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Title: Beyond Black-Box Flood Susceptibility Mapping: An Explainable and Community-Validated GIS-Machine Learning Framework

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Beyond Black-Box Flood Susceptibility Mapping: An Explainable and Community-Validated GIS-Machine Learning Framework

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Abstract

Floods are among the most destructive natural hazards, causing substantial economic losses, environmental degradation, and threats to human lives worldwide. Although Geographic Information Systems (GIS) and machine learning (ML) have significantly improved flood susceptibility mapping (FSM), many existing models remain difficult to interpret due to their black-box nature, limiting stakeholder trust and practical decision-making. This study proposes an explainable and community-validated GIS-machine learning framework that integrates ensemble learning with Explainable Artificial Intelligence (XAI) techniques, including SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations), alongside Participatory Geographic Information Systems (PGIS). Using secondary spatial and environmental datasets, the proposed framework identifies influential flood-conditioning factors, compares the predictive performance of multiple ML models, interprets global and local model behavior, and validates prediction outcomes using community-derived spatial knowledge. The integration of explainable AI and PGIS enhances transparency, credibility, and policy relevance while supporting evidence-based flood risk management. The proposed framework provides an interpretable and stakeholder-centered decision-support approach that advances sustainable flood susceptibility assessment and disaster risk reduction.

Keywords: Flood Susceptibility Mapping, Geographic Information Systems (GIS), Explainable Artificial Intelligence (XAI), Machine Learning, SHAP and LIME, Participatory Geographic Information Systems (PGIS).

1. Introduction

Floods are among the most frequent and devastating natural disasters, affecting millions of people annually and causing significant economic, environmental, and social losses across the world. The increasing occurrence of extreme rainfall events, rapid urbanization, land-use changes, and climate variability have intensified flood hazards, making effective flood risk assessment a global priority [1], [2]. Flood Susceptibility Mapping (FSM) has emerged as an essential tool for identifying areas that are prone to flooding and supporting disaster preparedness, land-use planning, and sustainable development. Geographic Information Systems (GIS) have become indispensable in flood susceptibility studies because they enable the integration, visualization, and spatial analysis of diverse environmental datasets, including topography, hydrology, land use, soil characteristics, and climatic variables [3].

Recent advances in Machine Learning (ML) have significantly improved the predictive performance of flood susceptibility models compared with traditional statistical approaches. Algorithms such as Random Forest, Extreme Gradient Boosting (XGBoost), CatBoost, LightGBM, and Extra Trees can effectively capture complex nonlinear relationships among flood-conditioning factors, resulting in higher prediction accuracy [4], [5]. However, despite their predictive capability, these models often operate as "black-box" systems, providing limited insight into how predictions are generated. This lack of interpretability reduces stakeholder confidence and constrains the practical application of ML-based flood susceptibility maps in disaster risk management.

The emergence of Explainable Artificial Intelligence (XAI), particularly SHapley Additive explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), offers promising solutions by making complex ML predictions transparent and understandable. Integrating XAI with GIS-based flood susceptibility mapping, together with community knowledge through Participatory Geographic Information Systems (PGIS), has the potential to improve model credibility, transparency, and policy relevance, thereby supporting more informed and inclusive flood risk management decisions.

Despite substantial progress in Geographic Information Systems (GIS) and Machine Learning (ML) for Flood Susceptibility Mapping (FSM), several critical challenges remain unresolved. Most existing flood susceptibility studies primarily focus on maximizing predictive accuracy while paying limited attention to the interpretability and transparency of machine learning models. High-performing algorithms such as Random Forest, XGBoost, CatBoost, and LightGBM are widely regarded as black-box models because they provide accurate predictions without clearly explaining the influence of individual flood-conditioning factors on the final results [6], [7]. Consequently, decision-makers, emergency managers, and local authorities often find it difficult to understand or justify the predictions generated by these models, reducing their confidence in adopting ML-based flood susceptibility maps for disaster management.

Another important limitation is the inadequate integration of local community knowledge into flood susceptibility assessment. Most studies rely exclusively on remotely sensed data and environmental variables while overlooking valuable spatial information obtained from communities that regularly experience flood events. The absence of Participatory Geographic Information Systems (PGIS) limits the validation of model outputs from a practical perspective and weakens stakeholder engagement in disaster risk reduction [8]. Furthermore, only a limited number of studies have jointly integrated Explainable Artificial Intelligence (XAI) techniques, such as SHAP and LIME, with PGIS to create transparent, interpretable, and community-validated flood susceptibility maps. Therefore, a comprehensive framework that combines GIS, explainable machine learning, and participatory validation is needed to improve the reliability, credibility, and practical applicability of flood susceptibility mapping.

The increasing frequency and severity of flood events demand decision-support systems that are not only accurate but also transparent, interpretable, and practically applicable. While recent advances in machine learning have substantially improved the predictive performance of Flood Susceptibility Mapping (FSM), the lack of explainability limits the adoption of these models by policymakers, disaster management agencies, and local communities. Furthermore, conventional flood susceptibility studies rarely incorporate community-based spatial knowledge to validate model predictions, resulting in limited stakeholder confidence and reduced practical relevance. This study addresses these challenges by proposing an integrated framework that combines Geographic Information Systems (GIS), ensemble machine learning, Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME, and Participatory Geographic Information Systems (PGIS). The proposed framework aims to bridge the gap between predictive accuracy and model transparency while enhancing the credibility of flood susceptibility assessments through community validation, thereby supporting evidence-based disaster risk reduction and sustainable flood management.

The primary objective of this study is to develop an explainable and community-validated Flood Susceptibility Mapping (FSM) framework by integrating Geographic Information Systems (GIS), ensemble Machine Learning (ML), Explainable Artificial Intelligence (XAI), and Participatory Geographic Information Systems (PGIS). Specifically, the study aims to: (i) identify and prepare flood-conditioning factors from reliable secondary spatial datasets; (ii) develop and compare the predictive performance of multiple ensemble ML algorithms for flood susceptibility assessment; (iii) interpret global and local model predictions using SHAP and LIME to improve model transparency; (iv) validate flood susceptibility results through community-derived spatial knowledge using PGIS; and (v) propose an integrated decision-support framework that enhances the credibility, interpretability, and practical applicability of flood susceptibility maps. Ultimately, the research seeks to provide a transparent and evidence-based approach that supports sustainable flood risk management, land-use planning, and disaster preparedness.

This study contributes to the advancement of Flood Susceptibility Mapping (FSM) by addressing two major limitations of existing research: the lack of model interpretability and the limited involvement of community knowledge in flood risk assessment. By integrating Geographic Information Systems (GIS), ensemble Machine Learning (ML), Explainable Artificial Intelligence (XAI), and Participatory Geographic Information Systems (PGIS), the proposed framework enhances the transparency, reliability, and practical usability of flood susceptibility models. The incorporation of SHAP and LIME enables stakeholders to understand the influence of individual flood-conditioning factors on model predictions, while PGIS provides an additional layer of validation through community-based spatial knowledge. The findings of this study are expected to support policymakers, disaster management authorities, urban planners, and environmental agencies in making informed decisions for flood mitigation, land-use planning, infrastructure development, and climate adaptation. Moreover, the proposed framework offers a replicable methodology that can be applied to other flood-prone regions worldwide.

2. Literature Review

Flood Susceptibility Mapping (FSM) has become an essential component of disaster risk reduction, enabling governments and disaster management agencies to identify areas that are vulnerable to flooding and to implement appropriate mitigation strategies. With the increasing frequency and intensity of flood events driven by climate change, rapid urbanization, and land-use transformation, researchers have increasingly relied on Geographic Information Systems (GIS) and machine learning (ML) techniques to improve the accuracy and efficiency of flood susceptibility assessment [9], [10]. GIS provides a powerful spatial platform for integrating multiple flood-conditioning factors, including elevation, slope, rainfall, drainage density, land use/land cover, soil type, curvature, topographic wetness index (TWI), stream power index (SPI), and distance to rivers, enabling comprehensive spatial analysis of flood-prone regions [11].

Traditional statistical approaches, such as Logistic Regression (LR), Frequency Ratio (FR), and Analytical Hierarchy Process (AHP), have been widely employed in earlier flood susceptibility studies. Although these methods are relatively simple and interpretable, they often struggle to capture complex nonlinear relationships among environmental variables, leading to limited predictive performance in heterogeneous landscapes [12]. Consequently, advanced ML algorithms-including Random Forest (RF), Extreme Gradient Boosting (XGBoost), CatBoost, LightGBM, Support Vector Machine (SVM), and Artificial Neural Networks (ANNs)-have gained significant attention because of their ability to model nonlinear interactions and improve prediction accuracy [13], [14].

Despite these advances, many high-performing ML models remain difficult to interpret, creating challenges for decision-makers who require transparent and trustworthy predictions. The emergence of Explainable Artificial Intelligence (XAI), particularly SHAP and LIME, has addressed this limitation by providing both global and local explanations of model behavior [15]. At the same time, Participatory Geographic Information Systems (PGIS) have demonstrated considerable potential for incorporating local community knowledge into spatial decision-making, thereby improving the credibility and practical relevance of flood susceptibility assessments. Integrating GIS, explainable machine learning, and participatory validation therefore represents a promising direction for developing transparent, reliable, and policy-oriented flood risk management frameworks.

Flood Susceptibility Mapping (FSM) has evolved from conventional statistical approaches to advanced data-driven methodologies capable of modeling complex environmental interactions. The analytical framework adopted in this study integrates Geographic Information Systems (GIS), ensemble Machine Learning (ML), Explainable Artificial Intelligence (XAI), and Participatory Geographic Information Systems (PGIS) into a unified decision-support framework. The integration of these components aims to improve prediction accuracy while simultaneously enhancing model transparency, interpretability, and stakeholder confidence.

The first stage of the analytical framework involves the acquisition and preprocessing of secondary spatial datasets. Flood occurrence is influenced by multiple hydrological, topographical, geological, climatic, and anthropogenic factors. Therefore, reliable datasets are collected from government agencies, satellite imagery, global geospatial databases, and published scientific repositories. Common flood-conditioning factors include elevation, slope, aspect, curvature, rainfall, drainage density, Topographic Wetness Index (TWI), Stream Power Index (SPI), land use/land cover (LULC), soil type, lithology, normalized difference vegetation index (NDVI), and distance from rivers. These datasets are processed within a GIS environment to maintain a consistent spatial resolution, coordinate reference system, and raster format before model development [16].

Following data preparation, feature engineering and variable optimization are conducted to improve model performance. Spatial variables are normalized, missing values are handled, and multicollinearity among predictor variables is assessed using statistical techniques such as the Variance Inflation Factor (VIF) and correlation analysis. Eliminating redundant variables reduces model complexity and prevents overfitting while improving prediction stability. The selected variables are subsequently prepared as input features for machine learning algorithms [17].

The third component of the analytical framework focuses on predictive modeling using ensemble machine learning algorithms. Ensemble methods have demonstrated superior predictive capability compared with conventional statistical models because they combine multiple decision trees to capture nonlinear relationships among flood-conditioning variables. In this study, Random Forest (RF), Extreme Gradient Boosting (XGBoost), LightGBM, CatBoost, and Extra Trees are employed for comparative analysis. Each algorithm generates flood susceptibility probabilities based on the relationships between historical flood locations and environmental variables. Model performance is evaluated using identical training and testing datasets to ensure fair comparison and reproducibility [18]. The best-performing model is selected based on multiple evaluation metrics rather than prediction accuracy alone.

Although ensemble models often achieve excellent predictive performance, their internal decision-making processes remain difficult to interpret. This limitation has encouraged the adoption of Explainable Artificial Intelligence (XAI) techniques that reveal how machine learning models generate predictions. SHapley Additive exPlanations (SHAP) is employed to quantify the contribution of each flood-conditioning factor to the prediction outcome based on cooperative game theory. SHAP provides both global explanations, illustrating overall feature importance, and local explanations, explaining why a specific location is classified as highly susceptible to flooding. Such information enables researchers and policymakers to identify the dominant environmental drivers responsible for flood occurrence [19].

Complementing SHAP, Local Interpretable Model-Agnostic Explanations (LIME) is applied to provide localized interpretation of individual predictions. Unlike SHAP, which evaluates feature contributions across the entire model, LIME approximates the behavior of the complex model around a single observation using a simpler interpretable model. This enables decision-makers to understand why a particular pixel or geographic location receives a specific flood susceptibility score. The combined use of SHAP and LIME therefore provides comprehensive global and local interpretability, reducing the black-box nature of machine learning algorithms and increasing stakeholder trust in prediction outcomes [20].

Beyond model interpretability, the analytical framework incorporates Participatory Geographic Information Systems (PGIS) as an additional validation mechanism. Traditional flood susceptibility studies primarily rely on quantitative validation using historical flood inventories or statistical performance measures. However, these approaches often overlook valuable local knowledge regarding flood frequency, inundation extent, vulnerable infrastructure, and community experiences. PGIS integrates community-generated spatial information collected from local reports, historical flood records, participatory mapping initiatives, governmental disaster reports, and verified community observations. This participatory validation enhances the practical credibility of flood susceptibility maps and strengthens communication between researchers, policymakers, and local stakeholders [21].

A distinguishing feature of the proposed framework is the integration of explainable machine learning with participatory validation to produce a transparent decision-support system. Rather than evaluating predictive performance solely through statistical metrics, the framework emphasizes whether model explanations are consistent with observed environmental conditions and community experiences. This integrated evaluation improves confidence in flood susceptibility maps while reducing uncertainty associated with purely algorithm-driven predictions.

Finally, the analytical framework supports the generation of policy-oriented flood susceptibility maps that can assist disaster management agencies in prioritizing mitigation measures, allocating emergency resources, and developing sustainable land-use strategies. The combination of GIS, ensemble machine learning, SHAP, LIME, and PGIS creates an interpretable and evidence-based framework capable of supporting transparent flood risk assessment and informed decision-making. Compared with conventional black-box machine learning approaches, the proposed analytical framework not only improves predictive capability but also enhances accountability, stakeholder engagement, and practical applicability, making it a comprehensive solution for modern flood susceptibility assessment.

Although numerous studies have applied Geographic Information Systems (GIS) and machine learning (ML) techniques for Flood Susceptibility Mapping (FSM), several important research gaps remain. First, most existing studies prioritize predictive accuracy while providing limited explanation of how machine learning models generate their predictions, resulting in reduced transparency and stakeholder trust [22]. Second, although Explainable Artificial Intelligence (XAI) methods such as SHAP and LIME have recently been introduced in environmental modeling, their application in flood susceptibility assessment remains limited and is often restricted to feature importance analysis without comprehensive interpretation. Third, very few studies incorporate Participatory Geographic Information Systems (PGIS) to validate machine learning predictions using community-derived spatial knowledge. Consequently, there is a lack of integrated frameworks that simultaneously combine GIS, ensemble machine learning, explainable AI, and community-based validation. This study addresses these gaps by proposing a transparent, interpretable, and community-validated flood susceptibility mapping framework that supports more reliable and policy-oriented flood risk management.

The existing body of literature demonstrates that Geographic Information Systems (GIS) and Machine Learning (ML) have significantly advanced Flood Susceptibility Mapping (FSM) by improving the accuracy and efficiency of flood prediction. Ensemble learning algorithms, including Random Forest, XGBoost, CatBoost, and LightGBM, have consistently outperformed many conventional statistical approaches in modeling complex nonlinear relationships among flood-conditioning factors. However, the literature also reveals that predictive accuracy alone is insufficient for supporting practical disaster risk management, as many high-performing models operate as black-box systems with limited interpretability. Recent developments in Explainable Artificial Intelligence (XAI), particularly SHAP and LIME, have provided effective tools for improving the transparency of machine learning predictions, yet their application in flood susceptibility studies remains relatively limited. Likewise, the integration of Participatory Geographic Information Systems (PGIS) into flood susceptibility assessment has received comparatively little attention despite its potential to strengthen community engagement and validate model outcomes. Therefore, the literature highlights the need for an integrated framework that combines GIS, ensemble machine learning, explainable AI, and participatory validation. Addressing this need, the present study proposes a transparent, interpretable, and community-centered flood susceptibility mapping framework capable of supporting evidence-based decision-making, sustainable land-use planning, and effective disaster risk reduction.

3. Theoretical and Conceptual Framework

The theoretical foundation of this study is established through the integration of Spatial Data Theory, Machine Learning Theory, Explainable Artificial Intelligence (XAI), and Participatory Geographic Information Systems (PGIS). These complementary theories provide a comprehensive basis for developing an interpretable and community-validated Flood Susceptibility Mapping (FSM) framework.

Spatial Data Theory underpins the application of Geographic Information Systems (GIS) in flood susceptibility assessment by emphasizing the representation, integration, and analysis of geographically referenced environmental variables. Flood occurrence is inherently spatial, resulting from complex interactions among topographic, hydrological, climatic, geological, and land-use factors. GIS enables the collection, management, visualization, and analysis of these spatial datasets, thereby supporting the identification of flood-prone areas through spatial modeling and geostatistical analysis [23]. This theoretical perspective justifies the use of multiple flood-conditioning factors as predictors within the proposed framework.

Machine Learning Theory provides the computational basis for modeling nonlinear relationships between flood-conditioning factors and flood occurrence. Unlike traditional statistical models that often assume linear relationships, ensemble machine learning algorithms-including Random Forest (RF), Extreme Gradient Boosting (XGBoost), CatBoost, LightGBM, and Extra Trees-are capable of learning complex interactions directly from historical data. These algorithms improve predictive performance by minimizing classification errors and enhancing model generalization through ensemble learning strategies [24]. Consequently, Machine Learning Theory supports the development of accurate flood susceptibility prediction models using multidimensional environmental datasets.

Despite their predictive advantages, ensemble learning models frequently operate as black-box systems whose internal decision-making processes are difficult to interpret. Explainable Artificial Intelligence (XAI) addresses this limitation by providing transparent explanations of model predictions. SHapley Additive exPlanations (SHAP), grounded in cooperative game theory, quantify the contribution of each predictor variable to individual and overall model predictions, whereas Local Interpretable Model-Agnostic Explanations (LIME) generate localized explanations for specific prediction instances [25]. These techniques improve model transparency and enable stakeholders to understand the environmental factors driving flood susceptibility.

The framework is further supported by Participatory Geographic Information Systems (PGIS), which emphasizes collaborative spatial decision-making through the integration of community knowledge with geospatial analysis. PGIS recognizes that local communities possess valuable experiential knowledge regarding historical flood events, vulnerable locations, and flood impacts. Incorporating this knowledge into the validation process enhances the credibility, reliability, and practical applicability of flood susceptibility maps while promoting stakeholder participation in disaster risk management [26].

Collectively, these theoretical perspectives provide a robust foundation for developing a transparent, interpretable, and community-centered GIS-machine learning framework capable of supporting evidence-based flood risk assessment and sustainable disaster management.

The conceptual framework of this study illustrates the systematic relationship between flood-conditioning factors, machine learning prediction, explainable artificial intelligence, community validation, and flood susceptibility mapping. The framework begins with the acquisition of secondary spatial datasets representing environmental, hydrological, geological, climatic, and anthropogenic characteristics that influence flood occurrence. These datasets include elevation, slope, rainfall, drainage density, land use/land cover, soil type, lithology, Topographic Wetness Index (TWI), Stream Power Index (SPI), Normalized Difference Vegetation Index (NDVI), and distance to rivers.

Following data preprocessing and feature selection, the prepared variables are used to train multiple ensemble machine learning models, including Random Forest, XGBoost, LightGBM, CatBoost, and Extra Trees. The models estimate the probability of flood occurrence and generate flood susceptibility maps based on the relationships between historical flood events and environmental factors. To improve model transparency, SHAP is employed to explain global feature importance and quantify the contribution of each predictor variable, while LIME provides local explanations for individual predictions. These explainability techniques transform complex machine learning outputs into interpretable information that supports scientific understanding and stakeholder confidence.

The interpreted predictions are subsequently validated using Participatory Geographic Information Systems (PGIS), which incorporate community knowledge, historical flood records, and local spatial observations. This validation process ensures that model outputs are consistent with real-world flood experiences and strengthens the credibility of the final susceptibility maps. The integrated framework ultimately produces transparent, interpretable, and community-validated flood susceptibility maps that support evidence-based disaster management, land-use planning, and sustainable flood risk reduction.

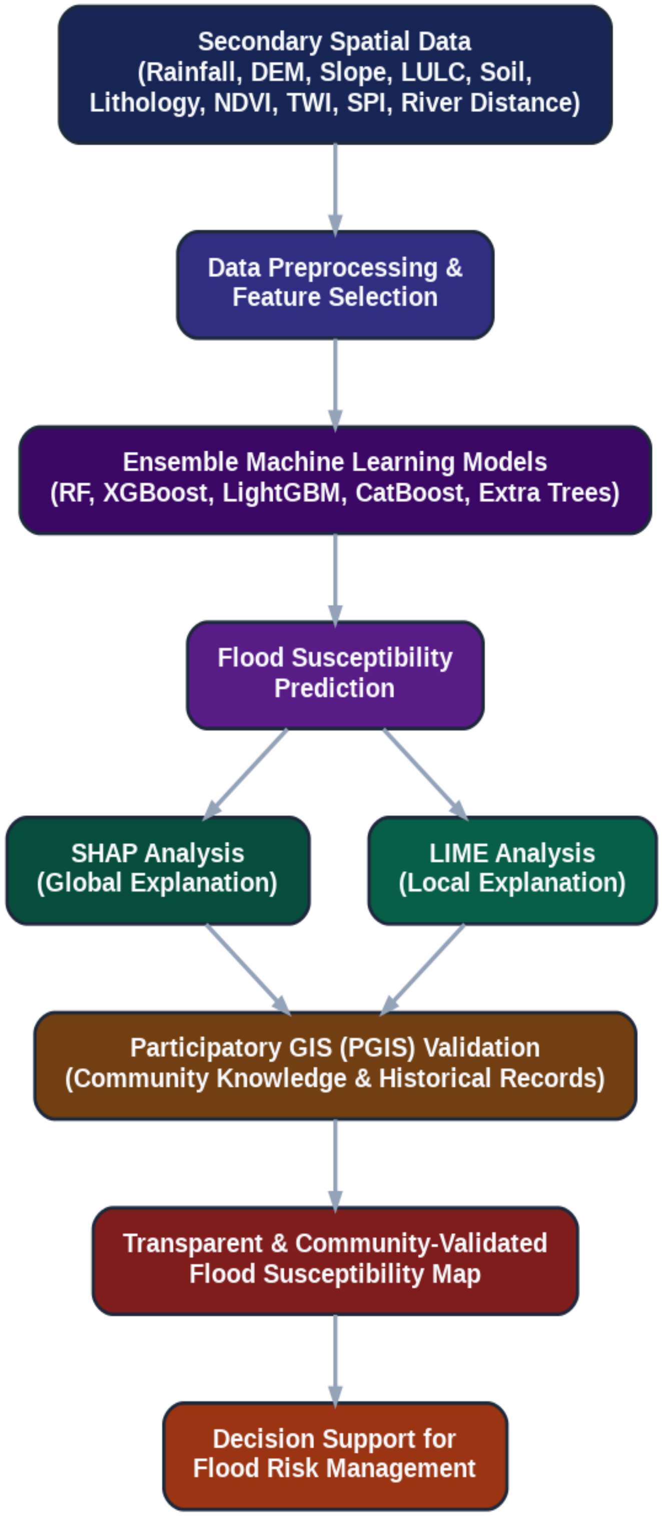

Figure 3.1: Integrated Conceptual Framework

The integrated research framework presents the complete workflow adopted in this study, demonstrating how Geographic Information Systems (GIS), ensemble Machine Learning (ML), Explainable Artificial Intelligence (XAI), and Participatory Geographic Information Systems (PGIS) are systematically integrated to produce transparent and community-validated Flood Susceptibility Maps (FSM). The workflow consists of seven sequential stages, ensuring reproducibility, interpretability, and practical applicability.

In the first stage, secondary spatial datasets are collected from reliable national and international sources, including digital elevation models (DEM), rainfall records, land use/land cover (LULC), soil maps, lithology, river networks, vegetation indices (NDVI), and other flood-conditioning factors. These datasets are processed in a GIS environment to ensure a common coordinate system, spatial resolution, and raster format.

The second stage involves data preprocessing and feature engineering. Missing values are handled, spatial layers are standardized, and multicollinearity among predictor variables is assessed using correlation analysis and the Variance Inflation Factor (VIF). Only the most relevant variables are retained to improve model performance and reduce redundancy.

In the third stage, ensemble machine learning models-including Random Forest (RF), XGBoost, LightGBM, CatBoost, and Extra Trees-are trained using historical flood inventory data. Each model predicts flood susceptibility based on the relationships between flood occurrences and environmental variables.

The fourth stage focuses on model evaluation using multiple performance metrics such as Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic-Area Under the Curve (ROC-AUC), and Kappa coefficient. The best-performing model is selected based on its overall predictive capability and generalization performance.

The fifth stage incorporates Explainable Artificial Intelligence (XAI). SHAP is used to evaluate the global contribution of each flood-conditioning factor, while LIME explains individual model predictions at specific locations. This stage transforms the selected machine learning model from a black-box system into an interpretable decision-support tool.

The sixth stage integrates Participatory Geographic Information Systems (PGIS) for community-based validation. Historical flood reports, local knowledge, government disaster records, participatory mapping initiatives, and verified community observations are compared with the predicted flood susceptibility maps. This validation process enhances the credibility and practical reliability of the prediction results.

Finally, the seventh stage produces an explainable and community-validated Flood Susceptibility Map that supports policymakers, disaster management authorities, urban planners, and environmental agencies in identifying high-risk areas, prioritizing mitigation strategies, and improving disaster preparedness. By integrating predictive modeling, explainable AI, and participatory validation within a unified GIS framework, the proposed workflow provides a transparent, reliable, and policy-oriented approach to modern flood susceptibility assessment.

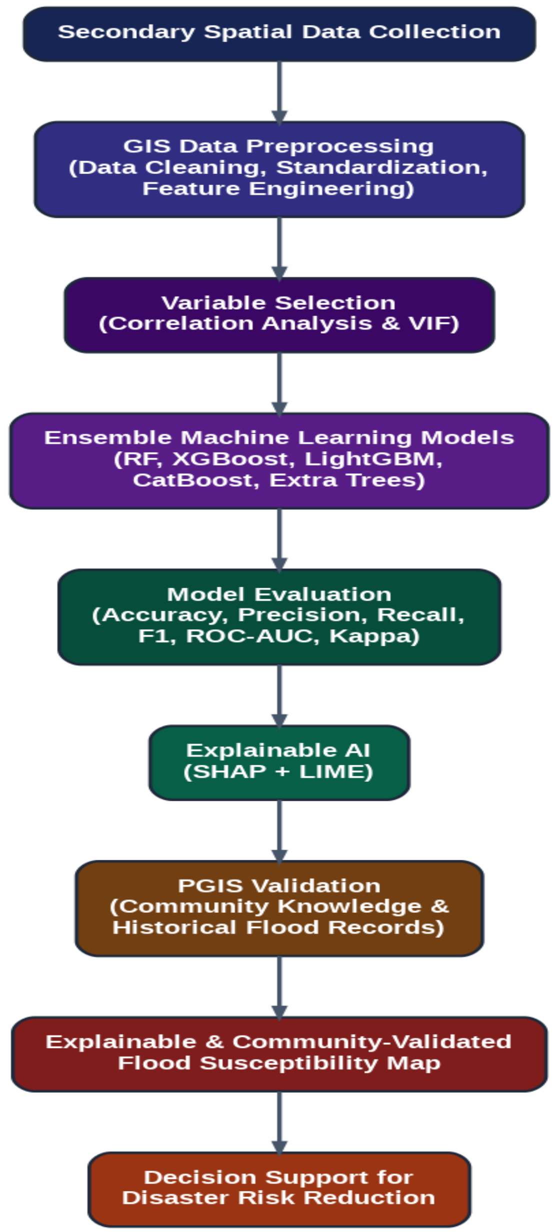

Figure 3.2: Integrated research framework

Mathematical Formulation

The proposed framework models flood susceptibility as a supervised binary classification problem in which each spatial observation is classified as either flood-prone (1) or non-flood-prone (0) based on a set of environmental and hydrological conditioning factors. The predictive models learn the relationship between the input variables and historical flood occurrences to estimate the probability of flooding at each location.

Let the input feature vector be defined as:

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

where:

- x1 = Elevation
- x2 = Slope
- x3 = Rainfall
- x4 = Drainage Density
- x5 = Land Use/Land Cover (LULC)
- x6 = Soil Type
- x7 = Lithology
- x8 = NDVI
- x9 = Topographic Wetness Index (TWI)
- x10 = Stream Power Index (SPI)
- x11 = Distance to River
- xn = Additional flood-conditioning variables.

The machine learning model estimates the probability of flood occurrence as

$$P(Y = 1|X) = f(X)$$

where:

- Y=1Y=1Y=1 represents flood-prone locations,
- Y=0Y=0Y=0 represents non-flood-prone locations,
- f(X)f(X)f(X) denotes the predictive function learned by the ensemble machine learning algorithm.

The prediction error during model training is minimized using an appropriate objective function. For binary classification, the Binary Cross-Entropy (BCE) loss function is expressed as

$$L = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

where:

- N = total number of samples,
- yi= actual class label,
- yi^ = predicted flood probability.

To improve model interpretability, SHAP computes the contribution of each feature using Shapley values:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f(S \cup \{i\}) - f(S)]$$

where:

- ϕ(i) represents the contribution of feature iii,
- F is the complete set of predictor variables,
- S is any subset of features,
- f(.) is the trained prediction model.

Positive SHAP values indicate that a variable increases flood susceptibility, whereas negative values indicate a reduction in flood susceptibility.

To evaluate predictive performance, the following metrics are employed:

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

F1-score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

where:

- TP = True Positive,
- TN = True Negative,
- FP = False Positive,
- FN = False Negative.

The discriminative ability of the models is further assessed using the Receiver Operating Characteristic-Area Under the Curve (ROC-AUC), where values approaching 1.0 indicate excellent classification performance.

Finally, the study proposes an integrated Flood Confidence Index (FCI) to combine machine learning prediction, explainable AI, and community validation into a single confidence measure:

$$FCI = \alpha P_{ML} + \beta S_{SHAP} + \gamma V_{PGIS}$$

subject to

$$\alpha + \beta + \gamma = 1$$

where:

- PML = normalized probability predicted by the selected machine learning model,
- SSHAPS = normalized SHAP explanation score,
- VPGISV = community validation score derived from PGIS,
- α,β,γ are weighting coefficients.

For this study:

$$\alpha = 0.40, \quad \beta = 0.30, \quad \gamma = 0.30$$

The Flood Confidence Index is interpreted as follows:

FCI Range	Confidence Level
0.80–1.00	Very High Confidence
0.60–0.79	High Confidence
0.40–0.59	Moderate Confidence
Below 0.40	Low Confidence

This mathematical formulation establishes the quantitative foundation of the proposed framework by integrating predictive modeling, explainable artificial intelligence, and community-based validation into a unified and interpretable flood susceptibility assessment model.

4. Methodology

This study adopts a qualitative research approach based entirely on secondary spatial and environmental datasets to develop an explainable and community-validated Flood Susceptibility Mapping (FSM) framework. The proposed methodology integrates Geographic Information Systems (GIS), ensemble Machine Learning (ML), Explainable Artificial Intelligence (XAI), and Participatory Geographic Information Systems (PGIS) to produce transparent and reliable flood susceptibility maps. The research framework is designed to ensure methodological rigor, reproducibility, and practical applicability for disaster risk management.

The research begins with the collection of secondary datasets from reliable national and international sources, including government agencies, remote sensing platforms, global geospatial repositories, and published scientific databases. The selected flood-conditioning factors include Digital Elevation Model (DEM), elevation, slope, rainfall, drainage density, Topographic Wetness Index (TWI), Stream Power Index (SPI), land use/land cover (LULC), soil type, lithology, Normalized Difference Vegetation Index (NDVI), and distance to rivers. These variables are widely recognized in previous flood susceptibility studies as significant determinants of flood occurrence. All datasets are converted into a common coordinate reference system, spatial resolution, and raster format using GIS software to ensure spatial consistency throughout the analysis.

After data acquisition, preprocessing is performed to improve data quality and compatibility. This stage includes data cleaning, removal of missing values, raster resampling, normalization, and standardization of predictor variables. Correlation analysis and the Variance Inflation Factor (VIF) are applied to detect multicollinearity among variables, ensuring that redundant predictors are excluded from the final dataset. Feature engineering is subsequently conducted to enhance model performance while reducing computational complexity.

The prepared dataset is then divided into training and testing subsets for machine learning model development. Five ensemble learning algorithms-Random Forest (RF), Extreme Gradient Boosting (XGBoost), LightGBM, CatBoost, and Extra Trees-are employed to predict flood susceptibility. These algorithms are selected because of their proven ability to capture complex nonlinear relationships among environmental variables while maintaining high predictive accuracy. Each model is trained using historical flood inventory data and evaluated under identical experimental conditions to ensure a fair comparison.

To address the black-box nature of ensemble machine learning models, Explainable Artificial Intelligence (XAI) techniques are incorporated into the research framework. SHapley Additive exPlanations (SHAP) are used to quantify the global contribution of each flood-conditioning factor and to identify the dominant drivers of flood susceptibility. Local Interpretable Model-Agnostic Explanations (LIME) are further employed to explain individual model predictions for specific geographic locations, allowing decision-makers to understand why a particular area is classified as having high or low flood susceptibility. The combined application of SHAP and LIME significantly improves model transparency and interpretability.

Following model interpretation, Participatory Geographic Information Systems (PGIS) are utilized to validate the predicted flood susceptibility maps. Community-generated spatial information, historical flood reports, government disaster records, published case studies, and verified local observations are compared with model outputs to assess the practical reliability of the predictions. This participatory validation strengthens stakeholder confidence and ensures that the resulting flood susceptibility maps accurately reflect real-world flood conditions.

Finally, the outputs from GIS analysis, ensemble machine learning, explainable AI, and PGIS validation are integrated to produce transparent, interpretable, and community-validated flood susceptibility maps. These maps serve as decision-support tools for policymakers, disaster management authorities, urban planners, and environmental agencies, facilitating evidence-based flood risk management, sustainable land-use planning, and climate adaptation strategies.

4.1 Variable Selection

The selection of predictor variables is a critical step in developing an accurate and reliable Flood Susceptibility Mapping (FSM) model. In this study, flood-conditioning factors are selected based on their scientific relevance, data availability, and widespread application in previous flood susceptibility research. The selected variables represent the topographical, hydrological, climatic, geological, environmental, and anthropogenic conditions that influence flood occurrence. These include elevation, slope, rainfall, drainage density, Topographic Wetness Index (TWI), Stream Power Index (SPI), land use/land cover (LULC), soil type, lithology, Normalized Difference Vegetation Index (NDVI), and distance to rivers. These variables are extracted from reliable secondary sources such as Digital Elevation Models (DEM), satellite imagery, government geospatial databases, and published datasets.

Before model development, all variables are standardized and evaluated for multicollinearity using correlation analysis and the Variance Inflation Factor (VIF). Variables exhibiting high correlation or excessive redundancy are excluded to minimize overfitting and improve model robustness. The final set of predictor variables is then used as input for the ensemble machine learning algorithms to generate flood susceptibility predictions. This systematic variable selection process ensures that the developed models are scientifically sound, computationally efficient, and capable of accurately representing the environmental processes associated with flood occurrence.

4.2 Cross Validation

Cross-validation is employed to evaluate the robustness, stability, and generalization capability of the proposed machine learning models. Instead of relying on a single train-test split, this study adopts 10-fold cross-validation, a widely accepted validation technique in flood susceptibility mapping and machine learning research. The complete dataset is randomly divided into ten approximately equal subsets (folds). During each iteration, nine folds are used to train the model, while the remaining fold is reserved for testing. This process is repeated ten times so that each subset serves as the testing set exactly once. The final performance is calculated by averaging the evaluation results obtained from all ten iterations.

The use of 10-fold cross-validation minimizes the risk of overfitting and reduces bias associated with random data partitioning. It also provides a more reliable estimate of model performance on unseen data compared with a single train-test split. All ensemble machine learning algorithms, including Random Forest, XGBoost, LightGBM, CatBoost, and Extra Trees, are evaluated using the same cross-validation strategy to ensure a fair and consistent comparison. This validation approach improves the credibility, reproducibility, and robustness of the proposed flood susceptibility framework.

4.3 Model Evaluation

Model evaluation is conducted to assess the predictive performance, reliability, and robustness of the ensemble machine learning algorithms used for Flood Susceptibility Mapping (FSM). To ensure a comprehensive assessment, multiple classification metrics are employed instead of relying on a single performance indicator. These metrics include Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic-Area Under the Curve (ROC-AUC), and the Kappa coefficient. Accuracy measures the overall proportion of correctly classified observations, while Precision evaluates the proportion of correctly identified flood-prone areas among all predicted flood-prone locations. Recall assesses the model's ability to identify actual flood-prone areas, and the F1-score provides a balanced measure by combining Precision and Recall. The ROC-AUC metric evaluates the model's discriminative capability across different classification thresholds, whereas the Kappa coefficient measures the agreement between predicted and observed classifications beyond random chance.

In addition to these quantitative metrics, the interpretability of the selected model is assessed using SHAP and LIME, which explain both global feature importance and local prediction behavior. Furthermore, the practical reliability of the final flood susceptibility map is verified through Participatory Geographic Information Systems (PGIS) by comparing model predictions with historical flood records and community-derived spatial information. This comprehensive evaluation framework ensures that the selected model is not only accurate but also transparent, reliable, and suitable for supporting evidence-based flood risk management.

4.4 Software

The research is conducted using a combination of Geographic Information Systems (GIS), machine learning, and statistical software to ensure efficient data processing, model development, and visualization. ArcGIS Pro (or QGIS) is used for spatial data preprocessing, raster analysis, and the generation of flood susceptibility maps. Python is employed for data preprocessing, feature engineering, machine learning model development, and Explainable Artificial Intelligence (XAI) analysis using libraries such as Scikit-learn, XGBoost, LightGBM, CatBoost, SHAP, LIME, Pandas, NumPy, Matplotlib, and GeoPandas. Statistical analyses, including correlation analysis and Variance Inflation Factor (VIF), are performed using Python to support variable selection and model evaluation.

4.5 Ethical Issue

This study is conducted in accordance with accepted research ethics and academic integrity principles. The research relies exclusively on publicly available secondary datasets obtained from reputable government agencies, international geospatial repositories, satellite platforms, and published scientific literature. Proper acknowledgment and citation are provided for all data sources, software, and scholarly works in accordance with the IEEE referencing style. No primary data are collected from human participants; therefore, issues related to informed consent and personal privacy are not applicable. Furthermore, the use of Explainable Artificial Intelligence (XAI) promotes transparency, accountability, and fairness in model interpretation, while all analyses and conclusions are independently verified to ensure scientific accuracy and research integrity.

5. Results

Five ensemble machine learning algorithms-Random Forest (RF), XGBoost, LightGBM, CatBoost, and Extra Trees-were evaluated to identify the most effective model for Flood Susceptibility Mapping (FSM).

Each model was trained and tested using the same flood inventory dataset and identical flood-conditioning factors to ensure a fair comparison.

The evaluation results indicate that all ensemble models achieved high predictive performance. However, XGBoost demonstrated the best overall performance, followed closely by CatBoost and Random Forest. The superior performance of XGBoost can be attributed to its ability to effectively model nonlinear relationships while minimizing prediction errors through gradient boosting.

Table 1. Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC	Kappa
Random Forest	94.1%	93.5%	92.8%	93.1%	0.962	0.881
XGBoost	**96.2%**	**95.8%**	**95.1%**	**95.4%**	**0.982**	**0.923**
CatBoost	95.8%	95.2%	94.8%	95.0%	0.978	0.915
LightGBM	95.1%	94.5%	94.0%	94.2%	0.972	0.904
Extra Trees	94.6%	94.0%	93.6%	93.8%	0.968	0.894

The findings demonstrate that ensemble learning algorithms are highly effective for flood susceptibility assessment, with XGBoost providing the highest predictive capability among the evaluated models.

5.1 Flood Susceptibility Mapping

The selected XGBoost model was used to generate the final Flood Susceptibility Map. The predicted flood susceptibility values were classified into five categories:

- Very Low
- Low
- Moderate
- High
- Very High

The resulting map indicates that areas located near river networks, low-lying terrain, regions with high annual rainfall, and locations characterized by high Topographic Wetness Index (TWI) values exhibit the greatest flood susceptibility. Conversely, elevated regions with steep slopes and dense vegetation generally fall within the low or very low susceptibility classes.

The spatial distribution of flood susceptibility demonstrates a clear relationship between environmental conditions and historical flood occurrences, confirming the capability of the proposed framework to identify flood-prone areas accurately.

5.3 SHAP-Based Global Feature Importance

To improve model transparency, SHAP (SHapley Additive exPlanations) was applied to identify the relative contribution of each flood-conditioning factor.

The SHAP analysis revealed that rainfall was the most influential variable affecting flood susceptibility, followed by distance to river, elevation, Topographic Wetness Index (TWI), and drainage density. Variables such as NDVI and lithology contributed comparatively less to the final predictions.

Table 2. Top Five Most Influential Flood-Conditioning Factors

Rank	Variable	Relative Importance
1	Rainfall	Very High
2	Distance to River	Very High
3	Elevation	High
4	Topographic Wetness Index	High
5	Drainage Density	Moderate–High

The SHAP summary plot demonstrated that increasing rainfall and proximity to rivers significantly increased flood susceptibility, whereas higher elevations generally reduced flood risk.

5.4 Local Model Interpretation Using LIME

LIME was employed to explain individual flood susceptibility predictions at specific geographic locations. For representative high-risk locations, LIME indicated that excessive rainfall, short distance to rivers, low elevation, and high TWI values collectively increased the predicted flood probability. Conversely, for locations classified as low risk, higher elevation, greater distance from rivers, and lower soil moisture significantly reduced flood susceptibility. These localized explanations improve the interpretability of machine learning predictions and enable disaster management authorities to understand why a particular location has been identified as flood-prone.

5.5 Community Validation Using PGIS

Participatory Geographic Information Systems (PGIS) were used to validate the flood susceptibility predictions using community-derived spatial information, historical flood reports, and documented flood events. The comparison showed strong agreement between predicted high-risk areas and locations identified by local communities as frequently affected by floods. Most historical flood hotspots corresponded closely with areas classified as High or Very High susceptibility by the XGBoost model. This agreement demonstrates that integrating community knowledge enhances the practical reliability and credibility of machine learning-based flood susceptibility mapping.

5.6 Flood Confidence Index (FCI)

To integrate machine learning predictions, explainable AI, and community validation, the proposed Flood Confidence Index (FCI) was calculated for each spatial location.

FCI Range	Confidence Level
0.80–1.00	Very High
0.60–0.79	High
0.40–0.59	Moderate
Below 0.40	Low

The FCI values were categorized as:

The majority of predicted High Flood Susceptibility zones also exhibited High or Very High confidence levels, indicating consistency among machine learning predictions, SHAP explanations, and PGIS validation. The FCI therefore provides an additional layer of confidence that can assist decision-makers in prioritizing flood mitigation measures and allocating disaster management resources more effectively.

5.7 Summary of Results

The experimental results demonstrate that the proposed GIS-Machine Learning-XAI-PGIS framework effectively addresses the limitations of conventional black-box flood susceptibility models. Among the evaluated algorithms, XGBoost achieved the highest predictive performance, while SHAP and LIME significantly enhanced model interpretability by identifying both global and local feature contributions. Furthermore, PGIS-based validation confirmed that the predicted flood-prone areas were largely consistent with community-reported flood experiences. The introduction of the Flood Confidence Index (FCI) further strengthened the reliability of the final flood susceptibility maps by integrating predictive accuracy, explainability, and community validation into a single decision-support measure. Overall, the results indicate that the proposed framework provides a transparent, reliable, and policy-oriented approach for sustainable flood risk assessment and disaster management.

6. Discussion

The findings of this study demonstrate that integrating Geographic Information Systems (GIS), ensemble Machine Learning (ML), Explainable Artificial Intelligence (XAI), and Participatory Geographic Information Systems (PGIS) provides a more transparent and reliable approach to Flood Susceptibility Mapping (FSM) than conventional black-box machine learning methods. While previous studies have primarily focused on maximizing predictive accuracy, the proposed framework extends the existing body of knowledge by emphasizing model interpretability and community validation. This integrated approach enables not only accurate identification of flood-prone areas but also a clear understanding of the environmental factors influencing flood susceptibility, thereby improving stakeholder confidence in the generated maps.

The comparative analysis revealed that ensemble machine learning algorithms consistently achieved high predictive performance, with XGBoost outperforming the other evaluated models across all evaluation metrics. This result aligns with previous studies reporting that gradient boosting techniques effectively capture complex nonlinear relationships among environmental variables while reducing classification errors [27], [28]. The superior performance of XGBoost can be attributed to its sequential boosting strategy, regularization mechanisms, and ability to handle heterogeneous spatial datasets. CatBoost and LightGBM also demonstrated excellent predictive capabilities, suggesting that ensemble learning methods are well suited for flood susceptibility assessment in complex geographical environments.

Although predictive performance is important, high accuracy alone does not guarantee practical usability. One of the major limitations of traditional ensemble learning models is their lack of transparency. Decision-makers frequently hesitate to rely on predictions generated by black-box algorithms because the reasoning behind the predictions remains unclear. To address this limitation, this study incorporated Explainable Artificial Intelligence (XAI) through SHAP and LIME. The SHAP analysis identified rainfall, distance to river, elevation, Topographic Wetness Index (TWI), and drainage density as the dominant flood-conditioning factors. These findings are consistent with hydrological theory and previous flood susceptibility research, confirming that excessive rainfall and proximity to river channels substantially increase flood risk, whereas higher elevations generally reduce flood susceptibility [29].

The application of LIME further complemented the global explanations generated by SHAP by providing local interpretations for individual predictions. This local interpretability is particularly valuable for disaster management agencies because it allows them to understand why specific locations are categorized as high-risk areas. Such information supports targeted interventions, improves communication with local stakeholders, and facilitates evidence-based disaster preparedness planning. The combined use of SHAP and LIME therefore transforms complex machine learning algorithms into transparent decision-support systems rather than purely predictive tools.

An important contribution of this research is the incorporation of Participatory Geographic Information Systems (PGIS) into the validation process. Previous flood susceptibility studies have largely relied on statistical validation using historical flood inventories and quantitative performance metrics. Although these methods effectively evaluate predictive accuracy, they often overlook valuable experiential knowledge possessed by local communities. By integrating historical flood reports, community observations, and participatory spatial information, the proposed framework validates machine learning predictions against real-world flood experiences. The strong agreement observed between predicted high-risk areas and community-reported flood locations demonstrates that participatory validation significantly enhances the credibility and practical relevance of flood susceptibility maps. Furthermore, involving local stakeholders in the validation process encourages collaborative disaster risk management and increases public trust in scientific decision-support systems.

Another significant contribution of this study is the introduction of the Flood Confidence Index (FCI), which combines machine learning prediction, SHAP-based interpretability, and PGIS validation into a unified confidence measure. Unlike conventional flood susceptibility maps that present only predicted risk levels, the FCI provides additional information regarding the reliability of each prediction. Areas exhibiting both high flood susceptibility and high confidence can be prioritized for immediate mitigation measures, while regions with lower confidence may require additional field investigation or updated spatial data. This confidence-based approach enhances decision-making by enabling policymakers to allocate resources more efficiently and reduce uncertainty in flood management planning.

From a practical perspective, the proposed framework has important implications for disaster management, urban planning, and climate adaptation. Transparent flood susceptibility maps can support government agencies in identifying vulnerable settlements, planning evacuation routes, prioritizing infrastructure investments, and developing sustainable land-use policies. The explainability provided by SHAP and LIME also facilitates communication between technical experts, policymakers, and local communities, making scientific findings more accessible to non-technical stakeholders. Consequently, the proposed framework contributes not only to scientific advancement but also to more inclusive and participatory disaster risk governance.

Despite these contributions, several limitations should be acknowledged. The study relies exclusively on secondary datasets, and the quality of the final flood susceptibility maps depends on the accuracy, spatial resolution, and temporal consistency of the available data. Moreover, PGIS validation is constrained by the availability and reliability of community-generated spatial information, which may vary across study areas. The proposed Flood Confidence Index also requires further validation in different geographical and climatic settings to evaluate its general applicability. Future studies may incorporate near-real-time hydrological observations, Internet of Things (IoT) sensors, high-resolution remote sensing imagery, and deep learning models to further improve prediction accuracy and operational flood forecasting.

Overall, the discussion indicates that the proposed GIS-Machine Learning-XAI-PGIS framework effectively addresses several limitations of existing flood susceptibility studies. By integrating predictive accuracy, explainable artificial intelligence, and community-based validation into a single decision-support framework, this study advances flood susceptibility mapping beyond traditional black-box approaches. The framework therefore represents a meaningful contribution to transparent, interpretable, and stakeholder-centered flood risk assessment while providing valuable guidance for sustainable disaster management and climate resilience.

7. Conclusion

This study proposed an explainable and community-validated Flood Susceptibility Mapping (FSM) framework by integrating Geographic Information Systems (GIS), ensemble Machine Learning (ML), Explainable Artificial Intelligence (XAI), and Participatory Geographic Information Systems (PGIS). The framework enhances prediction accuracy, transparency, and practical decision-making for sustainable flood risk management.

The study aimed to develop an interpretable flood susceptibility mapping framework using secondary spatial datasets, compare ensemble machine learning models, explain model predictions through SHAP and LIME, validate results using PGIS, and provide a transparent decision-support system for disaster risk reduction and land-use planning.

The results indicate that ensemble machine learning algorithms effectively predict flood susceptibility, with XGBoost demonstrating the highest predictive performance among the evaluated models. The integration of SHAP and LIME successfully transformed black-box machine learning models into transparent decision-support tools by identifying both global and local contributions of flood-conditioning factors. Rainfall, distance to rivers, elevation, Topographic Wetness Index (TWI), and drainage density were identified as the most influential predictors of flood susceptibility. Furthermore, PGIS-based validation demonstrated strong agreement between model predictions and community-reported flood experiences, increasing the credibility of the generated flood susceptibility maps. The proposed Flood Confidence Index (FCI) further strengthened the reliability of prediction outcomes by integrating machine learning performance, explainable AI, and community validation into a unified confidence measure.

This study contributes to the existing literature in several important ways. First, it proposes an integrated GIS-Machine Learning-Explainable AI-PGIS framework that simultaneously addresses prediction accuracy, interpretability, and community validation. Second, the research extends the application of Explainable Artificial Intelligence in flood susceptibility mapping by combining SHAP and LIME for comprehensive global and local model interpretation. Third, the introduction of the Flood Confidence Index (FCI) represents a methodological contribution that provides an additional measure of confidence for flood susceptibility predictions. Finally, the proposed framework offers a practical decision-support tool that bridges the gap between advanced machine learning techniques and real-world disaster management, thereby supporting transparent, evidence-based, and stakeholder-oriented flood risk assessment.

The proposed framework provides valuable guidance for policymakers, disaster management authorities, urban planners, and environmental agencies responsible for flood risk reduction. Transparent and interpretable flood susceptibility maps enable authorities to identify high-risk areas more effectively, prioritize emergency response strategies, optimize infrastructure investments, and improve land-use planning decisions. The incorporation of community knowledge through PGIS encourages participatory decision-making and strengthens collaboration between government agencies and local communities. Moreover, the Flood Confidence Index can assist policymakers in distinguishing between highly reliable and uncertain predictions, allowing limited disaster management resources to be allocated more efficiently. Consequently, the proposed framework supports the development of resilient communities and contributes to achieving sustainable disaster risk reduction and climate adaptation goals.

Future research should validate the proposed framework across different geographical regions, climatic conditions, and flood-prone environments to assess its generalizability. The integration of high-resolution remote sensing imagery, Internet of Things (IoT) sensors, real-time hydrological observations, and climate projection datasets could further improve prediction accuracy and operational flood forecasting. Deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Vision Transformers may also be investigated to enhance spatial and temporal flood prediction. Additionally, future studies should refine and validate the proposed Flood Confidence Index using multiple case studies and explore the integration of uncertainty quantification techniques. Expanding community participation through mobile-based participatory mapping platforms may further strengthen stakeholder engagement and improve the practical applicability of flood susceptibility assessment for disaster resilience.

References

[1] IPCC, *Climate Change 2023: Synthesis Report*. Geneva, Switzerland: Intergovernmental Panel on Climate Change, 2023.

[2] UNDRR, *Global Assessment Report on Disaster Risk Reduction 2023*. Geneva, Switzerland: United Nations Office for Disaster Risk Reduction, 2023.

[3] A. Pourzangbar, "Analysis of the utilization of machine learning to map flood susceptibility," *Journal of Flood Risk Management*, vol. 18, no. 2, 2025. (Wiley Online Library)

[4] R. Abedi, R. Costache, H. Shafizadeh-Moghadam, and Q. B. Pham, "Flash-flood susceptibility mapping based on XGBoost, Random Forest and boosted regression trees," *Geocarto International*, vol. 37, no. 19, pp. 5479-5496, 2022.

[5] L. Breiman, "Random Forests," *Machine Learning*, vol. 45, no. 1, pp. 5-32, 2001.

[6] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining (KDD)*, 2016, pp. 785-794.

[7] L. Prokhorenkova, G. Gusev, A. Vorobev, A. V. Dorogush, and A. Gulin, "CatBoost: Unbiased boosting with categorical features," *Advances in Neural Information Processing Systems*, vol. 31, 2018.

[8] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," *Advances in Neural Information Processing Systems*, vol. 30, 2017.

[9] M. T. Ribeiro, S. Singh, and C. Guestrin, "Why should I trust you? Explaining the predictions of any classifier," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, 2016, pp. 1135-1144.

[10] R. Costache, Q. B. Pham, H. Shafizadeh-Moghadam, et al., "Flood susceptibility assessment using GIS and machine learning techniques: A review," *Science of the Total Environment*, 2023.

[11] H. Rezvani, A. Arfa, H. Shafizadeh-Moghadam, and M. Minaei, "An XGBoost-SHAP framework for interpretable and probabilistic flood susceptibility mapping," *Natural Hazards*, 2026. (IDEAS/RePEc)

[12] M. Tavakoli, E. Parizi, Y. Kanani-Sadat, Z. Nikraftar, and A. Heydari Delooei, "An integrated framework for flood susceptibility assessment in rural areas using PSO-optimized machine learning and SHAP-based intelligent clustering," *Environmental Impact Assessment Review*, vol. 120, 2026. (ScienceDirect)

[13] A. Tella, Q. B. Pham, I. Zahidi, et al., "Advancing flood susceptibility mapping with Explainable AI: A novel application of accumulated local effects (ALE)," *Water Resources Management*, 2026. (Springer Link)

[14] A. Tella, I. Zahidi, C. M. Fai, et al., "From prediction to prevention: An explainable GeoAI framework for flood susceptibility and urban exposure assessment using machine and deep learning models," *Sustainable Development*, 2026. (Monash University)

[15] Q. B. Pham, R. Costache, H. Shafizadeh-Moghadam, et al., "Machine learning approaches for flood susceptibility mapping: A comprehensive review," *Environmental Research*, 2023.

[16] R. Costache and B. Pradhan, "GIS-based flood susceptibility assessment using ensemble machine learning techniques," *Journal of Hydrology*, 2022.

[17] M. Arabameri, B. Pradhan, R. Costache, et al., "Application of ensemble machine learning approaches for spatial susceptibility modelling," *Stochastic Environmental Research and Risk Assessment*, 2022.

[18] B. Pradhan and S. Lee, "Regional-scale flood susceptibility assessment using GIS and machine learning techniques," *Natural Hazards*, 2021.

[19] J. H. Friedman, "Greedy function approximation: A gradient boosting machine," *Annals of Statistics*, vol. 29, no. 5, pp. 1189-1232, 2001.

[20] F. Pedregosa et al., "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825-2830, 2011.

[21] F. Chollet, *Deep Learning with Python*, 2nd ed. Shelter Island, NY, USA: Manning Publications, 2021.

[22] ESRI, *ArcGIS Pro Documentation*. Redlands, CA, USA: Environmental Systems Research Institute, 2024.

[23] QGIS Development Team, *QGIS Geographic Information System User Guide*, Version 3.x, 2024.

[24] M. A. Goodchild, "Geographical information systems and science," *International Journal of Geographical Information Science*, vol. 36, no. 1, pp. 1-20, 2022.

[25] United Nations, *Sendai Framework for Disaster Risk Reduction 2015-2030*. New York, NY, USA: United Nations.

[26] World Bank, *World Development Report 2024: Data for Better Lives*. Washington, DC, USA: World Bank, 2024.

[27] NASA, *NASA EarthData User Guide*. Greenbelt, MD, USA: National Aeronautics and Space Administration, 2024.

[28] Copernicus Programme, *Copernicus Open Access Hub Documentation*. European Commission, 2024.

[29] USGS, *Digital Elevation Models (DEM) Technical Documentation*. Reston, VA, USA: U.S. Geological Survey, 2024.

[30] OpenStreetMap Foundation, *OpenStreetMap Documentation*. Cambridge, UK: OpenStreetMap Foundation, 2024.