

Landslide Susceptibility Mapping of West Central Nepal Lesser Himalaya Baglung Municipality, Baglung, Nepal

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Abstract: The study is mainly focused on the landslide susceptibility mapping. The different primary data were collected and systematic sampling was done to find the various geotechnical properties of earth materials. The Lesser Himalayan rocks are represented by phyllites, pelitic schists, white quartzite, Meta carbonates, graphitic schist, laminated quartzite and garnetiferous schists. These lithological units of the Lesser Himalaya are compared with the units of Nuwakot Complex in central Nepal. The phyllites are the oldest unit in the Lesser Himalaya of the study area and white quartzite is present towards the lower parts whereas phyllite occur in the lower and upper portion and metabasic rock (mainly amphibolites) is also present. There are numerous small-scale folds and normal faults present in the study area. In the south part lies major structure called Phalebas thrust. In the study area more than 200 m thick quaternary alluvial is present. The landslide distribution was identified with the assistance of Google earth to generate the landslide inventory. Logistic Regression Model was used for the preparation of landslide susceptibility map of the area. The causative factors such as elevation, slope, curvature, land use, geology, rainfall, soil type, soil thickness topographic wetness index, stream density, were used to prepare the landslide susceptibility map. All the thematic layers of these parameters were made using ArcGIS 10.4.1.

Keywords: Landslide, Geology, Logistic Regression, Susceptibility and GIS

1. Introduction

Nepal Himalaya occupies about one-third part (i.e., 800 km) of the 2400 km long Himalaya arc and extends in the east-west direction. The landslide damming is a normal geomorphic process in the narrow river valleys and common in the mountainous terrain. This results in the loss of life and property of human. Bringing together the findings of [1, 2], this section synthesizes the key aspects of the geological mapping, emphasizing the role of the Mahabharat Thrust in delineating the boundary between the Nuwakot and Kathmandu Complexes. The Nepal Himalaya is tectonically divided into four longitudinal units (the Siwaliks, the Lesser Himalaya, the Greater Himalaya and the Tibetan Tethys Himalaya) having different stratigraphic and evolutionary characters from South to North [3]. Cruden (1991) defined

the landslide as the movement of a mass or rock, debris or earth down a slope. The earthquake-induced landslide hazard mapping approach presented [4] in Nuwakot District, central Nepal. According to Naranjo et al. (1994) statistical analysis is the most appropriate approach for landslide hazard mapping at higher scales, because it is possible to collect sufficient data for landslide analysis. The broader regional understanding of geological processes. It discusses the implications of their findings for regional geology, tectonics, and natural resource management [5]. A variety of approaches has been developed for the landslide hazard analysis. Soeters and van Westen (1996) divided these approaches into inventory analysis, heuristic analysis, deterministic analysis, and statistical analysis. Dhital (2000) reviewed the landslide hazard mapping and rating systems in Nepal. He classified landslide hazard maps into the three categories: i) map of a region, ii) map of a corridor, and iii)

map of a site. Intensive geological investigations have been carried out by various researchers in the Nepal Himalaya [6-10]. Auden gave an overview of the geology of central Nepal. In his study he presented several cross-sections across the Himalaya supporting the nappe theory proposed by Argand [11], also recognized the synclinal nature of the Mahabharat range. Due to its dynamic nature and the rugged and fragile topography, Nepal Himalaya experiences a number of natural disasters like landslide, floods, earthquake, avalanches and glacial lake outburst flood during the heavy monsoon rainfall but the country also suffers from dry landslide. the structural implications of the triangle zone and imbricate faults identified by [12]. The system distinguishes between translational, rotational, complex, and other movement types, offering a comprehensive framework for characterizing the dynamics of landslides [13]. Dhital's classification scheme in the context of landslide hazard mapping in Nepal. It emphasizes how the categorization assists in optimizing resources for effective risk management and infrastructure development.

Bivariate statistical method involves the idea of comparing a landslide inventory map with maps of landslide influencing parameters in order to rank the corresponding classes according to their role in landslide formation [14]. Lee and Pradhan (2006), Lee and Sambath (2006), Chen and Wang (2007) and many other authors have used the logistic regression model for landslide hazard mapping, inverted metamorphism in the greater Himalaya. This section considers the broader geological context and regional variations contributing to the observed metamorphic phenomena. The logistic regression model is useful when the outcome variable (dependent variable) is binary or dichotomous [15, 16]. The dependent variable(y) for the analysis is the absence or presence of a landslide. A geomechanics classification method designed to provide a comprehensive assessment of rock mass class and quality. RMR considers various parameters, including rock strength, spacing of discontinuities, groundwater conditions, and ground support, offering a versatile tool for characterizing rock masses [17].

If 'p' is the independent variable, x_1, x_2, x_p affecting landslide occurrences, we define the vector

$$X = (x_1, x_2 \dots x_p).$$

The conditional probability that a landslide occurs is represented by $P (y=1/X)$. The logit of the multiple logistic regression models (Hosmer and Lemeshow 2000) is:

$$\text{Logit}(y) = b_0 + b_1 x_1 + b_2 x_2 + \dots + b_p x_p \quad (1)$$

Where b_0 is the constant of the equation $b_1, b_2 \dots b_p$ are the coefficients of variables $x_1, x_2 \dots x_p$.

The probability $p (y = 1/X)$ can be expressed in the logistic regression model:

$$p(y = 1/X) = 1/(1 + e^{-(b_0 + b_1 x_1 + b_2 x_2 + \dots + b_p x_p)}) \quad (2)$$

Where $e = 2.718$

Assume that we obtain a sample of n observations (X_j, y_j) , $j = 1, 2, n$, $X_j = (x_{1j}, x_{2j}, x_{pj})$, then y_j is either 1 or 0, $y_j = 1$ for a landslide event, and $y_j = 0$ for a nonevent. By fitting the multiple logistic regression model using the sample observations, we estimate the logistic regression coefficients b_i , $i = 0, 1, p$. Based on this model the probability of landslide occurrence in the future can be estimated using equation [18]. The logistic regression model within the framework of GIS for landslide hazard mapping in large mountainous areas. The logistic regression was used to establish relationship between the landslides and related environmental conditions, rank the importance of environmental conditions that cause the landslides, and predict future landslide [19] probabilities. The multivariate statistical analysis revealed that observed landslides, bedrock, surface materials, slope and difference between surface aspect and dip direction of bedding were the most important factors affecting the occurrence of landslides. The intrinsic variables determining hazards are the bedrock geology, topography, soil depth, soil type, slope gradient, slope aspect, slope curvature, elevation, engineering properties of soil material, land use pattern and drainage patterns whereas the extrinsic variables include heavy rainfall, earthquakes and volcanic activities [20]. The probability of landslide occurrence depends on both intrinsic and extrinsic variables, but the latter shows a temporal distribution which is more difficult to handle in modeling practice. So, for landslide hazard assessment, the extrinsic variables are not considered in determining the probability of landslide occurrence. Landslide activity is largely regulated by slope, aspect, geology, hydrogeology and road construction activities in the context of Nepal. Also, a single event landslide database is not enough for landslide hazard zonation. Multi-event-based zonation and rectification of zonation maps is necessary to produce a reasonably accurate hazard map. The factors responsible for the occurrence of landslide can be categorized as the causative (geology, geomorphology, slope, land use etc) and triggering (hydro-metrological event, earthquake, anthropogenic etc.) factors [21]. The landslide hazard map is prepared principally to understand the landslide hazard condition within an area of interest. He also mentions that most of rural roads in Nepal are constructed without due consideration to geological factor. Therefore, engineering geological investigation as well as landslide hazard maps should be prepared prior to road construction infrastructures.

2. Receiver Operating Characteristic (ROC) Curve

The Receiver Operating Characteristic (ROC) curve is a graphical plot that illustrates the performance of a binary classifier system as its discrimination threshold is varied. ([https://en.wikipedia.org/wiki/Receiver operating characteristic](https://en.wikipedia.org/wiki/Receiver_operating_characteristic)). The ROC curve is created by plotting the true positive rate (TPR) against false positive rate (FPT) at

various threshold settings. The true-positive rate is also known as sensitivity. The false-positive rate is also known as the fall-out and can be calculated as (1-specificity). The ROC is also known as relative operating characteristic curve, because it is a comparison of two operating characteristics (TPR and FPR) as the criterion changes. The ROC curve demonstrates following things (<http://gim.unmc.edu/dxtests/roc2.htm>): It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity). The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test. The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test. The area under the curve is a measure of test accuracy.

Table 1. Classification of ROC curve values for data accuracy.

Value	Class
1	0.9-1 Excellent
2	0.8-0.9 Good
3	0.7-0.8 Fair
4	0.6-0.7 Poor
5	0.5-0.6 Fail

Approaches of Landslide Susceptibility Mapping

Landslide susceptibility mapping involves a series of factors that cause landslides. A landslide susceptibility map identifies areas which are subject to landslides and the susceptibility is measured from low to high. The landslide susceptibility map takes into account where the landslides occur and what causes them. Varying conditioning factors play in the occurrence of landslides.

Table 2. Type of landslide susceptibility models.

Qualitative method	Quantitative method
Knowledge based Model	Data driven model
Direct method	Bivariate statistics
Geomorphological susceptibility maps	Weight of evidence
Indirect methods	Frequency ratio
Boolean logic	Information value
Fuzzy logic	Multivariate statistics
Multiclass overlay	Logistic regression
Spatial multi criteria evaluation	Discriminant analysis
	Cluster analysis
	Artificial neural network
	Physically based model
	Deterministic models
	Infinite slope model
	Profile based
	3-D models
	Dynamic methods
	Rainfall/snowfall
	Slope hydrology
	Seismic acceleration

2.1. Knowledge Based Model

A knowledge-based model is a qualitative approach carried out using either a direct or an indirect method. The basic idea of knowledge driven method is to work out the relationship between the landslide susceptibility and the conditioning factors for a certain area of study directly from the field. The knowledge based direct method uses the expert judgment to interpret the landslide susceptibility whereas an indirect method obtains the information from the field by observation of the geology, land forms and instabilities. The knowledge based indirect method assesses the landslide susceptibility by considering different factor maps in the GIS. The most commonly used knowledge driven indirect method are the Boolean logic, fuzzy logic, and multiclass overlays.

2.2. Data Driven Model

Data driven methods quantify data and statistically evaluate the probability of occurrence of landslides by examining the same condition factors that have triggered the landslides in the past. There are two types of data driven methods: i) Bivariate statistical method and ii) Multivariate statistical method.

2.3. Bivariate Statistical Method

The bivariate statistical method is based on the analysis of the functional statistical relationship between landslide-conditioning parameters and the known distribution of

landslides. The tendency of an area to experience landslides is determined from the functional relationship, where weights are calculated for each parameter from the landslide density. The importance of each landslide-conditioning parameter is analyzed individually by comparing the map of the parameter with the landslide distribution map. Landslide densities are calculated using the equation of Van Westen (1993) for each parameter map to obtain the weight. There are several types of bivariate statistical methods such as the weight of evidence, frequency ratio and information value. In the probabilistic weight of evidence method, the weight for each landslide conditioning factor is calculated based on the presence or absence of the landslides within the area [25].

2.4. Multivariate Methods

Multivariate statistical models evaluate the combined relationship between a dependent variable known as landslide occurrence and a series of independent variable of landslide controlling factors [22, 23]. This method calculates the presence or absence of landslide for all factors in sample units. The results are analyzed either by the assistance of multiple regression model or discriminate analysis. Logistic regression approach measures the probability of a certain event that has occurred by forming a regression relation between a dependent variable and a series of independent variables. The main advantage of this method is that an appropriate link function is added to the usual linear regression model to make the variable either continuous or discrete or maybe any combination of both types [24].

Logistic regression in the GIS environment cannot be performed quickly and with ease. It requires conversion of the data to another format that can be used in statistical package allowing reversion in a GIS database. Furthermore, the logistic regression model allows the user to form a multivariate regression relation between a dependent variable and a series of independent variables. Using the multivariate regression approach, the spatial relation between location where landslides have occurred and landslide related factors can be calculated [25]. The artificial neural network comprises of set of a node and a series of interconnected processing elements which assist for landslide susceptibility assessment. For the case of landslide studies, the factors responsible for occurrence of landslides (slope, aspect, geology, curvature, distance to drainage, rainfall, etc.) are considered as the input neurons. The selection of neurons can vary the accuracy of the landslide susceptibility maps [26].

2.5. Physically Based Model

The physically based modeling approach involves modeling of slope failure processes by the assistance of slope stability model. Locating slope failure could be a good approach to develop landslide susceptibility especially in large areas [27]. Infinite slope models are mainly used for the study of shallow landslides (less than a few meters in depth) at a local scale. The triggering factor for the shallow landslides may either be earthquake or rainfall. An example of physical based model is the stability index mapping of a region after an earthquake under different rainfall scenarios [28]. Most of the physically based models are usually dynamic and they can address the spatial and temporal changes in initiation of landslides. Physically– based models are used for the analysis of slope instability even in conditions when we do not have a complete landslide inventory. The parameters involved for this approach are often measurable and possess a unique value at a given space and time. Therefore, they are most suitable for quantitatively assessing the influence of individual parameters of landslide initiation. However, only disadvantage of this method is that it requires a large number of reliable data to generate convincing outputs [22].

3. Results

3.1. Geological Mapping

In the study area the details geological mapping were carried out and the geological map were prepared based on the field visit. The existence of the local fault and local fold were found as the major structure. In the study area. The details geology of the study area are presented in the map details below (Figure 1). Two different lithological units are mapped in the study area are Kuncha Formation and Fagfog Quartzite the majority of the landslide occur in the Kuncha Formation, Kuncha Formation has fragile and crushed lithology. Kuncha Formation and Fagfog Quartzite covered 81.2 %, 18.8 % land respectively and presence of landslide 73.5 % and 26.5 % Kuncha Formation and Fagfog Quartzite.

characteristics and implications of this fault within the Greater Himalayan context, addressing its role in the geological evolution of central Nepal [29]. Geology of the Nepal Himalaya" stands as a cornerstone in the understanding of the region's geological intricacies. This paper introduces the significance of Dhital's work, emphasizing its role in providing a comprehensive regional perspective on the classical collided orogen [30].

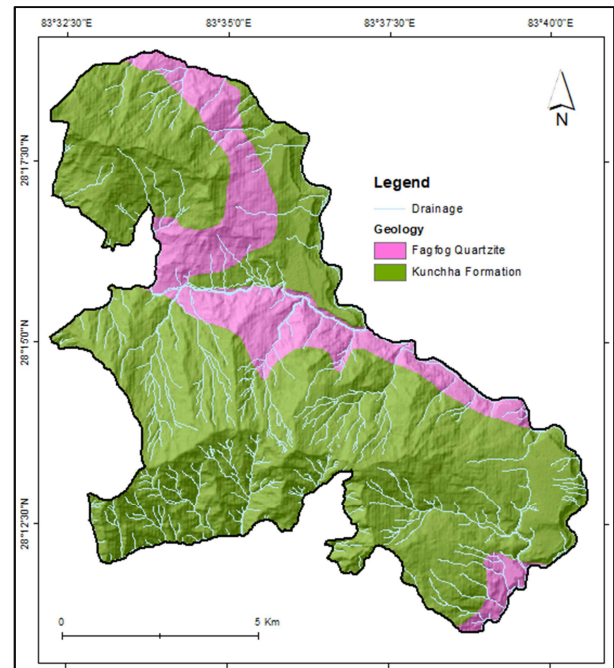


Figure 1. Geological map of the study area.

3.2. Landslide Susceptibility Mapping

3.2.1. Landslide Inventory Map

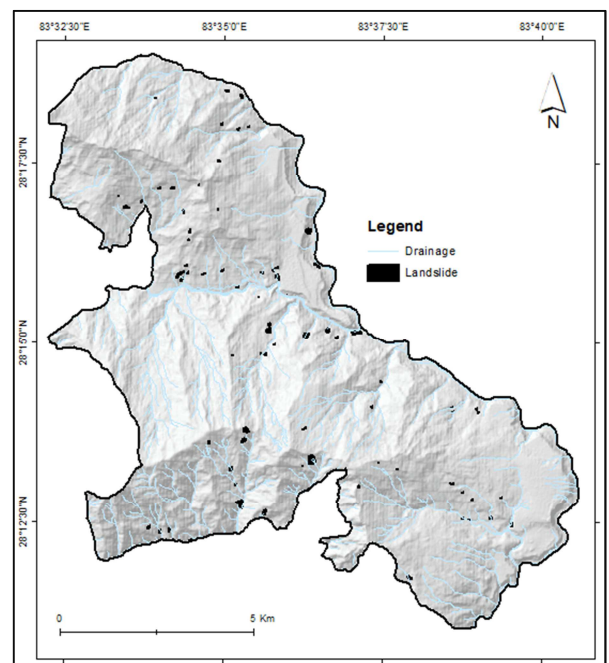


Figure 2. Landslide inventory map of study area.

A landslide inventory was prepared based on the database prepared from our previous study. In addition to that, visual interpretation and digitization of landslides over satellite images available in Google Earth captured from 2004 to 2021 (March, 2021) was used to update the landslide inventory remotely. More than 183 landslides were recognized and also using the aerial photo, field observation. Landslide is widely distribution in heterogeneous in the study area (Figure 2).

3.2.2. Soil Thickness

Based on the field observation and identification we prepared the map with different four classification based on the field observation. (0-1 m), (1-3 m), (3-10 m), (>10 m) by using the ArcGIS 10.4.1 we make polygon. Most of landslide occurred in class (1-3 m) (Figure 3).

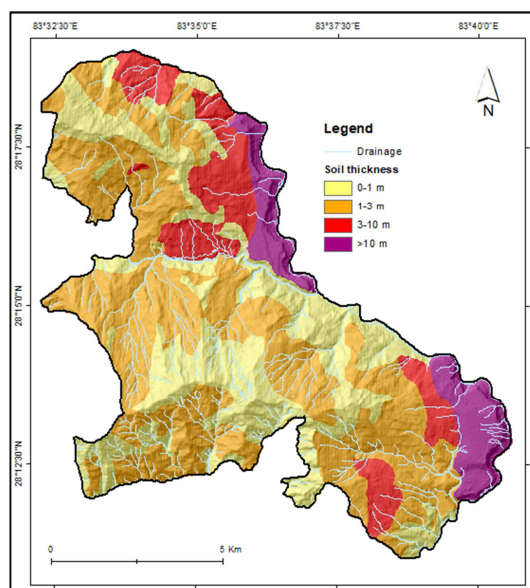


Figure 3. Soil thickness map.

3.2.3. Soil Distribution in Study Area

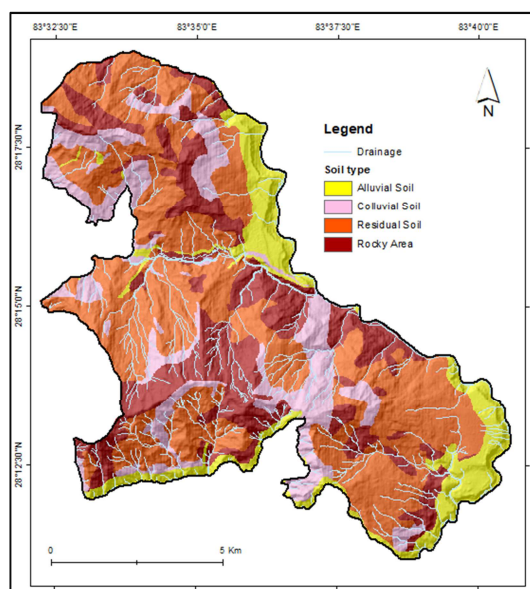


Figure 4. Soil distribution map.

Based on identification the soil distribution map of study area were then prepared the map with different three classification based on the field observation. Alluvial soil, Residual soil, colluvial soil and rock (Figure 4).

3.2.4. Elevation Map

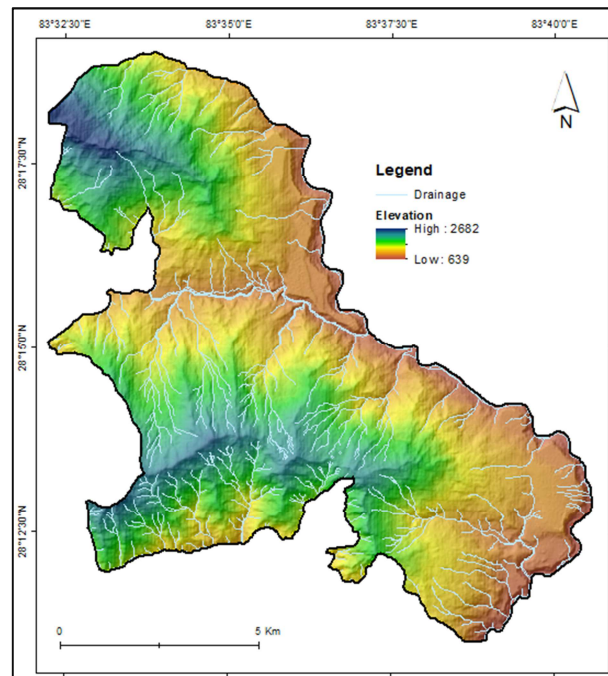


Figure 5. Elevation map.

The study area lowest elevation is 639 m in south and highest elevation is 2682 m in the North West. The elevation map, prepared from DEM 20 × 20 cell sizes for susceptibility map analysis. Elevation is divided into the several classes 639 -1060 m, 1060-1365 m, 1365-1661 m, 1661- 1973 m, 1973-2679 m. Elevation play the important role in susceptibility analysis, most of the landslide occur in the elevation 1060-1365 m and 636-1060 and 1973-2682 m these three classes is occupy the more land in the study area due higher elevation have higher rainfall and high rate of weathering it led to slope instabilities in higher elevation (Figure 5).

3.2.5. Land Use Map

Based on the field observation the land use map of the study area were prepared. The predicted probability value obtained for each class using more than 60 % of the area covered by cultivated land 28% land covered by forest. Most of the landslide found in crop land unpracticed agriculture improper irrigation and road infrastructure and forest area the dense and sparse forest were not differentiated in the study neither was cultivated land differentiated into irrigable and non-irrigable.

3.2.6. Slope

Generally steep slope is prone to sliding than the gentle ones as friction angle of the material and gravity force slope map, prepared from DEM 20×20 cell size The slope map of the study area is divided into the several class (0°-15 °), (15° - 25°), (25° - 35°), (35° - 45°), 45°. In the slope class (25° - 35°), (35° - 45°)

cover more landslide area than other class and the ($25^{\circ} - 35^{\circ}$), ($35^{\circ} - 45^{\circ}$) slope have more probability of mass wasting due to fragile geology other factors study area and (Figure 6).

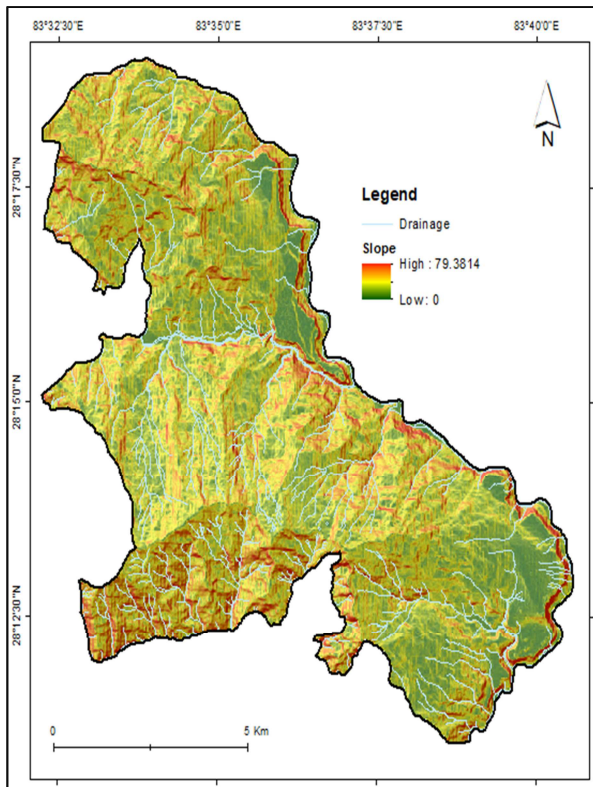


Figure 6. Slope map.

3.2.7. Curvature Map

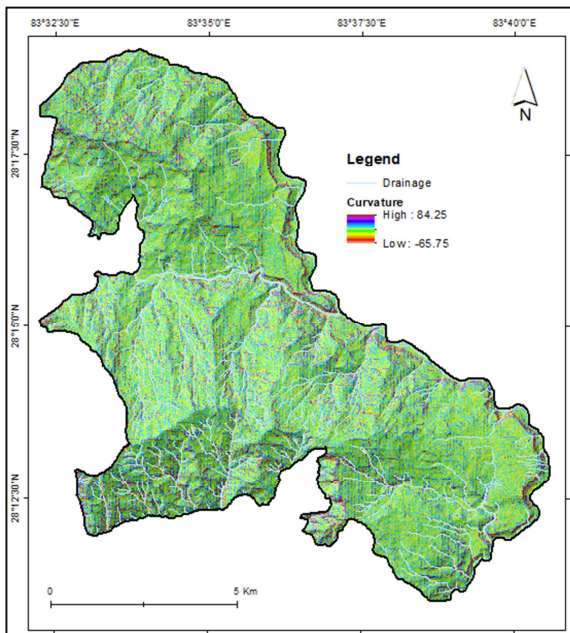


Figure 7. Curvature map.

Generally, the convex shape of the slope or divergent landform is considered to be the most stable for steep terrain followed by the straight or planar shape of the slope. Usually,

the concave shape of the slope or the convergent landform is least stable. The concave shape of the slope tends to develop relatively high pore water pressure increasing the driving force due to the concentration of water in small area finally initiating slope failure (Figure 7).

3.2.8. Topographic Wetness Index

Wetness index is the dimensionless relative value and map of the wetness index (Figure 8). The natural break method was also used to classify TWI into six groups: <2 , 2-5, 5-8, 8-11, 11-13, and >13 .

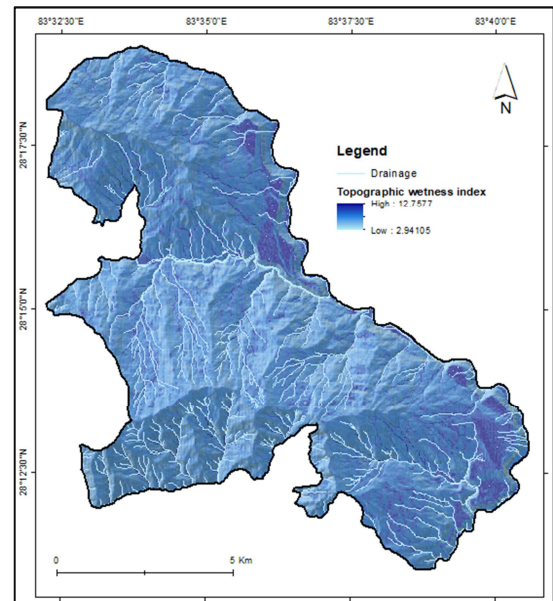


Figure 8. Topographic wetness index map.

3.2.9. Stream Power Index (SPI)

The Stream Power Index (SPI) is a measure of the erosive power of flowing water. It is calculated based upon slope and contributing area. Classify 0-3, 3-6, 6-9, and >9 (Figure 9).

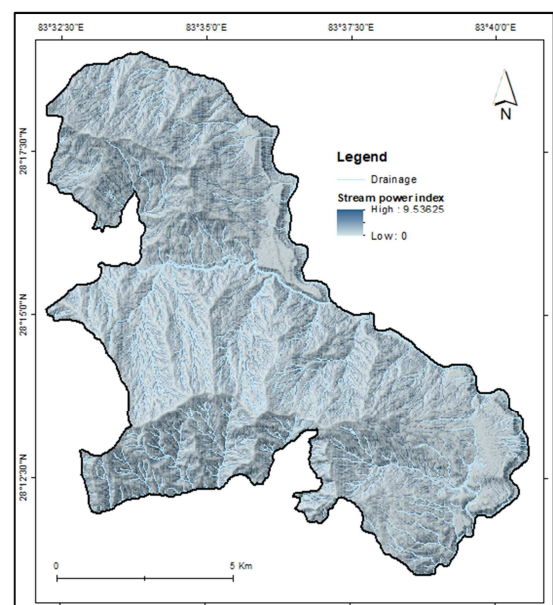


Figure 9. Stream power index map.

3.2.10. Sediment Transport Index

In the study area the value of the Sediment Transport Index value ranges from 0 to 282.621 and map is prepared by classifying this range into the different classes shown in (Figure 10). The Euclidean function in GIS was used to calculate six drainage proximity classes throughout the study: < 15, 15- 50, 50-100, 100-200, 200 -283 and >283.

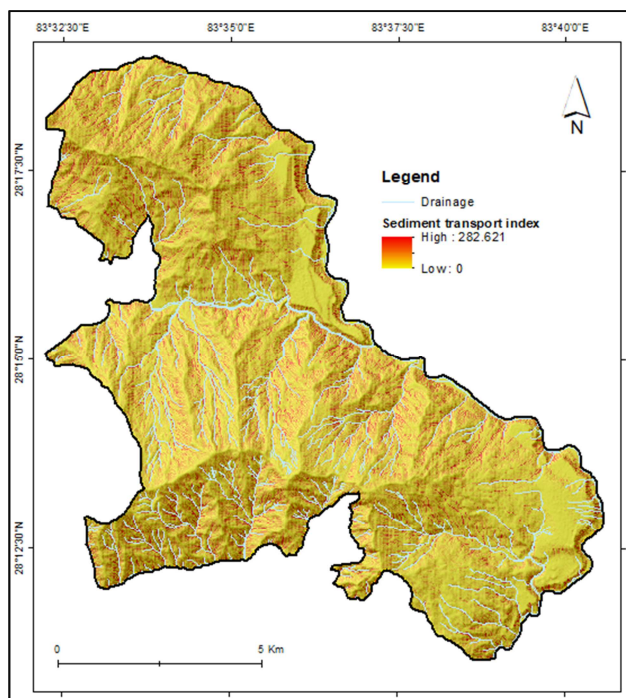


Figure 10. Sediment transport index map.

3.2.11. Drainage Proximity

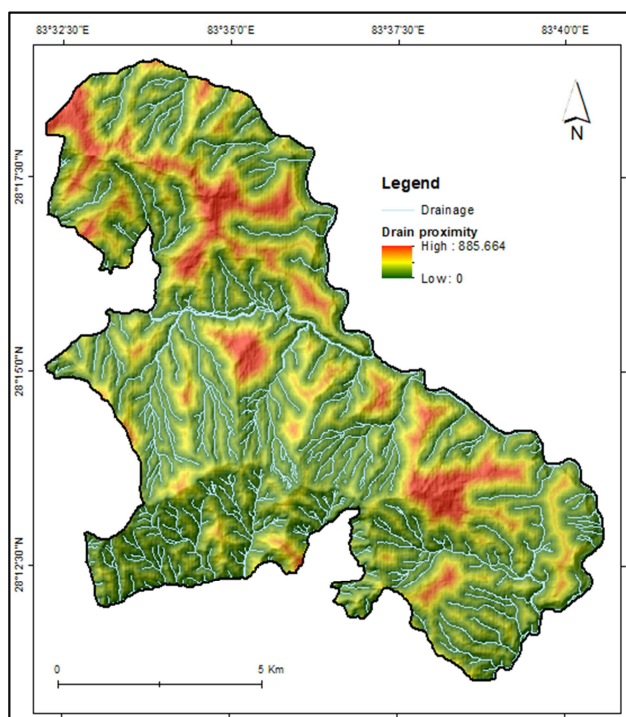


Figure 11. Drainage proximity map.

The effect of the stream on landslide occurrence the distance from stream or drainage was considered. It very importance factor for landslide contribution. The intensive gully erosion of the stream improper drainage management in road is the main cause for the mass wasting to occur (Figure 11). The distance stream was calculation by Euclidean tool of the GIS application and classification 0-100 m, 100-200 m, 200-300 m, 300-400 m, and 400-900 m.

3.2.12. Landslide Susceptibility Analysis Using the Logistic Regression Method

The logistic regression analysis, the data of landslide used are from all over the study area. This creates unequal proportions of landslide and non-landslide pixels. The pixel size taken for the study was 20×20 m for all the parameters. Altogether 247279 pixels of 20×20 m pixel size were formed within the study area. Using the logistic regression analysis, the probability value for all the pixels was calculated. All the pixels are located at a geographic position and position is defined by the value of X co-ordinate and Y co-ordinate in meter. The dependent variable landslide is dichotomous i.e., pixel with landslide and pixel without landslide. The pixel with landslide is given the id 1 and for the non-landslide pixel id 0 is given. The independent variable like DEM derived parameter (slope, elevation, curvature, Topographic wetness index, sediment transportation index, drainage proximity index) and some other variables are categorical such as land use, geology, soil type, thickness. The dependent variable is dichotomous and relationship of this dependent variable is non-linear with another independent variable. Therefore, binary (for dichotomous dependent variable) logistic (nonlinear relationship between dependent and independent variable) model is used for the landslide susceptibility mapping.

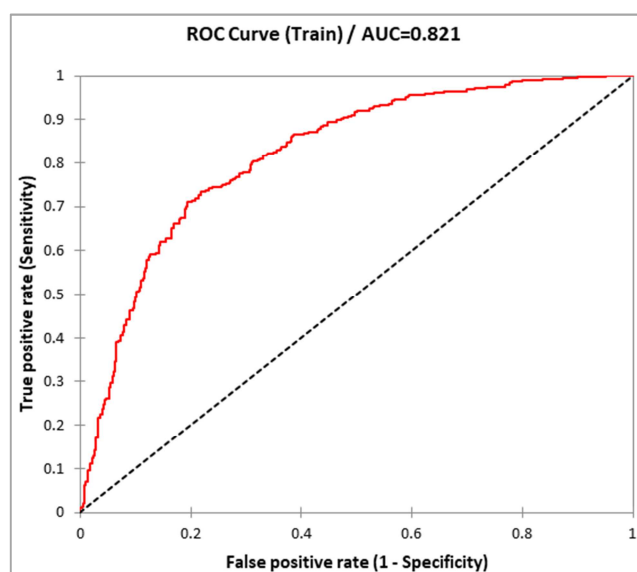


Figure 12. ROC area under curve for the landslide training data.

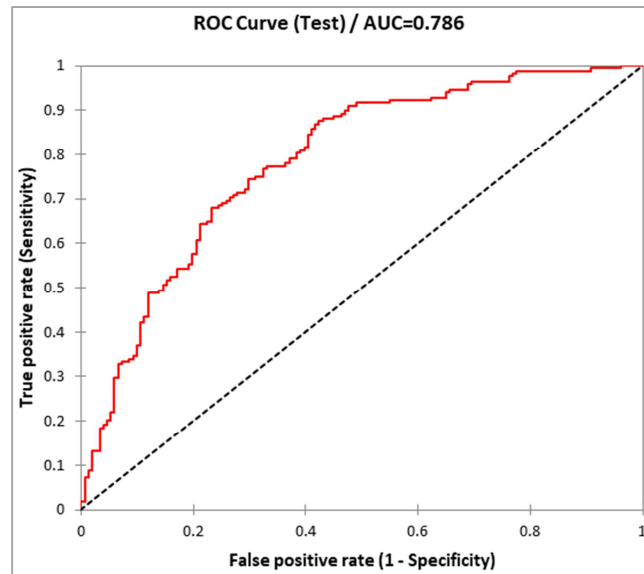


Figure 13. ROC area under curve for the landslide testing data.

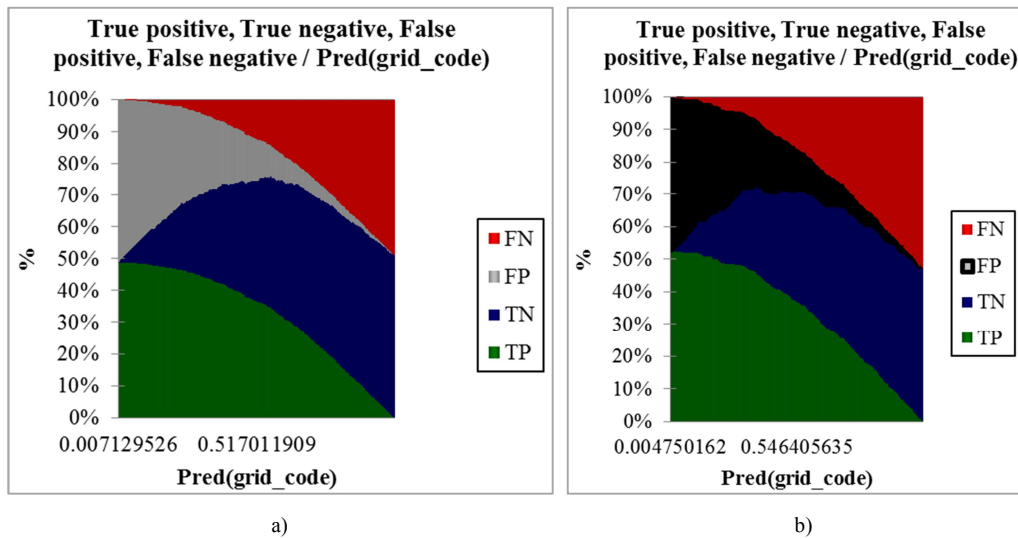


Figure 14. (a) and (b) True positive, True negative, false negative, false positive/ pred (grid code).

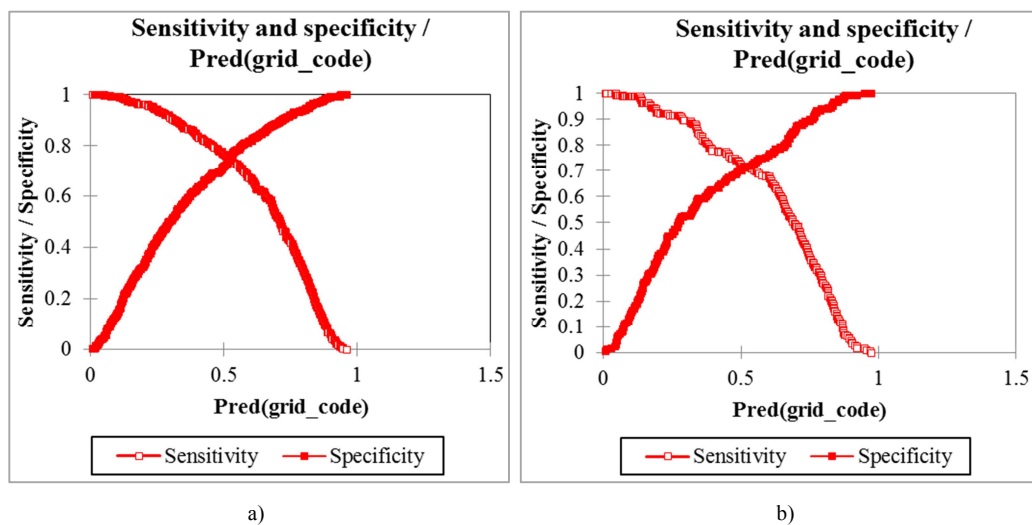


Figure 15. (a) and (b) Sensitivity and specificity / pred (grid cod).

3.2.13. Landslide Susceptibility Zonation

Training data testing data was considered for the preparation of landslide susceptibility zonation of the study area. The predicted probability value obtained from logistic regression of validation data were considered for the zonation. Considering the prediction rate of logistic regression from ROC curve five different classes of landslide susceptibility zone were defined in the study area. The percentage probability value is calculated for each predicted probability value obtained from logistic regression in SPSS. The cumulative percentage probability value is calculated which is used to break values for the zonation of susceptibility map. The landslide susceptibility zonation map of the Baglung Municipality area is shown in Figure 16. Class of landslide susceptibility zonation is as per Very low susceptible zone, Low susceptible zone, Moderate susceptible zone, High susceptible zone, Very high susceptible zone.

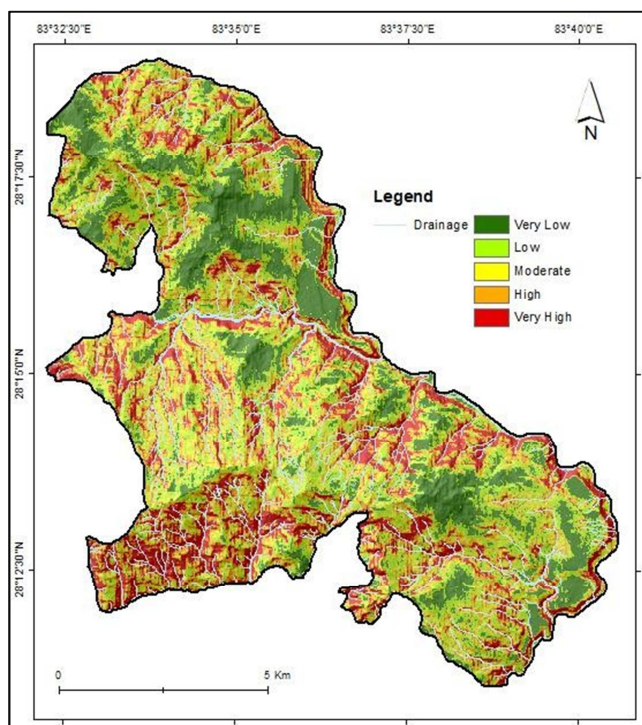


Figure 16. Landslide Susceptibility Zonation.

4. Discussion

A catastrophic loss on lives, property and environment has been increasing in these days due to increasing frequency of landslides [30]. Currently, many numerical approaches have been used in landslide susceptibility mapping such as Frequency Ratio Methods, Weight of Evidence Methods, Fuzzy Analysis, Logistic Regression, and Artificial Neural Network methods. Among them, Logistic Regression Model and Frequency Ratio Model were applied in this study, a maximum number of landslides occur on slopes whose inclination range between 25° to 45° . Similarly, the slopes up to 150 m away from streams or river show a high

concentration of failures. Landslide concentration is also high on soft rock and soil slope with 1 to 3 m depth. The landslide in study area is further increasing the vulnerability of the slope. From the field observation hydrologic factors and it was noted that toe cutting by rivers and road extension was also the prime factor triggering the landslides. The major effect of landslide in Khahare, Rayadada and Tityang are posing serious threat to the settlement. Many landslides occur on the slopes with a relative relief of more than 50 m. The probability of occurrence of landslide also increases with relief [31].

Most of the landslides appear on the slope facing the river. Maximum landslide percentage is noted along the elevation range of 1000 – 2100 m. The topographic wetness index has been used as the hydrological factors of the landslide. This gives a positive correlation of landslide when the index value is small. The least index value obtained 2.94 weight age which is very high after slope. Therefore, the second most important factor of the landslide is topographic wetness index because higher the value of $W+$, stronger the positive correlation. The landslide percentage as observed in plan curvature was somewhat closer for concave and convex class. But usually plan curvature with concavity has a higher occurrence of landslides. The concavity increases erosion and decreases the stability of slopes [32].

Geology is another factor that was kept for the landslide susceptibility analysis in this area. Geologically, this area is covered by the Lesser Himalayan Sequence. Rocks are fragile, highly weathered and interbedded sequences of hard and soft rocks. Also, these types of rocks associated with the active faults are always susceptible for land sliding. The Geology of the study area is characterized by two formations Kuncha Formation and Fagfoge Quartzite most of landslide occur in the Kuncha Formation and wedge failure and plane failure in the Fagfoge Quartzite Formation. Land use is another important factor used for landslide susceptibility analysis. The land use gives information about human activities and water management practices that we can easily relate with the landslide occurrence [33]. In this study area, maximum landslide is concentrated in the forest area. Maximum landslides were observed along the study area followed by forest cropland barren land.

Distance from stream and distance from road have always positive correlation with the landslide. The stream and road buffered with an interval 50 m up to 150 m. So, distance from stream gives a positive impact for landslide triggering for range 0-50 m though there are serious impacts seen from the stream. Soil type and its depth is another important factor used for landslide susceptibility analysis most of landslide occur in the colluvial soil due to less compact.

5. Conclusion

Baglung Municipality comprises fragile topography and consists of weak and, weathered gritty phyllite and pale white quartzite. Landslides have been occurring in the past in

Baglung Municipality due to its uneven topography, landscape with a high relief and hydrologic factors. During the monsoon time most of the area suffers from landslides. Landslide susceptibility is the key to find out the possible failure zones that can be used for mitigation of the primary as well as the secondary disasters. In this study, Logistic Regression Model based on multivariate statistics was used for determining the spatial probability of landslide occurrence where each factor layer was weighted according to the contribution on landslides. This method predicts the probability of landslide occurrence efficiently which was validated by positive correlations between the field conditions and the results obtained by the model. In study area the 183 landslides were identified and used for the preparation of factor maps. The result shows that slope greater than 25 degrees, topographic wetness index less than 12.75, other hydrological factor and fragile geology (Kuncha Formation) proximity to from drainage is the four primary factors influencing the landslide occurrence, other factors, land use, elevation, soil type and depth are other contributing factors. By analyzing all these factors, landslide susceptibility map was modeled. The landslide susceptibility map was further categorized in the following five classes: Very low, Low, Moderate, high, and very high. The landslide susceptibility maps are helpful to identify the potential sites that are prone to landslide in advance and therefore help to reducing the possible damage.

Conflicts of Interest

We declare that there is no any conflict of interest for this research publication.

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