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Modelling the effects of land use/cover change and rainfall variability on landslide hazards: The case of Nyabihu district, Rwanda

MASTER OF ENVIRONMENTAL SCIENCE

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Approval

This dissertation has been examined and approved as meeting the requirements for the award of the degree of Master of Science in Environmental Science.

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Statement of originality

This dissertation entitled "Modelling the effects of land use/cover change and rainfall variability on landslide hazards: The case of Nyabihu district, Rwanda" is the original work of the author that has been accomplished at University of Botswana along the period from November 2017 to March 2020. It has not been submitted in any other university for a degree or any other award.

Author's Signature: ……………………………..Date: ……31/03/2020……………

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Dedication

This dissertation is dedicated to Almighty God, my beloved parents, my brothers and sisters, all relatives and friends who supported me in one way or another during my studies.

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List of abbreviations and acronyms

ANN	Artificial Neural Network
DEM	Digital Elevation Model
ERDAS	Earth Resources Data Analysis System
ETM+	Enhanced Thematic Mapper Plus
GIS	Geographical Information System
GPS	Global Positioning System
IDW	Inverse Distance Weighted
IRS	Indian Remote Sensing
LRM	Logistic Regression Model
LULCC	Land Use and Land Cover Change
MIDIMAR	Ministry of Disaster Management and Refugee Affairs (Rwanda)
MINAGRI	Rwandan Ministry of Agriculture and Animal Resources
MINECOFIN	Ministry of Finance and Economic Planning (Rwanda)
MINEMA	Ministry of Emergency Management (Rwanda)
MININFRA	Rwanda Ministry of Infrastructure
NISR	National Institute of Statistics of Rwanda
OLI	Operational Land Imager
REMA	Rwanda Environmental Management Authority
RMA	Rwanda Meteorological Agency
RoR	Republic of Rwanda
RS	Remote Sensing
SPSS	Statistical Package for Social Science
USGS	United States Geological Survey

Abstract

Landslides have become the environmentally recognized hazard in hilly regions of Rwanda such as Nyabihu district. They are often characterized by the downslope movement of debris or other earth materials which damage or destroy everything found in their way such as infrastructures, croplands, and even cause a number of deaths. The intense rainfall has been noticed as the main trigger of landslides in Rwanda, together with land use/cover change. Therefore, the objectives of this study were; to assess the land cover change effects on landslide occurrences, evaluate the rainfall variability and its effects on landslide occurrences, and predict the occurrence of landslides in the study area. Land use/cover maps of 2005 and 2015 were generated and overlaid with mapped landslides. Maximum likelihood classification was used to classify the Landsat satellite images, and Mann Kendall test was used to assess the rainfall trends. The results revealed a remarkable decrease of agricultural land, while all other land use/cover types have increased along the mentioned period. It was noted that most of the landslides occurred in agricultural land. Also, areas with high rainfall were noted to have experienced more landslides than those with low rainfall. Despite the relation of rainfall to landslide occurrences, the rainfall variability over a period of time did not always correspond to the variation in landslide occurrences. The study also indicated the influence of controlling factors (such as slope, soil depth, and distance to road) on landslide occurrences. The occurrence of landslides was also predicted using logistic regression model. The model showed that an increase in slope angle increases the chances to landslide occurrences, while the changes in land use/cover, and rainfall do not necessarily imply the increase in landslide occurrences, though they significantly relate to landslide occurrences. The study results are expected to be useful for alerting landslide hazard management decisions, land use planning and management regulations so as to minimize the likely landslide occurrences and their resultant impacts.

Keywords: Geospatial techniques, modelling, landslide hazard, land use, land cover, rainfall variability

Definitions of keywords

Geospatial techniques are the techniques of collecting, managing and analyzing geospatial data or data associated with geographical location (UN, 2012).

Modelling is the scientific process or activity of making a particular world's phenomena easier to understand, define, quantify, visualize, and simulate (Waszkowski, 2018).

Landslide hazard is defined as the potential occurrence of a damaging slope failure within a given area, and during a given period (Guzzetti, 2005).

Land use denotes a series of human activities done on land to generate products or services (INTOSAI WGEA, 2013).

Land cover refers to the observed physical cover of Earth's surface, whether areas of vegetation, bare soil, hard surfaces, wet areas and water bodies (Eurostat, 2001).

Chapter 1: INTRODUCTION

1.1 Background to the study

Landslides are among the globally recognized environmental hazards that cause numerous fatalities and property damages, particularly in mountainous or hilly regions of the world (Huabin et al., 2005; Bennett et al., 2016). Worldwide, rainfall-triggered landslides killed 55 997 people between 2004 and 2016 (Froude & Petley, 2018). The Global Landslide Catalogue (GLC) indicates that 11,033 rainfall-triggered landslides occurred in the world between 2007 and 2019 (Kostis, 2019). Basically, landslide refers to the downslope mass movement of rock, earth or debris (Cruden, 1991; Vasudevan & Ramanathan, 2016). Furthermore, landslide hazards have been defined as the potential occurrence of a damaging slope failure within a given area, and during a given period (Guzzetti, 2005).

Worldwide, the severity and frequency of landslides differ from one region to another depending on triggering factors or drivers either physical (e.g. rainfall, slope, and soil properties, etc.) or anthropogenic (e.g. loading the slopes with buildings and infrastructure, changing vegetation cover, etc.) present in the area (Anderson & Holcombe, 2013). Various studies have grouped causative factors of landslides into internal and external causes. Internal causes include factors such as faults, freezing and thawing of rocks and soils, material properties such as compressive strength and shearing strength, etc. On the other hand, external causes include factors such as undercutting the foot of the hill slope when extracting minerals and excavating for creation of canals or roads, land cover change, exerting unbearable loads on slope such as buildings and water tanks, and also vibration induced by earthquakes, etc. (Prasad, 1995; Popescu, 1996; Huabin et al., 2005).

Climate change has been a global problem which brought several environmental hazards like landslides amongst others. With this, various attempts have been made to relate landslides with climate change (Schlögel et al.,2011; Gariano & Guzzetti, 2016; Jeffrey, 2016; Turkington et al., 2016). Different regions of the world have experienced tremendous changes in rainfall and temperature as a result of climate change, where in many cases landslides have been triggered by heavy rainfall particularly in mountainous areas (Lonigro, Gentile, & Polemio, 2015).

In Africa, climate change has remarkably affected rainfall patterns, where different parts on the continent have experienced high rainfall variability with a number of rainfall-induced landslides; for instance, the recent landslides triggered by tropical Cyclone Idai in March 2019 devastated Chimanimani region in Zimbabwe (Petley, 2019).

Numerous landslides have been noted in equatorial Africa (Kervyn et al., 2016) while in East Africa, landslides occur mostly in countries like Rwanda, Kenya, Uganda, Tanzania, and Ethiopia, (Knapen et al., 2006:151; Mwaniki et al., 2011; Broothaerts et al., 2012; Bizimana & Sönmez, 2015; Tegeje, 2017), which affected not only the environment but also the livelihoods, human properties and caused deaths. However, human activities like deforestation, clearing vegetation, improper agricultural practices, housing developments on steep slopes, road and railway construction, illegal mining, hill cutting, and dams, etc., all have direct or indirect effects on slope failure which results in landslide occurrence (Anderson & Holcombe, 2013; Dewitte et al., 2017; Froude & Petley, 2018).

Heavy rainfall, continuous land cover change mostly due to human activities, and other factors such as slope, soil depth and structure, and lithology have been noted to induce landslides in hilly regions of Rwanda (Bizimana & Sönmez, 2015; Nsengiyumva et al, 2018). These landslide hazards have serious negative impacts on socio-economic livelihoods, devastating croplands and settlements as well as causing deaths. According to Bizimana & Sönmez (2015), 108 people have died, ten thousand were displaced and left landless due to landslides that occurred in Rwanda from 2000 to 2014. In addition, the landslides affect the environmental state of the flora and fauna through altering microclimate, soil structure (e.g: soil nutrients and organic matter), seed dispersal and vegetation, and hence allowing the heterogeneity of the landscape (Schuster & Highland, 2004; Elias & Dias, 2009; Geertsema et al., 2009).

With the above mentioned impacts, landslides in Rwanda remain a challenge that requires proper monitoring, recording, and reporting throughout the country. Remote sensing and GIS have proven to be essential tools for landslide hazard investigations, and modelling of causative factors (Westen, 2001; Tofani et al, 2013; Scaioni et al, 2014). By using remote sensing imagery and aerial photography together with field investigation using Global Positioning System (GPS), landslide databases can be generated so as to generate landslide inventories (Shahabi et al, 2012).

Geospatial techniques could also be used to analyze landslide causes, and map landslide risky areas as well as produce relevant models for landslide predictions. Thus, the use of remote sensing and GIS techniques for landslide assessment, and creation of landslide prediction models have a key role in providing relevant information to decision makers. Moreover, rainfall models can also be used to evaluate the occurrence of landslides. Also, spatial-temporal rainfall models (Chandler & Wheater, 2002; Kenabatho et al., 2012) can be used to establish a link between rainfall and landslide occurrences, and in turn, used to predict their occurrence in the future at different sites. Furthermore, landslide hazard modelling is important for understanding the triggering or causative factors of landslides as the basis for enhancing both landslide risk and environmental management.

1.2 Problem statement

Landslide hazard is a serious issue in hilly regions of Rwanda resulting in a lot of damages and people losing their lives, destruction of croplands, and also leaving injuries as well as homeless families. Despite all this, only a few researches on landslide hazards have been done in the past (MIDIMAR, 2015; MININFRA, 2015). Throughout the country, landslide hazards have caused 74 deaths, 22 injuries, and destroyed or damaged 573 houses as well as affected 656 hectares of croplands in period between 2011 and 2013 and Nyabihu district is the most affected (MIDIMAR, 2015).

The observed drivers of landslides include high rainfall, steep slopes, soil types, and land use/cover change. So far high rainfall in steep slope areas has been noted to be the main triggering factor of landslides as the continuous high rainfall induces high water saturation in soils which reduces the strength of the soils (Bizimana & Sönmez, 2015).

Rainfall patterns have been changing as a result of climate change which implies the severity of rainfall-induced landslides occurring in different parts of the country (Muhire & Ahmed, 2015; Haggag et al., 2016). Nevertheless, no research has been done to adequately analyze the correlation between rainfall and landslide occurrences which could help predict the landslides, yet, the gravity of rainfall to cause landslide is also aggravated by human activities that destroy the natural land cover when growing crops or constructing houses in steep slope areas as result of population growth, and hence heightening the intensity, severity and frequency of landslides(REMA, 2015), though it is essential to analyze the relationship between land use/cover change and landslide occurrences. Since rainfall and land use/cover change on steep slopes have been identified as the main triggering factors of landslides, modelling rainfall and land use/cover could assist in predicting landslide occurrences. Furthermore, the application of geospatial techniques in providing consistent landslide vulnerability maps have so far received limited attention. The application of these techniques could assist in modelling the extent and effects of landslide hazards in vulnerable areas such as Nyabihu district.

1.3 Aim and objectives of the study

The aim of this research was to assess how and the extent to which causative factors such as land use/cover change and rainfall variability affect landslide occurrences in Nyabihu district of Rwanda.

Specific objectives

This study was based on the following set of objectives:

1. Assess the effects of land use/cover change on landslide occurrences.

2. Evaluate rainfall variability and its implications on the occurrence of landslides.

3. Predict the occurrence of landslides.

1.4 Research questions

Objective1: Assess the effects of land use/cover change on landslide occurrences.

-What are the pattern and rate of land use/cover change in Nyabihu District from 2005 to 2015?

-How did land use/cover change contribute to landslide occurrence?

Objective2: Evaluate rainfall variability and its implications on the occurrence of landslides.

-What are the characteristics and trends of rainfall in Nyabihu District?

-How does rainfall amount influence landslide hazard occurrences?

Objective3: Predict the occurrence of landslides

- What is the probability of landslide occurrences given the generated predictive model?

- What are the implications of landslide prediction model outcomes on landslide hazard management?

1.5 Justification of the study

In various regions of the world, landslides are one of the natural hazards that have been affecting both the environment and livelihoods of populations. Therefore much understanding about the causative factors of landslides from one region to another so as to come up with the appropriate mitigation measures is required. In Rwanda, landslides have been affecting different parts of the country, particularly the hilly regions of western, northern, and southern provinces, though the landslides were not recognized as devastating hazards (MIDIMAR, 2015).

Since 2010 after the establishment of the Ministry of Disaster Management (MIDIMAR) which then systematically recorded landslide events, it was noticed that landslides are among the most disastrous hazards in Rwanda due to the number of deaths, and several damages recorded as a result of various landslide events. The government of Rwanda has taken measures of mitigating or minimizing the landslide risks and vulnerabilities; yet, it is still required to have a comprehensive analysis of landslide causes, severity and frequency in hilly areas of the country. This must be based on scientific knowledge of mapping areas prone to landslides to identify factors responsible for triggering landslides and modelling landslide hazards based on these causative factors.

There is a need to develop landslide prediction models, for example based on rainfall as the main triggering factor of landslide in steep terrains of Rwanda, particularly in Nyabihu district so as to assist in decision making, and policy formulation related to landslide management.

1.6 Significance of the study

This study analyzed the causative factors of landslides in Nyabihu district. The results of the study will serve as baseline information for landslide hazard management and mitigation strategies. They may also help government institutions to draw the district landslide hazard preparedness plan. In addition, the results may contribute to policy improvement and enforcement to discourage settlements and improper agriculture practices in landslide prone areas.

Moreover, the study is quite linked to Sustainable Development Goals-Agenda 2030 under the 13th goal; "*Take urgent action to combat climate change and its impacts*", specifically stated in its target one "*Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries*"(UN, 2015, p.23). And hence the obtained results on effects of each of the landslide causative factors could serve as baseline to persuade the government to commit to implementing sustainable development goals in line with the national policy vision regarding sustainable disaster management practices (MIDIMAR, 2012).

1.7 Scope of the study

The study was limited to the landslide causative factors; particularly rainfall, slope and soils as well as land use/cover change from 2005 to 2015.

Geographically, the study covered Nyabihu district situated in northeast part of the western province of the country. It is bordered in the north by Musanze district and Virunga National Park, South by Ngororero and Rutsiro districts, East by Gakenke district and Rubavu district in the West (RoR, 2013). Nyabihu is one of the districts most affected by landslide hazard in Rwanda due to the presence of clay, volcanic and lateritic soils which are considerably permeable, and hence very susceptible to landslides (MIDIMAR, 2015; MINAGRI, 2018b).

1.8 Study area

1.8.1 Location and description of the study area

Nyabihu district is located in the western province of Rwanda between latitude 1°40.443' and 1°40.554' South of the equator and between longitude 29°38.295' and 29°21.955' East (figure 1.1).

Nyabihu district is characterized by a continental relief that consists of high, rocky and steep mountains with an altitude ranging between 1460m and 4507m (MINAGRI, 2018b). In general, the study area presents a mild climate with an annual average temperature of 15^0C, and receives the annual precipitation reaching 1400mm.

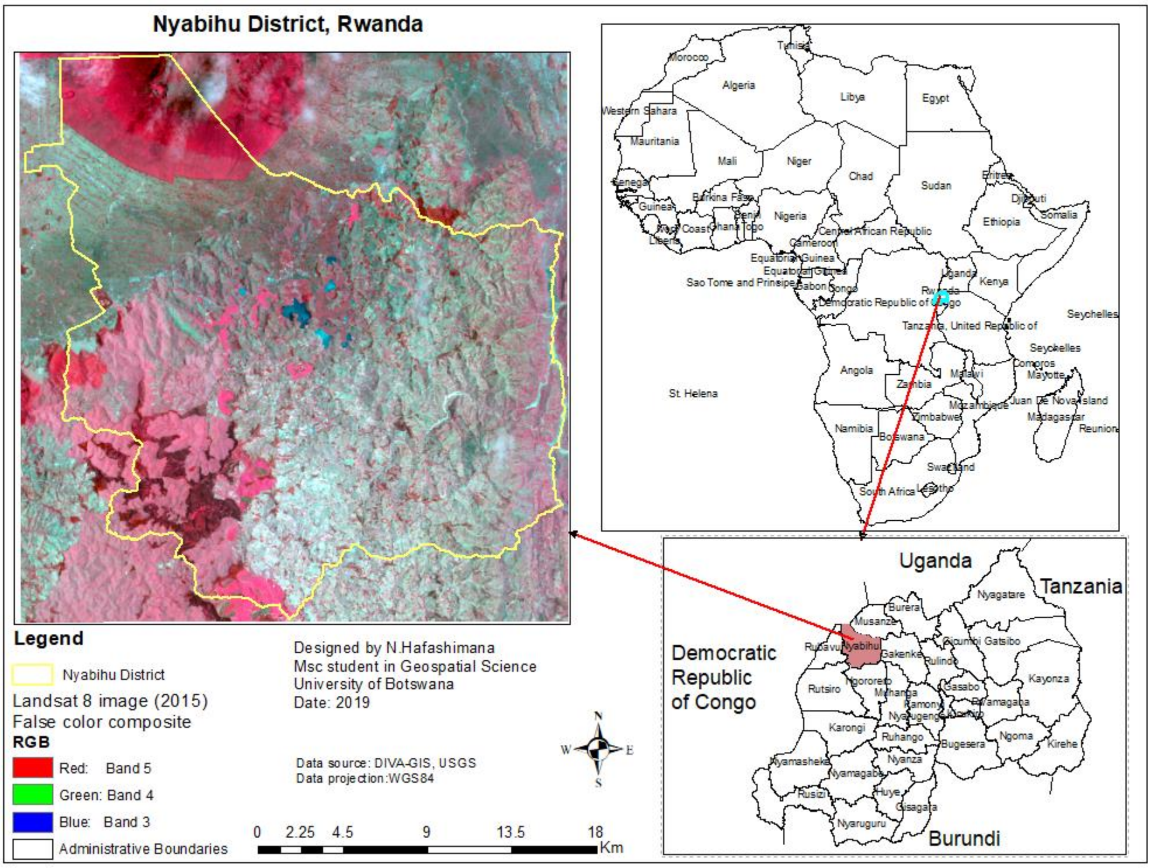
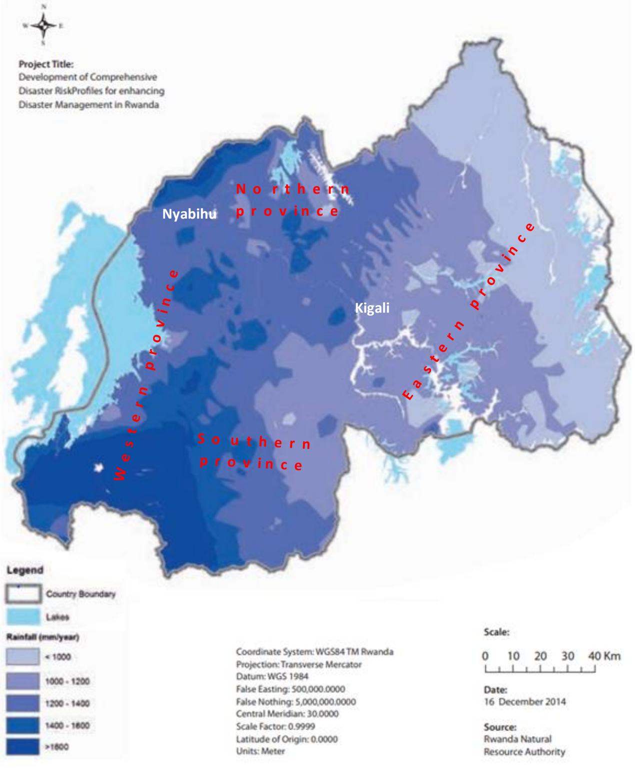


Figure 1.1: Location of the study area



Rwanda rainfall distribution (MIDIMAR, 2015)

Figure 1.2: Spatial rainfall distribution in Rwanda

Generally, Rwanda has two rainy seasons; the long rainy season which extends from March to May, and the short rainy period extending from October to December. The amount of annual precipitation ranges between 1000 mm and 1500mm, with an average annual rainfall of 800mm (Haggag et al., 2016). The precipitations are unevenly distributed throughout the country where the western and northern provinces receive higher rainfall than the eastern province (figure 1.2).

The soils in Nyabihu district are categorized into clay, sandy, lateritic and volcanic (ROR, 2013), which are usually susceptible to landslides.

The hydrological network of the district is comprised of several streams, and springs that fall in lowland valleys between steep mountains. In terms of vegetation, some parts of the study area are covered by exotic species such as eucalyptus on the hillsides and along the roadsides. Other areas comprise agricultural fields with a variety of crops, and also grazing lands.

The recently established Gishwati National Park in 2015(which is dominated by indigenous species, and situated in the southwestern part of Nyabihu district) has experienced deforestation (e.g. due to settlements, conversion of forest into agriculture and livestock farmlands) to the extent that the remaining intact natural forest is less than 7% of the original forest (MINAGRI, 2018b).

1.8.2 Population

Nyabihu district covers an area of 537.7 Km^2, hosting nearly 294740 inhabitants with population density of 555 inhab/km^2; i.e.34% of the country's population density. About 86.2% of the district inhabitants live in rural areas (NISR & MINECOFIN, 2012).

The majority population of Nyabihu district depends on agricultural activities for their livelihoods as the main source of food and income. The main crops grown in the district include Irish potatoes, maize, beans, sorghum, banana and wheat as well as tea plantation (MINAGRI, 2018a). Livestock is also one of the major sources of income for many farmers' households. Other sources of income include small trading businesses, selling surplus of agriculture produce, employment and other occasional small jobs (MINAGRI, 2018a).

Since land use/cover change is mostly attributed to human activities, the population growth in Nyabihu may lead to rapid land use/cover changes, which in turn may increase occurrences of landslide hazards in the study area.

Chapter 2: LITERATURE REVIEW

2.1 Overview of landslides

Landslides refer to environmental processes that lead to natural hazards. They become hazards when they threaten human life and property (e.g. buildings, roads, infrastructure), and harm the environment (Sears et al., 2019). Generally, landslides are manifested with a large mass of earth slides, rocks or debris materials that move down a slope due to natural processes or human activities. They mostly occur on steep slope areas or land that has been modified by human activities such as construction or deforestation. Landslides occur worldwide but some regions are more prone to landslides than others depending on the seriousness of causative factors in each region. As it was noticed by Mia et al., (2015), landslides are often caused by intense rainfall, slope failure and human activities such as cutting hills for construction and vegetation removal. Then, the uncovered land accelerates the water flows and permeability resulting in landslide incidents due to weak soil structure susceptible to sliding.

2.2 Slope failure and landslides

Landslides originate from slope failures due to different mechanisms such as geological, hydrological, and seismic factors, etc. It was noticed that geological conditions such as soil weathering, composition and type of rock, as well as the topography of the area are among the factors that cause slope failure (Evans et al., 2006; Rusydy et al., 2016). Furthermore, they identified massive rock failures like rockslides, rock avalanches, catastrophic spreads and rock falls as the major landslide hazards experienced in different parts of the world. Yet, slope failures can also be caused by the significant increase of soil moisture and high water infiltration during heavy rainfall, which then result in landslide hazards (Orense, 2004). It was also noticed that the cyclic shear during the earthquake induces slope failure through rapid increase of the pore water pressure inside the mudstone, which lessens considerably the safety factor of the slope and hence triggering the landslides (Nakamura, Cai, & Ugai, 2008).

2.3 Influence of anthropogenic activities on landslides

The common human activities that can induce landslide hazards include changing the natural drainage patterns, destabilizing the slopes of terrain, and removing the vegetation cover (Highland & Bobrowsky, 2008). Similarly, logging activities in steep slopes destroy plant roots which act as the natural mechanism of stabilizing slope materials. The disruption of surface vegetation cover alters the distribution of soil water and later obstructs the main drainage channels (Swanston, 1974).

In addition, Malgot and Baliak (2002) noticed that landslides in many cases can be triggered by deforestation, cultivation on steep slopes, and leakage of underground water pipelines. Also, land use/cover change decreases the natural vegetation cover, and increases the bare soils susceptible to landslides (Reichenbach et al., 2014). As it was noted by (Karsli et al., 2009), the spread of settlements or other housing construction on the steep slopes, and the extension of road network on hilly topography all destabilize the balance of the actual slope lands and then increase the chances of landslide occurrences.

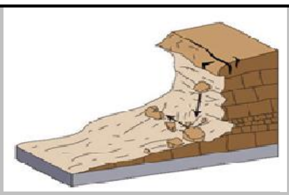
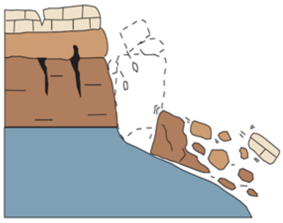
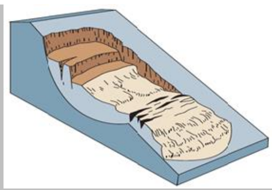
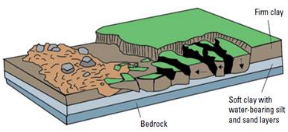
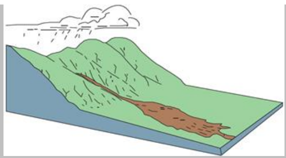
2.4 Influence of rainfall on landslide occurrences

Rainfall is the world most triggering factor of landslides (Polemio & Petrucci, 2000). Landslides are usually pronounced in environments that experience high and prolonged rainfall, but they can be accelerated when the rainfall is associated with other factors such as steep slopes, degraded natural land cover, vegetation, soils types and structure (Jeong et al., 2017). Due to intense rainfall, rain water penetrates into the soil which in turn loses its strength, making it susceptible to landslides. Rainfall together with runoff is an important agent to sliding of soil mass. The heavy intensity of rainfall accumulates high water runoff. Then, the rain water can penetrate into the rock cracks and joints, weakening that land portion which may later lead to landslides.

In most cases, the rainfall-induced landslides occur in tropical regions, and sometimes in temperate regions where residual soils prevail (Tohari, 2018).

2.5 Types of landslides

Table 2 1: Description of landslide types

Type of landslide	Schematic structure	Description
1. Falls		Falls refer to the abrupt mass movement of geological materials (e.g.; rocks, and boulders) that are usually detached from steep slopes or cliff. Falls can be induced by various factors such as gravity, mechanical weathering, and the presence of interstitial water (Highland & Bobrowsky, 2008,p.6).
2. Topples		Topples are attributed to the forward rotation out of a slope whether that of mass of soil or that of rock around a pivot point or axis below the gravity forces exerted by the displaced mass. Thus, Toppling can occur in different ways; including the influence brought by the forces of gravity due to the weight of earth material upslope from the displaced mass, and also the influence of water or ice in cracks in the mass. Hence, topples can be rock, debris or earth materials(Highland & Bobrowsky, 2008, p.8).
3. Slides		Slides refer to the downslope movements of mass of soils or rocks that occur on surface along earth rupture or on thin zones of intense shear strain. They are usually induced by the weakness of mass of soils or rocks that cause the detachment of slide material from the stable underlying earth material(Highland & Bobrowsky, 2008, p.10).
4. Spreads		Spreads consist of an extension of a cohesive soil or rocky mass that are combined with the subsidence of the fractured mass of cohesive material into softer underlying material. They can be triggered by liquefaction or flow of the softer underlying material(Highland & Bobrowsky, 2008, p.14).
5. Flow		A flow consists of continuous spatial movement in which the surfaces of shear are short-lived, closely spaced, or usually not preserved. There are various types of flow such as debris flow, volcanic debris flows (Lahars), debris avalanche flow, Earth flow, mud flow, and creep (slow Earthflow) as well as flows in permafrost(Highland & Bobrowsky, 2008, p.16).

Source: Highland & Bobrowsky, 2008

2.6 Impacts of landslides

2.6.1 Environmental impacts of landslides

Skrzypczak et al.,(2017) and Kjekstad and Highland (2009) noted several negative impacts of landslides on the environment. Landslides transform the natural landscape of an area, and intensify the erosion processes. Usually, landslides occur in different materials (e.g. debris, rocks, and earth) that move downslope. The mass movement of earth materials changes or modifies the landscape, leaving the disturbed land exposed to erosion processes. In some cases, landslides can damage forests and hence destroy wildlife habitats. They can modify the quality of the organic soil by removing the earth material from, or bringing materials to a certain location.

Landslides can transport excess sediments and deposit them into streams, rivers, and water bodies. The sediments can pollute water bodies, harming water quality and fish habitat as well.

The impacts of landslides do not always have to be negative as landslides can also balance the ecological system for both aquatic and terrestrial biodiversity. It was noticed that debris flows and other mass movement can maintain riffle habitat in streams mainly due to sediments and coarse debris supplied by landslides (Kjekstad & Highland, 2009).

2.6.2 Socio-economic impacts of landslides

In many cases, landslides affect the socio-economic livelihoods of people. In populated mountainous regions, landslides often result in huge property damage such as destruction of infrastructures (e.g settlements, roads), damages of crop fields where the grown crops at the time of landslide occurrence can totally be taken away or covered by the debris flows. Furthermore, devastating landslides can break the access to and from remote communities. This can impede provision of services like health, education, movement of goods and people and other social activities (Palmer et al., 2016). According to Kjekstad and Highland (2009), economic losses due to landslides can be classified into direct and indirect costs. Direct costs include the repair, replacement and maintenance of damaged property, and indirect costs include loss of industrial, agricultural, and forest production as well as the tourism revenues due to the damage of facilities or interruption of transportation systems, etc.

Winter and Bromhead (2012) summarize economic impacts of landslides into three different categories including direct economic impacts, direct consequential economic impacts, and indirect consequential economic impacts. Direct consequential economic impacts commonly refer to the costs induced by the destruction of a particular infrastructure or loss of utility such as the costs of closing a road for a given period, and the costs of deadly injuries. Thus, indirect consequential economic impacts mostly include the effects of landslides in remote rural areas where the economies usually depend on transport-dependent activities. The vulnerability can be extensively determined by the disruption of transport network rather than just the landslide event itself. This is determined by the challenges of accessing market places, which then limit the flow of products (e.g. agriculture produce), and hence affecting the market prices.

2.7 Rainfall and landslide hazards in Rwanda

Rainfall is a major weather and climate parameter that induces a number of hazards (such as landslides and floods) in Rwanda. During rainy periods, a number of landslides occur in the regions of the western, northern and southern provinces of the country (Western province being the most affected by landslides) due to their landscape characteristics of hills and mountains compared to the rest of the country(MIDIMAR, 2015).

Besides the high rainfall regime in the hilly topography of the regions, landslides are also influenced by other factors such as soil types and structure, anthropogenic factors like improper agriculture practices in steep slopes, human settlements and deforestation. Landslides in Rwanda are mainly categorized into debris flows (Bizimana & Sönmez, 2015) which move downslope from the upslope transporting everything attached to them and also anything found on their way including vegetation cover, houses, and other human properties. These types of landslides are often triggered by high rainfall which prolongs to the extent that the soil becomes unstable and ends up with downward sliding.

2.8 Modelling the occurrences of landslides

The occurrences of landslides have been modelled using different methods depending on pertinent landslide causes from one region to another. Various statistical-based models such as logistic regression, neural network analysis, data-overlay, index-based and weight of evidence analyses as well as machine learning methods have been used elsewhere to model landslide occurrences (Reichenbach et al., 2018). Using logistic regression model, Duman et al.,(2006) characterized the influence of different factors such as slope, aspect, elevation, stream power index geomorphology and geology units as well as lithological units in inducing the landslides occurrences and then successively (at 83.8%) generated landslide susceptibility map of the landslide prone areas. With the use of ANN and weight of evidence models, Wang et al.,(2016) analyzed and mapped landslides prone areas using landslide-occurrence factors similar to those used by Duman et al.,(2006) and obtained successful results at 82.51% and 79. 82% from ANN and weight of evidence models respectively.

In this study, logistic regression model was chosen over other methods due to its advantages in modelling the binary dependent variable (Korkmaz et al., 2012) through generating a fit model that best defines the relation between the dependent and independent variables. It was particularly proven useful when predicting the presence or absence of the dependent variable (the occurrence or non-occurrence of landslides in the context of this study) based on values of the predictor variables (Lee, 2005). Logistic regression method incorporates either continuous or discrete variables, or even combines both types without necessitating the normal distribution of variables (Rasyid et al., 2016). Compared to the Artificial Neural Network models which are more complex and susceptible to over fitting, logistic regression model was proved to be less complex and even minimize the risk of over fitting (Dreiseitl & Ohno-machado, 2003). Also, it is possible to test the statistical significance of variable coefficients in the logistic regression model.

2.9 Literature highlights

Table 2.2 presents a summary of literature highlights as shown below:

Table 2 2: Literature gap

Author (s)	**Title of the study**	**Key findings**	**Gaps identified**
Bizimana & Sönmez, (2015)	Landslide occurrences in the hilly areas of Rwanda, their causes and protection measures.	Causes of landslides identified, and preventive measures summarized	No spatial mapping of landslide events location, No quantitative analysis of correlation between triggering factors (e.g rainfall, land use/cover) and landsides.
Nsengiyumva et al.,(2018)	Landslide susceptibility assessment using spatial multi-criteria evaluation model in Rwanda.	Landslide susceptibility mapping at national scale	Landslide susceptibility mapping at small scale not yet done, no attempts made to predict landslide occurrences
MIDIMAR(2015)	The National Risk Atlas of Rwanda.	Landslide causative factors were spatially mapped	Lack of landslide susceptibility mapping at small scale, lack of quantitative analysis of relationship between causative factors (e.g. rainfall) and landslide occurrences, still no prediction of landslide, the location of landslide events were not mapped.

Source: Own, 2019

From the gaps left out by previous researches, this study focused on mapping the location of landslides in the study area, and analyzed the correlation between landslides and causative factors as well as predicted the probability of landslide occurrences.

2.10 Conceptual framework

Landslide is an environmental hazard resulting from different factors both natural and human induced. For the purpose of this study, landslide hazard in Nyabihu district of Rwanda was modelled by focusing on natural and anthropogenic landslide-triggers which are rainfall and land use/cover change respectively, but also taking into consideration the conditioning factors of landslides. The landslide conditioning factors in the study area include the slope, soil depth, and the distance to road.

This study quantitatively analyzed the influence of rainfall and land use/cover change in triggering landslides. Figure 2.2 presents the conceptual framework (Izuogu et al., 2015) on the relation of triggering and conditioning factors to landslide hazards. In this study, landslide conditioning factors are considered as necessary but not sufficient conditions for causing slope failure, while triggering factors are the external stimulus that aggravate the stresses or considerably reduce the strength of slope materials (Wieczorek, 1996).

Both conditioning and triggering factors are independent variables that cause landslides. Thus, intervening variables are considered as the actions that could be taken for landslide hazard management aiming to reduce the impacts of landslides. These can be usually assigned to the intervention of the government and its stakeholders through planning and implementation of policies and regulations regarding hazard management. For example, appropriate land use planning followed by successful implementation would minimize landslide occurrences resulting from improper infrastructure construction and agricultural practices on steep slopes.

On the other hand, the effective mitigation measures are essential in areas prone to landslides. Yet, the consistent mapping of landslide risky areas requires the adequate analysis of the significance of the causes of landslides. As an outcome, the effective landslide mitigation measures will not only reduce socio-economic impacts that could result from landslides in Nyabihu district, but also will minimize environmental impacts as long as the land use is properly managed.

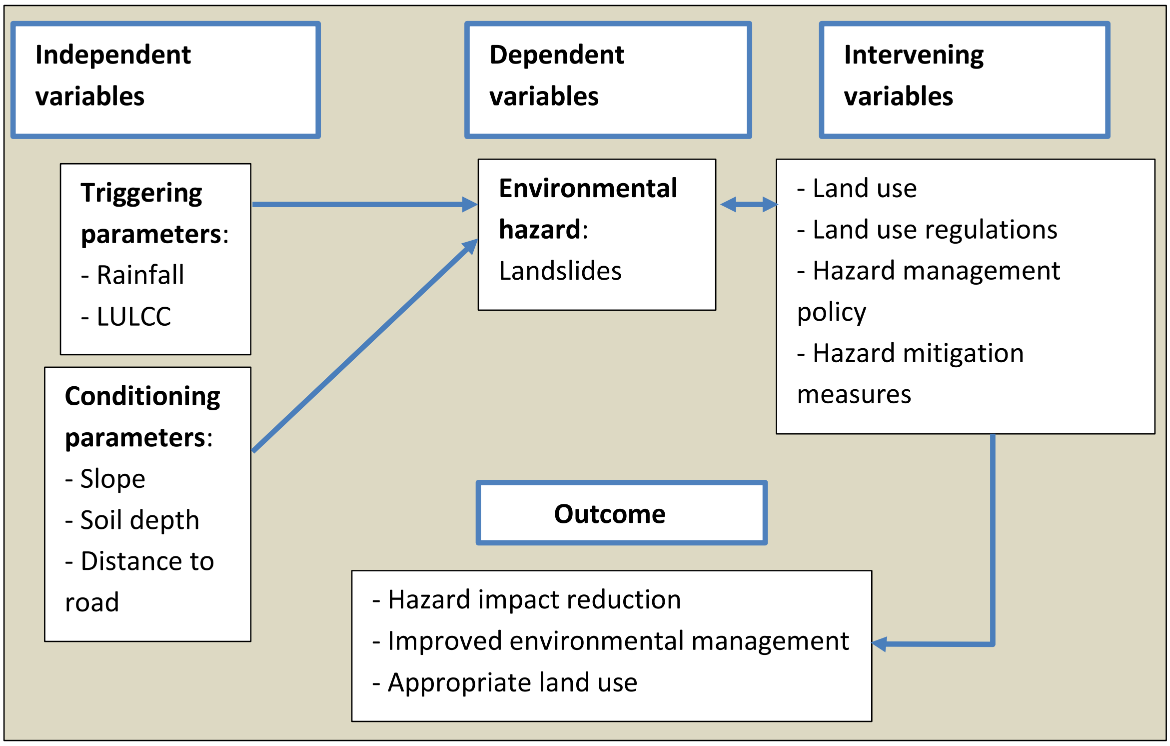


Figure 2.1: Conceptual framework adapted from Izuogu et al.,(2015)

Chapter 3: METHODOLOGY

3.1 Research design

This study used quantitative research methods to analyze the rate of land use/cover changes, and the relationship between landslides and their causative factors. The study applied remote sensing and GIS techniques and statistical analyses.

The study mostly used secondary data that were collected through different techniques, and analyzed in order to achieve the aim and objectives of this study as shown in the flow chart below (figure 3.1).

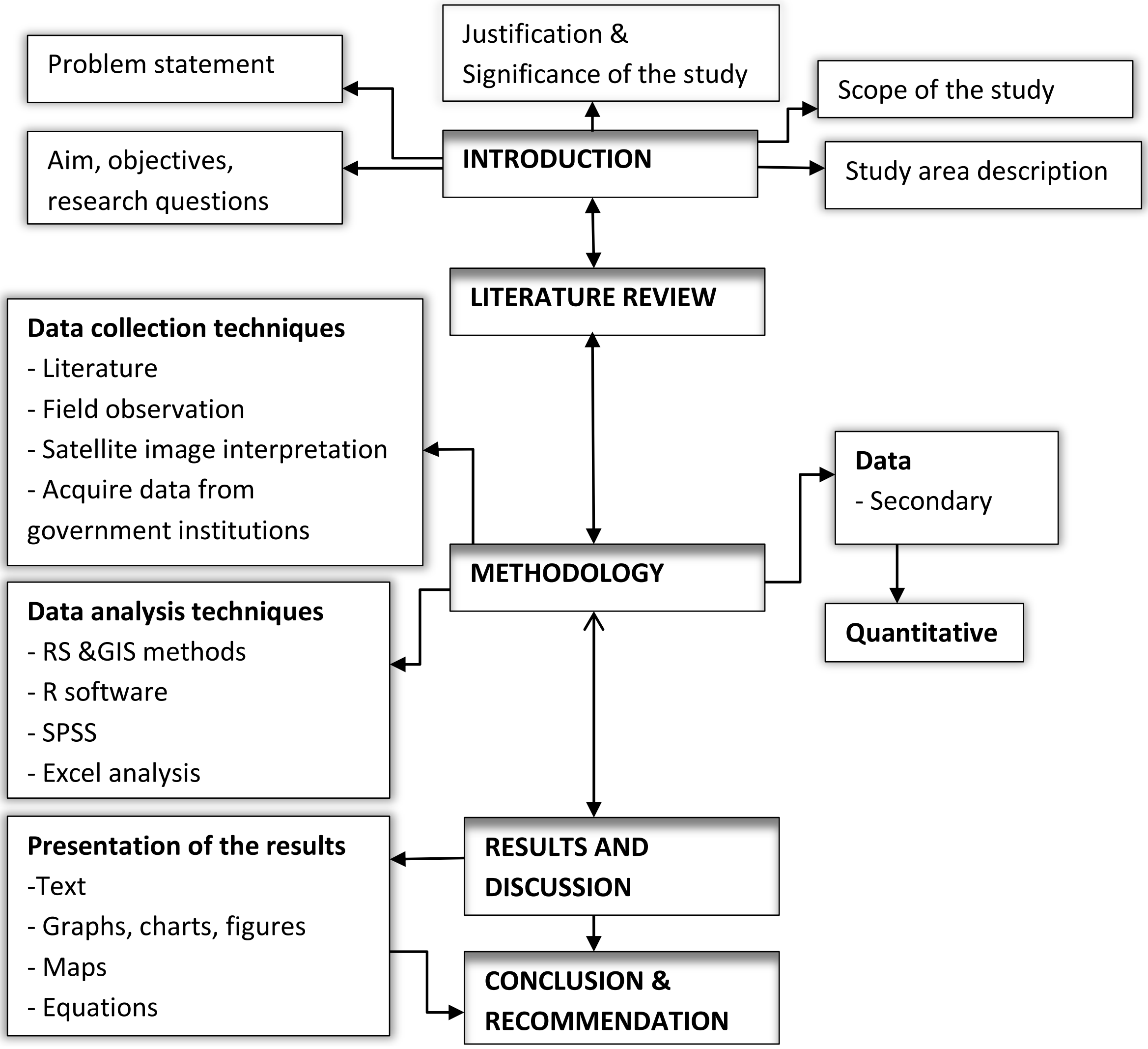


Figure 3.1: Research design

3.2 Materials and Data for the study

This study mostly used secondary data to achieve the aim and objectives. These data mainly came from spatial data (satellite images, raster data, and shapefiles), and rainfall data that were collected from Rwanda Meteorological Agency. Other ancillary data such as soil depth, slope, and road buffer were acquired from the district office.

A 30m DEM based on Aster imagery was collected from USGS whilst the topographic parameters such as slope and aspect were calculated from the DEM using ArcGIS software. There was no proper record of historical landslides. In fact, government institutions in charge of hazard management usually assess the impacts from landslides in a particular area with the aim of helping the affected families. So, recording the geographical coordinates of each occurred landslide was so far not taken into account. With this, the high resolution google earth imagery of 2005 and 2015 were used to extract the geographical coordinates of visible landslides. The satellite images that were used are presented in table below (table 3.1).

Table 3 1: The satellite images used in the study

Image	Acquisition date	Path/Row	Spatial resolution	Cloud cover
Landsat 7	2005	173/61	30 m	Free of cloud cover (0%)
Landsat 8	2015	173/61	30 m	cloud cover of 10.66% ,but free of cloud cover in the study area

Source: Own, 2019

The selection of the Landsat images is due to their long archive and free availability compared to other satellites such as SPOT images. However, it is a challenge to find a good satellite image of the study area due to the geographical location of the area which usually presents thick continuous cloud coverage for almost all months of the year. The Landsat satellite images of 2005 and 2015 were the sources of data from which geospatial techniques were applied to analyze the land cover change and produce land cover maps of the study area. These satellite images were downloaded from USGS (https://earthexplorer.usgs.gov/). As they were covering other areas that are not part of the study area, images were subsetted in order to have images covering only the study area. Table 3.2 presents the required data for this study.

Table 3 2: Required data and their sources

Data	Parameter	Data type	Type of variable	Level of measurement	Data source
Satellite imagery	Land use/cover type	Qualitative	Categorical	Nominal	USGS
	Land use/cover change (%)	Quantitative	Discrete	Ratio	USGS
DEM	Slope angle, aspect	Quantitative	Continuous	Ratio	USGS
Rainfall	Precipitation	Quantitative	Continuous	Ratio	RMA
Soil	Soil depth	Qualitative	Categorical	Nominal	Nyabihu district office
Distance to road	Road buffer	Quantitative	Discrete	Ratio	Nyabihu district office

Source: Own construct (2019)

3.3 Research Methods

3.3.1 Objective 1: Assess the effects of land use/cover change on landslide occurrences.

3.3.1.1 Image pre-processing

To carry out land use/cover classification and analyze land use/cover classes, Landsat 7 ETM+ (path 173, Row 61) acquired on 21st February 2005 and Landsat 8 OLI (path 173, Row 61) acquired on 21st September 2015 were downloaded and used for this project. These images were downloaded from (https://earthexplorer.usgs.gov/). After downloading, the satellite images were layer stacked and subset processes were done so as to prepare the images for further processing and analysis. ERDAS IMAGINE 2018 was used for carrying out the required preprocessing.

The images of the study area were subset using the boundary shapefile of Nyabihu district as the template. Different pre-processing techniques were used to prepare images for further processing and analysis techniques. These include; radiometric correction, atmospheric correction and topographic correction. Radiometric correction is “the removal or diminishment of distortions in the degree of electromagnetic energy registered by each detector” (Eastman, 2003).

Radiometric correction was carried out in order to calibrate the radiance of reflectance values in the images, and to allow more assessment of ground surface properties and then facilitate the analysis of the mentioned satellite images. With this, strips in Landsat 7 ETM+ were removed which allowed overcoming the limitation of lacking information in strips, and hence increasing the certainty in analyzing the image. On the other hand, atmospheric correction was not much of concern in this study since post-classification comparison method that was applied for detecting land use/cover change also compensates for variations in atmospheric conditions (Mausel et al., 2004).

3.3.1.2 Image processing and analysis

Supervised Classification was used to classify different land uses/covers in Nyabihu district for the periods 2005 and 2015. Supervised classification is “the method through which the analyst defines small areas called training sites on the image, which contains the predictor variables measured in each sampling unit, and assigns prior classes to the sampling” (Černá and Chytrý 2005 as cited in Al-doski et al., 2013).

Supervised classification was chosen for this study because it allows the user to fully control the information categories or classes that will be included in the final image classification (Enderle & Weih, 2005). Furthermore, the spectral information of LULC classes are distinctively examined in supervised classification while in unsupervised classification, the computer itself determines the spectral classes and then defines their information value (Al-doski et al., 2013).

Specifically, supervised maximum likelihood classification technique was used in this study. Supervised maximum likelihood classification is widely used not only due to its relative simplicity and robustness, but also due to its ability to define means, variances and covariances of training samples (Gao & Zhang, 2009).

For the classification of images of the study area, more than 30 training samples for each land use/cover class were taken to ensure the representativeness of pixels. Thereafter, Recode tool in ERDAS IMAGINE was used to correct the misclassified pixels during the classification process. Image Recoding allows the user to increase the certainty of classified images by correcting the errors in image classification results. This was done by using the Google earth images for 2005 and 2015, which were linked to the classified images of the corresponding mentioned years in order to check the correctness of the classification results.

After classifying the land use/cover classes for each image, the post-classification comparison method was utilized to detect land use/cover changes that have occurred between 2005 and 2015. Post-classification comparison separately classifies multi-temporal images into thematic maps and then compares the classified images, pixel by pixel (Mausel et al., 2004). This technique was preferably chosen due to its twofold advantages over other change detection techniques: Firstly, it minimizes the effects of atmospheric sensor and environmental differences between multi-temporal images, and secondly, it provides the complete matrix of change information (Mausel et al., 2004).

The rate and percentage of land use/cover changes are computed using the equations 1, 2, and 3.

$$\%\ of\ land\ use\ change = \frac{A_{year\ i+1} - A_{year\ i}}{\sum_{i=1}^{n} A_{year\ i}} * 100 \qquad (1)$$

$$Annual\ rate\ of\ change = \frac{A_{year\ i+1} - A_{year\ i}}{\boldsymbol{t}_{years}} \qquad (2)$$

$$\%\ annual\ rate\ of\ change = \frac{A_{year\ i+1} - A_{year\ i}}{\sum_{i=1}^{n} A_{year\ i} * t_{years}} * 100 \qquad (3)$$

Where, $\mathbf{A}_{year\ i}$ represents an area of cover **i** at the first date, $\mathbf{A}_{year\ i+1}$ represents the area of cover at the second date, $\mathbf{t}_{years}$ represents the period between the first and second dates, and **n** represents the number of years within an interval.

Finally, ArcGIS 10.5 was used to generate the land use/cover maps. Figure 3.2 illustrates the workflow followed in analyzing the satellite images.

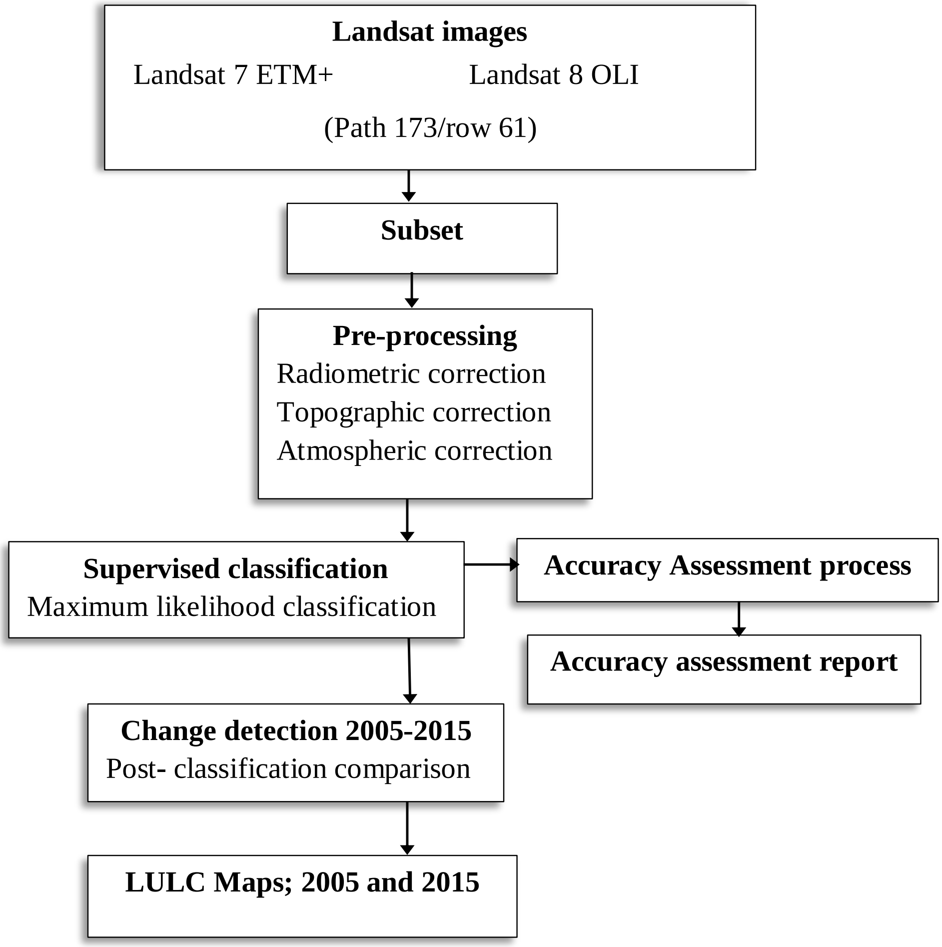
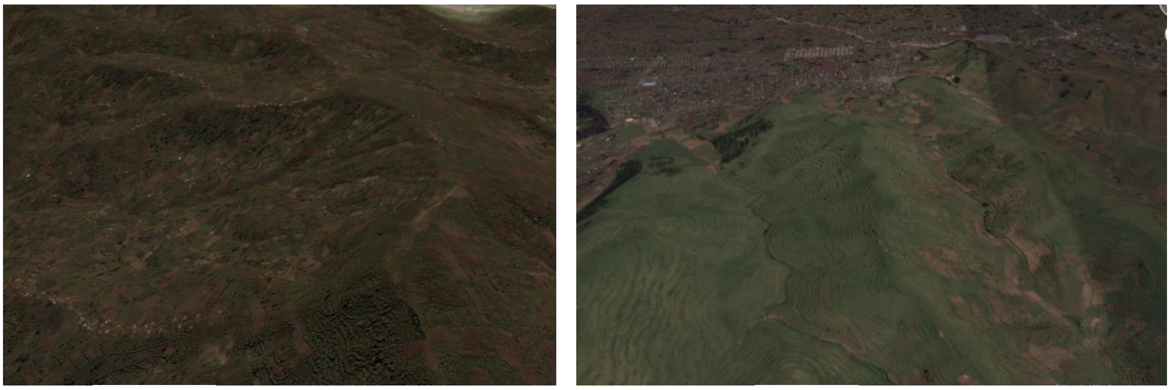


Figure 3.2: Workflow of image analysis

3.3.1.3 Classification accuracy assessment

Accuracy assessment is considered as the final step in satellite image analysis, aimed at verifying how accurate the produced results are after completing the interpretation or classification of the image. The accuracy assessment basically seeks to quantitatively assess how effective the pixels taken during the classification process are sampled into the correct land use/cover classes (Rwanga & Ndambuki, 2017). With this, a total of 120 equalized randomly sampled reference points were created in each classified image of the study area to assess the accuracy of the classified images. Figure 3.3 shows the Google Earth images of the study area for the two periods.



2005 2015

Figure 3.3: Google Earth image of the study area in 2005 and 2015

The obtained overall classification accuracy was 85% and 90% for 2005 and 2015 respectively (table 3.3). The overall Classification Accuracy equals to the number of correct points divided by the total number of sampled points. Generally, this overall accuracy is given by equation 4 below:

$$Overall\ accuracy = \frac{1}{N}\sum_{i=1}^{n} x_{ii} \quad (4)$$

Where, **x** represents the individual cell values, $\mathbf{x}_{ii}$ represents the total number of observations in row **i** and column **i, n** is the total number of classes, and **N** the total number of samples.

Furthermore, KAPPA is another multivariate statistical measure used in accuracy assessment (Cohen, 1960). It helps by comparing classification results from different regions of the classified image. KAPPA analysis results are presented as KHAT statistic which is also a measure of accuracy (Congalton, 1991).

KHAT statistic is given by the following formula:

$$\widehat{K} = \frac{N\sum_{i=1}^{n} X_{ii}\sum_{i=1}^{n}(X_{i}*X_{+i})}{N^2\sum_{i=1}^{n}(X_{i+}*X_{+i})} \quad (5)$$

Where;

n is the number of rows in the matrix,

Xii= the number of observations in the row i and column i,

X_{i+} and X_{+i}= the marginal totals of row i and column i respectively,

N= the total number of observations.

The Overall Kappa (K) statistics of classified images are 0.82 and 0.88 for 2005 and 2015 respectively (table3.3). According to KHAT's categories by Landis & Koch (1977), a KHAT value ranging between 0.81 – 1.00 represents a perfect agreement. With the fact that the obtained overall Kappa statistics (K) fall into that range, they are good enough to continue with further analysis. Producer's accuracy and user's accuracy (Patel & Kaushal, 2010) are calculated using the equations (6) and (7).

$$\text{Producer's Accuracy} = \frac{\text{Number of correctly classified pixels of a particular category}}{\text{Number of reference pixels of the same category}} * 100 \qquad (6)$$

$$\text{User's Accuracy} = \frac{\text{Number of correctly classified pixels of a particular category}}{\text{Number of classified pixels in the category}} * 100 \qquad (7)$$

Producer's accuracy refers to the probability that any pixel in a land use/cover category has been correctly classified, while user's accuracy refers to the probability that a classified pixel on the image represents actually that category on the ground.

Table 3 3: Image classification accuracy assessment results for 2005 and 2015

	Landsat 7 ETM+, image 2005		**Landsat 8 OLI&TIRS, image 2015**	
Land use/cover type	**Producer's accuracy (%)**	**User's accuracy (%)**	**Producer's accuracy (%)**	**User's accuracy (%)**
Agricultural land	64.52	100	73.08	95
Bare land	50	100	100	100
Built-up	92.86	65	93.33	75.00
Forest	89.47	85	86.96	100
Grassland	90.91	100	100	85
Tea plantation	93.75	75	94.74	90
Water	100	84.21	100	100
Overall classification accuracy	85%		90%	
Overall Kappa Statistics	0.8208		0.8804	

Source: Analysis, 2019

3.3.1.4 Identification of landslides

Since landslides spectral reflectance may be quite similar to bare land (such as exposed rocks, gravel roads, etc.) or ploughed fields, which could affect the accuracy of image classification results, Google Earth images were utilized to identify landslides in the study area by using computer screen-based visual image interpretation technique (Xu, 2015). Google Earth imagery has high spatial resolution which helps accurately discern landslides from other ground features. Visual image interpretation was chosen over supervised classification technique because it helped to precisely locate landslides based on their rough texture and shape which differ from the one of surrounding ground features (e.g. vegetation, and rectangular shape of croplands). From Google Earth images of 2005-2017, landslides points were identified and compiled in Excel. Then, landslides points were imported into ArcGIS to be processed and overlaid with classified images for further analysis. Using these techniques, 8 landslides were identified in Google Earth image of 2005 and 34 landslides were identified in that of 2015.

3.3.2 Objective 2: Evaluate rainfall variability and its implications on the occurrence of landslides.

Mann-Kendall test was applied to assess the rainfall trends recognized along the period from 1997 to 2017. Mann-Kendall refers to a non-parametric test or in other words implies its ability to work for all distributions without requiring any particular assumptions like the ones of normality and linearity amongst others (Libiseller & Grimvall, 2002). Two Mann Kendall test statistics (S and Z statistics) were used to evaluate the behavior of trends based on the number of data values. S statistic is used when the data values are less than 10, and Z statistic is used when the number of data values is greater than or equal to 10 (Hussain et al., 2015; Thenmozhi & Kottiswaran, 2016).

The Mann Kendall test Z statistic is calculated using the following equation:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{Var(S)}} & \text{if } S < 0 \end{cases} \quad \text{(Blain, 2013; Pohlert, 2018):} \tag{8}$$

Where, S is the Mann-Kendall test and Var (S) is the variance of S.

And the Mann Kendall test S statistic, on the other hand, is given by the equation below:

$$S = \sum_{i=1}^{n=1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \tag{9}$$

Where, x_j and x_i represents the annual values in years j and i (j> i), and n represents the number of data points, while sgn (x_j-x_i) is computed in the following equation (10)

$$sgn\ (x_j - x_i) = \begin{cases} 1 & \text{if } x_j - x_i > 0 \\ 0 & \text{if } x_j - x_i = 0 \\ -1 & \text{if } x_j - x_i < 0 \end{cases} \tag{10}$$

The statistical significance of the trend depending upon the number of data values is assessed using the two mentioned statistics, whereby the positive values of S and Z statistics indicate the upward (increasing) trends in the data series, while their negative values indicate the downward (decreasing) trends. On the other hand, Sen's slope is also a non-parametric test that was used to assess the significance of the trend. It is given by the following equation:

$$Q_i = \begin{cases} \frac{T_{n+1}}{2} & \text{if n is odd} \\ \frac{1}{2}\left(\frac{T_n}{2} + \frac{T_{n+2}}{2}\right) & \text{if n is even} \end{cases} \tag{11}$$

Where, Qi is the Sen's slope, and T is the slope of all data pairs calculated using the equation below:

$$T_i = \frac{x_j - x_k}{j-k} \quad \text{for } i = 1,2,3, \dots \dots \dots . n \tag{12}$$

With x_i and x_k; the data values at time j and k (j>k).

The positive value of Q_i shows the upward (increasing) trend while the negative value of Q_i indicates the reverse.

Mann Kendall test statistics were computed in R-software. The linear trend lines were plotted using Microsoft Excel 2010. The Inverse Distance Weighted (IDW) method using ArcGIS software was applied to interpolate the spatial distribution of precipitation in the study area. Moreover, the rainfall data and landslide data were integrated into ArcGIS software in order to map the spatial distribution of rainfall and the location of landslides.

3.3.3 Objective3: Predict the occurrence of landslides

3.3.3.1 Logistic regression model

In order to achieve the above mentioned objective, logistic regression was used. Unlike simple and multiple linear regression which assess the linear relationship between variables, logistic regression has been proven to be advantageous in determining the relationship among independent variables and a dichotomous variable (dependent variable) without assuming the linear function between them, or having a lot of requirements (Mousavi et al., 2011, Fang, 2013). In addition, in logistic regression the variables can be measured in all levels of measurements which are nominal, ordinal, interval and ratio. Logistic regression was used in this study to relate the selected landslide causative factors with the landslide occurrence by identifying which factors best fit the model. It was used to model the probability of landslide occurrences based on the observed values of predictor variables.

The probability of landslide occurrences as described in Lee (2005) and Akgun et al.,(2011), was modelled using the logistic regression equation expressed in the following form:

$$P = \frac{1}{1+e^{-z}} \quad \text{, with } 0 < P < 1 \qquad (13)$$

Where P represents the probability of landslide occurrence, and Z is the linear combination expressed as:

$$z = B_0 + B_1X_1 + B_2X_2 + \dots\dots + B_nX_n \quad \text{, with } -\infty < z < +\infty \qquad (14)$$

Where B0 is the intercept of the model and n is the number of independent variables. The Bi (i=0, 1, 2,…n) are the slope coefficients of the logistic regression model while the Xi (i=0,1, 2, …, n) are the independent variables. Hence, from equations (13) and (14), the equation of the logistic regression can be expressed in the extended form as:

$$P = \frac{1}{1+e^{-(B_0+B_1X_1+ B_2X_2 \ldots\ldots+B_n X_n)}} \qquad (15)$$

In this study, 34 landslide points identified on Google Earth image of 2015 were used in building the logistic regression model. Image of 2015 was selected over the one of 2005 because it was in 2015 that an important number of landslides occurred in comparison with only 8 landslides identified in the image of 2005. Also, landslides have been increasing in recent times. This required the use of the land use/cover classified from Landsat image of 2015 as well in order to match the period.

In addition to the total of 34 landslide points, other 34 points for non-occurrence of landslides in the study area were randomly created within ArcGIS environment (Mousavi et al., 2011). Hence, the value "1" was given to the occurrence of the landslide and the value "0" to the non-occurrence of the landslide in order to analyze the relationship between landslides (binary dependent variable) and causal factors (predictor variables).

All landslide causative factors selected for this research which are slope angle, aspect, soil depth, distance to the road, land use/cover, and rainfall of those 68 points were extracted using ArcMap 10.5. They were all projected to the same projection system (WGS_1984_UTM_Zone_ 35S) of the Landsat projection, and then input into the backward stepwise (Wald) logistic regression to carry out the statistical analysis.

Backward stepwise (Wald) logistic regression (also known as Backward elimination regression) begins a model in which all independent variables are initially included and then excludes the insignificant variables step by step, using the probability of Wald statistic

(Korkmaz et al., 2012; Muchabaiwa, 2013) in order to find a reduced model that best explains the data or in other words to maximize the predictive power of the model.

3.3.3.2 Logistic regression model assessment and validation

Before applying a model in any decision making purpose, it is good to check the adequacy of the model. According to Peng et al., (2002), an adequate logistic regression model has to be justified by some key parameters such as the overall test of all parameters, a statistical significance of each predictor, the goodness-of-fit statistics, the predictive power of the model, and the interpretability of the model. Yet, Nagelkerke R^2 was used to assess the efficiency of the model. As it was stated by Hosmer & Lemeshow (2000), the higher value of Nagelkerke R2 indicates the perfection of the model while the lower value indicates the poor relationship between dependent and independent variable.

In addition, Wald statistic is also a parameter used to assess the fitness of a model as it was suggested by Field (2009). The Wald statistic indicates the contribution of each predictor in logistic regression model, while other parameters assess the characteristics of the whole model. The variable that is important in the model has a coefficient with a p-value of the Wald statistic less than 0.05 (significance level) (Peng et al., 2002; Muchabaiwa, 2013). On the other hand, it was found that the small Hosmer-Lemeshow test statistic with a p-value that is greater than the significance level (0.05) implies the goodness of fit of the model (Hosmer & Lemeshow, 2000; Peng et al., 2002; Muchabaiwa, 2013).

The model was validated using Pseudo R^2 value of which the pseudo R^2 value of 1 indicates the best model fit, while a value of 0 implies that there is no relationship. Similarly, a pseudo R^2 value that is greater than 0.2 indicates a relatively good model fit (Sangchini et al., 2015; Kouhpeima et al., 2017). Furthermore, the area under ROC (receiver operating characteristic curve) has been proven useful in the assessment of the adequacy of logistic regression model (Bewick et al., 2005; Gorsevski et al., 2006). Thus, from the area under the ROC value ranging between 0.5 and 1, the value 1 indicates a perfect fit while the value 0.5 implies a random fit (Ayalew & Yamagishi, 2005).

In this study, the concerned dependent variable is the landslide which was assigned the value "0" for the non-occurrence of landslide and the value "1" for the occurrence of landslide.

Table 3 4: Variables used for logistic regression model

Independent variables	**Dependent variable**
Precipitation	Landslide
Land cover	
Slope Aspect	
Slope angle	
Soil depth	
Distance to road	

Source: Own, 2019

The values of independent variables were collected for each identified landslide point and organized within Excel. Thereafter, the values were imported into SPSS for logistic regression analysis.

Table 3 5: Summary of data collection and analysis techniques

Objective	**Research question**	**Variable (key word)**	**Data collection techniques**	**Data analysis techniques, and software**
Assess the effects of land use/ cover change on landslide occurrences	-What are the pattern and rate of land use/cover change in Nyabihu District from 2005 to 2015? -How did land use/cover change contribute to landslide occurrences?	-Land use/cover -Landslide	- Satellite images - Field visits - Acquire data from Nyabihu district office, and MINEMA	-Supervised maximum likelihood classification -Post-classification comparison method - ERDAS IMAGINE - ArcGIS
Evaluate rainfall variability and its implications on the occurrence of landslides	-What are the characteristics and trends of rainfall in Nyabihu District from 1997-2017? -How does rainfall amount influence landslide occurrences?	-Rainfall -Landslide	- Acquire data from RMA -Satellite images	- Mann-Kendall test - R-software - Microsoft Excel
Predict the occurrence of landslides	- What is the probability of landslide occurrences given the generated predictive model? -What are the implications of landslide prediction model outcomes on disaster management?	Landslide causative factors	- Acquire data from the above mentioned government entities - Satellite images	- Logistic regression model - SPSS - ArcGIS

Source: Own, 2019

3.4 Research ethics

Research ethics are broadly explained as "*a set of standards, values, and institutional arrangements that contribute to constituting and regulating research activities*" (NENT, 2016, p.5). In this study, it was the responsibility of the researcher to be honest with and show respect to people that participated in the research. Research participants included workers in government institution such as Nyabihu district office, MINEMA, RMA, and all other people who provided the information needed by the researcher.

The researcher ensured that the research is conducted with honesty, integrity, truthfulness, and objectivity. With all possible respect, the researcher sought consent for all participants for their participation in the research. Further, the researcher complied with the established regulations concerning research including the regulations of the University of Botswana. With this, the researcher sought the research permit from the University's office of the Research and Development. The research permit was always presented to participants that were to be consulted along the data collection process to ensure the confidentiality in using the provided data or the reliability and validity of the research. Government entities consulted in the data collection process include the Ministry of Emergency Management in Rwanda, Rwanda meteorology Agency, and the office of Nyabihu district.

3.5 Validity and reliability

Validity refers to "the extent to which a concept is accurately measured in a quantitative research" (Heale & Twycross, 2015). In line with this definition, the researcher went to the field to check the land use/cover categories available in the study area. In addition, all data provided were effectively crosschecked before engaging in any further analysis procedure.

Reliability, on the other hand, is defined as" a consistency of a measure" (Heale & Twycross, 2015) or "the extent to which a phenomenon provides stable and consistent results with repeatability"(Taherdoost, 2016). For this, the researcher took sufficient reference data points during the accuracy assessment of image classification results, and performed the assessment or validation of the generated statistical model to ensure that the produced results are accurate and replicable.

Chapter 4: RESULTS AND DISCUSSION

Overview

This chapter presents the results of satellite image classification and the results from land use/cover change detection, and then discusses the effects of land use/cover changes on areas affected by landslides. It also discusses the relation of some landslide conditioning factors to landslide occurrences.

4.1 Objective 1: Assess the effects of land use/cover change

4.1.1 Land use/cover in 2005

The results of image classification of 2005 indicated that the study area was dominated by agricultural land as a rural district where most of the inhabitants rely on growing crops or livestock keeping for their livelihood. The agricultural land occupying 411.67 Km^2 comprises the rain fed arable lands, cropland with non-permanent (e.g., potatoes, wheat, vegetables, etc.) and permanent crops such as banana and tea plantations, and fallow fields as well. Tea plantations were classified separately from the agricultural land as they appeared as a kind of vegetated area in the satellite image. The classified land use/cover map (figure 4.1) shows the distribution of land use/cover in the district.

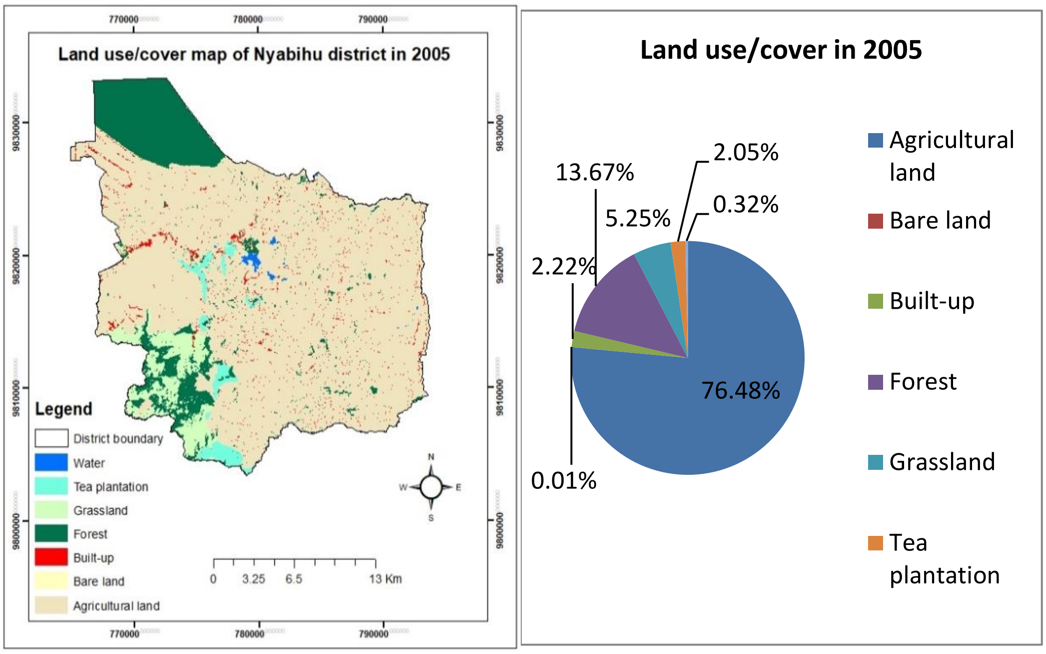


Figure 4 1: Land use/cover in Nyabihu district 2005

Grasslands include the pasture lands and other uncultivable land reserved for a specific purpose. Built-up comprises the single residential houses spread over the study area, the factories, roads, and other basic infrastructures such as schools, churches, health centers, etc. Bare land occupying less space comprises the unused spaces, rocky areas and cleared areas.

4.1.2 Land use/cover in 2015

Despite changes that occurred in land use/cover from 2005, agricultural land in 2015 was still predominant, followed by forest (figure 4.2). All together, they occupied 85.83% of the area covered by all land uses/covers in the study area (table 4.1).

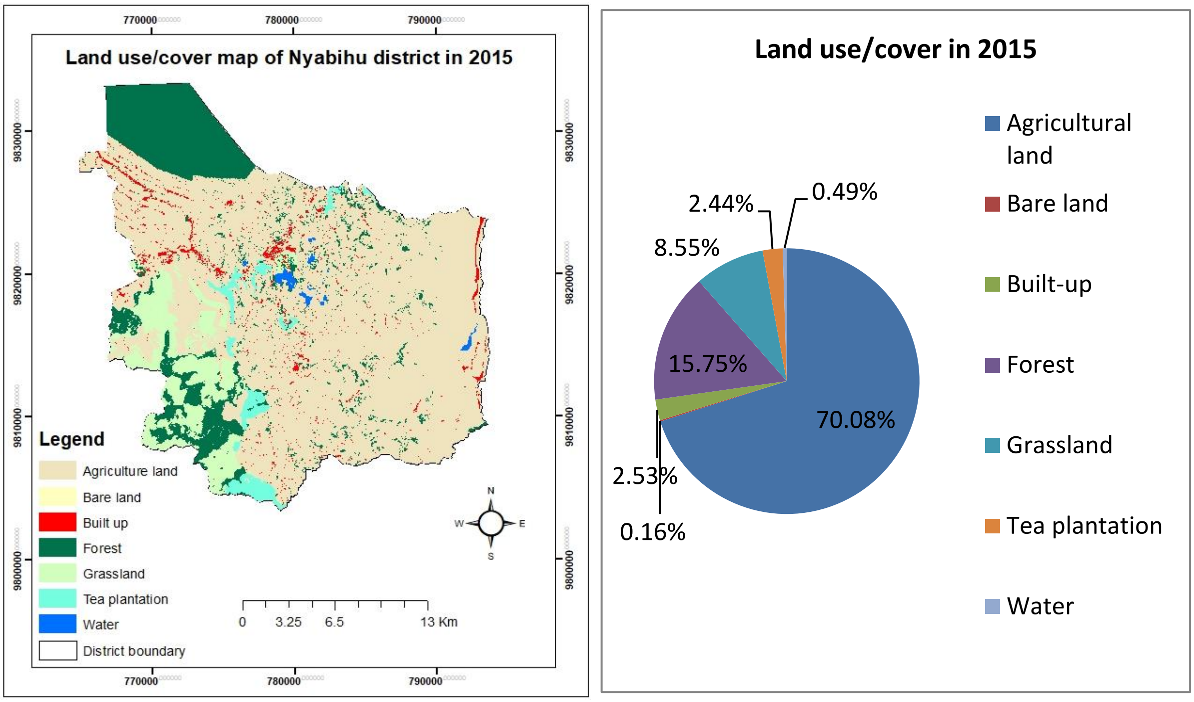


Figure 4 2: land use/cover in Nyabihu district 2015

Source: Analysis, (2019)

The table 4.1 presents the size of the area occupied by each land use/cover type.

Table 4 1: Size of each land use/cover category

Land use/cover	2005		2015		% of change
	Area (Km^2)	**Percentage (%)**	**Area (Km^2)**	**Percentage (%)**	
Agricultural land	411.69	76.48	377.23	70.08	-6.4
Forest	73.59	13.67	84.80	15.75	2.08
Grassland	28.26	5.25	46.03	8.55	3.33
Built-up	11.95	2.22	13.61	2.53	0.31
Tea plantation	11.04	2.05	13.15	2.44	0.39
water	1.71	0.32	2.63	0.49	0.17
Bare land	0.08	0.01	0.88	0.16	0.15
TOTAL	538.32	100.00	538.31	100.00	

Source: Analysis, (2019)

4.1.3 Land use/cover change from 2005 to 2015

The study area has undergone various changes in land use/cover between 2005 and 2015. The agricultural land has been taken away by other land uses/covers such as forest, grassland and built-up areas. The calculated percentages for land use/cover classes as presented in table 4.1 show changes that occurred in land use/cover from 2005 to 2015. The agricultural land decreased by 6.4% in this period, while forest, bare land, built-up, grassland, water, and tea plantation increased by 2.04%, 0.15%, 0.31%, 3.3%, 0.17% and 0.42% respectively in the period(figure 4.3, Table 4.1).

The matrix of land use/cover change presented in table 4.2 below shows how much in square kilometers (km^2) each land use/cover has increased or decreased between the years 2005 and 2015.

Table 4 2: Land use/cover change matrix

	LULC classes	Land use/cover 2015 (area in Km^2)							Total area
		Agriculture	Bareland	Built-up	Forest	Grassland	Tea plantation	Water	
Land use/cover 2005(Km^2)	**Agriculture**	362.1195	0.1980	10.9300	16.8089	17.8649	2.5734	1.1915	411.69
	Bareland	0.0092	0.0028	0.0004	0.0273	0.0202	0.0172	0.0001	0.0772
	Built-up	9.0412	0.0105	2.2301	0.4304	0.1534	0.0647	0.0170	11.947
	Forest	4.4268	0.1424	0.2808	64.4483	3.7750	0.4862	0.0354	73.595
	Grassland	0.4381	0.4709	0.0945	2.8881	24.1967	0.1724	0.0004	28.261
	Tea plantation	0.9120	0.0506	0.0724	0.1575	0.0180	9.8312		11.042
	Water	0.2835		0.0008	0.0352	0.0012		1.3857	1.7064
	Total area	377.2303	0.8752	13.6089	84.7957	46.0296	13.1450	2.6302	538.31

Source: analysis, (2019)

The diagonal in orange color shows the area in square kilometer that has not changed for each land use/cover. As it is presented in table 4.2, for example, the agricultural land decreased from 411.69 Km^2 (76.47%) in 2005 to 377.23 Km^2 (70.07%) in 2015, while 362.1195 Km^2 of agricultural land remained unchanged between 2005 and 2015. Thus, between 2005 and 2015, 0.198Km^2 of agricultural land changed to bareland, and 10.93Km^2 of agricultural land changed to built-up, etc. On the other hand, the forest increased from 73.595 Km^2 in 2005 to 84.80 Km^2 in 2015 whereas 64.4483 Km^2 of forest remained unchanged in this period. It is seen that the agricultural land was mainly converted to grassland (17.86 km^2), forest (16.80km^2) and built-up (10.93 km^2).

The remarkable increase of forest and grassland (which is mostly the pasture land) was due to the measures that were taken by the government to reforest a large area of Gishwati reserved forest. Reforestation efforts increased the forest from about 600 hectares in 2002 to 886 hectares in period between 2005 and 2008, which further increased up to 1,484 hectares between 2009 and 2010 (Kisioh, 2015).This forest was previously deforested by human encroachment through clearing of the forest for small-scale farming, large-scale cattle ranching projects and cattle grazing within the forest as well as the resettlement of returnees and internally displaced people in the aftermath of the genocide of 1994 (Kisioh, 2015).

Likewise, built-up increased from 11.95 Km^2 in 2005 to 13.60 Km^2 in 2015. The increase of built-up was undoubtedly due to the population growth which definitely implies the construction of new infrastructures including shelters amongst others.

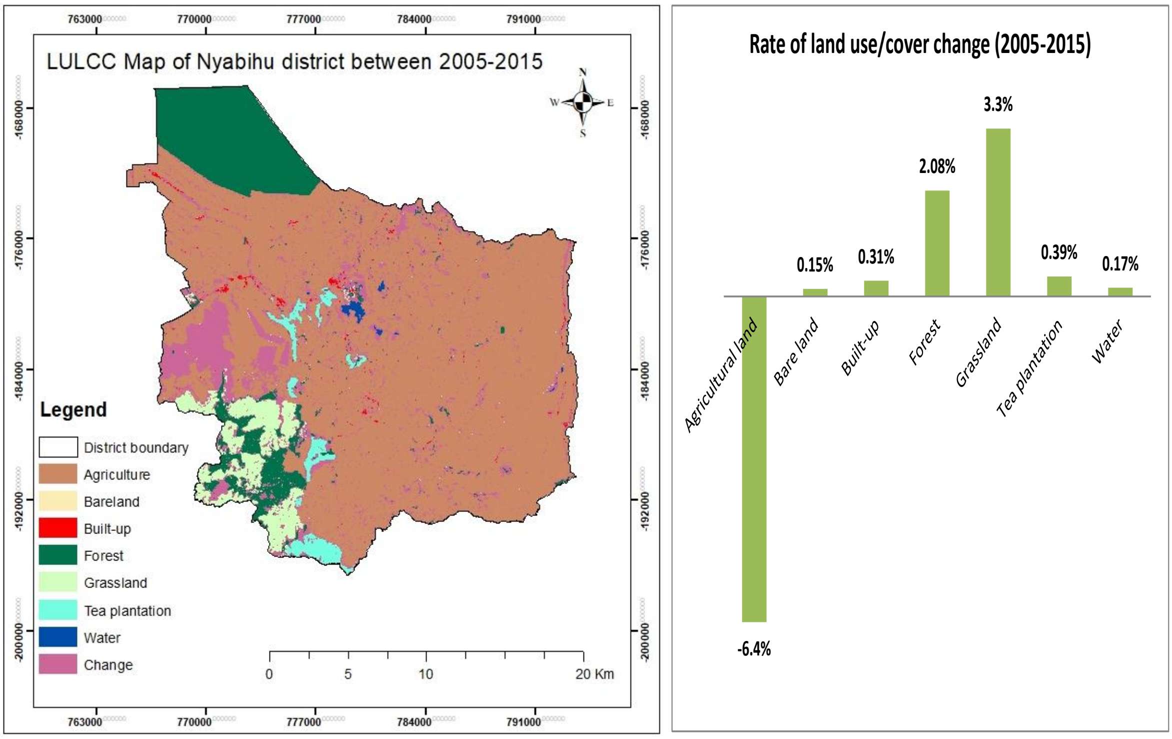


Figure 4 3: Land use/cover change and annual rate of change from 2005 to 2015

Source: Analysis, 2019

4.1.4 Land use/cover change and landslides in Nyabihu district

The produced landslide shapefiles were overlaid with the land use/cover of Nyabihu district in 2005 and 2015 (figure 4.4). The results indicated the occurrence of many landslides in 2015 compared to those occurred in 2005. It was seen that most of the landslides occurred in agricultural land. For instance, in 2005, almost all landslides (7 out of 8, representing 87.5% of the total number of landslides) were located in agricultural land while only one landslide (representing 12.5% of the total number of landslides) occurred in forest cover. Similarly, in 2015, the agricultural land experienced 27 landslides, while grassland, built-up, and forest experienced 4, 1 and 2 landslides respectively. This implies that agriculture land is mostly affected by landslides compared to other land uses/covers; possibly due to depletion of natural vegetation.

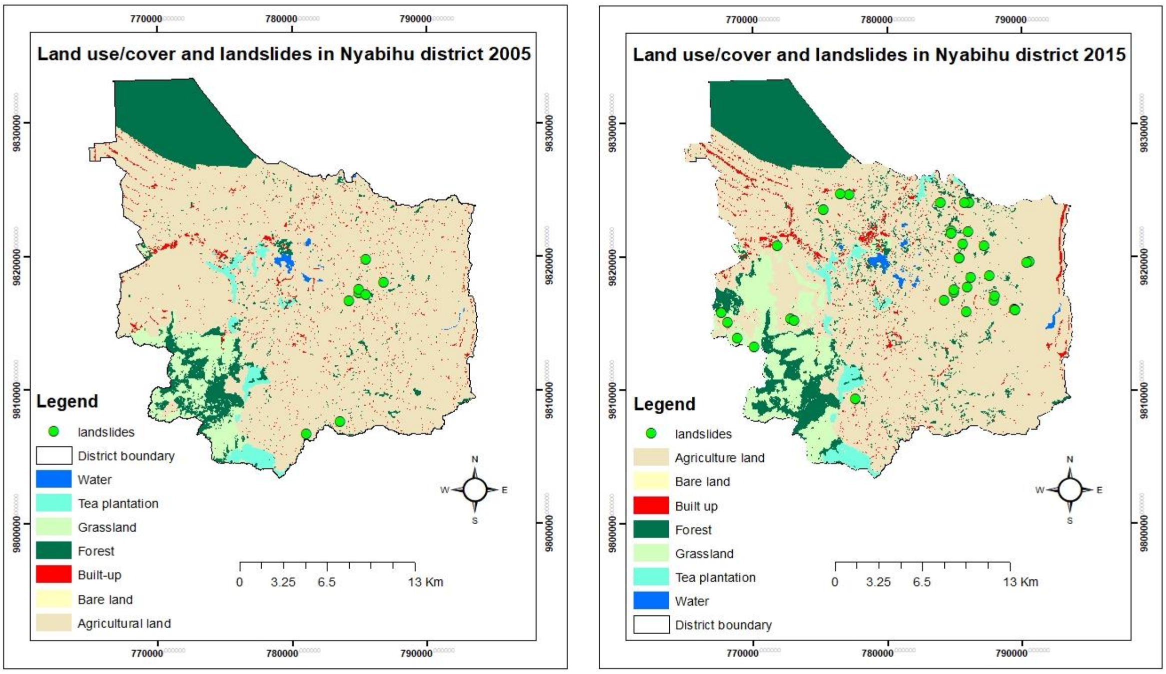
Land use/cover changes have an influence on slope failures that lead to landslides (Chen & Huang, 2012; Mugagga et al., 2012), due to inappropriate land coverage for holding the soils firmly. More often, changes in land use/cover are associated with some factors like undercutting the slope, vegetation removal and change of water flow directions which all weaken the soil capacity of absorbing water thereby causing landslides. It was seen that land use/cover changes mostly on slopes contribute more on landslide occurrences (Karsli et al., 2009; Reichenbach et al., 2014). The changes observed in the study area mainly refer to the decrease of agriculture land. Yet, the agriculture remains the main source of subsistence for the majority people in Nyabihu district. Also, the agricultural produce from this district feeds other regions countrywide including Kigali city.

The decline of agricultural land may lead to improper agricultural practices like cultivation of unsuitable slopes as the farmers would be interested in producing more yield while violating the soil protection measures, and hence exposing soils to erosion and landslides as well. With the same reasoning, the diminution of agricultural land (cropland) while the population increases, explains the pressure exerted on remaining scarce cropland, and hence inducing inappropriate agricultural practices in one way or another. According to (Gurung et al., 2013), inappropriate agricultural practices have been cited as being among the factors of landslide occurrences, which might be the case for Nyabihu district based on the obtained results. It was also noticed by Knapen et al., (2006) that the slope instability can be caused by cultivation on unsuitable steep slopes due to population growth pressure. The cultivation on steep slopes increases the chances to landslide occurrences when it is done without proper protection measures(Wasowski et al., 2010, as cited in Mugagga et al., 2012).

The study area has experienced a greater number of landslides in agricultural land (cropland) than other land uses/covers as the cropland in the area is mostly characterized by short-term crops (e.g. potatoes, beans, carrots, etc.) having roots with limited penetration in the depth of soil, while the progression of plant roots in the soil depth could increase the slope stability

(Noroozi et al., 2017). Furthermore, based on the argument that trees or woody vegetation provide the slope stability (MacNeil et al., 2001; Reichenbach et al., 2014), it confirms the prominent landslide occurrences in agricultural land since growing crops usually involves the removal of trees or vegetation for soil preparation.

The occurrence of landslides in cropland can be also attributed to other factors such as the absence of radical terraces and appropriate rainwater channels on steep slopes. This was also revealed by the obtained results which indicated that almost all landslides occurred in agricultural land were on steeper slopes, while the agricultural land on gentle slopes experienced few landslides, confirming the relation of land use/cover and slope gradient in inducing landslides.



2005 2015

Figure 4 4: Land use/cover and landslides; 2005 and 2015

Source: analysis, (2019)

Figure 4.5a shows the agricultural practices on steep slopes, and figure 4.5b shows the landslide occurred at the bottom edge of the agricultural land on steep slope area.

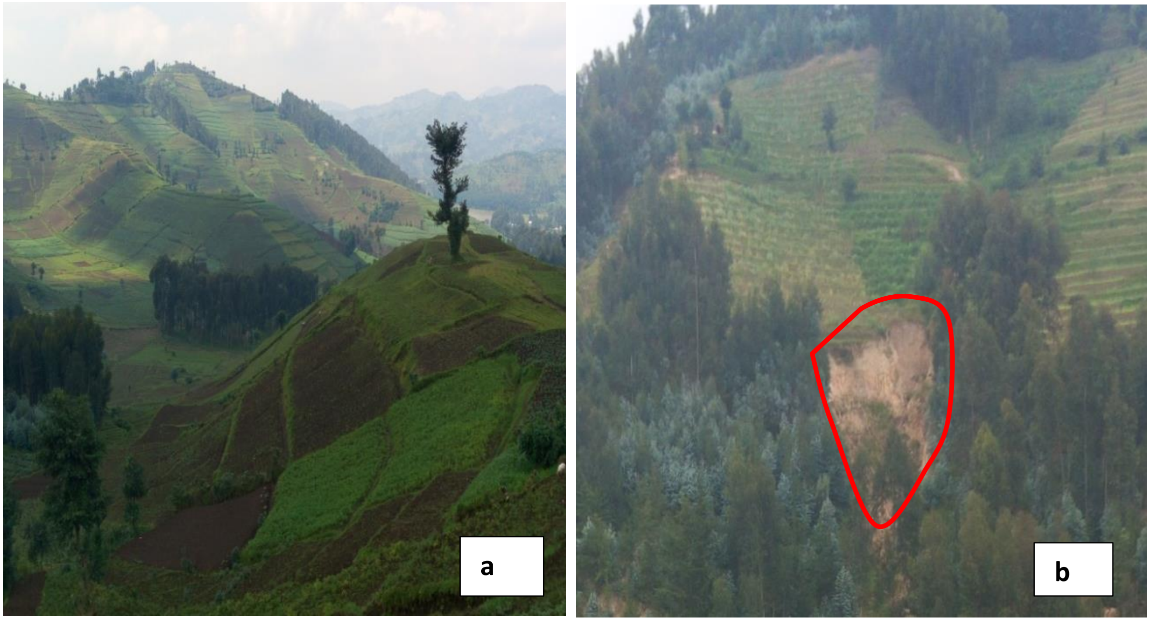


Figure 4 5: Agriculture on steep slopes (a), Landslide at the bottom edge of a field (b)

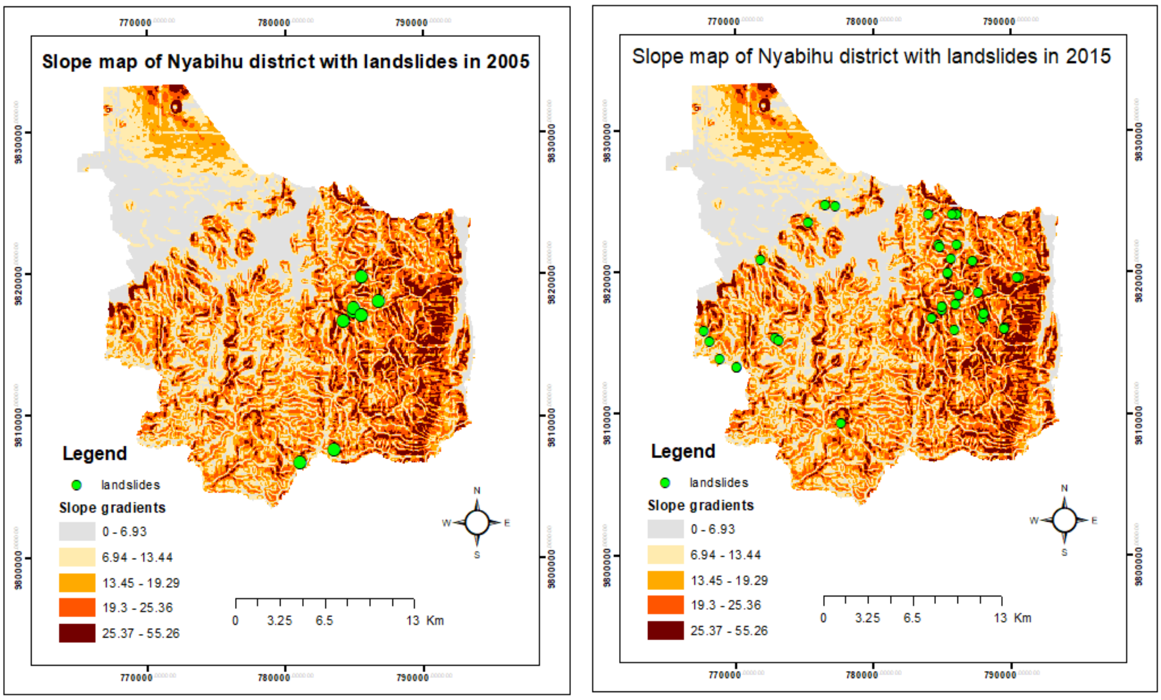
Source: Field work, 2019

4.2 Relationship between landslide conditioning factors and landslide occurrences

4.2.1 Slope angle and landslides in Nyabihu district

The slope angle has been noted to be connected with landslide occurrences in highlands (Jacobs et al., 2016; Skilodimou et al., 2018), though the influencing slope angle class may vary from region to region. In order to evaluate the occurrence of landslides in relation to the slope angle, a slope map was generated and overlaid with landslide occurrences in 2005 and 2015 (figure 4.6). Table 4.3 shows the number of landslides in relation to the slope angles.

The results revealed that the landslides generally occurred in medium slope ranging between 13.45-19.29° with 3 landslides in 2005, and 13 landslides identified in 2015. This might explain how the cultivation conducted on high steep slopes increase the instability of the slope.



2005 2015

Figure 4 6: Slope and landslides; 2005 and 2015

Source: Analysis, (2019)

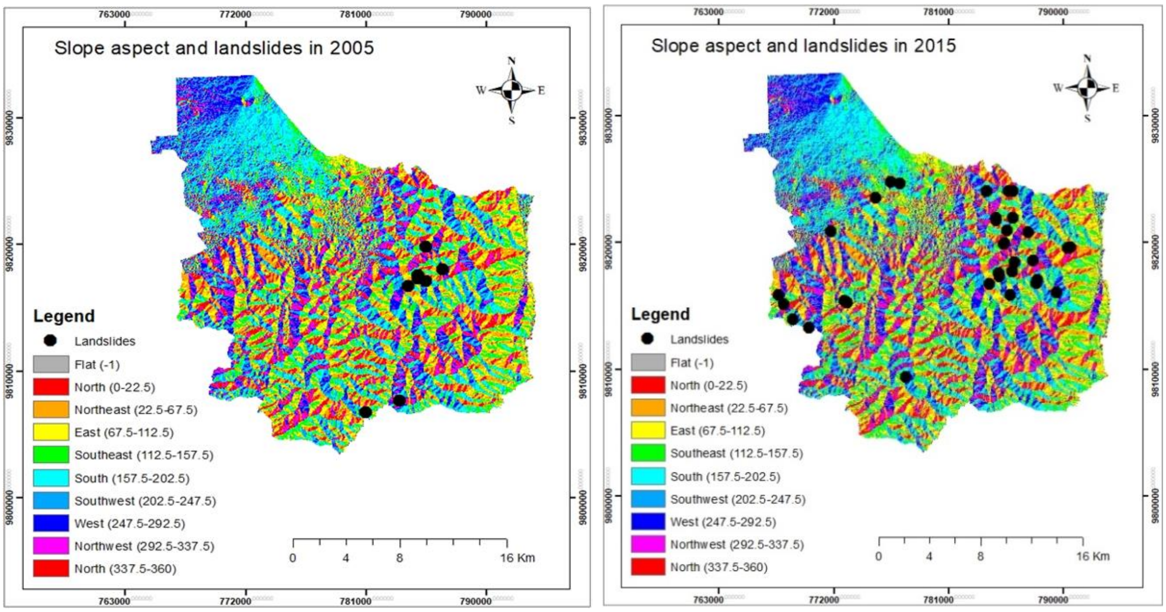
Generally, results showed that landslides often occurred in slope angles between 13.45 and 25.36°, while few landslides occurred in the highest slope angle of above 25.37°. In their study, (Jacobs et al., 2016) found that more landslides occurred in slope angles 25-30°, while at the same time the highest slope angles of above 30° experienced fewer landslides. It implies that chances of landslide occurrences do not necessary evolve with the increase in slope angles, though they are much connected with the steepness of the terrain. Donnarumma et al., (2013) argued that despite the relationship between the steepness and landslides, the high slopes do not always produce landslides. The idea was that sometimes the high slopes are comprised of stony layers that are not subjected to the slope failure. Furthermore, less cultivation at these slopes might contribute less to slope failure.

4.2.2 Slope aspect and landslides

In the assessment of the relationship between slope aspect and landslide occurrences, an aster DEM obtained from USGS was used by applying spatial analyst tools in ArcMap environment to derive slope aspect information. The derived information were classified into 9 classes named; Flat, North, Northeast, East, Southeast, South, Southwest, West, and Northwest. In this study area, most of the landslides occurred on south facing slopes (figure 4.7), which may explain that the south facing slopes experience the medium slope subjected to easy failure or where the prominent soil depth is the class very susceptible to landslides, otherwise the cultivation might be more on south facing slopes.

In a similar study, Capitani et al., (2014) noticed that shadow, coldness, and humidity which differ from one slope aspect to another may explain why some slope aspects are more subjected to landslides than others. Yet, the difference in wetness from slope aspect to another is an additional factor to take into consideration when analyzing the influence of slope aspect to the landslide occurrences.

Due to the hilly topography of the study area, it happens that the sunshine lasts longer on particular hillsides than on their opposite sides which may explain how some slope aspects are more exposed to a prolonged wetness while others are dry, and hence the disparity of landslide occurrences. It is what has been noticed by Caiyan et al., (2006) that the slope exposed to enough sunshine and hence dry, often experiences the low vegetation cover which can lead it to easy degradation by rainfall.



2005 2015

Figure 4 7: Slope aspect and landslides; 2005 and 2015

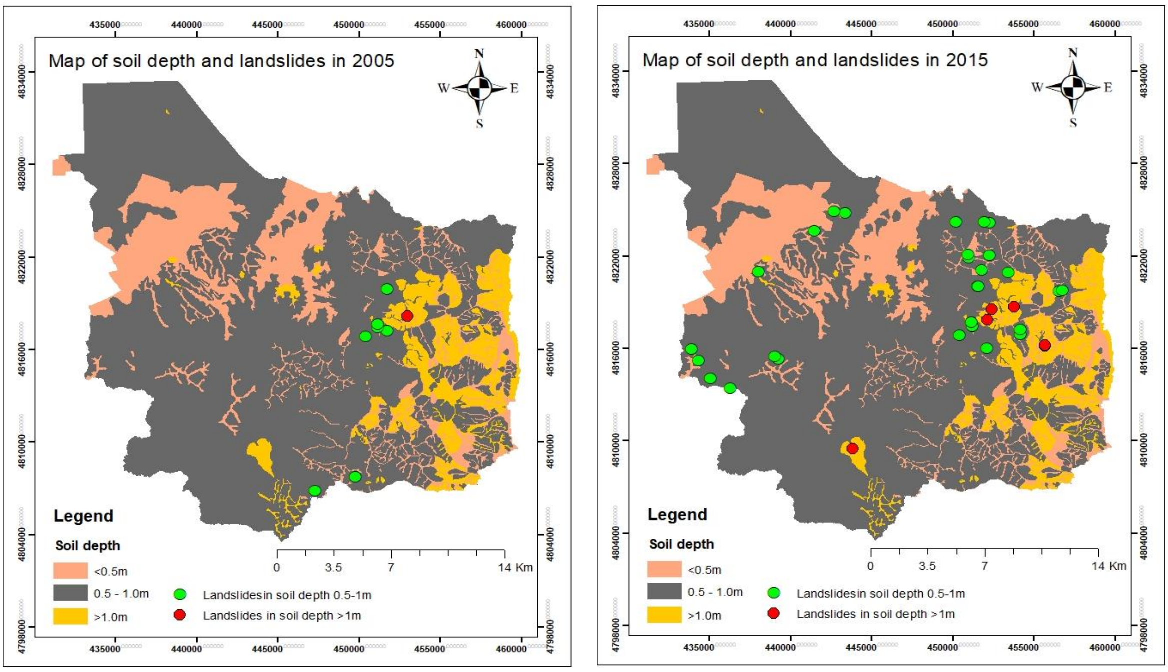
Source: Analysis, (2019)

Furthermore, some of the microclimatic factors (e.g. exposure to sunlight, windward and leeward conditions, rainfall intensity, soil moisture and weathering) controlling the properties of the slope are influenced by the slope aspect (Cevik & Topal, 2003; Tseng et al., 2015). The results of this study showed a clear relation of landslide occurrences to south facing slopes (S, SE, and SW) (figure 4.7).

4.2.3 Soil depth and landslide occurrences

From the overlay result of soil depth and landslides identified in 2015, it was clear that the majority of landslides (28 landslides) occurred on soil depth ranging between 0.5- 1m depth, while 5 landslides occurred on soil depth greater than 1m depth (>1m). No landslide occurred on soil depth less than 0.5m depth (<0.5m) (figure 4.8). Similarly, 7 landslides (among the 8 landslides) identified in 2005 occurred on soil depth ranging between 0.5 and 1m depth. Only one landslide occurred on soil depth greater than 1m (>1m) (figure 4.8). While researches proved that slope failures mostly occur on soil depth between 1.2m and 1.5m where the strength excreted by roots does not often reach (Bizimana & Sönmez, 2015), landslides in

Nyabihu district in both 2005 and 2015 occurred on soil depth ranging between 0.1m and 1m. Table 4.3 shows the landslide occurrences per soil depth class.



2005 2015

Figure 4 8: Soil depth and landslides; 2005 and 2015

Source: Analysis, (2019)

Sharma et al., (2010) argued that shallow soils are more susceptible to landslides since they are unstable compared to deep soils which are stable. This is based on the idea that the soil capacity to absorb the moisture increases with the increase in soil depth and hence reducing the runoff rate. Similarly, (Fan et al., 2016) noted that landslide activity increases in shallow soil depth than it does in deep soil depth. In contrast, results of this study proved that the deep soils experienced more landslides than shallow soils, though the study area comprises clay, and volcanic soils that are actually susceptible to landslides on steep slope areas.

4.2.4 Distance to the roads and landslides

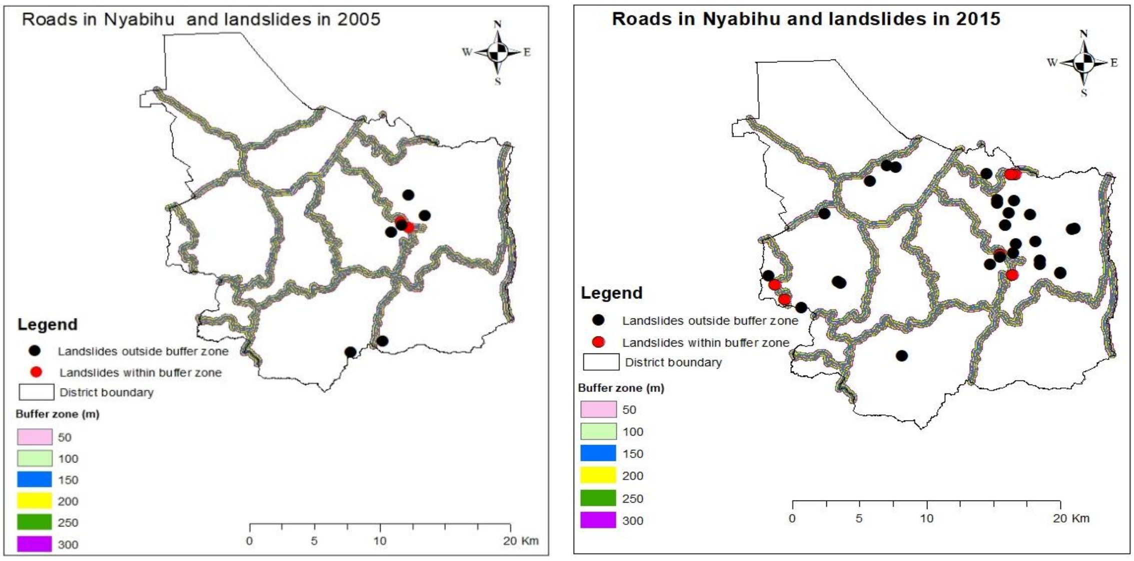
In this study, landslide occurrences in relation to the distance from the roads were analyzed by applying proximity analysis using GIS. In 2015, only one landslide was identified within a buffer zone of 25m, while other 33 landslides were located outside of the 50m buffer zone (figure 4.9).

Similarly, all landslides identified in 2005 were located outside the buffer zone of 50 m from the road (figure 4.9). With these results, it can be noted that the roads in Nyabihu district did not greatly induce slope failures as most of the landslides occurred at more than 50m from the road.

It was proven in the literature that landslides have been occurring near roads where vegetation cover has been cleared (Moghaddas & Ghafoori, 2007). In many cases, roads make slopes steeper and even direct the drainage channels to steep locations, all of which increase the chance to landslide occurrences (Das et al., 2010 cited in Hosseini et al., 2011).

The construction of roads along steep slopes which usually involves cutting slopes is among other causes of ground failure that ends up with causing landslides along roadside (Nayak, 2010). Yet, the vibration caused by heavy machine during road construction through excavation, and the force exerted by the movement of heavy loaded vehicles (e.g., trucks) cause cracks in the soils. It is believed that such vibration extends some distance from the road. Then, once the cracked soils absorb rainfall water that they are unable to hold, it finally leads to landslides. Similarly, the study concluded that the construction of roads in mountainous areas increases the chances of landslides (Nepal et al., 2019), as they usually result in inadequate drainage systems and mechanical destabilization of the steeper slopes through undercutting and overloading (Brenning et al., 2015).

On the other hand, the roadside cuts have been noted by Hearn et al., (2008) to be often exposed to higher wet ground water, perched water levels in soils and weathered rock masses, all of which are susceptible to landslides. Further, the blockage to roadside drains also facilitates the slope failures.



2005 2015

Figure 4 9: Distance to road and landslides; 2005 and 2015

Source: Analysis, (2019)

Figure 4.10a shows the road that runs through the steep slopes and figure 4.10b shows the landslide on the roadside which might have also been influenced by constructions on the steep slope area.

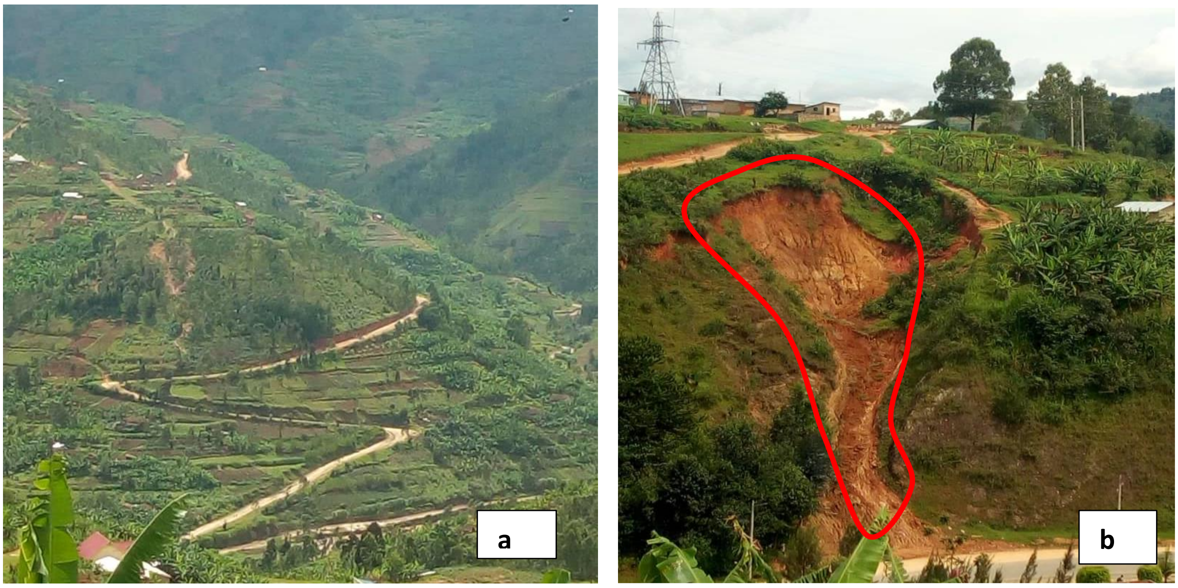


Figure 4 10: Road on steep slope area (a), Landslide on roadside (b)

Source: Field work, 2019

Although the above literature highlight the relation between road-based activities and the slope failures, the distance to road did not prove to be the eminent causative factor of landslides in this study area.

Table 4 3: Distribution of landslides in each landslide causative factor

		Number of landslides identified	
Causative factor	**Class**	**2005**	**2015**
Land use/cover	Agricultural land	7	27
	Bare land	0	0
	Built-up	0	1
	Forest	1	2
	Grassland	0	4
	Tea plantation	0	0
	Water	0	0
Slope angle (degrees)	0-6.93	2	5
	6.94-13.44	1	8
	13.45-19.29	2	11
	19.3-25.36	3	8
	25.37-55.26	0	2
Slope Aspect	Flat	0	0
	N	0	4
	NE	0	3
	E	1	7
	SE	1	6
	S	4	10
	SW	2	2
	W	0	1
	NW	0	1
Soil depth (m)	<0.5	0	0
	0.5-1.0	7	28
	>1.0	1	6
Distance to road (m)	0-50	1	1
	50-100	1	1
	100-150	0	1
	150-200	0	1
	200-250	0	0
	250-300	2	2
	>300	4	28
Precipitation (mm)	1095-1128		3
	1128-1161		3
	1161-1195		0
	1195-1228		1
	1228-1261		2
	1261-1294		8
	1294-1328		14
	1328-1361		3
	1361-1394		0

Source: Analysis, 2019

4.3 Objective 2: Evaluate rainfall variability and its implications on the occurrence of landslides.

4.3.1 Rainfall distribution and landslide occurrences in Nyabihu district

The spatial rainfall distribution in the study area was determined based on the precipitation recorded in 2015 for five rainfall stations as shown in figure 4.11b. This was to reflect on the 2015 Landsat satellite image presented in objective two. With five rainfall stations located within Nyabihu district, IDW method in ArcMap 10.5 was used to interpolate the spatial distribution of rainfall throughout the study area (figure 4.11b), and DEM served to generate an altitude map (figure 4.11a).

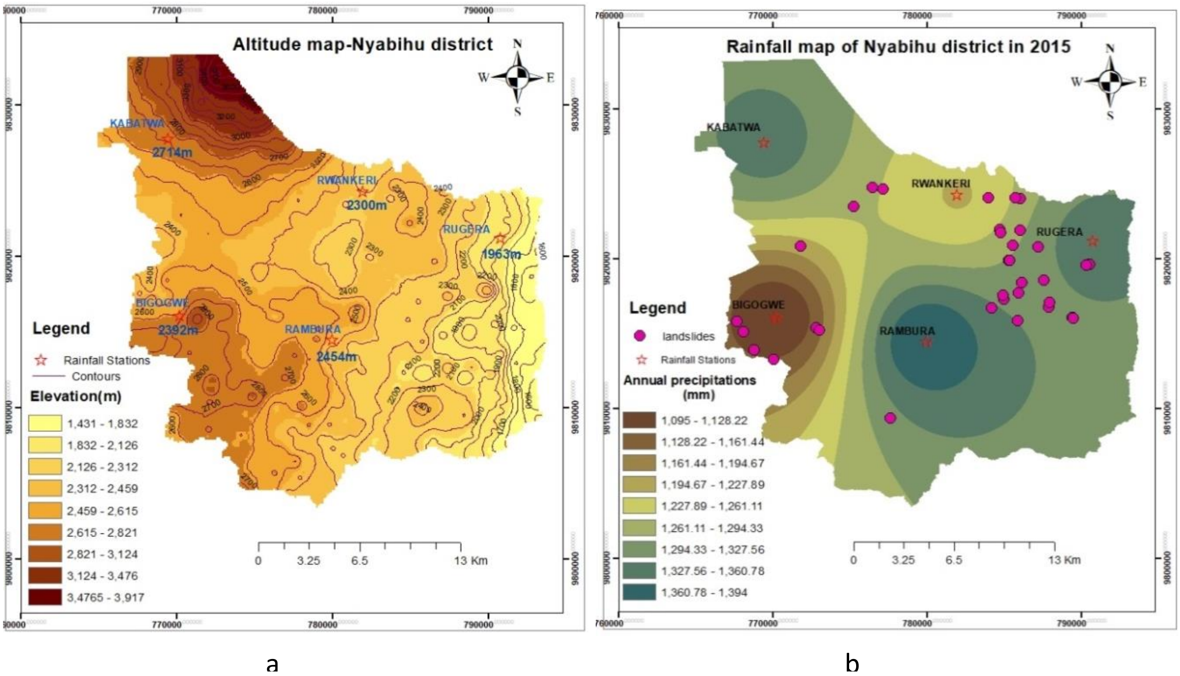


Figure 4 11: Altitude map (a), spatial rainfall distribution in Nyabihu district (b)

Source: Analysis, 2019

Then, landslides and precipitation layers were overlaid to assess the relation between precipitation amount and landslide occurrences (figure 4.11b). The results revealed that about 41.2% and 23.5% of the landslides occurred in the areas having high annual precipitation amount that ranges from 1294.33mm to 1327.56 mm and from 1261.11mm to 1294.33mm respectively. This reflects on results obtained by Lazzari and Piccarreta (2018), that heavy rainfall exacerbated the occurrence of landslides in their study area (Basilicata, Southern Italy). However, it is not only the heavy rainfall that causes landslides but also the low intensity rainfall prolonging for some days was noted to be the cause of landslide occurrences as well (Bizimana & Sönmez, 2015; Teja et al., 2019). Thus, this study also noticed the dominant occurrence of landslides in areas with high precipitation. Yet, this study did not analyze the effects of prolonged rainy days in triggering landslides due to the lack of efficient historical and timely landslide data. Nevertheless, the study established the relation between rainfall and landslide occurrences using the identified landslides on annual basis.

From the observation of the researcher, the high annual precipitations are spread on the steep slope areas. This can show the relation of precipitation amount to the slope gradient, confirming the usually experienced high rainfall in hilly regions all over the world (Alijani, 2008; Saeidabadi et al., 2016). Nevertheless, the analysis of rainfall in Nyabihu district was carried out separately for each of the rainfall stations located in the study area. Thus, the length of data record was not similar to all rainfall stations. Only one rainfall station (Bigogwe) had long record of rainfall data from 1997 to 2017, other four rainfall stations (Kabatwa, Rwankeri, Rambura, and Rugera) had rainfall data for a short period from 2014 to 2017(table4.4).

Table 4 4: Characteristics of rainfall for individual stations in the study area

Rainfall station	Period of data available	Mean annual rainfall (mm)	% of missing values
Bigogwe	1997-2017	1165	no missing value
Kabatwa	2014-2017	1122	no missing value
Rwankeri	2014-2017	1045	no missing value
Rambura	2014-2017	1301	no missing value
Rugera	2014-2017	1473	no missing value

Source: analysis, 2019

Hence, rainfall trend analysis was carried out only for Bigogwe rainfall station that had a long record of rainfall data (21 years). Line graphs were used to plot annual rainfall for other four rainfall stations with four years period of data record (Kabatwa, Rwankeri, Rambura, and

Rugera) in order to determine the relationship between annual rainfall and landslides identified on annual basis in that period.

4.3.2 Rainfall trends and variability in Nyabihu district

The rainfall trends were determined using Mann Kendall test together with the Sen's slope estimator (Hussain et al., 2015). As the number of data values for Bigogwe rainfall station was greater than 10 (21 years of data record length), Z statistic and Q_i statistic were used to assess the significance of rainfall trends at this station over the period between 1997 and 2017. However some researchers used Mann Kendall test statistic together with the p-value (Karmeshu, 2012; Chandubhai et al., 2017; Panda & Sahu, 2019) to assess the significance of the trend. Therefore, this study considered both sides in deciding whether the trend is significant or not.

4.3.2.1 Annual rainfall trend -Bigogwe station

The calculated Mann Kendall test Z and Sen's slope (Q_i) showed a downward (decreasing) annual rainfall trend at Bigogwe station due to the negative values of both Z and Q_i statistics (table 4.5). However, it can be said that although there is a decreasing rainfall trend (Q_i= -12.75), it is not statistically significant at 5% level based on the p-value which is greater than 0.05.

Table 4 5: Mann Kendall test statistics for rainfall trends, Bigogwe station from 1997-2017

Rainy Months	**Z**	**S**	**P-value**	**Sen's slope (Q_i)**
March	-0.82	-28	0.42	-1
April	-0.15	-6	0.88	-0.87
May	-1.78	-60	0.07	-2.13
October	-0.27	-10	0.79	-0.62
November	0.09	4	0.93	0.15
December	-2.26	-76	0.02	-4.23
Long rainy season	-0.57	-20	0.57	-3.75
Short rainy season	-0.48	-17	0.63	-3.19
Annual	-1.69	-57	0.09	-12.75

Source: Analysis, 2019

The added trend line in the annual rainfall trend (figure 4.12) indicates the general direction of downward rainfall trend from 1997 to 2017. It is a decreasing trend line implying that over the past years, there was much rainfall in comparison with the recent period. Bigogwe station recorded extreme rainfall in 2006 with annual precipitation reaching 1385mm. Thereafter, the rainfall instantly dropped to 1055mm in 2008, but later increased again to the high annual rainfall of 1359mm in 2010. From 2010, the rainfall kept decreasing and reached 866mm in 2013. The rainfall increased again from 2013 to reach the annual rainfall of 1228mm in 2016, and then promptly dropped to the low rainfall of 649mm in 2017 (figure 4.12).

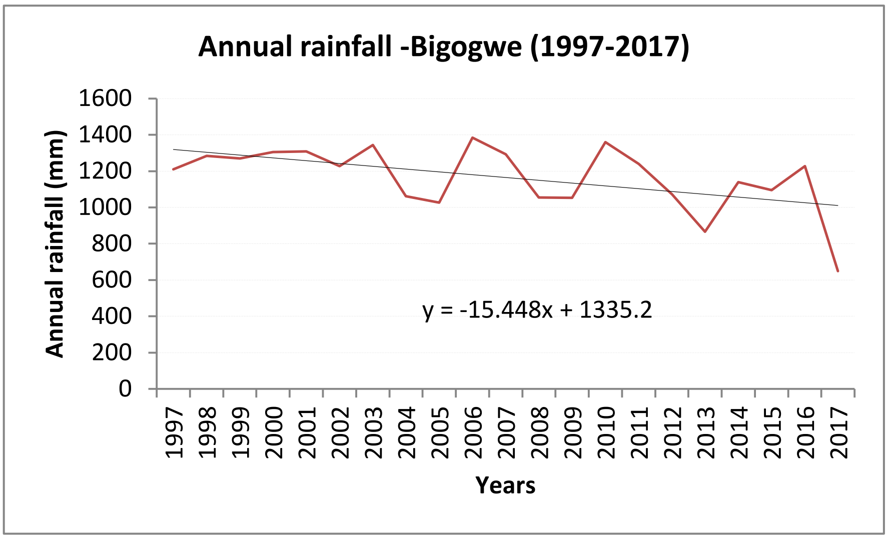


Figure 4 12: Annual rainfall trend for Bigogwe rainfall station from 1997-2017

Source: analysis, 2019

On the other hand, the study analyzed the relationship between rainfall and landslides identified in area close to Bigogwe rainfall station. Figure 4.13 shows the variation of landslides identified in area close to Bigogwe station from 2005 to 2017. While the rainfall increased between 2005 and 2006 and then decreased from 2006 to 2009, there was no landslide identified in area close to Bigogwe station in that period from 2005 to 2012. Also, the rainfall decreased from 2010 until 2012 while landslide occurrences increased in that period. Yet, the decrease of rainfall corresponded to the decline of landslide occurrences between 2012 and 2013. Both rainfall and landslide occurrences increased in period from 2013 to 2014 and declined from 2014 to 2015. But, the rainfall increased between 2015 and

2016 while the landslide occurrences decreased in this period, though all of them decreased again from 2016 to 2017. With all this, it can be said that there is no permanent defined relation of rainfall variation with the occurrence of landslides in the study area from 2005 to 2017; the rainfall variation does not always correspond to the variation of landslide occurrences whether positively or negatively.

In other words, there is no permanent positive or negative relationship that evolves constantly between rainfall and landslide occurrences over a period of time. It should be said that high rainfall triggers landslides depending on the presence of other causative factors for that particular moment.

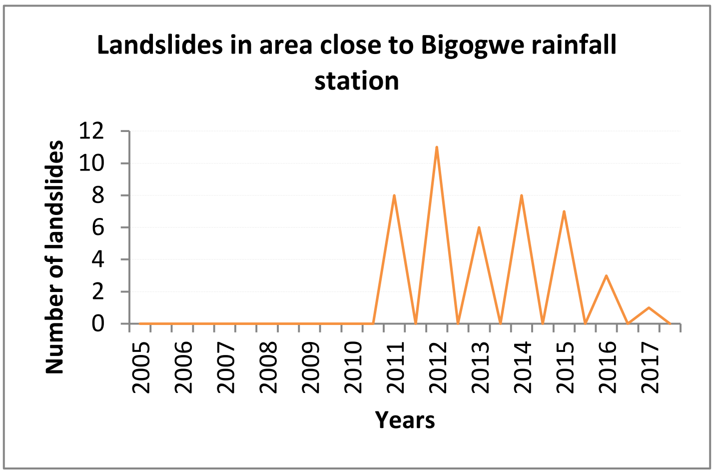


Figure 4 13: Landslides identified in area close to Bigogwe rainfall station

Source: analysis, 2019

4.3.2.2 Annual rainfall -Kabatwa station

In four years from 2014 to 2017, the annual rainfall recorded at Kabatwa rainfall station increased from 1056mm in 2014 to 1344mm in 2015 (figure 4.14). Then, the rainfall decreased to 1335mm in 2016 and further dropped to the low rainfall of 595mm in 2017. However, the data points are too few to establish any long term trends.

The area close to Kabatwa rainfall station did not experience landslides. This area is actually characterized by gentle slopes that are not very susceptible to slope instability.

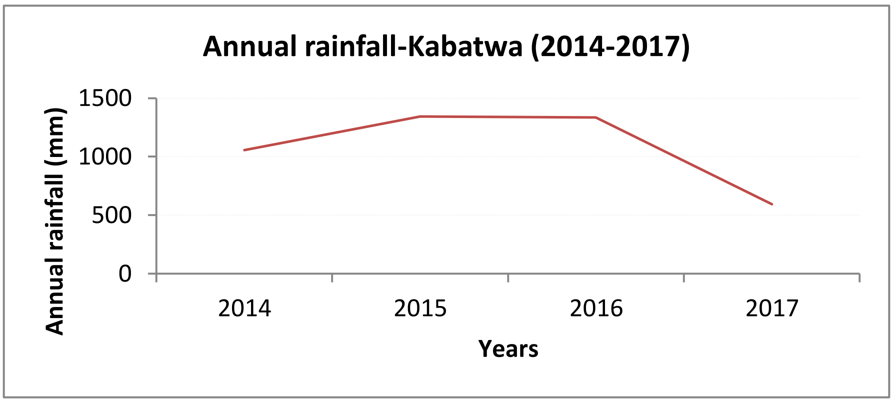


Figure 4 14: Annual rainfall at Kabatwa station from 2014 to 2017

Source: analysis, 2019

4.3.2.3 Annual rainfall -Rwankeri station

Figure 4.15 shows the annual rainfall at Rwankeri station. Annual rainfall increased from 1115mm in 2014 to 1281mm in 2016, and then decreased to 560mm in 2017.

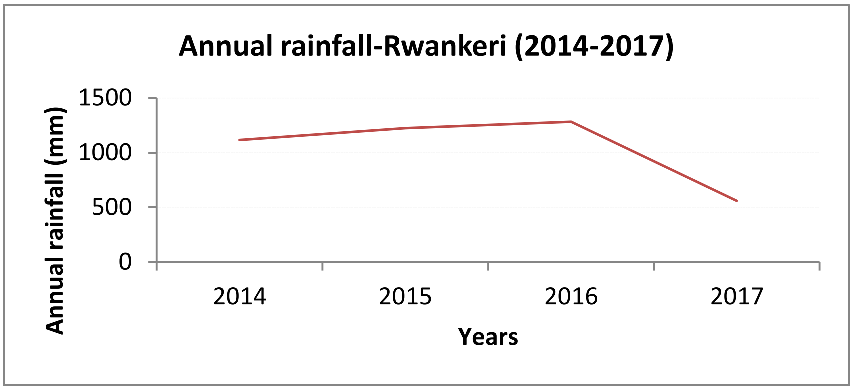


Figure 4 15: Annual rainfall at Rwankeri station from 2014 to 2017

Source: analysis, 2019

The landslides identified in area close to Rwankeri station showed a positive relationship with the rainfall in period between 2014 and 2017. Figure 4.16 shows the landslides occurred between 2014 and 2017 in surrounding area close to Rwankeri rainfall station. Both rainfall and landslide occurrences increased from 2014 to 2016 and then declined in 2017.

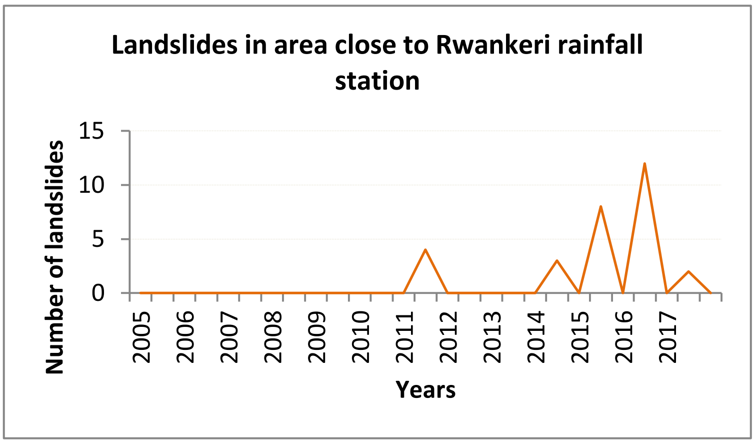


Figure 4 16: Landslides identified in area close to Rwankeri station

Source: analysis, 2019

4.3.2.4 Annual rainfall -Rambura station

The following figure 4.17 shows the annual rainfall from 2014 to 2017 at Rambura rainfall station. The rainfall has increased from 1222mm in 2014 to 1832mm in 2016, but later it dramatically dropped to 757mm in 2017.

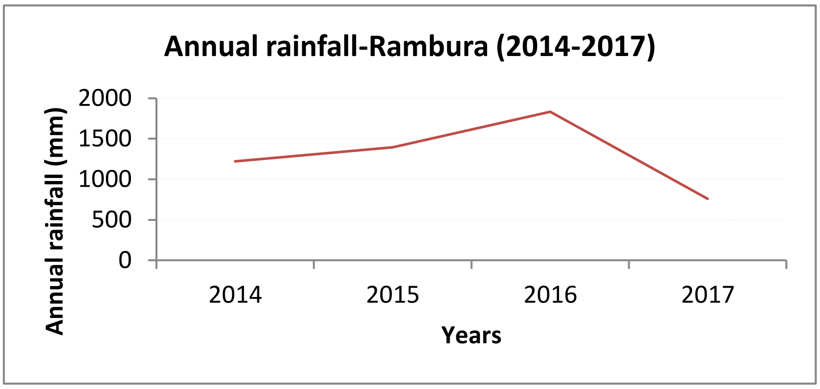


Figure 4 17: Annual rainfall at Rambura station from 2014 to 2017

Source: analysis, 2019

In the area close to Rambura station, there was no defined relationship between identified landslides and rainfall. The rainfall increased from 2014 to 2016 and decreased in 2017 while the landslides decreased between 2014 and 2015 and then increased from 2015 until 2017 (figure 4.18).

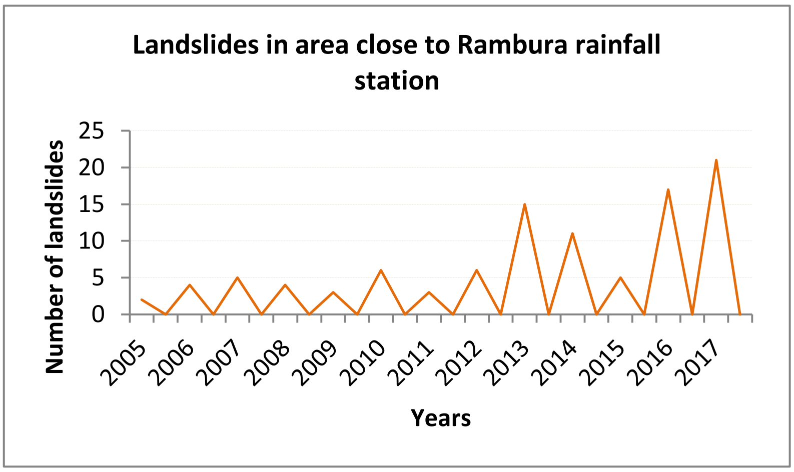


Figure 4 18: Landslides identified in area close to Rambura station

Source: analysis, 2019

4.3.2.5 Annual rainfall-Rugera station

In period between 2014 and 2017, Rugera station recorded high annual rainfall compared to other rainfall stations. The high annual rainfall of 2153mm was received in 2016 and low annual rainfall of 829 in 2017. Figure 4.19 shows the annual rainfall at Rugera station.

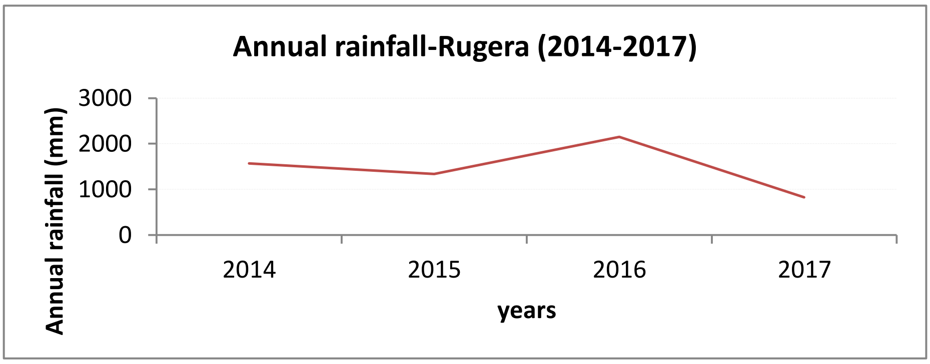


Figure 4 19: Annual rainfall at Rugera station from 2014 to 2017

Source: analysis, 2019

In area around Rugera rainfall station, the identified landslides showed an inverse relationship with the rainfall variation. The rainfall decreased from 2014 to 2015 while landslide occurrences increased in that period. The rainfall increased from 2015 to 2016 with a decline of landslide occurrences in the same period, and then rainfall decreased again in 2017 while landslides increased. Figure 4.20 shows landslides identified in area close to Rugera rainfall station.

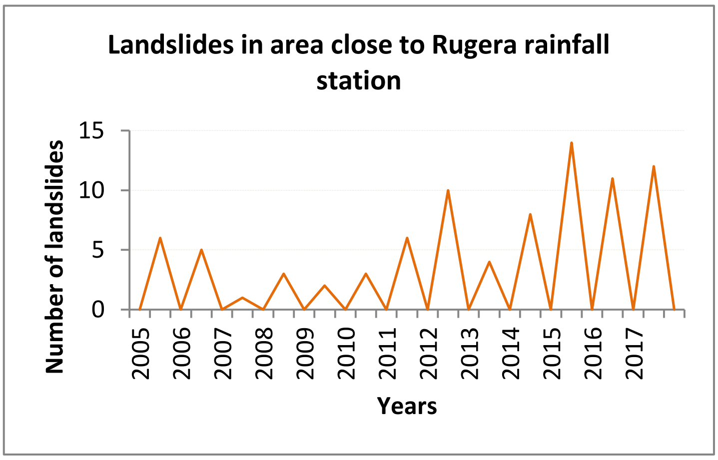


Figure 4 20: Landslides identified in area close to Rugera station

Source: analysis, 2019

In general, all rainfall stations in the study area received increasing annual precipitations in period from 2014 to 2016 and remarkable low precipitations in year 2017. However, the relationship of rainfall with landslides identified in area close to each of the rainfall stations showed a particularity from one station to another. This revealed that there is no defined relationship (either positive or negative) to be assigned between rainfall and landslide occurrences over the period mentioned in the study area. Yet, it does not mean that the influence of high rainfall in triggering landslides is meaningless, instead it depends also on the influence of other causative factors from one area to another in that particular period of time.

Generally from 2005 to 2017, the landslides occurred in area surrounded by four rainfall stations (Rwankeri, Rugera, Rambura, and Bigogwe) which are actually not located on high altitude compared to Kabatwa station. The dominance in landslide occurrences around those four rainfall stations may not refer to the altitude differences; instead it can be related to the amount of rainfall received in the area and steepness of slope together with improper cultivation practices on steep slopes. The area around Kabatwa station is characterized by gentle slopes which may contribute less on slope instability. Table 4.6 shows the landslides identified in area close to each of the rainfall stations from 2005 to 2017.

Table 4 6: Landslides identified in area close to each of the rainfall stations

	Number of landslides identified in area close to each of the rainfall stations					**Total**
Year	**Bigogwe**	**Kabatwa**	**Rambura**	**Rwankeri**	**Rugera**	
2005	0	0	2	0	6	8
2006	0	0	4	0	5	9
2007	0	0	5	0	1	6
2008	0	0	4	0	3	7
2009	0	0	3	0	2	5
2010	0	0	6	0	3	9
2011	8	0	3	4	6	21
2012	11	0	6	0	10	27
2013	6	0	15	0	4	25
2014	8	0	11	3	8	30
2015	7	0	5	8	14	34
2016	3	0	17	12	11	43
2017	1	0	21	2	12	36
Total	44	0	102	29	85	

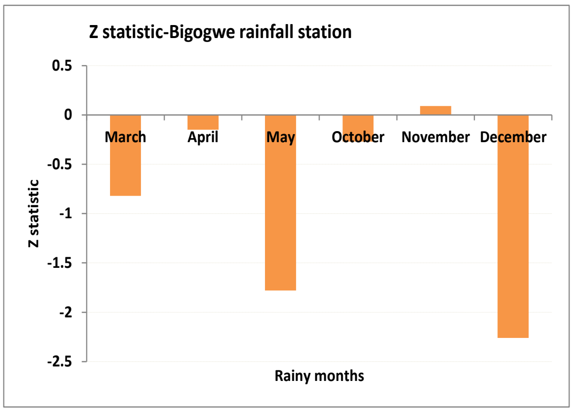
Source: analysis, 2019

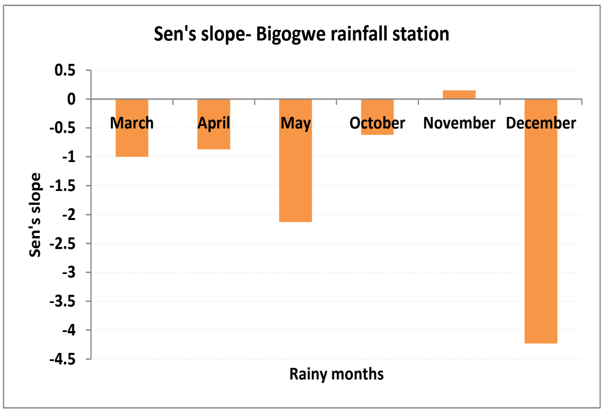
4.3.2.6 Monthly rainfall trends-Bigogwe station

The rainfall trends on a monthly basis were determined individually for each of the rainy months using the Mann Kendall test Z and Sen's slope (Q_i). The results indicated downward monthly rainfall trends in most of the months, while only one month showed upward rainfall trend. Five months (which are March, April, May, October, and December) had negative Z values which indicate decreasing monthly rainfall trends, and one rainy month (November) had positive value of Z statistic which indicates upward (increasing) monthly rainfall trend (figure 4.21a).

Moreover, the calculated Sen's slope (Qi) for each individual rainy month indicated that all five rainy months (March, April, May, October, and December) had negative Qi values which shows decreasing monthly rainfall trends, and only one rainy month (November) showed a positive Qi value, indicating increasing monthly rainfall trend(figure 4.21b).

As the five rainy months (March, April, May, October, and December) showed negative values for both Z statistics and Sen's slope (Qi), it can be concluded that they indicated significant decreasing monthly rainfall trends while one month (November) presented a significant increasing rainfall trend. However, based on p-value, it should be noted that only one month of December showed significant decreasing rainfall trend as it had p-value less than 0.05 and negative value of Z statistics (table 4.5).





a b

Figure 4 21: Mann Kendall for monthly trend analysis-Bigogwe; (a) Z statistic, (b) Q_i statistic

Source: analysis, 2019

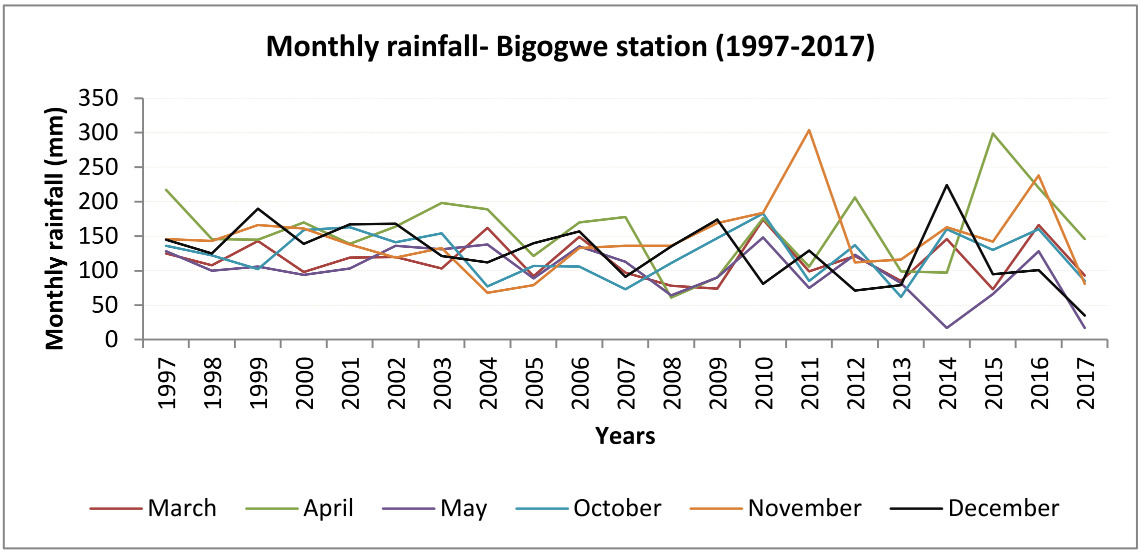


Figure 4 22: Monthly rainfall trends – Bigogwe station from 1997-2017

Source: Analysis, 2019

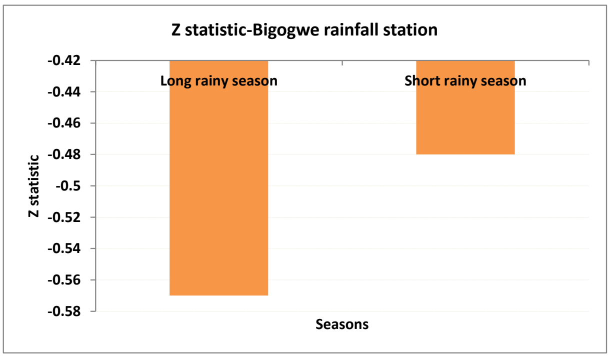
From 1997 to 2003, all rainy months (March, April, May, October, November, and December) experienced much rainfall varying between 100mm and 217mm. The similar amount of high rainfall was observed again in 2006 and 2016. Thus, at least three months among six rainy months could receive a small amount of monthly rainfall oscillating between 17mm and 100mm in years 2005, 2007-2009, 2011, 2013, 2015, and 2017 (figure 4.22). Yet, the highest monthly precipitation of 304mm was observed in November of 2011. Unlike other years in mentioned period, the year 2017 was generally characterized by low rainfall with monthly precipitations varying between 17mm and 93mm in five rainy months (March, May, October, November, and December) and only one month of April received a precipitation reaching 146mm.

With regard to the landslides, it was not possible to relate the individual monthly rainfall with landslide occurrences because this study used only the annual-based landslide data, though it is commonly known that the landslides in Rwanda occur in rainy months.

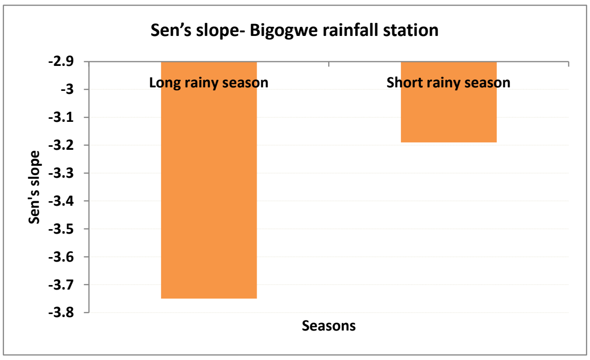
4.3.2.7 Seasonal rainfall trends- Bigogwe station

From the rainfall records of Bigogwe rainfall station, the results of Mann Kendall test indicated that two rainy seasons (long and short rainy seasons) had negative values of Z statistic, and hence showing the decreasing seasonal rainfall trends (figure 4.23a).

Similarly, the calculated Sen's slope showed negative values for both two rainy seasons which also indicated decreasing seasonal rainfall trends (figure 4.23b). Since both rainy seasons presented negative values for both Z and Q_i statistics, it can be noted that rainy seasons (long short rainy season, and short rainy season,) showed significant decreasing seasonal rainfall trends from 1997 to 2017. Yet, the p-values calculated were greater than 0.05 (table4.5), indicating that seasonal rainfall trends were not statistically significant.



a



b

Figure 4 23: Mann Kendall test: Z and S statistics, and Sens's slope

Source: analysis, 2019

From the results, it was noticed that the area did not have remarkable differences in the received rainfall amount between long rainy season (March-April-May) and short rainy season (October-November-December). In fact, the short rainfall season could even experience much rainfall than long rainfall season in some periods such as from 1998 to 2002, and from 2008 to 2009. Yet, the more extreme rainfall amount was observed in a short rainy season of 2014 with seasonal rainfall amount reaching 547mm (figure 4.24). The overall seasonal rainfall for both rainy seasons has been oscillating between 201mm and 547mm from 1997 to 2017.

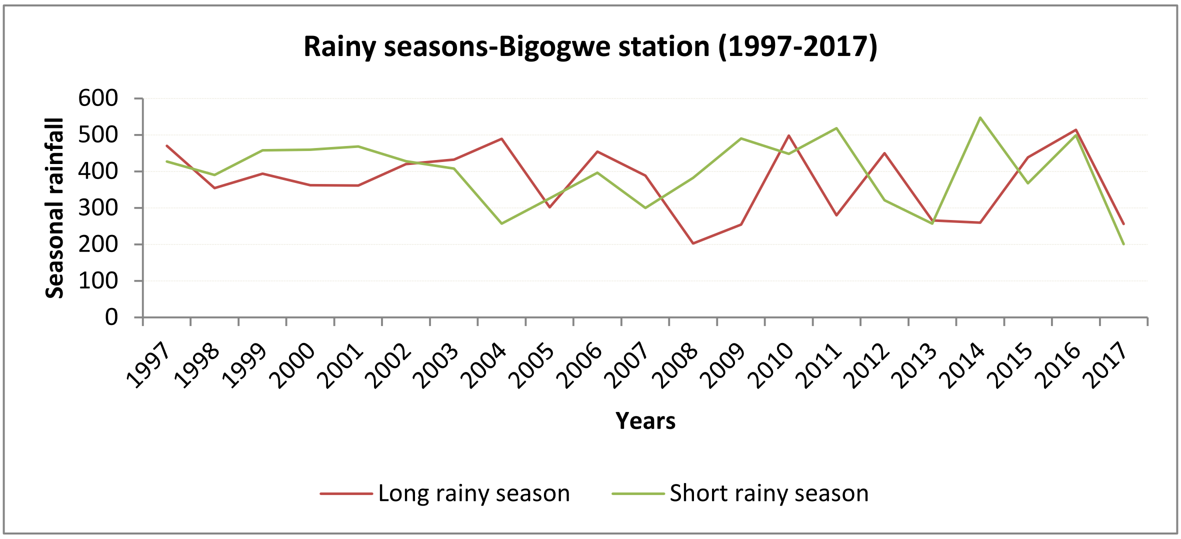


Figure 4 24: Seasonal rainfall- Bigogwe station from 1997-2017

Source: analysis, 2019

4.3.2.8 Seasonal rainfall -Kabatwa station

From 2014 to 2017, the rainfall in long rainy season (March-April-May) has been varying between 194mm and 650mm, with a high precipitation of 650mm observed in 2016. The short rainy season (October-November-December) experienced precipitations oscillating between 205mm and 545mm where the highest precipitation (545mm) was recorded in 2016 as well (figure 4.25).

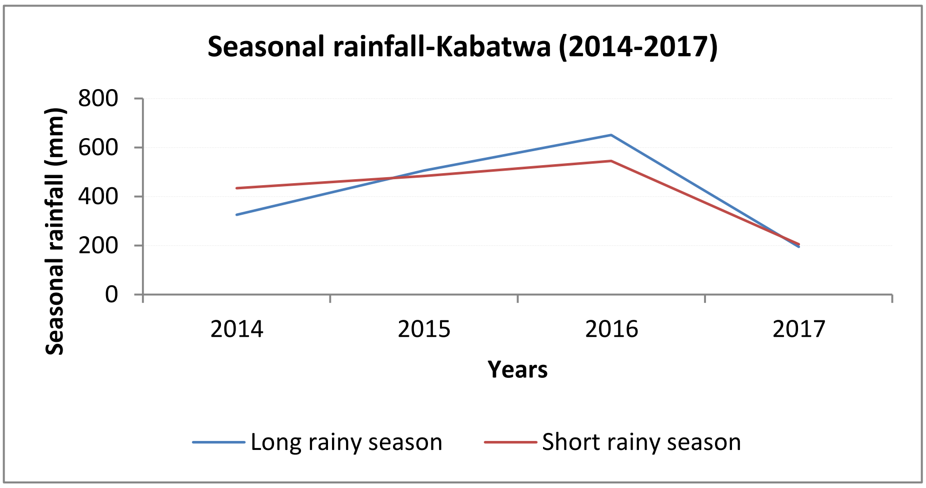


Figure 4 25: Seasonal rainfall- Kabatwa station from 2014-2017

Source: analysis, 2019

4.3.2.9 Seasonal rainfall -Rwankeri station

Rwankeri station received precipitations varying between 184mm and 621mm in long rainy season (March-May-April) and between 267mm and 446mm in short rainy season (October-November-December) from 2014 to 2017 (figure 4.26).

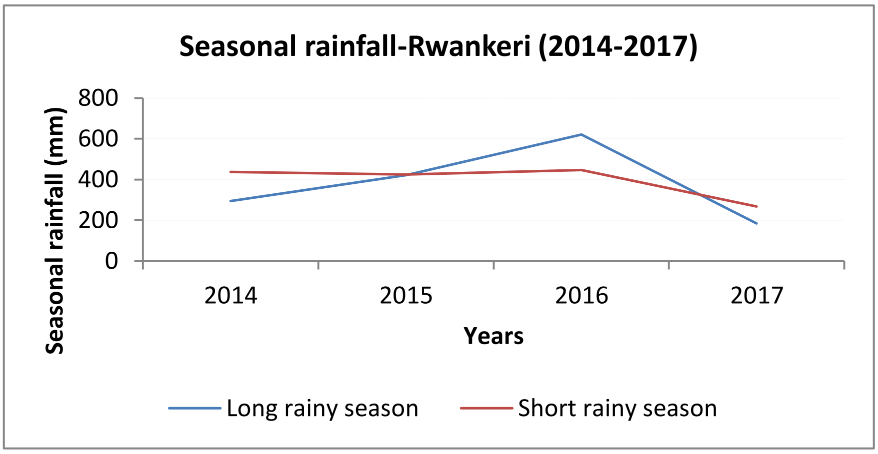


Figure 4 26: Seasonal rainfall- Rwankeri station from 2014-2017

Source: analysis, 2019

4.3.2.10 Seasonal rainfall -Rambura station

In period from 2014 to 2017, the rainfall received at Rambura station has been varying between 397mm and 893mm in long rainy season (March-April-May) and between 193mm and 612mm in short rainy season (October-November-December). Figure 4.27 shows seasonal rainfall at Rambura station.

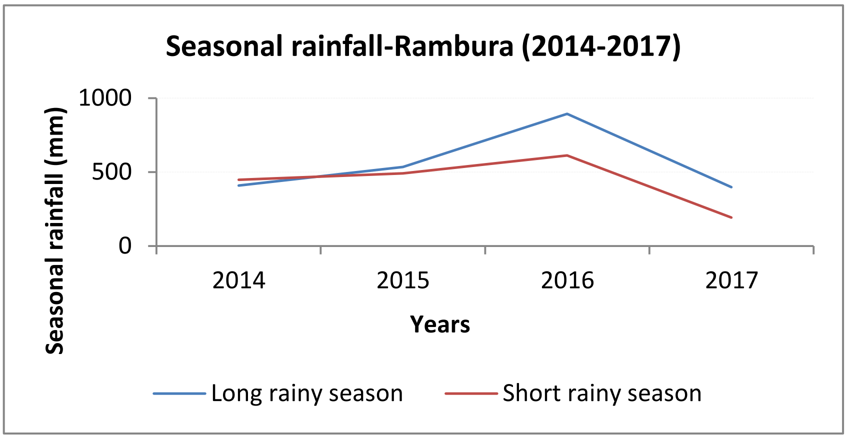


Figure 4 27: Seasonal rainfall- Rambura station from 2014-2017

Source: analysis, 2019

4.3.2.11 Seasonal rainfall -Rugera station

The rainfall in long rainy season (March-April-May) has been varying between 234mm and 1184mm while the short rainy season (October-November-December) received rainfall oscillating between 389mm and 415mm from 2014 to 2017 (figure 4.28).

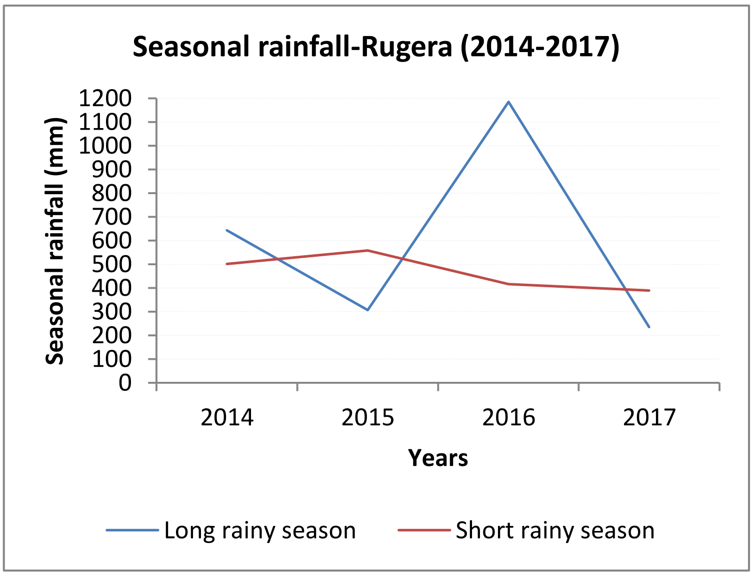


Figure 4 28: Seasonal rainfall- Rugera station from 2014

It has been remarked that the landslides in Rwanda occur during both the long and short rainy seasons due to high and persistent rainfall, and hence greatly destabilizing the soil. Yet, this study did not analyze the relation between seasonal rainfall and landslide occurrences because landslide data were only collected on annual basis.

4.4 Objective3: Predict the occurrence of landslides

4.4.1 Model fitting using backward stepwise (Wald) logistic regression method

After identifying classes for all landslide causative factors, the percentages of landslides per class of causative factor were calculated (figures 4.29&4.30).

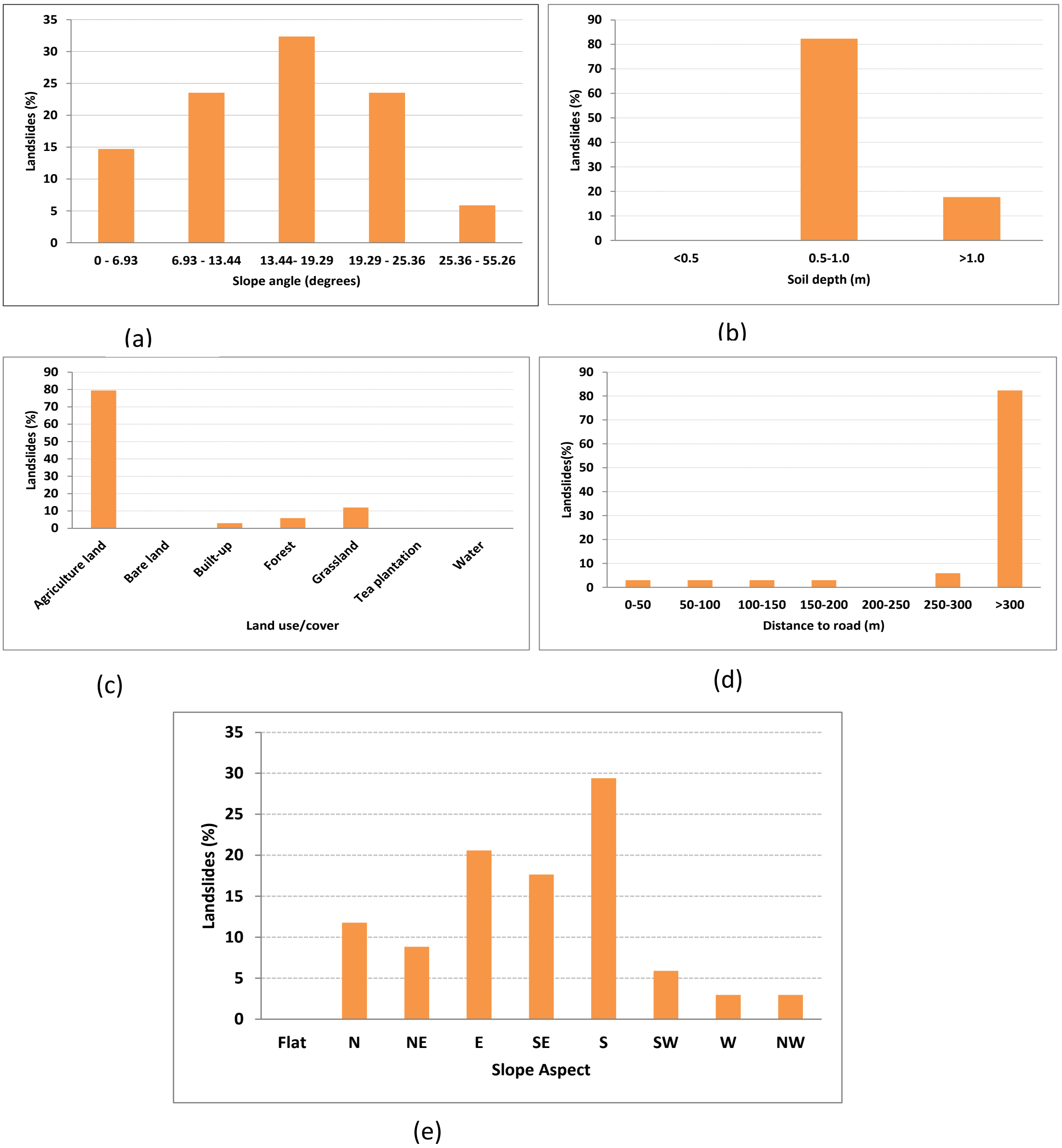


Figure 4 29: Percentages of landslides for each class of variable: Slope gradient (a), Soil depth (b), Land use/cover (c), Distance to road (d), and Slope aspect (e)

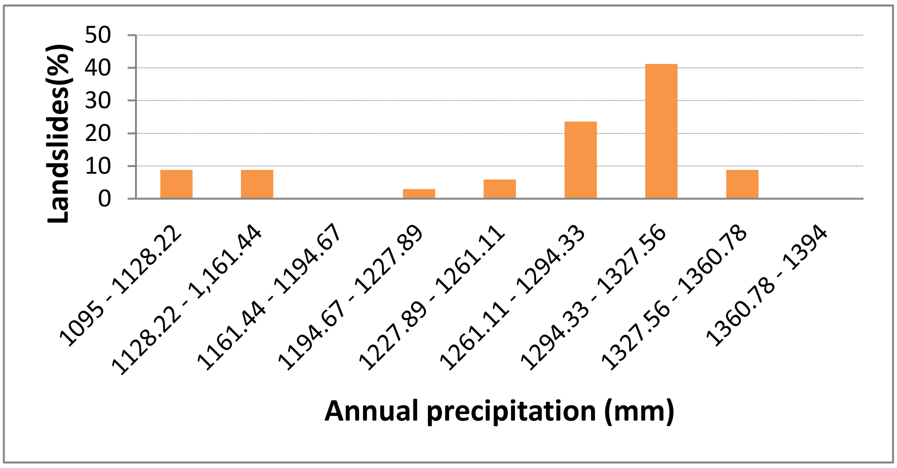


Figure 4 30: Percentage of landslides for each class of precipitation

Using the logistic regression model, the relation of landslide causative factors to the occurrence of landslides was assessed. All landslide causative factors were subjected to the backward logistic regression technique in which the insignificant variables were eliminated step by step until the significant variables to the model remained as shown in the table 4.7.

Table 4 7: Variables in logistic regression model equation

Variables in the equation							
		B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**
Step 4[a]	Land use/cover	-1.346	0.375	12.897	1	0.000	0.260
	Slope Gradient	1.025	0.370	7.665	1	0.006	2.786
	Precipitation	-0.985	0.285	11.965	1	0.001	0.373
	Constant	6.284	2.036	9.524	1	0.002	536.131

a. Variable(s) entered on step 1: Land use/cover, Slope Gradient, Slope Aspect, Soil Depth, Distance to Road, Precipitation.

Source: Analysis, 2019

Results showed that only 3 predictors (land use/cover, slope angle and precipitation) out of 6 independent variables were retained in the model as significant predictors of the landslide occurrences in the study area. The rest of the variables were excluded from the model explaining that slope aspect, soil depth, and distance to the road were all not significant predictors to the landslide occurrences.

From the table 4.7, the coefficients for land use/cover (LULC) and slope gradient (SG) formed the logistic regression model equation of which the generated linear combination (Z) was expressed as:

$$Z = 6.284 - 1.346(LULC) + 1.025\ (SG) - 0.985\ (PP)$$

Where, LULC is the land use/cover, SG the slope angle, and PP the precipitation.

For stepwise logistic regression, the literature insinuated that utilizing the significance level of 0.5 as an entry and removal level when choosing the predictors to be included in the model may result in exclusion of important variables from the model (Sarkar et al., 2010). It is in this essence that this study admitted the strong recommendation of Hosmer & Lemeshow (2000) of using 0.15 as an entry level and 0.20 as removal level when selecting the important predictors to be included in the stepwise logistic regression model. Therefore, the three significance levels; 0.000 and 0.006 and 0.001 for land use/cover, slope gradient and precipitation respectively proved as influence of these variables to the landslide occurrence as these p-values are less than 0.15 (significance level). Other variables had p-values greater than 0.20 (table 4.8), which is the reason why they were excluded from the model.

Table 4 8: Variables excluded from the model

Variables not in the Equation					
			Score	**df**	**Sig.**
Step 2[a]	Variables	Distance to Road	0054	1	0.816
	Overall Statistics		0.054	1	0.816
Step 3[b]	Variables	Slope Aspect	0.394	1	0.530
		Distance to Road	0.066	1	0.798
	Overall Statistics		0.453	2	0.797
Step 4[c]	Variables	Slope Aspect	0.238	1	0.626
		Soil Depth	2.325	1	0.127
		Distance to Road	0.253	1	0.615
	Overall Statistics		2.748	3	0.432

a. Variable(s) removed on step 2: Distance to Road.

b. Variable(s) removed on step 3: Slope Aspect.

c. Variable(s) removed on step 4: Soil Depth.

Source: Analysis, 2019

The significant influence of land use/cover to the occurrence of landslide was also noted by Chen et al.,(2019) in their study where they found a clear relation of land use/cover and landslide occurrence. They concluded that land use/cover change mainly emanating from the human engineering activities greatly increased the chance to landslide occurrence. However, results from this study revealed that most of the landslides occurred in agricultural land which explains its effects on slope instability in the study area. Generally, it should also be noted that the land use/cover can contribute more or less to landslide occurrences depending on the physical characteristic of the terrain together with the influence of conditioning factors or the prominent landslide triggering factor in that place.

The negative coefficients of land use/cover and precipitation imply the negative relationship of these causative factors with the landslide occurrences, which may show that the change in land use/cover and rainfall could not necessarily increase the chances to landslide occurrences. Although it is certainly true that land use/cover changes contribute to the landslide occurrence (Galve et al., 2015; Meneses et al., 2019; P. Reichenbach et al., 2014), what needs to be noted is that the land use/cover in conjunction with other causative factors in place act together in increasing the chances of the occurrences, especially when the occasional triggering factor poses tremendous pressure to cause the instability of the slope. Hence, in this study, the land use/cover was proven by the model to be a significant landslide factor.

The positive coefficient of slope gradient, on the other hand, implies a positive relationship of slope angle with landslide occurrence meaning that the probability of landslide occurrence slightly increases with the increase in steepness. It was noted in some studies that the increase in steepness of the slope usually increases the chances of its failures (Prasad, 2017), and hence leading to landslide occurrences. Shit et al., (2016) argued that the occurrence of landslides in higher slopes mostly originates from rocks with sparse or no vegetation cover which allows the easy instability of those slopes. However, it was noticed that sometimes the steepest slopes (highest slope angles) do not necessarily experience more landslides than the moderate slopes (Donnarumma et al., 2013, Wang et al.,2016). It should therefore be noted that the probability of landslide occurrence increases with the increase in slope angle but with some exceptions.

In many cases, more landslides occurred in medium class of slope angles depending on how every researcher classified the slope angles (Jacobs et al., 2016). In few or almost no cases, more landslides were identified in the highest class among the selected slope angle ranges.

By inserting the generated linear combination (Z) into the equation (15), the final logistic regression equation to estimate the probability of landslide occurrence (P) was expressed as:

$$P = \frac{1}{1 + e^{-(6.284 - 1.346\ LULC + 1.025\ SG - 0.985 PP)}}$$

Hence, $P = \frac{1}{1+e^{-4.978}} = 0.993$

This implies that the model predicts at almost 99% probability, landslides could occur due to land use/cover, slope angle and precipitation.

On the other hand, by considering only the land use/cover (keeping other predictors constant), the probability of landslide occurrence could be;

$P = \frac{1}{1+e^{-(6.284-1.346 LULC)}} = \frac{1}{1+e^{-4.938}} = 0.992$

This implies that the model could predict that at approximately 99.2%, landslides could occur due to land use/cover.

Whereas, by considering the precipitation while holding other predictors constant, the probability of landslide occurrences could be;

$P = \frac{1}{1+e^{-(6.284-0.985 PP)}} = \frac{1}{1+e^{-5.299}} = 0.995$ or 99.5%

Hence, the probability of landslide occurrences initiated by land use/cover, slope angle and precipitation is not to be ignored or just taken worriless in terms of disaster or hazard management. Looking at the already assessed impacts of landslides in the study area along the past years (MIDIMAR, 2015), it should be noted that these modeled variables have to be particularly taken into consideration for the minimization of the likely landslide occurrences.

4.4.2 Correlation of causative factors with the landslides

The study also analyzed the correlation between main predictor variables to the landslides. The purpose was to determine the influential extent of each variable on landslides (table 4.9).

Table 4 9: Correlation of landslides and causative factors

		Landslides
Land use/cover	Pearson Correlation	-0.375**
	Sig. (2-tailed)	0.002
Slope Gradient	Pearson Correlation	0.280*
	Sig. (2-tailed)	0.021
Precipitation	Pearson Correlation	-0.244*
	Sig. (2-tailed)	0.045

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Source: Analysis, 2019

In the analysis of the correlation between causative factors and landslides using Pearson correlation coefficient land use/cover, slope angle, and precipitation were all noted to be correlated to landslides (table 4.9). The land use/cover and precipitation were negatively correlated to landslides at 99% and 95% confidence levels respectively. However, their correlation to landslides was not that strong because their **r** coefficients (-0.375 and -0.244) respectively were weak. According to Taylor (1990), a strong correlation would be indicated by **r** coefficient that approaches ±1. On the other hand, the slope angle was positively correlated to landslides at 95% confidence level with a small **r** coefficient (0.280), implying a weak correlation between slope angle and landslides.

The negative coefficient for land use/cover and precipitation would indicate the negative relationship between these causative factors and the landslides while the positive coefficient for the slope angle would indicate the positive relationship between the slope angle and the landslides. The negative correlation could actually imply the inverse relationship between high rainfall and landslide occurrences. However, it could be noted that some areas experienced high rainfall with no landslides occurred while other areas received high rainfall together with more landslide occurrences depending on the influence of other causative factors. With all this, it should be said that the increase in rainfall amount does not always trigger more landslides.

4.4.3 Logistic regression model assessment and validation

4.4.3.1 Omnibus tests of model coefficients

Backward Stepwise method starts with the inclusion of all variables in a model, and then eliminates predictors one by one based on the statistical significance of their coefficient values (table 4.10) until the important predictors are retained.

Table 4 10: Omnibus Tests of Model Coefficients

Omnibus Tests of Model Coefficients				
		Chi-square	**df**	**Sig.**
Step 4[a]	Step	-2.519	1	0.112
	Block	35.700	3	0.000
	Model	35.700	3	0.000

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Source: Analysis, 2019

From table 4.10, the resultant model chi-square was 35.700, and the p-values for test of the contribution of independent variables to the prediction of the dependent variable indicate that all the coefficients equal to 0.000. Since, the p-value (0.000) is less than 0.05 (significance level), it implies that the removal of the independent variables improved the predictive power of the model.

4.4.3.2 Classification table

Literature recommends that a good logistic regression model should be indicated by the percentage of logistic regression correct classification that is higher than the base (cut value 0.5) (Sarkar et al., 2010). As the results showed that the classification was at almost 76.5% correct (table 4.11), it implies that the model is quite good.

Table 4 11: Logistic regression classification table

Classification Table					
	Observed		Predicted		
			Landslides		Percentage Correct
			non occurrence	Occurrence	
Step 4	Landslides	non occurrence	23	11	67.6
		Occurrence	5	29	85.3
	Overall Percentage		76.5		
The cut value is 0.500					

Source: Analysis, 2019

4.4.3.3 Hosmer and Lemeshow Test

Hosmer and Lemeshow Test has generally been used for assessment of goodness of fit for logistic regression models (Bartley, 2014).

Thus, the insignificant chi-squares (p-values greater than 0.05) implies an overall goodness of fit of the model. Hence, the chi-square values (table 4.12) were insignificant or, in other words the Hosmer-Lemeshow test was insignificant (p-value >0.05) indicating that there is no remarkable difference between the observed and predicted probabilities of which it is an indication of the good model fit.

Table 4 12: Hosmer and Lemeshow Test

Hosmer and Lemeshow Test			
Step	Chi-square	df	Sig.
4	4.107	8	0.847

Source: Analysis, 2019

4.4.3.4 The area under ROC curve

The area under ROC has been used to validate the logistic regression model (Midi et al., 2010). The value close to 1 indicates the perfect fit of the model while the value close to 0 indicates the poor fit (table 4.13).

Table 4 13: The area under ROC curve

Area Under the Curve			
Test Result Variable(s)	**Area**	**Asymptotic 95% Confidence Interval**	
		Lower Bound	**Upper Bound**
Precipitation	0.356	0.225	0.486
Land use/cover	0.277	0.148	0.405
Slope Gradient	0.658	0.528	0.789
a. Under the nonparametric assumption			
b. Null hypothesis: true area = 0.5			

Source: Analysis, 2019

The validation result indicated that slope gradient fitted the model very well (ROC value= 0.658), while the precipitation and land use/cover poorly fitted the model with ROC values; 0.356 and 0.277 respectively. As the value of the area under the ROC curve (figure4.31) for land use/cover and precipitation was low, it indicates that their predictive ability of the fitted model is not good.

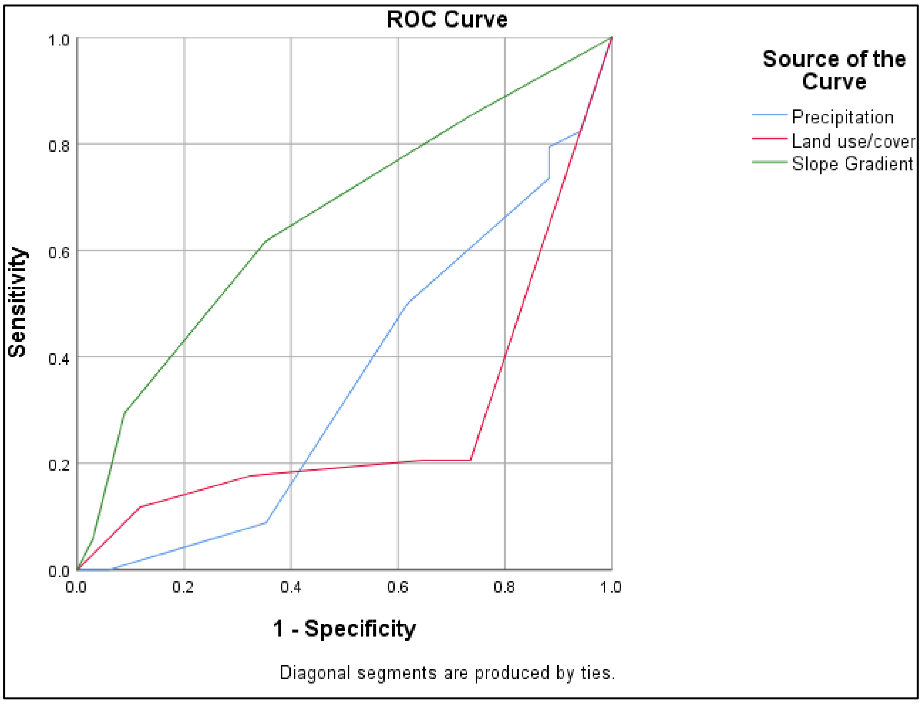


Figure 4 31: The area under the ROC curve.

Source: Analysis, 2019

Generally, based on the assessment made on the performance of the generated landslide predictive model, it can be concluded that the model was relatively good, though land use/cover and precipitation could not be used to predict the future landslide-occurrence probabilities due to their low values of the area under the ROC curve. However, this study showed the influence of land use/cover and rainfall on landslide occurrences of which this influence should not be ignored when developing strategies that are aimed at minimizing the likelihood of landslide occurrences.

Chapter 5: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

From the first objective, this study analyzed the land use/cover changes in Nyabihu district of Rwanda from 2005 to 2015. It was noted that there were various changes for each land use/cover category of which forest, grassland, tea plantation, bare land, and water all increased in their sizes while agricultural land remarkably declined as discussed in chapter 4. The results proved the effects of land use/cover changes on landslide occurrences where the agricultural land experienced the majority of landslides identified in the study area. Changing land use/covers particularly into cultivation activities on steep slopes was noted to be among the factors that can easily destabilize the slope and hence leading to landslides.

In the second objective, the study analyzed rainfall trends for Bigogwe station as the only one rainfall station that had long term data record. Annual precipitation for Bigogwe station was generally characterized by decreasing annual rainfall trends. Monthly rainfall at Bigogwe station showed decreasing rainfall trends for most of the rainy months (March, April, May, October, and December) and only November indicated an upward rainfall trend. Seasonal rainfall at Bigogwe station also experienced decreasing rainfall trend in both two rainy seasons. Most of the landslides occurred in areas that generally received high annual rainfall, confirming the relation between high rainfall and the occurrence of landslides. Thus, it could be noted that the amount of rainfall received in an area had some relation to landslide occurrences in a particular period of time. Yet, the study noted that there is no defined positive or negative relationship evolving constantly between rainfall and landslide occurrences.

From the third objective, causative factors were analyzed in order to determine which factors are significant for generating a model. Among the landslide conditioning factors analyzed in this study, only slope angle was proven to be a significant predictor variable to landslide occurrences. Other landslide conditioning factors (soil depth, slope aspect, and distance to road) were not proven as significant causal factors to landslide occurrences, and hence they were eliminated from the logistic regression model. The proven significant causative factors (which are land use/cover, slope angle, and precipitation) were used to generate a landslide predictive model.

The study also quantified the correlation of the significant factors to the landslides, and the results revealed that their correlation was not strong.

However, it can be noted that the continuous land/cover changes due to non-stop human activities together with the intense rainfall on steep slopes might still give more chances to landslide occurrences if no serious mitigation measures are taken.

5.2 Recommendations

- Land use/cover change will inevitably increase since the population of Rwanda keeps increasing and hence putting pressure on the already scarce land resource. The government and other stakeholders should act together to promote efficient land use management strategies. This may help in the overall management and minimization of landslides in these areas.
- The decrease in agricultural land in some cases due to population growth forces people to cultivate unsuitable steep slopes and hence accelerating the slope instability. This should be taken into consideration to enhance proper agricultural practices.
- In most cases, uncontrolled cultivation activities and other human activities may block the normal water channels of which the no-channeled water may easily erode the steep land surfaces increasing the instability of the slopes. With this, it is recommended to properly canalize the water, particularly rainfall water.
- Usually soil erosion processes destabilize the steep slopes. So, it is recommended that conservation measures focusing particularly on soil protection be promoted.
- Proper mitigation of landslide hazards requires efficient landslide inventory and timely monitoring through proper recording of geographical locations of landslides at each

time of their occurrences, which is still lacking in Rwanda. Therefore, there is a need of such timely landslide inventory and monitoring.

- Radical terraces have proven essential in weakening the damaging capacity of the rainfall water flowing down the steep slopes; therefore, terracing of steep slopes is recommended to reduce slope instability which may trigger landslides occurrences.

5.3 Areas of future research

There is still a need of using other techniques to analyze the causes of landslides, and compare techniques in determining which technique best predicts the landslide occurrences.

This study established a relationship between the rainfall amount and the landslide occurrences on an annual basis, but did not analyze the effects of prolonged rainy days in triggering landslides; hence further studies are required to determine how the prolonged daily rainfall can greatly trigger landslides.

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Annex: Research permit

UNIVERSITY of BOTSWANA

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7th August 2019

Nathaniel Hafashimana
University of Botswana
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RE: PERMISSION TO CONDUCT RESEARCH

Project Title: "Modelling the effects of land use/cover change and rainfall variability on landslide hazards: The case of Nyabihu District, Rwanda"

Dear Nathaniel Hafashimana,

I am pleased to inform you that the above mentioned study was reviewed and approved by the University of Botswana Chemicals and Hazardous Material Sub-Committee (UB CHMS).

This study has been exempted from the research permit requirements as the study is conducted outside Botswana and the research does not involve more than minimal risk.

Before proceeding with the study, you are required to ensure the following:

- EFFECTIVE DATE : 7th August 2019
- EXPIRATION DATE : This approval expires on 6th August 2020

  After this date, this project may only continue upon renewal. For purposes of renewal, a progress report should be submitted to ORD one month before the expiration date.

- REPORTING OF SERIOUS PROBLEMS: All serious problems impacting on study quality and progress (whether expected or unexpected) must be reported to ORD within 10 days.
- MODIFICATIONS: Prior approval is required before implementing any significant changes to the protocol.
- TERMINATION OF STUDY: On termination of this study, a report has to be submitted to ORD.
- **QUESTIONS**: Please contact ORD ext 2911 or e-mail on mary.kasule@mopipi.ub.bw.
- **Other:**
  - **The researcher may accordingly proceed with the above study in compliance with the above requirements.**

Kind regards,

The Secretariat, University of Botswana Chemicals and Hazardous Material Sub-Committee
Office of Research and Development

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