Information Value Model based Landslide Susceptibility Mapping at Phuentsholing, Bhutan

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Abstract

In the current study, statistical method of information value and geographic information system (GIS) were applied to develop Landslide Susceptibility Map (LSM) of Phuentsholing region, Bhutan. A total of 161 landslides, covering an area of 2.92 square kilometres were identified and 20% was randomly extracted for validation. Various factors causing landslide such as slope, aspect, elevation, proximity to road, drainage and fault, lithology, land use and normalised difference vegetation index (NDVI) were analysed to determine the contribution of each factors to the occurrence of a landslide. To evaluate the performance of the information value model in determining the LSM, overlay method and the Area under curve (AUC) of the receiver operating characteristic (ROC) were performed on the training and validation samples. The region was categorised mostly under high and moderate susceptibility, with land use, vegetation and elevation identified as most important contributing factors to landslide occurrences. The model has an AUC accuracy of 83.4% success rate and 83.5% prediction rate, with 77.5% of the validation samples lies under very high and high landslide susceptibility area when overlaid on the LSM.

Keywords: Landslide susceptibility map, Information value model, Geographic information system, Area under curve.

1 Introduction

The growing population over the world has forced settlement into geologically sensitive areas resulting in negative impact on the environment and substantially increasing the vulnerability of the inhabitants to the risk of natural disasters. This expansion of settlement has also increased human activities in terms of agricultural practices and infrastructure development, leading to massive deforestation and land use changes, thereby increasing the potential of occurrences of landslides.

Dai, Lee and Ngai, (2002) established that cutting slopes for infrastructure development is a triggering factor for most landslides. On the other hand, the occurrences of landslides have been a major problem for infrastructure development around the world especially in mountainous countries where landslide has hindered development of highways, railway lines, valleys, reservoirs, inhabited areas and agricultural lands. A landslide event could lead to blocking of traffic, destruction of fertile land, collapse of buildings, and loss of lives. Therefore, it is imperative that measures be taken to reduce the instances of landslides. One of the strategy to reduce the impact of landslide through preventions and mitigations, that has been adopted in many parts of the world is Landslide hazard, landslide risk and Landslide susceptibility mapping (Pardeshi, Autade & Pardeshi, 2013).

A landslide is the movement of rock, earth, or debris down a slope of land. It is a geological phenomenon of ground movement depending on the type of movement (fall, topple, spread, flow, slide and slope deformation), type of material involved (rock, earth, debris), and speed of the movement (Hungr, Leroueil & Picarelli, 2014; Varnes, 1978). Although the action of gravity is the primary driving force for a landslide, there are other factors triggering landslide such as earthquake, rainfall or human interaction (Guzzetti, 2003).

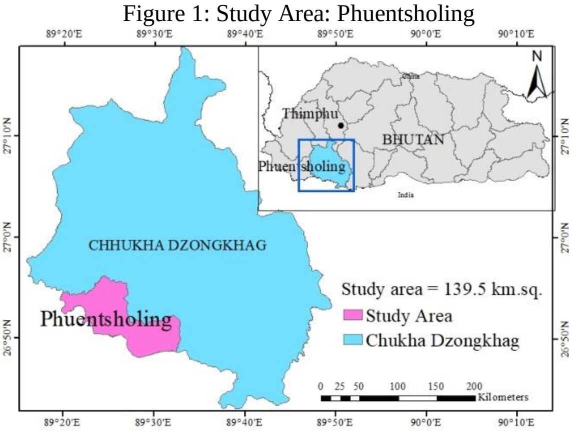
Numerous studies have been conducted on Landslide Susceptibility Mapping (LSM) to determine the influence of the causal factors on the occurrence of the event. The application of GIS with Multi-criteria decision analysis (MCDA) method based on analytical hierarchy process (Yalcin, 2008; Althuwaynee *et al.*, 2014), fuzzy logic (Feizizadeh *et al.*, 2014; Vakhshoori & Zare, 2016) and weighted linear combination (Ahmed, 2015) were shown to be useful in predicting the landslide susceptibility. Usefulness of Artificial Neural Network (ANN) method (Zeng-Wang, 2001; Kanungo *et al.*, 2006) were also evaluated relative to other methods. Logistic regression method to determine the weight of the causal factor is widely adopted by most researchers (Devkota *et al.*, 2013; Das *et al.*, 2012; Sangchini, Nowjavan & Arami, 2015; Yesilnacar & Topal, 2005; Rasyid, Bhandary & Yatabe, 2016; Althuwaynee *et al.*, 2014). Information value model (Chalkias, Ferentinou & Polykretis, 2014; Sarkar & Kanungo, 2006) and weight of evidence method (Pradhan, Biswajeet; Oh, Hyun-Joo ; Buchroithner, 2010; Quinn *et al.*, 2010) were also used with significant outcomes.

The aim of the current study is to develop a landslide distribution map and derive relative weight of different classes of landslide causative factors using statistical information value model. A landslide susceptibility map will be created in the ArcGIS environment.

1.1 Study area

Bhutan is located within seismic zone 5, the most severe seismic zone as classified by Bureau of Indian Standards and shares similar tectonic settings as Northern India and Nepal with major tectonostratigraphic units and structures including Siwalik Group, the Main Boundary Thrust (MBT), the Lesser Himalayan Sequence (LHS), the Main Central Thrust (MCT), the Higher Himalayan Crystalline Complex (HHC), and the South Tibetan Detachment (STD) (Kuenza, Dorji & Wangda, 1994; Petterson *et al.*, 2011). Landslide of varying degrees occurs frequently in southern Bhutan which is predominantly due to steep slopes, sparse vegetation and phyllite lithology (Cheki & Shibayama, 2008; Pasang & Kubíček, 2017; Thapa, Phuntsho & Chozom, 2015; Pasang, Sangey; Kubíček, 2017).

Figure 1: Study Area: Phuentsholing

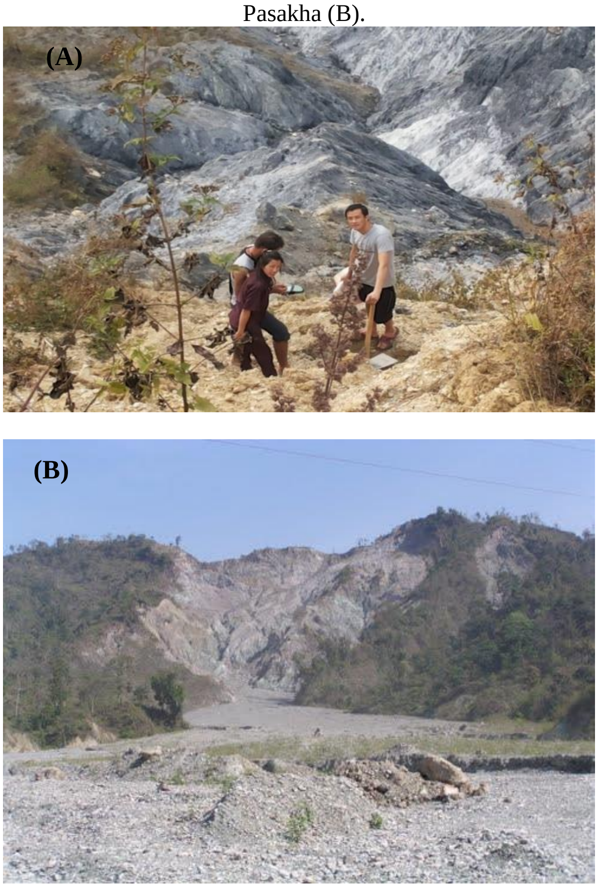


The study area (Figure 1) includes Phuentsholing, the main commercial centre of Bhutan connecting western Bhutan to its major economic partner, India and the Pasakha industrial estate. The total area of 139.5 square kilometers comprises of 15.6 square kilometers urban Phuentsholing (Population: 23,925) and Highway Road length of 192 km. The area is subjected to frequent occurrences of landslides of varying magnitudes at a number of locations (Figure 2).

2 Materials and Methods

Interpreting the likelihood of future landslide occurrences requires an understanding of conditions and processes controlling past landslides in the area of interest. Landslide distribution or inventory mapping is the basic information required in determining the size and features of a landslide (Guzzetti, 2003; Skidmore, 2002). To create thematic layers of landslide distribution and casual factors including slope angle, aspect, elevation, proximity from road, drainage and fault, lithology, land use and normalised difference vegetation index (NDVI), we used ArcGIS environment along with SPSS for data management and validation, and MS Excel for Information value analysis.

Figure 2: Landslides in Phuentsholing (A) and road section in Pasakha (B).



2.1 Landslide distribution map

Landslide inventory mapping is carried out by conventional ground survey, Remote Sensing (Kanungo *et al.*, 2006) and GIS depending on the scope, the extent of the study area, the scales of base maps and aerial photographs, and the resources available to carry out the work. Using multiple sets of aerial photos at different times, multi-temporal maps can be prepared.

A thematic layer for the distribution of landslide was prepared to derive the correlation of landslide occurrence to the casual factors. Due to unavailability of landslide inventory in Bhutan, a technical report by National Soil Services Centre (NSSC) & PPD (MoAF/RGoB, 2011), was used as the primary guidance for field visits and digitization using satellite imagery from google earth. A total of 161 landslides with an area of 2.92 square kilometres with the largest landslide measuring 304,625 square meters (Figure 3 and Table 1) were digitized. The layers of landslide distribution and the casual factors were rasterised for further analysis. For the purpose of validation of the LSM, 20 % of the landslide distribution pixel were extracted and the remaining pixel were prepared for statistical analysis.

Figure 3: Landslides distribution in study area.

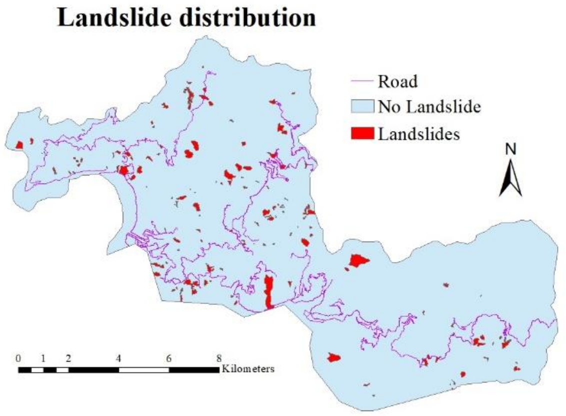


Table 1: Number of cells for sample layers

	Training sample (80%)		Validation sample (20%)	
	No. of cells	Percent %	No. of cells	Percent %
No Landslide	485258	97.9	122085	97.9
Landslide	10419	2.1	2594	2.1
Total	495677	100.0	124679	100.0

2.2 Landslide casual factors

In the present study, the factors causing landslide were considered from various literature and data available for the study area. Individual thematic maps for the casual factors were developed and divided into classes (Table 2) to determine the influence of each factor on the occurrence of a landslide.

The geomorphic causal factors such as slope angle, aspect and elevation were produced from ASTER DEM of 30 m resolution. The slope angle in degrees was divided into six classes of equal interval of 10 degrees. Aspect was categorised into eight classes of compass and one class for flat area. An elevation map with 11 classes of 200 m interval was produced. The lithological and fault details were digitized from 1:50,000 geological map of Bhutan from Journal of Maps 2011(Long *et al.*, 2011). Land cover maps from the archives of MoWHS, which was developed by National Soil Services Centre (NSSC) & PPD (MoAF/RGoB, 2011) were used to derive seven simplified broad land use categories to meet the aim of the study. NDVI was developed using Landsat 8 images to consider the influence of vegetation in landslide occurrence. Drainage map and road map were downloaded from the website of the Bhutan Geospatial portal. Layers of both casual factors were created with six equidistant buffers of 100 m each.

2.3 Information value method

Information value model, a simple statistical method to map landslide susceptibility by determining the influence of each class of the casual factors on the occurrence of the landslide in an area was found appropriate in many studies (Chalkias, Ferentinou & Polykretis, 2014; Sarkar & Kanungo, 2006; Nepal, Rao & Ho, 2015). In this model the information value I_i for a class *i* in a thematic layer is:

$$I_i = \log \frac{S_i / N_i}{S / N} \quad (1)$$

Where, S_i = number of pixels of the class containing landslide; N_i = number of class pixels; S = number of pixels with landslide in layer; N = total number of pixels in the layer.

After calculating the information values for each class of the causal factors, the raster maps were overlaid in GIS environment. The landslide susceptibility index was calculated as the sum of the information value that a pixel *j* has from each corresponding pixel of the casual factor.

$$LSI_j = \sum_{i=1}^{M} X_{ji} \times I_i \quad (2)$$

Where, X_{ij}=1 if class *i* exists in factor *j* and 0 if class *i* does not exist in factor *j*; M = number of classes considered.

From landslide susceptibility indices, five severity level of landslide were categorised.

2.4 Validation

To check the accuracy of the LSM, the validation sample of 20% landslide pixel is overlaid on the LSM. If the maximum pixel falls under the categories of high or very high level of severity, the LSM is considered to be valid.

Area under curve (AUC) of the receiver operating characteristic (ROC) (Pradhan, Biswajeet; Oh, Hyun-Joo ; Buchroithner, 2010; Yilmaz, 2009) was also performed on both the training sample and the control sample to evaluate the success rate and prediction rate of the information value against the occurrence of landslide.

3 Results and Discussions

3.1 Information Values and Landslide densities

The casual factor map was overlaid on the landslide distribution map to obtain the influence of each class on the occurrence of landslide with positive value as more influential and vice versa. The information values of each class under casual factors were determined by using Equation (1) and density of landslides by identifying affected area in each class (Table 2).

The factor contributing most to landslide occurrences are the degraded area class under land use followed by dry bare soil class (NDVI) and scrub class (land use). Region of Phyllite-Limestone, elevation between 200-300 m, 200-300m distance from road and southeast aspect were other significant contributors.

Table 2: Classes of causal factors with Information values and landslide densities

Causal Factors	Information Value	Landslide density
Slope (degree)		
0-10	-0.682	0.052
10-20	-0.026	0.212
20-30	0.073	0.349
30-40	0.099	0.293
40-50	0.081	0.090
>50	-0.567	0.004
Aspect Class		
Flat	-1.780	0.000
North	-1.029	0.035
North East	-1.061	0.024
East	-0.641	0.037
South East	0.345	0.175
South	0.256	0.210
South West	0.240	0.222
West	0.343	0.226
North West	-0.678	0.072
Elevation (m)		
0 - 200	-0.259	0.038
200 - 400	0.441	0.329
400 - 600	0.214	0.284
600 - 800	0.003	0.162
800 - 1000	-0.462	0.073
1000 - 1200	-0.708	0.047
1300 - 1400	-0.087	0.065
1400 - 1600	0.000	0.000
1600 - 1800	0.000	0.000
1800 - 2000	0.000	0.000
>2000	0.000	0.000
Distance from Road (m)		
0-100	-0.214	0.134
100-200	0.161	0.131
200-300	0.353	0.126
300-400	0.267	0.100
400-500	0.023	0.067
>500	-0.107	0.442
Distance from Drainage (m)		
0-100	0.122	0.589
100-200	-0.039	0.297
200-300	-0.300	0.089
300-400	-0.480	0.023
400-500	-2.504	0.001
>500	0.000	0.000
Distance from Fault (m)		
0-500	0.334	0.410
500-1000	0.130	0.309
1000-1500	-0.007	0.147
1500-2000	-0.484	0.056
2000-2500	-0.211	0.056
2500-3000	-0.930	0.021
>3000	-3.885	0.002
Lithology		
Phyllite-Limestone	0.345	0.374
Phyllite-Dolostone/Marble	-0.041	0.317
Quartzite-Mica/Schist	0.341	0.235
Schist/Phyllite-Quartzite	-1.081	0.073
Granite	0.000	0.000
Biotite-Quartzite	0.000	0.000
Land use		
Agriculture Land	-0.566	0.059
Built-up Area	-0.762	0.013
Degraded Areas	3.544	0.402
Forests	-0.712	0.350
Shrubs	0.550	0.134
Horticulture Land	-0.901	0.008
Water Bodies	-0.317	0.034
NDVI		
Water	0.121	0.006
Dry Bare soil	0.571	0.300
Vegetation	0.115	0.395
Dense Vegetation	-0.456	0.299

3.2 Landslide susceptibility Index

Equation (2) was used to determine the landslide susceptibility index by summing the information values of the classes under different causal factors corresponding to each pixel in the map. It was reclassified into scales of five severities of very low, low, moderate, high and very high using natural breaks (Jenks) method (Figure 4). The number of pixels and area falling under different scales of landslide susceptibility is indicated in Table 3.

Figure 4: Landslide susceptibility map indicating various scales of severity

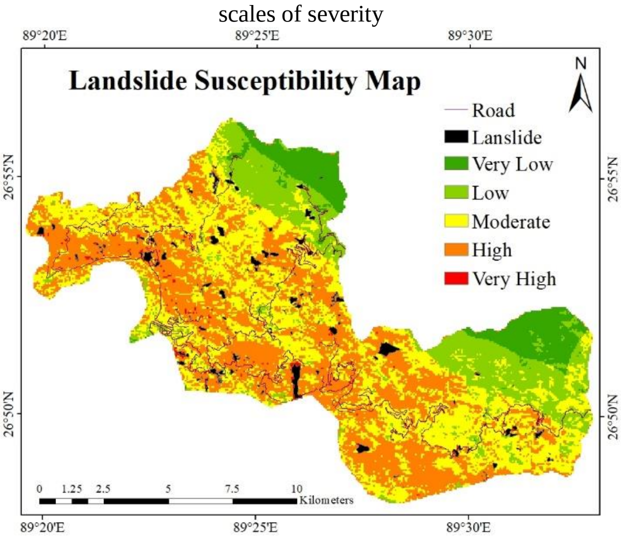


Table 3: Number of pixels and percentage area of layer corresponding susceptibility indices.

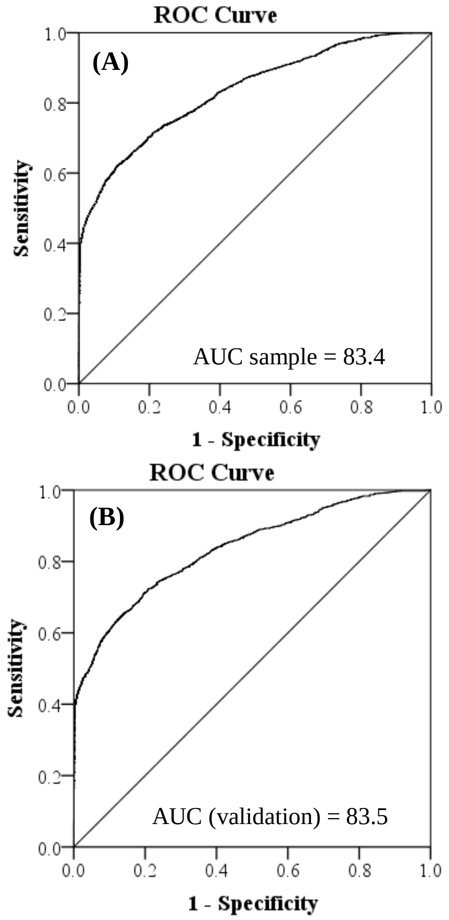
Susceptibility Index	Training Sample		Validation Sample	
	No. of Pixels	%Area	No. of Pixels	%Area
Very Low	2965	7.5	8	0.3
Low	6257	15.9	77	3.0
Moderate	15072	38.3	499	19.2
High	14535	36.9	1077	41.5
Very High	515	1.3	933	36.0
Total	39344	100	2594	100

3.3 Validation

The validation samples of landslide pixels were overlaid on the LSM to establish that 36 % of landslide pixels lies under very highly susceptible region followed by 41 % in high, 19.2 % in moderate, 3 % in low and 0.3 % with very low susceptibility (Table 3).

To evaluate the performance of the model using AUC for success and prediction rates of both training and the validation samples, various values considered for the diagnostics were 0.5 to 0.6 (fail), 0.60–0.70 (poor), 0.70–0.80 (fair), 0.80–0.90 (good), and 0.90–1.00 (excellent) (Rasyid, Bhandary & Yatabe, 2016). The AUC of ROC were 83.4 % and 83.5 % for the success and prediction rates respectively (Figure 5).

Figure 5: Area under curve (AUC) of the receiver operator characteristic (ROC) for the training sample (A) and validation sample (B).



4 Conclusion

A LSM of Phuentsholing area, indicating scales of severity of the occurrence of landslide was created. The model suggests that the occurrences of landslides are affected mainly by land use, vegetation cover and elevation. Since the results of the study also clearly indicate the severity of landslide occurrence and the influence of various classes of factors, socio-economic development plans can be made to avoid or minimize the cost resulting from future landslide. Since the AUC prediction rate is 83.5%, and 77.5% of the validation sample falls under very high and high landslide susceptibility area, it can be concluded that information value model is useful for a region similar to the study area.

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