

Journal Pre-proof

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PII: S2666-5921(26)00103-4

DOI: <https://doi.org/10.1016/j.nhres.2026.10.005>

Reference: NHRES 373

To appear in: *Natural Hazards Research*

Received Date: 19 July 2026

Revised Date: 8 October 2026

Accepted Date: 14 October 2026

Please cite this article as: Nguyen, Q.-V., Do Thi, V.-H., Nguyen Thi, H.-T., Nguyen, T.-H., Tran, D.-P., Interpretable Machine Learning for Regional-Scale Landslide Susceptibility Modeling in Central Vietnam, *Natural Hazards Research*, <https://doi.org/10.1016/j.nhres.2026.10.005>.

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Research Article

Interpretable Machine Learning for Regional-Scale Landslide Susceptibility Modeling in Central Vietnam

**Quang-Viet Nguyen¹, Viet-Huong Do Thi¹, Hong-Tinh Nguyen Thi³,
Thanh-Hoan Nguyen², Duy-Phien Tran^{2*}**

¹ Faculty of Geography and Geology, University of Sciences, Hue University, 77 Nguyen Hue, Hue City, Vietnam.

² Institute of Earth Sciences, Vietnam Academy of Science and Technology, 18 Hoang Quoc Viet, Nghia Do, Hanoi, Vietnam.

³ Faculty of Environmental and Natural Sciences, Duy Tan University, 254 Nguyen Van Linh, Danang, Vietnam.

* Author of correspondence: Duy-Phien Tran; email: phienrs@ies.vast.vn

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Abstract

Landslides are among the most destructive natural hazards in the mountainous regions of Central Vietnam, causing substantial losses to human life, infrastructure, and socioeconomic development. Accurate and interpretable landslide susceptibility mapping is essential for effective land-use planning, risk reduction, and informed decision-making. To address the challenges of regional-scale susceptibility modeling, this study develops an explainable machine learning framework that integrates predictive algorithm with SHapley Additive exPlanations (SHAP) to improve both predictive accuracy and model transparency. In this study, geographic information systems, remote sensing data, and a landslide inventory were integrated to assess landslide susceptibility using three machine learning models: Logistic regression, Random Forest, and eXtreme Gradient Boosting (XGB). Furthermore, model interpretability was further explored using the SHAP approach to quantify the relative importance of conditioning factors. A dataset comprising 466 landslide locations and an equal number of non-landslide samples, described by 13 conditioning factors, was used for model development, with spatial block-based splitting for training and validation. The XGB outperformed the other two models, achieving AUC scores of 0.982 and 0.970 for the training and testing datasets, respectively. In all three models, low and very low susceptibility classes dominate the landscape, occupying over 70% of the study area, whereas areas classified as moderate to very high susceptibility collectively represent less than one-quarter of the total extent. SHAP analysis identified NDVI, slope, and the LS factor as important predictors. Higher NDVI values generally reduced susceptibility, while slopes above approximately 20° and higher LS values contributed positively to susceptibility, although the LS response showed some variability across its observed range. These findings provide valuable insights for land use planning, infrastructure development, and landslide risk mitigation in mountainous regions.

Keywords: Landslide susceptibility; Machine learning; Random Forest; XGB; SHAP explainability; Central Vietnam

1. Introduction

Landslides are widely recognized as one of the most destructive natural hazards affecting mountainous regions, where millions of people are exposed to risks to life and critical infrastructure. A global inventory of fatal non-seismic landslides between 2004 and 2016 recorded 4,862 events that resulted in 55,997 fatalities worldwide. The findings indicate that an increasing number of landslides are associated with anthropogenic disturbances, including infrastructure development, unregulated mineral exploitation, and modification of natural slopes, suggesting a growing human influence on future landslide activity (Froude & Petley, 2018). Landslide occurrences are becoming more frequent as extreme precipitation events intensify under anthropogenic climate change (Gariano & Guzzetti, 2016). Landslides are complex geological phenomena governed by the non-linear interaction of multiple predisposing factors, including topography, geology, and hydrology, and are typically triggered by external

forces such as intense rainfall or earthquakes (Ghosh et al., 2013; Huang et al., 2024). Owing to their widespread occurrence, spatial variability, and often concealed characteristics, accurately identifying potential landslide-prone areas and assessing slope stability remains a significant challenge (Qi et al., 2023; van Westen et al., 2008). Landslide susceptibility Prediction (LSP) at the regional scale is widely regarded as a practical approach for overcoming these challenges and plays a critical role in landslide hazard evaluation, disaster risk reduction, and spatial planning (Huang et al., 2024). LSP describes the spatial probability of landslide occurrence in a given area based on the combined effects of multiple conditioning factors, without accounting for the timing or magnitude of potential landslide events (Guzzetti et al., 2005). LSP is based on the principle that areas sharing similar environmental and geomorphological conditions with previously recorded landslides are more likely to experience slope instability (Carrara et al., 1991).

To date, numerous approaches for landslide research have been proposed and implemented across different regions of the world. These approaches for landslide susceptibility assessment are generally classified into three main categories: qualitative, quantitative, and machine learning methods. Qualitative approaches evaluate landslide susceptibility by ranking and weighting conditioning factors according to expert judgment. Some techniques incorporate analytical tools for factor weighting and are therefore regarded as semi-quantitative approaches (Kouli et al., 2010). Widely used methods include the Simple Weighted Sum (Feizizadeh & Blaschke, 2013), Ordered Weighted Averaging (Ayalew et al., 2004; Feizizadeh & Blaschke, 2013), Analytic Hierarchy Process (Dutta et al., 2025), Analytic Network Process (Sujatha, 2021), and the Weighted Linear Combination method (Michael & Samanta, 2016). In contrast, quantitative approaches employ statistical techniques to analyze the relationships between conditioning factors and landslide occurrence, with commonly used models including the Index of Entropy, Frequency Ratio (FR), Certainty Factor, Logistic Regression (LR) (Chowdhury et al., 2024), and Evidential Belief Function (Zhao et al., 2022).

In recent years, machine learning (ML) techniques have gained increasing attention in landslide susceptibility assessment (LSA) because of their ability to model complex nonlinear relationships and enhance prediction accuracy (Achu, Thomas, et al., 2026; Tehrani et al., 2022; H. Wang et al., 2021). Commonly used algorithms include Artificial Neural Networks (Soma et al., 2019), Support Vector Machine (SVM) (Pandey et al., 2020), Decision Trees (Park et al., 2018), Random Forest (RF) (Li et al., 2024; Lu et al., 2024), Extreme Gradient Boosting (XGB) (Khan et al., 2025), etc. Deep learning models, particularly neural network architectures, have demonstrated strong capability in landslide susceptibility mapping using large and complex datasets (Achu et al., 2024; Azarafza et al., 2021). Among them, Convolutional Neural Networks (CNNs) have been extensively used to analyze spatial data for landslide prediction (Wu et al., 2024; Yang et al., 2024). Although advanced ML techniques often achieve high predictive performance, their interpretability remains a major challenge. Many models function as “black-box” systems, making it difficult to understand how individual environmental factors contribute to landslide occurrence (J. Lv et al., 2024). Future studies are expected to benefit from integrating explainable artificial intelligence techniques with high-performance ML

models, which can improve both prediction accuracy and the interpretability of LSA (Ebrahim et al., 2024; Kudaibergenov et al., 2025).

However, the performance of a model is not determined solely by the selected algorithm. A key challenge in susceptibility modelling lies in the validation framework used. In spatially structured settings, the assumption that training and validation samples are independent is frequently violated because of spatial autocorrelation (Chung & Fabbri, 2003; Meyer et al., 2019). This can result in overly optimistic estimates of model accuracy. This problem is especially important in pixel-based susceptibility modelling, where adjacent pixels commonly exhibit similar terrain characteristics. As a result, spatial dependence can unintentionally cause information leakage between the training and validation datasets (Quiroz, 2026).

The SHapley Additive exPlanations (SHAP) approach, rooted in cooperative game theory, quantifies the contribution of individual features to model predictions. This method enables a more thorough interpretation of model behaviour by revealing feature impacts from local, global, and spatial perspectives (Padarian et al., 2020). In recent years, the method has been increasingly employed to support landslide susceptibility mapping (Achu, Aju, et al., 2026; Al-Najjar et al., 2025; J. Lv et al., 2024). Compared with conventional feature-importance measures, SHAP provides a more comprehensive and theoretically grounded framework for interpreting machine-learning predictions. Conventional measures, such as Gini importance and permutation importance, primarily summarize the relative contribution or predictive relevance of features at the global model level, providing limited information about how individual feature values contribute to specific predictions (Breiman, 2001; Scott M. Lundberg et al., 2020; Strobl et al., 2007). In contrast, SHAP assigns an additive contribution value to each feature for an individual prediction, thereby enabling the direction and magnitude of each feature's contribution to be examined (Scott M. Lundberg et al., 2020; Scott M Lundberg & Lee, 2017). Furthermore, aggregating local SHAP explanations enables a global interpretation of complex nonlinear models and facilitates the identification of nonlinear relationships and potential threshold effects between predictors and model outputs (Scott M. Lundberg et al., 2020).

Vietnam is highly prone to landslides due to its predominantly mountainous terrain, which covers nearly three-quarters of the country, combined with high annual rainfall. Consequently, numerous studies have applied different methodological approaches to assess landslide susceptibility in various areas of Vietnam. For example, Das et al. (2024) employed the RF to conduct LSA in Quang Nam Province. Similarly, Tran Anh et al. (2024) applied deep learning model together with SVM and Naïve Bayes for landslide prediction in Phuoc Son District, Quang Nam Province. Other studies have applied decision-support methods, including the Analytic Hierarchy Process and FR, to assess landslide susceptibility in Quang Binh Province (Hoa et al., 2023). In addition, ensemble modelling techniques have been applied for LSP in Sin Ho District, Lai Chau Province (Bien et al., 2022). Earlier studies also explored advanced ML approaches, such as Rotation Forest-based Functional Trees for LSA in Kon Tum Province (Pham et al., 2018) and the integration of differential evolution optimization with Least Squares SVM for shallow landslide prediction (Tien Bui, Pham, et al., 2016). Despite these advances, most landslide susceptibility studies in Vietnam have been conducted at relatively small spatial scales, such as district or single-province levels, and have mainly

focused on improving prediction accuracy, while limited attention has been given to model interpretability and the quantitative explanation of the contributions of conditioning factors. However, extending susceptibility modelling to the regional scale remains challenging because mountainous regions exhibit substantial spatial heterogeneity in topography, geology, land cover, hydrology, and rainfall, which can result in spatially varying relationships between landslide occurrence and conditioning factors (Reichenbach et al., 2018; van Westen et al., 2008). Therefore, there is a need for regional-scale approaches that can account for heterogeneous environmental conditions while providing reliable predictions and interpretable insights into the contributions of conditioning factors.

To address the above research gaps, this study developed a regional-scale landslide susceptibility modelling framework that integrate ML algorithm with explainable artificial intelligence. Specifically, this study addressed three research questions: (1) how did LR, RF, and XGB perform in predicting landslide susceptibility at the regional scale ?; (2) which conditioning factors contributed most strongly to the modelled susceptibility, and how did their contributions vary across their observed ranges ? (3) can SHAP-based interpretation provide geomorphologically meaningful insights into the influence of conditioning factors on landslide susceptibility ? To answer these questions, a spatial block strategy was used to reduce the influence of spatial autocorrelation and provide a more robustness evaluation of model performance, while SHAP is employed to quantify and interpret the contribution and response patterns of individual landslide conditioning factors. The proposed framework aims to improve both the predictive assessment and process-oriented interpretation of regional landslide susceptibility, thereby providing scientific support for landslide risk mitigation and land-use planning.

2. Study area

The research region, known as Binh-Tri-Thien, lies in central Vietnam and spans approximately 17,851.6 km², representing nearly 6.5% of the country's total territory (Fig. 1). As of 2024, this region had a population of approximately 2.74 million, with an average population density of about 164 inhabitants per km² and a natural population growth rate of approximately 0.52%. The urban population accounts for 61.7% of the total population, while the remaining 38.3% resides in rural areas.

The study region is characterized by pronounced lithological diversity, with six major groups ranging from unconsolidated sediments and siliciclastic sedimentary rocks to carbonate, volcanic, plutonic/ultramafic, and metamorphic rocks. The topography is generally complex, with elevation gradually decreasing from west to east. It consists of diverse landforms, including medium-elevation mountains, low mountains, hilly terrains, coastal plains, sand dunes, and coastal lagoon systems. The region experiences mean annual temperature of approximately 23-25.2 °C, while yearly precipitation typically falls between 1,500 and 3,000 mm, with clear seasonal and spatial variability. The rainy season occurs primarily from September to December, during which monthly precipitation often exceeds 300 mm and the number of rainy days ranges from 15 to 29 days per month. Rainfall peaks in October and November, with monthly totals of approximately 600 - 700 mm, accounting for nearly 40 - 45%

of the annual precipitation. Regional precipitation exhibits a gradual increase from north to south and from east to west, with transitional zones occurring between areas characterized by high and low rainfall (H.-S. Nguyen, 2014; T. Nguyen & Nguyen, 2011).

The concentration of rainfall during the rainy season, together with tropical storms, saturates the soil, resulting in landslides occurring predominantly during this period. In recent years, mountainous areas of Central Vietnam have been affected by a number of flash floods and landslides, resulting in considerable loss of life and extensive damage to infrastructure. Several major disasters occurred in October 2020, including landslides associated with the Rao Trang 3 hydropower project in Phong Dien District (Thua Thien Hue Province) between 11 and 13 October, an event at the Economic - Defense Unit 337 in Huong Hoa District (Quang Tri Province) on 18 October, and another incident near the Cha Lo International Border Gate in Minh Hoa District (Quang Binh Province) on 19 October (Thục & Thủy, 2024). These events highlight the severe landslide hazards faced by mountainous areas in Central Vietnam.

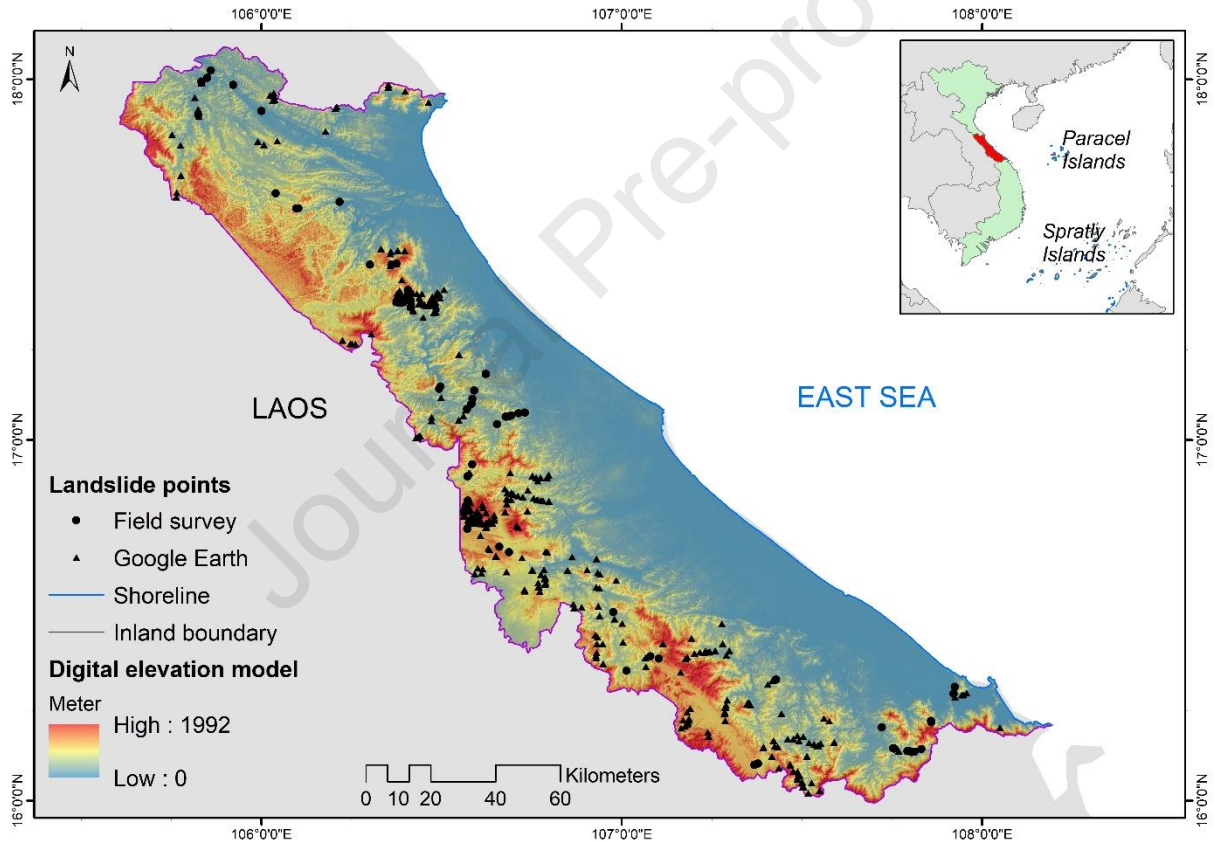


Figure 1. Study site and its landslide distribution

3. Data and Methods

3.1. Landslide inventory

This dataset provides essential information for developing ML models. Landslide occurrence points were collected through field surveys conducted from 11 to 17 May 2025 that were able to observe and access. For locations that are difficult to access, such as mountainous areas with steep slopes and limited transportation access, recent landslides were

identified using high-resolution satellite imagery available on Google Earth Pro. To accurately refine the landslide locations identified through field surveys, additional imagery from Google Earth was utilized to verify and adjust the landslide positions. All landslide inventory points were delineated and corrected to represent the central portion of the slope where landslide events occurred. As a result, a total of 466 landslide points were compiled from two main sources: satellite image interpretation (391 points) and field investigations (75 points) (Fig. 1).

3.2. Conditioning factors and data sources

Initially, the study considered and tested a broader set of potential predictors based on previous landslide susceptibility studies and the geomorphological, hydrological, geological, climatic, and land-use characteristics of the study area (Huang et al., 2025; Liao et al., 2022). To avoid redundancy among predictors and to ensure the robustness and interpretability of the models, we subsequently conducted multicollinearity and correlation analyses, as described in section 3.2.2. Therefore, the final set of 13 conditioning factors represents a statistically screened subset of the initially considered predictors, selected to retain complementary information while minimizing redundancy (Table 1 & Fig. 2).

3.2.1. Preparation of landslide conditioning factors

- Topography: A 30 m resolution Digital Elevation Model (DEM) derived from Shuttle Radar Topography Mission data was acquired through the EarthExplorer portal provided by the United States Geological Survey (USGS). This dataset provides essential topographic information for deriving terrain-related factors that influence landslide occurrence. To generate the topographic variables used as inputs for the ML models, the open-source software SAGA GIS was employed. Terrain parameters were extracted using the Terrain Analysis tools, including slope, aspect, slope length and slope gradient (LS factor), plan curvature, profile curvature, and topographic wetness index (TWI).

- Geology: A geological map with a scale of 1:200,000 was utilized to determine lithological units related to geological formations/complexes, as well as to delineate the regional fault system. Based on this dataset, six major lithological groups were identified within the study region. These include Neogene-Quaternary unconsolidated to weakly consolidated sediments (NQ); siliciclastic sedimentary rocks, mainly bedded sandstones, siltstones, and shales (CLASTIC); carbonate rocks such as limestone and dolomite, often associated with karst development (CARB); volcanic and volcanoclastic rocks including tuff, andesite, and basalt (VOL); plutonic/intrusive and ultramafic rocks, together with veins and dykes (PLUT); and metamorphic and metasedimentary rocks (META) (Fig. 2). Fault density was derived using the Line Density function in ArcGIS, with a search radius of 3 km to represent the spatial concentration of fault structures within the study area.

- Hydrology: River density was considered as one of the conditioning factors influencing landslide susceptibility. The drainage network was first extracted from the DEM using the Terrain Analysis tools in SAGA GIS. The Line Density tool in ArcGIS was then used to calculate river density, with a search radius of 3 km.

- Vegetation: In this study, Landsat 8 Operational Land Imager (OLI) scenes were utilized for Land use/Land cover (LULC) classification within the study area. The satellite data were retrieved and processed using the Google Earth Engine (GEE) platform. To ensure high classification quality, only scenes with minimal cloud cover were selected. Because the study area experiences persistent cloud cover during much of the year, January and April were chosen as representative dry and transitional periods, respectively, when atmospheric conditions are generally clearer and cloud contamination is minimal. More specifically, the dataset comprised imagery from Path/Row 126/48 (acquired on April 13 and 29, 2024) and Paths/Rows 125/48 and 125/49 (acquired on January 14, 2023) were selected. These were subsequently mosaicked to generate a cloud-free composite. Leveraging high-resolution imagery and existing land cover products, researchers identified 2,534 representative samples across five primary LULC categories: agriculture, built-up land, forest, bare land, and water bodies. The dataset was partitioned into a 70:30 ratio for training and validation purposes, respectively. Spectral bands (Blue, Green, Red, NIR, SWIR1, and SWIR2) and auxiliary spatial data (DEM, slope, Normalized Difference Vegetation Index - NDVI, and road density) were extracted at each sample location. The RF algorithm was then employed for LULC mapping at a 30-m resolution. The RF model achieved high performance, with an Overall Accuracy of 0.940 and a Kappa coefficient of 0.927, satisfying the rigorous quality requirements for input variables in subsequent landslide susceptibility analysis. The study area is characterized by five major land cover types, including agricultural land, bare land, built-up areas, forest, and water bodies (Fig.2l). Additionally, NDVI was derived from the cloud-free composite to serve as a key environmental factor in the landslide assessment (Fig.2m).

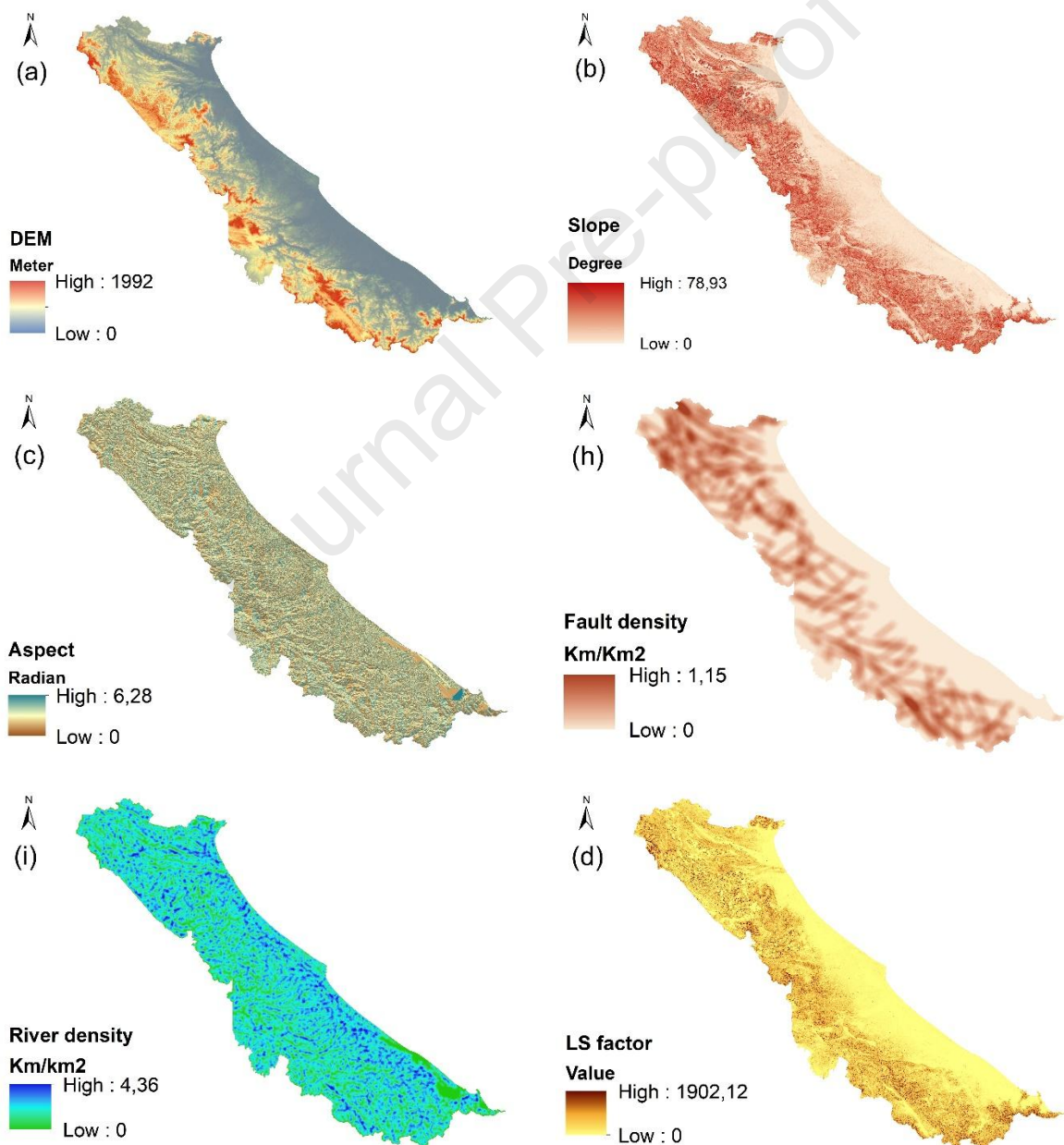
- Soil type: Information on soil types was obtained from the vector-based soil map of Vietnam. The study area comprises a variety of soil types, including Haplic Dystric Arenosols (C), Albic Luvic Arenosols (Cc), Rock (Da), Lithic Leptosols (E), Haplic Rhodic xanthic Acrisols (Fa), Haplic Xanthic Acrisols (Fp), Haplic Acrisols (Fq), Ferralic Acrisols (Fs), Rhodic Ferralsols (Fk), Histosols (H), Dystric Gleysols (J), Hapli Molli Salic Fluvisols (M), Fluvisols (P), Thionic Fluvisols (S), Acrisols (X), Haplic Acrisols (Xa), Gleyic Acrisols (Xg), water body (SON). These soil types were grouped into seven classes: Arenosols (Ar), Bare Rock and Eroded Soils (Ro), Strongly Weathered Soils (Wa), Acrisols (Ac), Hydromorphic Soils (Hs), Fluvisols (Fl), and Water Bodies (Wb). These groups represent distinct pedological and hydrological characteristics, ranging from highly permeable sandy soils and shallow rocky terrains to strongly weathered tropical soils, hydromorphic soils, and young alluvial deposits. Water bodies were considered non-soil surfaces and excluded from the landslide susceptibility modelling. All conditioning factors for the ML model and their sources were illustrated in Fig. 2 & Table 1.

Table 1. Datasets used for deriving landslide conditioning factors

Category	Factor	Source	Scale/resolution
Topography	Elevation	DEM	30 m
	Aspect	https://earthexplorer.usgs.gov/	-
	Slope		-
	LS factor		-

	TWI		-
	Plan curvature		-
	Profile curvature		-
Geology	Lithology	Geological maps	1/200,000
	Fault density		-
Hydrology	River density	DEM	30 m
		https://earthexplorer.usgs.gov/	-
Vegetation	LULC	Composited Landsat 8 (Jan 14, 2023,	30 m
	NDVI	Apr 13 & 29, 2024)	-
		https://earthexplorer.usgs.gov/	
Soil type	Soil group	Soil map of Vietnam	1/1,000,000

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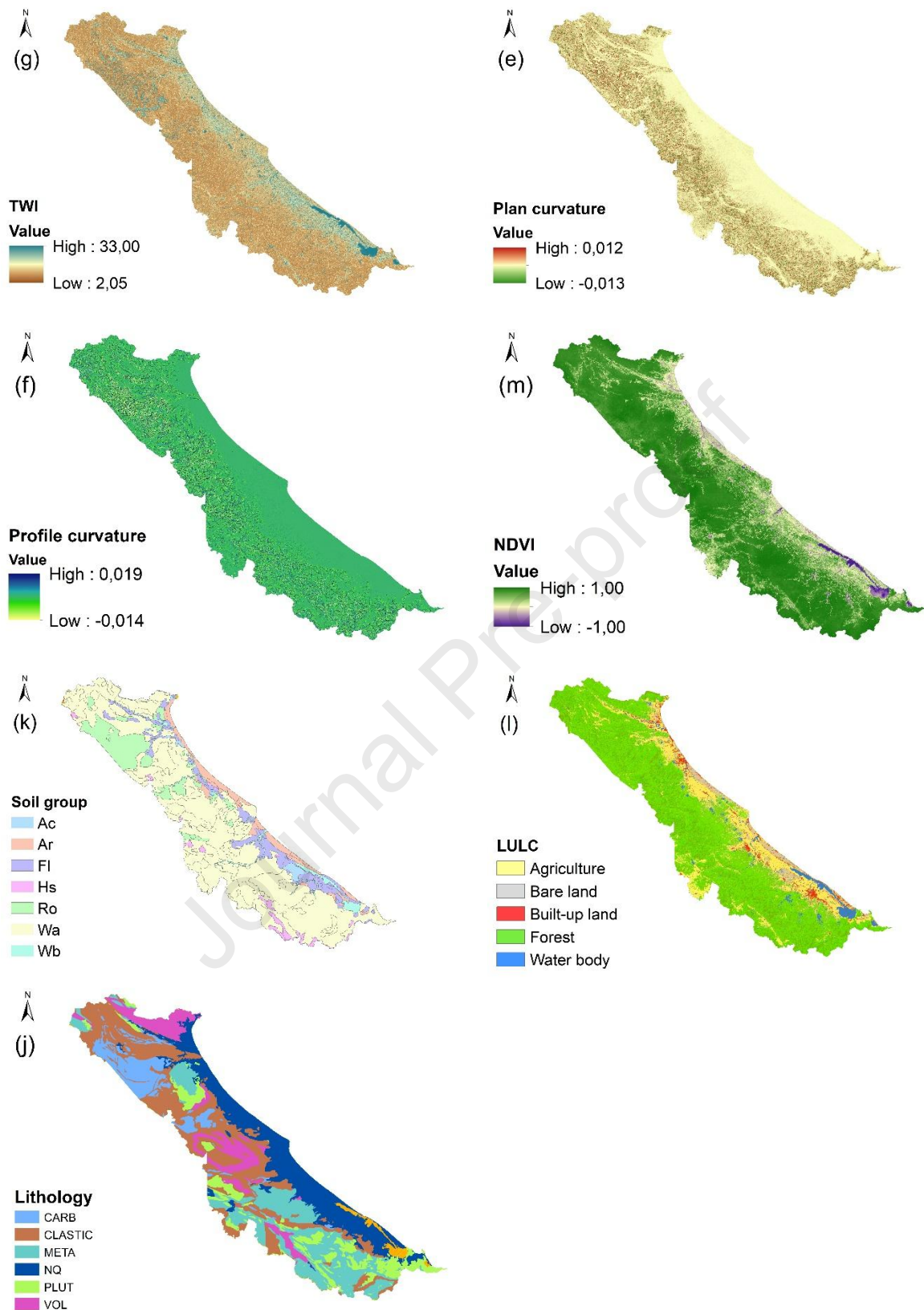


Figure 2. Conditioning factors for landslide susceptibility prediction

3.2.2. Multicollinearity analysis

In this study, categorical conditioning factors (e.g., soil type, lithology, and LULC) were transformed into numerical representations using the FR approach, whereas the remaining

factors were treated as continuous variables. To avoid redundancy and reduce multicollinearity among the conditioning factors, correlation analysis and multicollinearity diagnostics were conducted prior to model development. These analysis were conducted for continuous variables only, while categorical factors transformed by the FR method were not included.

Pearson's correlation analysis was first applied to examine the pairwise relationships among the predictor variables. Highly correlated variables were carefully evaluated to prevent redundancy in the modelling process. In addition, multicollinearity among the variables was further assessed using the Variance Inflation Factor (VIF) and tolerance values. Variables with VIF values greater than 10 or tolerance values lower than 0.2 were considered to exhibit significant multicollinearity and were therefore excluded from the analysis (Khan et al., 2025). As a result, only variables with acceptable multicollinearity levels were retained as input predictors for the subsequent machine learning models. The presence of multicollinearity among the explanatory variables was assessed using the VIF. The obtained values ranged from 1.01 to 2.28, suggesting that significant multicollinearity was not observed. Furthermore, the pairwise correlation coefficients among the variables ranged from 0.01 to $|0.53|$, suggesting relatively weak correlations between the predictors (Fig. 3).

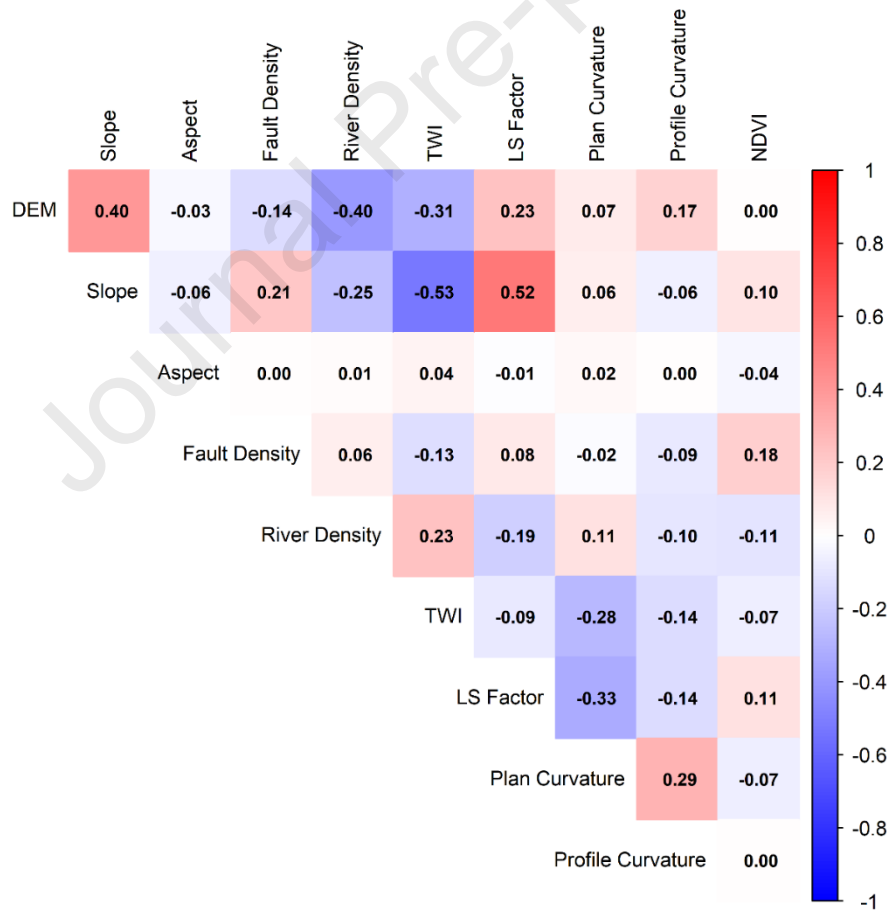


Figure 3. Correlation among numeric input variables

3.3. Sampling strategy

To obtain suitable data for developing a LSP model, non-landslide (Non-LS) points need to be generated. The landslide (LS) and Non-LS points then were used to construct the training and validation datasets for the ML models. The procedure for selecting non-landslide samples consists of three main steps:

Step 1: Input data preprocessing: The input datasets - comprising historical landslide inventory points, the study area boundary, and the LULC map were first preprocessed to ensure they share a consistent Coordinate Reference System. Next, unsuitable locations for landslide occurrence (e.g., water bodies, rivers, and urban/built-up areas) were identified from the LULC map. These restricted zones are merged to form the *Excluded_LULC_Area*, ensuring that future Non-LS points were not generated within these regions.

Step 2: Delineation of the available sampling area: To avoid selecting non-landslide samples too close to known landslide events, a 120-meter buffer zone (*Excluded_Buffered_Area*) was generated around each landslide point. This buffered region was also marked for exclusion during random sampling. The *Excluded_LULC_Area* and *Excluded_Buffered_Area* are then combined to form a single restricted layer (*Excluded_Area*). Finally, the potential sampling region (*Available_Area*) was determined by subtracting the *Excluded_Area* from the overall *Study_Area* using spatial difference operations.

Step 3: Random uniform sampling: To address class imbalance, a 1:1 sampling ratio relative to the LS points was maintained. A total of 466 Non-LS points were generated using a spatial random uniform sampling technique, with a spatial constraint ensuring all points strictly fall within the designated *Available_Area*.

The above process was executed using NumPy (v1.26.4), GDAL (v3.6.2), and GeoPandas (v1.0.1) within the Python programming environment (v3.8.10).

In total, the dataset used for model development comprised 932 samples, including both LS and Non-LS points. To evaluate the predictive performance and generalization capability of the machine learning models while mitigating the effects of spatial autocorrelation, a spatial block-splitting approach was implemented instead of a standard random point-based selection (Roberts et al., 2017). By preserving the spatial structure of the data during the splitting process, the configuration effectively simulates a realistic forecasting scenario where the model was evaluated on entirely unseen geographic zones, thereby preventing overoptimistic performance estimates and ensuring a robust assessment of landslide susceptibility.

In this study, a spatial split was applied by establishing the spatial partitioning of the study area based on the geographic coordinates of its bounding box. To evaluate whether model performance is sensitive to the spatial block configuration, we conducted a rigorous sensitivity analysis across 10 distinct grid sizes (ranging from 5×5 to 50×50 blocks, with increments of 5). For each grid size, 50 random sampling iterations of Non-LS points were executed using a RF baseline ($n_estimators = 15$, $max_depth = 2$). The sensitivity results (Fig. S1 in the Appendix) revealed the following insights: First, as the block size increases, predictive accuracy on the test set exhibits a slight downward trend. This behavior is expected because larger spatial blocks impose stricter spatial independence constraints between the training and validation folds.

Second, the 25×25 grid configuration achieves an optimal balance, yielding the narrowest accuracy gap between training and testing sets while preserving a high average accuracy level. This minimizes the risk of spatial overfitting. Beside, at 25×25 blocks, the spatial density of landslide events within individual blocks remains highly reasonable, ensuring a representative and balanced distribution of both positive events and environmental covariates across all spatial folds. Moreover, a 25×25 block guarantees adequate spatial separation between training and testing splits, effectively mitigating spatial autocorrelation and data leakage. Consequently, the 25×25 block configuration was selected as the optimal spatial partition scheme.

Finally, the domain was systematically divided into a regular grid of spatial blocks consisting of 25 intervals along both the horizontal (longitude) and vertical (latitude) dimensions (Fig. 4). Following the grid generation, the blocks having samples were randomly assigned to either the training set (70%) or the testing set (30%). Because the partitioning was executed strictly at the block level rather than the individual point level, the spatial distribution of LS and Non-LS points across the landscape naturally led to slight deviations from the exact 70/30 ratio in the final sample counts. However, this variation reflects the inherent spatial heterogeneity of the phenomena. The final dataset was partitioned into a training set (73.9%) (346 LS / 343 Non-LS points) and a testing set (26.1%) (121 LS / 122 Non-LS points). Moreover, we also evaluated the degree of environmental similarity between the landslide inventory (N1 = 466) and the randomly generated Non-LS background points (N2 = 466) across key environmental predictors (e.g., DEM, slope, aspect, fault density, river density, TWI, LS factor, plan curvature, profile curvature, and NDVI). This work conducted a two-sample Kolmogorov-Smirnov (K-S) test and plotted Kernel Density Estimation (KDE) distributions to quantify their distribution overlap (Fig. S2 in the Appendix). The substantial feature-space overlap across majority of environmental factors confirms that our Non-LS sampling strategy avoids unrealistic separation, thus preventing artificial discrimination while preserving realistic classification challenges for the machine learning models. Furthermore, to guarantee spatial independence between the partitioned datasets and prevent spatial autocorrelation, spatial distance metrics between training and testing samples were evaluated for the 25×25 block setup. The mean overall pairwise distance across the entire study area was 100.44 km. At the local scale, the mean Nearest-Neighbor Distance (NND) between testing points and their closest training counterparts was 4.98 ± 2.20 km (median: 4.72 km), with minimum and maximum NND values of 0.39 km and 11.13 km, respectively. These distance metrics confirm that the 25×25 spatial block configuration enforces an effective spatial separation buffer (averaging ≈ 5 km between adjacent train-test instances), thereby effectively mitigating spatial autocorrelation and preventing data leakage during model training and evaluation.

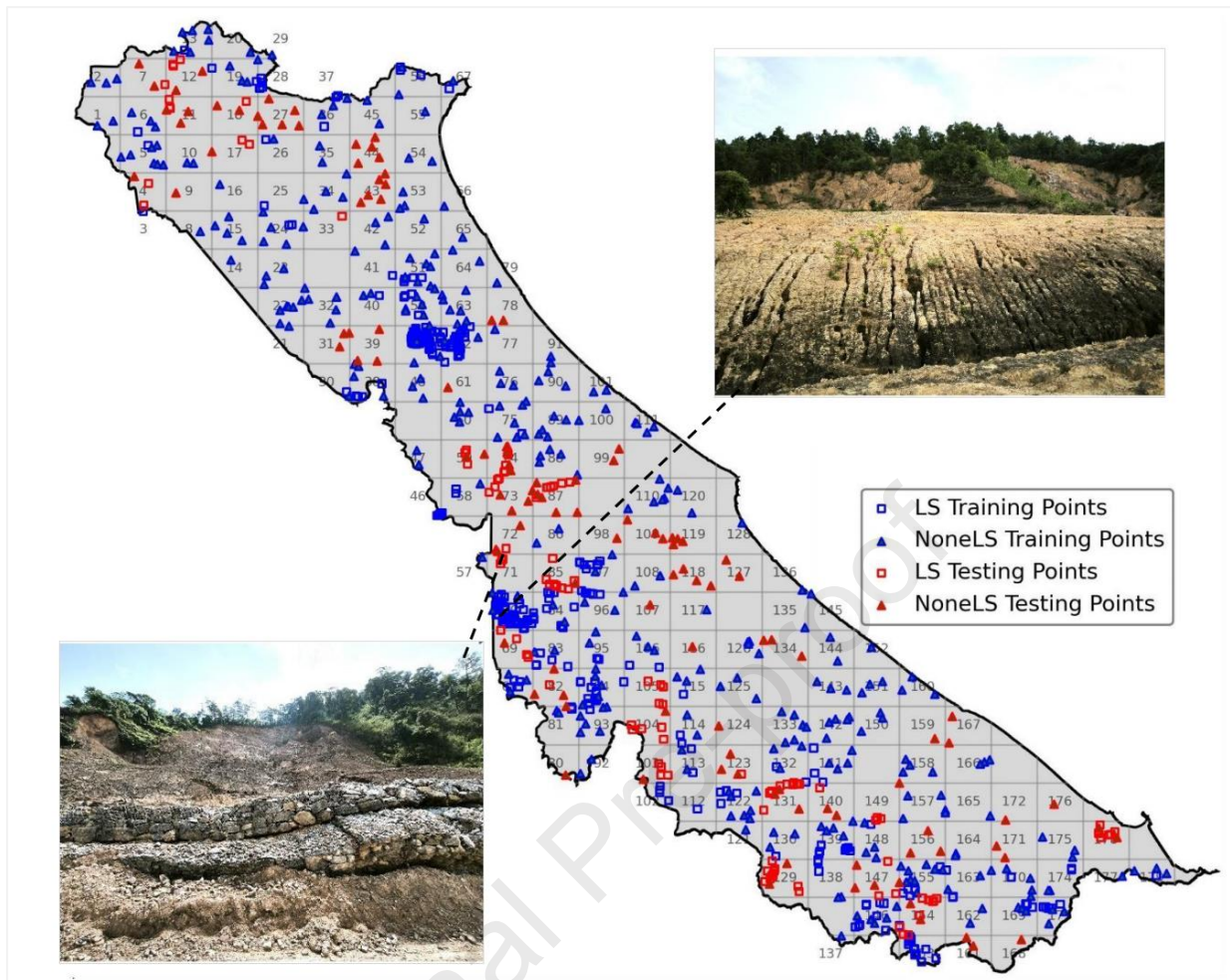


Figure 4. Spatial block-based split of training and validation samples

3.4. Machine learning models

3.4.1. Model used

Three widely used predictive algorithms were employed to develop landslide susceptibility models, including LR, RF, and XGB. LR is a multivariate statistical method used to analyze relationships between a binary dependent variable, typically coded as 1 (presence) or 0 (absence), and one or more independent variables. The model predicts the likelihood of the target event based on the set of explanatory variables (Menard, 2002).

RF, first proposed by Breiman (2001), is a nonlinear and non-parametric ensemble machine learning technique. The algorithm constructs numerous decision trees using bootstrap samples derived from the training dataset. During tree development, a randomly selected subset of predictor variables is evaluated at each node to identify the optimal split (Breiman, 2001; Stumpf & Kerle, 2011). This mechanism provides several advantages, including the capability to evaluate the relative importance of input variables, the absence of strict assumptions about data distribution, and enhanced predictive performance by mitigating the risk of overfitting.

XGB, is a tree-based learning algorithm that develops an ensemble model by sequentially adding regression trees, where each subsequent tree is trained to correct the

residual errors of the previously constructed trees. The framework integrates multiple tunable regularization parameters, allows compatibility with different computing environments, and applies various algorithmic optimizations. As a result, XGB provides an effective balance between model flexibility, overfitting control, and efficient use of computational and memory resources (Chen & Guestrin, 2016). The predictive models was executed within the Python programming environment (Python 3.8.10); specifically, the *scikit-learn* (v1.0.2) library was employed to implement the LR and RF algorithms, while the *xgboost* (v2.1.3) library was utilized for the XGB model (Chen & Guestrin, 2016; Pedregosa et al., 2011).

The efficacy of ML models is fundamentally dependent on the optimization of hyperparameters that govern the underlying learning mechanisms (Tran & Liou, 2024). This calibration process aims to identify an optimal configuration that maximizes predictive accuracy while minimizing estimation error. In this study, a grid search strategy was employed to systematically tune the hyperparameters for each algorithm. The modeling and optimization framework was implemented using the *scikit-learn* (v1.0.2) and XGB libraries (*xgboost* v2.1.3) within a Python 3.8.10 environment (Chen & Guestrin, 2016; Pedregosa et al., 2011). To mitigate the substantial computational overhead, the optimization was confined to a selection of critical hyperparameters, with remaining parameters maintained at their respective default factory settings (Chen & Guestrin, 2016; Pedregosa et al., 2011; Tran & Liou, 2024). Two critical hyperparameters were optimized within the RF framework: the quantity of decision trees (*n_estimators*) and the maximum hierarchical depth of each tree (*max_depth*). For RF, the search space comprised $\text{max_depth} \in [1, 10]$ with a step size of 1, and $\text{n_estimators} \in \{1, 2, 3, 4, 6, 8, 10, 13, 16, 20\}$. To balance model performance with computational efficiency, these parameters were assigned values of 2 and 20, respectively (Fig. 5). Hyperparameter tuning for the XGB algorithm focused on calibrating the tree depth and the number of boosting iterations. By employing a grid search strategy, various candidate configurations were assessed to identify the most effective parameters for the study area. For the XGB, the evaluation was performed across $\text{max_depth} \in [1, 10]$ (step size = 1) and $\text{n_estimators} \in \{1, 2, 3, 4, 5, 7, 10, 15, 20, 30\}$. Consequently, the optimal model was established using a *max_depth* of 2 and *n_estimators* of 10, reflecting a balance between model complexity and predictive accuracy (Fig. 6). As for the LR, the implementation of the algorithm involved an empirical hyperparameter tuning process to optimize performance. Specifically, the model utilized the *liblinear* optimization library, complemented by a ridge regression penalty (*penalty* = l2). The regularization parameter *C* was maintained at a default value of 1, while the *max_iter* threshold was extended to 300, providing sufficient computational steps for the solver to reach a stable solution.

In this study, a 3-fold cross-validation (3-fold CV) scheme was applied strictly during the hyperparameter tuning phase on the training dataset. The operational procedure was executed as follows. *Step 1*: The training dataset was partitioned into 3 balanced folds. *Step 2*: In each iteration, 2 folds (66.7% of the training data) were used for model fitting, while the remaining 1 fold (33.3%) served as the validation set. This process was repeated 3 times so that every fold acted as the validation set once. *Step 3*: The mean performance score across the 3 iterations was computed to evaluate each hyperparameter combination, as illustrated in Figures 5 and 6. Given the constrained sample size of the landslide inventory, adopting 3-fold CV

ensures that a sufficient proportion of positive landslide events is retained within each training partition, thereby preserving spatial representativeness and mitigating sample variance across folds compared to higher k-fold splits (e.g., 5 or 10-fold).

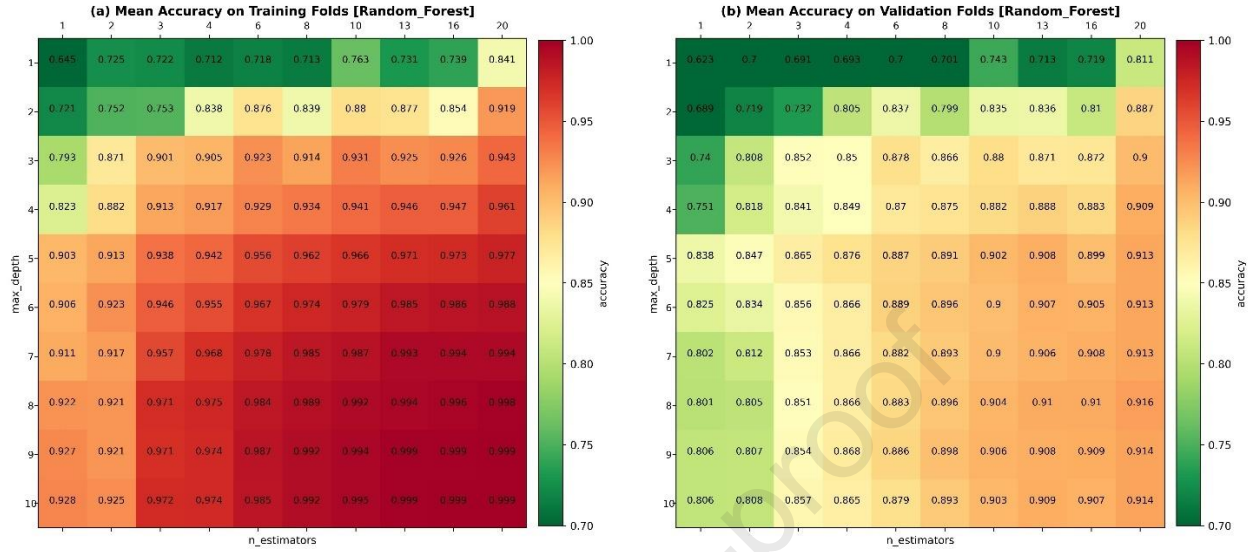


Figure 5. Optimizing hyperparameters for the RF

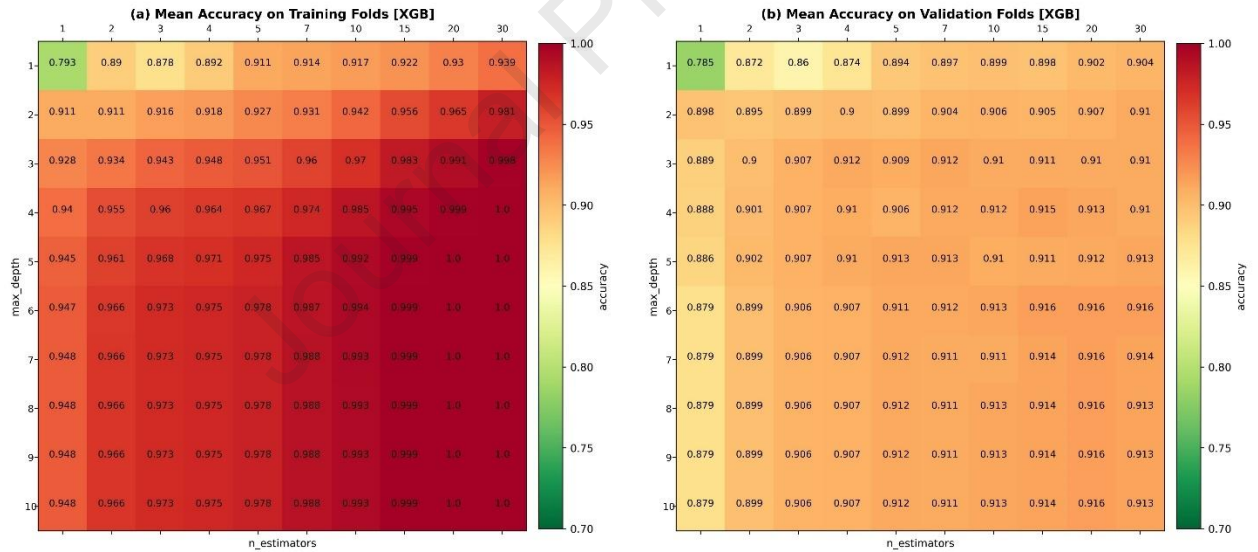


Figure 6. Optimizing hyperparameters for the XGB

3.4.2. Model validation

The predictive performance of the ML models was evaluated using accuracy, precision, recall, F1-score, Kappa coefficient, and the area under the ROC curve (AUC) (Halder et al., 2025; Hu et al., 2020; L. Lv et al., 2022). These metrics each provide different perspectives on model performance, and a comprehensive understanding of their roles is necessary for proper model assessment. Accuracy reflects the ratio of correctly classified samples to the total number of observations, considering both LS and Non-LS events, and is commonly used as a general indicator of model performance. The AUC is widely applied to assess a model's capability to

discriminate between landslide and non-landslide areas across different decision thresholds (Chang et al., 2023; Pham et al., 2017). The curve depicts the True Positive Rate, or recall, indicating correctly predicted landslide-prone areas, against the False Positive Rate, which reflects the proportion of Non-LS areas incorrectly classified as landslides (Pham et al., 2017; Sharma et al., 2024).

3.4.3. SHAP-based model interpretation

To interpret the ML models, the SHAP method was applied to quantify the contribution of each conditioning factor to LSP. SHAP is a post hoc model interpretation approach that evaluates the contribution of individual input variables to the predictions generated by ML models (Wen et al., 2024). SHAP estimates the influence of each variable by evaluating the change in model predictions when the feature is incorporated into all possible combinations of the remaining variables (Meng et al., 2020). The SHAP value quantifies how a particular feature influences the model output by either increasing or decreasing the predicted probability. These values provide insights into the relative contribution of conditioning factors to landslide susceptibility (Khan et al., 2025). The beeswarm plot provides a global visualization of how individual features contribute to the model's predictions across the entire dataset (Bostan, 2024). It displays the SHAP values for all variables, while the color gradient represents the magnitude of the corresponding feature values (e.g., high or low). Bar plots of mean absolute SHAP values illustrate the relative impact of each feature on the predictive models. SHAP dependence plots were further utilized to examine the effect of individual features on model predictions (M. K. Lee et al., 2022). In this study, the SHAP was applied to interpret the relative contributions of the conditioning factors in the best-performing ML model for landslide prediction, selected from three candidate models: LR, RF, and XGB. In this work, the SHAP was implemented in Python, using the *shap* library version 0.48.0.

The overall research workflow is illustrated in Fig. 7. The diagram summarizes the major steps of the study, including data preparation, conditioning factor analysis, development of ML models, and interpretation of model outputs using explainable AI techniques.

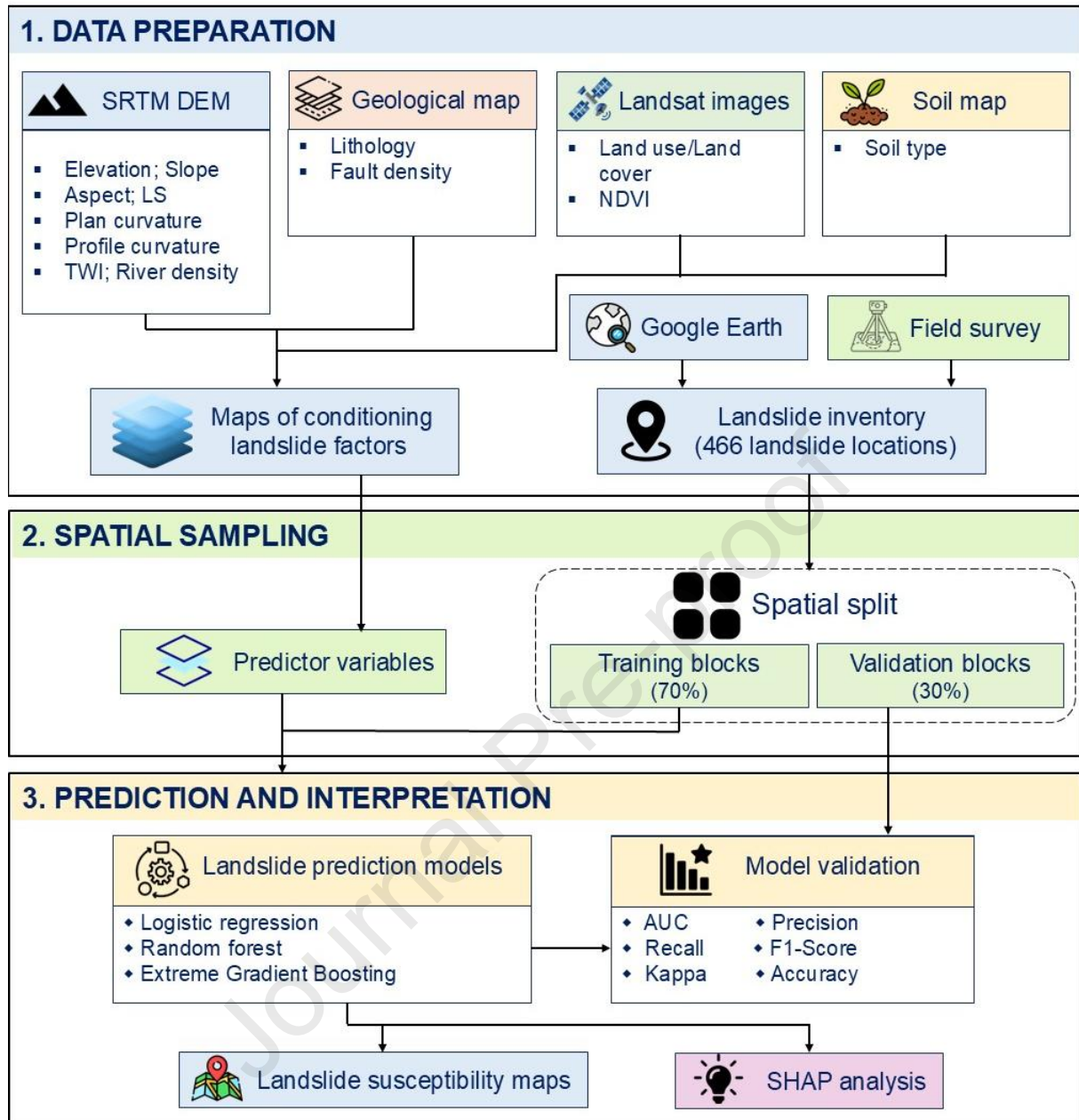


Figure 7. Overall workflow of the proposed regional-scale landslide susceptibility mapping framework.

4. Results

4.1. Model performance comparison

The predictive performance of the landslide susceptibility models was evaluated using Accuracy, Precision, Recall, F1-score, Kappa index, and AUC (Table 2 & Fig. 8). Overall, all three models showed strong predictive capability. The LR model achieved an accuracy of 0.891 and an AUC of 0.949 for the training dataset, and 0.817 and 0.901 for the testing dataset, indicating relatively stable performance. The RF model showed improved results, with testing accuracy and AUC values of 0.902 and 0.951, respectively.

Among the models, the XGB achieved the best performance, with the highest testing accuracy (0.915) and AUC (0.970). These results indicate that the XGB outperformed the other models in terms of predictive accuracy and reliability, followed by the RF and LR in the study area.

Table 2. Evaluation metrics of the ML model performances

Train/Test	Accuracy	Precision	Recall	F1_score	Kappa	AUC (95% CI)
LR_Train	0.891	0.890	0.893	0.892	0.782	0.949 (0.932 - 0.964)
LR_Test	0.817	0.880	0.717	0.790	0.631	0.901 (0.859 - 0.939)
RF_Train	0.919	0.903	0.939	0.921	0.837	0.969 (0.955 - 0.981)
RF_Test	0.902	0.909	0.885	0.897	0.804	0.951 (0.924 - 0.976)
XGB_Train	0.930	0.941	0.919	0.930	0.861	0.982 (0.974 - 0.990)
XGB_Test	0.915	0.912	0.912	0.912	0.830	0.970 (0.948 - 0.987)

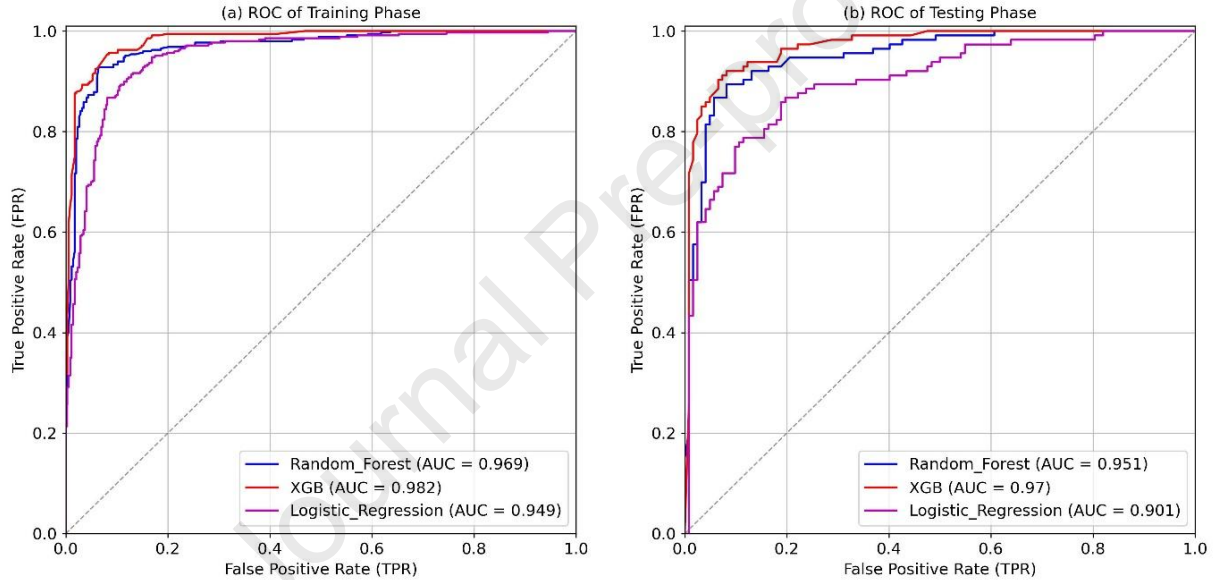


Figure 8. ROC curves of the landslide susceptibility models

To evaluate potential model overfitting and generalizability, performance metrics were systematically compared between the training and testing phases across all three algorithms. The LR exhibited notable performance degradation when evaluated on the unseen testing dataset. Specifically, its accuracy dropped from 0.891 to 0.817 ($\Delta = 0.074$), accompanied by a substantial decline in recall from 0.893 to 0.717 ($\Delta = 0.176$) and an AUC decrease from 0.949 to 0.901 (Table 2). This pronounced disparity indicates a susceptibility to overfitting and limited capability in generalizing to new spatial instances. In contrast, tree-based ensemble models demonstrated superior robustness and stability. The RF maintained consistent metrics, with accuracy decreasing slightly from 0.919 (train) to 0.902 (test) ($\Delta = 0.017$) and AUC changing from 0.969 to 0.951. The XGB achieved the best generalization capacity, exhibiting minimal performance divergence between training and testing sets ($\Delta_{\text{Accuracy}} = 0.015$; $\Delta_{\text{AUC}} = 0.012$, reaching 0.970 on testing data) (Table 2). These results confirm that the XGB effectively

controls overfitting while delivering optimal spatial predictive performance for landslide susceptibility mapping.

To evaluate the statistical significance of performance variations across the implemented models, pairwise non-parametric Wilcoxon signed-rank tests were executed using the continuous prediction probability matrices generated on the independent test set. As detailed in Table S1, all pairwise comparisons yielded statistically significant differences ($p < 0.05$). Specifically, the XGB demonstrated superior predictive capability over both the LR ($p = 0.004$, $Z = 2.894$) and RF ($p = 0.007$, $Z = 2.698$). Additionally, the RF exhibited significantly higher predictive power compared to the baseline LR model ($p = 0.034$, $Z = 2.119$). These results confirm that the performance gains of the XGB model are not due to random variation, but represent a statistically robust enhancement in capturing complex landslide susceptibility patterns.

4.2. Landslide susceptibility maps

The landslide susceptibility results were divided into five classes according to the natural breaks (Fig. 9). Comparison of the susceptibility outputs from the LR, RF, and XGB models indicates substantial variation in the area coverage associated with different susceptibility levels (Table 3). For the RF model, the *very low* susceptibility class covers the largest area (51.03%), followed by *low* (32.09%), *moderate* (7.88%), *high* (3.27%), and *very high* (5.73%). Similarly, the XGB model classifies the majority of the study area as *very low* susceptibility (67.75%), while the *low*, *moderate*, *high*, and *very high* classes account for 14.34%, 7.45%, 4.51%, and 5.95%, respectively. The LR model assigns 56.12% of the area to the *very low* class, followed by *low* (20.76%), *moderate* (10.90%), *high* (6.88%), and *very high* (5.34%). Overall, the RF, XGB and LR models concentrate a larger proportion of the study area in the very low and low susceptibility category.

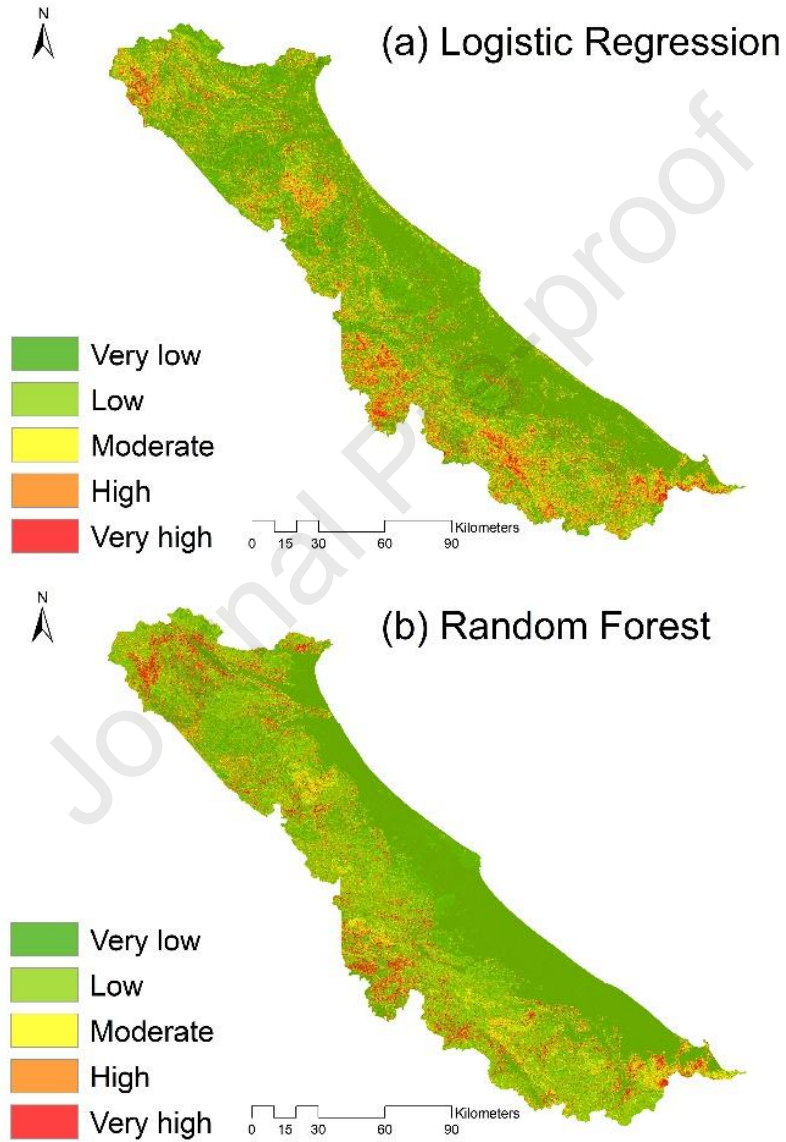
The performance of the landslide susceptibility results was further examined using FR analysis. This metric provides an indication of how effectively the models differentiate between various susceptibility classes. The FR analysis shows a clear increasing trend from the very low to the very high susceptibility classes for all three ML models, indicating that landslide occurrences are strongly concentrated in areas classified as highly susceptible. For the LR, the FR values increase from 0.05 in the very low class to 13.15 in the very high class. Similarly, the RF shows FR values ranging from 0.06 to 12.33, while the XGB records the highest FR value of 12.46 in the very high susceptibility class (Table 3). These results suggest that the XGB provides the most effective classification of landslide-prone areas among the three models.

Table 3. Landslide occurrence frequency by susceptibility classes

Model	Class	Number of landslide	Area_Per	Landslide_Per	Frequency ratio
LR	Very Low	14	56.12	3.04	0.05
	Low	26	20.76	5.65	0.27
	Moderate	41	10.90	8.91	0.82
	High	56	6.88	12.17	1.77
	Very High	329	5.34	70.22	13.15
RF	Very Low	15	51.03	3.26	0.06

XGB	Low	50	32.09	10.87	0.34
	Moderate	36	7.88	7.83	0.99
	High	34	3.27	7.39	2.26
	Very High	331	5.73	70.65	12.33
	Very Low	24	67.75	5.22	0.08
	Low	35	14.34	7.61	0.53
	Moderate	44	7.45	9.57	1.28
	High	16	4.51	3.48	0.77
	Very High	347	5.95	74.13	12.46

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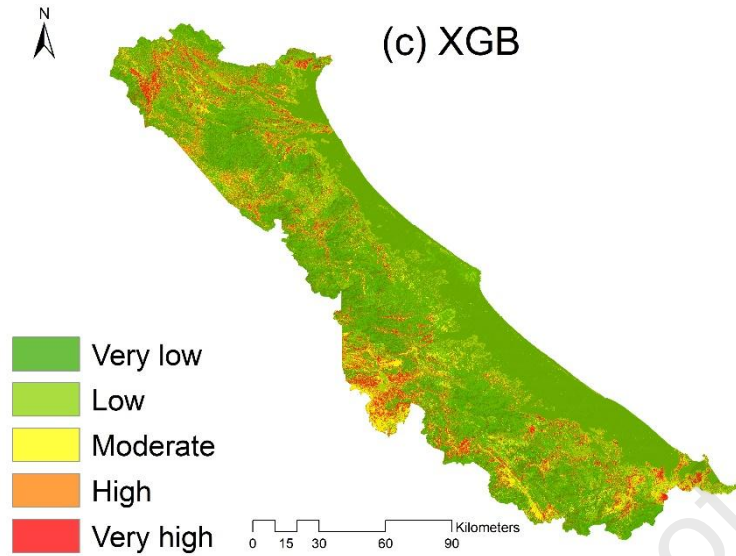


Figure 9. Landslide susceptibility maps generated using LR (a), RF (b), and XGB (c)

4.3. Factor importance analysis

To interpret the contribution of conditioning factors to landslide susceptibility model, feature importance was analyzed using the SHAP. The SHAP beeswarm plot (Fig. 10a) illustrates the relative importance and directional influence of each variable on model predictions. Among the investigated factors, NDVI was identified as the most influential predictor, followed by slope and LS factor, indicating that vegetation cover and terrain steepness play the greatest contributions to the LSP model. Lithology, soil group, and DEM also exhibited notable contributions to model predictions. In contrast, variables such as LULC, aspect, river density, profile curvature, plan curvature, TWI, and fault density showed comparatively lower impacts on the LSP model. The distribution of SHAP values further reveals that higher slope gradients and LS factor values generally contribute to higher model-predicted landslide susceptibility, whereas higher NDVI values tend to contribute to lower predicted susceptibility.

The SHAP analysis identified NDVI as the dominant predictor, with a mean absolute SHAP value of 1.50, substantially exceeding those of all other variables. Slope (0.53), lithology (0.29), and SL factor (0.26) showed moderate contributions, whereas DEM (0.10), soil group (0.09), and profile curvature (0.05) made relatively smaller contributions. In contrast, LULC, plan curvature, and other variables exhibited near-zero SHAP values, indicating negligible contributions to the LSP model (Fig. 10b).

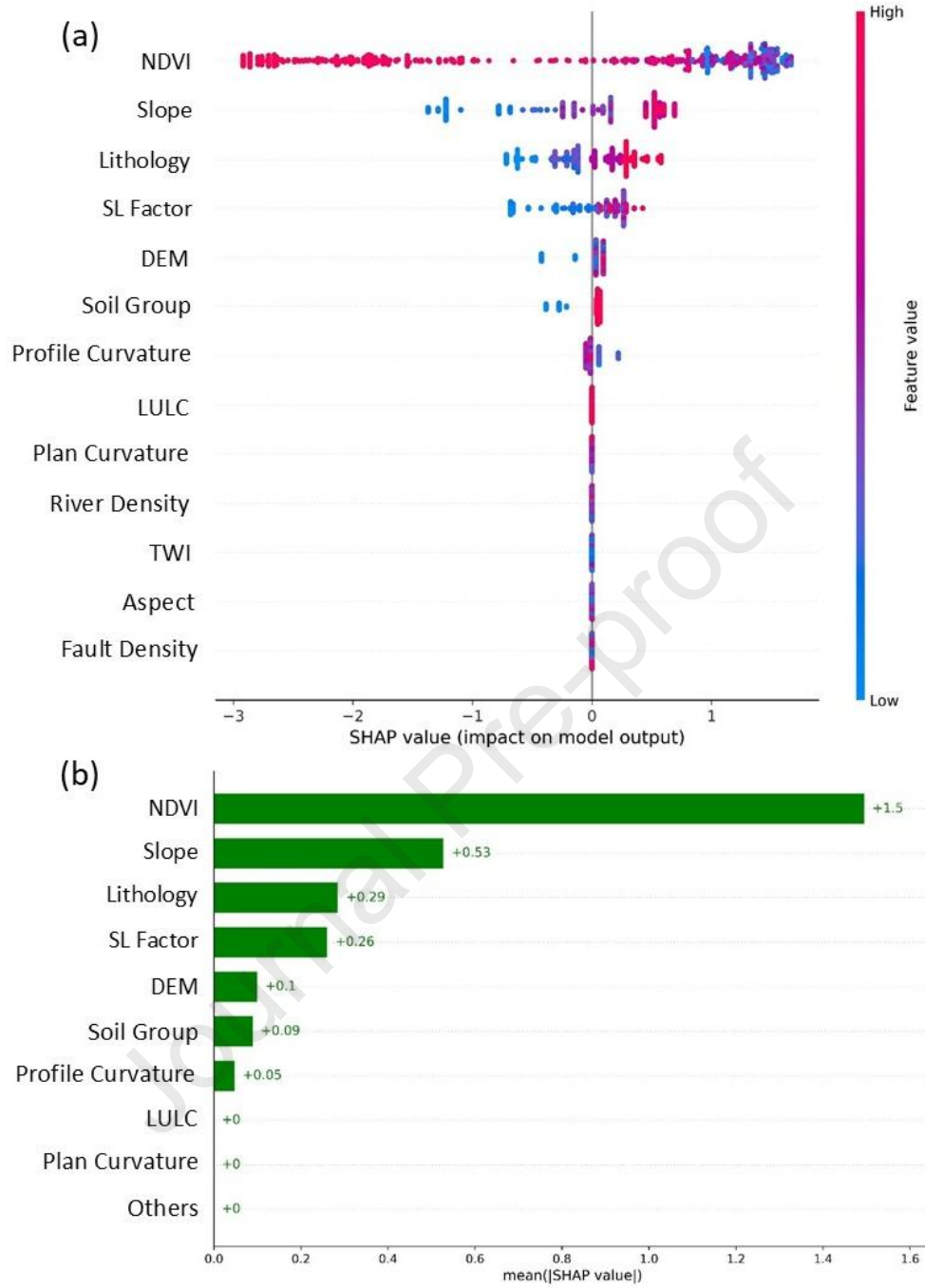


Figure 10. SHAP analysis of the XGB model: (a) beeswarm plot and (b) feature importance bar plot

The SHAP dependence plot for NDVI indicates a clear nonlinear pattern in its contribution to the LPS model. NDVI values below approximately 0.65 are generally associated with positive SHAP value ($SHAP > 1$), indicating higher model-predicted landslide susceptibility, whereas values above 0.7 - 0.8 are associated with SHAP values approaching zero or becoming negative, indicating lower predicted susceptibility (Fig. 11a). Slope also shows a nonlinear relationship with SHAP values, with relatively small contributions at lower slope values, followed by increasing positive contributions as slope increases, reaching approximately 0.5 at values above 20^0 (Fig. 11b). Similarly, the SHAP dependence plot

indicates a generally positive but nonlinear relationship between LS factor and their contributions to the LSP model. Low LS factor values are associated with negative SHAP values (approximately -0.6), indicating a lower contribution to the LSP model. As LS factor increases, SHAP values progressively shift to positive and stabilize around 0 - 0.4, indicating an increasing contribution to the LSP model. At higher LS factor values, the SHAP contributions tend to level off (Fig. 11c). DEM shows a weak nonlinear effect in its SHAP values, with negative values at low elevations and values approaching zero at higher elevations, indicating a limited overall contribution to the LSP model (Fig. 11d).

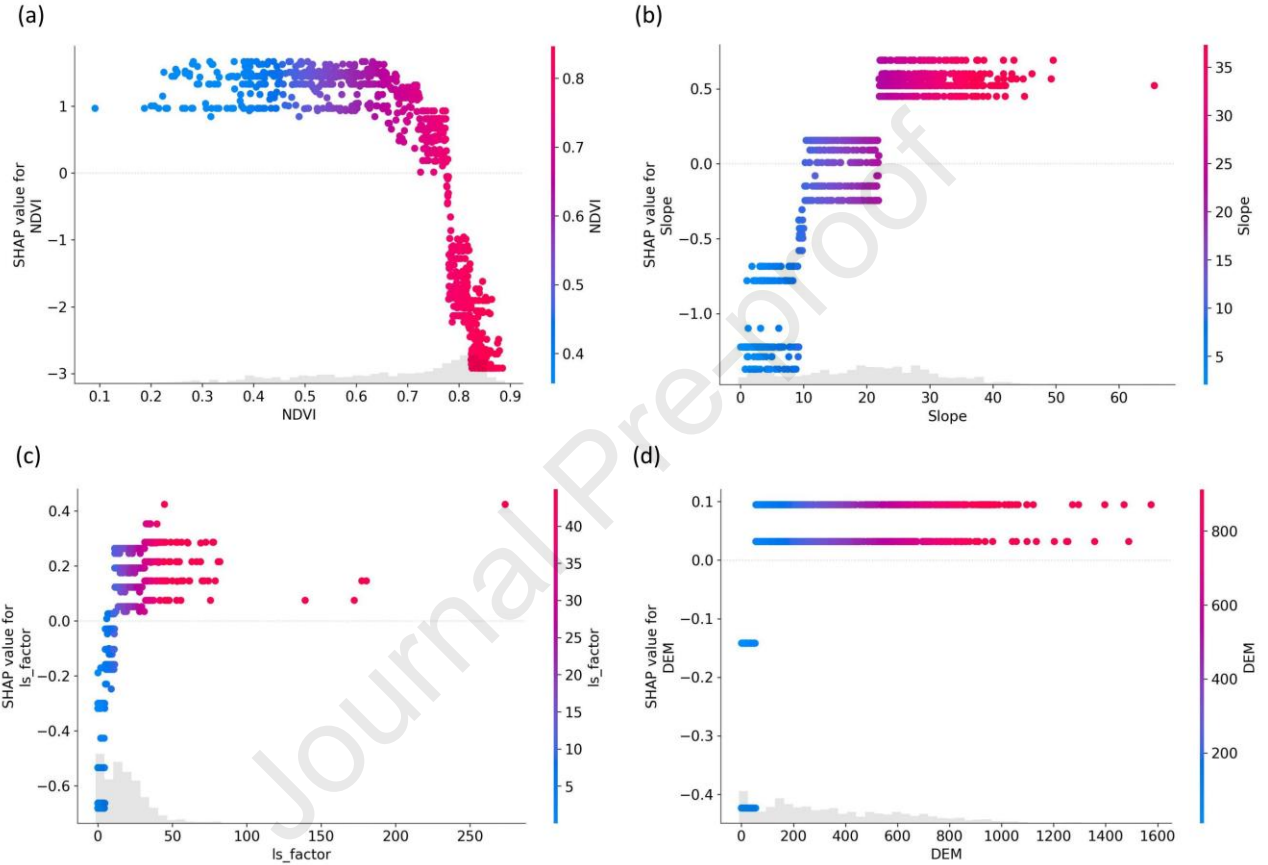


Figure 11. SHAP dependence plot of four numeric variables with highest SHAP values with the XGB model

5. Discussion

5.1. Comparison of model performance

Selecting appropriate ML algorithms is critical for reliable LSP, as different algorithms exhibit varying capabilities in handling data characteristics and complex environmental conditions (J. Lv et al., 2024). This study applied three different models: LR, RF, and XGB to assess their capability in predicting landslide susceptibility. The comparison results indicate that the XGB model outperformed the other approaches in both training and testing datasets according to all assessment indicators. This advantage is largely associated with the boosting-based learning strategy of XGB, where sequential trees are constructed to reduce prediction errors and to better represent nonlinear relationships among the influencing variables. In

addition, its built-in regularization mechanisms help reduce overfitting and enhance model generalization. Similar findings have also been reported in previous landslide susceptibility studies, where XGB consistently demonstrated superior predictive performance compared with conventional statistical and ML models (Alcântara et al., 2025; Halder et al., 2025; J. Lv et al., 2024; Sahin, 2023; Zhang et al., 2024).

5.2. Comparison with previous studies

All applied models showed strong capability in predicting landslide susceptibility. Notably, the XGB model achieved the best performance, as evidenced by its high AUC values, indicating excellent predictive accuracy, with an AUC of 0.982 for the training dataset and 0.970 for the testing dataset. These results are comparable to, or even higher than, those reported in previous landslide susceptibility studies employing the same algorithm or others (Das et al., 2024; Guo et al., 2023; Kainthura & Sharma, 2022; Khan et al., 2025; S.-M. Lee & Lee, 2024; J. Lv et al., 2024; Tien Bui, Ho, et al., 2016; Xu et al., 2024). This consistency further confirms the effectiveness and robustness of the XGB model for LSP. Unlike conventional random data partitioning, the spatial block strategy explicitly accounts for the spatial structure of landslide data by geographically separating training and validation samples. This reduces the potential influence of spatial autocorrelation and data leakage, thereby providing a more robust framework for evaluating model transferability across space.

The relative importance of predictors identified in this study is broadly consistent with, but also differs from, previous landslide susceptibility studies in Vietnam and other environments. In central Vietnam, previous studies have identified elevation, rainfall, lithology, and drainage-related factors among the most influential predictors (Das et al., 2025), while climate and soil have also been highlighted in Quang Binh (Hoa et al., 2023). In contrast, distances to rivers, roads, and faults were identified as important conditioning factors influencing LSP in Muong Lay, Vietnam (Phong et al., 2021). Slope, relief amplitude, and elevation were identified as the most influential factors, followed by distance to roads, rainfall, and land use in the landslide susceptibility prediction model for Phuoc Son, Quang Nam (Tran Anh et al., 2024). Curvature, geomorphology, and elevation were identified as the most influential factors in the model, followed by TWI, the stream power index, and rainfall in Hoa Binh, Vietnam (Hang et al., 2022). Focal flow, elevation, and lithology were identified as important factors in the landslide susceptibility model for the Son La hydropower reservoir, Vietnam (Dung et al., 2021). In contrast, the present study identified NDVI and slope as the most influential predictors, followed by lithology and LS factor. Previous studies have reported different rankings of conditioning factors, suggesting that their relative importance can vary with local environmental conditions, landslide inventories, predictor selection, and modelling approaches. Similar variability has also been reported in other study sites (Khan et al., 2025; Lv et al., 2024; Zhang et al., 2024). These comparisons indicate that the importance of individual conditioning factors is context-dependent, while the recurrent importance of topographic, geological, vegetation, and hydrological variables supports their relevance to landslide susceptibility assessment in tropical mountainous regions.

The SHAP analysis indicate that NDVI, slope, and LS factor were identified as the most influential predictors in the XGB model. The strong contribution of slope and LS factor reflects the topographic conditions plays an important role in the model's prediction of landslide susceptibility, which is consistent with the established influence of slope steepness and surface runoff on slope instability. The relatively high contribution of NDVI in the SHAP analysis should also be interpreted with caution. NDVI may act as a proxy for multiple environmental and landscape conditions, including land-cover characteristics, human disturbance, elevation-related gradients, and other factors associated with vegetation patterns. Therefore, the observed SHAP response of NDVI should be regarded as a model-specific association rather than direct evidence that NDVI independently controls slope instability.

It should be emphasized that this study represents one of the first attempts to apply SHAP to explicitly interpret the contribution of conditioning factors in LSP in Vietnam. In contrast, earlier studies conducted in the country have largely relied on qualitative or statistical approaches (Hoa et al., 2023; Linh et al., 2018) or have primarily focused on assessing the predictive accuracy of ML models (Bien et al., 2022; Cheon et al., 2025; Das et al., 2024; Das et al., 2025; Dung et al., 2021; Hang et al., 2022; Loke et al., 2026; Pham et al., 2018; Phong et al., 2021; Tran Anh et al., 2024), with limited attention given to model interpretability. Accordingly, integrating explainable AI techniques enables a clearer interpretation of the factors driving landslide susceptibility and promotes greater transparency in ML-based predictive models.

5.3. Geomorphological plausibility of the XGB susceptibility map

The geomorphological plausibility of the XGB-derived susceptibility map was assessed by comparing the landslide inventory and terrain characteristics across the five susceptibility classes. Landslides were strongly concentrated in the very-high susceptibility class, which covers only 5.95% of the study area but contains 74.13% of the mapped landslides ($FR = 12.46$). In contrast, the very-low class covers 67.75% of the area but accounts for only 5.22% of landslides ($FR = 0.08$). This contrast indicates that the model successfully delineated a relatively small area with a high concentration of observed landslides.

The terrain characteristics further support this pattern. Mean slope increased from 12.13° in the very-low class to 21.54° in the very-high class. The LS factor also showed an overall increase, from 10.80 to 21.60, although some variation occurred among the intermediate classes. The concentration of high susceptibility in steeper terrain is geomorphologically reasonable because steeper slopes increase gravitational driving forces, while higher LS values can enhance runoff and erosion, potentially contributing to slope instability.

These results are generally consistent with the SHAP analysis, which identified slope as an important conditioning factor and indicated higher susceptibility at steeper slopes. In contrast, the LS factor exhibited a non-monotonic SHAP responses, with an initial increase followed by fluctuations at higher values, indicating that its contribution varies across the observed range and may be influenced by interactions with other conditioning factors. Overall, the strong concentration of observed landslides in high-susceptibility areas, together with their

association with steeper terrain and higher LS values, provides complementary empirical and geomorphological support for the XGB susceptibility pattern.

5.4. SHAP-based interpretation and implications for landslide management

Building upon the insights derived from the SHAP analysis, the results provide several important implications for landslide risk management and land-use planning. The SHAP values quantify the contribution of individual conditioning factors to the model predictions, thereby helping identify the environmental and anthropogenic factors that play a greater role in distinguishing areas with higher or lower landslide susceptibility. In particular, the dominant variables identified by the model can serve as key indicators for prioritizing areas for risk assessment, monitoring, and mitigation.

These findings also have important implications for strategic land-use planning in mountainous regions. Local communities often cultivate steep slopes due to limited availability of agricultural land, while the expansion of transportation networks, infrastructure, settlements can increase human pressure on potentially unstable terrains. Therefore, areas characterized by combinations of high-contributing conditioning factors identified by the SHAP analysis should receive greater attention in land-use planning and development decisions.

The SHAP-based interpretability provides evidence that slope and vegetation cover are important controls on the spatial variability of landslide susceptibility. In particular, slope values above 20° were associated with increasingly positive SHAP values, indicating a stronger contribution to higher predicted susceptibility. This pattern is geomorphologically plausible because increasing slope steepness enhances the gravitational component acting downslope and consequently increases the driving forces relative to resisting forces. The SHAP analysis also showed that lower NDVI values, particularly below approximately 0.65, were associated with positive contributions to landslide susceptibility. This relationship is consistent with the geomorphological understanding that steep terrain enhances gravitational driving forces, while reduced vegetation cover weakens slope stability by limiting root reinforcement (Rawat & Pant, 2023; X. Wang et al., 2023) and increasing surface exposure to rainfall impact. Consequently, land use practices involving low-coverage crops should be strictly limited in high-slope environments (Cao et al., 2023), particularly in areas exceeding 20° inclination. The spatial coincidence of steep slopes and sparse vegetation therefore represents a geomorphologically plausible setting for enhanced landslide susceptibility, particularly where intense rainfall promotes infiltration and soil weakening. Rather than representing deterministic critical thresholds, the SHAP-derived values of approximately 20° for slope and 0.65 for NDVI should be interpreted as indicative ranges within which these predictors exert stronger contributions to the modelled susceptibility.

From a land management perspective, transportation infrastructure traversing steep hillslopes warrants special attention, especially in areas where slopes exceed approximately 20° , as these conditions were associated with increased SHAP contributions to landslide susceptibility. In such settings, appropriate slope management and protective measures, including retaining structures, slope stabilization systems, and surface protection layers, should be considered to reduce the potential impacts of slope failure (Tetteh et al., 2025).

Moreover, the LS factor was identified as an important conditioning factor in the model, with SHAP values generally increasing as LS values increased, although some variability was observed across its observed range. This suggests that the influence of LS on landslide susceptibility is more complex than a simple increase in susceptibility with increasing LS values. Nevertheless, the importance of LS is geomorphologically plausible because slope gradient and slope length jointly influence runoff generation, flow concentration, and surface erosion, which can contribute to hillslope weakening under intense rainfall conditions (Liou et al., 2022). The observed SHAP pattern therefore suggests that the effect of LS may depend on its interaction with other environmental conditions rather than acting as an independent linear control. From a land-management perspective, areas with terrain configurations associated with high erosional potential should be considered in conjunction with vegetation cover, drainage conditions, and slope characteristics when prioritizing erosion-control and slope-stability measures.

Taken together, the SHAP results indicate that slope, vegetation cover, and LS factor represent important controls on the spatial variability of landslide susceptibility in the study area. Their combined interpretation suggests that land-use activities on steep hillslopes should be carefully managed to minimize vegetation loss, excessive surface disturbance, and the alteration of natural drainage pathways. In this context, the landslide susceptibility maps provide a spatial basis for prioritizing field inspections, slope monitoring, and risk-reduction interventions, particularly in areas where multiple high-contributing conditions co-occur. The integration of model-derived susceptibility with SHAP-based interpretation can therefore support more targeted land-use planning and disaster risk reduction by identifying not only where susceptibility is elevated, but also the environmental conditions that contribute to the predicted susceptibility.

Although SHAP provides useful insights into predictor contributions to the XGB model, it explains model predictions rather than establishing causal relationships with landslide occurrence. Moreover, correlations and interactions among predictors may affect the contribution attributed to individual variables. Therefore, SHAP-derived responses, including non-monotonic patterns and apparent thresholds, should be interpreted as model-specific associations rather than universal physical or causal relationships.

5.4. Limitations and future work

Despite its contributions, this study is subject to several limitations.

First, the landslide inventory comprises 466 locations through field investigation and manual interpretation of high-resolution imagery from Google Earth Pro. However, this dataset may not represent the complete record of historical landslides in the study area, particularly those that were not documented or were difficult to identify from available imagery. Moreover, landslides were represented as point locations, rather than mapped as polygonal features. Therefore, a specific minimum mapping unit in terms of landslide area was not defined, because the actual dimensions of the identified landslides varied considerably. Each point represents the location of an observed landslide occurrence and does not imply its complete spatial extent. For the susceptibility modelling, the 30×30 m raster cell was used as the common spatial unit for

extracting predictor variables and constructing the models. Future studies should incorporate more comprehensive landslide inventories with polygon-based mapping, supported by field surveys, UAV data, or higher-resolution remote sensing data, to better characterize landslide extent and reduce inventory-related uncertainty.

Second, historical landslides and recent slope failure events were integrated into a unified landslide inventory without temporal stratification. We fully acknowledge that this approach introduces a temporal mismatch between the occurrence timestamps of individual landslide events and the observation periods of specific predictor variables, most notably dynamic environmental factors such as NDVI and LULC. Future studies could employ advanced spatiotemporal cloud gap-filling algorithms or integrate Synthetic Aperture Radar (SAR) time-series data to capture subtle seasonal vegetation dynamics. Further development of time-stamped, multi-temporal landslide inventories, together with temporally matched environmental covariates, would also improve the representation of temporal variability in landslide susceptibility and help reduce uncertainties associated with static inventories and predictors.

Third, rainfall is an important dynamic triggering factor for landslides, particularly in tropical mountainous environments. However, rainfall was not incorporated as an input variable due to the coarse spatial resolution of available satellite precipitation products and the limited number of ground-based rain gauge stations in the study area. Therefore, the present ML framework focuses on static spatial susceptibility rather than event-specific or time-dependent hazard. Accordingly, the relative importance and SHAP patterns of the environmental predictors should be interpreted within the available predictor set, and the high importance of variables such as NDVI, slope, lithology, and LS factor should not be interpreted as evidence of their independent physical control. Future studies could further evaluate and potentially improve the modelling framework by integrating higher-resolution environmental datasets, more comprehensive landslide inventories, and spatially and temporally consistent rainfall information, particularly antecedent and event-based rainfall characteristics, as well as by exploring advanced deep learning approaches for LSP.

Fourth, although the non-landslide sampling strategy was carefully designed to reduce spatial contamination and sampling bias, the definition and selection of non-landslide locations remains an inherent source of uncertainty in landslide susceptibility modelling (Gu et al., 2024). Areas where no landslide was identified in the available inventory cannot necessarily be regarded as confirmed stable locations, and their selection may influence model performance and susceptibility patterns. In this study, spatial block validation and environmental similarity analysis were additionally applied to reduce potential spatial dependence and assess sample representativeness. Nevertheless, some uncertainty associated with landslide inventory completeness and non-landslide sample selection cannot be completely excluded. Future studies using larger, more comprehensive inventories, independently verified stable locations, and more extensive spatial cross-validation (Saha et al., 2021), could further reduce this uncertainty and provide a stronger assessment of model generalisation.

The proposed framework may also be transferable to other regions where landslides are influenced by similar terrain and environmental conditions, particularly steep slopes, vegetation characteristics, and surface erosion processes. However, direct transfer of the susceptibility model should be approached with caution, as geological, climatic, rainfall, and land-use conditions may differ substantially among regions. Applying the framework to other mountainous areas would therefore require locally representative landslide inventories, appropriate conditioning factors, and independent spatial validation to assess and improve its transferability.

6. Conclusions

This study developed a GIS-remote sensing and ML framework for LSA in Central Vietnam, with spatial block-based validation used to provide a more spatially independent evaluation of model performance. The results demonstrate the effectiveness of ML models, particularly the XGB, in capturing complex and potentially nonlinear relationships between environmental conditioning factors and landslide occurrence. By integrating SHAP analysis, the study further moves beyond susceptibility prediction to provide an interpretable understanding of the factors contributing to model predictions. A key scientific contribution of this study is the identification of slope, NDVI, and the LS factor as important contributors to landslide susceptibility, while also demonstrating that their effects are not necessarily uniform across their observed ranges. In particular, the SHAP analysis highlights the importance of relatively steep slopes and low vegetation conditions, whereas the response of the LS factor is more complex and non-monotonic. This combination of predictive modelling and explainable AI provides additional insight into the spatial controls of landslide susceptibility and improves the interpretability of ML-based susceptibility mapping. Nevertheless, the results are subject to uncertainties arising from point-based representation of the landslide inventory, temporal mismatches between landslide events and dynamic predictors, and the exclusion of rainfall due to data limitations. Future research should develop time-stamped, polygon-based landslide inventories and integrate temporally matched, higher-resolution geological, environmental, and rainfall datasets to better capture the spatial and temporal variability of landslide processes. Further validation across different regions and the exploration of advanced spatiotemporal or deep-learning approaches could improve the robustness and transferability of the proposed framework.

Acknowledgments

This research was financially supported by University of Sciences, Hue University, through a Hue University-level research project (Grant No. DHH2025-01-224).

Appendix

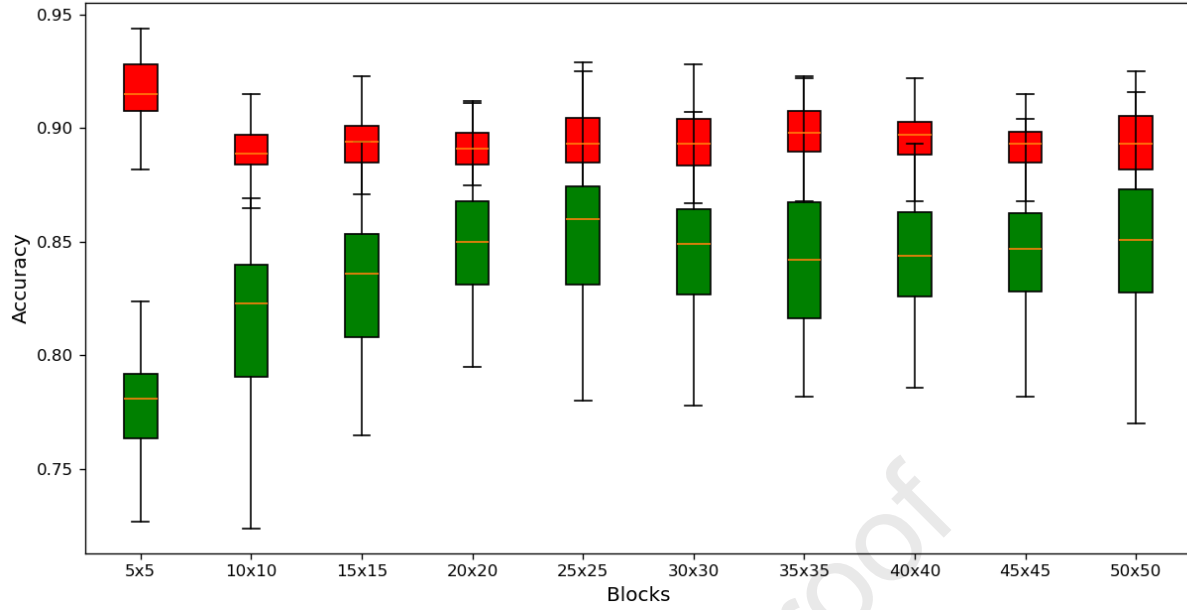


Figure S1. Model performance sensitivity to spatial block sizes and random realizations. Box plots show the accuracy distributions for training (red, 2 folds) and validation (green, 1 fold) sets across different block sizes

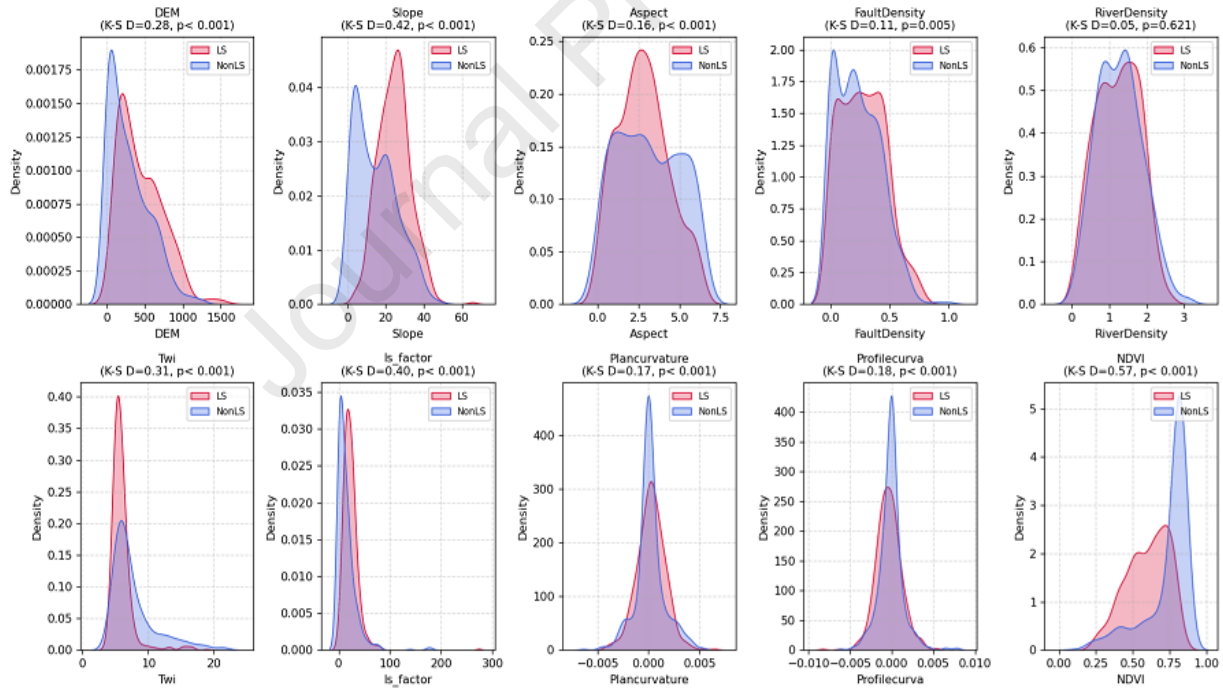


Figure S2. Density distributions and Kolmogorov-Smirnov (K-S) test results for key environmental predictors across landslide (LS) and non-landslide (NonLS) locations

Table S1. Pairwise Wilcoxon signed-rank test results based on predicted probability matrices

Model comparison	Test Statistic (Z)	p-value	Significance (p<0.05)
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XGB vs. RF	2.698	0.007	Yes (Statistically Significant)
XGB vs. LR	2.894	0.004	Yes (Statistically Significant)
RF vs. LR	2.119	0.034	Yes (Statistically Significant)

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Research Article

Interpretable Machine Learning for Regional-Scale Landslide Susceptibility Modeling in Central Vietnam

**Quang-Viet Nguyen¹, Viet-Huong Do Thi¹, Hong-Tinh Nguyen Thi³,
Thanh-Hoan Nguyen², Duy-Phien Tran^{2*}**

¹ Faculty of Geography and Geology, University of Sciences, Hue University, 77 Nguyen Hue, Hue City, Vietnam; nqviet@hueuni.edu.vn (Q.-V.N).

¹ Faculty of Geography and Geology, University of Sciences, Hue University, 77 Nguyen Hue, Hue City, Vietnam; dtvhuong@hueuni.edu.vn (V.-H.D.T).

² Institute of Earth Sciences, Vietnam Academy of Science and Technology, 18 Hoang Quoc Viet, Nghia Do, Hanoi, Vietnam; phienrs@ies.vast.vn (D.-P.T).

² Institute of Earth Sciences, Vietnam Academy of Science and Technology, 18 Hoang Quoc Viet, Nghia Do, Hanoi, Vietnam; nthoan@ies.vast.vn (T.-H.N).

³ Faculty of Environmental and Natural Sciences, Duy Tan University, Danang, Vietnam; nguyenthongtinh@dtu.edu.vn (H.-T.T.N)

* Author of correspondence: Duy-Phien Tran; email: phienrs@ies.vast.vn

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