Assessing the impact of land use on triggering Landslides: A case of Sabaragamuwa Province, Sri Lanka

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Abstract

Landslide is a result of a complex spatial-temporal interaction of geological, geomorphological, climate and land use factors. Dynamics of geological, geomorphological and climate factors expands over relatively longer periods whilst land use change in short run. Hence, land use has a significant influence on landslide frequency and distribution, even in a short time span. However, limited studies have been carried out to investigate the relative contributions of the changes of different land use types in triggering landslides. This study has analyzed land use changes occurred in Sabaragamuwa Province, Sri Lanka over a period of ten years and assessed 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 been obtained from National Building Research Organization, Sri Lanka. Then the study analyzed the land use changes at landslide occurrence locations including a range of spatial buffer zone areas. MOLUSCE (Modules for Land Use Change Evaluation) plugin in QGIS was utilized to identify the land use changes in each spatial buffer zone area. Thirdly, the study computed the magnitude of landslide damage of each location based on five criteria as number of deaths, number of injured people, number of partial damaged houses, number of fully damaged houses and number of affected people. Then, the study analyzed the relationship between the magnitude of a landslide damage and land use changes. For this purpose, the study utilized spatial analysis tools in QGIS environment. The results revealed 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 reported a greater influence on frequency of occurrence and the magnitude of landslide damage. These findings provide useful inputs to minimize landslides in the fields of land use planning and disaster management.

Keywords: MOLUSCE, QGIS, Land use changes, Landslide, Planning and disaster management

1. Introduction

Natural disasters have become a global development challenge that cause major damages to lives, properties and livelihoods (Ranjan & Abenayake, 2014). 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. Occurrence and frequency of landslide are caused by natural factors such as soil cover, slope stability, hydrology, drainage, precipitation and land form (Cruickshank, 1995) as well as anthropogenically- induced factors such as land use and

management. "Different land use types may control the stability of slopes, and in particular, slope stability is improved by vegetation ... 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 key 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). Similarly, a research conducted in 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

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human-induced land use variations on slope stability have revealed that in populated regions, the impact of human activities significantly increases 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 by 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 have 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 were regularly recovered through the natural grasses, shrubs, as the land use change class as the most prone areas 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 the occurrence and magnitude of landslide damages with reference to a Sri Lankan case study. Studying the influence of land use change on the frequency and magnitude of natural disaster is vital in mainstreaming disaster risk management into urban planning (Abenayake, Mikami, Matsuda, & Jayasinghe, 2018).

2. Methods and materials

2.1 Data Acquisition

This study is completely based on secondary data sources which were obtained from a national level database (Table 1).

Table 1: Data Acquisition

Item	Source
Landslide	GPS- point data and Drone Survey images from NBRO, Sri Lanka, 2017 Damages due to the landslide, from NBRO, Sri Lanka, 2017 and Disaster Mangment 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 Metelological Department, Sri Lanka, 2017

Source: Prepared by author

2.2 Selecting the study area

Sri Lanka, as a developing country with a tropical climate, is high vulnerable for the impacts of climate change including extreme weather conditions which have been recording 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 Lankan Disaster Knowledge Network of Ministry of Disaster Management reveals a growth of landslide occurrence from 2003 to 2017. Incidences 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 recorded 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 May, 2017 were selected for the study (Fig. 1).

2.3. Selecting an Open-Source GIS-based applications

Figure 1: Study area with 29 landslide prone locations

Geographic Information System (GIS) is a widely utilized 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 GIS 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, this study

utilized open-source software in GIS environment. When considering the role of the open source GIS in landslide studies, Quantum Geographic Information System (QGIS) software allows to perform quick and convenient analysis of land cover changes. (MOLUSCE – quick and convenient analysis of land cover changes, 2013). Hence, the study utilized MOLUSCE plugin tool which is in QGIS to identify the temporal changes of land use.

2.4. Mapping Causative factors of landslide occurrence

Causative factors of the occurrence of landslide hazards were identified through a comprehensive literature review.

Figure 2: Slope Type of Study Area

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 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,b, & Pons, 2015). Hence, this study has considered land use, slope, soil and precipitation as the causative factors subjected to the relative importance and data availability

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, the study utilized GPS point data and drone images.

2.5 Detecting the temporal Changes of Landuse

Then the study analyzed the temporal changes of land use at landslide hazard prone 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 were seven different types of land use changes as depicted in Table 2 (Fig. 4)

Figure 3: Soil Type of Study Area

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 3 for land use codes)

Table 3: Land Use Codes

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	CHC	Chena to Coconut
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 to 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	TCH	Tea to Chena
20.	CHC	Chena to Coconut			

This study employed specific buffers to the landslide occurrence locations vary from 500m to 5km. Figure 5 and 6 represent the buffer zone which used in this study.

Figure 5: Selected location with 29 land slide locations

Figure 6: Buffer Zones

2.6. Mapping the occurrence and magnitude of landslides

The study referred five indicators related to the magnitude of landslide damage; the percentage of death, injured, partially damaged buildings, fully damaged buildings and affected population as follows. The referred indicators were classified into five classes as depicted in table 4.

Equation 1 was employed to normalize the data into categorical variables of 5 classes.

Equation 1: Formula of equal interval classification method

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

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<

Equation 2 was employed in computing the percentage of deaths and Equa.3 was employed in computing the aggregated value of the magnitude of the landslide damage.

Equation 2: Formula of percentage of death

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

Equation 3: Formula of Final Damage

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

Slope, rainfall and soil values were also classified into 5 categories of equal class intervals (Table 5,6 and 7).

Table 5: 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

Table 6: Weighted table of Rainfall

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

2.7. Analyzing the association between the magnitude of landslide damage and land use changes

Next, the study tested the association between each landslide location (29 locations) and land use change locations (30 locations). This step was supported by MS-Excel spreadsheet and QGIS to calculating the land use change (39 land use change types) by area and percentage in each buffer (420 buffers).

This study conducted relationship analysis at three levels as follows. The first level is to detect whether the identified causative factors have influenced on the occurrence and non-occurrence of landslides statistically by utilizing ANOVA analysis. The second level is the identification of the degree and association of the selected causative factors with the magnitude of landslides damage by utilizing correlation analysis. The third level is validation of the causative factors using Multi-layer Perception Analysis. The graphical summary of the method of study is depicted in Fig.7.

Table 7: Weighted table of Soil

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

3. Results and Discussion

First, the study performed one-way ANOVA test in SPSS to identify the statistically significant differences between landslide occurrence and not occurrence groups with the identified causative factors (soil type, slope class, rainfall and land use changes). Table 8 indicates the summary results of the one-way ANOVA test. Statistical analysis of one-way ANOVA demonstrated a significant variance of slope ($P < 0.001$) and soil type ($P < 0.001$) between the groups of landslide-prone and landslide non-prone groups. Further, this variance was significant among land use change categories 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) ($P < 0.001$).

Secondly, the study analyzed the association between the causative factors and the magnitude of the occurrence of

landslides by utilizing Spearman's correlation coefficient analysis in SPSS. Figure 8 depicts the summary results of correlation analysis. The highly significant strong, positive correlations were revealed in the magnitude of landslides and land use changes including 'rubber to other' ($r = 0.7$ $p < .01$), 'forest to other' ($r = 0.7$ $p < .01$), 'tea to rubber' ($r = 0.6$ $p < .01$) and 'rubber to home garden' ($r = 0.55$ $p < .01$). Accordingly, it was clear that higher the extent of land use changes from high-canopy vegetation to low-canopy vegetation and vegetation to built-up areas, higher the magnitude of landslide damage.

Next, the study employed Multi-layer Perceptron Analysis (MPA) to validate the multiple influence of causative factors on occurrence of the landslide by expert's opinion. There were three stakeholder groups and the occurrence of the landslide was the dependent variable. In this analysis, dataset was formed into two samples as training and testing (65.3% - training data set and 34.7% - testing data set). Figure 10 depicts the model and Table 9 presents the network information of the model. The study categorized the occurrence of landslide into 6 groups such as 'no landslide occurrence' and landslide occurrences at different magnitudes from 1 to 5. Table 10 indicates the accuracy of the model. Error of the model is 1.131 and the percent incorrect prediction is 0.0%. It indicated that the model is accurate.

Figure 8 depicts the normalized importance of the identified causative factors on occurrence of landslide, which was derived from the model. The results of the model indicated that the soil type and land use changes such as 'rubber to any' within 1km and 2km buffer area; 'forest to any' within 3km buffer area; 'tea to any' within 1km buffer area have significant influence on occurrence of landslides (70% normalize importance). This indicates the changes of vegetative land uses such as forest, tea and rubber into any other type may trigger the landslide occurrences and damages.

Figure 7: Steps of the Study

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. Conclusion

The primary objective of this study was to investigate the extent in which land use changes are influenced on the occurrence and the magnitude of landslide damages. Sabaragamuwa province in Sri Lanka was selected as the study area. The research was executed in four steps as: secondary data collection on landslide occurrences and preparation of GIS database; preparation of database on land use changes with buffers (as 0m, 500m, 1km, 2km, 3km and 5km); identification of magnitude of the

landslide; and analyzing the degree of association between land use change and landslide damage. The study utilized open-source software applications including QGIS and MOLUSCE plugin. Relationship analysis were conducted in three levels by performing ANOVA analysis to identify the of factors influence on the occurrence of landslides; correlation analysis to test the association between causative factors and different types of land use changes; and multilayer perceptron Analysis to validate 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 a 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 the magnitude of landslide damage.

The findings can be useful in making land use planning decisions in minimizing landslide damages, particularly in the fields of land use planning and disaster management.

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Figure 8: Summary results of correlation analysis

Figure 9: Normalized importance of the identified causative factors on occurrence of landslide

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

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