Landslide Susceptibility Mapping Using Logistic Regression in Garut District, West Java, Indonesia

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ABSTRACT: Landslides are one of the major disasters that affect human settlements, especially in hilly regions. The mapping of Landslide Susceptibility is an important aspect of the decision making process in order to reduce the landslide's effect on human settlements. In this paper, we discuss one of statistical approaches which is known as Logistic Regression to map Landslide Susceptibility. This analysis was extended further to assess Population Exposure to Land Slide Susceptibility using gridded population data. "Garut District" which is located in West Java, Indonesia was used as a study area to demonstrate the applicability of this method. In this study area the Aspect, Lithology and Slope was discover as most contributing factors to the Landslide Susceptibility. Additionally, the large coefficient value of the "Distance from Fault" factor justify the fact that prominence of Seismically Induced Landslides in this Study Area.

1. INTRODUCTION

Landslides are complex geological phenomena. They have a significant impact on human settlements, especially in hilly regions. Landslides mostly result from triggering events, like earthquakes, intense rainfall, and snow melt. Besides triggering events, other factors can be responsible for the possibility of the occurrence of landslides in a particular location, including geology, land cover, slope geometry, surface and subsurface hydrology, and the role of people (Regmi et al., 2013). Assessment of the contributions from all these factors to determine the probability of a landslide occurrence is known as landslide susceptibility mapping.

The mapping of the landslide susceptibility help decision makers to make proper decisions to minimize the damage from landslides on humans and resources. Mainly there are 3 approaches to create landslide susceptibility maps: (1) the deterministic approach, (2) the qualitative or heuristic approach, and (3) the probabilistic approach (Regmi et al. 2013). The deterministic approach is based on modelling the slope instability with physical equations based on slope geometry, material, forces, etc. The qualitative / heuristic approach is based on expert judgement, which is a subjective approach. The probabilistic approach, which we are using in this paper. uses the statistical relationship between historical landslides with responsible factors in order to assess susceptibility.

There are many statistical methods in the literature for the the landslide susceptibility mapping including a neural network, logistic regression, etc. Basically, all approaches use some kind of curve fitting methods. Logistic Regression analysis is well known to be one of the most popular approaches which has been well explored in the literature with respect to landslide susceptibility (Chen and Wang, 2007; Lee and Sambath, 2006; Lee and Pradhan, 2007).

The output values of logistic regression model maps are values from zero to one (Akbari et al., 2014). This property of the logistic regression model make it ideal for the model's probabilities of occurrence. Additionally, it is easy to model and easy to understand the effect of the parameters, and it is available in many commonly used data analysis software programs (MATLAB, R, SPSS, etc.) as a readymade tool. The model for logistic regression is explained below;

$$p = \frac{e^u}{1 + e^u}$$

where p is the output of the model which is the probability of a landslide occurrence, and u is the independent variable which is a linear combination of the contributing factors (for example, the slope, geology, land cover, etc.). β1, β2, β3, etc. are corresponding coefficients to each of the respective contributing factors which indicate their contribution to landslide susceptibility. A graphical representation of the logistic regression is shown in Figure 1.

$$u = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \dots \dots$$

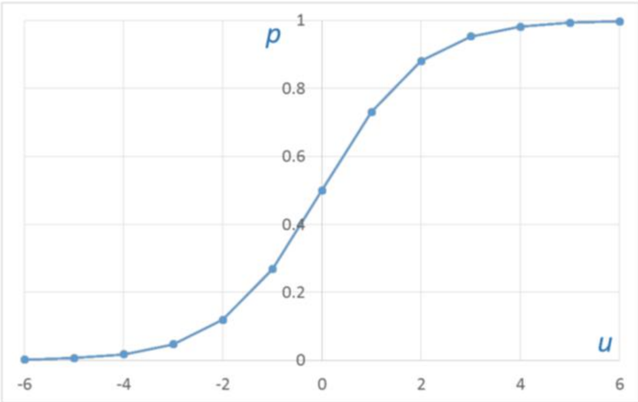


Figure 1: Logistic Regression Model

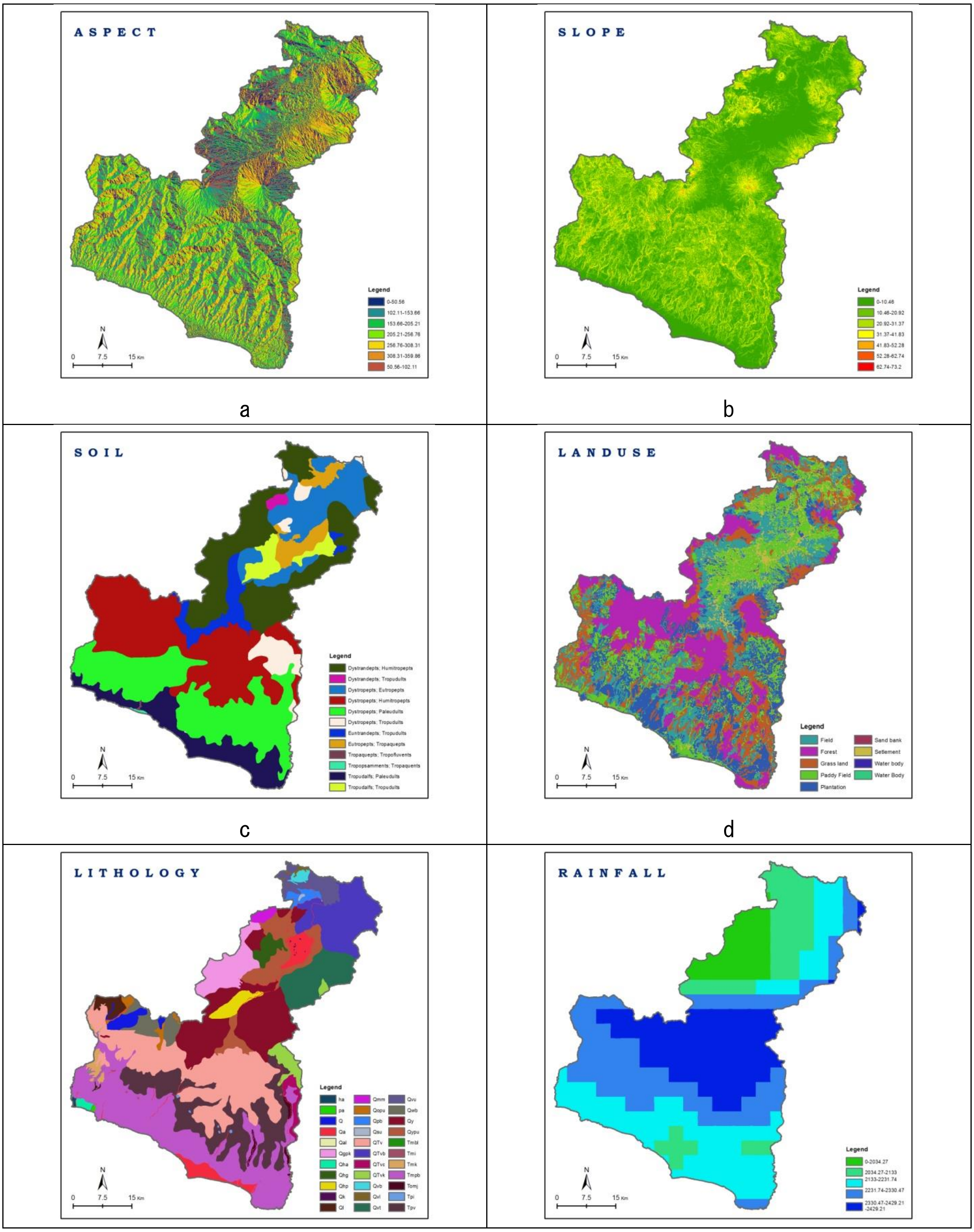
Indonesia is a large country with a special location between the Pacific Ocean and the Indian Ocean, and it is on a tectonic boundary. Due to this special location, Indonesia is prone to a large number of geological hazards and hydro-meteorological hazards. Based on the Agency for Disaster Management, Indonesia, (BNPB) data (dibi.bnpb.go.id), during the period from 2014 to 2015 there were 1,229 hazards, (30.9 % - landslides, 30.1% - hurricanes and 28.8 % - floods). In this paper, logistic regression was applied in a district in Indonesia to map the susceptibility to landslides which are a significant hazard in Indonesia.

2. STUDY AREA AND DATA USED

The study area for this analysis is Garut District which is located in West Java Province in Indonesia, with a population of 2,585,423. It covers an area of 3,074.07 sq.km. and geographically it lies between 6°57′ 34″ – 7°44′ 57″ south latitude and 107°24′ 34″ – 108°7′ 34″ east longitude (Wikipedia, 2016). According to the BNPB, Garut District is one of the high risk districts for landslides in Indonesia.

Figure 2. Study Area (Garut District)

The land use, soil, lithology, administration boundary roads, and river data were obtained through Indonesian Basemaps which were published by the respective government organizations. Rainfall data was obtained from JAXA GSMaP Satellite Rainfall which is freely available on the Internet. Additionally, elevation related maps were obtained from the SRTM digital elevation model which is freely available on the Internet. The most important component of landslide susceptibility mapping which is a landslide inventory map was created by digitizing historical landslides using Google Earth. Gridded population data for the final product (the population exposure to landslides) were obtained from the WorldPop project (WorldPop, 2016) data which are freely available on the Internet and which were gridded in 100m spatial resolution.



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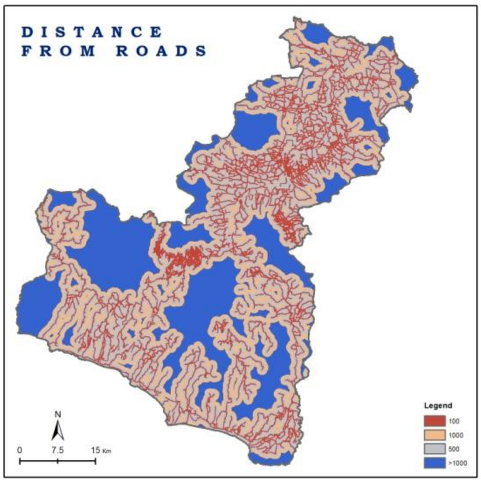

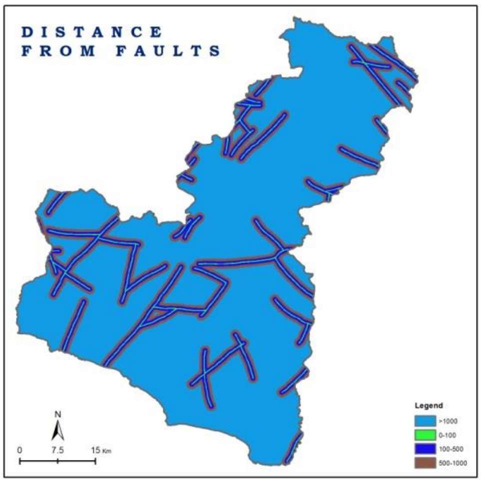

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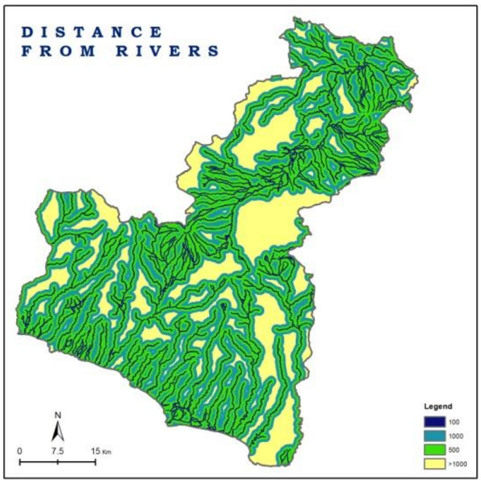

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Figure 3. a) Aspect map. b) Slope map. c) Soil map. d) Landuse map. e) Lithology map. f) Annual rainfall map. g) Distance from roads map. h) Distance from faults map. i) Distance from rivers maps

3. METHODOLOGY

All the data (Figure 3) which were obtained from various sources were pre-processed in the GIS environment in order to have the same extents, spatial resolutions, projections, etc. After that, a GIS buffering operation was used to generate different distance classes from the faults, rivers and roads layers. The lithology, landuse and soil layers were used as they are. The aspect and slope layers were prepared using a digital elevation model (SRTM). There is a detailed explanation of this workflow in Figure 4.

As a first step of the logistic regression, weights were assigned to the classes in each layer using the weight of evidence method (Regmi et al., 2013). Finally, those weighted layers were fitted with historical landslide locations using the logistic regression model. Later, this fitted logistic regression model was used to predict landslide susceptibility in the study area. The product of the logistic regression process which is the landslide susceptibility map (the probability of a landslide occurrence) is shown in Figure 5 by classification into 4 classes of landslide susceptibility. The table of the coefficients of the logistic regression model is shown in Table 1. A high value of a coefficient of a particular parameter indicates that, that parameter has a higher influence of landslide occurrence, whereas a lower coefficient indicates a lower influence.

Finally, in order to assess the influence of landslide susceptibility on the human population, a landslide population exposure map (Figure 6) was produced by multiplying the population layer by the landslide susceptibility layer. The rationale behind that is that, if the population is low and the susceptibility is high, the impact of a landslide on the population is less; and if the population is high and the susceptibility is high, the impact of a landslide is high, vice versa.

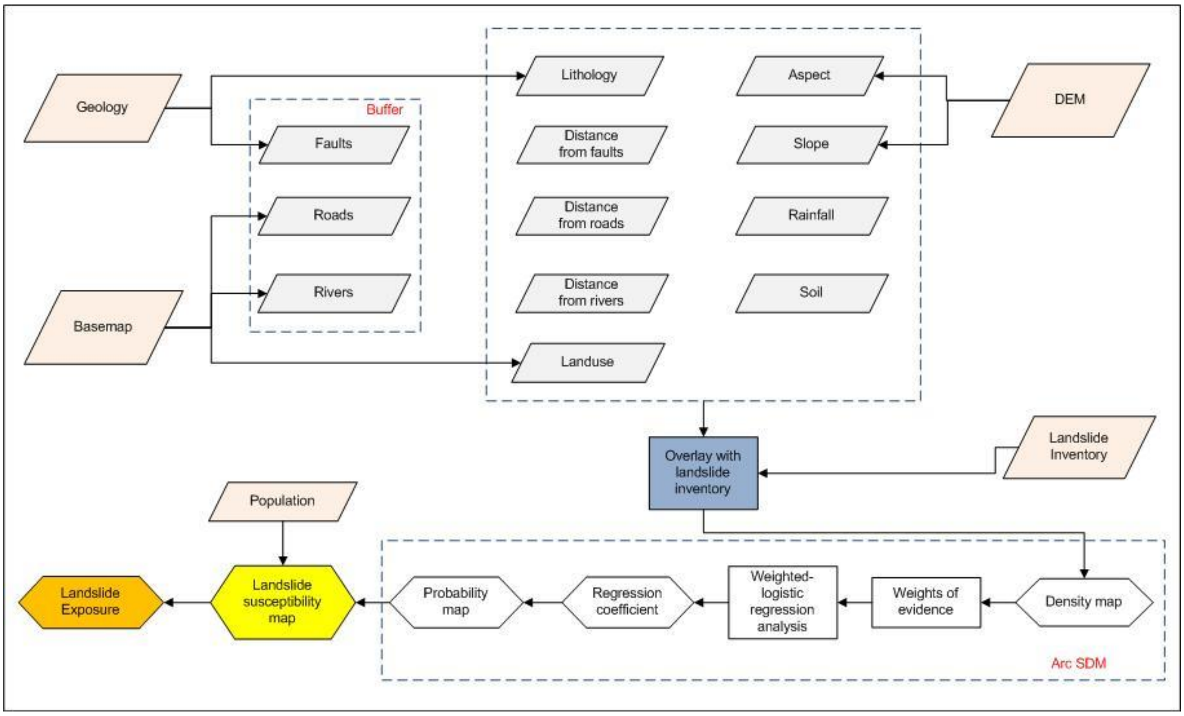

Figure 4. Flow chart of landslide susceptibility mapping

4. RESULTS

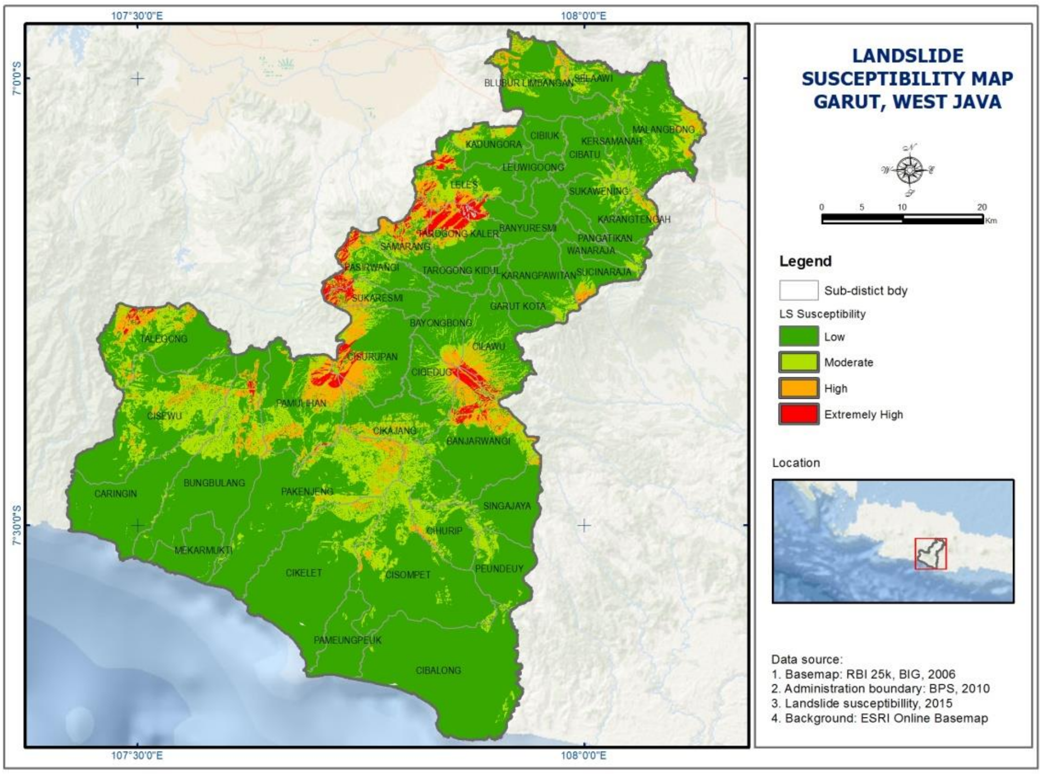

Figure 5. Landslide susceptibility map of Garut District.

Table 1. Coefficient of logistic regression for each layer

Parameter	**Coefficients of Logistic Regression**
Aspect	0.6519
Lithology	0.6320
Slope	0.5489
Distance from fault	0.4992
Landuse	0.4961
Soil	0.2844
Annual rainfall	0.1463
Distance from river	0.0329
Distance from roads	0.0053

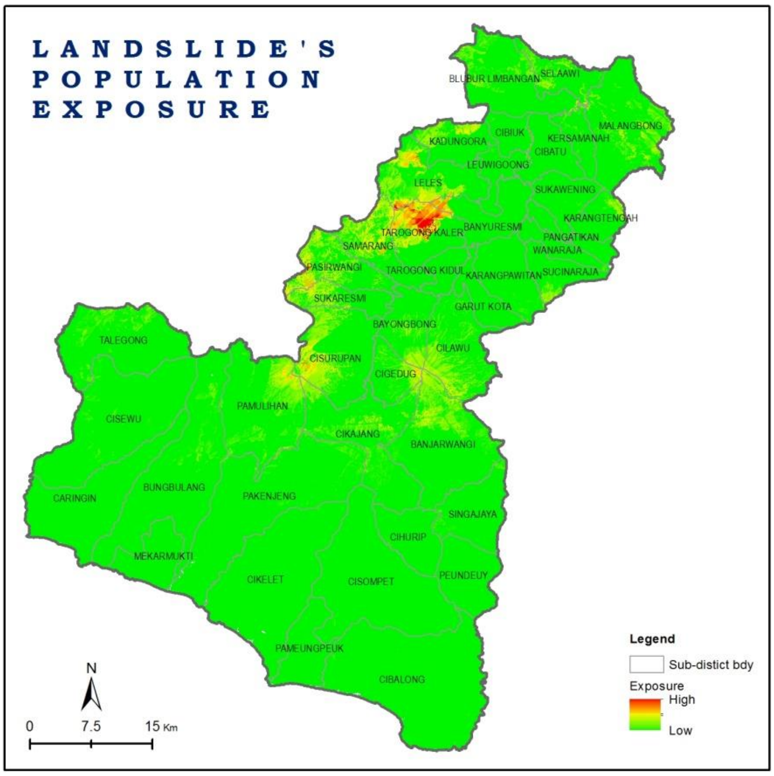

Figure 6. Population's exposure to landslides in Garut District.

5. CONCLUSION AND DISCUSSION

According to the coefficients of the logistic regression model, we can conclude that aspect, lithology, slope, distance from the faults and landuse are the most significant factors that control the susceptibility of the study area to landslides. Additionally, the lowest coefficients correspond to the distance from roads and rivers parameters, which can be insignificant in this study area.

In the case of the population's exposure to landslides in the study area, we can conclude that Targong Kaler, Pasirwangi and Samarang are three kecamatan (an administrative unit lower than a district in Indonesia) with a high population exposure to landslides in Garut District.

Visual inspection of the results from the logistic regression model provides similar results to the map of potential landslide zones produced by Indonesian government agencies. The high coefficient value for distance from faults in the model is evidence that most of the landslides in the study area are seismically induced landslides rather than rainfall induced landslides (there is a low coefficient for annual rainfall).

The inability to find a well distributed landslide inventory map is the main limitation of this study. However, in this study area, we were able to digitize a significant number of landslides using Google Earth due to large scale and frequently occurring landslides in the study area. Since, in order to statically represent all layers in the model, it's essential to have large number of landslide inventory data, distributed among all classes of all layers. If a study area has low frequent and small scaled landslides, it will be very challenging to extract landslides from Google Earth. In those cases, if available, use of country's Disaster Agency's historical landslide information is recommended.

In conclusion, we can conclude that logistic regression can be used as successful tool to map landslide susceptibility in areas which have well distributed landslide inventory data with significantly less effort.

6. RECOMENDATION

As a recommendation, it is recommended that a well distributed landslide inventory map that can capture the probability of landslide occurrences in different classes is essential for logistic regression analysis. In cases where an adequate landslide inventory map is not available, it is better to rely on the deterministic approach (based on a physical model) or the qualitative / heuristic approach (based on expert judgement) rather than on statistical approaches.

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