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

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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. Existing literature reveals limited assessment of road vulnerability to landslides in the mountain regions in Africa. The objective of this study was to investigate 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 of the study area. A total of 478 landslide sites were used in the model development. Ten conditional factors were applied for generating the dataset for training and validation of the model. 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 Area Under the Curve (AUC) of 83% and thus can be relied upon in landslide susceptibility mapping. The hotspot segments, which are high risk sections of the road network need to be prioritized for monitoring so as to initiate and strength existing risk mitigation strategies.

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, bridges among others. 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; Ramesh and Anbazhagan, 2015). In Uganda, based on the DisInventar disaster database of impacts (GDRR, 2019), landslides have led to over 1500 fatalities since the year 2000 The slides impact on the road network in numerous ways including direct damage to the sections of roads (Domini et al., 2016; Ramesh and Anbazhagan, 2015; Jacobs et al., 2015), 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). Mountainous regions in developing countries including Uganda 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' introduced by Brabb (1984) 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). Landslide susceptibility mapping describes the type, spatial extent and intensity of both past and present landslides in order to assess the future likelihood of the area in question to experience landsliding (Ramesh and Anbazhagan, 2015). 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 in Mt Elgon using statistical analysis model (ii) characterize the road segments in terms of landslide risk exposure 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 including 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 is 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; Ramesh and Anbazhagan, 2015). Landslide susceptibility modeling relies on various methods particularly statistical methods including bivariate statistical analysis (Nohami et al., 2019), logistic regression (Nohami et al., 2019; Youssef et al., 2015; Naurani et al., 2014), multivariate regression, analytical hierarchy process (Lee et al., 2003), weight of evidence (Ria et al., 2018; Youssef et al., 2015) and evidence belief function (Althuwaynee et al., 2012).

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 (e.g. Pham et al., 2018) 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. The performance evaluation of these methods suggests that SVM, ANN and LR are some of the best methods for the preparation of the LSM (Pham et al. 2018a; Bui et al., 2012). It is indicated (e.g. Niefeslioglu et al. 2008) that the use of ANN for production of LSMs provide more accurate prediction compared to the FR and LR models. Nevertheless, some criticism against the ANN models (e.g. Savic, et al., 1999) is that they represent their knowledge in terms of a weight matrix that is not accessible to human understanding at present. However, in view of the above literature review and also as further argued by Brabb (1984) and Shalo et al. (2020) there is no defined appropriate approach and methods for the evaluation of susceptibility and hazards to landslides. It is important to provide justification leading to a particular choice of method(s) (Shalo et al, 2020). Therefore, the current 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. This model is straightforward to understand and implement (Pradhan, 2009). Besides, it accepts data from any measurement scale and the weighting of evidence is controlled by the expert.

Study Area

Mt Elgon region is located in eastern Uganda along the border with Kenya (Fig. 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 dataset required for LSM is an accurate and representative landslide inventory. The inventory forms a significant aspect in prediction because it provides an understanding of conditions and processes which influences past landslide occurrences and therefore the evidence of future distribution (Ramesh and Anbazhagan, 2015). 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). In this study, existing historical/archived data, field survey mapping and 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 (UNRA) landslide data inventory was 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. In this study, use of landslide point data was preferred to polygons due to limitations imposed by some small sized landslide scars.

The ALOS PALSAR Digital Elevation Model (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 triggering 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 for computing the fuzzy logic membership. The factors included, altitude, 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 of the area (Fig. 2).

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). As further echoed by 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 using fuzzy logic model

Fuzzy logic method (Bui et al., 2015) was used to assess landslide susceptibility. The method was selected due to 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). The idea of fuzzy logic is to consider the spatial objects on a map as members of a set (Pradhan, 2009). 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. There are also no practical constraints on the choice of the fuzzy membership values (Pradhan, 2009). 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; Pradhan, 2009). This is consistent with Kumar and Anbaladan (2015), who indicated 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 and grey literature was applied to achieve fuzzy membership during fuzzification processes. Each conditioning factor was reclassified to manageable classes and ranks equivalent to level of influence to landslide was assigned. The weights ranged from 1 to 10, where 10 = most influential and 1 = least influential class. The assigned ranks (crisp values) were then normalized by dividing them by a factor of 10. The resultant value of each was then used to assign a membership functions e.g. Fuzzy-Linear, Fuzzy-Large, Fuzzy-Gaussian etc.

Fuzzification process of each conditioning factor

Slope aspect: This describes the direction of the slope and largely determines the exposure to the sun hence strongly influences the vegetation and evapo-transpiration rate. The slope aspect was divided into nine classes. Analysis reveal that the West, Northwest and Northeastern slope directions had the largest number of landslides. Fuzzy-Linear membership function with positive relationship was adopted as given by (Baalousha et al., 2021)

$$\mu\left(x\right) = \left(\left(x - min\right)\right) / \left(\left(max - \min\right)\right) \ldots \ldots . (1)$$

Where; max and min are the maximum and minimum values of the crisp value. However, for negative linear relationship, the model is denoted as

$$\mu\left(x\right) = 1 - \left(\left(x - \min\right)\right) / \left(\left(max - \min\right)\right) \ldots \ldots (2)$$

Slope gradient: This is one of the major topographic factors for investigating slope instability and preparing LSM (Reichenbach et al., 2018; van Westen, 2008). This parameter was divided into eight classes (0–5; 6–10; 11–15; 16–20; 21–25; 26–30; 31–35; >35) and class 26–30 was ranked highest. Studies by researchers (e.g. Nakileza and Nedala, 2020; Bamutaze, 2019; Nseka et al., 2018; Phama et al., 2018) indicated high risk of landslides in this slope category. Therefore, basing on this literature Fuzzy-Gaussian membership function which prioritizes midpoints value was applied to slope with class 26–30 as midpoint. The function is mathematically given by Baalousha et al, (2021); Akteret al., 2019); Iliadis et al., (2017) as.

$$\mu\left(x\right) = e^{\left(-f_1\left(x - f_2\right)^2\right)} \ldots . (3)$$

Where; f_1 and f_2 are and the spread and midpoint values respectively

Slope curvature : This is the curvature of a line formed by the intersection of a random plane with the surface. In the case of curvature map, based on Ramesh and Anbazhagan (2015), the negative values were classified as concave (<-0.005) positive values as convex (> 0.005), and values close to zero (-0.005 to 0.005) as flat. These surfaces influence the accumulation and flow of water. Most slides tend to occur on concave surfaces which accumulate water and moisture. In the current study profile curvature was classified in 6 classes as (-33.799 - -2.427, -2.426 - -0.597, -0.596–0.188, 0.189–0.972, 0.973–3.848 and 3.849–32.867) and plan curvature in 5 classified as (-32.14 - -1.107, -1.106 - -0.407, -0.406–0.293, 0.294–0.993 and 0.994–27.36). Fuzzy-small was applied for profile curvature denoted by (Akter et al., 2019) in (Eq. 4) while Fuzzy-Linear for plan curvature (Eq. 1).

$$\mu(x) = \frac{1}{(1 + (x/f_2)^{f_1}} \dots\dots(4)$$

Where; f_1 is the spread and f_2 is mean of input variable

Elevation

This 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 hence steepening the rate of erosion and landslides. However, studies (e.g. Mande et al, 2022; Nakileza & Nedala, 2020) have showed that landslide risk increase with increase in slope up to a certain point and decrease and class between 1200 to 2500 are the most problematic. Based on this literature, elevation was fuzzified using Fuzzy-Gaussian membership function with elevation class 1400–1500 as midpoint values using Eq. 3.

Distance to the road

This similarly affects landslide risk due to the excavation and undercutting that causes reduced stress (Talaei, 2018; Duo et al., 2017; Ramesh & Anbazhagan, 2015) or in some cases overloading due to backfilling and compaction effect. The distance classes created in this study are (0–50, 51–100, 101–250, 251–500, 501–750, 731–1000, 1001–2500, 2501–5000, 5001–10000, > 10001). A study by Chen et al. (2020) revealed that landslides distribution decreased with distance away from the road thus an inverse linear relationship. Ramesh & Anbazhagan, (2015) also found high landslide risk to road distance < 2000m. Based on the above researchers` findings, a Fuzzy-Small membership function (Eq. 4) was applied to achieve road distance membership class because it gives priority to small values.

Distance from drainage stream

This is an important factor influencing landslide occurrence through moisture and undercutting process. Undercutting of the slope face by a stream or river induces instability (Thongley & Vansarochana, 2021) and so is the moisture contribution to saturation. This factor presents a negative linear relationship with landslides (Chen et al., 2020). That is to say landslide risk reduces with increase in distance from streams. Higher landslide occurrences were generally observed within the 100m distance in the study area expressed as Fuzzy-Small in Eq. 4.**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 (Panoto et al., 2022; Wang et al., 2016). High SPI values (> 40) are associated with high erosion (Panoto et al., 2022). However (Wang et al., 2016) noted that for landslides, this is not the case since highest SPI values are located in the stream itself. This study adopted Panoto`s assumption of a positive linear relationship between SPI and landslide occurrence. Therefore, a Fuzzy-Linear membership function presented in Eq. 1 was adopted.

Topographic Wetness Index (TWI): This measures the degree of water accumulation at a site. The fuzzification of this parameter followed a Fuzzy-Linear function. Results by (Liu & Duan, 2018) have indicated a positive correlation between TWI and landslide distribution. Pourghasemi et al., (2012) results also presented similar trends. It is in this regard that Fuzzy-Linear membership function was applied as given in Eq. 1.

Sediment Transport Index

The index reflects the erosive power of surface overflow and it is equivalent to slope length (LS) factor of RUSLES model (Jaafari et al., 2014). In landslide susceptibility mapping, STI represents the hydrological impacts to slope stability by revealing areas of erosion (high values) and deposition (low values). The assumption is that the river has greater energy to transport material in upslope and less energy downslope. Jaafari et al., (2014) found this assumption true in their study where frequency ration results increased with increase in SPI. However, (Chen et al., 2020) and (Liu & Duan, 2018) found contradicting results where landslide were more concentrated in deposition areas. In this study, 21 SPI classes were generated andFuzzy-Linear membership function denoted in Eq. 1 was applied as suggested by (Jaafari et al., 2014) findings. His findings exhibited similar characteristics like in the Elgon where shallow landslides are common on cliffs and very steep slopes.

Defuzzification of conditioning factors

All conditioning factors were integrated into LSM map using Fuzzy AND operator. The model is mathematically denoted by (Çakıt & Karwowski, 2018 and Bui et al., 2015) as;

$$LSM = \min(\mu x_1, \mu x_2, \mu x_3, \ldots . . (5)$$

Where; μx_1, μx_2, and μx_3 represents fuzzified conditioning factors e.g. slope aspect, slope gradient, elevation etc. and min represents the minimum operator value.

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 (Fig. 3).

Validation and evaluation

The landslide inventory (Fig. 4) was randomly partitioned into a training dataset with 70% (337) landslides and the rest 30% (143) records for validation of the LSM map (Fig. 5). 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 presented in Figure 5. The five susceptibility zones depicted range from very low risk, low risk, moderate risk, high risk to very high risk. Their respective percentage areal coverage of the susceptibility classes is summarized in Figure 6.

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 dominated by steep sloping terrain. 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 depicted in Figure 6, 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 7a and b.

It is evident (Figure 7b) that 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 occurs in hot spot segments in all the districts. A few illustrations of the road segments affected by landslide hazards are depicted in Figure 8. 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 Wanale cliffs. Areas highly exposed in Sironko district include the Buhugu-Butandiga 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, which is part of the national road highway segment is highly exposed particularly the section of 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 from the roads (Figure 9). 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 of long run-out distances (Figure 10).

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 11 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 using the fuzzy logic model 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 (20º-35º) 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. In Rwenzori, Jacobs et al. (2015) observed destructive effects caused by rockslide and debris flow on some exposed sections of roads. 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 (Siddique and Khan, 2019; Tsangaratoset et 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. However, contrary to the findings in this study, Pham et al., 2018) observed that areas beyond 500m along the road experienced more landslides. They attributed it to the morphology of the area and the road construction method which was not disruptive.

Implications for road risk management

The findings reveal some sections of the road are exposed to landslides in virtually all the nine districts in the Mt Elgon region. Landslide occurrence can cause fatality but also tremendous economic losses and disruptions. Thus, they cannot be ignored. Innovative participatory monitoring systems need to be urgently 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 Early Warning System (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 observed in Mt Elgon. 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 aimed at determining the susceptibility of the Mt Elgon region road network to landslide occurrences using a statistical based model, the Fuzzy logic model. The results demonstrate 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 is good enough and can be adopted in other similar regions experiencing landslide risk. The results for the second objective on landslide road exposure risk revealed substantial spatial variation in this study area. This is similarly reported in other east African highland regions (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 implementing feasible risk management strategies. A participatory approach preferably the Participatory 3 Dimensional Model (P3DM) involving the local communities is suggested in developing monitoring and mitigation activities in such remote environments. This could be more effective in ensuring safety on the road networks. Furthermore, 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

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Figures

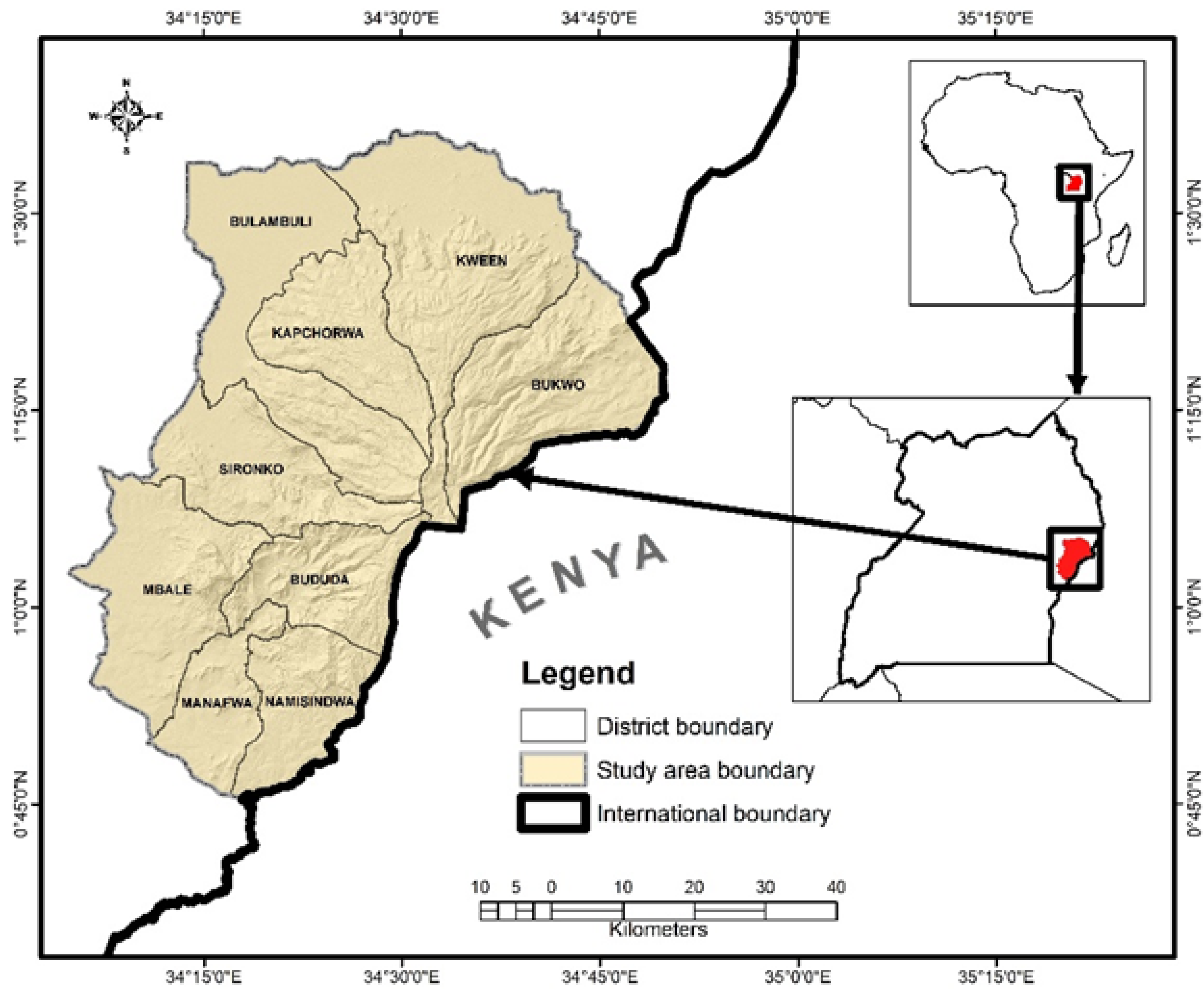


Figure 1

Location of the study area in Uganda, Africa.

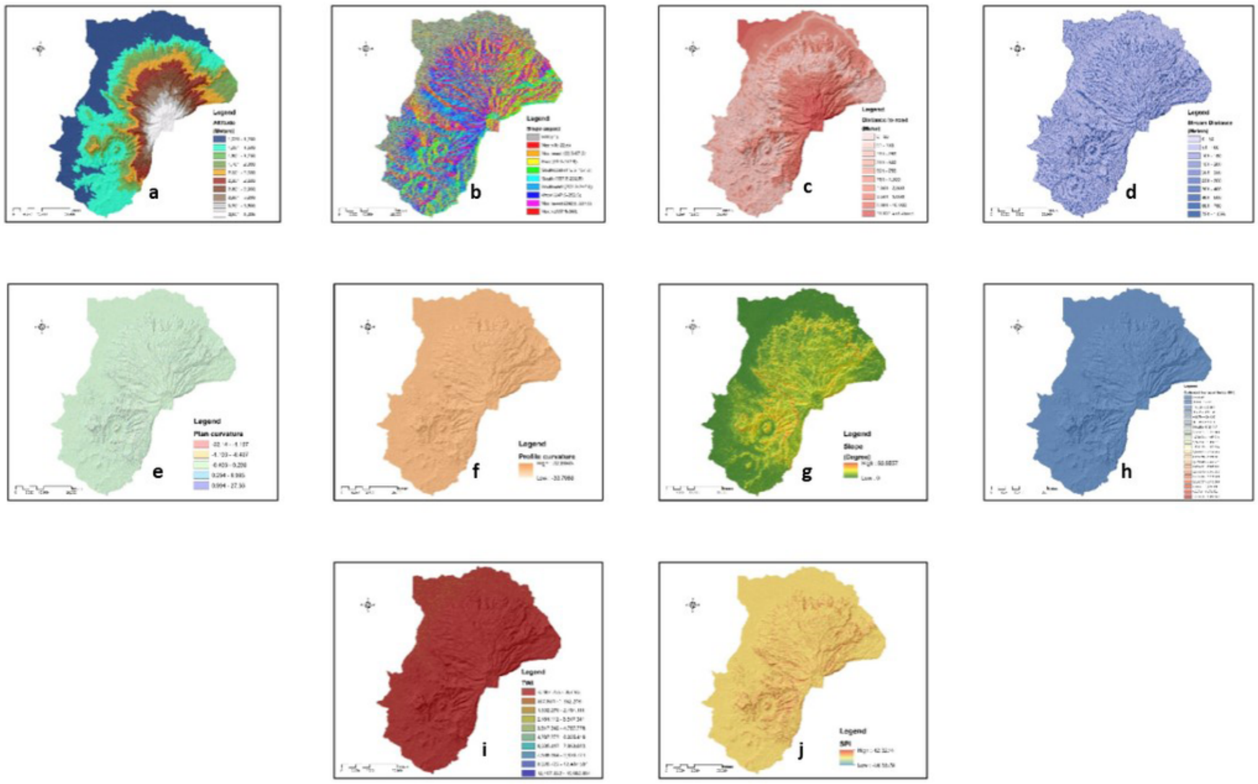


Figure 2

Factors by classes and landslides frequency: (a) Altitude (a),(b) Aspect, (c) Distance to road (d) Stream distance, (e) Plan curvature, (f) Profile curvature, (g) Slope, (h) SPI, (i) STI, (j) TWI

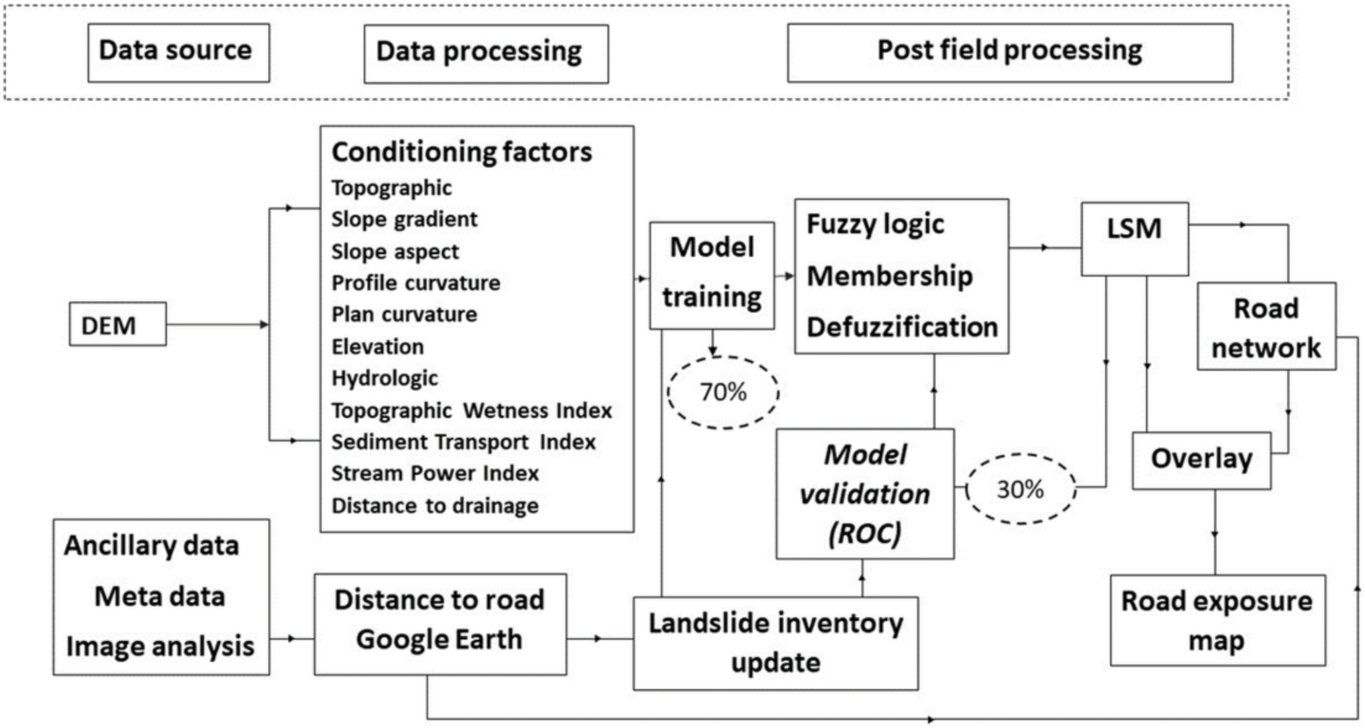


Figure 3

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

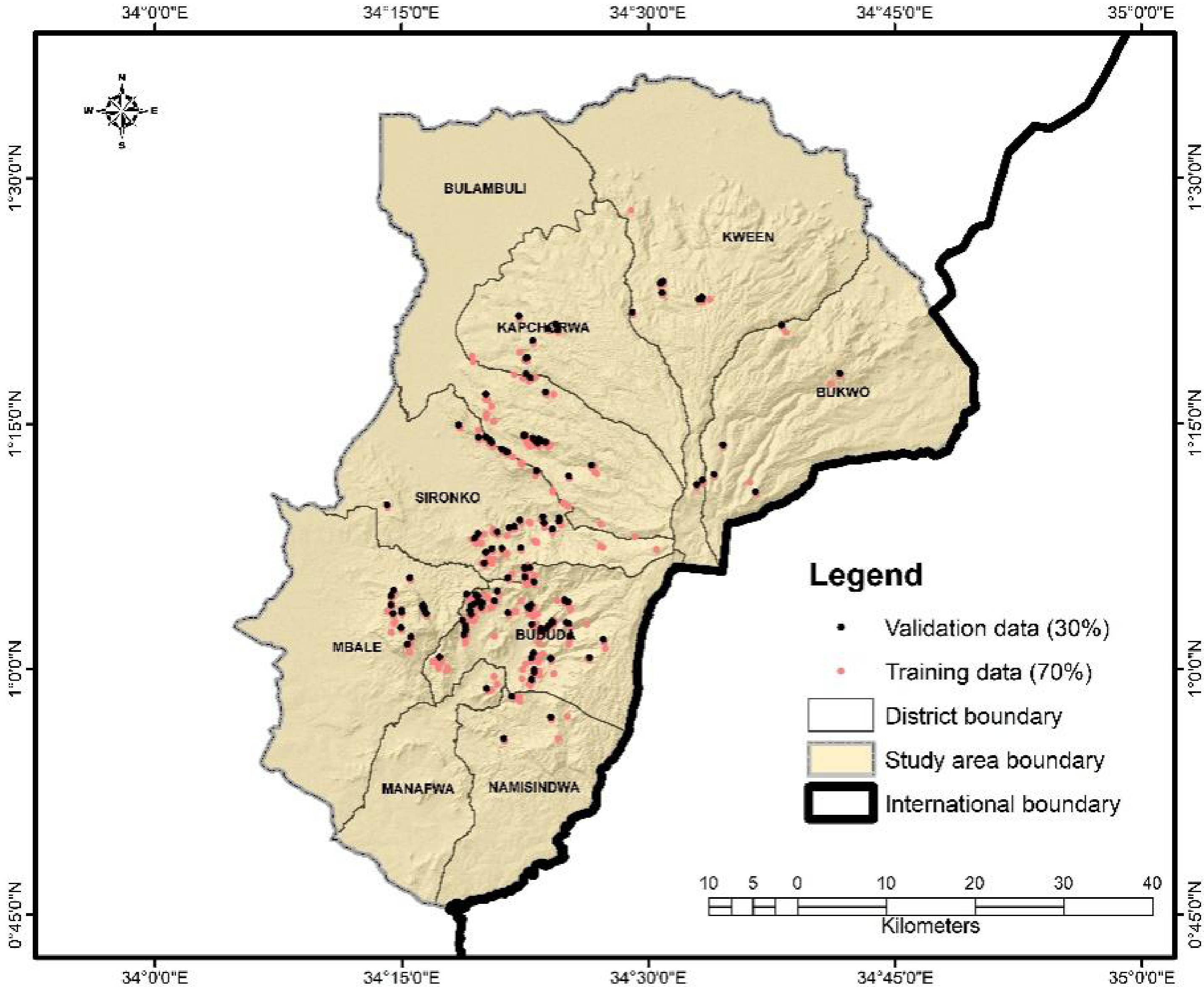


Figure 4

Validation and training landslide scar points in the study area

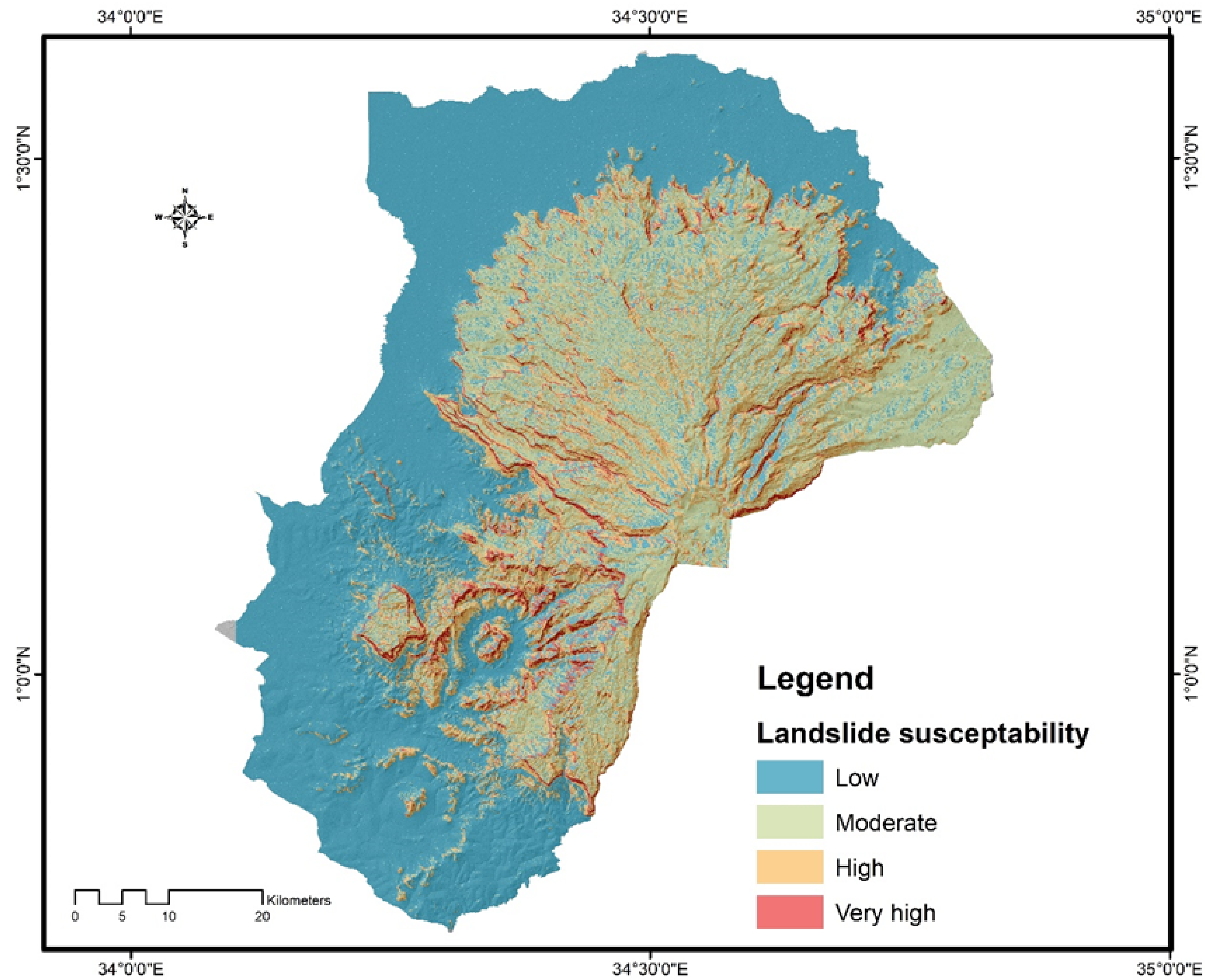


Figure 5

Landslide susceptibility map

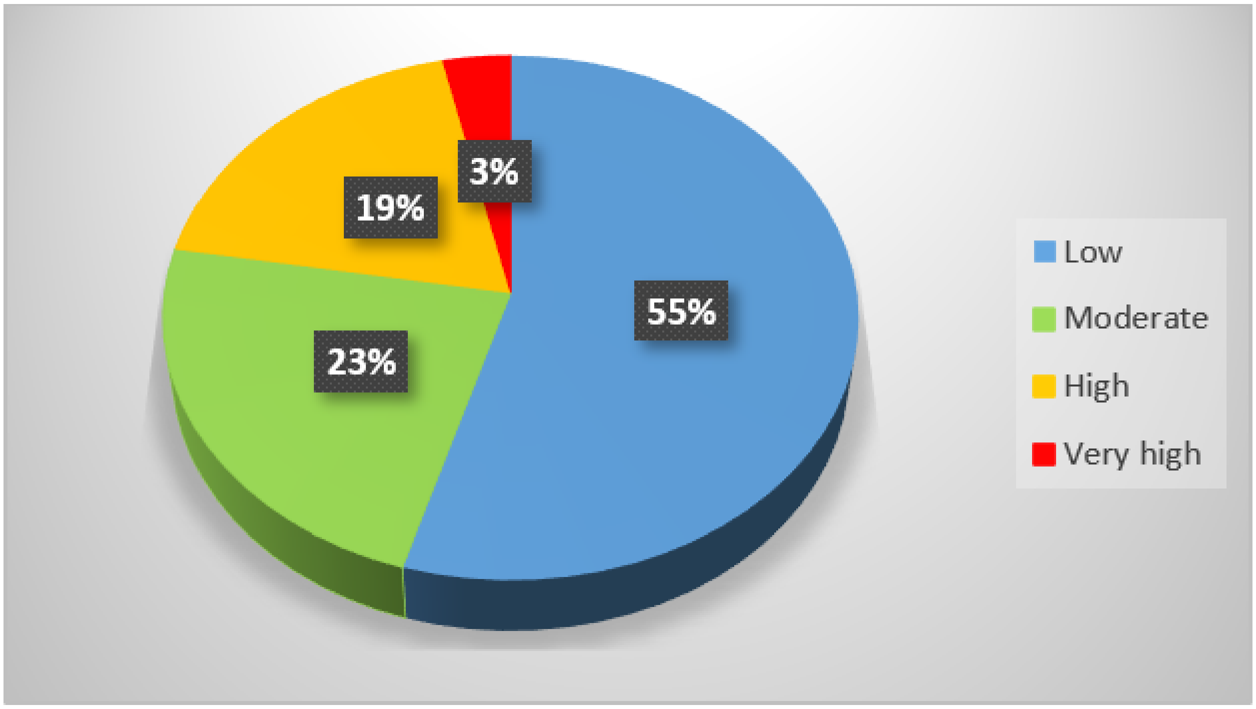
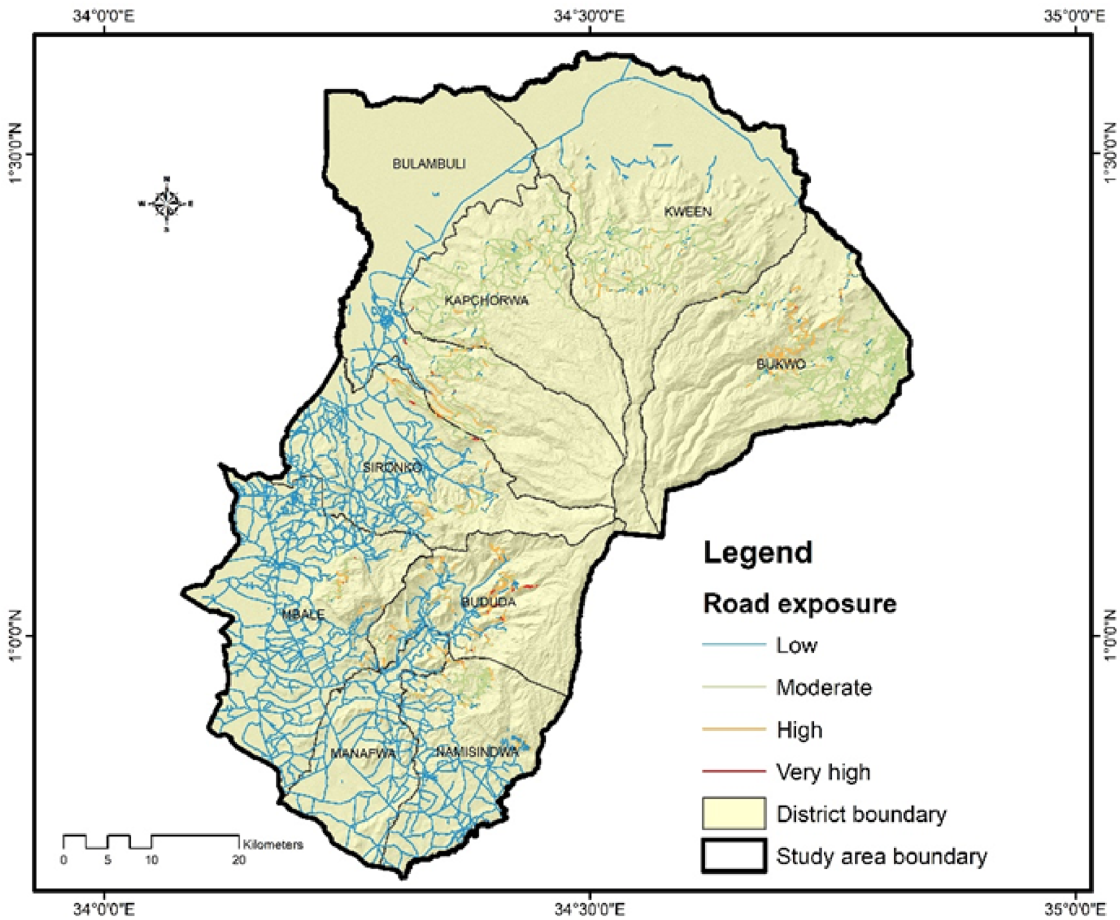


Figure 6

Percentage area by class category of landslide susceptibility



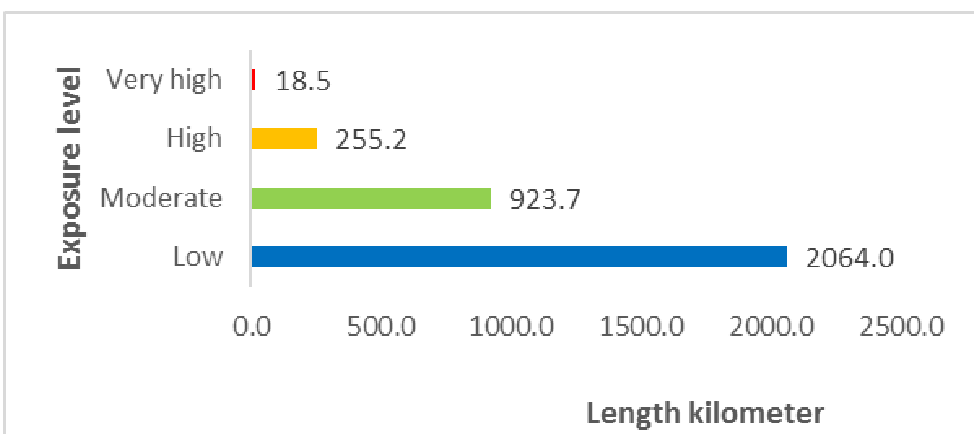


Figure 7

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

(b)Road network length exposed by LSM category classes

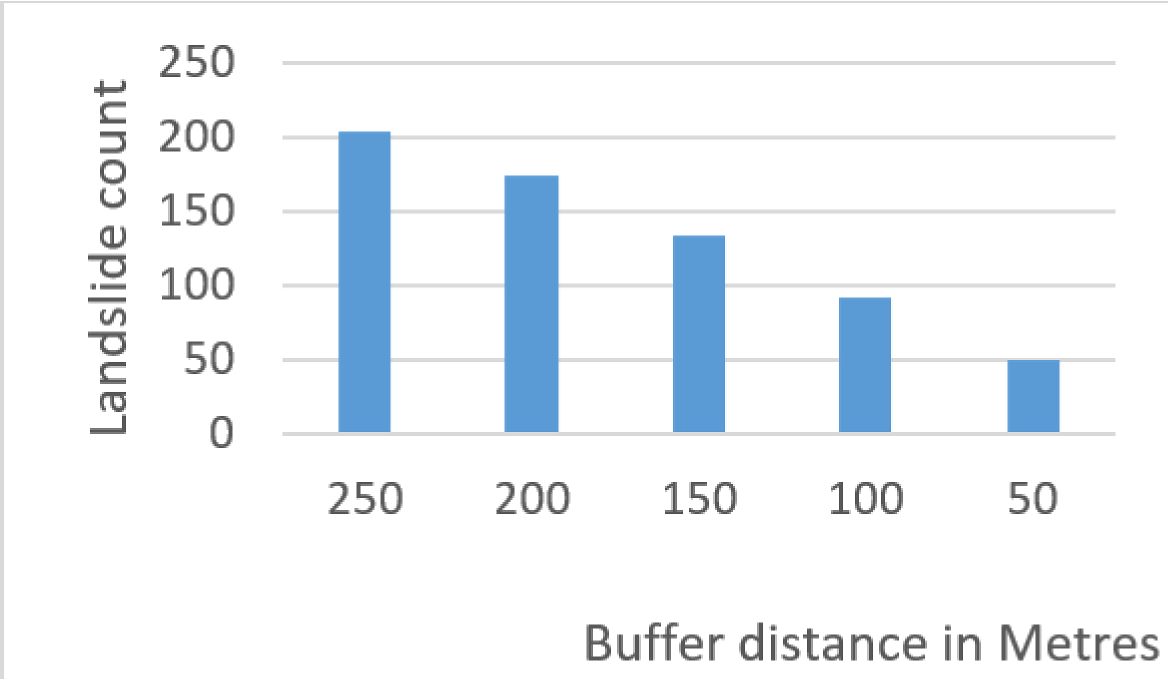


Figure 8

Landslide occurrence by road buffer distance in Mt Elgon region

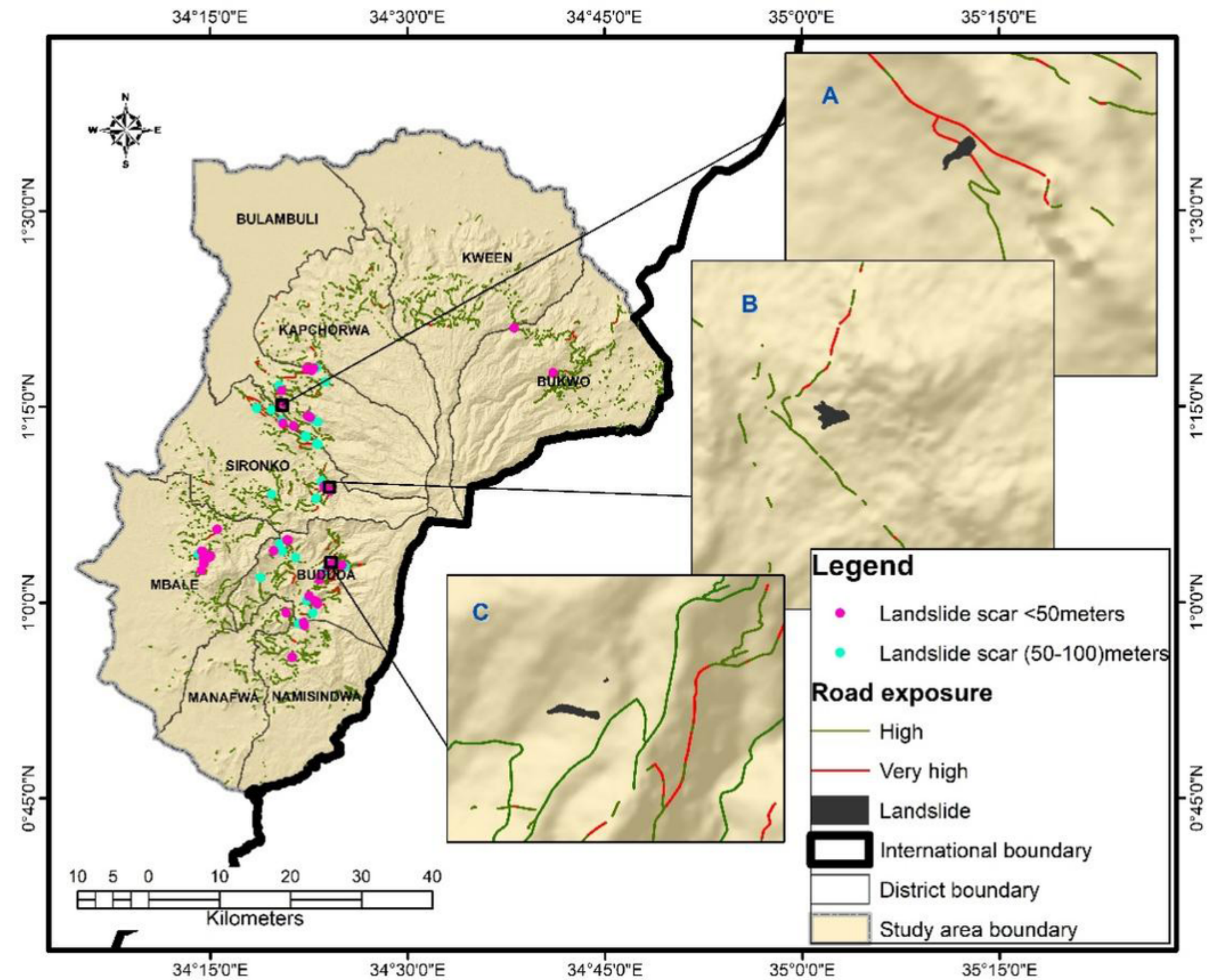


Figure 9

Road network exposure hotspots in Mt Elgon region

Figure 10

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.

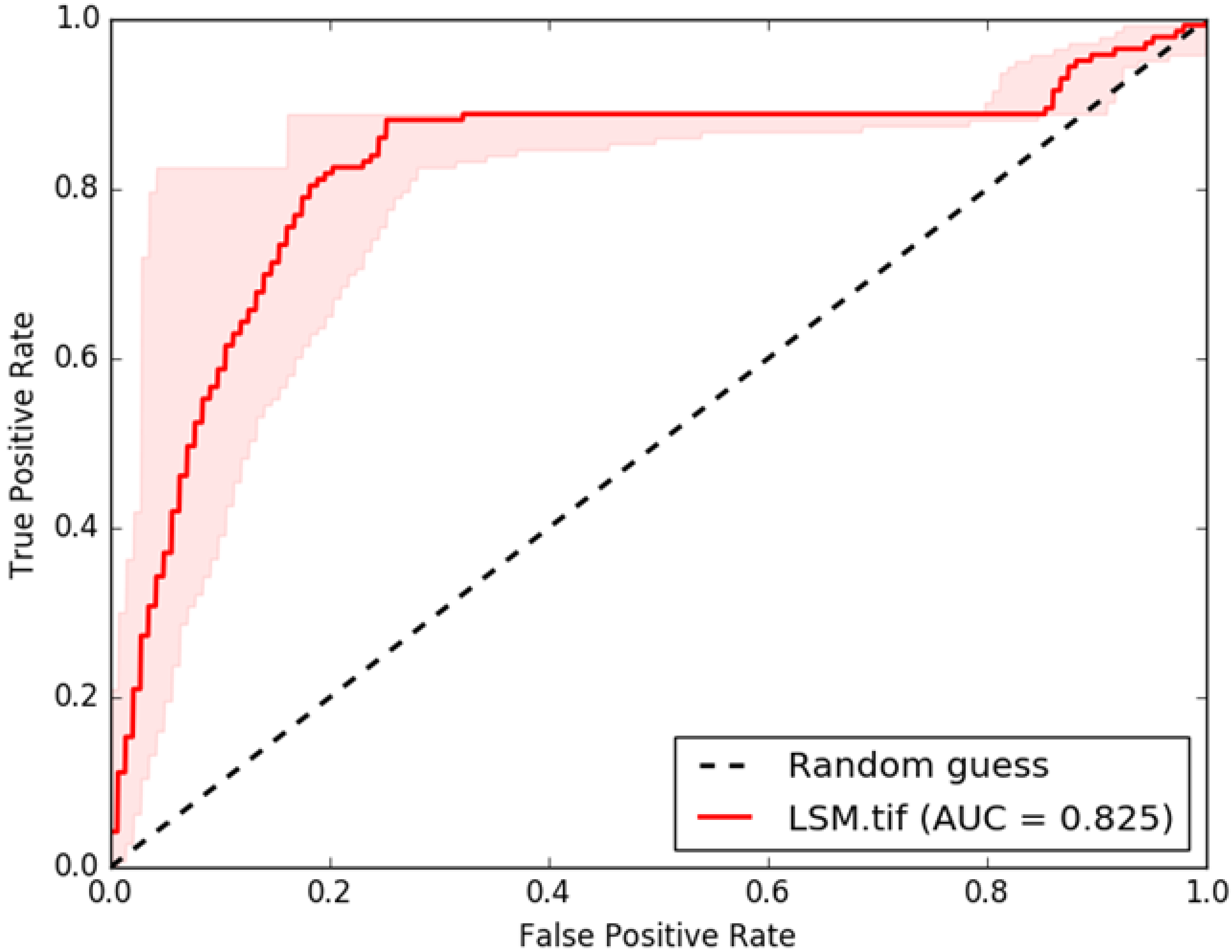


Figure 11

ROC curve for fuzzy LSM