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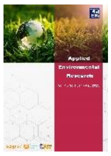

Research Article

Assessment of Landslide Susceptibility and Settlement Exposure via Geospatial Techniques in Bulambuli Distrcit, Eastern Uganda

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Abstract

Landslide susceptibility is a significant concern in Elgon County, Uganda, particularly during the rainy season. This vulnerability is attributable to several factors, including steep slopes, fertile soils, and dense settlements on volcanic ridges. Landslide susceptibility maps are important in mitigating the risk particularly at the local level. The objectives of this study were 1) to model landslide susceptibility via an interpretable machine-learning model, 2) to identify the most influential factors for landslide susceptibility in the study area, and 3) to assess the exposure of settlements to landslide risk. This study employed the XGBoost model trained on nine conditioning factors via GIS data. Exposure analysis was performed through the zonal statistics and spatial overlay of the landslide susceptibility map with the settlement footprint data and classified into four risk exposure classes. The results show that the XGBoost model attained an AUC of 95.2%, indicating its precision. The results further revealed that approximately 50% of the slopes are susceptible to landslides and that 76% of the settlements in the study area are highly exposed to landslide risk. Bulugunya, Sisiyi, Lusha, and Buginyanya subcounties located on the middle slopes are the most susceptible areas in Elgon County and have relatively high settlement exposure because of the overlap of dense settlements with unstable terrain. The SHAP analysis identified slope, elevation, and the NDVI as the key influencing factors of susceptibility. This study highlights the importance of conducting detailed, local-scale landslide susceptibility and risk exposure mapping as necessary for risk and vulnerability assessment. The generation of such maps has the potential to inform land-use planning and risk-reduction strategies, thus offering significant advantages over regional models. Furthermore, by interpreting the XGBoost model, this study provides valuable insights into the decision-making processes of machine learning models, promoting their practical application in designing appropriate disaster mitigation plans.

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Introduction

Landslides are among the most significant natural hazards affecting mountainous regions worldwide [1–2]. Landslides involve the mass flow/movement of rocks, debris, and earth downslope [3]. The estimated financial impact of these events on property damage is approximately US$4 billion per annum [4]. The continents of Asia, South America, and Africa have been particularly badly affected, with significant impacts on livelihoods as a result of their economic, social, political, and cultural vulnerabilities [5]. Landslides pose a serious hazard to densely populated mountainous areas in

Africa, including the Democratic Republic of the Congo, Uganda, and Cameroon [6].

The Sendai Framework is centered on promoting an enhanced understanding of disaster risk and governance [7] and emphasizes enhancing communities' disaster resilience. Detailed landslide inventories and landslide susceptibility (LSS) maps are considered indispensable tools for mitigating landslide risk. However, the absence of such data in many African countries has been identified as a significant impediment to the implementation of effective risk-reduction strategies [8]. Despite the absence of quantitative exposure evaluations in the creation of focused mitigation strategies and the allocation of resources, landslide susceptibility maps offer valuable insights into hazard potential [9].

The United Nations (UN) Sustainable Development Goals (SDGSs) prioritize community welfare, sustainable land use, and disaster resilience [10]. Landslide disasters result in enormous destruction of homes, farmland, and livelihoods, which impedes progress in attaining SDGs, especially SDGs 1 (no poverty) and 2 (zero hunger). Additionally, due to exposure due to settlement on unstable slopes, landslides also undermine SDG 11 (sustainable cities and communities) and impact SDG 3, which concerns good health and well-being due to deaths, injuries, and relocation. This research, therefore, contributes to the SDG agenda by offering creative geospatial modeling and emphasizing the need for local-scale risk assessment for development in the Bulambuli district.

The Mt. Elgon region of eastern Uganda is a relatively understudied region, with limited research on landslide susceptibility and exposure. The majority of landslide studies are case-specific in nature, with a focus on factors such as farmers' perceptions of landslides [11], soil and sediment yield [12], land use changes in landslides [13], and the topographic influence on landslides [14]. Several studies have addressed the issue of susceptibility, albeit at different geographical scales, LSS, and mobilization rates for the entire Mount Elgon region [1], susceptibility to road networks [15], and susceptibility of people with disabilities [16]. In relation to vulnerability and exposure, there is a paucity of research in this region. [17] studied the vulnerability of elements at risk in the Manafwa River catchment, and [8] studied the exposure of schools to landslides in the Bududa district. In other studies, the focus has been on the exposure of buildings in urban areas [18–19]. Urban areas, particularly in developed countries, are characterized by increased resilience levels. Consequently, the generalisability of such studies to developing countries, which are often associated with remote settlements on mountain slopes, is limited.

The Bulambuli District is located within the Mount Elgon region in eastern Uganda. This region is susceptible to landslides triggered by rainfall, which occurs almost annually during the rainy season [15,20]. The area's topography is characterized by rugged terrain, heavy rainfall, rapid erosion, and high population density [17]. These factors contribute to frequent landslides, often resulting in fatalities and significant livelihood disruption (e.g., damaged homes, farmland, and infrastructure). For example, on 29 November 2024, a landslide resulted in more than 28 fatalities and left several others missing (Figure 1). The region is subject to various mass wasting events, including rockfalls, mudslides, and landslides, which have been shown to result in severe consequences [1, 17]. Following the catastrophic Nametsi landslide, which resulted in the demise of more than 365 individuals in 2010 [13], the government of Uganda initiated a series of population relocation programs. This strategic intervention was intended to address overcrowding in upper Bududa slopes by relocating affected residents to specific areas within the Bulambuli district. This initiative has been met with several challenges [17], with people being unwilling to move to likely changes in social, cultural, political, and economic livelihoods. The region is considered one of Uganda's most densely populated areas, favored by its conducive climate and fertile soils. The distribution of settlements, which are predominantly composed of temporary structures dispersed across entire mountain slopes, has been identified as a contributing factor to high-risk exposure. Proposals for restructuring settlements into mini towns have been developed to increase their resilience to landslide hazards [17]. To complement the studies above, comparable research focusing on the effects of land use change and planning on landslides in mountainous areas highlights how integrated land use can reduce exposure to hazards, whereas deforestation, agricultural expansion, and unregulated settlements may exacerbate slope instability [21–23]. This indicates the urgency of applying geospatially informed planning techniques in Bulambuli, where land use and settlement expansion are unregulated, increasing the risk of landslides.

The geographical bias inherent in these LSS studies is evident, with a preponderance of research focusing on the Bududa District, whereas the other districts within the region receive comparatively less attention. Furthermore, none of these studies have focused on mapping LSSs via an interpretable model at the local scale, nor have they attempted to provide a comprehensive overview by assessing risk in the form of settlement exposure. It is imperative to recognize the pivotal role of local-level maps in comprehending risk and formulating suitable mitigation strategies, such as establishing early warning systems and planning resettlement reforms. This phenomenon is especially evident in Bulambuli, a resettlement area designated by the government of Uganda. Landslide exposure mapping is a rarely implemented tool that is nevertheless important for informing land use planning, establishing risk management policies, and implementing risk mitigation strategies [24]. The evaluation of risk necessitates the identification of potential hazards, the identification of elements that are susceptible to risk (or exposure), and the determination of their vulnerability.

LSS maps can be produced swiftly via machine learning models, given the automation associated with machine learning. However, their utility can be hampered by failure to comprehend how the model decisions are made (black-box models). Therefore, LSS model interpretability has become a key aspect of LSS studies to increase the practical utility of model outputs, especially given that maps may not conform to existing field conditions, resulting from inventory data bias. Recently, many model explanation techniques have emerged, including Shapley additive explanations (SHAPs), partial dependence plots, and permutation feature importance plots. These techniques, also known as post-hoc explanations, have been successfully used in various fields, including medical diagnosis, legal decision-making, and LSS mapping [25–26]. Post hoc explanation methods can help us understand how machine learning models predict landslides. This makes these complex models easier to understand. However, there is a dearth of research on the effective application and interpretation of these methods, specifically for landslide susceptibility analysis. Most studies have employed pretraining variable importance analysis [27–28], the Gini index [29], and partial dependency plots [30]. However, such analysis is not diagnostic and therefore provides no insights into the decision mechanisms of the machine learning model [31]. Pradhan et al. [25] applied SHAP summary and dependence plots to analyze the local and global contributions of individual features in their study. Nevertheless, the challenge is interpreting such plots by the end users, given their lack of familiarity with model interpretation techniques. Furthermore, given that standard SHAP outputs are purely local, applying them in thematic analysis may be challenging. To address this limitation, this study adopts a multi-resolution SHAP analysis that considers individual contributions and thematic global effects on the basis of aggregated feature groups. It is expected that this will enhance usability by making model outputs more accessible and actionable for both technical experts and practitioners.

To address the knowledge gaps identified, the objectives of this research are as follows: (1) to create the first higher-resolution LSS map for Elgon County, (2) to identify the most influential landslide conditioning factors through multiresolution SHAP analysis, and (3) to assess the settlement exposure to landslide risk, which is the first of its kind for the study area. These findings help to further refine our understanding of landslide hazards in the area and their most significant conditioning factors. Furthermore, these findings will be instrumental in evaluating landslide risk reduction strategies and informing policy decisions about land use planning, infrastructure development, settlement patterns, and agricultural practices. This work will also further the utility of SHAP-based interpretation in landslide modeling via machine learning.

Materials and methods

1) Study area

The present study was conducted in Elgon County, which is part of the Bulambuli District in the Elgon subregion of Eastern Uganda. The Bulambuli District is situated on the eastern slopes of the Mt. Elgon landscape, an extinct shield volcano believed to have formed during the late Miocene era. Elgon County is bordered by Sironko District to the south, Bulambuli County to the west, Kapchorwa District to the north, and Kween District to the east (Figure 2). The highest peak of the mountain is located at an altitude of 4,321 m above sea level [15, 32]. The district is composed of two counties, which are divided into two distinct physiographic zones: the upper mountain zone, also known as Elgon County, and the lower Bulambuli County, which is characterized by extensive plains that extend up to Lake Bisinia and is situated at an elevation of 1000 m above sea level. [20]. The district's population is approximately 230,000 people, predominantly residing on fertile slopes in Elgon County. Geomorphologically, Bulambuli is distinguished by a contrasting relief characterized by cliffs, ridges, steep and gentler slopes, and river valleys occupied by major rivers draining the area. The upper part of the county, extending toward the mountain peak at altitudes above 2,300 m, is characterized by a dense cover of natural vegetation, forming the protected expanse of Mount Elgon National Park. In contrast, the lower plains in Bulambuli County are characterized by a preponderance of cropland and settlements.

The study area is characterized by a tropical climate, marked by high annual precipitation levels that exceed 1,500 millimeters [33]. The region is further divided into two distinct wet seasons, with the wettest months being from March to December and the drier season running between December and March. The rainfall patterns are influenced by the prevailing winds, location, and altitude. The area experiences a high mean annual temperature of 23°C and average daily maximum and minimum temperatures of 28°C and 15°C, respectively [34].

Figure 1 Examples of landslides and their impacts in Bulambuli District. (a) Mudslide that killed more than 28 people in Masugu village (1.217441^0 N, 34.368746^0 E). (b) Damaged mud and wattle houses due to a recent landslide in Elgon County (1.217441^0 N, 34.373852^0 E).

The geology of the Mount Elgon region is characterized by the presence of ancient gneiss and granitic rocks. [35], which are dated to the Precambrian era. Additionally, younger carbonatite rocks of intrusive volcanic origin have been identified, estimated to be Oligocene to early Miocene in age, and they are believed to cover southern slopes. The rocks are weakened due to rock porphyrites and geological alteration [35]. These rocks are very susceptible to weathering processes, erosion, and landslides [32]. Scoon [35] reported that lava flows comprising nephelinite and basalt rocks, along with pyroclastic materials such as agglomerates and tuff, are predominant in the area. It is estimated that the last volcanic activity in the Mt. Elgon region occurred approximately 12 million years ago. In addition to the presence of volcanic rocks, the area is characterized by the prevalence of sedimentary rocks, particularly within the valleys of the numerous rivers originating from the mountain peak.

The area is characterized by deep, fertile, and well-drained soils of volcanic origin, which exhibit a dark and red complex. The prevalent soil texture in the region is clay, with clay loams and sandy clay loams also present. During the rainy season, the soil becomes exceedingly adhesive [36], a property that contributes to their elevated water retention and nutrient-holding capacity. This results in significantly denser soils, leading to increased susceptibility to landslides during the wet season, particularly on middle slopes, which experience a greater frequency of landslides than upper slopes do. The area is drained by two primary rivers, Simu and Sisi, and their tributary streams, which originate from the mountain summit and descend into the Sironko River before discharging into Lake Bisinia.

The major land use categories in the Bulambuli District include croplands, planted forests, natural forests, barren terrain, and built-up areas. Crop cultivation is the predominant agricultural practice in this region and is undertaken by smallholder farmers. This activity is primarily concentrated on slopes less than 2,000 m above sea level. Owing to rapid population growth, agricultural activities have encroached upon extant natural conservation areas. Indeed, a notable expanse of formerly forested land has been converted into areas suitable for crop and pasture cultivation over the past two decades [13]. It is hypothesized that this phenomenon is partly responsible for the degradation and erosion of land, which in turn leads to the instability of slopes.

2) Data

The present study utilized nine landslide conditioning factors/variables to model landslide susceptibility. These variables included seven topographic variables, namely, slope, elevation, topographic wetness index, relative slope position, aspect, profile, and plan curvature. In addition, a hydrological/distance variable (distance to stream) was utilized, with the understanding that only first-order and second-order streams were considered. Topographic and hydrological parameters were considered in this study on the basis of the literature and data access. These variables are crucial determinants of slope stability in the Elgon region [1,15]. Slope determines the gravitational force with which slope material is transported downslope. The steeper the slope is, the greater the chance of landslides. Elgon is dominated by slopes between 50 and 500 [33]. The slope influences the soil moisture retention capacity and microclimate through rainfall and solar energy. The angle of the slope determines the amount of solar radiation received on the slope, which affects the soil moisture retained in the soil. Soils with high moisture retention are susceptible to landslides because of the added weight from the soil water. Elevation is another frequently used variable in LSS studies since the coefficient of elevation variation in an area affects the probability of landslide occurrence. Regions characterized by hills and mountains, such as Elgon County, are more prone to landslides than relatively flat terrains. Relatedly, the relative slope position also influences the susceptibility of a slope to landslides. It is used to determine where the slope lies, i.e., near the ridge, in the middle slope, or valley bottom, and influences water accumulation, sediment movement, and stress distribution across the slope. Upper slopes are more prone to runoff flow, which may initiate shallow slides; the middle slope experiences erosion and deposition, making it prone to translational slides. The valley bottom/lower slope experiences more infiltration and deposition, which makes it less stable during the rainy season. Landslide density is highest on the lower and middle slopes because of higher moisture levels, sediment accumulation, and heightened instability [37].

Other variables include the normalized difference vegetation index (NDVI), which is used to measure the extent and condition of vegetation. Vegetated slopes are less prone to landslides than are bare slopes. The NDVI was derived via the Sentinel-2 bands (B4 -Red) and (B8 – Near infrared). The distance to a river or stream was also incorporated into the model as an indicator of slope instability. Rivers influence slope stability through erosion and incision; therefore, slopes nearer to streams are more unstable than those farther away. The topographic wetness index (TWI) measures the spatial distribution of water within a specific slope. This indicates the risk of landslides, as wet and heavy slopes are more susceptible than drier slopes are [38]. Curvature (profile and plan) is another conditioning factor used in this study. Plan curvature is defined as the measure of changes in the slope direction in the horizontal plane. Positive values indicate convex surfaces (e.g., ridges), whereas negative values indicate concave surfaces (e.g., hollows) [39]. Profile curvature is defined as the measurement of changes in the slope direction that are parallel to the steepest slope. Positive values indicate convex profiles, whereas negative values indicate concave profiles [40].

The aforementioned variables (Figure 3) were derived from the digital elevation model (DEM) via SAGA GIS at a resolution of 12.5 m. Stream distance was derived via Euclidean distance in ArcMap. The NDVI was derived from the Sentinel-2 image via surface reflectance values in the Google Earth Engine. The NDVI was selected to represent land cover, as it is a critical factor in slope stability and because part of the study area is a protected conservation forest. Soils and geology were not considered because of the coarse spatial resolution of the available data; the study area is classified as having uniform lithology and soil. All the variable maps were resampled to a uniform resolution of 12.5 m. A list of the variables and their respective data sources can be found in Table 1.

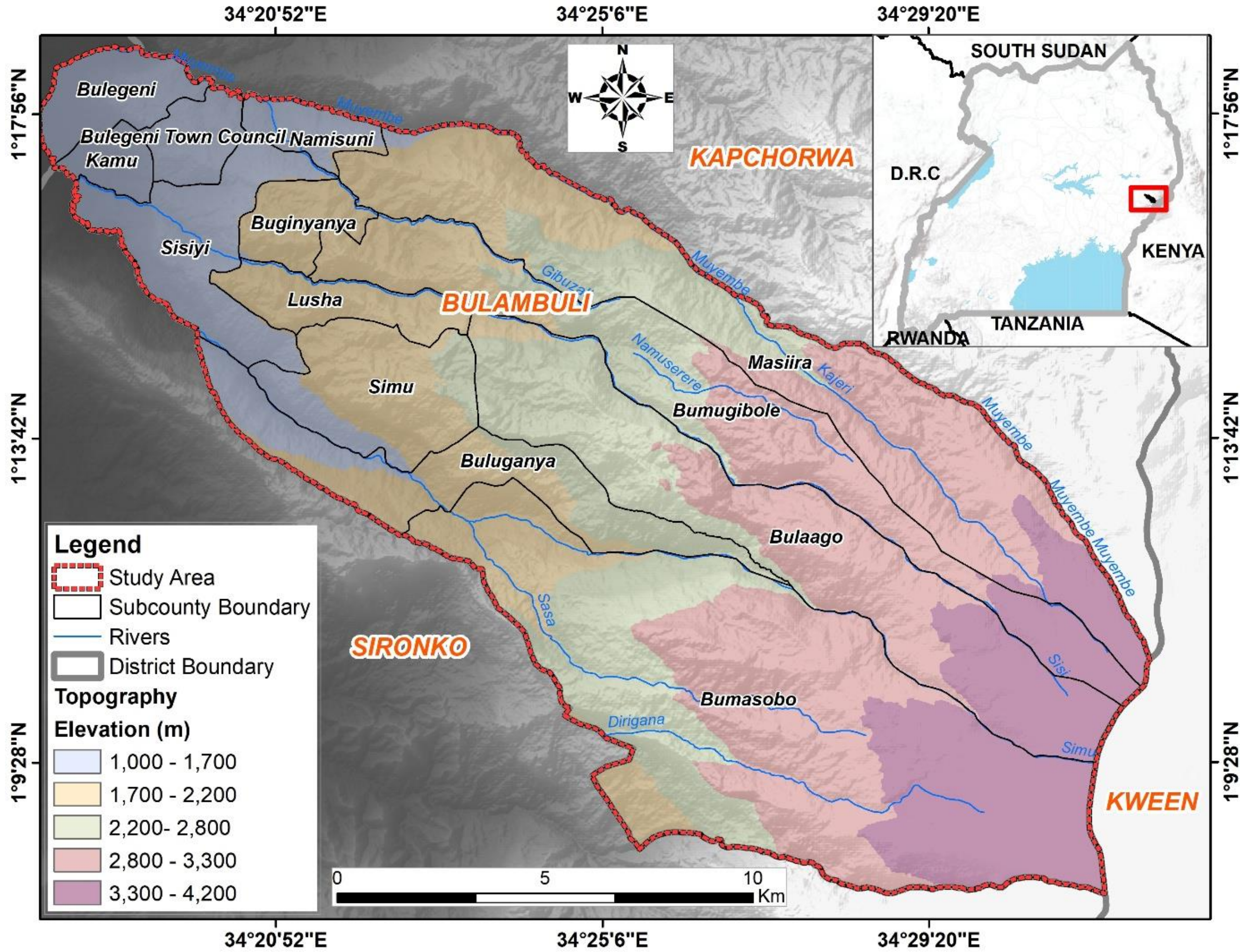

Figure 2 Study area, Elgon County, Bulambuli District.

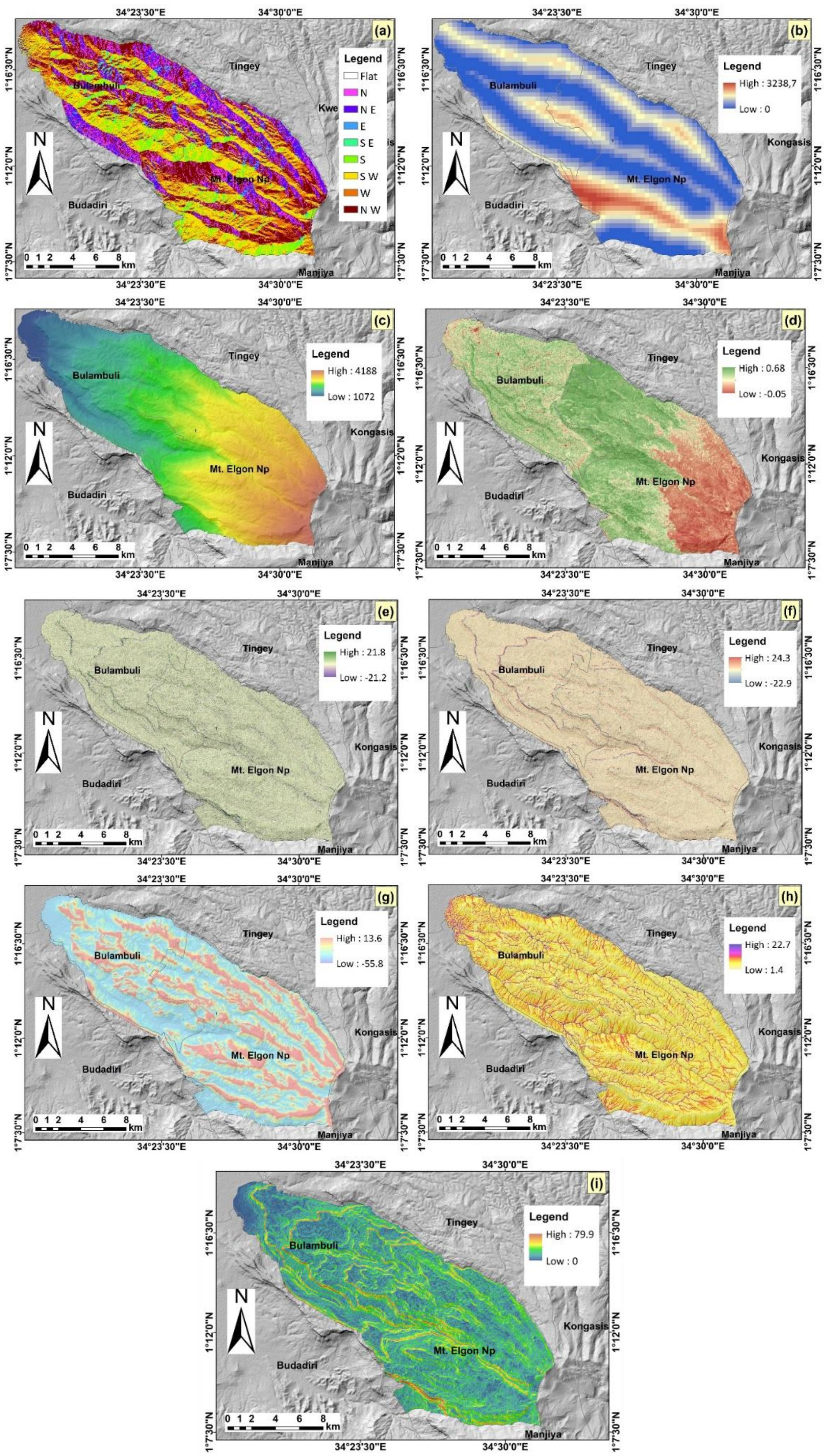

Figure 3 Landslide conditioning factors including (a) aspect, (b) distance to the stream, (c) elevation, (d) NDVI, (e) plan curvature, (f) profile curvature, (g) relative slope position, (h) topographic wetness index, and (i) slope.

Table 1 Description of the datasets used in the study and the variables

Dataset	Source	Derived variables	Resolution
ALOS Palsar DEM	The DEM was obtained from the Alaska satellite facility (https://asf.alaska.edu/)	• Elevation • Slope • TWI (Topographic wetness index • Relative slope position • Aspect • Profile curvature • Plan curvature • Distance to the river	12.5 m
Sentinel-2A	Google Earth Engine	• NDVI	10 m
The settlement footprints	The world settlement footprint (https://geoservice.dlr.de/web/maps/eoc:wsf2019)	• Lithology • Distance to Faults	10 m
Landslide database	Broeckx et al. [1]	• Landslide and nonlandslide points	30 m

The present study utilized a landslide database that was meticulously compiled by [1] and made available as supplementary material. This database was then updated via Google Earth images. A total of 181 landslide and rockfall locations were obtained for the designated study area. A scale of 1:1 was then used to generate 181 nonlandslide points randomly in ArcMap. For model training, an 80:20 split was employed to create training and testing datasets.

The World Settlement Footprint data [41] were used to extract the settlement footprint for Elgon County. These 2019 data use information from the Copernicus Sentinel-1 and Sentinel-2 spacecrafts to provide unparalleled detail and precision regarding human settlements worldwide. These data were used to assess landslide exposure impacting the settlements. The reliability of the data was verified by display on the Google Earth platform for review. The results of the exposure assessment were also verified via a recent preliminary report on landslides and affected households.

3) Methods

3.1) XGBoost landslide susceptibility model

The present study employed the extreme gradient boosting (XGBoost) machine learning model to derive landslide predictions for Elgon County in Bulambuli District. This ML model was chosen because of the capabilities afforded by its tree boosting learning strategy, which has made it one of the most popular models for regression and classification tasks, such as LSS mapping [42–43]. Owing to its efficient parallel processing, optimized memory usage, and effective handling of sparse data, the XGBoost model is considered to be more accurate than linear models but more difficult to interpret [26]. The XGBoost model predicts LSS through an iterative process involving sequentially structured decision trees. These decision trees derive predictions sequentially, with each tree outputting a prediction and an error score. These error scores eventually constitute the final prediction error. Similarly, the prediction process involves progressively adding the predictions from individual decision trees to the previous prediction to improve accuracy.

To obtain a satisfactory result, we trained the model for a specified number of boosting rounds, where the 10-fold CV strategy was employed. The CV is essential for model generalization and preventing overfitting [44]. To obtain optimal model parameters and enhance the robustness of the model, we conducted a thorough hyperparameter grid search. The hyperparameter values used in the grid search included the following: learning rate (0.001, 0.1, 0.3), maximum tree depth (3, 5, 7, 10), minimum child weight (1, 3, 5), subsample ratio (0.6, 0.8, 1.0), column sampling per tree (0.6, 0.8, 1.0), number of boosting rounds (100, 200, 500), and gamma regularization (0, 1, 5). Model performance evaluation utilized the area under the curve of the receiver operating characteristic (ROC AUC). The ROC curve is derived from the model's specificity and sensitivity to predictions. These metrics were selected because they quantify the model's ability to distinguish between positive and negative classes [45]. The higher the AUC score is, the better the model's performance. The trained model was used to predict the LSS and produce LSS index values. These were then classified via the equal interval method in ArcMap to produce the LSS map. The choice of the equal interval method to classify the landslide susceptibility index was based on the ability of the approach to produce uniform class ranges that facilitate comparisons of susceptibility across the study area. Unlike quantile classification, which may incorporate highly dissimilar susceptibility values within the same category, or natural breaks, which are dependent on certain distributions of the dataset, equal intervals offer clarity and consistency both for technical and nontechnical stakeholders [45–46]. Such clarity is particularly critical in local-scale risk communication, in which consistency and understandability are important objectives.

3.2) Model interpretation via Shapley additive explanation (SHAP)

To gain insights into decision mechanisms and overcome the 'black-box' nature and complexity of ML models, the present study employed SHAP values. The purpose of model interpretation is to increase the practical utility of the model outputs. This is achieved by indicating whether the results are geomorphically plausible and by rendering the outputs more comprehensible to planners and policymakers. The SHAP method was introduced by Lundberg and Lee [47] after being inspired by game theory. The use of SHAP facilitates the elucidation of the influence of a landslide conditioning factor on model prediction. The SHAP value, which is defined as a measure of a feature's contribution, is derived via Eq.1. During the training or testing of a model, each sample is subjected to prediction. SHAP subsequently calculates a "SHAP value" for each feature within a given sample, thereby indicating the feature's contribution to the prediction. Models that demonstrate high performance in training environments may exhibit suboptimal performance in real-world scenarios because of an absence of interpretability [25]. Scholars widely acknowledge that a model's predictive accuracy alone does not guarantee its reliability [48–50]. To enhance the generalisability and credibility of machine learning applications, it is necessary to improve the interpretability of these "black box" models. It is imperative to comprehend the rationale underpinning a model's predictions to ascertain its reliability and address any potential biases or aberrant behaviors. The following equations, as proposed by Chen & Guestrin [51], were used to derive the SHAP values. Eq.1 calculates the contributions of individual features, whereas Eq.2 aggregates the values of individual features on the basis of feature category to obtain the global importance of each landslide conditioning factor group/category.

$$\left(x^{(i)}\right) = \phi_0 + \sum_{j=1}^{M} \phi_j^{(i)} \qquad \text{(Eq.1)}$$

$$\text{SHAP}_{C_k} = \frac{1}{n}\sum_{i=1}^{n} \sum_{j\in\mathcal{J}_k} \left|\phi_j^{(i)}\right| \qquad \text{(Eq.2)}$$

where $f(x^{(i)})$ represents the model's prediction for the input i, $\Phi_j^{(i)}$ is the SHAP value, M is the number of input features, and c_k denotes the global contribution to the model's predictions.

In this work, the multiresolution SHAP model was used to interpret the model in terms of feature importance, which was grouped into 3 categories: topography factors, hydrology, and vegetation, and factor interactions were analyzed. The SHAP model was implemented in the RStudio environment via the "SHAP" library.

3.3) Settlement exposure to landslide risk

Disaster exposure is defined as the location of people, infrastructure, and other human assets in hazard/disaster-prone areas [52]. This can be defined on the basis of the number of people or settlements, vital infrastructure, or types of assets. Exposure is one of the aspects that makes up disaster risk (risk = exposure × hazard × vulnerability). Therefore, it forms a vital part of vulnerability and risk assessment. We assessed landslide risk to settlements by overlaying a landslide susceptibility map with the settlement location data. Zonal statistics were computed to determine the percentage of settlements in each susceptibility zone. This helped us to classify the levels of settlement exposure to landslides in Elgon County. This was classified into four classes: low, moderate, high, and very high exposure. Verification of the results was performed by comparing our classification results with a preliminary disaster report of the district disaster management committee, adopting an approach used by Luu et al. [9].

Results

This section discusses the results of landslide susceptibility mapping, model accuracy, model explanation, and assessment of settlement exposure.

1) Landslide susceptibility mapping

The trained XGBoost model was applied to raster maps to derive the landslide susceptibility index. To facilitate enhanced visualization, landslide susceptibility maps were developed within an ArcGIS environment, wherein susceptibility was categorized into four distinct landslide susceptibility classes through the implementtation of the equal interval method (Figure 4). As indicated by the cartographic representation, the regions designated high and very high susceptibility to landslides were confined to the mid-altitude zone (1,400-1,700 m asl) within the subcounties of the districts of Buginyanya, Bulugunya, Simu, Lusha, and Masiira. The higher altitude slopes are covered by the Mt. Elgon National Park conservation forest area, which is associated with very low susceptibility. The prevalence of low susceptibility has been observed in the lower elevation area encompassed by low-lying wetlands. The percentage area coverage per susceptibility class was computed as illustrated in Figure 5. The low-susceptibility group presented the highest percentage of LSS (52%), followed by the very high-susceptibility group (20%) and the moderate-susceptibility group (17%). The lowest area category was designated high susceptibility (11%). Upon aggregation, it becomes evident that the proportion of slopes demonstrating susceptibility to landslides is nearly equivalent to those exhibiting no such susceptibility. This observation is particularly pronounced when considering susceptibility levels categorized as high, moderate, and very high. It is also evident that the ridges characterized by steep slopes predominate in the high-susceptibility classes, whereas the largest area exhibiting low susceptibility is the conservation forest zone. This observation underscores the importance of forest cover in maintaining slope stability.

2) Model accuracy

In this study, the ROC curve was used to evaluate the efficacy of a landslide susceptibility prediction model. The ROC metric is frequently used for evaluating the performance of machine learning models. The AUC value of the ROC curve provides a quantitative representation of the model's accuracy in distinguishing between classes ranging from 0 to 1, with higher values indicating higher accuracy and reliability. An AUC value greater than 0.7 is indicative of a credible model [28]. The XGBoost model used in this study yielded an AUC value of 0.95 (Figure 6), indicating the model's ability to discriminate between landslide-prone areas and nonlandslide-prone areas.

3) Model explanation via SHAP

In the present study, SHAP values were applied to compute feature importance/contribution to the prediction result of the model and interaction between a selected pair of features via the SHAP dependence plot. The SHAP summary plot in Figure 7 shows the contributions of individual factors to the model predictions. The plot shows that slope and elevation strongly influence landslide occurrence in Elgon County. Higher altitudes generally have a lower landslide risk, whereas steeper slopes increase the risk. Slope influences the model prediction both positively and negatively, depending on the specific slope angle value, given the widespread of SHAP values in both the positive and negative directions. While slope angle is a major conditioning factor, the SHAP plots reveal that the NDVI and aspect also significantly contribute to landslide susceptibility in Elgon County or Bulambuli District. Areas with low NDVI values, which indicate a scarcity of vegetation, are associated with increased susceptibility to landslides, whereas areas with high values (indicating dense vegetative cover) are less susceptible to landslides. Furthermore, the plots show that the TWI and profile curvature are the least important features, with significantly lower average SHAP values (0.271 and 0.291, respectively). However, the narrow range of their values may suggest that these features have a more consistent influence on the model predictions. The plot further indicates that as the distance from the stream increases, the susceptibility levels also decrease, which is an indicator of the marked influence of stream erosion and incision on landslide occurrence in the Bulambuli District. The relative slope position is an equally important predictor in this area, with ridges and middle slopes being more prone to landslides than the valley bottom. However, the importance of this feature is clearly dependent on other features, such as slope steepness, elevation, and vegetation cover.

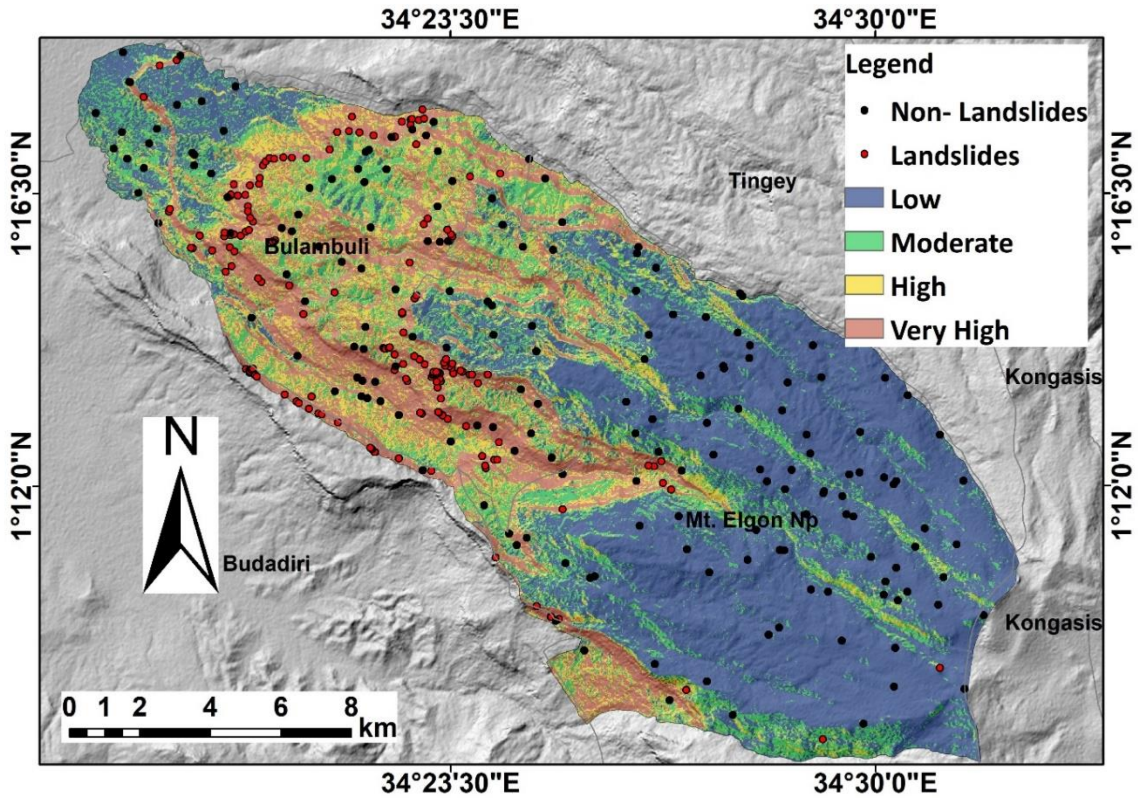

Figure 4 Landslide susceptibility map of Elgon County, Bulambuli District.

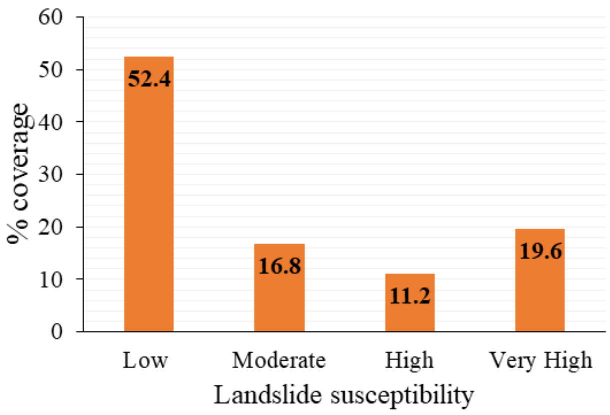

Figure 5 Percentage area per landslide susceptibility class in Elgon County.

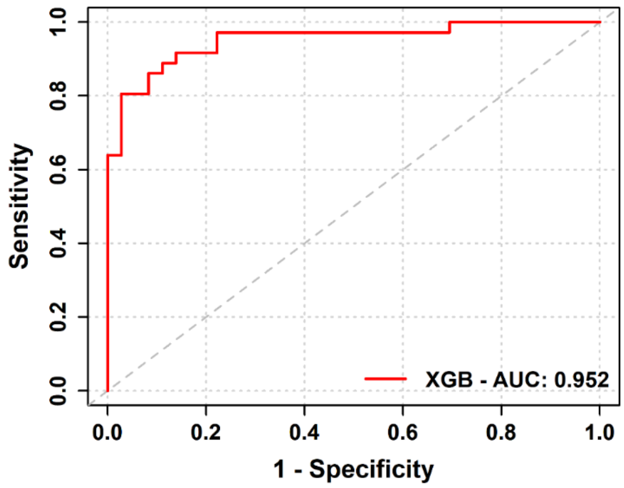

Figure 6 Area under the receiver operating characteristic curve as a measure of model performance.

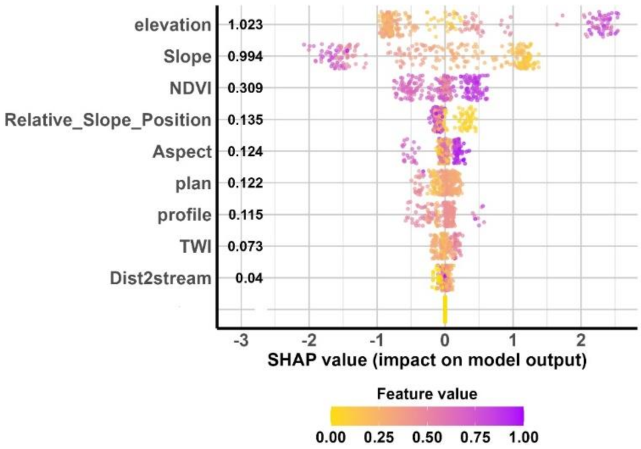

Figure 7 SHAP summary plot for the training data.

Furthermore, an analysis of the global SHAP contribution based on a grouped category of the landslide conditioning factor maps (Figure 8) corroborates these findings, underscoring the significance of the topographic variables in determining slope stability in this area. The vegetation factor is the second most influential factor, whereas hydrology is the least influential set of parameters. As illustrated in Figure 8, the global feature importance is based on absolute SHAP values, with each bar illustrating the contribution of each feature. The values indicate the average impact of each variable on the model's predictions, irrespective of the direction of influence, as is usually indicated in the SHAP summary plot. It is generally accepted that higher SHAP values are indicative of a feature that significantly contributes to the model's output. The green bars represent topographic variables, the blue bars represent vegetation factors, and the red color denotes hydrological factors. The color grouping is deemed suitable for thematic interpretation, which supports easy interpretation and geomorphic plausibility and may facilitate the prioritization of factors for future monitoring and field validation. Among the topographic factors under consideration, slope and elevation clearly contributed most significantly, followed by elevation. Conversely, aspect and curvature were found to be the least contributing factors. The NDVI demonstrates equivalent levels of contribution, whereas hydrological factors (i.e., distance to the nearest watercourse and the total water index) exhibit the least significant levels of contribution.

4) Assessment and verification of settlement expousre

Figure 9 shows the exposure of settlements to landslide risk zones. The low-exposure class for settlements in the Bulegeni subcounty comprises the smallest portion. The settlements in other subcounties are categorically classified as moderate, high, and very highly exposed. Figure 10 shows the percentage of settlements in the different landslide susceptibility classes; 76% of settlements are located in landslide risk zones, whereas only 24% of the total settlement area in Elgon County is classified as low-exposure settlements. Compared with the settlement density, high-risk exposure was concentrated in the Sisiyi, Buginyanya, Bulugunya, Simu, and Lusha subcounties, where dense settlement clusters coincided with highly susceptible zones.

We verified the accuracy of our results by comparing them with a preliminary disaster report following the landslide of 27 November 2024 in the Bulugunya sub-County, which was classified under high-risk and high-exposure zones on the basis of our findings. The report clearly indicates that 35 homesteads and 2 commercial buildings in Namakyere village and 27 homesteads and 1 school were affected in Musugu village (Table 2). The comparison results clearly confirm that Bulugunya subcounty is a highly susceptible area with very high settlement exposure. These results are in line with those of this study.

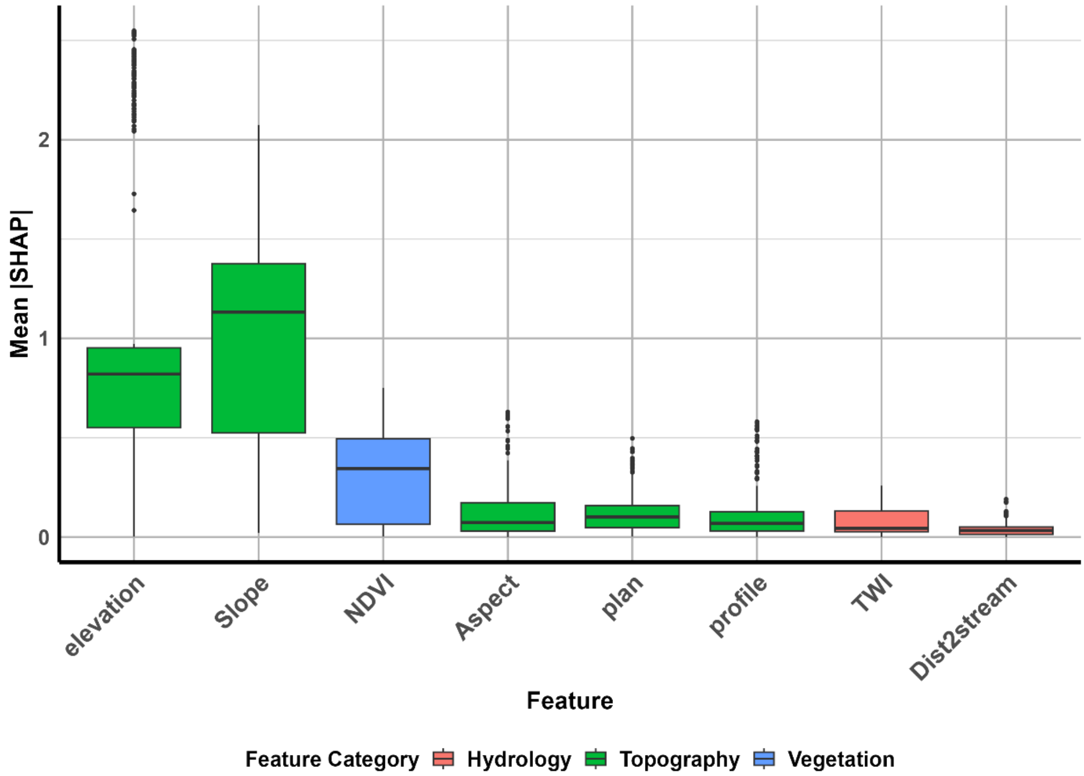

Figure 8 SHAP bar plot showing the global importance of the different landslide conditioning factors grouped by thematic category.

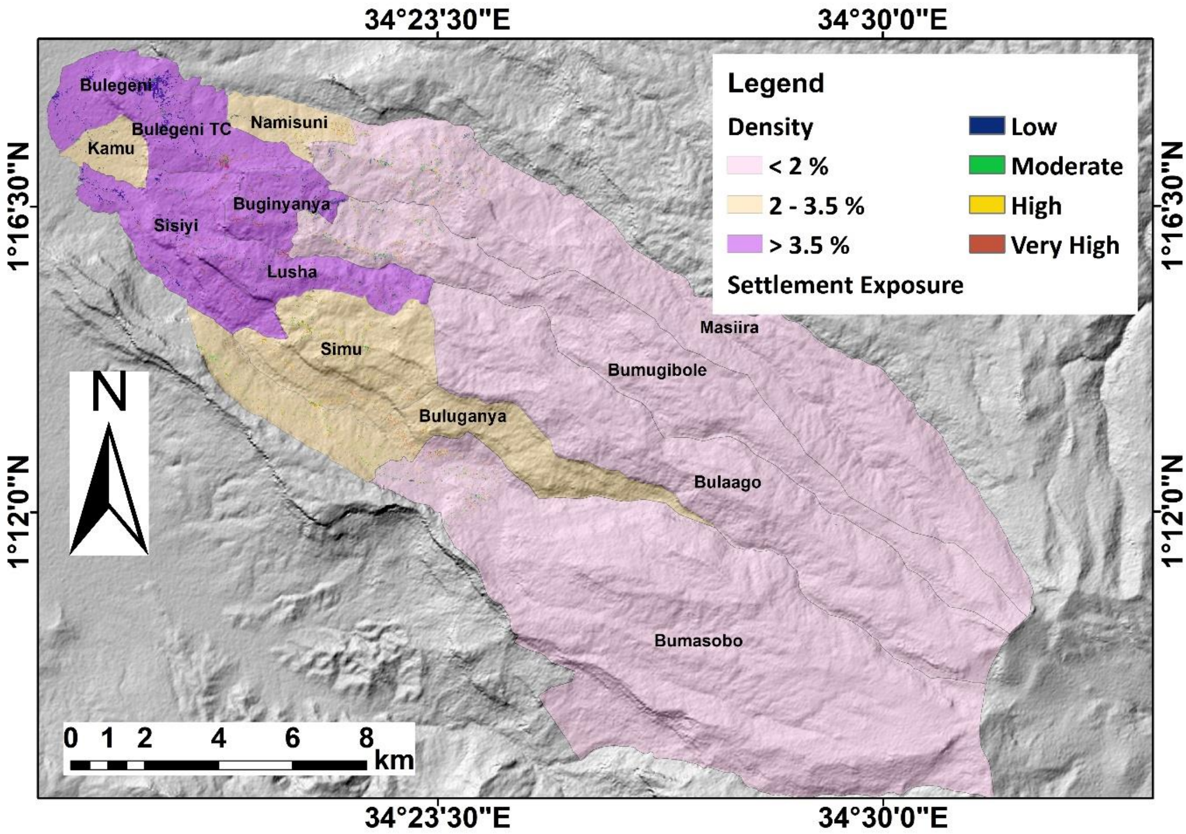

Figure 9 Settlement exposure to landslide-prone areas as predicted by the susceptibility model.

Table 2 Homesteads and facilities in the landslide-affected villages before and after the disaster in Buluganya subcounty, Bulambuli District, on November 27, 2024

Village	Homesteads	Commercial buildings	Schools	Homesteads	Commercial buildings	Schools
	Before			After		
Buwayo	0	0	0	0	0	0
Lusola	20	1	No data	0	0	0
Lula	22	6	No data	0	0	0
Buzemolili	9	1	No data	0	0	0
Mamolo	42	3	No data	7	0	0
Rukungiri	11	3	No data	0	0	0
Nakitali	33	2	No data	0	0	0
Namakyere	52	2	No data	35	2	0
Masugu	38	2	1	26	**1**	1
Tagalu	22	2	No data	7	0	0
Nayinyinya	37	No data	No data	0	0	0
Masola	52	6	0	4	0	0
Total	**338**	**25**	**1**	**79**	**3**	**1**

Source: Bulambuli District Disaster Management Committee

Discussion

This study employed an interpretable XGBoost algorithm to model landslide susceptibility in Elgon County, Bulambuli District. A total of 182 landslides, encompassing both rockfalls and other landslide types, were mapped. In addition, nine conditioning factors were identified. The dataset was divided into two parts: 80% was allocated for model training, while the remaining 20% was utilized to assess the model's robustness. The XGBoost model achieved an AUC of 95.2%, which is comparable to the performance reported by the logistic regression model used by [1] for modeling LSS in the broader Mt. Elgon region. This finding suggests that the XGBoost model can be effectively applied to map LSS. Many studies have previously been conducted on LSS in the Elgon region, employing various method-logies such as machine learning (ML), geographic information systems (GIS), and statistical models. Notably, the current model used also outperforms the fuzzy logic model used by [15] in terms of prediction accuracy for LSS studies. This study enhances the study of LSS in the area by incorporating exposure analysis, which also improves the practical utility of the model results.

The LSS mapping results indicate that Elgon County in the Bulambuli district is highly prone to landslides. This susceptibility is attributable to the slope steepness, aspect, elevation, and vegetation cover in the area, which represent key landslide conditioning factors. The LSS is highest in the middle slope zones (20–35 degrees) located at middle to high elevations (1,500–2,000 m). These findings align with previous research by [14, 53–54], who reported a predominance of shallow landslides on slopes ranging between 25^0 and 35^0. In a similar study, Hadmoko et al. [55] noted that slope angle and elevation were the leading factors influencing the spatial distribution of landslides on Java Island. The distribution of susceptible slopes in Elgon County also coincides with that of densely settled slopes, underscoring the impact of human activities on landslide occurrence, as reported by [13]. In contrast, the upper reaches of the county up to the mountain summit and forming part of Mt. Elgon National Park are classified as low-susceptibility areas since they are under dense vegetation cover. This highlights the importance of tree cover in ensuring slope stability.

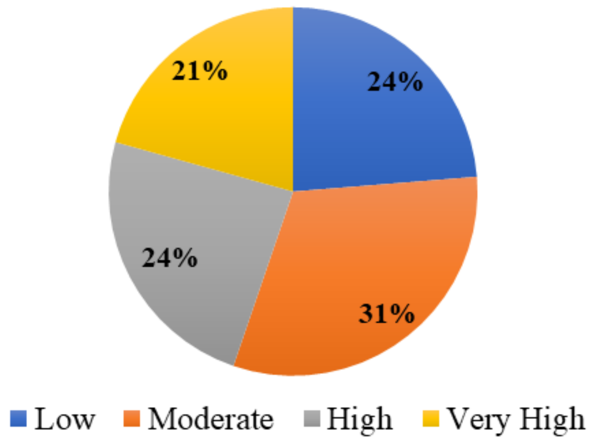

Figure 10 Percentage of settlements and their level of exposure to landslide risk.

As illustrated by the SHAP plot (Figure 7), topo-graphic factors and the NDVI had the most significant impacts on the model. This finding aligns with the prevailing landslide theory, which posits that steep slopes and elevated terrain are correlated with increased slope instability [53]. It is evident that topography exerts a predominant influence on the susceptibility of slopes in the Mount Elgon region, and the SHAP results add value by quantifying their relative contributions at a local scale. This assertion is further substantiated by the pivotal role played by all other factors, which collectively contribute to the complexity of terrain-related dynamics. Notably, NDVI has been identified as a primary indicator of slope instability in the region, demonstrating the strong role of vegetation dynamics and land use. Extensive vegetation clearance arising from increasing population pressure on available land resources has significantly depleted vegetative cover in Bulambuli, especially in the mid-slope areas where LSS is highest. Seasonal planting is a common practice that exposes soils on steep slopes to erosion agents, such as rainfall and runoff. On the other hand, low-susceptibility classes are associated with areas with dense vegetation cover, which make up the largest proportion of the low-susceptibility class, e.g., Mt. Elgon National Park. This demonstrates the dual role of the NDVI as both an indicator of biophysical slope protection and a proxy for anthropogenic land-use changes. This finding contradicts the conclusions of [1], who excluded landcover as a predictor because of its perceived limited influence.

The hydrological factors, such as the TWI and the distance from the stream, presented the lowest level of contribution. This phenomenon may be attributed to the overbearing influence of slopes in this particular study area and the inherent limitations of hydrological proxies derived from digital elevation models (DEMs) to capture the complex water-related processes that trigger landslides, such as rainfall and groundwater saturation. This finding is corroborated by the research of [56,57], who reported that drainage, infiltration, and pore pressure tend to accumulate over varying time scales, such that statistical proxies from DEM data may not capture such dynamics. Furthermore, the low impact of aspect, curvature, and the TWI could be attributed to the limited scope and scale of micro studies, which may have masked the influence of curvature, the TWI, and aspect [40]. An understanding of the impacts of terrain factors is needed to contextualize the patterns of exposure analysis in the mountainous region of Elgon County, Bulambuli District. In this area, landslides are frequently caused by difficult hilly topography, intense and protracted rainfall, geological instability, and land use activity.

A significant proportion of settlements in Elgon County have been identified as being exposed to high and very high risks of landslides, with more than 76% of all settlements falling into these categories. This figure is comparable to the findings reported by Ratemo and Bamutaze [17], who reported that over 90% of settlements within the Manafwa River catchment were deemed vulnerable to landslide risk. The co-occurrence of high-susceptibility and dense settlement clusters indicates increased disaster potential since more people and assets are concentrated in the most hazard-prone zones. These findings underscore the importance of prioritizing such subcounties in risk reduction planning and targeted interventions.

The multiresolution SHAP analysis used in the present study provides clarity to the model interpretation results and, in turn, enhances the usability of the model outputs. Unlike the older approaches, such as the Gini index, permutation importance, and correlation-based ranking, which are usually biased and noncausal [58], SHAP can offer model agnostics that offer both local interprettability and global interpretability [47]. The multiresolution SHAP design further extends this by capturing scale-dependent feature contributions, permitting the examination of how predictors influence susceptibility across different spatial contexts. The thematic level analysis used in this study is beneficial to nontechnical stakeholders because it makes use of meaningful thematic categories [59]. The approach offers both individual feature contributions and thematic contributions, which translate model behavior to more relevant domain explanations, hence enhancing the accessibility and usability of the model outputs by stakeholders. The thematic grouping of the model interpretations can enhance model interpretation and test whether the model output aligns with geomorphic processes, which is necessary for local understanding [60]. The correspondence between the model interpretation results and the observable exposure patterns, such as the concentrations of highly exposed settlements in Masugu and Namagugu villages, demonstrates the geomorphic plausibility of the LSS map. Furthermore, this relationship adds a layer of credibility to the overall exposure assessment conducted. As such, this study effectively addresses the historical gap between predictive modeling and actual disaster planning activities, particularly through effectively linking the outputs of explainable machine learning algorithms and the hazards that exist in the real world. In future research, the types of buildings and other structures should be considered in exposure analysis.

The modeling approach used in this study indicates that incorporating LSS mapping with multiresolution SHAP analysis can produce interpretable and spatially explicit model outputs that can provide crucial information for evidence-based policy formulation and disaster risk reduction planning. The LSS and exposure maps can be utilized by local governments and planners to inform the regulation of settlements. For example, by highlighting highly exposed settlement areas such as Masugu and Namagugu, LSS and exposure maps can be used by local governments to select when and where to relocate settlements and/or which mitigation measures should be undertaken. Local governments may serve as frontline officers and utilize these outputs in enforcing land use regulations, approving building plans, coordinating resettlement programs, sensitizing the community, and implementing early warning systems to translate these scientific findings into actionable points. This information is also important for settlement planners in the design and approval of building plans for settlements in high-risk zones. These maps can also guide planning for infrastructure such as new roads, schools, health facilities, and electricity distribution lines by ensuring that they are situated in low-susceptibility zones to reduce the risk of potential disruption from landslide occurrences. Early warning systems that prioritize monitoring and preparedness in high-risk hazard zones and planning for resettlement camps where displaced persons can access relief aid are planned. Hence, this research also contributes to the attainment of the SDG agenda by influencing safer land use and settlement planning, enhancing resilience to landslides caused by rainfall, and highlighting the function of vegetation cover in stabilizing slopes. The thematic SHAP analysis helps ensure that the model results are not only statistically sound but also geomorphologically plausible and simple to explain to nontechnical stakeholders. Accordingly, this enhances transparency and community trust and facilitates more inclusive and proactive risk governance, especially in high-risk areas such as Elgon County, where population pressure, terrain, and vulnerability intersect.

Despite the strengths of this approach, certain limitations persist. The world settlement footprint dataset is limited in that it does not contain key information needed for a more comprehensive exposure and damage analysis, e.g., details on building quality, type, and utility. This hinders the determination of the precise level of damage exposure. These insights will have implications for future research and policy, especially as post-disaster damage inventories will be needed to validate the model predictions. Furthermore, the study employed a landslide inventory that had been compiled up to the year 2018, with only limited updates derived from Google Earth images. Hence, the LSS map may not be representative of the current conditions in the field and might produce biased model outputs. Additionally, LSS maps present only a snapshot and not a long-term dynamic tool; however, hazard risk is dynamic. Therefore, LSS maps should be periodically updated to reflect land use changes, the expansion of settlements, and changing climatic patterns. This helps ensure that the LSS maps remain relevant for decision-making and accurately reflect the changing patterns of the LSS. The exclusion of soils, rainfall, and geology factors from the model is due to the absence of spatially distributed good-quality datasets. These factors are well-documented determinants of slope stability in the Mt. Elgon region [1, 61]. In addition to the absence of rainfall data, the temporal dynamics of rainfall, such as short-term high-intensity storms and antecedent wetness, which are crucial landslide triggers, are also missing in this study. This could lead to an underestimation of LSS in storm-prone areas. Therefore, excluding such key landslide conditioning factors could limit the model's ability to detect localized susceptibility patterns due to local variations in lithologies, rainfall intensity, and soil properties. Furthermore, with the projected increase in rainfall extremes due to climate change and land use pressure, susceptibility patterns may shift with time [62]. Although topography and vegetation can provide sufficient predictive capabilities, future research should integrate detailed soil and lithology data to produce more comprehensive susceptibility assessments.

Conclusions

The present study employed the XGBoost model to map LSS in Elgon County, Bulambuli district. The results revealed that mid-altitude zones with steep slopes are highly susceptible to landslides. The lower slopes and upper slopes under conservation forests are the least susceptible areas in Elgon County. This study represents the first county-level mapping of susceptibility and exposure analysis in the entire Mount Elgon region. The XGBoost model achieved a very high AUC of 95.2%. This is a very good performance compared with previous LSS studies in the area. This outcome demonstrates the model's potential for effective application in other comparable regions prone to landslides. The findings of this study indicate that the majority of settlements in Elgon County, Bulambuli District, are highly exposed to landslide risk (76%), with more than 50% of the slopes demonstrating susceptibility to landslides. Model interpretation results based on both the SHAP summary and thematic plots reveal that topographic factors (slope and elevation) and the NDVI are the key factors influencing landslide susceptibility in the region. The least impactful factors included the hydrological factors, aspect, and curvature. By linking susceptibility to observed settlement exposure, this study assesses the geomorphic plausibility of the model and offers guidance for targeted interventions, resource allocation, and mitigation planning. The findings of this study offer valuable insights for developers, planners, and engineers in implementing effective slope management and land-use planning strategies that are not only statistically plausible but also grounded in terrain reality. Moreover, this methodology can be effectively applied in other regions with similar geological and topographical characteristics. This research not only enhances scientific knowledge but also contributes to the attainment of the SDGs by correlating LSS mapping with safe settlements, climate resilience, and sustainable land management. Moreover, maintaining the utility of such maps will require periodic updating to ensure that future risk reduction strategies remain adaptive to changing land use patterns and evolving climate trends.

Potential future research should consider conducting a more comprehensive risk assessment by integrating all the exposed elements and conditioning factors not considered in this research, such as detailed geology, soils, and rainfall thresholds. Specifically, an investigation of the role of vegetation cover species on slope stability, which requires a systematic analysis of different cover types to ascertain their influence, would be valuable. Furthermore, incorporating high-resolution soil and geological datasets is essential for capturing localized slope instability processes that may not be fully represented by topographic and vegetation factors alone.

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