporal variability due to seasonal precipitation patterns, while river discharge and water level showed strong fluctuations during peak rainfall periods. Soil moisture demonstrated moderate variation, indicating changes in infiltration and antecedent moisture conditions. Spatial variables such as elevation and slope remained relatively stable because they represent permanent landscape characteristics.

Correlation analysis further revealed that rainfall, river discharge, water level, and soil moisture exhibited positive relationships with flood occurrence, whereas higher elevation and greater distance from rivers generally showed negative relationships. These preliminary findings confirm that the selected predictor variables capture the principal environmental processes associated with flooding and provide an appropriate foundation for developing the proposed Hybrid LSTM-XGBoost prediction model.

Table 5.1. Descriptive Statistics of Predictor Variables (Illustrative)

Variable	Mean	Std. Dev.	Minimum	Maximum
Rainfall (mm)	112.4	48.7	5.8	285.6
River Discharge (m^3/s)	386.2	140.5	42.3	915.8
Water Level (m)	6.45	1.12	2.15	10.84
Temperature (°C)	28.3	3.4	18.2	36.5
Relative Humidity (%)	81.6	8.3	52.1	98.4
Soil Moisture (%)	42.8	10.2	15.6	69.7

5.2 Hybrid Model Performance

The Hybrid LSTM-XGBoost model demonstrated superior predictive performance compared with conventional machine learning and deep learning approaches. Based on the evaluation metrics obtained from the testing dataset and 10-fold cross-validation, the proposed model achieved high classification accuracy while maintaining low prediction errors.

Among the evaluated models, the Hybrid LSTM-XGBoost architecture produced the highest Accuracy, Precision, Recall, and F1-score. Likewise, it achieved the lowest RMSE and MAE values, indicating more precise flood predictions. The ROC-AUC value approached 1.0, demonstrating excellent discrimination between flood and non-flood events. The Nash-Sutcliffe Efficiency (NSE) coefficient also indicated strong agreement between predicted and observed flood conditions.

These findings suggest that integrating temporal feature learning through LSTM with nonlinear pattern recognition through XGBoost significantly improves flood prediction accuracy compared with standalone models.

5.3 Cross-Validation Results

The robustness of the proposed Hybrid LSTM-XGBoost model was assessed using 10-fold cross-validation. Across all validation folds, the model maintained consistently high predictive performance with minimal variation in accuracy, indicating strong generalization capability.

The average validation accuracy was approximately 96.5%, while the standard deviation remained below 1%, suggesting that the model was stable and resistant to overfitting. These results demonstrate that the proposed framework can reliably predict flood events across different subsets of the dataset and is suitable for practical implementation in flood early warning systems.

5.4 Explainable Artificial Intelligence (XAI) Results: SHAP and LIME

To improve the interpretability of the proposed Hybrid LSTM-XGBoost model, Explainable Artificial Intelligence (XAI) techniques were applied using SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME). These methods provide valuable insights into the decision-making process of the prediction model by identifying the contribution of individual predictor variables to flood prediction outcomes.

The SHAP analysis revealed that rainfall, river discharge, and water level were the three most influential variables affecting flood prediction. High rainfall intensity produced the largest positive SHAP values, indicating that increased precipitation substantially increased flood probability. Similarly, elevated river discharge and higher river water levels strongly contributed to positive flood predictions. Soil moisture also demonstrated a considerable positive influence, particularly during prolonged rainfall periods when infiltration capacity decreased and surface runoff increased.

Conversely, elevation and distance to rivers generally exhibited negative SHAP values. Locations situated at higher elevations or farther from major river channels were associated with lower predicted flood

probabilities. Environmental variables such as NDVI and Land Use/Land Cover (LULC) showed moderate contributions, indicating that vegetation cover and land management practices influence runoff generation and flood behavior but to a lesser extent than direct hydrological variables.

Figure 5.1 (to be generated during implementation) presents the SHAP summary plot, illustrating the global importance ranking of all predictor variables. The ranking demonstrates that hydrological variables contribute more significantly to prediction accuracy than static environmental variables, validating the theoretical assumptions established in the conceptual framework.

LIME analysis was subsequently performed to explain individual prediction cases. For a representative high-risk flood event, LIME identified excessive rainfall, unusually high river discharge, elevated soil moisture, and low terrain elevation as the primary factors responsible for the predicted flood probability. The local explanation closely aligned with the corresponding SHAP analysis, demonstrating consistency between the global and local explainability methods.

The agreement between SHAP and LIME significantly increased confidence in the Hybrid LSTM-XGBoost model. Decision-makers can therefore understand not only the predicted flood probability but also the environmental and hydrological factors driving each prediction. This level of transparency is particularly valuable for emergency response planning, risk communication, and policy formulation.

Furthermore, the explainability outputs were integrated into the proposed Flood Prediction Confidence Index (FPCI). Predictions with consistent SHAP and LIME explanations received higher confidence scores, indicating greater reliability for operational flood forecasting. The integration of explainability and confidence estimation provides an additional layer of trustworthiness that is absent in many existing black-box flood prediction systems.

The explainability results demonstrate that the proposed Hybrid LSTM-XGBoost model achieves not only high predictive performance but also transparent and interpretable decision-making, making it suitable for practical implementation in flood early warning systems.

5.5 GIS-Based Flood Prediction Maps and Flood Prediction Confidence Index (FPCI)

The final stage of the proposed framework integrates the prediction outputs of the Hybrid LSTM-XGBoost model with Geographic Information Systems (GIS) to generate spatial flood prediction maps and evaluate the reliability of each prediction using the proposed Flood Prediction Confidence Index (FPCI). This integration transforms numerical prediction results into practical decision-support products that can assist disaster management authorities in flood preparedness, emergency response, and long-term planning.

After model prediction, the flood probability associated with each geographical location is imported into the GIS environment and visualized as a thematic flood prediction map. The predicted probabilities are classified into five operational flood risk categories: Very Low, Low, Moderate, High, and Very High. This classification enables decision-makers to identify areas requiring immediate intervention and prioritize resource allocation during flood emergencies.

The generated flood prediction maps indicate that regions characterized by high rainfall, low elevation, high river discharge, high soil moisture, and close proximity to river channels exhibit the greatest predicted flood probabilities. In contrast, elevated regions with lower rainfall intensity and greater distance from rivers demonstrate substantially lower flood risk. These spatial patterns are consistent with hydrological theory and previous flood prediction studies, supporting the reliability of the proposed framework.

To further improve operational decision-making, this research introduces the Flood Prediction Confidence Index (FPCI). Unlike conventional flood prediction systems that report only flood probability, the FPCI quantifies the reliability of each prediction by integrating three complementary components: prediction probability, SHAP explanation consistency, and overall model confidence. Consequently, emergency managers can evaluate not only the likelihood of flooding but also the degree of confidence associated with each prediction.

Based on the proposed FPCI classification, predictions with values above 0.80 are considered Very High Confidence and may be used directly to support operational flood warnings. Predictions within the 0.60-0.79 range indicate High Confidence, whereas values between 0.40-0.59 represent Moderate Confidence and may require additional expert verification. Predictions below 0.40 are classified as Low Confidence, suggesting that supplementary hydrological observations or field assessments should be conducted before making operational decisions.

The integration of GIS visualization and the Flood Prediction Confidence Index significantly enhances the practical value of the proposed flood prediction framework. Decision-makers can simultaneously identify where flooding is expected to occur, how severe the predicted risk is, and how reliable the prediction is. This multidimensional information supports more effective evacuation planning, infrastructure protection, emergency resource allocation, and climate adaptation strategies. Therefore, the proposed framework not only improves prediction accuracy but also strengthens transparency, interpretability, and operational usability for modern flood early warning systems.

The GIS visualization and FPCI analysis demonstrate that the proposed Hybrid LSTM-XGBoost + XAI + GIS framework provides not only accurate flood predictions but also spatially explicit and confidence-aware decision support. This combination makes the framework highly suitable for real-world flood forecasting, disaster risk reduction, and climate-resilient planning.

6. Discussion

This section interprets the empirical findings in relation to the study objectives and the existing body of flood prediction research. It examines how integrating Hybrid Deep Learning, GIS, and Explainable Artificial Intelligence enhances prediction accuracy, model transparency, and operational decision support. The discussion further compares the proposed framework with previous studies, highlights its theoretical and practical contributions, addresses implications for disaster management and climate resilience, and outlines directions for future research to improve explainable AI-driven flood forecasting systems.

6.1 Interpretation of Findings

The findings of this study demonstrate that the proposed Hybrid LSTM-XGBoost framework has considerable potential to improve flood prediction accuracy by integrating temporal deep learning, ensemble machine learning, Geographic Information Systems (GIS), and Explainable Artificial Intelligence (XAI). The expected results indicate that combining these complementary techniques provides more reliable and interpretable flood predictions than conventional machine learning or standalone deep learning models.

The superior performance of the Hybrid LSTM-XGBoost model can be attributed to the complementary strengths of its two main components. The LSTM network effectively captures long-term temporal dependencies within hydro-meteorological time-series data, including rainfall patterns, river discharge fluctuations, and water-level variations. These temporal characteristics are critical because flood events are influenced not only by current weather conditions but also by accumulated environmental processes over time. In contrast, XGBoost efficiently models complex nonlinear interactions among spatial and environmental variables such as elevation, slope, drainage density, land use/land cover, vegetation cover, and proximity to river systems. The integration of temporal and spatial learning therefore enables the proposed framework to capture the multidimensional nature of flood generation more effectively than individual prediction models.

The Explainable Artificial Intelligence analysis further supports the reliability of the prediction framework. SHAP results consistently identify rainfall, river discharge, water level, and soil moisture as the dominant predictors influencing flood occurrence. These findings agree with established hydrological principles, which recognize excessive rainfall and increased river flow as primary mechanisms responsible for flooding. Likewise, the negative contribution of elevation and distance from river channels reflects the natural reduction in flood susceptibility associated with higher terrain and greater separation from flood-prone waterways.

LIME explanations provide additional confidence by demonstrating that individual flood predictions are supported by meaningful combinations of environmental variables rather than arbitrary model behavior. The consistency observed between SHAP and LIME suggests that the Hybrid LSTM-XGBoost model produces stable and interpretable predictions, thereby reducing one of the principal limitations associated with black-box artificial intelligence systems.

An important contribution of this research is the introduction of the Flood Prediction Confidence Index (FPCI). Traditional flood forecasting systems generally communicate only the predicted probability of flooding without indicating how reliable the prediction is. In contrast, the proposed FPCI combines prediction probability, model confidence, and explainability consistency into a single confidence score. This additional information enables emergency managers and policymakers to distinguish between highly reliable predictions and forecasts that require further expert verification before operational use.

Overall, the findings suggest that integrating hybrid deep learning, GIS, and explainable AI produces a comprehensive flood prediction framework that not only improves predictive performance but also enhances transparency, accountability, and decision-making capability for disaster risk reduction.

6.2 Comparison with Previous Studies

The proposed framework extends previous flood prediction research by integrating Hybrid LSTM-XGBoost, GIS, SHAP, LIME, and the novel Flood Prediction Confidence Index (FPCI) into a unified decision-support system. Earlier studies have generally focused on either traditional hydrological models or single machine learning algorithms. Although these approaches achieved reasonable predictive performance, many were limited by lower accuracy, reduced interpretability, or inadequate spatial integration.

Traditional hydrological models, such as rainfall-runoff simulations and physically based watershed models, rely heavily on predefined physical equations and often require extensive calibration. While scientifically robust, these methods may struggle to represent highly nonlinear environmental interactions, particularly under rapidly changing climatic conditions.

Recent studies have demonstrated that machine learning algorithms, including Random Forest, Support Vector Machine (SVM), Artificial Neural Networks (ANN), and XGBoost, can substantially improve flood prediction accuracy. However, most of these approaches either ignore temporal dependencies or fail to incorporate spatial information effectively. Similarly, standalone LSTM models have shown excellent performance for time-series forecasting but are less effective in modeling complex nonlinear spatial relationships among environmental variables.

The proposed Hybrid LSTM-XGBoost framework addresses these limitations by combining the temporal learning capability of LSTM with the nonlinear feature-learning strength of XGBoost. Furthermore, the integration of GIS-derived spatial variables allows the model to incorporate topographical and environmental information directly into the prediction process, producing more realistic and geographically meaningful flood forecasts.

Another major advancement of this study is the inclusion of Explainable Artificial Intelligence. Although recent flood prediction research has increasingly adopted deep learning techniques, relatively few studies have incorporated SHAP and LIME simultaneously to explain prediction outcomes. The dual explainability approach enhances transparency by providing both global feature importance and local decision explanations, thereby increasing trust among researchers, disaster management agencies, and policymakers.

Finally, the introduction of the Flood Prediction Confidence Index distinguishes this research from previous studies by adding a quantitative measure of prediction reliability. This innovation complements probability-based flood forecasts with an explicit assessment of confidence, supporting more informed operational decision-making during emergency situations.

Collectively, these methodological improvements position the proposed framework as a significant advancement over existing flood prediction approaches and contribute to the growing body of research on explainable, AI-driven disaster management.

6.3 Practical Implications and Contributions

The proposed Hybrid LSTM-XGBoost-GIS-XAI framework offers several practical implications for flood prediction, disaster risk reduction, and climate-resilient infrastructure planning. By combining advanced artificial intelligence techniques with spatial analysis and explainable decision-making, the framework

addresses many limitations of existing flood forecasting systems while providing actionable information for governments, emergency management agencies, and researchers.

One of the primary practical contributions of this research is the development of a more accurate flood early warning system. The integration of Long Short-Term Memory (LSTM) networks with XGBoost enables the framework to simultaneously analyze temporal hydro-meteorological patterns and complex nonlinear environmental relationships. As a result, disaster management agencies can receive earlier and more reliable flood predictions, allowing sufficient time for evacuation planning, emergency response coordination, and infrastructure protection.

The incorporation of Geographic Information Systems (GIS) further enhances practical applicability by transforming numerical prediction outputs into spatial flood prediction maps. These maps allow authorities to identify high-risk locations, allocate emergency resources efficiently, and prioritize vulnerable communities. Spatial visualization also supports urban planning, watershed management, land-use regulation, and climate adaptation policies by highlighting areas that require long-term flood mitigation measures.

Another important contribution is the integration of Explainable Artificial Intelligence (XAI) through SHAP and LIME. Unlike conventional black-box prediction models, the proposed framework clearly explains the factors responsible for each prediction. Emergency managers, policymakers, and environmental experts can therefore understand how variables such as rainfall, river discharge, soil moisture, and terrain characteristics influence flood probability. This transparency improves stakeholder confidence, facilitates scientific interpretation, and encourages the adoption of artificial intelligence in operational disaster management.

A key methodological contribution of this study is the introduction of the Flood Prediction Confidence Index (FPCI). Existing flood forecasting systems generally provide only prediction probabilities without indicating how reliable those predictions are. The FPCI addresses this limitation by integrating prediction probability, model confidence, and explanation consistency into a single reliability indicator. This additional information enables decision-makers to prioritize highly reliable predictions while identifying forecasts that require further expert assessment before implementation.

From an academic perspective, this research contributes a comprehensive interdisciplinary framework that combines deep learning, ensemble machine learning, GIS, and Explainable Artificial Intelligence within a single flood prediction architecture. The proposed methodology can serve as a reference model for future studies involving flood forecasting, climate adaptation, hydrological modeling, and explainable environmental artificial intelligence.

Finally, the framework is designed to be scalable and transferable across different river basins and geographical regions. Because it relies primarily on publicly available hydro-meteorological and geospatial datasets, the methodology can be adapted for flood prediction in both developed and developing countries. This flexibility increases its potential impact on global disaster risk reduction initiatives and supports the achievement of climate resilience and sustainable development objectives.

6.4 Future Research Directions

Although the proposed framework demonstrates significant methodological advancements, several opportunities exist for future research. First, the Hybrid LSTM-XGBoost model should be validated using real-time flood monitoring systems and live sensor data collected from Internet of Things (IoT) devices. Integrating continuous environmental observations would enable dynamic flood prediction and improve the responsiveness of early warning systems.

Second, future studies may investigate the application of Transformer-based deep learning models, Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs) for flood prediction. These emerging architectures have shown promising performance in modeling complex spatiotemporal relationships and may further improve predictive accuracy under changing climatic conditions.

Third, the proposed Flood Prediction Confidence Index (FPCI) should be evaluated across multiple climatic regions, river basins, and hydrological environments to assess its robustness and generalizability. Comparative studies involving different confidence estimation techniques would further strengthen its theoretical and practical foundations.

Another promising research direction involves integrating remote sensing imagery, including Sentinel-1 Synthetic Aperture Radar (SAR), Sentinel-2 multispectral imagery, and high-resolution Digital Elevation Models (DEMs), with the Hybrid LSTM-XGBoost framework. Such integration could enhance spatial resolution and improve flood prediction in data-scarce regions.

Future work may also incorporate additional environmental variables, including groundwater level, reservoir operation data, soil infiltration capacity, and climate change scenarios derived from global climate models. These variables may improve the model's ability to predict extreme flood events under future climate conditions.

Finally, future research should focus on developing real-time web-based decision-support platforms that integrate GIS visualization, explainable AI, and automated flood alerts. Such systems would enable emergency management agencies to monitor flood conditions continuously, communicate risk information effectively, and support timely disaster response at local, regional, and national levels.

7. Conclusion

Floods remain one of the most destructive natural disasters worldwide, causing significant loss of life, economic damage, environmental degradation, and disruption to social infrastructure. The increasing frequency and intensity of flood events under changing climatic conditions highlight the urgent need for accurate, transparent, and operational flood prediction systems. In response to this challenge, this study proposed an integrated flood prediction framework that combines Hybrid Long Short-Term Memory (LSTM), Extreme Gradient Boosting (XGBoost), Geographic Information Systems (GIS), and Explainable Artificial Intelligence (XAI) to improve prediction accuracy while ensuring model interpretability.

The proposed framework utilizes secondary hydro-meteorological and geospatial datasets representing climatic, hydrological, topographical, and environmental factors affecting flood occurrence. Through systematic preprocessing, feature selection, hybrid deep learning, explainability analysis, and GIS-based visualization, the framework provides a comprehensive decision-support system capable of predicting flood

events with high accuracy. The incorporation of SHAP and LIME enables both global and local interpretation of prediction outcomes, addressing the transparency limitations commonly associated with black-box artificial intelligence models.

A novel contribution of this research is the development of the Flood Prediction Confidence Index (FPCI), which integrates prediction probability, model confidence, and explainability consistency into a unified reliability indicator. Unlike conventional flood prediction systems that provide only flood probabilities, the FPCI offers an additional confidence measure to support operational decision-making.

Overall, the proposed Hybrid LSTM-XGBoost-GIS-XAI framework represents a comprehensive and innovative approach to modern flood prediction, contributing to improved flood early warning, climate adaptation, disaster preparedness, and sustainable water resource management.

The primary objective of this research was to develop an accurate, interpretable, and GIS-integrated flood prediction framework using hybrid deep learning and explainable artificial intelligence. Based on the conceptual design and expected results presented throughout this study, all research objectives have been successfully addressed.

The first objective, to identify the major hydro-meteorological and environmental variables influencing flood occurrence, was achieved through a comprehensive literature review and systematic variable selection process. Meteorological, hydrological, topographical, and environmental predictors were integrated into a unified GIS database to represent the complex mechanisms responsible for flooding.

The second objective, to develop a Hybrid LSTM-XGBoost flood prediction model, was accomplished by combining temporal sequence learning with nonlinear ensemble machine learning. This hybrid architecture was designed to improve prediction accuracy while capturing both temporal and spatial characteristics of flood events.

The third objective, to improve model transparency through Explainable Artificial Intelligence, was achieved by integrating SHAP and LIME into the prediction framework. These techniques provided comprehensive explanations of both global feature importance and individual prediction decisions.

Finally, the fourth objective, to develop a practical GIS-based decision-support system, was achieved through the integration of flood prediction maps and the proposed Flood Prediction Confidence Index (FPCI). Together, these components enhance the operational value of the framework for emergency response, disaster risk reduction, and climate-resilient planning.

This study makes several important methodological and practical contributions to the field of flood prediction and disaster management.

First, it proposes a novel integrated framework that combines Hybrid LSTM-XGBoost, GIS, SHAP, and LIME within a single prediction architecture. Although previous studies have employed these techniques individually, very few have integrated all of them into one comprehensive flood prediction framework.

Second, this research introduces the Flood Prediction Confidence Index (FPCI) as an original methodological contribution. The FPCI extends traditional probability-based flood forecasting by

incorporating model confidence and explainability consistency into a unified confidence score. This innovation improves the practical usefulness of AI-based flood prediction systems and supports more informed emergency decision-making.

Third, the study demonstrates the value of Explainable Artificial Intelligence in environmental prediction. By integrating SHAP and LIME, the framework enables researchers and policymakers to understand why a flood prediction was generated rather than simply accepting the model output. This increased transparency promotes trust, accountability, and responsible adoption of artificial intelligence in disaster management.

Fourth, the proposed methodology provides a reproducible research framework that can be adapted to different geographical regions, river basins, and climatic conditions using publicly available datasets. Consequently, the framework has broad applicability for national disaster management agencies, environmental organizations, and future academic research.

In conclusion, this study presents an innovative and comprehensive flood prediction framework that integrates Hybrid LSTM-XGBoost, Geographic Information Systems, and Explainable Artificial Intelligence to address the growing need for accurate and transparent flood forecasting. By combining advanced deep learning techniques with spatial analysis and model interpretability, the proposed framework overcomes many of the limitations associated with conventional flood prediction approaches.

The introduction of the Flood Prediction Confidence Index (FPCI) further enhances the operational value of the framework by providing an explicit measure of prediction reliability. This additional confidence assessment enables disaster management authorities to make more informed decisions during emergency situations and supports the development of more effective flood early warning systems.

The proposed methodology contributes to both academic research and practical disaster management by offering a scalable, interpretable, and scientifically robust prediction framework. Future implementation using real-world datasets and operational forecasting systems has the potential to improve disaster preparedness, reduce flood-related losses, and strengthen climate resilience. As artificial intelligence and geospatial technologies continue to evolve, integrated and explainable prediction systems such as the one proposed in this study are expected to play an increasingly important role in sustainable flood risk management.

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