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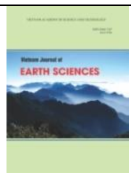

Landslide susceptibility in Phuoc Son, Quang Nam: A deep learning approach

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ABSTRACT

Advanced machine learning and deep Learning modeling applications for landslide susceptibility mapping are becoming increasingly popular. This study applied a deep learning model (DL) with a multilayer neural network to landslide research in the Phuoc Son district, Quang Nam province. Two methods for selecting conditioning factors, Correlation Attribute and OneR, were used to choose 12 condition parameters for landslides (Slope, Relief, Elevation, Distance to road, Rainfall, Land use, Weathering crust, Geology, Aspect, Soil, Distance to fault, and Curvature). Comparing the predicted results with two standard models, Naïve Bayes (NB) and Support Vector Machine (SVM), showed that the DL model has higher and better prediction performance. Accordingly, the prediction performance of the DL model on the training dataset was ACC = 92.12%, AUC = 0.970, and on the validation dataset was ACC = 87.52, AUC = 0.944. The LSM developed based on the DL model indicates that areas with high landslide susceptibility are primarily concentrated in the southern part of the study area. These findings could be highly beneficial for urban planning management, risk management, and efforts to prevent and mitigate the damage caused by landslides in Phuoc Son.

Keywords: Phuoc Son, Quang Nam, deep learning, LSM, machine learning.

1. Introduction

Landslides are recognized as one of the most impactful natural hazards affecting people and societies. (Alcántara-Ayala, 2002; Froude and Petley, 2018; Novellino et al., 2024). Over the past 20 years, research on landslide evaluation has experienced significant growth, employing various methods. (Carrión-Mero et al., 2021). From a spatial research perspective, landslide study methods can be categorized into two main groups: (1) methods for assessing specific landslide mass and (2) for mapping. In group (1), commonly used methods include determining slope stability factors, monitoring displacement in boreholes, measuring displacement using surveying techniques,

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field assessments, and mapping landslide structures. (Pham Van et al., 2023; Soga et al., 2016). In group (2), some standard methods include creating landslide maps from field surveys combined with satellite imagery and GIS analysis; developing susceptibility and risk maps using weighted analysis models (AHP), machine learning models, and artificial intelligence; and analyzing ground deformation from SAR imagery for early landslide warning systems (Novellino et al., 2024). Landslides are complex processes influenced by various factors; thus, the choice of research methods should be tailored to the specific characteristics of the study area (He et al., 2024).

Recent advances in machine learning have proven to be important in generating landslide susceptibility maps, with commonly used models including Random Forest (RF), Artificial Neural Network (ANN), Support Vector Machines (Badola and Parkash, 2024; Sharma, Saharia and Ramana, 2024), and Naïve Bayes (Madhu et al., 2024). Numerous studies have demonstrated that machine learning and DL models outperform previous methods (Chen et al., 2024; Kshetrimayum, H and Goyal; Sharma, Saharia and Ramana, 2024). As a subfield of machine learning, Deep Learning focuses on developing and applying deep neural networks (DNN). These models can learn and extract complex features from input data to perform classification, prediction, and recognition (LeCun, Bengio and Hinton, 2015). Experimenting with and adjusting the parameters of machine learning and DL models can enhance landslide prediction performance for specific research areas (Dao et al., 2020). Several notable examples highlight the superiority of DL in LSM research and development. For instance, Azarafza et al. (2021) developed a deep convolutional neural network (CNN-DNN) model for LSM generation in Isfahan Province, Iran (Azarafza et al., 2021). This study compared the performance of the CNN-DNN model with six typical machine learning models, including support vector machine (SVM), logistic regression (LR), Gaussian naïve Bayes (GNB), multilayer perceptron (MLP), Bernoulli Naïve Bayes (BNB), and decision tree (DT) (Azarafza et al., 2021). The results showed that the CNN-DNN model achieved the optimal performance with AUC = 90.9%, IR = 84.8%, MSE = 0.17, RMSE = 0.4, and MAPE = 0.42 (Azarafza et al., 2021). In a broader example, Yang et al. (2024) analyzed 77 papers related to the application of DL in landslide research from 2015 to 2022, based on the Web of Science (WoS) database (Yang et al., 2024). The study revealed that DL is increasingly utilized in research, and DL models outperform traditional machine learning models, particularly with the highly flexible U-Net architecture) (Yang et al., 2024). The paper also highlighted DL's limitations, such as data collection challenges and the predominance of labeled data for supervised classification tasks (Yang et al., 2024).

The previously mentioned examples demonstrate the strength of DL as a model for predicting and generating landslide susceptibility maps. However, DL also has limitations regarding data collection levels, labeled data structure, and the architecture of DL models, leading to varying performance across different DL models (Yang et al., 2024). Consequently, the predictive capabilities of each DL model differ depending on the specific research area. Given the limited research on DL for LSM development in Vietnam, this study focuses on developing a DL model based on a deep neural network (DNN) with hyperparameters optimized specifically for LSM generation in Phuoc Son. Phuoc Son District is one of the areas most affected by landslides in Quang Nam Province (Fig. 2). According to Quang Nam Provincial People's Committee statistics, natural disasters caused economic losses of up to 1.016 trillion VND in the first eight months of 2022 [http://www.quangnam.gov.vn]. Therefore, creating an LSM for Phuoc Son provides a crucial reference tool for policymakers. This study presents the results of applying the DL model and compares them with two popular models (SVM, and NB) for landslide susceptibility mapping in Phuoc Son, Quang Nam. The results show that the DL model demonstrates the highest performance and prediction accuracy. The LSM in Phuoc Son serves as a valuable tool for managers in disaster risk management caused by landslides, as well as for effective urban planning and land use in the area.

2. Study area

Phuoc Son is a mountainous district in the west of Quang Nam province with a geographical boundary of 15°11'N-15°35'N in latitude and 107°38'E-108°02'E in longitude (Fig. 1). A complex geological structure, a thick weathered crust, and destructive solid faults characterize the study area. Most of the site is mountainous terrain with steep slopes, a high drainage density, and a complex cleavage.

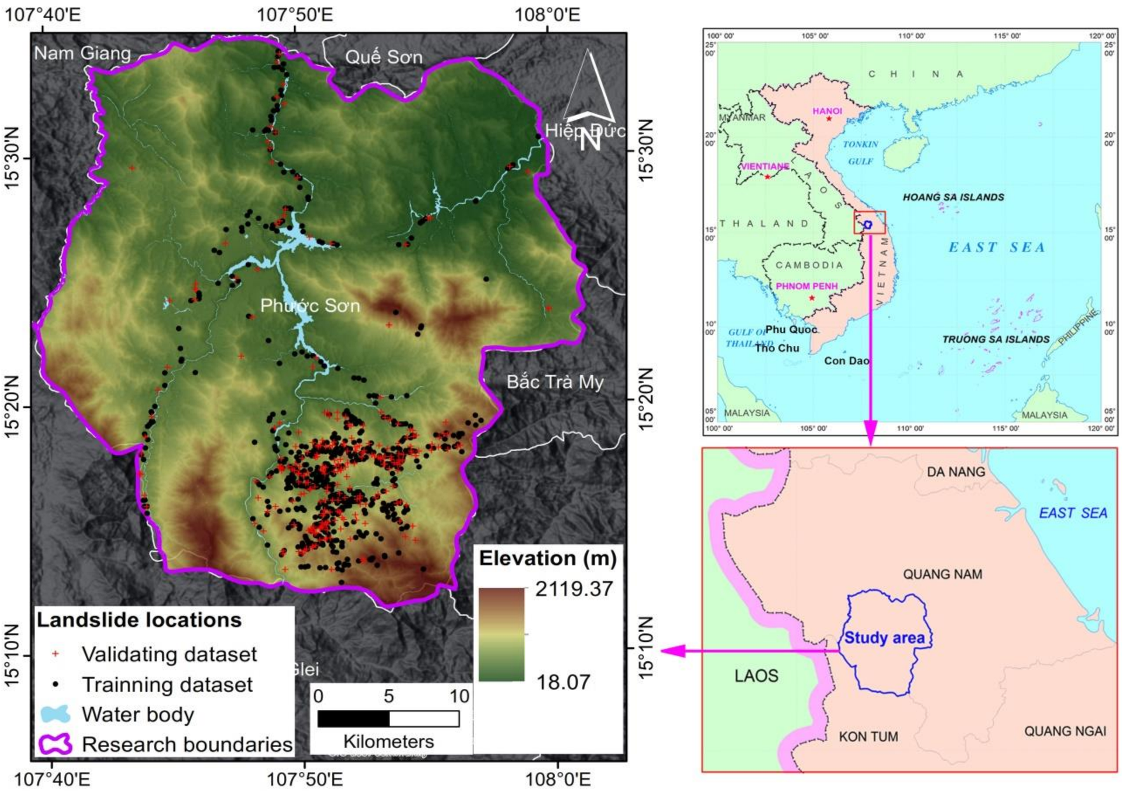

Figure 1. Study area in Phuoc Son district, Quang Nam province

The average annual rainfall was 3680 mm in 2019-2021 at Phuoc Son station and concentrated from September to November every year. Typical economic activities such as terraced hydropower system development, including Đăk Mi 2 (147 MW), Đăk Mi 3 (63 MW), Đăk Mi 4A (148 MW), Đăk Mi 4B (42 MW), and Đăk Mi 4C (18 MW) along with the construction of road systems, infrastructure, and residential planning caused drastic changes in land use and forest cover in recent years. Notably, the terraced hydropower system construction had remarkably re duced the area of watershed forests. Besides, the way of backward rudimentary farming and slash-and-burn cultivation by ethnic minorities have also been impacting vegetation cover. Natural conditions and human activities mentioned above have increased the number of natural disasters (Thuc, Thanh Thuy and Huong, 2023).

Landslides are a typical natural disaster that occurs widely during the annual rainy and cyclone seasons, causing noteworthy damage to humans and the economy in the research area.

The study site has recorded many serious landslide events causing terrific damage in the 2020 rainy season. For example, landslides combined with debris flow with material amounts estimated at more than 50.000 m^3 occurred in 1 and 3 villages, Phuoc Loc commune, Phuoc Son district at 2:00 p.m on October 28, 2020, burying 32 houses and killing 13 people. Another landslide occurred on the same day in Phuoc Loc commune, missing two local officials while mobilizing people to prevent Typhoon Molave. Figure 2 shows some landslide events during the field investigation.

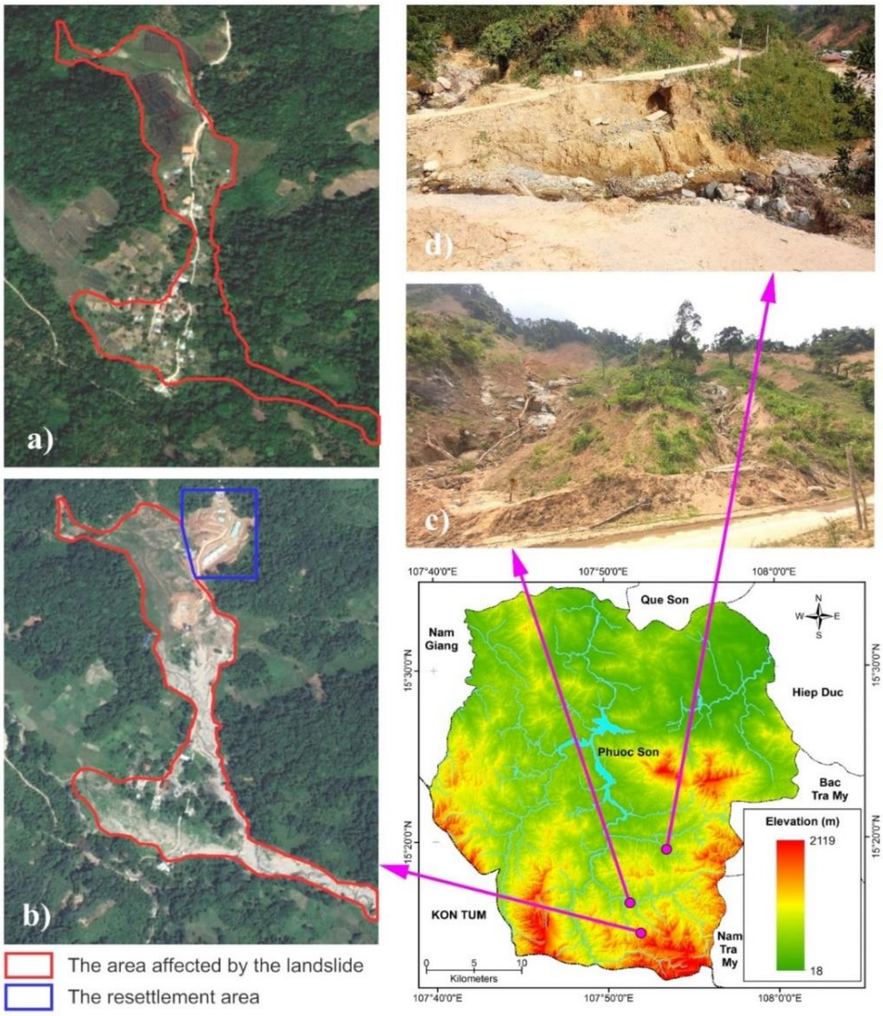

Figure 2. Some typical landslides in the study area are illustrated in the picture: a) Before the landslide occurred (March 2019); and b) After the landslide occurred (October 2021) at Village 3, Phuoc Loc commune buried 32 houses, 13 people died; c) The landslide caused loss of 2 people; and d) The landslide at Village 3, Phuoc Kim commune causing road damage. The Image was taken in April 2021 (source: Tran Anh Tuan)

3. Methods and data used

3.1. Methods

The research methodology in this paper can be summarized in five steps (Fig. 3):

Step 1: Data Collection: Gather data on the current status of landslides (locations of landslide and non-landslide points); collect data on the conditions influencing landslides, including 12 parameters (Fig. 3).

Step 2: Data Processing: Normalize the data to a unified map framework with the same coordinate system and spatial resolution, and divide the data into a training set (70%) and a validation set (30%). ArcMap v10.8 is the software used.

Step 3: Modeling: Employ the DL model, NB, and SVM for modeling. Weka 3.8.6 is the software used for modeling, with the deep learning model utilizing the WekaDeepLearning4j toolkit (Lang et al., 2019). The detailed hyperparameters of the models are presented in Table 1.

Step 4: Evaluation of the models: Assess the results using classification evaluation parameters such as ROC curve, Accuracy (ACC), Area Under the Curve (AUC), Sensitivity (SST), Specificity (SPF), Positive Predictive Value (PPV), Negative Predictive Value (NPV), Root Mean Square Error (RMSE), and Kappa Index.

Step 5: Result Selection: Select the optimal LSM based on the evaluation from Step 4.

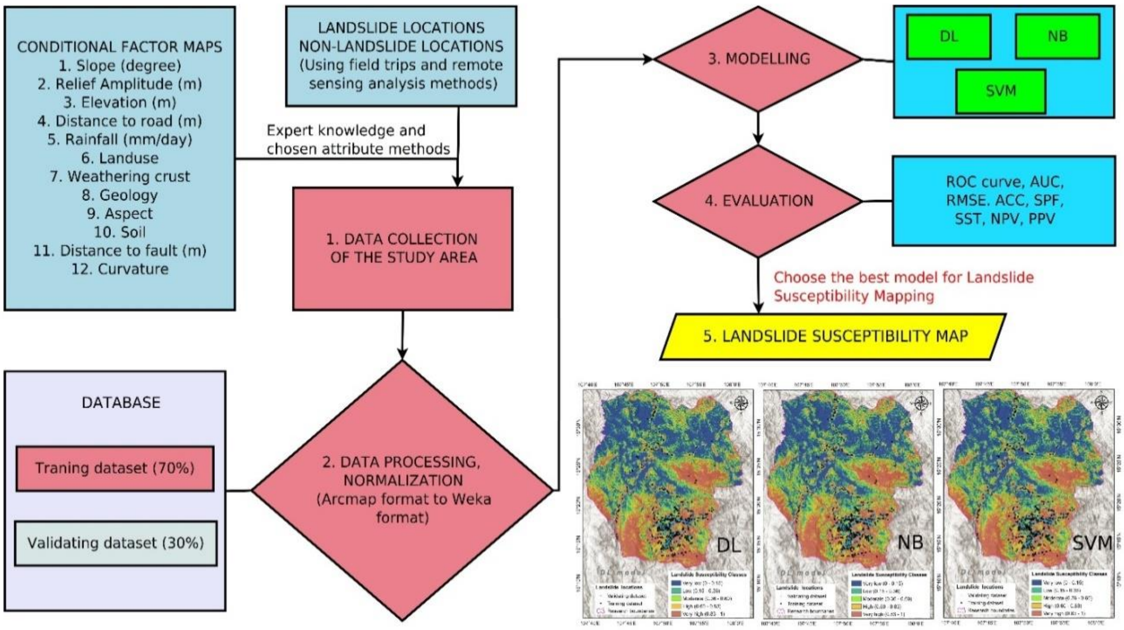

Figure 3. A flow chart illustrating landslide susceptibility mapping in Phuoc Son, Quang Nam

Table 1. The hyperparameters of models used in landslide prediction in this research

No	Hyperparameters	Models		
		DL	NB	SVM
1	Activation Function	Softmax	-	-
2	Loss Function	MCXENT	-	-
3	Optimization Algorithm	Stochastic gradient descent	-	-
4	Weight initialization method	XAVIER	-	-
5	Bias initialization	0	-	-
6	gradient normalization method	none	-	-
7	gradient normalization threshold	1.0	-	-
8	Attribute normalization	standardize training data	-	-
9	Batch Size	100	100	100
10	Number of Decimal Places	2	2	-
11	Seed	1	-	1
12	Coefficient	-	-	0
13	Cost	-	-	1
14	Degree	-	-	3
15	EPS	-	-	0.001
16	Gamma	-	-	0
17	Loss	-	-	0.1
18	The value of nu	-	-	0.5

3.1.1. Deep Learning (DL)

DL is a subfield of Machine Learning that focuses on constructing and training deep learning models to perform automatic learning tasks from data (Janiesch, Zschech and Heinrich, 2021). Typically consisting of multiple layers of computational units (neurons), deep learning models are designed to automatically learn complex features from data (Janiesch, Zschech and Heinrich, 2021; LeCun, Bengio and Hinton, 2015). This is one of the most crucial areas in modern artificial intelligence, leading to significant application advancements (LeCun, Bengio and Hinton, 2015). Below is a presentation of the basic information about DL:

Deep Learning basics

Neural Networks: DL models primarily rely on artificial neural networks. A neural network consists of interconnected layers of neurons (computational units). Neurons in one layer receive inputs from the neurons in the previous layer and pass outputs to neurons in the subsequent layer (Janiesch, Zschech and Heinrich, 2021).

Layers: A neural network typically comprises multiple layers:

(1) Input Layer: From the data, input is received.

(2) Hidden Layers: Learn features from the data and process information. These layers can be numerous and deep, forming the deep learning model.

(3) Output Layer: Provides the model's prediction or final output.

Activation Functions: By introducing non-linearity into the model, activation functions (such as ReLU, Sigmoid, and Tanh) enable the network to learn more complex relationships between inputs and outputs

Training: Optimization algorithms, such as Gradient Descent, are used to train a DL model to adjust the network's weights to predict the model increasingly accurately with the training data.

Transfer Learning: This method involves using a model that has been pre-trained on big data to address new problems with less data. It is a common approach to leverage pre-trained models like Residual Network (ResNet) for new tasks (Ma et al., 2024).

Major DL Architectures

Convolutional Neural Networks (CNNs): Mainly used in image recognition and signal processing, It can learn spatial data such as images (Song et al., 2019).

Recurrent Neural Networks (RNNs): A design specifically tailored to handle sequential data, like text or time series, is employed. Popular variants of RNNs include Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU), which enhance the ability to learn from long-term sequential data (Yu et al., 2019).

Generative Adversarial Networks (GANs): The system comprises two adversarial neural networks, namely the Generator and Discriminator, which generate new data resembling the training data used in producing images, videos, and audio (Pradhyumna and Mohana, 2022).

Transformer Networks: Widely used in natural language analysis, such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) models. Transformer models rely on the attention mechanism to process the relationships between words in a sentence (Denis and Antonio, 2022).

Figure 4 presents an illustration of the operation of Deep Learning in landslide prediction used in this research:

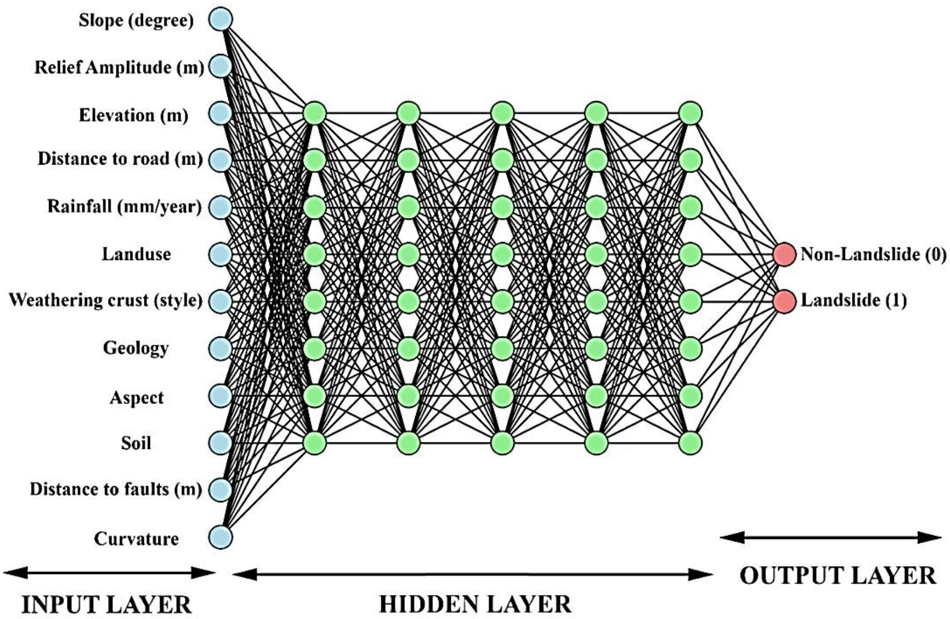

Figure 4. The illustration of the neural network in deep Learning for landslide prediction in Phuoc Son, Quang Nam

3.1.2. Naïve Bayes (NB)

The NB model is a classification approach grounded in probability theory, leveraging Bayes' theorem to assume independence among features. It is among the simplest and most effective classification algorithms, mainly when the number of features is large, or the data exhibits evident classification characteristics (Wickramasinghe and Kalutarage, 2021).

Fundamental Principles

Bayes' Theorem: This is the theoretical foundation of the NB model. Bayes' theorem describes an event's probability, utilizing prior knowledge of related conditions. This is the formula:

$$P(D|X) = \frac{P(Y|D).P(D)}{P(Y)} \qquad (1)$$

where: $P(D|X)$ represents the posterior probability of class D given the data Y.

$P(Y|D)$ presents the likelihood of data Y given class D. $P(D)$ denotes the prior probability of class D. $P(Y)$ denotes the prior probability of class Y.

NB operates under the assumption that attributes are independent of each other within each class. While this assumption may not always hold in practice, it significantly reduces the model's complexity and often yields good results.

Types of NB Model

Gaussian NB is used when the features are continuous and assumed to follow a Gaussian (or normal) distribution (Ontivero-Ortega et al., 2017).

Bernoulli NB: Suitable for binary features (0 or 1) and is often used in text classification problems where words are treated as binary features (present or absent) (Artur, 2021).

Multinomial NB: Appropriate for features that follow a multinomial distribution, commonly used in text classification tasks and applications where features are counts or proportions (Jiang et al., 2016).

3.1.3. Support Vector Machine (SVM)

The SVM is a powerful and versatile classification method in artificial intelligence (Badola and Parkash, 2024). Although SVM was developed for classification and regression problems, it is most renowned for its performance in binary classification tasks. The SVM model seeks to optimize a hyperplane that separates data into distinct classes. SVM is among the most commonly used models in landslide prediction (Badola and Parkash, 2024; Sharma, Saharia and Ramana, 2024). Below is some basic information about SVM:

Fundamental Principles

Hyperplane: A hyperplane in a multidimensional space is a flat surface capable of dividing data into classes. SVM aims to identify the optimal hyperplane that maximizes the margin between the classes, i.e., the maximum distance achievable between the hyperplane and the classes.

Support Vectors: Support vectors, which are the data points nearest to the separating hyperplane, establish the hyperplane's position and orientation. Support vectors are the most critical data points in the SVM model.

Margin: The distance between the hyperplane and the support vectors of the two classes defines the margin. SVM optimizes the hyperplane to maximize this margin, thereby improving the model's generalization ability.

Types of SVM

Binary SVM: Designed to classify data into two classes. The SVM determines the optimal hyperplane that maximizes the margin, effectively separating the data of the two classes (Ke et al., 2024).

Multiclass SVM: An extension of binary SVM to handle multiclass classification problems. The two main approaches are "One-vs-One" (OvO) and "One-vs-Rest" (OvR) (Nie, Hao and Wang, 2024).

Kernel SVM: Applied in cases where the data cannot be separated linearly. It applies a kernel function to transform the data into a higher dimension where the classes can be linearly separated (Liu et al., 2024). Common kernel functions include :

- Linear Kernel: Utilized when the data allows for separation by a linear hyperplane.
- Polynomial Kernel: Transforms the data into a higher dimension using different degrees of polynomials.
- Gaussian Kernel: Uses a Gaussian function to handle data that a linear hyperplane cannot separate.

3.1.4. Accuracy Assessment Methods

Classification metrics are employed to evaluate models used to predict landslide susceptibility, including AUC, PPV, NPV, SST, SPF, ACC, Kappa, and RMSE (Tharwat, 2021). Expressed as percentages, the metrics PPV, NPV, SST, SPF, and ACC are computed from four parameters of the confusion matrix, which are True Positive (TP) and False Positive (FP), representing the number of correctly and incorrectly predicted landslides, and True Negative (TN) and False Negative (FN), representing the number of correctly and incorrectly predicted non-landslides (Le Minh et al., 2023). Improved model performance is indicated by higher PPV, NPV, SST, SPF, and ACC values and lower RMSE values (Tharwat, 2021). AUC, a key parameter for assessing classification model performance, is derived from the ROC curve, which combines SST and SPF values across different threshold levels of the predicted values. AUC values span from 0 to 1, where values approaching 1 indicate superior model performance (Tharwat, 2021). The Kappa Index is a statistical measure to assess the agreement between predicted and actual values (Banerjee et al., 1999). The range of Kappa values is from 0 to 1, with values closer to 1 indicating greater prediction accuracy. A model is deemed highly reliable if Kappa exceeds 0.6. The formulas for calculating the above metrics are as follows:

$$PPV = \frac{TP}{TP+FP} \quad (2)$$

$$NPV = \frac{TN}{TN+FN} \quad (3)$$

$$SST = \frac{TP}{TP+FN} \quad (4)$$

$$SPF = \frac{TN}{TN+FP} \quad (5)$$

$$ACC = \frac{TP+TN}{TN+FN+TP+FP} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum(x_i-\hat{x}_i)^2}{M-K}} \quad (7)$$

where x_i and $\hat{x}_i$ are the actual and predicted values of landslide susceptibility. M is the number of estimated parameters, including the constant. K is the number of landslide points.

$$Kappa = \frac{P_0 - P_n}{1 - P_n} \quad (8)$$

Where P_0 represents the recorded consensus among raters and P_m represents the likelihood of agreement occurring by chance.

3.1.5. Ranking and Selection Methods for Conditional Factors

Correlation Attribute Evaluation (CAE)

The CAE coefficient measures the linear correlation between two continuous variables. It quantifies their linear relationship's strength and direction (Nettleton, 2014). The range of the coefficient extends from -1 to 1. This study calculates the correlation coefficient between the conditional factor and the occurrence of landslides or non-landslides in the training dataset (Lucchese, de Oliveira and Pedrollo, 2020). The correlation value is adjusted to a scale from 0 to 1. A coefficient close to 1 signifies a strong positive correlation, indicating that the conditional factor significantly affects the likelihood of landslides. Conversely, a coefficient near 0 reflects a weak linear relationship between the influencing parameter and landslides. The formula for computing the correlation coefficient is provided below (Nettleton, 2014):

$$R = \left|\frac{\sum(x_m-\bar{x})(y_m-\bar{y})}{\sum(x_n-\bar{x})^2 \sum(y_n-\bar{y})^2}\right| \quad (8)$$

where x_m and y_n represent the values of the two variables and $\bar{x}$ and y are their respective means.

OneR Method

OneR (OneRule) is a straightforward and comprehensible machine learning method for data classification. This method falls under the category of classification algorithms and can be considered a technique for ranking and reducing the number of features (Witten and Frank, 2005).

Principle of Operation

Rule Construction: OneR generates a classification rule for each attribute in the dataset. The process involves:

- Creating Rules: Formulating a classification rule for each value of the attribute.
- Calculating Accuracy: Evaluating the accuracy of each rule based on its ability to classify data samples correctly.
- Selecting the Best Rule: After constructing rules for all attributes, OneR selects the attribute with the rule that has the highest accuracy and uses it as the final classification model.

Detailed Process

Accuracy Calculation: For each attribute, OneR constructs a classification table for each attribute value.

Rule Evaluation: To evaluate the rule, OneR calculates accuracy, defined as the ratio of correctly classified samples to the total number of samples.

Selecting Best Rule: The accuracy of the rules from all attributes is compared. The attribute with the rule having the highest accuracy is chosen for classification.

3.2. Data used

Landslide Inventory

The landslide inventory map includes 858 landslide occurrences collected from primary sources, including field investigation (275), and visual analysis from Google Earth satellite images (583). The landslide inventory dataset was randomly divided into two parts for landslide susceptibility analysis: 70% (601 landslides) was used for modeling, and 30% (257 landslides) was used for validating (Fig. 1).

Conditional Parameters

In this study, 12 condition parameters are used to model landslide susceptibility maps in Phuoc Son, Quang Nam. The data sources for these 12 parameters are presented in Fig. 5 and Table 2. The selection of condition parameters is based on a synthesis of expert methods, consideration of the specific conditions of the study area, and the comparison of statistical evaluation methods (Correlation Attribute Evaluation, OneR). Specifically, the elevation (m) represents the "terrain energy," where higher elevations are more conducive to landslides (Dao et al., 2020). The weathering crust (style) indicates the degree of weathering of the bedrock, which relates to the stability of the soil and rock (Regmi et al., 2013). The geology includes formations, each representing a combination of soil and rock with common characteristics regarding age, formation conditions, and lithological features (Ohlmacher, 2000). The soil reflects different soil types, each having varying impacts on landslide susceptibility (Ho et al., 2012). Land use represents the vegetative cover on soil and rock; generally, areas with dense forest cover have a lower probability of landslides (Glade, 2003; Nguyen Huu et al., 2024). Relief amplitude denotes the vertical distance between the highest and lowest points within a specified area (Fang-fang et al., 2008). It measures the terrain's elevation variability and describes the ruggedness or unevenness of the landscape. In geographical and geological contexts, relief amplitude helps understand the morphological characteristics of an area and is often used in terrain analysis, erosion studies, and landslide susceptibility assessments (Fang-fang et al., 2008). Rainfall (mm/year) is an indicator of landslide-triggering factors (Doan et al., 2024). When rainfall occurs, water infiltrates the soil and rock, saturating them and weakening their original cohesion (Finlay, Fell and Maguire, 1997). Higher precipitation levels increase the likelihood of landslides. In this study, rainfall is averaged annually. Distance to road (m) infrastructure reflects human impact on landslides (Moayedi et al., 2019). Human activities such as road construction through hilly areas disrupt the original slope stability. Generally, the closer the proximity to roads, the higher the landslide risk. Distance to faults (m) indicates the degree of rock and soil destruction due to tectonic factors; proximity to faults results in more significant destruction and higher susceptibility to landslides (Moayedi et al., 2019). The slope (degree) gradient is a crucial factor for landslide occurrence, with gradients between 5° and 45° being more prone to landslides (Dao et al., 2020). The aspect that characterizes windward slopes is indirectly related to the moisture absorption capacity of soil and rock from humid wind currents (Gorokhovich and Vustianiuk, 2021). The Curvature describes the surface features of the terrain, where flat terrain with curvature values between -0.05 and 0.05 is less prone to landslides, while concave (<-0.05) and convex (>0.05) terrains are more conducive to landslides (Bien et al., 2022).

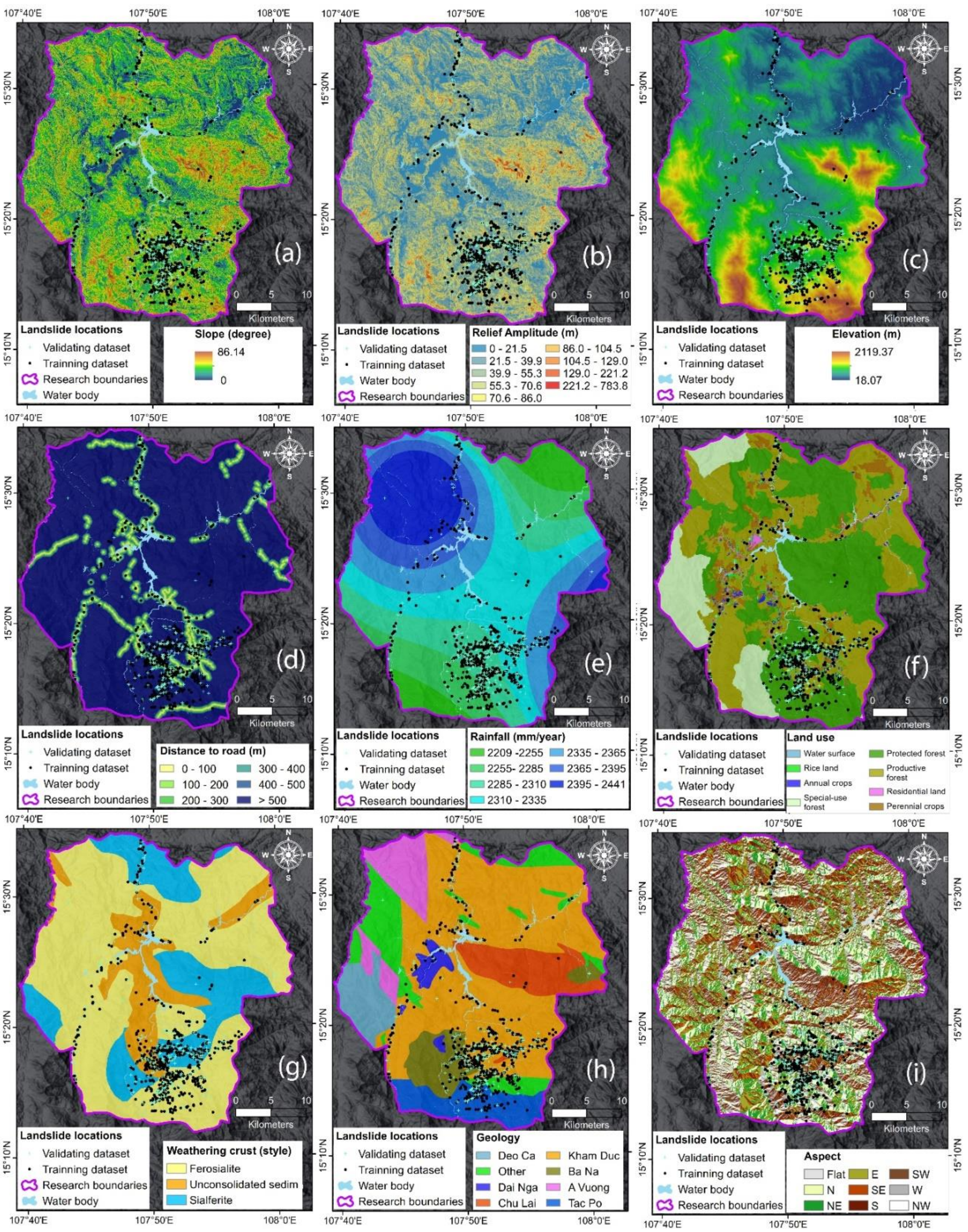

Figure 5. Condition maps for landslide susceptibility in the study area: (a) Slope (degree), (b) Relief Amplitude (m), (c) Elevation (m), (d) road distance (m), (e) Rainfall (mm/year), (f) Land use, (g) Weathering crust (style), (h) Geology, (i) Aspect, (j) Soil, (k) Distance to faults, and (l) Curvature

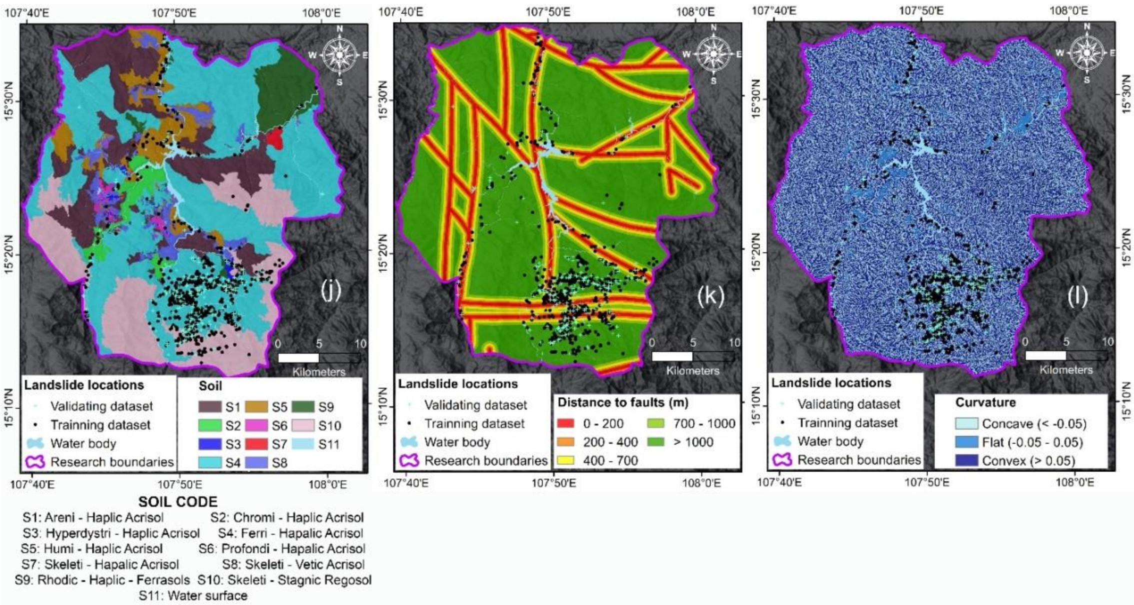

Figure 5. Cont.

Table 2. Data sources for condition parameters related to landslides in Phuoc Son, Quang Nam

No	Factor	Scale / Resolution	Source
1	Slope (degree)	20 m/pixel	Generate from DEM
2	Relief Amplitude (m)	20 m/pixel	Generate from DEM
3	Elevation (m)	20 m/pixel	Generate from DEM
4	Distance to road (m)	20 m/pixel	Generate from National topographic maps
5	Rainfall (mm/year)	20 m/pixel	Vietnam Meteorological and Hydrological Administration
6	Landuse	20 m/pixel	Esri Inc
7	Weathering crust (style)	1: 100,000	(Hung, 2012)
8	Geology	1: 50,000	The Vietnam Geological Department
9	Aspect	20 m/pixel	Generate from DEM
10	Soil	1: 50,000	Soil and Fertilizers Institute
11	Distance to fault (m)	20 m/pixel	Generate from Geological map
12	Curvature	20 m/pixel	Generate from DEM

4. Results

4.1. Ranking of Attribute Results

The ranking results of the conditioning parameters reflect the significance of each factor concerning landslides in the study area. Both the CAE and OneR evaluation methods consistently rank the three most influential factors in order of importance, which are slope (degree), relief amplitude (m), and elevation (m) (Table 3). A divergence begins at the fourth rank, where CAE ranks distance to road (m), while OneR ranks soil. The fifth and sixth ranks are consistently assigned to rainfall (mm/year) and Land use by both methods. The Weathering crust (style) is ranked seventh by CAE but only eleventh by OneR. Geology is consistently ranked eighth by both methods. Aspect is ranked ninth by CAE and tenth by OneR. Distance to faults (m) is ranked eleventh by CAE and is considered the least influential by OneR. Curvature is ranked last (twelfth) by CAE but seventh by OneR. Overall, the assessment of the importance of conditioning factors for landslides using different methods reveals that these factors each have a certain degree of influence on the causes of landslides (Table 3). The most critical factors include Slope (degree), Relief Amplitude (m), Elevation (m), Rainfall (mm/year), Land use, Soil, and Distance to road (m).

Table 3. Ranking of Conditional parameters

Ranked	Methods			
	Correlation Attribute Evaluation		OneR	
	Average merit	Factor	Average merit	Factor
1	0.676	Slope (degree)	80.634	Slope (degree)
2	0.629	Relief Amplitude (m)	80.291	Relief Amplitude (m)
3	0.527	Elevation (m)	78.577	Elevation (m)
4	0.339	Distance to road (m)	73.179	Soil
5	0.303	Rainfall (mm/year)	72.493	Rainfall (mm/year)
6	0.279	Landuse	66.923	Landuse
7	0.176	Weathering crust (style)	66.152	Curvature
8	0.129	Geology	63.410	Geology
9	0.090	Aspect	62.639	Distance to road (m)
10	0.048	Soil	57.069	Aspect
11	0.043	Distance to fault (m)	55.955	Weathering crust (style)
12	0.012	Curvature	49.700	Distance to fault (m)

4.2. Performance evaluation of the models

The models' reliability and accuracy were assessed based on key parameters, including AUC, PPV (%), NPV (%), SST (%), SPF (%), ACC (%), Kappa, and RMSE. The numerical evaluation results are presented in Fig. 6 and Table 4. Among the models, the Deep Learning (DL) model demonstrated the best performance on the validation set, achieving an AUC of 0.944, a PPV of 83.98%, an NPV of 91.05%, an SST of 90.34%, an SPF of 85.09%, an ACC of 87.52%, a Kappa of 0.75, and an RMSE of 0.30 (Fig. 6b, Table 4).

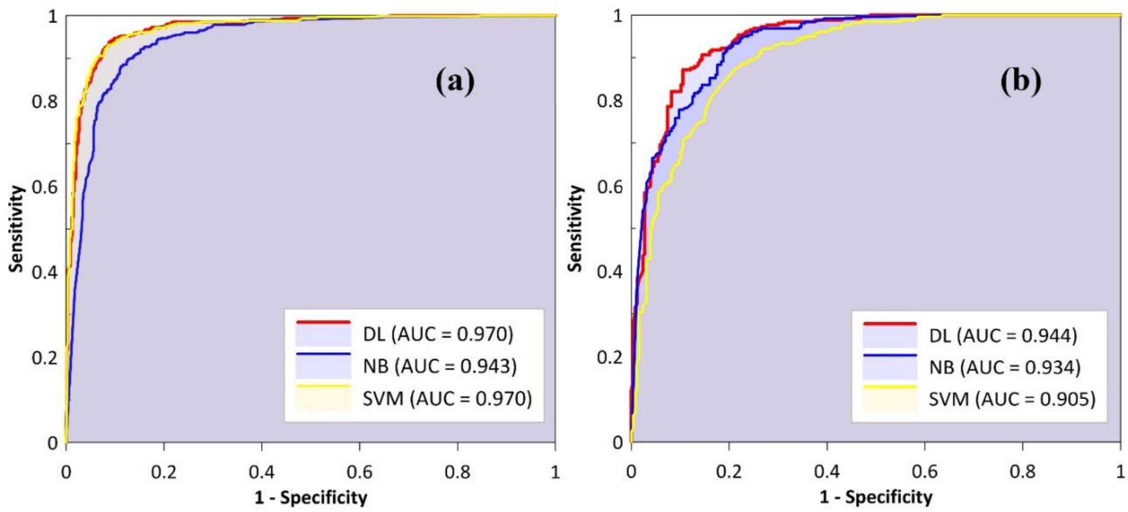

Figure 6. The performance of models used the ROC curve and AUC methods, (a) training dataset, and (b) validation dataset

Table 4. Performance evaluation results of the models

No	Parameters	Models					
		Training dataset			Validating dataset		
		DL	NB	SVM	DL	NB	SVM
1	TP	519	487	519	215	208	151
2	TN	556	545	557	234	234	249
3	FP	48	80	48	41	48	105
4	FN	44	55	43	23	23	8
5	PPV (%)	91.53	85.89	91.53	83.98	81.25	58.98
6	NPV (%)	92.67	90.83	92.83	91.05	91.05	96.89
7	SST (%)	92.18	89.85	92.35	90.34	90.04	94.97
8	SPF (%)	92.05	87.20	92.07	85.09	82.98	70.34
9	ACC (%)	92.12	88.43	92.20	87.52	86.16	77.97
10	Kappa	0.84	0.77	0.84	0.75	0.72	0.56
11	RMSE	0.25	0.30	0.25	0.30	0.34	0.38

4.3. Landslide susceptibility mapping

The landslide susceptibility maps were generated using sample datasets covering the entire study area. A total of three landslide susceptibility maps were created, corresponding to three models: DL, NB, and SVM (Fig. 7). The susceptibility classes for each map, determined using the natural break method, consist of five categories: very low, low, moderate, high, and very high (Fig. 7). According to the susceptibility classes, the DL model has the largest area in the very low class (31.13%), followed by the very high, low, high, and moderate classes with areas of 26.05%, 15.86%, 13.89%, and 13.07%, respectively (Fig. 7c, Table 5). The frequency of landslide and non-landslide occurrences was calculated as a percentage of susceptibility classes based on the validation dataset. The landslide susceptibility map generated using the DL model shows an increasing frequency across the classes, from very low to very high, with values of 0.06, 0.27, 0.45, 0.87, and 2.91, respectively. Conversely, the frequency of non-landslide occurrences increases from the very high to the very low classes, with values of 0.28, 0.48, 0.60, 0.69, and 2.16, respectively (Fig. 7c, Table 5). Similar results for the maps generated using the NB and SVM models are detailed in Table 5 and Figures 7a and 7b. The evaluation results indicate that the landslide susceptibility map generated using the DL model provides the most stable and optimal outcomes.

Table 5. Performance evaluation based on the frequency of landslide susceptibility map classes (*note: LS - Landslide; FR-Frequency ratio*)

Model	Class	Number of pixels	LS pixels	Non-LS pixels	% pixels	% LS	% Non-LS	FR LS	FR Non-LS
DL	Very low	900600	5	172	31.13	1.95	67.19	0.06	2.16
	Low	458916	11	28	15.86	4.28	10.94	0.27	0.69
	Moderate	378187	15	20	13.07	5.84	7.81	0.45	0.60
	High	401973	31	17	13.89	12.06	6.64	0.87	0.48
	Very high	753659	195	19	26.05	75.88	7.42	2.91	0.28
NB	Very low	889585	11	189	30.75	4.28	73.83	0.14	2.40
	Low	267661	8	14	9.25	3.11	5.47	0.34	0.59
	Moderate	229737	13	8	7.94	5.06	3.13	0.64	0.39
	High	290605	18	13	10.04	7.00	5.08	0.70	0.51
	Very high	1215747	207	32	42.02	80.54	12.50	1.92	0.30
SVM	Very low	243125	3	115	8.40	1.17	44.92	0.14	5.35
	Low	141816	1	22	4.90	0.39	8.59	0.08	1.75
	Moderate	444540	13	44	15.36	5.06	17.19	0.33	1.12
	High	1315811	73	53	45.48	28.40	20.70	0.62	0.46
	Very high	748043	167	22	25.85	64.98	8.59	2.51	0.33

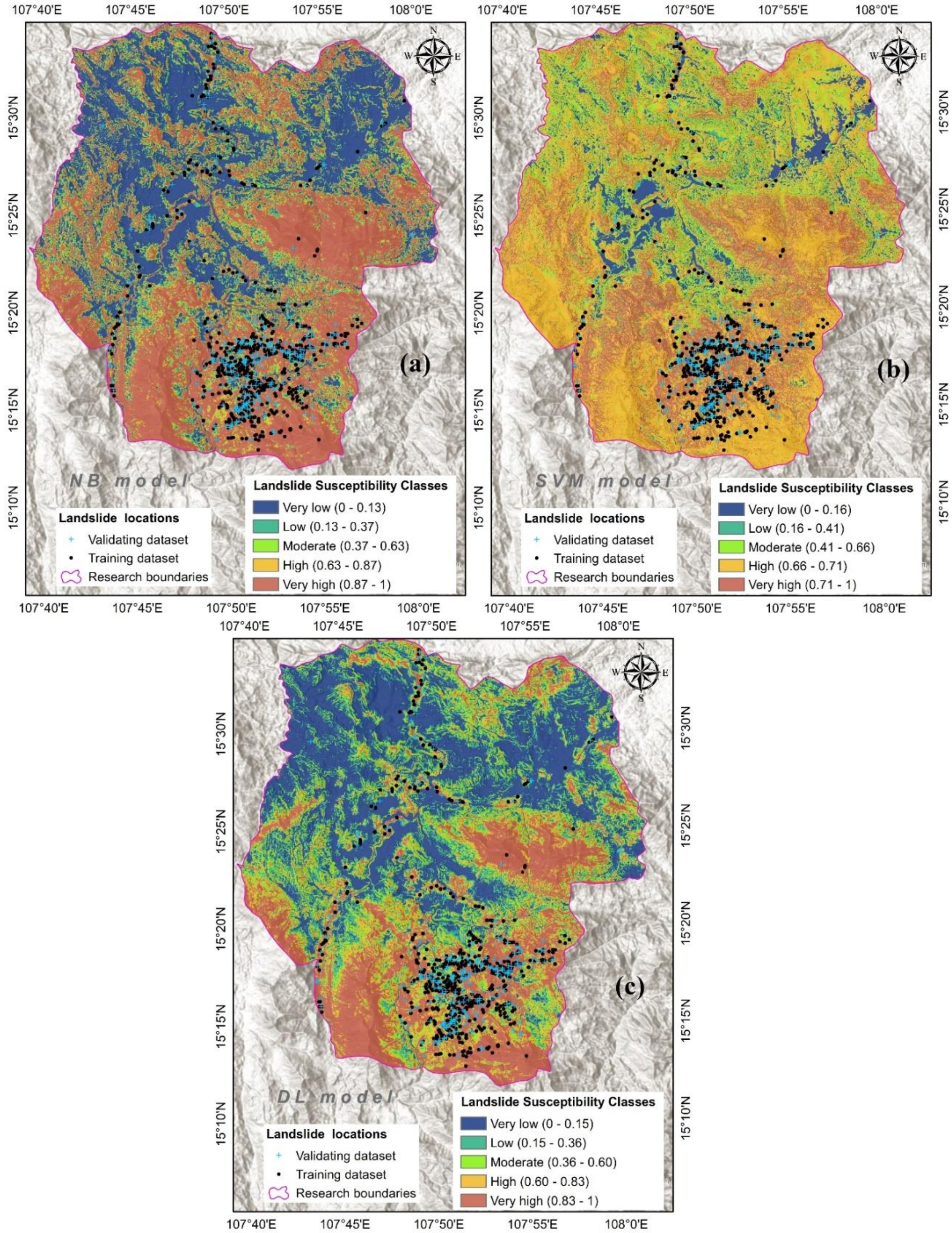

Figure 7. Landslide susceptibility maps in Phuoc Son, Quang Nam based on different machine learning models, a) Naïve Bayes Model, b) Support Vector Machine Model, c) Deep Learning Model

5. Discussions

The results presented in Section 4 demonstrate that the DL model outperforms the NB and SVM models in generating landslide susceptibility maps for Phuoc Son, Quang Nam. This finding is consistent with several studies (Dao et al., 2020; He et al., 2024), showing that Deep Learning is an effective model for predicting and generating landslide susceptibility maps. However, it is important to note that Deep Learning requires substantial data to achieve optimal performance (Janiesch, Zschech and Heinrich, 2021; Sharma, Saharia and Ramana, 2024). In landslide research, collecting large datasets is challenging due to the need to gather numerous parameters over extensive areas (Zhong et al., 2020). Therefore, the trend of using transfer learning techniques with Deep Learning models is necessary for the future to improve landslide prediction results in data-scarce regions and for larger study areas (Wang, Wang and Zhang, 2023). Additionally, utilizing high-resolution satellite imagery with wide coverage can provide a significant source of data for landslide research (Ma et al., 2024; Sharma, Saharia and Ramana, 2024; Zhong et al., 2020).

Moreover, the selection of influencing parameters impacts the model's outcomes. For instance, the parameter of slope aspect has been debated in the literature. Some studies suggest that aspect has little to no impact on landslides (Capitani, Ribolini and Bini, 2013). However, other studies in different regions indicate that aspect can influence landslides, particularly during severe storms (Gorokhovich and Vustianiuk, 2021). In this study, based on the attribute ranking results presented in Table 3, the aspect was ranked 9th out of 12 influencing parameters according to the CAE method and 10^{th} out of 12 according to the OneR method. Therefore, we chose to include the aspect as a conditioning factor for landslides in Phuoc Son, Quang Nam. However, depending on the specific conditions of each area, the aspect may or may not be selected as an influencing factor. Additionally, the selection of non-landslide sites and the ratio of landslide to non-landslide instances also affect the performance of machine learning and DL models (Shao et al., 2020; Yang et al., 2023). We believe that the use of weighted labeling techniques for landslide prediction is one of the approaches that future experiments should explore to enhance prediction performance.

Landslide prediction is a complex issue, particularly the challenge of accurately predicting the timing of landslides (Lombardo et al., 2020). Therefore, detailed spatial and temporal landslide data, along with the development of new techniques and methods, are essential for advancing landslide research. Deep Learning remains a promising model for the future due to its complex "thinking" capabilities (LeCun, Bengio and Hinton, 2015). We believe that experimenting with modifications and developments of Deep Learning parameters in the context of landslide prediction also helps improve prediction performance. This study successfully applied the Deep Learning model for the first time to generate landslide susceptibility maps in Phuoc Son, Quang Nam. The results from these maps will assist in urban planning, disaster prevention, and mitigation efforts against landslide-related damages in Phuoc Son. We recommend applying the DL model in other areas with similar conditions.

6. Conclusions

This study focuses on a comparative experiment of applying Deep Learning (DL) against two widely used models, Naïve Bayes (NB) and Support Vector Machine (SVM), in the development of landslide susceptibility maps in Phuoc Son, Quang Nam. The evaluation results indicate that the DL model demonstrates the highest and most optimal performance. The DL model is recommended for generating landslide susceptibility maps in other areas with similar conditions. Among the 12 conditioning parameters, each evaluation method reveals varying impacts of these conditions. The primary influencing factors include Slope (degree), Relief Amplitude (m), Elevation (m), rainfall (mm/year), Land Use, Soil, and Distance to Road (m).

The models identified that approximately 39.94% of the study area has the highest landslide susceptibility, primarily concentrated in the southern part of the region. The distribution of landslide susceptibility classes provides critical scientific information for government authorities in managing and planning future construction projects and implementing preventive measures to mitigate landslide risks. This study highlights the necessity of continued research to enhance landslide prediction performance further. Future landslide prediction models can be improved by developing and modifying Deep Learning model parameters, applying transfer learning techniques combined with high-resolution and large spatial coverage remote sensing data, and experimenting with selecting input parameters for Deep Learning models.

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