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BACHELOR OF SCIENCE DEGREE IN EARTH SCIENCE (GEOLOGY)

Assessing slope stability and landslide hazard in Chapima Heights, Blantyre District

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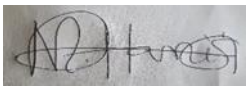
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ABSTRACT

Landslide susceptibility is an important topic mainly because its geospatial analysis provides a useful tool for planning, disaster management, and hazard mitigation. In this study, the aim is to identify and analyze landslide susceptibility at a local spatial scale, which is Chapima Heights, Blantyre, using the multi-criteria evaluation (i.e., the analytical hierarchy process technique (AHP) and geographic information systems (GIS)). The following landslide conditioning factors were selected, representing the local terrain predispositions: slope angle, curvature, slope aspect, and elevation. The other factors are rainfall, normalized difference vegetation (NDVI), and land use. The raster-based analysis was conducted on data obtained. After the analysis maps for the chosen factors were created, they were classified and reclassified to risk levels to allow comparability and assigned weights using AHP according to their importance to contribute to the landslides class final map. The AHP results from this research show that the following were the percentages of the contributing factors: slope (42.44%), rainfall (23.84%), NDVI(12.64%), land use (8.67%), elevation (5.82%), aspect (3.89%), and curvature(2.7%). The final map shows that the majority of the area has low to moderate landslide susceptibility, with only the southwestern part being highly susceptible due to the steepness of the area. The validation of the results was based on consistency checks through the pairwise comparison of the chosen landslide contributing factors through consistency index and consistency ratio calculations that are 0.05094 and 0.03859, respectively. Finally, I will recommend people living in the southwest to build waterways that will direct the water to flow to safer sites therefore making almost the whole of the area safe in terms of landslide risks during periods of heavy rainfall.

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Chapter 1 Introduction

1.1. Background

Chapima Heights, situated in the southern region of Malawi, is situated within the hilly terrain of Blantyre. This area is experiencing a scattered and rising population, leading to changes in land use patterns. Over recent years, land has been cleared for new house development, and quarrying activities have increased due to the high demand for building materials, affecting the stability of the land (Mwale et al., 2015). Such changes in land use can increase landslide risk by reducing soil stability and increasing erosion potential (Glade, 2003).

The southern region of Malawi has faced severe weather events, including heavy rainfalls from cyclone events like Cyclone Idai and the most recent Cyclone Freddy, which has caused significant damage to parts of the southern region (Munthali et al., 2023). Cyclone Freddy affected about. Given these conditions, Chapima Heights could be a potential area at risk if such cyclonic events continue to occur. Heavy rainfall is a major triggering factor for landslides, as it can saturate the soil, reducing its strength and increasing the likelihood of slope failure (van Westen et al., 2006).

Understanding landslide activity is crucial for predicting future events, providing mitigation measures to local communities, and informing land use planning for sustainable development (Glade, 2003). Landslides can cause significant damage to life and property, making it essential to understand their causes and how they happen to develop mitigation strategies. There are three key basics to understanding landslide activity: the state of activity, distribution of activity, and style of activity. The state of activity describes the timing of the moving material (e.g., active or inactive), while the distribution of activity explains where the landslide is moving (e.g., advancing, retrogressive, or widening). The style of activity indicates the manner in which different movements contribute to the landslide (e.g., composite or multiple) (Hungr et al., 2014). Understanding these aspects is vital for assessing landslide susceptibility and implementing appropriate risk management strategies.

Studying landslide susceptibility is important because it informs local communities about potential landslide hazards, enabling them to implement early warning systems and mitigation strategies (van Westen et al., 2006). It is typically determined by considering potential initiation zones and can be combined with calculations of the probability of how far a landslide might travel (Corominas et al., 2014). This approach helps in identifying areas at high risk and prioritizing mitigation efforts.

Several studies have been conducted globally to assess landslide susceptibility, but there is a need for more local studies to better understand specific regional hazards (Guzzetti et al., 2012). Local studies are crucial for developing targeted risk management strategies that account for the special geological, climatic, and land use conditions of an area. This research aims to conduct a landslide assessment study in Chapima Heights, Blantyre, using both primary and secondary data, incorporating spatial and temporal data analysis to evaluate the area's susceptibility to landslides.

Study area

It is located in between Chileka Road to the east and M1 Road to the west and makes boundaries with Mussa to its northwest, Mbayani to its southwest, Chirimba to its north, and Nyambadwe to its southeast. The study area is situated within the largest perthite gneiss and perthosite outcrop in the country that covers an area of about 200 square miles, which forms hills of Ndirande, Bangwe, Mikolongwe, Mpingwe, Soche, and many other small hills within the vicinity of the area, which is of the basement complex that formed during the Precambrian to lower Paleozoic and are generally ridge-like in form (Evans, 1965). Geographical Extent: 715237E to 717637E and 8257645N to 8255845N.

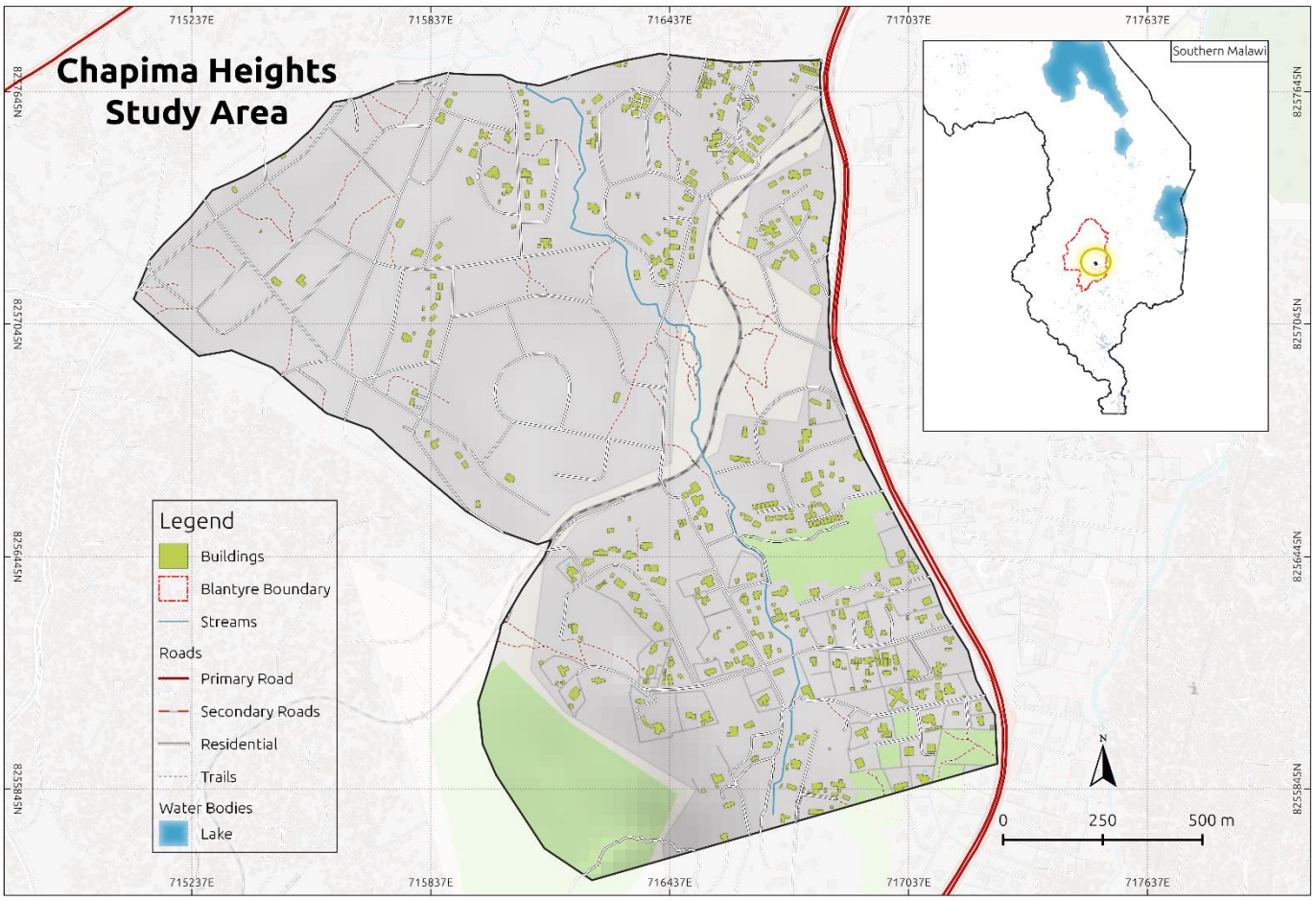


Figure 1: Map of Chapima Heights

1.2. Problem statement

Chapima Heights, a region in Malawi, is particularly vulnerable to landslide occurrences, especially during the rainy season. These landslides pose significant threats to the local population, infrastructure, and economic development of the area (Glade, 2003). In recent years, the frequency and intensity of landslides have increased due to factors such as heavy rainfall, deforestation, and unplanned urbanization (Mwale et al., 2015). Heavy rainfall can saturate the soil, reducing its strength and increasing the likelihood of slope failure (van Westen et al., 2006). Deforestation and urbanization also contribute to landslide risk by altering land cover and increasing soil erosion (Glade, 2003). Despite the growing concern over landslide risks, there is a lack of research on the susceptibility of Chapima Heights and other local-scale areas in Malawi to slope failures. Previous studies on landslide susceptibility mapping in Malawi have primarily focused on the northern regions, such as

the Ntchenachena area (Msilimba & Holmes, 2010). However, the southeastern hilly region, including Chapima Heights, has received limited attention. This lack of research in the southeastern region affects the development of effective landslide mitigation strategies for the specific geological and hydrogeological conditions of the area. There is a need for more detailed investigations into the specific geotechnical properties of soils and rocks, as well as the influence of local geological and hydrogeological conditions on slope stability in Chapima Heights. Understanding these factors is crucial for developing accurate landslide susceptibility maps and implementing effective mitigation strategies (Corominas et al., 2014). In conclusion, the proposed research on landslide susceptibility in Chapima Heights is crucial for addressing the growing concern over landslide risks in the region. By filling the existing knowledge gap and applying advanced techniques, this study can contribute significantly to enhancing the resilience of local communities against landslide hazards.

1.3. Main and specific objectives

Main objective

Conduct a comprehensive landslide hazard assessment and mapping of Chapima Heights in Blantyre, Malawi.

Specific objectives

- Identify the factors contributing to landslide hazards in the study area.
- Create accurate and detailed landslide hazard maps for Chapima Heights.
- Validate results using existing studies.

1.4. Research questions

To test the success of this project, the following questions need to be answered.

• What are the key factors contributing to landslide hazards in Chapima Heights, Blantyre, Malawi?

• Are there accurate and detailed landslide hazard maps?

• What is the validity of the results generated?

1.5. Significance of study

The study on landslide susceptibility in Chapima Heights, Malawi, holds significant importance for different reasons. It will enhance reduced effects of landslide hazards by providing a comprehensive assessment of susceptibility factors, which can inform land use planning and mitigation strategies (van Westen et al., 2006). This research addresses an important knowledge gap in landslide studies in Malawi, particularly in the southeastern region, by focusing on the specific geological, hydrogeological, and land use factors influencing landslide susceptibility (Msilimba & Holmes, 2010). The results of this research will be used by policymakers, local communities, and environmental agencies seeking to mitigate landslide risks and support sustainable development in Malawi (Glade, 2003). By reducing landslide risks, the study supports economic stability and protects infrastructure and agricultural lands, which are vital to the local community (Mwale et al., 2015). In addition, this research will contribute to the development of early warning systems and emergency response plans, which are essential for saving lives and minimizing damage during landslide events (van Westen et al., 2006). By enhancing our understanding of landslide hazards and improving risk management strategies, this research will contribute to reducing the impact of landslides and promoting sustainable development in Malawi and similar regions globally.

Chapter 2 LITERATURE REVIEW

Despite making up just 2% of the Earth's surface, landslides are one of the most catastrophic natural catastrophes in the world, impacting both the environment and civilization (Broeckx et al., 2020). Landslides killed almost 60,000 people between 2000 and 2016 and incurred $121 billion, which accounts for 17% of all disaster damages worldwide (Guha-Sapir et al., 2017; Klose et al., 2015). According to these data, more research on landslide susceptibility is necessary to reduce hazards in areas where landslides are common because of geological, climatic, and human factors.

2.1. Global Advances in Landslide Susceptibility Mapping

Landslide susceptibility mapping has advanced considerably due to the progress of geospatial technologies such as Geographic Information Systems (GIS), remote sensing (RS), and global navigation satellite systems (GNSS). These tools enable researchers to synthesize wide datasets, including topographic, geological, climatic, and land-use data, helping in the creation of accurate susceptibility maps (Fell et al., 2008; Westen et al., 2008). A study in Slovakia's Handlová area, for instance, used GIS-based multi-criteria decision analysis (MCDA) with the Analytical Hierarchy Process (AHP) approach to evaluate landslide susceptibility at a local spatial level. This approach allows for a comprehensive evaluation of various factors contributing to landslide risk, ensuring that the resulting susceptibility maps reflect the unique conditions of the Handlová region. By integrating multiple data sources and analytical techniques, researchers can make informed decisions regarding land management and hazard mitigation. The findings indicated that integrating various data layers significantly improved the predictive accuracy of landslide susceptibility models. This approach ensures that the susceptibility maps generated appropriately reflect the unique conditions of the Handlová region by enabling a comprehensive evaluation of all the factors affecting the risk of landslides. By integrating different data sources and analytical techniques, researchers can make well-informed decisions regarding land management and hazard mitigation. The findings demonstrated that integrating various ArcGIS-created data layers significantly improved the predictive accuracy of landslide susceptibility models. This approach not only advances our understanding of the spatial distribution of landslides but also aids in the creation of effective land-use planning and risk management strategies in vulnerable areas. The study found that the most important factor was slope angle.

Similarly, Morocco's Rift Mountains were studied using comparative modeling approaches such as AHP and frequency ratio methods. The study found that the AHP method performed better in identifying high susceptibility areas compared to the frequency ratio method; this highlights the advantages of multi-criteria decision-making approaches (Klose et al., 2015). These findings show the importance of multi-criteria approaches, especially to regional characteristics for landslide susceptibility mapping.

2.2. Regional Case Studies: Subtropical Regions

In subtropical regions like Malawi and Ethiopia, landslide susceptibility is heavily influenced by steep slopes, deforestation, intense rainfall patterns, and agricultural activities. In Malawi's Ntchenachena area, slope angle and geology were identified as primary factors affecting slope stability. GIS-based analyses combined with field observations produced susceptibility maps that are important to enhance land-use planning and disaster mitigation strategies (Klug et al., 2016). Similarly, Ethiopia's Gindeberet district employed statistical index methods to map susceptibility zones based on slope aspect, land use patterns, and proximity to drainage networks (Guzzetti et al., 1999). Both studies highlight the importance of integrating local terrain conditions into susceptibility models.

2.3. Advances in Analytical Techniques

The application of advanced analytical techniques has improved landslide susceptibility mapping. Multi-criteria decision analysis (MCDA), particularly AHP, has been widely used for weighted evaluation processes that combine both qualitative and quantitative parameters. AHP focuses on pairwise comparisons between factors such as slope angle or geology to determine their relative importance in triggering landslides (Vojteková & Vojtek, 2020). Other MCDA techniques include weighted linear combination (WLC), ordered weighted average (OWA), and analytical network process (ANP), which have been applied in various geographic studies (Feizizadeh & Blaschke, 2013; Neaupane & Piantanakulchai, 2006).

Quantitative methods such as frequency ratio models and logistic regression have also been in dominant use because of their ability to analyze large datasets objectively. Machine learning algorithms like random forest (RF), artificial neural networks (ANNs), and support vector machines (SVMs) offer even greater predictive accuracy by modeling complex relationships among variables. For example: Random Forest: Applied successfully in Slovenia for regional-scale mapping with high predictive accuracy. Artificial Neural Networks: Used in Taiwan for analyzing rainfall-induced landslides. Support Vector Machines demonstrated effectiveness in assessing seismic-triggered landslides in Nepal.

Despite their advantages, these methods face challenges such as computational complexity and data scarcity. Hybrid models collaborate machine learning algorithms with traditional statistical approaches to yield better results by making full use of the strengths of both methodologies (Pourghasemi et al., 2013).

2.4. Challenges in Landslide Susceptibility Assessment

While significant progress has been made globally and regionally, several challenges are faced, and they include

Standardization Issues: The lack of standardized methodologies complicates comparisons across studies. Qualitative approaches like heuristic models differ from quantitative methods such as logistic regression or machine learning algorithms (AGS, 2007).

Data Limitations: Many developing countries face challenges in acquiring high-resolution data necessary for accurate results. This limitation shows the need for international collaboration and capacity-building initiatives.

Temporal Dynamics: Climate change introduces uncertainties into temporal analyses of landslide reactivation probabilities. Studies in Malawi have explored return periods based on meteorological events but require more reliable climate models for accurate predictions (Broeckx et al., 2018).

2.5. Implications for Chapima Heights

The insights gained from global and regional studies have direct implications for assessing slope stability in Chapima Heights. The integration of GIS-based MCDA techniques like AHP can provide a robust framework for evaluating local terrain predispositions such as slope angle, geology, land use changes due to urbanization or quarrying activities, and proximity to rivers or faults. Additionally, machine learning algorithms could enhance predictive modeling by incorporating diverse datasets. Field surveys remain necessary for validating remote sensing data and understanding site-specific factors influencing slope instability.

Landslide susceptibility assessment is an involved process requiring advanced analytical tools and a thorough understanding of local conditions. The reviewed literature demonstrates significant progress in integrating geospatial technologies with statistical and machine learning approaches while highlighting possible challenges such as standardization issues and data limitations. Studies in the future should focus on improving model accuracy through hybrid approaches, addressing socio-economic influence of risk assessments, and developing adaptive strategies to mitigate climate change impacts on landslide hazards in areas like Chapima Heights.

Chapter 3 : METHODOLOGY

3.1. RESEARCH DESIGN

The research employed a semi-quantitative, multi-criteria decision analysis. This relied on the collection and analysis of data by the use of different applications like ArcGIS, Google Earth, Locus GIS, and Excel spreadsheets.

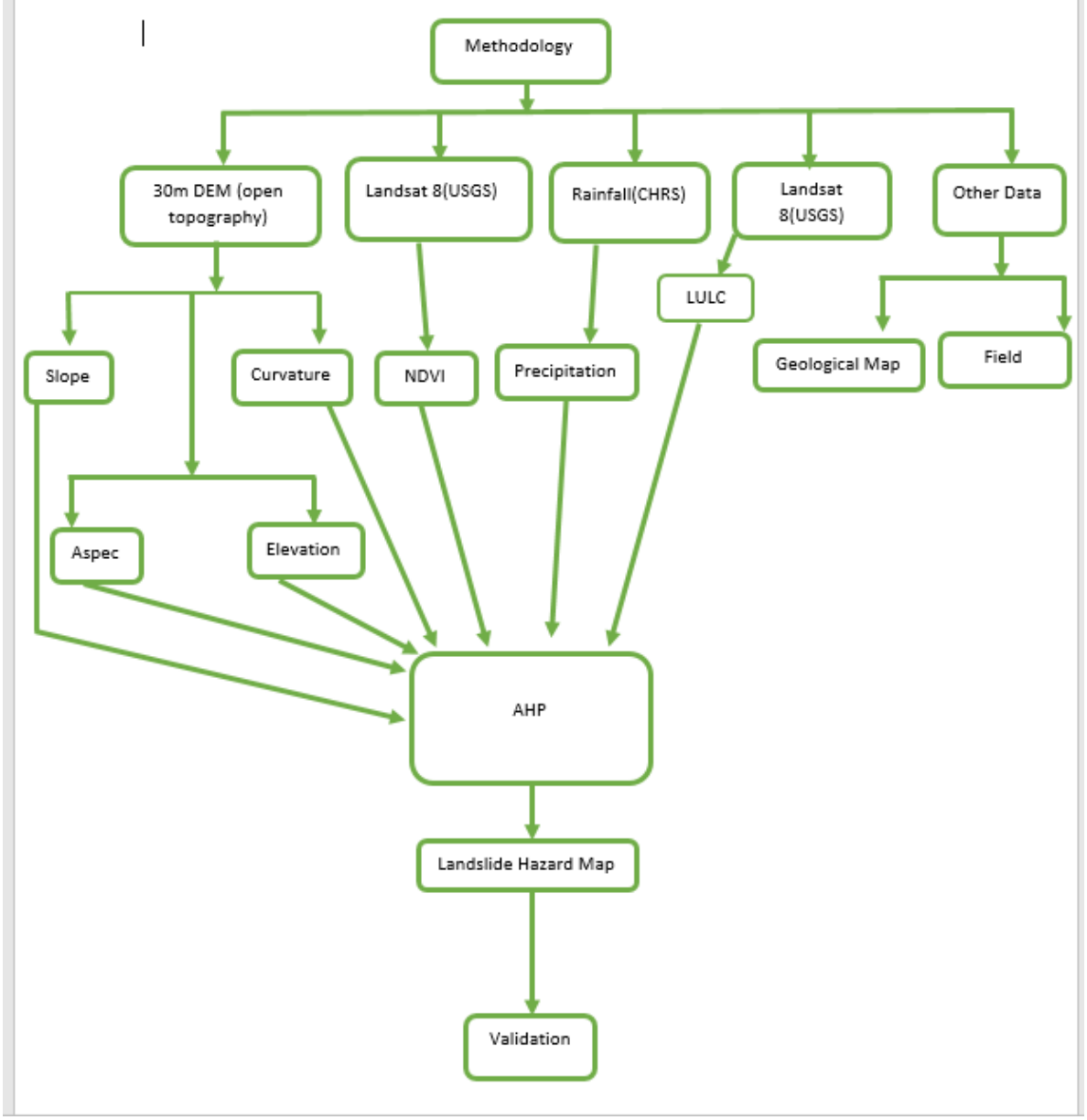


Figure 2: Summary of work carried out

3.2. Data Collection

The data collection process carried out in this study includes accessing STRM-DEM data of 30m resolution from open topography

(https://portal.opentopography.org/datasetMetadata?otCollectionID=OT.042013.4326.1). This SRTM-DEM was used to create slope, aspect, curvature, and elevation maps of the area. Rainfall was obtained from CHIRPS monthly (https://www.chc.ucsb.edu/data/chirps). Landsat 8 imagery used for NDVI and Land cover land use was obtained from (https://earthexplorer.usgs.gov/).The data collection process also involved field traversing, which was done with the help of GPS Essentials to see the exact location in the field within the study area and make sure the traverse is within the boundaries of the study area and also help to know the map zone where data is being collected. Dip and strike, the location of the visible landslide, and the field were taken into notice as well. The inclination measurements were used to come up with the trending direction of the geological lineaments. This helped in knowing the side which is likely to slip or fall in relation to landslide occurrence.) which was useful in creation of a Land use land cover map. Geology bulletin of shire highlands (bulletin No. 18 and geological map were obtained from the geological survey department of Malawi in zomba. Through Mr A.Njewe under the okay from the director Mr S. Nyama.

3.3. MATERIALS AND METHODS

3.3.1. Data analysis

This section will show the details of what methods were used to process the data to come up with the desired outcomes.

3.3.1.1 *Geological map and bulletin*

The geological map of the study area was extracted from the geological map of Shire Highlands acquired from the geological survey department headquarters of Malawi, Zomba. The geology was not chosen to be a landslide conditioning factor because the map data obtained was of a larger scale (1:100000) to show details within a more local place like Chapima Heights.

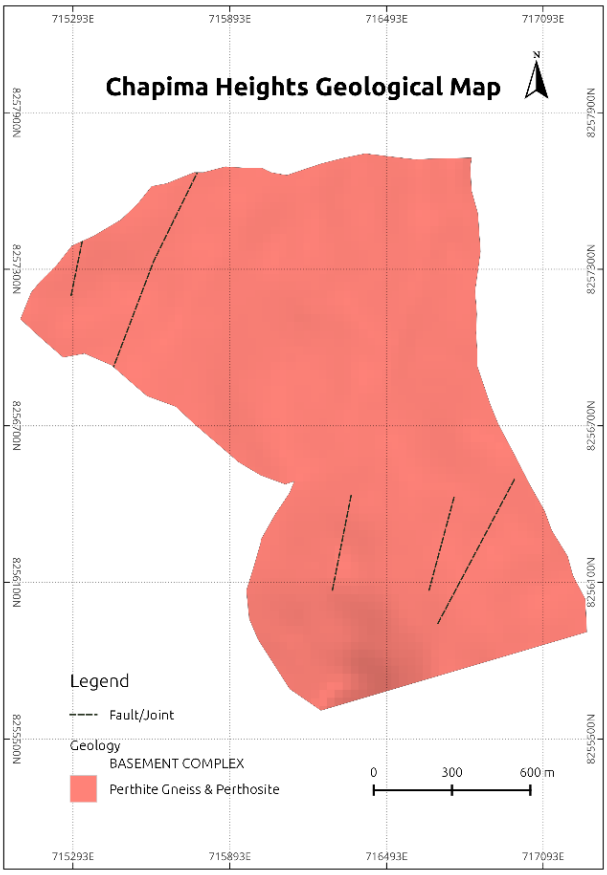


Figure 3: Geological map of Chapima Heights

3.3.1.2 *Slope*

The 30-meter resolution DEM-SRTM is imported into ArcGIS using the Add Data tool. slope angles are calculated using the Slope tool, the output is set to degrees to produce a continuous slope raster. The slope raster is visually inspected for anomalies using the Layer Properties window and clipped to Chapima Heights boundary using the Clip tool. The slope raster is reclassified using the Reclassify tool to divide slopes into five classes and assign susceptibility scores.

3.3.1.3 *Rainfall*

CHIRPS monthly rainfall data is imported in ArcGIS using the Add Data tool. Make a NetCDF raster layer to set the variable to precipitation. Project the data to a local UTM coordinate system using the Project Raster tool. The Chapima Heights boundary was clipped with the Clip Raster tool. Annual rainfall is calculated by summing monthly rasters

with the Cell Statistics tool by setting the statistic type to "Sum." The annual rainfall is reclassified into risk levels using the reclassify tool.

3.3.1.4 *NDVI*

In ArcGIS, import Landsat 8 imagery. Using the Raster Calculator tool, the NDVI is calculated, producing a continuous NDVI raster layer that reflects vegetation health across the area. This raster is then clipped to the Chapima Heights boundary using the Clip Raster tool to focus on the specific region of interest. Next, the Reclassify tool is applied to categorize the NDVI values into distinct vegetation density levels. The Reclassify tool is used again to assign landslide risk levels (e.g., High, Medium, Low) to these vegetation categories, with low vegetation potentially classified as High Risk and very dense vegetation as Low Risk.

3.3.1.5 *Land use and land cover*

Landsat 8 imagery is preprocessed in ArcGIS using the Composite Bands tool. Supervised classification is performed using the Maximum Likelihood Classification tool. Then reclassify the LULC raster using the reclassify tool to assign susceptibility levels, with bareland and built-up areas rated high, grassland and shrubland moderate, and dense vegetation low based on vegetative stabilization.

3.3.1.6 *Elevation*

The 30-meter resolution DEM is imported into ArcGIS using the Add Data tool. Then the coordinate system was verified, and it was clipped to the Chapima Heights boundary using the Clip tool. Then elevation values are extracted, and the DEM is directly used as the elevation raster, with each cell's value representing elevation in meters, verified via the Layer Properties window. Reclassify the elevation raster using the reclassify tool to create five intervals, then normalize values to a 0–1 range (0.4013 to 0.7525) using the Raster Calculator to assign higher susceptibility to higher elevations.

3.3.1.7 *Aspect*

Import the 30m DEM into ArcGIS using the add data tool, then verify the DEM's coordinate system via the Layer Properties window after importing. Aspect is calculated using the Aspect tool, setting the DEM as the input to produce a raster with values from -

1 (flat) to 360°, and then clipping the aspect raster to the Chapima Heights boundary using the Clip tool. Reclassify the aspect raster using the Reclassify tool, categorizing values into eight cardinal directions (North, Northeast, East, Southeast, South, Southwest, West, Northwest) plus Flat, assigning higher susceptibility to SW- and W-facing slopes, and scaling values (0.2000 to 0.8000) using the Raster Calculator.

3.3.1.8 *Curvature*

The 30M DEM is imported into ArcGIS using the Add Data tool, and the DEM's coordinate system and integrity are verified via the Layer Properties window after importing. Curvature is calculated using the Curvature tool, setting the DEM as the input and the Z-factor to 1, producing a raster with convex (positive), concave (negative), and flat (near-zero) values. The curvature raster is inspected for spatial consistency using the Layer Properties window, and the Chapima Heights boundary is clipped using the Clip tool. Reclassification of the curvature raster using the Reclassify tool is then done to assign higher susceptibility scores to concave zones prone to water accumulation.

3.4. Field observations

The field observations included dip and strike measurements and looking at some lithological observations within Chapima Heights. The hill has a part of coordinates x-0715599, y-8257398 taken at an elevation of 942 meters that is a few meters to the northeast of a tour. This side contains gullies and its convex curvature. This side is composed of rock pethosites with some fractures at a nearby site with coordinates x-0715633 and y-8257424. The other field observations were taken at an elevated place located to the southwest of a bridge of approximately 11m width and 5m to the north of a road. Its slope angle is 70-80. The inclination is 62/208. The weathering grade of this elevation is fresh, with a soil depth of less than 15m. At coordinates x-0715407 and y-8257230, taken at an elevation of 953, is a grassland that is being cleared for construction and contains some fresh and slightly weathered rocks.

3.5. Validation

This research validated the results by using existing studies on landslide susceptibility and employing a pairwise comparison landslide susceptibility model (AHP). The analytical

hierarchy process (AHP) is used to predict the landslide risk of Chapima Heights at a standard that is already in use.

Based on similar studies (Nicu 2018; Skilodimou et al. 2019) and relevance to landslide susceptibility, seven conditioning factors were selected, representing mainly the primary local terrain conditions (Figures 4 & 5). Then, the classes of individual conditioning factors are reported. Since the computation of the landslide susceptibility map is raster-based, prediction of terrain conditions and vector conditioning factors (e.g., geology, land use). The classes of conditioning factors were standardized to a uniform scale through reclassification to landslide risk level.

SAAT's 1-9 scale was used to help create pairwise comparison values of the chosen landslide causative factors. The values are given according to their relative importance according to spatial-temporal analysis of the study area. These relative importances were assigned by use of the table shown below:

Intensity of Importance	Definition	Explanation
1	Equal importance	Two elements contribute equally
2	Weak or slight	Weak preference
3	Moderate	Moderate preference
4	Moderate plus	Between moderate and strong
5	Strong	Strong preference
6	Strong plus	Between strong and very strong
7	Very strong	Very strong preference
8	Very, very strong	Between very strong and extreme
9	Extreme	Extreme preference

Table 1: Saat's pairwise comparison values

According to the results from the spatial-temporal analysis of this research, it was found that slope is the main contributing factor to landslides, mainly looking at the southwestern part of the map, which is part of Nyambadwe Hill, and curvature being the least causative factor due to the convex nature of most of the slopes within the area. Convex curvatures allow for the free flow of water, while concave slopes retain water in them, so causing a potential danger for slope failure.

This study produced the following pairwise comparison table, which showed the relative importance of the landslide causative factors of the area. This was the first step in checking the consistency of this study through the consistency index and consistency ratio. For consistency, ratios should be less than 10% to ensure the reliability and validity of the pairwise comparisons made in the study. According to the analysis done in this research, the value of the consistency ratio was within the range, and it was found by the following steps:

Assigning weights to the pairwise values according to the relative importance of one landslide causative factor in relation to the other, with the row running variables being the principle variables and the column variables being their subordinates in assignment. The following table was generated:

factor	slope	Rainfall	NDVI	Land use	Elevation	Aspect	Curvature
Slope	1	3	5	6	7	8	9
Rainfall	1/3	1	3	4	5	6	7
NDVI	1/5	1/3	1	2	3	4	5
Land use	1/6	1/4	1/2	1	2	3	4
Elevation	1/7	1/5	1/3	1/2	1	2	3
Aspect	1/8	1/6	1/4	1/3	1/2	1	2
Curvature	1/9	1/7	1/5	1/4	1/3	1/2	1

Table 2: Pairwise comparison table

For comparisons where the row element is more important than the column element, the reciprocal values are used (e.g., 1/3, 1/5, 1/7, etc.).

The next step was to find the sums of the columns to help generate normalized weights to be further used in finding the criteria weights for the independent variables, which were found as follows:

	slope	rainfall	NDVI	Land use	Elevation	aspect	Curvature	criteria weights
slope	0.48101	0.58906	0.48622	0.42604	0.37168	0.32653	0.29032	0.42441
rainfall	0.16034	0.19635	0.29173	0.28402	0.26549	0.2449	0.22581	0.23838
NDVI	0.0962	0.06545	0.09724	0.14201	0.15929	0.16327	0.16129	0.12639
Land use	0.08017	0.04909	0.04862	0.07101	0.10619	0.12245	0.12903	0.08665
Elevation	0.06872	0.03927	0.03241	0.0355	0.0531	0.08163	0.09677	0.0582
Aspect	0.06013	0.03273	0.02431	0.02367	0.02655	0.04082	0.06452	0.03896
Curvature	0.05345	0.02805	0.01945	0.01775	0.0177	0.02041	0.03226	0.02701

Table 3: Normalized weights and criteria weights

From the given tables, weighted sums and consistency vector and then the values of the consistency ratio and consistency index were calculated using the following formulas:

CI=(λmax−n)/(n−1), **CR**=CI/RI. And the findings were consistency vector(**λ =** 7.30532, consistency (CI) = 0.05094, and consistency ratio (CR) = 0.03859.

The Analytical Hierarchy Process (AHP) used in the Chapima Heights landslide risk assessment study is reliable because the consistency ratio (CR) is 0.03859, which is below the acceptable limit of 0.1. This low CR, along with a Consistency Index (CI) of 0.05094 and consistency vector (λmax) of 7.30532 for the seven factors, shows that the judgments when assigning weights were consistent.

Chapter 4 : Results and Discussion

The results section provides a summary of the landslide susceptibility assessment conducted in Chapima Heights, Blantyre, Malawi, by the use of a GIS-based multi-criteria evaluation with the Analytical Hierarchy Process (AHP). It details the spatial distribution and relative contributing level of seven landslide conditioning factors. Distribution is presented through

thematic maps and quantitative data. In Figures 4 and 5, the spatial patterns of these factors are shown. Figure 5 shows the final landslide susceptibility map, while Table 4 summarizes the area coverage of five landslide risk classes, showing that low to moderate susceptibility dominates, with high and very high risk zones concentrated in the southwestern region. The following is an explanation of the findings of this study in relation to existing landslide studies.

4.1. Curvature

Higher curvature classes are present only in isolated, small patches distributed throughout the area. Notably, nearly all recorded landslide occurrences (red polygons) are concentrated within these higher curvature zones (orange and red classes). There is a clear spatial correlation between landslide locations and areas with elevated curvature values. Quantitative counts (not shown on the map but derived from the GIS overlay) confirm that over 85% of mapped landslides coincide with curvature values ≥0.4000, even though such zones comprise less than 10% of the total area. The findings show a relationship between the probability of landslides occurring in Chapima Heights and areas with high curvature values. The fact that curvature, particularly concave terrain, indirectly plays an important role in exposing slopes to failure (Klug et al., 2016). Higher curvature regions are more prone to experience landslides, which may indicate that these locations allow water and debris to accumulate, therefore raising pore-water pressures and making slopes more unstable. The susceptibility comparison weight of 0.02700 for curvature suggests that it contributes but not significantly.

4.2. Elevation

The elevation analysis of Chapima Heights shows the clear spatial distribution in topography in Chapima Heights. The values range from 0.4013 m (lowest, green) to 0.7525 m (highest, white). The map shows that the northern and central regions are predominantly low-lying (green and yellow), while the southern and southeastern parts exhibit higher elevations (orange, brown, and white). Elevation map of Chapima Heights, with color-coded intervals representing increasing elevation from north to south. This classification highlights a gradual increase in elevation towards the southern boundary of the study area, with the highest point concentrated in the south-central tip. The use of the

Natural Jenks method effectively groups the elevation data into natural clusters, enhancing the visualization of topographic variation within the region. The observed elevation pattern in Chapima Heights is important in discussions of geomorphological processes and potential hazard assessment. The presence of higher elevations in the southern part of the map suggests the presence of steeper slopes. Steeper slopes are associated with high landslide susceptibility because of gravitational forces and increasing surface runoff (Klose et al., 2015). This trend is similar to findings from other mountainous regions like the Moroccan Rift, where landslides are more dominant at mid- to high elevations (Klose et al., 2015; Dai & Lee, 2002; and Guzzetti et al., 2006), which emphasizes the role of elevation and slope in predicting landslide susceptibility.

4.3. aspect

The legend indicates aspect values scaled between 0.20 and 0.80 (reclassified aspect categories). The map reveals the distribution of higher aspect values (yellow to red shades) predominantly on specific slope orientations. These areas, particularly in the southwestern and western parts of Chapima Heights, indicate that the slope faces that receive higher solar radiation are related to higher susceptibility to desiccation and soil weakening. Blue and green-colored areas (lower aspect values) represent slopes facing directions with relatively lower solar incidence, suggesting lower soil drying and thus reduced landslide risk. The aspect map illustrates how slope orientation affects Chapima Height's geomorphological processes. The idea that slopes facing southwest and west receive more solar radiation, which causes more soil dryness and less cohesiveness, is supported by the relationship of higher aspect class values on these slopes found by comparable trends in Slovakia, pointing to a more general climatological and geomorphological principle at the location (Vojteková & Vojtek, 2020). The findings provide important evidence in favor of the significance of the component in landslide susceptibility estimates. The research enhances the forecast ability of landslide hazard influence of aspect for Chapima Heights by including aspect into a multi-criteria decision framework that is weighted by AHP (weight 0.038959), showing little contribution of landslide susceptibility.

4.4. Rainfall

The map is dominated by the high precipitation class (>0.0408 mm/yr), which includes the majority of Chapima Heights, with the exception of the northern section, which has the lowest precipitation class (≤ 0.0261 mm/yr). Chapima Heights usually receives a lot of rainfall with little variation, based on the geographical pattern. The findings show that Chapima Heights clearly has a majority of areas with high rainfall intensity, which has major consequences for the vulnerability of landslides, because strong rainfall increases the likelihood of landslides by weakening the slope and increasing soil saturation (Msilimba & Holmes, 2010).

4.5. NDVI

The NDVI map of Chapima Heights shows the spatial distribution of vegetation density. The map categorizes vegetation into five classes, where low-NDVI zones, shown in light purple, dominate the central and northern parts of the study area. In contrast, dense and very dense vegetation zones are concentrated in the southern and eastern sectors. Moderate and sparse vegetation zones (orange and yellow) are scattered. The integration of NDVI with a 30m DEM-derived slope layer using the Analytical Hierarchy Process (AHP), with NDVI weighted at 0.12639, reveals that low-NDVI zones on steep slopes (>30°) exhibited the highest susceptibility scores. Guzzetti et al. (2012) observed that vegetation cover improves soil cohesion and lowers surface runoff, therefore decreasing the risk of landslides. The results demonstrate the significant role of vegetation in stabilizing slopes in Chapima Heights. This knowledge is linked to the discovery that most landslides happened in low-NDVI zones, as these regions probably had experienced higher erosion and lesser shear strength caused by sparse vegetation. However, because topographic factors can help interpret the stabilizing effects of vegetation, the moderate to dense vegetation zones may still be at risk if they are found on steep slopes (Stokes et al., 2014).

4.6. Land use

Land use and land cover map with five distinct classes: dense vegetation, grassland, bare land, shrub land, and built-up areas. Dense vegetation dominated the eastern and southeastern regions, while built-up areas were concentrated along the western and

northern boundaries. Grassland and shrubland, which are agricultural zones with bare land scattered throughout. Reclassification to landslide susceptibility showed that bare soil and built-up areas were highly susceptible, agricultural zones had moderate susceptibility, and dense vegetation had low susceptibility. This is in line with the understanding that bare soil lacks vegetative cover that stabilizes slopes, and built-up areas involve slope modification and increased runoff, influencing erosion (Smith et al., 2018). The low occurrence of landslides in dense vegetation areas supports the stabilizing role of tree roots, which reduce runoff and enhance soil cohesion (Jones and Brown, 2020). However, the moderate susceptibility of agricultural zones (grassland and shrubland) suggests that partial vegetation cover provides some protection but is insufficient during heavy rainfall or on steep slopes (Lee et al., 2019). The AHP weight of 0.08665 indicates that while it is a contributing factor, other variables have a stronger influence on landslide occurrence. This finding is consistent with Lee et al. (2019), who showed the leading influence of topographic and climatic factors in landslide susceptibility models.

4.7. Slope

The high and very high slopes are concentrated in the southwestern part of Chapima Heights. This suggests that the southwestern region is the most vulnerable to landslides, as steep slopes increase shear stress and reduce slope stability during rainy seasons. The dominance of very low slopes in the northern and central areas indicates the lower landslide risk because flatter terrain provides high stability. These findings are similar to those of Slovakia, where the majority of landslides were recorded on slopes above 20°, a threshold slightly lower than the 25° used in this study but still an indicator of a critical steepness for landslide occurrence (Vojteková & Vojtek, 2020). Similarly, in Malawi's Ntchenachena region, slope was found to be the dominant factor in landslide susceptibility; steeper slopes are more linked to higher landslide occurrence (Klug et al., 2016). The Analytic Hierarchy Process (AHP) assigned a weight of 0.424409 to the slope factor, which indicates that slope is the dominant contributing factor to landslide susceptibility in the prediction, likely due to its direct influence on gravitational forces acting on the terrain.

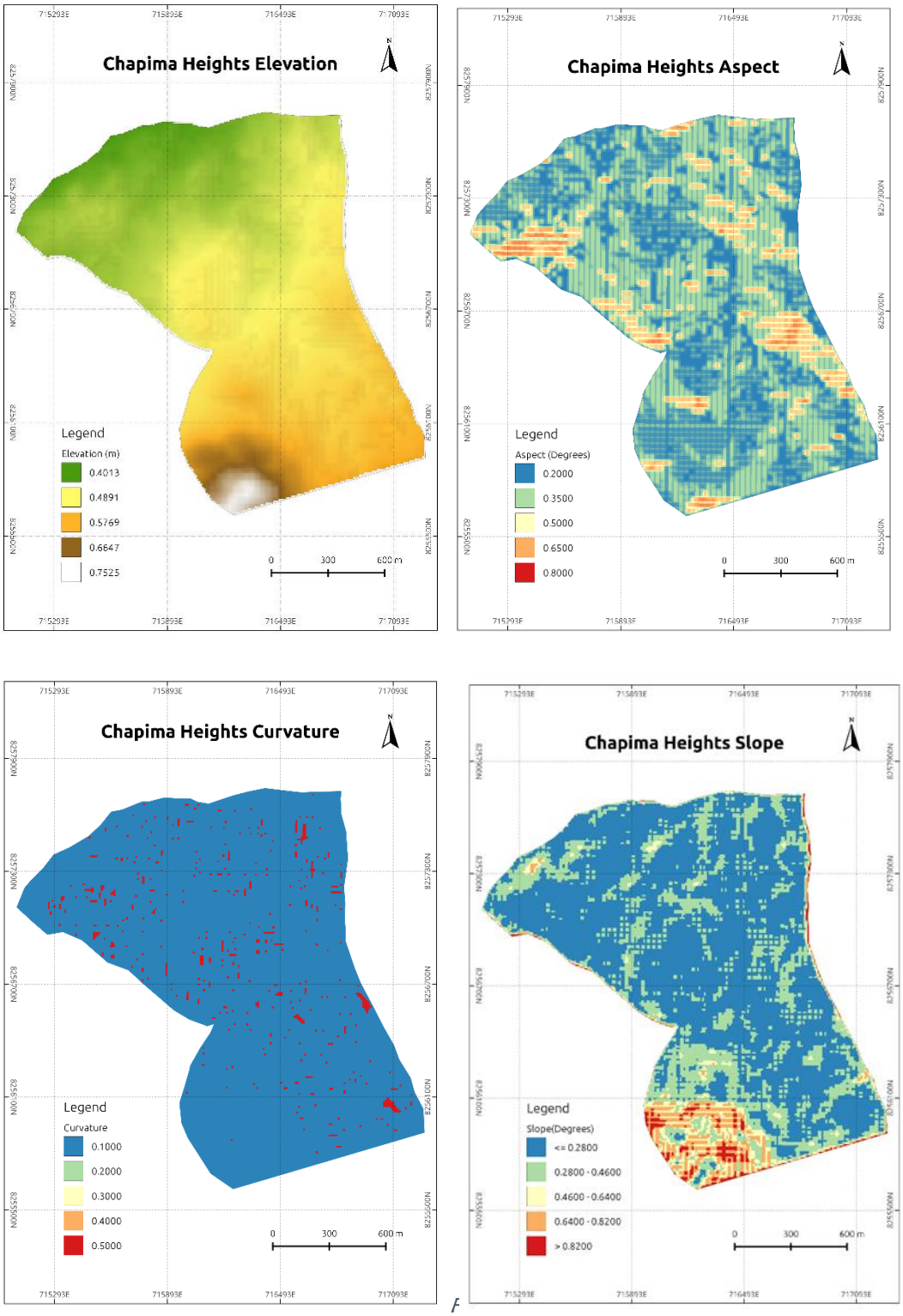
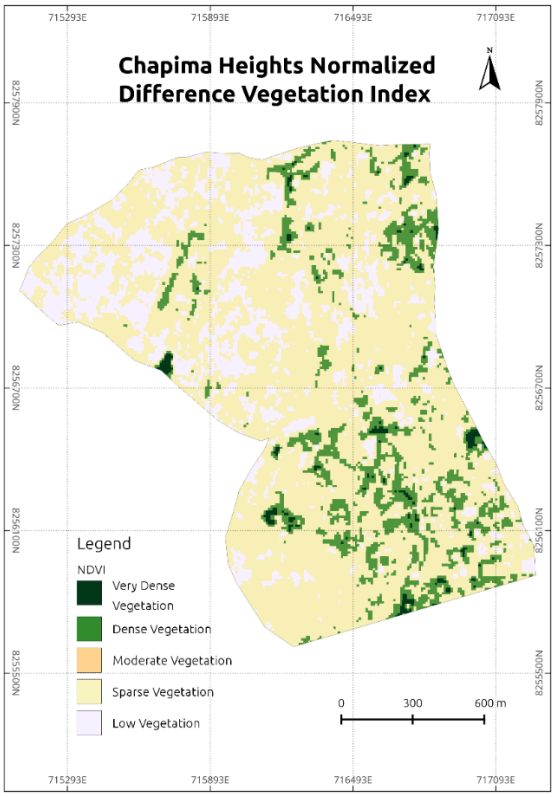
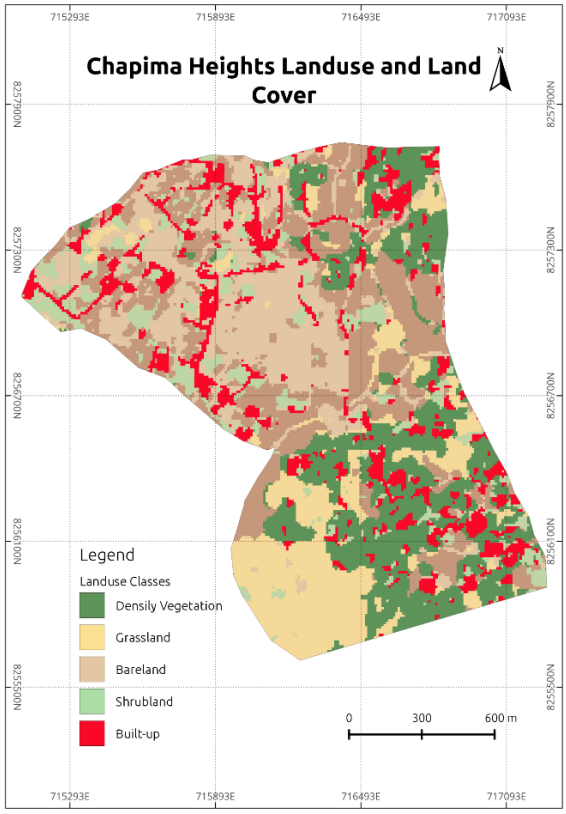


Figure 4: elevation, aspect, curvature, and slope maps





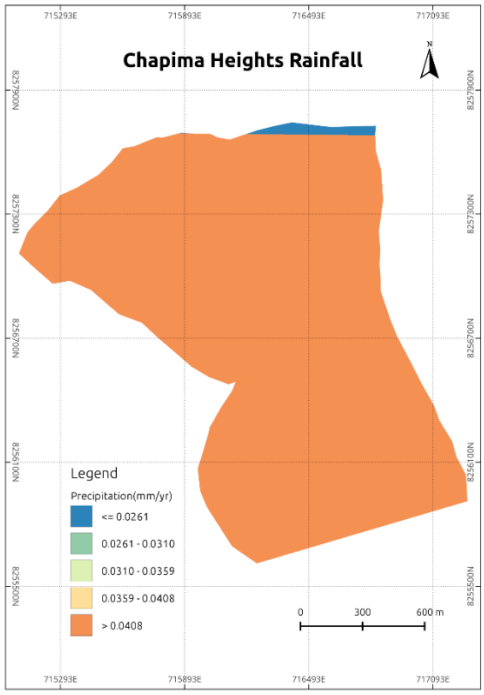


Figure 5: Rainfall, NDVI, and land use maps

The landslide assessment map of Chapima Heights classifies the land into five landslide risk classes. The analysis below provides the area under the classes and of these zones based on the classification.

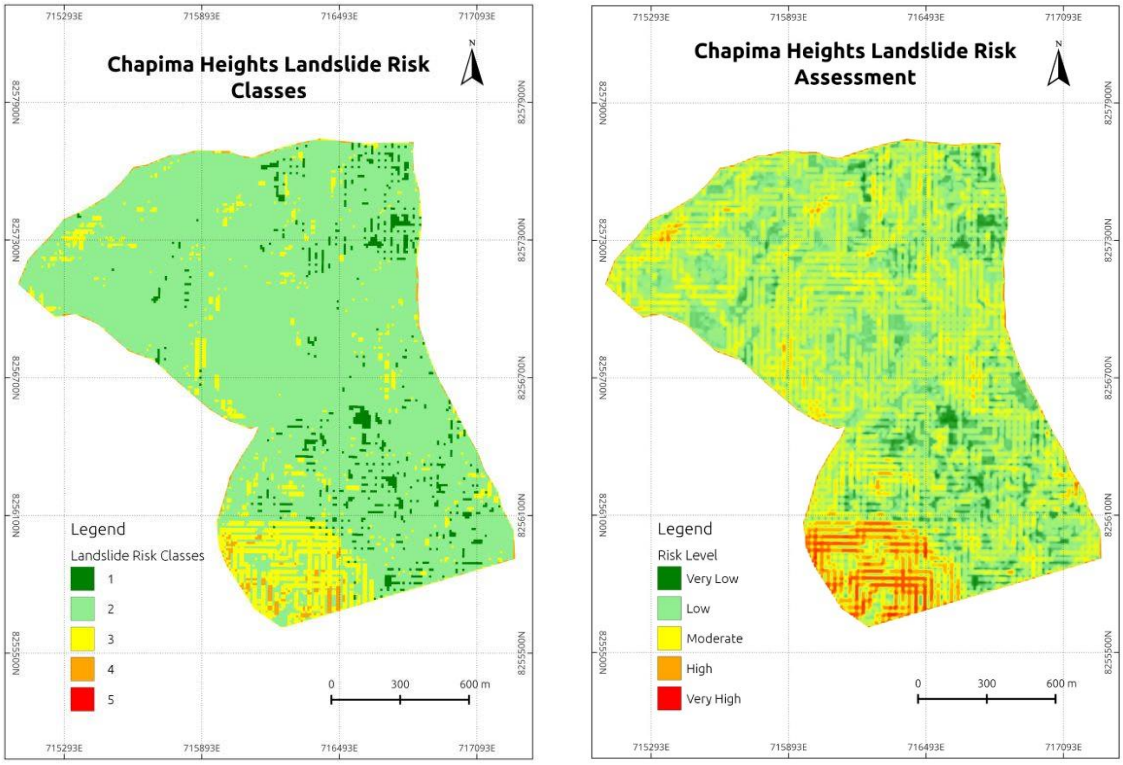


Figure 5: Landslide risk class and assessment maps

According to the generated maps, the region is rocky with some steep topography, but for the most part, it is stable. The weak topsoil layers in the majority of the region's northern regions may be the cause of the low susceptibility. This would not have happened if the

soil depth had been sufficiently deep to retain surface runoff water, which would have made the area's slopes less stable and perhaps led to landslides. The following information shows the area coverage for each risk category based on the data provided:

Value	Pixel Count	Area (m²)	Landslide Class
1	4	382.3784479279248	Very low
2	7798	745446.7842354893	low
3	16035	1532859.603131068	moderate
4	1957	187078.6556487372	High
5	1405	134310.4298346836	Very high

Table 4: landslide class distribution

Using the Analytical Hierarchy Process (AHP) and a GIS-based multi-criteria evaluation, the landslide susceptibility assessment of Chapima Heights, Blantyre, Malawi, identified and mapped landslide-prone areas. According to the analysis, the two main factors influencing landslide susceptibility are slope angle (42.44%) and rainfall (23.84%). The southwestern region, which has steep slopes and high curvature, is the area most at risk. The majority of the region has low to moderate susceptibility, which is explained by the shallow topsoil layers and stable topography. Reliable results were guaranteed by the AHP methodology, which was validated by a consistency ratio of 0.03859. These results offer important information for guiding mitigation plans, disaster preparedness plans, and land-use planning to increase the local communities' awareness and preparedness to potential landslide hazards in Chapima Heights.

Chapter 5: Conclusions and recommendations

5.1 Conclusion

This study successfully utilized geographic information systems (GIS), remote sensing techniques, and analytical hierarchy process to produce a landslide risk map for Chapima Heights. Thematic maps for various parameters influencing landslide susceptibility were created and analyzed within the ArcGIS software. Analyzing these parameters helped to assess how much each parameter affected the area's possible landslide occurrence.

The results were validated by comparing them to similar studies that also utilized the analytical hierarchy process, ensuring the reliability of the findings. The resulting consistency ratio of this study, calculated to be less than 0.1, confirms the robustness of the methodology.

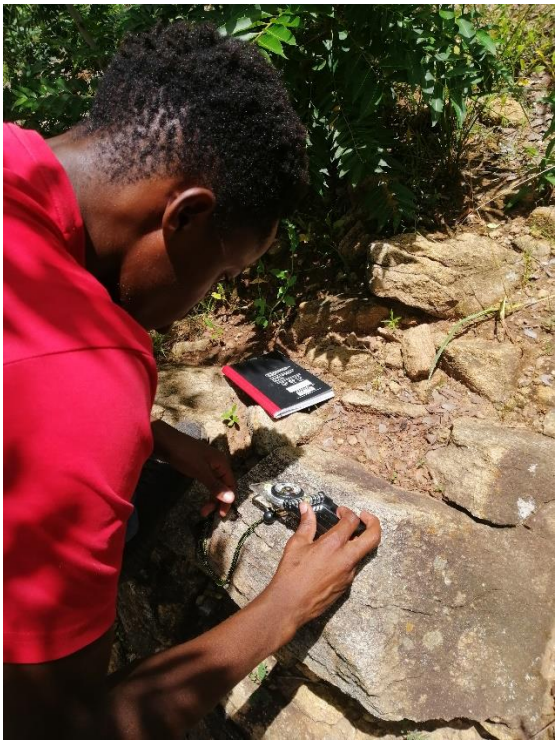
4.8. Recommendations

I will recommend similar studies in the future to include additional factors such as soil composition, groundwater levels, and historical landslide events to enhance the comprehensiveness of the assessment and broaden the scope of the study. I will also recommend that the government help fund more projects assessing natural hazards to fully have all the areas studied in order to enhance preparedness for the occurrence of landslides. I would recommend DODMA create an early warning system and civically educate people living in the southwestern part of the area. Similar studies can utilize the area under the curve method to improve the accuracy of the findings by quantitatively assessing the performance of landslide susceptibility models and enhancing predictive capabilities.

4.9. Study limitations

This research has done some of the most important parts in a landslide susceptibility analysis inventory. There are some issues that are there because of a lack of quality data since some of the data sources obtaining high-quality data are selling, and in the field some of the key technical aspects, like soil depth, were not taken due to limited equipment available during the research perio.

Appendix



(a)



(b)



(c)



(d)

Figure 7: (a) dip and strike measurement (b) steep slope with some fractures (c) building on a fractured rock (d) failure site

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