Efficacy of using Radar Induced Factors in Landslide Susceptibility Analysis: case study of Koslanda, Sri Lanka.

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Abstract. Through the recent technological developments of radar and optical remote sensing in (i) the areas of temporal, spectral, spatial, and global coverage, (ii) the availability of such images either at a low cost or free of charge, and (iii) the advancement of tools developed in image analysis techniques and GIS for spatial data analysis, there is a vast potential for landslide studies using remote sensing and GIS as tools. Hence, this study aimed to assess the efficacy of using Radar Induced Factors (RIF) in identifying landslide susceptibility using bivariate, Information Value method (InfoVal method) and multivariate, Multi Criteria Decision Analysis based on Analytic Hierarchy Process statistical analysis. Using identified landslide causative factors, four landslide prediction models as bivariate without and with RIF, multivariate without and with RIF were generated. Twelve factors as topographical, hydrological, geological, land cover and soil plus three RIF are considered. The weight of index for landslide susceptibility is calculated by using landslide failure map and susceptibility regions are categorized into four classes as very low, low, moderate, and high susceptibility to landslides. With the integration of RIF, boundary detection between high and very low susceptible regions are increased by 7%, and 4% respectively.

1   Introduction

Landslides are one of the major types of geo-hazards in the world as approximately 09% of global natural disasters are recorded as landslides (Chae et al., 2017, Chalkias et al., 2014). The recent statistics on landslide disasters per continent, from year 2000 to 2017, summarized in the Emergency Disaster Database (EM-DAT). The database indicates that landslides cause around 16500 deaths and affect 4.5 million people worldwide, with property damages of about US $3.5 million (OFDA/CRED, 2016). The spatial prediction of landslide disasters, incorporating statistical analysis to identify areas that are susceptible to future land sliding is one the important areas of geo-scientific research. These studies are based on the knowledge of past landslide events, topographical parameters, geological attributes, and other possible environmental factors, is one the important areas of geo-scientific research (Park et al., 2013).

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Presently, remote sensing ~~technology~~ has been used extensively to provide landslide-specific information for emergency managers and policy makers in terms of disaster management activities in the world (Baroň et al., 2014, Martha, 2011).~~In recent years, there is an increasing demand for high resolution satellite data to be used for extracting geometric object~~
5   ~~information and mapping.~~ The spatial resolution of space-borne optical data is now less than 1m in panchromatic images, and at the same time, ~~the interest in~~ Synthetic Aperture Radar (SAR) sensors and related processing techniques has also increased. Radar is considered to be unique among the remote sensing systems, as it is all-weather, independent of the time of day, and is able to penetrate into the objects. Additionally, radar images have been shown to depend on several natural surface parameters such as the dielectric constant and surface roughness. The dielectric constant is highly dependent on soil
10   moisture due to the large difference in dielectric constant between dry soil and water (Kseneman et al., 2012). ~~The forest and the vegetation cover of the earth surface is well sensed by the remote sensing techniques, where the shorter wave length regions as X and C radar bands identify the forest canopy clearly in radar remote sensing.~~

It is accepted in the scientific community that remote sensing techniques do offer an additional tool for extracting
15   information on the causes of landslides and their occurrences. Especially for deriving various parameters related to the landslide predisposing and triggering factors at global and regional scales, remote sensing plays a vital role (Corominas et al., 2014, Muthu et al., 2008, Pastonchi et al., 2018). Most importantly, landslide susceptibility analysis has greatly aided the prediction of future landslide occurrences, which is important for humans who reside in areas surrounded by unstable slopes. It is therefore identified that remote sensing techniques are significant in order to extract the landslide susceptibility regions
20   by providing most suitable landslide predisposing factors at smaller scale.

~~It can be observed that t~~There is massive potential for applicational research in the area of disaster management, if, conventional remote sensing data and radar are integrated. This is because each method has its inherent disadvantages and shortcomings, as well as advantages, and integrating the two ~~could~~ potentially complement each other. As such, this study
25   combines the predisposing factors derived from both optical and radar satellite data for landslide susceptibility analysis. Furthermore, significant landslide predisposing factors like ~~the~~ soil moisture ~~content~~, surface roughness, and forest biomass ~~will be~~ are derived from radar images, and the impacts of these factors on landslide susceptibility ~~will be~~ are examined. ~~Hence, this study aims to investigate the efficacy of using Radar Induced Factors (RIF) for landslide susceptibility analysis under bivariate and multivariate nature.~~
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1.1   ~~Statistical~~ Methods for Landslide Susceptibility Analysis

There are inherent limitations and uncertainties in landslide susceptibility analysis, and yet, several methods have been utilized and successfully applied in the past (Kanungo et al., 2009). These methods ~~employed~~ have been of both qualitative

and quantitative nature. Generally, qualitative methods are based on expert opinions while the quantitative approaches, such as statistical and probabilistic approaches, depend on the past landslide experiences.

Qualitative methods simply make use of landslide inventories to identify areas with similar geological and geomorphologic properties that show susceptibility for land failures. These methods can be divided into two groups as geomorphologic analysis, and map combination. In geomorphologic analysis, the landslide susceptibility is determined directly either in the field or by the interpretation of images through geomorphologic analysis (Bui et al., 2011). Map combination is based on combining a number of predisposing factor maps for landslide susceptibility analysis. However, map combination analysis comprises of a semi-quantitative nature by integrating the ranking and weighting of landslide susceptibility (Ayalew et al., 2004, Kavzoglu et al., 2014, Saaty, 1980). The analyses based on the quantitative approaches depend on numerical data and statistics, expressing the relationship between instability or predisposing factors with landslides (Reis et al., 2012). These methods are categorized into two groups as bivariate and multivariate statistical analysis. Within the context of this work, popular Information Value method (InfoVal) as bivariate and Multi-Criteria Decision Analysis (MCDA) based on Analytic Hierarchy Process (AHP) as multivariate methods are compared with respect to their performances in landslide susceptibility modelling analysis.

The InfoVal method determines the susceptibility at each point or pixel, jointly considering the weight of influence of all predisposing factors. The weight of influence is based on the landslide inventory map of the particular area. When constructing a probability model for landslide prediction, it is necessary to assume that the landslide occurrence is determined by landslide related factors, and that future landslides will also occur under the same, or almost similar, conditions as past landslides(Remondo et al. 2013, Saha et al. 2005). Hence, at the beginning of the analysis, the landslide inventory map is divided in to two samples as training and validation, enabling the use of this data for landslide susceptibility analysis and validation of results respectively.The Log function is used to control the large variation of weights in calculations. Larger the weight of influence, the stronger the relationship between landslide occurrence and the given factor's attribute.

The MCDA method integrates all the independent predisposing factors with the inclusion of relative contribution of each factor by putting more emphasis on the predisposing factors that contribute to landslide occurrence. The same predisposing factors without or with radar, are used to investigate the landslide susceptibility regions from AHP technique within the GIS domain. In AHP, each pair of factors in a particular factor group is examined at one time, in terms of their relative importance. Relative weights for each factor are calculated based on a questionnaire survey from experts in the field. However, expert knowledge could be subjective at times, or may cause to assign different weights for each factor, when dealing with a large number of causative factors. Hence, in order to avoid this inconsistency, Consistency Ratio (CR) is

1.2   Landslide predisposing factors

It is understood that landslides may occur as consequences of complex predisposing and triggering factors. Topographical and geological factors, together with local climatic conditions, lead to landslide occurrences. The selection of these factors, and preparation of corresponding thematic data layers, are vital for models used in landslide susceptibility analysis (Jakob et al., 2006, Lee et al., 2017). There are no universal guidelines regarding the selection of predisposing factors in landslide susceptibility analysis. Some parameters may be important factors for landslide occurrences in a certain area but not for another one. Scientists (van Westen, 1997, van Westen and Getahun, 2003, van Westen et al., 2003) show that every study area has its own particular set of predisposal factors which condition landslides. Determination of appropriate causal factors is a difficult task, and no specific rule exists to define how many factors are sufficient for a specific landslide susceptibility analysis. Hence, the selection of predisposing factors are dependent on the nature of the study area, opinions of the experts, and the availability of data for generating the appropriate spatial and thematic information (Kavzoglu et al., 2015, Shahabi and Hashim, 2015).

2   Study Area

Koslanda in Sri Lanka is located at the geographical coordinates of 06° 44' 00" North and 81° 01' 00" East, and the elevation is around 700 – 1000 m from the above Mean Sea Level (MSL). It is a remote, hilly area with harsh weather conditions, where the monthly rainfall ranges from 60 mm to 200 mm, and average temperature is 20^0 C. The area has rains for most of the year, with very short, dry period during the months of February to April. The population is around 5000 people, and the study area has an extent of 19 km^2 within the Koslanda area. Koslanda has been the site for of several massive landslides over the years, and both the Naketiya landslide in the year 1997, and Meeriyabedda landslide in the year 2014, are very distinct in Fig. 1, and within a span of two years, major landslides have occurred three times at the same location. When consider the typology of landslides in this study area, basically the falling, toppling, subsidence, lateral displacements, and debris flows are prominent (NBRO, 2016).

The geomorphology of the area is described as a gently inclined talus slope, with a thick, loosely compacted colluvium deposit at the foot of the near vertical rocky scarp. Koslanda is situated at the middle part of the slope, with the lower area showing a fairly steep surface as well. The composition of the colluvium deposit in the area includes a randomly arranged mixture of weathered clayey and sandy materials, with the organic matter making the deposit act as a spongehighly absorbing entity with high water content. The study area was an abandoned tea land in which the properly maintained surface drainage system has been neglected" (Somaratne, 2016). Geology refers the physical structure and the substance of

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the Earth. Mainly the area consists of undifferentiated charnockitic biotite gneisses and Quartzites, according to the 1:10000 geological map from Geological Survey Mines Bureau (GSMB), Sri Lanka. Such geomorphological and geological formation, together with improper land use management practices, has made the area extremely vulnerable for landslide events.

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FIGURE 1

3 Data and methodology

3~~3~~.1 Data

10 The most important phases in landslide prediction analyses are the collection of data from different sources, and the construction of a spatial database ~~for these data~~on a common platform (Lan et al., 2004). The data utilized for the landslide prediction analysis include the topographical, hydrological, geological, soil, and land cover factors. All factors are derived from optical images (Landsat-8, Sentinel-2), radar images (Sentinel-1, TerraSAR-X), Digital Elevation Model (DEM) derived from aerial triangulation and other available data sources (geology, rainfall). Stereo aerial photographs from 1993

15 are used to generate the 7 m resolution DEM using aerial triangulation. ~~An inventory map of landslides~~Landslide inventory map for the study area was constructed by integrating the interpreted multi-temporal aerial photographs, satellite images, and some temporal images from the Google Earth (Figure 2). Verifications are carried out through field investigations. In this research, the predisposing factors were selected from among the most widely considered factors in literature and opinion from the experts.~~as depicted in the Table 1.~~

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Most data are derived as primary data from remote sensing techniques for a large area with up-to-date information. As such, fifteen predisposing factors are selected for the landslide susceptibility analysis by using bivariate and multivariate statistical techniques. Of these, twelve factors (elevation, slope, aspect, planar curvature, profile curvature, Topographical Wetness Index (TWI), land use, lineament density, distance to water bodies, soil moisture, geology, and rainfall) are derived from

25 optical images, DEM and auxiliary data, while three more factors (soil moisture from Delta Index, surface roughness, and forest biomass) are derived from radar images. These factors were then combined in order to analyse the performance of this integration for landslide susceptibility analysis.

~~**TABLE 1**~~

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3.13.1.1 Topographical Factors

The topographical factors include elevation, slope, aspect, planar curvature, profile curvature and surface roughness of the terrain. The first four factors are derived from the 7 m resolution DEM and surface roughness is derived by using Sentinel 1 radar image. The elevation is important to study the local relief of the terrain and ranges from 446 -1537 m above MSL in the study area. Since the area contains high mountains, more than a 1000 m difference in elevation can be observed. The basic parameter for the slope stability analysis is the slope angle. The slope angle of the study area ranges from 0^0 to 80^0, showing a significant increase of slope within a relatively small area. Additionally, the area with steep slopes ranging from 60^0 - 80^0 can be seen in the northern part of Koslanda. Aspect is defined as the direction of maximum slope of the terrain surface, or the compass direction of a particular slope. The curvature is theoretically defined as the rate of change of slope (or slope), of the focused slope. Planar curvature describes convergence and divergence of the flow across a surface, while the profile curvature refers to acceleration or deceleration of the flow across a surface.

Under radar configuration, the magnitude of radar backscatter is defined as a function of surface roughness and moisture content. Similar studies from Rahman et al., 2008 and Septiadi and Nasution, 2009 emphasized the extraction of surface roughness from radar data using textural analysis. Hence, to estimate the surface roughness without the use of any ancillary field data, a Sentinel-1 radar image on 12th March 2015 under the dry climatic condition was used to reduce the effect of the moisture component from the radar backscatter. The texture is the structure, or appearance, of the surface, and as such, describes the coarseness or the homogeneity of the image structure. One of the most prominent methods for texture analysis is Grey Level Co-occurrence Matrix (GLCM), which is based on the second order probability density function. The GLCM describes how often a grey level occurs at a pixel located at a fixed geometric position relative to its neighbourhood pixels. The surface roughness is normally a measure of finer surface irregularity in the surface texture. These texture features extracted from the GLCM would be the best descriptors for quantifying the state of surface roughness (Septiadi and Nasution,2009). Hence, the GLCM texture analysis is performed using a window size of 9*9 pixels and the homogeneity or dissimilarity criterion is used to determine the surface roughness of the study area.

3.23.1.2 Hydrological Factors

Distance to hydrological features, rainfall, and TWI defined by Eq. (1) are selected as the hydrological factors for this landslide susceptibility analysis. Proximity to the hydrological features is an important factor when considering the landslide susceptible analyses (Sar et al., 2016, Shahabi and Hashim, 2015). TWI is a solid index that is capable of predicting areas susceptible to saturation or wetness of land surfaces, and the areas that have the potential to produce an overland flow. Within the Sri Lankan context, heavy and prolonged rainfall is the main triggering factor for the landslides. The monthly average rainfall data for the years 2014 to 2016 from 10 nearby stations to Koslanda were used in this study. Monthly

rainfall data from 10 rain gauge stations are averaged, and the average rainfall map for the study area is generated using the Inverse Distance Weighting (IDW) interpolation method within the ArcGIS environment. TWI has been used to study the spatial scale effects, or topographic control, on hydrological processes. This index was developed by Beven and Kirkby, 1979 and can be defined in Eq. (1) as;

$$TWI = \ln[\propto / \tan \beta] \qquad (1)$$

where $\propto$ is the local upslope area draining through a certain point per unit of contour length, and β is the gradient of the local slope in degrees. The applicability of the TWI in the calculation and validation of landslide susceptibility analysis has been shown by Kavzoglu et al., 2014 and Sørensen et al., 2006 among others.

3.33.1.3 Soil Factors

The Soil Moisture Index (SMI) defined in Eq. (2) and Delta Index defined in Eq. (5) are the soil factors focused upon in this research. Surface soil moisture is one of the most important parameters in land susceptibility analysis (Carlson et al., 1994, Zhan et al., 2002). Several methods have been proposed to estimate the surface soil moisture conditions accurately with insitu measurements. However, these methods are time consuming and costly when the area of interest is large, and the scale of work is small. Hence, this research uses the Universal Triangle relationship between Soil Moisture, Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) derived from Landsat-8 image bands as an optical remote sensing approach, and the Delta Index derived from two radar images, as wet and dry conditions, as a radar remote sensing approach. Band 5 (Near Infrared (NIR), 30 m resolution), band 4 (Red, 30 m resolution) and band 11 (Thermal, TIR-2, 100 m resolution) of Landsat-8 image of 3rd July 2015 is processed for extracting the soil moisture index in the Thermal-NDVI space. The SMI is "0" along the dry edge and "1" along the wet edge. According to the studies from (Wang and Qu, 2009, Zenga et al., 2004), SMI can be defined in Eq. (2) as;

$$SMI = \frac{(T_{max} - T)}{(T_{max} - T_{min})} \qquad (2)$$

where T_{max}, T_{min} are the maximum and minimum surface temperature for a given NDVI, and T is the remotely sensed derived surface temperature at a given pixel for a given NDVI. The simple regression relationship between T and NDVI is formulated in Eq. (3) and Eq. (4) as;

$$T_{max} = a_1 \cdot NDVI + b_1 \qquad (3)$$
$$T_{min} = a_2 \cdot NDVI + b_2 \qquad (4)$$

where, a_1 = -5.2362, b_1 = 300.14, a_2 = 2.9254, and b_2 = 289.11.

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Radar remote sensing provides advantages for extracting near surface soil moisture (0-5 cm), including timely coverage with repeat passes during day and night, under all weather conditions. Radar imagery from space can provide broad scale information on near surface soil moisture as radar signal return is responsive to changes in soil moisture. Technically, the surface roughness and vegetation affect radar backscatter much more than soil moisture. Hence, both the surface roughness and vegetation have to remain unchanged during the image acquisition for soil moisture estimation (Thoma et al., 2006). Delta Index is a modified, image differencing technique, and many studies (Barrett et al., 2009, Sano et al., 1998, Thoma et al., 2004) have proven it to be a good predictor for near surface soil moisture extraction. This index describes the change of wet scene backscatter relative to the dry scene backscatter, and is defined by Thoma et al., 2004 in Eq. (5) as;

$$Delta\ Index = \left| \frac{\sigma^0_{wet} - \sigma^0_{dry}}{\sigma^0_{dry}} \right| \qquad (5)$$

where, σ^0_{wet} is the radar backscatter (decibels) from a pixel in the radar image representing wet soil conditions, and σ^0_{dry} is the radar backscatter (decibels) from a pixel in the same geographic location representing dry soil conditions at a different time. Sentinel-1 images with 10m spatial resolution and VV polarization is used in the presented study. The dry reference image was acquired on 12th March 2015 and the wet image was acquired on 24th November 2014 after the landslide in Meeriyabedda, Sri Lanka. Therefore, the topographical changes like roughness and vegetation density showed no significant changes during these four months' time.

3.43.1.4 Land Use

The major land uses existing in this study area are identified as tea, scrub, forest, rock, rice, water, and residential. The Sentinel-2A image from 10th October 2016 is used to extract the desired land uses from the study area by applying supervised classification. Scrub areas are typically the tea estates that are in abundance, while the residential areas are the rooms of tea workers. It is noted that most of the devastating landslides in this area had occurred within the extensive tea estates. Hence, the main reason for the continuous occurrence of these landslides can be identified as the lack of proper land use management in the area.

Forest biomass is a significant factor that can control the landmass failures or landslides. The main limitations of using optical remote sensing for forest biomass estimation is the near constant tropical cloud cover, and the insensitivity of reflectance to change of the biomass in older and mixed forests. Radar has potential to overcome the above limitations due to its all-weather, day and night capability, with the positive relationship of radar backscatter and forest biomass. The spatial, spectral, temporal, and polarization characteristics of radar backscatter has known influence with the forest biophysical

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properties. Kuplich et al., 2005 and Caicoya et al., 2016 related the radar image texture derived from GLCM to the forest biomass. An experiment was conducted by Kuplich et al., 2005 with seven texture measures, but only the GLCM derived contrast increased the correlation between the backscatter and the log of biomass in Eq. (6) as;

$$Log \ of \ Biomass = 2.24 + 0.33b + 0.0001c \qquad (6)$$

where, b is the radar back scatter and the c are the GLCM contrast texture for the particular radar image. TerraSAR-X spot light image from 2nd November 2014, with 3 m resolution and dual polarization (HH and VV), was used to estimate the forest biomass in this research.

3.53.1.5 Geological Factors

Geology refers to the physical structure and the substance of the Earth. In order to investigate the land mass failures, the geological structure of that particular area have to be analysed carefully. In addition to the Geology of the area, lineament density has also been considered as a factor. The geological information of the particular area is obtained from the geological map available at the Geological Survey Mines Bureau (GSMB), Sri Lanka at 1:100,000 scale, and seven types of different geological structures are contained in the selected study region. Mainly the undifferentiated charnockitic biotite gneisses and Quartzites are prominent with Garnet-sillimanite and Garnetiferous quartzofeldspathic gneiss in the study area. Lineaments are extractable linear features which are correlated with the geological structures of the earth. When considering the analysis of lineaments with respect to the landslide potentiality, lineaments exhibit the zones of weakness surfaces as faults, fractures, and joints (Adiri, et al., 2017, Kati, et al., 2018, Mandal and Maiti, 2015). This study uses the Sentinel-2 optical satellite image, with 10 m resolution, for the extraction of lineaments of the study area.

3.2 Methodology

The InfoVal method determines the susceptibility at each point or pixel, jointly considering the weight of influence of all predisposing factors. The weight of influence is based on the landslide inventory map of the particular area. When constructing a probability model for landslide prediction, it is necessary to assume that the landslide occurrence is determined by landslide-related factors, and that future landslides will also occur under the same, or almost similar, conditions as past landslides (Remondo et al., 2013, Saha et al., 2005). Hence, at the beginning of the analysis, the landslide inventory map is divided in to two samples as training and validation, enabling the use of this data for landslide susceptibility analysis and validation of results respectively as in Fig 2. Log function is used to control the large variation of weights in calculations. Larger the weight of influence, the stronger the relationship between landslide occurrence and the given factor's attribute.

FIGURE 2

This method overlay all individual predisposing factors as thematic maps with the landslide inventory map to calculate the density of the landslide detachment zones for each class of the selected factors. The density of landslide pixels represents the weight of influence of each predisposing factor in Eq. 7 as;

$$W_i = Log\left(\frac{Densclass}{Densmap}\right) = Log\left(\frac{N_{pix}(S_i)/N_{pix}(N_i)}{\sum_{i=1}^{n} N_{pix}(S_i)/\sum_{i=1}^{n} N_{pix}(N_i)}\right) \qquad (7)$$

Where, W_i is the weight given to the parameter class, $Densclass$ is the landslide density within the parameter class and $Densmap$ is the landslide density within the entire map. $Npix(Si)$ is the number of landslide pixels within parameter class i, and $Npix(Ni)$ is the total number of pixels in the same parameter class. It means that, if the parameter class contains no landslide occurrence, it will have no correlation with the landslide inventory map (Bui et al., 2011, Kavzoglu et al., 2015).

The MCDA method integrates all the independent predisposing factors with the inclusion of relative contribution of each factor by putting more emphasis on the predisposing factors that contribute to landslide occurrence. The same predisposing factors without or with radar, are used to investigate the landslide susceptibility regions from AHP technique within the GIS domain. In AHP, each pair of factors in a particular factor group is examined at one time, in terms of their relative importance. Relative weights for each factor are calculated based on a questionnaire survey from experts in the field. These relative weights are then used to generate a pair-wise comparison matrix which is the basic measurement mode when applying the AHP procedure. The selected predisposing factors, and relevant relative weights, are used to generate the normalized matrix with final average weights. However, expert knowledge could be subjective at times, or may cause to assign different weights for each factor, when dealing with a large number of causative factors. Hence, in order to avoid this inconsistency, Consistency Ratio (CR) is calculated. For better predictive models, the CR should be less than 0.01, else each factor has to be generated with the proper pairwise comparison.

The calculated final weights for twelve landslide predisposing factors without RIF as elevation, slope, aspect, planar curvature, profile curvature, TWI, land use, lineament density, distance to water bodies, soil moisture, geology, and rainfall were 0.030, 0.172, 0.022, 0.018, 0.014, 0.074, 0.149, 0.052, 0.045, 0.094, 0.185, and 0.145, respectively. The CR is 0.089, making it less than the 0.1, the value showed the reasonable level of consistency in the pairwise comparison.The final weights for fifteen predisposing factors with RIF as elevation, slope, aspect, planar curvature, profile curvature, TWI, land use, lineament density, distance to water bodies, SMI in NDVI-T domain, geology, rainfall, soil moisture (Delta index),

surface roughness, and forest biomass are 0.022, 0.145, 0.016, 0.013, 0.011, 0.053, 0.126, 0.039, 0.033, 0.065, 0.153, 0.124, 0.088, 0.088, and 0.027, respectively. When considering the fifteen predisposing factors, the CR is calculated as 0.092, which is less than the 0.1 thereby showed a realistic level of consistency in the pairwise comparison matrix.

5   After decisive analysis of the types of predisposing factors, the presented work proceeded to consider fifteen predisposing factors that are derived from optical, radar and other available auxiliary data sources. Three significant causative factors as surface roughness, soil moisture from Delta Index, and forest biomass were estimated by using radar satellite images. Thus, this work investigated the performance of landslide susceptibility analysis using bivariate and multivariate methods with the inclusion of RIF and described the processing steps in Fig.~~2~~3.

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The weight of influence of all predisposing factors as thematic maps are added in bivariate and multivariate nature to obtain the contribution of all predisposing factors for landslide susceptibility analysis. After calculating the cumulative percentage of failures of the weighted susceptibility maps, value ranges for each percentage of failure are obtained from quantile classification for 10 classes. The entire study area of each landslide susceptibility map is then discretized in to four classes as 15   0%, 10%, 30% and 60% of failure regions for very low, low, moderate, and high susceptibility classes, respectively.

FIGURE ~~2~~3

4   Results ~~and Discussions~~

Four Landslide prediction models, (i) bivariate without RIF (BiNR), (ii) bivariate with RIF (BiWR), (iii) multivariate 20   without RIF (MNR), and (iv) multivariate with RIF(MWR) are discussed. The region has been analysed and classified into four (04) landslide susceptibility regions as; high, moderate, low, and very low.

4.1   Bivariate InfoVal method Without and With RIF

Susceptible regions are identified from the bivariate InfoVal method without RIF as 12% for high, 45% for moderate, 38% 25   for low, and 5% for very low as shown in Fig.~~3~~4(a). Hence, 57% areas from the total study area are predicted as having high and moderate susceptibility for the landslide hazard. Very steep slope mountains in the North, North West, and East regions are identified as very low susceptibility areas, given that the area was free from historical landslides. The middle regions with 30^0-50^0slope are detected as having a high probability for landslide occurrences. The bivariate InfoVal method with RIF identified 19% of failure regions for high susceptibility, 39% for moderate, 33% for low, and 9% for very low susceptible 30   regions as presented in Fig.~~3~~4(b). Therefore, 58% of the total study area is predicted as having high and moderate susceptibility for landslides. Very steep slope mountains in the North, North West, East, and South East regions, the area

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near the Eruwendumpola Oya, are identified as having very low susceptibility for landslides. Similar to the bivariate analysis without RIF, the middle regions with 30^0-50^0 slope are detected as having high probability for landslide occurrences and the reason for this is mainly with the past experience from Naketiya and Meeriyabedda landslides that had taken place in the same area.

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4.2 Multivariate MCDA based on AHP Without and With RIF

All fifteen weighted predisposing factors were grouped as without and with RIF, and weighted overlay is performed

10 separately in order to obtain the landslide susceptibility regions. The calculated weights for elevation, slope, aspect, planar curvature, profile curvature, TWI, land use, lineament density, distance to water bodies, SMI in NDVI T domain, geology, and rainfall are 0.030, 0.172, 0.022, 0.018, 0.014, 0.074, 0.149, 0.052, 0.045, 0.094, 0.185, and 0.145, respectively. The Consistency Ratio (CR) is a measure of consistency in subjective judgement, and ranges from 0 to 0.1, where 0 indicate the maximum inconsistency of relative judgement and 0.1 indicate the maximum consistency of relative judgements. For the

15 present work, the CR for the relative judgement of weighting predisposing factors is 0.089 in the pairwise comparison. The weights for the fifteen predisposing factors with RIF, as elevation, slope, aspect, planar curvature, profile curvature, TWI, land use, lineament density, distance to water bodies, SMI in NDVI T domain, geology, rainfall, soil moisture (Delta index), surface roughness, and forest biomass are 0.022, 0.145, 0.016, 0.013, 0.011, 0.053, 0.126, 0.039, 0.033, 0.065, 0.153, 0.124, 0.088, 0.088, and 0.027, respectively. When considering the fifteen predisposing factors, the CR is 0.092, which is less than

20 the 0.1 thereby showing a realistic level of consistency in the pairwise comparison matrix.

Figure 34(c) illustrates the landslide susceptibility map from the multivariate method without RIF and is able to identify 18%

25 for high, 44% for moderate, 36% for low and 2% for very low susceptible regions. Hence, 62% of areas from the total study area are predicted to be of high and moderate susceptibility for the landslide hazard. In the landslide susceptibility map from the multivariate method with RIF, from the total area, 21% of the area show a high susceptibility to landslides, with 40% of area as moderate, 34% area as low, and 5% of area as having very low susceptibility as shown in Fig.34(d). Hence, 61% of areas from the study area are predicted as having high and moderate susceptibility for the landslide hazard. In a similar

30 manner to the InfoVal method, the top of the mountains in the North, North West, East, and South East regions, area near to the Eruwendumpola Oya, are identified as having a very low susceptibility to landslide hazards, while the middle regions with 30^0-50^0 slopes are detected as having high and moderate probability for landslide occurrences.

5   Discussions

The area identified as having high and moderate susceptibility classes in these four approaches (57%, 58%, 62%, and 61% respectively in BiNR, BiWR, MNR, and MWR) are close in value, but shows an increase in multivariate analysis when compared with bivariate analysis as tabulated in Table 21. Moderate and low landslide susceptibility areas show very small ((1-2)%) changes between these four types of analysis. With the integration of RIF as surface roughness, near surface soil moisture from Delta Index, and forest biomass in bivariate and multivariate analysis, the high and very low susceptible areas are increased significantly (high: 7% - bivariate, 3% - multivariate and very low: 4% - bivariate, 3% - multivariate). However, when comparing the high and very low susceptibility areas from bivariate and multivariate analysis, high susceptibility areas show a considerable increase (without radar: 6% and with radar: 2%) while, very low susceptibility areas have a noteworthy decrease (without radar: 3% and with radar: 4%).

TABLE 21

4.35.1 Results Validation

The landslide susceptibility maps derived from the bivariate and multivariate analysis are validated using the selected validation samples from the landslide failure map. The most commonly used and scientifically recognized Receiver Operating Characteristics (ROC) curves are used to analyse the prediction and validation performances. ROC is a graphical plot that illustrates the performance of classification, and is considered as a powerful tool for the validation of landslide susceptibility analysis for many years (Neuhäuser et al., 2012). The Area Under Curves (AUC) for the four different approaches, as bivariate and multivariate without and with RIF, are calculated and graphed in Fig.45.

FIGURE 4

The areas under the success rate curves measure how the landslide prediction analysis fit with the training data set, while the areas under the prediction rate curves measure how well the landslide prediction models and landslide causative factors predict the landslides. If the area under the ROC curve is closer to 1, the result of the test is excellent and vice versa, and when AUC is closer to 0.5, the result of the test is fair or acceptable (Kamp et al., 2008).

The AUC of all the success rates are more-or-less near 0.80, indicating good prediction performances according to the definition. The AUC of all the prediction rates are having values above 0.50, thereby indicating that they are within the acceptable range as per the definition. As such, they indicate that the accuracy of prediction rate of land susceptibility and

the selection of land causative factors are acceptable, but not excellent, even though the fit between the landslide prediction and the training data set are excellent as compared in Table 32. The incompleteness of the available landslide inventory map, as well as an insufficient number of validation samples in the study area can be shown as reasons for the discrepancy. As a whole, better prediction and validation capabilities are shown by the bivariate analysis when compared with the multivariate approaches.

TABLE 32

56   Conclusions

This study focused on the applicability of remote sensing and GIS for rapid landslide prediction analysis at finer scale. Further, by considering the significance of radar data for landslide analysis, this study mainly investigates the efficacy of radar induced factors for landslide prediction analysis which is not well experimented in the current researches. Most significant predisposing factors as surface roughness, soil moisture, and forest biomass derived from radar are incorporated to examine the landslide prediction analysis. The prediction analysis is performed by using bivariate and multivariate statistical analysis. The main objective of this study is to analyse the efficacy of using radar induced predisposing factors for landslide susceptibility analysis using bivariate and multivariate analysis.

The main difference between bivariate and multivariate analysis is that in multivariate analysis, selected predisposing factors are also weighted by considering, how each of them are influenced for landslides susceptibility. This study investigated fifteen landslide predisposing factors as elevation, slope, aspect, planar curvature, profile curvature, TWI, land use, lineament density, distance to hydrology, SMI in NDVI-T domain, geology, rainfall, soil moisture (Delta Index), surface roughness, and forest biomass. Most of the factors are derived from radar and optical remote sensing techniques, where smaller scale studies with up-to-date information allows the work to be conducted at the meter-level accuracy, and repeated analysis simultaneously.

From the results obtained, it can be concluded that the bivariate and multivariate statistical analysis, without and with RIF, can be used for landslide prediction analysis. However, with the integration of RIF as surface roughness, near surface soil moisture from Delta Index, and forest biomass, the detection of the boundary between the high and very low susceptibility areasregions is increased. When comparing the bivariate analysis with the multivariate analysis, the increase of area identified as high and very low susceptibility regions are increased while very low susceptibility regions decreasedhigh in bivariate than multivariate. In landslide prediction analysis, the most important susceptibility classes are high and very low classes, as they provide significant information about the danger from a disaster. Hence, with the integration of radar induced factors, by increasing the accuracy of prediction for high susceptibility regions, the possibility of mitigating dangers can be

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considerably improved. When the accuracy and prediction of very low susceptibility regions are increased, the use of such lands can be encouraged for residential, community places, and safe areas when a landslide occurres. ~~As a whole, there is an improvement of prediction and validation performances of bivariate analysis than multivariate analysis.~~

5 ~~This study focused on the applicability of remote sensing and GIS for rapid landslide prediction analysis at finer scale. Further, by considering the significance of radar data for landslide analysis, this study mainly investigates the efficacy of radar induced factors for landslide prediction analysis which is not well experimented in the current researches. Most significant factors as surface roughness, soil moisture, and forest biomass derived from radar are incorporated to examine the landslide prediction analysis.~~ Successful prediction and validation of prediction analysis via ROC curves are achieved. Even

10 though this study was tested for a sample area, the same methodology can be applied for any landslide prone area to investigate the landslide prediction analysis using radar induced factors by using bivariate and multivariate analysis. This is because the radar induced factors can be derived for any area, as long as the data are available, and at any time under whatever the weather conditions as radar are weather independent. Additionally, the technology can be learned easily and anyone can be trained to use this methodology to predict landslide susceptibility areas, and this is especially helpful for

15 developing countries who do not have up-to-date data at fine resolutions. With the increasing availability of free data in optical, radar, and DEM, it is possible to derive more landslide predisposing factors as thematic maps. Further, there are many statistical analyses developed in qualitative and quantitative natures for spatial data analysis. Hence, further investigations ~~will result in~~have to be performed for landslide susceptibility analysis even focusing the changing nature of the environments.

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Competing Interests

35 The authors declare that we have no conflict of interest.

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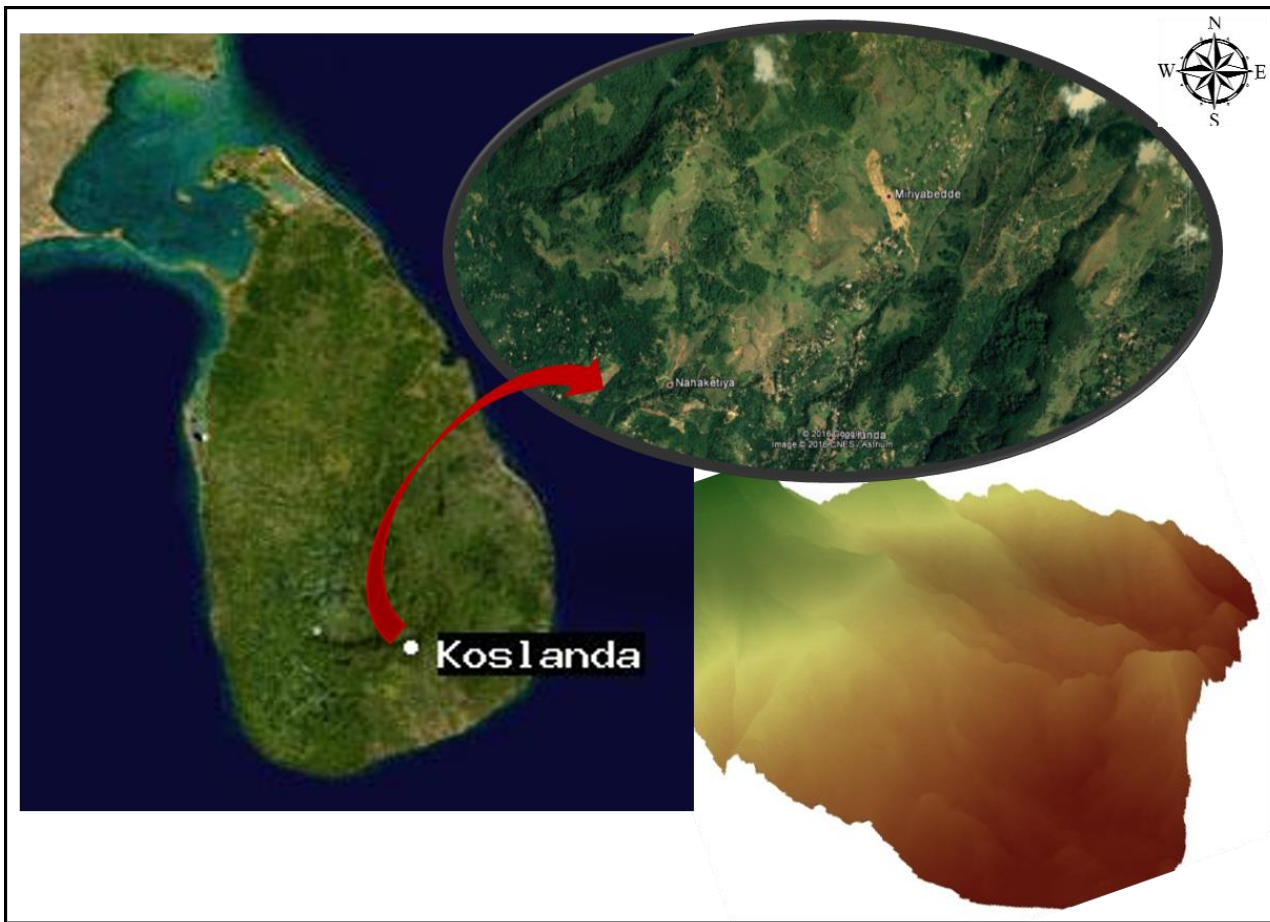
Figure 1 :Topographical formation of Koslanda, Sri Lanka with its previous Landslides Signatures

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Figure 2 : Landslide failure map of the Koslanda area with two different training and validating samples
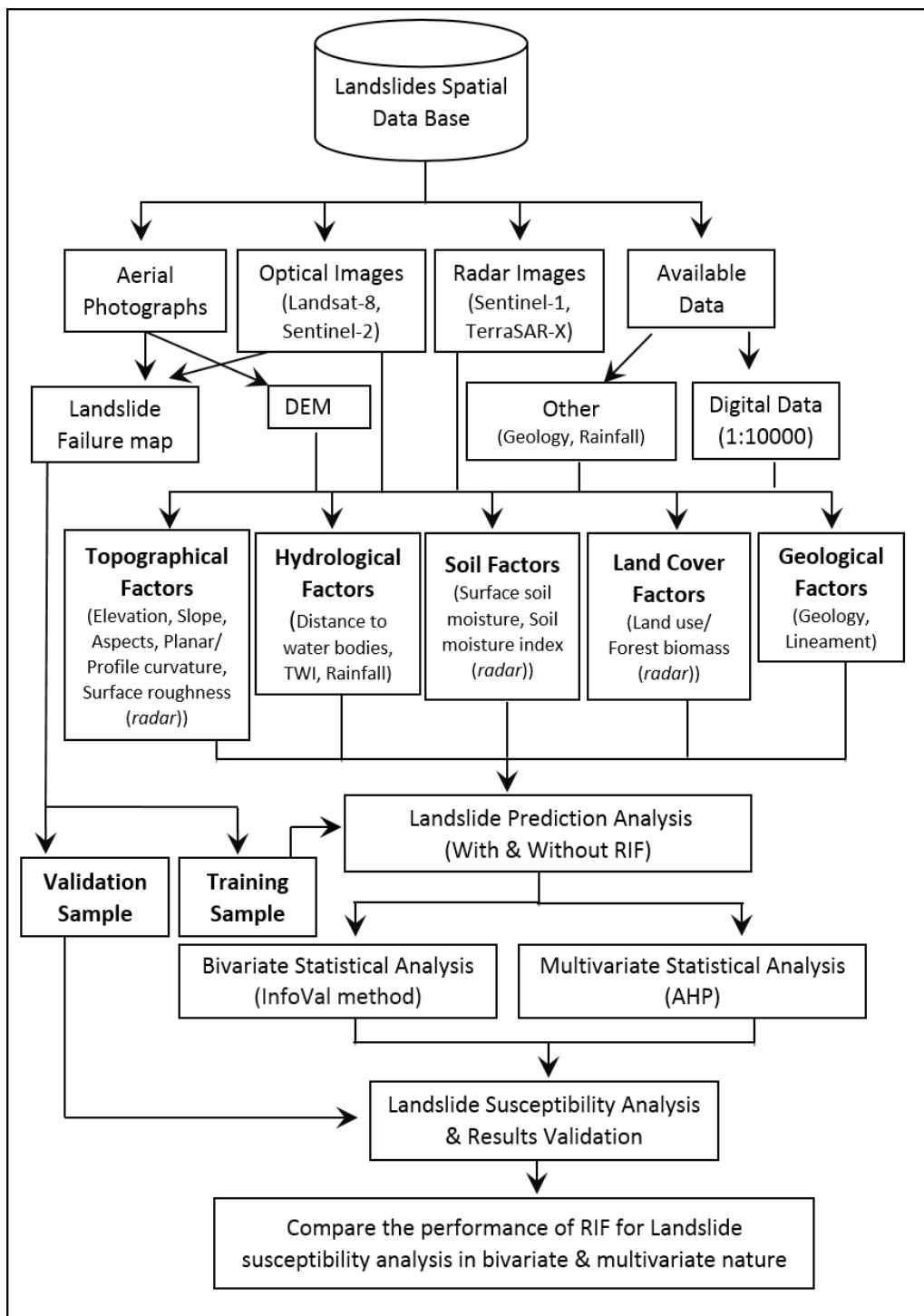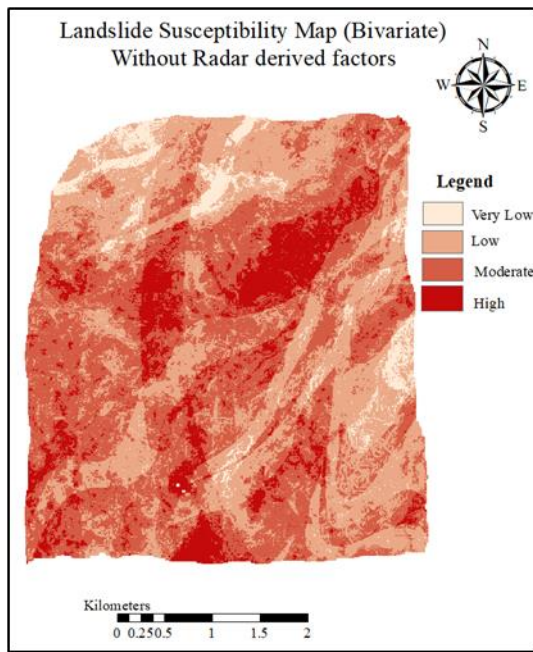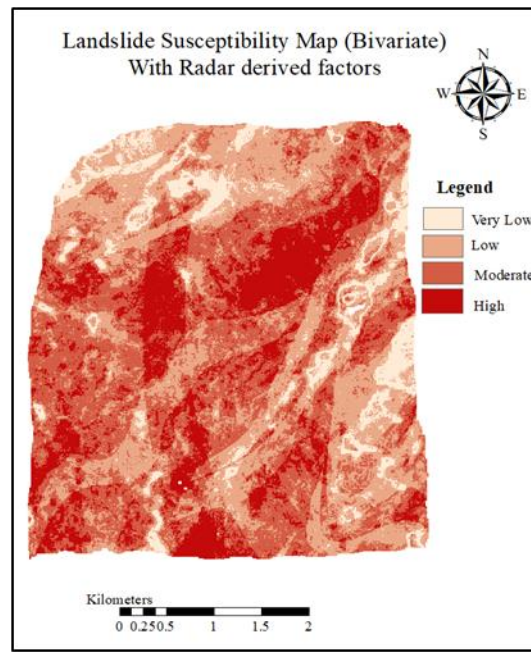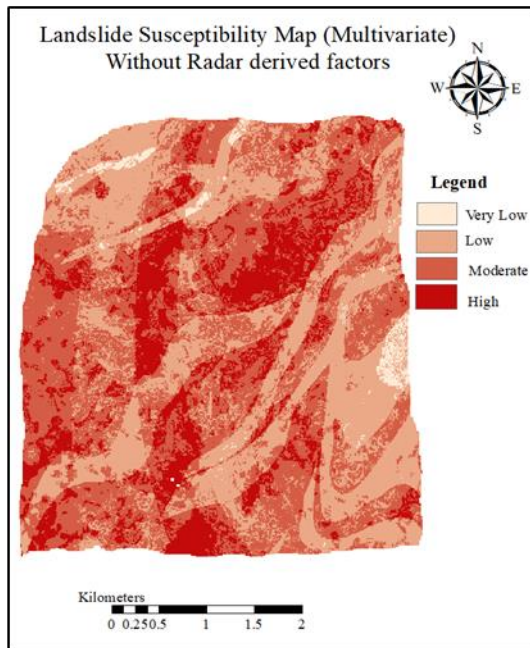
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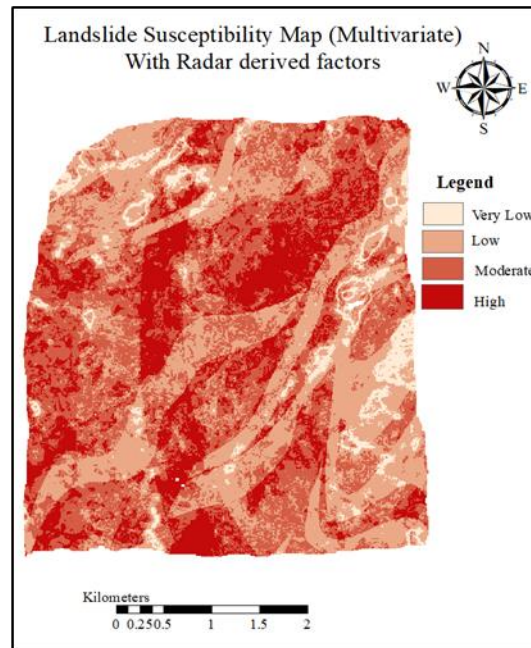**Figure 3 : Methodological flow of the Landslide susceptibility analysis using Bivariate and Multivariate approaches**

Figure 4 : Landslide susceptibility maps from bivariate and multivariate analysis without and with RIF. (a)- bivariate without RIF, (b)- bivariate with RIF, (c)- multivariate without RIF, and (d)- multivariate with RIF
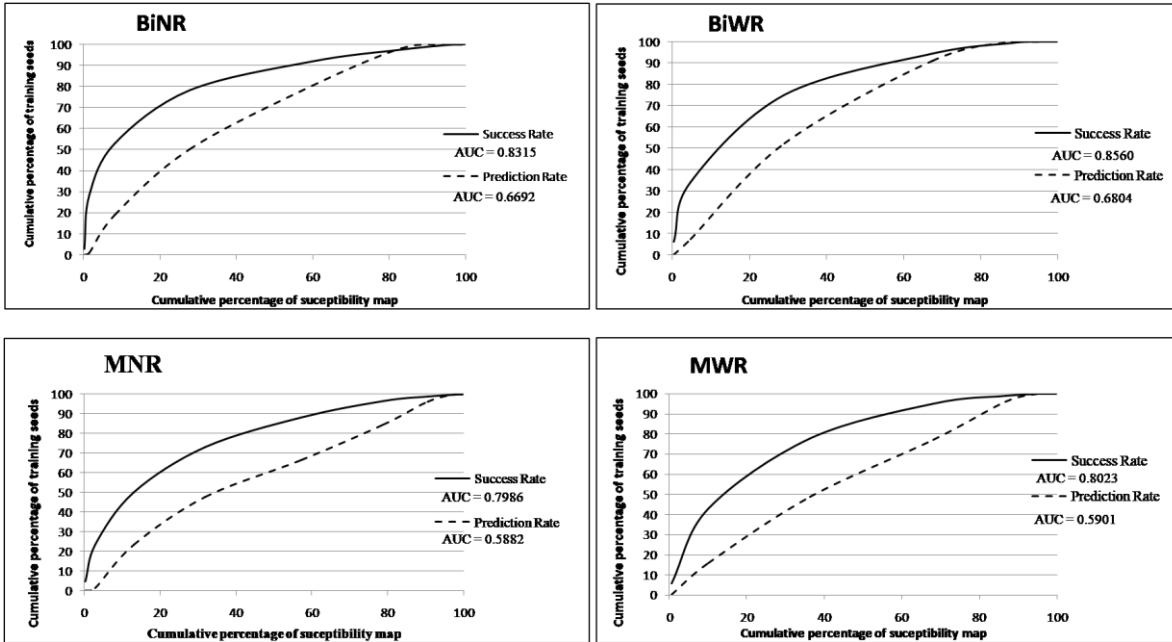
Figure 5 : Success rate and Prediction rate curves with AUC for the bivariate and multivariate analysis without and with RIF. X axis denotes the Cumulative percentage of Susceptibility regions and Y axis denotes the Cumulative percentage of training samples. From left to right and top to bottom BiNR- bivariate analysis without RIF, BiWR- with RIF, and MNR- multivariate analysis without RIF, and MWR- with RIF

Table 1:Landslide susceptible area comparison from bivariate and multivariate analysis without and with RIF,BiNR -Bivariate analysis without RIF, BiWR -Bivariate analysis with RIF, MNR -Multivariate analysis without RIF, MWR -Multivariate analysis with RIF

	BiNR	BiWR	MNR	MWR
High	12%	19%	18%	21%
Moderate	45%	39%	44%	40%
Low	38%	33%	36%	34%
Very Low	05%	09%	02%	05%

Table 2 : Comparison of area under Success rate and Prediction rate curves for bivariate analysis without RIF (BiNR), with RIF (BiWR), and multivariate analysis without RIF (MNR), and without RIF (MWR).

AUC	BiNR	BiWR	MNR	MWR
Success rate	0.8315	0.8560	0.7986	0.8023
Prediction rate	0.6692	0.6804	0.5882	0.5901