Assessment of Landslide susceptibility and risk to road network in Mt Elgon, Uganda

Bob Roga Nakileza (nakilezabob@gmail.com)
Makerere University College of Agricultural and Environmental Sciences https://orcid.org/0000-0002-9718-0460
Frank Mugagga
Makerere University College of Agricultural and Environmental Sciences
Paul Musali
Makerere University College of Agricultural and Environmental Sciences
Shafiq Nedala
Makerere University Institute of Environment and Natural Resources: Makerere University College of Agricultural and Environmental Sciences

Research Article

Keywords:

Posted Date: June 27th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1673620/v1

Abstract

Globally landslides occurrence is reportedly frequent particularly in the mountainous regions causing both direct and indirect effects to various sectors including the road transport. Landslides directly cause physical impact on the road network such as deposition of debris and impartial or total erosion of road segments. This leads to increased damage costs. Indirectly landslides cause disruption of the trade and movement whenever roads are blocked and alternative routes are resorted to. Existing literature reveals limited assessment of road vulnerability to landslides in the mountain regions in Africa. This study aimed at closing this information gap by investigating the risk to different segments of the road network in the Mt Elgon region. A fuzzy logic model was used to assess and map the landslide susceptibility into low, moderate, high and very high categories. The results reveal that mid to high altitude steep and rugged areas are more susceptible to landslides. The model performance was good as revealed by high AUC of 83%. Hotspot segments, which are high risk sections of the road network need to be prioritized for monitoring and risk mitigation.

Introduction

Landslides entail outward and downward slope movement of soils, rocks and or a combination of other materials (Varnes, 1978) under the influence of gravitational force. The sliding occurs when the shear stress overcomes the shear strength of the materials on slopes (Mugagga et al., 2011). Increasing landslide occurrence across the globe is closely linked to population pressures, land use change and compounded by climate change (Nseka et al., 2021; Nseka et al., 2019; Mugagga et al., 2015; Mugagga et al., 2012). Landslide occurrences results in varying consequences including fatalities and damage to natural resources, properties and infrastructure including roads. Road construction along the deep river valleys and mountainous regions result in high probability of landslides causing enormous loss and damage to human life and properties (Nepal, et al., 2019). In Uganda landslides have led to over 1500 fatalities since the year 2000 based on the DisInventar disaster database of impacts (GDRR, 2019). The slides impact on the road network in numerous ways including direct damage to the sections of roads (Domini et al., 2016), interference with traffic flow (Bordoni et al., 2018), disruption of regional economies and network reliability (Schlögl et al. 2019). Weather related hazards including landslides affect network reliability which is defined to comprise of network availability and network safety (Schlögl et al. 2019). Road works inside and outside the protected areas are also affected. For instance, forest roads have been reportedly affected by landslides in Turkey (Kadi, et al., 2019). Developing countries including Uganda and in particular the mountainous regions frequently suffer from landslides. Yet there is paucity of information on the risk of landslides to the road networks, which could provide a basis for planning, monitoring and effective emergency response. It is further noted by Hearn et al. (2019) that despite the impact posed to the road due to landslides limited significant efforts have been made to extensively map landslide-prone areas in relation to the road infrastructure in Uganda. The serious damage to such infrastructure negatively impacts on the economy. Besides, blockage of roads sometimes causes serious disruptions since there are limited alternative routes in the mountain environments, where there are sharp cliffs, rugged terrain and v-shaped steep sided valleys.

The concept of 'Landslide susceptibility' was introduced by Brabb (1984) and refers to the spatial probability of occurrence of landslide based on a set of geoenvironmental factors. It is largely the potential for failures to occur in a given locality depending on surficial and subsurface conditions as well as processes (Daniel, et al. 2021). The current paper provides a comprehensive assessment of landslide susceptibility and risk exposure to the road network in Mt Elgon. Specifically, the objectives of the paper were to (i) determine the spatial probability of landslide occurrence along the road corridors using statistical analysis model (ii) characterize the road segments in terms of landslide risk exposure [density and terrain] and (iii) analyse the implications to road risk management. Landslide susceptibility mapping provides evidence about vulnerable locations and therefore provides guidance to potentially reduce infrastructure damage caused by mass wasting (Abdullah, et al. 2019). According to Yin et al. (2020) a comprehensive understanding of highway landslide disasters (HLDs) from the spatial perspective constitutes a basis for decision making on reduction of damages. As indicated by Hearn et al. (2019) it is important that the stability of the road reserve and its associated engineering assets are maintained as a priority for the Uganda National Road Authority as well as District Local Governments, and that this necessitates consideration of earthworks slopes as well as the wider landscape in which the road is constructed. Susceptibility mapping and zoning can reveal the spatial differentiations of HLDs (Yin et al., 2020) and this combined with use of Algorithm can reveal alternative safer and less risky routes for road construction (Kadi et al., 2019).

The data on the annual frequency and magnitude of landslide disasters in not easily available and therefore use of landslide susceptibility is crucial. The landslide susceptibility provides information on the proneness to landsliding, in terms of initiation areas, based on a set of relevant environmental conditions (Persichillo et al., 2017). Landslide susceptibility modeling has relied on various methods particularly statistical methods including bivariate statistical analysis, logistic regression, multivariate regression, analytical hierarchy process, weight of evidence (Ria et al., 2018) and evidence belief function. In more recent past due to uncertainties and imprecision associated with combining landslide susceptibility assessment in GIS, approaches have adopted the use of Fuzzy and machine learning techniques. Other researchers have gone further to adopt the tree-based learning models (e.g. the IDS decision trees, the Random forest, classification and regression tree). Sudyartamo et al. (2019) have applied an evidenced-based statistical approach, using the Information Value Method (IVM) for landslide susceptibility mapping in Indonesia. This study adopted the use of fuzzy modeling approach combined with expert-knowledge, and relied upon a quality landslide inventory based on field information and high resolution imagery.

The next section provides an overview of the study area background information followed by a description of the methods applied, which details the data type, acquisition and integration. Subsequently the focus is on results and discussion which cover the LSM, the Road exposure and model performance.

The final section covers the conclusion and recommendation for road landslide risk mitigation and future direction of research.

Study area

Mt Elgon region is located in eastern Uganda along the border with Kenya (Figure 1) and occupies approximately 4,203.3km^2. Much of this study area is a mountainous terrain with varying moderate to steep slopes and with sharp side valleys in some locations. The general altitude of the area extends from 1200m to 4231m ASL. However, much of the densely populated and intensively cultivated terrain varies from 1200 to 2500m ASL. This partly contributes to road network vulnerability to slope failures with consequent exposure of the vehicular traffic. Major soils of the area include the acrisols, nitisols, vertisols, leptosols and andisols. The high clay content soils such as vertisols and nitisols present challenges when it rains; they are not only slippery but also delay water penetration. This usually induces slope failures. The main lithology consists of volcanic rocks (e.g. agglomerates and conglomerates) and fenitized basement rocks of Pre-Cambrian age.

A bimodal rainfall pattern is experienced in much of the Mt Elgon region. Generally high rainfall (1200-1800mm per annum) is received though varying with slope orientation and increased altitude. For instance, rainfall is higher at the southern and western slopes (1500-2000 mm/yr) than at the eastern and northern slopes (1000-1500 mm/yr) (Kitutu, 2010). High rainfall potential contributes to slope instability in this highland region (Ngecu et al., 2004). The main land uses in the area include forests, wetlands and agriculture. The agricultural land is intensively cultivated with mixed crops including coffee, bananas, irish potatoes, maize, wheat, beans etc. The only land that is expected not to be cultivated is occupied by the protected areas (the National Park and Forest reserves) However, there are incidences of encroachment in some areas (Mugagga et al. 2012). Roads and other infrastructure also occupy some areas and contribute to slope failures. The area is drained by a dense network of streams and major rivers such as Manafwa, Sironko, Simu and Sipi. This dense network increase on the erosivity of the area; the area frequently suffers from soil erosion and landslides. Flash floods are also common. Flash floods may also induce failures due to undercutting thus causing mud- and –debris flows.

Materials And Methods

Data type and acquisition

Landslide inventory

The most critical data set required for LSM is an accurate and representative landslide inventory. The significance of using a reliable and quality landslide dataset has been echoed by numerous scholars (e.g. Nohan et al., 2019; Daniel et al., 2021). Existing historical/archived data, field survey mapping and remote sensing or imagery data were used in building the landslide inventory. The Google Earth multi-temporal images extending from 1990 to 2020 were analysed for remote identification of the landslide scars. The landslide inventory data were compiled from historical records and validated using field surveys. During field surveys the locations of the new landslide scars were mapped using a GPS (Garmin 64sx). Existing inventories such as the web-based Uganda National Road Authority landslide data inventory were consulted. The UNRA inventory has records of landslide events and impacts (Hearn et al., 2019). The current study then integrated these different inventories to produce a single database for modeling the landslide susceptibility.

The DEM and satellite data from Google satellite (https://mt1.google.com/vt/lyrs=s&x={x}&y={y}&z={z}) were overlaid as base maps, to aid tracking, identification and digitization of spatial locations of past landslides and field investigation. The resultant maps were converted into geotiff files and uploaded into “Avenza Maps”, a mobile application utilized for verification and updating geological and landslide information in the field. A total of 478 landslides were identified and used in the LS modeling.

Field survey

Sections of the roads affected frequently by landslides were surveyed to gather more information related to the possible causes of instabilities and realized impacts. Data was gathered on the landslide location using GPS and also on individual failure characteristics. A Buffer of 50-100m on either side of the selected road sections was made and crossed with environmental causative conditions (soils, lithology and slope angle and landuse).

Information was sought from local government departments including engineering on incidences of landslide occurrences affecting roads, drainage conditions, clearance and repair reports after landslide events and presence of stabilisation measures applied in various hotspot sections/segments of the roads.

Predisposition to landslide factors

To evaluate the landslide susceptibility mapping (LSM), it is essential to know the preparatory and trigging factors and to prepare the necessary thematic layers (Mallick et al., 2018). Therefore, this study selected 10 conditional geomorphic and hydrological factors based on literature review, field observations and expertise. The factors included, slope gradient, slope aspect, Plan curvature, Profile curvature, SPI, STI, TWI, distance to road, and distance to stream. The importance of each landslide conditioning factor was evaluated individually by comparing a map of each parameter with the landslide distribution map. The graphical nature of these relationships between conditional factors and landslides are summarized in Fig. 2.

Figure 2 Preconditional factors for landslides; 1 = Slope gradient, 2 = Altitude, 3 = Aspect, 4 = Plan curvature, 5 = Profile curvature, 6 = Distance to road, 7 = Sediment index, 8 = Topographic wetness index, 9 = Stream Power index, 10 = Distance to river.

Slope gradient is one of the major topographic factors when investigating slope instability and in preparing LSM (Reichenbach et al., 2018; van Westen, 2008). This parameter was derived from a 12.5 X

12.5 m DEM and divided into eight classes (0–5; 6–10; 11–15; 16–20; 21–25; 26–30; 31–35; >35). The slope class with the highest percentage of landlides was 26–30. Studies by researchers (e.g. Nakileza and Nedala, 2020; Bamutaze, 2019; Nseka et al, 2018) indicate the proness of this slope category to landslide risks. Elevation is another geomorphometric parameter derived from the DEM and it plays a key role in influencing rainfall. Higher elevation areas are associated with high rainfall and first order streams that therefore affect slope steepeninng hence rate of erosion and landslides. The distance to the road similarly affects landslide risk due to the excavation and undercutting that causes reduced stress (Talaei, 2018; Duo et al., 2017) or in some cases overloading due to the filling in effect. The distance classes created in this study (0–50, 51–100, 101–250, 251–500, 501–750, 731–1000, 1001–2500, 2501–5000, 5001–10000, > 10001) revealed that generally the landslides distribution decreased with distance away from the road. This also demonstrates the anthropological influence of landsliding. Distance from drainage stream is an important factor influencing landslide occurrence. Slope undercutting by the stream causes instability and so is the moisture contributing to saturation. Higher landslide occurrences were generally observed within the 100m distance in the study area (Fig. 2.6). The stream power index (SPI) is a compound topographic attribute which measures the erosive power of flowing water based on the assumption that discharge is proportional to the catchment area. The class with 0.33 to 1.49 had the greatest erosive power as demonstrated by high percentage of landslide distribution (50%). The TWI measures the degree of water accummulation at a site. The lowest class (-6907.75-357.67) had the greatest percentage distribution of landslides.

Data sources

Topographic wetness index, altitude, and stream power index were derived from the Advance Land Observing Satellite/Phased Array type L-band Synthetic Aperture Radar (ALOS/PALSAR) DEM available at https://search.asf.alaska.edu/#/. According to Persichillo et al. (2017) the use of input data simply derived from DEMs allows to obtain a good level of accuracy and predictive efficiency also in case of lack of exhaustive field information. Therefore, the ALOS/PALSAR DEM suited this study because of its high resolution (12.5m) and free availability (Alahmadi, 2019). The data is further geometrically and radiometrically terrain corrected (Logan et al., 2014) thus ready for use in morphological modeling (Albino et al., 2015). Thus, according to Alahmadi (2019) ALOS/PALSAR DEMs are accurate enough for hydrological and morphological studies because of high accuracy.

Road network data was obtained from the UNRA database and supplemented with ICPAC Geoportal road data available at http://geoportal.icpac.net/layers/geonode%3Aigad_roads#more. This data is open sources, regularly updated and has been widely used (Wolff et al, 2021; Laktabai, 2020).

Data processing: integration and analysis

Fuzzy logic method (Bui et al., 2015) was used to assess landslide susceptibility in the model builder (Fig. 3). The method was selected because of its novel advantage over classical set theory methods such as weighted overlay, where an object belongs or not to a set thus it has a membership value of 1, or not 0 respectively (Gemitzi et al., 2011). In the fuzzy logic method however, fuzzy set theories apply fuzzy membership functions whose membership values range between 0 and 1 reflecting the degree of certainty of membership. Nevertheless, fuzzy set theories do not generate fuzzy membership values of landslide conditioning factors and their classes (Bui et al., 2015). Instead expert knowledge or frequency ratios may be applied (Bui et al., 2015). This is consistent with Kumar and Anbaladan (2015), who indicate that landslide susceptibility mapping requires determination of fuzzy membership function of causative factors, which can be determined subjectively or objectively.

In this study, expert knowledge was applied to achieve membership values by reclassifying conditioning factors from 1 to 10 and dividing them by a factor of 10. The resultant value of each conditioning factor was then assigned a membership class (Table 1) and overlaid by fuzzy overlay method to produce a landslide susceptibility map (Fig. 4).

Table 1
Fuzzy membership values for different landslide conditioning factors

Distance from Streams and rivers		**Fuzzification**	**Membership**
0–50	1	0.1	
51–100	2	0.2	
101–150	3	0.3	
151–200	4	0.4	
201–250	5	0.5	Fuzzy Linear
251–300	6	0.6	
301–400	7	0.7	
401–500	8	0.8	
501–750	9	0.9	
751–1,056	10	1	
Distance from Road			
0–50	1	0.1	
51–100	2	0.2	
101–250	3	0.3	
251–500	4	0.4	
501–750	5	0.5	
751–1,000	6	0.6	FuzzyLinear
1,001–2,500	7	0.7	
2,501–5,000	8	0.8	
5,001–10,000	9	0.9	
10,001 and above	10	1	
Altitude			
1,029 – 1,200	1	0.1	
1,201–1,500	7	0.7	
1,501–1,700	8	0.8	
1,701–2,000	10	1	
2,001–2,300	9	0.9	

Distance from Streams and rivers		Fuzzification	Membership
2,301–2,600	6	0.6	
2,601–2,900	5	0.5	FuzzyLarge
2,901–3,200	4	0.4	
3,201–3,500	3	0.3	
3,501–4,306	2	0.2	
Aspect			
North (0-22.5)	1	0.1	
Northeast (22.5–67.5)	3	0.3	
Northwest (292.5-337.5)	4	0.4	FuzzyLinear
South (157.5-202.5)	6	0.6	
Southwest (202.5-247.5)	9	0.9	
West (247.5-292.5)	7	0.7	
Southeast (112.5-157.5)	8	0.8	
East (67.5-112.5)	10	1	
Slope			
0–5	1	0.1	
6–10	2	0.2	
11–15	3	0.3	
16–20	4	0.4	FuzzyGaussian
21–25	7	0.7	
26–30	8	0.8	
31–35	6	0.6	
35 and above	5	0.5	
Plan curvature			
-32.14 - -1.107	5	0.5	
-1.106 - -0.407	4	0.4	
-0.406–0.293	3	0.3	FuzzyLinear
0.294–0.993	2	0.2	

Distance from Streams and rivers	Fuzzification	Membership	
0.994–27.36	1	0.1	
Profile Curvature			
-33.799 - -2.427	4	0.4	
-2.426 - -0.597	3	0.3	
-0.596–0.188	1	0.1	FuzzySmall
0.189–0.972	2	0.2	
0.973–3.848	5	0.5	
3.849–32.867	6	0.6	
Topographic Wetness Index (TWI)			
-6,907.75–357.65	1	0.1	
357.66–1,332.28	2	0.2	
1,332.29–2,484.11	3	0.3	
2,484.12–3,547.34	4	0.4	FuzzyLinear
3,547.35–4,787.78	5	0.5	
4,787.79–6,205.42	6	0.6	
6,205.43–7,888.86	7	0.7	
7,888.87–9,926.72	8	0.8	
9,926.73–12,407.59	9	0.9	
12,407.6–15,685.88	10	1	
Sediment Transport Index (STI)			
0–23.264	1	0.05	
23.265–116.32	2	0.10	
116.321–255.904	3	0.14	
255.905–418.753	4	0.19	
418.754–604.865	5	0.24	
604.866–814.241	6	0.29	
814.242–1,023.617	7	0.33	
1,023.618–1,232.993	8	0.38	FuzzyLinear

Distance from Streams and rivers		Fuzzification	Membership
1,232.994–1,465.634	9	0.43	
1,465.635–1,698.274	10	0.48	
1,698.275–1,930.914	11	0.52	
1,930.915–2,163.555	12	0.57	
2,163.556–2,372.931	13	0.62	
2,372.932–2,605.571	14	0.67	
2,605.572–2,838.211	15	0.71	
2,838.212–3,070.852	16	0.76	
3,070.853–3,326.756	17	0.81	
3,326.757–3,745.509	18	0.86	
3,745.51–4,327.109	19	0.90	
4,327.11–4,978.502	20	0.95	
4,978.503–5,932.327	21	1.00	
Stream Power Index (SPI)			
-56.86 - -5.13	1	0.1	
-5.12 - -2.01	2	0.2	
-2 - -0.85	3	0.3	FuzzyLinear
-0.84–0.32	4	0.4	
0.33–1.49	5	0.5	
1.5–42.33	6	0.6	

The generated landslide susceptibility map was then overlaid with a road network map in a GIS environment to produce roads exposure to landslides hazard in the region

Validation and evaluation

The landslide inventory used in validation of the LSM was 143 (30%) of 478 landslide records and the rest were used in model training (Fig. 8a). The ROC curve constructed on sensitivity (True positives) against specificity (True negatives) was used to evaluate the performance of the model as described by Razavi-Termeh, et al. (2021) and Hong et al. (2015). The parameters were computed from true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN) (Thongley & Vansarochana, 2021) in ArcSDM 5.03 package where area under curve (AUC) was estimated. Also the study paid little emphasis on landslide and road construction dating thus conditional independences were not computed.

Results

Landslide susceptibility mapping

The derived LSM based on Fuzzy logic model is depicted in Figure 4. The five susceptibility zones depicted range from very low risk, low risk, moderate risk, high risk and very high risk. Their respective percentage areal coverage of the susceptibility classes is summarized in Figure 4.

The high to very high risk landslide areas were confined to the mid-altitude (1400 to 1700m asl) in the districts of Bududa, Mbale, Sironko, Bulambuli and Kapchorwa, which are largely steep sloping areas. However, areas of very low and low risk landslide susceptibility were rather dominant in the high altitude natural vegetated areas in the Mountain Elgon National Park (MENP) and the lower altitude dominated by low-lying wetlands in virtually all the districts. As shown in Figure 4, the largest percentage LSM class was under the low category (55% followed by the moderate class (23%). The least area category was the very high (3%).

Road network landslide risk exposure

The LSM was crossed with a road network to derive a road exposure map and the results are depicted in Figure 5a and b.

It is evident (Figure 5b) there is spatial variation in the susceptibility of the road network system. Thus, not all the entire road network in the study area is uniformly exposed to the landslide risk. High exposure of the roads occur in hot spot segments in all the districts. A few illustrations of the road segments affected by landslide hazards are depicted in Figure 6. In Bududa, the highly exposed road network is found in the areas of Bulucheke, Bushika and Bubita sub counties. In Mbale the highly exposed road network occurs in Wanale and Bunghoko, including the area just below the cliffs. Areas highly exposed in Sironko district include the Buhugu-Butadiga and Budadiri-Bumulo road stretches, which are under the control of the local government. The highly exposed road segments in Bulambuli include the road stretch from Kibanda to Bumwambu, Buluganya to Pondo and along Simu to Kamu. In Kapchorwa the central road also referred to as the national road highway segment highly exposed include the Sipi-Sarajevo and the Kween to Bukwo. Very high exposure of the road segment was observed in Bududa along the Bukalasi road.

There was observed variation in the number of landslides with increasing buffer distance away from the roads. Most of the areas with high landslide occurrence were over 200m. Areas close to the roads (<100m) had fewer landslide occurrences. Despite the low occurrences great damage or disruption is frequently caused whenever the slides are characterized by long run out distances (Figure 7).

Validation of the results of LSM

Prediction of accuracy assessment was done to obtain the consistence in LSM. The accuracy of the LSM is the capability to delineate the landslide free and landslide prone areas. Prediction accuracy of LSM were performed on the basis of receiver operating characteristic (ROC) curves in the present study. Relative ROC curve of the analysis results is presented in Figure 8 and the area under the curve (AUC) was used for validation. The results reveal a good predictive accuracy of the model as evidenced by the high computed AUC value (0.83), which is 83%.

Discussions

The Landslide susceptibility assessment revealed variability in spatial distribution, which is explained by the differences in the predisposing factors such as slope angle, slope aspect, landuse among others. The high to very high risk areas coincide with steep terrain (20^{o}-35^{o}) and mid to high altitude areas (1500-2000m asl). This is consistent with the findings by Kubwimana et al. (2021); Bamutaze (2019) and Nseka et al. (2017) who observed that shallow landslides dominate slopes above 25 to 35 degrees. The road network risk exposure varies accordingly with the steep terrain and altitude. High to very high road exposure segments occur in steep terrain, which are more sensitive to disturbances associated with construction works. In the highland steep sloping parts of Burundi, Kubwimana et al. (2021) observed abandoned section of a road due to multiple landslide incidences. Dou et al. (2017) similarly observed that areas close to roads were susceptible to landslide occurrence. Elsewhere in related mountain environment, Nepal et al. (2019) found that the slope category 50-60 degrees was most susceptible to landslides on the Nepal to China highway in the Himalayas mountain. Road construction contributes to slope undercutting which lead to slope instability due to reduced shear stress. Yifru (2015 observed that poor road slope cut design experienced high landslide occurrences in Dominica in Caribbean Islands. The increase of the slope steepness and the undermining of support along the base of the slopes such as that due to the construction of roads may reduce the safety factor and augment the chances of a landslide occurrence in the absence of any mitigation measures (Tsangaratoset al., 2017). In this regard as well, Islam et al. (2017) stresses the need for geotechnical studies before any risk reduction measures for mitigating landslides.

Implications for road risk management

Innovative participatory monitoring systems need to be designed for the Elgon region. Hearn et al. (2019) recognizes that community liaison and cross-agency co-ordination on aspects of slope management beyond the road reserve are crucial to road asset management within the road reserve. This can be backed up by a community action plan (CAP) for effective implementation. Elsewhere Nepal et al. (2019) proposed use of a combination of monitoring and set up of an EWS with the participation of the local communities as an effective measure for landslide risk management in hard to access areas with complex land use. Such a system if adopted in Elgon can empower local people not only in providing solutions for addressing risk to the road network but also lessening on the expenses and improving on efficiency during response in case of a landslide hazard.

Regular monitoring and evaluation of the landslide occurrence by earth scientists (Ngecu et al., 2004) with the assistance of local community involvement is very important for designing relevant mitigation measures. This is more required particularly in remote hotspot areas at higher altitude and topographically complex areas. Interactions during field studies revealed that the local communities living adjacent the main road networks are rarely deliberately targeted or integrated in the main road highway maintenance.

Some landslide risky road segments entail road cuts and embankment filling. The geotechnical properties of the exposed surfaces during excavation need to be clearly understood particularly since volcanic rock agglomerates and ash are prone to weathering. The cracks created during cutting provide easy pathways for water penetration thus easing weathering and accelerating instability.

Conclusion

This study employed a Fuzzy logic model and demonstrates that much of the mid-altitude with steep terrain is highly susceptible to landslide risk. The model prediction accuracy in mapping the landslides as revealed by the AUC value for the ROC was relatively high (83%). This shows the model can be adopted in other similar regions of landslide risk. The landslide road exposure risk varied spatially in this study area as also reported in other east African highland region (e.g. Kubwimana et al., 2021). The riskiest road exposure segment was the topographically complex Bulucheke-Bukalasi area in Bududa district. Thus, priority should be given to such areas in the region in terms of monitoring and risk management. A participatory approach involving the local communities in monitoring and mitigation activities in such remote environments could be more effective in ensuring safety on the road networks. Further participatory research involving local communities is needed to underpin the interactions for the hazard processes under whichever mitigation measures are promoted in landslide risky segments.

Declarations

Disclosure statement

The authors declare no existence of conflicting interests.

Author contributions

NB: Writing- conceptualization, initial draft & field validation, FM: Writing- conceptualization, review and editing, SN: GIS analysis & review, PM: Writing-review & editing. All authors red and approved the final draft.

References

1. Abdullaha A. F., Aimrun W., N. M. Nasidia, K. Hazari S. A. F., L Mohd. Sidek, Zalilah Selamat. 2019. Modelling erosion and landslides induced by farming activities at hilly areas, Cameron Highlands,

Malaysia. 81:6 (2019) 195–204 www.jurnalteknologi.utm.my eISSN 2180–3722. DOI: https://doi.org/10.11113/jt.v81.13795.

2. Alahmadi, F. S. Evaluation of global digital elevation model ALOS/PALSAR using aerial LiDAR.
3. Albino, F., Smets, B., d'Oreye, N., & Kervyn, F. (2015). High-resolution TanDEM-X DEM: An accurate method to estimate lava flow volumes at Nyamulagira Volcano (DR Congo). *Journal of Geophysical Research: Solid Earth*, *120*(6), 4189-4207.
4. Bordoni, M., M. G.Persichillo, C. Meisina, S. Crema, M. Cavalli, C. Bartelletti, Y.Galanti, M. Barsanti, R. Giannecchini, and G. D'Amato Avanzi. 2018. Estimation of the susceptibility of a road network to shallow landslides with the integration of the sediment connectivity. *Hazards Earth Syst. Sci.,* 18, 1735–1758, 2018 https://doi.org/10.5194/nhess-18-1735-2018.
5. Brabb E E 1984 Innovative approaches to landslide hazard mapping; In: *Proceedings 4th International Symposium on Landslides, Toronto* **1** 307–324.
6. Bui, D. T., Pradhan, B., Revhaug, I., Nguyen, D. B., Pham, H. V., & Bui, Q. N. (2015). A novel hybrid evidential belief function-based fuzzy logic model in spatial prediction of rainfall-induced shallow landslides in the Lang Son city area (Vietnam). *Geomatics, Natural Hazards and Risk*, *6*(3), 243-271.
7. Daniel MT, Ng TF, Abdul Kadir MF and Pereira JJ (2021) Landslide Susceptibility Modeling Using a Hybrid Bivariate Statistical and Expert Consultation Approach in Canada Hill, Sarawak, Malaysia. Front. *Earth Sci.* 9:616225. doi: 10.3389/feart.2021.616225.
8. Donnini, M., Napolitano, P. Salvati, F. Ardizzone, F. Bucci, F.Fiorucci, M. Santangelo, M. Cardinali and F. Guzzetti. 2016. Impact of event landslides on road networks:a statistical analysis of two Italian case studies. *Landslides* DOI 10.1007/s10346-017-0829-4.
9. Duo GL, Zhang YS, Iqbal J, et al. (2017) Landslide susceptibility mapping using an integrated model of information value method and logistic regression in the Bailongjiang watershed, Gansu Province, China. *Journal of Mountain Science* 14 (2). DOI: 10.1007/s11629-016-4126-9.
10. Global Facility for Disaster Risk Reduction, GDRR. 2019. Uganda Risk Profile. https://www.gfdrr.org/sites/default/files/publication/uganda_low.pdf.
11. Galanti Y., A. Cevasco, P.i Brandolini and J. P.Galvee. 2017. Shallow landslides susceptibility assessment in different environments. *GEOMATICS, NATURAL HAZARDS AND RISK,* 2017 VOL. 8, NO. 2, 748–771 http://dx.doi.org/10.1080/19475705.2016.1265011.
12. Gemitzi, A., Falalakis, G., Eskioglou, P., & Petalas, C. (2011). Evaluating landslide susceptibility using environmental factors, fuzzy membership functions and GIS. *Global NEST Journal*, *13*(1), 28-40.
13. Hearn, G., Lekea, A., Mbabazi, E., Ruse, M. and van Oostenrijk, A. Landslide Management on the Ugandan National Road Network. https://pre-proceedings-abudhabi2019.piarc.org/ressources/files/6/IP0338-HEARN-E-Full.docx.pdf.
14. Hong, H., Xu, C., & Bui, D. T. (2015). Landslide susceptibility assessment at the Xiushui area (China) using frequency ratio model. *Procedia Earth and Planetary Science*, *15*, 513-517.
15. Islam, M.A., Murshed, S., Kabir, S.M.M., Farazi, A.H., Gazi, M.Y., Jahan, I. and Akhter, S.H.

16. (2017) Utilization of Open Source Spatial Data for Landslide Susceptibility Mapping at Chittagong District of Bangladesh—An Appraisal for Disaster Risk Reduction and Mitigation Approach. International Journal of Geosciences, 8, 577-598. https://doi.org/10.4236/ijg.2017.84031.
17. Laktabai, V. K. (2020). Using Gis To Assess The Risk Of Terrorism: A Case Study Of Garissa County(Doctoral dissertation, University of Nairobi).
18. Logan, T. A., Nicoll, J., Laurencelle, J., Hogenson, K., Gens, R., Buechler, B., ... & Guritz, R. (2014). Radiometrically terrain corrected ALOS PALSAR Data available from the Alaska Satellite Facility. *AGUFM*, *2014*, IN33B-3762.
19. Kadi F., F. Yildirim & E. Saralioglu (2019): Risk analysis of forest roads using landslide susceptibility maps and generation of the optimum forest road route: a case study in Macka, Turkey, *Geocarto International*, DOI: 10.1080/10106049.2019.1659424.
20. K. G.M. 2010. Landslide occurrence in the hilly areas of Bududa district in eastern Uganda. PhD Thesis. Makerere University. Uganda.
21. Kubwimana, D., Ait Brahim, L. Nkurunziza, P. Dille, A. Depicker, A. Nahimana, L. Abdelouafı, A. Dewitte, O. 2021. Characteristics and Distribution of Landslides in the Populated Hillslopes of Bujumbura, Burundi. *Geosciences*, 11, 259. https://doi.org/3390/geosciences11060259.
22. Mallick J., Karan Singh., M. A. AlAwadh., S. Islam., R. Abad Khan. And M. N. Qureshi (2018) GIS-based landslide susceptibility evaluation using fuzzy-AHP multi-criteria decision-making techniques in the Abha Watershed, Saudi Arabia. *Environmental Earth Sciences*, 77:276 https://doi.org/10.1007/s12665-018-7451-1.
23. Mugagga, F., Nagasha, B., Barasa, B., M. Buyinza. (2015). The Effect of Land Use on Carbon Stocks and Implications for Climate Variability on the Slopes of Mount Elgon, Eastern Uganda. *International Journal of Regional Development (IJRD*), 2(1), 58 – 75. doi:10.5296/ijrd.v2i1.7537.
24. Mugagga, , V. Kakembo., M. Buyinza. (2012): Land use changes on the slopes of Mount Elgon and the implications for the occurrence of landslides. *Catena* (2012),39-46, doi:10.1016/j.catena.2011.11.004
25. F., V. Kakembo., and M. Buyinza (2011): A Characterization of the Physical Properties of Soil and the Implications for Landslide occurrence on the Slopes of Mount Elgon, Eastern Uganda. *Natural Hazards*. DOI: 10.1007/s11069-011-9896-3.
26. Nepal N., J. Chen, H. Chen, X. Wang, T. Prasad and P. Sharma. 2019. Assessment of landslide susceptibility along the Araniko Highway in Poiqu/ Bhote Koshi/Sun Koshi Watershed, Nepal Himalaya. *Progress in Disaster Science 3 (2019) 100037*http://dx.doi.org/10.1016/j.pdisas.2019.100037.
27. Ngecu, W.M., C.M, Nyamai and G. Erima 2004. The extent and significance of mass-movements in Eastern Africa: case studies of some major landslides in Uganda and Kenya. DOI 10.1007/s00254-004-1116-y *Environmental Geology*, 46:1123–1133.

28. Nohani, E., Moharrami, M., Sharfi, S., Khosravi, K., Pradhan, B., Pham, B. T., Melesse, A. M. (2019). Landslide Susceptibility Mapping Using Different GIS-Based Bivariate Models. *Water, MDPI*(11), 2-22. doi:10.3390/w11071402.
29. D., Mugagga. F., Opedes. H., Ayesiga. P., Wasswa. H., Mugume. I., Nimusiima. A., Nalwanga. F. (2021). The damage caused by landslides in socio-economic spheres within the Kigezi highlands of South Western Uganda. *Envir. Socio.-econ. Stud*. 9, (1), 23-34. DOI: 10.2478/environ-2021-0003 Environ.
30. D, Y. Bamutaze, F. Mugagga, B**.** Nakileza. (2019). The Fragility of Agricultural Landscapes and Resilience of Communities to Landslide Occurrence in the Tropical Humid Environments of Kigezi Highlands in South Western Uganda. DOI: https://doi.org/10.1007/978-3-030-12974-3_13. *Agriculture and Ecosystem Resilience in Sub Saharan Africa*, Climate Change Management, Springer.
31. Persichillo M. G., M. Bordonia, C. Meisina, C. Bartelletti, M. Barsantic, R. Giannecchinib, G. D'Amato Avanzib, Razavi-Termeh, S. V., Shirani, K., & Pasandi, M. (2021). Mapping of landslide susceptibility using the combination of neuro-fuzzy inference system (ANFIS), ant colony (ANFIS-ACOR), and differential evolution (ANFIS-DE) models. *Bulletin of Engineering Geology and the Environment*, *80*(3), 2045-2067.
32. Riaz M.T., M. Basharat, N.Hameed & M. Shafique.2018. Data-Driven Approach to Landslide-Susceptibility Mapping in Mountainous Terrain: Case Study from the Northwest Himalayas, Pakistan. *Hazards Rev*., 2018, 19(4): 05018007.
33. Sudaryatno, P. Widayani, T. W. Wibowo*, B. Wiratmoko, and W. Nurbandi. 2019. Evidence-Based Landslide Hazard Mapping in Purworejo using the Information Value Model. Forum Geografi, 33(1), 2019; DOI: 23917/forgeo.v33i1.7592.
34. Talaei R. 2018. A Combined Model for Landslide Susceptibility, Hazard and Risk Assessment.
35. AUT *Civil Eng*., 2(1) 11-28. DOI: 10.22060/ajce.2018.14235.5465.
36. Tsangaratos, P., · C. Loupasakis., Nikolakopoulos., V. Angelitsa., I. Ilia. 2017. Developing a landslide susceptibility map based on remote sensing, fuzzy logic and expert knowledge of the Island of Lefkada, Greece. *Environmental Earth Sciences* (2018) 77:363. .https://doi.org/10.1007/s12665-018-7548-6.
37. Van Westen, C. J., Castellanos, E., & Kuriakose, S. L. (2008). Spatial data for landslide susceptibility, hazard, and vulnerability assessment: an overview. Engineering geology, 102(3-4), 112-131.
38. Wolff, S., Mdemu, M. V., & Lakes, T. (2021). Defining the Peri-Urban: A Multidimensional Characterization of Spatio-Temporal Land Use along an Urban–Rural Gradient in Dar es Salaam, Tanzania. *Land*, *10*(2), 177.
39. Yifru J. 2015. National scale landslide hazard assessment along the road corridors of Dominica and Saint Lucia, Caribbean Islands. MSc Dissertation, University of Twente, Netherlands.
40. Yin C, Li H, Che F, Li Y, Hu Z, Liu D (2020) Susceptibility mapping and zoning of highway landslide disasters in China. PLOS ONE 15(9): e0235780. https://doi.org/10.1371/journal. pone.0235780.

Figures

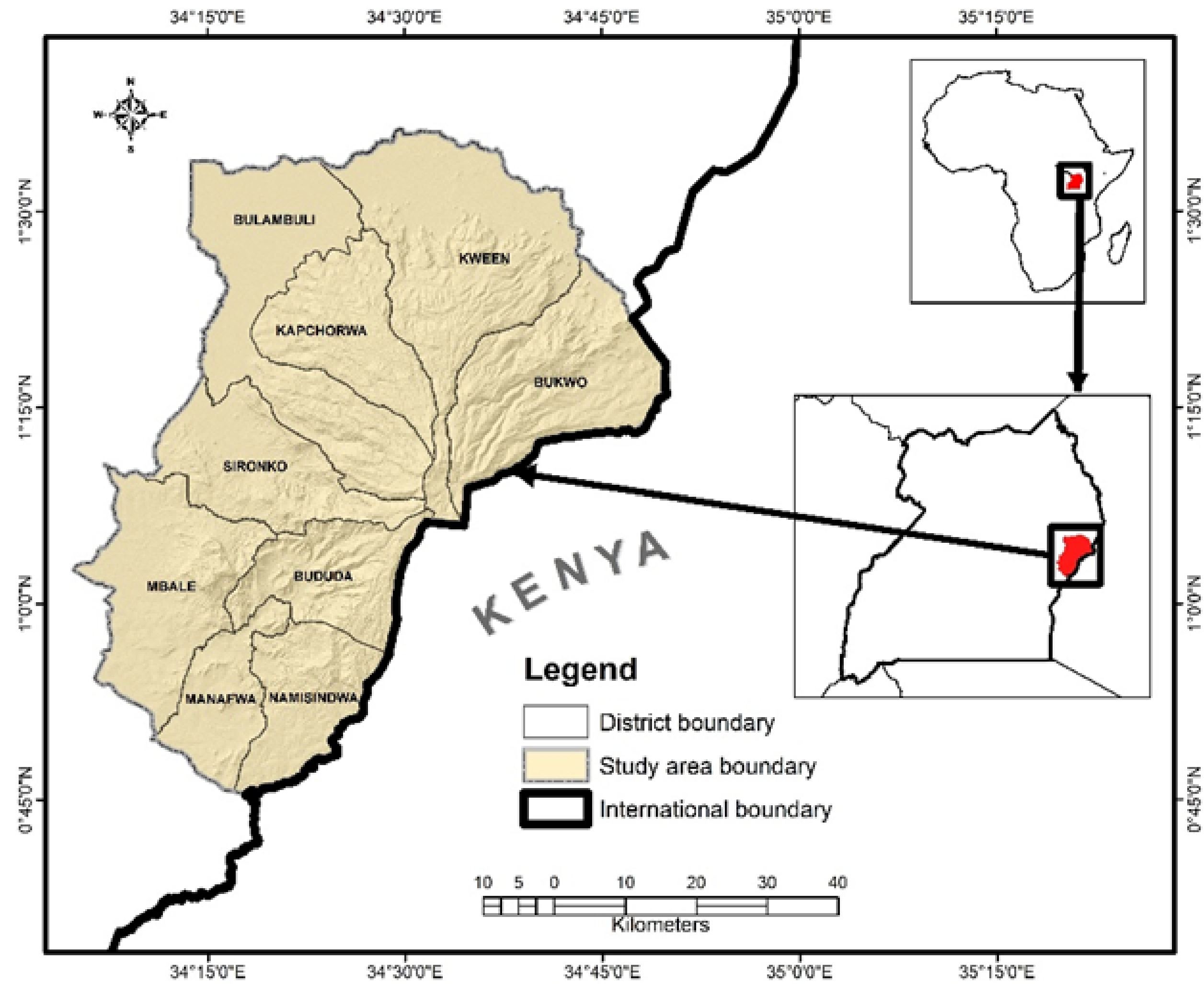


Figure 1

Location of the study area in Uganda, Africa

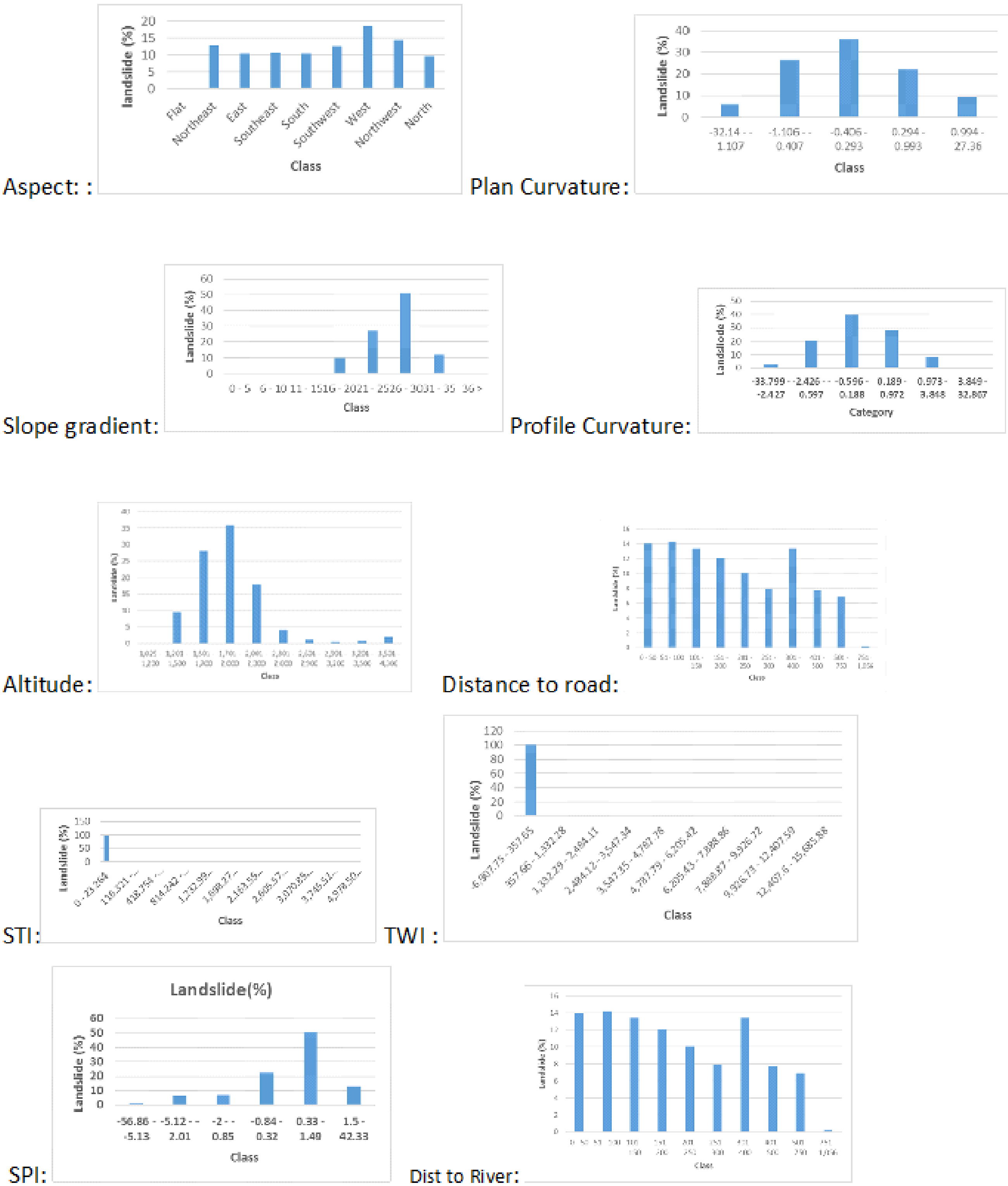


Figure 2

Preconditional factors for landslides; 1= Slope gradient, 2= Altitude, 3= Aspect, 4 = Plan curvature, 5= Profile curvature, 6= Distance to road, 7= Sediment index, 8= Topographic wetness index, 9=Stream Power index, 10= Distance to river.

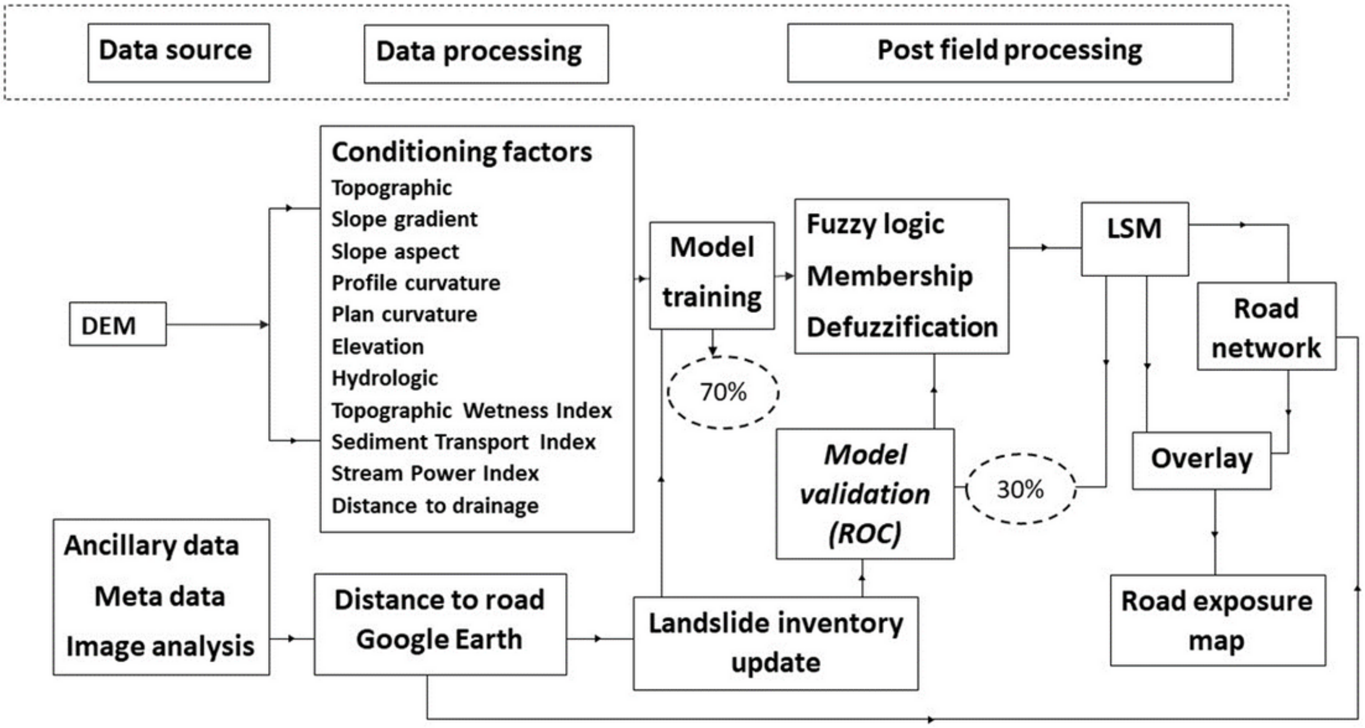
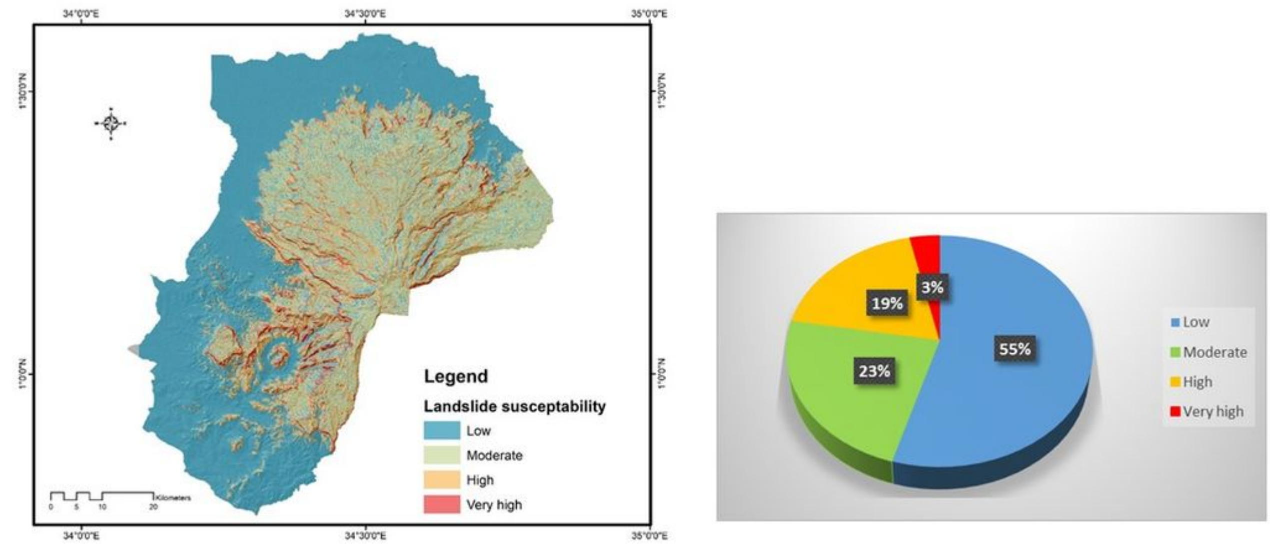


Figure 3

Fuzzy logic landslide susceptibility model: flow of the procedures and data used in the analysis.

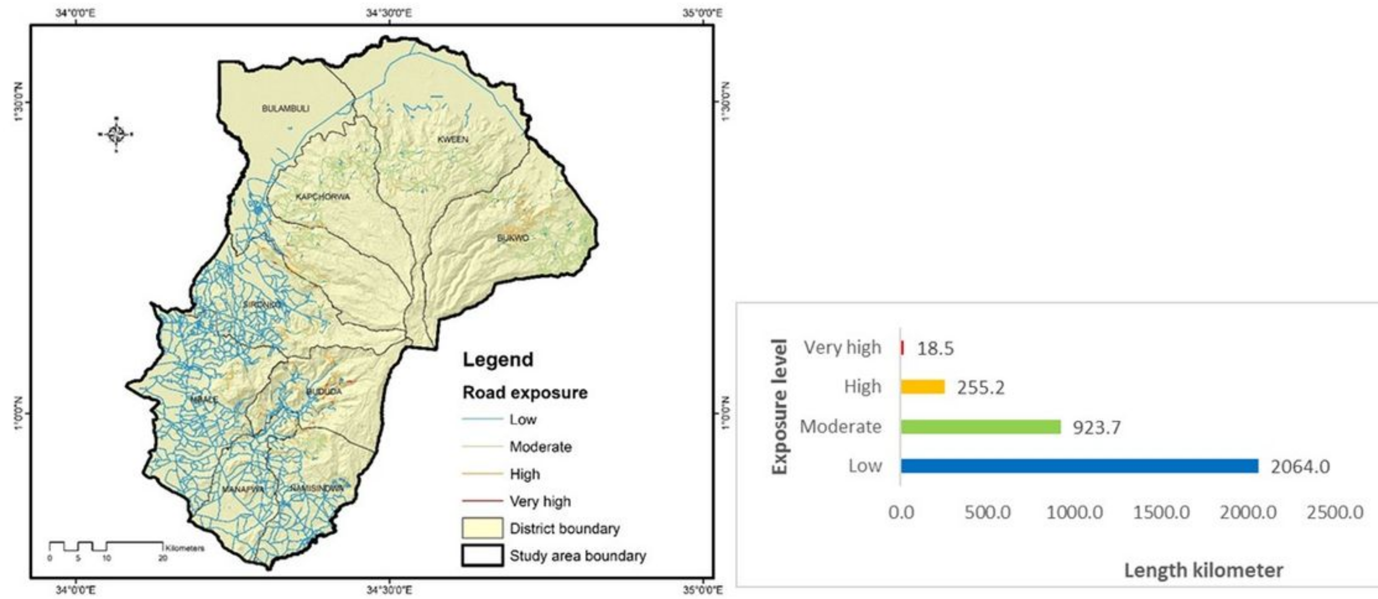


a) Landslide susceptibility map

b) Percentage area by class category of landslide susceptibility

Figure 4

Landslide susceptibility map



a) Level of road exposure to various category of landslide susceptibility in Mt Elgon

b) Road network by LSM category class

Figure 5

(b)Road network by LSM category class

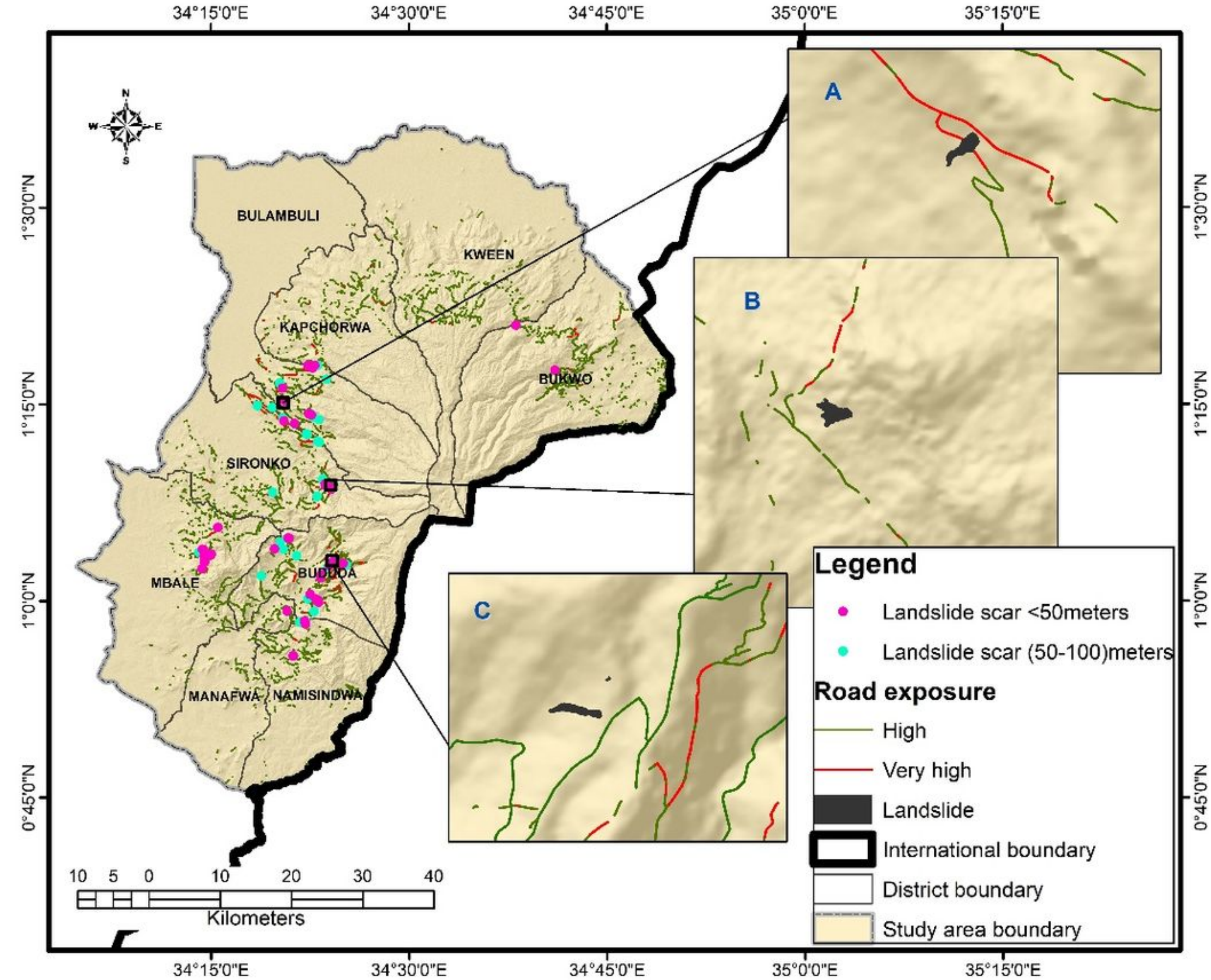
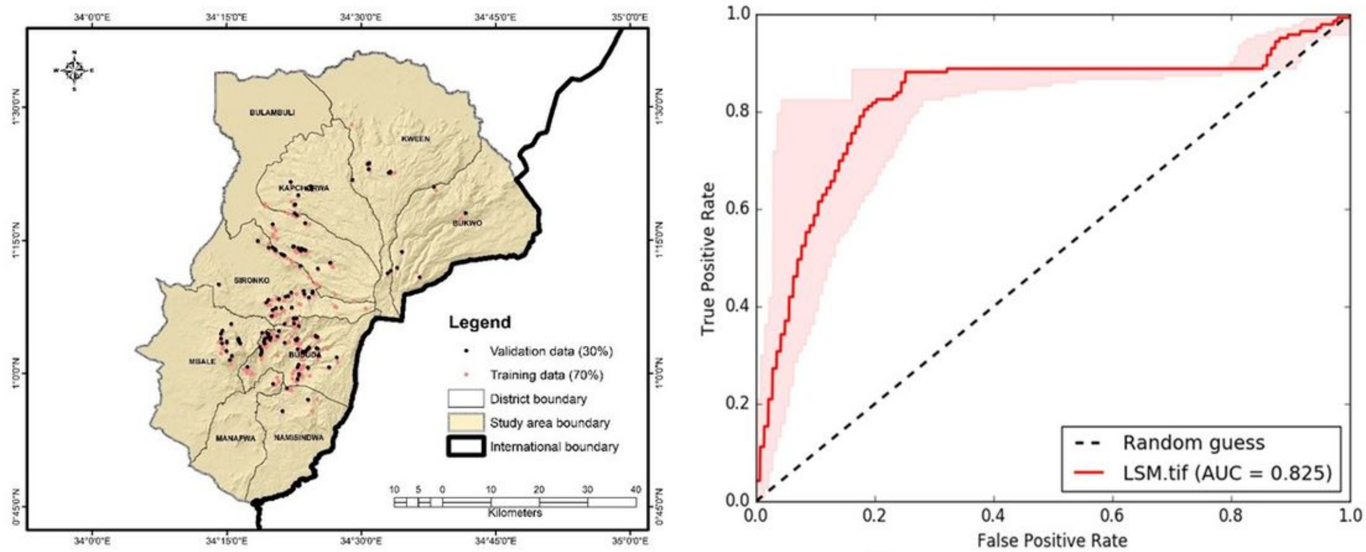


Figure 6

Road network exposure hotspots in Mt Elgon region

Figure 7

Portions of the road network system impacted by different landslides in various hotspot areas of Mt Elgon; (a) landslides with long runout causing road destruction (b) Road blocked by Mudflow in Bukalasi (c) Road deformed by a slow translational slide in Namisindwa town council (d) and (e) Debris slide at Sipi Hill along the Kapchorwa high way and Buginyanya-Bumwambu road stretch in Bulambuli district.



a) Validation and training landslide scar points

b) ROC curve for fuzzy LSM

Figure 8

Model validation