Landslide Susceptibility Analysis and Hazard Zonation in Nuwakot District, Nepal

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KEYWORDS

Bivariate analysis, Frequency ratio, Entropy index, Landslide susceptibility analysis

ABSTRACT

Landslide mostly occurred in highly rugged topography, erosional steeply sloping land form and fragile geological structural in mountainous region. Landslide susceptibility describe the likelihood relation of occurring landslide in an area controlled with their local terrain condition. Landslide susceptibility analysis (LSA) work is used to determine the spatial distribution of landslides prone area and applicable to predict the future landslides occurrences, which is vital for averting and mitigating regional landslide disasters. LSA. In this study, LSA is carried with the bivariate analysis incorporating twelve causative factors of landslide. The frequency ratio (FR) technique were used for computing the relative frequency (RF) as priority rank and entropy index (E) as weight of causative factor. Result of LSA shows that the probability of occurring landslides is 80 percent, with 27 percent of that risk being high risk, 38 percent being medium risk, and 15 percent being low risk. The prediction accuracy of the model is 87.89 percent, showing reliable and satisfactorily validation rates with good accuracy. So, the present study demonstrates that the quantitative assessment methods explored may have a promising potential for landslide assessment and prediction in the high hill and Himalaya regions.

1. INTRODUCTION

Landslides are global geomorphological phenomena occurring in all geographic regions in response to a wide range of triggering factors. It is linked to the combination of geological, geomorphological, and climatic factors in response to trigger mechanisms mostly represented by heavy rainfall events, seismicity, or human action. It occurs through the movement of a debris, rock or soil mass down the slope (Cruden, 1991) and plays an important role in landform evolution and cause serious destructive natural hazards (Seyedeh et al., 2011). It impacts directly and indirectly on a territory, causing fatalities and huge socioeconomic losses also due to rapid population growth and environmental degradation that requires correct land use policies and best practices for long-term risk mitigation and reduction.

Geographically, Nepal is a one of the most vulnerable countries in the world to landslide. Rugged topography, unstable geological structures, soft and fragile rocks, along with heavy and concentrated rainfalls during monsoon periods collectively cause severe land sliding problems and related phenomena in the mountainous part of Nepal (Dahal, 2012). Also, Nuwakot district covers mostly rugged terrain, erosional and past glacier land form and fragile geological structural mountainous region and consequently highly vulnerable to the occurrence of landslides. Landslide susceptibility describe the likelihood relation of occurring landslide in an area controlled with their local terrain condition (Joshi et al., 2017). The aim of this paper is to determine the spatial distribution and likelihood of landslides through landslide susceptibility analysis (LSA) in geographic information system (GIS) environment. LSA indicates the landslide-prone areas that can be used by policy-makers, and general public to avoid catastrophic landslides. It represents a fundamental step toward assessing landslide hazards and developing mitigation strategies (Dong et al., 2023). Therefore, conducting landslide susceptibility modeling and mapping research is essential.

2. STUDY AREA

Nuwakot District, a part of Bagmati Province, is one of the seventy-seven districts of Nepal. The district, is located at latitude from $27^0 45'37.54''$ to $28^0 05'27.72''$ and longitude from $84^0 59'26.43''$ to $85^0 29'57.87''$ having extent 1121 km^2. The demographic situation of this districts covers population of 263,391 and population density 235 per km^2 in 2021 (NSO, 2023). The district consists of 12 local units having two municipalities as Bidur and Belkotgadhi, and 10 rural municipalities as Kakani, Likhu, Panchakanya, Dupcheshwar, Suryagadhi, Tadi, Shivapuri, Kispang, Tarkeshwar, and Myagang. The location diagram of Nuwakot district is shown in Figure 1.

Figure 1: Study Area

3. METHOD AND MATERIALS

3.1 Data used

The data collected from secondary source that utilized to create the landslide inventory mapping, causative factors as criterion map and determine the potential site for susceptibility of landslide area. The detail of data and its source is shown in Table 1.

Table 1: Data & data sources

Data Type	Source	Year
ZY-3 Satellite Image	Survey Department	2024
Topographical map (1:25000 & 1:50000) and its digital layer	Survey Department	2023
Rainfall Data	Department of Hydrology and Metrology	2000-2023
Geological Map (1:50000)	Department of Mine and Geology	2022
Land System Map (1:50000)	Survey Department	2020
Past Landslide Data	District Disaster Committee, Nuwakot	2023

3.2 Method adopted

LSA was carried out using bivariate statistical analysis with frequency ratio (FR) technique in GIS environment. The FR technique has used to compute the weight and its influencing rate based on the possibility of landslide occurrence and relation with the characteristics of causative factors. The FR technique was used to establish the relationships between the distribution of landslide occurrence locations and each causative factor based on the reveal correlation between these factors. The weight for each causative factors of the landslide was firstly determined, then landslide susceptibility indexes map was generated by weighted summation of causative factor in GIS.

The conceptual framework of bivariate analysis based FR model associated with the parameters of LSA is explained in Figure 2.

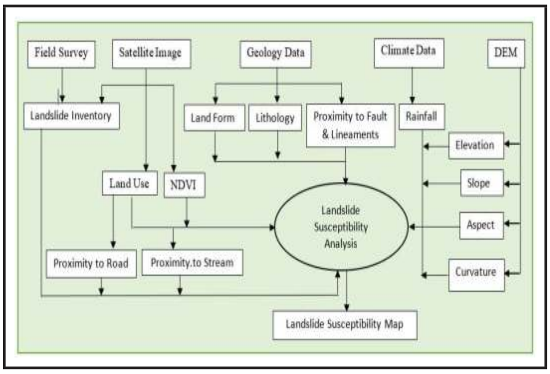

Figure 2: Landslide Susceptibility Analysis

The weight of each causative factor was defined as the natural logarithm of the landslide density in the class over the landslide density in the factor map as follows (Van Westen et al., 1997; Dou et al., 2015).

$$Wi = \ln\left(\frac{N_{pix}(S_i)/N_{pix}(N_i)}{\sum N_{pix}(S_i)/\sum N_{pix}(N_i)}\right) \quad \dots \text{(i)}$$

where, Wi is the weight given to a certain causative class of factor parameter. Density class is the landslide density within the parameter class, Density Map is the landslide density of the entire factor map for all classes, Npix(Si) is the number of landslide pixels in a certain class and Npix(Ni) is the total number of pixels in all classes. The entropy index was used to estimate the difference between the average shares of single causative factor with proportion from the total causative factors used in the whole system. The entropy index (E) of each causative factor parameter was computed based on the information coefficient of parameter with the parameter value to total value ratio (Bednarik et al., 2010)

$$Eij = \frac{FR}{\sum_{j=1}^{n} FR} \quad \dots\text{. (ii)}$$

The landslide susceptibility map (LSM) was computed from the values of parameters classes with influencing landslides as entropy index (E) and weight of causative factor based on FR together as follows (Nohani et al., 2019).

$$LST = \sum_{j=1}^{n} (W_j \, x \, E_i) \quad \dots\text{. (iii)}$$

where, W.j is the weight of causative factor based on FR, Ei is the causative factor map product from FR value of i classes of causative factors j, and n is the number of causative factors and LST is the landslide susceptibility index for potential hazard for landslide risk.

In this study, the performance of LSE was validated through the receiver operating characteristic (ROC) curve and the area under the curve (AUC). Generally, ROC is used to quantify the quality of deterministic and probabilistic detections and to determine the accuracy of the LSA (Akgun et al., 2012). The ROC curve is drawn by plotting specificity on the X axis and sensitivity on the Y axis where sensitivity represents the false positive rate and specificity as the false negative rate based on the number of observed landslides predicted accurately compare to the predicted landslides. The AUC was used to identify the model accuracy based on the validation samples landslide and ability in predicting future landslides based on the training samples landslide. The range of the AUC ranges from 0.5 to 1 with the AUC of 1 representing perfect prediction and the closer the value of the AUC to this number, the better the performance of the model (Tehrany et al., 2013). In general, AUC of range between 0.9–1.0 is excellent, 0.8–0.9 is good, 0.7–0.8 is fair 0.6–0.7 is medium and 0.5–0.6 is poor (Kantardzic, 2011). In the model evaluation by AUC, there is two evaluation process based on the success rate and the prediction rate. The results for the success rate achieved on the basis of training data and the prediction rates attained by a set of validation data (Karna, 2024). The results of the success rate have represented the fitness of the model for the training data; used in model building and not useful in assessing the predicting power of the model (Nohani et al., 2019).

4. RESULT AND DISCUSSION

4.1 Landslide inventory mapping

Initially, landslide inventory map was prepared based on the past landslide occurrences. The accuracy of the data on past and present landslides were used for predicting future landslides. In this research, extensive field survey was conducted for collecting the past and present landslides and interpreted with help of topographical map and satellite images, and other relevant documents and reports. The total of 206 landslides sites (locations) were determined and mapped for preparing the landslide inventory map. The inventory data was randomly categorized into two parts; one containing about 70% of landslide occurrences (144 locations) for building the model, called training dataset and another about 30% of landslide occurrences (62 locations) which was not being used in the training step but applied for validating the model performance, called the validation dataset. The distribution of landslide area is represented in Figure 3.

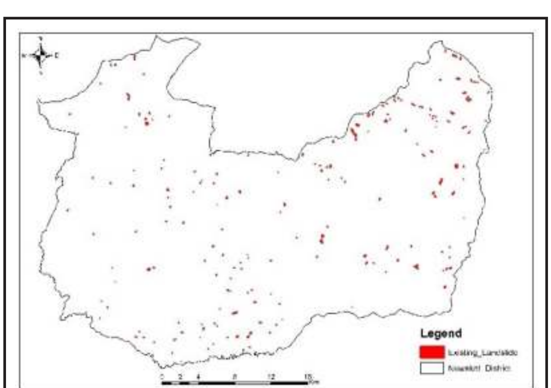

Figure 3: Landslide Distribution

4.2 Causative factor

For the assessment of susceptibility of landslides, identifying the landslide causative factors is essential. Landslide causative factors have some characteristics such as easy obtainability, representativeness, and practicality (Oh & Pradhan, 2011). In this research, twelve causative factors affecting the occurrence of landslides were determined for LSA based on the literature review and field surveys. The mechanism of landslide occurrence were identified and related to the factors of hydrology, geomorphology, geology, climatic etc. These factors includes: slope degree, slope aspect, curvature, elevation, proximity to fault line, lithology, land form, Normalized Difference Vegetation Index (NDVI), rainfall, proximity to stream, proximity to road, and land use. The map of these causative factors maps were prepared in GIS. Among these causative factors, the slope angle relates with shear stress and contributes to the displacement of the hill slope and the most significant in the occurrence of landslides. The surface of terrain with sufficient thickness of soil depends on slope angle and increased the slope angle depicts hill/mountain more unstable. The slope angles in the area under study area was directly derived from digital elevation model (DEM) and reclassified into five groups as 0–5, 5–15, 15–30, 30–45, and greater than 45 degrees.

The slope aspect is another significant factors has affected the occurrence of landslides due to various wetness of the aspect. It affected through the hydrological processes by evapotranspiration and influenced with soil moisture and vegetation cover. The information about the slope aspect was taken from DEM and divided into five categories as flat, north, east, south and west. Likewise, the curvature represents the morphological characteristics of the topography and controls surface runoff and factors on the impact of landslide occurrence. The curvature was straight derived from the

DEM and categorized into three classes of negative curvature as concave (≤0.05), zero curvature as flat (-0.05–0.05) and positive curvature as convex (≥0.05).

The heavy and concentrated rainfalls directly influences the occurrences of landslide as climatic factors. The rainfall intensity was derived from the mean rainfall intensity data from 2000-2023 at the surrounding metrological stations and categorized into three groups as less than 2000, between 2000 to 3000 and greater than 3000 mm per year. The intensity of rainfall and tectonics plate movement depends on the range of the elevation. So, the elevation also acts as influencing factor for the landslide occurrences indirectly. The elevation was represented through DEM and categorized into six groups' elevation range as 354–1000; 1000–2000; 2000–3000; 3000–4000; 4000–5000; and above 5000m from mean sea level.

The fault line indicates the tectonic racks that weaken the rock and cause discontinuities in the soil and rock. This indicates the likelihood that numerous landslides will be caused by seismic and geological processes. The fault line layer was derived from the geological map of the study area, then the distance from the fault was extracted using the multiple ring buffers with five classes of 0–100, 100–200, 200–500, 500-1000 and greater than 1000 m. The lithology represents the structure of work based on the different formations with various structures, compositions, and permeability, which influence the formation material (rock type) strength. The confluence of rock type with curvature and slope steepness are influenced remarkable occurrences of landslide. The lithological structure was also derived from the geological map of the study area, which consisted of 4 units as slate, gneisses, quartzite and schists. Landform mainly morphological identification play an important role in the occurrences of landslide because, for each individual slope the process that occurs is different, which in turn produces different materials (Malik et al., 2017). In addition, these differences of process and material have different effects on the frequency of landslide occurrences. The morphological landform was derived from land system map and it covers alluvial plains and fans, erosional terraces and tars, steeply sloping terrain, past glacier lower attitudinal mountain, and past glacier upper attitudinal mountain.

The NDVI represents the vegetation cover index in which greater the value, the more amount of vegetation cover and the root of vegetation leads to stabilization of the hill slope and reduction in landslide occurrences. The NDVI map was generated through ZY-3 MSS images. The range of NDVI values were categorized into four categories as less than zero as water body and high moisture condition and probability of high landslide occurrences; the value between 0.00 to 0.30 represented the built-up, bare soil and agriculture land with moderate landslide occurrences; between 0.30 to 0.45 represented the shrub land with low landslide occurrences and greater than 0.45 represented dense forest as very low occurrences of landslide. The water of the river are considered as an important factor in LSA having condition of wet land and high soil moisture. The water contains factor was extracted for the river layer through buffering in distance ranges and classified into five classes including distance less than100, 100–200, 200–500, 500-1000 and greater than 1000m. Existing landslides are typically found close to road systems, where they are caused by discontinuities in the rock and soil that are prone to landslides, or by cutting slope hills for roads that are steeper than 15 degrees. The distances to the roads was obtained from buffering in distance ranges and classified into four classes including distance less than 100, 100–200, 200–500, 500-1000 and greater than 1000 m. Land use acts as significant factor that caused by human beings and affects the probability to landslides in the study area. The land use map of study area in 2023 was created from topographical map and applied in LSA.

4.3 Computation of weight and entropy index

The entropy index (E) in terms of parameter weight of each causative factor was computed from association of FR values using equation (ii) and shown in Table 2.

Table 2: Entropy index and weight of Factors

S.N.	Factor	E Value	Weight
1	Proximity to Stream	0.08	8
2	Land Use	0.11	11
3	Lithology	0.06	6
4	Elevation	0.1	10
5	Proximity to Road	0.07	7
6	Curvature	0.06	6
7	Land From	0.07	7
8	Aspect	0.1	10
9	NDVI	0.1	10
10	Proximity to Fault line	0.07	7
11	Slope	0.1	10
12	Rainfall Intensity	0.07	7

4.3 Potential landslide susceptibility area

Potential landslide susceptibility area was produced based on the influencing weight and relative frequency derived from the FR of causative factors using equation (iii) is shown in Figure 4.

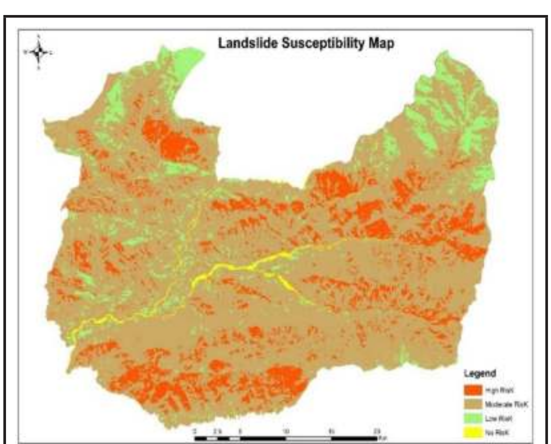

Figure 4: Landslide Susceptibility Map

From the landslide susceptibility analysis data, it's showed that the 80% of municipality extent land has occurred in the landslide risk in which the distribution of the high risk occupied 27%, medium risk occupied 38 % and low risk occupied 15%.

4.4 Validation of susceptibility model

The ROC curve with AUC for success rate was generated from the training dataset of landslide and potential landslide susceptibility map. Likewise, the ROC curve with AUC for prediction rate was generated from the validation dataset of landslide and potential landslide susceptibility map.

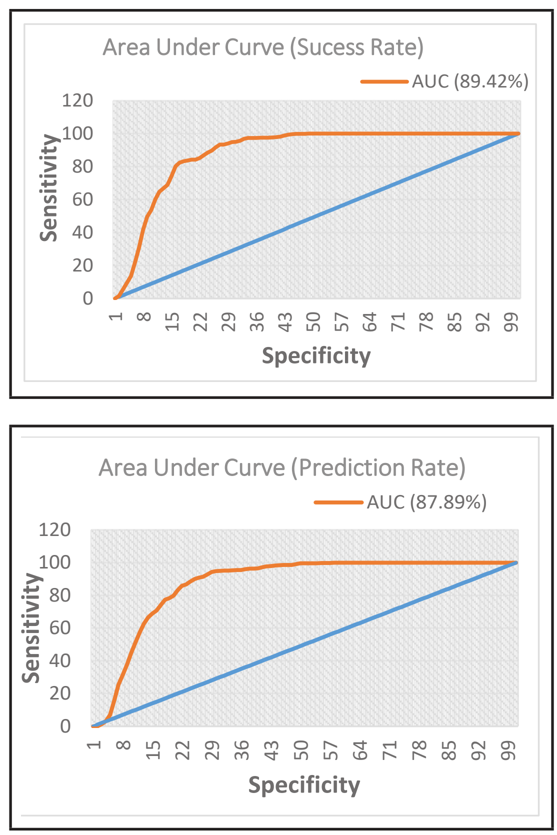

Figure 5: LSA Model Validation

The area under the curve of the success rate showed 0.89 and prediction rate 0.88 representing the prediction accuracy of the model is 87.89%. So, LSA is reliable and showed all satisfactorily validation rates with good accuracy.

4.5 Potential hazard zonation and impact

The impact of potential landslide assessment was carried out by the process of spatial overlay operation using zonal statistics of landslide susceptibility layer with land use layer 2023. The potential landslide risk in the land use categories is shown in Table 3. In overall risk, total 79.85 percent land has occurred in the potential landslide risk prone zone in Nuwakot district. The 84.39 percent of land under agriculture use is found in risky zone of the landslide. Also, 74.63 percent of forest land is occurred in the risk by landslide Likewise, 77.96 percent of built-up area, is found under the threat of landslide risk.

Table 3: Potential risk and impact on landuse

S.N.	Land Use Type	Landslide Susceptibility (area in Sq. Km)					Overall Risk (%)
	Description	High	Medium	Low	Total	%	
1	Agriculture	215.52	226.24	90.50	532.26	84.39	44.61
2	Forest	80.14	202.93	81.17	364.24	74.63	30.53
3	Waterbody	22.67	11.04	4.41	38.12	74.18	3.19
4	Built-up	5.13	8.37	3.35	16.84	77.96	1.41
5	Barren Land	0.77	0.34	0.14	1.25	88.82	0.11
	Total	324.23	448.92	179.57	952.72		79.85

5. CONCLUSION

LSA based on bivariate FR based quantitative technique is more appropriate to evaluate the probability assessment of landslides in the study area. The causative factors identified and applied in LSA is the local situation of Nuwakot District and might be used in other part of Nepal. The result of LSA shows that the steeply sloping terraces having rugged geological structure in the erosional land form area are occurred in high and medium risk of landslides. Also, landslide susceptibility depicts the most portion of the area in high risk that affected the serious threats to life, property, infrastructures and ecological system. The present study demonstrates that the quantitative assessment methods explored may have a promising potential for landslide assessment and prediction in the Himalayas.

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