INTEGRATING GIS AND REMOTE SENSING TO ASSESS THE RISK OF LANDSLIDE IN NKHULAMBE COMMUNITY, PHALOMBE

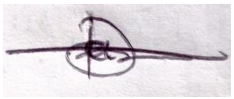
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Dissertation submitted to Ndata School of Climate and Earth Sciences of the Malawi University of Science and Technology in partial fulfilment of the requirements for the Bachelor of Science degree in Disaster and Risk Management.

21th May 2025

DECLARATION

I, Daniel Maneya declare that this research project represent my work and that it has never been submitted to this institution or any other institution for any academic purpose. All sources of information have been appropriately acknowledged.

Signature: 

Date: 20th May 2025

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ACKNOWLEDGEMENTS

First and foremost, praise and thanks to God, the Almighty, for His showers of blessing when I was writing this dissertation.

I express my great appreciation and special gratitude to my supervisor, Mrs. T. Nthara for the support and encouragement throughout the duration of this research. Her guidance, feedbacks and dedication have been important in shaping this work. Am grateful for her patience and willingness to share her expertise.

I also give thanks to my loving parents for their invaluable love, support and encouragement and working prayers, for their endless support both morally and financially. Your words of encouragement kept me going until I have finished this research project.

Lastly, many thanks to the entire Malawi University of Science and Technology (MUST) Lecturers particularly those from the Ndata School of climate and earth sciences for all the skills I have been taught, May God bless you all.

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ABSTRACT

Landslides pose a major threat to communities in mountainous regions, especially in developing countries like Malawi, where disaster risk management is hindered by weak institutional capacity and limited data. The Nkhulambe Community in Phalombe District, affected by events like Cyclone Freddy in 2023, was the focus of this study, which used GIS and remote sensing to assess landslide risk and support local and national disaster preparedness.

The research integrated Sentinel-2A satellite imagery, SRTM DEM data, and socio-economic surveys to evaluate landslide susceptibility using the Information Value Method (IVM). Nine factors slope, elevation, aspect, soil depth, land use, rainfall, distance to streams, landform and lithology were analyzed. The susceptibility map showed that central and northern areas faced very high risk due to steep slopes, sedimentary rock type, proximity to river banks, and high rainfall. Physical vulnerability was assessed by mapping infrastructure and agricultural land, with high-risk zones overlapping susceptibility areas, particularly around villages like Nachuma, Nagoli A, and Nititha. Social surveys revealed strong awareness of landslide risks but poor preparedness: only 12% had access to early warning systems, and 76% did not know how to respond during an event.

A final landslide risk map combined susceptibility and vulnerability layers, identifying zones of varying risk levels. This tool supports land-use planning and emergency response strategies. Key recommendations include integrating GIS-based maps into local planning, strengthening early warning systems, improving meteorological collaboration, and launching education campaigns to boost community resilience. This study contributes to GIS-based landslide risk assessment in data-limited settings and aligns with global frameworks like the Sendai Framework and SDG 11, offering a replicable model for disaster risk management across Malawi and similar contexts.

Keywords: Landslide risk, GIS, Remote Sensing, Vulnerability, Susceptibility, Nkhulambe, Phalombe, Disaster Risk Management.

ACRONYMS/ABBREVIATIONS

GIS:	Geographical Information System
CRED-EM:	Central for Research on the Epidemiology of Disasters – Emergency Events
LEM:	Limit Equilibrium Method
FEM:	Finite Element Method
SHALSTAB:	Hydrological Model, Shallow Landslide Stability Model
FR:	Frequency Ratio Method
LR:	Logistic Regression
WoE:	Weight of Evidence
ANN:	Artificial Neural Network
SVM:	Support Vector Machine
IVM:	Information Value Method
AHP:	Analytics Hierarchy Process
MUSTREC:	Malawi University of Science and Technology Research Ethics Committee
MUST:	Malawi University of Science and Technology
NSO:	National Statistics Office

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1. Chapter 1: Introduction

1.1. Background

Around the globe, landslide disasters cause numerous fatalities, loss of livelihoods, injuries, destruction of property and environment harm. The term "landslide" is defined as the movement of a mass of rocks, debris or earth down the slope (Crozier & Glade, 2005). These landslides can be triggered by several factors including prolonged rainfall, earthquakes, rapid snow melting and various anthropological activities. There are different types of landslide movements, including falls, topples, slides, spread and flow, each characterized by its unique kinematic behavior(Hungr et al., 2014).

In recent years, GIS and remote sensing have changed the way vulnerability is assessed. These tools have allowed high precision mapping of areas at risk and the integration of various geospatial datasets, improving both early warning systems and disaster preparedness. For example, advanced remote sensing techniques like LiDAR and high resolution satellites imagery have been effectively used to map landslide-prone areas in various regions around the world.(Choi et al., 2024).Despite all the destructive effects landslides may cause, societies often view them as infrequent events, underestimating their potential impacts. Major landslides disasters that affects societies are often unexpected (Davies & Rosser, 2021). In many countries, social-economic losses due to landslides are huge and expanding as human development pushes into unstable hill areas (G. Msilimba, 2012).

In Malawi, landslide disasters are common and cause significant loss of life and property damage. Malawi, being a developing country, struggles whenever faced with this disaster. For example, on March 10th, 1991, Malawi experienced a devastating landslide in Phalombe, triggered by continuous heavy rains, which led to a massive rock avalanche from Michesa and Mulanje mountains. This tragic event resulted in the loss of over 500 lives and caused extensive damage to villages, crops, bridges, buildings and property worthy US $720, 000(Thiery et al., 2024). Malawi has faced many landslides, devastating one have occurred in Phalombe district in the southern part. This region has a hilly topography with steep slopes, experiences heavy seasonal rainfall and human activities like deforestation and farming on hill side makes this area more prone to landslide. The area is vulnerable to landslides risks,

and still systematic studies on landslide susceptibility at local level remains adequate and there is an immediate need for application of better methods for assessing as well as mitigating landslides within the district.

In this highly technological era, GIS and Remote Sensing have provided tools to determine the risk of societies towards landslides. As they help in mapping of landslide location, identifying elements at risk and enabling the application of strategies to reduce risk. This study will integrate GIS and remote sensing to assess the landslide risk of Nkhulambe community. It will identify areas prone to landslides by mapping key determining variables, such as slope, soil composition, vegetation cover and rainfall pattern and give appropriate risk reduction strategies. It is hoped that the outcome of the study will add value to disaster preparedness in Malawi with valuable geospatial data to inform policy making and community-based disaster management.

1.2. Problem Statement

The risk of a person to die of a landslide is acceptable at a level of about 10^{-6} per year (Finlay et al., 1997). This means that on average, for everyone million people, one person is expected to die from a landslide risk in a given year. This suggests that this level of risk is manageable by society. If the risk of dying from a landslide in a specific area is surpasses its acceptable level, it may require authorities to act such as risk assessment and mapping, improving early warning systems and better land management practices. In recent studies Corominas et al., (2014) have shown that loss of life is intense in less developed countries, in this case Malawi where there is relatively little investment to understand hazards and risks associated with landslides due to lack of appropriate resources, supportive research and capacity building efforts are required to support the local and national administration in charge of landslide risk management in this country. As one way to assess landslide risk, GIS and remote sensing tools will be used in the study to analyze rainfall patterns and terrain characteristics, as these are the most significant factors to influencing landslide occurrence in Nkhulambe. Therefore this study was conducted in Nkhulambe, a landslide prone area due to the steep terrain surrounding the area.

1.3. Research Objectives

1.3.1. Main Objective

The main research objective was to assess landslide risk in Nkhulambe. Thereby providing insights for improving land-use planning, disaster risk reduction and promoting sustainable development.

1.3.2. Specific objectives

The study had the following specific objectives to support the main objective;

1. Identify areas that are susceptible to landslides in Nkhulambe.
2. Map elements at risk of landslide around Nkhulambe.
3. To develop a landslide risk map for Nkhulambe.

1.4. Research Questions

1. Why are the areas prone to occurrence of landslide?
2. What are the elements at risk in Nkhulambe if a landslide occurs?
3. How will you develop a landslide risk map for Nkhulambe?

1.5. Significance of the Study

Due to the presence of fertile soil deposited by the various streams from Mulanje Mountain, access to social services and financial generating opportunities e.g. farming and trade, People start to settle in areas similar Nkhulambe, exposing themselves to hazards like floods and landslides(F. Wang & Gao, 2020). Therefore, it is necessary to carry out landslide risk assessment and thereby mapping out the landslide prone areas. This will enable the community for their effective preparedness and response plan to landslide events. In additional, the research also aligns with Sustainable Development Goal number 11 of the Sendai Framework for Disaster Risk Reduction, which focus on making cities and human settlements inclusive, safe, resilient and sustainable.

2. Chapter 2: Literature Review

2.1. General introduction to Landslide Risk Management

Studies on the global distribution of landslide conducted by Nadim et al., (2013) provide a detailed assessment of landslide disasters in the CRED-EM database, suggesting that countries that are exposed to landslide risk are located in south Asia, along the Himalayan belt, east Asia, south-eastern Asia, and Central and South America but in many developed country a with high landslide hazard, the landslide event rarely results into a disaster. For example in European countries they put much effort to use advanced technologies, public awareness and strict building codes to manage landslide risk(Jaedicke et al., 2014), in United States the government has developed landslide risk management strategies, including mapping landslide-prone areas, implementing early warning systems and enforcing land-use and regulations to minimize exposure(Godt et al., 2022). In japan landslide risk managed through extensive monitoring networks, community based preparedness and engineering solutions to stabilize slopes (Alcántara-Ayala & Sassa, 2023). Reducing exposure in landslide prone zone and implementing appropriate risk management actions are essential strategies that could also be applied to manage landslide risk in Malawi.

2.2. Landslide Hazard Assessment

According to Miccadei et al., (2022) landslide hazard assessment is described as the process of evaluating the likelihood of a landslide occurring in a particular area based on its environmental factors such as lithology, geological setting and land-use. The process involves understanding how these factors interact. Landslide susceptibility assessment is critical when we need to understand landslide risk. Shano et al., (2020) found that slope gradient and soil composition play a direct role in influencing landslide, mentioning that steeper slope gradient and loose soil composition have greater chances of causing landslides. Similar studies have also been conducted in Malawi for instance Thiery et al., (2021) found out that many landslide are being triggered by climatic incident, especially tropical cyclones.

Human activities, including deforestation, construction and urbanization, also contributed to the occurrence of landslides. (Jaedicke et al., 2014). For example Maki Mateso et al., (2021) compared naturally induced and human induced landslide and the results showed that regions

with high human activity, the frequency and severity of landslide occurrence were high than in natural induced. Indicating a strong correlation between human actions and landslide events.

The integration of remote sensing and GIS has become increasingly important for assessing and monitoring landslide susceptibility in mountainous and hilly regions worldwide (Hammad et al., 2020). These technologies allow data collection and analyzation to identify and map out landslide-prone areas. Researchers can then use statistical and deterministic models to predict the landslide likelihood.

2.2.1. Approaches for Susceptibility Mapping

There are various methods that have been developed to create these maps and there are classified into three categories; qualitative, quantitative and the deterministic approach (Batar & Watanabe, 2021). Shano et al., (2020) Highlighted that the qualitative methods like geomorphological analysis and Heuristic techniques depends much on expert judgement and terrain knowledge. This method is then mainly applied in regions where data correction is challenging and situation where immediate assessment is required. The deterministic approach involve the indirect estimation of slope instability using engineering principles expressed in terms of factor safety (Bednarik et al., 2024). Examples of these approach include Infinite Slope Model, Limit Equilibrium Method (LEM), Finite Element Method (FEM), Hydrological Model, Shallow Landslide Stability Model (SHALSTAB) and Seepage Model.

The quantitative approaches (Statistical methods) relies on statistical or mathematical models to assess the likelihood of landslide based measurable factors such as slope, aspect soil type and precipitation data (An et al., 2018). The most common used quantitative methods include Frequency Ratio (FR) method, Logistic Regression (LR), Weight of Evidence (WoE), Artificial Neural Network (ANN), Support Vector Machine (SVM), Information Value Method (IVM), and Analytics Hierarchy Process (AHP). Each method depends on data availability, computation recourses and the nature of the study area (Corominas et al., 2014)

2.3. Landslide Vulnerability Assessment

Vulnerability is the degree to which individual, environment or community is susceptible to the impact of landslides. It is shaped by physical, social-economic and environmental factors

that increase the likelihood to hazards (UNDRR, 2007). Effective landslide risk assessment combines the likelihood of landslides susceptibility with potential impacts of the event (Arrogante-Funes et al., 2021). Combining the two will help to not to only understand where the landslide may occur or what caused the event but it will also provide insight on what might be the effect on people, properties and environment.

Previous studies focused on susceptibility modelling alone, forgetting to understand the broader vulnerability of the population. However Birkmann & Pelling, (2006) argued that focusing only on susceptibility offers limited information to understand risk, supporting for the addition of social-economic and environmental factors in vulnerability assessment. In Malawi vulnerability is mainly influenced by social-economic factors which increase the susceptibility of the country to hazards. G. G. Msilimba & Holmes (2010) documented a historical landslide in Rumphi, highlighting deforestation, unplanned urbanization, agriculture practices, poverty and lack of awareness and preparedness played a role in increasing vulnerability.

2.3.1. Social Vulnerability

Social vulnerability encompasses demographic and social-economic factors (e.g. poverty, lack of access to social services and crowded settlements) that adversely affect communities exposed to hazards (Flanagan et al., 2011). Social vulnerability is quite complex as it involve both qualitative and quantitative approach and focuses on two perspective, firstly being the intangible assets e.g. environment, culture and institutional assets and the other focus is on social-economic factor such society preparedness and capacities of the community (Ciurean et al., 2013).

2.3.2. Physical Vulnerability

Meslem & Lang, (2017) define physical vulnerability as the potential of a given physical component or element to be affected or damaged under a certain hazard. The focus of this vulnerability is mainly on susceptibility of built up environment to hazards. With the vulnerability often influenced by factors like construction material, the age of buildings and location of the physical assess to the hazard prone-region (Ford et al., 2018).

Building characteristics such as structural integrity, design standard and type of material used if they do not meet the safety regulation they become prone to damage. Ngoma et al., (2019) studied building standards in Malawi and found that many buildings in central and southern region are constructed using informal methods and cheap materials that do not meet the standards making them vulnerability to hazards. A similar study was conducted in Karonga by Gondwe & Manda, (2017) to how land-use planning and zoning increases physical vulnerability to flood risk. The study emphasized on need to conduct hazard-informed planning to reduce vulnerability.

Research, such as the work by Kappes et al., (2012), indicates that evaluating the vulnerability of physical assets should not only consider their exposure to risks but also their ability to resist damage. This usually involves using models and simulations to predict possible damage under different risk conditions. Additionally, improving existing structures and designing them to be more resistant to hazards are seen as effective ways to lower vulnerability, especially in places frequently affected by hazards like earthquakes.

2.3.3. Vulnerability Assessment Methods

Most vulnerability assessment are conducted at local levels i.e. household or individual but the data to conduct this assessment is limited for that reason national-level assessment can be employed(Ciurean et al., 201z3). However, they also argued that down scaling will cause too much assumption of the data. In additional to the approach GIS and remote sensing tool allow vulnerability analysis at both local, regional and global level (Upadhyay, 2024). Apart from GIS and remote sensing tools we can also use, index-based methods such as Social Vulnerability Index, Physical Vulnerability index and Ecological Vulnerability Index. These tools offers a standardized way to group vulnerability across various scale and balancing these indices will help to produce an effective assessment (Smits & Huisman, 2024).

2.4. GIS and Remote Sensing as a Tool for Landslide Risk Assessment

GIS and remote sensing have merged as powerful tools for assessing and modeling landslide susceptibility globally. In Malawi Moses (2019) used a combination of satellite imagery and GIS to identify areas prone to landslide susceptibility in Chiweta. The research integrated

factors such as slope, land use, and rainfall to produce susceptibility maps and highlighted areas for further monitoring.

Thiery et al., (2024) developed a comprehensive landslide hazard assessment and mapping at national level for Malawi, by combining literature review, visual remote sensing and field survey. This demonstrated the potential of integrated data sources for national-scale landslide risk assessment.

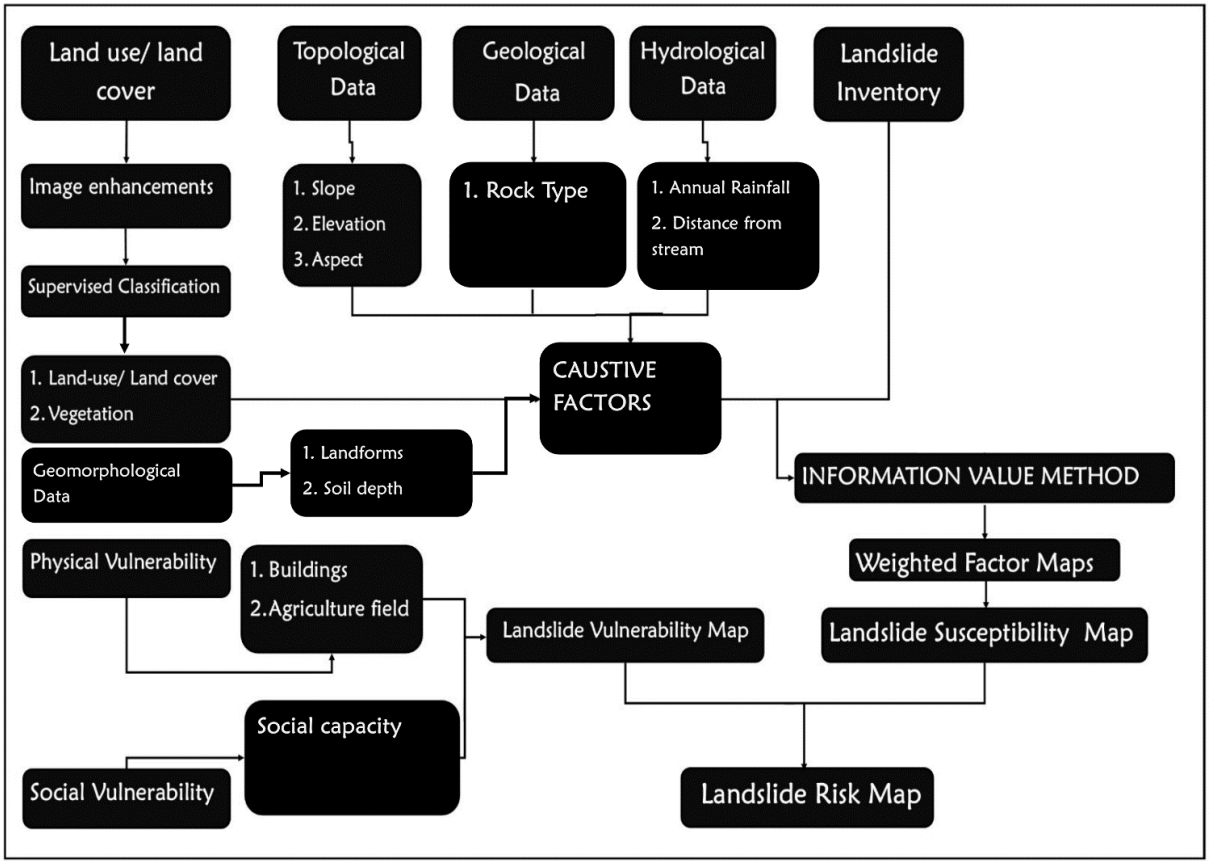
While GIS and remote sensing offer essential tools for landside risk assessment in Malawi, challenges still remains, particularly data availability and quality, which limits the accuracy of landslide susceptibility maps. In additional to that validating of landslide models is critical but is often hindered by lack of historical landslide data.

Despite the difficulties faced in this area of study the application of GIS and remote sensing is raising quickly. Innovations, like drone sensing, artificial intelligence and vast geodata are creating ways for enhancing landslide risk mitigation. Thiery et al., (2021) conducted a quantitative a landslide hazard assessment for Malawi, producing maps that provide valuable insights for national decision makers.

3. Chapter 3: Methodology

Research Design

This study employed a GIS-based quantitative research design to assess the risk of landslides in Nkhulambe community, Phalombe. The design integrated environmental and social data to develop a comprehensive landslide risk map. By utilizing Geographical Information Systems and Remote Sensing,



Study Area

Figure 1: Shows the research design

Phalombe is a district located at Latitude -15.803333 and longitude 35.65333, in the Southern Region of Malawi, it covers an area of about 1394 sq. Km (NPC, 2024). According to (NSO, 2018) the district has a population of 429,450 people contributing to 2.4 percentage of

Malawi's population. Nkhulambe community is located at latitude -15.984973° and longitude 35.786503° under Traditional Authority Nkhulambe, the community has many villages including Nagoli, Manyamba, Mudeni and Mugambe. Its climate is mild and generally warm and temperate. The average annual temperature is 27.59°C.

The Area is located to the east side of Mulanje Mountain and south of Michesi Mountain, these steep inclines increases susceptibility to landslide especially when the soil get saturated with water. Especially after several weather like Cyclone Freddy in 2023 which had a devastating impact on Nkhulambe. Rivers and streams that runs through the area increases landslide risks by eroding riverbanks and destabilizes nearby slopes.

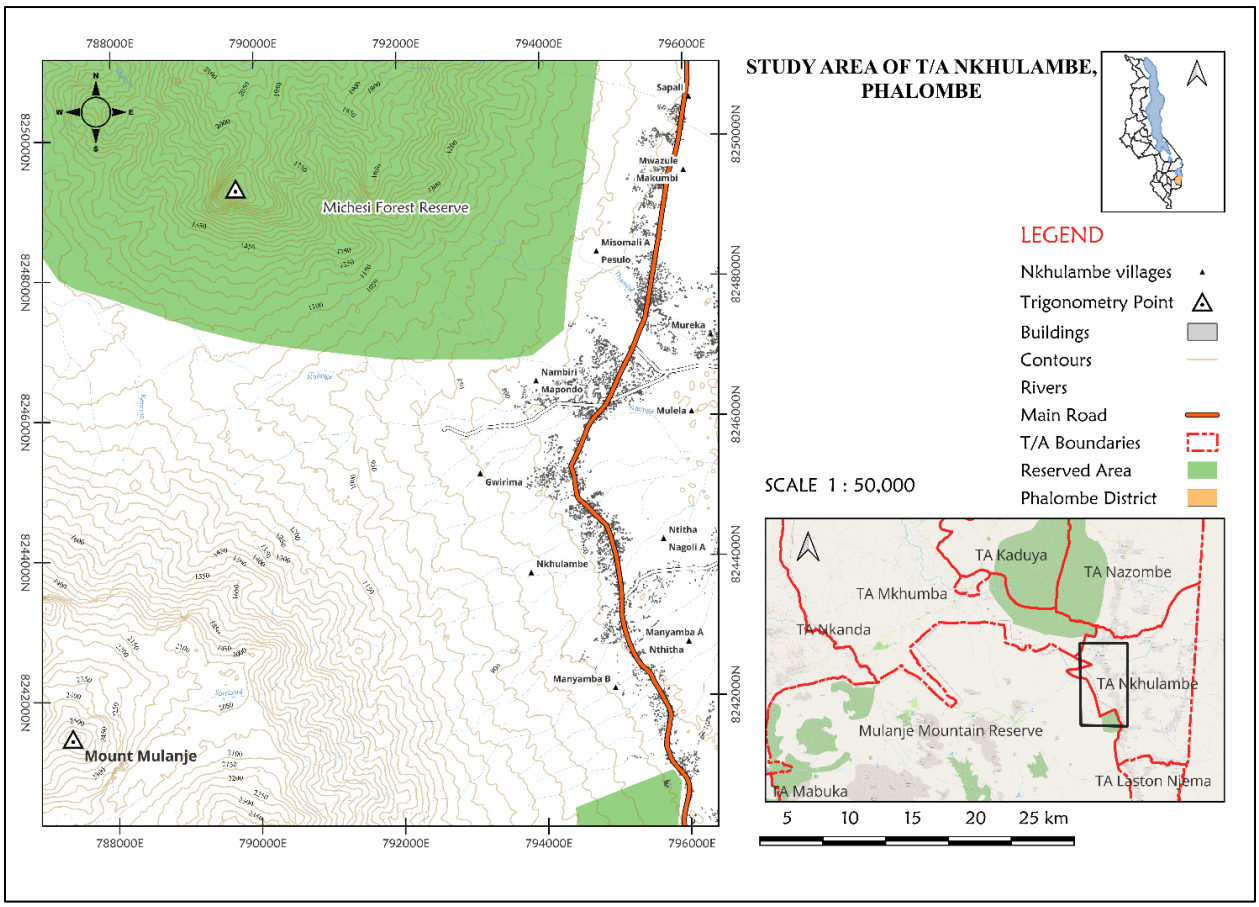


Figure 2: Shows the study area map of Nkhulambe Community

3.1. Data Collection

3.1.1. Landslide inventory data

This research used sentinel-2A satellite images to identify the pre-landslide event and post-landslide events, the data was obtained from Copernicus Data Space Ecosystem (Copernicus data space ecosystem). The pre-landslide events satellite image was taken on 4 January 2023, and the post-landslide satellite image data was taken on 25 April 2023. On this image landslides events showed scars and a light tone. But some areas showed the reflectance as if landslide events also occurred therefore, image enhancements and band-combination were applied to highlight the landslides in the barren areas. A total number of 18 landslides were identified in the area. Additionally these landslides were also verified during field survey.

3.1.2. Landslide Predisposing Factors

3.1.2.1. Topological Data

In this study, a 30m SRTM DEM obtained from the USGS Earth Explorer, (https://earthexplorer.usgs.gov/) was used to derive thematic maps for elevation, slope, and aspect. Elevation plays a crucial role in shaping climate, hydrology, geology, and soil conditions, all of which contribute to landslide occurrence. Among these factors, slope gradient serves as a key driving force (Nakileza & Nedala, 2020).

Elevation

The elevation in the study area ranged from 652 to 2,979 meters and was classified into four distinct categories using an equal interval approach. The low elevation class (652-1,300 m) represented the gentlest terrain with minimal environmental constraints, while the moderate elevation class (1,301-1,949 m) characterized transitional zones with intermediate influences. The high elevation class (1,950-2,599 m) encompassed more rough areas where elevation-driven processes became noticeable, and the very high elevation class (2,600-2,979 m) denoted the most extreme and unstable terrain.

Slope

The slope angle was calculated in degrees and categorized into five distinct classes based on its influence on landslide susceptibility. The first class included slopes below 15°, which were classified as "very low" due to their minimal contribution to landslide occurrences. The second

class, ranging from 16° to 30°, was labeled as "low," while the third class, with slopes between 31° and 45°, was categorized as "medium." The fourth class, encompassing slopes from 46° to 60°, was assigned as "high," indicating an increased likelihood of landslides. Lastly, slopes exceeding 60° were classified as "very high," representing the most unstable terrain with a significant risk of failure. This classification method is widely used in landslide susceptibility assessments as slope gradient is a primary factor influencing stability (Cellek, 2020).

Aspect

Lastly, Aspect which is defined as the maximum slope direction of the land's surface, measured in degrees (Cellek, 2021). In this study the aspect ranged from -1° to 337 .9° and was categorized into nine classes: North (N), Northeast (NE), East (E), Southeast (SE), South (S), Southwest (SW), West (W), Northwest (NW), and Flat. Aspect influence landslides by affecting various environmental factors such as precipitation, erosion, and soil moisture distribution. Its impact become more noticeable with increasing slope angle and elevation, primarily due to its role in shaping local climatic conditions.

3.1.2.2. Geological data

Rock Type

This study considered rock type as a crucial factor in assessing geological stability and landslide susceptibility. Different rock formations exhibit varying degrees of resistance to weathering, erosion, and structural failure, which directly influence terrain stability (H. Wang et al., 2023). The data for this study was gathered from the Northern Regional Geological Survey as shapefiles and then each rock was classified based on its rock type by adding a new field to the attribute table and lastly converted to raster using the rasterize too in QGIS. The area shown the present of both igneous and sedimentary rocks. Igneous rocks, which dominated the region and they are generally more resistant to weathering and provide greater slope stability. In contrast, sedimentary rocks are more prone to erosion and structural weaknesses, making them more susceptible to landslides.

3.1.2.3. Geomorphological Data

Landform

Landform data obtained from Malawi Spatial Data Portal (MASDAP) to examine the distribution of distinct geomorphological features across the study area. The terrain was classified into specific landform types, including bottomlands, dissected hillsides, escarpments, and uplands, each exhibiting unique characteristics that influence landslide susceptibility. Since landforms directly govern slope steepness, drainage efficiency, and soil stability. Since the data was in vector format, it was then converted into raster using the rasterize tool in QGIS this classification was instrumental in identifying zones with heightened vulnerability prone to landslides (Crozier, 2010).

Soil Depth

To further evaluate landslide susceptibility, soil depth data from MASDAP was analyzed, categorizing the study area into three depth classes: moderate (50–100 cm), deep (100–150 cm), and very deep (>150 cm). Soil depth played a critical role in determining slope stability, as deeper soils tend to retain higher moisture content, elevating pore water pressure and reducing shear strength during prolonged rainfall. On the other hand, areas with shallower soils exhibited lower cohesion, making them prone to shallow landslides. By integrating soil depth variations with landform characteristics, this study provided a comprehensive understanding of how subsurface conditions interact with surface geomorphology to influence landslide dynamics.

3.1.2.4. Hydrological Data

Annual Rainfall

This study incorporated two key hydrological parameters rainfall distribution and proximity to streams to evaluate their influence on landslide susceptibility. Annual rainfall data for 2023 was acquired from the CHRS Data Portal and spatially interpolated in QGIS to generate a continuous rainfall surface across the study area. To do this, the downloaded tif file was assigned its projected coordinate system, then extracted the region of interest using the "extract by mask" tool and then output was then converted to points by using the from raster "to point" tool finally, to produce rainfall coverage IDW tool was applied to the points. The

interpolated rainfall data was classified into four intensity categories: Low (1372–1508.24 mm), Moderate (1508.25–1644.49 mm), High (1644.50–1780.74 mm), and Very High (1780.75–1919.99 mm).

Distance from Stream

Additionally, stream proximity was analyzed as a critical hydrological factor using data derived from the Shuttle Radar Topography Mission (SRTM) DEM. The stream network was extracted by using the flow accumulation tool in ArcGIS and Euclidean Distance analysis was applied to categorize distances into five 50-meter interval classes.

3.1.2.5. Land cover/ Land-use

Vegetation Cover

Normalized Difference Vegetation Index (NDVI), was calculated as NDVI = (NIR - Red) / (NIR + Red), where NIR represents near-infrared reflectance and Red represents visible red reflectance, to quantitatively analyze vegetation cover as part of land cover/land use classification. The NDVI values obtained ranged from -0.02 to 0.74 across the study area and were classified into three distinct categories: (1) no vegetation (-0.02 - 0.19), (2) moderate vegetation (0.2 - 0.49), and (3) dense vegetation (0.5 - 0.74).

As a key parameter in the land cover/land use classification, the NDVI-based vegetation analysis was integrated with other environmental factors including topography, soil characteristics, and hydrological features to develop a comprehensive landslide susceptibility model.

3.1.3. Vulnerability Data

The study assessed physical vulnerability by collecting geospatial data on buildings, roads, bridges, and agricultural fields. Building locations were extracted from OpenStreetMap (OSM) using the OSM Downloader plugin in QGIS, while roads and bridges were manually digitized from Google Earth imagery. Agricultural fields were manually digitized form Google earth base map in QGIS to evaluate potential economic impacts. This spatial analysis helped determine which infrastructure and land areas were most exposed to landslides, supporting risk mapping and mitigation planning.

To evaluate social vulnerability, the research conducted community surveys to gauge awareness, preparedness, and response capabilities. Questionnaires assessed residents' knowledge of landslides, the availability of early warning systems, and local risk reduction practices. Additionally, discussions with community leaders provided insights into gaps in disaster management. The combining of physical and social vulnerability data ensured that both infrastructural and human factors were considered for effective risk mapping.

Sampling Method

The study used random sampling method to provide equal probability to every individual and ensure that the questionnaire reaches a large population and it included various individuals from different backgrounds and experience. The study used the Taro Yamane formula to estimate the sample size.

$$n = \frac{N}{1 + N \cdot e^2}$$

Where:

n = sample size

N= total population size

e = margin of error (15%).

3.2. Data Analysis

3.2.1. Landslide susceptibility mapping

The landslide susceptibility map was developed using the Information Value Method (IVM), integrating eight key parameters and for each data set 10 x 10 grid cell was used as the study unit. These parameters included slope, elevation, aspect, soil depth, land use/land cover, Annual rainfall, Distance to rivers, geomorphology and lithology to assess landslide-prone areas. Each parameter was assigned an information value based on its statistical correlation with past landslides, where higher values indicate a stronger association with landslide occurrence. The weighted values of all parameters were then combined to generate a

susceptibility map, categorizing areas into four levels of risk (Low, moderate, High and Very High).

IVM is a statistical method derived from information theory to assess landslide susceptibility (Luo et al., 2019). It quantifies the influence of prompting factors on landslides occurrence by calculating their information value. The Information Value I (xi, H) for each factor was determined using the formula

$$I(x_i, H) = \ln\left(\frac{N_i/N}{S_i/S}\right)$$

where H represents the likelihood of landsliding, S is the total number of study units from the study area, N is the total area of landslides in the study area which is the sum of area of all landslide points in the study area, Si is the number of the study units with the presence of predisposing factor xi, and Ni is the total area of landslides with the presence of predisposing factor xi which is the sum of area of the landslide points with the presence of predisposing factor xi.

The total information (I) of each parameter was then determined by summing the information values of all prompting factors (Ba et al., 2017).

$$\mathrm{I} = \sum_{I=1}^{N} \mathrm{I}(x_i, H) = \sum_{I=1}^{N} ln\frac{N_i/N}{S_i/S}$$

When (I < 0), the likelihood of a landslide occurring is lower than average. When (I = 0), the likelihood is average, and when (I > 0), the likelihood is higher than average. A higher information value indicated a greater probability of landsliding.

This study utilized QGIS to integrate landslide inventory data with parameter raster data for calculating the Information Value (IV). The landslide inventory provided spatial distribution details, while the parameter rasters represented various predisposing factors. Using QGIS, the data layers were combined together using raster calculator to have the number of landslide pixel in each class, and the IV for each factor was computed based on the statistical relationship between landslide occurrences and influencing parameters. The final susceptibility

map was generated by summing the IV values of all factors, enabling a comprehensive landslide risk assessment.

3.2.2. Vulnerability Mapping

3.2.2.1. Physical Vulnerability

To create a comprehensive vulnerability map, the study adopted a systematic approach that integrated infrastructure and agricultural field data with landslide susceptibility information. The process began by preparing two key datasets for each sector: vector data representing infrastructure (buildings as polygons) and agricultural fields (also as polygons), alongside a raster dataset modeling landslide susceptibility across the study area. The raster dataset depicted spatial variations in landslide risk, with each cell containing values indicating susceptibility levels (low, medium, high and very high). Both vector and raster datasets were loaded into QGIS, and their coordinate reference systems (CRS) were aligned to ensure compatibility for spatial analysis. For the infrastructure data, zonal statistics were used to extract susceptibility values, as buildings were represented as polygons rather than points. Specifically, the Zonal Statistics tool calculated the average susceptibility within each building polygon, providing a representative measure of exposure to landslide risk for each structure. Similarly, for agricultural fields, the same tool quantified the mean susceptibility value for each field by analyzing the overlap between the field polygons and the raster pixels.

The extracted susceptibility values were then combined using the merge vector layers tool to compute a final vulnerability layer. Buildings located in areas with higher susceptibility were assigned elevated vulnerability levels, reflecting their increased exposure to potential landslides. To integrate both sectors into a unified vulnerability dataset, the vector layers for infrastructure and agricultural fields were first converted into raster format using the Rasterize tool in QGIS. This ensured consistency in resolution and alignment, allowing the two datasets to be combined effectively. A weighted overlay approach was then applied, assigning appropriate weights to infrastructure and agricultural vulnerability based on their relative importance in the context of landslide impacts. The resulting combined vulnerability raster

was classified into four categories low, medium, high, and very high. This final vulnerability map highlighted areas where infrastructure and agricultural fields were most at risk.

3.2.2.2. Social Vulnerability

To evaluate the social capacity of the Nkhulambe community regarding landslide risks, a structured questionnaire was designed and administered using Kobo Toolbox, a digital data collection platform. This approach was selected to prioritize understanding how systemic inequities shape disaster risk, as landslides extremely impact marginalized groups such as low income households, elderly individuals(Choong et al., 2025). By assessing awareness, preparedness, and response mechanisms, the study aimed to uncover disparities in knowledge and accessibility (e.g., language barriers, distrust in institutions) to inform targeted interventions that align with the community's unique cultural and contextual needs. Additionally, the research examined livelihood dependencies, such as subsistence farming, which tether households to high-risk areas due to economic necessity. These insights enable the development of equitable, context-specific strategies that address root causes of vulnerability.

Demographic Information

Questions on age, gender, education level, and primary occupation were included to understand the socio-demographic profile of respondents. For example, respondents were asked to select their age group (Below 25, 26-35, etc.), gender, highest level of education (Primary, Secondary, Tertiary), and primary occupation (Farming, Business, Civil servant). This information helped contextualize the community's responses and identify potential differences in knowledge and preparedness.

Landslide Awareness and Experience

Respondents were asked whether they had experienced landslides in the past and how frequently such events occurred in their area. For instance, one question asked, "How frequently do landslides occur in your area?" with options like "Rarely (once in 10 years or more)" or "Very frequently (every year)." They were also prompted to identify perceived causes of landslides (e.g., heavy rainfall, deforestation, poor farming practices). Additionally,

questions assessed their awareness of past landslide-related disasters and whether they felt adequately informed about landslide risks.

Community Preparedness and Response

This section focused on the presence and effectiveness of early warning systems. Respondents were asked how they received information about potential landslides (e.g., community meetings, radio/TV, and Mobile messages) and whether they knew what actions to take upon receiving a warning. For example, one question asked, "Do you know what actions to take in case of a landslide warning?" Questions also explored whether households or communities had received training on responding to landslides and what measures they had taken to mitigate risks (e.g., tree planting, building structures away from slopes).

Community Resilience and Support

Open-ended questions addressed the challenges faced by the community in responding to landslides and the type of support needed to enhance resilience. For example, respondents were asked, "What challenges does your community face in responding to landslides?" and "What support do you think would improve the community's ability to handle landslides?" Data was collected digitally through face-to-face interviews using Kobo Toolbox, ensuring clarity and accommodating varying literacy levels. Participation was voluntary, and ethical considerations, such as confidentiality and informed consent, were strictly observed.

Once the data was collected via Kobo Toolbox, it was downloaded and analyzed using qualitative methods in Microsoft Excel. The findings were presented through visual aids such as graphs and pie charts to facilitate interpretation and communication of results. These visualizations provided a clear depiction of the community's social capacity identify gaps in awareness, preparedness, and response mechanisms.

3.2.3. Landslide Risk Mapping

The final landslide risk map was created by integrating the susceptibility map (derived from the Information Value Method assessing eight geological and environmental factors) with the physical vulnerability map (based on proximity of infrastructure and agricultural land to

hazard zones) through spatial overlay analysis in QGIS. Areas were classified as highest risk where zones of High/Very High Susceptibility overlapped with High Vulnerability locations containing critical infrastructure like buildings, roads and bridges. Additionally, Moderate Susceptibility areas containing exposed agricultural fields or settlements were identified as secondary priority zones. This combined spatial analysis produced a comprehensive risk assessment that clearly delineates danger levels across the landscape,

3.3. Ethics Consideration

The Malawi University of Science and Technology Research Ethics Committee (MUSTREC), Department of Ndata School of Climate and Earth Sciences, approved this study, and the Group village head granted authorization to conduct the research. Because confidentiality and privacy are vital, the names of the respondents was replaced with numbers. First, the participants were informed about the questionnaire, as well as the importance of conducting the study. Participants were permitted to participate in the study voluntarily rather than being forced to do so.

4. Chapter 4: Results and Discussion

4.1. Results

4.1.1. Landslide inventory maps

This image, captured using Sentinel-2A satellite data, served as a baseline for assessing the pre-landslide conditions of the area. It provided a critical reference for comparing post-landslide imagery, allowing identification of changes in land cover, slope stability, and other factors that may have contributed to the landslide event.

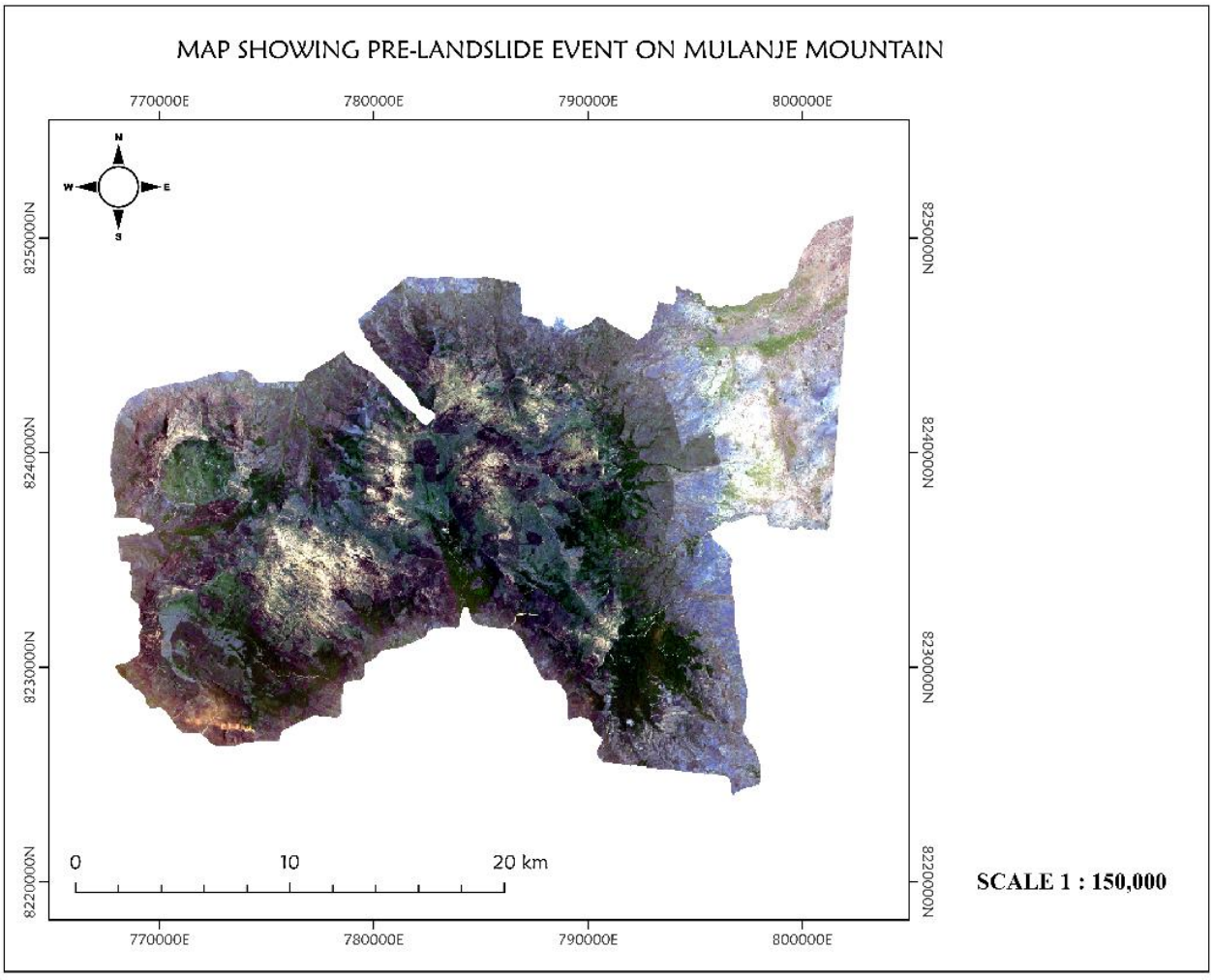


Figure 3: Shows Sentinel-2A satellite image pre-landslide event on 4 January 2023 (Band combination RGB=432)

Figure 4: Shows a Sentinel-2A satellite imagery of post-landslide events on 25 April 2023 (Band combination: RGB=831)Figure 4 served as a post-landslide map of Mulanje Mountain. It provided a detailed view of the area following the landslide event, highlighting changes in land cover. The vibrant color palette, derived from a band combination (RGB=831) to detect areas affected by the landslide, such as exposed soil, altered vegetation patterns and disrupted terrain.

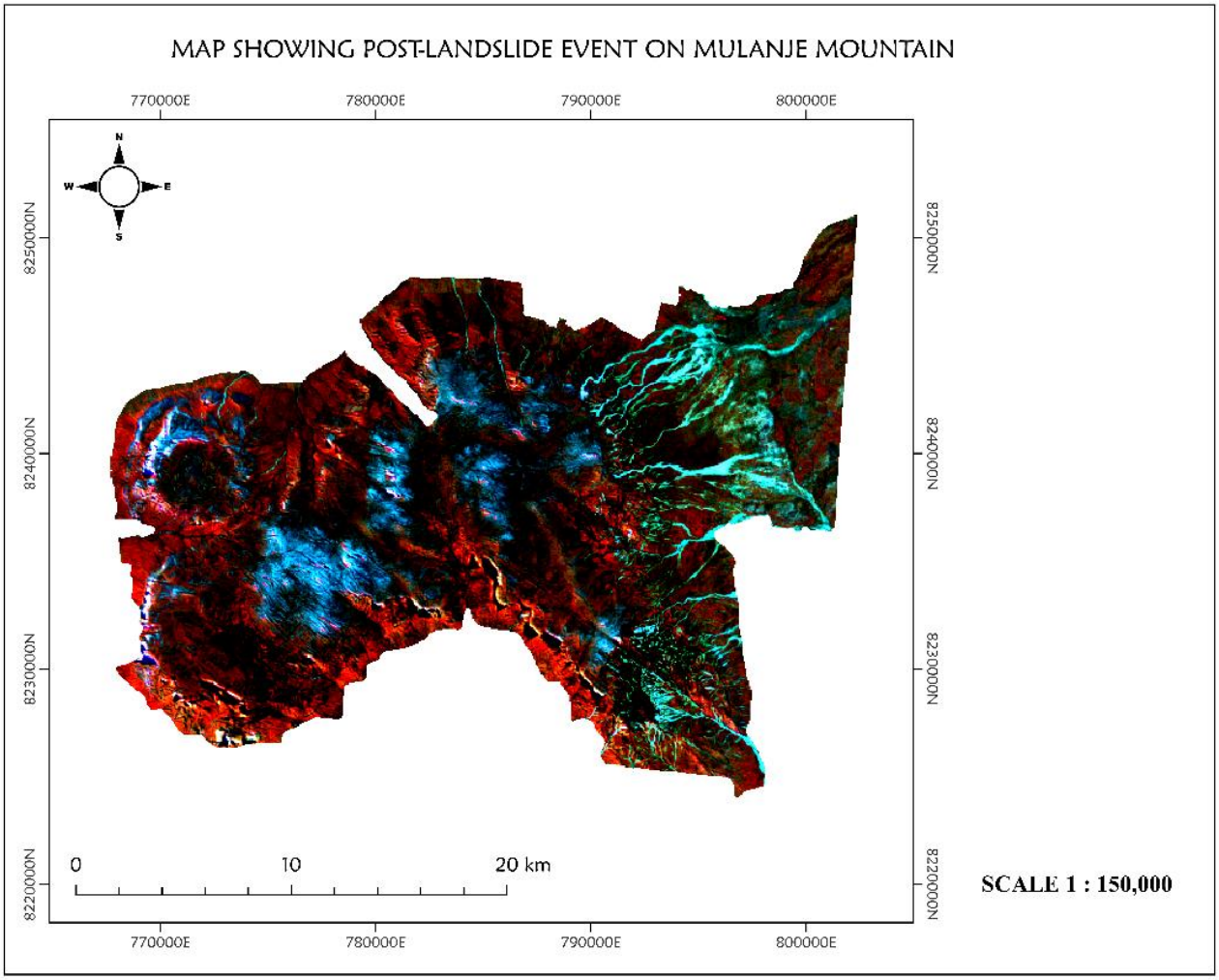


Figure 4: Shows a Sentinel-2A satellite imagery of post-landslide events on 25 April 2023 (Band combination: RGB=831)

Figure 5 provided the classified landslide inventory database that was used to overlay with the predisposing factors during calculation for information values to find out how each environmental factor influence the occurrence of landslide in the area.

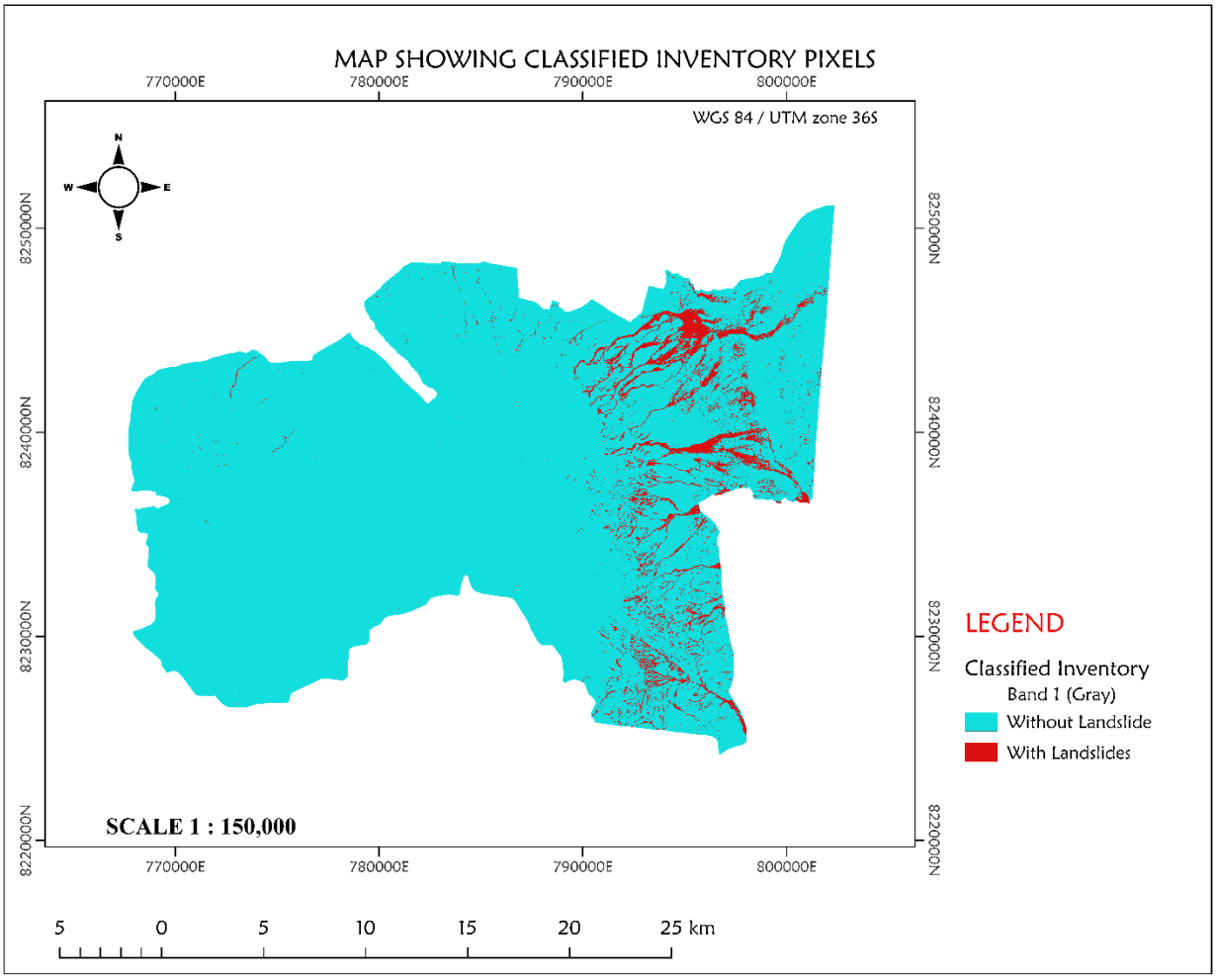


Figure 5: Classified Satellite imagery for overlaying with predisposing factors

4.1.2. Landslide Predisposing Factors

4.1.2.1. Topological Data

Elevation

The elevation map provided a clear depiction of the topography around Mulanje Mountain, showing a distinct gradient from very high elevations (2,600–2,979 m) in the center and east to low elevations (652–1,300 m) in the edge. The map highlighted the mountain's distinctions and the steepness of its slopes, which were critical for understanding geological processes, landslide risks, and environmental dynamics in the region.

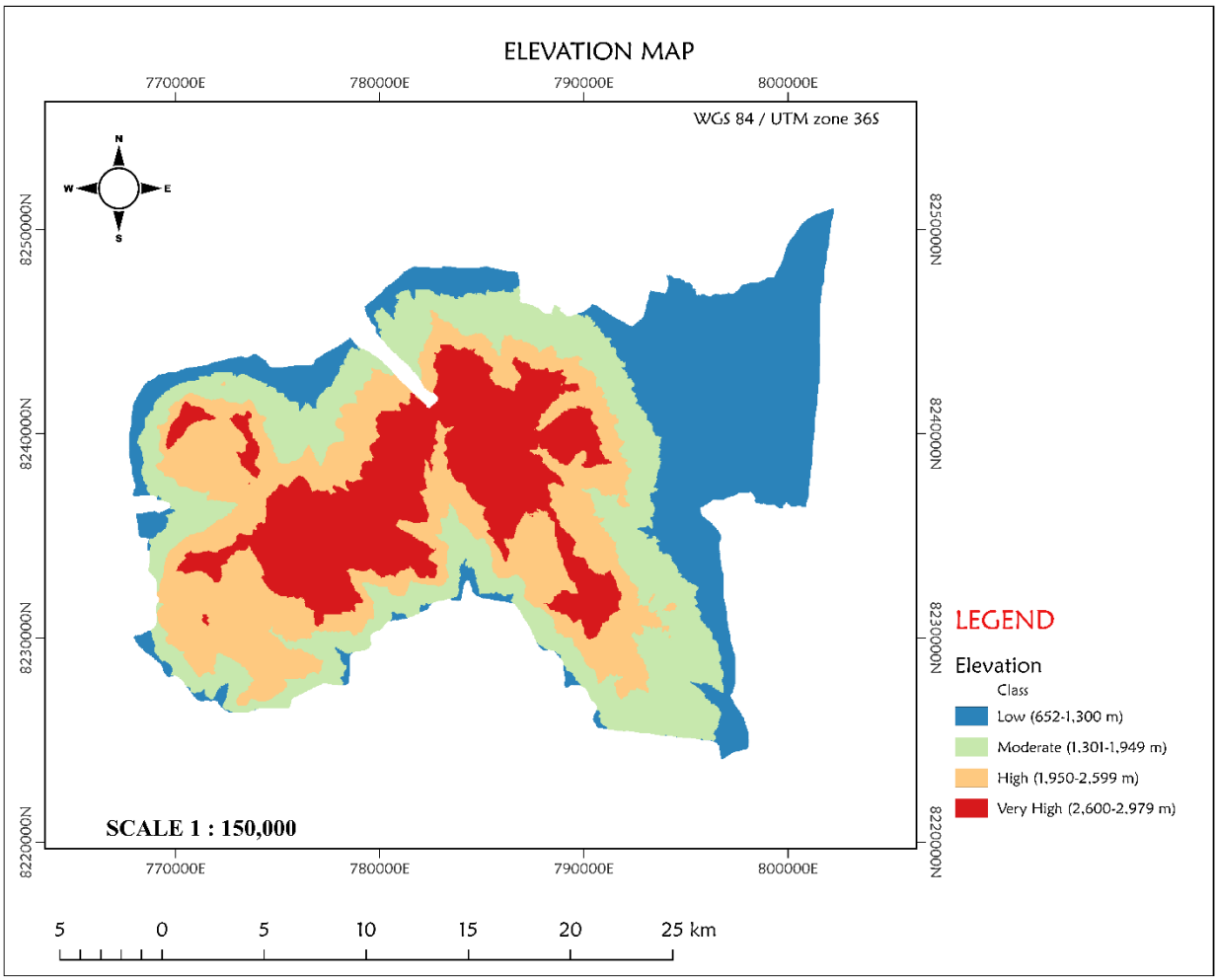


Figure 6: Shows a Classifies Elevation Map

Slope

The slope map effectively illustrated the spatial distribution of slope classes across the study area, highlighting the steepness of the terrain. The map revealed that the central and eastern parts of the region had very high slopes (>60°), making them highly susceptible to landslides. In contrast, the periphery featured gentler slopes (<15°), indicating flatter terrain.

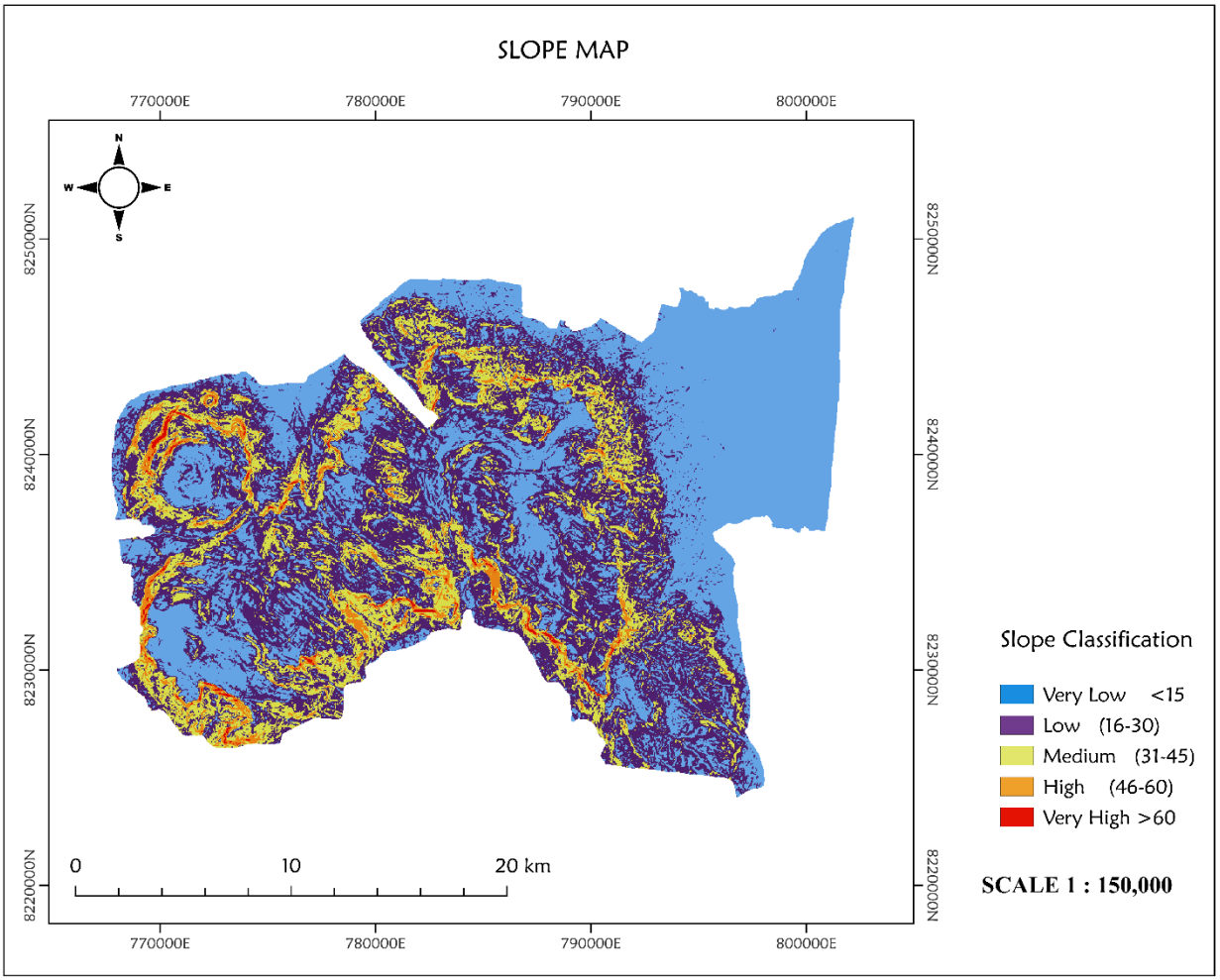


Figure 7: Shows a Classified Slope Map

Aspect

The aspect map effectively illustrated the directional orientation of slopes across the study area, highlighting how different parts of the landscape faced various compass directions. The map revealed a diverse range of aspects, with the majority aspect direction appearing to be

East-facing slopes (green). This is followed closely by North-facing slopes (blue), which also cover a substantial area.

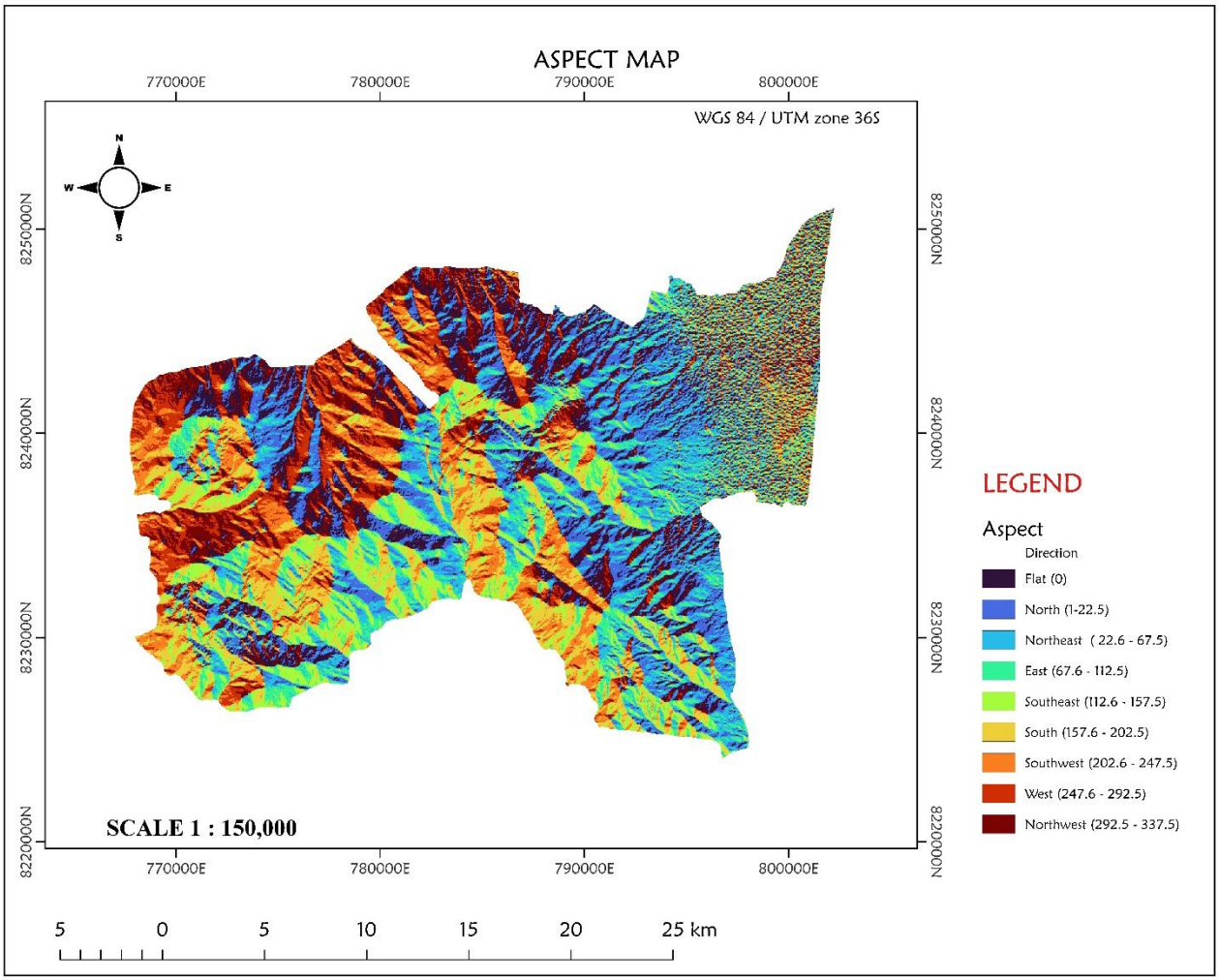


Figure 8: Shows a classified Aspect map

4.1.2.2. Geological data

Rock type

The geological map effectively illustrated the distribution of rock types across the study area, highlighting the spatial variation in geology. The area revealed a clear dominance of Igneous Rock, which covers the majority of the region, particularly in the central and western parts. This is followed by Sedimentary Rock (cyan), which is present in distinct areas, especially along the eastern boundary and scattered within the igneous regions,

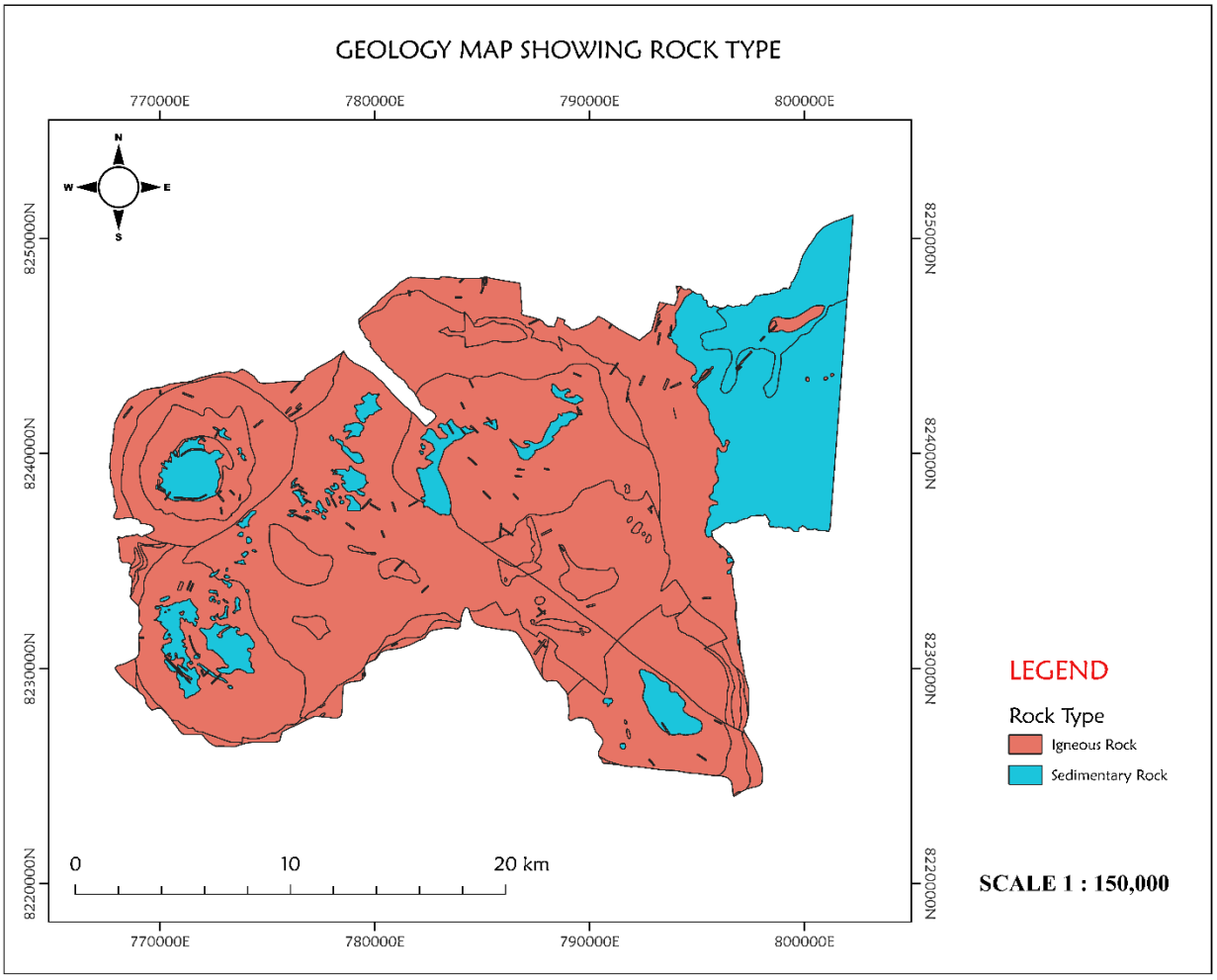


Figure 9: Shows the Rock type of the study area

4.1.2.3. Geomorphological data

Landforms

The landform map provided a clear depiction of the geomorphological features across the study area, emphasizing the spatial diversity of landforms. It showed that dissected hillsides (green) are the most predominant landform, dominating extensive areas in the central and southern regions. These dissected hillsides are marked by steep slopes and complex drainage systems, which make them particularly prone to landslides(Nakileza & Nedala, 2020). The widespread presence of this landform indicates that a substantial portion of the region is at significant risk, especially during periods of heavy rainfall.

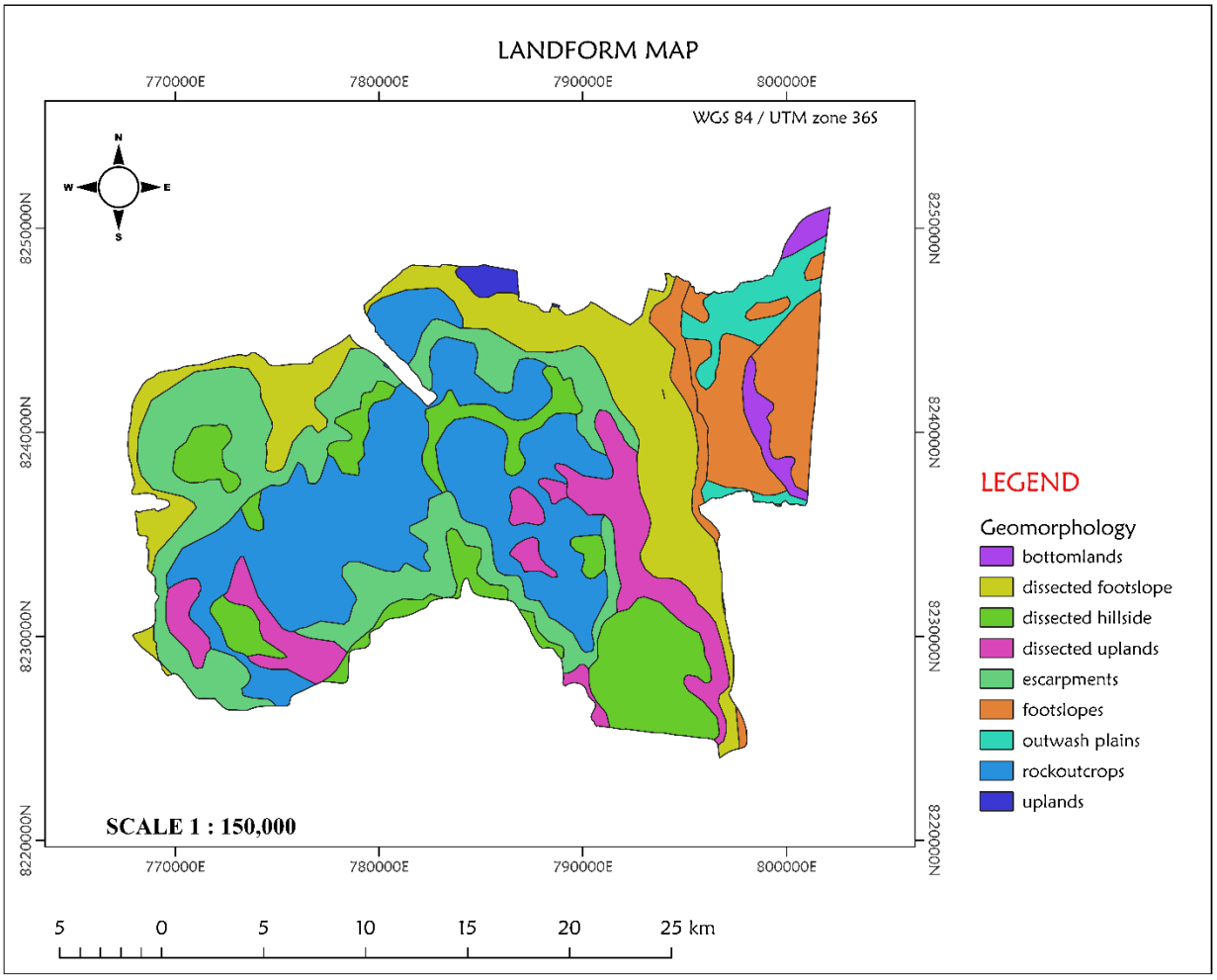


Figure 10: Shows various landforms that are present within the study area

Soil Depth

The soil depth map clearly depicted the distribution of soil depths across the study area, emphasizing variations in soil levels. It showed that very deep soils (cyan) , which typically indicate stable and well-developed profiles capable of supporting vegetation, were the most widespread, dominating the central and northern regions. However, in steeper areas, these very deep soils (>150 cm) are prone to saturation during heavy rainfall, increasing landslide risks if combined with unstable geology or slope conditions(Kim et al., 2016). Additionally, deep soils (purple) appeared in scattered patches across the central and southern parts, while moderate soils (yellow) were less extensive, primarily found along the eastern boundary and in localized zones.

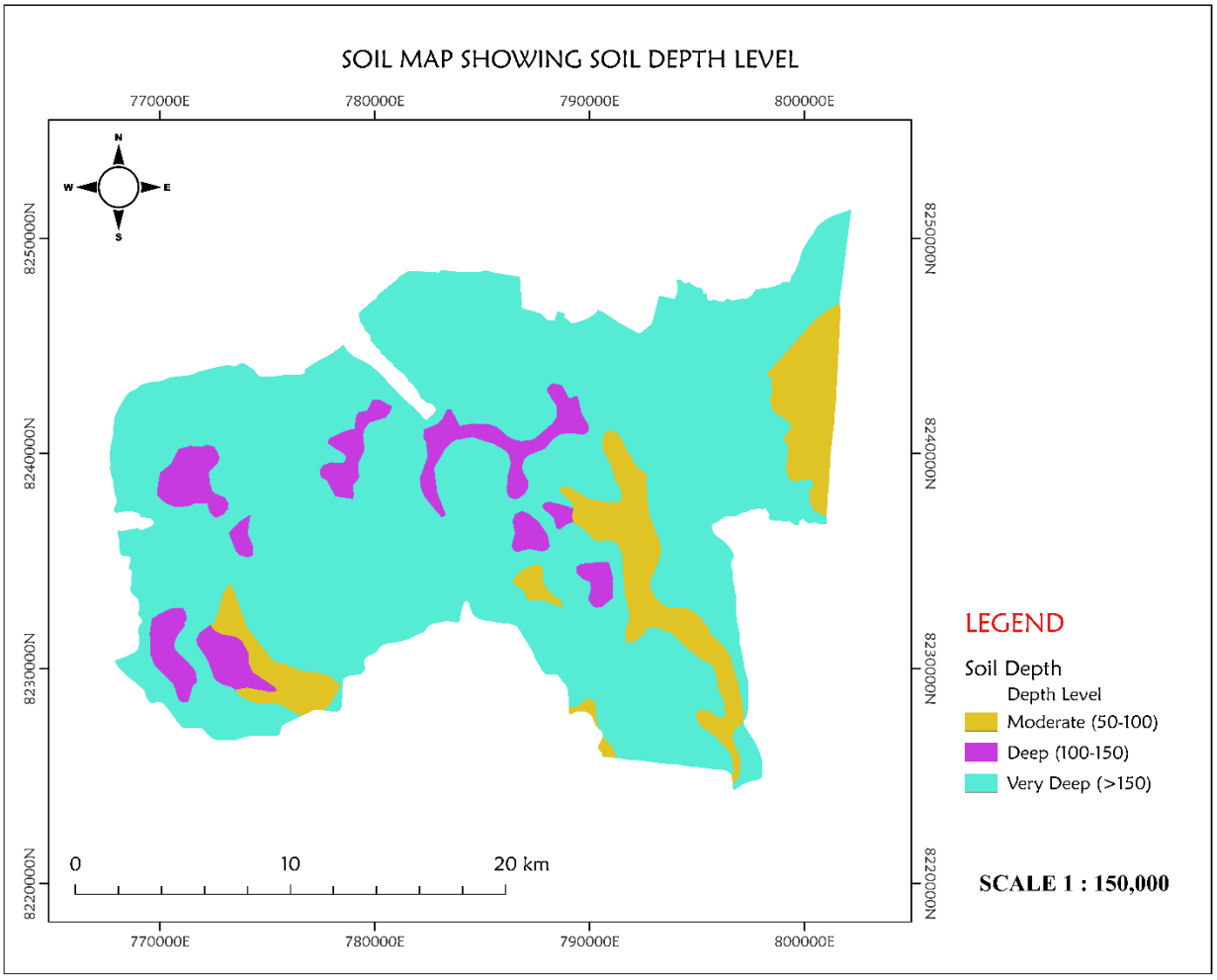


Figure 11: Shows the soil depth within the study area

4.1.2.4. Hydrological Data

Annual Rainfall

The 2023 Annual Rainfall Distribution Map effectively illustrated the spatial variation in annual rainfall across the study area. It revealed that very high rainfall (>1,780.75 mm) was concentrated in specific areas, particularly in the central and southern regions, while moderate rainfall dominated other parts of the map. Intense rainfall plays a critical role in slope failure and landslide susceptibility, as excessive water saturates the soil, reducing its cohesion and increasing pore water pressure.

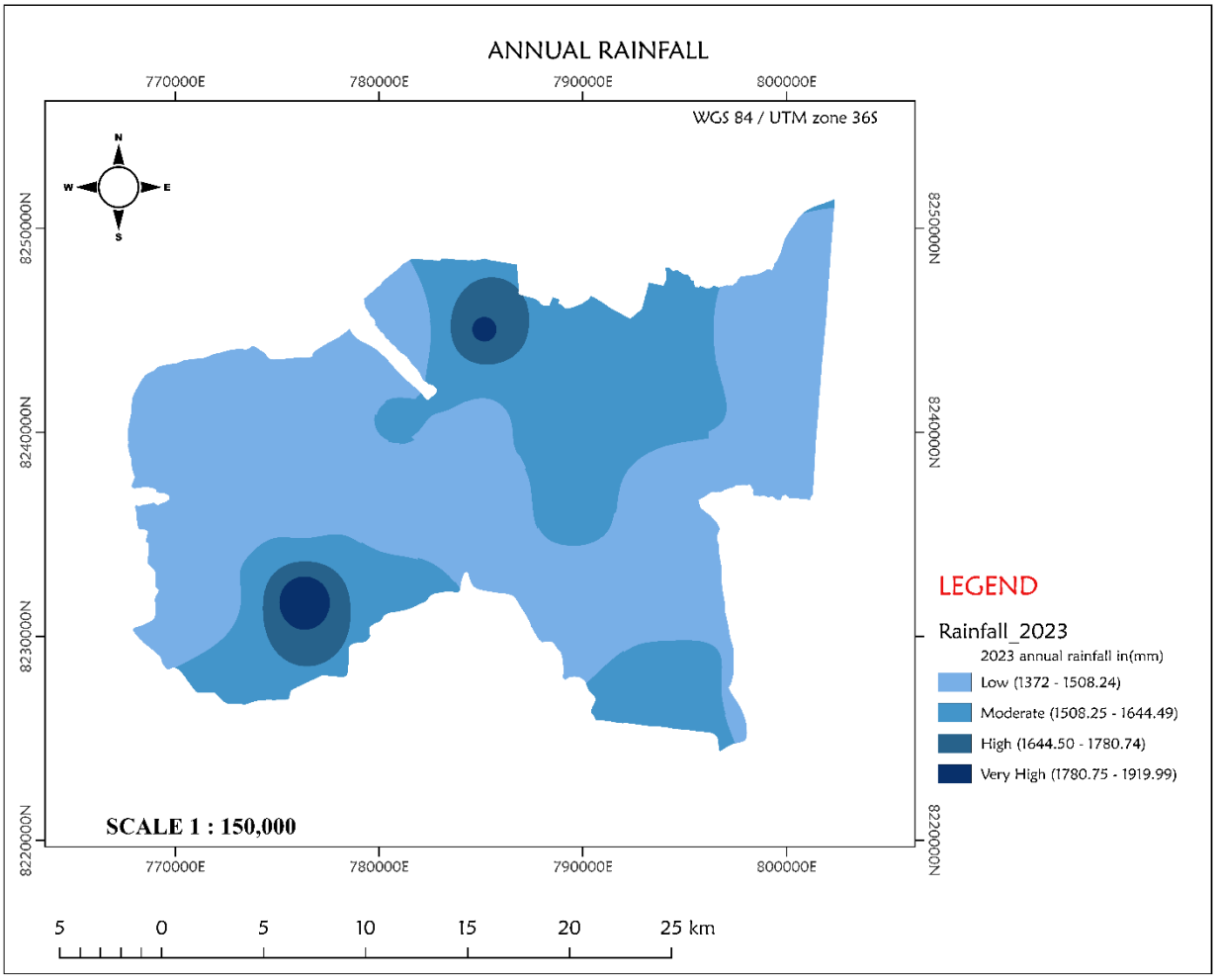


Figure 12: Shows the Distribution of 2023 annual rainfall

Distance from Stream

The Distance to Stream Map effectively demonstrated how the proximity to streams influenced landslide susceptibility by affecting soil saturation, erosion, and hydrological processes. Areas located within 0–50 meters of streams are especially at risk, as prolonged soil moisture and heightened pore water pressure made them more prone to instability, particularly when combined with steep slopes or heavy rainfall(Tsyplenkov et al., 2025).

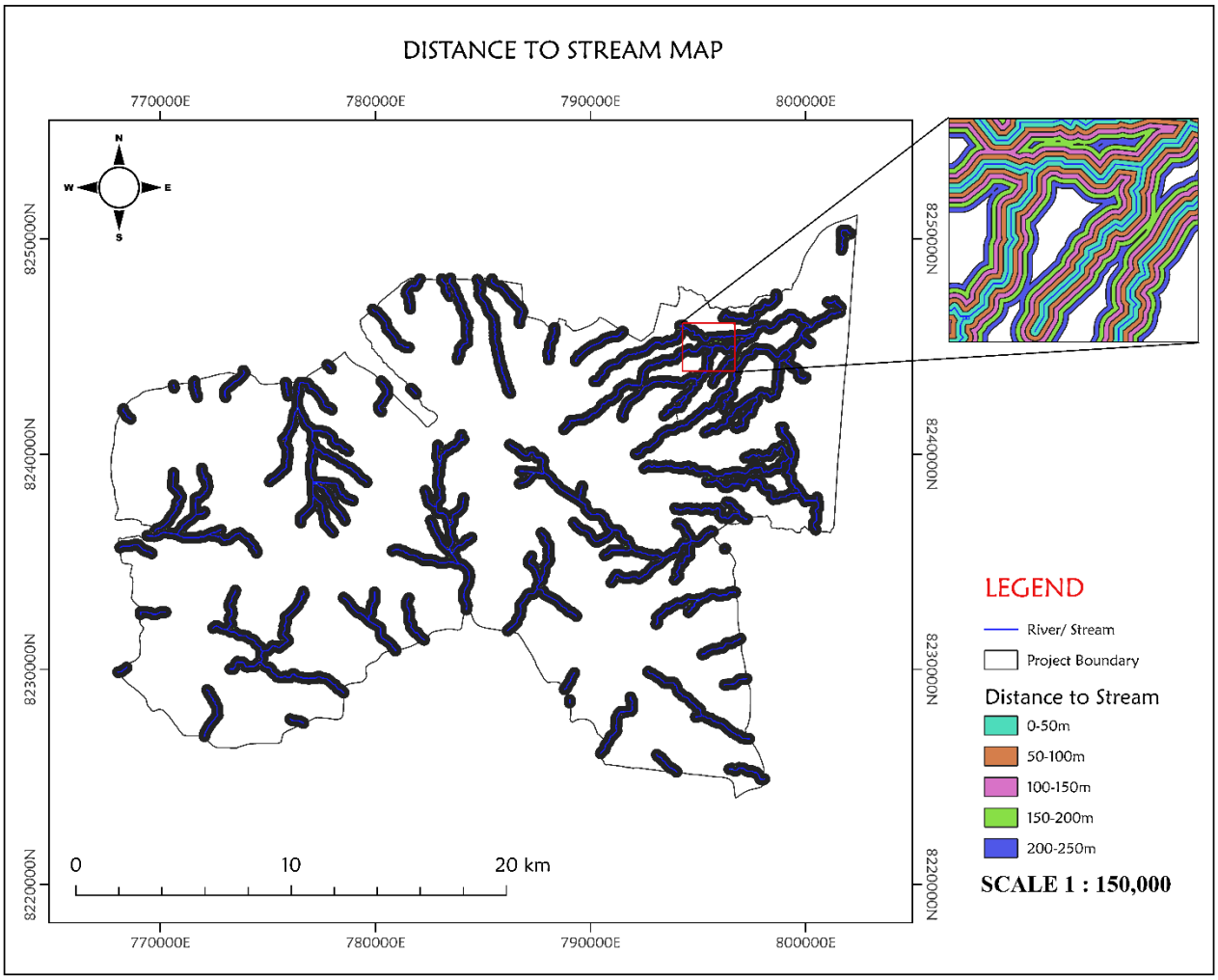


Figure 13: Shows the distance from stream map

4.1.2.5. Land cover

Vegetation

The vegetation map provided a comprehensive overview of the spatial distribution of plant cover across the study area, emphasizing distinct patterns of vegetation density. It revealed that high vegetation (dark green, NDVI 0.5–0.74) was the dominant cover type, extensively covering the central and eastern regions. These densely vegetated zones likely represented mature forests or thick shrublands, which played a critical role in stabilizing soils and supporting biodiversity.

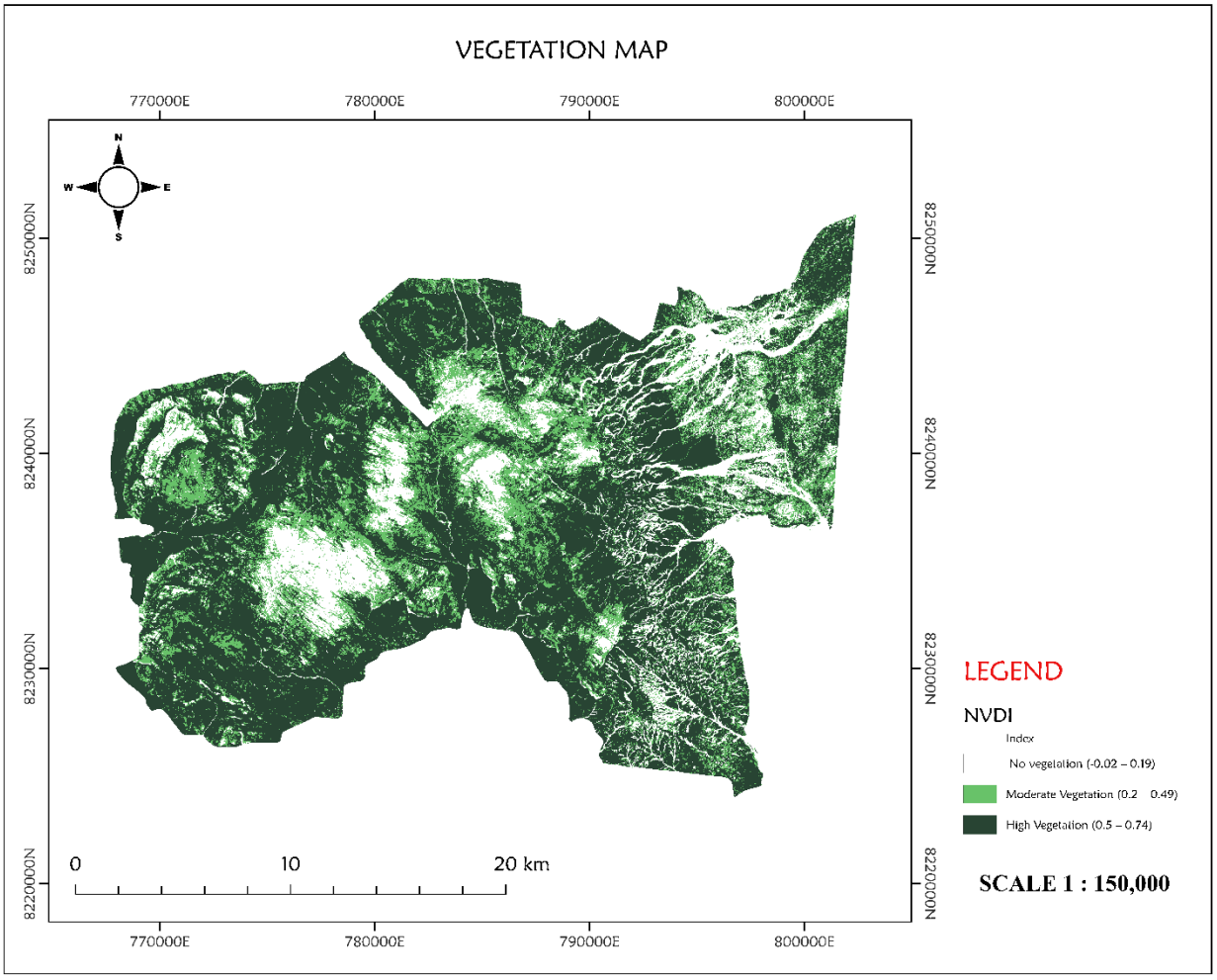


Figure 14: Shows the vegetation cover map for the study area

4.1.3. Information Values

The information value table (Table 1) quantified the influence of each predisposing factor on landslide occurrence by comparing the spatial distribution of landslides relative to each class.

1. Landform

Dissected foot slopes (IV: 0.353) and dissected hillsides (IV: 0.340) exhibited moderate positive IVs. These steep, dissected terrains were prone to landslides due to unstable slopes and concentrated water flow.

Outwash plains (IV: 1.347) had the highest IV, likely due to loose sediments and high saturation from water flow, which amplified instability.

Rock outcrops (IV: -2.575) and escarpments (IV: -1.157) displayed strongly negative IVs, as solid bedrock or steep cliffs resisted sliding.

2. Soil Depth

Very deep soils (IV: 0.057) and moderate soils (IV: 0.217) showed slight to moderate positive IVs, as deeper soils likely retained more water, reducing soil cohesion.

Deep soils (IV: -3.744) paradoxically had a strongly negative IV. This may have reflected misclassification or the presence of deep soils in stable areas (e.g., flat terrain).

3. Stream Distance

Proximity to streams (0–50m, IV: 0.586) was highly influential, as saturated soils near water channels were prone to liquefaction and erosion.

Distances >100m showed negative IVs, indicating reduced risk due to lower saturation and erosion.

4. Aspect

North-facing slopes (IV: 0.467) and northeast-facing slopes (IV: 0.581) were more landslide-prone, likely due to higher moisture retention and vegetation density, which destabilized slopes when saturated.

South-facing slopes (IV: -1.020) and southwest-facing slopes (IV: -1.063) were drier and less prone to landslides.

5. Rainfall

High (IV: 0.043) and very high rainfall (IV: 1.696) correlated with increased landslides due to pore-water pressure buildup.

Moderate rainfall (IV: -1.562) had a strongly negative IV, suggesting these areas were less saturated and more stable.

6. Rock Type

Sedimentary rocks (IV: 0.881) were more prone to landslides due to weathering and layering (e.g., shale, sandstone).

Igneous rocks (IV: -0.397) were more resistant, reducing landslide risk.

7. Vegetation

No vegetation (IV: 1.503) had the highest IV, as the lack of root cohesion and surface protection exacerbated erosion.

Dense vegetation (IV: -1.815) stabilized slopes, reducing landslide likelihood.

8. Slope

Steep slopes (IV: 0.598) showed increased susceptibility, while very steep slopes (IV: -2.348) had a negative IV, possibly due to limited soil cover or data bias.

9. Elevation

Very high elevation (IV: 0.232) correlated with landslides, likely due to steeper slopes and higher rainfall in mountainous areas.

Information Value Table

Table 1: Shows the Information Value of each causative class indicating how they influence landslide occurrence

Predisposing Factor	Value	Class Name	No. of Pixel	With landslide	Si/S	Ni/N	Information Value
Landform	1	Bottomlands	84590	1183	0.015	0.033	**0.772**
	2	Foot slopes	517503	8497	0.094	0.238	**0.932**
	3	Dissected Foot slopes	924759	8505	0.168	0.239	**0.353**
	4	Outwash plains	178863	4445	0.032	0.125	**1.347**
	5	Uplands	35937	42	0.007	0.001	**-1.710**
	6	Rock outcrops	1480452	729	0.268	0.020	**-2.575**
	7	escarpments	1064788	2163	0.193	0.061	**-1.157**
	8	Dissected hillside	724184	6577	0.131	0.185	**0.340**
	9	Dissected uplands	503734	3501	0.091	0.098	**0.073**
Total			**5514810**	**35642**			
Soil Depth	1	Very Deep	4502314	229064	0.816	0.863	**0.057**
	2	Moderate	599674	35808	0.109	0.135	**0.217**
	3	Deep	416645	474	0.075	0.002	**-3.744**
Total			**5518633**	**265346**			
Stream Distance	1	0-50m	278326	50158	0.200	0.359	**0.586**
	2	50-100m	280026	30021	0.201	0.215	**0.067**
	3	100-150m	280062	22991	0.201	0.164	**-0.200**

	4	150-200m	278739	19158	0.200	0.137	**-0.378**
	5	200-250m	276997	17489	0.199	0.125	**-0.463**
Total			**1394150**	**139817**			
Aspect	1	Flat	704143	41415	0.129	0.156	**0.189**
	2	North	753299	58494	0.138	0.220	**0.467**
	3	Northeast	691182	60120	0.127	0.226	**0.581**
	4	East	559120	36269	0.102	0.137	**0.287**
	5	Southeast	575106	18570	0.105	0.070	**-0.410**
	6	South	588012	10315	0.108	0.039	**-1.020**
	7	Southwest	544862	9160	0.100	0.034	**-1.063**
	8	West	498808	11786	0.091	0.044	**-0.723**
	9	Northwest	543429	19514	0.100	0.073	**-0.304**
Total			**5457961**	**265643**			
Rainfall	1	Low Rainfall	3396486	138481	0.611	0.765	**0.224**
	2	Moderate	1849000	12644	0.333	0.070	**-1.562**
	3	High	249843	19007	0.045	0.047	**0.043**
	4	Very High	61903	10998	0.011	0.061	**1.696**
Total			**5557232**	**181130**			
Rock Type	1	Igneous Rock	4503128	146882	0.812	0.546	**-0.397**
	2	Sedimentary Rock	1043781	122206	0.188	0.454	**0.881**
Total			**5546909**	**269088**			
Vegetation	1	No vegetation	222251	261538	0.160	0.719	**1.503**
	2	Low vegetation	533085	74981	0.384	0.206	**-0.621**
	3	Dense Vegetation	633920	27004	0.456	0.074	**-1.815**
Total			**1389256**	**363523**			
Slope	1	Very Low	2332988	159449	0.426	0.598	**0.339**
	2	Low	2105309	50652	0.385	0.190	**-0.705**
	3	Moderate	827314	38891	0.151	0.146	**-0.035**
	4	High	181641	16094	0.033	0.060	**0.598**
	5	Very High	286700	1334	0.052	0.005	**-2.348**
Total			**5733952**	**266420**			
Elevation	1	Low	210234	141159	0.255	0.237	**-0.074**

	2 Moderate	154399	57943	0.187	0.097	**-0.655**
	3 High	162834	126113	0.198	0.212	**0.069**
	4 Very high	296285	270070	0.360	0.454	**0.232**
Total		**823752**	**595285**			

4.1.4. Susceptibility Map

The landslide susceptibility map provided a spatial assessment of risk across the study area, classified into five categories: Very Low (blue), Low (green), Moderate (yellow), High (orange), and Very High (red). High-risk zones (orange/red) were concentrated in the eastern and southeastern regions, aligning with steep slopes, dissected foot slopes, and outwash plains, which exhibited high information values (IV) due to their inherent instability. These areas correlated with proximity to streams (0–50m) on Figure 13, sparse vegetation (IV: 1.503) indicated in Figure 14, sedimentary rock types (IV: 0.881), and high rainfall (IV: 1.696) on Figure 9 and Figure 12 simultaneously, all of which amplified landslide susceptibility. In contrast, low-risk zones (green/blue) dominated the central and western regions, characterized by flat terrain, dense vegetation (IV: -1.815), and igneous rock formations (IV: -0.397), which stabilized slopes. Moderate-risk zones (yellow) formed transitional areas, reflecting mixed influences such as moderate slopes and intermittent rainfall. The analysis revealed that stream distance, vegetation cover, slope steepness, and geological factors were the strongest predictors of landslide occurrence, as indicated by their IV scores.

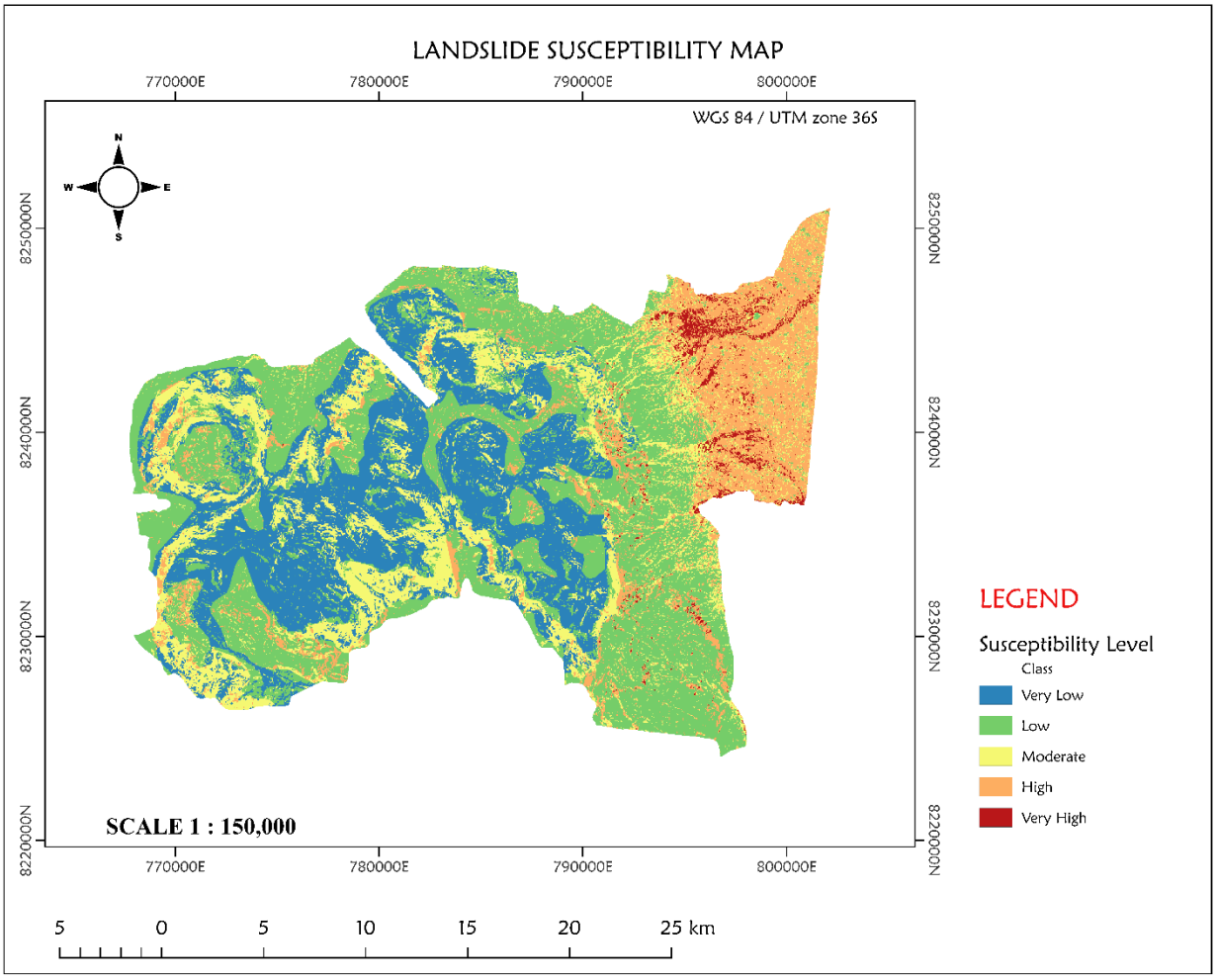


Figure 15: Shows the landslide susceptibility Map

4.1.5. Study Area Susceptibility map

The susceptibility map (Figure 16) revealed distinct spatial patterns across the Nkhulambe Community. Areas with very high susceptibility were concentrated in certain regions, particularly in the central and northern parts of the community. High susceptibility was widespread across the central region, indicating a significant area at risk. Moderate susceptibility was scattered throughout the community, often surrounding the high-risk areas. Low susceptibility was primarily located in the eastern and southern regions, suggesting lower risk in these areas.

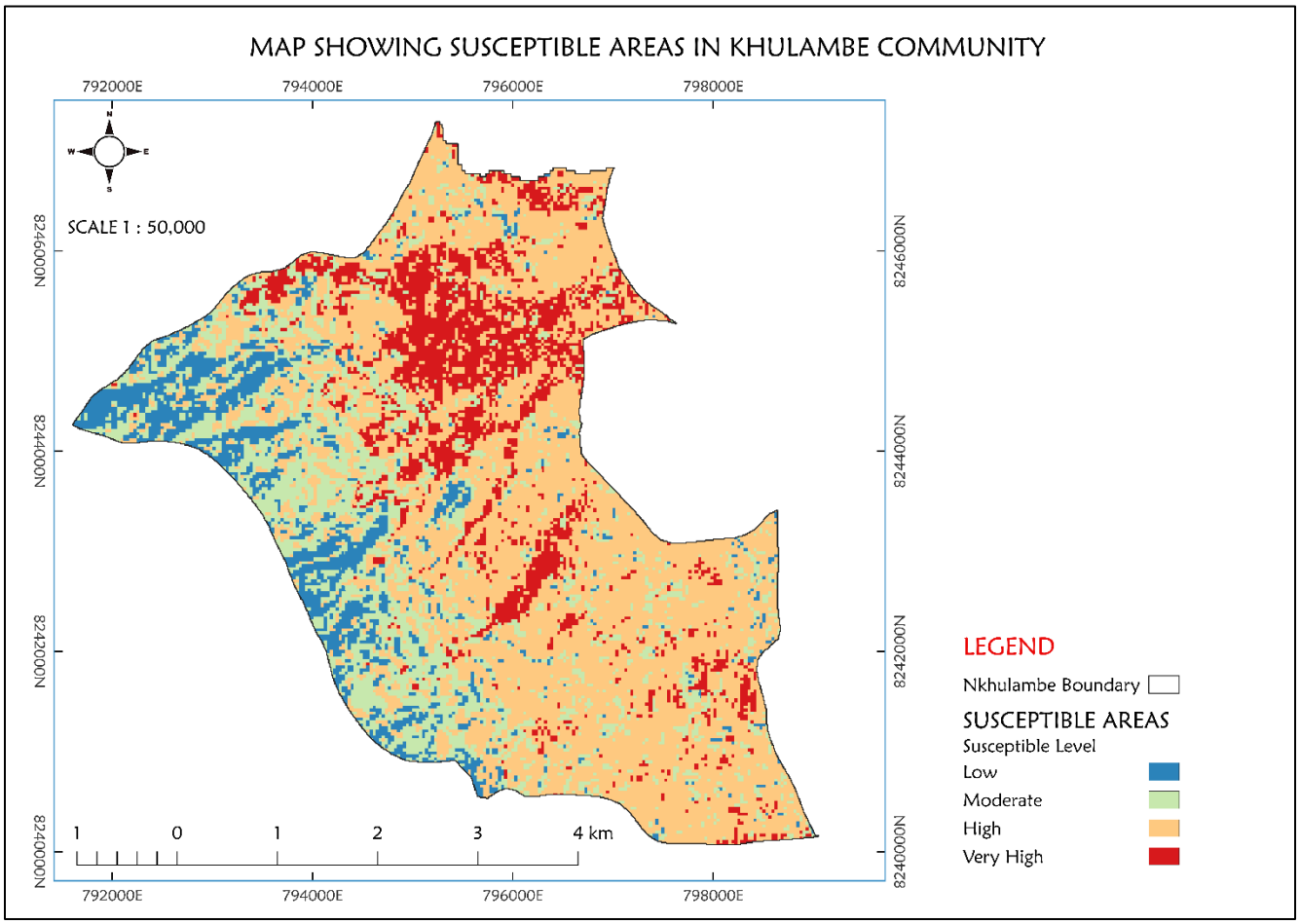


Figure 16: Shows the Susceptibility map for T/A Nkhulambe

4.1.6. Vulnerability

4.1.6.1. Physical Vulnerability

The Building location map (Figure 17) revealed how proximity to susceptibility areas impacted the structural safety of buildings across the Nkhulambe Community. Buildings with very high vulnerability were concentrated in specific regions, particularly in the central and northern parts of the community, including villages like Nagoli, Nititha, and Nachuma. These structures were likely located in hazardous zones making them highly susceptible to landslides. Additionally, areas with high vulnerability were widespread across the central region, indicating a significant number of buildings at risk due to their proximity to these hazards. In contrast, moderate vulnerability was scattered throughout the community, often surrounding

high-risk areas, suggesting that these buildings were less prone to failure but still required monitoring.

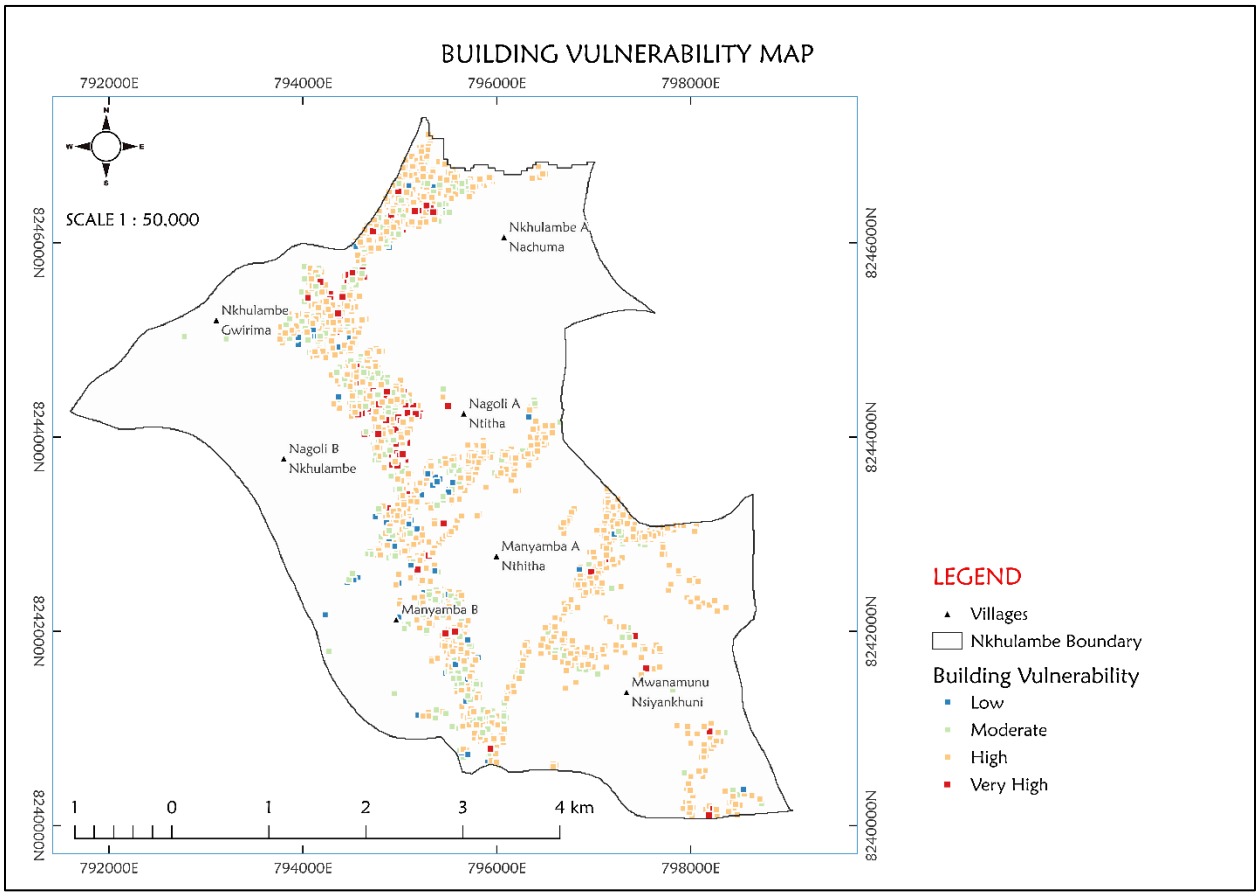


Figure 17: Shows proximate level of building susceptible to landslides

The Agricultural Fields Vulnerability Map similarly demonstrated how proximity to susceptibility areas affected agricultural productivity and resilience. Fields with very high vulnerability were clustered in hazard-prone zones, particularly in the central and northern parts of the community. High vulnerability was also observed in some central and southern areas. Finally, areas with low vulnerability, primarily located in the eastern and southern parts of the community, suggested agricultural fields that were less exposed to hazards, likely due to favorable topography or land-use practices.

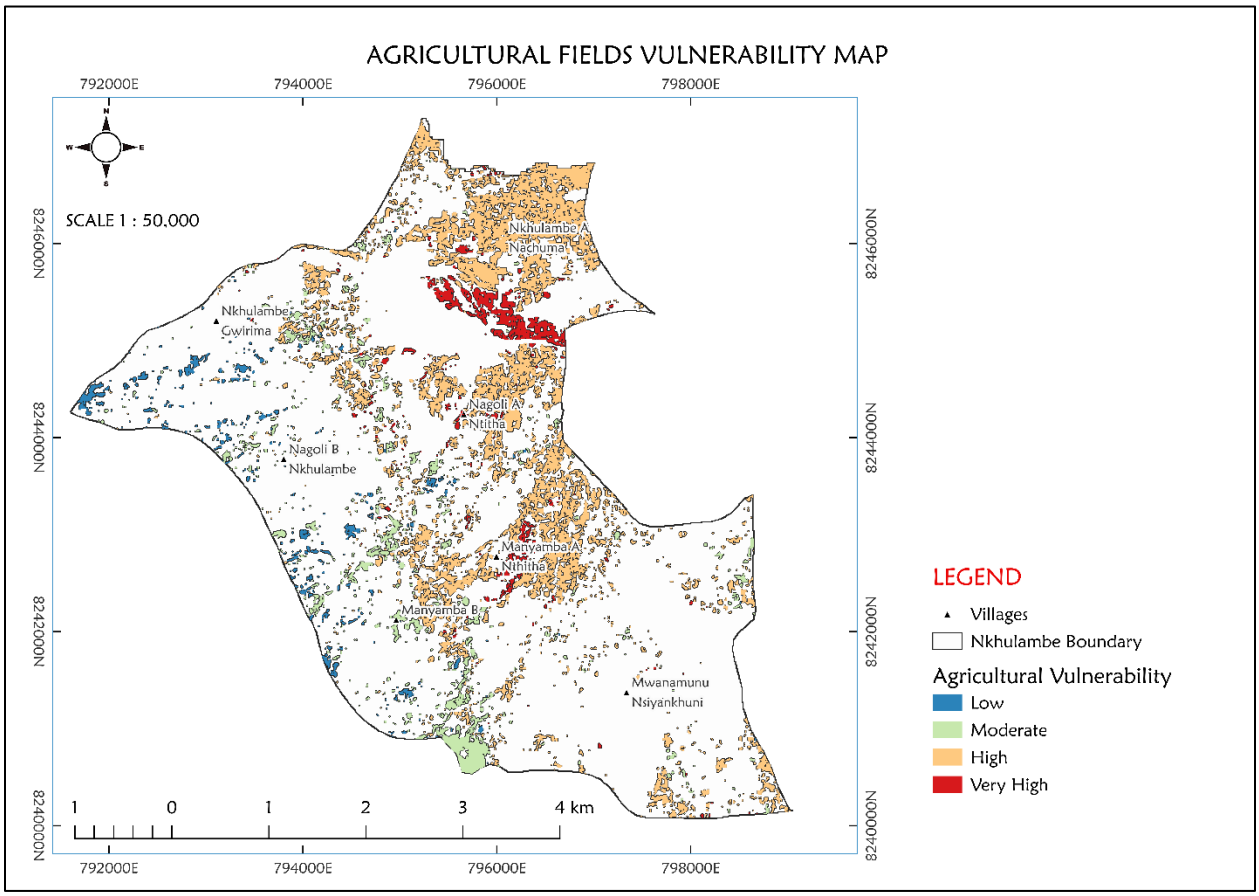


Figure 18: Shows the susceptible level of agricultural fields

4.1.6.2. Community Capacity

Demography Information

Gender Distribution

The gender distribution in the study showed that 64% of participants were male and 36% were female, visually indicated by blue for males and orange for females. This suggested an underrepresentation of women, which may have introduced bias and restricted the generalizability of findings related to social capacity. To address this, future research should strive for more balanced sampling to ensure diverse perspectives are adequately represented.

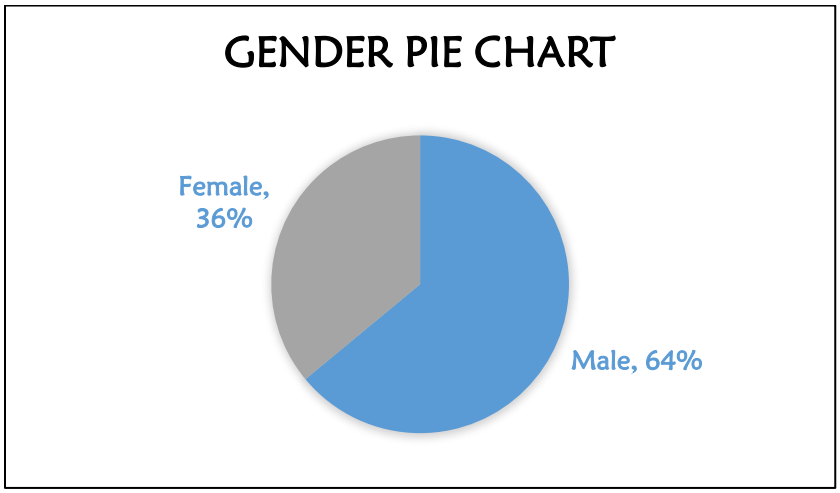


Figure 19: Shows the gender percentage incorporated in the study

Educational Level

60% of participants in Nkhulambe had secondary education, while 24% had primary education, and only 16% possessed tertiary education. This indicated a community with a strong foundation of basic literacy but limited advanced knowledge or specialized skills to address landslide risks effectively. While the majority with secondary education could support awareness and basic preparedness, the low proportion of tertiary-educated individuals highlighted a gap in leadership and technical expertise for comprehensive risk management.

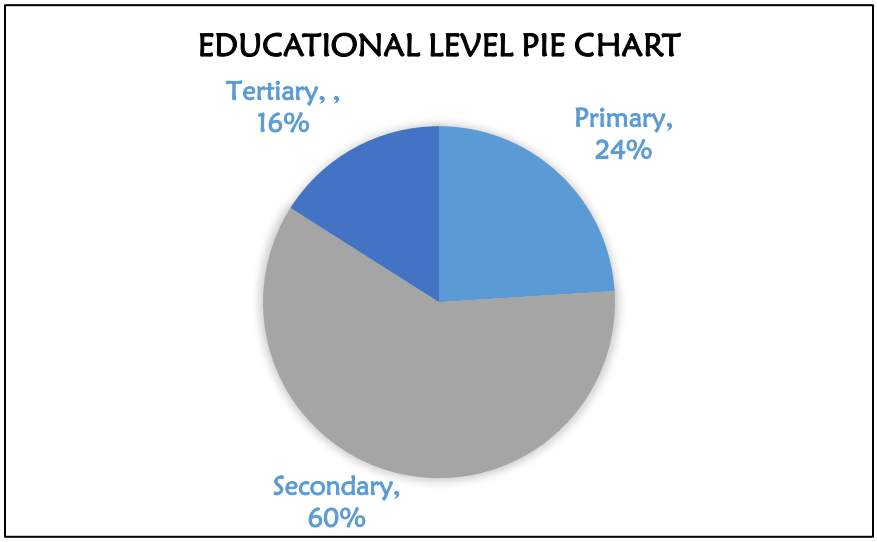


Figure 20: a pie chart representing the education level

Age Range

The study's age range covered from 25 years and below to 46 years and above, with participants distributed across four distinct age groups, revealing significant demographic patterns relevant to social capacity and connectivity in Nkhulambe. The majority of participants (40%) fell within the 36-45 age range , followed by the 26-35 age group at 28%, while both the 25 Below and 46 and Above groups were equally underrepresented, each accounting for only 16% of the sample. This distribution demonstrated that middle-aged adults formed the core of the study, likely contributing valuable experience and leadership to community resilience efforts. However, the limited inclusion of younger individuals and older adults highlighted gaps in incorporating innovative ideas from youth and traditional knowledge from elders, which impacted the comprehensiveness of risk management strategies.

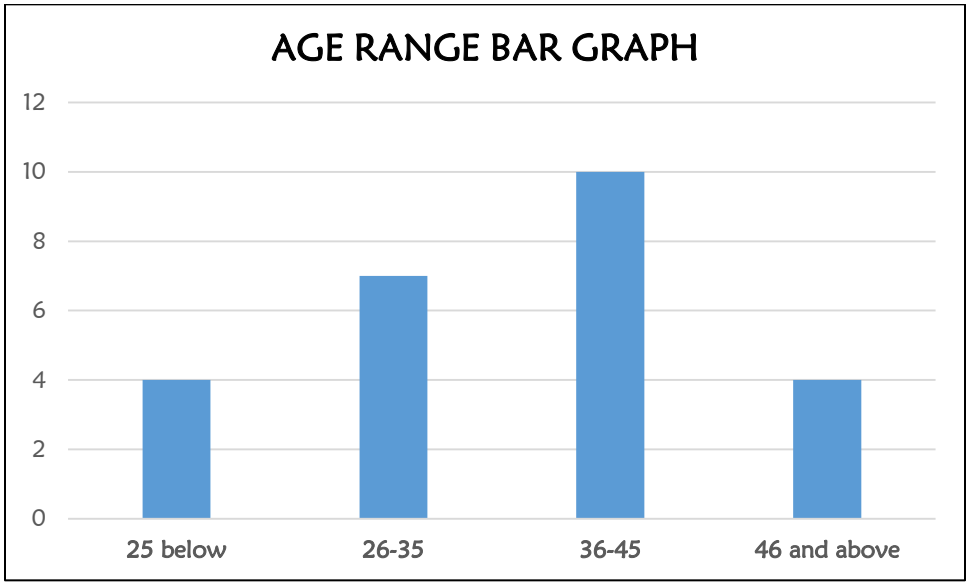


Figure 21: Shows a bar graph representing age range enrolled in the study

Primary Occupation

The study's occupational distribution revealed that farming was the dominant primary occupation, accounting for 56% of participants, while business (12%), civil service (16%), and other professions (16%) made up the remainder. This highlighted the community's heavy reliance on agriculture, with farmers being particularly vulnerable to landslide risks due to their dependence on land-based livelihoods. The presence of business owners and civil

servants suggested some diversity in skills and resources, which could have facilitated cross-sector collaboration and enhanced formal disaster preparedness efforts.

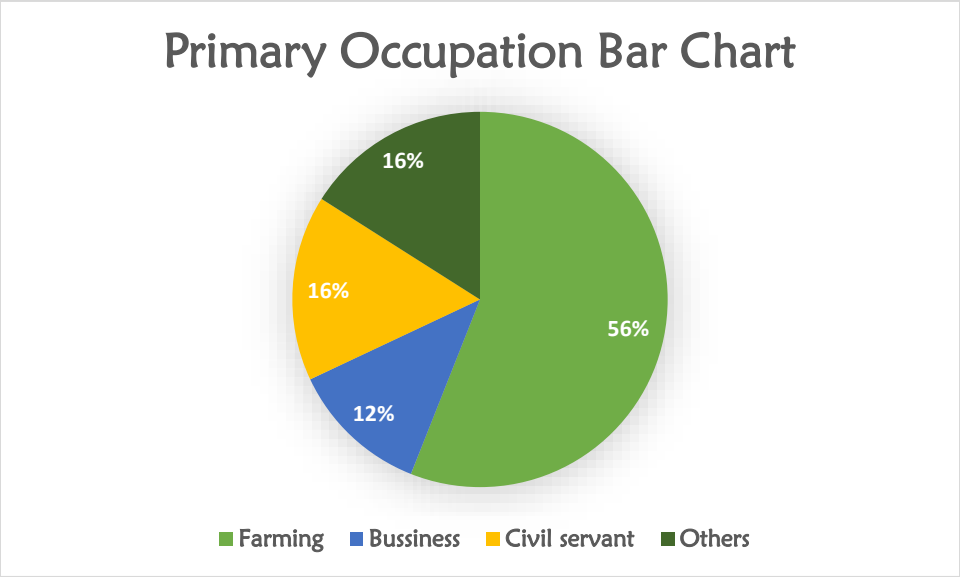


Figure 22: Shows a pie chart indicating primary occupation of participant

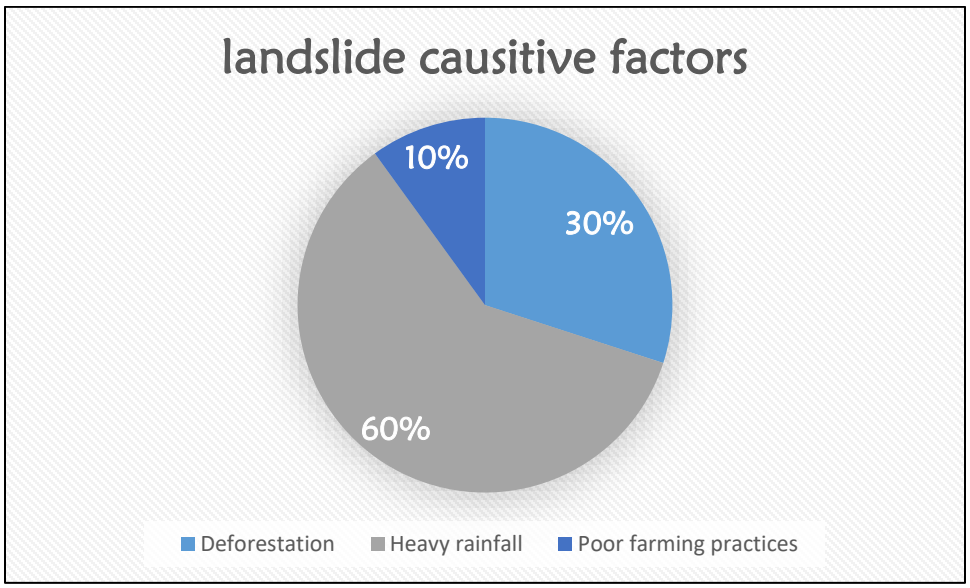
Awareness and Experience

The survey responses revealed that all participants had personally experienced landslides in Nkhulambe, as every respondent answered "Yes" to whether they had encountered such an event. This indicated that landslides were a recurring and impactful phenomenon in the area, significantly affecting residents despite their infrequency. When asked about the frequency of landslides, 100% reported that they occurred rarely, specifically once in ten years or more. The community explained that they did not experience landslides frequently, and in fact, the last landslide they experienced before the 2023 event was in 1991(Relief web, 1991)a. Although landslides were not frequent, their significance was marked, as all respondents recalled these events being intensely.

When respondents were asked about the causes of landslides in Nkhulambe, 60% of participants attributed them to heavy rainfall, highlighting the community's strong awareness of hydrological triggers. Additionally, deforestation was cited by 30% of respondents, while

poor farming practices were identified by around 10%, demonstrating an understanding of human-induced environmental degradation

Figure 23: Shows a pie chart indicating causative factors of landslides



Community Preparedness and Response

In terms of preparedness 88% of the community said that there is no specific early warning for landslide installed to warn in people in time. As such this may cause panic and confusion leading to people making poor decision due to lack of information.

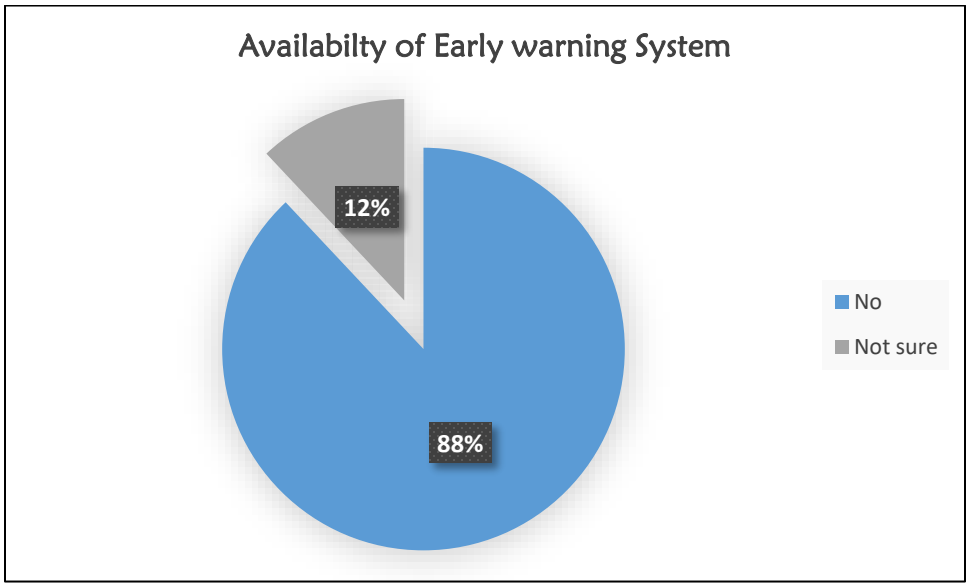


Figure 24: Shows a pie chart validating the presence of a landslide early warning system in Nkhulambe community

In this section the study also gathered insight to understand if the community knows what actions to take when they receive a landslide warning the results showed that 76% of the population don't know what to do and 24% knows what to do when they receive a landslide warning information.

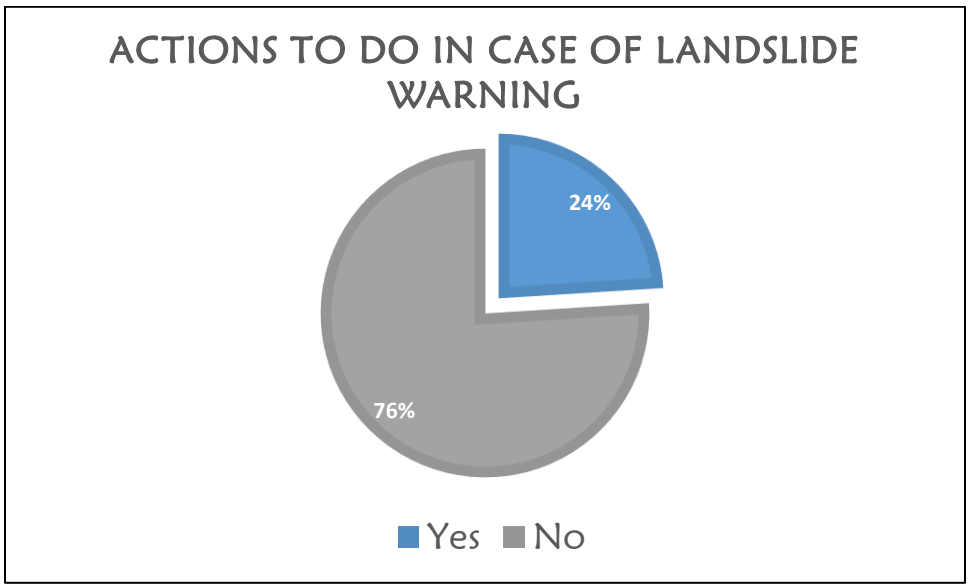


Figure 25: Shows a pie chart indicating preparedness level of people in case of landslide warning

Community Resilient and Support

A majority of respondents reported having received external support following landslides, indicating that some level of assistance was available during and after disaster events. The types of support mentioned included food, shelter, funds, and other forms of aid, suggesting that external organizations or government agencies had provided relief in the past.

The challenges faced by the community in responding to landslides were multifaceted, with several key issues emerging. A lack of funding was frequently mentioned, highlighting financial constraints as a significant barrier to effective disaster response. Hunger was also emphasized as a critical concern, reflecting the severe impact of landslides on food security and livelihoods. Poor communication of needs was identified as a recurring problem, pointing to inefficiencies in disseminating information and coordinating emergency efforts. Additionally, some respondents expressed confusion about landslide dynamics, such as whether mud, trees, or water were the primary debris carriers, indicating a lack of awareness about the phenomenon. Furthermore, many respondents noted uncertainty about how to respond after a landslide, underscoring the need for clearer guidance and training to enhance preparedness and recovery efforts

The most common suggestions for improving the community's ability to handle landslides included a combination of practical and educational measures. Afforestation and tree planting were widely suggested, reflecting an understanding of the role vegetation plays in stabilizing slopes and reducing landslide risks. Community awareness and education were highlighted as a priority. Additionally, physical interventions such as building landslide blocks or wire barriers were proposed to mitigate landslide impacts, while support in knowledge awareness was emphasized to address confusion and uncertainty surrounding landslide dynamics and post-disaster actions.

Vulnerability Map

The vulnerability map (Figure 26) revealed distinct risk patterns across the Nkhulambe Community. A weighted overlay approach was applied to generate this map, assigning appropriate weights to infrastructure and agricultural vulnerability based on their relative importance in the context of landslide impacts. The results showed that very high vulnerability

(red) was concentrated in the northern and central parts of the area, particularly affecting villages such as Nachuma, Nagoli A, and Nititha. This high risk was likely due to their proximity to rivers and steep slopes. High vulnerability (orange) was widespread across the central region, including areas like Manyamba A and Nthitha. Moderate vulnerability (yellow) appeared scattered around high-risk zones, such as in Gwirima, while low vulnerability (light green) was mainly observed in the eastern and southern regions, covering villages like Manyamba B and Nsiyankhuni. Furthermore, the map was aligned with a Google Earth base map to clearly illustrate how buildings constructed along the rivers were associated with higher vulnerability, reflecting the increased risk linked to their proximity to potential landslide hazard.

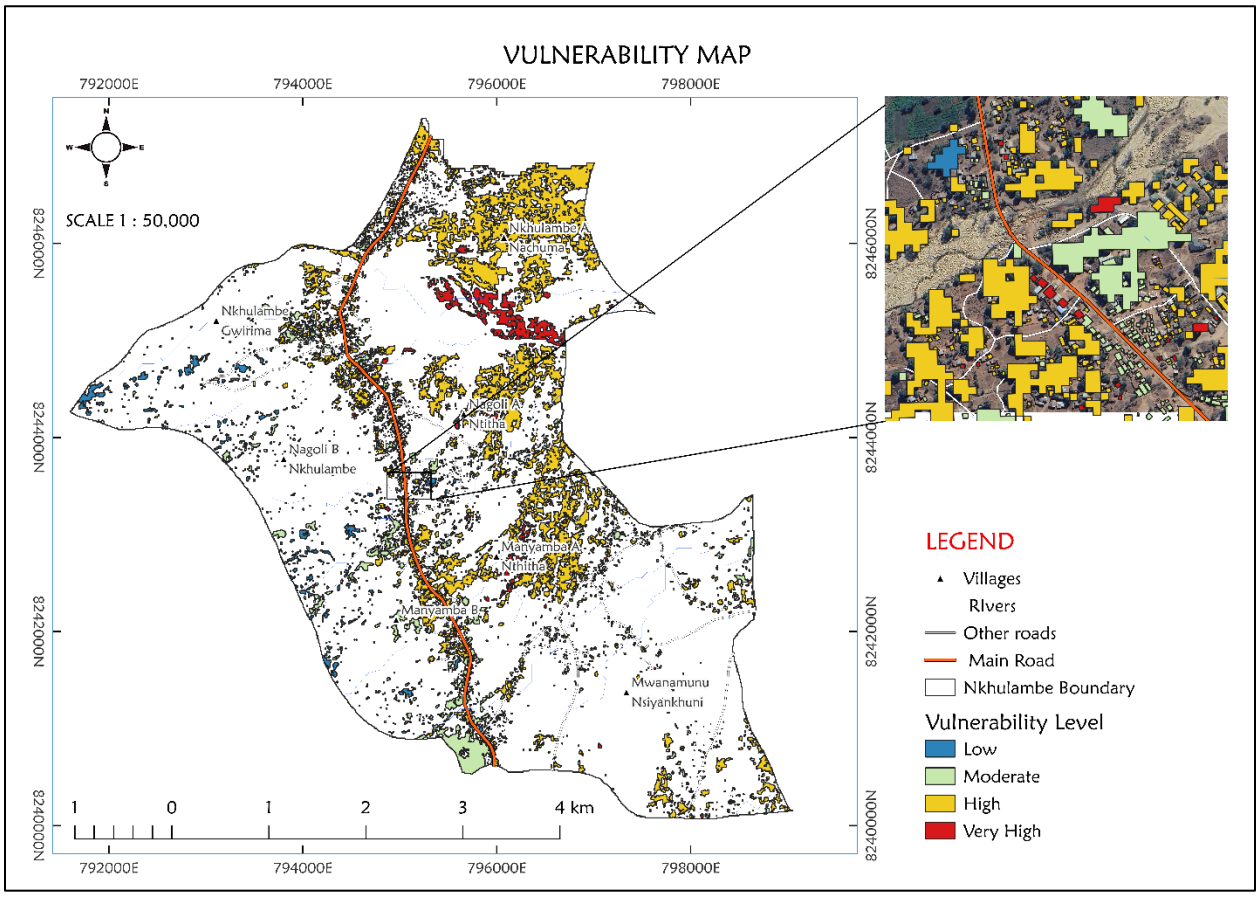


Figure 26: Shows the Vulnerability Map for Nkhulambe Community.

4.1.7. Landslide Risk Map

The landslide risk map (Figure 27) was developed by integrating the susceptibility map produced using the Information Value Method to assess eight geological and environmental factors with the physical vulnerability map, which considered the proximity of infrastructure and agricultural land to hazard-prone areas. This integration was carried out through spatial overlay analysis in QGIS, combining zones of high/very high susceptibility with locations of high vulnerability such as buildings, roads, and bridges to identify the highest risk areas, particularly in the central and northern parts of Nkhulambe Community including villages like Nachuma, Nagoli A, and Nititha. High-risk zones were also widespread in the central region and parts of the south, while moderate risk areas surrounded these zones, often covering agricultural fields or settlements, and low-risk areas were mainly found in the east and south

such as Manyamba B and Nsiyankhuni, resulting in a clear spatial delineation of risk levels that supports targeted disaster risk reduction strategies

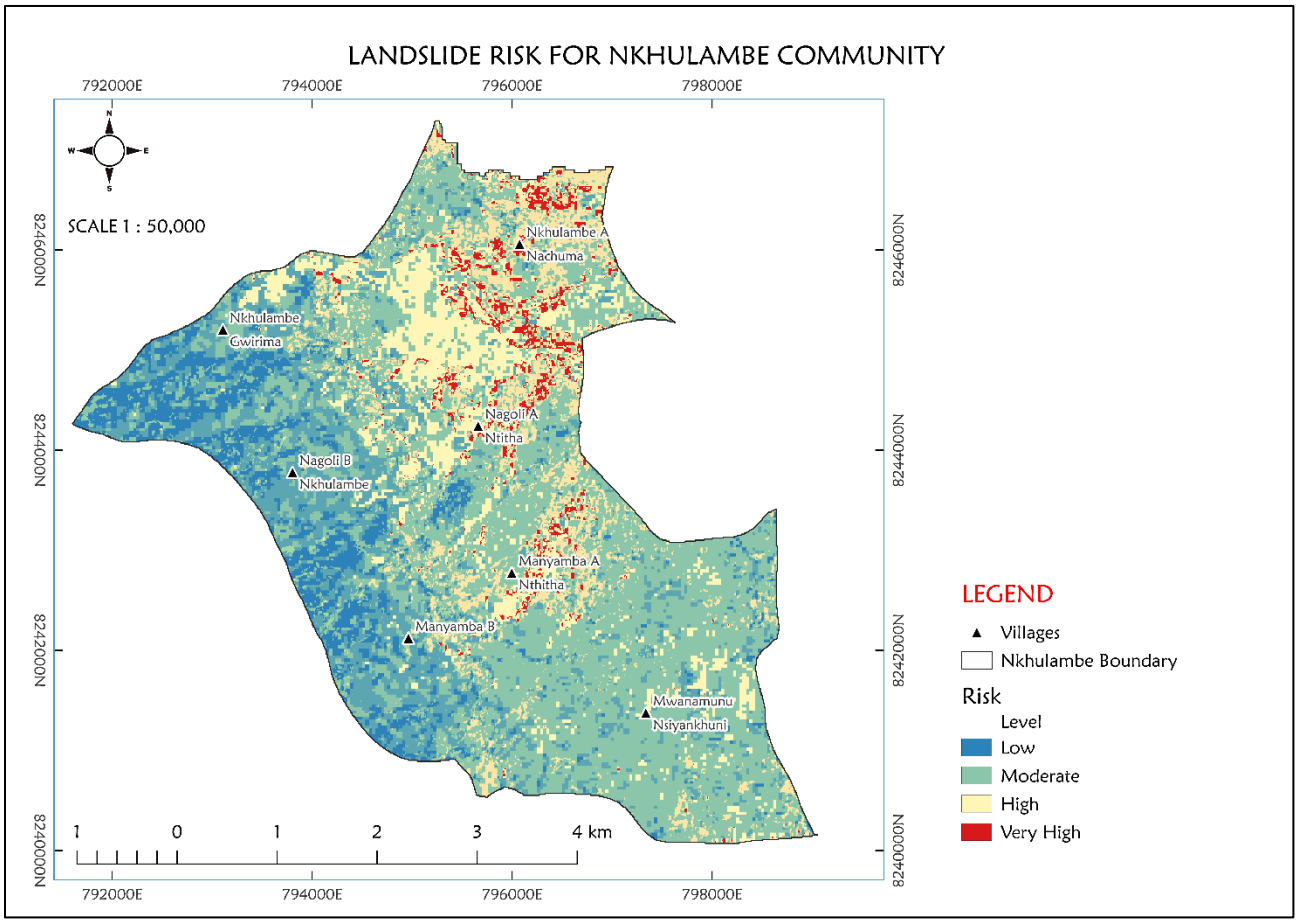


Figure 27: Shows the landslide risk map for T/A Nkhulambe

4.2. Discussion

The assessment of landslide risk in the Nkhulambe Community using integrated GIS and remote sensing yielded critical insights that informed both local risk reduction efforts and broader disaster management strategies. The results demonstrated a strong spatial correlation between environmental factors such as steep slope gradients, soil depth, landform types, and proximity to streams, and landslide occurrence. This aligned closely with prior studies (e.g., Shano et al., 2020; Nakileza & Nedala, 2020), validating that dissected hillsides and outwash plains were especially prone to slope failures, particularly during intense rainfall. The susceptibility and risk maps confirmed that the central and northern regions of Nkhulambe

were especially vulnerable, collaborating findings from Thiery et al. (2024), which identified Phalombe District as one of Malawi's landslide hotspots.

Notably, the integration of the Information Value Method (IVM) revealed relationships among factors. For instance, while high slopes (>60°) were theoretically expected to be highly susceptible, the IV score was surprisingly low (-2.348). This could have indicated limited soil accumulation or errors in inventory data, thus pointing to a limitation in how landslide scars were mapped and verified. This contradiction calls for future ground-truthing efforts and validation of susceptibility models, as emphasized by Luo et al. (2019). On the other hand rainfall information value showed to surpass other predisposing factor with (IV: 1.696). This finding comparing with the community understanding on what may be the causes of landslides in Nkhulambe, 60% of attributed them to heavy rainfall, highlighting the community's strong awareness of hydrological triggers.

The vulnerability assessment also expanded understanding by incorporating both physical and social dimensions. The clustering of highly vulnerable buildings and agricultural fields in the same regions flagged as high susceptibility zones indicated a spatial overlap of hazard exposure and human settlement patterns. These findings reflected the conclusions by G.G. Msilimba & Holmes (2010), who found that poor land-use practices and informal construction exacerbated vulnerability in Malawian settings. Furthermore features that were located at a distance of 50m from the stream indicated to be at higher vulnerable do to proximate of exposure.

Social vulnerability, as determined through community surveys, added further depth to the analysis. The results showed that despite a high awareness of past landslide events (100% of respondents had experienced one), preparedness levels were critically low only 12% of respondents reported the presence of an early warning system, and 76% did not know what actions to take during an emergency. This disconnect between awareness and preparedness reflected the gaps identified by UNDRR (2007) in communities with high hazard exposure but weak institutional support. Social vulnerability assessment further pointed out that Farming was the dominant primary occupation, accounting for 56% of participants. This

indicated that farmers are particularly vulnerable whenever a landslide happens since they depend much on land-based livelihoods.

Although the study incorporated a thorough range of parameters, several methodological limitations warranted further discussion. The use of Sentinel-2A imagery and 30m SRTM DEM data, while accessible and widely used, limited the precision of landslide detection and terrain modeling. The resolution may not have captured micro features that were crucial in triggering shallow landslides. Moreover, the vulnerability analysis relied heavily on visual interpretation and digitization from OpenStreetMap and Google Earth, which may not have reflected up-to-date or ground-truth data.

Additionally, the IVM's assumption of statistical independence between predisposing factors could have oversimplified the complex interactions among terrain, soil, and hydrology. For instance, areas with both steep slopes and shallow soils may not simply have added to the risk linearly but could have had a compounded, nonlinear impact. This revealed a potential bias in risk estimation, suggesting the need for future modeling approaches that accounted for multi-collinearity or employed machine learning techniques (e.g., Random Forest or Support Vector Machines).

The sampling strategy also presented challenges. While random sampling was employed, women and elderly respondents were underrepresented due to trauma from the 2023 landslide event. This gendered gap in data collection could have skewed social vulnerability results, as women often played critical roles in household risk management and recovery strategies (Flanagan et al., 2011).

Furthermore, rainfall data was interpolated using IDW rather than obtained from the Department of Meteorology due to data unavailability. This introduced a source of uncertainty in classifying rainfall-driven susceptibility zones, especially since rainfall was a temporal variable prone to high spatial variability in mountainous terrain.

Although the study was temporally bounded by data from 2023-25, the outcomes presented valuable long-term insights. The susceptibility and risk maps could support future land-use planning, inform early warning infrastructure, and guide community-based disaster risk

reduction. However, without continual updates and the integration of real-time rainfall and land-use change data, the study's predictive value might diminish over time.

From a policy perspective, this study strengthened the case for integrating GIS-based hazard mapping into national disaster management frameworks. It also aligned with SDG 11 on building resilient cities and communities and directly supported the Sendai Framework's call for the use of geospatial data in risk governance.

Policy Implications

1. Integrate GIS-based risk maps into land-use planning frameworks

The susceptibility and risk maps generated through this study should be formally incorporated into local and national land-use planning frameworks to guide infrastructure development, settlement expansion, and agricultural activities away from high-risk zones, particularly in the central and northern parts of the Nkhulambe Community.

2. Strengthening Early Warning Systems and Community Preparedness

Institutional support must be enhanced to establish functional early warning systems in vulnerable areas. This includes community-based disaster preparedness training, as findings revealed that while awareness of landslide events was high, only 12% of respondents reported having access to early warning mechanisms.

3. Enhanced Collaboration with Meteorological Institutions

There is a need to establish stronger collaboration with the Department of Meteorology to access real-time and historical rainfall data. This will improve the accuracy of rainfall-driven susceptibility modeling and support dynamic, time-sensitive risk assessments.

4. Community Education and Awareness Campaigns

Targeted public education campaigns should be implemented to enhance understanding of landslide risks and appropriate emergency responses, especially in high and very high vulnerability zones where preparedness levels were found to be critically low.

5. Chapter 5: Recommendation and Conclusions

5.1. Conclusion

This study set out to assess landslide risk in the Nkhulambe Community of Phalombe District by integrating GIS and remote sensing technologies to spatially analyze susceptibility, vulnerability, and overall risk. The primary aim was to provide actionable data that could enhance disaster risk reduction strategies and inform local land-use planning. This objective was effectively achieved through the development of landslide susceptibility, vulnerability, and risk maps, supported by community-level social and physical data.

Key findings of the investigation confirmed that the central and northern parts of Nkhulambe were highly susceptible to landslides, primarily due to steep slope gradients, proximity to streams, sedimentary rock types, shallow soils, sparse vegetation, and high annual rainfall. Vulnerability assessments further revealed that buildings and agricultural fields within these high-susceptibility zones were especially at risk. Socially, the study uncovered significant gaps in preparedness, particularly in early warning systems and response knowledge, which elevated the community's overall vulnerability.

The integration of the Information Value Method (IVM) with spatial analysis techniques in QGIS demonstrated the practical applicability of GIS and remote sensing for risk modeling in data-constrained environments. Moreover, the study's approach of combining environmental and social datasets provided a holistic framework for disaster risk assessment at the community level.

Despite its contributions, the study was limited by data accessibility, particularly regarding historical rainfall records and accurate landslide inventory verification. Sampling constraints, such as gender imbalance in survey responses and reliance on medium-resolution satellite data, may have introduced bias or reduced model precision.

Nonetheless, the research made a significant contribution to local hazard mapping and policy discourse. It supported the Sendai Framework for Disaster Risk Reduction and SDG 11 by

providing localized, data-driven insights into risk exposure, with potential applications for early warning, community training, and policy formulation

5.1. Limitation of the study

The study faced a lot of limitation the first one being lack of funds to support the study in terms of data, collection and accommodation during field visit. Unwillingness of respondent to participate in answering the questioner, many women didn't want to participate in answering questions about landslide as it reminded them of their lost loved ones during the 2023 landslides event in the area. This led to the study not to incorporate the targeted sample. Furthermore the department of climate change and meteorological services did not provide annual rainfall data for the study.

5.2. Recommendation

Based on the findings and limitations encountered, the following recommendations are proposed:

Establishment of Community Based Early Warning Systems (EWS):

- The study found that 88% of participants lacked access to early warning mechanisms. Authorities, in partnership with NGOs and local leadership, should prioritize the installation of low-cost landslide EWS using rainfall thresholds and geo-sensors.

Enhanced Land Use and Zoning Policies:

- Given the concentration of vulnerable infrastructure in high-risk zones, the Phalombe District Council should incorporate the risk maps generated in this study into their zoning regulations to guide safe construction and agricultural practices.

Capacity Building and Awareness Campaigns:

- With 76% of respondents unsure of what to do during landslide warnings, there is an urgent need for targeted education campaigns focusing on landslide preparedness, evacuation procedures, and risk communication.

Increased Investment in Data Infrastructure:

- Government agencies should strengthen data collection mechanisms, including establishing a centralized national landslide inventory and improving access to meteorological data. This would enhance the accuracy of future modeling and validation efforts.

Further Research Using High Resolution and Machine Learning Techniques:

- Future studies should incorporate higher-resolution elevation and land-use datasets, as well as advanced modeling techniques such as Random Forest or Deep Learning to improve the predictive accuracy of landslide risk assessments.

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7. Appendices

Questionnaire on Social Capacity to Landslides in Nkhulambe

Introduction:

Hello, my name is Daniel Maneya, a fourth year student from Malawi University of Science and Technology. I am conducting research on Integrating GIS and Remote Sensing to assess the Risk of landslide in Nkhulambe.

This questionnaire is thereby focusing on understanding community preparedness awareness and capacity to support the findings on desktop review. Your participation is entirely voluntary and you may skip any question you're not comfortable with. Your responses will remain confidential and will only be used for academic purposes.

Do you agree to participate in this interview?

Yes ☐ No ☐ (if **Yes**, continue with the interview, if **No** stop interview)

If you have any question, please feel free to ask.

Section A: Demographic Information

1. What is your age?
   ☐ Below 25
   ☐ 26-35
   ☐ 36-45
   ☐ 46 and above
2. What is your gender?
   ☐ Male
   ☐ Female
   ☐ Prefer not to say
3. What is your highest level of education?
   ☐ No formal education
   ☐ Primary
   ☐ Secondary
   ☐ Tertiary
4. What is your primary occupation?
   ☐ Farming
   ☐ Business
   ☐ Civil servant
   ☐ Other (Specify) _____

Section B: Landslide Awareness and Experience

5. Have you ever experienced a landslide in Nkhulambe?
   ☐ Yes
   ☐ No
6. If yes, how frequently do landslides occur in your area?
   ☐ Rarely (once in 10 years or more)
   ☐ Occasionally (every 5-9 years)
   ☐ Frequently (every 1-4 years)
   ☐ Very frequently (every year)
7. What do you think are the main causes of landslides in your area? *(Select all that apply)*
   ☐ Heavy rainfall
   ☐ Deforestation
   ☐ Poor farming practices
   ☐ Construction activities
   ☐ Other (Specify) _____

8. Are you aware of any past landslide-related disasters in your community?
   ☐ Yes
   ☐ No
9. Do you feel that your community is well-informed about landslides and their risks?
   ☐ Yes
   ☐ No
   ☐ Not sure

Section C: Community Preparedness and Response

10. Are there any early warning systems for landslides in your area?
    ☐ Yes
    ☐ No
    ☐ Not sure
11. How do you receive information about potential landslides? *(Select all that apply)*
    ☐ Community meetings
    ☐ Radio/TV
    ☐ Mobile messages
    ☐ Word of mouth
    ☐ Other (Specify) _____
12. Do you know what actions to take in case of a landslide warning?
    ☐ Yes
    ☐ No
13. Has your household or community received any training on how to respond to landslides?
    ☐ Yes
    ☐ No
14. What measures has your household taken to reduce the risk of landslides? *(Select all that apply)*
    ☐ Tree planting
    ☐ Building structures away from slopes
    ☐ Following proper farming techniques
    ☐ No specific measures taken
    ☐ Other (Specify) _____
15. Do you have an emergency plan in case of a landslide?
    ☐ Yes
    ☐ No

Section D: Community Resilience and Support

16. Who do you rely on for help after a landslide? *(Select all that apply)*
    - ☐ Government
    - ☐ NGOs
    - ☐ Community members
    - ☐ No one, we handle it ourselves
17. Have you or your community ever received external support (e.g., food, shelter, funds) after a landslide?
    - ☐ Yes
    - ☐ No
18. Do you think the local government has enough resources to help during and after landslides?
    - ☐ Yes
    - ☐ No
    - ☐ Not sure
19. What challenges does your community face in responding to landslides? *(Open-ended)*

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20. What support do you think would improve the community's ability to handle landslides? *(Open-ended)*

THANK YOU FOR YOUR TIME. !!!