Evaluation of Different Landslide Susceptibility Analysis Methods: A Case Study of Bagmati Rural Municipality

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Abstract

This study is focused on the evaluation of the different statistical methods of landslide susceptibility analysis in the Himalaya. For the evaluation, Bagmati Rural Municipality is selected as a typical study site. Various statistical methods are used to determine the relationship between thirteen landslide causative factors (viz., slope, aspect, profile curvature, tangential curvature, Normalized Difference Vegetation Index, Normalized Difference Water Index, elevation, distance from fault, distance from river network, distance from road network, geology, land use pattern and soil type) and landslide occurrence. Furthermore, a landslide inventory map of 154 landslides was prepared and 70% landslides were randomly selected for generating a model and the remaining 30% were used for validation proposes. These factor maps and the inventory are analyzed in a geographic information system. The evaluation between the three statistical bivariate methods was performed using the success rate and prediction rate. The study revealed that all susceptibility analysis techniques performed well, with the Certainty Factor Method having the best success and prediction rates for the study area, at 90.53% and 92.07%, respectively.

Keywords: *Bagmati rural municipality, Certainty factor method, GIS, Intrinsic parameters, Landslide susceptibility*

Introduction

Nepal has a unique landscape that differs with the rise in altitude. So, from plain agricultural land in the southern belt to the high Himalayas in the northern belt, makes Nepal geology very unique and different. As the Himalayas were formed 50 million years ago due to the collision of the Indian Plate and Eurasian Plate, the process is continuous resulting fragile geology and broken topography responsible for different natural disasters (Dewey et al., 1989). Every year during monsoon season these catastrophes, especially landslides mark the presence, with devastating outcomes resulting in huge human, material, economic and environmental losses. A landslide is a downward and outward movement of slope forming material under the influence of gravity (Varnes, 1978). The occurrence of landslide is due to the stresses that is active on a mass of rock or soil on the slope(Alkema et al., 2011). Various factors influence the increase of instability of slope, mainly, the intrinsic factors include geological, geotechnical, and morphological conditions whereas extrinsic factors include triggers such as rainfall, earthquakes and human activities (Ming, 2022; Upreti, 2001).

Landslide studies in a systematic way which includes, inventory mapping, susceptibility mapping, hazard mapping, and risk assessment, helps to mitigate or control problems caused by landslides (Upreti & Dhital, 1996). And, with an abrupt development of computers after 1990, GIS has become one of the essential tools for landslide hazard assessment. In susceptibility mapping, a region considered susceptible to landslides when the terrain condition at that site are comparable to those in the region where a slide has occurred (Soeters & Van Westen, 1996). Thus landslide susceptibility is the likelihood of landslide occurrence in an area based on the conditions of the local terrain. There are various methods to prepare landslide susceptibility maps (models) using statistical methods and geographic information system (GIS) tools.

In Nepal, intense rainfall may be regarded as the main triggering factor of landslides because most landslide disasters occur in the monsoon period every year making a great number of people suffer heavily from large and small scale landslides throughout the country (Dahal, 2017). The major source of rainfall is in summer and approximately 80% of the total annual precipitation takes place in the monsoon periods i.e., June to September, whereas western winds are responsible for limited winter monsoon i.e., November to February (Dahal, 2012).

As various development activities are going on in Nepal Himalayas and also the region is constantly being hit by landslide problems, the development of a susceptibility map not only gives an idea of the present condition of landslide situation in this region but also can be a preliminary planning tool for future development activities (Dahal & Dahal, 2017). However, infrastructures development in rural parts are using conventional methods, ignoring the geological and other natural phenomena associated with the region, the developments have turned into the devastation in many areas due to different hazards. Therefore, determining the most appropriate method of landslide susceptibility analysis is crucial for proper planning of resilient infrastructure. In this context, this research focuses on the evaluation of different bivariate statistical method for their applicability on the Nepal Himalayas.

Objectives

The main objective of this research is to evaluate the different statistical bivariate methods in Lesser Himalayan geological setting for landslide susceptibility mapping.

Literature review

Landslides are one of the normal landscape building processes in mountainous regions and they become a problem when they interfere with human activities (Dahal, 2017). Thus prior identification of landslides to reduce future losses is very essential which can be obtained from susceptibility analysis. Susceptibility is the probability of an event happening in a specific zone, depending on the correlation of the instability determining factors with the distribution of the past movement (Brabb, 1987). Currently, bivariate and multivariate statistical methods are frequently used for susceptibility and hazard analysis (Dahal & Dahal, 2013; Pradhan et al., 2012).

While developing a landslide susceptibility map by using the bivariate statistical analysis, each factor map is combined with the landslide inventory map, weight values are obtained based on landslide distribution in the area and causative class itself (Regmi et al., 2014). Thus bivariate statistical analysis involves the analysis of two variables to determine the empirical relationship between them based upon the statistical relationship between past landslides and various factors map. The weighted value of the classes of each parameter is calculated based on the landslide density in each class.

Soeters and Westen (1996) have divided influencing parameters into five groups;

- Geomorphological factors such as data of terrain unit, geomorphological sub-unit, and types of landslide.
- Topographic factors include digital terrain model, slope direction and length and concavities.
- Engineering geological factors such as data of lithology, material sequences, the structure of geology and seismic acceleration.
- Land use factors such as data of infrastructure development and land use map
- Hydrological factors include drainage, catchment area, rainfall, temperature, evaporation and water.

The selection of the parameters should be based on the study area so it may not be necessary to include all the factors. Also, optimum results for evaluating landslide hazard is obtained by using fewer key parameters relevant to the study area (Soeters & Van Westen, 1996).

Frequency Ratio Method (FRM)

This method is based on the assumption that landslide occurrence is determined by factors related to landslides and future landslides will occur under the same conditions as past landslides. Thus, the relation between landslides occurring in an area and landslide related area can be distinguished from the relation between landslides not occurring in an area and landslide related CF. The following formula is used for the frequency ration method:

$$W_{ij} = \frac{f_{ij}^*}{f_{ij}} = \frac{A_{ij}^*}{A_{ij}} * \left(\frac{A - A^*}{A_{ij} - A_{ij}^*}\right)$$

Greater the ratio above unity, the stronger the affinity between landslide occurrence.

Landslide Susceptibility Analysis (LSA)

Landslide susceptibility analysis is used to determine the importance of different variables for landslide occurrence (Norhisham & Roslee, 2019). Weighting factors are determined, to evaluate the influence of each parameter, which compare the calculated density with the overall density in the area.

$$W_{ij} = 1000 * \left(f_{ij} - f\right) = 1000 * \left(\frac{A_{ij}^*}{A_{ij}} - \frac{A^*}{A}\right)$$

Certainty Factor Method (CFM)

Certainty factor is a number to measure the expert's belief. Its value range from -1 to 1. A positive value indicates an increasing certainty in landslide occurrence, while a negative value corresponds to a decreasing certainty in landslide occurrence (Wang et al., 2019). When a value is close to 0, it means that the prior probability is very similar to the conditional one, which makes it difficult to give any indication about the certainty of landslide occurrence.

$$CF_{ij} = \frac{f_{ij} - f}{f_{ij}(1 - f)} \ if \ f_{ij} \geq f \ else$$

$$CF_{ij} = \frac{f_{ij} - f}{f\left(1 - f_{ij}\right)} \ if \ f_{ij} \leq f$$

Where,

CF_{ij} = Certainty Factor of class i of parameter j

Here f_{ij} is the conditional probability having several landslide events occurring in class and f is the prior probability having the total number of landslide events occurring in the study area.

Methodology

Study Area

The Bagmati Rural Municipality is located in the southern part of the Lalitpur district in Bagmati Province of Nepal. The site lies at 85o14'1.7"- 85o24'12.72" E longitude and 27o24'28.92"- 27033'43.93" N latitude (Figure 1). The elevation of this region ranges from 436m to 2394m. The total population of this region is 10,598 with 2644 households. 60% of the population belongs to Tamang community and the majority of the people depends on agriculture and livestock for their living. The municipality has 7 wards that cover 111.49 km2 and have a population density of 111.04 person per square kilometer. Kanti Lokpath is the major highway of this region which is still under construction. The Bagmati River in the southern periphery of this municipality separates it from the parts of Makwanpur and Kathmandu district. The Thosney and Khani Khola are the major rivers in this region. Colluvium is the main slope material above bedrock and most of the region is either covered with forest or cultivable lands.

As Department of Hydrology and Meteorology, considering the rainfall data from 1998 to 2021, the region have highest average monthly rainfall in July and least in November. Also highest daily rainfall recorded so far in this region is 280mm which took place in 23rd July, 2002.

The rural road construction has been the major triggering factor for landslides in the region. The conventional process of using heavy machinery without the prior slope study of the region seems to have influence the impact of landslides.

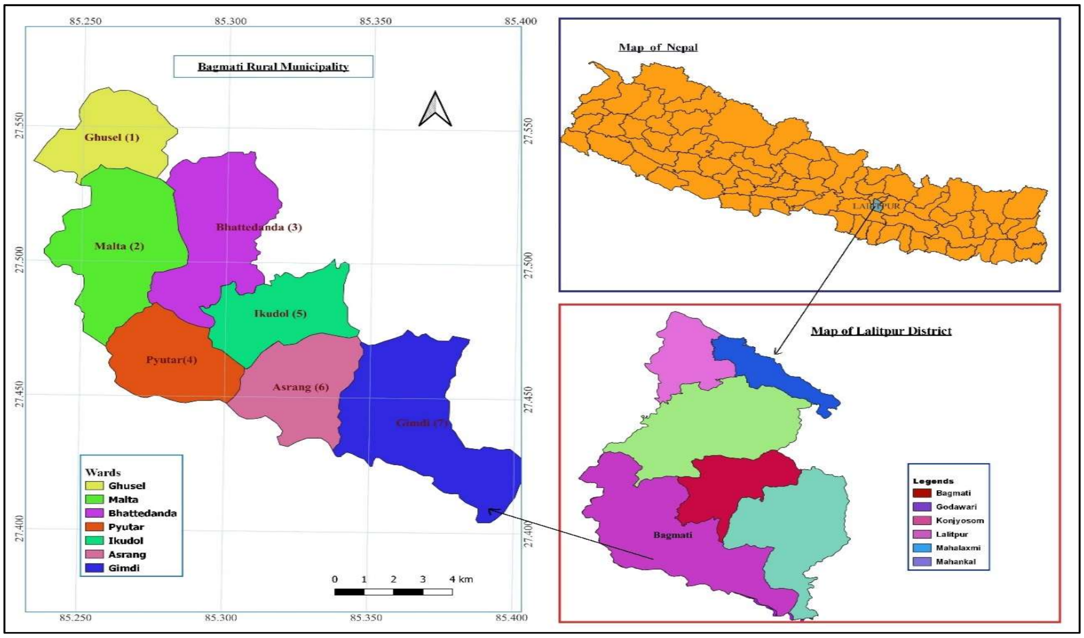

Figure 1: Location map

Geological Setting

Bagmati Rural Municipality falls under Lesser Himalayan Region. The Lesser Himalayan region mainly has unfossiliferous, sedimentary, and metasedimentary rocks such as slate, phyllite, schist, quartzite, limestone, etc., ranging in age from Precambrian to Eocene (Dahal, 1999). Also, some granitic intrusions can be found in this region. Similarly, as this region falls under Mahabharat Range, the annual rainfall in this region is comparatively higher and the frequency of high-intensity rainfall is also high(Dahal, 2012). Thus, the areas get extensive problems of floods, debris flows and shallow landslides. Also, the Mahabharat ranges are considered very active regions in terms of vulnerability to landslides The soil map received from the Department of Survey (DOS) has divided the region into twelve major classes based on United Nations Department of Agriculture (1993) soil texture classification; sand, loamy sand, sandy loam, loam, silt loam, silt, sandy clay loam, clay loam, silty clay loam, sandy clay, silty clay, and clay. Usually, the principal constituent particle sizes are used to designate the classification. The characteristics of soil, including infiltration, structure, porosity, and water-holding capacity, are influenced by the texture of the soil.

Preparing Landslide Inventories

Landslide inventories prepared from remote sensing data and field surveys have been used for the preparation of susceptibility and hazard maps (Martha et al., 2013). As Google Earth is one of the reliable and effective tools to receive spatial data information, this study also used it for identifying the landslides in the region of our interest. Each identified landslide is marked using polygons and saved as a KML file which is used in QGIS to create landslide inventory map. The landslide identified by using remote sensing data is then verified by doing an actual field visit where then position was collected using GPS. Also, local people and the IT officer of the municipality is consulted for further information about the landslides.

For the susceptibility mapping of this region, landslide inventory mapping consisting of 154 landslides were created (Figure 2). These landslide locations were then randomly divided into a 70/30 ratio for the purposes of training and validating the model.

Figure 2: Landslide Inventory Mapping

Factor maps

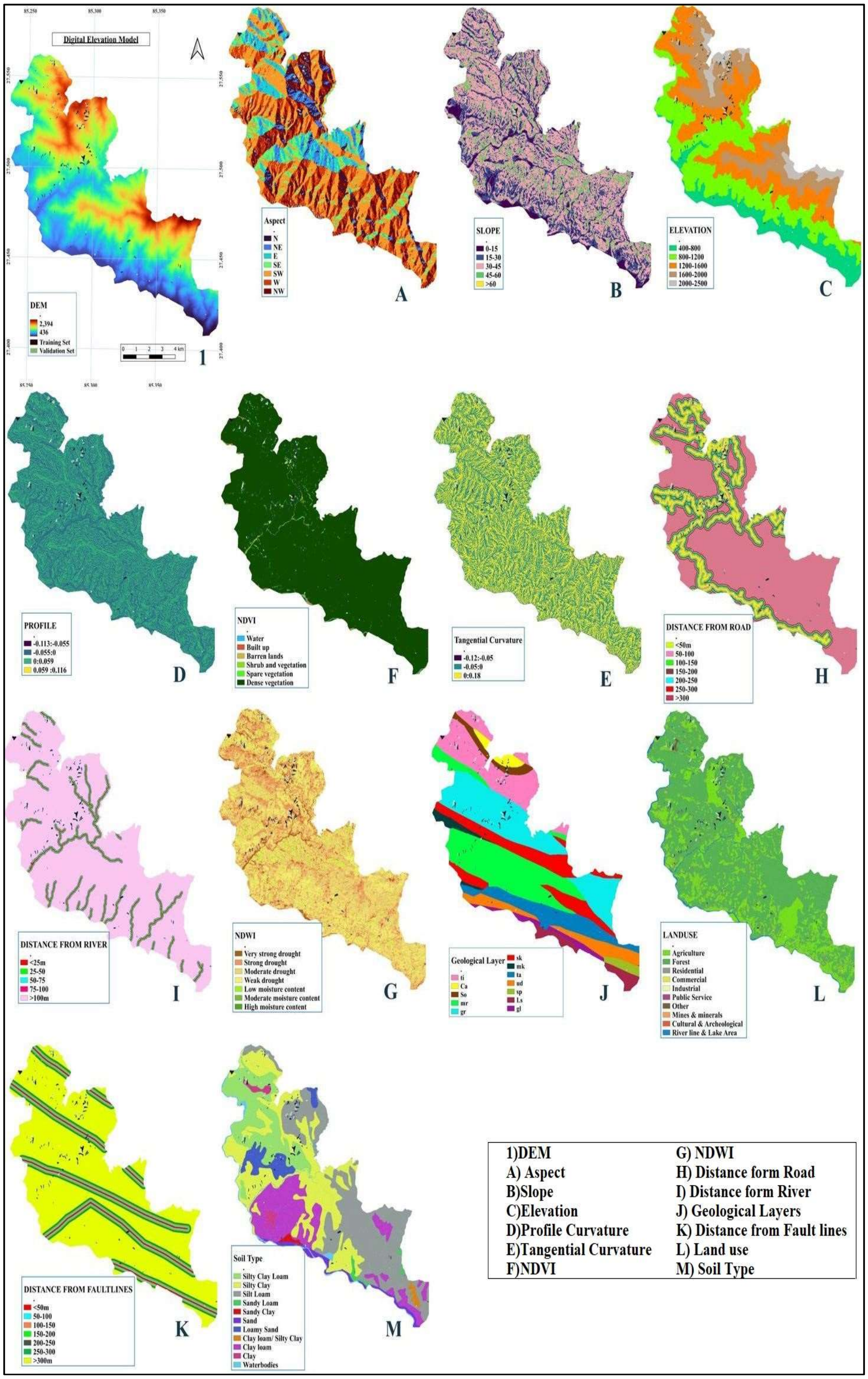

Figure 3: Factors map used in the susceptibility analysis

Different causative factor maps are prepared from the data collected through various sources and field visit. The data layers and the source is presented in Table 1. The study is mainly based upon the factor maps and the landslide inventory. Some data layers have been regenerated from the DEM (Figure 3) i.e., slope, aspect, elevation, distance to drainage and curvature map. Similarly, NDVI and NDWI map are derived from Sentinel-2 data. Furthermore, the land use and soil type maps were obtained from DOS. DOS has classified the regions into ten different classes in the land use map and twelve classes in soil type map. Geological factor maps are prepared by digitization of map obtained from Department of Mines and Geology (DMG) and the road network map is derived from Open Street Map.

Table 1: Data types and sources

Classification	**Map**	**Data Type**	**Source**
Landslide Inventory	Landslide Inventory Map	Vector (Polygon)	Google Earth Imagery, Site Verification
Digital Elevation Model (DEM)	Slope	Raster Grid (12.5 x 12.5)m	Derived from ALOS palsar, downloaded from USGS
	Aspect		
	Tangential Curvature		
	Profile Curvature		
	Elevation		
	Distance to River Network		
Vegetation & Water Index	Normalized difference vegetation index (NDVI)	Raster Grid(10 x 10)m	Derived from Sentinel-2, downloaded from USGS
	Normalized difference water index (NDWI)		
Road Network	Distance from the Road Network	Vector (Shapefile)	Open Street Map
Geological Map	Geology Map		Department of Mines and Geology(DMG), Scale 1:350,000
	Distance from Fault/thrust		
Land use pattern and Soil type	Land use		Department of Survey(DOS), Scale 1:350,000
	Soil type		

Statistical Analysis

Here, CFM, LSA and FRM bivariate methods were used for the comparison. In all of these methods, the relationship of 13 CFs with the landslides were examined. The landslides were divided into a 70/30 ratio to get the success rate and prediction rate curve.

Statistical Validation

Statistical validation is comprised of success and prediction rate curves (Chung & Fabbri, 2003). Success rate is based on the comparison of the susceptibility map with the landslide used in modelling i.e. the training dataset. It is obtained by plotting the cumulative percentage of observed landslide occurrences against the areal cumulative percentage in decreasing total weight. The area under the curve can quantitatively assess the prediction accuracy. The success rate indicates how much percentage of all landslides occurs in the classes with the highest value of susceptibility (Dahal, 2017).

According to Chung and Fabbri (2003), the area under the curve (success rate curve and prediction curve) was used to evaluate model compatibility and predictability. Here instead of an independent population same landslide set is used which determines how well the model fits the data.

Result

Among the 154 landslides identified, 108 (70%) training set data is used to prepare the model and the 46 (30%) landslide is used for validation of susceptibility mapping. If we look at the landslide inventory mapping it is seen that ward 3 is highly affected followed by ward 1 and ward 2. In these two ward there is huge road construction activities going on using heavy machinery and it may be the major reason for which impact of landslides in these regions.

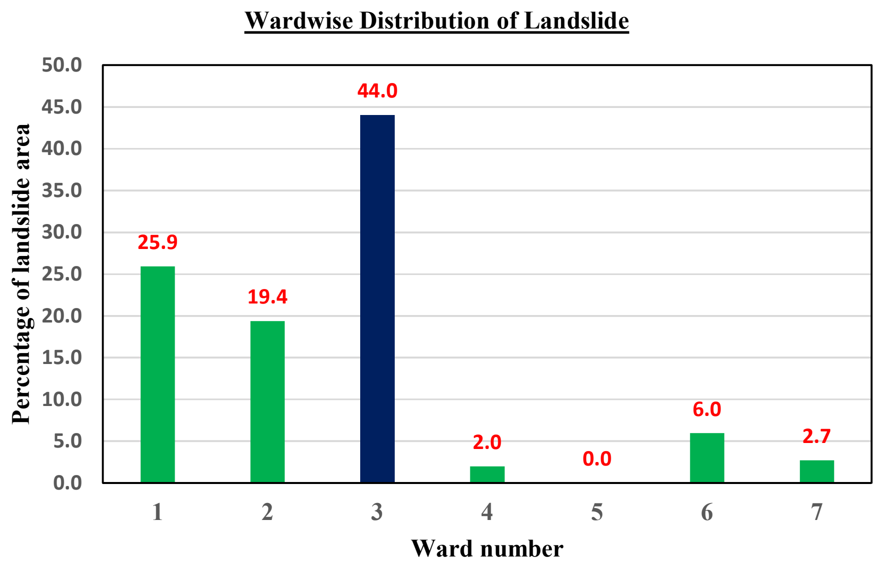

Figure 4: Ward-wise distribution of landslide area

The relationship between various classes of factor maps and the landslide is given by the susceptibility weightage (Table 2). From the result, relationship between the aspect factor and landslide events indicated that the North-West, North and North-East facing slopes had higher susceptibility than other aspects. The risk of landslide becomes higher as the slope becomes steeper, here also slope angles greater than 30^0 were prone to landslide. Similarly, weathering factor plays an important role in a landslide and is closely related to elevation (Pradhan & Kim, 2014), landslides are more frequent in locations with elevations between 1200 and 2000 meters.

Table 2: Comparison of weightage of different bivariate methods

Parameter	Class	FRM	CFM	LSA
Slope	0-15°	0.007	-0.891	-4.329
	15-30°	0.009	-0.480	-2.327
	30-45°	0.011	0.125	0.692
	45-60°	0.074	0.477	4.475
	>60°	2.589	0.342	8.909
Aspect	N	0.161	0.539	5.616
	NE	0.124	0.390	3.080
	E	0.035	-0.285	-1.380

Parameter	Class	FRM	CFM	LSA
	SE	0.009	-0.826	-4.014
	S	0.000	-1.000	0.000
	SW	0.009	-0.382	-1.852
	W	0.034	0.255	1.652
	NW	0.053	0.310	2.165
NDVI	Water	0.000	-1.000	-4.820
	Built Up	45.329	0.974	152.587
	Barren Land	70.701	0.970	134.872
	Shrub and Vegetation	22.432	0.964	114.289
	Spare Vegetation	9.743	0.939	68.643
	Dense Vegetation	0.003	-0.461	-2.218
NDWI	Very strong drought	1.590	0.931	60.599
	Strong drought	0.020	0.136	0.753
	Moderate drought	0.002	-0.842	-4.053
	Weak drought	0.002	-0.912	-4.395
	Low moisture content	0.002	-0.990	-4.771
	Moderate moisture content	0.000	-1.000	-4.820
	high moisture content	0.000	-1.000	-4.820
Profile Curvature	-0.113:-0.055	0.000	-1.000	-4.862
	-0.055:0	0.011	0.067	0.350
	0- 0.059	0.009	-0.071	-0.343
	0.059 -0.116	0.000	-1.000	-4.862
Tangential Curvature	-0.12:-0.05	62.925	0.831	23.176
	-0.05:0	0.011	0.087	0.459
	0 - 0.18	0.009	-0.093	-0.451
Distance from River	< 25 m	0.041	-0.783	-3.772
	25-50	0.116	-0.231	-1.111
	50-75	0.126	-0.167	-0.800
	75-100	0.152	-0.080	-0.386
	>100m	0.006	0.038	0.191
Elevation	400-800m	0.012	-0.648	-3.120
	800-1200	0.013	-0.166	-0.798
	1200-1600	0.020	0.205	1.235
	1600-2000	0.033	0.279	1.857
	2000-2500	0.065	-0.351	-1.685
Distance from Road Network	<50m	0.184	0.730	12.804
	50-100	0.133	0.554	5.929

Parameter	Class	FRM	CFM	LSA
	100-150	0.117	0.380	2.935
	150-200	0.089	0.102	0.544
	200-250	0.100	0.052	0.263
	250-300	0.081	-0.271	-1.299
	>300	0.003	-0.659	-3.173
Geology	Tistung	0.062	0.465	4.149
	Chandragiri	0.947	0.682	10.196
	Sopyang	0.791	0.746	13.867
	Markhu	0.011	-0.486	-2.339
	Granites	0.035	0.387	3.020
	Sarung Khola	0.011	-0.716	-3.448
	Maksang	0.096	-0.651	-3.131
	Tawa Khola	0.019	-0.616	-2.965
	Udaipur	0.029	-0.615	-2.960
	Shiprin khola	0.000	-1.000	-4.821
	Lower Siwalik	0.000	-1.000	-4.821
	Galyang	0.024	-0.899	-4.333
Distance from fault	<50m	0.026	-0.761	-3.662
	50-100	0.045	-0.576	-2.771
	100-150	0.055	-0.498	-2.393
	150-200	0.065	-0.399	-1.920
	200-250	0.070	-0.363	-1.747
	250-300	0.058	-0.481	-2.312
	>300	0.008	0.158	0.896
Land use	Agriculture	0.017	-0.112	-0.533
	Forest	0.007	0.048	0.239
	Residential	0.337	0.001	0.005
	Commercial	0.000	-1.000	-4.804
	Industrial	0.000	-1.000	-4.804
	Public Service	0.311	0.234	1.455
	Other	8.008	0.643	8.540
	Mine & Minerals	0.000	-1.000	-4.804
	Cultural & Archeological	0.000	-1.000	-4.804
	River line & Lake Area	0.079	-0.491	-2.353
Soil Type	Silty Clay Loam	0.073	0.559	6.020
	Silty Clay	0.017	-0.025	-0.121
	Silt Loam	0.015	-0.015	-0.073

Parameter	Class	FRM	CFM	LSA
	Sandy Loam	0.178	-0.743	-3.564
	Sandy Clay	0.000	-1.000	-4.804
	Sand	0.007	-0.970	-4.659
	Loamy Sand	0.612	0.178	1.035
	Clay loam/ Silty Clay	0.000	-1.000	-4.804
	Clay loam	0.003	-0.895	-4.300
	Clay	0.438	0.134	0.738
	Waterbodies	0.080	-0.410	-1.966

In terms of profile curvature which indicates the acceleration and deceleration of flow across the surface (Mitášová & Hofierka, 1993), the affinity of landslide is towards the negative value which indicates the upwardly convex is more susceptible. While, the tangential curvature which indicates the convergence and divergence of flow across the surface (Buckley, 2010), the weightage of landslide is maximum towards the surface having a negative plan which indicates the slope with sideward concave is more susceptible. As NDVI indicates the richness of the surface in terms of vegetation and the value is higher for the areas having good vegetation and negative towards the region deprived of vegetation (Brown, 2015), here in this study also the affinity of landslide is more towards the region having negative value. The weightage is maximum in the built-up region followed by the barren lands and bushes region. Similarly, NDWI indicates the water molecules of the vegetation and if water content decreases, then in SWIR channels reflectance increases significantly, therefore the NDWI value decreases showing dry vegetation under drought stress (Gulácsi & Kovács, 2015). Basically, NDWI is used to measure the water molecules of the vegetation and its value greater than zero is considered to be water surface and lower than zero is non-water surface (Raut et al., 2020). Here, the drought regions have negative NDWI value.

Also, from the thematic map of soil type obtained from DOS, the areas rich in clay and silty clay loam have higher landslide density values. According to Unified Soil Classification System, clayey soil creates very small pore spaces resulting in poor aeration and poor water drainage. Also, clay soil takes longer than sandy soil to dry after a rainfall. Similarly, the silty clay loam which has a lower percentage of sand (0-20%) has similar characteristics to clayey soil. So we can see that the region which has greater water holding capacity can be seen as the region having higher chances of landslide. Also, in terms of the shallow types of a landslide which is greatly affected by the antecedent rainfall during monsoon season (Dahal, 2012) can be related to the type of soil and their affinity to landslide in this region. Since this region does not have a big drainage network apart from the Bagmati River which only touches the outskirt of the southern boundary of the region, the smaller rivers (Thosney Khola, Khani Khola) do not show that much of higher susceptibility to landslide in this region. In terms of the road network though, the construction of rural roads in this region seems to be the major reason for landslides in this municipality. Almost 70 % of the landslide identified in this region falls within just 200 meters of buffer distance from the road network. Due to road cutting on the toe of the slope, the region below the cutting are vulnerable as the slope stability has been disturbed. Also haphazard deposition of material obtained from road cutting on downslope covering the existing vegetation has increased the slope instability. Similarly, if we examine the land use pattern map received from DOS, we can see that the weightage of the landslide is greater in the region where there is more human intervention. This indicates the role of anthropogenic activities as the major triggering agent of landslides in this region.

In terms of the lithology, based on the map received from DMG the whole region is divided into 12 different lithological units. Among the different formations, the Sopyang showed higher weightage followed by Chandragiri and Tistung formation. Sopyang formation is composed of dark argillaceous and marly (unconsolidated sedimentary rocks or soil consisting of clay and lime) slates with thin limestones. The Chandragiri formation consist of light fine-grained crystalline limestones, partly siliceous, thick to massive white quartzite in the upper part, whereas Tistung formation has dull greenish grey coloured phyllites, pink purplish tinted sandstones with sandy limestones, ripple marks, clay cracks, and worm tracks are found in abundance, pebbly beds are near the base. Also from the map given by DMG the marking of faults and thrust in this region was done and as the MBT touches only a small portion of the southern tips of the region, the weightage value given to different buffer distances from the fault/thrust region does not show a significant value. Thus in terms of the distance from the fault/ thrust region the region is not susceptible to landslide within the buffer distance of 300 meters.

Discussion

Here most of the regions that are highly affected by landslides are those touched by human intervention. As from the thematic map of land use pattern, NDWI and NDVI which has shown landslides located in barren lands or residential areas. This showed the importance of vegetation and its relationship with the landslide. Vegetation plays a vital role in slope stability and the soil erosion process (Upreti & Dhital, 1996). Vegetation intercepts rain, reducing its energy and preventing its erosion. It also slows runoff, reduces sheet erosion, and anchors and reinforces, the soil with its root system(Morrow et al., 2017). The region falls under the Mahabharat range where the settlements are concentrated along the ridge and gently dipping northern slopes (Upreti & Dhital, 1996). Thus, the concentration of landslide is in higher elevation region having northern slope aspect. In most of the papers, it is mentioned that the landslide density increases with an increase in slope (Paudyal & Dhital, 2005; Pradhan & Kim, 20014), here also the landslide density gradually increased from 30^0. This may be because the slope steeper than 40^0 contains thin soil cover (Joshi et al., 2000). Soil depth can greatly influence the types of plants that can grow in them (Abd-Elmabod et al., 2017). Thus the regions of small bushes, grassland and barren lands are the regions having smaller soil depth and hence are mostly susceptible to landslide.

The landslide susceptibility is higher in Sopyang, Chandragiri, Tistung formation and granites region in descending order. These regions are mainly composed of phyllites, slates, limestones, quartzite and granites. A study of the Kulekhani watershed (Pradhan et al., 2012) showed that phyllites, slates and schists are the highly weathered rocks in which the chances of landslide occurrence are high. Also, granitic rocks are those which are mechanically and chemically weathered rock. Similarly, the presence of limestone and quartzite along the Tulsipur-Kapurkot road section (Poudel & Regmi, 2016) has made the section more prone to failure. A study of landslide hazard on the Thankot-Chanlakhel area (Paudyal & Dhital, 2005) also showed that landslide density is higher in the limestone terrain owing to its highly jointed nature and the presence of argillaceous partings. The clayey soil types are considered fragile in terms of their affinity to landslides as initial moisture conditions enhance the formation of wetting front within the soil profile (Schilirò et al., 2019). Also as colluvium is the major deposit over the bed rock in the region with intense rainfall during the monsoon season, the shallow type of landslides is inevitable.

The road construction in this region seems to be the major contributing factor for landslide occurrence. Various writers in their papers have also mentioned the influence of road construction on landslides. Poudel &Regmi (2016) has informed about the influence of improper road construction practices and how this procedure exposes the joints and fractures that make the natural slope unstable. The informal road construction often creates landslides by undercutting slopes, providing pathways for water to seep into potential slide planes and producing debris that is easily mobilized during heavy rainfall(McAdoo et al., 2018). The performance of the different bivariate statistical methods for landslide susceptibility mapping using the same set of 13 CFs was compared. Regmi (2014) verified the landslide susceptibility maps created by three different bivariate statistical methods (FRM, SIM and WOE). The study showed all three method have similar accuracy rate with frequency ratio method being the most accurate marginally. By comparing the AUC results (Figure 5, 6) it was seen that the CFM method was significantly more accurate than the other methods (FRM, LSA). Both LSA and FRM have higher success rates than CFM prior to the 13% of the cumulative study area. While CFM has a success rate that is significantly higher than the other methods for the cumulative area of 13 to 50%, resulting the overall highest success rate. Similarly, all three approaches show a success rate curve-like tendency in the prediction rate, with the CFM showing the highest prediction percentage.

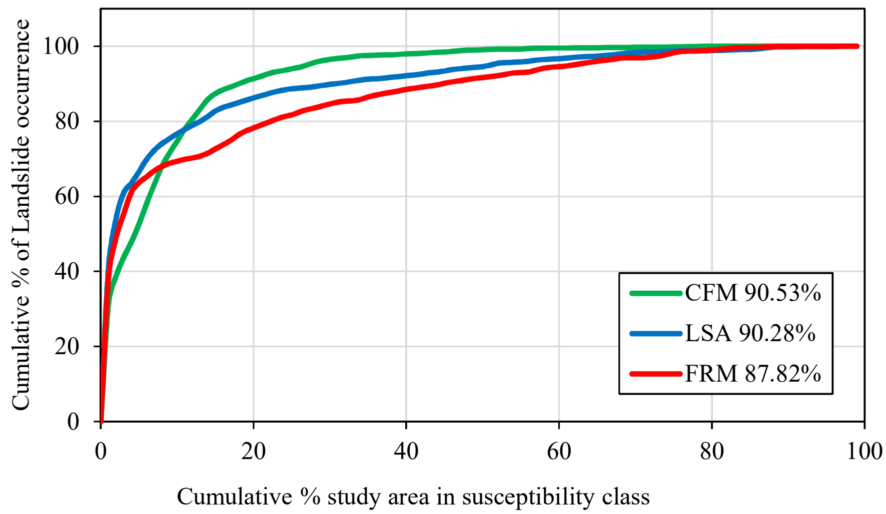

Figure 5: AUC showing the success rate

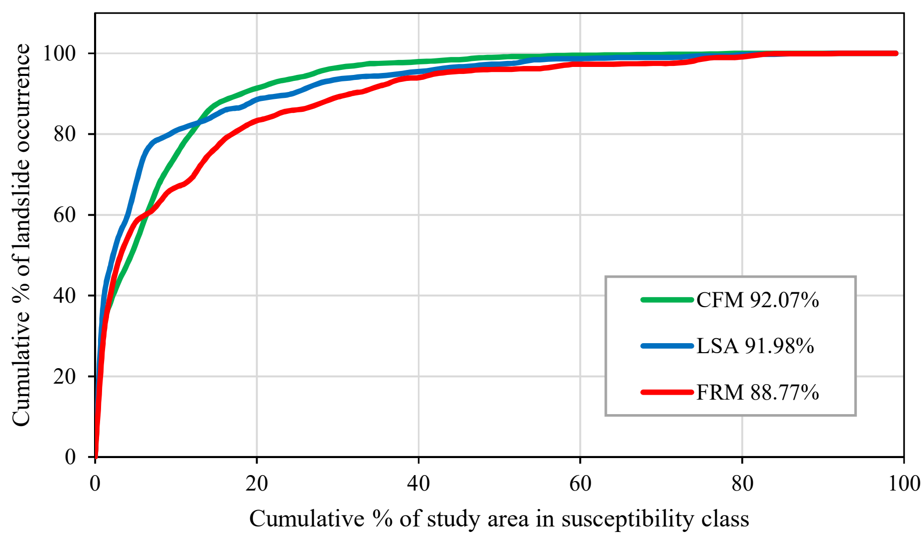

Figure 6: AUC showing the prediction rate

Finally, CFM method was used to obtain the final susceptibility map (Figure 7) by integration of all the weight maps. The distribution of the total weight value was analyzed and the map was classified as very high, high, moderate, low and very low classes based on the AUC curve for success rate.

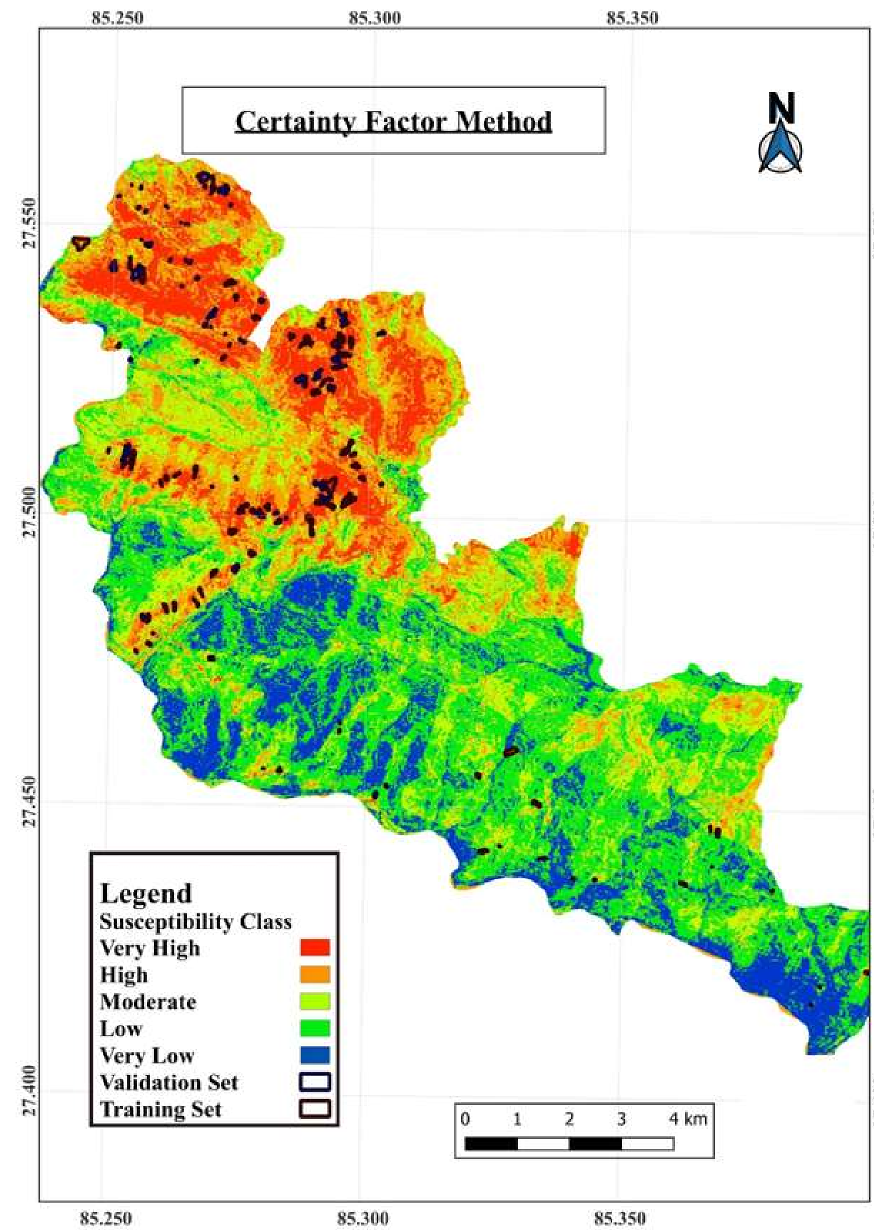

Figure 7: Landslide susceptibility map based on RE method

Conclusion

Landslide susceptibility mapping is very important for the demarcation of landslide-prone areas. For the evaluation of three bivariate statistical methods 13 causative factors were chosen based on the availability of data. A landslide inventory map consisting of 154 landslides was prepared using Google Earth image and a field survey. From these 154 mapped landslides, 108 (70%) were randomly selected for generating a model and the remaining 48 (30%) were used for validation proposes. The comparison between three statistical bivariate methods infers that all of the three models showed almost equal performance with the Certainty Factor Method (CFM) being the best one (success rate 90.53%; prediction rate 92.53%). Therefore, all three methods have good prediction capability, they can be considered for studying landslides in the similar areas along the Himalayan region. Finally, a landslide susceptibility map was obtained using the Certainty Factor Method (CFM) where the regions were divided into five susceptibility classes (i.e. very low, low, moderate, high and very high). Also from the analysis, it was seen that the landslides were mainly distributed in the regions where there is less vegetation and more anthropogenic activities, especially road construction in the region seems to be the major causative factor for landslides. Also, these kinds of maps will be a useful tool for land-use planning as well as for implementing future development works in the region.

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