

Assessing the Effect of Land Use Changes on Landslide: A case of Sabaragamuwa Province, Sri Lanka

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Abstract

Landslides are the results of the complex spatial-temporal interaction of geological, geomorphological, climate and land use factors. Geological, geomorphological and climate factors change in relatively long periods whilst land use change in short term. Accordingly, land use has significant influence on landslide frequency and distribution, even in a short time span. However, limited studies have been carried out to investigate which land use changes have more influence on landslides. In this study, have been analyzed land use changes occurred in Sabaragamuwa Province, Sri Lanka in order to assessing the effect of specific land use changes on landslides. The study is executed in four phases. Firstly, study mapped locations of landslides in QGIS environment. For this purpose, the study used secondary data which has obtained from National Building Research Organization, Sri Lanka. Then the study analyzed the land use changes at landslide occurrence locations as well as a range of spatial buffer zone area from landslide occurrence locations. MOLUSCE (Modules for Land Use Change Evaluation) plugin in QGIS was used for identify the land use changes between study period in each spatial buffer zone areas. Thirdly, the study computed the magnitude of a landslide of each location based on five criteria's as number of death, number of injured people, number of parcel damage, number of full damage and affected people. Then the study analyzed the relationship between magnitude of a landslide and land use changes. For this purpose, the study used spatial analysis tools in QGIS environment. The results show that land use changes such as forest to rubber, rubber-to-garden, rubber-to-any, tea-to-rubber, tea-to-any, forest-to-any have recorded greater influence on high occurrence of high magnitude of landslides. These findings represent an important step towards the better understanding of the influence on land use changes by types on land slide. This observation can be useful input for further studies in order to minimize landslide in the fields of land use planning and disaster management.

Keywords: MOLUSE, QGIS, Land Use Changes, Landslide, Land use Planning and Disaster Management Application

1. Introduction

Natural disasters have become a global development challenge that cause major damages to lives, properties and livelihoods. Hence, human settlements are in an urgent need for Disaster Risk Reduction initiatives to minimize the adverse impacts.

Landslide is the most frequent type of natural disasters reported in mountainous regions. Causative factors of landslides such as soil cover, slope stability, hydrology, drainage, precipitation and land

form are natural (Cruickshank, 1995) whereas land use and management is a human-induced cause. "Different land use types may control the stability of slopes, and in particular, slope stability is improved by vegetation in relations of automatic and hydrological features" (Greenway, 1987). Works of Beek, et al., have applied "a physical model to a 1.5 km² catchment in the Alcoy region ... to assess the special effects of land use change on the spatial and sequential activity of slope variability. They have observed that the abandonment of cultivated grounds encourages an important reduction in land sliding incidence, and in deposit distribution" (Beek & Asch, 2004).

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Similarly, a research conducted Taihe area in Taiwan has revealed a relationship between changes in vegetation cover over the landslide frequency – area distribution. Recent works focused on the effects of human-induced land use variations on slope stability have revealed that in populated regions, the impact of human activities significantly increase the initiation and reactivation of landslides (Bakker, et al., 2005); (Alewell & Meusburger, 2008); (Eeckhaut, 2009).

Rossi et.al. have worked in Messina, Italy “to understand the effect of land use change on the vulnerability zonation using different land use scenarios” (Rossi, Mondini, Busca, & Reichenbach, 2014). Further, that study has evaluated and quantified the effect of land use change over a period of 60 years over the land susceptibility zonation. The study has developed a method to evaluate the consequences of land use change on landslide vulnerability and risk

Recent works of Giuseppina et.al in Italy; Rio Frate, Versa and Alta Val Tidone area has examined the land use changes, “specifically by studying the time based changing aspects of land use differences, specifically in abandoned agricultural lands”. The results revealed the abandoned cultivated lands, which regularly recovered through the natural grasses, shrubs, as the land use change class that was most prone to shallow landslides. (Giuseppina, Bordoni, & Meisina, 2017).

Acknowledging the fact that landslide is a natural hazard, management of land use provides an effective solution to control the probability of landslide incidences. Scientifically validated research on the magnitude of the impact of land use changes over natural disasters facilitate spatial planners in making disaster-responsive land use planning decisions (Mahanama, Wimaladasa, & Abenayake, 2014). In the given context, this study attempts to contribute to the domain of work on disaster-responsive land use planning by overcoming the key limitations of existing studies. Most of the existing studies have verified the relationship between land use and landslide incidents based on the modelled vulnerability zones and broadly classified land-use zones. Few studies which were based on empirical data too limited to spot data of hazards that do not consider the variations of the magnitude of the landslides.

The primary objective of this study is to investigate the extent in which land use changes influence on

occurrences of landslides of different magnitudes with reference to a Sri Lankan case study.

2. Methods and materials

2.1 Selecting the study area

Sri Lanka, as a developing country with a tropical climate, is high vulnerability for the impacts of climate change including extreme weather conditions which records during unpredicted or unexpected periods of the year (Mahanama P. , Abenayake, Jayasinghe, & Bandara, 2014); (Abenayake, M, Marasinghe, & Takashi, 2016). National Building Research Organization (NBRO) has declared 1/3 land of Sri Lanka as landslide vulnerable areas. Data by Sri Lanka Disaster Knowledge Network of Ministry of Disaster Management reveals a growth of landslide occurrences from 2003 to 2017. Occurrence of landslides in Sri Lankan context are mostly rain-induced. Recent precipitation variation studies in Sri Lanka have revealed a significant increase of rainfall in terms of intensity and frequency (Bandara, Jayasinghe, Abenayake, & Mahanama, 2013); (Abenayake, Jayasinghe, & Mahanama, 2013). Further, “Changes in land uses have caused “human-induced” landslides which are estimated at 80% of total landslide incidents” (Sugathapala & Presanna, 2009) .

Landslide-prone districts in Sri Lanka are Kalutara, Galle, Hambantota, Nuwara Eliya, Matale, Kandy, Kegalle, Ratnapura, Matara, and Badulla. Sabaragamuwa province, that consists of Kegalle and Rathnapura districts has the highest vulnerability to landslides. Sabaragamuwa Province is one of the nine provinces of country which is 4968 sq.km in extent and holding 2 million population.

29 locations within the province, which were prone to landslides in 2017 May were selected for the study (Fig. 1).



Figure 1: Study area with 29 landslide prone locations
Figure 1 represent the location, which was selected for this study (study mapped locations of landslides in QGIS environment).

2.2. Selecting an Open-Source GIS-based application

Geographic Information System (GIS) is a widely used computer-based tool in disaster-responsive decision-making, particularly in analysing temporal variations generalized by mathematical rules and represented by visual symbols (Mahanama, Jayasinghe, Jayasinghe, Bandara, & Abenayake, 2014); (Jayasinghe, Mahanama, Senanayake, Bandara, & Seifert, 2013). Though it offers a promising technical solutions to humanitarian complexities, planning and policy decision-making in developing countries often lacks funds to invest on expensive GIS applications (Mahanama, Abenayake, & Jayasinghe, Challenge of Local Responses to Climate Change; Perceptions of Urban Planning Practitioners in Sri Lanka, 2014). (Mahanama, Jayasinghe, Jayasinghe, Bandara, & Abenayake, 2014); (Jayasinghe, Mahanama, Senanayake, Bandara, & Seifert, 2013). Hence, in this study utilized open-source software for GIS-based applications. When consider the role of the open

source GIS in land slide studies, QGIS software allows to perform quick and convenient analysis of land cover changes. (MOLUSCE – quick and convenient analysis of land cover changes, 2013). To identify the temporal changes of land use, the study utilized MOLUSCE plugin tool which is in QGIS.

2.3. Identifying Causative factors of landslide occurrence

Causative factors of landslide hazards were selected through a comprehensive literature review. According to NBRO Causative factors of landslide hazards are bedrock geology, hydrology & drainage, Soil, slope angle range, Land use and Landforms (Munasinghe & Wijegunaratne, 2015). Many authors have mentioned land use, slope, and soil as the key factors (Bhandari, Perera, & Weerasinghe, 1995); (Munasinghe S. , 2012); (Iqbal, 2014). Some authors have emphasized slope and land use as the most prominent factors among the others (Rossi, Mondini, Busca, & Reichenbach, 2014); (Moréd, Ninyerolac, Regosa, & Pons, 2015). Hence, this study has considered Land use, Slope, Soil and precipitation as the causative factors subjected the relative importance and data availability.

2.4. Data Acquisition

This study is completely based on secondary data sources which were obtained from national level database.

Table 1: Data Acquisition

Item	Source
Landslide	GPS- point data and Drone Survey images from National Building Research Organization, Sri Lanka, 2017 Damages due to the landslide, from National Building Research Organization, Sri Lanka, 2017 and Disaster Management Center, 2017
Land use	Land use maps, 1:50,000 scale, from Survey Department, Sri Lanka, 1986 Land use maps, 1:10,000 scale, from Survey Department, Sri Lanka, 2010
Slope	Contour map, 1:50,000 scale, from Survey Department, Sri Lanka, 1986
Soil	National Soil Maps, 1:1,000,000 scale, Land Use Division, Sri Lanka, 1988
Rainfall	Monthly Rainfall (1987-2017), from Meteorological Department, Sri Lanka, 2017

2.5. Preparing baseline maps for causative factors

As the initial step, thematic maps were prepared for the Slope (Fig. 2) Soil (Fig. 3), and Land use in order to represent the baseline status. For that, used GPS point and drone images which collect by National Building Research Organisation. Quantum Geographic Information System (QGIS) & Google earth to obtain high accuracy supported this step.

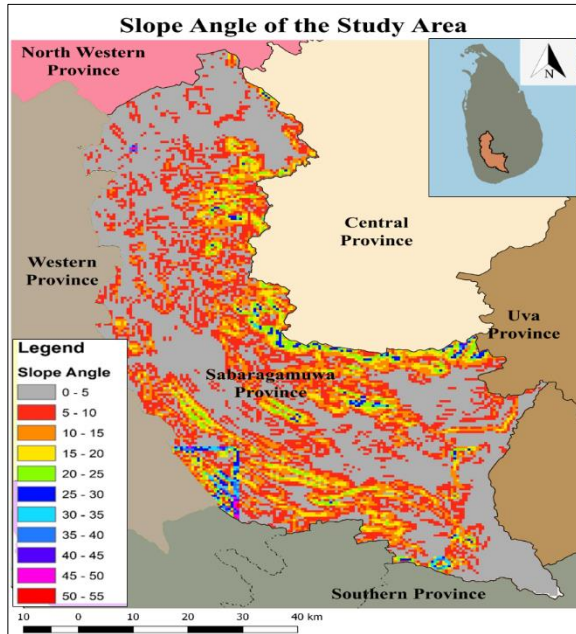


Figure 2: Slope Type of Study Area

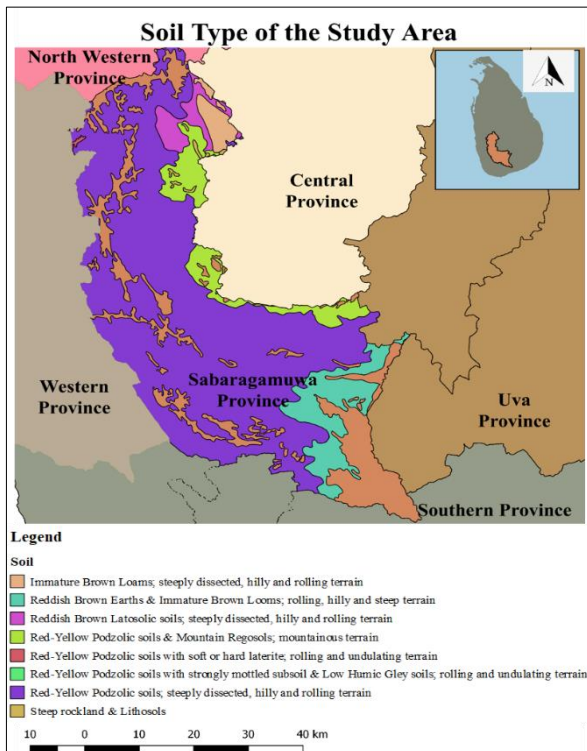


Figure 3: Soil Type of Study Area

2.5.1. Detecting the temporal Changes of Landuse

Then the study analyzed the temporal changes of land use at landslide hazard locations as well as within a range of spatial buffer zone areas from each landslide hazard locations. MOLUSCE (Modules for Land Use Change Evaluation) plugin in QGIS was utilized in identifying the land use changes from 1986 to 2017. There are seven different types of land use changes as depicted in Table 2.

Table 2: Land Use Changes

Category	Land Use changes 1986 – 2010 (sq.m) (With in location)
Garden to Tea	81.25
Rubber to Other	38.7
Chena to Tea	27
Tea to Rubber	7.45
Garden to Rubber	154.494
Chena to Coconut	0.2
Rubber to Coconut	12.25

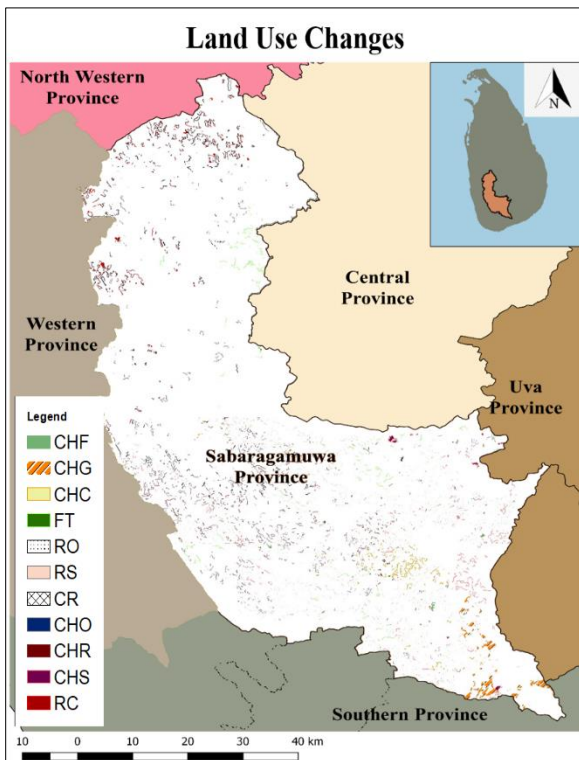


Figure 4: Land Use Change Location (Refer Table no 3 for land use code)

Table 3: Land Use Code

No	Code	Description	No	Code	Description
1.	ST	Scrub to Tea	21	SF	Scrub to Forest
2.	RT	Rubber to Tea	22	CHF	Chena to Forest
3.	GT	Garden to Tea	23	RCH	Rubber to Chena
4.	GR	Garden to Rubber	24	CHO	Chena to Other
5.	FS	Forest to Scrub	25	OG	Other to Garden
6.	PS	Paddy to Garden	26	FR	Forest to Rubber
7.	FT	Forest to Tea	27	SF	Scrub to Forest
8.	SR	Scrub to Rubber	28	FO	Forest to Other
9.	RG	Rubber to Garden	29	FG	Forest to Garden
10.	TS	Tea to Scrub	30	PS	Paddy to Scrub
11.	SG	Scrub to Garden	31	TCH	Tea to Chena
12.	PO	Paddy to Other	32	OR	Other to Rubber
13.	RC	Rubber to Coconut	33	CR	Coconut to Rubber
14.	RO	Rubber to Other	34	OC	Other to Coconut
15.	RS	Rubber to Scrub	35	FCH	Forest to Chena
16.	CR	Chena Rubber	36	SCH	Scrub to Chena
17.	TR	Tea to Rubber	37	CHT	Chena to Tea
18.	TG	Tea to Garden	38	CHG	Chena to Garden
19.	CS	Chena to Scrub	39	CHC	Chena to Coconut
20.	CHC	Chena to Coconut			

2.6. Preparing a hazard map with magnitude

Then study analysis the influence of different factors in different buffer zones. Then analysis each land use category in each landslide locations (29 location) and land use change location (30 location). And analysts the slope and soil type of each landslide locations, land use change locations within landslide location to 5km buffers (around 8520 locations within 5km buffer zones). Also, this step supported by MS-Excel spreadsheet & QGIS to calculating the land use change(39 land use change types) area and percentage vice calculation in each buffer (buffers 420). Also supported by drone survey photograph collected by NBRO, report, DMC database etc. In the literature used study area as catchment or region with more land use locations to study the influence of land use change on landslide occurrence but not used specific land use category. Therefore, in this study, I used specific buffers for the lands slide locations. Also cannot apply continuous buffers like 100m, 200m. So used 500m to 5km buffers. Figure 5 & 6 represent the buffer zone which used in this study.

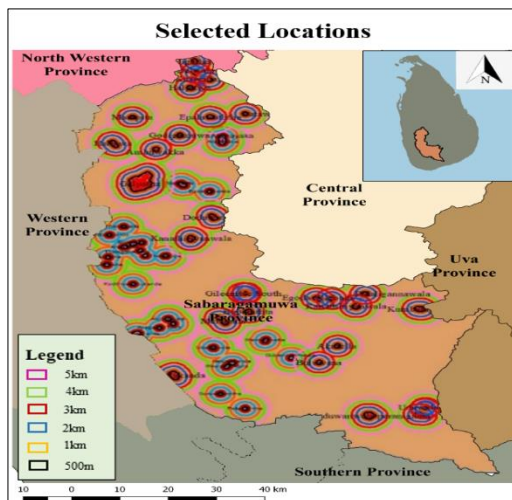


Figure 5: Selected location with 29 land slide locations

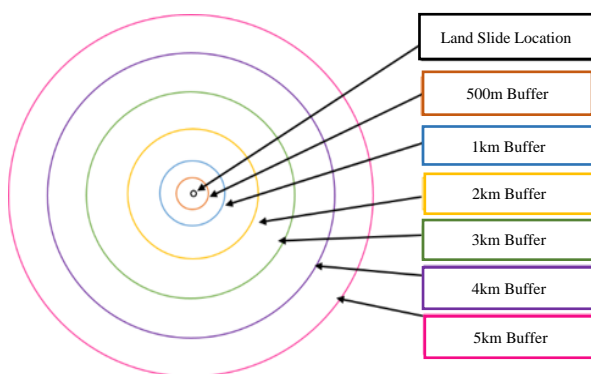


Figure 6: Buffer Zones

Third step is to prepare weighted table for damage & landslide occurrence factors. This step helps to identify the high, moderate & low landslide location buffers according to above four criteria. For that, this study used equal interval classification method & NBRO weighted score because they are the responsible government body in Sri Lanka regarding Landslide.

Since there were 5 categories of damage, 11 categories in slope, 6 categories in soil and 6 categories in rainfall, it was necessary to classify them into few categories for the convenience of analysis. When considering the damage weight it classify based on equal interval classification method.

Equation 1: Formula of equal interval classification method

$$\frac{\text{Range of data}}{\text{Number of class}} = \frac{(\text{Highest value} - \text{lowest value})}{\text{Number of class}}$$

According to that table 5 show the weight of the Factors.

Table 4: Weighted Table

Weight	Death	Injuries	partially damage building	Full damage building	Affected
1	<29	<19	<29	<30	<1015
2	30-59	20-39	30-59	31-61	1016-2031
3	60-89	40-59	60-89	62-92	2032-3047
4	90-119	60-79	90-119	93-123	3048-4063
5	120<	80<	120<	124<	4064<

After that find the percentage of death, injured, partially damage building, fully damage building and affected as follows.

Equation 2: Formula of damage percentage

$$\text{Percentage of death} = \frac{\text{Death}}{\text{Damage total}} * 100$$

After multiply by all percentages to get final damage weight.

Equation 3: Formula of Final Damage

$$\text{Final damage weight} = \text{death} * \text{injured} * \text{partially damage building} * \text{full damage}$$

Then again, classify those into 5 categories. It based on equal interval method. Slope, soil and rainfall classify according to the NBRO classification. Below tables, represent it.

Sabaragamuwa province consists with tow soil type. Mainly Red-Yellow Podzolic soils; steeply dissected hilly and rolling terrain type and other one is Red-Yellow Podzolic soils & mountain Regosols; mountainous terrain.

Table 5: Weighted table of Rainfall

Rainfall weight	Weight	Description
<335	1	Low
335-670	3	Medium
>670	5	High

Table 6: Weighted table of Soil

Soil type	Soil weight	Description
All other	1	Low
Red-Yellow Podzolic soils & Mountain Regosols; mountainous terrain	3	Moderate
Red-Yellow Podzolic soils; steeply dissected, hilly and rolling terrain	5	High

Table 7: Weighted table of Slope angle

Slope range	Weight	Description
0-5/5-10	1	Low
20-45	3	Medium
10-20/45-50	5	High

Fourth step is relationship analysis. This step discussed the analysis, which was carried out in this study to achieve the research objectives. This study conducted relationship analysis on three levels as follows. The first level is the identification of factors influence on the occurrence of landslides using ANOVA analysis. The second level is the identification of factors influence on the magnitude of landslides using correlation analysis. The third

level is prioritization of factors influence on the magnitude of landslides and model development using Multilayer Perceptron Analysis.

3. Result & Findings

First, the study performed one-way ANOVA test in SPSS to identify the statistically significant differences between landslide occurrence and not occurrence groups with identified causative factors (soil type, slope type, rainfall and land use changes). Table 8 indicates the summary results of one-way ANOVA test. Statistical analysis by one-way ANOVA demonstrated significant effect of slope ($P<0.001$) and soil ($P<0.001$) on occurrence of landslide. Further, one-way ANOVA demonstrated significant effect of land use changes such as forest to rubber (FR) ($P<0.001$), rubber to coconut (RC) ($P<0.001$), rubber to home gardens (RG) ($P<0.001$) and rubber to other land use (RO) ($P<0.001$) have significant influence on occurrence landslides.

The second stage was to identification of factors influence on magnitude of landslides. This analysis carried out by using Bivariate Pearson correlation coefficient analysis in SPSS. Figure 7 depicts the summary results of correlation analysis. The highly significant correlations are found with magnitude of landslides and land use changes such as RO-rubber to other ($r= 0.7$ $p<.01$), FO-forest to other ($r= 0.7$ $p<.01$), TR-tea to rubber ($r= 0.6$ $p<.01$) and RG-rubber to home garden ($r= 0.55$ $p<.01$),

Next, the study employed Multilayer Perceptron Analysis (MPA) to find the multiple influence of causative factors on occurrence of the landslide. This analysis supported by SPSS software. There are three layers in this analysis. In this analysis dataset was brake into two sample as training and testing (65.3% - training data set and 34.7% - testing data set). Figure 10 depicted the model and Table 9 represent the network information of the model. The occurrence of the landslide is the dependent variable. The study categories occurrence of landslide 6 groups as no landslide occurrences and landslide occurrences as 1,2,3,4 & 5 category. Those categorizations are based on magnitude of the landslide. Table 10 indicated the accuracy of the

model. In this model error is 1.131 and percent incorrect prediction is 0.0%. It indicated that this model is accurate.

Figure 8 depicts the normalized importance of identified causative factors on occurrence of landslide, which is derived from the model. The model results indicated that soil type and land use changes such as rubber to other 2km buffer area, rubber to other 1km buffer area, forest to any 3km buffer area, tea to any 1km buffer area, rubber to any 2km buffer area have significant influence on occurrence of landslides (70% normalized importance).

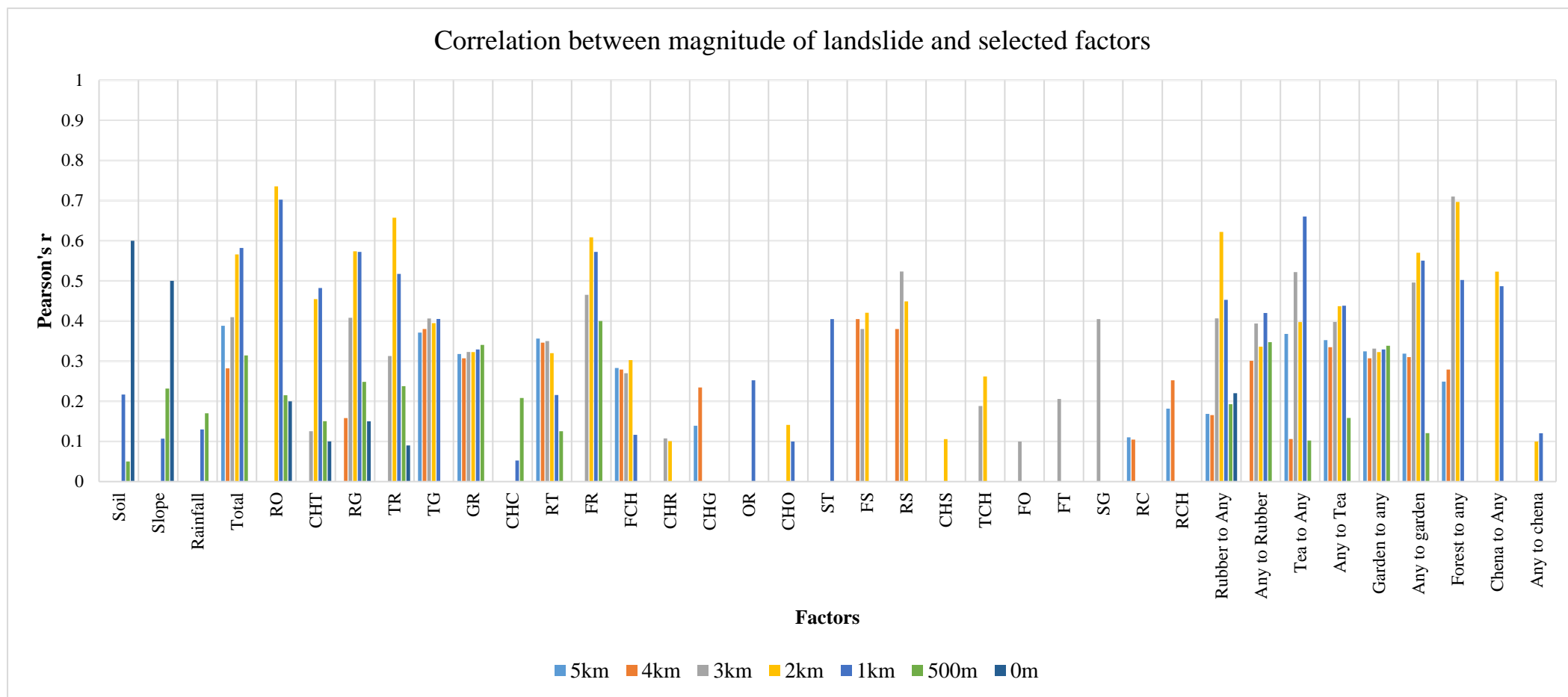


Figure 7: Summary results of correlation analysis

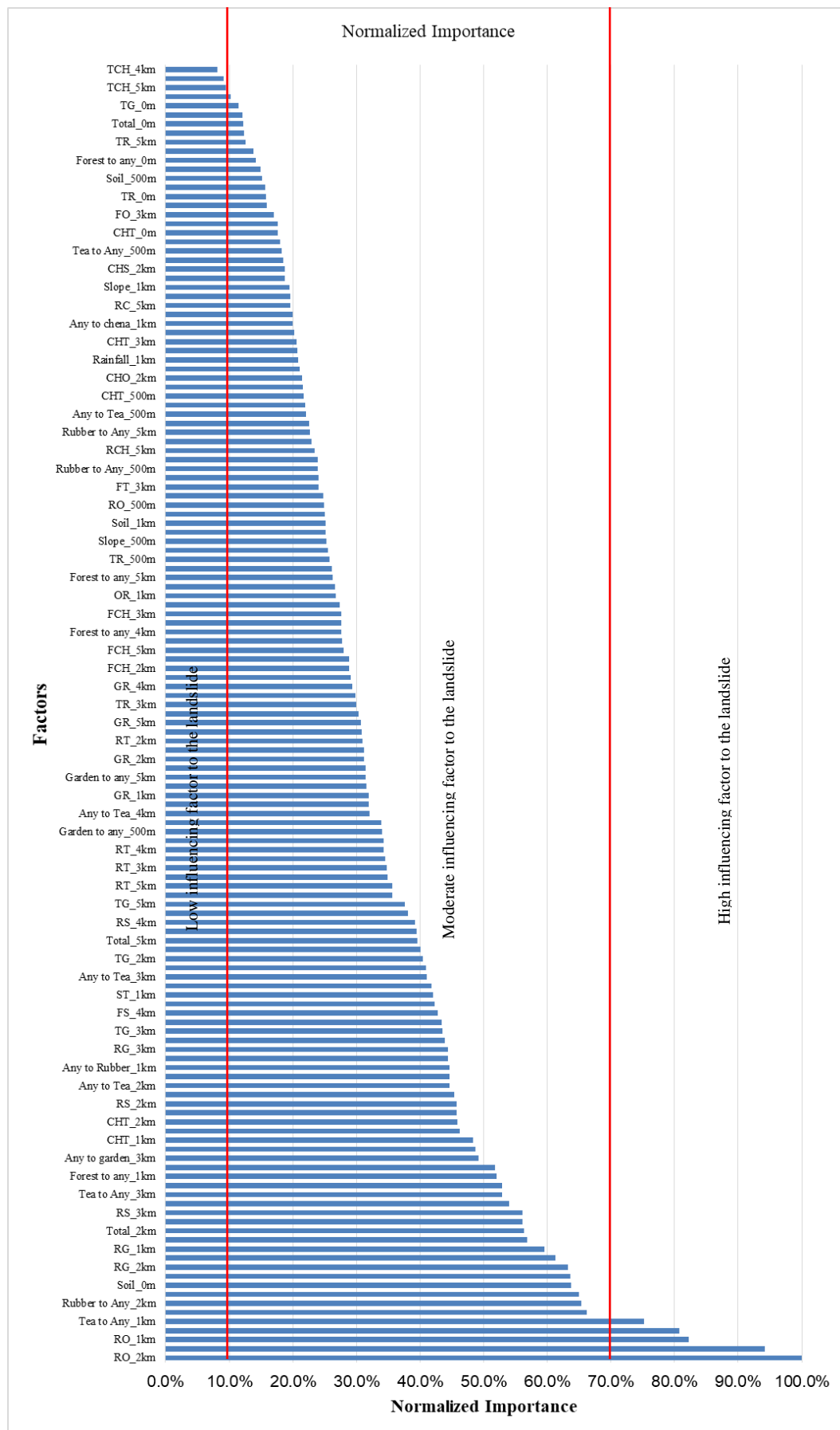


Figure 8: normalizes importance of identified causative factors on occurrence of landslide

Figure 9: Steps of the Study

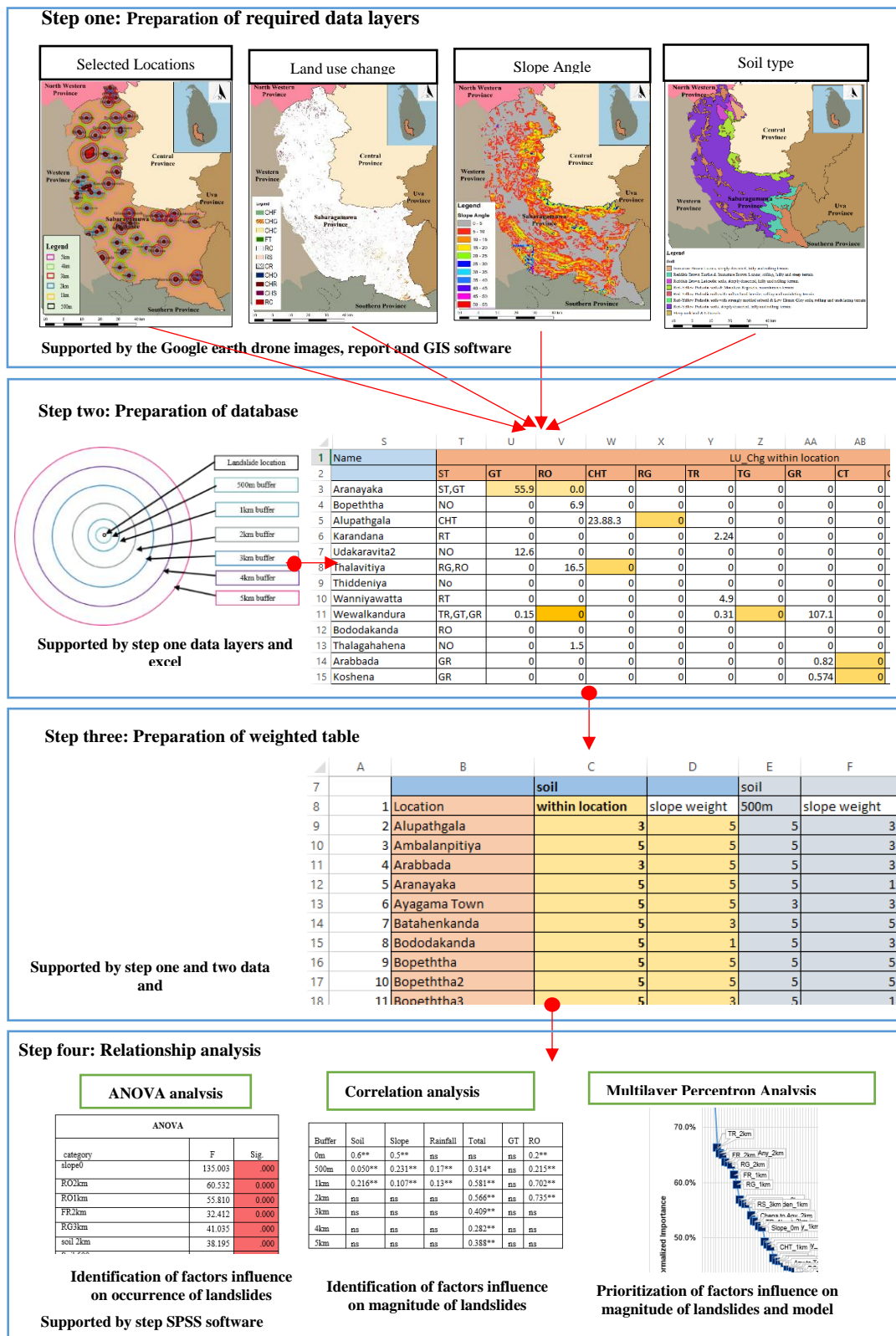


Table 8: Summary of ANOVA Analysis

Buffer	Slope	Soil	Rainfall	FR	RC	RT	TG	RG	TR	CHR	FCH	RO	GR	CHT
0m	0.000	0.000	0.003					0.097	0.073			0.016		
500m	0.004	0.000	0.003	0.041		0.037		0.011	0.042			0.001		
1km	0.000	0.015	0.003	0.000	0.000	0.003	0.005	0.008						
2km	0.000	0.000		0.000		0.001	0.003	0.000	0.002			0.000	0.000	0.006
3km	0.000		0.003			0.002	0.038	0.000	0.009	0.048	0.050			
4km			0.003					0.010						
5km						0.043					0.013			
<div>0.000 Highest significant ($P < 0.000$)</div> <div>0.004 Secondly significant ($P < 0.01$)</div> <div>0.015 Thirdly significant ($P < 0.05$)</div>														

Figure 10 : Diagram of multilayer perceptron analysis

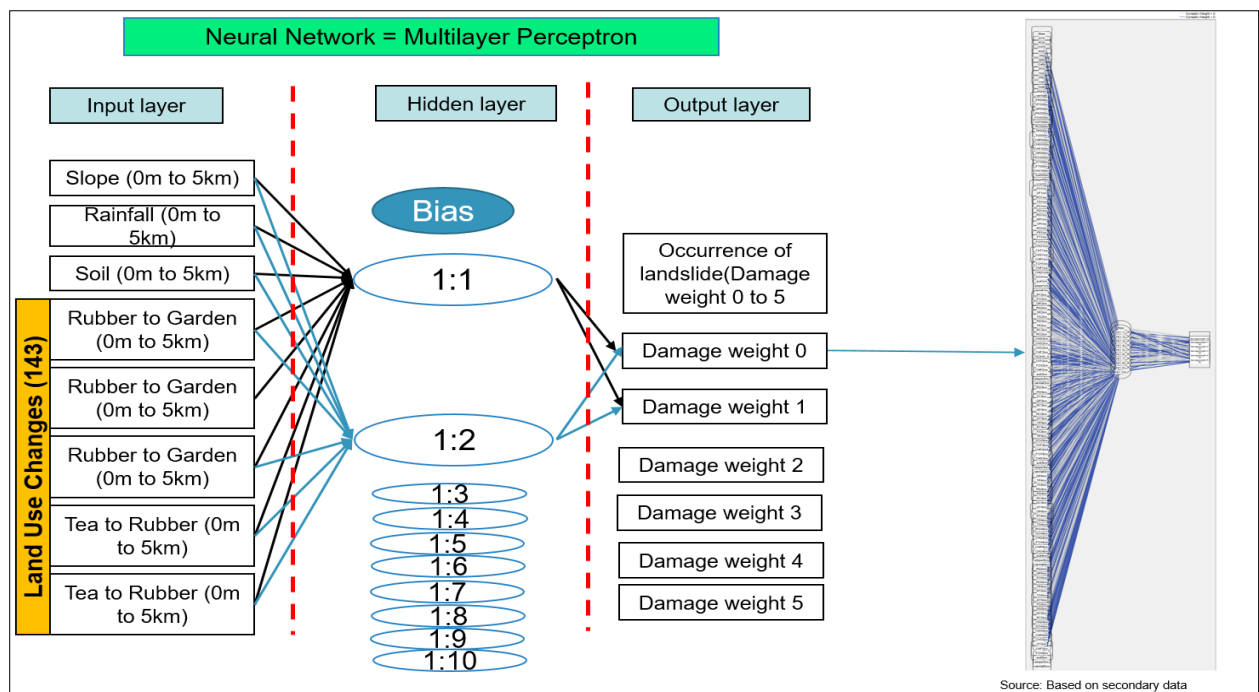


Table 9: Network Information

Network Information		
Number of Factors		143
Rescaling Method for Covariates		Standardized
Hidden Layers	Number of Hidden Layers	1
	Number of Factors in Hidden Layer 1	10
	Activation Function	Hyperbolic tangent
Output Layer	No. of Dependent Variables	1
	Dependent Variable	Occurrence of Landslides
	Number of Units	6
		(0,1,2,3,4,5)
	Activation Function	Softmax
	Error Function	Cross-entropy

Table 10: Accuracy of the Model

Model Summary		
Training	Cross Entropy Error	1.131%
	Percent Incorrect Predictions	0.0%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	5S
Testing	Cross Entropy Error	2.072%
		1.7%
Dependent Variable : Damage Weight		
a. Error Computations are Based on the Testing Sample		

4. Discussion & Conclusions

The primary objective of this study is to investigate the extent in which land use changes influence on occurrences of landslides of different magnitudes. Sabaragamuwa province

in Sri Lanka has been selected as the study area. The research is executed in four phases Firstly, primary data collection on landslide occurrences and preparation of GIS database. Then the study prepared to database on land use changes with buffers (as 0m, 500m, 1km, 2km, 3km and 5km). Thirdly, identification of magnitude of the landslide, for that purpose the study weight value based on a number of deaths, injured, partially damage, fully damage and affected assigned values based on NBRO standard. The study utilized open-source software applications. The study used QGIS. To identify the temporal changes of land use changes, the study utilized MOLUSCE plugin. Analysis was conducted in three level, first used ANOVA analysis to the identification of factors influence on the occurrence of landslides, secondly used correlation analysis and next multilayer Perceptron Analysis to Prioritization of factors influence on the magnitude of landslides and model development.

The study identified that land use changes such as forest to rubber, rubber-to-garden, rubber-to-any, tea-to-rubber, tea-to-any, forest-to-any have recorded greater influence on high occurrence of high magnitude of landslides. These findings represent an important step towards the better understanding of the influence on land use changes by types on land slide. This observation can be useful input for further studies in order to minimize landslide in the fields of land use planning and disaster management.

4. Acknowledgements

The study team express the warm and sincere thanks NBRO, Disaster Management center & Department of meteorological who were given free access to data.

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