

Flood Susceptibility Mapping Based on Supervised Machine Learning Algorithms with Integrated Uncertainty and Explainability Analysis: A Case Study in Quang Nam, Vietnam

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Abstract

Flood is among the natural hazards that have occurred with increasing frequency and have changed in complex ways, with serious impacts on people's lives. A flood susceptibility map, the basis for zoning areas at risk of flooding, has become a necessary tool not only for managers but also for residents to adapt to the broader context of climate change. This study aims to present the use of a supervised machine learning model to create a flood susceptibility map of Quang Nam province (now Da Nang city, Vietnam). Four algorithms, including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) were tested. Based on the evaluation metrics and uncertainty analysis, RF not only achieved the best predictive performance (AUC of 0.9418) but also demonstrated higher stability and reliability. An explainability analysis using Shapley additive explanation (SHAP) and Leave-One-Covariate-Out (LOCO) was conducted to assess the contribution of conditioning factors and interpret the RF model's predictions. The result is a flood susceptibility map based on the RF model, with levels ranging from very low to very high. Low-lying plains in the lower reaches of the Vu Gia - Thu Bon River frequently flood and are the most heavily affected areas in Quang Nam. This map was validated with 2025 flood marks data, which served as an independent data source not involved in the model construction process. The results show that the majority of actual flooding points are concentrated in moderate-, high-, and very high-susceptibility areas, accounting for 98.2%, while points in low-susceptibility areas are negligible. Generally, the results will help disaster management agencies develop effective adaptation and risk mitigation policies at the commune level in flood-prone areas. Future studies should integrate flood susceptibility with exposure and vulnerability indicators to support a more comprehensive flood risk assessment.

Keywords: Flood Susceptibility, LOCO, Supervised Machine Learning, SHAP, Uncertainty Analysis

1. Introduction

The main cause of the increasingly severe flooding is recognized as climate change, which is accompanied by extreme weather. Flood is a natural hazard that occurs on a large scale and can be visually detected instantaneously. That also means that the damage it causes to people and the socio-economy can be observed and recorded immediately after the flood occurs. As one of the most devastating natural hazards worldwide and in Viet Nam, floods leave lasting memories, visible flood marks as evidence of past extreme events, and cause severe human, economic, and environmental damage across many regions and countries [1]. In 2024, Europe

experienced historical floods, a state of emergency was declared, and thousands of people had to be evacuated, underscoring the danger posed by the floods [2]. In Vietnam, before the 21st century, many major floods were documented. In 1971, there was a terrible flood in the Red River Delta [3]; a disaster in the Central region, with the number of dead and missing people reaching more than 700 people in 1999 [4]. In Southern Vietnam, people in the Mekong Delta are still haunted by the historic flood in 2000 which caused hundreds of fatalities and damaged thousands of houses [5].

In the 21st century, the frequency of major floods tended to increase, especially in the Central provinces, which are considered Vietnam's flood-prone areas. These were the years 2007, 2009, 2013, 2016, 2017, and 2020 - with widespread flooding and heavy damage [6]. The estimated damage figure from the 2020 flood is nearly 40,000 billion VND, the largest historical flood in the Central region since 1999. These historical floods show that although the meteorological conditions differ among events and regions, low-lying plains adjacent to major river systems in all three major regions of Vietnam have consistently suffered severe flood impacts. More recent floods have continued to cause substantial socio-economic losses, highlighting the increasing complexity of flood disasters and indicating that the flood challenge remains ongoing in Vietnam.

The damage figures from each flood, regardless of the country, cause great harm to people. Therefore, faced with the urgent need to reduce flood-related risks, many scientists around the world have employed various methods and made significant advances in research on this issue. Previously, researchers used many historical sources to understand the recurrence of historical flood events, focusing on flood frequency and severity [7] and [8]. Collecting information sources requires a large and time-consuming task, and sometimes it can be unclear about the time of flood occurrence (day/month) [9] and [10] and thresholds of recorded floods [9], causing data gaps. Although these are considered foundational studies, they also pose challenges in the new era, requiring the incorporation of other data sources and the use of modern technologies.

Following previous studies, many international and Vietnamese studies have utilized meteorological and hydrological observation data, such as rainfall, flow volume, and water level, combined with hydrological and hydraulic models for flood simulation and flood mapping. The HEC-RAS (Hydrologic Engineering Center's River Analysis System) model was widely employed for flood analysis across different river basins, including flood risk assessment in the Luvuvhu river in South Africa [11] and the Slatvinec stream area in Kružlov village, Slovakia [12], demonstrating its effectiveness in simulating flood-prone areas [13]. The MIKE hydraulic modeling software developed by DHI (Danish Hydraulic Institute), was used as a reliable tool in many studies, for example, to simulate river floods in Vietnam [14], and to assess urban flooding risks [15]. However, these methods require large data series over long periods, making them unsuitable for many areas due to their failure to meet these requirements.

Therefore, if relying solely on the hydrometeorological monitoring network, the data may not be adequate to reflect the flood situation in an area. Hydrological stations are often sparse and do not cover large regions, while floods occur over extensive areas. Therefore, when remote sensing technology emerged with the mission of observing Earth, it marked a turning point in natural disaster research. Large coverage, direct and continuous information, and savings in time and costs are the advantages that remote sensing offers. Scientists are gradually shifting their focus to this method not only because of the above advantages but also because remote sensing offers many free image data sources, offering many opportunities for scientific research. Free Radar image data has become a popular approach, such as Sentinel 1 images [16] and [17], or combining both Radar and optical images to quickly estimate flood areas [18]. Along with remote sensing, GIS (Geographic Information System) technology has also proven effective for assessing flood risks and other natural hazards.

While flood zoning studies focus on the details of flood levels for each scenario, local authorities need susceptibility maps to identify dangerous areas, thereby enabling appropriate policies for local development. Identifying locations with high flood potential will help people prepare for and respond to floods, contributing to disaster risk reduction [19]. To generate flood susceptibility maps, approaches used different influencing factors (topography, hydrometeorology, etc.) and decision rules based on expert experience, statistical models, or machine learning. GIS and Analytical Hierarchy Process (AHP) to comprehensively assess flood vulnerability have shown success in studies [19][20][21][22][23] and [24]. In Idukki district of India, a flood extent map was generated using twelve weighted parameters through AHP and achieved an AUC (Area Under the Curve) value of 0.91 [22]. A susceptibility map with a high AUC score of 0.90 was also found in a similar study in Texas, USA [24].

Recently, the emergence of machine learning algorithms has been considered a major step forward in flood research across different geographical areas. The effectiveness of combining geospatial technology with machine learning to map flood risk is more evident. Recent works have relied on many machine learning algorithms in individual or integrated situations. For example, several machine learning models, including Random Forest (RF), Classification and Regression Trees (CART), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost) were compared in the prediction of flood risk in the Metlili basin, Morocco [25]. The results of this study, shown in AUC values

of 0.807, 0.780, 0.756, and 0.727, respectively, indicate that the RF model performed better than the other models. Similarly, high predictive performance was also reported in another study, where RF achieved the highest AUC value of 1.00, followed by RF and gradient boosting ensemble (0.96), gradient boosting (0.95), and AdaBoost (0.83) [26].

Machine learning algorithms have also been increasingly adopted and widely used in Vietnam in recent years. Light Gradient Boosting Machine (LGBM) model was chosen to build a flood susceptibility zoning map in Quang Trach district, Quang Binh province, with seven parameters [27]. The results of this study are evaluated with high accuracy, as evidenced by an AUC of 0.88. Other models were also tested in flood risk mapping in Huong Khe District, Ha Tinh Province, including K-Nearest Neighbor (KNN), SVM and Artificial Neural Network (ANN), all of which resulted in over 90% overall accuracy and AUC values [28]. Overall, the studies demonstrate that this approach provides cost-effective solutions for flood susceptibility mapping, especially in data-scarce areas, for disaster risk management and sustainable development planning. Machine learning enables rapid exploitation of spatial technology (remote sensing – GIS) to build susceptibility maps with high accuracy.

Flood susceptibility maps are a fundamental step in developing early warning systems, as they help delineate vulnerable areas in advance. In general, modern methods have addressed limitations in data availability, especially in field data. In Quang Nam province (now part of Da Nang city) – an area that faces flooding of varying severity annually – although some studies have been conducted on flooding and flood risk in the area, the methods mainly focus on GIS and AHP [29][30] and [31]. To date, machine learning has not been widely developed in flood research in the study area. A typical example in 2024 used RF and CART for the purpose of mapping flood vulnerability, but the focus has primarily been on exposure-level analysis [32]. Therefore, conducting further research on flood susceptibility mapping is essential.

Instead of proposing novel machine learning or hybrid models, this study emphasizes improving the quality of input data at the terrain layer and the model's interpretability, aspects that remain largely unexplored in flood vulnerability prediction mapping. Therefore, the research objectives are (1) to compare four supervised learning algorithms including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and XGBoost implemented on Google Colab to select two better methods, (2) to assess model uncertainty to choose

the optimal model, (3) to explain model using Shapley additive explanation (SHAP) and Leave-One-Covariate-Out (LOCO), and (4) to map and evaluate the accuracy of the map with independent flood marks.

2. Material and Method

2.1 Study Area

According to the report "Project on compiling and supplementing hydro-climatic characteristics of Quang Nam province 1980-2020", in Quang Nam, on average, there are 4 floods from level I or higher every year, with the most floods being 8 to 9 in a year [6]. The exceptionally large floods of 1998, 1999, 2007, 2009, 2013, 2017, 2018, and 2020 caused trillions of dong in damage and claimed hundreds of lives. Among them, the floods of 2007 and 2009 had severe consequences, with total damages reaching 5,700 billion VN dong [33]. The October - November 2025 flood is considered one of the most severe flood events in recent decades, with extreme rainfall and widespread inundation reported across the region (see Figure 1). Water levels at all monitoring stations were above alarm level III, with flood peaks exceeding alarm level III by 1.5-1.8 m. Alarm Level III represents the highest flood warning threshold defined for each hydrological station in Vietnam, indicating severe flood conditions with a high risk of widespread inundation (see Figure 2). Because of its susceptibility to recurrent flooding, Quang Nam province (which is now part of Da Nang City) is selected for this research.

The areas are often subject to flooding due to heavy rain and storms. Located in the Central region of Vietnam, Quang Nam (old) (which belongs to Da Nang City now), in general, is affected by the tropical monsoon climate. As a coastal area of the East Sea, the area cannot avoid the influence of the Pacific climate, a strong tropical convergence zone, accompanied by warm ocean currents, causing the danger when storms come to this area to increase. The rainy season in the research area usually runs from September to December each year. The total rainfall in these months accounts for 65-70% of the annual rainfall [6]. This is also the main time of year when floods occur in the area.

2.2 Data

2.2.1 Flood marks and SAR Sentinel - 1 image

Flood marks play an essential role in flood risk research [34]. These data were utilized to construct flood depth maps in Quang Nam [30]. Accordingly, we employed them to develop the flood susceptibility model.

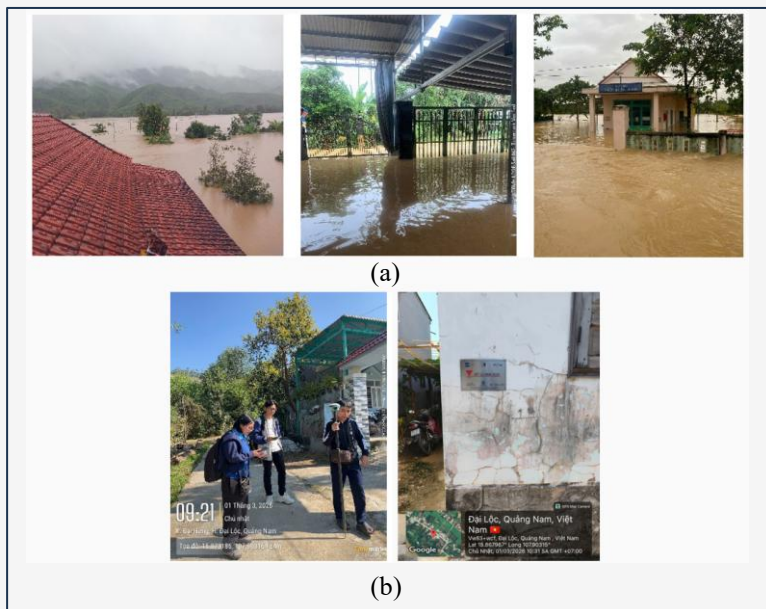


Figure 1: (a) The floods of October-November 2025 in the study area, and (b) flood mark survey in 2026

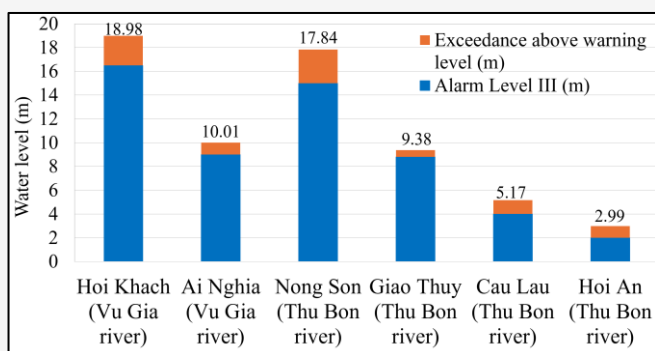


Figure 2: Water levels on October 29th 2025 [35]

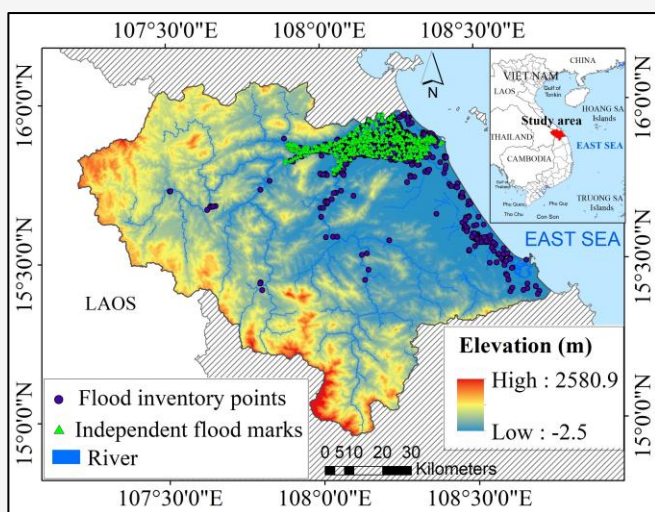


Figure 3: Location of Quang Nam, Vietnam

Flood mark data were compiled from various sources, including historical data of 2009, 2013 and 2020 provided by the Quang Nam Provincial Steering Committee for Natural Disaster Prevention and Control, together with flood mark data corresponding to the 2017 flood event and part of the 2020 event obtained from previous field surveys. All of these points were used to build the flood inventory dataset for training and testing the flood modelling. In addition, flood marks of 2025, independent flood marks in Figure 3, which were collected from the recent field survey in March 2026, were separated and used as an independent validation dataset to assess the reliability of the flood susceptibility map after the model was developed.

Sentinel-1 was selected for rapid zoning of the flooded area for the period from 2015 to 2024. The essence of this method is based on the timing of flood occurrence: calculating the difference in Sentinel-1 radar backscatter values before and after the flood to detect changes. This is the basis for further verification of flood points (marked 1), and points falling in the outer area will be selected as not flooded (marked 0). A total of 913 flood inventory points were considered from the monitored flooded areas (Figure 3); 70% (639 points) were used for modeling, and 30% (274 points) for model evaluation. Equal to the number of flooded points, non-flooded points were randomly selected throughout the study area to avoid all the flooded areas identified based on the flood marks and flooded areas extracted from Sentinel - 1 images.

2.2.2 Flood-affected factors

Input factors in the study, including: factors related to terrain (elevation, slope, slope direction, curvature, Topographic Wetness Index (TWI), Terrain Position Index (TPI), Height Above Nearest Drainage (HAND) calculated from Digital Elevation Model (DEM); rainfall; traffic - hydrological factors, landcover factors (landcover, Normalized Difference Vegetation Index (NDVI), soil type, geological factors (Figures 4 and 5).

DEM greatly affects the extent and severity of flooding [36]. Low-lying areas (plains, riverbanks) are at risk of flooding because water tends to flow from high to low, and when it accumulates, it can cause flooding. Forest And Buildings removed Copernicus DEM (FABDEM) is a terrain dataset derived from the Copernicus DEM by removing the influence of vegetation and built structures, aiming to represent a more realistic bare-earth surface [37]. Compared to the original Copernicus DEM, FABDEM provides a corrected elevation model that reduces biases in areas with dense vegetation and urban infrastructure. Recent studies highlight

significant differences in vertical accuracy between these datasets. For instance, global evaluations across flood-prone environments using LiDAR reference data indicate that FABDEM generally provides more consistent vertical accuracy than the Copernicus DEM [38]. Therefore, the study used FABDEM rather than the Copernicus DEM, which is expected to better represent actual terrain conditions and improve the predictive performance of flood susceptibility models. The datasets have been made available for use at 30 m resolution, published by the University of Bristol on the website <https://data.bris.ac.uk/data/dataset/s5hqmjcdj8yo2ibzi9b4ew3sn>, version FABDEM V1.2.

Slope determined from elevation data is also one of the important terrain features in flood susceptibility [39]. In regions with low slopes, such as flat terrain or low-lying areas, slow flow speeds make drainage difficult, leading to stagnation and prolonged flooding. Aspect is an indirect factor affecting the flow path created by heavy rain. Heavy rain will flow down the slope towards rivers and streams, concentrating in low-lying areas and causing flooding. Thus, the lower the slope value, the less water has the conditions to flow away, creating stagnant low-lying areas. Profile curvature shows curvature parallel to the main slope direction (parallel to the flow direction). It affects the speed and acceleration of water on the surface. Negative values decrease the flow, and positive values accelerate it. While plan curvature is perpendicular to the main slope direction, called transverse curvature (curvature in the plane direction). It is related to the degree of convergence or divergence of flow on the surface.

TWI (Topographic Wetness Index) measures the amount of runoff accumulated at each location of the drainage basin. Areas with high TWI values are usually low-lying areas, prone to flooding. The TWI is calculated based on Equation 1 [40]:

$$TWI = \ln \left(\frac{A_s}{\tan \beta} \right) \quad \text{Equation 1}$$

Where A_s is the flow accumulation obtained from the DEM based on flow direction and β is the slope in radians. These parameters were also presented in Equation 2.

The stream power index (SPI) represents the flow energy on the terrain surface, calculated based on slope and flow accumulation [41]. SPI is defined in Equation 2:

$$SPI = A_s \tan \beta \quad \text{Equation 2}$$

Topographic Position Index (TPI) is an index that describes the relative elevation of a point compared to the surrounding terrain. A positive TPI indicates that the point is located in a mountainous area, a negative or zero value indicates a low-lying or plain area, thereby identifying areas with a high risk of flooding. TPI is calculated according to Equation 3:

$$TPI = z_0 - \frac{1}{n} \sum_{i=1}^n z_i$$

Equation 3

Where z_0 is the elevation at the center point to be calculated, z_i is the elevation of the neighboring points in the analysis window, n is the number of neighboring points to be calculated.

HAND represents the relative elevation of a point with respect to the nearest watercourse (drainage channel) [42]. It is widely used as a proxy for flood susceptibility, as areas with lower HAND values are more likely to be inundated. Rainfall plays a crucial role in causing floods. Heavy and prolonged rain causes a large flow, water cannot drain fast enough, so the river water rises rapidly. Rainfall data were collected from 74 hydrological stations from 2011 to 2024 by the Ministry of Natural Resources and Environment, the Vrain website of Quang Nam. The dataset includes daily rainfall records, which are then aggregated over the years and subsequently averaged annually. It was spatially interpolated using inverse distance weighting (IDW) to construct a rainfall distribution map for the entire area.

NDVI (Normalized Difference Vegetation Index) is a measure of vegetation health and has an indirect effect on flooding. NDVI values range from -1 to 1 [43]. Low NDVI indicates sparse vegetation (urban land, bare land), poor water absorption, and increased surface runoff. High values indicate vegetation retains water and reduces runoff velocity, helping to minimize flooding. Sentinel-2 satellite imagery with a spatial resolution of 10 m was used to calculate the NDVI index for the period 2015–2024 on Google Earth Engine (GEE) platform. NDVI is defined in Equation 4:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Equation 4

Where *NIR*: near-infrared band, *RED*: red band.

Land cover influences flood through its permeability, water retention, surface runoff, and the degree of

flow resistance of object classes [44]. Areas with dense vegetation cover generally improve water infiltration, reduce surface runoff velocity, and limit the risk of flooding. In contrast, built-up or urban areas with poorer water infiltration increase surface runoff, thereby increasing the risk of flooding. Land cover data were obtained from the Esri Land Cover dataset at 10 m resolution, available at <https://livingatlas.arcgis.com/landcover/>.

Traffic and river network data were collected from the Quang Nam province database at a scale of 1:50,000 and used to construct distance-to-road and distance-to-river layers, as well as to calculate several topographic indices such as SPI. Areas near rivers are at higher risk of flooding than other areas. In the study, the Vu Gia–Thu Bon river system was assessed as posing a high risk to localities near it. The shorter the distance, the higher the risk of flooding. Similarly, areas near roads are more prone to flooding due to increased surface runoff and limited natural drainage capacity. Two factors were calculated using the Euclidean Distance tool.

In addition, soil type, lithological, and geohydrological data were collected from specialized agencies in Vietnam at a scale of 1:50,000 to reflect the characteristics of the substrate material and its impact on water infiltration and storage capacity in the study area. Soil type plays an important role in flood susceptibility by controlling infiltration capacity and surface runoff generation. Soils with low permeability tend to increase flood risk due to reduced infiltration and higher surface flow, whereas well-drained soils can mitigate flood occurrence. Lithology flooding can be influenced by rock composition and geological structure due to their impact on soil porosity and permeability. Geohydrology, the presence of groundwater, allows us to speculate on the formation of floods. If the groundwater level is high, the soil is easily saturated, increasing the risk of flooding.

2.3 Methodology

The workflow of this study is illustrated in Figure 6. First, factors influencing floods were constructed and checked for multicollinearity through VIF and tolerance coefficients to eliminate redundant variables. The flood dataset was constructed from flood marks, Sentinel-1 images, and field surveys, then divided into a training set (70%) and a testing set (30%). Four machine learning models, including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and XGBoost, were used to select the appropriate model for constructing a flood susceptibility map for the study area.

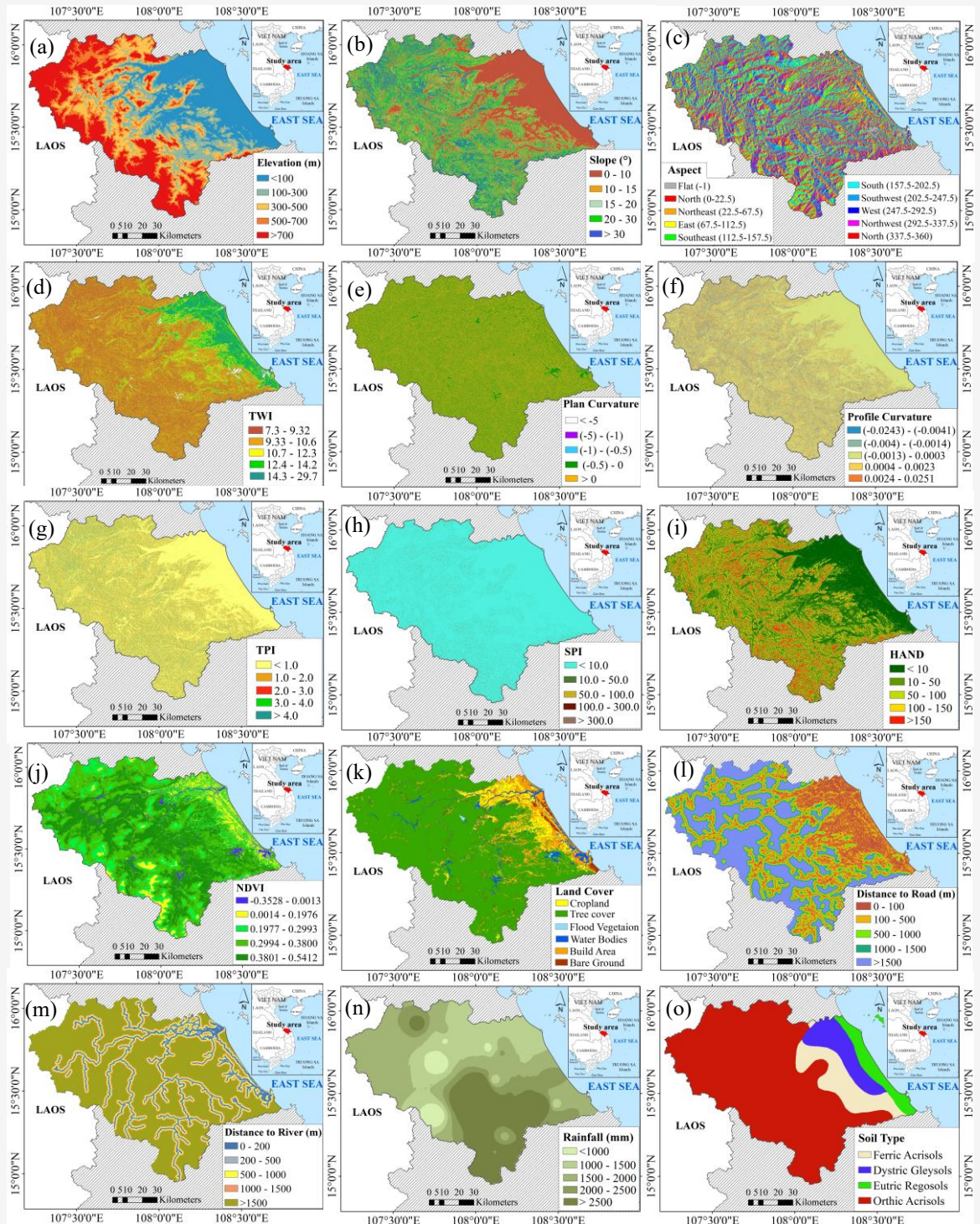


Figure 4: Maps of the flood-related variables: (a) elevation, (b) slope, (c) aspect, (d) TWI, (e) plan curvature, (f) profile curvature, (g) TPI, (h) SPI, (i) HAND, (j) NDVI, (k) land cover, (l) distance to road, (m) distance to river, (n) rainfall, and (o) soil type (continue next page)

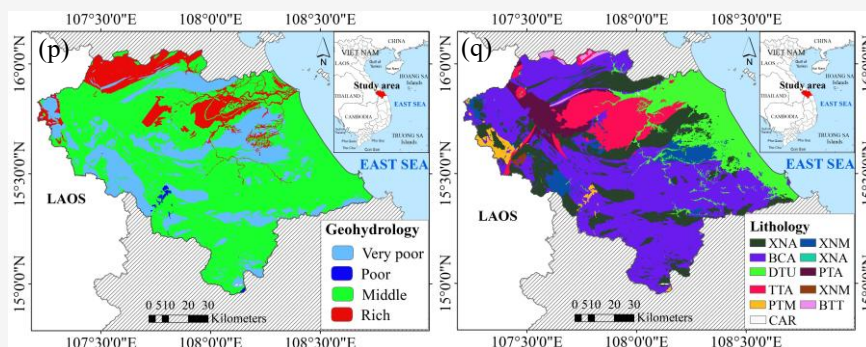


Figure 5: Maps of the flood-related variables: (p) geohydrology, and (q) lithology

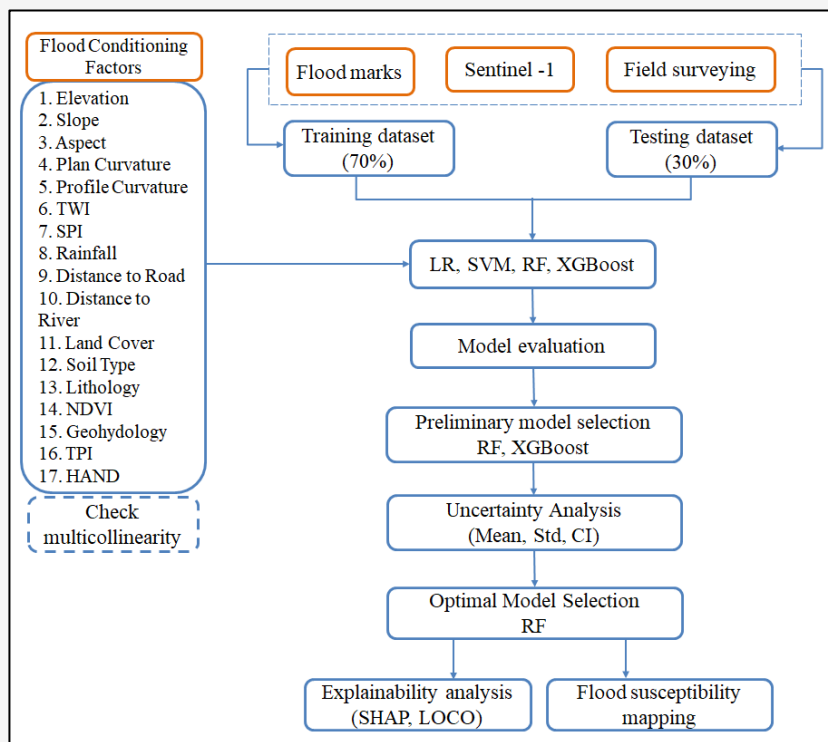


Figure 6: Workflow for mapping flood susceptibility

Model performance was evaluated using ROC curve (Receiver Operating Characteristic) – AUC, accuracy, precision, recall, and F1-score. Based on the evaluation results, two models, RF and XGBoost, were selected for further analysis. Uncertainty analysis was conducted using confidence intervals (CI) and standard deviation to determine the optimal model. Finally, the optimal model (RF) was selected to construct the flood susceptibility map. Simultaneously, an explainability analysis using Shapley additive explanation (SHAP) and Leave-One-Covariate-Out (LOCO) was conducted to clarify the role of conditioning factors and interpret the RF model's predictions.

2.3.1 Supervised machine learning model

Four machine learning models, including LR, SVM, RF, and XGBoost, were employed to evaluate flood susceptibility. They represent different groups of supervised learning algorithms, including linear, margin-based, and ensemble tree-based approaches (bagging and boosting). LR is a statistical model originally formulated in terms of the logit [45]. This method is used to predict the probability of occurrence of a binary dependent variable (flood/non-flood). Unlike linear regression, LR applies a sigmoid (logistic) function to map the predicted values to the interval [0, 1], which represents the probability of occurrence.

Due to its simplicity and interpretability, LR has been widely applied in flood susceptibility mapping, modeling the relationship between flood occurrence and environmental, hydrological, and topographic factors [46] and [47]. In this study, it was used as a baseline model to compare with advanced machine learning methods.

SVM is a supervised machine learning algorithm widely used for binary classification. The purpose of SVM is to find an optimal hyperplane to separate data points belonging to two different classes, such that the distance from the hyperplane to the nearest points of each class (called the margin) is maximized [48]. The linear SVM decision function is defined in Equation 5:

$$f(x) = w^T x + b \quad \text{Equation 5}$$

Where:

W is weight vector
 b is intercept coefficient
 x is feature vector

SVM is used to map data into a higher-dimensional feature space via kernel functions, SVM can efficiently handle nonlinear relationships among factors influencing flood risk, such as topography, vegetation cover, rainfall, etc. [49] and [50].

RF was derived from the decision tree algorithm, in which multiple decision trees are constructed and combined to improve predictive performance [51]. In this approach, each tree is trained on a different random subset of the data and a subset of input features, and the final prediction is obtained by majority voting across all trees. From an initial dataset of N samples, RF creates multiple subsets using bootstrap sampling. Each subset is used to train an independent decision tree. At each node of the tree, instead of considering all input variables, RF randomly selects a subset of variables to find the optimal splitting point. This reduces the correlation between trees and improves the overall generalization performance of the model. RF has been widely applied in flood-related studies and often achieves higher accuracy than many other machine learning models [52].

XGBoost is a machine learning algorithm based on the gradient boosting framework, with additional regularization and computational optimizations [53] to improve prediction performance and speed compared with traditional boosting methods. XGBoost builds additive models, adding decision trees sequentially to reduce the error of previous models. Mathematically, at iteration t , the model's prediction is represented as follows Equation 6:

$$\hat{y}_i^t = \sum_{k=1}^t f_k(x_i), \quad f_k \in F \quad \text{Equation 6}$$

Where:

f_k is a decision tree belonging to the space of functions F , representing the k -th regression tree
 i is the i -th data sample

The hyperparameters of the machine learning models were selected through empirical tuning to balance performance and overfitting. In particular, tree-based models require careful hyperparameter optimization due to their large parameter spaces and sensitivity to parameter settings [53][54] and [55]. On the other hand, flood susceptibility studies using LR don't report formal hyperparameter optimization; instead, they focus on variable selection and model diagnostics [47]. In the study, hyperparameter tuning was performed using GridSearchCV combined with K-fold cross-validation (fold=5) on the training dataset. Key hyperparameters are shown in Table 1, while other parameters were kept at their default values.

2.3.2 Variance inflation factor and tolerance

Variance Inflation Factor (VIF) and Tolerance are used to detect multicollinearity among independent variables. Multicollinearity is a situation that occurs when variables have a linear relationship with each other, that is, there is a dependent relationship between one variable and another [56] and [57]. This not only degrades the results but also affects the reliability of the model. In general, these two coefficients can be understood as measuring the degree of overlap between variables. The higher the VIF index and the lower the Tolerance index, both indicate a high degree of multicollinearity. To check this, VIF measures the degree of variance inflation of the regression coefficient caused by multicollinearity and is expressed through the following Equation 7 [58]:

$$VIF = \frac{1}{1 - R_i^2} = \frac{1}{\text{Tolerance}} \quad \text{Equation 7}$$

In which R_i^2 is the coefficient of determination when the independent variable X_i is regressed on all other independent variables. The Tolerance coefficient measures the degree of independence of a variable compared to other variables in the model. It is expressed through Equation 8:

$$\text{Tolerance} = 1 - R_i^2 \quad \text{Equation 8}$$

Table 1: The key hyperparameters of the machine learning models

Model	Type	Key hyperparameters
Logistic Regression	Linear model	Default settings
Random Forest	Ensemble (bagging)	n_estimators = 300; max_depth = 10
SVM	Kernel-based	kernel = RBF
XGBoost	Ensemble (boosting)	n_estimators = 200; max_depth = 5; learning_rate = 0.05

2.3.3 Evaluate the accuracy of the model

To comprehensively assess the performance of the model, a combination of multiple indicators was employed to ensure a comprehensive evaluation. The predictive performance of the models was first evaluated using ROC–AUC analysis to assess their overall discrimination ability. ROC is a visual graph of the model's performance, representing the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) for different thresholds, offering a global view in distinguishing flooded from non-flooded areas. TPR (also known as the recall or sensitivity) indicates the percentage of objects classified as “flooded” that are detected by the model. The higher this index, the fewer points are missed. In contrast, the False Positive Rate (FPR) represents the proportion of non-flooded areas that are incorrectly classified as flooded, and is often interpreted as the false alarm rate [59]. TPR and FPR were calculated from the confusion matrix components True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) [60]. Besides, AUC evaluates the model's discrimination ability, representing the overall measure of the binary classification model (0 and 1). A high AUC shows that the model is able to clearly distinguish between flooded and non-flooded areas, so the reliability is high [59].

In addition, confusion matrix-based metrics, including Accuracy, Precision, Specificity, and F1-score, were calculated to examine classification performance. Overall Accuracy (OA) was used to estimate the proportion of correctly classified samples over the total number of observations [60]. Precision was used to assess the reliability of predicted flooded areas, reflecting the proportion of correctly identified flood pixels among all predicted flood cases. Meanwhile, Specificity was used to measure the ability of the model to correctly identify non-flooded areas, thereby providing additional insight into how well false alarms are controlled [61]. Given that flood susceptibility datasets are often imbalanced, the F1-score was used as a harmonic mean of precision and recall to balance these two aspects. TPR, FPR, OA, Precision, Specificity and F1-score were calculated using Equations 9 to 14, respectively.

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

Equation 9

$$FPR = \frac{FP}{TN + FP}$$

Equation 10

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

Equation 11

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

Equation 12

$$Specificity = \frac{TN}{TN + FP}$$

Equation 13

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

Equation 14

2.3.4 Uncertainty in the machine learning model

In recent years, in addition to evaluating model performance through the indicators in Section 2.3.3, the reliability and stability of forecast models have received increasing attention [62]. Measures of uncertainty reflect the reliability of model results, thereby supporting interpretation and improving the reliability of decisions about the likelihood of flooding [63]. Uncertainty is understood as the lack of certainty in forecasts, stemming from limitations of data, parameters, and model structure [64]. In this study, model uncertainty is assessed by examining the variability of performance indices across datasets, along with statistical measures that reflect the stability and reliability of the flood prediction model. Standard Deviation (SD): is used to measure the degree of dispersion of model performance across iterations (bootstrap) A low SD value indicates a more stable model. In addition, a 95% confidence interval (CI) is used to assess the reliability of performance indicators, particularly AUC.

2.3.5 Model explanation

Explainable Artificial Intelligence techniques, including Shapley Additive explanations (SHAP) and Leave-One-Covariate-Out (LOCO), were applied to interpret model behavior. SHAP quantifies the extent of each variable's contribution and the direction of its influence, LOCO assesses the variable's actual impact by measuring the degree of model performance degradation when the variable is removed. SHAP is used for interpreting model predictions using Shapley values [65]. Shapley values quantify the contribution of each conditional variable to a model's prediction. It provides both global and local explanations of the contributions of topographic features, enabling a better understanding of the spatial patterns of flood risk [66].

The contribution of each conditional factor is assessed using LOCO. This method is a model-free approach to evaluate variable importance by comparing prediction performance between full and reduced models [67]. In the study, the model was trained with all input variables, and performance was calculated on the test set. Then, each variable was removed sequentially, the model was retrained, and the attenuation of AUC and F1-score was recorded. A greater attenuation indicates that the removed variable is more important to the flood susceptibility prediction process.

3. Results and Discussion

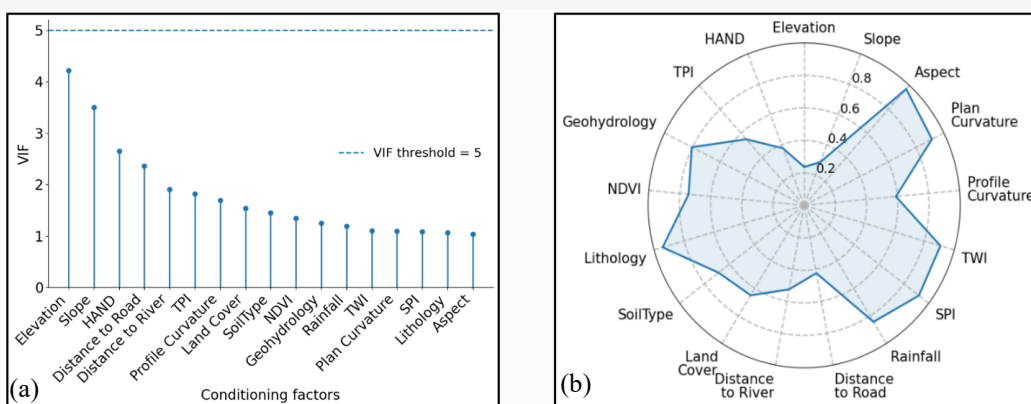
3.1 Evaluating Multicollinearity of Input Variables

Variables with VIF values greater than 5 are considered to exhibit multicollinearity, while values greater than 10 indicate severe multicollinearity [68]. Correspondingly, there is a multicollinearity problem

a serious problem. The VIF threshold of less than 5 and the tolerance greater than 0.2 were chosen to assess multicollinearity among input variables [69] and [70]. Figure 7 shows VIF and tolerance values for seventeen input factors. All also satisfied the conditions of VIF and Tolerance, demonstrating that no multicollinearity occurred. So they were retained to ensure the stability and reliability of the predictive model.

3.2 Model Accuracy

Figure 8 and Table 2 demonstrate the applicability of all four models, with values high, exceeding 80% in most of the evaluation indicators such as AUC, overall, Precision, Recall and F1-score. The RF achieved the highest AUC value on the test set (0.9418), followed by XGBoost (0.9391), indicating better differentiation between flood and non-flood areas. LR and SVM showed significantly lower performance, with the AUC of 0.9086 for LR and 0.9151 for SVM. Other metrics besides AUC also show consensus that the model performances of RF and XGBoost outperform LR and SVM on both the training and test sets. High F1 scores in RF and XGBoost indicate that each model maintains a balanced performance between flood detection and minimizing false alarms. A higher recall indicates that these two models successfully identified most flood-prone locations, which is critical for disaster risk management. Compared with LR and SVM, RF and XGBoost models significantly improved the evaluation metrics, reflecting a higher degree of fit between predicted and actual results. This confirms the effectiveness of ensemble-based models in capturing the nonlinear relationship between



among the selected variables when the Tolerance is less than 0.2, whereas values lower than 0.1 indicate

influencing factors and flood phenomena for susceptibility analysis [71].

Figure 7: Multicollinearity assessment: (a) VIF, and (b) tolerance

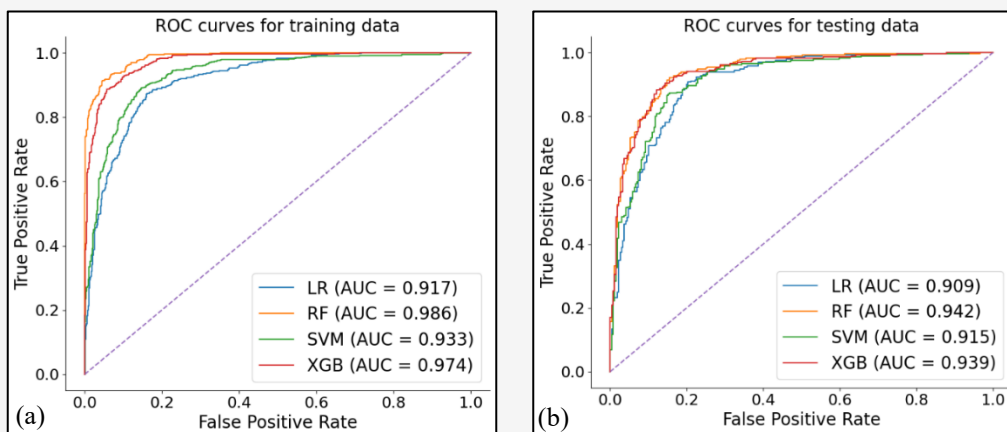


Figure 8: ROC Curves on training and testing of four machine learning models: (a) training, and (b) testing

Table 2: Accuracy of four machine learning models

Model	Dataset	AUC	OA	Precision	Recall	Specificity	F1-score	FPR
LR	Training	0.917	0.841	0.802	0.898	0.786	0.847	0.214
LR	Testing	0.909	0.847	0.807	0.928	0.760	0.863	0.240
RF	Training	0.986	0.922	0.905	0.941	0.904	0.923	0.096
RF	Testing	0.942	0.876	0.870	0.894	0.856	0.881	0.143
SVM	Training	0.933	0.868	0.842	0.901	0.837	0.871	0.163
SVM	Testing	0.915	0.847	0.826	0.894	0.797	0.859	0.203
XGBoost	Training	0.974	0.912	0.896	0.929	0.895	0.912	0.105
XGBoost	Testing	0.939	0.879	0.868	0.904	0.852	0.886	0.148

Table 3: Uncertainty analysis of RF and XGBoost

Model	Metric	Mean	SD	CI95 Lower	CI95 Upper
RF	AUC	0.937	0.002	0.932	0.942
RF	F1-score	0.880	0.007	0.866	0.894
XGBoost	AUC	0.935	0.004	0.928	0.941
XGBoost	F1-score	0.878	0.006	0.867	0.890

However, the performance differences between RF and XGBoost were negligible. RF tended to achieve slightly higher AUC and F1-score, while XGBoost showed a slightly higher overall accuracy. The difference between the two models was small and did not represent a significant performance difference. Therefore, RF and XGBoost were chosen for further analysis, as they offered the most stable and reliable performance. Further analytical steps and uncertainty assessment were performed only on these two models to ensure the effectiveness and consistency of the research methodology.

3.3 Model Reliability through Uncertainty

To assess model stability, uncertainty analyses were performed on both the RF and XGBoost models using an iterative bootstrap analysis (bootstrap=100). In each iteration, the training set was resampled with

replacement, the model was retrained, and predictions were made on the test set. Two performance metrics, AUC and F1-score, were calculated for each iteration. Table 3 presents the uncertainty analysis results for the two models, RF and XGBoost, using AUC and F1-score indices, estimated via bootstrap resampling. Overall, both models exhibit high performance and good stability, with small standard deviation (SD) values and relatively narrow 95% confidence intervals (CI95). Specifically, for the AUC index, RF achieved a higher mean value (0.937) than XGBoost (0.935), while also having a lower standard deviation (0.002 vs. 0.004), indicating that RF's discriminatory ability is more stable. The confidence interval of RF ([0.932; 0.942]) is also narrower than that of XGBoost ([0.928; 0.941]), further reinforcing the conclusion that this model is more reliable. For the F1-score, RF

achieved a higher mean value (0.880 vs. 0.878), however, XGBoost had a slightly lower standard deviation (0.006 vs. 0.007), indicating comparable stability between the two models. Overall, the uncertainty analysis results show that RF and XGBoost have comparable performance and stability. However, considering all factors, from model evaluation to uncertainty, RF tends to be slightly superior in both mean value and stability, especially in the AUC, the main indicator in flood risk zoning. Therefore, RF was selected as the optimal model for further analysis.

3.4 Model Interpretation

The SHAP plot of the RF model (Figure 9(a)) shows the extent to which factors influence its flood risk prediction results. The variables are arranged in decreasing order of importance, with *Distance to River*, *Elevation*, and *Rainfall* having the greatest influence on the model's results.

Distance to River plays the most dominant role, with small values (near the river) tending to increase flood risk (positive SHAP), while greater distances reduce flood risk. Similarly, *Elevation* has a significant influence: low-elevation areas (low values – blue) are generally associated with higher flood susceptibility, while high-elevation areas reduce the likelihood of flooding. For *Rainfall*, high values (red) are mainly associated with negative SHAP values, indicating that high rainfall does not necessarily correspond to greater flood susceptibility, although rainfall is generally considered the primary factor causing floods [72]. In the study, the recorded rainfall is higher in the mountainous area (see Figure 4) but flooding is less frequent due to steep slopes and rapid drainage. Conversely, lowland areas receive less rainfall but are more prone to flooding because of flat terrain, dense river networks, and poor drainage. This suggests that flood occurrence in the study area is not only controlled by rainfall intensity, but also by spatial heterogeneity.

Topographic factors such as *Slope* and *HAND* also show significant influence, albeit to a lesser extent, with steep terrain and relative elevation to the river contributing to the regulation of flood risk distribution. The remaining variables, such as *NDVI*, *Soil Type*, *Land Cover*, and *TWI*, have moderate to low influence. Some topographic variables such as *Aspect*, *TPI*, and *Curvature*, show negligible influence, with SHAP values concentrated near 0, possibly because *Elevation*, *Slope*, *HAND* already captured the major terrain controls related to flood occurrence. The SHAP results clearly confirm the

main hydrological factors; some topographic variables play a role in controlling flood risk. Environmental factors have a small but explainable influence. Results have also been observed in earlier studies [73] and [74]. However, another opinion suggests that road network density is the main factor influencing floods [75]. These differences may be attributed to variations in spatial scale, model, and the distribution of the original samples [74].

In addition, LOCO analysis in Figure 9b also revealed that *Distance to River*, *Rainfall*, and *Elevation* were the three most important variables in RF. Removing the *Distance to River* variable resulted in the largest decrease in AUC (0.0162), followed by *Rainfall* (0.0125) and *Elevation* (0.0085). The group of variables with moderate influence includes *Soil Type*, *Land Cover*, and *NDVI*, with AUC reductions ranging from 0.003 to 0.006. These factors regulate surface characteristics and water infiltration capacity, thereby indirectly affecting flood. Meanwhile, variables such as *Distance to Road*, *Profile Curvature*, *Lithology*, and *Geohydrology* showed low influence, with AUC reductions of less than 0.002. This indicates that these factors contribute little to the model's predictive ability. Some variables, such as *Plan Curvature*, *Slope*, and *SPI*, showed negative or near-zero AUC decrease values. This suggests that these variables may contain redundant information or noise, indicating that removing them did not reduce model performance. The LOCO results confirm that factors directly related to hydrology and topography play a decisive role in flood susceptibility models, and provide a scientific basis for selecting and optimizing the input variable set. Overall, the important variables identified by LOCO are consistent with SHAP results, indicating agreement between the two model explanation tools. The consensus among different model interpretation methods has contributed to strengthening the reliability of research results and improving the interpretability of machine learning models in the flood risk assessment problem.

3.5 Mapping Flood Susceptibility Using the RF Model

The flood susceptibility map was constructed using the RF model – the optimal model in the study, with probability values classified into five levels: very low (0–0.2), low (0.2–0.4), moderate (0.4–0.6), high (0.6–0.8), and very high (0.8–1.0) (Figure 10). This classification provides a clear spatial representation of flood susceptibility, effectively supporting risk assessment and management

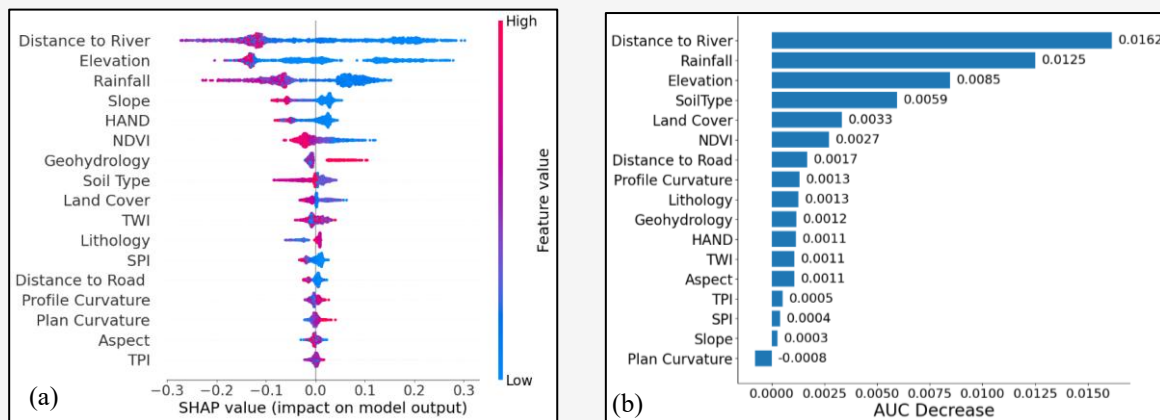


Figure 9: RF model analysis: (a) SHAP, and (b) LOCO

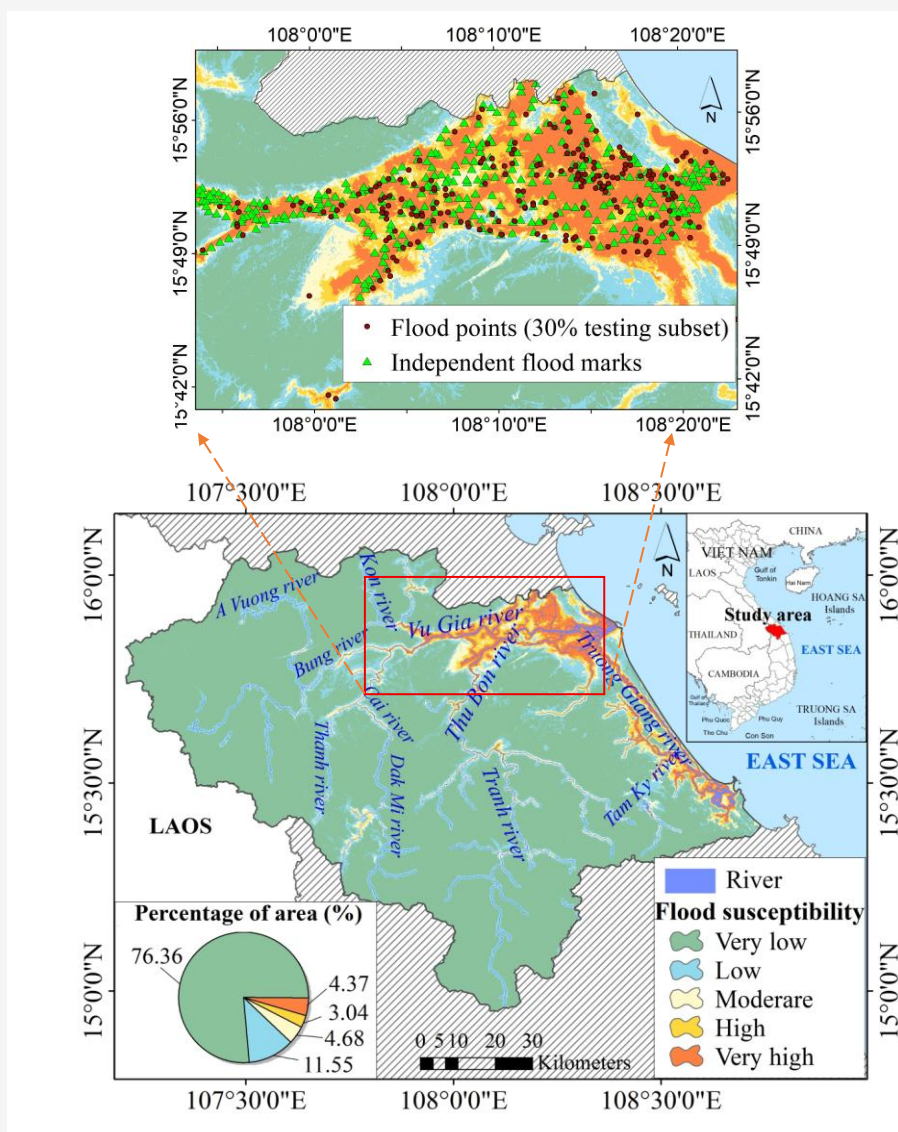


Figure 10: Flood susceptibility using RF model

Table 4: Validation results of two datasets across flood susceptibility classes

Susceptibility class	Flood points (30% testing subset)		Independent flood marks	
	Number	Percentage	Number	Percentage
Very high	171	62.4	245	62.8
High	77	28.1	95	24.4
Moderate	21	7.7	43	11.0
Low	5	1.8	7	1.8
Very low	0	0.0	0	0.0
Total	274	100.0	390	100.0

The results in Figure 10 show that areas with high and very high flood susceptibility are mainly concentrated in the downstream floodplains and low-lying areas, covering approximately 78317.325 ha (7.41% of the study area). In contrast, areas with very low susceptibility are mainly distributed in higher-elevation zones. Moderate susceptibility zones cover 49449.136 ha (4.68%) and represent transitional areas between low- and high-risk regions. These spatial distributions are similar to those reported in previous flood susceptibility and flood hazard assessments for Quang Nam [30] and [32]. The lowland along the Vu Gia - Thu Bon river system faces high and very high flood susceptibility, which is characterized by low elevation, dense river network and limited drainage capacity, leading to water accumulation during prolonged rainfall events. In addition to the Vu Gia–Thu Bon basin, high flood susceptibility is also observed around Tam Ky and adjacent coastal areas, where the Tam Ky and Truong Giang rivers, together with low-lying terrain and tidal backwater effect, further increase the likelihood of flood. These local characteristics explain why high flood susceptibility is not limited to the main river basin. In contrast, mountainous areas in the west of the province are characterized by low susceptibility because of higher elevation and slope, more rapid surface runoff.

Although the identified flood-prone areas are broadly consistent, the differences among studies should be acknowledged. These differences may be due to variations in objectives, flood inventory datasets, spatial resolution, DEM sources, the variables, and modelling approaches used to map flood. The current study used RF model with 17 factors, while previous studies have applied GIS-based spatial multi-criteria analysis integrating AHP [29] and [30], or different input datasets [32], which may lead to local differences in flood susceptibility or vulnerability maps. Nevertheless, the similarities in spatial distribution increase the reliability of the flood susceptibility map created in the study, while highlighting the primary influence of topography and river systems on flood occurrence in Quang Nam.

Consistency with previous studies is also demonstrated in the identification of key factors affecting flood occurrence. A previous study in Quang Nam has also identified rainfall and distance to river as the main factors influencing the likelihood of flooding [32]. This agreement shows that the key predictive factors identified are consistent with the hydrological characteristics of the study area, thereby strengthening the validity and reliability of the proposed flood probability prediction model in the study. To assess the reliability of the flood susceptibility map, two datasets were used, including 274 flood points from the 30% testing subset and 390 actual flood marks collected in 2026 which represent independent field data. The use of these data objectively reflects the model's predictive capabilities under both independent testing and real-world conditions.

Figure 10 provides a zoomed view of the spatial distribution of the 30% testing flood points and independent flood marks compared with the predicted flood susceptibility map. Besides, the number and percentage of flood observations in each susceptibility class are summarized in Table 4. The results show that the majority of flooding points in two cases are concentrated in moderate-, high-, and very high-sensitivity areas, accounting for 98.2%, while very few are in low-susceptibility zones (1.8%). Specifically, 171 points (62.4%) of the 30% testing subset were in the very high susceptibility class, while 103 points (37.6%) occurred outside this class. Similarly, 245 points (62.8%) of the independent flood marks were located within the very high susceptibility class, with the remaining observations distributed among the other susceptibility classes. This demonstrates a good agreement between the model's results and the actual flood situation. Moreover, it confirms that the model captures the underlying physical processes governing flood occurrence in the study area. Therefore, the use of independent flood marks provides additional validation beyond conventional statistical metrics, reinforcing the reliability of the flood susceptibility map for practical applications in flood risk management and planning.

4. Conclusion

This study developed a flood susceptibility map for the study area using machine learning models. From four initial models, RF and XGBoost were selected for performance comparison. The evaluation results showed that both models achieved high, comparable performance across AUC, F1-score, and other evaluation metrics. However, RF demonstrated higher stability, particularly in AUC, and had slightly better overall performance than XGBoost. Therefore, RF was chosen as the optimal model for constructing the flood susceptibility map in this study. The flood susceptibility zoning map is classified into five levels (very low, low, moderate, high, and very high) and shows a clear spatial distribution consistent with the area's natural conditions. High-susceptibility areas are concentrated in low-lying areas, near the main river system, and heavily influenced by rainfall, while low-risk areas are distributed in higher terrain, far from rivers, and with good drainage conditions.

To clarify the model's operating mechanism, explanatory methods including SHAP and LOCO were applied. The results showed that factors such as distance to the river, elevation, and rainfall play the most important role in determining flood susceptibility. The consistency between SHAP and LOCO results confirms the reliability of the input factors and the model's explanatory power. In addition, the use of actual flood marks as an independent verification source showed that the majority of observation points are located in high- and very high-risk areas. This result not only confirms the model's accuracy but also demonstrates the map's practical applicability for flood risk management and mitigation. Overall, the study has developed a methodological framework that combines machine learning models, explanatory power analysis, and uncertainty assessment, thereby contributing to improved reliability and transparency in flood susceptibility zoning. The research results are not only scientifically significant but also highly practical for supporting decision-making and disaster-prevention planning in the study area.

Although the current study utilizes multi-source remote sensing imagery, FABDEM, and other relevant datasets, combined with machine learning algorithms to map flood risk, considering hybrid machine learning or deep learning algorithms could further improve the accuracy of the results. Furthermore, estimating flood depth is also a key area for assessing damage and supporting effective response. Additional factors containing socio-economic information, such as population density, population age, income, infrastructure, etc., are necessary to assess flood vulnerability in the study area. Therefore, future studies should aim to

incorporate these data and adopt new models linked to climate models to improve predictability.

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