Landslide Susceptibility Mapping of Western Sarawak via Artificial Neural Network

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Abstract

Landslides are the third most frequent form of natural disaster in Malaysia, following floods and storms. It can cause significant damage to anything in its path, depending on the size and velocity of its debris. Due to the danger that it poses, determining the susceptibility of an area to landslides is a crucial step in risk mitigation. Landslide occurrences are dependent on the numerous environmental variables, which can provide information on the level of susceptibility of other locations with similar variables. To quantify the significance of each variable to landslide occurrence, a supervised Machine Learning model – an Artificial Neural Network was developed for this study. Furthermore, landslide occurrences have been associated with the disturbance of natural slopes to accommodate development, which was the main reason behind the selection of Western Sarawak as the area of interest in this study. The model was developed to understand and make landslide susceptibility predictions based on aspect, curvature, elevation, lithology type, rainfall intensity, slope angle, soil type, and TWI. Evaluating the area under the curve score and recall for the model revealed that, based on the available inputs, the model performed well with a score of 1 and 0.99, respectively.

Keywords: *Landslide, Machine Learning, Sarawak, Spatial data.*

1. Introduction

A landslide is a natural disaster in which slope-forming material detaches from the slope and moves downward under the influence of gravity. Depending on the scale and material, landslides can be very destructive [1]. In a tropical country such as Malaysia, landslide occurrences are mostly tied to the wet season, as it is triggered by heavy rainfall [2]. Most landslide cases in Malaysia are identified as shallow rotational landslides where the thick surface soils are easily displaced by heavy rainfall. In

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recent years, landslide occurrences have been observed to be on the rise, where the increase has been linked to numerous factors such as settlement expansions on susceptible grounds, and extreme weather conditions that have brought heavier rainfall and an increase in surface soil weathering rate [3]. With the severity of the impact that landslide has, and the increase in frequency, it is an utmost importance to determine which areas are the most susceptible, to ensure an effective mitigation plan is conducted.

Landslides are complex due to the variety of variables that can influence their occurrences. Moreover, each variable influences landslides at a different rate, making it difficult to hypothesize the relative weight of each variable's contribution. Thus, contemporary approaches in understanding the relationship between the landslide factors and their occurrence are done through a supervised Machine Learning (ML) based approach [4]. The application of ML models to determine the landslide variable weightages is based on Tobler's first law of geography, which, in the case of landslides, can be simplified as "if a location has experienced landslides in the past, other locations with similar conditions may also experience them in the future". Through ML, the significance of each variable is determined solely through the training data used to develop the model, and the accompanying hyperparameters of the model itself [5].

There are numerous ML algorithms suitable for the task. However, this study was conducted solely through Artificial Neural Network (ANN), which has been observed to have high predictive performance on relatively small datasets in previous studies [6]. Furthermore, it is available in the form of packages for numerous programming languages [7]. As for the study area, Western Sarawak was chosen due to the rapid expansion and development of the region, making the determination of high landslide susceptibility areas in the region crucial for a safe expansion.

2. Materials and Methods

2.1. Study area

Western Sarawak consists of several districts, which are Bau, Lundu, Kuching, Kota Samarahan, and Serian. Because past landslide data were unavailable for Lundu and Kota Samarahan, these districts were excluded. The remaining regions include Sarawak's most densely populated areas, home to about 38% of the state's population [9]. 47 past landslide points were identified based on the information provided by local authorities, which is visualised in Figure 1, with most of the points condensed in the highly elevated parts of the region, with the rest on moderate and lowly elevated areas. However, the clusters of landslide points were spread throughout the region, reducing the risk of predictive performance degradation due to spatial autocorrelation [8]. Furthermore, this study greatly aligns with Malaysia's National Slope Plan for 2025 – 2030, under the slope risk mapping section [9].

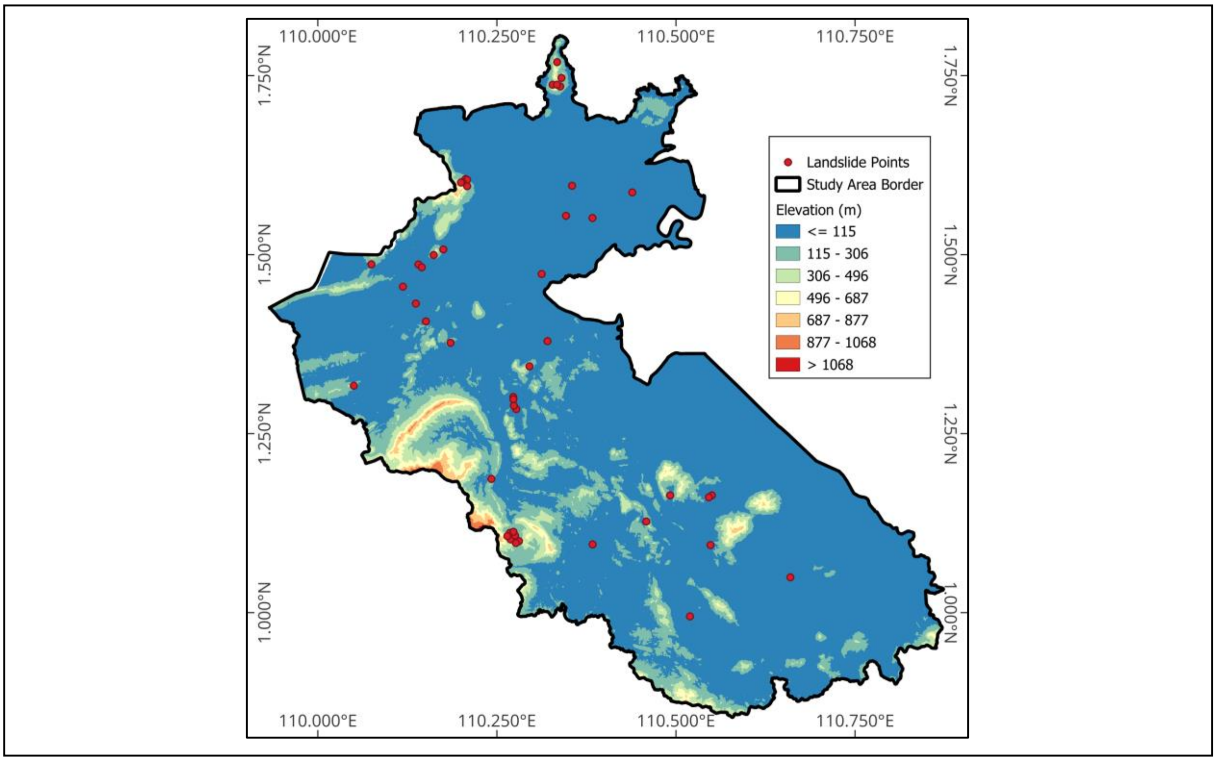


Figure 1. Study area in Western Sarawak with past landslide points

2.2. Data extraction

Data is the foundation of any ML model, where in a supervised model, the required data are in the form of features – landslide factors, and targets – landslide or non-landslide condition. The primary sets of data used in the model development consist of training data and testing data. In this study, the training and testing data were derived from a single main dataset and randomly split at a ratio of 80:20. This ratio was adopted as a rule of thumb for dataset partitioning, particularly in cases where the data pool is relatively small [10].

Aspect – maximum slope face orientation, curvature – profile curvature, slope angle, and Topographical Wetness Index (TWI) were topographically based features derived from the digital elevation model raster file provided by the National Space Agency [11]. Landslide susceptibility has been observed to increase as the terrain ruggedness increases in higher elevations and steeper slopes [12]. Aspect influences localized weather conditions due to differences in sunlight exposure, which in turn contributes to varying levels of landslide susceptibility depending on slope orientation [13]. Curvature, on the other hand, determines the reaction of the terrain towards surface runoff, where, depending on the type of surface, curvature with the most ponding tendency is more likely to experience landslides [14]. TWI is a measure of wetness, where areas with higher TWI values are more susceptible to landslides, resulting from the increased moisture content [15].

Lithology and soil type represent the geological characteristics of the study area, with each dataset provided by the local authorities and the Food and Agriculture Organization, respectively [16]. Softer geological features are more prone to landslides in comparison to harder ones. As Western Sarawak is located in the tropics and outside the ring of fire, rainfall is the primary landslide triggering factor in the region [17]. This was observed through the average rainfall intensity (mm/pentad) raster provided by the Climate Hazard group during the wet season, where a majority of the landslide points were located in the region with moderate to high rainfall intensity [18].

As the landslide points were provided by the local authorities, the non-landslide points were generated through a combination of the grid unit and slope unit methods. These points were randomly generated non-landslide points based on the maximum distance from the landslide points and the maximum slope angle [19]. In this study, the maximum distance to the landslide points was 100 m, with a maximum slope angle of 5° - based on the Landslide Hazard and Risk Assessment threshold developed by Fiener (1999) [20]. To prepare the main dataset, the targets were used to sample the value of each feature using the raster sampling tool in Quantum Geographical Information System (QGIS) version 3.4 [21].

2.3. Multicollinearity assessment

Multicollinearity is a condition where two features behave almost similarly, providing the same information to the ML model, causing degradation in the model's predictive performance by providing redundant data [22]. In this study, multicollinearity was evaluated through Microsoft's Excel data analysis plugin correlation function to find the correlation in the form of a matrix as a method to determine the direction of the correlation, and Variance Inflation Factor (VIF) through R's "car" package for a more thorough review through Equation (1) [23], [24]. In Microsoft Excel's correlation analysis, the highly correlated features have a minimum correlation coefficient of 0.8, while VIF provides more information on which feature should be removed where a VIF coefficient of less than 1, 1 to 5, 5 to 10, and more than 10 indicates features with low, moderate, high, and very high multicollinearity, respectively. If no significant multicollinearity amongst the input variables was observed, the primary dataset was split into training data and testing data, whereas if high multicollinearity amongst a pair of input variables was observed, one of the input variables was to be removed.

$$VIF_i = \frac{1}{1 + R_i^2} \tag{1}$$

Where, VIF_i is the VIF value of a feature, and R_i^2 is the unadjusted coefficient of determination for regressing the i^{th} features on the remaining ones.

2.4. Data preprocessing

Data preprocessing was conducted after the multicollinearity assessment. It is an integral part of ML development, where raw values are pre-processed into analysis analysis-ready format that provides better information to the ML model as compared to unprocessed values. In this study, there were two types of features, processed through different approaches, which were numerical and categorical features.

Numerical features are best represented numerically, where the values of the features increase linearly [25]. Numerical features consisted of elevation, rainfall intensity, slope angle, and TWI as seen in Figure 2(a) through Figure 2(d), which were processed through min-max scaling as seen in Equation (2) [8]. Min-max scaling normalises the variable values to be in the range of 0 to 1, to avoid any imbalance towards variables with large values, such as elevation to other numerical features in this study.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

Where x' is the processed value for the numerical feature, x is the raw feature value, x_{min} is the minimum feature value, and x_{max} is the max feature value

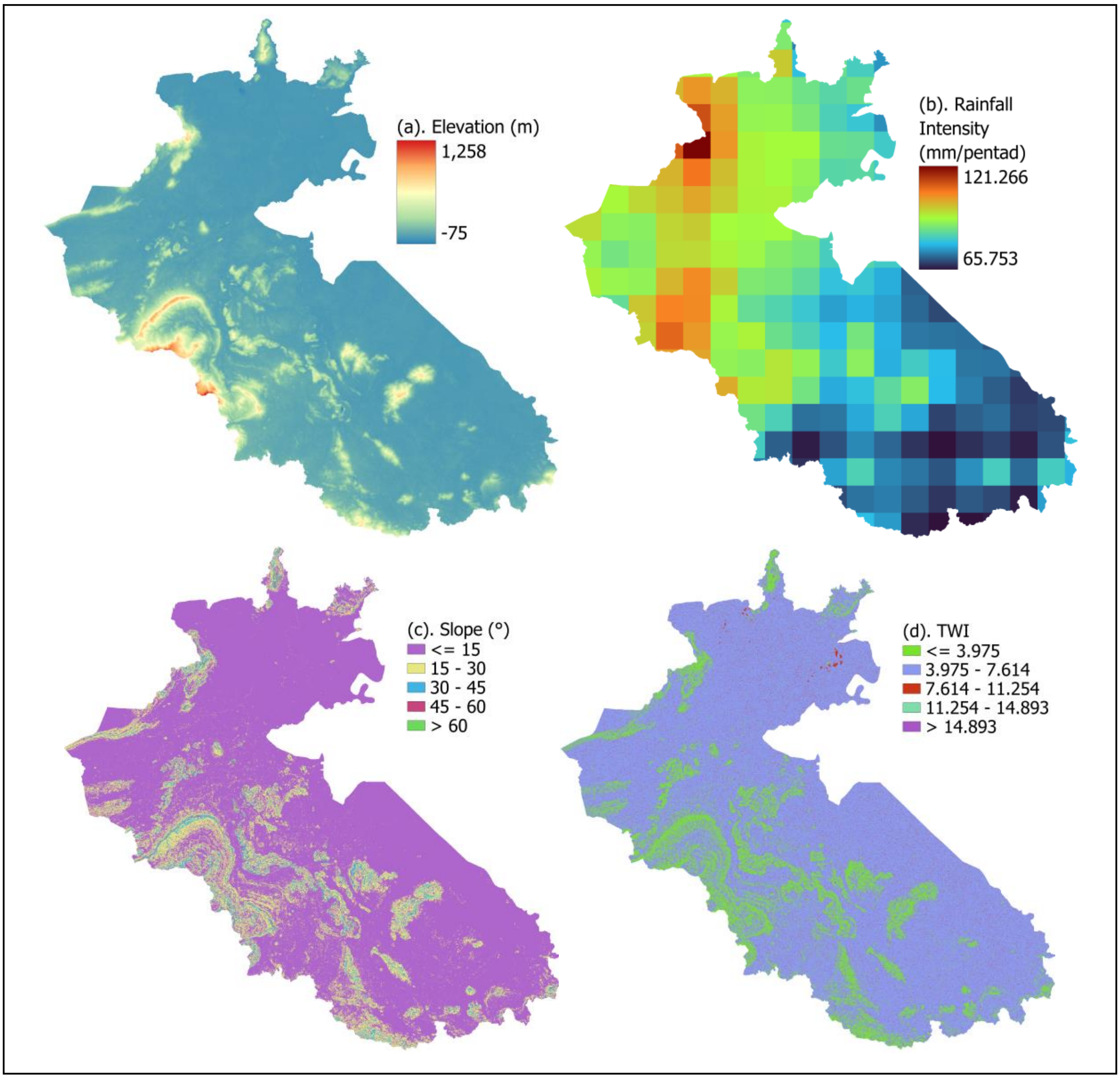


Figure 2. Numerical features distribution of (a) Elevation, (b) Rainfall intensity, (c) Slope angle, and (d) TWI

Categorical features are not suitable for numerical representation, as the values are not on a linear scale. Instead, it is more appropriate to represent these features based on distinct groups. The categorical features were classified into groups using one-hot encoding, which created a matrix where if the value of the feature belongs to a class, it was marked as 1, and 0 for otherwise [26]. In this study, the categorical features were aspect, curvature, lithology type and soil type as seen in Figure 3(a) through Figure 3(d), respectively.

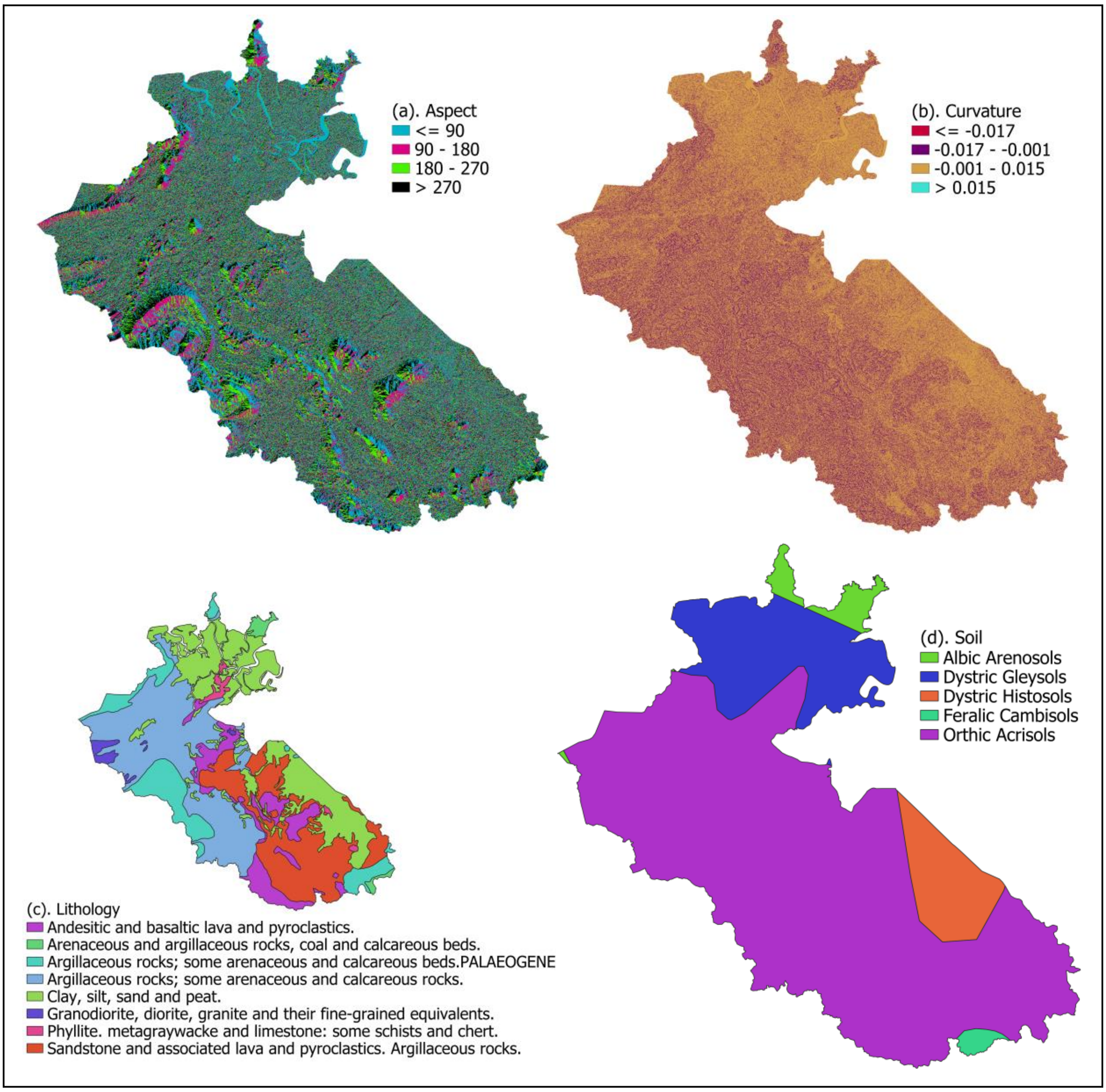


Figure 3. Categorical features distribution of (a) Aspect, (b) Curvature, (c) Lithology type, and (d) Soil type

2.5. ANN model development and evaluation

The ANN model in this study was developed in R using RStudio with the “neuralnet” package, which allows several hyperparameters to be tuned [27]. The hyperparameters were tuned to obtain the best achievable results while limiting the risk of overfitting or underfitting. In this study, the hyperparameters tuned were the number of neurons in the hidden layer (n), the learning rate, and the maximum weight adjustment steps (stepmax). As a preliminary check before verifying the model performance with the testing data, the provided Root Mean Squared Error (RMSE) as seen in Equation (3) that came with the package was used. RMSE measures the potential error in a similar unit as the output for the prediction [28].

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{3}$$

Where $\hat{y}_i$ is the predicted value, y_i is the actual value, and n is the number of observations.

The activation function, which determined the scale of the final output, was kept as "sigmoid" to give the model an understanding of the conditions of moderate susceptibility based on the binary targets [29]. The landslide susceptibility scale was decided based on the activation function as seen in Equation (4), which regresses the output to be from 0 to 1. The learning algorithm was kept uniform as backpropagation, as it has shown favourable results in capturing the relationship between the features and targets for similar prior studies with small datasets [30].

$$Output = \frac{1}{1 + e^{-(b + \sum w * x)}} \tag{4}$$

Where b is the bias assigned by the ANN model, x is the processed variable values, and w is the weightage of each x assigned by the ANN model.

As the number of landslide cases was the minority in comparison to non-landslides in the target, recall was used to evaluate the ANN model's predictive performance on the positive instances [31]. Recall, as seen in Equation (5) is an evaluation metric which determines the true positive rate based on the ratio of correctly predicted minority instances. Hence, it is more sensitive to the landslide case prediction. However, as an overall evaluation of the model performance, Area Under the Curve (AUC) evaluations were also conducted by finding the area under the curve for recall vs false positive rate [32].

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

Where TP is true positive instances, and FN is false negative instances.

2.6. Landslide susceptibility map plotting

To plot the LSM, the features raster files must first be converted into a numerical data frame through the "terra" package in R [33]. Then, the same data pre-processing steps that were applied to the training data and testing data were also applied to the converted raster files' numerical data frame. Then, and only then, can the LSM be deployed to make predictions on the landslide susceptibility. To plot the LSM itself, only the coordinates and the predicted landslide susceptibility score were kept to create the landslide susceptibility map raster file.

3. Results and discussion

3.1. Multicollinearity evaluation on primary dataset

High multicollinearity in a correlation analysis through Microsoft's Excel data analysis plugin is determined by a correlation coefficient of more than 0.8 [8]. The results of the correlation analysis can be seen in Table 1, represented through a correlation matrix. The highest positive correlation coefficient in this study was between slope angle and elevation, with 0.707. On the other end, the highest negative correlation was between slope angle and TWI, with a coefficient of -0.452.

Table 1. Multicollinearity matrix of primary data

	aspect	*curvature*	*elevation*	*lithology*	*rain*	*slope*	*soil*	*TWI*	*Target*
aspect	1								
curvature	0.012	1							
elevation	-0.020	0.035	1						
lithology	0.031	0.021	0.197	1					
rain	0.006	0.073	0.099	-0.064	1				
slope	0.052	-0.016	0.707	0.106	0.142	1			
soil	-0.034	-0.012	0.029	-0.289	0.054	-0.019	1		
TWI	-0.135	-0.126	-0.295	-0.077	-0.063	-0.452	-0.001	1	

High +ve correlation

High -ve correlation

Note: lithology is lithology type, rain is rainfall intensity, slope is slope angle, soil is soil type

Reviewing multicollinearity further through VIF, as seen in Table 2, revealed that there were no significant issues regarding multicollinearity amongst the features, with the highest VIF being 2.377 for slope angle, followed by 2.118, with the rest being less than 2. Only moderate levels of multicollinearity existed as the VIFs were less than 5 [30]. Thus, based on the multicollinearity assessment through Microsoft's Excel data analysis extension function for correlation, and VIF analysis through the "car" package in R, no significant multicollinearity existed, and no features were removed from the developmental dataset.

Table 2: VIF values for each feature

Variables	Aspect	Curvature	Elevation	Lithology	Rain	Slope	Soil	TWI
VIF	1.026	1.035	2.118	1.158	1.035	2.377	1.109	1.310

Note: lithology is lithology type, rain is rainfall intensity, slope is slope angle, soil is soil type

3.2. ANN model configuration and performance evaluation

The final configuration of the ANN model hyperparameters was highly dependent on the resulting RMSE. The hyperparameter configuration which resulted in the smallest RMSE was deemed favourable as it indicates a smaller error during the training phase [34]. The model's hidden layer was kept singular as the first trial shows that the RMSE was already at a favourable score of 0.0116, as seen in Table 2. On the other hand, the number of neurons in the hidden layer, the learning rate, and Stepmax were adjusted to obtain the lowest RMSE. Five trials were conducted, with the final trial yielding the lowest possible RMSE of 0.0057 based on the training data, indicating that when the model is developed with the hyperparameter of said configuration, the predictions may deviate from the actual values by 0.57% [35].

Table 3. ANN model hyperparameter and resulting RMSE

Trial	Hyperparameter			
	n	Learning rate	Stepmax	RMSE
1	8	0.01	1.00E+10	0.0116
2	8	0.01	1.00E+10	0.0093
3	6	0.001	1.00E+10	0.0279
4	18	0.001	1.00E+08	0.0285
5	8	0.001	1.00E+08	0.0057

Post training, the model performance was evaluated through AUC, and recall for both the training data – to determine how well the model had learned - and the testing data – to quantify the model's performance based on unseen data. Evaluating the model performance based on the training data revealed that all targets were accurately classified, as seen in Figure 4(a), which solidifies the RMSE of the training phase. The results showed an AUC and a recall of 1 for the respective metrics. As for its performance in predicting landslide susceptibility based on the testing data, the model scored an AUC of 0.99 and a recall of 1, as seen in Figure 4(b). Here, a single non-landslide point was wrongfully predicted as a landslide. Thus, it was concluded that the model training was a success, with great performance on unseen data, and suitable for landslide susceptibility mapping of Western Sarawak.

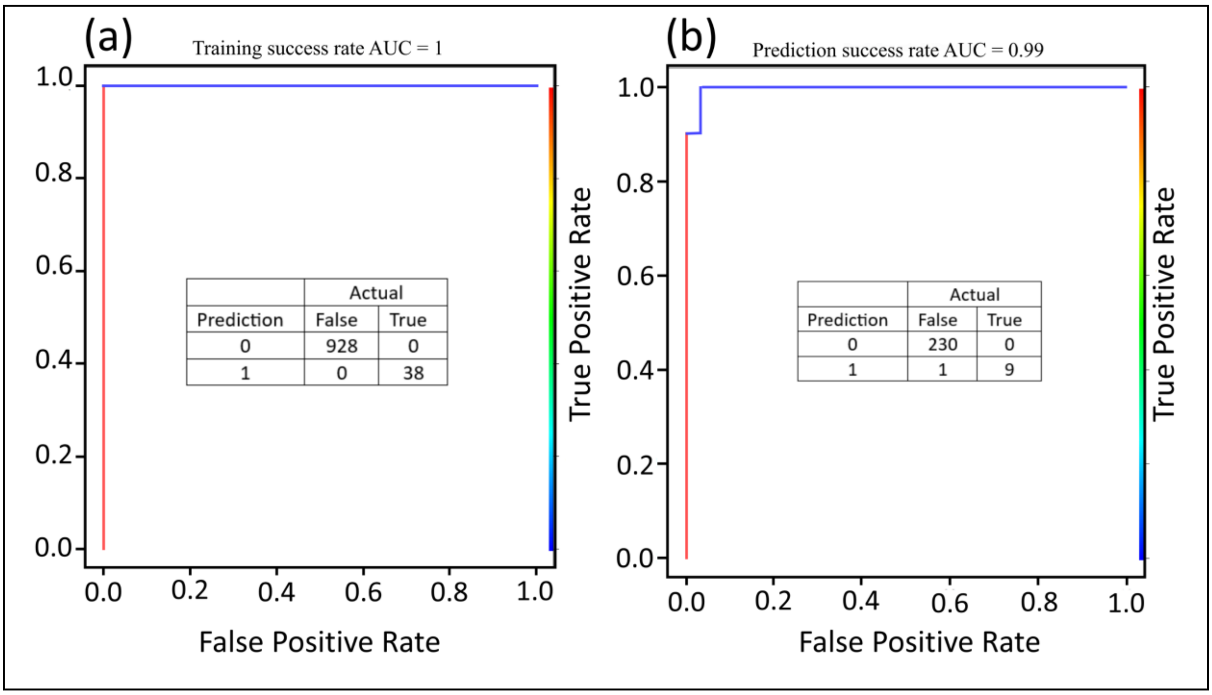
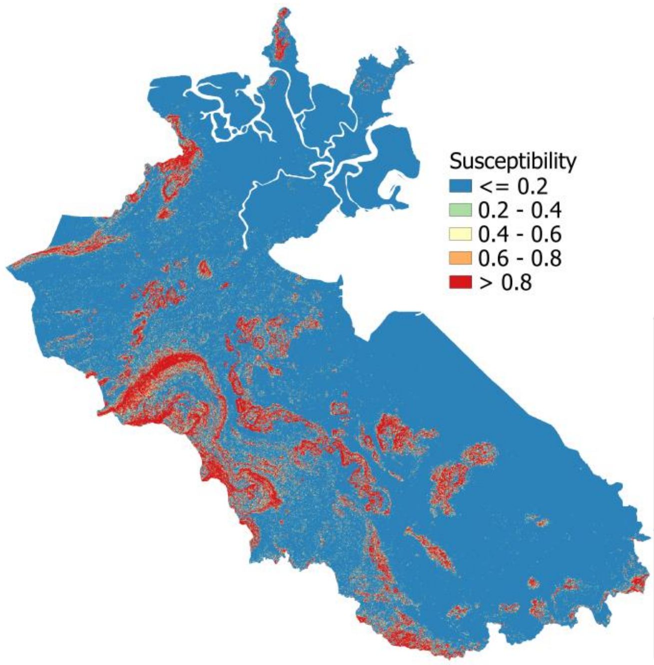


Figure 4. ANN model evaluation in (a) Training phase, and (b) Testing phase

3.3. Landslide susceptibility map of Western Sarawak

The LSM of the study area was plotted by deploying the ML model on pre-processed raster files data frame of aspect, curvature, elevation, lithology type, rainfall intensity, slope angle, soil and TWI to obtain the landslide susceptibility index. The result can be seen in Figure 5: the susceptibility index ranges from 0 to 1, as a result of the sigmoidal activation function scaling. 0 signifies an area with very low landslide risk, whereas 1 indicates that the area has a very high landslide risk. Since the LSM is in the form of a raster file, each pixel can provide information on the area of interest in the region when loaded in a geospatial platform.

Through a pixel counter developed in python, it was revealed that as of the study, 82.51% of Western Sarawak's surface area is located in the very low landslide susceptibility region with susceptibility levels being a maximum of 0.2, 3.48% is in the low susceptibility region, 2.42% is in the moderate susceptibility region, 2.54% is in the high susceptibility region, and 9.06% is in the very high susceptibility region with susceptibility index of more than 0.8. This information is subject to changes, as this study did not incorporate the element of time to predict future levels of landslide susceptibility for Western Sarawak. Nevertheless, this project has greatly aligned with the nation's slope master plan for landslide susceptibility mapping.



Susceptibility Levels	Area Coverage (%)
0.0 to 0.2	82.51
0.2 to 0.4	3.48
0.4 to 0.6	2.42
0.6 to 0.8	2.54
0.8 to 1.0	9.06

Figure 5. LSM of Western Sarawak

4. Conclusion

As landslides are a major natural disaster in Malaysia, it is essential to study the susceptibility of areas of interest to reduce the risk of exposure. In this study, an ANN model was developed to determine the landslide susceptibility of Western Sarawak through the features of aspect, curvature, elevation, lithology type, rainfall intensity, slope angle, soil type, and TWI. The targets used in this study were actual past landslide points in the region recorded by local authorities, whereas the non-landslide points were generated through a combination of slope unit and grid unit methods. The performance of the ANN model was evaluated through AUC and recall, where, based on the testing data, the model has achieved an AUC of 0.99 with a recall of 1, with only a single non-landslide instance predicted as a landslide. Although verifiably accurate based on the data used in this study, the LSM that has been predicted and plotted by the ANN model should only serve as a preliminary view for the landslide susceptibility of the region due to the small data pool. Future research should look into methods that can create the "dummy" landslide points that can be used as a guideline in areas which has no prior recorded landslide cases.

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Conflict of Interests

The authors have declared no conflict of interest in this study.

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