Landslide Susceptibility Assessment: Identification and Hazard Mapping of Gandaki Province, Nepal

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ABSTRACT

Landslides considered as a common hazard, affecting constantly the administrative territory of Gandaki province, located in the central part of Nepal. Impact of landslides is significant due to its specific geological, anthropic, vegetation and other circumstances. The main aim of this study was to identify the factors determining landslides and forming a landslide susceptibility mapping of study area. The fieldwork was conducted, where 128 GPS locations was recorded throughout the study area. This study also used the maximum entropy model using MaxEnt software, taking into account of various landslide-causing factors, resulting major variables of landslides risk and formed susceptibility mapping of landslide. It is identified that slope and land use land cover are most important variables to increase the landslide risk. Findings highlight that lands around the riversides and steep slopes are more risky area in terms of landslides. Moreover, it is found that the area of 3371.32 km^2 measured as landslide risk zone in this province, where Gorkha district categorized as most vulnerable place for landslide, comprising of largest area of landslide risk zone while Parbat district has low amount of risk land. Since the human casualties and property loss are the major consequences of the disaster, it is essential to identify and analyse the factors determining for landslide and developing the landslide susceptibility mapping of Gandaki province, which could be taken into account while developing mitigation and coping strategies.

KEYWORDS: Landslide susceptibility, hazard mapping, risk factors, MaxEnt modelling

INTRODUCTION

Landslides define as descending or outward movements of slope mass (Cruden & Varnes, 1996). It is a common hazard; it describes as the transfer of rock, debris, mud, or other mass of earth by gravity (Davis & Blesius, 2015). It is natural course generally driven by the geological, hydrological, vegetation and climatic circumstances, however, consider as major hazard in hilly and mountain regions like Nepal, where more than 80% of total land accounted for (Duncan, Masek , & Fielding, 2003). Nepal is considered as high vulnerability to landslides that cause huge economic and human casualties every

year (Government of Nepal, 2009). About 3246 landslide cases were recorded over the period of 45 years, starting from 1971 to 2016 (MoHA, 2017). Landslides are one the most notable and precarious environmental hazards, comprising economic loss, affecting the infrastructure and cities (Kornejady, Ownegh, & Bahremand, 2017). So, the magnitude of consequences impacts not only on natural phenomena but also in many social and economic spheres, resulting in loss of people lives, becoming homeless, destroying physical infrastructures and many more.

Over the last 50 years, the issue of considering landslide susceptibility mapping has brought wide attention, driven by two reasons: the increasing pressure of urbanization and the rising awareness of the socio– economic implication of landslides (Aleotti & Chowdhury, 1999). Hazard is the possibility of incidence of a specifically destructive phenomenon highlighting a particular spam of time and area because of a set of presented or expected conditions (Deoja, Dhital, Thapa, & Wagner, 1991). Hazard mapping is the method that defines the probability of occurrence of any damaging phenomena can be predicted in any given area (Markus, 1985). In terms of developing landslide hazard mapping, it is important to identify the factors that determine the significance and impacts. A hazard map that comprises the location of old landslides to denote potential vulnerability, or as complex as a quantitative map integrating possibilities on the basis of variables such as precipitation thresholds, angle of slope, soil type, and land use/land cover (Varnes, 1984). Thus, it is a vital technique in forecasting the probability of incidence of any natural circumstances within any specific region. Hence, to minimize the damage of properties, lives and ecosystem, it is crucial to predict and signify the area of hazards. This study is mainly focused on to identify and the mapping of landslide risk area of the study area. In addition, it is also recognized the factors that are related to determine its impact at various levels.

Figure 1: Location map of the study area

STUDY AREA

This study is focuses on Gandaki province (27^0 26' 15" N - 29^0 19' 15" N and 82^0 52' 45" E - 85^0 12' 01" E), one of the seven provinces of Nepal. It is situated at central
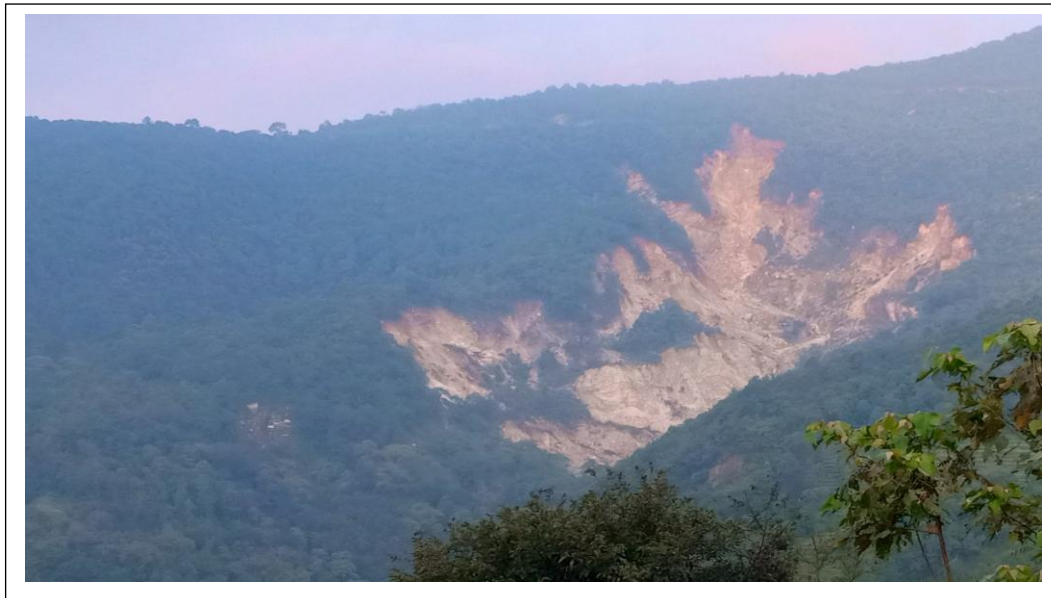
Photo by Author: Andherikhola Landslide-2019, Kaski

part of Nepal by covering the 11 districts: Nawalpur, Tanahun, Gorkha, Lamjung, Kaski, Syanjya, Parbat, Baglung, Myagdi, Manang, and Mustang. Similarly, there are only 85 local governing bodies in Gandaki Province whereas: 1 Metropolitan City, 26 Municipalities and 58 Rural Municipalities (MoITFE, 2018). The total area of this province is 21,976.34 km^2, i.e. 14.93% of the total area of Nepal.

According to the census 2011, the total number of families in this province is 57,821 and total population is 24,03,022 whereas males is 10,90,213 and females is 13,12,809 population. The altitude is spread from the lowest of Gandaki Canal of Narayani River (104m) above sea level to the highest elevation at Dhaulagiri with 8,167m. It has unique landscape having Terai, Bhabar, Inner Terai, Churia, Duns, river basin, valleys and hills. On this basis the province is divided into eight different physical features.

Due to varied geological and geographical diversities the Gandaki province faces with different types of natural hazards, unplanned settlement, steep slope, fast flowing rivers, plenty of uncultivated land, human encroachment on the natural environment leads to cause of hazards.
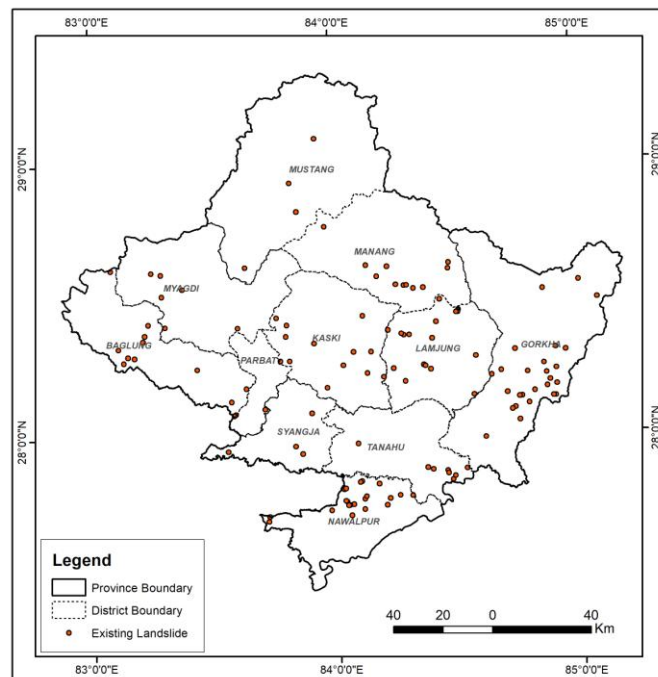

Figure 2: Location of existing landslide

MATERIALS AND METHOD
Materials

Primary data were collected over the period of two months of last year spring. First, discussion with government officials (staffs district administration office, district police office, district co-ordination committee, municipality/rural municipality), staffs/members of Red Cross society and elected community leaders were conducted in all 11 districts of the province to identify the potential risk zone and locations of hazards. Researchers visited the identified existing landslide locations for collection of 128 GPS points for modelling and mapping (Figure 2).

The environmental variables were downloaded from freely available sources (Table 1) and pre-processed in ArcGIS (ESRI, 2017) to make appropriate format (ASCII) and same spatial resolution (30 m). Some variables with vector features (i.e. point and line) were also converted into raster format having the same resolution (30 m). The environmental variables were divided into four categories as follows.

Table 1: Environmental variables used for the study

Category	Variables	Source	Unit
Topographic	Aspect	(USGS, 2019)	degree
	Elevation		m
	Slope		degree
	Distance to water	(Geofabrik, 2019)	km
Climatic	Mean precipitation	(WorldClim, 2019).	cm
	Mean temperature		degree
	Mean solar radiation		
Vegetation Related	Mean EVI	(MODIS, 2019)	dimension less
	Forest	Global forest change(Hansen, et al., 2013)	dimension less
Anthropogenic	Land use land cover	(ICIMOD, 2010)	type
	Distance to road	(Geofabrik, 2019)	km
	Distance to path		km
	Distance to settlement	Department of survey, Nepal	km

Methods

MaxEnt is a software program used to model species distributions by using geo-referenced occurrence data and environmental variables to predict suitable habitat for a species (Phillips, Anderson, & Schapire, 2006). The model has been used to predict the distribution of plants, and animals (Guisan, Theurillat, & Kienast, 1998);(Pearce & Ferrier, 2000); (Gillespie & Walter, 2001)&(Phillips, Anderson, & Schapire, 2006). These species distribution models are used to predict the risk of landslides (Goetz, Guthrie, & Brenning, 2011). Variables listed in Table 1 were incorporatedinto MaxEnt (version 3.4.1) along with occurrence data of hazards to determine potential disaster risk zone. It selected ten 1000 maximum iterations and 10 replicates during modeling (Barbet-Massin, Jiguet, Albert, & Thuiller, 2012). Then 70 percent of data was used to train and rest to validate the model. According to Liu et al. (2013) the maximum sum of sensitivity and specificity (MaxSSS) threshold is appropriate to convert the continuous

probability map to binary map when only presence data are available from the field. Therefore, this threshold was used to produce the landslide susceptibility map of study area.

Accuracy Assessment

It is important to obtained valid and reliable susceptibility map, requiring accuracy assessment for its detail inspection. It was validated by two methods: threshold independent and threshold dependent. In the threshold independent method, the value of accuracies was directly obtained from the model but in the threshold dependent method it was provided the threshold to maximize the sum of specificity and sensitivity. The area under the receiver-operator curve (AUC) was used as the threshold independent method. An AUC <0.7 denotes poor model performance, 0.7–0.9 denotes moderately useful model performance, and >0.9 denotes excellent model performance (Pearce & Ferrier, 2000). The true skill statistics (TSS) was selected as the threshold dependent method. TSS = Sensitivity + Specificity − 1, and ranges from −1 to 1, where values less than 0 indicate a performance no better than random and 1 indicates a perfect fit (Allouche, Tsoar, & Kadmon, 2006). The calculated TSS for all 10 model outputs, and the final TSS was averaged from all ten replications (Jiang, et al., 2014). Models which have presence-only data the threshold to maximize the TSS is recommended (Liu, White, & Newell, 2013) so it was used this threshold to convert the continuous map to a binary map.

FINDINGS AND DISCUSSIONS
Factors Determining the Landslide Risk Zone

One of the objectives of this study was to determining the factors contributing to landslide, and highlighting among them to focus on core issues. The obtained result from MaxEnt indicates the various factors caused to landslide based on regularized training gain. The regularized training gain explains how much better the model distribution fits the presence data relative to a uniform distribution. "With all variables" indicates the results of the model when all variables are run; "with only variable" denotes the effect of removing that single variable from the model and "Without variable" denotes the results of the model when an only that variable is run (Phillips S. J., 2017). In other words, lower the regularized training gain value while taking an only that variable, higher the impact it has on landslide and vice versa.
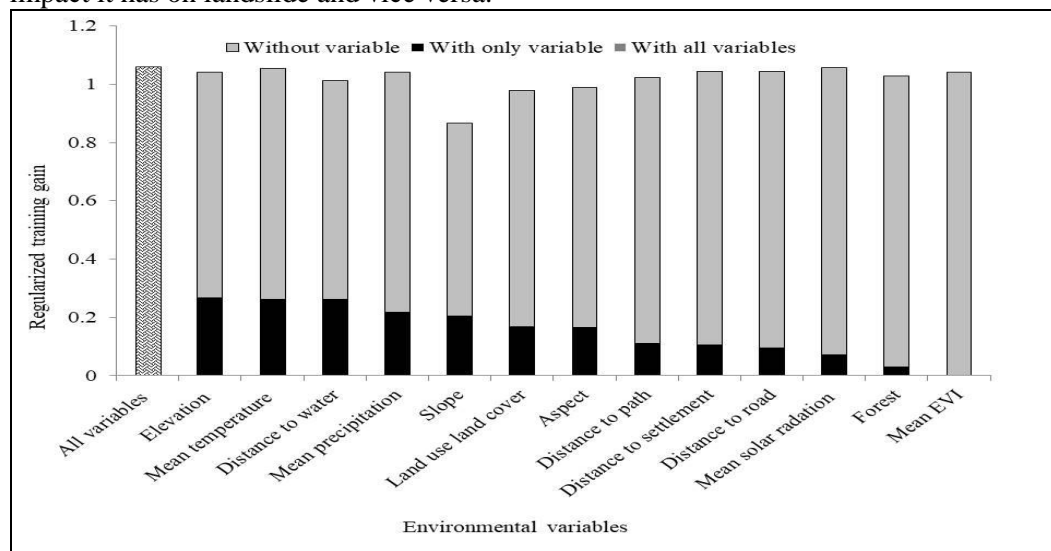

Figure 3: Importance of variables to train the landslide risk model

Since the lesser the regularized training gain value, higher the degree of contribution to landslide. According to the result of MaxEnt model, it is found that slope and land use/land cover are top most contributors of the landslide risk zone modelling as regularized training gains without these two variables were less than others (Figure3). In other words, these variables contain more information for landslide zone modelling purpose. Aspect, distance to path and distance to water are moderately useful variables for the model. Other variables are least important for the model.
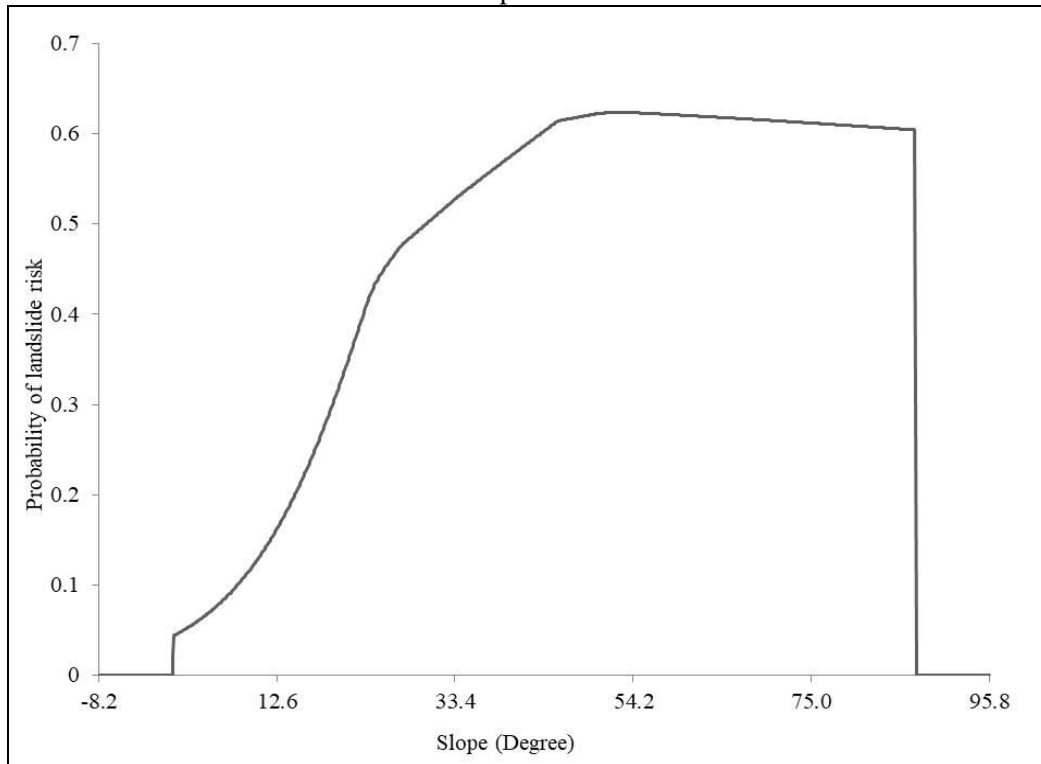

Figure 4: Response of landslide risk to slope

As it noted above, slope is one of the major factors contributed to landslide. Some of the studies show that the major driving force of the landslide is gravity(Davis & Blesius, 2015). Gravity directly depends upon slope; higher slope land mass should face the high gravity power. Consequently, area having high slope is vulnerable to the landslide. The study identified that the lands having slope higher than 10-degree to about 90-degree have higher risk of landslide (Figure 4). The field study also found most of the past landslide locations have steep slope, which comes under that range. However, it can be observed that lands having less than around10-degree slopes are nearly safe from the landslide. Similarly, the land which has more than above 90-degree slope has low risk of landslide. This result is used while producing the susceptibility mapping of landslide.

As previous result showed that land use land cover is another vital contributor of landslide, it is important to fetch the types of land cover land use that affect most. The finding clarifies that out of eleven-land use/land cover types; areas near to the rivers are more susceptible to the landslide (Figure 5). The field observation also found that many landslides occurred nearby river side, particularly during monsoon season. Similarly, agricultural lands and grasslands are also face significantly the landslide risk during the rainy season. In contrary, other land cover types such as forest, built-up area and snow-covered land are less likely to face landslide risk.
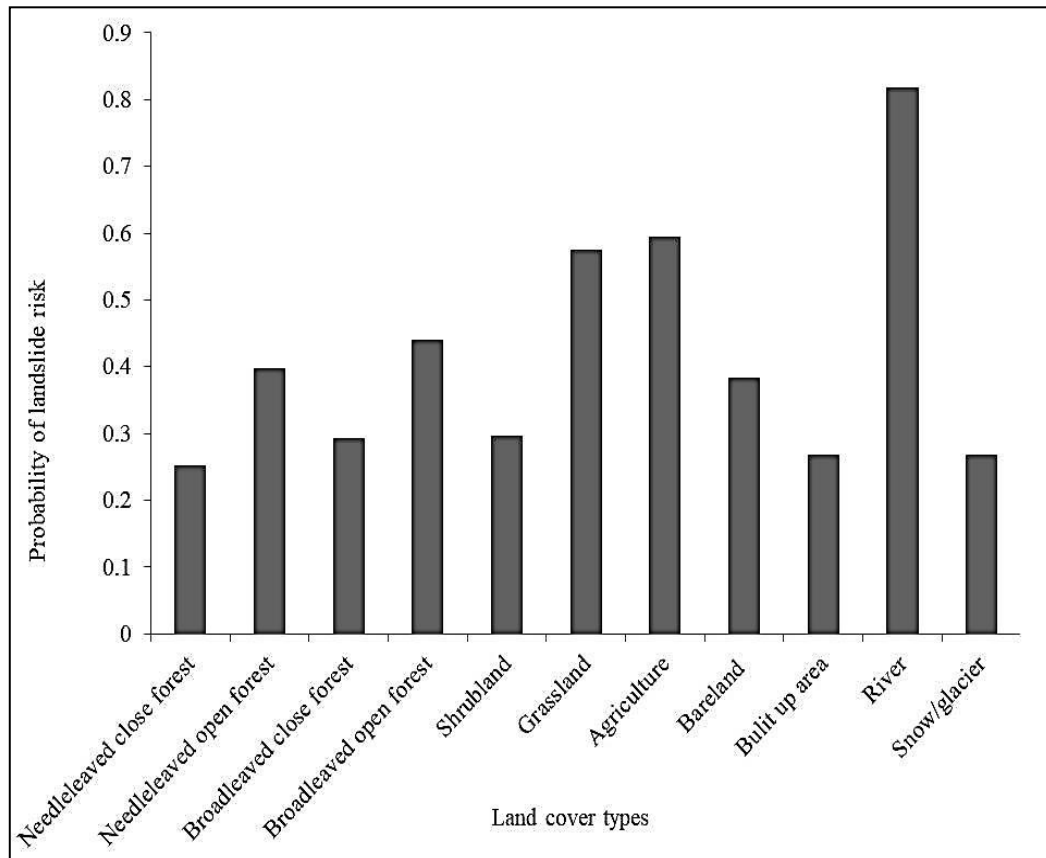
Figure 5: Response of landslide risk to land use land cover types

Landslide Susceptibility Mapping of Gandaki Province

Finally, this study identified and mapped the landslide risk zone throughout the Gandaki province (Figure 6). Slope and riverside area are identified as major factors contributing on landslide risk zone.

In general, 3,371.32km^2 area is identified as landslide risk zone in Gandaki province. As per the basic understanding of vulnerability, it is necessary to differentiate and isolate the area of risk from other less vulnerable places. Threshold (0.303) to maximize the sum of sensitivity and specificity was used to convert the probabilistic map to binary risk/risk free zone. The flat area and area covered by vegetation have low landslide risk. After running the MaxEnt software, it is highlighted that the obtained values were categorised into two zones, considering the natural breakdowns represents as landslide susceptibility or risk zone and no risk zone. It is clear that the risk zones require more attention from respective concerns individuals, organisations and government.

The Gandaki province, which just been formed due to political reformation (federalism), requires knowledge of understanding the risk of disaster like landslide in order to protect both lives: physical properties and nature. So, further analysis was done to find out which area of this region is more vulnerable. Comparing the 11 districts of the province, it is identified that Gorkha and Lamjung districts have more landslide risk area than other districts whereas Parbat and Nawalpur districts have the least landslides risk area (Table 2). In case of Nawalpur, this district has the least amount of slope area, while it occupies most area of forest than that of other districts of province.
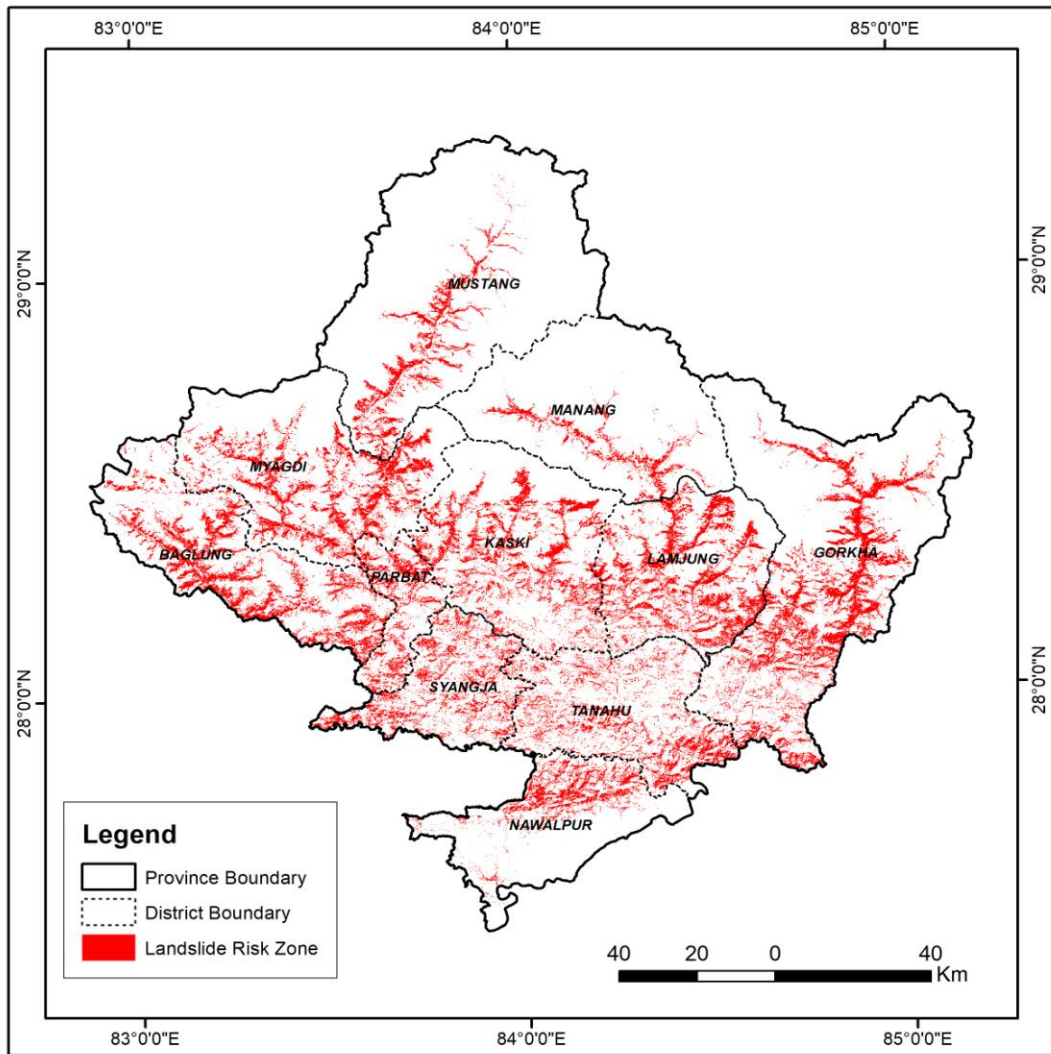
Figure 6: Landslide risk zone of Gandaki province

The following Table 2 presents the district-wise landslide hazard risk area in the Gandaki province.

Table 2: District-wise landslide hazard risk area

S.N.	District	Landslide risk zone	
		Area (Km^2)	Percentage
1	Baglung	409.93	12.16
2	Gorkha	602.62	17.87
3	Kaski	377.52	11.20
4	Lamjung	427.08	12.67
5	Manang	114.54	3.40
6	Mustang	199.17	5.91
7	Myagdi	397.60	11.79
8	Nawalpur	169.92	5.04

9	Parbat	138.05	4.09
10	Syangja	239.30	7.10
11	Tanahun	295.59	8.77
	Total	**3371.32**	**100.00**

Model Accuracy of Landslide Risk Modeling

Accuracy measures of the model are presented in Table 3, which is presented below.

Table 3: Accuracies of different replications of landslide risk modelling

Replication	0	1	2	3	4	5	6	7	8	9	Average	Std
Threshold	0.46 0	0.1 50	0.3 40	0.3 30	0.2 60	0.3 30	0.2 70	0.3 30	0.3 30	0.2 30	0.30 3	0.0 82
AUC	0.82 9	0.7 90	0.8 61	0.8 47	0.8 68	0.8 08	0.8 34	0.8 25	0.8 58	0.8 39	0.83 6	0.0 24
TSS	0.58 6	0.5 30	0.6 92	0.6 74	0.6 48	0.5 87	0.6 34	0.6 10	0.6 66	0.6 08	0.62 3	0.0 49

Note: AUC = area under the receiver-operator curve, TSS = true skill statistics

As shown in the table, the validation of landslide susceptibility mapping was checked by using the threshold, AUC and TSS. The threshold independent method, AUC gives 0.836+/-0.024, as an AUC <0.7 denotes poor model performance, 0.7–0.9 denotes moderately useful model performance, and >0.9 denotes excellent model performance, it has come under moderate performance model, just about excellent one. Similarly, the threshold dependent method TSS gives 0.623+/- 0.049, which means its value is over 0, meaning model fit averagely good. The threshold value 0.303 gives the maximum value of threshold to maximize the sum of sensitivity and specificity. It is used this threshold to calculate the TSS and to convert the continuous risk map to a binary risk/risk free map. Thus, findings of accuracy assessment indicates that the obtained landslide susceptibility mapping is valid, which can be used to understand the overall circumstances while taking the effective measure for mitigation and coping strategies.

CONCLUSIONS

The process of developing landslide mapping is a complex issue, requires huge effort in assembling a landslide database for its accurate completion. This study used the maximum entropy model using MaxEnt software, taking into account of various landslide-causing factors. It is found that slope and land use/land cover are the major determinants of landslide zones. Land that is nearby the riversides and having steep slope are more risky area in terms of landslides occurance possiblities, while other factors like aspect, distant to water and path is also considerable factors for landslide susceptibility mapping.

In terms of assessment of landslide susceptibility mapping of Gandaki province, it is found that this province comprise the area of 3,371.32 km^2 under landslide risk zone. It is also identified that among 11 districts, Gorkha district is the mostlandslide risk district of the Gandaki province, in contrast, comparatively Parbat district has low probability of risk areas.

The findings of this study may help to reinforce coping capacity and strategic development to minimize the effects of landslides in Gandaki province. In order to save human and properties from this hazards the study recommend that the physical

constructions should not be done in steep slope (more than10-degree) and near to the riverside. Furthermore, in terms of risk zone area, sinceGorkha has more landslide risk area, provincial government should focus on this district to mitigate the effect of the disaster.

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