Landslide susceptibility mapping Frequency ratio, Pairwise comparison- AHP and Logistic Regression

ABSTRACT

This study presents to its reader the landslide susceptibility mapping of the Phuentsholing and Sampheling area under Chhukha Dzongkhag. The study area was found to receive the highest rainfall recorded in the area of 270 mm per year and this factor had caused a lot of losses of properties and lives. With the help of Logistic regression and multi-criteria decision-making modeling with Geographic Information system (GIS) based, landslide susceptibility map was developed for the area. For the modeling of the statistical methods, nine sets of causative factors were considered based upon the geographic conditions and their effect on the result of accuracy. Factors considered are namely slope, aspect, elevation, and distance from road, distance from drainage, and distance from fault, land cover, NDVI, and geological formation. A total area of 15.6 km^2, comprising the main commercial and financial gateway connecting Thimphu, the capital city of Bhutan with India and also the main industrial area in Bhutan (Sampheling also known as Pasakha). The area is populated with 23,925(structural survey 201) with more than 26 factories. The susceptibility maps were validated and compared using Area under curve (AUC) of the receiver operating characteristic (ROC). All the models showed a good result of accuracy of above 80% which concludes that any of the 3 methods can be applied for the development of the susceptibility maps for the use of designing and planning of the future land use pattern.

Keywords: Landslide susceptibility map, Geographic information system (GIS), Multi-criteria evaluation, Frequency ratio, Logistic regression, Pairwise Comparison (AHP).

1. Introduction

Landslide or mass wasting is the downward movement of the earth which consists of rocks, debris, soil mass or a mixture of rocks and soil mass which mainly occurs when the gravitational pull exceeds the strength that's holding the earth mass together in a slope. Landslip risk is defined as the predicted extent of loss due to landslides in a given area and for a specified time period (in terms of loss of life, injuries, damage properties and disruption of economic activity). For a given class of risk elements, the specific risk can be measured as the product of vulnerability, the number of risk elements and the likelihood that a specific hazard scenario will occur with a given return period in a given area. (Pellicani, Argentiero, & Spilotro, 2017).

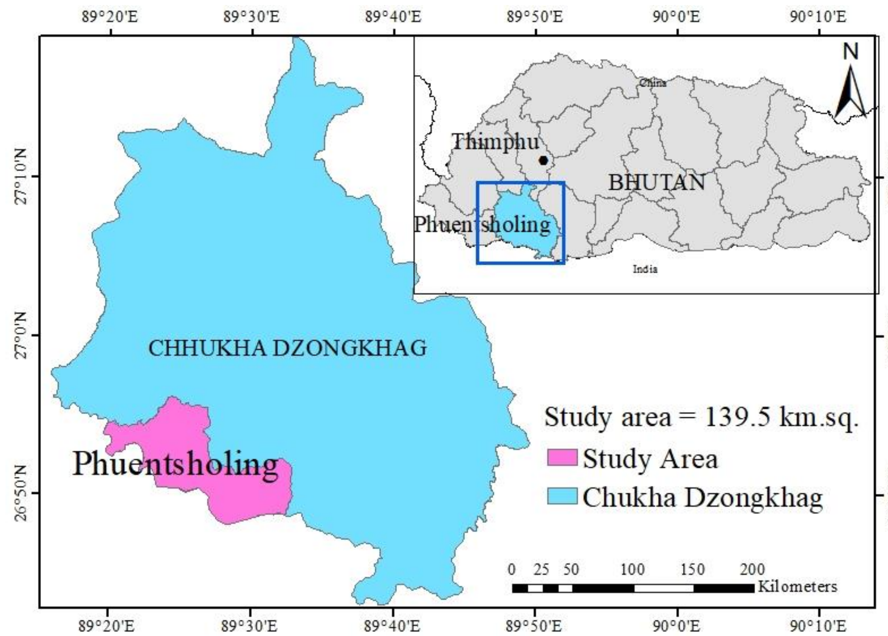
Bhutan is located in the eastern Himalayas which is one of the most landslide occurring zone have witnessed numerous landslide events and suffered a huge loss in term of property and life. A study of a global database of landslide occurrence from 2004-2016 showed that 75% of the landslide happened in Asia, with most of it happening around the Himalayan regions. (Sarkar &

Dorji, 2019). From these numerous landslides, it was found out that most of the slides were a shallow landslide that is caused or triggered by the rainfall factor.

Landslide is a frequently occurring geological hazard. (Gentile, 1978).It has been one of the most prominent and life-threatening events occurring mostly during the rainy season and mostly at the southern belt of the country. 161 numbers of various landslides were recorded in Phuentsholing and Sampheling which falls under Chhukha Dzongkhag. These landslides were mostly sliding fall and flow type of landslide. To study these landslides and induce the susceptibility map for the area, multi-criteria approach of Frequency ratio, Pairwise comparison- AHP and logistic regression method is used. Comparing the two methods, a susceptibility map was developed for the study area.

2. Study Area

Fig 1. Phuentsholing- Pasakha (Sampeling) highway



Bhutan is located in the eastern part of Himalayas, falls under the seismic zone 5 and is indeed one of the landslide-prone zones. Surrounded by the two giant nations, Bhutan's elevation ranges from 100m to 7500m above sea level. Phuentsholing dungkhag ranges from an elevation of 1000m to 4200m. According to the national hydrology and metrology, the annual average rainfall (area average) was 1649.9 mm in 2018. Overall the country receives the near-normal rainfall slightly above average. The highest rainfall was recorded in Phuentsholing region with 270mm followed by Sipsoo, Bhur, and Deothang. Numerous landslides triggered by the rainfall was recorded in these areas.

Fig 2. Study area map of Phuentsholing

The study area (Fig 2.) includes the main commercial and financial gateway connecting Thimphu, the capital city, with India and also the main industrial area in Bhutan. It covers an area of 15.6 square kilometers (structural plan) in Phuentsholing which is the urban area with a population of about 23,925(structural survey 201). The road length in the area is 192km connecting more than 26 factories in the sampheling region (Pasakha). It was found out that the landslide was mainly due to intense rainfall and the anthropogenic changes. The road stretch is subjected to the frequent occurrence of landslide with fluctuating magnitude at various locations.

3. Materials and Methods

In general landslide susceptibility mapping, most of the scientists or most of the researchers focus on mainly two types or two takings or two approaches which are derived from Bivariate Statistical Approach or Multivariate Statistical based Approach. Bivariate statistical approach from the two of the approaches is the simplest and easiest approach that is easy to apply and update but it has its drawbacks related to not considering the mutual interrelationships among the independent factors. The common example under this approach is Probability statistics like Frequency Ratio Method (FR). Whereas in the Multivariate Statistical based Approach, it is more realistic, more accurate and sensitive to the independent factors and it has more statistical tests about the relations of the variance and also considers the mutual interrelationships among the independent factors. The most common methods are Machine Learning such as ANN (Artificial Neural Network) and regression methods like Logistic Regression.

There are two main factors:

1. Dependent factors: prediction targets locations inventory such as landslides inventory map or groundwater.

2. Independent factors: predictors or conditioning factors such as landcover, slope angle, and lithology.

The process goes as firstly the identification and mapping of a set of dependent and independent factors that are directly or indirectly correlated. Secondly, estimating the relative contribution of these independent factors in predicting of dependent factors. The general methodology is given by the figure below (Fig 3.)

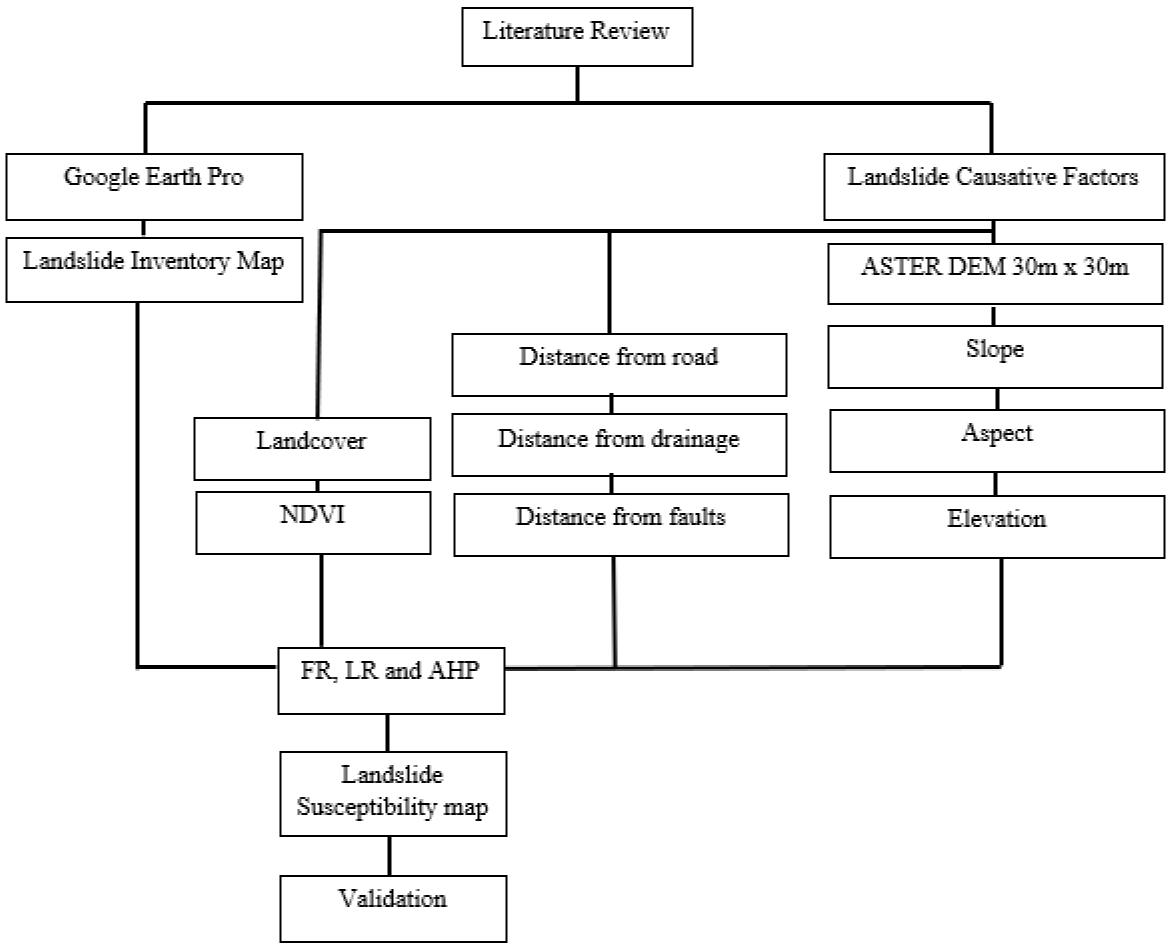


Fig 3. Methodology flowchart of the study

3.1. Landslide Inventory Map

The landslide inventory (Fig 4.) for the study site was acquired with the use of Google Earth Pro by examining the locations where there has been an occurrence of a landslide in the past. Each of the landslides which were mapped has been checked in the site area and the detailing of the marked landslides has been altered correspondingly.

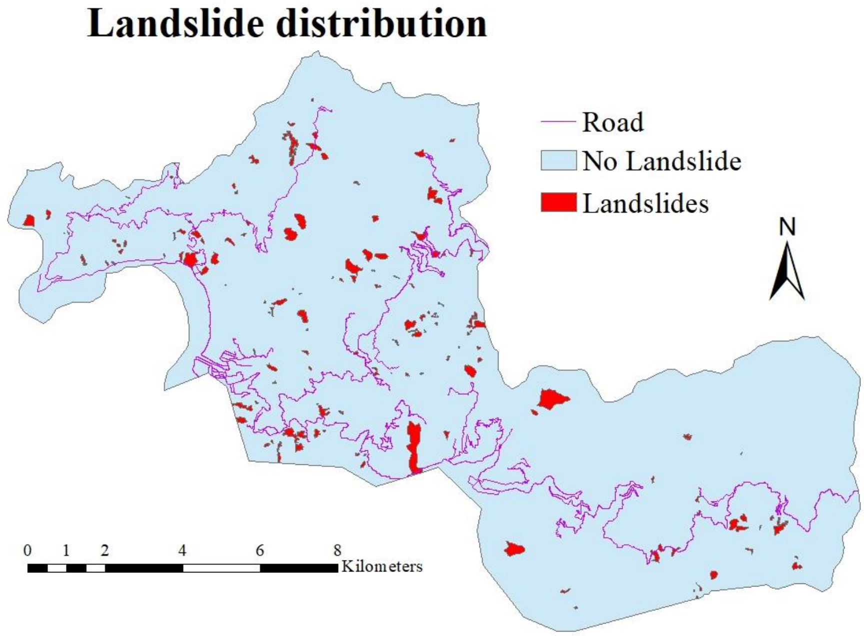


Fig 4. Landslide inventory map for Phuentsholing

3.2. Landslide Causative Factors

Nine independent variables were selected (i.e. Slope, aspect, elevation, distance from road, distance from drainage, distance from fault, land cover, normalized difference vegetation index and geological formation) for landslide susceptibility mapping.

3.2.1. Slope

The slope of the terrain determines the spatial distribution and landslide intensity. (Shafique., 2016). The gradient of the study location was evaluated using ArcGIS 10.6.1 from the ASTER DEM of cell size 30m × 30m. The generated slope chart was then graded into six groups, namely 0-10, 10–20, 20–30, 30–40, 40–50,50-60 and >60.

3.2.2. Aspect

The aspect of the slope gives the direction of slope and affects the water retention, strength of soil and vegetation cover. (García-Rodríguez, 2008, Basharat, 2014). The gradient of the study location was evaluated using ArcGIS 10.6.1 from the ASTER DEM of cell size 30m × 30m.

Aspect of the location was classified into classes of nine, namely flat, north, east, west, south, northeast, southeast, southwest and northwest.

3.2.3. Elevation

The elevation is extensively used to evaluate the susceptibility to landslides. The divergence in elevation can be associated with environmental parameters, such as vegetation and rainfall. The gradient of the study area was evaluated using the ArcGIS 10.6.1 from the ASTER DEM of cell size 30m × 30m.

3.2.4. Distance from roads

In rugged terrain, the network construction, which includes roads and railways, which time and again leads to instability of slope and ultimately to landslides. The road was rasterized in ARCGIS 10.6.1 and added more road from Google earth by digitizing-buffered by multi-ring buffered-clipped again with AOI-union with AOI file.

3.2.5. Distance from drainage

One of the key factors leading to destabilization is the influence of water on a steep mountainside. Knowledge of water pressure and runoff method is significant for the interpretation of stabilization and the preparing of measures to ensure stability on the hillside. The distance from drainage was rasterized in ArcGIS 10.6.1.

3.2.6. Distance from faults

Spatial distribution and structure of fault lines assess mainly the occurrence and frequency of landslides which are not earthquake-induced (Kamp, 2008,). The fault was rasterized in ARCGIS 10.6.1 and the fault range was separated into buffer zones of six at intervals of 500 m

3.2.7. Land cover

This has a significant impact on landslide distribution, also areas of the forest have fewer landslides relative to deserted areas. Forested areas that have their system of root very strong and intact often help in stabilizing the slopes. For the study area, the land cover was digitized and rasterized. In the map, the NDVI considered 1 to 0 as water, 0-0.15 as bare soil, 0.15-0.3 sparse vegetation, 0.1-0.6 dense vegetation.

3.2.8. NDVI (Normalized Difference Vegetation Index)

Although there are several indices for vegetation, the NDVI is one of the most commonly known. The NDVI range is between+ 1.0 and -1.0. The barren rock, sand, or snow areas typically have very low NDVI values (e.g. 0.1 or less). Sparse vegetation such as shrubs and grasslands or senescent crops may contribute to medium NDVI values (around 0.2 to 0.5). High

NDVI values (approximately 0.6 to 0.9) are the same as those found in tropical forests with the temperate climatic condition.

3.3. Frequency Ratio (Model 1)

Frequency Ratio is a Bivariate statistical analysis method, based on the spatial distribution (Probability) of dependent factor (landslides. pollutants), and as considered conditioning factors (slope, aspect, rainfall).

Frequency Ratio can be calculated with the equation given below: (Rasyid, Bhandary, & Yatabe, 2016)

$$FR = \frac{PixcL\,(ij)/\sum PixcL}{Pix(ij)/\sum Pix}$$

Where; $PixcL\ (ij)$= number of pixels with landslide in class i of j Variable

$\sum PixcL$= total pixel with landslide of j Variable

$Pix(ij)$= number of pixels in class i of j Variable

$\sum Pix$= total pixel of j Variable

To generate the landslide susceptibility index (LSI) using the frequency ratio, all the raster map landslide factors ratio (FR) have been added up.

LSI = FR (slope) + FR (Aspect) + FR (Elevation) + FR (Road) + FR (Drainage) + FR (Fault) + FR (Formation) + FR (Landcover) + FR (NDVI)

LSI's higher value suggests high susceptibility to Landslide at the site and vice versa.

3.4. Logistics Regression (Model 2)

The logistic regression (LR) is based on the problem analysis in which one or more independent factors determine a result measured as 0 and 1 or true and false with dichotomous variables. The LR model was used to describe the relationship between the occurrence and non-occurrence of landslides (dependent factor) and a set of independent factors as the susceptibility of each factor. (Quantified in Step 2). The modeling area region was divided into 20 * 20m pixels and 5,488 pixels were considered to be a landslide occurrence, while 5,488 pixels were selected without landslides to be included in the LR along with the landslide occurrence pixels. In order to implement this regression method, to calculate the correlation between the landslide and each of the causative factors, the SPSS software as used. The LR equation is as follows

$$Z = b_o + b_1x_1 + b_2x_2 + .. + b_nx_n$$

Where,

Z = Linear combination of independent variables

b_o= intercept of the equation

b_1, b_2, b_n= coefficient of independent variable x_1, x_2, x_n

(Rasyid, Bhandary, & Yatabe, 2016)

3.5. Pairwise comparison – AHP (Model 3)

Landslide susceptibility map can be developed using various methods like statistical methods, fuzzy logic, and AHP. Analytical Hierarchy Process is a theory of measurement for dealing with quantifiable and intangible criteria that has been applied to numerous areas, such as decision theory and conflict resolution (Moradi, Bazyar, & Mohammadi, 2012).

AHP is a multi-objective and multi-criteria decision-making approach that allows the user to arrive at a preference scale drawn from a set of alternatives.(Semlali, Ouadif, & Bahi, 2019). The method allows the user to work on some of the complex and multi-criteria decision-making processes. The method has the advantage of permitting a hierarchical structure of criteria that provides users with a better focus on the specific criteria (factors) and sub-criteria (classes) when allocating the weight. (Ahp, The, & District, 2019). After the structure is formed, it becomes easier for the user to interpret and compare among the various classes and using the analytical knowledge of the user, susceptibility map can thus be formed for a particular study area.

AHP has gained a wide area of application starting from site selection, suitability analysis, regional planning and landslide susceptibility analysis (Moradi et al., 2012). In the recent years,

$$PR = \frac{(SA_{max} - SA_{min})}{(SA_{max} - SA_{min})_{min}}$$

PR = Prediction rate

SA = Spatial Association Index

the use of AHP in the field of analysis of the landslide and preparing its susceptibility map has been increasing due to the fact that the method utility showed more accuracy and reliable results.

(Althuwaynee, Pradhan, Park, & Hyun, 2014)

4. Results and Discussion

4.1. Frequency Ratio (Model 1)

The derived weights show that the slope map (Fig 6.a) as a significant impact on the distribution of slides, which is compatible with other mountainous regions (Shahabi et al., 2014).

Landslide occurrences increase with an increase in terrain gradient, but the weight for the slope of > 50 is lowered.

The sloping terrain between 30-40° is most vulnerable to landslides with a frequency ratio of 1.10 and the sloping terrain of < 10° is less prone to landslides with a frequency ratio of 0.51.

The aspect chart frequency ratio indicates that the land facing south-east and west has a peak frequency ratio of 1.41 (Table 1) which were followed by south and southwest with a frequency ratio of 1.29 and 1.27 respectively. It was found that at a distance of 200-300, <100 and <500 from the road, drainage, and fault were susceptible to landslide with a peak frequency of 1.42, 1.13 and 1.40 respectively.

Table 1.Weights of landslide causative factors

	Total No. of pixel in class	*Pixel Percent (y)*	*No. of landslide pixel in class*	*Landslide Percent (x)*	*Frequency Ratio (x/y)*
Slope in Degree					
0-10	50630	10.2	538	5.2	0.51
10-20	107710	21.7	2205	21.2	0.97
20-30	161041	32.5	3641	34.9	1.08
30-40	131489	26.5	3052	29.3	1.10
40-50	41286	8.3	941	9.0	1.08
>50	3521	0.7	42	0.4	0.57
	495677	100	10419		**5.31**
Aspect Class					
Flat	282	0.1	1	0.0	0.17
North	48443	9.8	364	3.5	0.36
North East	34228	6.9	249	2.4	0.35
East	34851	7.0	386	3.7	0.53
South East	61582	12.4	1827	17.5	1.41
South	80511	16.2	2185	21.0	1.29
South West	86342	17.4	2308	22.2	1.27
West	79333	16.0	2351	22.6	1.41
North West	70105	14.1	748	7.2	0.51
					7.29
Altitude					
0 - 200	24355	4.9	395	3.8	0.77

200 - 400	104881	21.2	3428	32.9	1.55
400 - 600	113832	23.0	2963	28.4	1.24
600 - 800	80333	16.2	1693	16.3	1.00
800 - 1000	57716	11.7	764	7.3	0.63
1000 - 1200	47620	9.6	493	4.7	0.49
1300 - 1400	35390	7.1	682	6.5	0.92
1400 - 1600	11219	2.3	0	0.0	0.00
1600 - 1800	8334	1.7	0	0.0	0.00
1800 - 2000	8429	1.7	0	0.0	0.00
>2000	3217	0.6	0	0.0	0.00
					6.60
Distance from Road					
0-100	82150	16.6	1394	13.4	0.81
100-200	55227	11.1	1364	13.1	1.17
200-300	43816	8.8	1311	12.6	1.42
300-400	37865	7.6	1040	10.0	1.31
400-500	32604	6.6	701	6.7	1.02
>500	244015	49.2	4609	44.2	0.90
					6.63
Distance from Drainage					
0-100	258509	52.2	6139	58.9	1.13
100-200	153305	30.9	3098	29.7	0.96
200-300	59721	12.0	930	8.9	0.74
300-400	18755	3.8	244	2.3	0.62

400-500	4656	0.9	8	0.1	0.08
>500	731	0.1	0	0.0	0.00
					3.53
Distance from Fault					
0-500	145689	29.4	4275	41.0	1.40
500-1000	134393	27.1	3218	30.9	1.14
1000-1500	73243	14.8	1529	14.7	0.99
1500-2000	45024	9.1	583	5.6	0.62
2000-2500	34123	6.9	581	5.6	0.81
2500-3000	26174	5.3	217	2.1	0.39
>3000	37031	7.5	16	0.2	0.02
					5.37
Geological Formation					
LHZ_Phuentsholing Formation (Baxa Group)	131437	26.5	3900	37.4	1.41
LHZ_Pangsari Formation (Baxa Group)	163782	33.0	3304	31.7	0.96
LHZ_Shumar Formation (Daling-Shumar Group)	82889	16.7	2451	23.5	1.41
LHZ_Daling Formation (Daling-Shumar Group)	107157	21.6	764	7.3	0.34
LHZ_Orthogneiss (Daling-Shumar Group)	7009	1.4	0	0.0	0.00

LHZ_Jaishidanda Formation	3403	0.7	0	0.0	0.00
					4.12
LandUse					
Cultivated Agriculture Land	51841	10.5	619	5.9	0.57
Built-up Area	13970	2.8	137	1.3	0.47
Degraded Areas	5756	1.2	4188	40.2	34.61
Forests	353302	71.3	3645	35.0	0.49
Shrubs	38308	7.7	1396	13.4	1.73
Horticulture Land	9367	1.9	80	0.8	0.41
Water Bodies	23133	4.7	354	3.4	0.73
					39.01
NDVI					
Water	2571	0.5	61	0.6	1.13
Dry Bare soil	84093	17.0	3129	30.0	1.77
Vegetation	174403	35.3	4114	39.5	1.12
Dense Vegetation	233655	47.2	3113	29.9	0.63
					4.647

From the susceptibility map (Fig. 5.), 34.5% of the area was found to be highly susceptible to landslide. Approximately 39% and 23.3% of the area were highly and moderately vulnerable to landslide. Only about 0.2% to 3% area had low susceptibility.

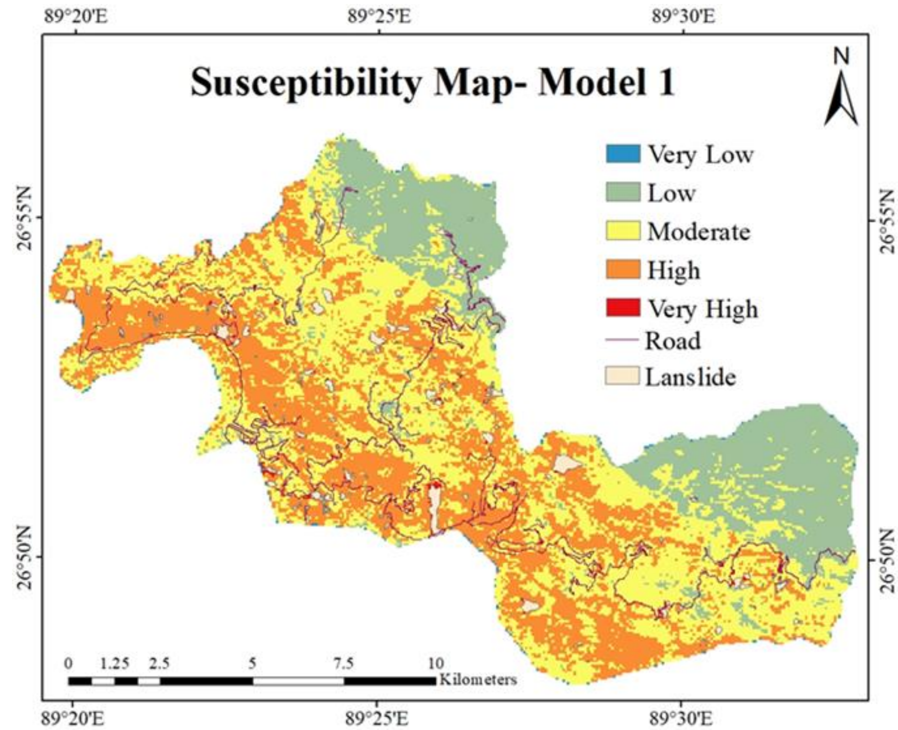


Fig 5. Susceptibility map for FR

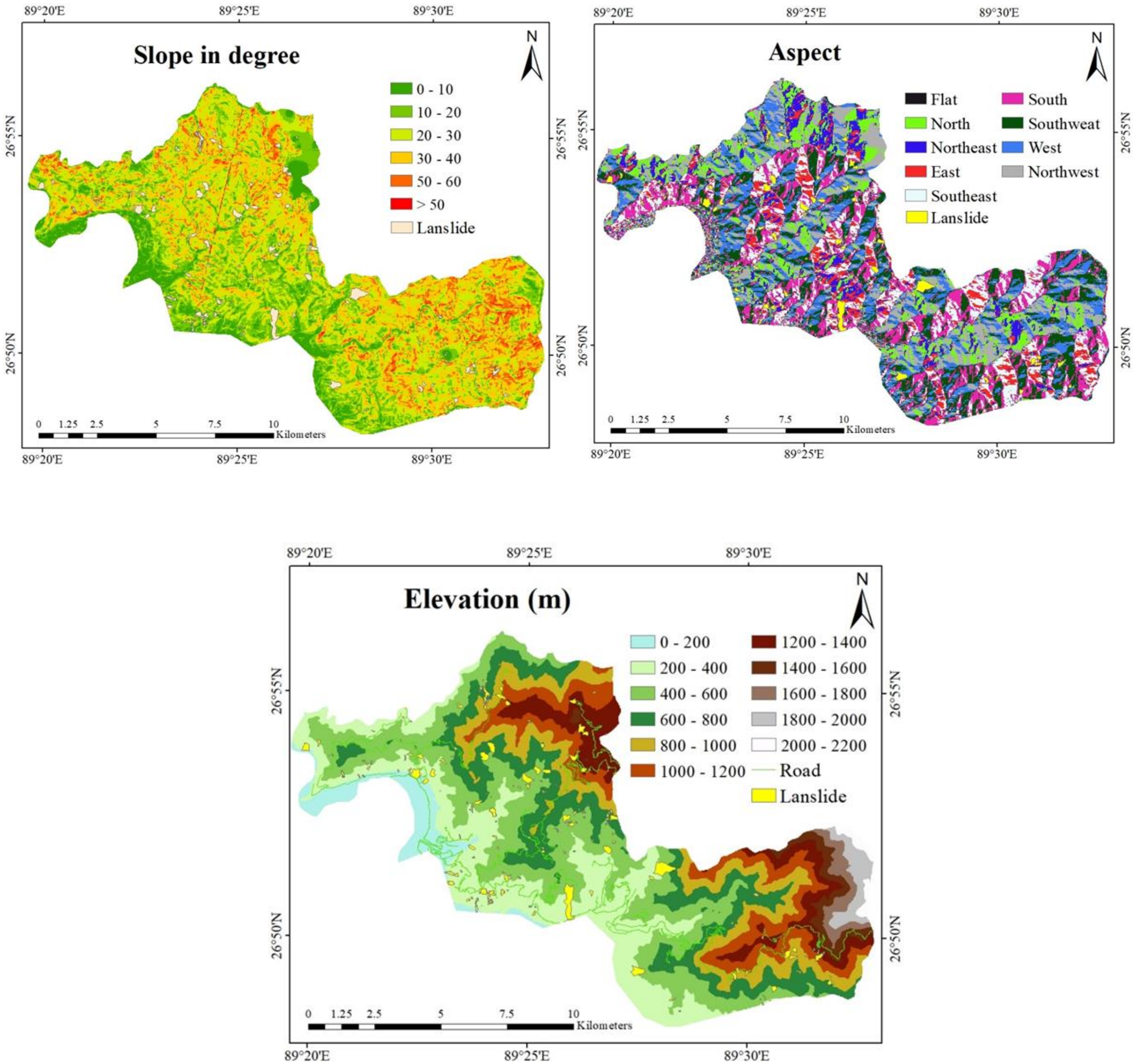


Fig. 6. Landslide parameters: a) Slope b) Aspect c) Elevation

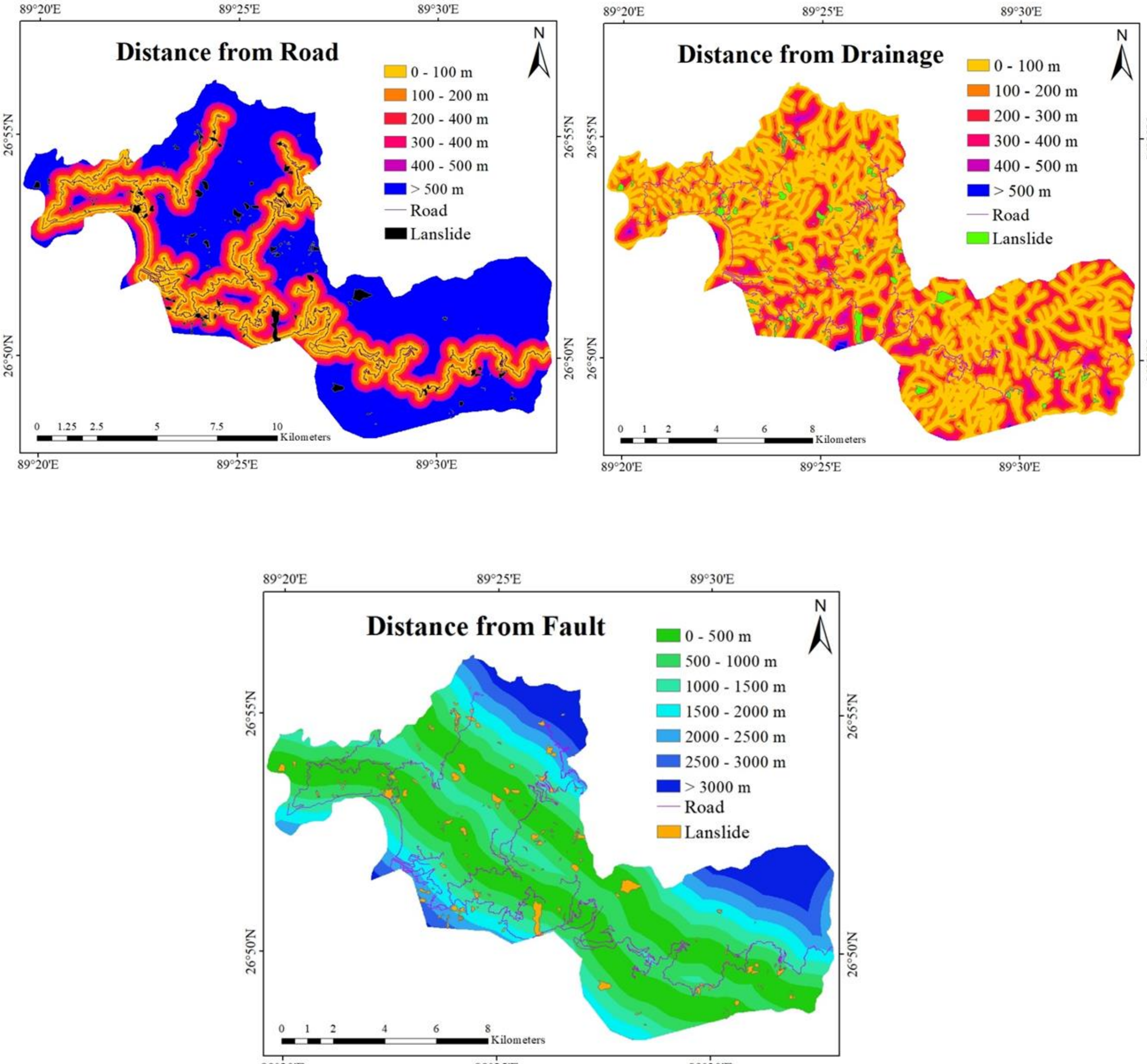


Fig. 6 (contd.) d) Distance from road e) Distance from drainage f) Distance from fault

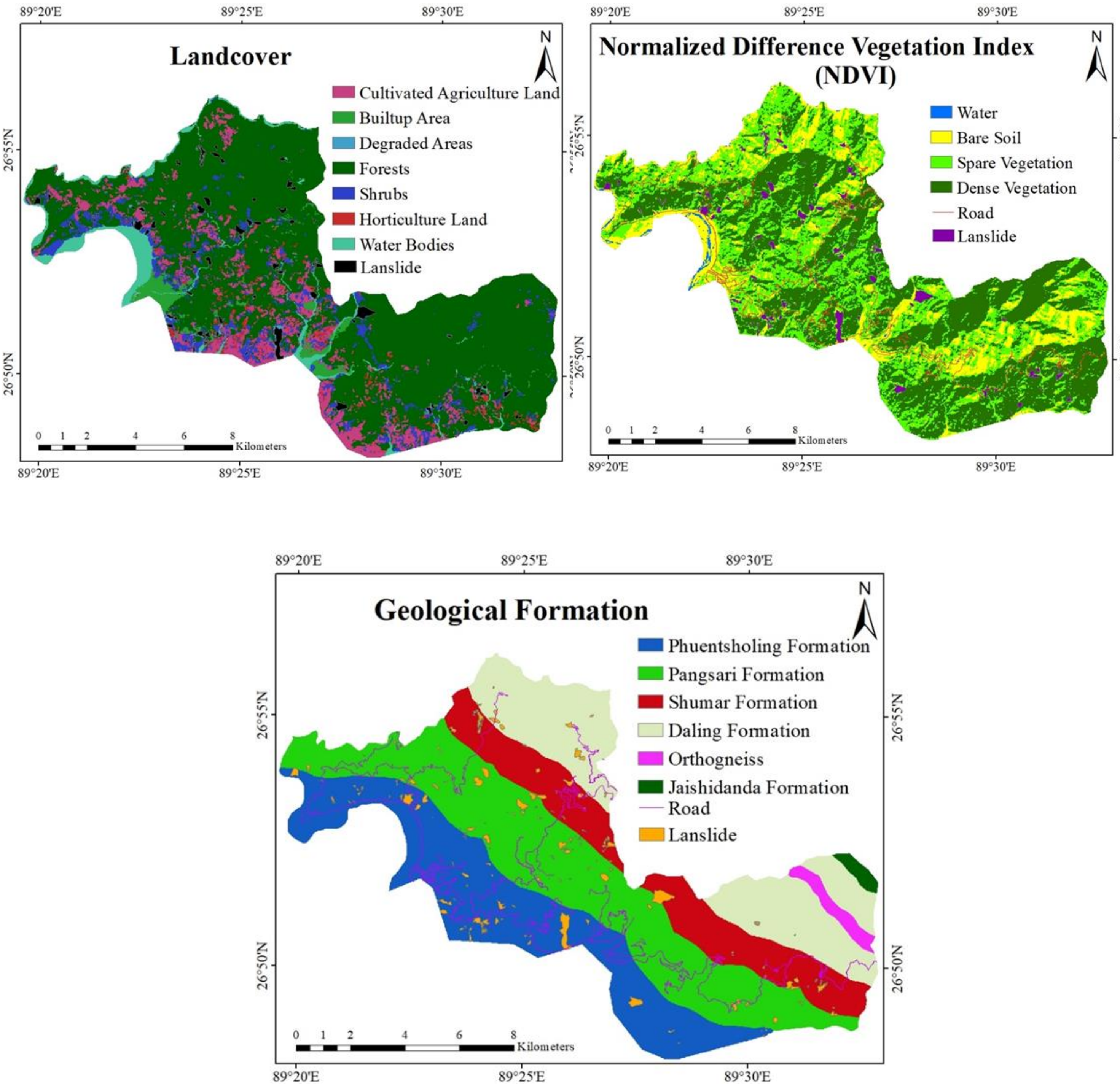


Fig. 6 (contd.) g) Land cover h) NDVI and i) Geological

4.2. Logistics Regression (Model 2)

From the table (Table 2), it is seen that slope is the significant cause for landslide in the study area with the highest coefficient and large weighting. The aspect and NDVI also make a significant contribution to the severity of landslides. The geological formation had the least contribution to the distribution of landslide a hence can be neglected.

Table 2. LR coefficients

Variables	**Coefficients**
Slope	2.216
Aspect	1.351
Elevation	.724
Distance from Road	.402
Distance from Drainage	.363
Distance from Fault	.865
Formation	.100
Land cover	.150
NDVI	1.241
Constant	-12.104

Landslide susceptibility Map (LSM) was obtained from the equation below:

Z = 2.216 (slope) + 1.351(Aspect) + 0.724 (Elevation) + .402 (Road) + .363 (Drainage) + .865 (Fault) + .100 (Formation) + .150 (Land cover) + 1.241(NDVI) -12.104

From the susceptibility map (Fig. 7.), about 30.1% and 34.6% of area was found to be high and very high susceptible zone respectively. Approximately 26.0 % of the area was moderately susceptible. Only about 1.9% and 7.4% of the area had very low and low susceptibility.

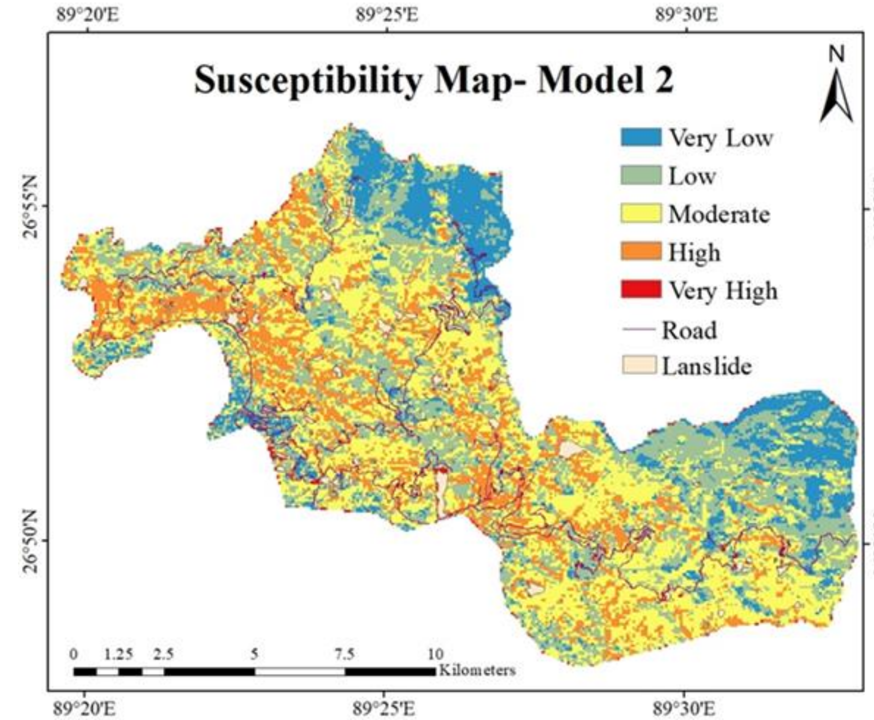


Fig 7. Susceptibility map for LR

4.3. Pairwise comparison – AHP (Model 3)

Landslide susceptibility index (LSI) was determined by the sum of the product of Pairwise Comparisons and the standardized raster map of the landslide causal factors:

LSI = “Slope"*4 + "Aspect"*6 + “elevation"*8 + "Road"*3 + “Drainage"*11 + "Fault"*9 + "Formation"*12 + "landcover"*30 + "NDVI"*8

Table 3. Pairwise comparison weights

Variables	**Prediction rate**	**Pairwise comparisons weight**
Slope	1.21	4
Aspect Class	1.84	6
Elevation	2.53	8
Distance From Road	1.00	3
Distance From Drainage	3.44	11
Distance From Fault	2.76	9
Geological Formation	3.69	12
Landcover	9.44	30
NDVI	2.63	8

From the susceptibility map (Fig 8.), approximately 40.4% area was found to be very highly susceptible to landslide; about 31.3% and 20% of area were high and moderate susceptible zone. Roughly 7.1% and 1.2% area were low and very low susceptible zone.

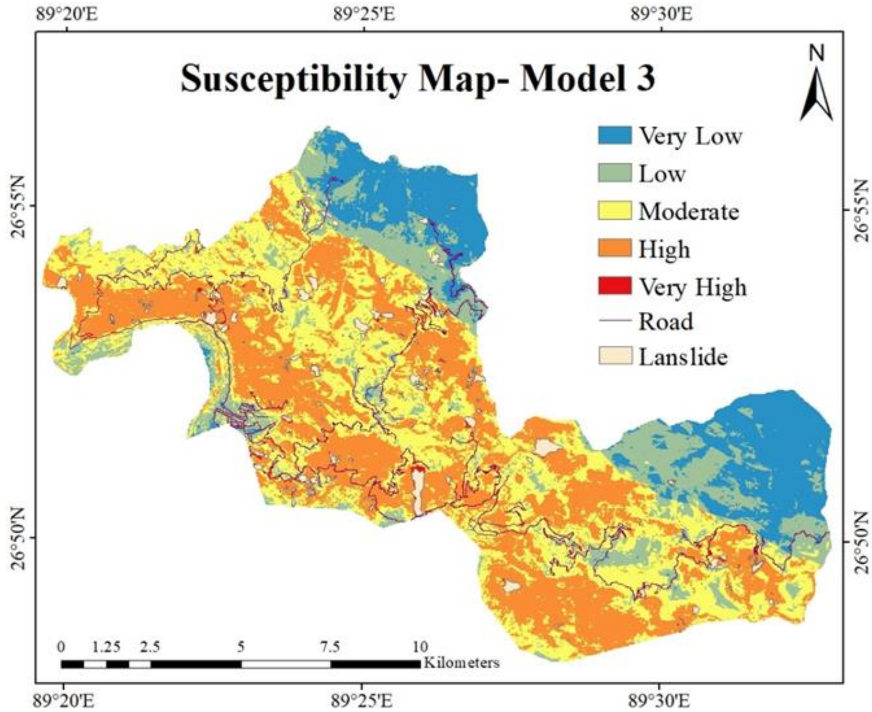


Fig 8. Susceptibility map for Pairwise comparison

5. Validation

A ROC curve is the most commonly used way to visualize the performance of a binary classifier meaning a classifier with two possible output classes.

The test result variable(s): The models predict has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

Table 4. Validation tables for the models

	Model 1- Frequency Ratio		Model 2- Logistic Regression		Model 3- Pairwise Comparison	
Susceptibility Classes	*Training Sample*	*Validation Sample*	*Training Sample*	*Validation Sample*	*Training Sample*	*Validation Sample*
	%Area	%Area	%Area	%Area	%Area	%Area
Very Low	0.57	0.19	13.48	1.85	14.42	1.16
Low	21.04	2.97	28.64	7.40	16.35	7.13
Moderate	43.64	23.32	37.46	25.98	34.18	20.05
High	33.66	39.01	18.76	30.15	33.89	31.30
Very High	1.08	34.50	1.65	34.62	1.16	40.36
Total	100	100	100	100	100	100

For the FR model, the LR model and AHP model AUC values of 0.833, 0.851 and 0.823 were showed respectively. This shows that the map obtained from the FR model provides greater accuracy in the classification of existing landslide areas. For the statistical capacity assessment of the landslide models, the predictive rate curve was obtained using the landslide pixels in the validating dataset (20 percent of the total observed landslides).

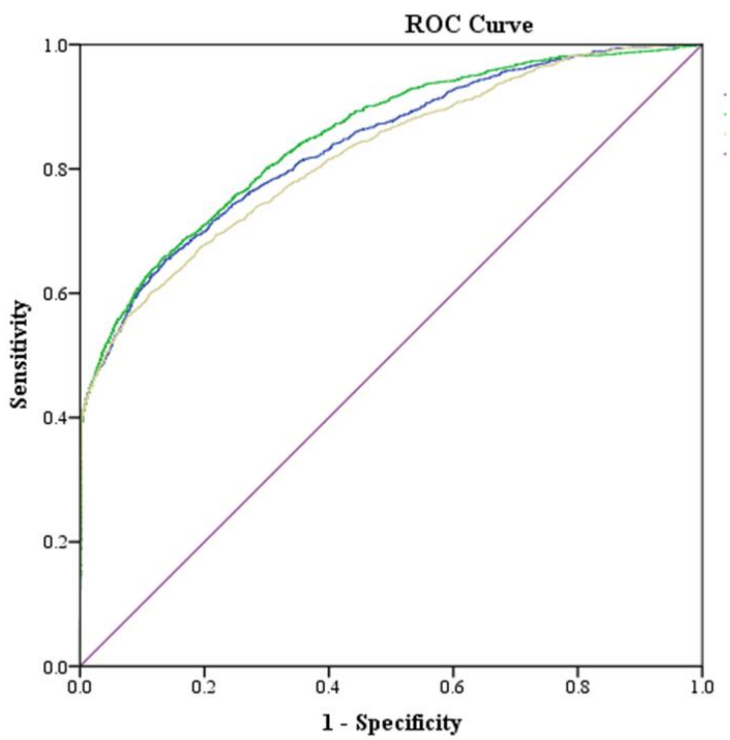


Fig 9. ROC for the models.

6. Conclusion.

The study provides the landslide susceptibility mapping of Phuentsholing and Sampheling geog that can be used for planning and designing future land use patterns. Susceptibility mapping was developed using statistical modeling. All the models were found to be favorable for deriving the landslide susceptibility indices in a mountainous landscape as shown by the validation samples falls in high and very high susceptibility area.

For the modeling, a total of nine causative factors were considered depending upon the geological conditions. The factors considered are namely slope, aspect class, elevation, and distance from road, distance from drainage, and distance from fault, geological formation, land cover and NDVI (normalized difference vegetation index). These factors were selected due to the fact that these factors were the main triggering cause for the various landslides in the area.

Basically, 3 models were prepared for the study area and from the three models, the model 2(pairwise comparison model or AHP) has a slightly higher AUC of the receiver operating characteristic (ROC). Model 1(Frequency Ratio) and model 2(Logistic Regression) were never the less had not much of difference. Model 1 had an accuracy of 0.836, model 2 0.851 and model 3 with 0.819 for the area under curve rate.

From the Validation curve, it can be seen that model 2 and model 3 have a higher percentage area under very low susceptibility whereas model 1 suggests that there is a lesser percentage area with both very low and very high susceptibility.

For the modeling of the susceptibility maps using for the frequency ratio, logistic regression, and pairwise comparison various factors had a different scale of effects on the results. Slope, Aspect, and NDVI are the important causal factors of landslide in model 2 (LR) whereas, in model 1(FR) and model 3(pairwise comparison), the land cover had more influence on the occurrence of the landslide. Since the validation is above 80% for every model, any of these models can be used to predict the occurrence of a future landslide so as to safely plan and design the land use pattern.

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