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Landslide susceptibility mapping using Weight of Evidence Method in Haku, Rasuwa District, Nepal

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ABSTRACT

The 2015 Gorkha Earthquake resulted in many other secondary hazards affecting the livelihoods of local people residing in mountainous area. Plenty of earthquake induced landslides and mass movement activities were observed after earthquake. Haku region of Rasuwa was also one of the severely affected areas by co-seismic landslides triggered by the disastrous earthquake. Statistics shows that around 400 families were relocated from Haku Post-earthquake (MoFA, 2015). A total of 101 co-seismic landslides were focused during the study and were verified during the fieldwork in Haku village. The conditioning factors used in this study were slope, aspect, elevation, curvature (plan and profile), landuse, geology and PGA. The conditioning factor maps were prepared in GIS working environment and further analysis was conducted with the assistance of Google earth. This study used Weight of Evidence (WoE), a bivariate statistical model and its performance was assessed. The susceptibility map was further characterized into five different classes namely very low, low, high, medium and very high susceptibility zones. The statistical analysis obtained from the results of the susceptibility map prepared by using WoE model gave the results that maximum area percentage of landslide distribution was observed in medium and high susceptibility classes i.e. 38% and 33% followed by very high (13%), low (10%) and very low classes (5.8%) About 25% of the total landslides are separated to validate the prepared model used in the landslide susceptibility zonation. The overlay method predicts the reliability of the model.

Keywords: Gorkha Earthquake, Earthquake induced landslides, Weight of Evidence, Susceptibility, PGA

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INTRODUCTION

The active tectonic setting of the Nepal Himalaya makes it one of the most earthquake susceptible countries in the globe (Dewey and Burke, 1973). In addition, diverse geological structures, fragile topography, high precipitation, deeply weathered rock material and active tectonics altogether with the socio-economic instability makes Nepal vulnerable to several natural disasters. Landslides are one of the major natural disasters in Nepal which leads to huge social and economic losses. Landslides can occur under several climatic, topographic and geological conditions. In Nepal, more than 80% land is covered by mountainous area and that are prone to landslide which have led to monetary losses of billions in last few decades (Amatya, 2016). Landslides can be triggered by various external factors such as incessant rainfall, earthquakes, extreme precipitation or rapid stream erosion.

A catastrophic earthquake with moment magnitude of 7.8 shook Nepal at local time 11:56 on 25th of April 2015. The statistics by the Ministry of Home Affair (MoHA, 2015) gives the information that as a result of the earthquake 8962 people were killed and thousands of people became homeless. Rasuwa is one of the worst affected districts by the 25th April earthquake. Approximately, 430 people have been reported killed and 753 injured (MoFA, 2015) after the 2015 Gorkha Earthquake. Large co-seismic landslides were triggered along Haku VDC of Rasuwa posing serious issues to the settlement. Approximately 400 families were displaced from Haku and relocated after the earthquake disaster (MoFA, 2015). According to Keefer (1994), earthquakes can trigger different types of secondary natural hazards; among them landslides are the most common. Earthquake induced landslides have garnered the interest and attention among the researchers as the shaking generated due to the earthquake may weaken the slope which may fail the hillslope when triggered by rainfall or a new earthquake.

The topography of this area is highly dissected and rough, with high north-east relief which made it susceptible for such earthquake induced landslides. Approximately 400 families were displaced from Haku and relocated after the earthquake disaster (MoFA, 2015). Absence of proper roadways hindered the identification of earthquake induced landslides in Haku, Rasuwa district Post-Earthquake. The topography of this area is highly dissected and rough, with high north-east relief which made it susceptible for such earthquake induced landslides which therefore necessitates the need of a detailed study. It is important to identify the landslide prone area to conduct quicker and safe mitigation program to ensure replication of such study in other landslide prone areas as well. The statistical approach

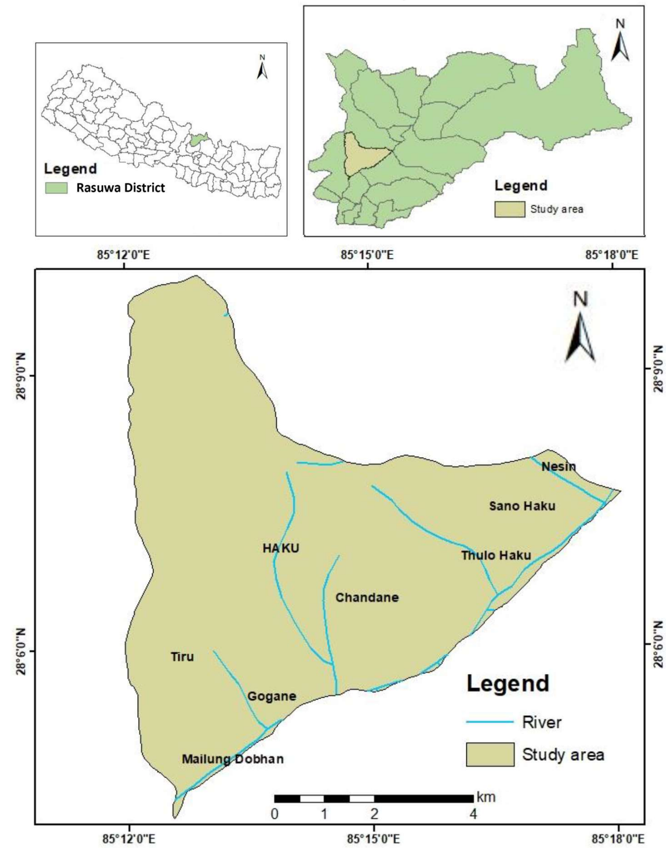

Fig. 1: Location map of study area

usually incorporates factors namely slope, elevation, drainage proximity etc. with peak ground acceleration (PGA) as the triggering factor (Miles and Keefer 2007; 2009a; 2009b). Landslide susceptibility mapping approaches for earthquake induced landslides vary from heuristic (Knowledge based) approach to data driven approach (Statistical approach). This study uses bivariate statistical method, Weight of Evidence method for preparing the susceptibility map. Bivariate statistical method can be a very approach to derive which factors are responsible for the occurrence of landslide event in an area. In some cases, the performance simulated and success rate of weight of evidence is very high compared to other approaches (Pradhan and Lee, 2010).

STUDY AREA

The Haku area lies towards the southern part of the Rasuwa District, Nepal (Fig. 1). The topography of the area is highly dissected and rough which makes it susceptible to landslides. According to the statistics to MoHA around 400 families were displaced after the 2015 Gorkha earthquake. The altitude of the area ranges from 740 m to as high as 4032 m and the total area under study is 49.82 sq. km. The study area is bounded by 28°10'0" N to 28°4'00" N latitude and 85°12'0" E to 85°18'00" E longitude. The study area can be accessed by the Pasang Lhamu Highway. It is also linked with many graveled road and foot trails.

Climate in Haku area can vary from sub-tropical to full glacial, rainy season characterized by high and intensive rainfall from June to September caused by the monsoon from the southwest, with precipitations around 1,990 mm per year (Acharya et al., 2006; Sill and Kirby, 2013). The study area is full of diverse vegetation as there is variation in altitude.

Due to steep slope, rugged topography and the fragile rock condition, the Haku area is susceptible to many slope instability issues.

METHODOLOGY OF STUDY

The landslide inventory of the study area was developed by the aid of Google Earth. The Post-Earthquake and Pre-Earthquake images were analyzed with the help of Google Earth historical archive tool (Fig. 2 (a)). Field verification was conducted to check on randomly selected landslide polygons in the study area. Several past landslides were reactivated after the 2015 Gorkha Earthquake (Fig. 2 (b)).

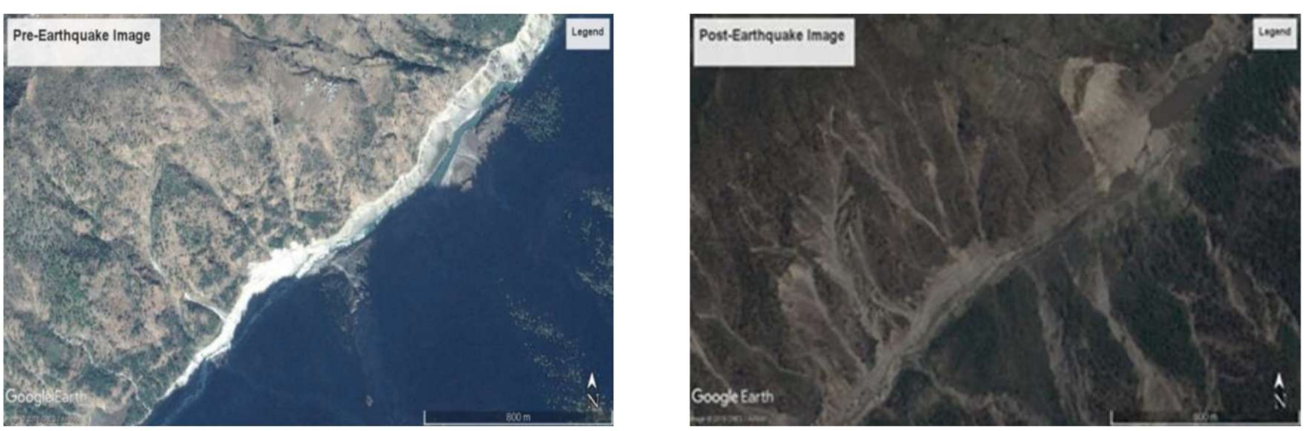

Fig. 2: Google earth image of the study area (a) Pre-Earthquake image (b) Post Earthquake image near Tiru village, Rasuwa

Fig. 3: Landslide representing Thulo Haku and Sano Haku, Rasuwa

Altogether 101 earthquake induced landslides were identified by studying Google image preparing landslide inventory by comparison of Pre-earthquake (23rd April, 2015) and Post-earthquake image (4th May, 2015) (Fig. 4).

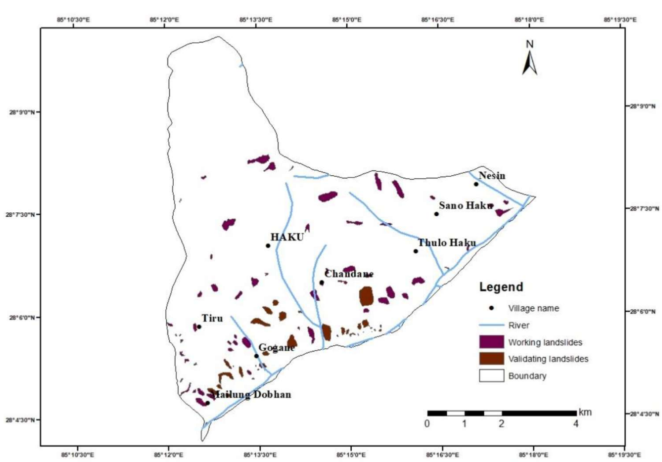

Fig. 4: Landslide inventory of study area

Landslide influencing factors

The selection of factors contributing landslides is a very complex phenomenon. The contributing factors were identified and selected in this study based on the presence or absence of the factors and their importance. The landslide conditioning factors incorporated the geological, geomorphological, anthropogenic and extrinsic factors. In this study, 8 conditioning factors were considered to prepare the landslide susceptibility map namely, peak ground acceleration (PGA), slope aspect, slope, landuse, geology, elevation and curvature.

PGA

Peak Ground Acceleration (PGA) is an extrinsic parameter considered in this study. Peak ground acceleration (PGA) is equal to the maximum ground acceleration that occurred during earthquake shaking at a location. PGA is equal to the amplitude of the largest absolute acceleration recorded on an accelerogram at a site during a particular earthquake. Earthquake shaking generally occurs in all three directions. Therefore, PGA is often split into the horizontal and vertical components. Horizontal PGAs are generally larger than those in the vertical direction but this is not always true, especially close to large earthquakes. PGA is linked with the seismic intensity produced due to the earthquakes. Generally, the number of earthquake induced landslides has a proportional relationship with the PGA value. This means the number of earthquake induced landslides abruptly increases with the rise in the PGA values (Liao and Lee 2000). The PGA attribute of the study area was extracted from the PGA map related to the Gorkha earthquake (USGS 2015), which was released by the US Geological Survey (USGS,). From the spatial distribution analysis of the landslide, it shows a very good correlation with PGA. It can be seen that the landslide was mainly distributed, where the PGA is high. In comparison with the felt earthquake intensity, 0.6 and a higher PGA indicate violent to extreme shaking. This can thus generate a large number of co-seismic landslides in steep mountain slopes (Regmi et al., 2016) The PGA data was obtained from the United States Geological Survey (USGS) by the use of the PGA map prepared after the Gorkha earthquake. The PGA map of the Haku area is shown in Fig. 6 (a). From the analysis of the distribution of the earthquake induced landslides we find a positive correlation between the number of landslides and PGA values (Shrestha et al., 2018). The study shows that the landslide distribution is maximum for area with higher PGA.

Topographic Parameters

Digital elevation model (DEM) has been used as an important factor in the study of earthquake induced landslides (Kamp et al., 2008; Wang et al., 2015). A DEM of cell size 30* 30 prepared from the digital contour obtained from Department of Survey, Nepal was used to extract the topographic factors like slope, aspect, curvature (plan and profile). Research shows an increase in the probability of landslide occurrence for higher elevation although there is absence of any direct relationship

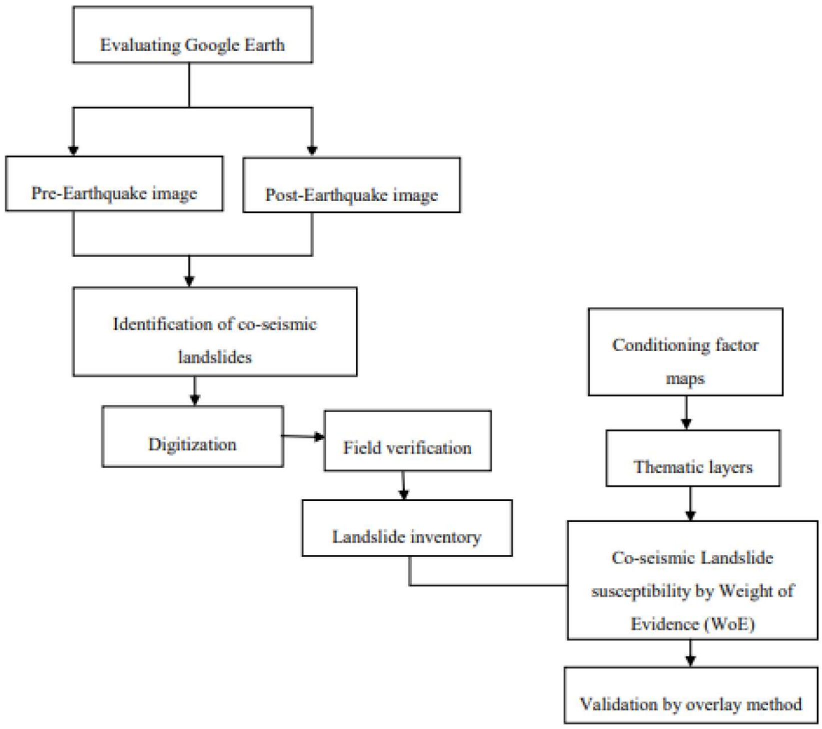

Fig. 5: A simplified flowchart showing methodology of study

between the elevation and landslide occurrence (Ercanoglu et al., 2004). The elevation ranges in the study area from 500–4500 m as represented in Fig. 6 (b). The landslide concentration was maximum for elevation range 1500–2500 m. The steepness of the slope is another major topographic factor used in landslide susceptibility studies (Wang et al. 2015; Kamp et al., 2008; Regmi et al., 2016; Regmi et al., 2010; Pradhan and Lee, 2010). The slope ranges from 0°–70° as shown in Fig. 6 (c). The landslide concentration was maximum along the slope range from 35°–45° because the soil deposits are resting on these slopes and they became unstable during the earthquake shocks. The aspect of the slope resembles the moisture retention and it's relation to attitude of bedding of the rock formation which in turn affects the physical properties of slope material and it's susceptibility to failure (Dai et al., 2001). In this study, aspect to the south and south east contributes mostly to landslides (Fig. 6(d)). It is usually because most of the river segment trend towards E-W and many landslides appear on the slope towards the river.

The shape of the slope can play major role in triggering landslide as it has a strong influence on creating slope instability. In curvatures, the landslides are usually distributed in convex slopes (Figs. 6(e) and 6(f)). The convex slopes usually have earthquake induced landslides (Reneau and Dietrich, 1987).

Geological Factor

The digital Geological map prepared by the Department of Mines and Geology, Government of Nepal was used during the study. The study area lies at a close distance from the Main Central Thrust (MCT). The MCT crops out on both sides of the Trishuli Valley. The study area consists of the Ulleri Formation which comprises of the Augen gneiss, muscovite biotite, gneisses feldspathic schists and the Seti Formation which comprises of grey, greenish grey gritty phyllites, gritstones with conglomerate and white massive quartzite, with basic intrusions noted in the upper parts (Fig. 6(g)). From the correlation of the geological factor with landslide distribution it was noted that maximum landslides occurred in the Seti Formation. This formation consists of highly fractured and jointed rocks that were severely affected by the earthquake.

Anthropogenic Factor

Landuse is considered to be one of the landslide conditioning factors as the variation in the landuse might play a role in changing the vegetation cover varying the mechanical (e.g. soil strength and slope behavior) and hydrological (e.g. Greenway, 1987; van Westen et al., 2003; Reichenbach et al., 2014). The variation in land use distribution may be either natural, human induced or a combination of both. Landuse map was generated by digitizing the attributes in Google Earth Image and exporting them to GIS for final extraction of the landuse of the study area of cell size 30x30 m (Fig. 6(h)).The weight values depict that the correlation of grassland and barren land that is 2.004 and 0.404898 respectively is stronger than other land use classes and our results contrast in the respect that we have obtained maximum landslide area in forest class. This might be because the forest covers the maximum area from the total study area.

A brief summary of the methodology employed during the study is given in Fig. 5.

WEIGHT OF EVIDENCE METHOD

In the study area, Weight of Evidence Method, a bivariate statistical approach was employed to make the susceptibility map of earthquake induced landslides.

The Weight-of-Evidence (WoE) method is a statistical tool that uses the prior probability of occurrence of an event to find out its posterior probability based on relative role of landslide-controlling parameters (van Westen, 2002). This method utilizes the historical data events to obtain the conditioning parameters for the occurrence of landslide (Sumatra et al., 2014).

Prior and posterior probabilities of a landslide occurrence (L), given the presence or absence of any parameter class in binary pattern (Mi or Mi) are calculated using the following equations:

Prior probability = P (L) = [Total Landslides/ Total study area]

Posterior probability = P (L/M) = (P(L∩Mi)) /(P(Mi))

In the raster form, all the data are in pixel form. So, the above equation can be rewritten as:

P (L) = (Npix (Landslide))/ (Npix (Total)); and

P (L/M) = (Npix (L∩Mi))/ (Npix (Mi))

Where, Npix (L) and Npix (Total) are the number of pixels that existing landslides belong, and number of pixels covering total area, respectively.

For the calculation of weights, Positive (W+) and negative (W-) weights are developed using conditional probabilities as following.

W+ =loge [(P (Mi| L))/ (P (Mi /‾L))]

W- =loge [(P (‾M i | L))/ (P (‾M i /‾L))]

where, W+ indicates the importance of the presence of a parameter class/ conditioning factor for the occurrence of landslides. W- indicates the importance of the absence of a parameter class for the occurrence of landslides.

A total weight of each multiclass factor map was estimated by adding the positive weight of a class to the total negative weight of the same factor map as:

Wmap = Wplus + Wmin (total) – Wmin

where

Wmin (total) = the total of all negative weights in a multiclass map

The weights are finally used to derive the contrast value (C) given by:

C= W + - W –

RESULTS AND DISCUSSION

The study represented that maximum number of landslides occurred along the Trishuli Ganga river section. Most of the landslides in study area were further increasing the vulnerability of the slope. From the field observation it was noted that toe cutting by river was also one of the prime factors triggering the landslide. The major effect of the landslide in the Haku area however was posing serious issue to the settlement. The weight values were calculated individually for the eight conditioning factors to produce estimated evidence. The results of the weight value calculation are given in Table 1. Higher the values of W+ stronger get the positive correlation (Sumatra et al., 2014) which is validated by our study for different factors as well high positive correlation to the landslides are observed for the angle greater than 45° and then in the angle ranges within 35°– 45°. For aspect class, landslides are more correlated on slopes facing south and south east. The elevation range 1500–2500 meters alone shows a positive correlation as observed from Table 1 which is nearly1.Similarly, for the plan curvature, maximum correlation was obtained for concave slopes which clarifies that landslides are more prone to concavity of the slopes. The correlation of landslides to concave surface in plan curvature is 0.122775 as obtained from Table 1. The geological class, the Seti Formation shows maximum correlation compared to Ulleri which is 1.945618. The correlation value is nearly 2, which represents that the correlation is significant enough. The weight values for landuse class grassland and barren land that is 2.004 and 0.404898 respectively is greater than other land use classes and our results contrast in the respect that we have obtained maximum landslide area in forest class. This might be because the forest covers the maximum area from the total area. The PGA value of range 0.56-0.68 shows positive correlation with the occurrence of landslide which is 1.012 as observed from Table 1. Also, this study shows that maximum landslides were reported in this PGA class which validates the similar results obtained from the model. Therefore, the statistical analysis obtained from the results of the susceptibility map prepared by using WoE model gave the results that maximum area of landslide distribution was observed in medium and high susceptibility class i.e. 38% and 33% followed by very high (13%), low (10%) and very low classes (5.8%).

VALIDATION OF MODEL

The susceptibility map prepared is given in Fig. 7. For the validation of the landslide susceptibility map, first the total number of landslides was divided into two parts. First 75% of landslides were tested for the models and remaining 25% of landslides were used for the validation of the models. The numbers of landslides were selected as per the representation for all the contributing factors used in the study and the validation

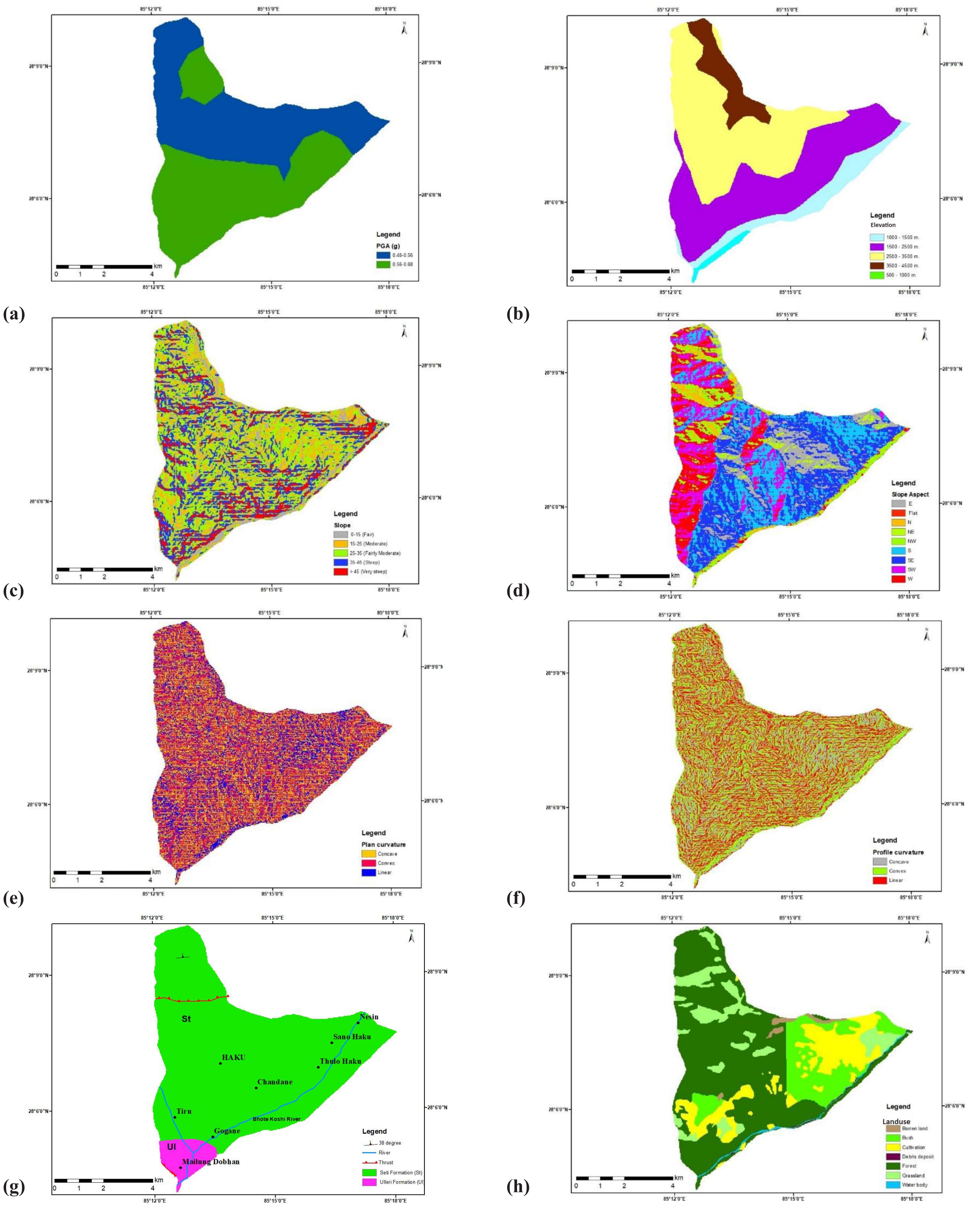

Fig. 6: (a) PGA map of study area (1g= 981 gals), (b) Elevation map of study area, (c) Slope map of study area (d) Slope Aspect map of study area, (e) Plan curvature map of study area, (f) Profile curvature map of study area, (g) Geological map of study area, and (h) Landsue map of study area

Table 1: Weight values of respective contributing factors

S.N.	Class	Pixel count of total area in a class	Pixel count of landslide area in a class	Pixel count of landslide area outside the class	Pixel count of stable area in a class	Pixel count of stable area outside the class	Wplus	Wminus	Weight
1	**Slope (degree)**								
	0-15	5152	76	2636	5076	63175	-0.97604	0.04886	-1.0249
	15-25	16006	307	2405	15699	52552	-0.709	0.141252	-0.85025
	25-35	24278	609	2103	23669	44582	-0.4346	0.17154	-0.60614
	35-45	17782	937	1775	16845	51406	0.33638	-0.14045	0.476829
	>45	7745	783	1929	6962	61289	1.040416	-0.23309	1.273509
	Total	**70963**	**2712**		**68251**	**61289**			
2	**Aspect**								
	Flat	2	1	2711	1	68249	-0.63273	0.086534	-0.71926
	N	611	1	2711	610	67640	-0.60258	0.042654	-0.64523
	NE	1910	6	2706	1904	66346	-0.70258	0.04678	-0.74936
	E	8394	180	2532	8214	60036	-0.30215	0.036542	-0.33869
	SE	18541	1017	1695	17524	50726	1.378391	-0.17327	1.551661
	SE	15082	1061	1651	14021	54229	1.28973	-0.26635	1.556077
	SW	10095	337	2375	9758	58492	-0.13719	0.021158	-0.15835
	W	9623	105	2607	9518	58732	-1.28147	0.110704	-1.39218
	NW	5473	4	2708	5469	62781	-1.06543	0.082048	-1.14748
	N	1232	1	2711	1231	67019	0	0.018216	-0.01822
		70963	**2712**		**68250**				
3	**Elevation (in m.)**								
	2500-3500	29335	646	2066	28689	39687	-0.56613	0.271926	-0.83806
	1500-2500	27251	1647	1065	25604	42772	0.483542	-0.46557	0.949116
	500-1000	991	5	2707	986	67390	-2.05688	0.01268	-2.06956
	3500-4500	6475	152	2560	6323	62053	-0.50073	0.039354	-0.54009
	1000-1500	7036	262	2450	6774	61602	-0.02517	0.002729	-0.0279
		71088	**2712**		**68376**				
4	**Plan Curvature**								
	Concave	25516	1050	1662	24466	43785	0.077011	-0.04576	0.122775
	Linear	17745	553	2159	17192	51059	-0.21134	0.062169	-0.2735
	Convex	27702	1109	1603	26593	41658	0.048316	-0.03211	0.080427
		70963	**2712**		**68251**				
5	**Profile Curvature**								
	Convex	30278	1212	1500	29066	39185	0.048208	-0.03732	0.085532
	Linear	23247	1037	1675	22210	46041	0.161295	-0.08821	0.249508
	Concave	17438	463	2249	16975	51276	-0.37626	0.098769	-0.47503
		70963	**2712**		**68251**				
6	**Landuse**								
	Forest	39681	1304	1408	38377	29987	0.06321	-0.42318	0.48639
	Barren land	7945	424	2288	7521	60843	0.351439	-0.05346	0.404898
	Water body	11214	122	2590	11092	57272	-1.2828	0.131006	-1.4138
	Grassland	872	189	2523	683	67681	1.942412	-0.0622	2.004609
	Cultivated land	10566	661	2051	9905	58459	0.520119	-0.12284	0.642957
	Bush	641	10	2702	631	67733	-0.91756	0.005579	-0.92314
	Debris deposit	157	2	2710	155	68209	-1.12312	0.001532	-1.12465
	Total	**71076**	**2712**		**68364**				
7	**Geology**								
	Ulleri	4088	351	2361	3737	64711	1.86316	-0.08246	1.945618
	Seti	67072	2361	351	64711	3737	-0.3426	0.863136	-1.20574
	Total	71160	2712		68448				
8	**PGA (gals)**								
	0.56-0.68	37337	2024	688	35313	33051	0.367985	-0.64486	1.012843
	0.48-0.56	33739	688	2024	33051	35313	-0.64486	0.367985	-1.01284
	Total	**71076**	**2712**		**68364**				

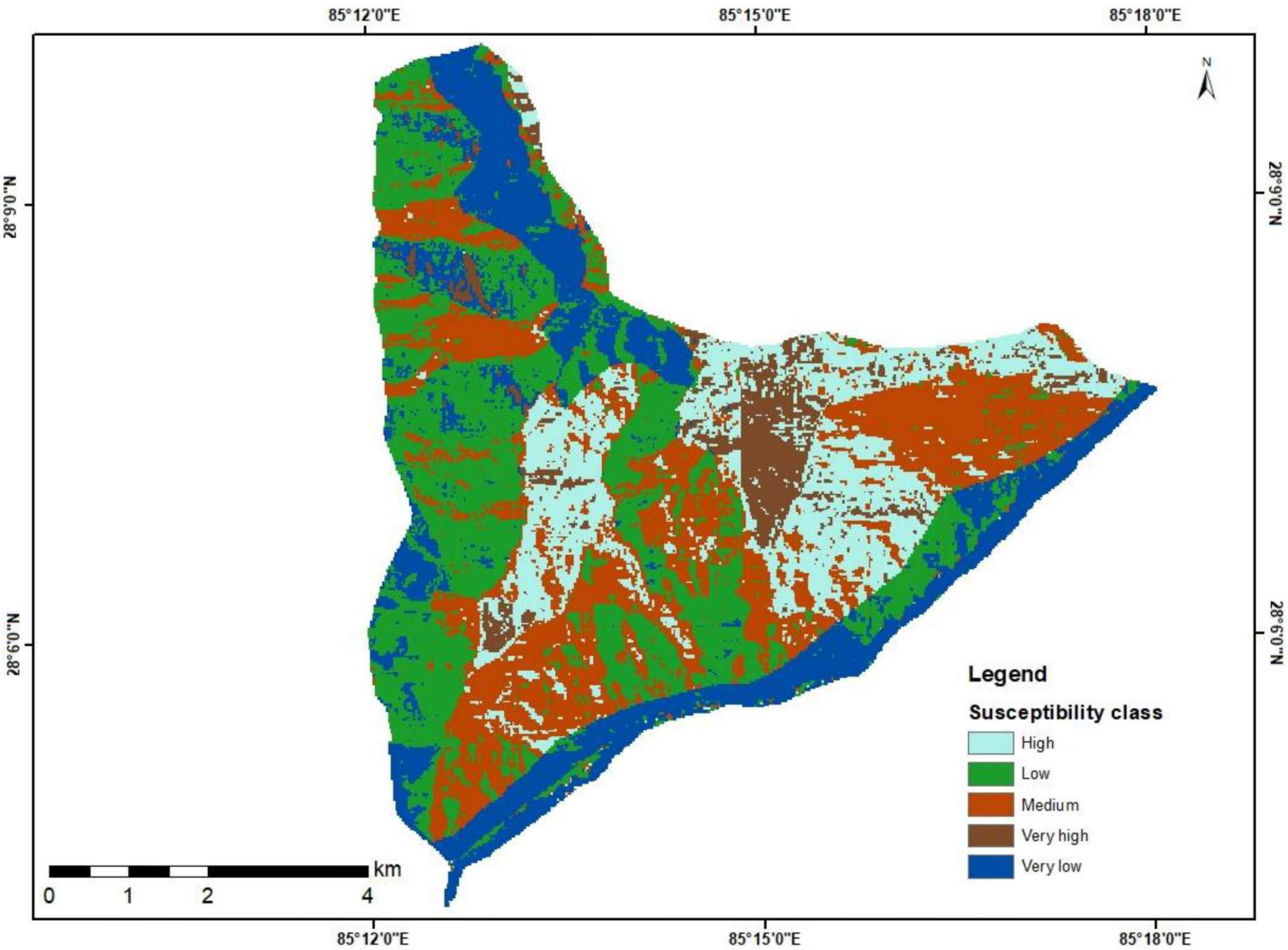

Fig. 7: Susceptibility map of study area

was conducted along with field study. For the validation, overlay method was used. Validation of landslides further shows that the WoE method is significant as most of the landslide area lies in moderate, high and very high susceptibility class (Figure 8). The probability value however estimated in these kinds of predictive models are not always absolute and represent relative degree of susceptibility only (Dahal et al., 2008). Though, such predictive values can be an initiation for measure of study of the landslide susceptibility in the study area.

CONCLUSION

In this study, Weight of Evidence model based on bivariate statistical method was used for determining the spatial probability of landslide occurrence where each factor layer was weighted according to the contribution on landslides. This method predicted the probability of landslide occurrence efficiently which was validated by positive correlations between the field conditions and the results obtained by the model. A total of 101 landslides were identified in this study from the preparation of factor maps, it is found that landslides are more influenced by higher slopes or increasing relief. It was observed that the slope angle less than 15 degrees didn't induce landslide. The results suggested that the landslides are mostly common in slope facing towards south and south east. While the curvature suggested that concave curvature is the role player to predict landslides. For the study of elevation suggested the increase in number of landslide till 2500 m and then a sudden decline in area percentage of landslide. The Seti Formation comprising of gritty phyllite, quartzite and conglomerate suggested maximum landslide distribution due

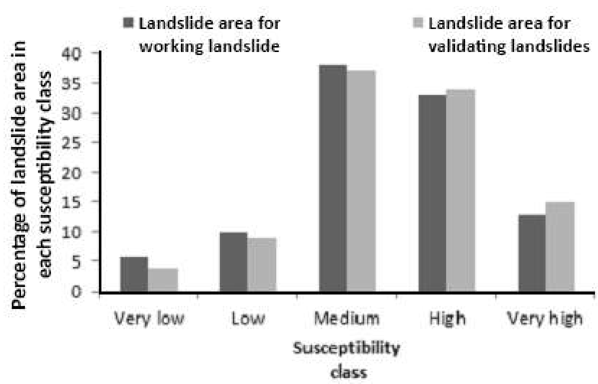

Fig. 8: Bar-graph showing validation of the model

to the fragile weathered rock. The forest area followed by barren land covered maximum area in the Haku region as obtained from the results. It was found from the study that the PGA value had a direct correlation with the landslide event as the landslide distribution increased with the PGA value. PGA is a conditioning factor and is associated with seismic intensity. In general, co-seismic landslides increase with PGA values (Liao and Lee 2000). The statistical analysis obtained from the results of the susceptibility map prepared by using WoE model gave the results that maximum area of landslide distribution was observed in medium and high susceptibility class i.e. 38% and 33% followed by very high (13%), low (10%) and very low classes (5.8%). Similarly, the validating landslides showed similar results as obtained from the model. Among the different factors determined, slope, aspect, and geology were found to be the major contributors to trigger the earthquake induced landslides in the Haku area.

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