ARTICLE

Landslide susceptibility analysis of La Trinidad, Benguet using logistic regression

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ABSTRACT

The analysis and identification of landslide-prone areas are essential in minimizing the precarious impacts of landslide hazards, which can result in fatalities, damage to infrastructure, and destruction of natural resources. This study was conducted to analyze the landslide susceptibility of La Trinidad, Benguet by examining the relationship between the historical landslide occurrences and various factors (aspect, elevation, distance to rivers and roads, land use and land cover (LULC), lithology, normalized difference vegetation index (NDVI), precipitation, slope, and soil texture) using logistic regression. Landslide susceptibility map was divided into two categories: susceptible and not susceptible, through the binary classification method. The findings revealed that 6.06% of the total land area (463.54 ha) were susceptible to landslides while 93.94% (7,181.44 ha) were classified as not susceptible. The areas classified as susceptible to landslides exhibited characteristics often associated with human activity and development, such as a high population density, extensive settlements, and significant infrastructure. This suggests that human-induced factors, particularly road expansion and construction activities, contribute to slope instability in these locations. The analysis identified distance to road, slope, and NDVI as the most significant variables influencing landslide susceptibility in the study area, contributing 65.37%, 11.21%, and 8.01%, respectively. The logistic regression model showed excellent discriminative ability (ROC = 0.90) and suggests good model accuracy which is better than random chance (TSS = 0.66). The evaluation metrics indicated that the landslide susceptibility analysis was effective and accurately classified landslide-susceptible areas within the study area. The results of this study will provide significant information, highlighting the importance of integrating landslide susceptibility assessments to land-use planning, sustainable development, and disaster risk reduction.

INTRODUCTION

Landslide is the downward movement of soil and rock materials influenced by gravitational force and often triggered by heavy rainfall, seismic activities, and human disturbances (Kalantar et al. 2018; Cemiloglu et al. 2023; Wang et al. 2023; Yadav et al.

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KEYWORDS

disaster risk reduction management, multicollinearity test, receiver operating characteristics (ROC), and true skills statistics (TSS)

2023). It is considered to be the most occurring hazard, especially in the mountainous areas, which often results in loss of lives and damage to infrastructures, crops, properties, and the natural environment (Sujatha and Sridhar 2021; Yadav et al. 2023; Zhao and Chen 2023). According to the United Nations Educational, Scientific, and Cultural Organization (UNESCO), landslides are a significant global hazard that contributes to 14% of total casualties (Froude and Petley 2018). Approximately $4 billion in losses and nearly 1,000 fatalities in a year are due to landslides (Lee and Pradhan 2006).

Due to the increasing frequency and intensity of landslides caused by different factors such as climate change, urbanization, and development, landslide susceptibility analysis and prediction have become significant for disaster risk reduction management (DRRM), preparedness, and risk mitigation (Zhao and Chen 2023; Chowdhury et al. 2024). Landslide susceptibility analysis (LSA) is a crucial aspect of natural hazard assessment. It involves several techniques including geomorphological hazard mapping (Reichenbach et al. 2005), heuristic methods, landslide inventories (Zhao and Chen 2023), and statistical methods (Bui et al. 2011; Sujatha and Sridhar 2021; Cemiloglu et al. 2023; Wang et al. 2023). Among these several techniques, statistical modeling plays a significant role in landslide susceptibility analysis as it enables the prediction of the probability of future landslide occurrence and the identification of key factors affecting its occurrence. Statistical modeling, particularly the logistic regression method (LR), is the most popular and has been utilized by several researchers (Jade and Sarkar 1993; Guzzetti et al. 1999; Sun et al. 2018; Sharma et al. 2023; Chowdhury et al. 2024). The advantages of this method include its ability to process limited and complex datasets such as continuous and categorical data or their combination, which allows the inclusion of different landslide contributing factors in modeling landslide susceptibility. Additionally, the results are easy to interpret since the outcome is always binary which can be either categorized as susceptible or not susceptible (Sun et al. 2018; Sujatha and Sridhar 2021; Cemiloglu et al. 2023). It is also highlighted that LR is capable of eliminating irrelevant variables which is significant in producing a more reliable prediction. Furthermore, it can also quantify the relative impact of the different variables which is significant in understanding the causes and factors of the landslide occurrence (Chowdhury et al. 2024).

Logistic regression is a data-driven technique used in predicting areas that are prone to landslides based on various environmental, geological, hydrological, and geomorphological factors, which are usually called causative and triggering factors (independent variables). Another crucial type of data required for a data-driven technique in landslide analysis includes historical landslide occurrence data, referring to the samples that show the conditions under which landslides have occurred. Additionally, it is essential to collect landslide absence data or samples that represent the condition in which no landslides have been documented. The importance of LR in LSA lies in its effectiveness in handling complex, non-linear relationships between causative and triggering factors and historical landslide occurrences, which allows the development of probabilistic maps that can assist the local government, in both urban and rural areas, especially areas that are prone to landslide hazards, in risk assessment, land-use planning, and hazard management. Hence, this study was conducted to analyze the landslide susceptibility of La Trinidad, Benguet, using the LR method. Additionally, this study determined the variables primarily influencing the occurrence of landslides.

MATERIALS AND METHODS

Study Site

La Trinidad, the capital of Benguet, has a total area of 7,644.98 ha constituting 2.7% of Benguet province and the most populated municipality (Figure 1). It has a Type I Climate Classification based on Corona System with a rainy season from May to October and a dry season from November to April every year (PAGASA n.d.). La Trinidad is characterized by steep mountains, cliffs, and high terrain surrounding the center of the municipality. Several creeks and major water bodies, including the Balili River, flow through its landscape. It has an elevation ranging from 500 to 1,700 meters above sea level (masl) and a gentle to very steep slope. The rugged topography and unstable geologic composition due to its proximity to fault systems and variety of rock types presents the municipality as highly susceptible to landslides (Carranza & Hale 2002; Potter 1974). The soil type consists of gravelly loam, clay loam, silt loam, and sandy loam. The existing land uses in the municipality include residential, commercial, institutional, forest, agricultural, and water bodies. Among these land uses, residential areas, followed by commercial, account for the largest uses in the municipality, which serves as the central business district in the province (Office of Municipal Planning and Development 2021).

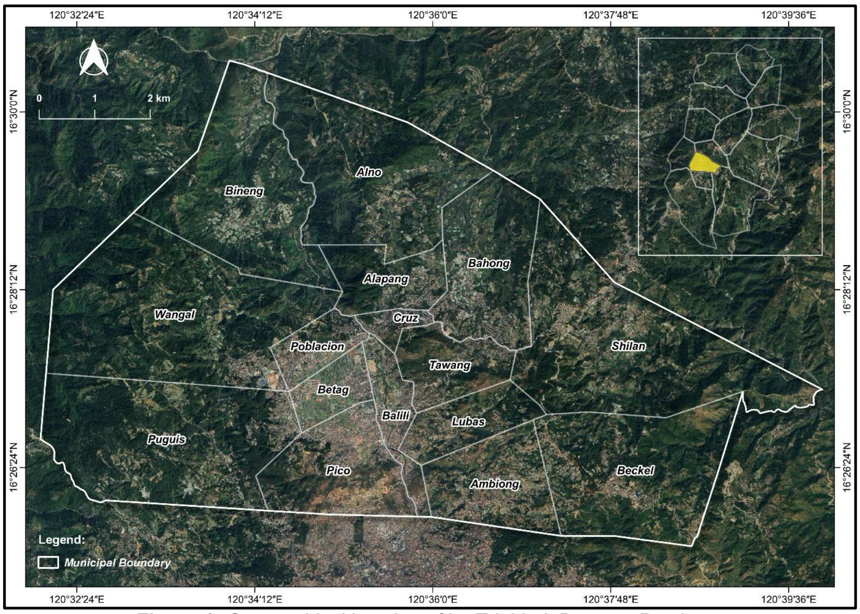

Figure 1: Geographical location of La Trinidad, Benguet Province.

Data Collection

Landslide Occurrences

In LSA, data on historical landslide occurrences is required. The historical landslide records, including their spatial attributes, covering the period between 2009 and 2024, were acquired from the available records of the Municipal and Provincial Disaster Risk Reduction and Management Office (MDRRMO & PDRRMO) of La Trinidad and Benguet Province. There were 189 total landslide incidents recorded during this period, which mostly occurred and were triggered by road cuts and heavy rainfall brought by major typhoon events (Figure 2). These incidents represent shallow landslides, characterized by surface-level soil erosion, mudslides, and debris flows, often affecting existing infrastructure like roads, riprap, footpaths, and residential structures. The landslide occurrence data was randomly divided into training and testing, where 70% (132 landslide points) were utilized for training the model, and 30% (57 landslide points) were used for validation purposes.

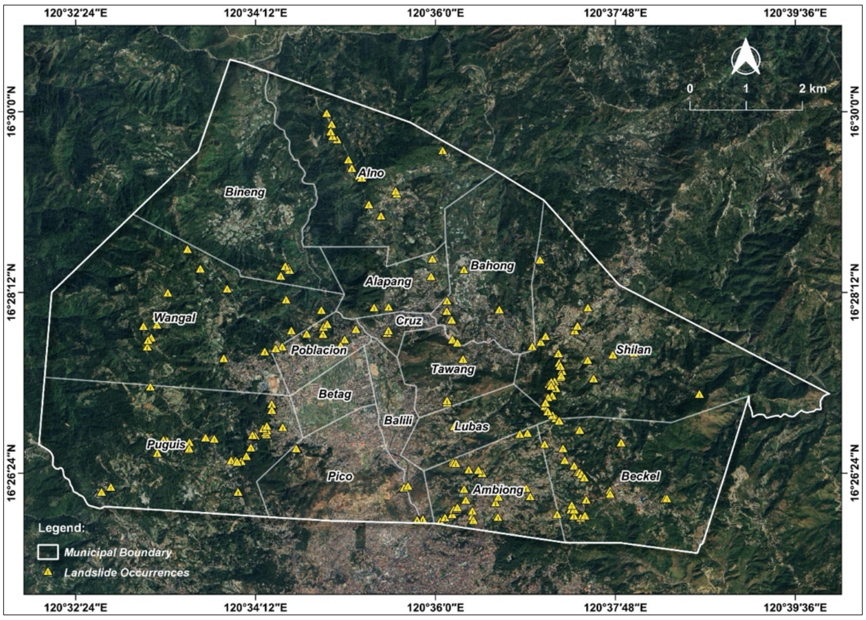

Figure 2: Geographical location of the landslide occurrences in La Trinidad, Benguet showing recorded incidents from 2009-2024

Landslide susceptibility mapping is a binary classification where landslide indices are categorized into two classes: landslide occurrence and absence data. The historical landslide occurrence data are available on the landslide inventory of the local government units, while the landslide absence data is not directly available and is often generated by estimating the location and condition where no landslide has been recorded. In this study, the landslide absence data (pseudo-absences) were generated using the disk method, performed through the statistical software R. The disk method uses the minimum-maximum radius to randomly generate pseudo-absences within a given distance from recorded occurrence points. The number of pseudo-absences that can be generated varies depending on the study area and the sampling method. In this study, to ensure that the landscape in the study area is adequately represented, a total of 10,000 pseudo-absence points were randomly generated, where the maximum distance from the known landslide occurrence point was set to 2,000 m.

Causative and Triggering Factors

Several factors contribute to the occurrence of landslides, and one of the key steps in landslide analysis is the selection of suitable causative and triggering factors. According to Ayalew and Yamagishi (2005), there are no standard criteria for selecting these variables. In this study, the selected factors (Figure 3) were based on a comprehensive review of existing literature, as well as the availability and relevance of the data to landslide occurrence. The selection was guided by previous research on landslide susceptibility analysis (Yesilnacar and Topal 2005; Bui et al. 2011; Sun et al. 2018) and supported by the specific characteristics of the study area. Factors such as aspect, elevation, distance to rivers and roads, LULC, lithology, NDVI, precipitation, slope, and soil texture (Table 1) were chosen.

Table 1: The various factors used and their corresponding source of data, year, and resolution.

Data	Sources	Year	Spatial Resolution
Elevation	European Space Agency Copernicus Open Access Hub – (https://dataspace.copernicus.eu/)	2015	30m x 30m
Aspect	Generated through the elevation data	2015	30m x 30m
Slope	Generated through the elevation data	2015	30m x 30m
Distance to Road	Open Street Map (OSM)	2023	5m x 5m

Distance to River	National Mapping and Resource Information Authority (NAMRIA)	2023	5m x 5m
Lithology	Mines and Geosciences Bureau (MGB) – Cordillera Administrative Region (CAR)	1990	5m x 5m
Soil Texture	Bureau of Soil and Water Management (BSWM)	2015	5m x 5m
LULC	NAMRIA	2020	30m x 30m
NDVI	Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS)	2024	30m x 30m
Precipitation	WorldClim (www.worldclim.org)	1970-2000	5m x 5m

Elevation is the measure of distance above sea level, and technically, areas in the higher elevations are susceptible to landslides. This variable is often used in assessing landslide susceptibility by several researchers (Lee and Evangelista 2005; Chowdhury et al. 2024). The digital elevation model (DEM) of the study area, with a 30 m resolution, was utilized to generate the aspect and slope data. Aspect represents the slope direction, which affects vegetation growth, surface evaporation rate, concentration of soil moisture, and temperature. Aspect is also significant and has previously been integrated into determining landslide susceptibility by some researchers (Sharma et al. 2023; Chowdhury et al. 2024). On the other hand, the slope refers to the steepness of the Earth's surface and is measured as an angle. In the study area, the slope ranges from 0°–65°, or gentle to very steep slopes. Technically, as the slope angle increases, the shear stress also increases (Khan & Wang 2021).

The distance to roads is also often considered a primary factor due to its influence on landslides where several incidents may occur on the road due to the changes in the natural conditions of the slopes brought by road constructions that affect shear strength and directly influence slope failure (Wang et al. 2023). The distance to the rivers is also an important parameter that influences the stability of a slope by saturating the base, leading to slope failure (Kouhpeima et al. 2017; Kalantar et al. 2018; Sun et al. 2018).

Landslides are also directly associated with rock properties, considering their slope-forming properties and characteristics, which directly affect the strength and permeability of the slope (Kalantar et al. 2018; Kouhpeima et al. 2017; Hong et al. 2016). Soil texture refers to the varying sizes of mineral particles, which influence the soil's porosity and structure. This variation is usually categorized into sand, silt, and clay. Soils rich in clay exhibit resistance to detachment, whereas sandy soils are more susceptible to detachment, thus compromising the stability of soil aggregates (Phogat et al. 2015). The study of Sharma et al. (2023) on landslide analysis included soil texture as a contributing factor to landslide occurrence. The different soil textures present in the study area include clay, loam, clay loam, gravelly loam, sandy loam, silt loam, and rough mountainous land.

NDVI determines the extent of vegetation with values ranging from -1 to 1, whereas a negative value indicates the presence of water bodies, a low value indicates barren land and built-up areas, and a value closer to one indicates the presence of denser vegetation. In this study, the NDVI was computed through the raster calculator in the Geographic Information System (GIS) software, using 30 x 30 m imagery from the archives of Landsat 8 OLI/TIRS.

NDVI was calculated using the following equation (Lee 2005):

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

where NDVI is the normalized difference vegetation index, NIR is near infrared of the electromagnetic spectrum, and R is the red portion of the electromagnetic spectrum (Sun et al. 2018).

Precipitation or rainfall is another significant triggering factor of landslide occurrence (Bui et al. 2011; Sun et al. 2018). Rainfall, especially heavy rainfall, can trigger landslides by saturating the soil, which reduces its shear strength.

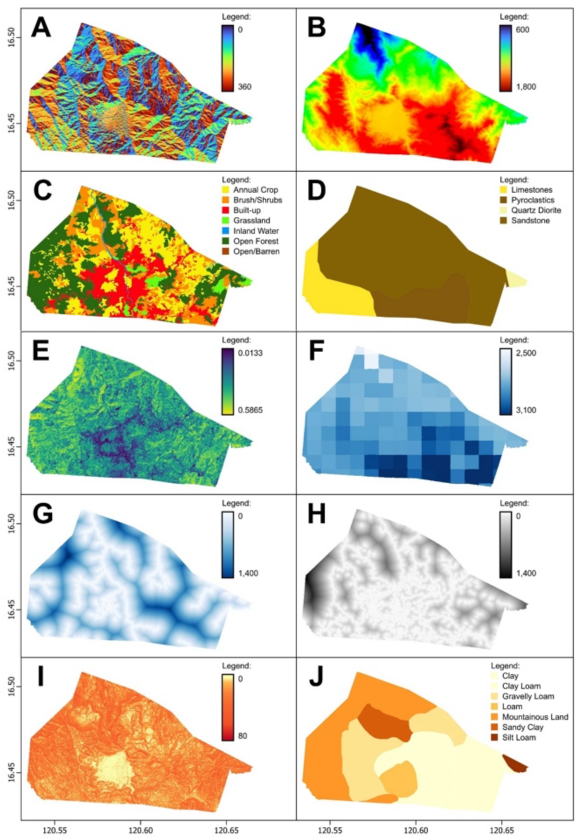

Figure 3: Ten (10) causative factors used landslide susceptibility analysis of La Trinidad, Benguet. A) aspect; **B)** elevation; **C)** LULC; **D)** lithology; **E)** NDVI; **F)** precipitation; **G)** distance to river; **H)** distance to road; **I)** slope; **J)** soil texture.

Ambiong, Beckel, and Longlong were always identified as the most highly susceptible areas due to their steep, cut slopes and vulnerable settlements. Ambiong consistently experiences numerous landslide and soil erosion incidents, particularly affecting houses located downslope of slides and areas where riprap has eroded. Balili and Stonehill areas face moderate susceptibility due to steep slopes and highly fractured rock formations with solution-enlarged cavities, experiencing mud and rock flows along the Halsema Highway that damage infrastructure like footbridge foundations. Longlong in Puguis is explicitly identified as prone to rain-induced landslides due to slope material saturation, with incidents affecting schools and homes. Tawang exhibits critical erosion zones with unstable boulders on mountain slopes, inadequate drainage systems, and recurring issues of eroded riprap and damaged footpaths across various puroks like Banig and Dengsi. Road-related vulnerabilities are prominent in Alapang, Alno, and Wangal, where road cuts, eroded shoulders, and collapsed riprap affect major provincial roads, sometimes making them impassable and forcing road closures. Heavy rainfall from typhoons (Ineng, Lando, Fabian, Maring) and monsoon events consistently trigger these geological hazards, causing damage ranging from eroded slopes and mudslides to major structural threats, power disruptions, and forced evacuations in residential areas. Shilan suffers frequent riprap erosion and road slides that cause total damage to residences, demonstrating that settlements and infrastructure near road cuts, river systems, and areas with poor drainage bear the greatest risk across these communities (MDRRMC 2023). The incident report of these events was used as a basis for selecting the causative factors to develop the model.

Multicollinearity Test

In LSA using LR, the absence of collinearity among the factors is required. Multicollinearity among factors affects the model performance and can lead to inaccurate prediction results. This test is conducted to ensure that each variable contains unique information and does not explain the same information as other variables. This technique is significant for selecting the most appropriate factor to be used in the landslide susceptibility analysis, which leads to reliable results. Hence, a multicollinearity test using the variance inflation factor (VIF) was conducted to assess the multicollinearity among the 10 factors that were considered. A VIF value greater than or equal to 10 signifies multicollinearity; thus, variables with a higher value must be excluded in the analysis and modeling (Chowdhury et al. 2024).

Landslide Susceptibility Analysis

LR was utilized to analyze the landslide susceptibility of La Trinidad, Benguet, based on the different dependent and independent variables. The dependent variable is the landslide data, which includes the occurrence (1) and absence (0), while the independent variables refer to the 10 causatives and triggering factors. In LR analysis, the predicted value is always binary, which falls between 1 (presence) and 0 (absence). The simplified method for modeling the probability is described using the following equation:

$$P = \frac{1}{(1 + exp^{-z})}$$

where P is the probability of occurrence with an estimated value that varies between 0 and 1, and z is the assumed linear combination of the independent variables:

$$z = ^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots \beta_i X_i}$$

where βi reflects the contributions of the independent variables, βo is the constant coefficient, Xi denotes the number of independent variables (Chowdhury et al. 2024). LSA was conducted using the R statistical software, comprising the following steps: performing LSA using LR based on the generalized linear model (glm) function; calculating the contribution of each causative and triggering factor.

Variable importance and contribution were calculated using a permutation-based randomization method that works by systematically evaluating how much each predictor variable contributes to model predictions. One variable was taken at a time and shuffled (randomized) its values across all observations while keeping all other variables unchanged. The model then made predictions using this dataset with the randomized variable, and these predictions were compared to the original predictions made with unshuffled data by calculating the Pearson's correlation between them. The final importance score is computed as one minus this correlation value, meaning that higher scores indicate greater variable importance. A score of 0 indicates the variable has no influence on model predictions, while higher values reflect increasing importance.

Validation of Model Performance

The result of the landslide susceptibility was validated using receiver operating characteristics (ROC) and true skill statistics (TSS) metrics. These evaluation metrics are utilized by several researchers in landslide map validation. The ROC is one of the statistical index-based techniques in evaluating model performance by comparing sensitivity against the false positive rate. The ROC probability curve shows the true-positive rate or sensitivity (ratio of the correctly classified landslide points) on the vertical axis and the false-positive rate or 1-specificity (landslide absence cells that are incorrectly classified as present) on the horizontal axis using a two-dimensional graph (Sharma et al. 2023).

The area under the ROC (AUROC) is the numerical value of the summary of the information under the ROC curve, which is used to estimate the effectiveness of the model in classifying and predicting the landslide susceptibility in the study area. The AUROC values were classified into five classes: low (0.5–0.6), moderate (0.6–0.7), good (0.7–0.8), very good (0.8–0.9), and excellent (0.9–1) (Yesilnacar and Topal 2005) while AUROC values from 0.0–0.49 are considered not acceptable.

On the other hand, the TSS was used to measure the reliability of the classification. This method is similar to Kappa statistics, which considers the omission and commission errors (Allouche et al. 2006). The TSS is calculated using the equation

$$\mathrm{TSS} = \mathrm{TPR} - \mathrm{FPR},$$

where TSS is the True Skill Statistics, TPR is the True Positive Rate, and FPR is the False Positive Rate. The value of the TSS ranges from 0 to 1 and was classified into: poor or not acceptable (0.0–0.49), useful (0.5–0.8), and good to excellent (0.8 and above) categories (Coetzee et al. 2009).

RESULTS AND DISCUSSION

Multicollinearity Test

The different causative and triggering factors were evaluated for multicollinearity. The result showed that the soil texture and distance to road factors, with VIF values of 3.35 and 1.07, had the highest and lowest VIF scores, respectively (Table 2). The result of the multicollinearity test is consistent with the study of Chowdhury et al. (2024), where the distance to road factor also had the lowest VIF value.

The VIF values of all the factors are less than 10, indicating that there is no multicollinearity among the factors considered. A low VIF value ensures the reliability of the model, and the influence of each factor on landslide occurrence can be accurately represented. Therefore, the 10 causative and triggering factors considered were utilized in the landslide susceptibility analysis.

Table 2: Multicollinearity test of the causative and triggering factors.

Variables	VIF Scores
Soil texture	3.35
Elevation	2.34
Precipitation	2.07
Lithology	1.80
Distance to river	1.40
Land use and land cover	1.20
Slope	1.19
Aspect	1.17
NDVI	1.16
Distance to road	1.07

Landslide Susceptibility Analysis

The landslide susceptibility map of the study area (Figure 4) was divided into two categories, susceptible and not susceptible, based on the binary classification. Based on the result, 463.54 ha, corresponding to 6.06% of the total land area, is susceptible to landslides. On the other hand, 7,181.44 ha, which corresponds to 93.94%, falls within the not susceptible classification. Among the areas classified as susceptible to landslides, most of these are observed in the area of Beckel, Puguis, Ambiong, Shilan, and Poblacion, with a corresponding area of 83.03 ha, 46.50 ha, 45.61 ha, 42.23 ha, and 38.31 ha, respectively. On the other hand, Betag, with a susceptible area of 0.29 ha, has the lowest landslide susceptibility since it is located in an area with the lowest elevation and flat terrain.

Areas identified as landslide-susceptible exhibit similar patterns, such as high settlement and infrastructure density, and are intensively modified for agriculture and other economic activities. In addition, human-induced factors, particularly road expansion and construction activities, have also been identified as significant contributors to slope instability.

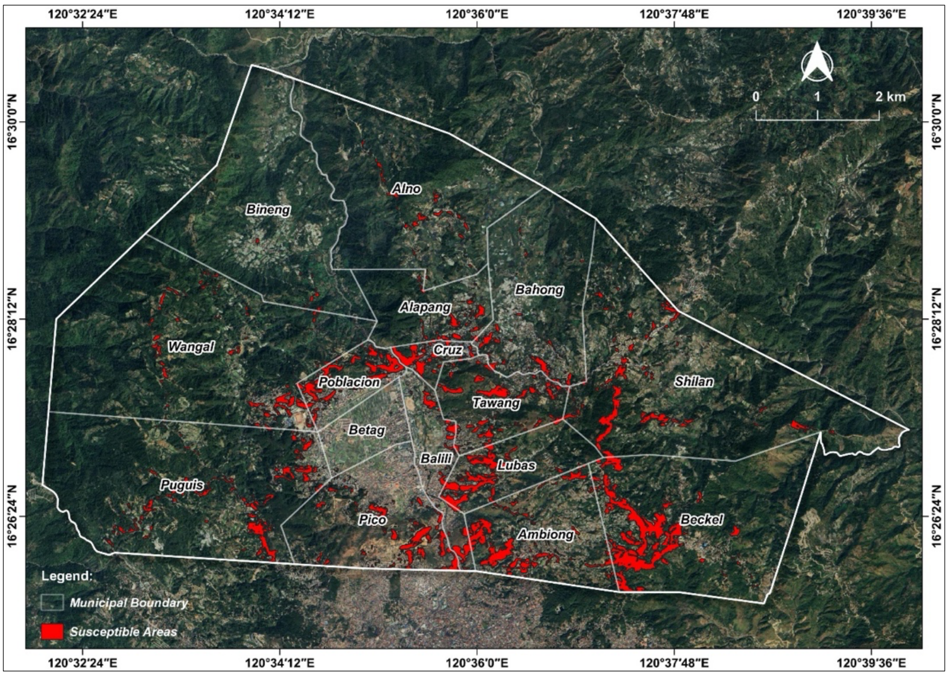

Figure 4: Landslide susceptibility of La Trinidad, Benguet using logistic regression

Results showed that, among the 10 independent variables, the distance to road, slope, and NDVI, with a percentage contribution of 65.37%, 11.21%, and 8.01%, respectively, are observed as the most influential variables that highly contribute to the landslide susceptibility of the study area (Table 3). Based on the result, highly susceptible areas are mostly observed within a distance range of 0–400 m from the road. In addition, the closer to the road, the higher the risk of a landslide. This signifies that structures, industrial and residential buildings within that distance range are prone to landslides and must be inspected and evaluated for relocation or suspension of activities and operations. The result is consistent with the study of Sekarlangit et al. (2022) where the distance to road was one of the leading contributors to landslide occurrence since the areas exposed along the road cuts are particularly susceptible to slides and soil erosion. Upon examining the collected historical landslide occurrences, a considerable number occurred near the road networks. This only indicates that human activities such as the construction of linear infrastructure, including roads and highways, reduce shear resistance, which causes slope instability in the municipality. Roads in the study area are the center of socio-economic activities and also serve as entry and exit points, connecting other municipalities in the region. However, its susceptibility to landslides poses a threat to infrastructure and settlements near the road networks. Additionally, it can cause significant disruptions to transportation, which can affect local economies and access to essential services.

Table 3: Percentage contribution of the various factors to the occurrence of landslides.

Factors	Contribution (%)
Distance to road	65.37
Slope	11.21
NDVI	8.01
Precipitation	7.20
Aspect	6.80
LULC	5.79

Elevation	5.15
Lithology	3.33
Soil	0.40
Distance to river	0.27

Furthermore, results showed that a slope of 0 – 10° indicates a low probability of landslide occurrence, while a slope between 10°–40° is highly vulnerable to landslide, having a susceptible area of 458 ha. However, areas in the municipality with a slope angle of 40° and above (Balili, Poblacion, and Betag) have a low frequency of landslide occurrence due to the existence of vegetation cover with NDVI ranging from 0.429–0.598, signifying the presence of dense vegetation cover. Vegetation cover modifies the stability of the slope by increasing shear resistance. Moreover, NDVI, or the measure of vegetation extent, made notable contributions to the occurrence of landslides in the study area, where the landslide susceptibility increases as the NDVI values decrease. Based on the result, the areas with an NDVI value ranging from 0–0.353, characterized by water bodies, barren land, built-up areas, and sparse vegetation, are mostly susceptible to landslides. The result indicates that high vegetation cover reduces the probability of landslide occurrence since vegetation acts as a crucial element in stabilizing slopes by intercepting rainfall impact, reducing soil saturation, and anchoring soil with its root systems (Murgia et al. 2024). Several research on LSA (Sun et al. 2018) revealed that NDVI significantly influences landslide occurrences, which must be considered in the analysis, especially in areas with varying vegetation densities. With regards to lithology, limestone presents moderate risk through chemical dissolution along joints, while sandstones create high susceptibility due to weak shales interbedded with stronger rocks, leading to differential weathering and failure along contacts. Marine clastics and pyroclastics pose the highest risk, as these poorly consolidated materials contain clay minerals and volcanic components that weaken significantly when saturated. In contrast, quartz diorite intrusive rocks have low susceptibility when fresh but become highly prone to landslides when weathered, as feldspar alteration creates weak clay layers that can slide over the underlying competent bedrock (Hadji et al. 2019; Geiser & Sansone 1981; Henriquet et al. 2020).

The occurrence of landslides in these landslide-prone areas can have devastating impacts, including loss of lives, destruction of infrastructure like roads and settlements, damage to agricultural areas, and environmental degradation, which often leads to socio-economic setbacks. Therefore, this study emphasized the use of the LR method, a statistical modeling technique, in developing landslide susceptibility maps and understanding the environmental aspects that cause slope instability. The result provides preliminary information needed to facilitate decision-making and develop mitigation strategies, which are significant in reducing risks associated with landslides. It will also help the local government and policy makers in land use planning and in identifying suitable areas for future developments. Moreover, the result serves as a baseline in developing an early warning system (EWS), which is crucial in strengthening response and preparedness in mitigating landslide risks by providing warnings and information on its probability of occurrence and its potential impacts.

Evaluation of Model Performance

The accuracy and validity of the model were evaluated using the ROC and TSS metrics. Based on the result of the evaluation, the calculated value of AUROC is 0.90, while the TSS has a generated value of 0.66, corresponding to 90% and 66%, respectively. The obtained values of the two evaluation metrics signify that the LR method effectively and correctly classified the outcomes of the LSA in the municipality of La Trinidad. The evaluation of the result showed that there is a good to satisfactory agreement between the generated landslide susceptibility map and the observed or collected historical landslide points in the study area. The result indicates that the LR method can accurately predict and classify LSA.

To further validate the result, a field validation, with the assistance of the MDRRMO, was conducted to compare the landslide susceptibility map with the observed landslide occurrences. During the validation, it was observed that most of the recorded landslide occurrences fell within the areas classified as highly vulnerable, mostly near and within the road networks. According to the record of the MDRRMO, the barangays identified as highly vulnerable have been experiencing numerous landslide occurrences, which caused loss of lives and destruction of houses, roads, and farmlands, leading to negative impacts on the socio-economic aspects of the municipality. The field validation further confirms the reliability of the LR method for landslide susceptibility mapping. The findings of this study are significant, emphasizing the need to consider landslide susceptibility assessment into the municipality's land-use planning, sustainable development, disaster risk reduction management, and decision-making process.

CONCLUSION

The findings revealed that 463.54 ha (6.06%) is susceptible to landslides, while 7,181.44 ha (93.94%) is classified as not susceptible. Susceptible areas are specifically found in barangay Beckel, Puguis, Ambiong, Shilan, and Poblacion. These areas are characterized by high density of population, settlement, and infrastructure. Additionally, three (3) factors, namely distance to road, slope, and NDVI, made notable contribution to the occurrence of landslide. Based on the result, 0–400 m distance from the road exhibits high susceptibility to landslide occurrences, due to the construction and advancement of road networks. Moreover, areas with a slope of 10–40° are susceptible to landslide due to the steepness of the slopes. The absence of vegetation cover also has a significant impact on landslide occurrence in the study area, wherein areas with low NDVI values, characterized by water bodies, barren land, and built-up areas, are mostly susceptible to landslides. Values of the AUROC and TSS metrics, 0.90 and 0.66, respectively, indicate the reliability and accuracy of logistic regression in predicting and analyzing landslide susceptibility in the study area. The result of the analysis provides significant information, highlighting the importance of integrating landslide susceptibility map, in land-use planning, developing sustainable development initiatives, and in crafting policies and developing appropriate measures to minimize landslide risk and potential impact on the community.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

CONTRIBUTIONS OF INDIVIDUAL AUTHORS

G.P.T. was involved in the original draft of the manuscript and, together with M.N.T.L., contributed to the literature review and data analysis. J.P.M.P. contributed to the research methodology and interpretation of results. R.I.C.L. led the conceptualization and methodology, project leadership, secured funding, and performed a critical review of the manuscript. D.M. coordinated project activities. R.I.C.L., K.A.L., L.J.T., and Q.A.G. supervised the project. K.A.L, L.J.T, Q.A.G, J.P.M.P, and M.N.T.L were involved in the review of the manuscript, while R.I.C.L, J.P.M.P, Q.A.G, and M.N.T.L contributed to editing of revisions. G.P.T., M.N.T.L., D.M., and Q.A.G. were involved in data collection.

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