Journal of the Korean Society of Surveying, Geodesy, Photogrammetry and Cartography
Vol. 34, No. 4, 443-451, 2016
http://dx.doi.org/10.7848/ksgpc.2016.34.4.443

ISSN 1598-4850(Print)
ISSN 2288-260X(Online)
Original article

Landslide Susceptibility Mapping for 2015 Earthquake Region of Sindhupalchowk, Nepal using Frequency Ratio

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Abstract

Globally, landslides triggered by natural or human activities have resulted in enormous damage to both property and life. Recent climatic changes and anthropogenic activities have increased the number of occurrence of these disasters. Despite many researches, there is no standard method that can produce reliable prediction. This article discusses the process of landslide susceptibility mapping using various methods in current literatures and applies the FR (Frequency Ratio) method to develop a susceptibility map for the 2015 earthquake region of Sindhupalchowk, Nepal. The complete mapping process describes importance of selection of area, and controlling factors, widespread techniques of modelling and accuracy assessment tools. The FR derived for various controlling factors available were calculated using pre- and post- earthquake landslide events in the study area and the ratio was used to develop susceptibility map. Understanding the process could help in better future application process and producing better accuracy results. And the resulting map is valuable for the local general and authorities for prevention and decision making tasks for landslide disasters.

Keywords : Landslide, Susceptibility, Mapping, Process, Earthquake, Sindhupalchowk, Nepal

1. Introduction

Many part of the world are exposed to several types of hazards, each of them have their own spatial characteristics. Landslides, are major natural geological hazards in hilly regions, responsible for enormous annual property damage involving both direct and indirect costs (Petley, 2012).

Landslides are natural phenomenon, defined as the movement of a mass of rock, debris or earth down a slope (Cruden, 1993). It is a gravitational movement which does not require any transportation medium such as water, air or ice (Crozier, 1986). Landslides are usually classified on the basis of the material involved (rock, debris, earth, mud) and the type of movement (fall, topple, avalanche, slide, flow, spread). Thus, the generic term landslide also refers to mass movements such as rock falls, mudslides and debris flows. Volcanic mudflows and debris flows are also called lahars. Shallow landslides usually involve only the soil layer and upper regolith zone, while deep-seated landslides additionally involve bedrock at higher depth. Landslide volume can vary from some tens of cubic meters to several cubic kilometers for giant landslides, while landslide speed may range from a few centimeters per year for slow-moving landslides to tens of kilometers per hour for fast, highly destructive landslides. According to the state of activity or movement, existing landslides can be classified as active, dormant (potentially reactivated) or inactive (often relict or fossil). It can occur singularly or in groups of up to several thousands. Multiple landslides, for example, occur almost simultaneously when slopes are shaken by an earthquake or over a period of hours or days when failures are triggered by intense rainfall or snow melting (Guzzetti *et al*., 2005).

Received 2016. 07. 26, Revised 2016. 08. 16, Accepted 2016. 08. 31
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Landslides are triggered by different natural phenomena or human activities or by any combination of these processes. Natural phenomenon includes meteorological changes, such as intense or prolonged rainfall or snowmelt, rapid tectonic forcing, such as earthquakes or volcanic eruptions, undercutting by rivers or sea waves and permafrost thawing) whereas human activities such as slope excavation and loading (e.g. road and buildings construction, open-pit mining and quarrying), land use changes (e.g. deforestation), rapid reservoir drawdown, irrigation, blasting vibrations, water leakage from utilities etc. (Guzzetti *et al*., 2005). More detail on trigging factors can be found in van Asch *et al*., (2007) and Varnes and IAEG (1984). With increasing anthropogenic activities coupled with heavy and prolonged precipitation have increased the risk of landslides in future.

Disaster events cannot be prevented but the scale of damage can be reduced, which can be done by understanding the mechanism of occurrence, prediction through susceptibility assessment and zonation and early warning system (Dai *et al*., 2002; Sassa and Canuti, 2008). In such case, preparation of landslide susceptibility zone maps can be an initial step towards mitigation and control. These assessments can help authorities prevent and reduce damage through proper land use management for infrastructural development and environmental protection (Bui *et al*., 2013). Due to the complex nature of landslides, modeling and developing reliable maps are big challenges among researchers. The best landslide model for an area depends not only on the quality of the data used (Jebur *et al*., 2014) but also strongly on the employed modeling approaches (Yilmaz, 2009). To address this, a broad range of methods and techniques have been proposed from different points of view to understand their controlling factors and to predict their spatial-temporal distribution.

With the advancement of computing technology and availability of cheap powerful computers, several modeling techniques have been applied for the assessment of landslide susceptibility. These approaches have been applied single, multiple or comparative in different locations by researchers. This article discusses the process of landslide susceptibility mapping used in the current literatures. Some of the early good reviews on landslide hazard assessments can be found on: Kanungo *et al*., (2009), and Pardeshi *et al*., (2013). Also, a case study of developing landslide susceptibility map in the 2015 earthquake hit region of Sindhupalchowk, Nepal using FR (Frequency Ratio) has been conducted. FR is widely used methodology that could be easily applied in GIS (Geographic Information System) environment. The method has not been used in the area previously.

2. Landslide Susceptibility Mapping

The Landslide susceptibility can be defined as the spatial probability of landslides on the basis of the relationships between distribution and a set of conditioning factors (Guzzetti *et al*., 2005). Similarly, landslide susceptibility mapping allows for the identification of slopes for which failure probability is high and to consequently make prevention and protection decisions accordingly (Guillard and Zezere, 2012). Landslide susceptibility zonation, which can formally be defined as the division of land surface into near-homogeneous zones and then ranking these according to the degrees of actual or potential hazard due to landslides.

All the available approaches for landslide susceptibility mapping are based upon assumptions that landslides in future are more likely to occur under similar geological, geomorphological, hydrogeological and climatic conditions, which were and are responsible for the occurrence of past and present landslides. Landslides with distinct geomorphological features can be identified, classified and mapped both through field surveys and remote sensing image interpretations and are controlled by identifiable internal factors (i.e., inherent attributes of the ground) known as causative factors, which can also be mapped from field surveys and remote sensing image interpretations.

Landslide susceptibility mapping involves the following methods:

2.1 Selection of study area

Selection of study area will incorporate the available historical landslide inventory which will train the models and based on them the susceptible zones are classified. In various studies, area are selected inside a polygon, watershed or administrative boundaries based on rainfall or earthquake events at various scale.

2.2 Landslide inventory preparation

Preparation of a landslide inventory is an essential primary step of any landslide zoning and is a critical requirement in understanding pre- and post- disaster hazard and risk management (Martha *et al*., 2010). Cruden (1991) defined landslide inventory as 'the simplest form of landslide information which records the location and where known, the date of occurrence, type of landslides that have left identifiable traces in the area'. Field investigation, examination of historical archives, analysis of stereoscopic aerial photographs, geological and geomorphological field mapping, engineering geological slope investigations, visualization and analysis techniques of satellite images, has been used to detect and prepare inventories. Earlier reviews on landslide inventory maps can be can be found on Guzzetti *et al*., (2012). Similarly, Xu (2015) has describes the principles for preparing inventory maps of earthquake-triggered landslides, focusing on varied methods and their criteria.

2.3 Spatial database of controlling factors

Landslides vary in their morphology greatly and caused by several factors. It is difficult to identify exact factors. But relationships with various controlling factors can be established with the present and past landslides events. The relationship can help in zonation of different hazard levels. The controlling factors can be divided into internal (existing) and external (triggering) factors (Crozier, 1986). Internal factors represent the inherent attributes of the ground which reduce the shear stress ratio and makes the slopes susceptible to failures. Their effect are show which could take long period of time. But, the external factors could trigger movement in an instant. Internal factors include geomorphology, lithology of slope material, structural features, vegetation and hydro-geologic conditions, whereas external factors are seismicity, climatic (rainfall) and anthropogenic (landuse) factors.

2.4 Landslide susceptibility modelling and mapping

Landslide susceptibility modeling, have experienced extensive development during the last few decades. Many methods have been carried out in to evaluate landslide susceptibility at the regional and basin scale, road corridor sections and on Himalayas in most landslide prone countries like China, Philippines, India, Indonesia, Pakistan, Nepal, Vietnam, Malaysia, Japan and so on. Following are the broad groups of methods available in literatures (Guzzetti, 2006):

- Geomorphological mapping: Geomorphological mapping of landslide susceptibility is a direct and qualitative method that is subjective based on the ability and judgment of the investigator to recognize actual and potential slope failures, including their evolution and possible consequences.
- Distribution analysis: Distribution analysis are simply analysis of past events inventory by preparing landslide distribution and density maps.
- Heuristic methods: Heuristic methods are indirect qualitative methods that assigns empirical ranking to controlling factors based on prior knowledge.
- Statistical methods: Statistical methods determines the quantitative estimates of spatial distribution of landslides, based on the functional relationships of the past landslide events and set of controlling factors.
- Physically process based models: Process based (deterministic or physically based) models for the assessment of landslide susceptibility rely upon the understanding of the physical laws controlling slope instability.

In recent years, with the availability of many GIS technology and of user friendly statistical packages, statistical models have has been widely used compared to heuristic (knowledge based) approach. It has not only minimized the impact of subjectivity, but also facilitate greater reproducibility.

In literature, frequency ratio, weight of evidence, logistic regression model, decision tree, artificial neural networks, support vector machines etc. are commonly used methods for landslide susceptibly mapping. Single as well as multiple methods for comparison have been applied in various case studies (Hong *et al*., 2016; Bui *et al*., 2016; Xu *et al*., 2016; Mohammady *et al*., 2012; Yilmaz, 2010; Pradhan and Lee, 2010). The susceptibility maps are classified in different categories from low, medium, high, and very high (Guzzetti *et al*., 1999; Lee and Min, 2001).

2.5 Evaluation and validation

The results from the landslide susceptibility mapping need to be evaluated for accuracy. For this purpose, the collected landslide inventory is itself used by randomly splitting in two groups: one for analysis and one for validation (Regmi *et al*., 2014; Bui *et al*., 2014; Xu *et al*., 2012). The analysis is carried out in part of the study area or model and tested in another with different landslides. In literature, statistically, the accuracy assessment is carried by using error rates, receiver operating characteristics (ROC) curve, success and prediction rate curve and Area under curve (AUC) these curves (Regmi *et al*., 2014; Lee *et al*., 2007).

3. Case Study of 2015 Earthquake Region of Sindhupalchowk, Nepal

Nepal was hit by massive two earthquakes on 25th April and 12th May, 2015 with many aftershocks causing massive loss of lives and damage of properties. Sindhupalchowk and Gorkha district along with Kathmandu valley suffered much loss. The case study area is about 60 km away from capital and remote rural watershed located in Sindhupalchowk district of Nepal. It covers an area of 33 square kilometers, and lies between latitude 27°51'56.00"N to 27°56'38.00"N and longitude 85°49'18.00"E to 85°52'58.00"E (Fig. 1).

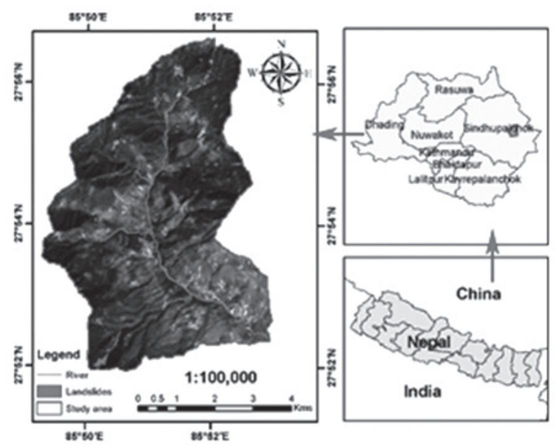

Fig. 1. Location map of case study area in natural colour Landsat 8 bands with landslide inventory

Even though the area is small, the area is sloppy and elevation ranges from 1079 to 3478 meters above sea level. The climate of the area is subtropical, temperate, and alpine having temperature range of 28.5 to 4.0 degree Celsius and average annual rainfall of 3604.3 millimeters of which 80% occurring in monsoon season. There is a high chance that the area will suffer from future landslides (Acharya *et al*., 2015). The area has six settlement areas inside it and two around the border which are at high risk of landslide at any time.

A total of 65 landslide events were detected in the area. The methods applied for the development of inventory can be found in Acharya et al. (2016). Out of the total landslides, 75% pixels were randomly selected for calculation of the frequency and remaining 25% were used for the accuracy assessment of the result. The controlling factors play very important role in determining landslide susceptibility. Hence, all the available and derived controlling factors namely: elevation, slope, aspect, curvature, plan curvature, profile curvature, dominant soil and annual rainfall and landuse (unsupervised) and NDVI (Normalized Difference Vegetation Index) derived from Landsat 8 acquired in 07th October, 2015 were used for the mapping. Fig. 2 shows the various controlling factors and their classes used for FR.

The susceptibility of landslide in any region can be estimated on the basis of the contribution of causative factors and the relationship between them. Here, we used the summation of FR of each controlling factors available. FR is the simplest spatial relationship between landslide occurrence and factors contributing it. It is then used to calculate the ratio of the cells with event occurrence in each class for a reclassified factor or categorical factor (i.e., geology and land use), and the ratio is assigned to each factor class again (Lee and Sambath, 2006). The FR of each factor's type or class, C, is then expressed by:

$$FR_c = P_c(P)/P_c(O) \qquad (1)$$

where, *P(P)* denotes the area ratio for the class or type for a given number of unit cells containing a percentage of pixels in the domain for the class, and *P(O)* denotes the percentage of occurrence in the total event.

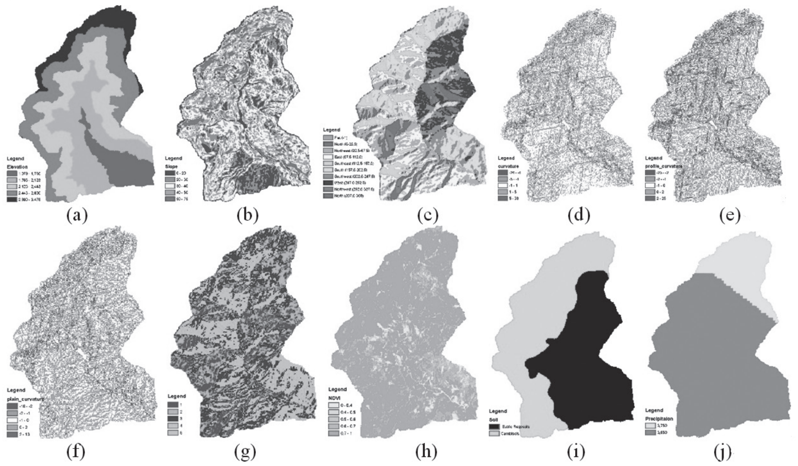

Fig. 2. Controlling factors maps of the study area: (a) Elevation, (b) Slope, (c) Aspect, (d) Curvature, (e) Profile curvature, (f) Plain curvature, (g) Unsupervised class, (h) NDVI, (i) Dominant soil, and (j) Annual rainfall

Using the probability model, the FRs for all the ten controlling factors were calculated as shown in the Table 1. The table shows the relationship between landslide occurrence and each factor, where the landslide are more abundant. The value 1 is an average value. However, when the FR value is greater than 1, then the percentage of the landslide area in the class is higher than the percentage of the class in the total area which indicates abundance of landslides occurrence and strong relationship with the factor whereas the value lower than 1 means a less frequent occurrence.

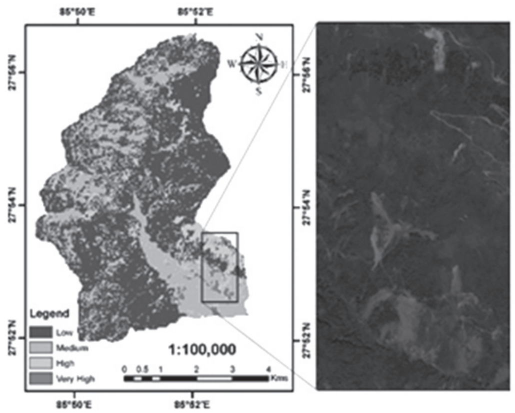

Fig. 3. Landslide susceptibility map using frequency ratio in case study area with Google Earth high resolution panchromatic image taken on 02 June, 2015

All the FRs were related to their class in raster layers, and finally the land susceptibility map was derived by summing up all the raster maps based on them. Fig. 3 shows the derived landslide susceptibility map of the study area. The result show that around 10% of the area belongs to high and very high risk of landslide.

For the evaluation and accuracy assessment of the result, the remaining 25% were used. The ROC (Receiver Operating Characteristic) curve was constructed and the AUC (Area Under the Curve) was used for the accuracy assessment of the results. AUC characterizes the quality of a forecast system by describing the system's ability to predict correctly the occurrence or non-occurrence of predefined 'events'. The model with higher AUC is considered to be the best, which with the value of 1 indicates a perfect model whereas 0 indicates a non-informative model (Lee and Sambath, 2006). The AUC showed that the accuracy of proposed model to be 86.54%, which indicated high production accuracy of the map in the study area. Similarly, the result have AUC value of 0.893 (Fig. 4), which exhibited a good performance.

In previous studies done on the area prior to earthquake cases showed higher risk in lower region of the Sindhupalchowk district (Acharya and Yang, 2015) and after the earthquake the risk has been increased. But in the case study areas, due to dense forest and lesser human interaction, the risk is low in much area. But the risky area are mostly

Table 1. Results of the frequency ratio model for each factors

Factors	Range	Total Pixel	Landslide Pixel	% Pixels of class	% Pixel of Landslide	Frequency Ratio (FR)
Elevation (meter)	1,079 - 1,765	4082	177	11.204	34.638	3.092
	1,765 - 2,123	8916	71	24.472	13.894	0.568
	2,123 - 2,443	10458	146	28.704	28.571	0.995
	2,443 - 2,800	9266	105	25.432	20.548	0.808
	2,800 - 3,478	3712	12	10.188	2.348	0.230
Slope (degree)	0 - 20	4616	41	12.669	8.023	0.633
	20 - 30	9011	90	24.732	17.613	0.712
	30 - 40	12678	175	34.797	34.247	0.984
	40 - 50	7580	143	20.805	27.984	1.345
	50 - 75	2549	62	6.996	12.133	1.734
Aspect	Flat	1124	7	3.085	1.370	0.444
	North	1959	13	5.377	2.544	0.473
	Northeast	5651	111	15.510	21.722	1.401
	East	5486	46	15.057	9.002	0.598
	Southeast	4981	79	13.671	15.460	1.131
	South	6535	146	17.937	28.571	1.593
	Southwest	5207	65	14.292	12.720	0.890
	West	3579	20	9.823	3.914	0.398
	Northwest	1912	24	5.248	4.697	0.895
Curvature	< -5	854	16	2.344	3.131	1.336
	-5 – -1	9013	178	24.738	34.834	1.408
	-1 – 1	16640	186	45.672	36.399	0.797
	1 – 5	9126	118	25.048	23.092	0.922
	5 – 33	801	13	2.198	2.544	1.157
Plan Curvature	-18 – -2	1446	27	3.969	5.284	1.331
	-2 – -1	3740	71	10.265	13.894	1.354
	-1 – 0	13126	183	36.027	35.812	0.994
	0 – 2	16675	207	45.768	40.509	0.885
	2 – 13	1447	23	3.972	4.501	1.133
Profile Curvature	< -2	2251	26	6.178	5.088	0.824
	-2 – -1	3917	63	10.751	12.329	1.147
	-1 – 0	12303	146	33.768	28.571	0.846
	0 – 2	15612	235	42.850	45.988	1.073
	2 <	2351	41	6.453	8.023	1.243
Landuse (unsupervised)	1	3612	23	9.914	4.501	0.454
	2	8263	58	22.679	11.350	0.500
	3	11068	66	30.378	12.916	0.425
	4	10046	62	27.573	12.133	0.440
	5	3445	302	9.455	59.100	6.250
NDVI	0.0 – 0.4	758	267	2.080	52.250	25.115
	0.4 – 0.5	1960	58	5.380	11.350	2.110
	0.5 – 0.6	4765	41	13.078	8.023	0.613
	0.6 – 0.7	14167	54	38.884	10.568	0.272
	0.7 – 1.0	14784	91	40.577	17.808	0.439
Dominant Soil	Regisol	17813	212	48.891	41.487	0.849
	Cambisol	18621	299	51.109	58.513	1.145
Annual Rainfall (mm)	3750	6556	88	17.994	17.221	0.957
	3850	29878	423	82.006	82.779	1.009

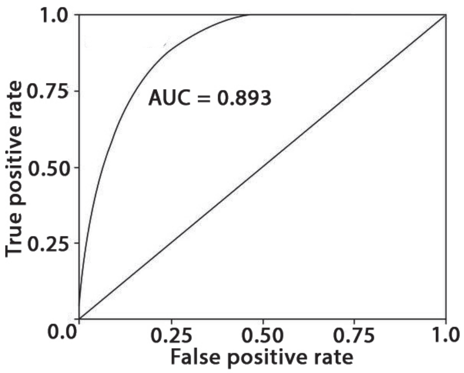

Fig. 4. ROC curve of the FR model

found to be settlement areas or open space and road lines. The map could be used by local public and decision makers as basic information for slope management and land use planning in such areas to reduce future damage by means of prevention and mitigation.

3. Conclusion

Landslides susceptibility mapping are very important for the purpose of decision making process for prevention and reduction of loss and management process. Researchers all around the world are using various methods to understand the spatial distribution of occurred landslide events and predict the probability of occurrence with relation to the controlling factors. A reliable landslide susceptibility map requires good selection of area under study, complete landslide inventory, proper modelling with respect to controlling factors. Yet, there are many part of the world not studied. Also, there is no certain agreement on accurate assessment methodology. Moreover, the frequency of landslides are increasing due to increasing human activates and changing climate change. Under such situation, more studies are needed; more accurate models are to be developed. In this work, a case study of landslide susceptibility map in Sindhupalchowk area, Nepal where, massive earthquake hit in 2015, was developed using FR. It showed the risk in certain specific areas. Continuous update and increase in accuracy of these maps could help prevent huge damage and mitigate loss. With advancing technology and researches, more regional and global real time susceptibility maps can be produced in near future.

Acknowledgment

This work has been supported by 2015 Research Grant from Kangwon National University.

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