Landslide Susceptibility Mapping of BLISTT (Baguio, La Trinidad, Itogon, Sablan, Tuba, Tublay), Benguet Using GIS-Based Binary Logistic Regression Modeling

Laurelly Joyce A. Aporto[1], Hainer P. Albuero[1], Madonna C. Daquigan[1], Dymphna Nolasco-Javier[1]

[1]College of Science, University of the Philippines Baguio, Baguio City, Benguet, Philippines – (laaporto1, hpalbuero, mcdaquigan, dnjavier)@up.edu.ph

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Abstract

The BLISTT (Baguio City, La Trinidad, Itogon, Sablan, Tuba, Tublay) area in Benguet, Philippines is highly prone to landslides driven by various factors including mountainous terrain, intense rainfall, seismic activity, and human-induced activities. Thus, there is a need to implement reliable landslide monitoring and mitigation approaches in the region. This study uses geographic information systems (GIS) together with remote sensing-based binary logistic regression to analyze and map landslide susceptibility across the BLISTT area. Twelve conditioning factors were considered, namely slope angle, slope aspect, profile curvature, lithology, soil type, land cover, Topographic Wetness Index (TWI), Normalized Difference Vegetation Index (NDVI), distances to roads, rivers, and lineaments, and precipitation. The resulting model demonstrates strong performance, obtaining an ROC value of 0.809. Analysis of these factors reveals the significant influence of geophysical, environmental, and anthropogenic variables on landslide susceptibility, particularly highlighting soil type, land cover, lithology, rainfall, and topographic parameters. Highly susceptible areas are identified in Tublay, Sablan, Tuba, and mountainous regions characterized by steep slopes. Conversely, urbanized areas like Baguio City exhibit lower susceptibility levels due to favorable topographic conditions.

1. Introduction

1.1 Landslide

Landslides pose a significant global threat to human life and economic livelihoods, ranking among the most hazardous disasters with the potential to cause varying degrees of social and economic destruction (Glade et al., 2012). In the Philippines, landslides rank among the most frequent natural hazards, largely influenced by the country's geographic, climatic, and geotectonic characteristics. The country's susceptibility to typhoons and its position along the Pacific Ring of Fire contribute significantly to its vulnerability.

The Philippines experiences a significant proportion (46%) of rainfall-triggered landslides in Southeast Asia, and among these, 42% are associated with typhoons (Froude & Petley, 2018). Human activities, including deforestation, development, and urbanization, further amplify the risk of landslides (Beroya-Eitner, 2016).

The province of Benguet, located in the southwestern portion of the Cordillera Administrative Region (CAR) in the Philippines, experiences landslides as a predominant natural hazard due to its mountainous topography (Cruz et. al., 2019). In Benguet, the Baguio City-La Trinidad-Itogon-Sablan-Tuba-Tublay (BLISTT) area is considered a center of commercial and industrial development in the Cordillera Administrative Region by the National Economic and Development Authority (NEDA). As a center of economic activity, BLISTT houses various establishments, including businesses, tourism centers, healthcare facilities, and educational institutions, thereby contributing significantly to the overall development of CAR (Luga, 2022).

The BLISTT region is characterized by physical, climatic, and geological factors that contribute to landslides, including mountainous topography, heavy rainfall, frequent typhoons, earthquakes, and human activities such as mining, infrastructure development, and agriculture, which lead to land erosion (Saldivar-Sali & Einstein, 2007). Thus, there is a need for effective landslide monitoring and mitigation measures in BLISTT to minimize casualties.

1.2 Landslide Susceptibility Mapping

One approach to mitigation is landslide susceptibility mapping, which is used to identify landslide-prone areas and supports informed decision-making to reduce associated risks. Assessing landslide susceptibility involves determining the probability of landslide occurrence in an location by analyzing the spatial relationships between multiple causal factors.

In recent years, studies of landslide susceptibility mapping have been made possible by the emergence of new technologies, such as Geographic Information Systems (GIS), and by access to a variety of remotely sensed satellite data on landslide causal factors (Shahabi & Hasim, 2015).

Quantitative GIS-based susceptibility modeling involves a variety of statistical approaches that have often been used to model landslide susceptibility over large regions (Goetz et al., 2015). Among established statistical methods for landslide susceptibility modeling, Binary Logistic Regression (BLR) is widely preferred due to its broad applicability and availability of supporting software (Lee, 2005; Lombardo & Mai, 2018). BLR is a statistical method used to analyze the relationship between several independent variables, which might be discrete or continuous, and a binary dependent variable. In addition, BLR does not require a normal distribution (Sujatha & Sridhar, 2021). Recent studies of landslide susceptibility modelling using BLR applied to smaller areas in Benguet have yielded high accuracy (Jones et al., 2023; Nolasco-Javier & Kumar, 2021).

The objective of this study is to use binary logistic regression to model landslide susceptibility in the BLISTT area. The method considers various landslide causal factors — topography, basic geology, hydrological environment, and surface land cover — specific to BLISTT, and incorporates a larger, more recent landslide dataset and additional landslide causal factors than in previous studies. The findings of this research can offer valuable information and guidance for local government units and relevant agencies involved in disaster prevention and mitigation efforts. This would enable local government units to prioritize areas within their jurisdictions that are more prone to landslides.

2. Materials and Methods

2.1 Study Area

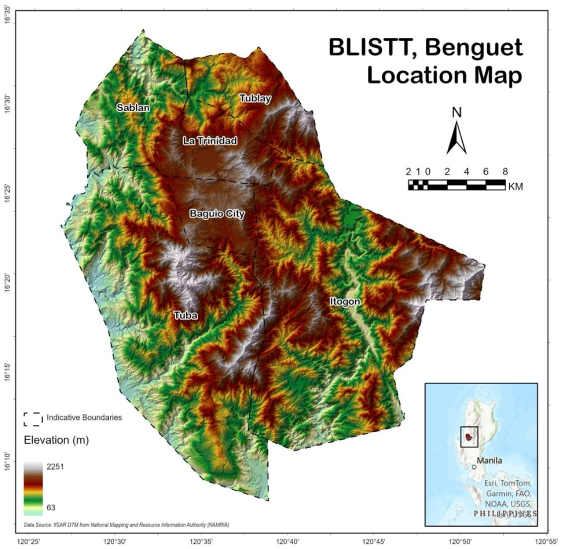

Figure 1. Map of the study area: BLISTT, Benguet.

The BLISTT Area (Figure 1), which includes Baguio City along with the municipalities of La Trinidad, Itogon, Sablan, Tuba, and Tublay in Benguet Province, lies within the Cordillera Central mountain range in northern Luzon. BLISTT is situated at an average elevation of approximately 1,500 meters above sea level and has a land area of 1,095 square kilometers.

2.2 Landslide Inventory

The identification and delineation of landslide locations are crucial for landslide susceptibility assessment. The introduction of Google Earth® in 2005 has enabled the use of high- and very high-resolution optical satellite imagery worldwide for various applications, including the detection and mapping of landslides (Sato & Harp, 2009).

Landslide extents within the study area spanning from 2003 to 2023 are digitized by extracting information from high-resolution Google Earth imagery, high-resolution satellite imagery, government agency reports, and field surveys. The delineation of landslide extents in satellite imagery relied on visual interpretation keys for before-and-after images: landslides often exhibit a sharp transition from bare soil (typically brown in satellite imagery) to vegetated areas (green), downslope features, displaced masses, or irregular surface disturbances. Landslide-prone locations, such as steep slopes and river valleys, were also thoroughly investigated for existing landslides.

A total of 3,071 polygons delineating landslide areas are identified and used as landslide inventories for subsequent analyses (Figure 2). The landslide polygons are converted into a binary raster, where pixels representing landslides are assigned a value of 1 and those without landslides are assigned a value of 0.

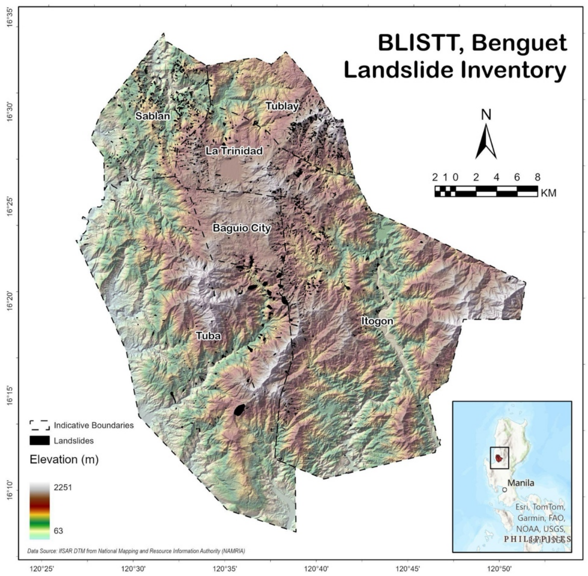

Figure 2. Landslide inventory map derived from Google Earth in BLISTT, Benguet.

2.3 Landslide Causal Factors

In susceptibility modeling, it is important to select causal factors based on the local geoenvironmental setup (Sujatha & Sridhar, 2021). Logistic regression modeling requires the inclusion of numerous independent variables that enhance the model, provided they significantly contribute to predicting the dependent variable.

However, selecting independent variables with substantial influence poses a challenge. While there are no criteria or guidelines universally accepted in studies, the general consensus emphasizes that each independent variable should: (1) exhibit a certain degree of correlation with the dependent variable, (2) be representative of the entire study area, (3) be spatially non-uniform and measurable, and (4) non-redundant (Ayalew & Yamagishi, 2004).

In this study, twelve causal factors (Figure 3) were selected. The choice of these variables was informed by existing literature, data availability, and the physical and environmental characteristics of the BLISTT region. The factors considered include topographic factors such as slope angle, slope aspect, profile curvature, and Topographic Wetness Index (TWI); geological factors including lithology and soil type; surface indicators such as land cover and the Normalized Difference Vegetation Index (NDVI); as well as distance-based parameters measuring proximity to roads, rivers, and lineaments, along with rainfall conditions.

Topographic causal factors were derived from the 2012 5m by 5m Digital Terrain Model (DTM) covering the BLISTT area, which was resampled to 10m by 10m. Using ArcGIS Pro, slope angle, slope aspect, and profile curvature were generated. Slope angle reflects the steepness of terrain, while slope aspect indicates the compass direction of the slope, and profile curvature represents the rate of downslope slope change, which affects water flow across the surface. TWI was calculated to quantify potential water accumulation, a key driver in slope failure. TWI was derived using flow direction and flow accumulation raster based on the DTM, and can be expressed by Equation 1:

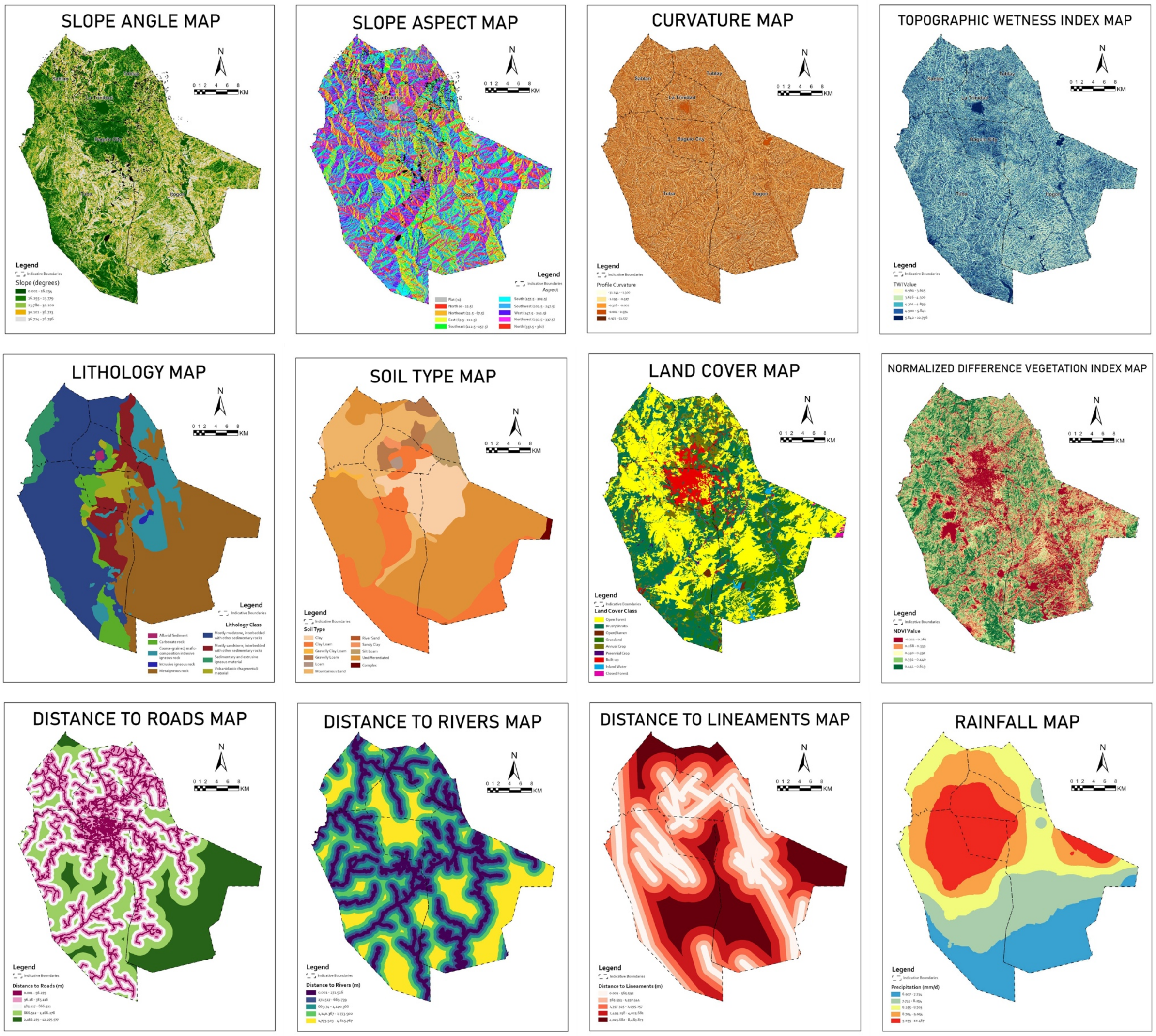

Figure 3. Twelve (12) landslide causal factors used for landslide susceptibility modeling.

$$\mathrm{TWI} = \ln\left(\frac{a}{\tan\beta}\right) \tag{1}$$

where a = flow accumulation
$\tan(\beta)$ = local slope (β is in radians)

Geological factors were integrated using a lithological map from the Mines and Geosciences Bureau – Cordillera Administrative Region (MGB-CAR), which categorized the area into nine lithologic classes. Complementing this, soil data were sourced from the Bureau of Soils and Water Management (BSWM), which identified 10 distinct soil types across the region.

Land cover data were obtained from the 2020 Land Cover Map of NAMRIA, which classifies the area into categories such as forest, croplands, built-up areas, and water bodies. Vegetative cover was further assessed using the NDVI calculated from Sentinel-2 imagery acquired for the entire year of 2023 via Google Earth Engine using the red (R) and near-infrared (NIR) bands. NDVI values, ranging from -1 to +1, indicate vegetation density and are calculated using Equation 2:

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{2}$$

Proximity to roads, rivers, and geological lineaments was also evaluated as landslide causal factors. Road data were sourced from NAMRIA at a 1:50,000 scale, while river features were extracted from the 2020 Land Cover Map. Lineament data, which represent fractures or faults, were obtained from the Philippine Institute of Volcanology and Seismology (PHIVOLCS). All vector datasets were rasterized to 10m resolution and converted into proximity rasters using the Proximity (Raster Distance) tool in ArcGIS Pro.

The Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS), accessible via Google Earth Engine, provided the precipitation data. The annual average rainfall was computed using data from 2000 to 2023. Since CHIRPS data have a coarse resolution of 5.5km, Inverse Distance Weighted (IDW) interpolation was applied to resample the data to 10m resolution.

2.4 Landslide Susceptibility Assessment

2.4.1 Binary Logistic Regression Modeling: Logistic regression describes the relationship between dependent and independent variables by generating a best fitting model (Ohlmacher and Davis, 2003). Binary logistic regression modeling requires a binary response variable — in this study, the dependent variable is the occurrence of landslide in a pixel, denoted by 1 for landslide pixels and 0 for no landslide pixels. The general form of LR is shown in Equations 3-5.

$$y = a + b_1x_1 + b_2x_2 + b_3x_3 + \ldots + b_mx_m \quad (3)$$

$$y = log_e\left[\frac{P}{1-P}\right] \quad (4)$$

$$P = \frac{e^y}{1+e^y} \quad (5)$$

where $x_1, x_2, \ldots, x_m$ = causal factors
y = linear combination function of variables
$b_1, b_2, \ldots, b_m$ = regression coefficients
P = probability of landslide occurrence

The expression for the function y is $log_e\left[\frac{P}{1-P}\right]$, which represents the natural logarithm (base e) of the likelihood ratio that the dependent variable is 1. The construction of a LR model involves the following steps: (i) selecting independent variables, (ii) p-value significance testing of selected variables, (iii) ensuring that the independent variables are not correlated using collinearity statistics, (iv) formulating the LR model, and (v) model validation using Area Under the Curve (AUC) and landslide density function (Sujatha & Sridhar, 2021). The methodology flowchart of the binary logistic regression in this study is shown in Figure 4.

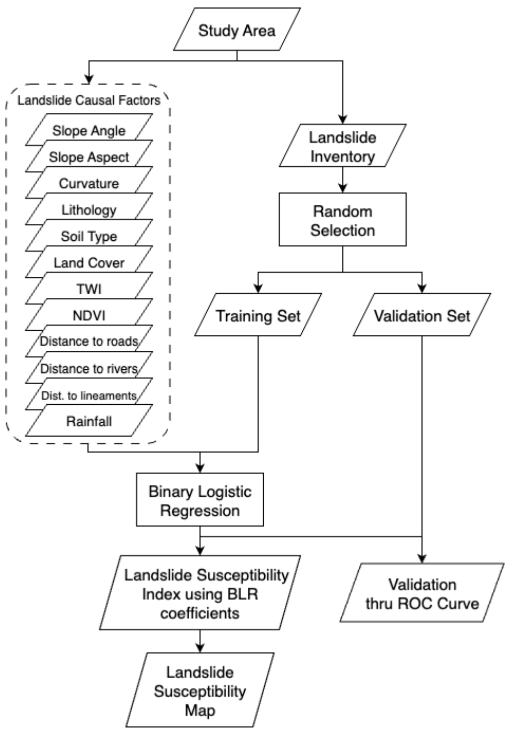

Figure 4. Methodology flowchart for binary logistic regression in the study.

2.4.2 Calculation of Landslide Densities: One issue in logistic regression is the conversion of categorical variables to continuous, numerical variables for statistical analysis. Typically, categorical variables are converted to numerical variables by creating dummy variables for each class. However, for variables with many classes, this can lead to a large number of dummy variables (Zhu & Huang, 2006). As an alternative to this method, studies have calculated landslide densities from categorical variables, which account for the relative percentage of landslide areas within each variable (Yesilnacar and Topal, 2005). The formula for landslide densities is given by Equation 6.

$$FR = \frac{(B_i/A_i)}{\sum_{i=1}^{N}(B_i/A_i)} \quad (6)$$

where A_i = area of the i^{th} class of a categorical variable
B_i = landslide area
N = total number of classes for the categorical variable

The categorical variables lithology, soil type, and land cover are rasterized and reclassified into corresponding landslide densities for each class.

2.4.3 Multicollinearity Diagnostics: Multicollinearity is a statistical phenomenon generally avoided in logistic regression modeling. It implies high correlation within variables in a model, which can lead to inconsistent estimates and imprecise variances. Thus, this study performs multicollinearity diagnostics using tolerance and variance inflation factor (VIF) for the 12 independent variables before proceeding with logistic regression modeling. Tolerance indicates the degree of multicollinearity; low values (below 0.1) suggest that variables are highly correlated and therefore cannot be used in the model. Likewise, a VIF exceeding 2 indicates a significant degree of multicollinearity (Allison, 2001). Table 1 shows the tolerance and VIF values for all variables, indicating the absence of multicollinearity.

Variable	VIF	Tolerance
Slope	1.287	0.777
Aspect	1.006	0.994
Curvature	1.104	0.906
TWI	1.321	0.757
Lithology	1.148	0.871
Soil Type	1.213	0.824
Land Cover	1.046	0.956
NDVI	1.062	0.942
Distance to Roads	1.512	0.661
Distance to Lineaments	1.245	0.803
Distance to Rivers	1.244	0.804
Rainfall	1.324	0.755

Table 1. Multicollinearity diagnostics of landslide causal variables.

2.4.4 Formulation of Landslide Susceptibility Index: The implementation of the BLR model was conducted using R. In the study, the available landslide inventory comprises only about 0.99% of the total study area, with 117,332 landslide pixels and 11,877,244 non-landslide pixels, making the landslide pixels significantly smaller than the non-landslide pixels. Consequently, the challenge of handling sampling sizes and proportions arises. In logistic regression, it is generally recommended to use equal proportions of pixels labeled as 1 and 0. Balanced data improves the predictive capability and reduces the variability of the LR model's parameters, leading to statistically sound results (Salas-Eljatib et al., 2018). However, since landslide density is computed across the entire study area (Ayalew & Yamagishi, 2004), this study uses data from the entire study area for the binary logistic regression model.

The coefficients derived from the logistic regression model (also known as the landslide susceptibility index) are assigned as weights for the thematic layers in GIS software to produce the landslide susceptibility map of the BLISTT area. Landslide probability values were classified using quantile-based thresholds into low, moderate, high, and very high susceptibility. To evaluate the model's predictive capability and performance, the area under the curve (AUC) was computed for both the training data and the validation data.

3. Results and Discussion

3.1 Landslide Susceptibility Index

Table 2 presents a summary of the binary logistic regression model. A higher coefficient indicates a stronger impact on the dependent variable, and the coefficient's sign indicates the direction of the correlation.

Variable	Estimate	Std. Error	z value	Pr (>|z|)
(Intercept)	-4.085	0.011	-383.94	< 0.05
Slope	0.058	0.000	1004.88	< 0.05
Aspect	-0.001	0.000	-255.66	< 0.05
Curvature	0.049	0.000	111.38	< 0.05
TWI	0.070	0.000	189.79	< 0.05
Lithology	2.749	0.013	206.1	< 0.05
Soil Type	6.386	0.008	763.41	< 0.05
Land Cover	4.547	0.007	617.1	< 0.05
NDVI	-0.028	0.005	-5.22	<0.05
Distance to Roads	-0.001	0.000	-704.05	< 0.05
Distance to Lineaments	0.000	0.000	-97.23	< 0.05
Distance to Rivers	0.000	0.000	0.08	0.94
Rainfall	0.181	0.001	167.48	< 0.05

Table 2. Summary of binary logistic regression model.

The model summary reveals that the most significant causal factors in the study are the categorical variables of soil type, land cover, and lithology, highlighting the influence of geographic and geologic conditions on landslide occurrences within the study area. Additionally, rainfall, slope, and profile curvature are positively correlated with landslides, whereas NDVI is negatively correlated. Proximity factors, such as distance to roads, rivers, and lineaments, have minimal impact on the dependent variable, as indicated by their near-zero coefficients. Notably, the p-value of proximity to rivers is 0.94, considerably exceeding the significance threshold of 0.05, indicating non-significance.

The landslide susceptibility index used in the weighted overlay of layers is constructed from the logistic regression coefficients. The proximity variables are excluded from the index as their coefficients are deemed negligible; however, these variables are not excluded from the model as exclusion of these variables leads to poorer model performance. The binary logistic regression-derived landslide susceptibility index, denoted as $f(x)$ is defined in Equation 7.

$$f(x) = -4.085 + 0.058S - 0.001A + 0.049C + 0.07TWI + 2.749L + 6.386ST + 4.547LC - 0.028NDVI + 0.181RF \quad (7)$$

where S = slope angle
A = slope aspect
C = profile curvature
TWI = topographic wetness index
L = lithology
ST = soil type
LC = land cover
$NDVI$ = normalized difference vegetation index
RF = rainfall

3.2 Area Under the Curve

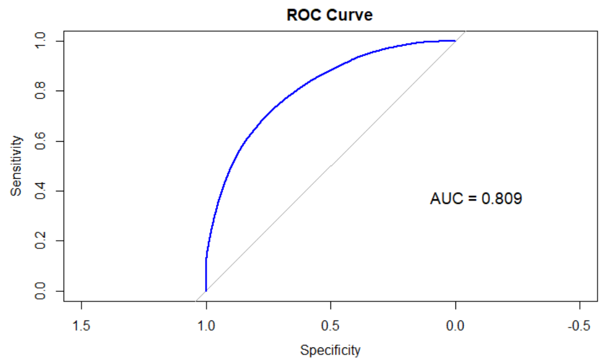

Figure 5. Area Under the ROC Curve of the BLR model.

For validation, the area under the curve (AUC) is calculated using 20% of the dataset for training. The close correspondence between the success and predictive rates indicates the efficacy of logistic regression in forecasting landslides (Meten et al., 2015). The Area Under the ROC (receiver operating characteristic) curve is 0.809. The model is considered good, as it falls within the 0.80-0.90 range. Figure 5 shows the model's AUC plot.

3.3 Landslide Susceptibility Map

The landslide susceptibility map of BLISTT, depicted in Figure 6, is derived from the landslide susceptibility index and categorized into four (4) classes using quantile classification: low, moderate, high, and very high susceptibility based on their LSI values. While susceptibility mapping commonly employs quantile and natural breaks (Jenks) classifiers (Milevski et al., 2019), this study found that quantile classification yielded a more balanced spatial distribution across susceptibility classes and better correspondence with landslide occurrences in the inventory.

Susceptibility Class	Area (km^2)	Area (%)	Landslide Area (km^2)	Landslide Area (%)
Low	295.456	24.652	0.632	5.391
Moderate	310.632	25.918	1.237	10.558
High	309.053	25.787	2.183	18.624
Very High	283.355	23.643	7.668	65.427

Table 3. Area statistics of landslide susceptibility map classes.

Table 3 illustrates the spatial distribution of landslide susceptibility classes in the generated map. The *Area* column pertains to the area of each susceptibility class, while the column *Landslide Area* denotes landslide area (as per the inventory) that falls within each class. Findings reveal that nearly 50% of the study area exhibits high to very high susceptibility to landslides. Analysis of Table 3 reveals a notable increase in landslide occurrences as susceptibility classes go higher. 84.05% of the landslides in the inventory fall within the high to very high susceptibility classes, which suggests that the map coincides with the situation on the ground, and that the model effectively assesses the susceptibility of areas in the study region to landslide events.

The landslide susceptibility map analysis reveals several key findings within the BLISTT area. A significant portion of Tublay, located in the southeast, exhibits very high landslide susceptibility. The high susceptibility is attributed to the cumulative influence of various factors, with soil type, land cover, and lithology emerging as prominent contributors.

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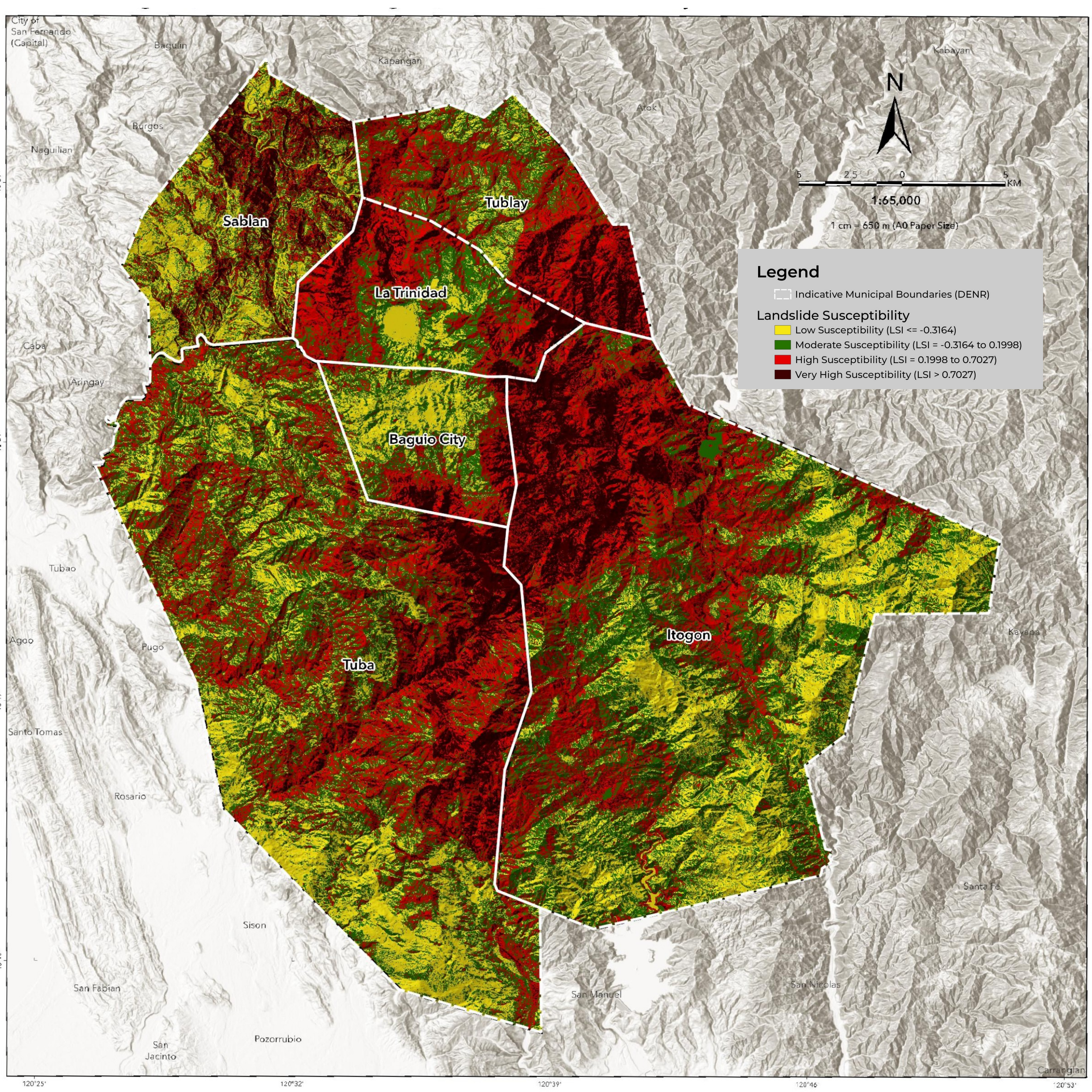

Figure 6. Landslide susceptibility map of BLISTT using BLR model.

Additionally, areas characterized by "Open/Barren" land cover are highly susceptible, as the absence of vegetation and tree roots, typically found in forested areas, contributes to soil instability, according to multiple studies (Chen et al., 2019).

Rainfall also emerges as a dominant contributing factor, particularly in Sablan and the northern portion of Tuba, where high- and very-high-susceptibility areas are prevalent. The significant coefficients associated with rainfall underscore its role in triggering landslide events in these regions. Furthermore, while slope did not yield comparably high coefficients, the concentration of high and very high susceptibility areas in mountainous terrain suggests that topographical factors play a crucial role in exacerbating landslide susceptibility, particularly in areas characterized by steep slopes especially in the municipalities of Sablan, Tuba, the northwestern portion of La Trinidad, some areas in Itogon, northwest portion of Tublay, and the outskirts of Baguio City.

Notably, despite being an urbanized area, Baguio City predominantly exhibits low- and moderate-susceptibility classes. This can be attributed to the relatively low slope values observed in the city compared to other regions within the BLISTT area. While urbanization typically increases landslide susceptibility due to factors such as deforestation and land modification, Baguio City's topographic characteristics may mitigate these effects, resulting in lower susceptibility.

Further analysis reveals that high-susceptibility classes tend to concentrate in water catchment areas located between sloping mountainous regions, which aligns closely with the spatial distribution of the TWI causal factor.

4. Conclusions

The landslide susceptibility of Baguio City, La Trinidad, Itogon, Sablan, Tuba, Tublay (BLISTT) area in Benguet, Philippines is modeled and mapped using binary logistic regression. For the regression modeling, twelve landslide causal factors based on the local environment, expert opinion, and existing literature are used: slope angle, slope aspect, profile curvature, lithology, soil type, land cover, TWI, NDVI, proximity to roads, proximity to rivers, proximity to lineaments, and precipitation. The resulting model achieves an area under the receiver operating characteristic (ROC) curve of 0.809, which classifies it as "good," indicating its accuracy and performance. This study contributes originality through its integration of updated datasets, the inclusion of a comprehensive set of geophysical, environmental, and anthropogenic factors, and the development of a statistically robust model (AUC = 0.809) that supports localized disaster risk reduction and land-use planning in the BLISTT area.

Statistical analysis of 12 landslide causal factors in the BLISTT area reveals the influence of geophysical, environmental, and anthropogenic variables on landslide susceptibility. The results highlight the significance of key factors, including soil type, land cover, lithology, rainfall, and topographic parameters, in driving landslide occurrences. The categorical variables soil type, land cover, and lithology are found to be substantially influential on landslide occurrences, as indicated by their coefficients and odds ratios. Moreover, the positive correlation of rainfall, slope, and profile curvature with landslides, coupled with the negative correlation of NDVI, provides valuable insights into the dynamic relationships between environmental variables and landslide occurrence.

Notably, the proximity factors, including distance to roads, rivers, and lineaments, exhibit minimal impact on landslide susceptibility, as indicated by their near-zero coefficients and non-significant p-values. This suggests that while these factors may influence local geomorphological conditions, their overall contribution to landslide susceptibility is relatively limited within the study area.

The derived landslide susceptibility map, categorized into four classes using quantile classification, reveals spatial patterns across the study area. Analysis of the susceptibility map reveals that most landslide polygons in the inventory lie within the high and very high susceptibility classes, confirming the adequacy of the model and the index. Highly susceptible areas in Sablan, Tuba, Tublay, and other mountainous regions are identified, characterized by steep slopes and specific soil and land cover types. Conversely, urbanized areas like Baguio City exhibit lower susceptibility levels, attributed to favorable topographic conditions. Further analysis indicates high susceptibility classes tend to concentrate in water catchment areas, closely aligning with hydrological factors such as TWI.

It is worth noting that this study has certain limitations, particularly potential biases in the landslide inventory and resolution constraints in some datasets, which may affect the accuracy of the susceptibility mapping. This emphasizes the need for future studies to conduct ground validation and to use more complete inventories and higher-resolution datasets.

Considering the findings, several recommendations for future studies are proposed. Firstly, leveraging in-situ ground data as predictor variables is advised to enhance model accuracy. In the absence of such data, higher resolution remote sensing data should be considered to capture fine-scale variations in landslide susceptibility. Additionally, experimenting with the selection and number of landslide causal factors is recommended to optimize model performance. Alternative approaches to handling categorical variables, aside from dummy variables and landslide densities, warrant exploration to mitigate unintended biases. Moreover, future research should incorporate temporal analyses of landslide occurrence and integrate climate change projections to better capture long-term trends in susceptibility. Other avenues for exploration in future work include linking susceptibility zones with land-use, population, and infrastructure data, as well as incorporating temporal analyses and machine learning to enhance predictive accuracy.

The study's findings have important implications for land-use planning and disaster risk reduction in the BLISTT area. High-susceptibility zones in Sablan, Tuba, and Tublay highlight areas where stricter land-use regulations and slope-stabilization measures may be prioritized. On the other hand, the relatively lower susceptibility in Baguio City underscores the role of topographic setting and vegetation cover in mitigating landslide risk, which can be considered for future urban expansion. Watershed management is also a key recommendation; the concentration of high susceptibility in water catchment areas suggests that hydrological processes must be considered in infrastructure development. These results can serve as a decision-support tool for local government in enhancing resilience to landslide hazards.

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