Landslides Hazard Mapping in Rwanda using Bivariate Statistical Index Method

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Abstract: Landslides hazard mapping (LHM) is essential in delineating hazard prone areas and optimizing low cost mitigation measures. This study applied the Geographic Information System (GIS) and statistical index (SI) method in landslides hazard mapping in Rwanda. Field surveys identified 336 points which were employed to construct a landslides inventory map. Ten landslides predicting factors: normalized difference vegetation index, elevation, slope, aspects, lithology, soil texture, distance to rivers, distance to roads, rainfall, and land use were analyzed. The factor variables were converted into categorized variables according to the percentile divisions of seed cells. Then values of each factor's class weight were calculated and summed to create landslides hazard map. The estimated hazard map was split into five hazard classes (very low, low, moderate, high and very high). The results indicated that the northern, western and southern provinces are largely exposed to landslides hazard. The major landslides hazard influencing factors are elevation, slope, rainfall and poor land management. Overall, this landslides hazard mapping would help policy makers to recognize each area's hazard extent, key triggering factors and the required hazard mitigation measures. These measures include planting trees to enhance vegetation cover and reduce the runoff, and construction of buildings on low steep slope areas to reduce people's hazard exposure; while agroforestry and bench terraces would reduce sediments which take out the exposed soil (erosion) and pollute water quality.

Keywords: Hazard; Landslides; Geographic Information System; Rwanda.

1. Introduction

Landslides are among the global widespread geological hazards responsible for considerable human injury and death, natural resources degradation, infrastructure damage, and loss of cultural and natural heritage (Lian et al. 2014; Riedel et al. 2010).The term landslide describes a wide range of processes responsible for downward and outward movement of slope forming material composed of rock, soil, artificial fills or a combination of all these down a slope (Fey et al. 2015; Fan et al. 2018; Lee et al. 2015; Capitani et al. 2013). Landslides occurrence depends on intrinsic and extrinsic variables. Intrinsic variables include soil depth and soil type, slope aspects and slope curvature, elevation, vegetation cover and other anthropogenic activities such as deforestation, road construction and cultivation on steep slope which change the land cover and land use patterns then inversely impact on mass movement process. The extrinsic variables include extreme rainfall, earthquake and volcanic activities (Yiping et al. 2014; Zhu et al. 2007; Kelman 2017; Kannan et al. 2013; Van Westen et al. 2008).

Hazard is the probability of occurrence of a particular damaging phenomenon, within a specified period of time and a given area due to different existing or predicted conditions (Kim et al. 2018; Riedel et al. 2010). The unprotected land increases the slope instability which causes soil erosion, mudslides and landslides, and pollutes water quality by the loaded wastes (Xu et al. 2018). Thus, landslides hazard mapping can help to identify the hazard level and areas that are susceptible to soil loss and water quality pollution. The process also indicates safe zones for human constructions and other social, economic and environmental activities, and strengthens the mitigation and adaptation to future occurrence (Naidu et al. 2017; Reis et al. 2009; Jaafari et al. 2015). Hazard mapping can be broadly divided into: (1) direct hazard mapping, where the degree of hazard is determined by the knowledge of the terrain conditions and (2) indirect hazard mapping in which either statistical or deterministic models are used to predict landslides prone areas based on triggering factors. The latter is the most commonly applied due to its advantage of describing the functional relationship between factors, and the past, present and the predicted distribution of slope failures (Dou et al. 2015; Di et al. 2017; Lei et al. 2014; Bobrowsky and Highland 2013; Tian et al. 2017; Frodella et al. 2018; Micheletti et al. 2014; Fey et al. 2015).

Different indirect approaches including not limited to bivariate and multivariate method, fuzzy logic and artificial neural networks, analytical hierarchy process, evidential belief function, support vector machine, random forest and logistic regression have been used for landslides hazard mapping (Nichol et al. 2006; Shi-Biao et al. 2009; Kazakis et al. 2015; Hong et al. 2016; Kim et al. 2010; Banerjee et al. 2018; Sharma et al. 2014; Lian et al. 2014). In Rwanda, previous disaster related studies (Nahayo et al. 2017; Piller 2016; MIDIMAR 2014; Nduwayezu et al. 2015) were general combining different hazards like flood and landslides, drought and flood, without specific attention attributed to one hazard. These studies have only considered the hazards already occurred by using descriptive, secondary data sources and social approaches, and were limited to case studies like districts and provinces. This expresses lack of a thorough analysis to indicate the root causes of the considered hazard for the adaption and exposure reduction countrywide. Thus, this study considers the whole Rwandan territory and applies GIS-based statistical index method in landslides hazard mapping.

The bivariate statistical index method is selected among others due to its advantage that in case landslides inventories are available, hazard assessment integrates knowledge from the overlap of observed incidents and maps of different triggering factors (Van Westen et al. 1997). Also, its validation proves its performance effectiveness as it bases on the fitness between the produced landslides hazard and observed landslides. This as a result, gives extensive knowledge of the location and landslides causal factors, extent of community hazard exposure, future occurrence likelihood, and potential exposure hotspots for sustainable planning and prevention of future losses (Van Westen et al. 2008; Van Westen et al. 1997). As a new attempt in landslides hazard mapping countrywide, the authors chose to use the bivariate statistical index method to test its performance in landslides hazard mapping regardless of the strengths and/or weaknesses of other approaches mentioned above. In the future, authors plan to test the effectiveness of other landslides hazard mapping approaches in this area.

2. Materials and Methods

2.1 Study Area

Rwanda is a poor and densely populated East African country with a green and mountainous landscape. The country (Fig.1 (a)) is bordered by the Democratic Republic of Congo in the west,

Uganda in the north, Burundi in the south and Tanzania in the east. The country records rainfall between March and May and from late September to early December. The average monthly rainfall is about 110-200 mm. The dry season occurs from late December to the end of February, and between June and early September. The average temperature ranges between 19 to 27ºC (Nsengiyumva et al. 2018). In this area, high annual rainfall intensity and population pressure on land expose the hilly topographic nature to runoff risks. This causes severe environmental disasters and encroachment on fragile ecosystems. Among which landslides and floods are the frequently recorded (Piller 2016; Nduwayezu et al. 2015; Nsengiyumva et al. 2018).
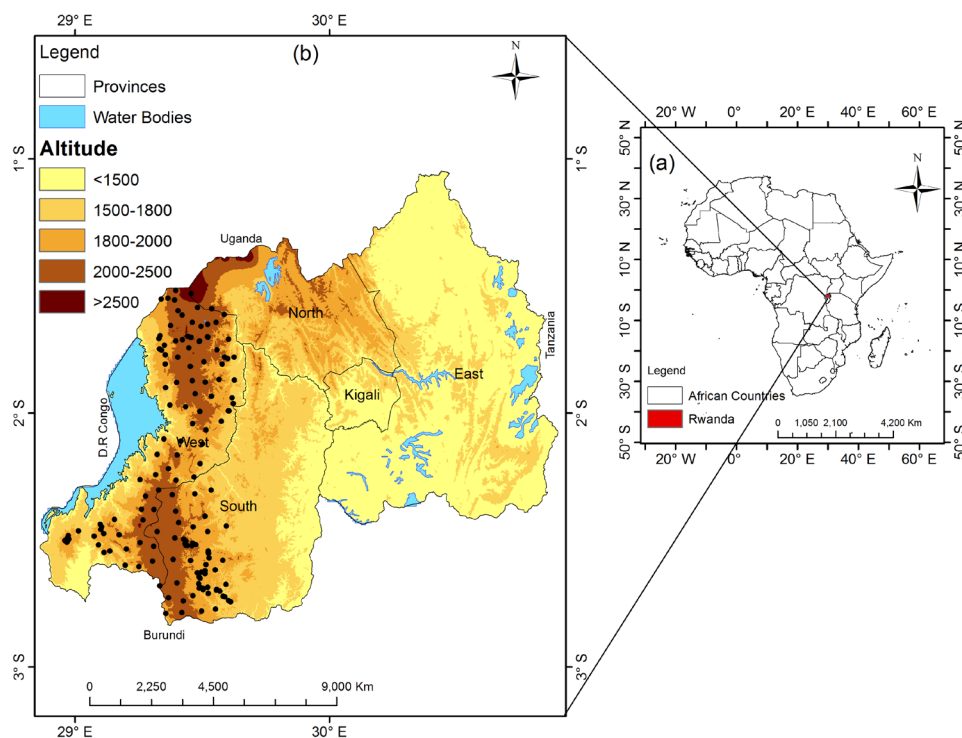

Figure 1 Geographical location of (a) Rwanda in Africa and (b) its landslides inventory

2.2 Datasets

2.2.1 Landslides inventory

Landslides inventory map, also known as landslides map, landslides inventory or inventory map records the location, date of occurrence and types of movements that have left noticeable traces in the area (Guzzetti et al. 2012). This can be prepared by different techniques and the selection of the techniques to employ relies on the purpose of the inventory, scale of the base maps and

extent of the study area, and available resources (Alvioli et al. 2018; Van Westen et al. 2008). For landslides hazard assessment, the report of Van Westen et al., (2008) suggested to take into account the fact that, the conditions that led to past landslides in the area of study if reoccurred may result from the same causative factors. Hence, authors recognized the assumption and for this study, a total of 336 landslides were identified by using the Global Positioning Systems (GPS) during field surveys facilitated by local residents who helped to localize last landslides events in their living areas. The produced landslides inventory map (Fig.1 (b)) considered landslides occurrence and frequency based on the affected people (killed, injured and homeless), cropland damaged, destroyed infrastructures and livestock lost between 2000 and 2017 in Rwanda.

2.2.2 Landslides hazard triggering factors

The authors selected landslides hazard influencing factors in Rwanda based on the review of the literature and field observation (Fig.1 (b)). Also, national disaster risk management policy, and contingency plan for flood and landslides in Rwanda (MIDIMAR 2014) along with the landslides hazard and risk assessment of the United Nations International Strategy for Disaster Reduction (UNISDR, 2017) were used as experts' opinions. The terrain attributes like slope, slope aspects, curvature and elevation which represent spatial variation of elevation (i.e., altitude or height) are the most substantial causes of landslides. Their higher values express high likelihood of landslides occurrence (Jaafari et al. 2015; Frodella et al. 2018; Riedel et al. 2010). For this study, the employed elevation, slope and aspects (Fig.2) were derived from Digital Elevation Model (DEM) of 30 m resolution acquired from the United States Geological Survey Earth Explorer (USGS 2018).
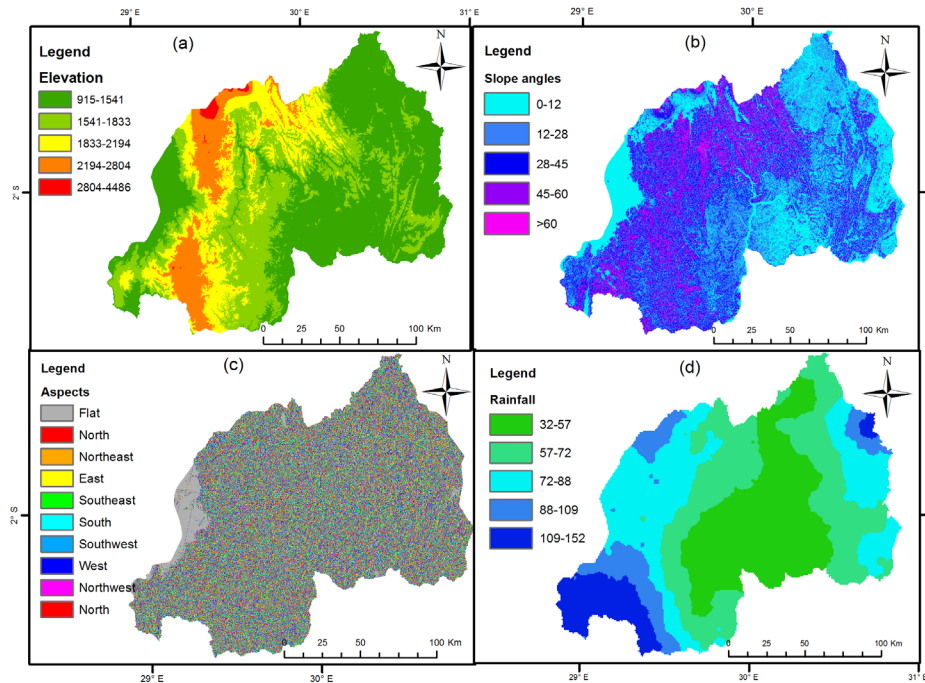
Figure 2. **Selected landslides hazard conditioning factors in Rwanda: (a) elevation, (b) slope, (c) aspects and (d) rainfall**

Rainfall-induced landslides are highly recorded within mountainous regions (Alvioli et al. 2018). Similarly, more than 70% of landslides recorded in Rwanda are rainfall-induced (MIDIMAR 2014). Authors recognized this fact, and then added rainfall among the employed datasets. The mean monthly rainfall data (Fig.2 (d)) were interpolated using 27 years (1990-2017) rainfall data acquired from meteorological stations located in Rwanda. The used rainfall data were provided by the Rwanda Meteorology Agency (RMA 2018). Each rock and soil class influences the type and intensity of landslides. Therefore, their classification would help to demonstrate each class's contribution (Mertens et al. 2018). The lithological and geological features employed by this study (Fig.3) were derived from the geological, mining and soil map databases of Rwanda (Rushemuka et al. 2014). The distance to roads were added among the datasets (Fig.3) of the current study due to the fact that, cutting of slopes for roads construction or road widening in hilly regions can cause slope failures and lead to landslides losses among the exposed nearby populations (Dou et al. 2015). The distance to rivers was used (Fig.3) based on the fact that the proximity to rivers increases the likelihood of landslides occurrence because the slopes on the banks of the river often suffer river erosion. Thus, at a closer distance to rivers, the probability of landslides occurrence is high due to strong erosion (Cao et al. 2016; Fan et al. 2017). The

shapefiles of rivers and roads were acquired from an online database (http://www.diva-gis.org/gdata), and both were produced by creating Euclidean distance in ArcMap-Spatial Analyst extension.
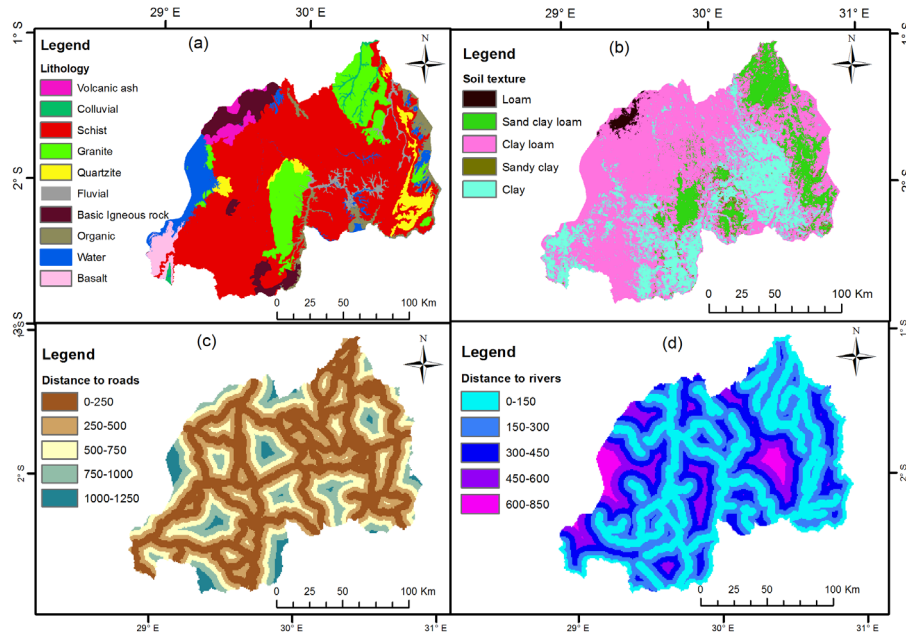

Figure 3. Selected landslides hazard conditioning factors in Rwanda: (a) lithology and (b) soil texture classes, and (c) distance to roads and (d) distance to rivers

Rwanda's update land use and land cover map of July 2018 was produced form multispectral Landsat-8 Operational Land Imager (OLI) images. These images were acquired from the United States Geological Survey Earth Explorer (USGS 2018). The land use/cover map was classified with the supervised maximum classification method based on the East African Classification of the Regional Center for Mapping of Resources for Development (RCMRD 2018). Then five land use and land cover classes (Fig.4 (a)) were produced. The normalized difference vegetation index (NDVI) reveals the presence or absence of vegetation in a given area. Thus, the removal of vegetation leaves a slope much more exposed to surficial landslides due to the loss of the stabilizing root systems (Ibrahim et al. 2015; Xu et al. 2018). For this study, the used NDVI (Fig.4 (b)) was acquired from Moderate Resolution Imaging Spectroradiometer (MODIS, 250M resolution) downloaded from an online database (ladsweb.nasacom.nasa.gov/data/html). The NDVI values were calculation based on the following equation:

$$\text{NDVI} = \frac{IR - R}{IR + R} \tag{1}$$

Where IR is the infrared portion of electromagnetic spectrum and R value is the red portion of electromagnetic spectrum.
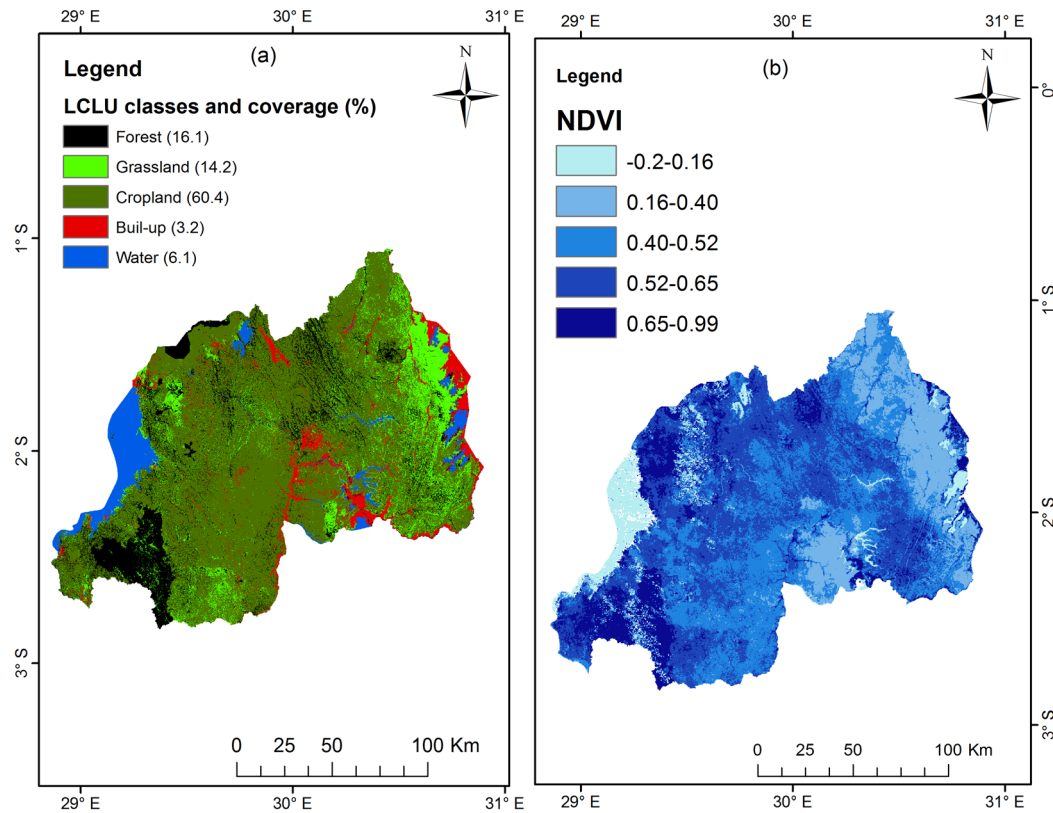

Figure 4. Selected landslides hazard conditioning factors in Rwanda: (a) land use and land cover classes and coverage in percentage and (b) Normalized Difference Vegetation index values

2.3 Methodology

2.3.1 Modeling approach

Authors applied the Statistical Index (SI) model accepted as bivariate statistical method (Van Westen et al. 1997). The model has a basis requiring calibration from correlation between known incidents. In the model, the weighting value for each conditioning factor class is defined as the natural logarithm of the landslides density in a class divided by landslides density in the entire map (Van Westen et al. 1997). The statistical index (SI) is calculated as follows:

$$Wij = In\left(\frac{DensClasij}{DensMap}\right) = In\left[\frac{\frac{N\ pix\ (S\ ij)}{N\ pix\ (N\ ij)}}{\frac{\sum_j N\ pix\ (S\ ij)}{\sum_j\ \ N\ pix\ (N\ ij)}}\right] \qquad (2)$$

Where W_{ij} is the weight for class j within the triggering factor map *i*, DensClasij is density of landslides in class *j* within the triggering factor map *i*, *DensMap* is the density of landslides in the entire map, N_{pix} (S_{ij}) is the number of pixels in class *j* within the triggering factor map *i* and N_{pix} (N_{ij}) is the number of pixels in class *j* within the triggering factor map *i*. Thereafter, landslides hazard map was produced by using the following equation.

$$\begin{aligned}LHIsi = {}& Wsi\ (elevation) + Wsi\ (slope\ angle) + Wsi\ (slope\ carvature) + Wsi\ (rainfall) \\ & + Wsi\ (lithology) + Wsi\ (soil\ texture) + Wsi\ (distance\ to\ roads) \\ & + Wsi\ (distance\ to\ rivers) + Wsi\ (Land\ Use) + Wsi\ (NDVI) \qquad (3)\end{aligned}$$

The obtained landslides hazard map was reclassified into five landslides hazard classes, namely: very low (2-3.18), low (3.18-3.77), moderate (3.77-4.5), high (4.5-5.7) and very high (5.7-8.8) based on the review of literature, experts' opinions and field observation.

3. Results

3.1 Spatial distribution of landslides hazard in Rwanda

The results on the spatial relationship between landslides hazard and its influencing factors, as estimated by the statistical index model (Table 1) indicated that for elevation, the higher and positive SI values of 1.82 and 0.42 were generated by the elevation ranges of 2194-2804 m and 1833-2194 m, respectively. For the relationship between landslides hazard and slope angles, the results in Table 1 showed that slope angles' range of 28-45^0 generated a high SI value (0.36). The findings also revealed that the west-facing slope (0.64) and northwest-facing slope (0.49) have positive high SI values. For the rainfall, the results in Table 1 revealed that the range of 72-88 mm and 109-152 mm have the highest positive values of SI; 0.84 and 0.78, respectively. In addition, as illustrated in Table 1, the schist is the main lithological dominating class with highest positive SI value (0.71) and granite class represented the lowest negative SI value at -2.13. The clay (0.37) and clay loam (0.12) soil texture classes revealed high SI value. Moreover, land use and land cover classes revealed that grassland possess the highest SI value (0.62) along with forest (0.68). The obtained relationship between NDVI and landslides hazard (Table 1) revealed

that the NDVI range of 0.53-0.65 has a highest and positive SI value of 0.89. Furthermore, the distance to rivers mainly, the ranges of 0-150 m and 150-300 m have high SI values: 0.59 and 0.04, respectively. Finally, the results in Table 1 showed that for the distance to roads, the range of 250-500 m possess high positive SI value of 0.01. Hence, the closer to roads and rivers, the greater is the landslide occurrence probability and hazard exposure.

Table 1 Spatial relationship between landslides hazard and triggering factors by SI model

Factors	Classes	Class domain (%)	No.of landslides	Landslides density (%)	landslides pixels	SI
Elevation	2804-4486	0.7	2	2.09	3036	0.32
	2194-2804	8.8	192	63.3	3499	1.82
	1833-2194	12	87	32.7	3168	0.42
	1541-1833	31.2	64	1.6	1596	-0.67
	915-1541	22.3	21	0.31	1372	-0.02
Slope	>60	0.2	1	1.1	3369	-0.26
	45-60	49.4	202	59.7	4427	0.21
	28-45	19.4	98	24.9	3791	0.36
	12-28	16	54	12	2548	0.23
	0-12	26	11	2.3	1978	-0.82
Rainfall	109-152	18.2	97	13	2614	0.78
	88-109	10.2	69	17.3	3320	0.29
	72-88	7	144	64.8	2719	0.84
	57-72	62.3	22	3.6	2201	0.32
	32-57	2.3	9	1.3	1123	0.47
Lithology	Volcanic ash	0.6	22	9.3	2408	0.74
	Basic igneous rock	4.4	44	4	2647	-1.21
	Schist	89.02	196	74.2	4642	0.71
	Quartzite	0.05	36	8.4	3496	0.29
	Granite	0.03	19	2	2458	-2.13
	Colluvial	0.02	0	0	23	- 0.79
	Fluvial	0.2	0	0	630	-0.52
	Organic	0.2	0	0	29	0.39
	Water	4.9	0	0	0	0.04
	Basalt	0.4	9	2.1	1325	- 0.46
Soil texture	Loamy	0.9	9	18.4	2039	-0.26
	Sandy clay loamy	2.1	4	7.7	1651	-1.24
	Clay loamy	68	154	32	3419	0.12
	Sand clay	0.6	0	0.6	1242	0
	Clay	28.4	169	51.3	4984	0.37
LULC	Built-up land	3.2	6	4.3	1237	-1.29
	Cropland	60.4	247	59.7	4828	-1.13
	Grassland	14.2	31	11.4	1101	0.62
	Forest	16.1	52	24.6	1971	0.86
	Water Bodies	6.1	0	0	1003	-0.31
NDVI	0.65-0.99	19.6	63	26.5	2759	-0.55
	0.53-0.65	42	31	9.1	1621	0.24
	0.40-0.53	33.8	157	36.9	3827	0.89
	0.16- 0.40	4.4	23	8.2	1086	-0.8
	-0.2-0.16	0.2	62	19.3	1083	0-19
Distance to rivers	650-800	0.4	0	0	1011	-0.67
	450-600	3.6	18	4	1023	-0.89
	300-450	12	44	29	2109	-0.01
	150-300	31	31	20	3262	0.04
	0-150	54	243	47	3807	0.59
Distance to roads	1,000-1,250	4.2	8	0.7	1018	-0.32
	750-1,000	8	52	2.1	1214	-0.69

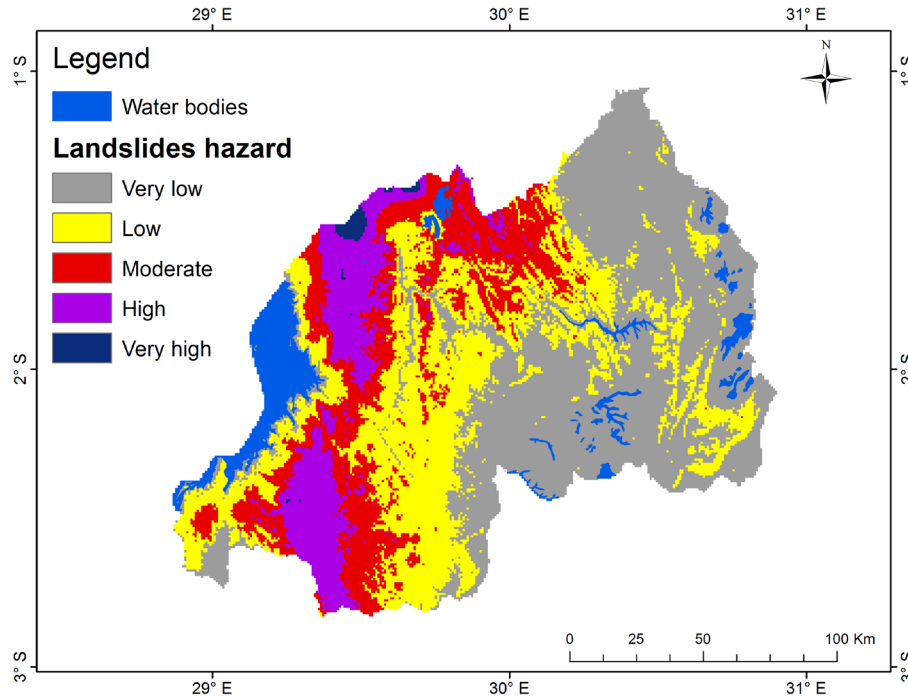|					
	500-750	16	31	16	2313	- 0.05
	250-500	28.2	58	33	2548	0.01
	0-250	43.6	187	48.2	3807	-1.21
Aspects	Flat	0.6	0	0	450	-0.03
	Northeast	8.3	4	4.9	1356	-0.18
	East	2.3	0	1.3	1719	-0.08
	Southeast	2	0	0.1	2008	-0.46
	South	10	26	10.3	2148	0.18
	Southwest	13.3	38	17.6	2981	0.23
	West	12.4	145	31.1	3198	0.64
	Northwest	39.2	96	20.3	2349	0.49
	North	11.2	27	12.4	2027	0.21

Figure 5. **Spatial landslides hazard distribution over Rwanda**

Table 2 Landslides hazard's population exposure per province in Rwanda

	Hazard classes	Area (%)	Population (%)
	Very low	22.3	20.7
	Low	48.5	40.3
Southern	Moderate	10.2	17.9
	High	19	21.1
	Very high	0	0
	Very low	0.9	2.3
	Low	9.1	19.6
Northern	Moderate	34	30.8
	High	52	36
	Very high	4	11.3
	Very low	1.2	3.9
	Low	12	20.2
Western	Moderate	30	31.6

	High	52.1	38.1
	Very high	4.7	6.2
	Very low	64.5	44.4
	Low	29.2	37.5
Kigali	Moderate	6.3	18.1
	High	0	0
	Very high	0	0
	Very low	67.3	58.6
	Low	32.4	38
Eastern	Moderate	0.38	3.4
	High	0	0
	Very high	0	0
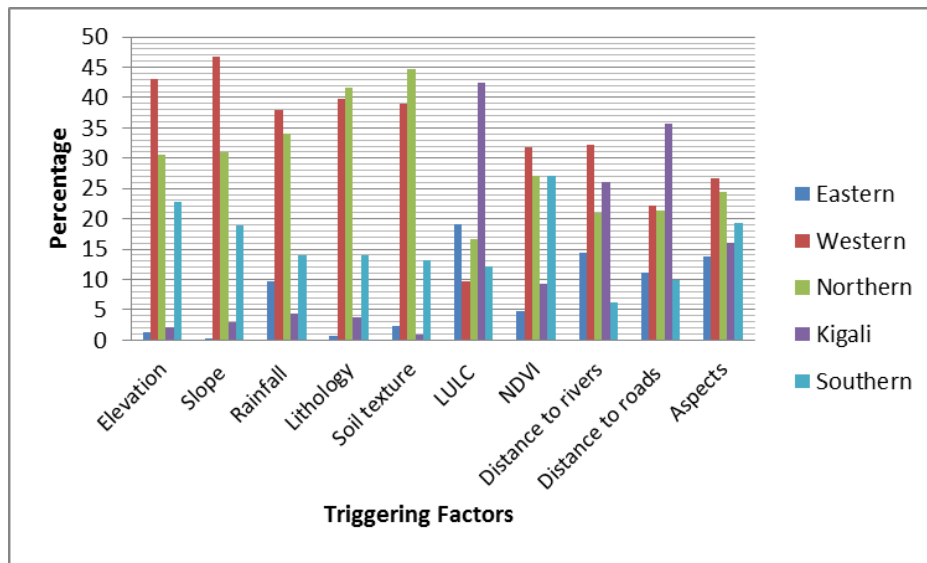
Figure 6. Estimated causal factor's contribution to landslides hazard per province

3.2 Validation of landslides hazard map

There are different ways of testing the validity of the model. The basic assumption underlying the goodness of fit test is that future landslides will occur in the same places as the past or existing movements in the study area. In case a hazard map coincides well with the inventory then maps are considered satisfactory (Guzzetti et al. 2012; Van Westen et al. 2008). For this study, landslides inventory databases (Fig.1 (b)) were used to test the goodness of the classified landslides hazard. Then, cumulative percentages of hazard classes corresponding to cumulative percentage of observed landslides were presented. The validation results in Fig.7 and Table 3 revealed that the statistical index model employed by this study generated good results because it confirmed that the constructed landslides hazard map coincided with past events. The results

showed that a high number of past landslides (216 of 336) was observed within high landslides hazard zone which occupies 42.7% of the total landslides hazard in Rwanda.
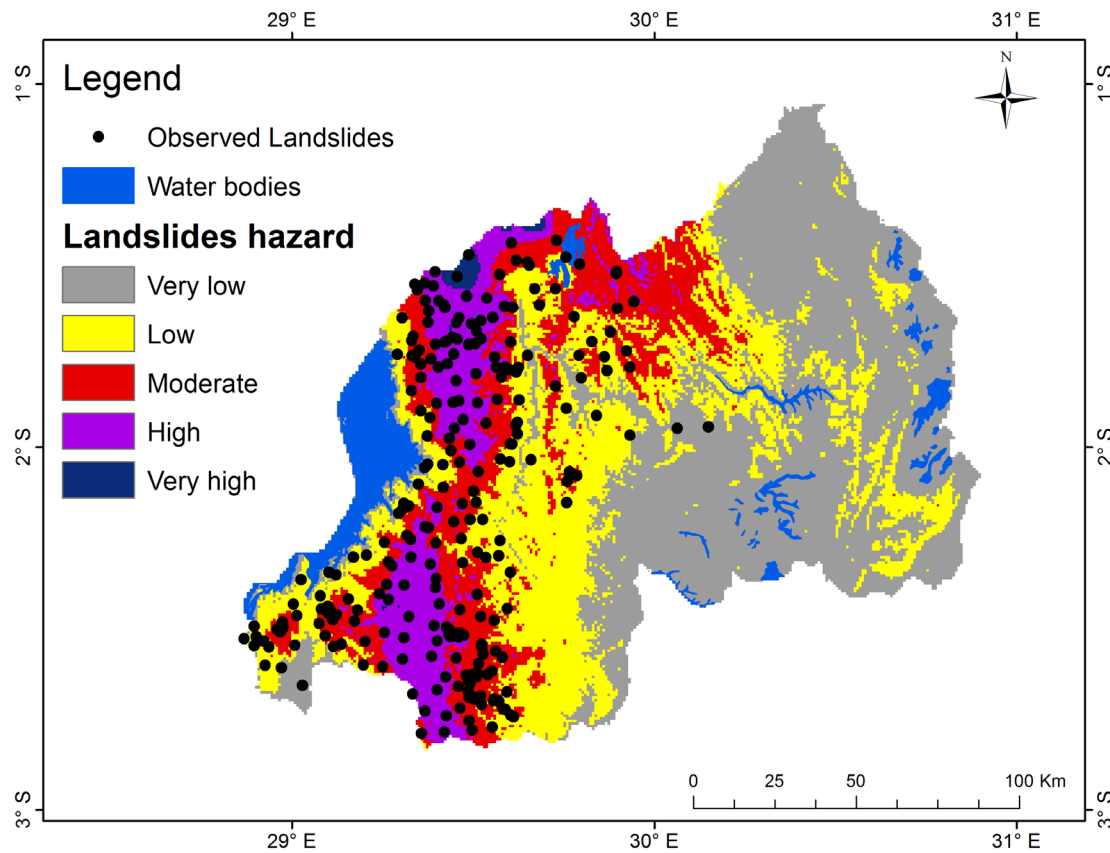

Figure 7. Prediction of future landslides occurrence likelihood based on previously observed events and its current spatial distribution in Rwanda

Table 3 Validation of the observed landslides per estimated hazard classes

Hazard class	Hazard area (%)	No. landslides	Landslides area (%)
Very low	2.3	5	3.1
Low	12.6	43	21.9
Moderate	39.1	68	32.2
High	42.7	216	36.6
Very high	3.3	4	6.2
Total	100	336	100

4. Discussion

Landslides hazard mapping is an important step in landslides investigation and landslides risk management. The process divides and ranks the land surface according to the degree of actual potential hazard from landslides (Di et al. 2017; Frodella et al. 2018; Ambrosi et al. 2018). Landslides inventories and databases are critical to support investigations of where and when landslides have happened and may occur in the future (Huang et al. 2013). In Rwanda, landslides severely impact on community and environmental safety. However, lack of precise knowledge of the key conditioning factors and historical database are among the challenges in hazard risk reduction (MIDIMAR 2014). The authors recognized this fact and employed ten landslides conditioning factors (Fig.2, 3 and 4) in order to produce a landslides hazard map (Fig.5), show the extent of each area's hazard exposure (Table 2) and the major triggering factors by hazard zone (Fig.6).

It is reported that within mountainous areas, high elevation and slope easily facilitate the runoff during intense rainfall then cause landslides (Petley 2012; Tian et al. 2017). This is congruent to Rwanda, dubbed: "a country of thousand hills" due to its mountainous landscape (MIDIMAR 2014). Accordingly, the results of this study (Fig.5) indicated that in Rwanda, moderate and high hazard zones record high precipitation, altitude and slope. Thus, for hazard risk reduction, it is good to expand areas under forest and promote the bench terraces and agroforestry practices along with rainfall harvest to minimize the runoff facilitated by its high elevation and slope. Hazard risk reduction requires a community-based approach through its direct participation in decision making, regular hazard-related meetings and timely information sharing, trainings and education delivery (Devkota et al. 2013; Tong et al. 2012). Such approaches enhance people's understanding on the types of hazard under record in their living areas, main causes and the kind of behaviour to adopt for the risk management. This can be applied in Rwanda with particular focus on the landslides hazard highly exposed areas (Fig. 5 and Table 2) in order to enable the residents to either settle in low hazard zones or ensure practices which minimize their landslides hazard exposure.

The occurrence of landslides does not only cause loss of human life, but also destroys natural habitat and causes species extinction, and destruction of other ecological services and natural heritage (Yalcin 2007; Kelman 2017; Capitani et al. 2013). In most cases, human activities are the key factors which exacerbate the impact of landslides. For example, the results in Fig.5

classified Kigali city between low and moderate landslides hazard zones (Fig.5). This is due to the reason that the area records expanded built-ups, low vegetation cover, and is close to rivers and roads (Fig.3 and 4) which result from anthropogenic activities. This consequently, destroys infrastructures and causes water and soil pollution because during landslides occurrence, the exposed upper soil layers and other sediments are easily transported downslope then pollute the quality of water and soil as well (Nahayo et al. 2018). Hence, the prepared landslides hazard map (Fig.5) can indicate to the environmental and construction engineers the hazard level (from very low to very high). And this enhances the awareness on the safe places to install buildings and ways of minimizing the wastes that can be loaded into water during landslides, and the required water and soil pollution control and natural environment management policies.

The knowledge on the fact that past landslides occurrence expresses the future likelihood helps to predict and prepare for the future (Urlaub et al. 2013). As illustrated in Fig.7, landslides hazard map validated with previous landslides revealed that 284 of 336 landslides are localized within the moderate and high hazard zones which occupy 78.8% of the total landslides hazard. Thus, if landslides reoccur in Rwanda, people and their belongings, and natural resources located in moderate and high hazard zones may record greater losses and damages. For such areas, soft engineering, known as biotechnical slope stabilization technique, if applied, can help to stabilize the slope due to its advantage of combining both the use of vegetation and man-made structural elements (Popescu and Sasahara 2009). In addition, residents from high landslides hazard areas (Fig.5) can be transferred to safe hazard zones like eastern province (Table 2) with low values of triggering factors (Fig.6). This saves people's life and ensures proper land use and management.

5. Conclusion

The aim of this study was to produce a landslides hazard map of Rwanda. Authors applied GIS-based statistical index model to analyze ten landslides causal factors. And the identified 336 points were used to produce a landslides inventory and validate the prepared landslides hazard map. The produced hazard map was divided into five hazard classes, i.e., very low, low, moderate, high and very high in order to differentiate landslides hazard, and enhance the knowledge on the hazard magnitude and major drivers across Rwanda. The results showed that the northern, southern and western provinces are highly exposed to landslides hazard due to high

elevation, slope, rainfall and poor land management. The proposed method revealed reasonable results because 284 of 336 previous landslides events are observed within moderate and high landslides hazard classes which occupy 78.8 percent of total hazard. It is concluded that for reducing landslides hazard in Rwanda, it is good to envisage strong population growth control, and set up appropriate building and environmental/natural resources management strategies. These include not limited to (a) avoiding to emplace new constructions on steep slope or to stabilize the slope before starting new constructions, (b) directing surface and ground water away from landslides hazard prone areas, (c) minimizing the irrigation of surface soil, (d) removing mass from the top of slope so that its weight may not force the layer to slide, and (e) ensuring that bank rivers are protected to minimize runoff during landslides occurrence in order to enhance water quality and reduce soil loss. Further assessment on the effectiveness of the hazard risk reduction policies under execution is suggested.

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Conflict of Interests

All authors declare no conflict of Interests

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