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Landslide Susceptibility Assessment Using Bivariate Statistical Methods: A Case Study of Gulmi District, western Nepal

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Abstract: Landslides are one of the most recurrent natural hazards occurring each year in the hilly and mountainous regions of Nepal causing massive loss of life and property. Natural hazards such as landslides cannot be avoided completely but the processes and consequences can be mitigated. The main objective of the study was on the application of Geographic Information System (GIS), and statistical calculations for landslide susceptibility modeling of Gulmi District, western Nepal. The models were derived using two different statistical approaches including Frequency Ratio (FR) and Shannon Entropy (SE). A landslide inventory of the Gulmi district was developed. The landslide inventories were used to derive the quantitative relationships between landslide occurrences and landslide causative factors. In this study, ten landslide influencing factors were used which include slope, aspect, curvature, lithology, geology, land use land cover, distance from the river, distance from the road, and distance from fault and soil type. Individual factor maps were prepared as thematic layers. After determining the weights of each class from the proposed two models, the landslide susceptibility maps were ready with five classes (very low hazard, low hazard, moderate hazard, high hazard and very high hazard) using GIS. The values of Area Under Curve (AUC) of success rate for FR and SE methods were found to be 81.8% and 80.6% respectively. The model shows that more than 15 % of the area falls under low and very low susceptibility level while 44% of the area has a high probability of landslide occurrence. The result of the present study indicates that integration of GIS has increased the quality and effectiveness of the overall process of susceptibility modeling and prediction mapping. To enhance the planning strategies for disaster mitigation and ensure sustainable development a reliable landslide hazard forecasting and risk assessment is a key component.

Keywords: Landslide; Gulmi District; Frequency Ratio (FR); Shannon Entropy (SE)

1. Introduction

Landslide is one of the most common natural hazards that has caused massive damages to infrastructure, property as well as loss of lives around the world. The country which is most affected by the landslide was China with 695 landslide-persuaded deaths that are followed by Indonesia with 465 deaths, India - 352, Nepal - 168, Bangladesh - 150 and Vietnam - 130 (ILC, 2007). Approximately 89.6% of the total fatalities around the world were caused by landslides set off by prolonged or intense rainfall. (D. Petley 2008).

Nepal is composed of about 83% of the mountainous land with weak and fragile geological structures. So, Nepal is prone to a variety of human-induced disasters and natural hazards. More than 80 percent of the total population of Nepal is likely to suffer from natural hazards such as landslides, floods, earthquakes, fires, windstorms, hailstorms and GLOFs (NDRR 2019). Among various natural hazards, the landslide is very common in the hilly region of Nepal.Landslides in Nepal cause a significant number of fatalities, economic losses and is one of the major restraint in development (Petley, et al. 2007). The various reasons causing landslides as mentioned by Varnes (1958) are geological, morphological and human causes. The major factors causing critical landslides and related phenomena in the mountains and hilly part of Nepal are rugged topography, frequent earthquakes, soft and fragile rocks, heavy rainfall during monsoon and unstable geological structures (Dahal and Hasegawa 2008). The deformation of land occurs due to slow but continuous seismic activities and also a sudden change in geographic structure due to sudden changes such as earthquakes (Ansari, 2014; Ansari et al 2018). This type of deformation of land can cause severe landslides. According to (NDRR 2019), the landslide hazard risks are further aggravated by anthropogenic activities like encroachment into vulnerable land slopes, improper land use, unplanned and random development activities such as the construction of canals, roads, tunnels without convenient protective measures in the vulnerable hilly and mountain belt. NDRR (2019) also claims that based on the Himalayan range and their geology, the hilly area of Nepal is located in the Mahabharata range, Siwalik, Mid-land and higher altitudes of the Himalayas are more vulnerable to landslide.

Detailed knowledge about the expected frequency, character, pattern and magnitude of slope failures in an area can lead to successful mitigation of landslide hazards. For conducting quicker and safer mitigation programs over a specific area identification of landslide-prone regions is essential. In recent years, greater awareness of disasters due to landslides has brought attention to the government level. Despite many types of research, there have been limited standard methods that can develop a reliable model for the prediction of landslide events. Only a few attempts have been made to predict the landslides or prevent the losses due to such events. Hence, the probable landslide hazard and their impacts on various aspects of the geo-environment becomes a remarkable issue of study. Landslide Susceptibility Assessment is the measure of spatial probability of a landslide occurring in an area under the local geo-environmental condition depicting the extent to which terrain can be affected by future landslides (Kai, Dong and Wei 2016). The new technology resources and software in the field of geographic information domain have provided sophisticated functionalities to integrate spatial/non-spatial data to study, model, analyze and predict the consequences of such disasters. This research work will be made on the different landslide causative factors, determination of their weights, preparation and analysis of the landslide susceptibility model and accuracy assessment while using two GIS-based statistical methods.

2. Study area

Gulmi district is one of the seventy-seven districts of Nepal. It lies in Lumbini Pradesh. The district with Tamghas as its district headquarters covers an area of 1149 square kilometers. According to the census data, 2011 the total population of Gulmi district is 280,160 comprising 120,995 males (56.8%) and 159,165 females (43.2%) residing in 46,835 households. This district lies in the mid-hilly region of Nepal. Geographically the district spreads from 83° 01' E to 84° 37' E longitude and 27° 55' N to 28° 16' N latitude. This district is rich with its geographic, biological, social, economic, religious and cultural diversity and has abundant tourism potential. The district has an average length of 63.04 km and an average width of 29.27km. (CBS 2012) . There are various small to medium-sized streams joining the major rivers (Gyawali et al 2019; Prajwol et al 2021) . Overall river structure is dendritic with a steep gradient and deep valley cut. The total average length of small and big rivers inside this district is about 677 km. The average rainfall of the area is recorded to be 1377 mm and the elevation ranges from 463-2676m (Figure 1).

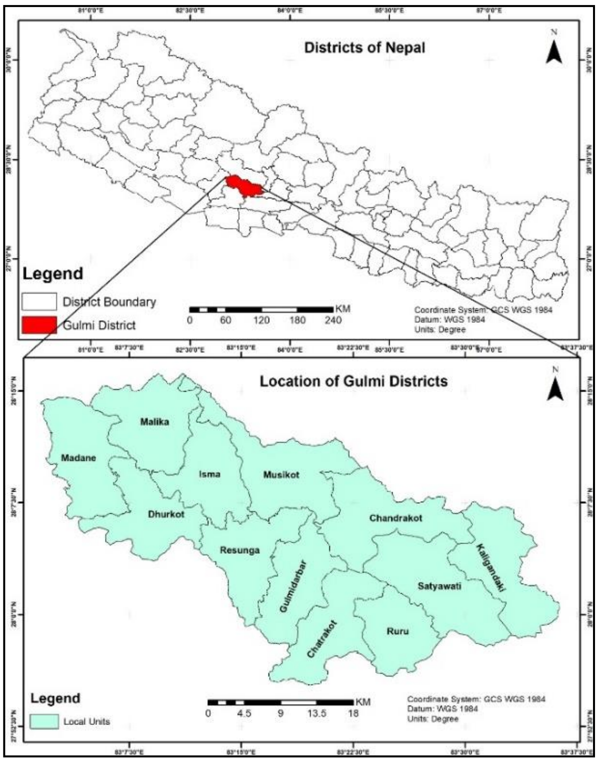

Figure 1: Location map of Gulmi district

3 Methodology

3.1 Data Acquisition

The data required for the overall assessment were obtained from different sources. A brief description of the data, their sources, features and analysis procedures are presented as below (Figure 2):

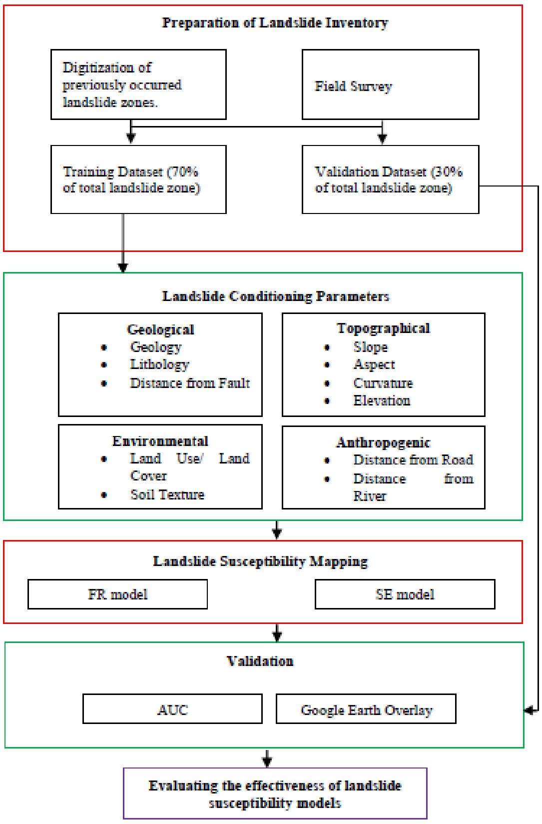

Figure 2: Flow chart of adopted methodology.

3.2 Preparation of Landslide Inventory

A landslide inventory is a detailed register of the distribution and characteristics of past landslides (Hervas 2013). It reflects the location of landslides digitized from existing maps with information of its types, date of occurrence, size volume and causes. The landslide inventory provides insights into the types, failure mechanism, location, trigger as well as the frequency of occurrence, its density and damage related to landslide (Van Westen 2008). In this research, in total 143 landslide areas were collected and mapped for preparing a landslide inventory map. The historic images of different years were interpreted visually to locate the slipped area. The verification of such areas was done with field visits. Later the polygons were randomly split into two subsets where data were divided into 70% and 30% as a training and testing data set. The two subsets of landslide inventory are explained shortly below.

3.3 Training Data

Among the total landslide data, 70% of the data were used for developing the model as training data. A sum of 100 landslide locations were used for the prediction of future landslides. The training data were determined by digitizing the landslide areas using Google Earth. The total landslide pixels covered by training data is 2796.

3.4 Validation Data

Among the total landslide data, 30% of the data were used for validating the model as validation data. A sum of 43 landslide locations was used for validating the predicted landslide area. The validation data were also determined by digitizing in Google Earth. The ratio of 70/30 was used for dividing the training and validation data based on the suggestion of (Pham, et al. 2015).

3.5 Landslide Conditioning Parameters

The factors that cause the large mass of rock, debris or earth to move down a slope are landslide conditioning parameters. To obtain an assessment method for the analysis of susceptibility to landslides, identifying the landslide conditioning factors is crucial (Ercanoglu and Gokceoglu 2002).

In this study, the four various landslide conditioning factors have been collected from different sources like USGS earth explorer, Humanitarian Data Exchange, ICIMOD, Department of Mines and Geology, Survey Department of Nepal, digitation from Google Earth and direct field survey to validate the result obtained from this analysis. This study has included four sets of major parameters under which ten (10) landslide conditioning parameters affecting the occurrence of landslides were taken into account for analysis. These are classified as the geological, topographical, environmental and anthropogenic parameters.

a) Geological parameter

Geology: Geology plays a vital role in the land susceptibility model. In this analysis, geology is categorized into 7 classes. These are Galyang formation, Lakharpata formation, Ranimatta formation, Sangram formation, Siuri formation, Swat formation and Syangja formation (Figure 3). The different formation has different lithology, structure and permeability which affect the formation materials strength (H. Hong, et al. 2016).

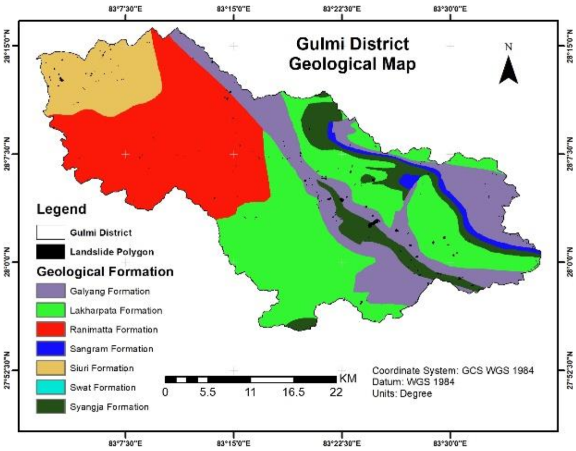

Figure 3: Geological map of Gulmi district.

Soil Type: Soil have different physical and chemical properties that influence the formation material strength (H. Hong, et al. 2016) so that convergence of these parameters with curvature and slope steepness has a remarkable influence on landslide occurrences (Nguyen, et al. 2019). Steep soils are likely to be eroded and lose their topsoil as they form. Dominant Soil and Parent material maps were clipped from the Soil and Terrain Database (SOTER) for Nepal. The soil map was classified into 3 classes based on fertility and chemical composition (dominant soil) of soil namely Cme, CMg and CMx (Figure 4).

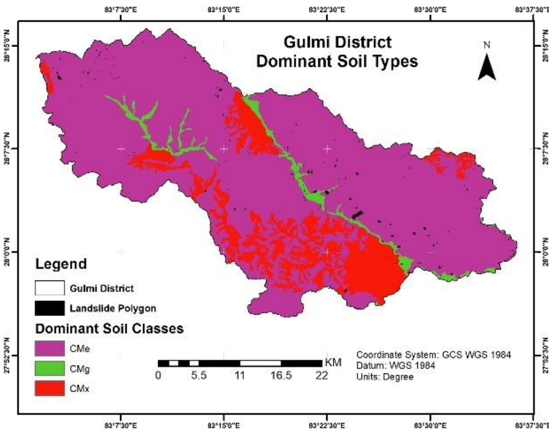

Figure 4: Soil Distribution of Gulmi district.

Distance from fault: The fault means the discontinuity between the soils and rocks (Ayalew and Yamagishi 2005). The rocks around the faults are more disturbed so that strength is highly reduced and hence, the region around these tectonic features more susceptible to failure (Poudel, Deep and Amar 2016). The fault map was derived from the geology map of Nepal and then after Euclidean distance (raster buffer) was created (Figure 5).

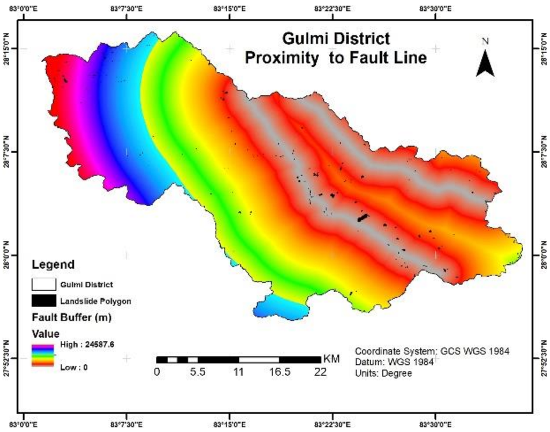

Figure 5: Faults Buffer map of Gulmi district.

b) Topographical parameter-

Slope: Slope affects the soil water content (surface and subsurface) and formation of soil, erosion potential. It has been widely shown that landslides tend to occur more frequently on steeper slopes (Poudel, Deep and Amar 2016). The increase in slope angle results in unstable terrain. The slope angles in the area under the study are reclassified into seven groups ; 0-10, 10-20, 20-30, 30-40,40-50, 50-60 and >60 degree (Figure 6).

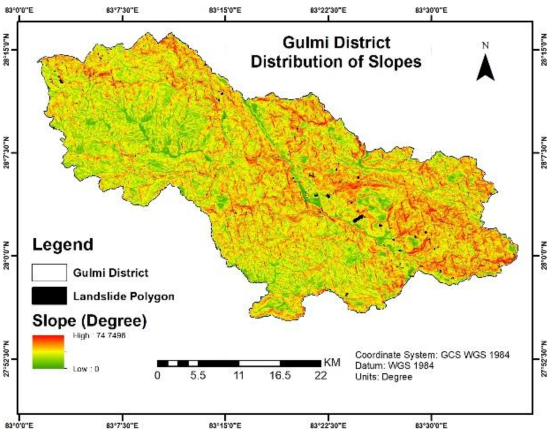

Figure 6: Slope distribution map of Gulmi district.

Aspect: Aspect is the direction of slope and is expressed in degree in the clockwise direction. The slope aspect is also one of the most significant factors affecting the occurrences of landslides due to various wetness of the aspect (Pham, et al. 2018). The aspect map was also produced from DEM and divided into 10 classes as Flat (-1), North (0-22.5), North (337.5-360), North-east (22.5-67.5), East (67.5-112.5), South-east (112.5-157.5), South (157.5-202.5), South-west (202.5-247.5), West (247.5-292.5), North-west (292.5-337.5) (Figure 7).

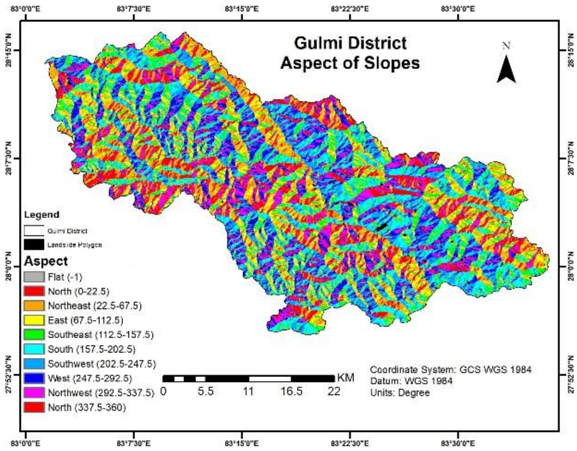

Figure 7: Aspect map of Gulmi district.

Curvature: Curvature is parallel to the direction of the maximum slope. The morphology of the topography was identified by curvature (Pourghasemi, Moradi and Aghda 2013). It controls the surface runoff so that it has an impact on the landslide occurrences (Pham, et al. 2018). The curvature was derived from DEM and divided into three classes of negative curvature (<-0.05), zero curvature- flat (-0.05-0.05) and positive curvature (>0.05) (Nohani, et al. 2019) (Figure 8).

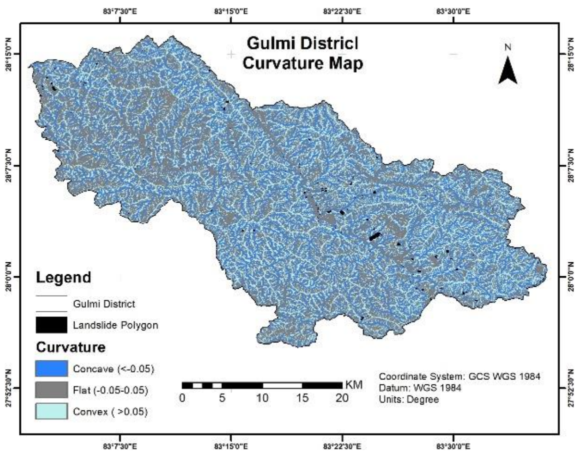

Figure 8: Cuvature pattern map of Gulmi district.

Elevation: The elevation is a widely used factor for the assessment of landslide susceptibility. Elevation affects the large number of biophysical parameters and anthropogenic activities (Poudel, Deep and Amar 2016). The elevation is also related to different environmental parameters such as vegetation cover, rainfall, temperature, etc. Elevation map was produced from DEM with 30m*30m grid size which is reclassified into 8 classes from 463 m to 2676 m (Figure 9).

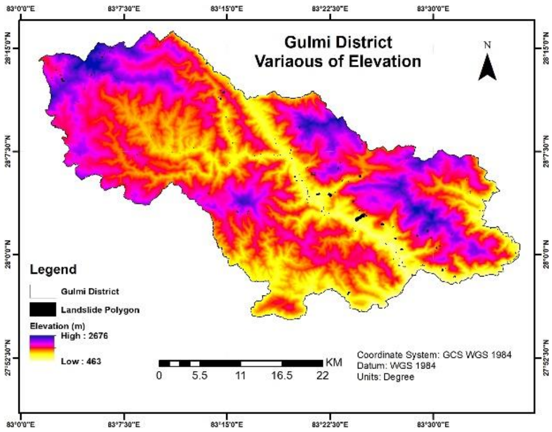

Figure 9; Elvation variation of Gulmi district.

c) Environmental parameter

Land use/Landcover: It is a significant factor that affects landslides. For landslide susceptibility mapping, it is required to understand the current land use/ land cover and how it is being used, along with accurate means of monitoring over time (Caldwell 2019). The land use map is categorized into 7 classes namely Agriculture Area, Barren Area, Buildup Area, Forest, Grassland, Shrubland and Cutting (Figure 10).

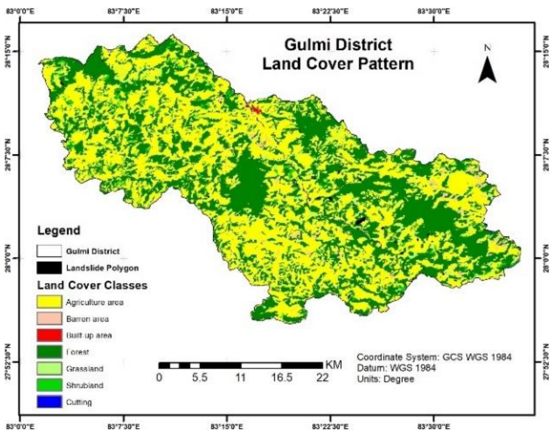

Figure 10: Landuse pattern map of Gulmi district.

d) Anthropogenic parameter

Distance from Road: In the study, (Tuan and Dan 2012) explains that landslides were mostly distributed near the road system. By cutting more than 10 degrees of slope in hills to build roads, discontinuity is created in soil and rock. Therefore, the area nearer to the road can be prone to landslides (Ayalew and Yamagishi 2005).The distance from the road were divided into seven classes; 0-75, 75-150,150-225, 225-300, 300-375, 375-450, >450 m (Figure 11).

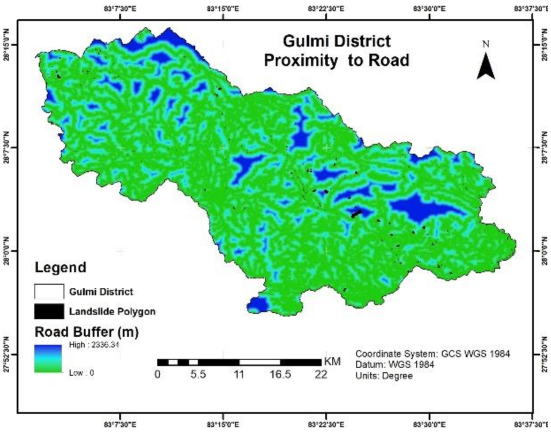

Figure 11:Road buffer map of Gulmi district.

Distance from River: In the research, (Binh Thai, Dieu and Indra 2017) found that 65.12% of landslides occurred in the vicinity of first-class of the river at a distance of 0-40m. For that reason, it is a very important parameter in LSM. This parameter was extracted from the river layer through raster buffering and classified into seven classes; 0-75, 75-150,150-225, 225-300,300-375,375-450, >450 m (Figure 12).

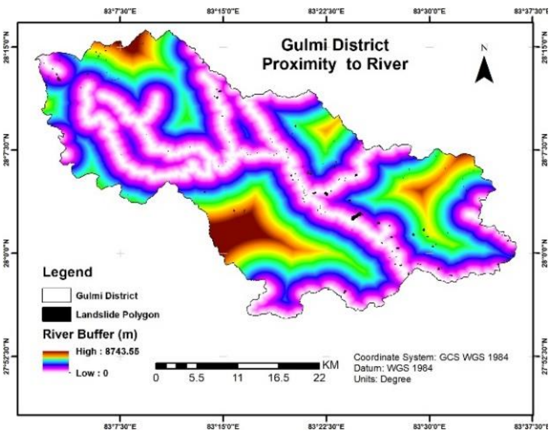

Figure 12: River buffer map of Gulmi district.

3.6 Landslide Susceptibility Mapping

The final step in landslide susceptibility mapping concerned analyzing the area of focus with the probable condition of landslide in the near future (Cascini 2008). The unique sequence of various spatial input datasets develops a susceptibility map illustrating several susceptible classes such as: very high, high, moderate, low and very low (Soeters and van Westen 1996); (Brabb, Colgan and Best 1999). For the preparation of the landslide susceptibility map, the FR model and SE model approaches were applied.

The listed two models were applied in this study to estimate the landslide susceptible area of Gulmi district based on the observed and surveyed relationship between the areas of the landslide that occurred in the past and causative factors. Following various literature (Khan, et al. 2019); (Fayez, et al. 2018); (Yilmaz 2009) for the FR model and (Roodposhti, et al. 2016); (Pourghasemi, Pradhan and Gokceoglu 2012) for SE model. These two models were selected in such a way that the geography, frequency of occurrence of landslide, elevation range and topological structure were similar to the study area.

3..7 Frequency Ratio

Frequency ratio is a quantitative technique for landslide susceptibility assessment using GIS techniques and spatial data (Khan, et al. 2019). Frequency Ratio provides the correlation between the existing landslide locations and the various influencing factors related to the landslide. It was choosen for this study as a basic analysis for a preliminary probabilistic assessment due to the mathematical simplicity and comparatively rapid assessment time. Future landslide hazards can be assumed to occur from similar conditions as past landslides. From this assumption, the relationship can be developed between the area of occurrence of landslide and landslides not occurring in an area with factors relating to landslide. It can be expressed as a Frequency Ratio that represents the quantitative relationship between landslide occurrences and different causative parameters (Pradhan et al., 2012). The formula for the calculation by frequency ratio is as follows:

$$FR = \frac{N_l^p \,/\, N}{N_i^{lp} \,/\, N^l}$$

Where, N_l^p = number of pixels in each landslide conditioning factor class

N = number of all pixels in total the study area

N_i^{lp} = number of landslide pixels in each landslide conditioning factor class

N^l = number of all landslide pixels in total the study area

The relative frequency was calculated as:

$$RF = \frac{FR_i}{\sum_{n=1}^{i} FR}$$

Where, FR_i = Frequency Ratio of each class of a factor

$\sum_{n=1}^{i} FR$ = summation of Frequency Ratio of each class

The prediction rate was computed as:

$$PR = \frac{Max_{RF} - Min_{RF}}{(Max - Min)_{Min_{RF}}}$$

Where, Max_{RF} = Maximum Relative Frequency

Min_{RF} = Minimum Relative Frequency

$(Max - Min)_{Min_{RF}}$ = Minimum Relative Frequency of subtraction of Min_{RF} from Max_{RF}

Meena et al. (2019) have prepared landslide susceptibility maps using the statistics-based approach. In their study, the FR model was implemented using GIS tools. The weight was defined as the area for landslide occurrence to the total study area. According to Meena et al. (2019), the FR value which is greater than 1 shows a high correlation and lower than 1 shows a lower correlation.

FR model has been used by (Yilmaz 2009) for LSM along with logistic regression and artificial neural networks. Further, the results explain that the frequency ratio is one of the best tools in landslide susceptibility assessment if there are sufficient number of input data. The input process, computations and output procedures are readily understood in the FR model.

3.8 Shannon Entropy

In information theory, entropy is the measure of system imbalance, instability, disorder and uncertainty and thus, can predict or forecast the development trend of a certain specified system (Lotfi and Fallahnejad 2010). In present days, the Shannon Entropy has been used widely to determine the weighted index in natural hazards (example landslide hazard) and in the integrated estimation of natural-environment phenomena such as droughts, debris flows, sandstorms and so on (Mon, Cheng and Lin 1994)

In the case of landslides, the Shannon Entropy assesses the diversity or dissimilarity in the natural environment. Further, the extent of various factors that influence landslides is also referred to as the entropy of landslides. The greater the influence of landslide factors, the greater is the entropy index (Sujatha 2012). The steps for the calculation of Shannon Entropy is shown below:

1. Normalizing the frequency of landslide occurrence:

Normalization is the process to adjust certain weights. The formula for calculating the normalized weight is shown below:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

Where, P_{ij} = normalized weight of the landslide occurrence zone

x_{ij} = frequency rate of landslide occurrence of the class of certain factor

2. Computation of entropy:

The entropy of the diverse sets of value is calculated by the following formula:

$$E_j = -k \sum_{i=1}^{m} P_{ij} \ln(P_{ij})$$

$$k = \frac{1}{\ln{(m)}}$$

Where, E_j = entropy of a class of certain factor

k = a coefficient

m = number of classes of a factor

P_{ij} = normalized weight of the landslide occurrence zone

3. Defining weight:

Finally, the weight is computed in Shannon Entropy analysis is shown below:

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)}$$

Where, E_j = entropy of a class of certain factor

w_j = weight of the factor using Shannon Entropy

3.9 Validation

After the development of the models, validation was carried out to check and analyze the prediction accuracy. The validation is required to ensure the models are correct and can be useful for the future estimation of landslides. The validation of the models was accomplished by the following processes:

AUC Curve: The AUC was used to assess the accuracy of the models. The results of the success rate were obtained based on training data and the results of the prediction rate were obtained based on validation data. AUC graph between sensitivity and 1-specificity was developed for each model.

Google Earth Overlay: Google Earth overlay is one of the methods for assessing the accuracy by overlaying the models in the Google Earth image. Google Earth is a reliable tool for checking and visualizing the results over series of historic images. Thus, Google Earth was used for validating purposes by taking a sample of certain portions of the model and overlaying them over Google Earth for visual interpretation and prediction accuracy.

Evaluating the Effectiveness of Models: Eventually, the evaluation of the effectiveness of models was executed after the validation process. The accuracy of each model was obtained from the AUC along with the success rate and prediction rate. Based on the accuracy, the comparison among the proposed models was carried out and the assessment of the models was performed regarding which technique would be more useful for the determination of the landslide susceptible zone of the study area.

4. Results and Discussion

4.1 Landslide Susceptibility Assessment Using Frequency Ratio

The weight of each landslide conditioning factor was assigned using Frequency Ratio for the preparation of LSM. The higher value of FR represents the stronger correlation of the parameters with landslide occurrence. The values of FR greater than 1 indicate a strong correlation whereas the values of FR lower than 1 indicate a weak correlation (Pradhan n.d.). The table below shows the results of the FR method showing the weights obtained for each class of various factors (Table 1).

Table 1: The weight of each classes of ten factors using FR method

Data Layers	Class	FR	PR
Slope (Degree)	0-10	0.056	2.376
	10-20	0.314	
	20-30	0.820	
	30-45	1.606	
	45-55	1.663	
	55-65	2.351	
	>65	1.105	
Plan Curvature	Concave (<-0.05)	1.263	1.439
	Flat (-0.05-0.05)	0.947	
	Convex (<0.05)	0.744	
Aspect	Flat (-1)	0.809	1
	North (0-22.5 and 337.5-360)	1.224	
	North-east (22.5-67.5)	1.058	
	East (67.5-112.5)	0.616	
	South-east (112.5-157.5)	1.069	
	South (157.5-202.5)	0.480	
	South-west (202.5-247.5)	1.052	
	West (247.5-292.5)	1.731	
	North-west (292.5-337.5)	0.852	
Elevation (m)	463-810	1.449	2.151
	810-1017	1.873	
	1017-1199	0.792	
	1199-1379	0.310	
	1379-1571	0.492	
	1571-1792	0.907	
	1792-2067	2.495	
	2067-2676	0.247	
Land Use	Forest	0.863	3.131
	Shrubland	5.617	
	Grassland	0.857	
	Agriculture area	0.850	
	Barren area	5.049	
	Cutting	8.183	
	Built-up area	0.000	
Distance To Fault	0-75	1.199	2.442
	75-150	0.570	
	150-225	0.290	
	225-300	0.000	
	300-375	0.363	
	375-450	0.576	
	>450	1.028	
Soil	Cme	1.082	4.594
	CMg	2.315	
	CMx	0.263	
Geology	Siuri Formation	2.140	2.744
	Syangja Formation	1.173	
	Swat Formation	0.000	
	Ranimatta Formation	0.045	
	Galyang Formation	2.127	
	Lakharpata Formation	0.785	
	Sangram Formation	0.122	
Distance to Roads	0-75	0.628	1.576
	75-150	1.023	
	150-225	1.681	
	225-300	2.000	
	300-375	1.213	
	375-450	0.517	
	>450	0.652	
Distance to Rivers	0-75	2.189	1.000
	75-150	2.060	
	150-225	1.764	
	225-300	2.192	
	300-375	2.439	
	375-450	1.694	
	>450	0.832	

The result signifies that the most frequent landslide occurrences are observed in 50-60 class of slopes and has a frequency ratio of 2.351. Regarding the landslide conditioning parameter of curvature, concave curvature has the highest impact with a value of 1.263 and convex and flat curvatures has a smaller impact on the landslides weighing 0.744 and 0.947 respectively. The impact of aspect is higher in the West, North and South-East weighing1.731, 1.224 and 1.069. Furthermore, another important factor for landslide occurrence is elevation. The lowest elevation that ranges from 463-810 has impact with a weight of 1.449 whereas highest impact with a weight of 2.495 in 1792-2067 range of elevation.

The table illustrates that the less distance from the fault (i.e. 0-75) has a high impact weighing 1.199 and the greater distance from the fault (i.e. 225-330) has less impact weighing of zero. Similarly, the land covered with Barren land and Bank cutting is observed to have a strong impact with a weight of 5.049 and 8.183 respectively. The soil type of CMg which is considered a high impact on landslide occurrence with a weight value of 2.315. Another affecting factor for the landslide is the distance from the road. The effects of landslide seem to be higher for class (225-300)m which weights 2.000 and lower as the distance from the road increases. Similarly, the area between (0-75) m distance from the river is highly effect with a FR value of 2.189 (Figure 13).

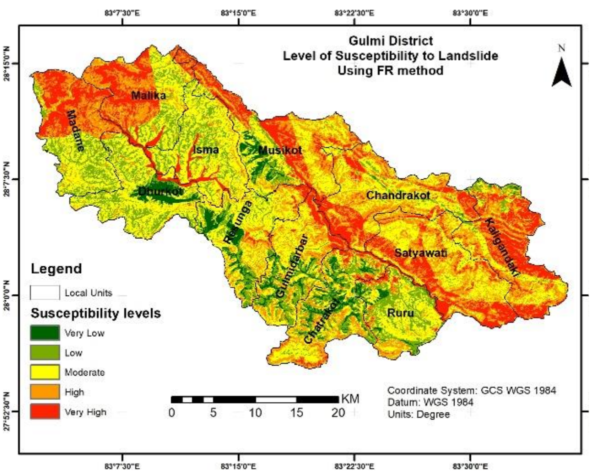

Figure 13:Levels of Landslide Susceptibility in Gulmi district using FR Method.

Another result was obtained using the Shannon Entropy method which is usually preferred for LSM because of its flexibility of fuzzy memberships and ambitious evaluation of factor weights. In MADM, the greater the value of the entropy corresponding to a special attribute, which implies the smaller attribute's weight, the less the discriminate power of that attribute in the decision-making process (Lotfi and Fallahnejad 2010) (Table 2).

Table 2:The weight of each classes of ten factors using SE method

S. N	Data Layers	Class	SE
1	Slope (Degree)	0-10	0.082
		10-20	
		20-30	
		30-45	
		45-55	
		55-65	
		>65	
2	Plan Curvature	Concave (<-0.05)	0.013
		Flat (-0.05-0.05)	
		Convex (<0.05)	
3	Aspect	Flat (-1)	0.077
		North (0-22.5 and 337.5-360)	
		North-east (22.5-67.5)	
		East (67.5-112.5)	
		South-east (112.5-157.5)	
		South (157.5-202.5)	
		South-west (202.5-247.5)	
		West (247.5-292.5)	
		North-west (292.5-337.5)	
4	Elevation (m)	463-810	0.071
		810-1017	
		1017-1199	
		1199-1379	
		1379-1571	
		1571-1792	
		1792-2067	
		2067-2676	
5	Land Use	Forest	0.197
		Shrubland	
		Grassland	
		Agriculture area	
		Barren area	
		Cutting	
		Built-up area	
6	Distance To Fault	0-75	0.086
		75-150	
		150-225	
		225-300	
		300-375	
		375-450	
		>450	
7	Soil	Cme	0.249
		CMg	
		CMx	
8	Geology	Siuri Formation	0.178
		Syangja Formation	
		Swat Formation	
		Ranimatta Formation	
		Galyang Formation	
		Lakharpata Formation	
		Sangram Formation	
9	Distance to Roads	0-75	0.035
		75-150	
		150-225	
		225-300	
		300-375	
		375-450	

		>450	
10	Distance to Rivers	0-75	0.012
		75-150	
		150-225	
		225-300	
		300-375	
		375-450	
		>450	

From the weight values in the above table, it is seen that the factor soil having the SE value 0.249 among other values is the highest factor supporting the landslide susceptibility. from the result, it is also clear that the factors land use and geology having values 0.197 and 0.178 respectively are the factors that highly boost the probability of occurrence of landslide. Similarly, the factors such as plan curvature, distance to fault, distance to road, distance to the river have low values 0.013, 0.086, 0.035 and 0.012 respectively in comparison to other factors which indicate that these factors have less effect on landslide occurrence.

Using the above table, SE values for each factor was developed which was finally used to prepare the LSI map (Figure 14) using the following equation:

$$LSM_{SE} = 0.081710 * Slope_{FR} + 0.012933 * Plan\ Curvature_{FR} + 0.077042 * Aspect_{FR} + 0.071133 * Elevation_{FR} + 0.196986 * Land\ use_{FR} + 0.086176 * Distance\ to\ Fault_{FR} + 0.248782 * Soil_{FR} + 0.178246 * Geology_{FR} + 0.034731 * Distance\ to\ Road_{FR} + 0.012262 * Distance\ to\ River_{FR}$$

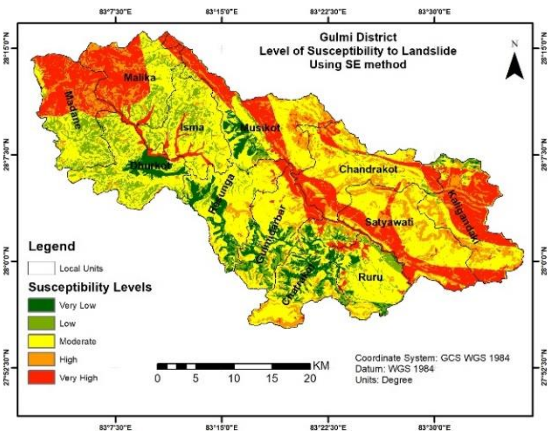

Figure 14:Levels of Landslide Susceptibility in Gulmi district using SE Method

5. Conclusion

Landslide Susceptibility Modeling remains one of the most important and challenging tasks in the assessment of the risk of landslides. Since many methods are proposed for landslide predictability, an appropriate method is a must for the susceptibility and risk analysis. The detailed process of landslide hazard assessment in this work is an example set for the regional scale implementation. Statistical models can be a powerful technique for the analysis of landslide hazards using GIS software. The study was carried out by combining a GIS-based approach with a different statistical bivariate modeling method. Two bivariate statistical modeling approaches namely FR and SE are used in landslide susceptibility mapping of Gulmi district in Lumbini province, Nepal.

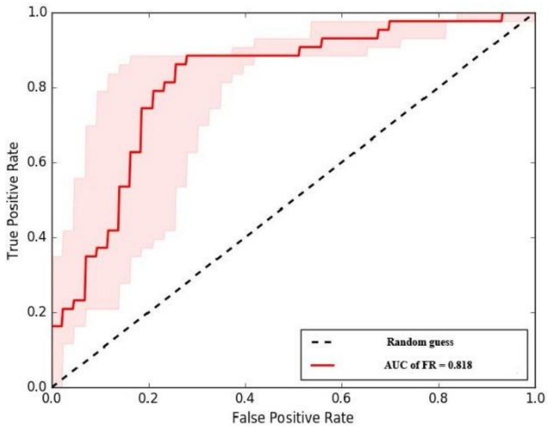

Figure 15: AUC of success rate of FR method.

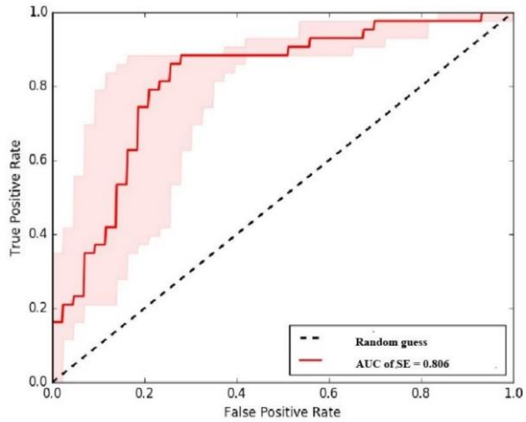

Figure 16: AUC of success rate of SE method.

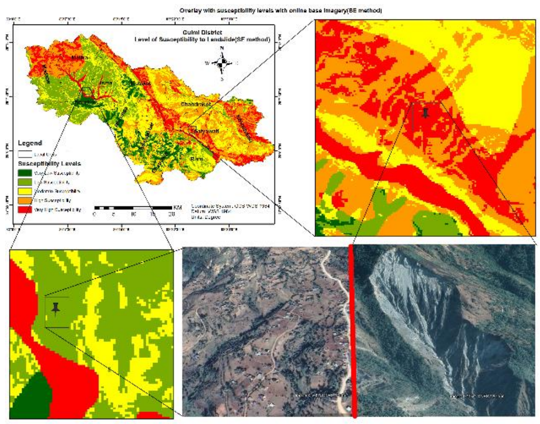

Figure 17: landslide susceptibility map of Gulmi district is validated with World base imagery.

A total of 143 locations of landslides were determined by Google Earth digitization and field surveys which were used to create a landslide inventory map of the study area. Out of total landslides polygons, 70% (100) were used for training whereas the rest 30% (43) were applied for validation. Based on characteristics of the area under study and availability of data 10 landslide conditioning factors:1) land cover; 2) slope; 3) geology; 4) distance from fault; 5) aspect; 6) elevation; 7) distance from road; 8) distance from river; 9) curvature and 10) soil type was used for landslide susceptibility analysis of the study area. Finally, a series of landslide susceptibility maps were prepared based on two approaches mentioned above and mapped with five susceptibility classes (very high, high, moderate, low, very low). The results show that a total of 44% using the FR model and 37% for the SE model is under the high susceptible zone.

The produced maps were evaluated using both training and testing datasets with the AUC method. The evaluations show that the success rate and prediction rate for the FR model is 81.8 (Figure 15) and the SE model is 80.6% (Figure 16) respectively . The FR model having the highest AUC and was evaluated as the most accurate model among the two applied models. The AUC value of these two models is relatively high with model predictions. Moreover, landslide susceptibility maps were overlaid on World Base Imagery to check the correctness through visualization. The results after comparison with the base imagery verifies the facts presented in the Figure 17 . Therefore, the results of landslide susceptibility modeling are accurate and can be used in real-world landslide risk and vulnerability assessment.

The outcomes of this research can be used in predicting future landslides. Similarly, it can be helpful in planning activities for infrastructure development and resettlement planning. For the improvement of effective land use planning and engineering techniques, various triggering factors such as slope, elevation, geology, land cover, soil type, etc. should be considered. Hence, such study can be of great utility to land-use planners, policy and decision-makers as well as implementing agencies. To sum up, the findings of this study can remain an important asset to stakeholder organizations who work in the field of disaster control and management such as the Ministry of Home Affairs, Department of Hydrology and Meteorology, UN agencies and so on.

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