GEOGRAPHIC INFORMATION SYSTEMS BASED LANDSLIDE SUSCEPTIBILITY INDEX MAPPING USING INFORMATION VALUE METHOD – A CASE STUDY OF SINDHUPALCHOK DISTRICT, NEPAL

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SUMMARY

Landslide susceptibility is the likelihood of a landslide occurrence in an area predicted on the basis of local terrain conditions. Study deals with bivariate statistical approach for Landslide Susceptibility Index (LSI) map for a part of Sindhupalchok district, Nepal using Geographic Information Systems. Information Value Method has been applied to prepare the LSI map. Landslide inventory map for this study has been prepared using google earth. The landslide inventory has been divided into two dataset, one dataset for LSI map preparation and second for map validation. Slope, aspect, slope curvature, distance to drainage, drainage density, distance to thrust fault , distance to road, distance to settlement, soil type, geomorphology, landuse/landcover, Normalized Differentiated Vegetation Index and surficial deposits are factor maps used in modeling the landslide susceptibility in the study area. The distribution of landslide over each of the factor map have been studied and analyzed. Weight for each of the classes within these factor maps have been obtained using the Information Value Method. Final LSI value for each pixel within the study area has been obtained by summing up the weight derived for that pixel in all of the factor maps. The resultant LSI map has been classified in five landslide susceptibility classes. The prediction accuracy of the map has been assessed using Receiver Operating Characteristics (ROC) and success rate and prediction rate curve. About 80% area lied under the ROC curve and the success rate and prediction rate curve exhibited same general trend.

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1. INTRODUCTION

Landslides involve downward movement of earth materials resulting in slope modification. Nepal is a landlocked mountainous country where occurrence of landslide is a common phenomenon and more frequent in rainy seasons. With increase in population, human settlements are expanding along the hill slopes which could be vulnerable to landslides. In recent days, risk of landslides has been raised by unmonitored expansion of rural transport network in hill regions, leading to terrain alterations and other negative impacts of environment (Petley, 2012). Landslides are natural phenomena which occur under favorable terrain conditions and are usually triggered by rainfall, human activities or earthquakes. Prediction of landslides could help in saving lives and property. Landslides occur due to combination of trigger mechanisms and susceptibility factors such as fragile and complex geology, steep slopes, rugged topography, variable climatic and microclimatic conditions, rainfall, earthquake and vegetation degradation (Gerrard *et al*., 2002; Hasegawa *et al*., 2009).

Landslide susceptibility is the likelihood of landslide occurring in an area on the basis of local terrain conditions (Brabb, 1984).When landslides are talked of in Nepal, last three decades of landslide record reveals that road and human sttlement slopes are more vulnerable to landslide than ordinary natural slopes. This suggest that there is significant influence of human intervention, particularly in terms of road cutting, land development, agricultural practices, etc (Bhandary *et al*., 2013). An area is declared susceptible to landslide when the terrain conditions at that site are comparable to those in an area where a slide has occurred (Van Westen *et al*., 1997). Geographic Information Systems (GIS) is an essential tool for analysis of causative factors and landslide susceptibility mapping. Various modelling techniques such as heuristic model, physically based model and statistical model have been used for landslide susceptibility mapping (Ruff *et al*., 2008; Van Westen, 1993; Yalcin, 2008; Sorbino *et al*., 2010; Carrara *et al*., 1991).

In statistical methods, landslide causal factors or parameters are derived and combined with landslide inventories to predict the future occurrence of landslides (Dai *et al*., 2001). Statistical methods can be distinguished into multivariate and bivariate methods. In the former all relevant landslide causal factors or parameters are treated together to obtain landslide prediction map. In bivariate stastical method, each landslide causal factor is combined with landslide inventory. The weights of each class within the factor maps are derived from either landslide abundance or densities in each attribute class. Mainly three weight estimation techniques have beed used in bivariate statistical methods: Information value method (Sarkar *et al*., 2013), Weight of evidence method (Kayastha *et al*., 2012; Pradhan *et al*., 2010) and Landslide Nominal Susceptibility Factor (LNSF) method (Adhikari, 2011; Gupta *et al*., 1990).

In this study bivariate statistical approach using infortmation value method has been employed to obtain landslide susceptibility index map for part of Sindhupalchok District.

This method is simple and has rarely been tested in context of Nepal for landslide susceptibility mapping.

2. STUDY AREA

The area under investigation is part of Sindhupalchok district lying between 85º30'E to 86º00'E Lat. and 27º45'N to 28º00'N Long (Fig.1). The region lies on the central northern part of Nepal and borders China on Northeastern side. It covers area of 1310.55 sq.km with altitude ranging from 695m to 4408m. The Araniko highway connecting Kathmandu to China passes through this region. The annual rainfall is about 2,500 mm and temperatures vary from 7.5 ºC to 32 ºC (Department of Hydrology and Meteorology, Nepal). The monsoon season runs from June to September and rest of the months are usually dry. Tropical, Subtropical, Temperate and Sub-alpine climate can be experienced here. The Bhotekoshi, Indrāvati, Sunkoshi and Balephi Khola are the rivers flowing through this region. Major landslides have occurred in the past in this area, few of them are listed in the Table 1.

Table 1: List of Major Landslides in Sindhupalchok

1982	Balefi, Sindhupalchok	97 persons died and 15 houses
1987	Sunkoshi, Sindhupalchok	98 persons died
1996	Larcha, Sindhupalchok	54 persons died and 18 houses
2014	Mankha, Sindhupalchok	156 person died and 436 people

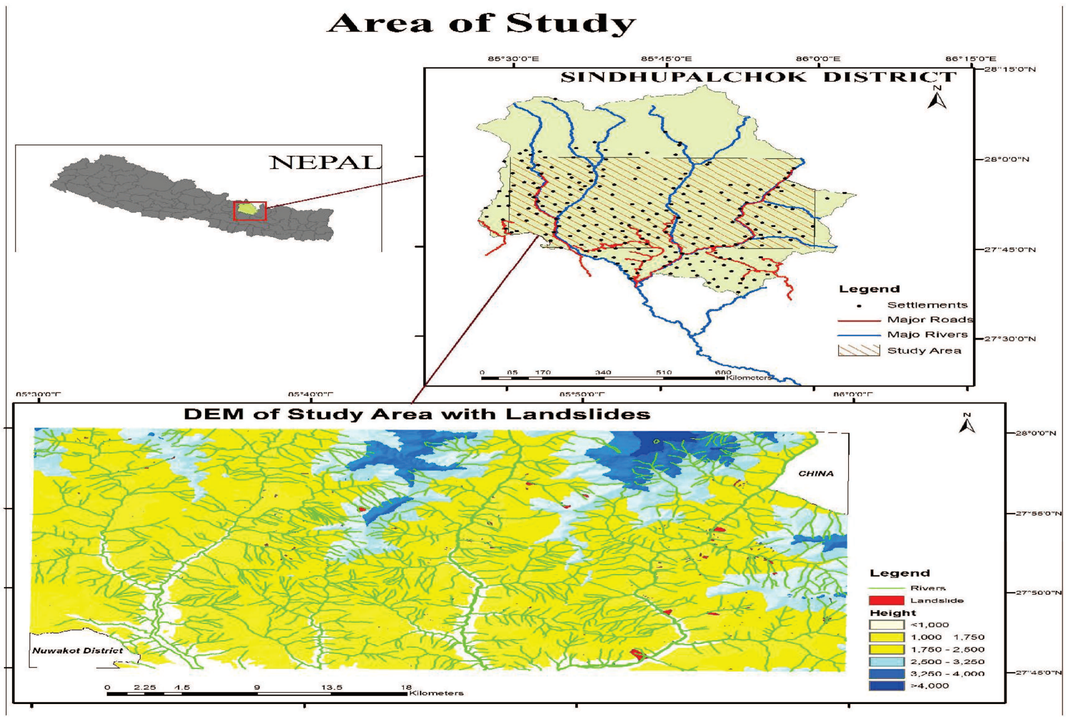

Figure 1: Location Map of study area with DEM and landslide distribution

3. METHODOLOGY

The objective of this study is to prepare Landslide Susceptibility Index Map (LSIM) using Information value method. Information Value method was used for calculation of weight for each class in a factor map and obtained by rationing the density of landslide in each factor class to the density of landslide in the total map area. This method was originally suggested by Yin and Yan in 1988 (Yin *et al.*, 1988). The weight is mathematically obtained by:

$$W_i = ln \frac{Density\ of\ landslide\ within\ a\ class\ of\ a\ factor}{Density\ of\ landslide\ within\ the\ study\ area}$$

$$= ln \frac{\frac{Npix_{(Si)}}{Npix_{(Ni)}}}{\frac{\Sigma Npix_{(Si)}}{\Sigma Npix_{(Ni)}}}$$

Where, W_i = Weight of a factor class;

$Npix_{(Si)}$ = Number of pixel of landslide within class i;

$Npix_{(Ni)}$ = Number of pixel of class i;

$\Sigma Npix_{(Si)}$ =Number of Pixel of landslide within the whole study area;

$\Sigma Npix_{(Ni)}$ = Number of pixel of the whole study area.

Use of natural logarithm yields negative weights where density of landslide in lower average and positive when density is higher.

Landslide inventory data is created from Google Earth. About 314 landslide polygons covering area of 4.20 sq.km are mapped from Google Earth images from 2004 A.D to 2014 A.D. Out of these 227 landslides covering area of 3.7555 sq.km were used as training data for preparation of LSI map and the remaining landslide data covering area of 0.445 sq.km were used for map validation. Overlaying the training landslide data over individual factor map the weights were obtained for each map class.13 factor maps with 96 classes in total have been used to prepare the LSI map. Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) 1 arc second DEM was used to prepare Slope, Aspect and Curvature map.

Thrust fault data, surficial deposit data, drainage data and road network data were obtained by diziting the Geological map obtained from Department of Mines and Geology, Nepal and Distance to Thrust fault map, Surficial deposit map, Distance to Drainage map, Drainage density map and Distance to Road map were derived from those data. Geomorphological map, Landuse/Landcover map, Soil map and Distance to settlement map were derived from World Soil and Terrain (SOTER) database (Dijkshoorn *et al.*, 2009). Landsat 8 imagery of 5th November 2014 was used to prepare NDVI map.

To prepare landslide susceptibility map, Landslide Susceptibility Index (LSI) value for each pixel was obtained by:

$LSI_i = Sw_i + Aw_i + Cw_i + GEOw_i + Lw_i + SOw_i + DSw_i + DDw_i + DDENw_i + DRw_i + DTw_i + Nw_i + SWw_i$

Where LSI_i is Landslide Susceptibility Index value for ith pixel and Sw_i, Aw_i, Cw_i, $GEOw_i$, Lw_i, SOw_i, DSw_i, DDw_i, $DDENw_i$, DRw_i, DTw_i, Nw_i & SWw_i are weights obtained for i^{th} pixel in Slope map, Aspect map, Curvature map, Geomorphology map, Landuse/Landcover map, Soil map, Distance to settlement map, Distance to drainage map, Drainage density map, Distance to road map, Distance to thrust fault map, NDVI map and Surficial deposit map respectively (Table 2).

4. RESULT AND DISCUSSION

Table 2: Weights calculated for all the classes in each factor map

Factor Map	Class	Description	Class Pixel	% Map Area	Landslide Pixel	% Landslide	Weights
Slope	1	0° - 10°	65391	4.52	98	2.34	-0.6400
	2	10° - 20°	325183	22.47	398	9.50	-0.8425
	3	20° - 30°	542560	37.49	1343	32.06	-0.1382
	4	30° – 40°	355594	24.57	1709	40.80	0.5253
	5	40° – 50°	124417	8.60	595	14.20	0.5204
	6	50° - 60°	29252	2.02	45	1.07	-0.6138
	7	> 60°	4738	0.33	1	0.02	-2.6002
Aspect	1	Flat	87	0.01	0	0.00	0.0000
	2	North	162313	11.22	568	13.56	0.2080
	3	North East	164006	11.33	184	4.39	-0.9295
	4	East	163805	11.32	126	3.01	-1.3069
	5	South East	167980	11.61	639	15.25	0.2915
	6	South	190311	13.15	514	12.27	-0.0510
	7	South West	202089	13.96	741	17.69	0.2547
	8	West	204622	14.14	570	13.61	-0.0201
	9	North West	191922	13.26	847	20.22	0.4401
Curvature	1	Concave	658737	45.52	2284	54.52	0.1988
	2	Flat	124053	8.57	348	8.31	-0.0131
	3	Convex	664345	45.91	1557	37.17	-0.1928
Soil map	1	Chromic Cambisols	370071	25.57	75	1.79	-2.6529
	2	Eutric Cambisols	170062	11.75	969	23.13	0.6834
	3	Eutric Regosols	578468	39.97	2561	61.14	0.4311
	4	Gelic Leptosols	16883	1.17	15	0.36	-1.1749
	5	Gleyic Cambisols	11803	0.82	0	0.00	0.0000
	6	Humic Cambisols	299848	20.72	569	13.58	-0.4160

Geomorphological map	1	Steeply to very steeply sloping mountainous terrain	180325	12.46	607	14.49	0.1571
	2	Past glaciated mountainous terrain above upper altitudinal limit of arable agriculture	481372	33.26	1305	31.15	-0.0593
	3	Past glaciated mountainous terrain below upper altitudinal limit of arable agriculture	4851	0.34	0	0.00	0.0000
	4	Moderately to steeply sloping mountainous terrain	44131	3.05	64	1.53	-0.6849
	5	Ancient lakes and river terraces (tars) (erosional)	364449	25.18	425	10.15	-0.9029
	6	Alluvial plains and fans (depositional)	9738	0.67	12	0.29	-0.8478
	7	Alluvial plain fans	362201	25.03	1776	42.40	0.5333
	8	Active Alluvial Plain (depositional)	68	0.00	0	0.00	0.0000
Landuse/ Landcover	1	Cultivation	594968	41.11	1458	34.81	-0.1603
	2	Grassland	76446	5.28	457	10.91	0.7314

Map	3	Bush	358725	24.79	1045	24.95	0.0126
	4	Sand	13665	0.94	63	1.50	0.4716
	5	Water Body	1436	0.10	0	0.00	0.0000
	6	Cutting, clif	698	0.05	191	4.56	4.5552
	7	Forest	369463	25.53	533	12.72	-0.6902
	8	Barren Land	31734	2.19	442	10.55	1.5773
Distance to Drainage Map (distance in meters)	1	0 – 50	220959	15.27	918	21.91	0.3673
	2	50 – 100	192244	13.28	827	19.74	0.4021
	3	100 – 150	176207	12.18	658	15.71	0.2606
	4	150 – 250	248819	17.19	847	20.22	0.1680
	5	250 - 350	186867	12.91	423	10.10	-0.2400
	6	350 – 500	178160	12.31	237	5.66	-0.7716
	7	500 – 750	140576	9.71	210	5.01	-0.6556
	8	750 – 1000	54961	3.80	51	1.22	-1.1317
	9	> 1000	48342	3.34	18	0.43	-2.0449
Drainage Density Map	1	0 – 1	483873	33.44	994	23.73	-0.3514
	2	1 – 2	640096	44.23	1437	34.30	-0.2505
	3	2 – 3	294704	20.36	1747	41.70	0.7223
	4	>3	28462	1.97	11	0.26	-2.0076
Distance to Settlement Map (distance in meters)	1	0 – 500	136167	9.41	554	13.23	0.3421
	2	500 – 1000	384220	26.55	1344	32.08	0.1910
	3	1000 – 1500	431234	29.80	1027	24.52	-0.1934
	4	1500 – 2000	239951	16.58	484	11.55	-0.3595
	5	2000 – 2500	107268	7.41	502	11.98	0.4821
	6	2500 – 3000	65213	4.51	263	6.28	0.3333
	7	> 3000	83082	5.74	15	0.36	-2.7729
Distance to Road Map (distance in meters)	1	0 – 50	372455	25.74	760	18.14	-0.3436
	2	50 – 100	276084	19.08	653	15.59	-0.1959
	3	100 – 150	205332	14.19	609	14.54	0.0304
	4	150 – 250	227337	15.71	876	20.91	0.2922
	5	250 – 350	130188	9.00	496	11.84	0.2808
	6	350 – 500	98721	6.82	564	13.46	0.6860
	7	500 – 750	64017	4.42	175	4.18	-0.0511
	8	750 – 1000	24025	1.66	3	0.07	-3.1372
	9	> 1000	48976	3.38	53	1.27	-0.9778
Distance to Thrust fault Map (distance in meters)	1	0 – 500	367470	25.39	937	22.37	-0.1209
	2	500 – 1000	273675	18.91	657	15.68	-0.1812
	3	1000 – 1500	236815	16.36	1040	24.83	0.4227
	4	1500 – 2000	185340	12.81	775	18.50	0.3737
	5	2000 – 2500	132699	9.17	515	12.29	0.2991

	6	2500 – 3000	83698	5.78	131	3.13	-0.6090
	7	3000 – 7500	167438	11.57	134	3.20	-1.2797
NDVI Map	1	-1 – 0	2614	0.18	143	3.41	2.9453
	2	0 - 0.3	899214	62.14	3018	72.05	0.1542
	3	>0.3	545307	37.68	1028	24.54	-0.4226
Surficial Deposit Map	1	Jk	11197	0.77	0	0.00	0.0000
	2	Sg	1696	0.12	3	0.07	-0.4870
	3	Rb	120868	8.35	400	9.55	0.1394
	4	Dhd	362334	25.04	758	18.10	-0.3192
	5	Gyl	60697	4.19	1	0.02	-5.1632
	6	Hdk	111849	7.73	303	7.23	-0.0607
	7	Dh	61709	4.26	165	3.94	-0.0738
	8	Srm	171744	11.87	217	5.18	-0.8234
	9	Spn	52241	3.61	47	1.12	-1.1630
	10	Ml	25976	1.79	52	1.24	-0.3633
	11	Kn	205942	14.23	1130	26.98	0.6451
	12	Fg	25275	1.75	115	2.75	0.4578
	13	Np	1222	0.08	3	0.07	-0.1592
	14	Bg	177753	12.28	948	22.63	0.6166
	15	Png	42750	2.95	46	1.10	-0.9841
	16	Alv	13882	0.96	1	0.02	-3.6879

From the above Table 2 it can be seen that the class Cutting cliff of Landuse/landcover map has the highest weight of 4.5552 followed by barren land and grassland classes with weights 1.5773 and 0.7314. Areas with NDVI value -1 to 0 obtained weight of 2.9453 and areas with drainage density value 2-3 possessed 0.7223 weight.

Landslide Susceptibility Index Map was obtained, the values of the LSI ranged from -14.1493 to 8.5718. The map was then classified into 5 ranked classes of susceptibility index Very Low, Low, Moderate, High and Very High on the basis of histogram analysis and manual interpretation of the original LSI map.

Table 3: LSI Map classification details

Class	LSI value	Description	Area in Square Kilometers	% Area of Map
1	-14.1493 to -9	Very Low	23.5449	1.81
2	-9 to -4	Low	330.9489	25.41
3	-4 to 0	Medium	602.1585	46.23
4	0 to 3	High	326.8251	25.09
5	3 to 8.5718	Very High	18.9441	1.45

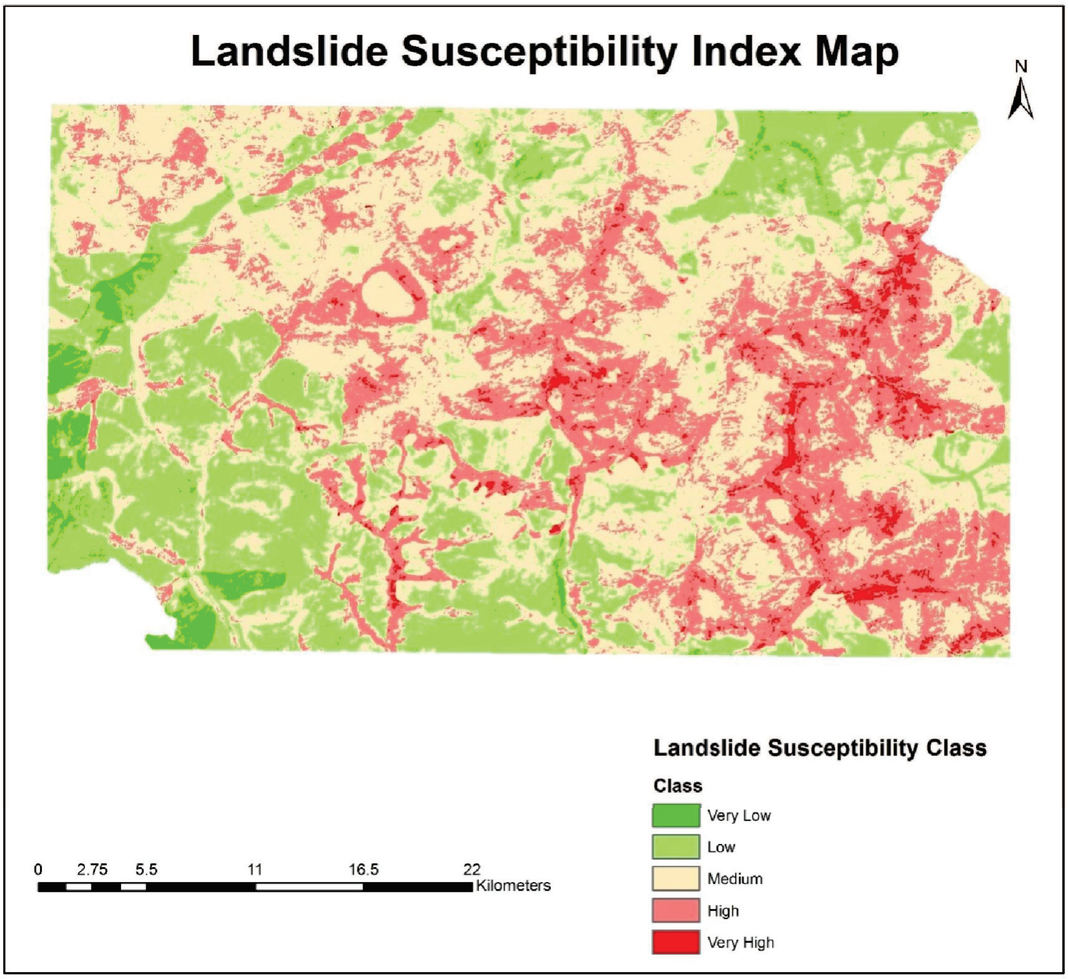

Figure 2: Landslide Susceptibility Index Map

Overlaying LSI map over factor maps it was seen that 26.11% and 30.64% of area lying at a distance of 0-500 meters and 500-100 meters respectively from settlement point map lied in high susceptible zone. 19.05%, 22.73% and 27.75% of area lying at a distance of 0-50, 50-100 and 100-150 meters from road networks were in high landslide susceptibility zone. 34.63%, 34.99% and 32.98% of area lying at a distance of 0-50, 50-100 and 100-150meters respectively from any water source were in high landslide susceptible zone. When landuse/landcover map was overlaid over the final LSI map it was seen that cutting clif land type showed high affinity to landslides, 77.65% of such area were found under very high landslide susceptibility zone and. 24.07% of cultivation area, 46.61% of grassland area, 31.58% of area covered by bushes, 16.11% of forest area and 14.55% of barren land were classified as high landslide susceptible zone. 7.61% of grassland area were found to be in very high landslide susceptibility zone.

Overlaying slope map over the LSI map it was found that 34.95%, 36.33% and 27.68% of map area with slope 30º-40º, 40º-50º and 50º-60º respectively were detected in high landslide susceptibility class along with 3.87% and 2.87% of area with slope 40º-50º and 30º-40º in very high landslide susceptibility. When NDVI map was overlaid over LSI map it was obtained that 37.15% of the area with NDVI value -1 to 0 lied in very high susceptibility zone.

5. VALIDATION

In prediction modelling, the most important and the absolutely essential component is to carry out a validation of the prediction results. Without some kind of validation, the prediction model and image are not useful and have hardly any scientific significance (Chang-Jo *et al*., 2003). To assess the accuracy of prediction of the model two methodology have been used.

5.1 Success Rate and Prediction Rate Curve

In this study, we have divided the landslide inventory data into two group i.e., training data for landslide susceptibility mapping and test data for map validation. Success rate curve was obtained by plotting the cumulative percentage area of training landslide data against the cumulative percentage of map area. Whereas, prediction rate curve is obtained by plotting the cumulative percentage area of landslides not considered in the model against the cumulative percentage of map area. More the curve lie close to each other higher the performance of the model.

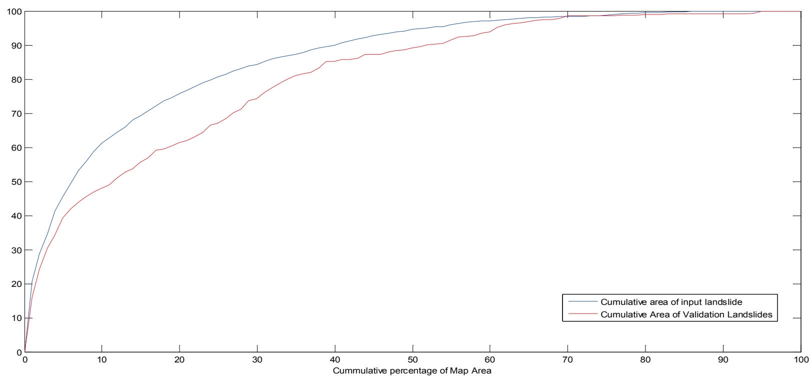

Figure 3: Success Rate and Prediction Rate Curve

The graph showed that the general trend of both the curve was same with slight distance between the curves in the middle region. The slight difference between the two curves indicate that the less map area was predicted to be susceptible to landslide. The graph in general indicates that the 13 factors maps used for the landslide prediction and Information value method were able to predict the spatial occurrence of landslides.

5.2 Receiver Operator Characteristics (ROC)

The ROC curve is the plot of the probability of true positives (sensitivity) vs. the probability of false positives (1-specificity) as the cut-off probability varies (Gorsevesky *et al*., 2000). The ROC analysis allows one to assess the performance of binary classification methods with rank order or continuous output values. ROC analysis is applied to assess the performance of spatial models that produce a "probability" map, which presents the sequence in which the model selects grid cells to determine the occurrence of a certain event, e.g., land use change, presence of a species, landslide, forest fire, etc. We use the term "probability" although the value is not always true a probability, in the statistical sense depends on the algorithm used to generate the value (Jean-François *et al.*, 2013). The ability of the model to correctly classify cases with a certain condition and cases without the condition is measured by the area under the ROC curve.

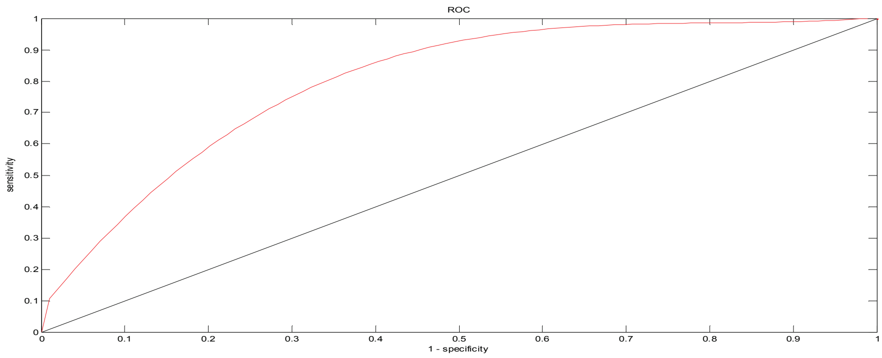

Figure 4: ROC Curve

ROC curve was obtained for the classified landslide susceptibility map. It obtained by plotting the cumulative area of susceptibility zones (1- specificity) versus the cumulative area of landslides (sensitivity). About 80 % of the area was under the curve

6. SUMMARY AND CONCLUSION

Natural hazards such as landslide are the biggest challenges for the development activities in mountainous areas. Very high relief, steep slopes, complex geology and unscientific construction and cultivation approach has made Nepal susceptible to landslides hence landslide susceptibility mapping is very important planning and carrying out development works. The main objective of this study is to prepare a Landslide Susceptibility Map for a part of Sindhupalchowk District, using Information Value Method. To assess the spatial probability of landslide occurrence, bivariate statistics based Information Value Method was used, where each factor layer was weighted on the basis of previous landside occurrence. Information value method of landslide susceptibility mapping is simple free from complex mathematical analysis and yet yields scientifically reliable result.

Result showed that 18.94 and 326.82 sq. km of the study area lied in very high and high landslide susceptibility zones respectively. 602.16, 330.95 and 23.54 sq. km of study area respectively lied in medium, low and very low landslide susceptible zones. From the result it can be realized that landuse/landcover map class cutting cliff has the most probability of being affected by landslide as the weight obtained for it was 4.555157 and 77.65% of this area lied in very high landslide susceptibility zone. Also it was obtained that map area with low NDVI value ranging from -1 to 0 are second most susceptible to landslide occurrence. Analysis of Surficial deposit map showed that region with Kn deposit (surficial deposit class 11 i.e., Serictic-chloritic green to grey thinly bedded phyllites, gritty phyllites with thin intercalation of white quartzite and amphibolites) were more prone to landslides. About 69.18% of landslides were found to have occurred within 250 meters of road lines thus illustrating the need of more scientific approach to road construction. Within 1 kilometer of settlement points 45.31% of landslide were observed. Areas lying near to the drainage and with slope 30-40 degrees were found more likely to be affected by landslides. ROC and Success Rate & Prediction Rate techniques used for validating this landslide susceptibility mapping model evaluated the obtained result as good.

Geographic Information Systems is an excellent tool for developing landslide susceptibility mapping models. Spatial analysis of various landslide controlling factors and their affect can be studied using GIS. Remote Sensing data are effective for mapping and monitoring remote mountainous region. In Nepal where natural disasters that occur in higher mountainous region go undetected, Remote Sensing technology has vast application and should be brought more into practice. If no previous landslide inventory data are present, the landslides occurred in the area can be mapped using freely available high resolution satellite imageries such as google earth.

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APPENDIX

Surficial Deposit	Description
Alluvial Deposits(Alv)	Clay, silt, sand, gravel and conglomerates
Robang Phyllite(Rb)	Chloritic-sericitic granetiferous phyllite with thin intercalation of white quartzite and chloritic gneiss.
Benight Slate(Bg)	Thinly bedded, dark grey to black slate, grey phyllites with bands of Jhiku carbonate (Jk).
Malekhu Limestone (Ml)	Thinly bedded yellowish grey limestone with dolomite band.
Dhading Dolomite(Dh)	Grey to dark grey thinly bedded dolomites and limestones, with intercalation of slate
Nourpul Formation(Np)	Thinly bedded, pinkish phyllite with quartzite ad dolomite.
Fagog Quartzite(Fg)	Thinly bedded, white fine-grained quartzite with thin intercalation of slate.
Kunchha Formation(Kn)	Serictic-chloritic green to grey thinly bedded phyllites, gritty phyllites with thin intercalation of white quartzite and amphibolites.
Hadi Khola Schist(Hdk)	Thin to medium bedded, fine garnet-biotite schist, calc. schist with Sanegauda Quartzite (Sg) and gneiss bands.
Dhad Khola Gneiss(Dhd)	Porphyroblastic gneiss, augen gneiss with thin bands of quartzite and schist, migmatitic gneiss.
Gyalthung Quartzite(Gyl)	Medium to thick bedded, light grey to dark grey, garnet-biotic quartzite with bands of crystalline quartzite and fine grained biotite schist.
Sermanthang Formation(Srm)	Interbedded feldspathic schist, augen gneiss, quartzite and biotic-feldspathic schist.
Simpani Formation(Spn)	Kyanite-biotite schist, migmatite and biotite feldspathic schist with bands of quartzite.
Pangang Formation(Png)	Thick bedded sillimanite bearing gneiss, tourmaline-feldspar migmatitic gneiss and granetiferous fine-grained schist

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