
Geographical Information Systems (GIS) and Remote Sensing (RS) Analysis for Landslides Susceptibility Mapping

Zahor Zahor 

Department of Geography, University of Dar es Salaam
Email: zahor81@yahoo.co.uk

Nestory E. Yamungu

Department of Geography, University of Dar es Salaam
Email: nestory.yamungu5@gmail.com

ABSTRACT

This paper presents the results of an integration of Geographical Information Systems (GIS) and Remote Sensing (RS) techniques to delineate landslide susceptible areas in Lushoto district, Tanzania. To achieve this, the study has examined the distribution of landslide events and identified susceptible areas in the district. The study collected data through a handheld Global Positioning System (GPS), open-source databases and on-screen digitization. Analytical Hierarchy Process (AHP) technique was used to evaluate factors influencing landslides and Quantum GIS software was used to analyse landslides data through multi criteria technique to generate landslide susceptible areas. The study reveals that past landslides are more concentrated in the southern habitable areas of Lushoto district in which mudflow and rock falls are more dominant. The findings further expose that rainfall (29.97%) and slopes (21.72%), are the factors that have a higher influence on the occurrence of landslides while proximity to rivers (2.48%) and NDVI (1.69%) have very low influences. Further, the findings reveal that about 45% of the total area falls under moderate to very high landslides susceptible areas. This study concludes that a large area of Lushoto district's southern part is at risk of being battered by landslides resulting from the influence of rainfall and slopes. As such the study recommends that governmental and non-governmental organizations should intervene through the formulation of policies against human activities that induce landslides in susceptible areas and to use these geospatial results to officially demarcate these areas to minimize fatalities and other economic and environmental impacts.

Keywords: Landslide susceptibility, geographical information system, landslide influencing factors

<https://dx.doi.org/10.4314/udslj.v17i2.6>

Introduction

Landslides are defined as events or series of events where a mass of rocks, soil, or debris falls down a slope (Abay et al., 2019), in a process that results from effects of gravity (Abedini et al., 2019). Landslide events are among the most common global natural disasters and the destruction they cause is critical (Abay et al., 2019). It is estimated that during the period between 1998 and

2017, landslides accounted for 5.2% of the whole world's total natural hazards (Aditian et al., 2018). Although it looks small, this percentage of disasters has been responsible for annual damage of about 18 billion Euros (Chen et al., 2018) and approximately 66,438 deaths by the year 2020 (Abay et al., 2019).

Landslides occurrence is a complex process that can be induced by various combinations of multiple endogenic and exogenic factors such as slope conditions and slope angle, lithology, soil type, hydrological or meteorological factors, altitude, distance to roads, distance to streams, and distance to faults (Abay et al., 2019). Globally, landslides are progressively increasing, resulting in adverse impacts on people's lives, the economy, and the environment at large (Bernard et al., 2021). These impacts are more likely to increase due to population growth and increase in human activities as people continue to expand their settlements and other activities along landslide-prone zones (Bernard et al., 2021). As such, deliberate efforts are needed in response.

In Africa, although landslides occur almost in every region, they are more frequently reported in Sierra Leone, DR Congo, Nigeria (Bostjančić et al., 2021), Cameroon (Borgomeo et al., 2014), Ivory Coast, Kenya, Uganda, Rwanda, Ethiopia, and Tanzania (Anderson, et al., 2018). In most highlands of East Africa, such as Ruwenzori in Uganda, Elgon in Uganda/Kenya, Aberdare Ranges in Kenya, and Bukavu in the Democratic Republic of Congo, landslides are more common (Arjmandzadeh, et al., 2020) and have diverse impact on the environment and society. Although there are many landslide incidents in Africa and their effects are very large, the use of GIS technology and remote sensing to reduce their effects is still limited. Instead, old methods of dealing with this problem to reduce its effects are still in use; something that increases the difficulty of finding a permanent solution.

The situation in Tanzania is not very different from that elsewhere in Africa. Various types of landslides have been widely documented and reported from different regions of the country. These include large quaternary debris avalanches that have taken place on Meru and Kilimanjaro Mountains (Bostjančić, et al., 2021), Oldonyo Lengai, Kerimasi Mountains Broeckx et al., 2018), Uluguru Mountains (Broeckx et al., 2018), and Rungwe Mountains (Chalise, et al., 2019). Apart from that, reports of mudflows on Usambara Mountains in Tanga region, and Rondo and Makonde Plateaus in the southern regions of Tanzania have been made on various occasions. As a result of these incidences, various environmental impacts have been felt, including soil erosion, loss of biodiversity, death of living organisms and people, as well as loss of properties. In response, researchers have adopted different approaches to understand these developments. These include integration of various causative factors from different disciplines including slope angle, geomorphology, aspect, slope, lithology (Al-Mulali, et al., 2015), relief, surface roughness, distance to streams (Al-Mulali et al., 2015), slope aspect, rainfall, altitude, land use Chalise, et al., (2019), elevation, curvature, distance from drainage, distance from roads, land cover (LULC), and distance from lineament (Chalise, et al., 2019). However, despite the ongoing efforts, landslides continue to take place, leaving noticeable effects that appear to increase day by day and affect many people and their properties, the environment, and infrastructure.

Geographical Information systems (GIS) and remote sensing technologies have been extensively employed in developed countries and proven to be useful in reducing effects of landslides (Agliardi et al., 2012). These technologies are capable of managing large datasets both



in terms of data volume and geographical scales, as well as undertaking dynamic and ongoing landslide susceptibility zonation, representing an important requisite for proper management of land and risk mitigation on the earth's surface (Chalise, et al., 2019). Often, the technologies combine various datasets collected through innovative techniques such as satellite remote sensing and light detection and ranging (LiDAR) images (Chalise, et al., 2019). Furthermore, the technologies are widely integrated with numerous statistical models and approaches that have been suggested and extensively used in landslides susceptibility mapping studies globally including; frequency ratio (FR) (Broeckx et al., 2018), index of entropy (Chen et al., 202).

Apparently, although a considerable amount of knowledge has been generated about landslides in Tanzania, this disaster type is yet to be adequately studied and much of what is known is confined to a few areas. For instance, although there have been considerable efforts to document and identify landslide-prone sites in the area, the usage of traditional methods to do so has resulted in limited success. This insufficiency of spatial temporal distributions information makes precise identification of landslide-prone areas for landslide adaptation and mitigation difficult hence endangering lives, the environment, and properties. It is this limited availability of scientific information on landslides and their spatial extent that necessitated this scientific research and its thorough use of spatial technology (GIS and RS) to better delineate landslide susceptible areas by identifying and scaling landslides causative factors (criteria) with respect to their relative influence on landslides occurrence. The use of spatial technology has enables this study to provide an informative landslides spatial framework, knowledge, and digital datasets that can be used by planners and decision-makers to design and implement plans for reducing landslide risks and enhance preparedness and management. In order to achieve this, the study integrated GIS and RS to examine the distribution of landslide events in Lushoto district, and identify the potential landslide susceptible areas in Lushoto district.

Literature Review

Trend and Distribution of Landslides

Landslides are more common than any other geological event, and can occur anywhere on the planet. It has been reported that the world experienced a total of 3876 landslide incidences between 1994 and 2014, resulting in a total of 163,658 deaths and 11,689 injuries. These incidences are most common in the Northern Hemisphere between June and December, and in the Southern Hemisphere between December and February (Chen et al., 2021). In Latin America and the Caribbean, landslides are more pronounced with many fatalities and environmental destruction mostly caused by inter-annual variations of the El Niño and La Niña cycles. Geographical landslide distribution in these regions is extremely heterogeneous with high landslide events in Haiti, Central America, and Brazil. It is indicated that from 2004 to 2013, about 611 landslide events occurred in these areas, resulting in 11,631 deaths and various effects on the society and environment (Bernard et al., 2021). Landslides are also one of Nepal's deadly incidents that results in fatalities. The country is partly the least developed due to recurring landslide events resulting from shaking of the Indian and Himalayas tectonic plates. It is reported that from 2004 to 2016, a total of 643

fatal landslide events occurred, resulting in a total of 4718 deaths, which are estimated at an annual average of 36 landslide events and 363 deaths (Bernard et al., 2021)

In Africa, the frequency of landslides events and their spatial patterns are under-reported. The few accessible studies are also limited to a few places. However, it is estimated that by the year 2018, a total of 18,050 landslide events were recorded within the continent (Bernard et al., 2021)). The majority of these incidents have occurred in the highlands of Sierra Leone, the Democratic Republic of Congo, and Nigeria, where devastating consequences on society have been registered. According to Bernard et al., (2021) in 2017, devastating landslides killed over 500 people and displaced 2000 more in Sierra Leone. Since 1950, a total of 1200 fatal landslides events have been recorded in Burundi (El-Fengour, et al., 2021) while 8000 have been recorded in Kivu, DR Congo but details of their effects are unknown (Chalise, et al., 2019).

Landslide incidences occurring in Tanzania are increasing day by day and their effects are clearly visible. Different types of landslides have been reported in different parts of the country. Bulky debris avalanches have been reported on Mt. Meru and Kilimanjaro (Delcamp et al 2017), Oldonyo Lengai and Kerimasi Mountains (Ayalew, & Yamagishi, 2005). Uluguru Mountains in eastern Tanzania and Rungwe Mountains in the southern highlands of Tanzania (Fontijn et al, 2012). Furthermore, the northeastern highlands of Tanzania, areas along Lake Tanganyika in western Tanzania, and Rondo and Makonde Plateaus in Lindi and Mtwara regions are the other places known to experience many landslides (RRSCB 013). The impacts of these incidences are devastating. For instance, Goha ward in Kilimanjaro region lost 24 people and about 285 households were affected by shock and temporary relocation while 8 families were left homeless. The landslide also resulted in 100m of the road getting completely buried under debris (Chalise, et al., 2019). Reports also show that a mixture of rainwater, mud, and rock debris from the west-facing slopes of the South Pare Mountains (SPMs) killed 5 people and destroyed 10 residential houses and some school buildings in Makuyuni and Kijomu villages (Bernard et al., 2021).

Factors Influencing the Occurrence of Landslides

Occurrence of landslides depends on various factors, including geological, geomorphological, climatic, environmental, soil types, and LULC (Bernard et al., 2021). These factors contribute differently to landslides specific to various areas. Among the just mentioned factors, extreme rainfall has been reported globally as the main landslide triggering factor. It is reported that in China about 94.2% of all landslide events are caused by heavy rainfall (Zhou et al., 2021). This factor was also reported by Dou et al., (2019) who researched the human cost of global warming deadly landslides and their triggers from 1995 to 2014. The results of this study revealed that more than half of landslide events in the world are due to extreme rainfall. On the other hand, Chalise, et al., (2019) researched the role of human activities in shallow landslides in Italy and found that the landslide occurrence is heavily influenced by morphological complexity, which is heavily influenced by human changes such as construction and land-use change. A study conducted by Fiorucci, et al., (2019) claimed that a slope gradient triggers mass movements due to gravity effects acting on the slope, creating a sliding plane Chen et al., 2021 However, mass removal is highly accelerated when a threshold of the surface angle of inclination reaches 30°. Similarly,

Chen et al., (2021) suggested that steep slopes are more susceptible to landslide processes, especially in mountainous areas. In a different study, Abraham et al., (2021) suggested that sometimes landslides are triggered by glacier movements that cause paraglacial readjustment that favours mass removal process within an area. As noted earlier, the factors behind these events are not the same in all places. In fact, these factors normally reflect the geological, climatic, hydrogeological, and topographical conditions of the area in question. Nonetheless, efforts have been made or continue to be made to establish each factor's percentage contribution to the occurrence of landslides, which is used to rank them in relation to other causative factors (Broeckx et al., 2018). As stated earlier, since each part of the world has its own geomorphology and different landscape characteristics, factors that stimulate the occurrence of landslides in various regions differ. For this reason, working with these factors for each region to rank them is important.

GIS and RS in Landslides Management

Landslides occurrence is unpredictable by nature, hence the complexity of their analysis. However, GIS and Remote Sensing (RS) technologies provide useful remote earth's surface information that can be used together with other multi-disciplinary spatial factors to reduce landslides impacts in a given area. RS technique, in particular, is used in the acquisition of remotely sensed multispectral images and other physical characteristics of the earth's surface. On the other hand, GIS technology provides room for analysing remote and other spatial datasets that are then used in planning and managing natural and socio-economic environments (Ayalew et al., 2004). In landslides studies, GIS is mostly applied in the preparation of various datasets on various factors, including slopes, drainage density, and elevations (Ayalew et al., 2004), and in the integration of these factors to better identify landslides susceptible areas (Broeckx et al., 2018). This technique has been widely employed in the analysis and management of landslides worldwide, in both large and small-scale studies, and has been largely successful. Kervyn et al., (2014), employed GIS and RS in landslides susceptibility mapping based on morphometric and geological multi-criteria techniques in India. Similarly, Kervyn et al., (2014), carried out a landslides susceptibility evaluation using GIS, RS, and AHP multi-criteria evaluation decision-making methods in the Abha watershed, Saudi Arabia and confirmed that it is the right approach to manage landslides and reduce their effects. Many scientific studies suggest that the application of GIS and RS, coupled with the involvement of non-spatial techniques, can add value to landslide disaster reduction and management (Kervyn et al., (2014).The use of remote sensing data (satellite imageries and digital elevation model [DEM]) in geo-hazard studies is common and in demand nowadays (Cervi, 2010). The advancement in earth Observation (EO) techniques facilitate effective landslide detection, mapping, monitoring and hazard landslides analysis (Broeckx et al., 2018). Remote sensing data are the major source of information required for landslide risk information assessment and analysis. As such, it was considered necessary and essential to use GIS and RS tools in designating landslide-prone zones in Lushoto district. This approach has not only allowed for the depiction of diverse landslide patterns via maps but also allowed for a thorough analysis of multiple datasets via an integrated system in determining landslide-prone locations in the district.

Research Gap

GIS and RS technologies have been widely used in a variety of landslide investigations around the world, where they have been used in collaboration with a variety of statistical and mathematical computational methodologies (Chalise, et al., 2019). On the other hand, numerous landslide influencing elements (criteria), such as surface slope, elevation, aspect, soil type, lithology, and proximity to faults have been used (Campbell, & Wynne, 2011). Furthermore, traditional approaches such as field drawings, field observation, photograph interpretation, and people's perception techniques have also been used to study landslides (Capello, 2011). Overall, the bulk of the literature reviewed focused on the causes of landslides and used a few landslides influencing factors, with the majority using less than seven factors to generate qualitative information on landslides. In contrast, there have been few landslide studies with focus on spatial distribution and demarcating potential landslide areas using spatial technologies (GIS & RS). Moreover, these studies have used conventional methods despite their limitations in capturing spatial evidence. As such, this study sought to close this gap by mapping and quantifying landslide information in the study area by incorporating nine (9) landslide causative factors using GIS, RS, and AHP techniques; thus putting location and spatial theory into practice.

Research Design

This study has employed a qualitative-quantitative mixed approach that has been influenced by the objectives of the paper. Various ways of primary and secondary data collection were employed. Data editing, correction, and analysis were performed in the GIS environment. MCDA model based on the AHP method was engaged in the evaluation, weighting, and ranking of influencing factors involved based on the relative importance of each on landslide occurrences. Various methods have been reviewed in different kinds of literature in which statistical techniques such as AHP have been noted to perform best in the same kind of spatial challenges worldwide. There are numerous methods of Landslides Susceptibility Mapping (LSM) that engage both qualitative and quantitative approaches depending on the availability of data as discussed in the literature review section. However, the reliability of LSM produced rests on the quality of data available, the amount of influencing factors employed, the scale of the area under investigation, and the LSM method used.

Location of the Study Area

Lushoto district lies on the toes of Usambara Mountain, making it one of the eight districts of Tanga region in Mainland Tanzania. The district is bordered by Kenya on the North-eastern side, Muheza district on the Eastern side, Kilimanjaro region on the Northwest side, and Korogwe district on the Southern side. It is located along the latitudes 4.16° and 5.32° South and longitude of 37° and 39° East, covering a total area of 4125.17 km² (Figure 3.1). The district was selected for this study because it is often affected by landslides triggered by unstable slopes, heavy rainfalls, and earthquakes and characterized by complex geomorphological settings residing on the toes of Usambara Mountain at an average of 2500m above the mean sea level. See Figure 1 for details.



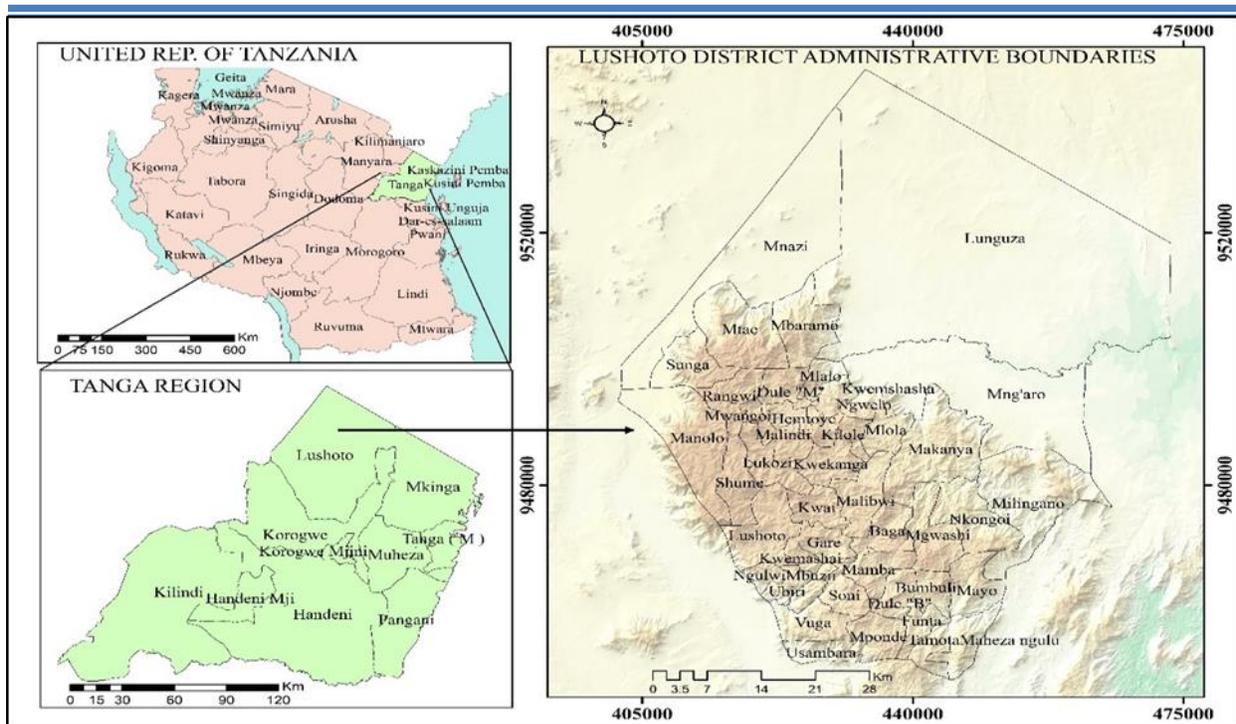


Figure 1: Location of Lushoto District in Tanga Region, Tanzania
 Source: (Author, 2022)

Data Types and Sources

Different primary and secondary datasets were collected from different sources (see Table 1). These included structural maps, soil and geological maps dataset acquired from the Geological Survey of Tanzania (GST), and rainfall datasets for the period from 1901 to 2021 acquired from the Centre of Environmental Data Analysis (CEDA) archive (<https://crudata.uea.ac.uk/cru/data/hrg/>). Roads datasets were downloaded directly from open street maps (<https://www.openstreetmap.org>) in form of shapefiles. Shuttle Radar Topographic Mission Digital Elevation Model (SRTM DEM) datasets and soil data were downloaded directly from the USGS earth explorer website (<https://earthexplorer.usgs.gov/>) and used for further analysis to generate slopes and elevation datasets of the study area as well as its drainage systems, which were further processed to generate proximity values from drainage systems. Furthermore, Landsat 8 OLI satellite imageries were downloaded from (<https://earthexplorer.usgs.gov/>) in which band 5 (near-infrared) and band 4 (red band) were used to generate the Normalized Difference Vegetation Index (NDVI) of the area. Table 1 presents details of these datasets.

Table 1: Datasets Used in the Current Research and their Sources

Data type	Format	Sources	Purpose
Slope angle			Determine Surface inclination
Proximity to drainage systems	Raster format (30m resolution)	USGS earth explorer Digital Elevation Model (DEM)	Determine proximity distances
Elevation			Determine geographical heights
Soil variation layer	Shapefiles	USGS earth explorer	Determine various soil types in the area
Roads	Raster (30m resolution)	Open street map	Determine proximity distances from roads
Landsat 8 OLI	Raster (30m resolution)	USGS earth explorer	Determine ranges of NDVI values
Rainfall datasets	Raster (30 resolution)	CEDA archive	Used to determine rainfall variation in the area
Landslides coordinates(X,Y)	Shapefiles	Field survey WITH GPS	Determine distribution of landslides events and validation

Source: Author, 2022

Data Collection Methods

Handheld Global Positioning System (GPS) Survey

This field method involved the usage of a handheld GPS Garmin 60 to record landslide spatial points (coordinates). This information was recorded in form of X and Y format, with the UTM zone 37S projected coordinate system. To collect accurate information, the GPS receiver was waited on until the accuracy was less than 3 meters. The data were recorded and saved directly on the internal GPS receiver memory and later downloaded and exported into Quantum GIS in the form of raw spatial data for editing and further analysis. The data that were recorded are rock fall and mudflow points, damage to infrastructure and people's residences near the landslides, potential areas for landslides and cold spot areas from landslide.

Spatial Datasets Downloading from Open Source Databases

The Digital Elevation Model (DEM) and Landsat 8 OLI satellite imageries were directly acquired from the USGS earth explorer's database (<https://earthexplorer.usgs.gov>) to generate NDVI values of the study area. Rainfall datasets were also downloaded from the universal rainfall archive (<https://crudata.uea.ac.uk/cru/data/hrg/>). Interpolation technique was then used to generate rainfall datasets of the study area. In contrast, structural, soil and lithological maps were obtained from the Geological Survey of Tanzania (GST) for the purpose of determining the geological faults, soil, and geological characteristics of the study area. Apart from that, road network datasets were also downloaded from the open street map (<https://www.openstreetmap.org>) in the form of shapefiles to produce road proximity values during the analysis phase.

On-Screen Digitization of Faults from Existing Structural Maps

Faults datasets were digitized from the existing structural map of the study area. Digitization was undertaken to extract datasets of the study area, but before the hardcopy fault map was scanned and geo-referenced, on-screen digitization was performed to extract particular data in digital format for analysis. A new shapefile was then created in which lines format was selected and attribute information was imported to faults shapefiles. This was undertaken to obtain faults in form of shapefiles for later use in the calculation of proximity from faults values used in the analysis.

Data Processing

This was done before data analysis as the collected datasets needed editing according to the fitness of use of this study. In this study, editing entailed specialized labelling of datasets such as soil and geological units in accordance with the worldwide system of soil names, as well as their synonyms. Editing also involved removing any missing information, changing text size, and filling the sinks in the downloaded SRTM DEM datasets with the fill tool in ArcGIS 10.8 environment. Spatial data processing also involved dataset merging, clipping and masking of the datasets to match the study area (Area of Interest), dissolving to determine the study area boundary, and exporting the datasets to the desired format. After this, the data were rasterized and bands were combined. This was followed by the atmospheric correction for landsat 8 to eliminate noise, water vapour, haze and clouds in the image to improve brightness values and increase image contrast.

Data Analysis Methods

Firstly, to show landslide types and spatial distribution, the shape file point "feature class type" of landslide coordinates were placed on the working space in Quantum GIS (QGIS) for management and data analysis. The data view tool was then activated. The data view provided a geographic window for displaying maps and querying the mentioned data on the map. To query the data for

preparing the map, property layer allowed the researcher to use appropriate tab in the Layers Properties dialog box that was opened to incorporate changes. Under ‘categories’ field, unique values were selected for layer display. This allowed for setting layer category example ‘types of landslide’ and assigning symbols based on this field. Each landslide type was displayed using a specific colour. The layout view was used to allow the use of the map layout elements such as titles, north arrows, and scale bars, along with the data frame for map visualization. Thereafter, the maps were exported and saved in JPG format. The map showed landslide types and spatial distribution.

Secondly, to find landslides susceptibility, the first step of this analysis was to convert each data layer to raster format for analysis. As a result, a proximity raster was generated. These are also known as Euclidean distances, where each pixel in the output raster represents the distance to the nearest pixel in the input raster. This resulting raster can then be used to determine suitable areas within certain distance from the input. After that, the data was reclassified to create discrete values through calculator algorithm. Using the reclassification toolset; proximity values close to faults, high rainfall and elevation, and steep slopes were given a higher reclassification value of 5 (high influence) as they are more susceptible to landslides and away from a value of 1 (very low influence). This was followed by the calculation of proximity distances from the lineaments based on other kinds of literature and classified into five classes as informed by other studies; 0 – 200m, 200 – 500m, 500 – 800m, 800 – 1200m and greater than 1200m. After this, overlaying analysis was done by combining factors for suitability analysis.

The aforementioned reclassified landslide influencing factors employed in the current study were analysed by the WLC technique to produce LSM of Lushoto district. The raster technique employs a mathematical algorithm that multiplies influencing factors’ weights and their conforming reclassified thematic layers. Thus, using the raster calculator toolset available in the map algebra toolset of the spatial analyst tools, all reclassified factors were imported, one by one, where multiplication and addition algorithms were selected and the final landslides susceptibility index was finally computed. The above mathematical algorithm employed in QGIS pro-environment enables the production of the LSM single landslides index of the study area which is ranked from 1 (very low landslides susceptibility) to 5 (very high susceptibility). Raster calculator was used to define weights. Thus, factors with higher influences on landslides occurrence, for example rainfall and slopes, were given higher weights by employing the AHP method.

Results

Distribution of Landslides Events in Lushoto District

Different types of landslide points were collected from the field in which spatial locations were recorded in the form of coordinate points (Northing and Easting) on a meter’s measurement scale (Table 3). A total of 11 landslide spatial coordinates were obtained within the study area, of which 9 are rock falls types of landslides and the remaining 2 are mudflows (see Table 3).

Table 3: Coordinates and Types of Landslides in Lushoto District



S/N	Northing	Easting	Landslides types
1	9460247.4	423362.4	Rock falls
2	9458019.5	423547.7	Rock falls
3	9461136.8	427620.2	Rock falls
4	9453960.5	426398.1	Mudflow
5	9452870.5	430307.4	Mudflow
6	9478703.1	426119.1	Rock falls
7	9489297.2	409301.8	Rock falls
8	9500046.5	416014.2	Rock falls
9	9477756.9	454510.4	Rock falls
10	9494974	427619.1	Rock falls
11	9484828.6	417869.1	Rock falls

Source: (Authors, 2022)

The analysed data shows that rock falls are the dominant type of landslides in most parts of the study area, particularly in the south west and northern part of the map. In contrast, mudflows were noted as common in a few southern areas of Lushoto district. The results indicate that most parts of the western side of the study area are more prone to landslides caused by human intervention. Most wards accessed by road networks such as Vuga and Soni have frequently reported landslides events and this has been confirmed by the coordinates taken in the field as shown on the map in Figure 4.

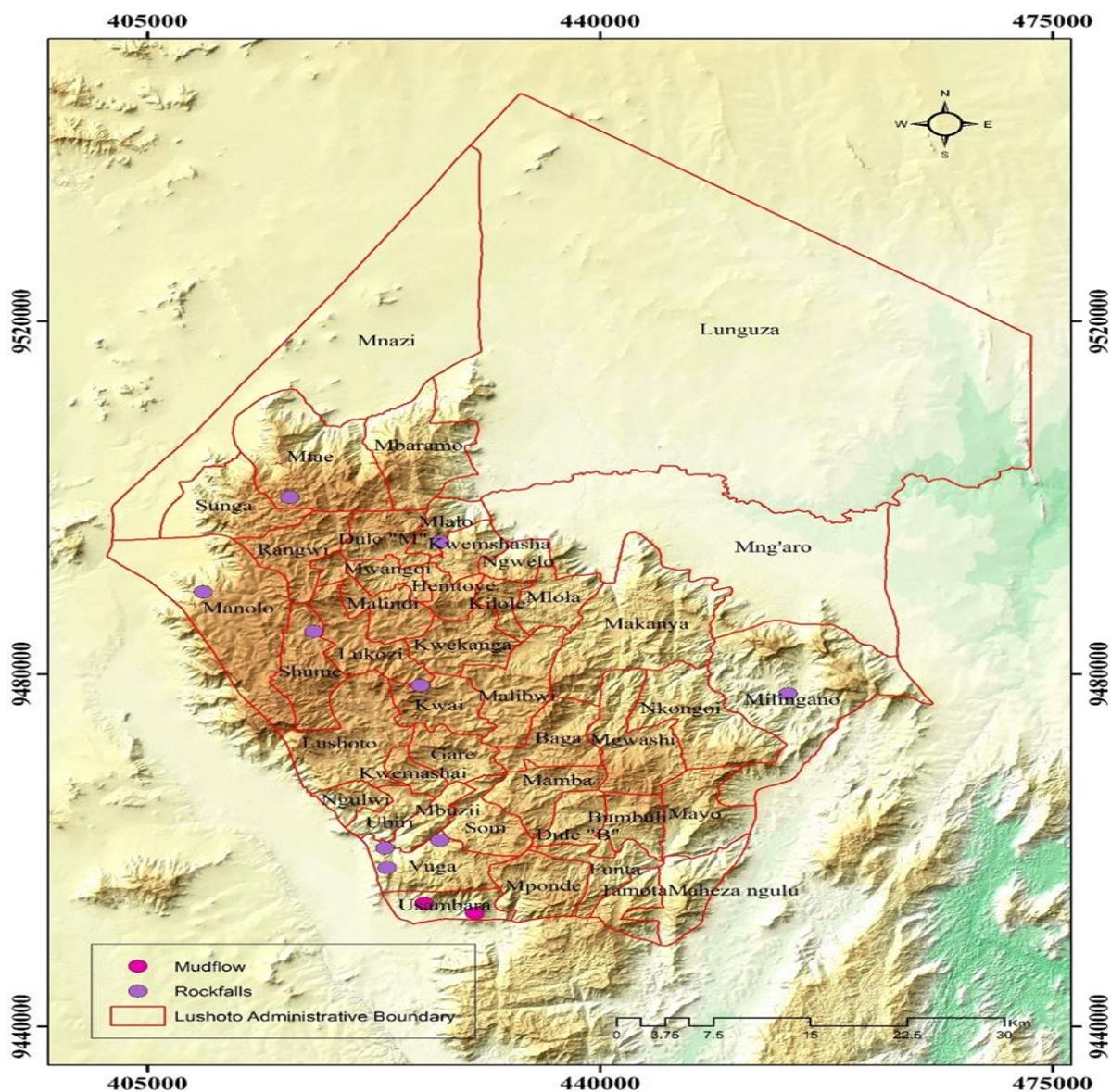


Figure 4: Landslides Events Distribution in Lushoto District
 Source: (Author, 2022)

Factors Influencing the Occurrence of Landslides

All employed factors influencing the occurrence of landslides were analysed using the Analytical Hierarchy Process (AHP) evaluation technique based on their respective influence on the occurrence of landslides within the study area. These criteria were then weighted, ranked, and prioritized based on what is said about them in literature and by researchers from around the world. According to the findings, rainfall, slope angles, and elevation of the area have the greatest

influence on the occurrence of landslides, with percentage weights of 29.97%, 21.7%, and 15.7%, respectively. In contrast, soil types, proximity to faults, and lithological types have moderate influences of 11.8%, 8.35%, and 4.9%, respectively. On the other hand, proximity distance from roads, rivers, and NDVI values have been found to have the least influence on landslides occurrence in the area, with percentage influence weights of 3.41%, 2.48%, and 1.69%, respectively (see Table 4).

Table 4: Landslides Examined Factors' Levels of Influences

Factors	Value Range	Area (Km ²)	Area (%)	Influence Levels	Weight (%)
Rainfall	1000 – 1100	454.6566	11.12	Very low	29.97
	1100 – 1200	653.7402	15.99	Low	
	1200 – 1300	1240.4214	30.34	Moderate	
	1300 – 1400	813.3111	19.89	High	
	>1400	926.325	22.66	Very high	
Slope Angle	0 – 7	1716.6	41.99	Very low	21.72
	7 – 15	965.8	23.62	Low	
	15 – 23	747.6	18.28	Moderate	
	23 – 34	507.3	12.41	High	
Elevation	34 -76	151.3	3.70	Very high	15.68
	215 – 600	1910.6	46.73	Very low	
	600 – 1000	582.1	14.24	Low	
	1000 – 1300	493.4	12.07	Moderate	
Soil Type	1300 – 1700	585.3	14.32	High	11.77
	1700 – 2300	517.1	12.65	Very high	
	Eutric leptosols	1114.6	27.26	Very high	
	Umbric acrisols	1104.9	27.02	High	
Proximity to Faults	Haplic luvisols	2.4	0.06	Moderate	8.35
	Chromic luvisols	1866.5	45.65	Low	
	0 – 200	90.9	2.22	Very high	
	200 – 500	133.8	3.27	High	
Lithology	500 – 800	131.4	3.21	Moderate	4.94
	800 – 1200	173.5	4.24	Low	
	>1200	3558.8	87.05	Very low	
Proximity to roads	Neoproterozoic granulite complexes	3054.0	74.70	High	3.41
	Neoarchaeon rocks with neoproterozoic overprint	1034.3	25.30	Very low	
Proximity to roads	0 – 200	365.3	8.94	Very high	3.41
	200 – 500	453.3	11.09	High	
Proximity to roads	500 – 800	392.6	9.60	Moderate	3.41

	800 – 1200	454.9	11.13	Low	
	>1200	2422.3	59.25	Very low	
Proximity to Rivers	0 – 200	401.5	9.82	Very high	
	200 – 500	543.3	13.29	High	
	500 – 800	494.1	12.08	Moderate	2.48
	800 – 1200	583.6	14.27	Low	
	>1200	2066.1	50.53	Very low	
NDVI	(-0.04) - 0.017	309.6	7.57	Very high	
	0.17 - 0.23	480.9	11.76	High	
	0.23 - 0.31	566.5	13.86	Moderate	1.69
	0.31 - 0.39	980.4	23.98	Low	
	0.39 - 0.64	1751.2	42.83	Very low	

Source: (Author, 2022)

The findings further indicate that furthest wards of Lushoto district are more pounded by rock falls mainly as a results of human intervention that weakens the surface of slopes and changes in surface water level within the study area. The findings also signpost that this type of landslides is common in elevated and mountainous areas of the district because of their high slope angles.

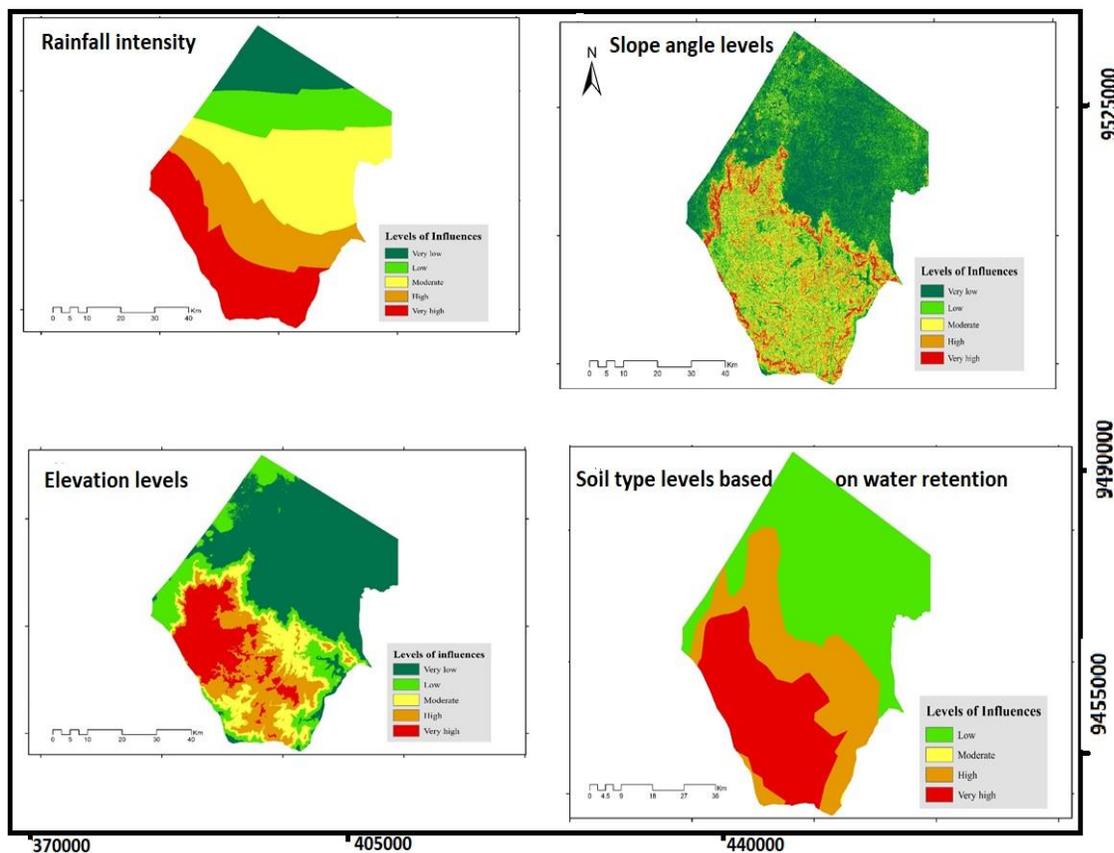


Figure 5: Landslide Susceptibility Fundamental Factors in Lushoto District
Source: (Author, 2022)

Landslide Susceptible Areas of Lushoto District

The landslides susceptibility areas' map was generated from the Weighted Linear Combination (WLC) GIS analysis. The results generated by the analysis reveal that about 97669.65 ha of land, which account for about 24.03% of the total study area, have very low landslides susceptibility levels while low susceptibility levels were found in about 123105.84 ha of land, which is equivalent to 30.28% of the study area. Highly and very highly susceptible areas were found to cover about 45423.43 ha and 57.78 ha respectively, which are equivalent to 11.17% and 0.01% of the study area respectively (see Table 5). This indicates that about 185746.00 ha of land in the study area are likely to be affected by landslides. This also means that the area affected by landslides is not very large and therefore, if precautions are taken and deliberate efforts are made, effects of landslides may not be felt or kept to a minimum. Table Five has these results.

Table 5: Landslides Susceptibility Level Ranks, Area and their Percentage

Landslides Susceptibility Levels	Rank	Hectares	Percentage
Very low	1	977.52	24.03
Low	2	1232.10	30.28
Moderate	3	1403.83	34.50
High	4	454.62	11.17
Very high	5	0.58	0.01

Source: (Author's Analysis, 2022)

The study further reveals that most southern and central mountainous regions of the study area are more susceptible to landslides since they lie on very susceptible zones. High landslides susceptibility is also noted in the central, western and south eastern parts of the study area. Furthermore, the results show that low susceptible areas are concentrated in the outer central parts of the low lying slopes of Usambara Mountain while places that are safe from landslides are located in the north-eastern parts of the study area, with small patches of low landslides susceptibility. See Figure 6:

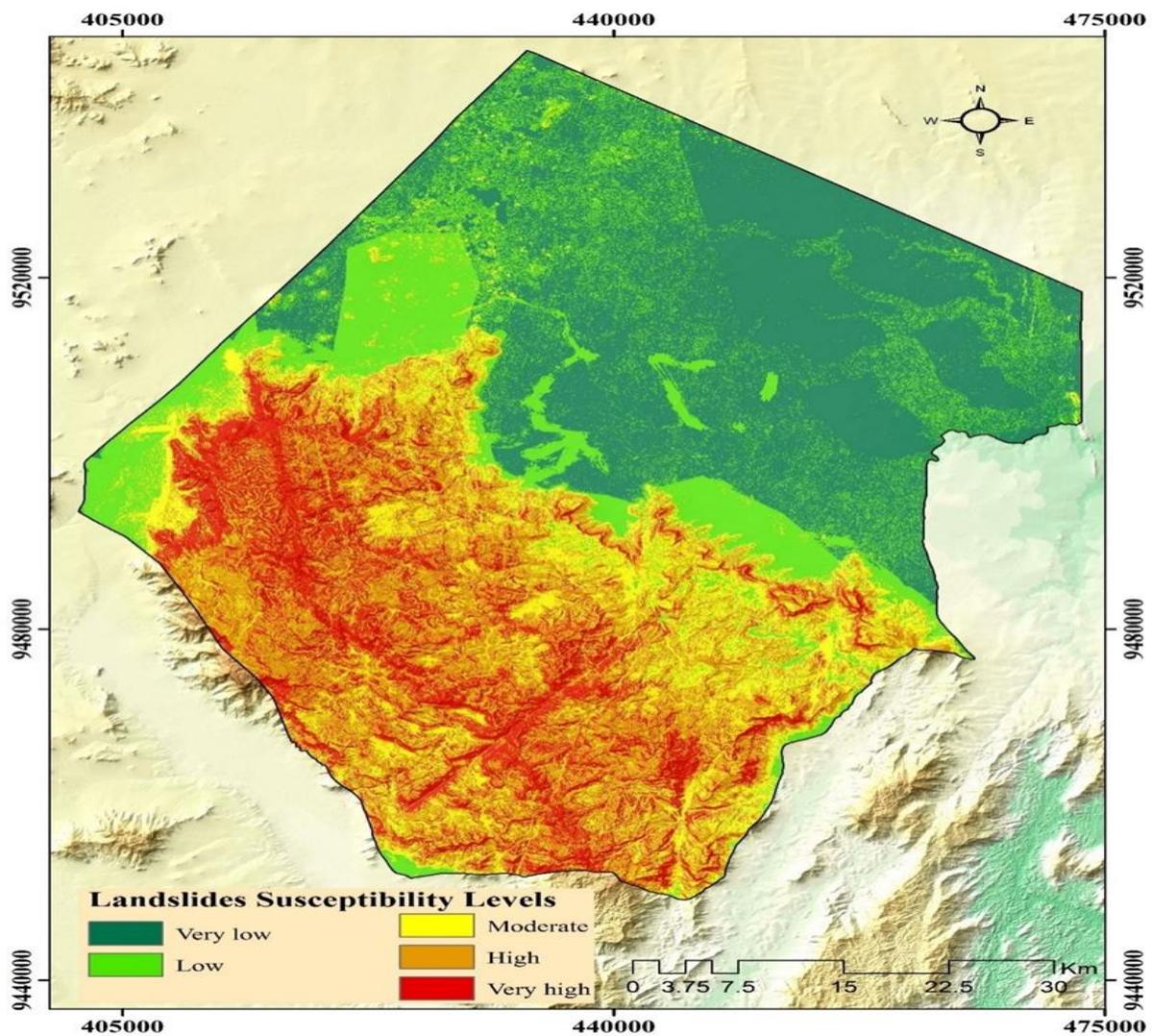


Figure 6: Landslides Susceptibility Map of Lushoto District
Source: (Author, 2022)

Landslides Susceptibility with Respect to Major Community Centres

After getting a real picture of landslides occurrence and distribution, and knowing the areas that are potentially at risk of being affected by landslides, deliberate efforts were made to find out the location of people's shelters. The findings reveal that the majority of community centres in Lushoto district lie on highland areas around the Usambara Mountains. Additionally, these centres are located in moderate to very low landslide susceptible areas. Field visits and observation were done to verify this fact. The results also show that some of the community centres are located in the south-western, central, and southern parts of the area where Vuga, Shume, Manolo, Kwai, Lukozi, Soni, Mponde, Usambara, Baga, and Mamba wards are located. These are areas with higher probability of landslide events. Furthermore, the community centres of the north-eastern and

south-eastern sides of the study area, including Makanya, Milingano, Nkongoi and some parts of Mng'aro centres have moderate to low probability of experiencing landslides. However, the analysis indicates that northern region wards, which include Lunguza, Mnazi, and some parts of Mng'aro have very low probability of landslides occurrence (see Figure 7).

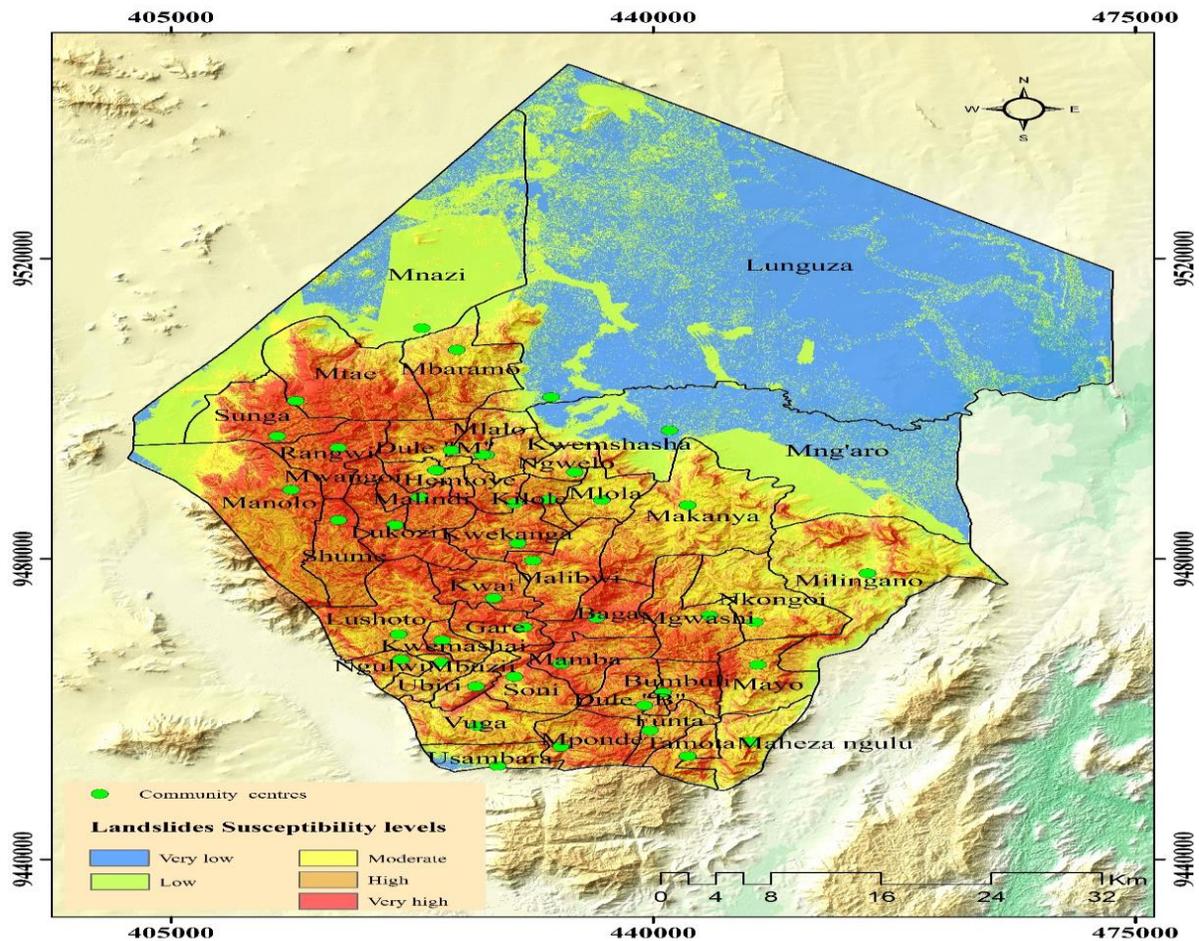


Figure 7: Landslides Susceptibility Levels with Respect to Major Community Centres
Source: (Author, 2022).

Validation of LSM by Landslides Events

Eleven previous landslide spatial sites collected by handheld GPS in the field were overlaid with Landslides Susceptibility Map (LSM) data, and about eight of them (73%) were exactly matched with high to very high landslide susceptibility levels. This demonstrates the accuracy of the results. The remaining geographical sites also correctly matched moderate and low susceptibility levels hence further demonstrating the accuracy of the results (see Figure 8).

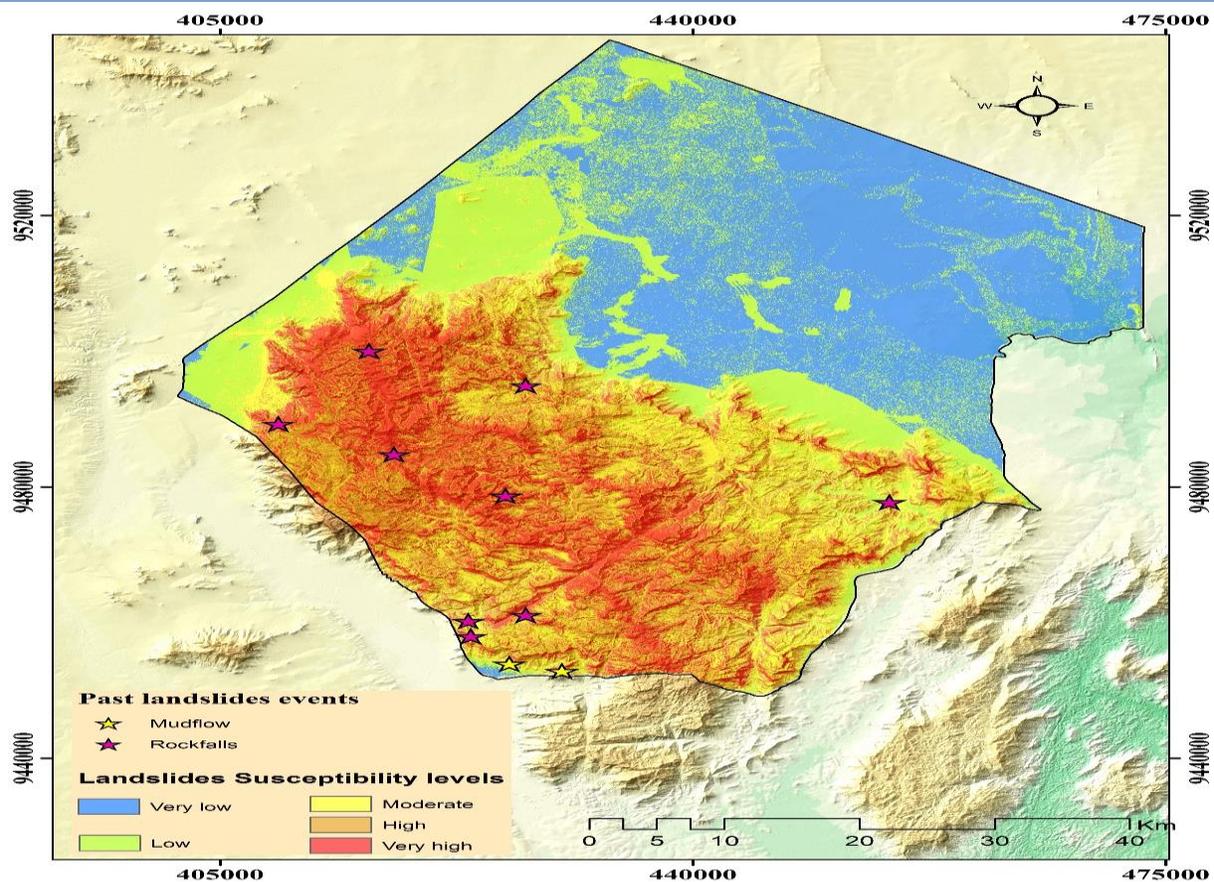


Figure 8: Results Validation by Landslides Events
Source: (Author, 2022).

Discussion

Distribution and Factors Influencing the Occurrence of Landslides

The study clearly shows that places like Manolo, Kwai, Shume, Miling'ano, Usambara, and Mtae are more affected by landslides compared to places like Makanya, Mlola and Mcheza Ngulu. The main reason for this is the location of these wards on the western part of the study area, which is the most susceptible due to human intervention and being on the windward side of the Usambara Mountain that receives a high amount of rainfall which triggers landslides due to water infiltration. Apart from that, the findings further indicate that mudflow landslides are more common in the southern parts of the study area in the Usambara ward because of the elevation of the area. The area has the lowest elevation and faced the windward side of the mountain hence receiving high intensity of surface water flow from the mountainous higher elevated wards such as Mamba and Dule. These types of landslides are normally associated with high destruction of properties and loss of lives because they usually carry unconsolidated materials, mud, and logs which are normally agents of destruction as they travel long distances destroying whatever is in their way (Cascini 2008),

Death rates ranging from hundreds to thousands of people are foreseeable when mudslides occur in populated areas. These findings closely agree with Chalise, et al., (2019) who researched on landslides management. These researchers claim that most mudflow landslides are common in lowlands which normally acts as the surface runoff mouth and that they have great impact on people's lives because they usually destroy homes, take lives and other important properties and resources. In almost all the inventoried landslides, long duration of rainfall with varying intensities was perceptually reported as the main trigger of mudflow landslides in Tanzania, East Africa and the world at large. This is also supported by Chen et al., (2021), who have revealed extreme rainfall and human activities as the main landslide triggering factors in Tanzania and globally. In fact, more than half of mudflow landslide events in the world are due to extreme rainfall (Chalise, et al., 2019). According to the findings of this study, rock fall landslides are more widespread in the northern and western zones because these areas are elevated and have high slope angles that are easily weakened and affected by earth's movement and human intervention. These results greatly agree with those of other scholars that have mapped landslides, including Chalise et al., (2019) who found that most rock fall types of landslides are common in mountainous areas or in most elevated areas as these areas easily experience weathering.

Generally, the results show that the main factors that lead to the occurrence of landslides in the study area are rainfall, slope and elevation. High rainfall intensity has also been reported as a key factor in landslide events in many parts of the world (Fontijn et al., 2012) because it loosens the surface landmass by increasing soil pore pressure. Delcamp et al., (2017) discovered that rainfall is an important factor to consider in landslide susceptibility mapping after discovering that excessive rainfall contributed to approximately 30% of the landslides. Furthermore, Delcamp et al., (2017) found that approximately 80% of landslide occurrences were due to rainfall, thus highlighting making it the key trigger of landslides worldwide. Apart from rainfall, very high slope angles are responsible for landslides occurrence. This is also reported by Kervyn et al., (2014), who have argued that slope failure due to instability of the underlying mass causes landslide. Furthermore, Kervyn et al., (2014) indicated that slopes are commonly affected by water permeability, thus controlling slope stability and landslide susceptibility. Similarly, findings reported by Chen, (2019), and Chalise, et al., (2019) show that elevation has a significant role in landslides occurrence as these events normally increase with the increase in elevation of the area.

Landslide Susceptible

This study has clearly identified the areas in which human communities live and areas where landslides occur regularly or areas at high risk of landslides. The study shows that some communities are located in landslide prone zones. These are highland areas that have signs of landslides occurrence. The study has also shown areas that are far and safe from landslides. Sites that are prone to rock falls and mudflows have been quantitatively and qualitatively identified using systems such as the Rockfall Hazard Rating System. Now that high risk sites have been identified, responsible agencies can design and install rock fall and mudflows mitigation systems (Kervyn et al., (2014). Therefore, this study presents responsible institutions with spatial

information that can be used as a baseline for coming up with plans to save people's lives and their properties. These agencies should take urgent measures, such as demarcating and zoning these high to very high landslide susceptible areas to limit further human interventions that may result in property loss and loss of human life in the study area (Arjmandzadeh, et al., 2020). This quantitative analysis of the fragmental rock falls and mudflow provides useful information for risk assessment and designing both stabilization and protection measures (Bostjančić et al., 2021). It is necessary for relevant institutions to take serious and deliberate precautions for areas that are prone to landslides as they have been indicated by this study and especially those occupied by people to see how effects can be controlled by formulating and framing risk reduction strategies, and mitigation and prevention measures (Delcamp et al., 2017)

Conclusion and study implications

GIS and RS technologies have been integrated in this study to establish the landslide susceptibility of areas in Lushoto district while AHP has been employed in the evaluation, weighting, and ranking of the included landslide influencing factors. Apart from that, the WLC techniques have been employed to integrate the landslides influencing factors to produce the final LSM of the district. The study concludes that landslides occurrence likelihood is mainly concentrated in the southern, central and western parts of the study area. These areas are susceptible to both rock falls and mudflows. In these areas, the wards that are most affected are Manolo, Kwai, Shume, Miling'ano, Mtae, Usambara and Shume as shown by records of past incidents. This study has found that some of areas prone to landslides are close to local communities and their surrounding environment. As such, it is clear that care must be taken to incorporate appropriate spatial knowledge pertaining to landslides disasters as these are critical in designing policies and laws to manage and mitigate these disasters.

With the findings presented, this study also presents knowledge that can be used to facilitate future sustainable land and settlement management plans. Town planners, environmentalists, and other stakeholders should consider these scientific results in their development plans and policies. These findings should also serve as a basis for regular monitoring of these landslide prone areas using geospatial techniques (GIS and RS) and applying restrictions of any developmental activities near dangerous areas to avoid loss of lives and properties. Apart from this, the study can be useful in creating awareness among the general public (particularly people who live in hilly areas and the foot of Usambara Mountain), the government, and other concerned stakeholders on the susceptibility to landslides of areas in Lushoto district. Landslides pose serious threat to the environment and the society, therefore, this study presents a valuable contribution to Tanzanian' efforts to attain sustainable cities and communities and other sustainable development goals.

References

- Abay, A., Barbieri, G., & Woldearegay, K. (2019). GIS-based landslide susceptibility evaluation using analytical hierarchy process (AHP) approach: The case of Tarmaber District, Ethiopia. *Momona Ethiopian Journal of Science*, 11(1), 14-36.
- Abedini, M., Ghasemian, B., Shirzadi, A., Shahabi, H., Chapi, K., Pham, B. T., Bin Ahmad, B., & Bui, D.T. (2019). A novel hybrid approach of bayesian logistic regression and its ensembles for landslide susceptibility assessment. *Geocarto International*, 34(13), 1427-1457. <https://doi.org/https://doi.org/10.1080/10106049.2018.1499820>
- Abraham, M.; Satyam, N.; Rosi, A.; Pradhan, B.; Segoni, S. (2021). Usage of antecedent soil moisture for improving the performance of rainfall thresholds for landslide early warning. *Catena* 2021, 200, 105147.
- Aditian, A., Kubota, T., & Shinohara, Y. (2018). Comparison of GIS-based landslide susceptibility models using frequency ratio, logistic regression, and artificial neural network in a tertiary region of Ambon, Indonesia. *Geomorphology*, 318, 101-111. <https://doi.org/https://doi.org/10.1016/j.geomorph.2018.06.006>
- Agliardi, F., Crosta, G. B., & Frattini, P. (2012). 18 Slow rock-slope deformation. In: *Landslides: Types, mechanisms and modeling Cambridge University Press, Cambridge*, pp 207-221.
- Al-Mulali, U., Ozturk, I., & Lean, H. H. (2015). The influence of economic growth, urbanization, trade openness, financial development, and renewable energy on pollution in Europe. *Natural Hazards*, 79(1), 621-644. <https://doi.org/https://doi.org/10.1007/s11069-015-1865-9>
- Anderson, W. (2018). Linkages between tourism and agriculture for inclusive development in Tanzania. *Journal of Hospitality Tourism Insights*, 1(2), 168-184. <https://doi.org/https://doi.org/10.1108/JHTI-11-2017-0021>
- Arjmandzadeh, R., Sharifi Teshnizi, E., Rastegarnia, A., Golian, M., Jabbari, P., Shamsi, H., & Tavasoli, S. (2020). GIS-based landslide susceptibility mapping in Qazvin province of Iran. *Iranian Journal of Science Technology, Transactions of Civil Engineering*, 44(1), 619-647.
- Ayalew, L., & Yamagishi, H. (2005). The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. *Geomorphology*, 65(1-2), 15-31. <https://doi.org/https://doi.org/10.1016/j.geomorph.2004.06.010>
- Ayalew, L., Yamagishi, H., & Ugawa, N. (2004). Landslide susceptibility mapping using GIS-based weighted linear combination, the case in Tsugawa area of Agano River, Niigata Prefecture, Japan. *Landslides*, 1(1), 73-81. <https://doi.org/https://10.1007/s10346-003-0006-9>
- Bernard, B., Takarada, S., Andrade, S. D., & Dufresne, A. (2021). Terminology and strategy to describe large volcanic landslides and debris avalanches. In *Volcanic Debris Avalanches* (pp. 51-73). Springer.
- Borgomeo, E., Hebditch, K. V., Whittaker, A. C., & Lonergan, L. (2014). Characterising the spatial distribution, frequency and geomorphic controls on landslide occurrence, Molise, Italy. *Geomorphology*, 226, 148-161.
- Bostjančić, I., Filipović, M., Gulam, V., & Pollak, D. (2021). Regional-Scale landslide susceptibility mapping using limited LiDAR-Based landslide inventories for Sisak-Moslavina County, Croatia. *Sustainability*, 13(8), 4543-4557.

<https://doi.org/https://doi.org/10.3390/su13084543>

- Broeckx, J., Vanmaercke, M., Duchateau, R., & Poesen, J. (2018). A data-based landslide susceptibility map of Africa. *Earth-Science Reviews*, 185, 102-121.
- Campbell, J. B., & Wynne, R. H. (2011). *Introduction to remote sensing*. Guilford Press.
- Capello, R. (2011). Location, regional growth and local development theories. *Location, Regional Growth and Local Development Theories*, 58, 1-25.
- Cascini, L. (2008). Applicability of landslide susceptibility and hazard zoning at different scales. *Engineering Geology*, 102(3-4), 164-177.
<https://doi.org/https://doi.org/10.1016/j.enggeo.2008.03.016>
- Cervi, F., Berti, M., Borgatti, L., Ronchetti, F., Manenti, F., & Corsini, A. (2010). Comparing predictive capability of statistical and deterministic methods for landslide susceptibility mapping: a case study in the northern Apennines (Reggio Emilia Province, Italy). *Landslides*, 7(4), 433-444.
- Chalise, D., Kumar, L., & Kristiansen, P. (2019). Land degradation by soil erosion in Nepal: A review. *Soil Systems*, 3(1), 12. <https://doi.org/https://doi.org/10.3390/soilsystems3010012>
- Chen, W., Shahabi, H., Shirzadi, A., Hong, H., Akgun, A., Tian, Y., Liu, J., Zhu, A., & Li, S. (2019). Novel hybrid artificial intelligence approach of bivariate statistical-methods-based kernel logistic regression classifier for landslide susceptibility modeling. *Bulletin of Engineering Geology and the Environment*, 78(6), 4397-4419.
- Delcamp, A, Kervyn M, Benbakkar M, & Peter D. (2017). Large volcanic landslide and debris avalanche deposit at Meru, Tanzania. *Springer Berlin Heidelberg*, 14(3), 833-847.
- Dou, J.; Yunus, A.P.; Bui, D.T.; Merghadi, A.; Sahana, M.; Zhu, Z.; Chen, C.W.; Khosravi, K.; Yang, Y.; Pham, B. (2019). Assessment of advanced random forest and decision tree algorithms for modeling rainfall-induced landslide susceptibility in the Izu-Oshima Volcanic Island, Japan. *Science of the Total Environment*, 662, 332–346.
- El-Fengour, M.; El Motaki, H.; El Bouzidi, A. (2021). Landslides susceptibility modelling using multivariate logistic regression model in the Sahla Watershed in northern Morocco. *Sociedade & Natureza*, 33 (2021). <https://doi.org/10.14393/SN-v33-2021-59124>
- Fiorucci, F.; Ardizzone, F.; Mondini, A.C.; Viero, A.; Guzzetti, F. (2019) Visual interpretation of stereoscopic NDVI satellite images to map rainfall-induced landslides. *Landslides*, 16, 165–174.
- Fontijn, K., Williamson D., Mbede E., & Ernst G.G. (2012). The Rungwe Volcanic Province, Tanzania-A volcanological review. *Journal of African Earth Sciences*, 63, 12-31.
<https://doi.org/10.1016/j.jafrearsci.2011.11.005>
- Kervyn, M., Wyk de B., Walter, R., Njome, S., Suh, E., & Ernst, J. (2014). Directional flank spreading at Mount Cameroon volcano: Evidence from analogue modeling. *Journal of Geophysical Research: Solid Earth*. 119 (10), 7542–7563.
<https://doi.org/10.1002/2014jb011330>
- Zhou, X.; Wu, W.; Lin, Z.; Zhang, G.; Chen, R.; Song, Y.; Wang, Z.; Lang, T.; Qin, Y.; Ou, P. (2021). Zonation of landslide susceptibility in Ruijin, Jiangxi, China. *International Journal of Environmental Research and Public Health*, 18 (11), 5906-5920.