Dear Editor in Chief

We are pleased to submit a revised manuscript entitled *Efficacy of using Radar Derived Factors in Landslide Susceptibility Analysis: case study of Koslanda, Sri Lanka* for publication in the Journal of Natural Hazards and Earth System Sciences. A revised copy of the manuscript is provided with changes to the manuscript requested by the editor and reviewers indicated in the attached document, together with detailed responses to the editor's and reviewers' comments.

Yours Sincerely

AKRN Ranasinghe

Responses to editor and reviewer comments on the paper " Efficacy of using Radar Derived Factors in Landslide Susceptibility Analysis: case study of Koslanda, Sri Lanka"

We wish to thank the editor and all reviewers for their constructive comments. Both the editor and the reviewers felt that the paper has to be well organized and the introduction part should be reduced by moving some parts to the methodology. Specifically, the description of the study area should be made a little larger by adding information about the geology and the typology of the landslides. Further, they have commented on the rewriting of the abstract and the conclusions according to the conducted research work. All reviewers stated on the inclusion of colour figures as they are more visually appealing. Consequently, the paper has been rearranged, the abstract rewritten, introduction reduced, methodology rearranged, and the study area expanded. Additionally, the Results and Discussion were separated and Conclusions changed accordingly. All the figures were inserted in colour by preserving the colour blindness using the colour scales. The details of these changes are provided below, along with the responses to the comments.

In the following, the comments of the editor and reviewers are shown in italics and our responses indented in normal text. References to the edited lines are according to those found in the revised manuscript, unless specifically referred to in the original manuscript.

Response to Editor

After carefully revising your paper and the discussion, we believe that your manuscript is of potential interest to the journal but not ready for publication. A significant improvement could be reached by introducing major changes which, according to the referee's reports, should mainly focus on:

1) *Modifying the paper structure by reducing the introduction, increasing the geological and geomorphological description of the test site, separating results from the discussion and modifying the methods section, as well.*

The introduction part has been improved by reducing the extra information where unnecessary. The following lines have been deleted; page 1 line 29, lines 32-34, page 2 lines 1-3, line 13, and lines 19-20.

Furthermore, part of the statistical methods for landslide susceptibility analysis was moved to the methodology part. (page 2 lines 41-42 and page 3 lines 1-17 to page 7 lines 35-39, page 8 lines 1-4, lines 18-22 and lines 25-28).

Remote sensing for susceptibility map purposes and for extracting the parameters are already explained in page 2 lines 5-11.

The geomorphological information to the test site is already included in the manuscript in page 4 lines 1 – 6, but additional geological information is inserted in to page 4 lines 6-10 as;

"Geology refers to the physical structure and the substance of the Earth. The study area consists mainly of undifferentiated charnockitic biotite gneisses and Quartzites, according to the 1:10000 geological map from the 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."

Data and Methodology sections have been separated, while improving the methodology part. (page 4 line 15, page 7 line 33 to page 9 line 11).

Table 1 is removed from the manuscript (page 4 line 35), while inserting the types of predisposing factors in to the text (page 4 lines 29-32) as;

"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 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."

The Discussion part has been separated from the Results section. (page 9 line 14)

In the results section, four colour landslide susceptibility maps were inserted in to the manuscript. (Figure 4)

Resultant susceptibility regions as high, moderate, low and very low regions are numerically compared with the spatial formation in the study area. (page 9 lines 20-31) and (page 10 lines 12-21)

2) *Rewriting the abstract so it is self-contained and can stand alone*

The abstract has been rewritten. (page 1, lines 9 – 20)

3) *The methods used and the procedural steps are not adequately described. It seems that the approach you follow is not clear and could not be based on robust standards. Could you please explain and improve this section?*

Data and Methodology sections have been separated, while improving the methodology part. (page 4 line 15, page 7 line 33 to page 9 line 11).

Statistical analysis of bivariate and multivariate methods for landslide susceptibility analysis is inserted in to the manuscript. (page 7 lines 35-39, page 8 lines 1-4, page 8 lines 18-22, and lines 25-28).

The details of the relative weight calculation in bivariate, information value method (page 8 lines 8 – 16) and multivariate, MCDA based on AHP is inserted in to the manuscript (page 8 lines 18 – 28).

4) *Introducing some quantitative approach to validate the efficiency of your method*

All the susceptibility analysis and validations are quantitative. In susceptibility analysis, all the predisposing factors are overlaid with the training sample from landslide failure map and the weight of susceptibility index for landslide occurrences was calculated. Then, by using the bivariate and multivariate analysis, landslide prediction models are generated with and without radar derived factors. Hence, all the landslide prediction analysis is quantitative. Similarly, all the validations are performed by overlaying the validation samples on the four different landslide susceptibility maps and calculating the

Cumulative landslide seeds in training and validation samples with respect to the landslide susceptibility classes providing quantitative approach of AUC.

5) *As a side (but important) issue: I would personally advise against using the expression "radar Induced factors" both in the title and in the text. Radar methods are mainly a measuring tool and it is very unlikely that they will be able to induce any landscape factor or to modify it.*

Corrected "radar induced factors" as "radar derived factors" in the whole paper, starting from the topic as "Efficacy of using Radar Derived Factors in Landslide Susceptibility Analysis: case study of Koslanda, Sri Lanka". (page 1 line 1)

The phrase "Radar Induced Factors (RIF)" has been replaced with "Radar Derived Factors (RDF)" in the complete manuscript.

Response to Anonymous Referee #1.

Dear authors, the manuscript titled "Efficiency of using Radar Induced Factors in landslide susceptibility analysis: case study of Koslanda, Sri Lanka" deals with the application of 4 methods for assessing the landslide susceptibility map: Bivariate InfoVal, Bivariate InfoVal with RIF, Multivariate MCDA based on AHP, Multivariate MCDA based on AHP with RIF. The work generally fits the aim of the journal, but needs several modifications and some lacks needs to be filled. The required improvements interest several parts of the work, mainly the data and methodology.

RC1-1 Why all the images are black and white? Please provide the coloured images.

All the figures have been inserted in to the manuscript in colour using the given colour scales. (Figure 1, 2, & 4)

RC1-2 The Abstract has to be rewritten because it cannot stay alone to explain the conducted work.

The abstract has been rewritten. (page 1, lines 9 – 20)

RC1-3 The Introduction, besides it is quite long, partially misses in state-of-the-art about the landslide susceptibility methods and, mainly, in the use of remote sensing data for susceptibility map purposes and for extracting the parameters then utilized.

The introduction part has been improved by reducing the extra information where unnecessary. The following lines have been deleted; page 1 line 29, lines 32-34, page 2 lines 1-3, line 13, and lines 19-20.

Furthermore, part of the statistical methods for landslide susceptibility analysis was moved to the methodology part. (page 2 lines 41-42 and page 3 lines 1-17 to page 7 lines 35-39, page 8 lines 1-4, lines 18-22 and lines 25-28).

Remote sensing for susceptibility map purposes and for extracting the parameters are already explained in page 2 lines 5-11.

RC1-4 The study area is not well presented. It is not well localized (also because the images are B/W) and described. Furthermore, no geological and geomorphological information of the area were inserted. These information have to be added.

A colour image with topographical information, with previous landslide signatures, has been inserted as Figure 1.

The geomorphological information to the test site is already included in the manuscript in page 4 lines 1 – 6, but additional geological information is inserted in to page 4 lines 6-10 as;

"Geology refers to the physical structure and the substance of the Earth. The study area consists mainly of undifferentiated charnockitic biotite gneisses and Quartzites, according to the 1:10000 geological map from the 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."

RC1-5 Data and methodology section has to be deeply improved. Add more info and images of the used data, while Table 1 can be removed because it is useless and it no add information with respect to the text. The used methodologies are no described, as well as no images of the described and used factors are present.

Table 1 is removed from the manuscript (page 4 line 35), while inserting the types of predisposing factors in to the text (page 4 lines 29-32) as;

"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 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."

The information and the images used to extract all landslide predisposing factors are already within the manuscript under all predisposing factors. However, some information has been added as (page 4 line 39 – page 5 line 1)

Available information is, for example, topographical factors –"Sentinel-1 radar image on 12th March 2015" (page 5 line 13), Soil factors – "Landsat-8 image of 3rd July 2015" (page 6 line 10) and "dry reference image on 12th March 2015 and the wet image on 24th November 2014" (page 6 lines 32-33).

Data and Methodology sections have been separated, while improving the methodology part. (page 4 line 15, page 7 line 33 to page 9 line 11).

When considering the guide-lines for manuscript preparation, even though the individual figures from fifteen predisposing factors are really significant, it is difficult to add them all to the manuscript. Hence, all the fifteen predisposing factors (in colour figures) were added as supplementary materials (Sup 1-3).

RC1-6 How did you extract factors by Sentinel-2 and Landsat images? The resolution of the images was enough? Please clarify.

Sentinel – 2 images with 10 m resolution is used to extract Land use (page 8 lines 13 – 15) and Lineament predisposing factors. Landsat-8 with 30 m resolution (NIR & R bands) and 100m resolution Thermal band is used to extract surface soil moisture from

Universal Triangle relationship between Soil Moisture, Normalized Difference Vegetation Index (NDVI), and Land Surface Temperature (LST). The study area is approximately 19 km^2 and since this study is primarily focused on the applicability of remote sensing (radar and optical) for landslide susceptibility analysis on smaller scale, the freely available Sentinel–2 and Landsat–8 image with Thermal band was sufficiently enough for this research study.

RC1-7 Insert the landslide inventory map derived by the multi-temporal analysis.

Landslide inventory map with training and validation samples for Landslide susceptibility analysis has been inserted in to the manuscript as Figure 2. (page 8 line 6)

RC1-8 Table 1 can be maintained if the relative weights are included, with a short explanation about how they were calculated and the addition of the "questionnaire survey form" in the text or as supplementary material.

Table 1 is removed from the manuscript (page 4 line 35), while inserting the types of predisposing factors in to the text (page 4 lines 29-32) as;

"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 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."

The details of the relative weight calculation in bivariate, information value method (page 8 lines 8 – 16) and multivariate, MCDA based on AHP is inserted in to the manuscript (page 8 lines 18 – 28).

The sample questionnaire has been attached as a supplementary material (Sup 4)

RC1-9 Results and discussion also need improvements. I suggest to separate the results and discussions. In the results session the four resulting landslide susceptible maps calculated (please with colours) have to be inserted and described.

The Discussion part has been separated from the Results section. (page 9 line 14), Four colour landslide susceptibility maps have been inserted in to the manuscript under the results section (Figure 4)

Resultant susceptibility regions as high, moderate, low and very low regions are numerically compared with the spatial formation in the study area. (page 9 line 20-31, and page 10 lines 12-21)

RC1-10 To make readable and comparable all the percentage of the four maps and relative classes, please summarize them in a table. Then the comparison between then can be insert in the discussions session.

Percentages of susceptibility classes in four landslide prediction maps are already summarized in Table 1. The comparison between them are inserted in to the Discussion section (page 10 lines 24-32) as follows;

RC1-11 Consequently, to all the required modifications and suggestions the conclusion has to be reviewed accordingly.

The Conclusion has been rearranged according to the revisions made in the previous sections (page 11 line21 - page 12 line 23)

Minor issues

RC1-12 Add some more recent references about the "landslide-specific information for emergency and disaster management activities in the world". See for example Solari et al., 2018

Four recent references have been added in to the reference list and cited in the text (page 1 line 23, page 2 line 8, page 7 line 31).

RC1-13 Add references of already published methods, e.g. IDW, NDVI and LST

For NDVI and LST, references are already there in the manuscript (page 7 lines 13-14 and lines 22).

IDW is a standard interpolation method and is used to interpolate the rainfall data through out the study area for better computations.

RC1-14 Pay attention to the tenses. You write some parts using the present form and other the past.

Tenses have been corrected in the manuscript. (page 2 line 27)

RC1-15 Please check – Line 24 page 2 - remove "could"

Deleted. (page 2 line 24)

RC1-16 Substitute "from the Mean Sea Level" with a.s.l. (above sea level) – Line 26 page 4

Corrected. (page 4 line 17)

RC1-17 Line 3 page 5 remove "for these data"

Corrected. (page 5 line 11)

RC1-18 Line 7 page 5 - Substitute "an inventory map of landslide" with "landslide inventory map"

Corrected. (page 5 lines 15-16)

Response to Anonymous Referee #2.

The paper deals with a topic of interest for the journal. I think it could be of interest for the readers. However, in my opinion there is still work to be done in order to make it suitable for publication.

RC2-1 As the other reviewers, I think itis not well organized.

Please see responses to RC1-1,RC1-3, RC1-4.

RC2-2 The abstract is "strange". It is not a good summary of the paper.

Please see response to *RC1-2* of the Anonymous Referee # 1, *RC2-3 I think also that the introduction is not well focused and too long.*

Please see response to *RC1-3* of the Anonymous Referee # 1,

RC2-4 And I see too long sentences which sometimes makes difficult the understanding. Can you improve it?

Has been addressed (page 1 lines 23-29) as;

RC2-5 The quality of the figures is poor. Why do not use colour figures?

Please see response to *RC1-1* of the Anonymous Referee # 1,

RC2-6 The analysis of the results is also very qualitative.

All the predisposing factors are overlaid with the training sample from the landslide failure map and the weight of susceptibility index for landslide occurrences have been calculated. Then by using bivariate and multivariate analysis landslide prediction models are generated with and without radar derived factors. Hence, all the landslide prediction analysis is quantitative. However, in order to make the models are more interpretable for the users, weight of indices is discretised in to four classes as 60%, 30%, 10%, and 0% of failure regions for high, moderate, low, and very low landslide susceptibility classes respectively.

RC2-7 In the conclusion, the authors say that "with the integration of RIF as surface roughness, near surface soil moisture 15 from Delta Index, and forest biomass, the detection of the boundary between the high and very low susceptibility areas is increased". However, it is not well demonstrated from the given results and explanation. Can you improve it?

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, describes the particular results and under the Discussions section, the results are explained further (page 13 lines 3-11) Please note that the RIF has been replaced with RDF, for Radar Derived Factors.

RC2-8   I am not sure that from the result one can conclude that RIF helps to improve the results. I see very similar results by using and by not using the RIF parameters. Please, can you improve your analysis in order to be more convenient or change the conclusion?

All prediction and validation analysis are based on the past landslide experiences in the same area, thereby minimizing bias and errors from human intervention. In multivariate analysis, weights are calculated by using expert knowledge. However, consistency ratio is measured in order to confirm the consistency of relative importance. Hence, all prediction results are depending on the past landslide occurred in this study area and the statistical analysis. Table 1 compares the landslide susceptible areas from four different landslide prediction models by bivariate and multivariate with and without radar induced (derived) factors numerically. Even though they appear to be similar, I confirmed that all the analyses are numerical, and give different meanings, especially within the context of the study.

Response to Short Comment #1.

The manuscript shows the comparison among different approaches (bivariate/multivariate analyses) using different sets of data (classic/classic + radar data) to produce a landslide susceptibility map of an area located in Sri Lanka. The work in general seems appropriate for the journal but it is not very well organized. In the paper a reader would expect to read: 1) a comprehensive introduction with proper literature,2) a detailed description of the study area and its problematic in terms natural hazard;3) a description of the adopted methodology; 4) the presentation of the results, 5) a discussion of the obtained results; 6) final remarks. I think the manuscript contains some of these issues but not well organized.

SC1-1   The introduction session is very long with respect to the rest of the paper.

Please see response to *RC1-3* of the Anonymous Referee # 1

SC1-2   The authors should add some background knowledge about the use of remote sensing data and in particular of radar data to infer topographical, soil and land cover information.

“Use of radar remote sensing for topographical information” is added to page 6 lines 19-23, for soil information in page 8 lines 3-4, and for land cover information in page 8 line 30 -page 9 line1.

SC1-3 The literature review part in the first part of the Introduction needs to be improved. The second part (Statistical methods for landslide susceptibility analysis) should be reduced and part of it should be moved in to the methodology description.

The introduction section was improved by reducing the extra information where unnecessary. The following lines , page 2 lines 3-5, lines 10-12, line 22, and lines 28-29 have been deleted.

Further, as commented, a section from the statistical methods (give references) for landslide susceptibility analysis has been moved to the methodology section (give references to the new locations).

SC1-4 The description of the study area is very short. Please add some information about the geology of the study area and about the typology of the landslides which affect the study area.

Geological information about the study area has been inserted to page 4 line 31 -page 5 line 4 as;

Typology of the landslides of the particular area has been inserted to page 4 lines 22 – 24 as;

SC1-5 The section “Data and methodology” is actually a list of the data available. There is nothing about the bivariate or multivariate methods. I suggest to show a map for each considered predisposing factor.

The Data and Methodology section has been separated, and the methodology section has been improved by making additions to page 9 line 20 – page 11 line 3as;

Statistical analyses of bivariate and multivariate methods have been inserted to page 9 line 22 – page 11 line 3 as;

When considering the guidelines for manuscript preparation, even though the individual figures from fifteen predisposing factors are really significant, it is difficult to add them all to the manuscript. Hence, all the fifteen predisposing factors (in colour figures) were added as supplementary materials (Sup 1-3).

SC1-6 Some factors need for a more accurate description, for example you need to describe the geology of the study area (Geological factors), in this paragraph information about the geology of the study area and the used classes totally lack.

The geological information of the study area has been inserted in to the manuscript (page 4 line 31 – page 5 line 4) as;

Additional geological information and used classes have been included under the Geological factors on page 7 lines 27 – 29 as;

“Primarily the undifferentiated charnockitic biotite gneisses and Quartzites are prominent with Garnet-sillimanite and Garnetiferous quartzofeldspathic gneiss in the study area.”

SC1-7 How do you decide the weight of influence of all predisposing factors?

The details of the relative weight calculation in bivariate, information value method (page 8 lines 8 – 16) and multivariate, MCDA based on AHP is inserted in to the manuscript (page 8 lines 18 – 28).

SC1-8 I suggest to split the results from the discussion. In the results section you need to present the landslide susceptibility maps and to explain their significance in terms of predisposing factors. In the discussion you can compare all the obtained maps highlighting advantages, drawbacks and limitation.

The Discussion and the Results have been separated into two, and described accordingly (page 10 line 23).

Under the Results section, four (04) colour landslide susceptibility maps have been inserted to the manuscript by preserving the colour blindness. (Figure 4)

SC1-9 Figure 1: I think that a colour figure can have more appeal, the same for figure 3.

Please see response *RC1*-1 to the Anonymous Referee # 1,

Minor issues

SC1-10 Page 1 Line 23: I think that you mean 90% and not 09%

According to the literature Chalkiaset al., 2014, landslides from all natural hazards are 9% not 90%.

SC1-11 Page 2 Line 11: Earth and not earth

When reducing the Introduction section by removing unnecessary information, the particular line has been deleted.

SC1-12 Page 2 Line 33: delete "employed"

Corrected. (page 2 line 24)

SC1-13 Page 4 Line 24: "act as a sponge" does not sound really scientific

Inserted the word "act as a highly absorbing entity" instead of *"act as a sponge"* (page 4 lines 4-5)

SC1-14 Page 5 line 5: how much is the DEM resolution?

DEM resolution has been added in to the manuscript (page 4 line 21).

SC1-15 Page 7 line 6: what does "Thermal-NDVI space" mean?

There is a unique relationship between soil moisture, NDVI, and Land Surface Temperature for a given region. This relationship is described as the “Universal Triangle” and results have been confirmed through theoretical studies using soil-vegetation-atmosphere-transfer (SVAT) model (Wang and Qu, 2009, Zenga et al., 2004).

SC1-16 Page 9 Line 2: How do you extracted the lineaments from Landsat and Sentinel 2 images? Are you sure that joints and fractures can be observed with the resolution of Landsat and Sentinel?

This study only used 10m resolution Sentinel-2A image (not Landsat) for the lineament extraction of the study area. Most recent studies such as Kati et al., 2018 and Adiri et al., 2017 confirmed the use of 10m resolution Sentinel 1 and 2A images for lineament extractions.

SC1-17 Several references are not reported in the reference list: (van Vesten 1997; Somaratne, 2016; Rahman et al., 2008; Septiadi and Nasution 2009; Zhan et al., 2002)

Missing references have been added to the reference list.

Efficacy of using Radar ~~Induced~~ Derived 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~~ Derived Factors (~~RIF~~RDF) 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~~RDF, multivariate without and with ~~RIF~~ RDF were generated. Twelve factors as topographical, hydrological, geological, land cover and soil plus three ~~RIF~~ RDF 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~~RDF, 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).

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 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 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 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 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 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.~~

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 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.~~

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 considering 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 ~~sponge~~[R1]highly 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 to the physical structure and the substance of the Earth. ~~Mainly the~~The study area consists mainly of undifferentiated charnockitic biotite gneisses and Quartzites, according to the 1:10000 geological map from the 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.

FIGURE 1

3 Data and methodology

~~3~~3.1 Data

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 are used to generate the 7 m resolution DEM using aerial triangulation. ~~An inventory map of landslides~~The 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.~~

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 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**~~

~~3.1~~3.1.1 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 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 12^{th} 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.

~~3.2~~3.1.2 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;

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

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.

~~3.3~~3.1.3 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;

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

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;

$$T_{max} = a_1 \cdot NDVI \ + b_1 \quad (3)$$

$$T_{min} = a_2 \cdot NDVI \ + b_2 \quad (4)$$

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

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;

$$Delta\ Index = \left| \frac{\sigma_{wet}^0 - \sigma_{dry}^0}{\sigma_{dry}^0} \right| \quad (5)$$

where, σ_{wet}^0 is the radar backscatter (decibels) from a pixel in the radar image representing wet soil conditions, and σ_{dry}^0 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.

~~3.4~~3.1.4 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 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.

~~3.5~~3.1.5 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. Primarily 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 overlays 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;

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

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 RDF 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 RDF 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.

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~~ RDF and described the processing steps in Fig.~~2~~3.

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 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~~ RDF (BiNR), (ii) bivariate with ~~RIF~~ RDF (BiWR), (iii) multivariate without ~~RIF~~ RDF (MNR), and (iv) multivariate with ~~RIF~~RDF(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~~RDF

Susceptible regions are identified from the bivariate InfoVal method without ~~RIF~~ RDF as 12% for high, 45% for moderate, 38% 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~~ RDF identified 19% of failure regions for high susceptibility, 39% for moderate, 33% for low, and 9% for very low susceptible 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 near the Eruwendumpola Oya, are identified as having very low susceptibility for landslides. Similar to the bivariate analysis without ~~RIF~~RDF, the middle regions with 30^0-50^0slope 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.

FIGURE 3

4.2 Multivariate MCDA based on AHP Without and With ~~RIF~~RDF

All fifteen weighted predisposing factors were grouped as without and with ~~RIF~~RDF, and weighted overlay is performed separately in order to obtain the landslide susceptibility regions. ~~The calculated weights forelevation, 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 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 the 0.1 thereby showing a realistic level of consistency in the pairwise comparison matrix.~~

~~FIGURE 3~~

Figure ~~3~~4(c) illustrates the landslide susceptibility map from the multivariate method without ~~RIF~~ RDF and is able to identify 18% 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~~RDF, 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.~~3~~4(d). Hence, 61% of areas from the study area are predicted as having high and moderate susceptibility for the landslide hazard. In a similar 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 ~~2~~1. Moderate and low landslide susceptibility areas show very small ((1-2)%) changes between these four types of analysis. With the integration of ~~RIF~~ RDF 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 ~~2~~1

~~4.3~~5.1 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~~RDF, are calculated and graphed in Fig.~~4~~5.

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 ~~3~~2. 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 ~~3~~2

~~5~~6 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~~derived 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 landslide~~s~~ 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~~RDF, can be used for landslide prediction analysis. However, with the integration of ~~RIF~~ RDF 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 ~~areas~~regions 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 decreased~~high 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 derived factors, by increasing the accuracy of prediction for high susceptibility regions, the possibility of mitigating dangers can be 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 occurs. ~~As a whole, there is an improvement of prediction and validation performances of bivariate analysis than multivariate analysis.~~

~~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 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~~ derived factors by using bivariate and multivariate analysis. This is because the radar ~~induced~~ derived 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 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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A.K.R.N. Ranasinghe performed the Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Validation, Visualization, and Writing – original draft and R. Bandara accomplished the Supervision, and writing - review and editing. U.G.A. Puswewala and T.L. Dammalage executed the Supervision.

Competing Interests

The authors declare that we have no conflict of interest.

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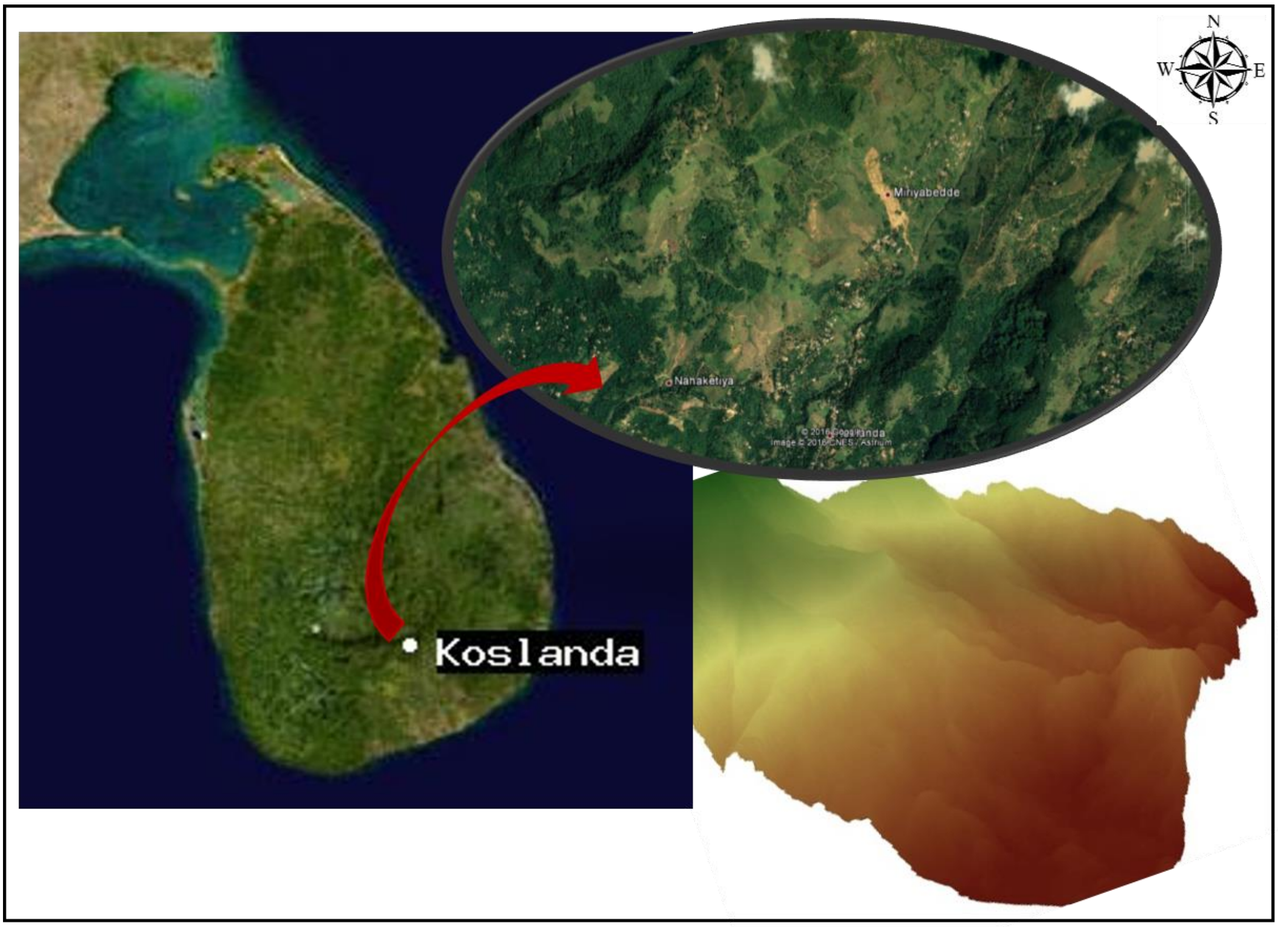

Figure 1 :Topographical formation of Koslanda, Sri Lanka with its previous Landslides Signatures

Figure 2 : Landslide failure map of the Koslanda area with two different training and validating samples

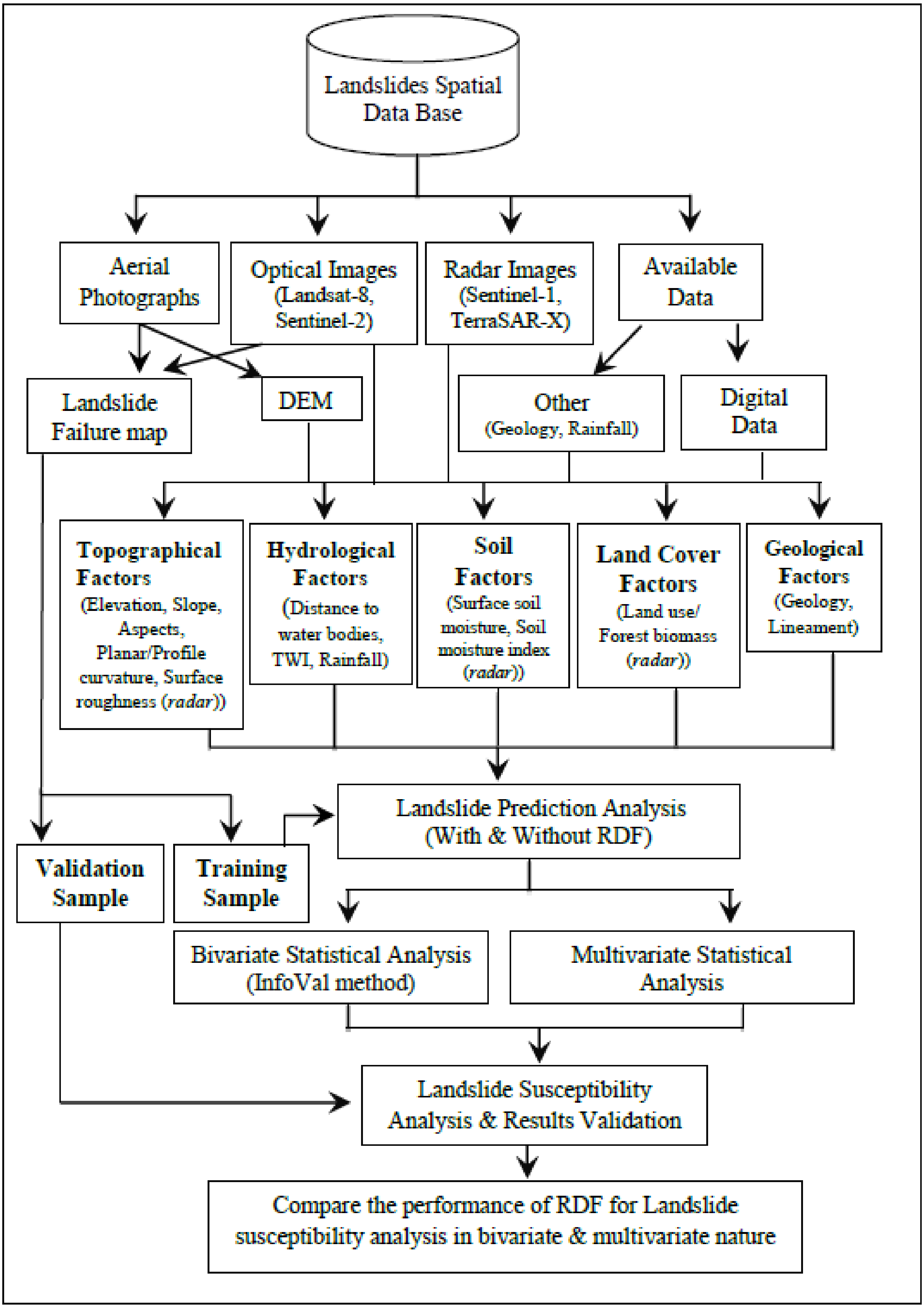

Figure 3 : Methodological flow of the Landslide susceptibility analysis using Bivariate and Multivariate approaches

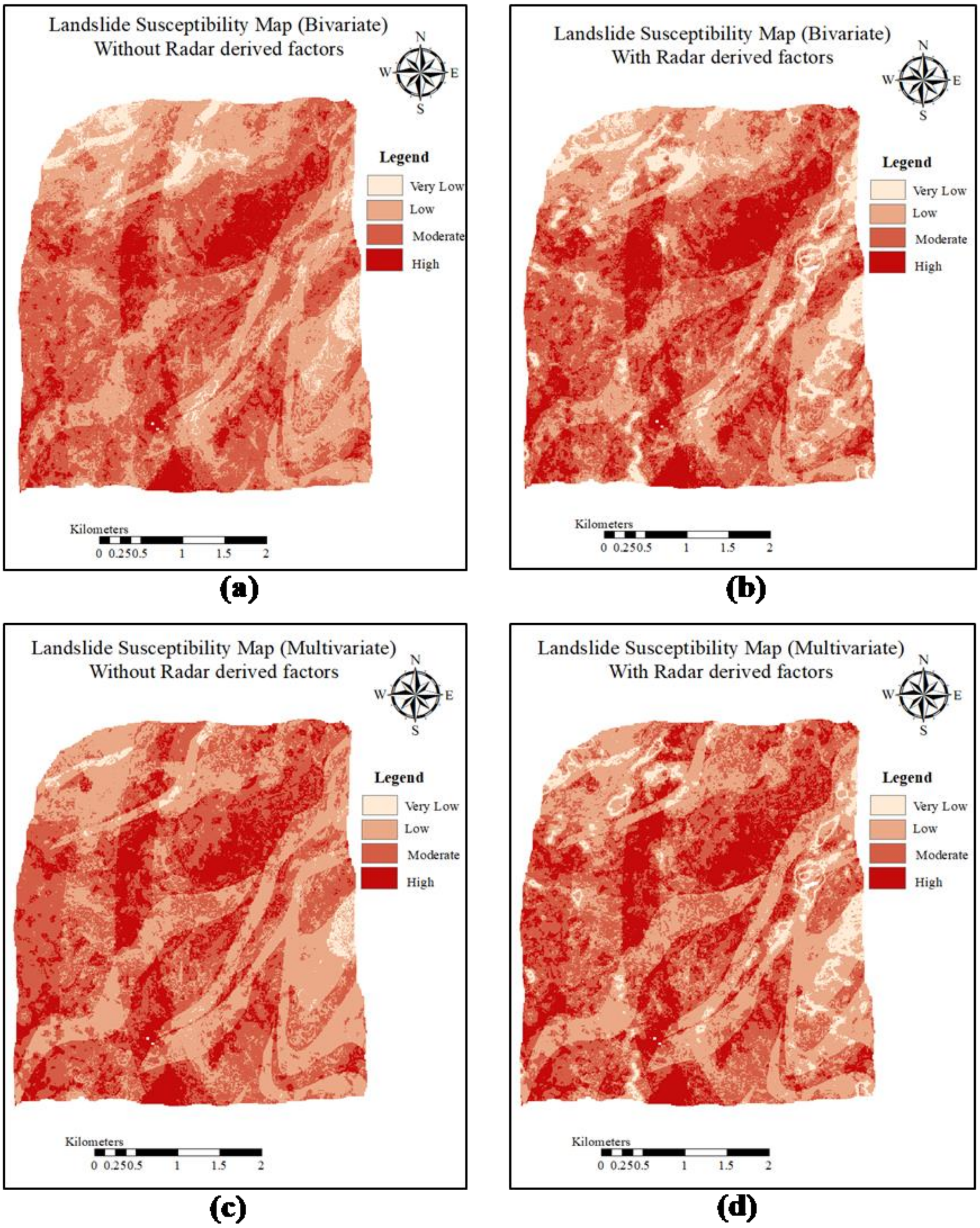

Figure 4 : Landslide susceptibility maps from bivariate and multivariate analysis without and with ~~RIF~~RDF. (a)- bivariate without ~~RIF~~RDF, (b)- bivariate with ~~RIF~~RDF, (c)- multivariate without ~~RIF~~RDF, and (d)- multivariate with ~~RIF~~RDF

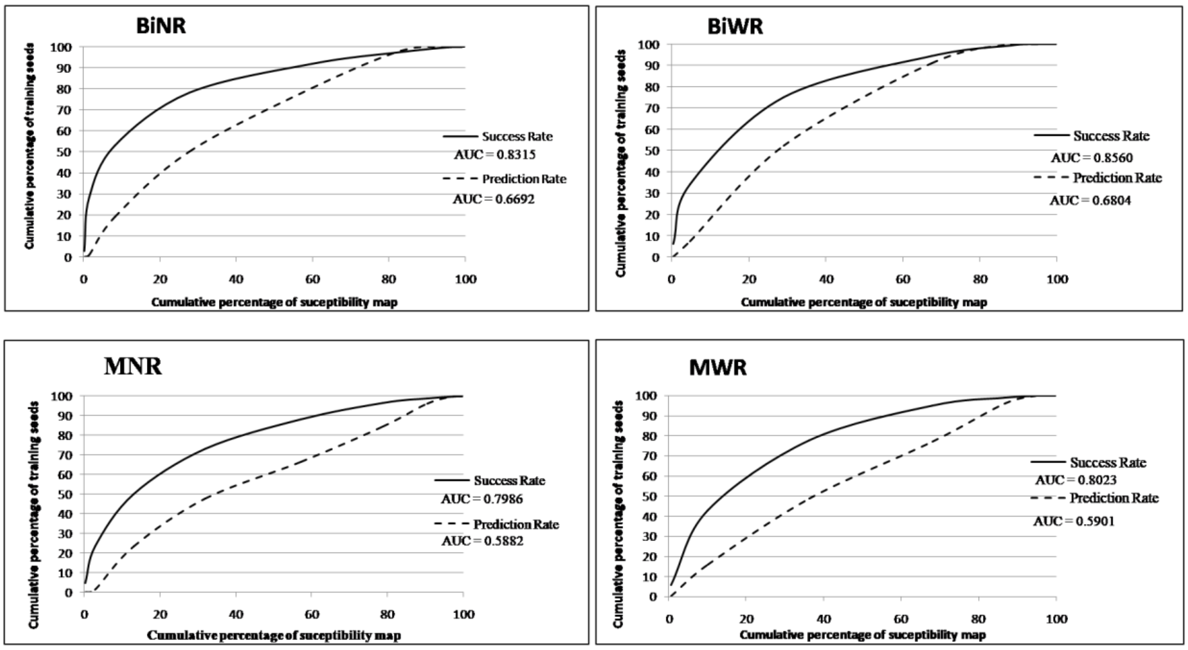

Figure 5 : Success rate and Prediction rate curves with AUC for the bivariate and multivariate analysis without and with ~~RIF~~RDF. X axis denotes the Cumulative percentage of Susceptibility regions and Y axis denotes the Cumulative percentage of training samples. From left to right and top to bottom BiNR- bivariate analysis without ~~RIF~~RDF, BiWR- with ~~RIF~~RDF, and MNR- multivariate analysis without ~~RIF~~RDF, and MWR- with ~~RIF~~RDF

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

	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~~ RDF (BiNR), with ~~RIF~~ RDF (BiWR), and multivariate analysis without ~~RIF~~ RDF (MNR), and without ~~RIF~~ RDF (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