LANDSLIDE PREDICTION USING REMOTE SENSING AND GIS -A CASE STUDY OF KOSLANDA, SRI LANKA

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ABSTRACT: Landslides are one of the major natural and widespread geological hazards occurring in all over the world in every year. In the recent past, various landslide events have taken place in several regions in Sri Lanka due to a long spell of rain. It generates lots of fatalities and financial losses than the any other type of natural disasters as flood, cyclones, droughts, wind storms, coastal erosion and sea level rise. Thus, predicting the areas that are susceptible for landslides is essential for the purpose of effective land-use and disaster management activities in Sri Lanka. Koslanda is the most vulnerable area for landslides in Uwa Province of Sri Lanka and recently more devastating landslides are occurred resulting more damages to the human life and property. Hence, this area is selected as the study area for the landslide prediction modeling.

With the recent developments of satellite images with high resolution, image analysis techniques and Geographical Information System (GIS) for spatial data analysis, variety of application using remote sensing and GIS as tools are emerging. The goal of this study is to generate landslide prediction models by using bivariate and multivariate statistical analysis on the thematic maps produced in GIS and remote sensing environment. Basically, the topographical, hydrological, land cover and soil factors are considered in order to determine the landslide susceptibility regions. The prediction levels of susceptibility regions are distinguished and categorized in to four susceptibility classes as Very low, Low, Moderate and High. Currently, the statistical methods are more applicable for landslide prediction than the qualitative approaches. Hence, the Information Value method (InfoVal method) as a bivariate and Multi Criteria Decision Analysis (MCDA) based on the Analytical Hieratical Process (AHP) as a multivariate statistical analysis had been performed.

The InfoVal method combines the failure map with each thematic map to determine the weight of influence on terrain susceptibility for each parameter class. Integration of all weights of influences determines the terrain susceptibility levels for the landslides. The AHP is the structured technique for analysing and weighting multi criterions through the pair wise comparison. Hence, each thematic map are analysed through the MCDA based on the AHP theoretical concepts. Discretized landslide susceptible regions from InfoVal method and MCDA based on AHP are validated by using the relative failure density values generated from the validation samples in the failure map. Finally, as this research depict, despite their simplicity, bivariate statistical methods have more acceptable precision than multivariate methods, and consequently, they are more compatible with the landslide prediction modeling. Therefore, the result of this study can be used in the preliminary hazard mapping and selecting suitable location for future land use planning.

1 INTRODUCTION

Landslides are one of the major types of geo-hazards in the world as almost 09% of global natural disasters are recorded as landslides (Chalkias, et al., 2014). The recent statistics of landslide disasters per continent from year 2000 to 2016 are summarized in the Emergency Disaster Database (EM-DAT) as the landslides cause around 14000 deaths and 4 million people affected in worldwide, with property damage of about US $3 million (OFDA/CRED, 2016).

The spatial prediction of landslide disasters is one the important field of geo-scientific research incorporating statistical analysis (Park, et al., 2013). The aim of this study is to identify areas that are susceptible to future land sliding, based on the knowledge of past landslide events and topographical parameters, geological attributes and other possible environmental factors. Through the most recent technological developments of satellite remote sensing in the field of temporal, spectral, spatial, global coverage and the availability of such images in low cost or free and the advanced tools developed in image analysis techniques and GIS for spatial data analysis, variety of applications using remote sensing and GIS as tools are promising (Reis, et al., 2012).

Sir Lanka is a tropical island contains mountains in the central region. Every year, Sri Lanka experiences landslides, resulting in property damage and casualties during winter months due to two monsoons. The combination of the geological formation, improper land use practices and heavy rainfall has caused for irregular landslides throughout the hill country. Approximately 20% of the area from 65,000 km2 of total area in Sri Lanka was identified as the landslide susceptible areas by the National Building Research Organization (NBRO) as the nodal governmental agency engaged in landslide studies in Sri Lanka. These landslide prone areas are spread over in Badulla, Nuwara Eliya, Kandy, Matale, Ratnapura, Kegalle, Kalutara, Galle, Matara and Hambantota districts. Investigations carried out by NBRO indicate that the haphazard and unplanned land use, inappropriate construction methods and wanton human intervention have led to an increase in landslide susceptibility in Sri Lanka (NBRO, 2016).

Koslanda in Badulla Districts, Uwa Province of Sri Lanka is a significant area in the memories of the people due to its high sensitivity of devastating landslides recently. Although there are a number of studies which have done to evaluate the sensitivity of the area to the landslides, most of them have done without considering several prominent factors as soil moisture, topographical wetness and ignoring sophisticated statistical techniques.

At present, the statistical methods are more appropriate for landslide prediction analysis than any qualitative approaches. Hence, this study aims to use InfoVal method as a bivariate and MCDA based on AHP as a multivariate statistical analysis for the landslide prediction modeling in Koslanda area. Remote sensing images and the DEM derived from aerial triangulation are make use as the major tool for spatial data extraction and spatial prediction analysis are performed through the GIS techniques.

1.1 Study Area

Koslanda is located in the geographical coordinates of 6° 44' 0" North and 81° 1' 0" East and is a remote or hilly area with geographically difficult access facing many hard weather conditions. Badulla is the capital of Uwa province and is approximately 28 km away from Koslanda. The distance from Koslanda to the Colombo where the capital of Sri Lanka is approximately 131 km. The population is around 5000 peoples and most of them are working in tea states. Koslanda is one of the most beautiful valleys in Sri Lanka, being the home for the breathtaking waterfall of Diyaluma being the sixth highest waterfall in the world. The study area consists of around 19 Km^2 from the Koslanda area (See Figure 1).

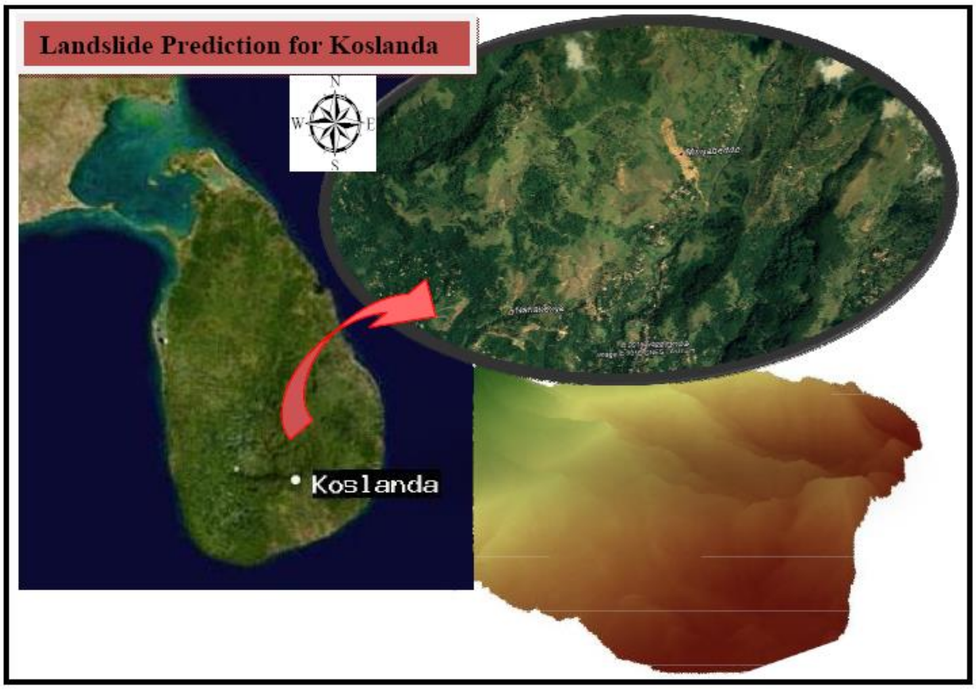

Figure 1 : Study area of the research

With the recent memories of the devastating landslides occurred in Sri Lanka in year 2014, Meeriyabedda landslide and Naketiya landslide in year 1997, many landslide research studies are led to consider the Koslanda area as the study area. Even though the area is most significant in the phase of tourism with beautiful cultural heritage, due to its topographical and geomorphological formation, the area is more vulnerable to natural disasters as landslides, rock falls, rock slides and cutting failures particularly in the heavy rainy season (SAARC, 2010).

Central mountains and south-eastern hilly regions in Sri Lanka are naturally landslide prone areas because of their geological characteristics and high monsoonal and inter-monsoonal prolonged rainfall. Further, the unplanned land clearing for tea and other plantations, forest degradation, changing the existing natural drainage patterns and dramatically reduced vegetation covers, improper management of land use and land cover make far larger areas are more vulnerable to Landslides. Further, the NBRO have revealed that the landslide frequency has been increased in the Badulla district especially with the increases of human activities, deforestation and unplanned developments in hilly areas (DMC, 2010; Bandara, 2005).

2 DATA AND METHODOLOGY

Collection of data from different sources and construction of a spatial database for them in a common platform are the most important phases in landslide prediction analyses (Lan, et al., 2004). Preliminary data acquisition, processing stages for the spatial database and the methodological flow followed through this study are discussed in this section.

2.1 Data

Basically the data include the topographical, hydrological, soil and land cover factors for this landslide prediction analysis. All factors are derived from Landsat-8, digital data and DEM derived from aerial triangulation. 1993 stereo aerial photographs are used to generate the DEM from the aerial triangulation. Imagine photogrammetry tool from ERDAS Imagine 2014 (Earth Resource Data Analysis System) software is used. Camera calibration, interior orientation, exterior orientation by using 25 Ground Control Points (GCPs) are performed in order to generate the DEM from aerial triangulation. Band 5(Near Infar Red (NIR), 30m resolution), band 4(Red, 30m resolution) and band 11 (Thermal, TIR-2, 100m resolution) of Landsat-8 image on 03rd July 2015 is processed for extracting the soil moisture index in the Thermal-NDVI space.

An inventory map of landslides for the study area was constructed by integrating the interpretation of multi-temporal aerial photographs, satellite images, and some directions from the Google earth. All the verifications are carried through the field investigations.

2.2 Methodology

Landslide inventory map and the topographical, hydrological, soil and land cover factors are processed in order to gain the landslide susceptible areas from bivariate and multivariate statistical analysis. The general flow chart shown in Figure 2 gives a quick look into the overall set up of this study to achieve for the expected outcomes. Topographical factors, elevation, slope and aspect are derived from DEM and to calculate the Topographical Wetness Index (TWI) as soil factor, the same elevation data from DEM is utilized. The NDVI and the thermal information derived from Landsat-8 image is used for extracting the Soil Moisture Index. Land use/cover and water bodies are obtained from the digital data available in 1:10000 scale. Afterwards, the landslide inventory map and the derived causative factors (topographical, hydrological, soil and land cover) are cross-checked to calculate the weight index for the landslide susceptibility predictions.

Validating the results of predictions are paramount important to confirm the significance of the analysis and the results. In this research, the landslide failure map derived from previous landslide occurred in this study area are separated in to two independent samples as training and validating. Training samples are used to generate the landslide susceptibility regions and the validation samples are for validating results from the landslide prediction analysis (Remondo, et al., 2003; Saha, et al., 2005).

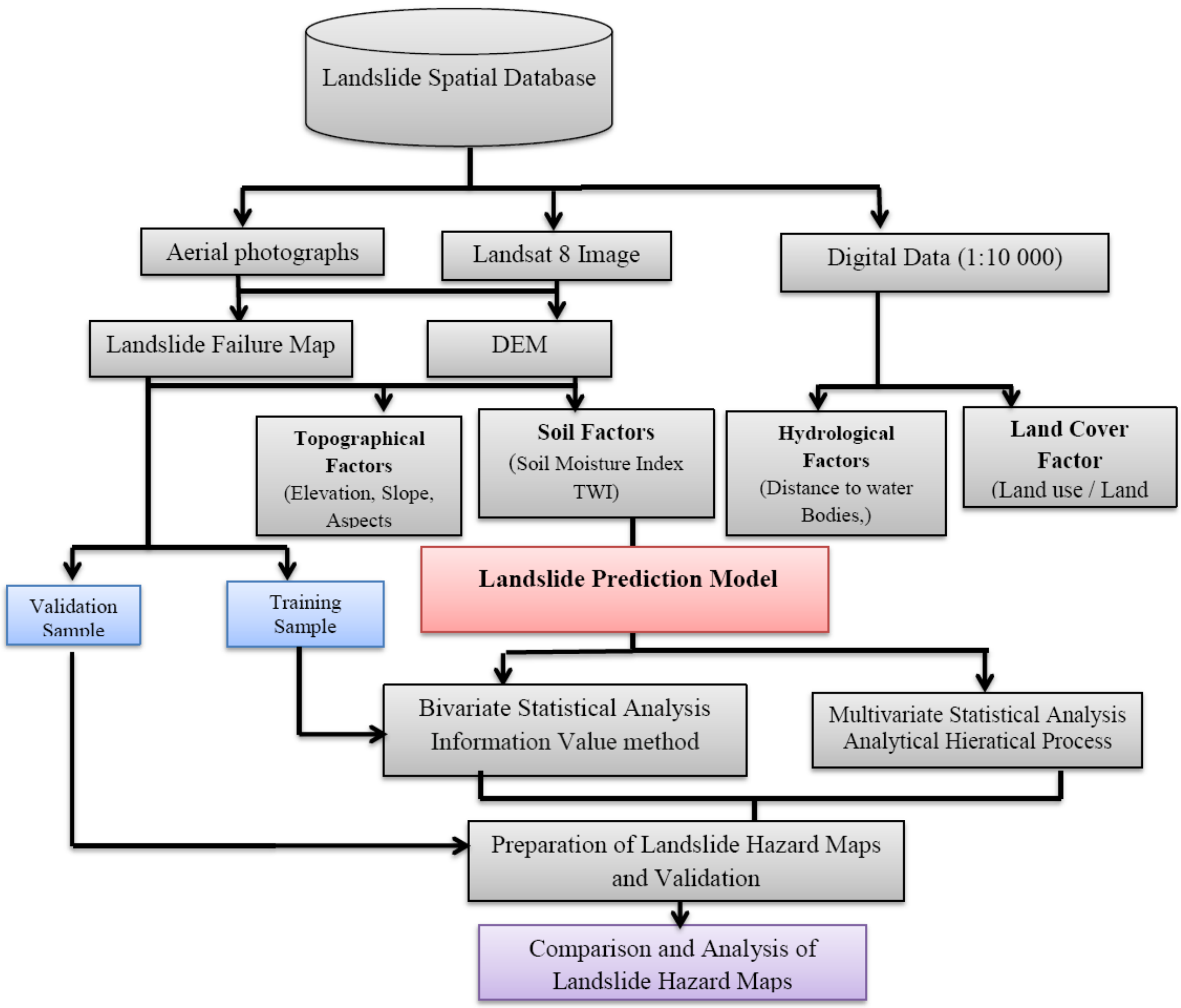

Figure 2 : Methodological flow of the landslide prediction using bivariate and multivariate techniques

3 SELECTED FACTORS TO IDENTIFY LANDSLIDE SUSCEPTIBLE REGIONS

Landslides might occur as a consequence of a number of predisposing and triggering factors. In this research, the predisposing factors were selected by considering among the most widely used in literature and opinions from the experts. Most data are derived as primary data from remote sensing techniques for a large area with acceptable accuracy and up to date information. Basically, seven predisposing factors are selected for the landslide susceptibility analysis by using bivariate and multivariate statistical techniques.

Table 1: Selected predisposing factors for landslide prediction analysis

Factors	
Main Factors	**Sub Factors**
Topographical	Elevation
	Slope
	Aspect
Soil	Soil Moisture Index
	Topographical Wetness Index
Hydrological	Distance to Water Bodies
Land cover	Land Cover Type

3.1 Topological Factors

Basically, the topographical factors include elevation, slope and aspect properties of the terrain. The elevation of the study area is ranging from 446m -1547m from the Mean Sea Level. Since the area contains high mountains more than 1000m difference of elevation can be seen. Slope of the area also increased significantly from 0^0 to 80^0 degrees. However, the area with steep slopes from 60^0 - 80^0 are in the northern part of the study area. Aspect is the compass direction that a slope faces and many regions from the study area are from south-east and north-west oriented.

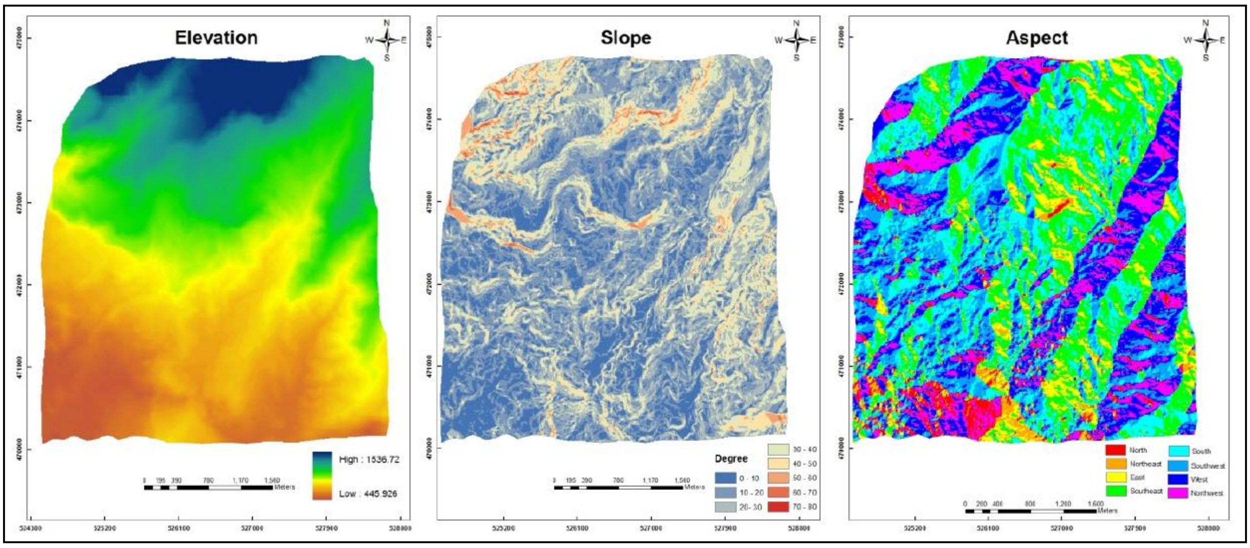

Figure 3 : Selected Topographical factors as Elevation, Slope and Aspect that are used in the landslide prediction analysis

3.2 Soil Factors

The soil factors selected in this study are Soil Moisture Index (SMI) and Topographical Wetness Index (TWI). Surface soil moisture is one of the most important parameters in land susceptibility analysis. The use of remotely sensed data is potentially of great interest and prominently used. Several methods have been proposed to estimate the surface soil moisture conditions accurately with in situ measurements. However, these methods are time consuming and costly with respect to the study of larger area in smaller scale. Hence, this study uses the detection of SMI using surface temperature (T) and vegetation index (NDVI) derived from Landsat-8 image bands.

The combination of T-NDVI space is the most widely used and has been successfully employed to determine the soil moisture information. In this space, surface temperature is primarily determined by soil moisture emitted from the land surface and vegetation index (NDVI) is determined by land-surface reflectance. The combination of these two variables (T and NDVI) from remotely sensed measurements apparently carries information about soil moisture under different vegetations expressed by NDVI. The SMI is "0" along the dry edge and "1" is along the wet edge. SMI can be defined as $SMI=(T_{max}-T)/(T_{max}-T_{min})$, where T_{max}, T_{min} are the maximum and minimum surface temperature for a given NDVI and T is the remotely sensed data derived surface temperature at a given pixel for a given NDVI (Zenga, et al., 2004). Calculated soil moisture index is ranging from -0.08 to 1 and describes the high indexes are scatter in the top of mountains [See Figure 4 (a)].

TWI is a solid index that is capable of predicting areas susceptible to saturated or wetted land surfaces and areas that carry the potential to produce overland flow. TWI has been used to study spatial scale effects on hydrological processes. TWI can be defined as $TWI=\ln[\propto/\tan\beta]$, where $\propto$ is the local upslope area draining through a certain point per unit of contour length, and β is the local slope gradient in degrees. The best results can be achieved from high resolution DEMs [See Figure 4 (b)].

3.3 Land use/ cover

Basically, the main land use covers existing in this study area are identified as tea, scrub, forest, rock, paddy, water and residential. Land use covers are extracted from 1:10 000 digital data available from survey department of Sri Lanka. Frequently, such images are updating by the survey department of Sri Lanka by field verifications. Mainly the tea and scrub areas are prominent in this study region with some forest covers and residential. Scrub are typically abundant tea states and residential are rooms from tea workers [See Figure 4 (c)]. It is very clear that most of the devastating landslides in this area are occurred in the abundant tea states. Hence, main reason of occurring such landslides are basically because of the lack of proper land use management in this area.

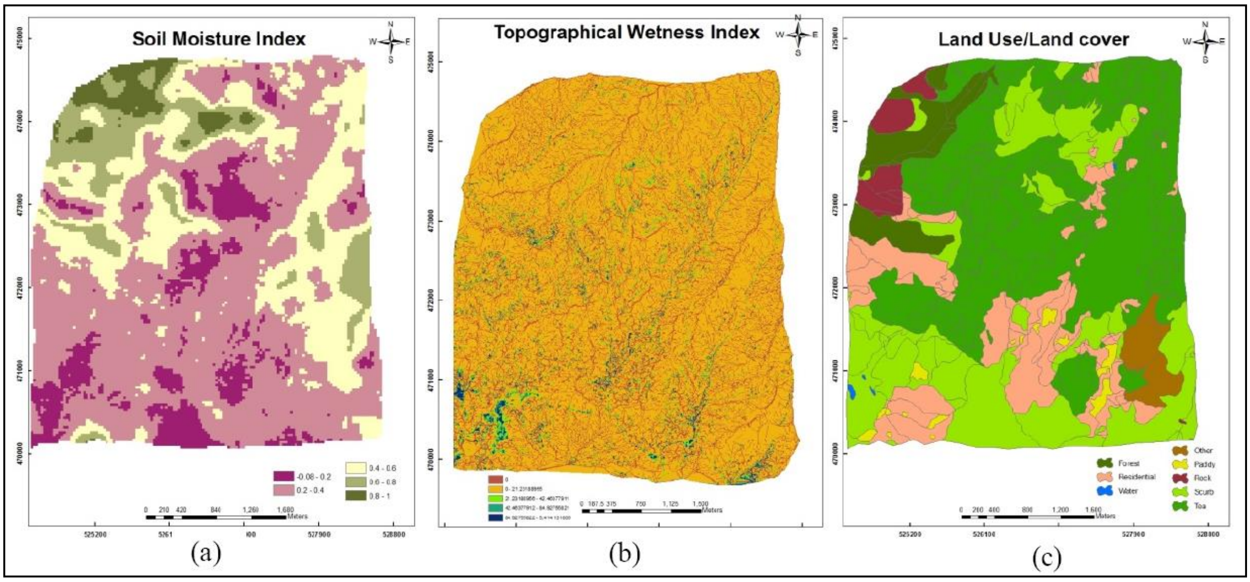

Figure 4 : Soil Moisture Index (SMI), Topographical Wetness Index (TWI) and Land use/ cover used for land prediction analysis

3.4 Hydrological Factors

Closeness to the hydrological features are also an important factors when considering the landslide susceptible analysis. Hence, this study investigated the weight of affection of this parameter for the landslide prediction analysis. The Eruwendumpola Oya river is along the valley in lower slope of the study area and debris flow materials from Meeriyabedda landslide was finally accumulated to this river. In fact, there are many small streams and drainages are spreaded and run along from top of the mountainous regions to the down. So, the area closeness to the hydrological features are also added for this landslide prediction analysis [See Figure 5].

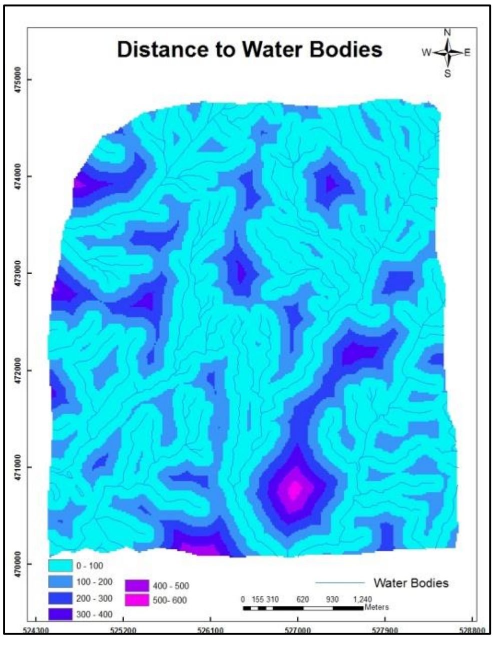

Figure 5 : Distance to water bodies in the study area

4 BIVARIATE METHOD FOR LANDSLIDE PREDICTION

In bivariate probability models for the landslide prediction, the susceptibility at each point or pixel is jointly considered the weight of influence of landslide susceptibility in all input factors. When constructing a probability model for landslide prediction, it is necessary to assume that landslide occurrence is determined by landslide-related factors, and that future landslides will occur under the same conditions as past landslides. After decisive analysis of types of factors that utilized in the same previous research studies and seven basic relevant factors are selected.

Many research studies have been proposed the Information Value (InfoVal) method for landslide prediction analysis (Guinau, et al., 2007; Saha, et al., 2005; van Westen, et al., 1997). This method combine the landslide failure map from landslide inventory with each selected predisposing factors as thematic maps to determine the weight of influence on terrain instability for each factors. The failure map only training samples are used in this overlapping. The Information Value method can be defined as;

$$Wi = Log\left(\frac{Densclass}{Densmap}\right) = Log\left(\frac{Npix(Si)/Npix(Ni)}{\sum_{i=1}^{n} Npix(Si)/\sum_{i=1}^{n} Npix(Ni)}\right) \quad (1)$$

Where Wi is the weight given to the ith factor class of a particular predisposing factor, $Densclass$ is the failure density in the factor class and $Densmap$ is the failure density in the whole thematic map. $Npix(Si)$ is the number of landslide pixels in the ith factor class, $Npix(Ni)$ is the number of pixels in the ith factor class and n is the number of classes in a predisposing factor. The Log function is used to control the large variation of weights in calculations. The weight of influence for each factor type are calculated from its relationship to landslide events using training samples of landslide failure map. Larger the weight of influence is, the stronger the relationship between landslide occurrence and the given factor's attribute. Finally all thematic maps with weights of influence are added to obtain the contribution of all predisposing factors for landslide susceptibility analysis. The whole study area is then discretized in to four classes as 0%, 10%, 30% and 60% of failure regions for very low, low, moderate and high susceptibility classes respectively [See Figure 6].

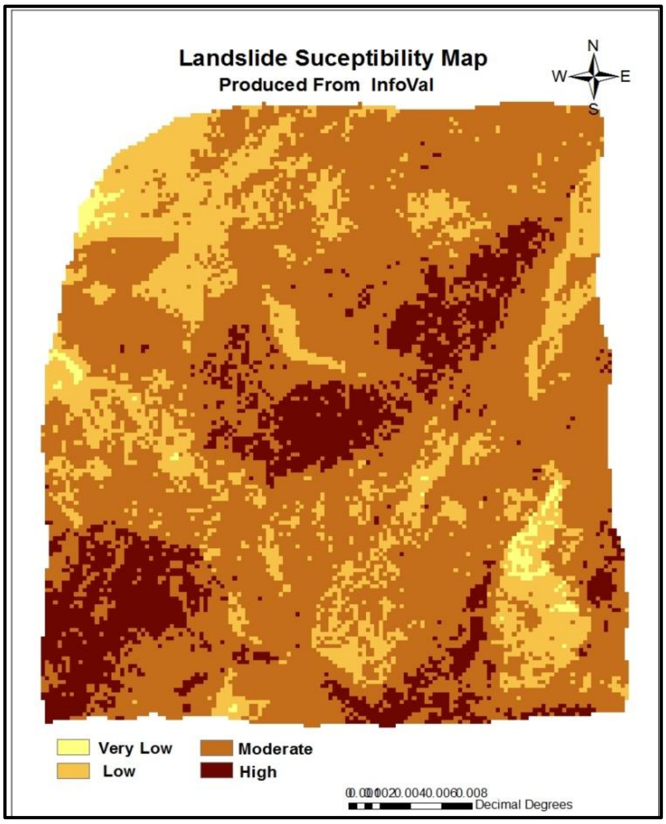

Figure 6 : Landslide Susceptibility map from bivariate Information Value Method

15% for high, 65% for moderate, 19% for low and 1% for very low susceptible regions are identified from the bivariate information value method. Hence, 80% areas from the total study area are predicted as the high and moderate susceptibility for landslide hazard. Very steep slope mountains in the North West region is identified as low and very low susceptibility areas as the area was free from historical landslides. Basically the middle regions with 30^0-50^0 slope are detected as high probability for landslide occurrences with the past experience from Naketiya and Meeriyabedda landslide.

5 MULTIVARIATE METHOD FOR LANDSLIDE PREDICTION

In multivariate analysis, same seven predisposing factors are used to investigate the landslide susceptibility regions from AHP technique in GIS domain. Theoretical concepts in the AHP technique are used for weighting each factors and weighted overlay is performed in order to obtain the landslide susceptibility regions by integrating all selected factors.

The AHP provides an effective means to deal with complex decision making. It can assist with identifying and weighting of multi criteria, analyzing the collected data, and expediting the decision making process (Saaty, 1980). In AHP, each pair of factors in a particular factor group is examined at a time, in terms of their relative importance. Relative weights for each factors were based on a questionnaire survey from field of expert. Slope, elevation, aspect, SMI, TWI, land use and distance to water bodies are 0.338, 0.05, 0.027, 0.152, 0.073, 0.245 and 0.115 respectively. Finally, multi criteria decision making using AHP theories, multivariate approach is performed to obtain the landslide susceptibility regions for the study area. As in the bivariate method, the whole study area is discretized in to four classes as 0%, 10%, 30% and 60% of failure regions for very low, low, moderate and high susceptibility classes respectively [See Figure 7].

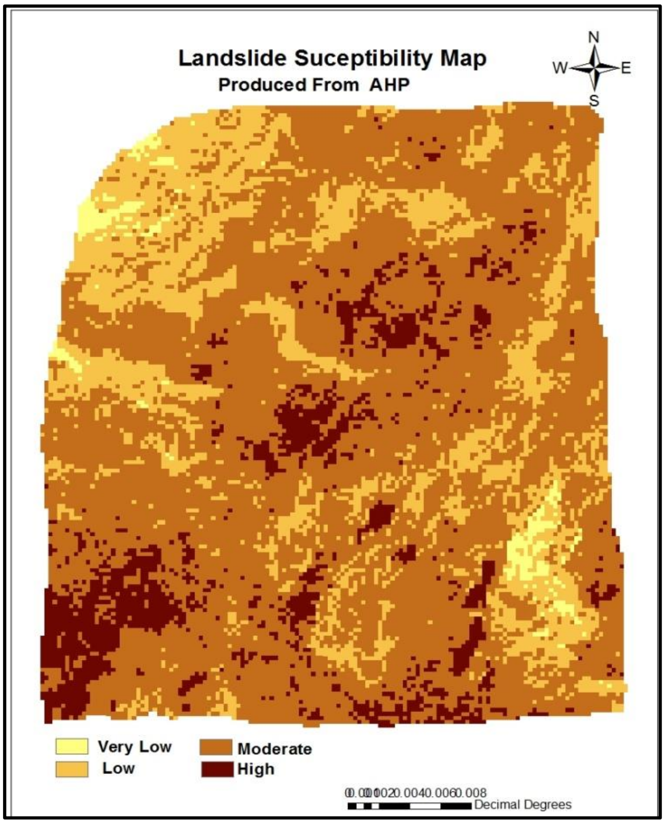

Figure 7 : Landslide Susceptibility map from multivariate AHP technique

10% for high, 65% for moderate, 23% for low and 2% for very low susceptible regions are identified from the multivariate AHP technique. Hence, 75% areas from the total study area are predicted as the high and moderate susceptibility for landslide hazard. When compare the results with bivariate method, Very steep slope mountains in the North West and South East regions are identified as low and very low susceptibility areas. As same as in bivariate method, the middle regions are detected as high probability for landslide occurrences. However, two methods are depicting the landslide regions approximately same in different landslide susceptibility classes.

6 RESULTS VALIDATION

At last, the landslide susceptibility maps from bivariate information value method and multivariate AHP techniques are validated using validation samples from landslide failure map. A Relative Failure Density (RFD) is used to quantify the accuracy of the method (Dai, et al., 2002; Guinau, et al., 2007; Remondo, et al., 2003).

$$RFDi = 100.(Npix(Si)/Npix(Ni))/\sum_{i=1}^{n}(Npix(Si)/Npix(Ni)) \quad (2)$$

Where, $Npix(Si)$ is the number of pixels failed in the i^{th} factor class, $Npix(Ni)$ is the number of pixels in the i^{th} susceptibility class and n is the number of susceptibility classes. Figure 8 describes the relative failure density in each susceptibility classes from bivariate and multivariate analysis. The validation results from both techniques imply the prediction results are in acceptable form with analysed predicted susceptibility classes.

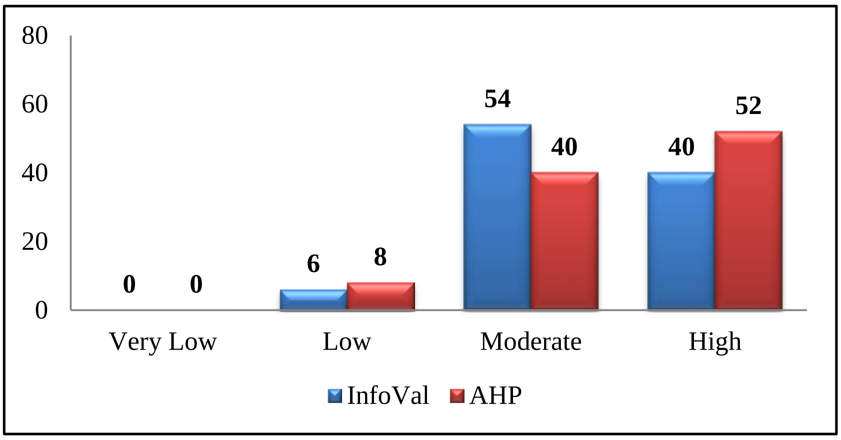

Figure 8 : Graphic showing validation results for each landslide susceptibility class from bivariate and multivariate technique

7 DISCUSSION AND CONCLUSION

Landslide prediction is paramount important in disaster management and development activities in any country. Specially, the central region of Sri Lanka is prone to landslide disasters. From the recent years, Koslanda in Uwa province is significantly prone to the landslide disaster. Naketiya landslide in year 1997 and Meeriyabedda landslide in 2014 gain the severe damages to the human life and their properties. By investigations from NBRO, Sri Lanka, they have revealed that the area around Naketiya is still active with slow land movements. Hence, a reliable study with available data for landslide studies are utmost important.

Various statistical models have been developed and used for landslide susceptibility analysis in many research studies. The main difference of bivariate and multivariate analysis is in multivariate, selected predisposal factors are also weighted by considering the weight of affection of them for landslide hazard. This study investigated slope, elevation, aspect, SMI, TWI, land use and distance to water bodies. Most of the factors are derived from remote sensing techniques in order to obtain up to date and large area information simultaneously. Even though, the analysis are more complex and time consuming, with the recent advancement of GIS tools and other computation techniques, the analysis are performed with the expected level.

Validation results from two different techniques describe the prediction results from bivariate and multivariate techniques are good fit with the prediction analysis. Because, it is very clear that, the very low susceptible regions from prediction analysis are validated as 0% from these two prediction techniques. The validation results from multivariate technique with AHP analysis illustrate the gradual increase of RFD (8%, 40%, 52%) from low to high susceptibility classes. The gradual change has some different in bivariate information value technique (8%, 54%, 40%) but as a whole prediction analysis from two methods are basically can be considered as in acceptable form. Further, the validation results confirm the careful selection of predisposal factors and suitable methodology. Finally, it can be concluded that, the multivariate approach is more consistent and the prediction results are more reliable than the bivariate technique. However, the results from bivariate technique also not beyond from the acceptable limit.

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