DESIGNING A TERRITORIAL EARLY WARNING SYSTEM FOR RAINFALL-INDUCED LANDSLIDES: THE CASE OF BLANTYRE CITY, MALAWI.

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ABSTRACT

Landslides triggered by heavy rainfall pose a significant threat to Blantyre City. Climate change is expected to further increase frequency and intensity of these events. The overall goal of this study was to design a Territorial Early Warning System that provides sufficient lead time. For this goal, the study involved comprehensive review of relevant literature (including published and unpublished sources) to identify relevant components that constitute the EWS. Additionally, a susceptibility analysis using the Frequency Ratio (FR) Model was conducted with historical landslide data (from 2022 to 20223) and Causative Factors (including 2023 annual rainfall as trigger) to create landslide susceptibility map for Blantyre City. The susceptibility map revealed areas surrounding hills and mountains such as Soche, Chigumula, Bangwe, Bangwe Mthandizi, Mpingwe, Nyambadwe, Michiru and Ndirande to be highly susceptible to rainfall-induced landslides. The proposed EWS consists of a network of sensors; rain gauges for monitoring rainfall, extensometers for measuring slope movement, and piezometers for monitoring pore pressure. These sensors will collect and transmit data (rainfall amounts, pore pressure, and slope movement) to an administrative analysis and forecasting center. The center will analyze the data and trigger phased warnings (gradually escalating warnings based on the severity of the threat) to all key stakeholders through various communication channels, especially media outlets. It has been emphasized that the proposed system should be managed by relevant government institutions in collaboration with other key departments and stakeholders due to the multidisciplinary nature of Rainfall-Induced landslides forecasts.

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ACRONYMS/ABBREVIATIONS

CSV:	Comma-Separated Values
DAU:	Data Acquisition Unit
DCCMSs:	Department of Climate Change and Meteorological Services
DEM:	Digital Elevation Model
DRMO:	Disaster Risk Management Officer
DSMW:	Digital Soil Map of the World
EWS:	Early Warning System
FAO:	Food and Agriculture Organization
FR:	Frequency Ratio
GIS:	Geographical Information System
GSD:	Geological Survey Department
LSI:	Landslide Susceptibility Index
MQTT:	Message Queuing Telemetry Transport
SRTM:	Shuttle Radar Topography Mission
Te-EWS:	Territorial Early Warning System
UNISDR:	United Nation International strategy for Disaster Reduction
USGS:	United States Geological Survey

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1.0. CHAPTER ONE: GENERAL INTRODUCTION

1.1. Background of the Study

Rainfall-induced landslides are geological events where the stability of a slope is compromised due to heavy or prolonged rainfall, leading to the movement of rock, earth, and debris down the slope under the force of gravity (USGS, 2018). When the force of gravity acting on a slope exceeds the strength of the material forming the slope, then the slope will fail and movement occurs. Debris flows, Mudslides, Rock flows, lateral spreading, earthflows, Transitional slides and Rotational slides are the main types of rain-induced landslides. Both Rainfall and earthquake triggered landslides are caused by complex interaction of conditioning factors such as geology, Lithology, slope angle, land use, distance from road/stream and aspect (Peng et al., 2023).

Rainfall-induced landslides constitute a significant threat to communities across the globe (Chikalamo et al., 2020). The increasing frequency and intensity of rainfall due to climate change Coupled with land use changes, population growth and uncontrolled urbanization of hazardous areas have amplified the risk of rainfall-induced landslides, resulting in loss of life, destruction of property, infrastructure destruction, economic damage, and landscape and ecosystems disruption (Chikalamo et al., 2020). Current estimates of landslide impacts suggest that they cause thousands of fatalities and billions of dollars of economic damage annually (Emberson et al., 2020). From 2004 to 2016, there were 4,862 rainfall-induced fatal landslides worldwide, resulting in a total of 55,997 lives lost (Froude & Petley, 2018).

Malawi is one of the less developed countries in Southern Africa which is prone to landslides due to its topography, climate, and geological characteristics. The 1946 Zomba mountain landslides, the 1991 Phalombe landslides, the 1997 Banga landslide, the 2003 Rumphi and Ntcheu landslides are some of the rainfall-induced landslides that hit Malawi in history (Msilimba, 2007). The Phalombe landslides, which are considered the worst fatal landslides, left 500 people dead, 50,000 homeless and 30,000 hectares of crops washed away. Recently, this year (mid-march 2023), Cyclone Freddy induced mudslides which

also claimed a lot of lives and displaced many people in some parts of Blantyre, Phalombe, Mulanje, and Chiladzulu districts (Government of Malawi, 2023).

To reduce these risks and enhance the safety of vulnerable populations, designing and development of Early Warning Systems for rainfall-induced landslides has gained importance (UNISDR, 2006, cited in Pecoraro et al., 2019). For example, an Early Warning System in Sundrawati Village (central Nepal Himalaya) saved 495 people from 117 households in August 2018 (P. S. Thapa & Adhikari, 2019). This study is prompted to provide a basis for the development and implementation of an effective Territorial Early Warning System to protect the people of Blantyre City from potential risks induced by future landslides. Basically, the rainfall patterns, topography, geology, and soil characteristics of most areas in Blantyre city, coupled with high population density and dangerous construction increase the susceptibility of this city to landslides. Blantyre City was one of the worst-affected areas in Malawi by mudslides triggered by Tropical Cyclone Freddy.

In this study, data on historical Landslides, rainfall distribution variations and landslides conditioning factors were collected and analyzed in order to determine specific areas for the installation of system's components. The system involves monitoring sensors like Automatic rain gauge system, slope moisture sensors, and ground displacement sensors to detect and collect data about the changes in rainfall intensity, soil moisture content, and ground/slope movements respectively. The changes will be automatically sent to the administrative analysis and forecasting center (government institution or department) for analysis purposes. Upon thorough process of consultation, triangulation and expert judgment and when the predetermined thresholds are reached/exceeded, phased alerts would be issued and disseminated to the local Communities, emergency responders, and rail and road network operators, and key other stakeholders through Media (Social Media, TV News Stations, Radio Stations and Telecoms Firms). The System incorporates community engagement through public awareness campaigns, preparedness and education programs to ensure effective response plans and sense of ownership, reducing potential cases of instrument vandalism.

1.2. Problem Statement

Tropical Cyclone Freddy is one of the worst cyclones to have hit Malawi hard recently. The torrential rains induced by the cyclone, triggered one of the fatal mudslides in Blantyre city where areas like Chilobwe, Chigumula, Bangwe and Ndirande townships were significantly affected. For example, as of 14th March 2023, more than 30 people were found dead and dozens were missing in the Chilobwe area (CNN, 2023). Over 65% of Blantyre city's population live in informal settlements (Kuria, 2011). Population density is increasing at an alarming rate due rapid urbanization, yet still there are no early warning systems which can specifically address landslides on various slopes.

This leads to haphazard constructions on unstable terrain, which exacerbate landslide risk due to the lack of proper infrastructure and land-use planning. Additionally, the absence of a Landslides Early Warning System means residents are not alerted to potential dangers, increasing their vulnerability to landslides. Despite having some past landslide-related studies around this City, none of them clearly indicates where exactly early warning instruments such as ground motion sensors, Slope moisture sensors and automatic rain gauge system could be installed to ensure system's effectiveness. This study has therefore designed a theoretical Territorial Early Warning System for Rainfall-Induced Landslides in this area based on the variations of rainfall distribution, conditioning factors and previous rainfall-induced landslides.

1.3. Research Broad Objective

The main aim of this study was to design a Territorial Early Warning System for rainfall-induced landslides with enough lead time in Blantyre City.

1.4. Specific Objectives

The broad objective of this research was achieved by the following specific objectives:

i. To map historical landslides (from 2022 to 2023) across Blantyre City
ii. To map rainfall zones across Blantyre City
iii. To analyze conditioning factors for Rainfall-Induced Landslides
iv. To conduct susceptibility mapping using Frequency Ratio model

v. To develop the conceptual framework of the Territorial Early Warning System

1.5. Research Questions

i What is the spatial and temporal distribution of the previous landslides across Blantyre City?

ii How does rainfall distribution vary across Blantyre City?

iii What are the significant conditioning factors for the occurrence of these landslides?

iv Which locations can the system's components be installed?

v What is the composition of the system?

1.6. Significance of the study

According to DTE Staff (2019), for every $1 invested in Early Warning System, there is a return of $6.0 in benefits. And with the economic status of Malawi, relocating people from landslides-prone areas or embracing structural measures to reduce the risk of landslides seem to be unviable. In line with the Hyogo Framework of Action which aims at Building the resilience of nations and communities to disasters, this study exposes the urgent need to invest in EWS. Additionally, landslide susceptibility map and the system's conceptual framework for the study area will inform development/implementation of effective Landslides Early Warning System by government and/or any other key development actors. This would help to reduce the number of casualties from the possible upcoming landslides through provision of timely alerts to the community and authorities allowing for swift evacuation and response efforts. Not only that but it would also prompt other researchers and give them a basis for further research on different topics related to Territorial Early Warning System for rainfall-induced landslides.

2.0. CHAPTER TWO: LITERATURE REVIEW

2.1. Rainfall-induced Landslides

Apart from Earthquakes, rainfall is also one of the major primary triggers of landslides(Zhang et al., 2019). As predicted by Gariano and Guzzetti (2016), global warming resulting from human activities and further expansion of land use in mountainous areas has increased the frequency and intensity of severe rainfall events hence resulting in rapid-moving landslides. Rainfall-induced landslides has been defined as geological events characterized by the downslope movement of soil, rock or debris in environments that provide a prolonged and intense rainfall, steep slopes, sparse vegetation and an abundant source of incoherent fine-grained soils, including colluvium and residual soils (Tohari, 2018).

Rainfall-induced landslides happen when a protracted period of rainfall saturates the soil or rock mass, disrupting the equilibrium between the forces keeping the slope materials in place and the gravitational force pressing on them (SVS, 2015). This leads to reduction of soil strength and consequently slope instability. Two basic mechanisms, shear failure caused by pore water pressure buildup and erosion by surface water runoff when flow velocity exceeds a critical value, can both result in triggering rainfall-induced landslides (Nadim & Sandersen, 2009). Hence, causative factors for predicting landslide susceptibility must be carefully assessed on the basis of relevance, availability and scale for L-EWS designing purposes. Mudslides which affected some parts of Blantyre, Phalombe, Chiladzulu and Mulanje are typical examples of rainfall-induced landslides. (Government of Malawi, 2023)

As with many natural disasters, the effects of rainfall-induced landslides are disproportionately severe in developing countries. For example, between 1950 and 2011, developing countries experienced an average of 23 fatalities per debris event, while economically advanced nations had an average of 6 deaths per such occurrence (West, 2018). This difference may reflect a number of factors, including the resilience of basic infrastructure and emergency services; the availability of health care to treat people who are injured or left homeless; and patterns of development that determine where people live. Another significant contrast is that, in

numerous instances, developed nations possess early detection mechanisms capable of notifying individuals about impending dangers.

2.2. Territorial Early Warning System (Te-EWS)

Given the alarming rate of negative impacts from rainfall-induced landslides on human life, property, and infrastructure, Early Warning Systems have been increasingly adopted worldwide as compared to relocation and other engineering measures, aiming to reduce the risk (Pecoraro et al., 2019). This has been the case because Early warning systems have relatively lower economic costs and environmental impacts coupled with the ongoing creation of new landslide monitoring technology and the expansion of trustworthy databases that can be used to calibrate warning model databases have also enhanced implementation of Early Warning systems (Krøgli et al., 2017). Territorial (geographical/regional) Early Warning Systems are systems that are designed to address or predict behavior of several landslides on various slopes or wide areas; at municipal, regional and national scale (Piciullo et al., 2020).

These Systems are usually managed by Government Institutions in collaboration with geological, hydro-meteorological, and disaster risk management departments (Krøgli et al., 2017). The majority of early warning systems for landslides caused by rainfall are, at their most basic, predicated on the notion that there is a correlation between the environmental factors (geology, soil type, land use/cover, slope angle, and distance to streams), the trigger variable (rainfall amount or duration), and the occurrence of landslides (Thiebes et al., 2017). Therefore, rainfall, slope moisture, and ground motion data obtained from gauge networks, ground motion sensors, and slope moisture sensors, respectively, can be used to provide landslide forecasts. The majority of TEWSs are always in operation and deliver forecast data at predetermined times, usually on a daily basis. Additionally, most warnings are manually triggered, informed by a process of consultation, triangulation and expert judgment (SHEAR Knowledge Brokers Team, 2021).

The Te-EWS reduces the number of casualties through provision of timely information before the catastrophic landslides event which enables exposed communities, emergency responders,

rail and road network operators, and other stakeholders to take precautionary actions. A real world example of Te-EWS is a National Landslides Early Warning System in Norway which is run by the Norwegian Water Resources and Directorate. The system provided good forecasting of landslides that took place between March and July (2012) ad May (2013) assisting the road and rail ways authorities as well as local authorities and policy makers to take precautionary measures before the events (Krøgli et al., 2017). In addition to that, the Emilia-Romagna region in Italy has a EWS that integrates rain gauges, Extensometers and inclinometers (Lagomarsino et al., 2014). It is managed by the Civil protection Agency of the Emilia Romagna Region. This system successfully issued warnings before landslides triggered by heavy rainfall in November, 2014). The warning helped to evacuate residents and likely prevented casualties.

According to DiBiagio and Kjekstad (2007), an efficient EWS should comprise the following activities; (I) monitoring, including data acquisition, transmission and maintenance of the instruments; (ii)analysis and forecasting, which can be done by using thresholds, expert judgment, forecasting methods and so on; (ii) warning, i.e. the dissemination of understandable messages alerting for the impending threat; (iv) response, concerning if people are able to understand and how they react to the warning. In addition to that, the system encompasses more than just a collection of monitoring systems or a failure forecast; it also takes into account things like risk scenario analysis, emergency preparedness strategies, societal considerations, public awareness, etc. Each of these parts is essential; if one fails, the entire chain would break, rendering the system unusable (Intrieri et al., 2012). For instance, poor monitoring or forecasting can result in a missed incident or, conversely, a false alert and the ensuing decline in system confidence. However, a poorly thought-out evacuation might result in destruction and financial losses (Intrieri et al., 2012)

2.3. Susceptibility Analysis

Basically, monitoring sensors and other components should be installed in right areas to enhance accurate forecasting and warnings, and effective response plans. In line with this, identifying and prioritizing suitable locations (areas at risk of landslides) for the installation of the components would largely depend on susceptibility mapping which include hazards

characterization and modeling (Aleotti & Chowdhury, 1999). The most obvious approach to every study of landslide susceptibility is to compile a landslide inventory and analyze the relationship with possible causative factors to predict landslides prone areas which inform designing of EWS (Long & De Smedt, 2019).

2.3.1. Frequency Ratio Model

There are several statistical techniques which have been proposed for assessing landslide susceptibility. Particularly, in Bivariate statistical analysis, the importance of each causative factor is determined on the basis of the observed landslide density within each class of a factor map, after which all factors are combined (overlaid) by weighting procedure to obtain susceptibility map. This map expresses the relative likelihood for the landslide occurrence within the study area. There are several ways in which such analysis can be performed. Frequency Ratio, a Statistical Index Method is one of the most used techniques. This method is simple, easy to use and less time consuming, and it can be performed rather easily with most GIS software packages (Pradhan, 2010).

The FR is the ratio of the probability of an occurrence to the probability of a non-occurrence for given attributes (Bonham-Carter 1994). This approach is based on the observed relationships between distribution of landslides and each landslide-related factor, revealing the correlation between landslide locations and the causative factors in the study area. The FR is calculated using the following formula;

$$\mathbf{FR} = \frac{p(landslide\ events)}{P(Non{-}landslide\ events)}$$

The larger the ratio is, the stronger the relationship between landslide occurrence and given factor's attribute. The Landslide susceptibility map is made using Landslide Susceptibility Index (LSI) values (Pradhan, 2010). To calculate the LSI, each factor's class (range/interval) frequency ratio values are summed using equation shown below;

$$\mathbf{LSI} = Fr_1 + FR_2 + \ldots\ldots + FR_n$$

The landslide susceptibility index value represents the relative susceptibility to the landslide occurrence. So the greater the value, the higher the susceptibility to landslide occurrence and the lower the value, the lower the susceptibility to landslide occurrence (Pradhan, 2010).

3.0. CHAPTER THREE: METHODOLOGY

3.1. Research Design

This study used quantitative research design. Mainly, it focused on collecting and analyzing numerical data to draw conclusions and make predictions. In particular, Correlational (Non-experimental) quantitative design was applied whereby data on various factors, such as rainfall, slope angle, land use/Land cover, geology, Soil type, distance to rivers, and historical landslides, were collected with the aim of assessing the relationships among them to identify patterns which helped to predict locations where rainfall-induced landslides are likely to occur. This informs designing of the system through identification of areas where the instruments can be installed to ensure correct detection and forecasting. There was no manipulation of the variables during analysis.

3.2. Study Area

The study was conducted in Blantyre City (in Blantyre district), southern region of Malawi. This city was established by the Scottish missionaries in the 1870s and declared a planning area in 1 897 (Mawenda et al., 2020). Its rugged terrain characterized by multiple hills and river systems makes it vulnerable to landslides. It has varied topography ranging from an elevation of about 780 to 1,599 meters above sea level and it lies within the latitude 15◦47010" S and longitude 35◦00020.10" E, as shown in Figure 1. The main mountains include, Ndirande, Soche, Bangwe and Michiru (Mawenda et al., 2020). And the main livers include Mudi, Likhubula, Limbe, Chisombezi and Lucheza.

Blantyre city currently hosts nearly 5% of Malawi's national population and it boasts the highest population density in the country. It has 23 wards covering an area of 240.2 km2 with 800,264 people and 3,332 people/km^2 as its total population and population density respectively (National Statistics Office, 2021). The literacy rate for Blantyre city is 90%. Generally, the rainy season is from November to April, with continuing light cold showers locally known as chiperoni from the end of May to July. The average annual rainfall is about 1,127 mm, of which about 80% falls within 3.5 months between November and March

(DCCMSs, 2022). Rapid and unplanned urban growth has led to adverse environmental and social consequences.

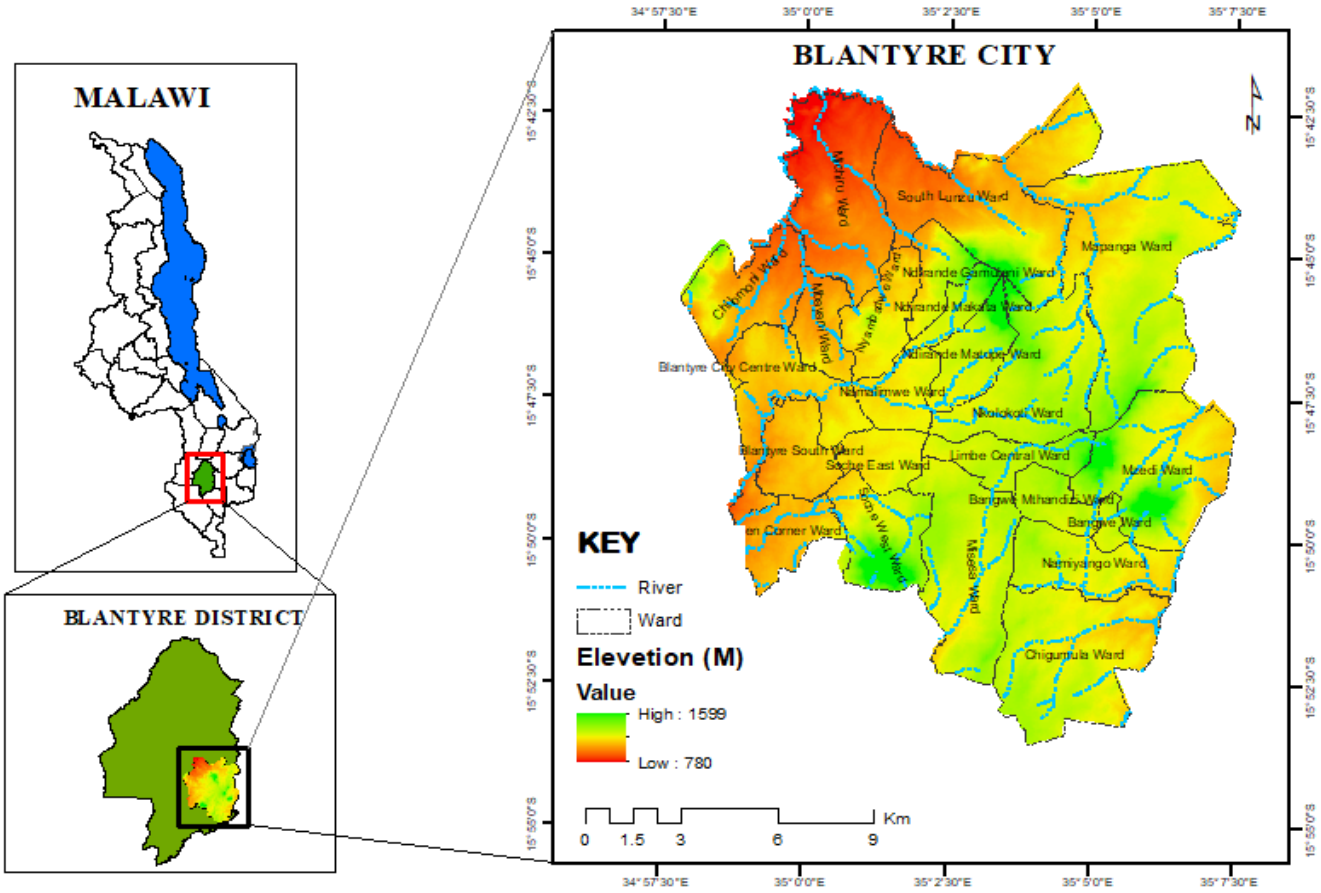


Figure 1. Map of the Study Area

3.3. Data Preparation and Sources

This study did not involve direct collection of original data like through structured questionnaires and interview schedules. It has only utilized data from secondary sources.

3.3.1. Historical Landslides Data

Previous landslides data is crucial for the inventory map which is one of the significant factors in susceptibility analysis (D. Thapa & Bhandari, 2019). Landslide polygons were generated

through visual interpretation and digitizing the landslides over satellite images available in google earth images captured on 22/07/ 2022 and 05/03/2023. A total of 79 landslides were identified and digitized by evaluating the aerial photos in 1:10 000 scale. It was observed that much of the landslides in the study are concentrated along Ndirande hill as shown in Figure 2., (Landslide Inventory map). Most of the landslides are mudflows, shallow landslides and rock falls.

To validate the landslide locations, the study engaged a Disaster Risk Management Officer (DRMO) from Blantyre City Council, who provided historical landslides reports for the area. Field verification was also conducted to check on randomly selected landslide polygons in the study area. Randomly selected Polygons on accessible/reachable slopes in Soche (3 ways area), Bangwe and Machinjiri were visited and coordinates were recorded. This visit helped to identify other landslides that were left un-digitized on google earth pro. Not only that, but the visit also helped to recognize some mining trenches and other features that were considered as landslide features during the digitization process. Some of the images that were taken during field visit in Soche (3 ways area) have been attached in the appendix.

3.3.1.1. Landslide Inventory Preparation

The most basic result of direct landslide mapping that displays observable landslides is a landslide inventory. Because an inventory map is necessary for an extensive study, it is a crucial component in the Frequency Ratio modeling used to analyze landslide susceptibility (Park et al., 2012). Selected landslides provide the most representative classes for thematic data in GIS analysis and help assess the area's total landslide scenario.

The digitized landslide polygons (79 landslide events) were imported into ArcMap for the preparation of the inventory map. These landslide polygons were randomly divided into 55 (70%) for training and 24 (30%) for validating the landslide susceptibility map. The landslide polygons were rasterized for FR calculation purposes.

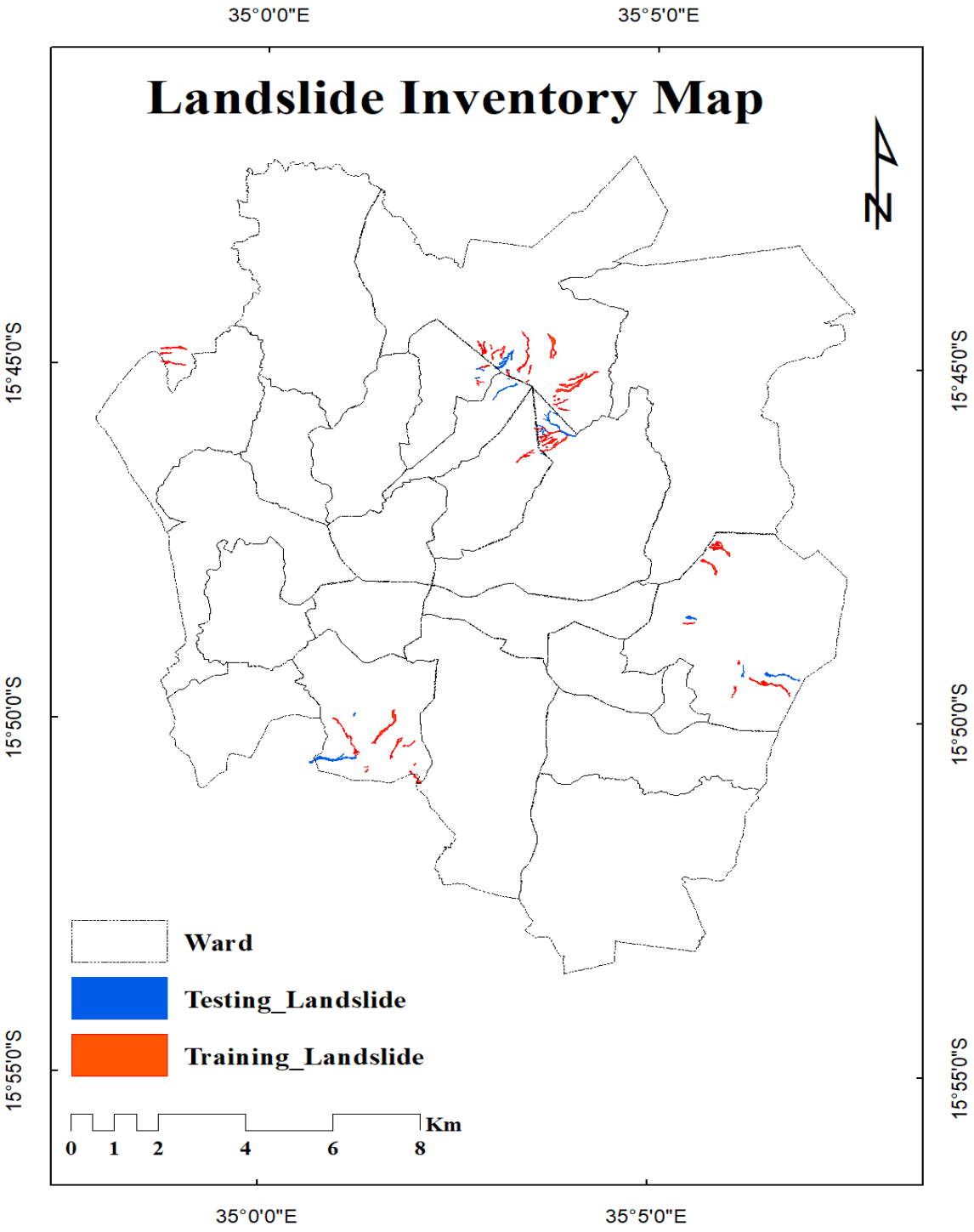


Figure 2. Landslide Inventory of Study

3.3.2. 2023- Annual Rainfall data (As Triggering Factor)

Precipitation data serves as one of the important inputs for landslide susceptibility modeling and prediction. In this study, annual precipitation was selected as a rainfall causative factor for the analysis. This provides a generalized understanding of the areas' annual rainfall which can be used to identify locations with consistently high precipitation and potential landslides throughout the year (Long & De Smedt, 2019). 2023-monthly precipitation recorded from three local stations (Mpemba, chichiri and Ndirande) was collected from the Department of Climate Change and Meteorological Services (DCCMSs). Using excel, the annual rainfall was calculated by summing all the monthly rainfall amounts.

3.3.2.1. Precipitation Map Preparation

A thematic data layer depicting rainfall for landslide susceptibility analysis is generated through creation of classified precipitation maps for particular areas (Dahal et al., 2008). In this study, Preparation of the precipitation map involved converting the annual rainfall data into CSV (comma delimited) format using Excel and imported to ArcGIS (ArcMap). Inverse Distance Interpolation was applied in ArcGIS in order to estimate precipitation for the locations with unknown rainfall measurements (Locations with no weather stations). Inverse Distance Interpolation process uses the following formula;

A (xo, yo) = ∑wi. P (xi, yi), Where: A = unknown precipitation at location (xo, yo), while P = precipitation at location (xi, yi) and wi = weights (inverse of the distances). Thereafter, the resulting map was sliced to give a raster map with five classes: 1582.2– 1648.3, 1648.3–1727.7, 1727.7–1770.5, 1770.5–1823.8, 1823.8–1913.4 (mm).

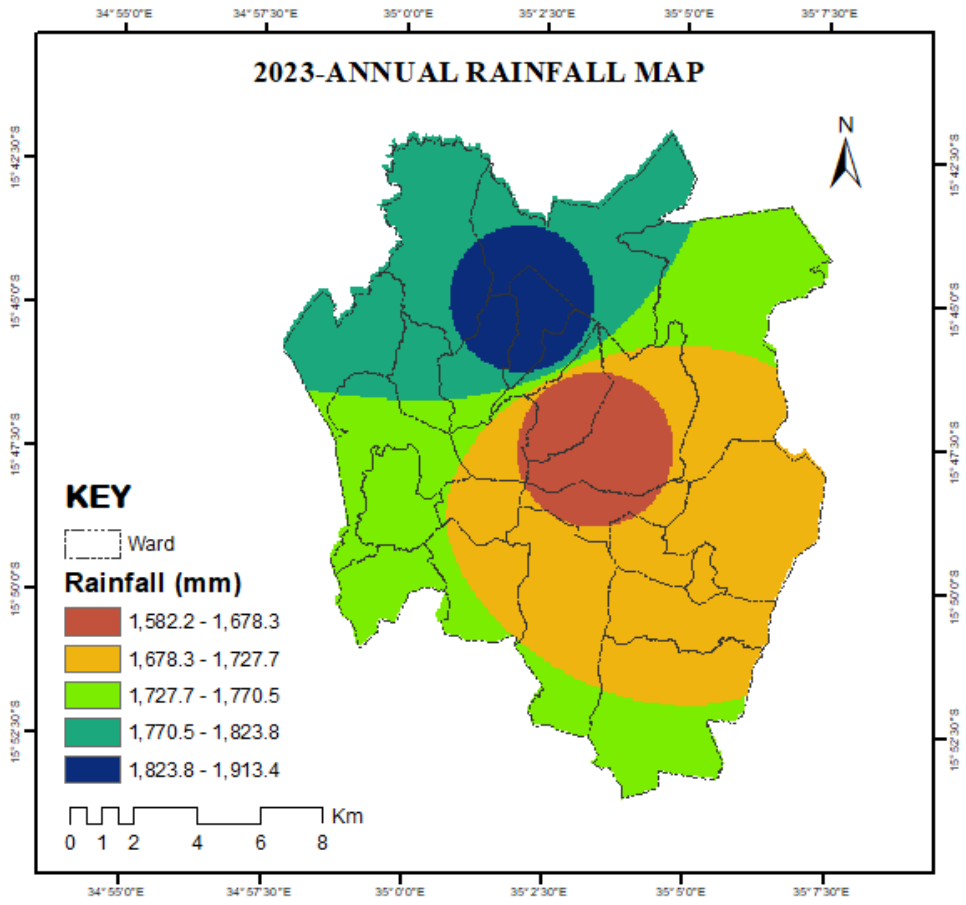


Figure 3. Precipitation Map

3.3.3. Rainfall-Induced Landslides Conditioning Factors

The process of selecting conditioning factors contributing to rainfall-induced landslides remains a challenging task (Gadtaula & Dhakal, 2019). In this study, the conditioning factors were identified and selected based on the presence and or absence of the factors and their importance. Six conditioning factors were considered in this study for the purpose of Frequency Ratio modeling and preparation of susceptibility map. These factors are, Slope angle, Geology, Land use/cover, soil type, Elevation, and distance to rivers.

I. Slope Angle

Slope has a major influence on the occurrence of rainfall-induced landslides. Steeper slopes are more prone to landslides because they experience greater gravitational force acting on the soil or rock mass(Yalcin & Bulut, 2007) . As rainfall infiltrates the soil, it increases the

weight of the material on the slope, making it more susceptible to failure, especially if the slope angle exceeds the angle of repose. The slope angle data was collected from the Copernicus Global Digital Elevation Model, distributed by OpenTopography. https://doi.org/10.5069/G9028PQB.

II. Geology

The underlying geology has a significant influence on the stability of slopes. Rock types with fissures, faults or jointed structures are more susceptible to weathering and erosion, increasing the potential for landslides during heavy rainfall events (Nadim & Sandersen, 2009). In addition to that, geological formations, such as shale or schist, may have inherent weaknesses that make them prone to failure. The geological data for Blantyre City was obtained from the Geological Survey Department (GSD).

III. Land use/Land cover

Human activities and land use practices can significantly alter the national landscape, affecting landslide susceptibility. Deforestation, urbanization and improper land management practices can remove vegetation cover, disturb soil stability, and alter drainage patterns, all of which contribute to increased landslide risk during rainfall (Glade, 2003). Vegetation having a well-spread network of root systems increases shearing resistance of the slope material and reduces action of erosion and vice-versa.

In this study, the Land use/Land cover data was downloaded from Sentinel-2 10m Land use/Land cover – Esri and Impact Observatory, ArcGIS Living Atlas of the World.

IV. Soil type

Different soil types have varying degrees of cohesion and permeability, which affect their stability during rainfall. For example, loose soils are more prone to erosion and saturation, leading to increased landslide risk, while cohesive clay soils may experience swelling and loss of strength when saturated, also increasing the likelihood of landslides (Dahal et al., 2008). The soil data of the study was downloaded from Food and Agricultural Organization (FAO) Digital Soil Map of the World (DSMW).

V. Distance to the rivers

The slope's Proximity to rivers or bodies of water can also influence landslide occurrence. Increased rainfall can saturate the soil near streams, leading to higher pore water pressures and reduced soil strength, which can trigger landslides. Additionally, stream erosion can undercut slopes, further destabilizing the likelihood of landslides(Jebur et al., 2014). Data for rivers was obtained from OpenStreetMap.org.

VI. Elevation

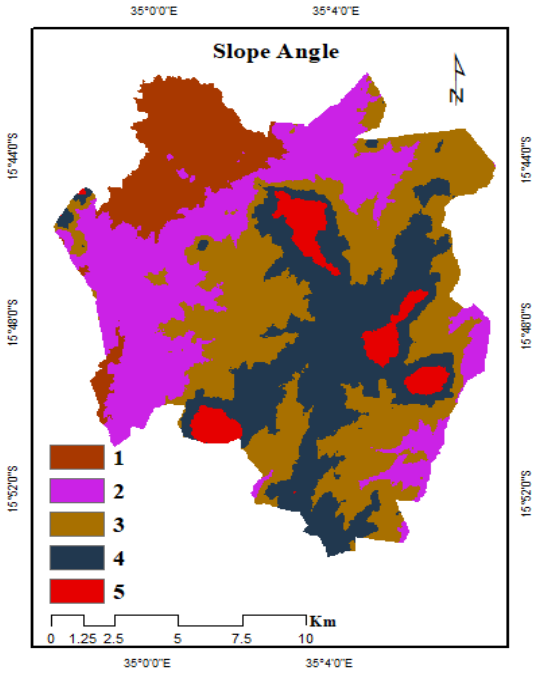
Elevation plays a significant role in the occurrence of landslides, particularly in relation to rainfall-induced landslides. Elevation affects slope stability and rainfall patterns in an area (Park et al., 2012). In many regions, higher elevations experience heavier and more intense rainfall due to orographic lifting. This intense rainfall can saturate the soil, reduce its shear strength, and increase pore water pressure, all of which contribute to landslides. Hence, there is an increase in the probability of landslide occurrence for higher elevations. Elevation data was collected from the Copernicus Global Digital Elevation Model, distributed by OpenTopography. https://doi.org/10.5069/G9028PQB.

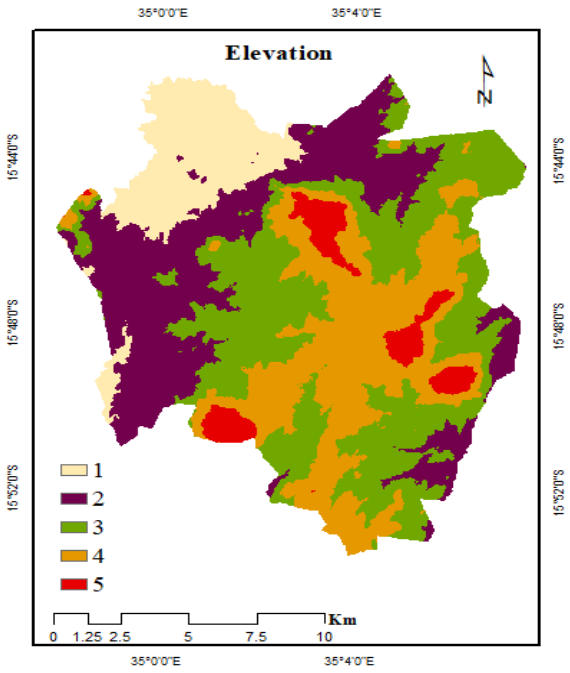
Conditioning Factor Maps Preparation

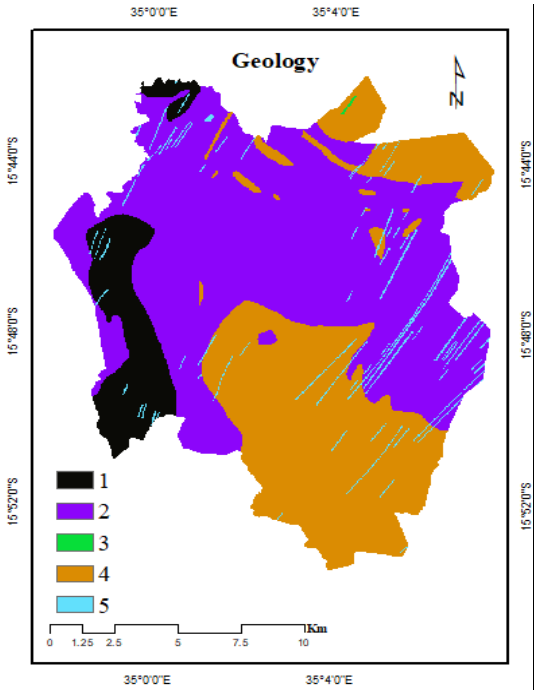
All condition factor maps were prepared and Rasterized in ArcGIS. In particular, preparation of distance to rivers map involved multiple ring buffer analysis to come up with classes of distances (in kilometers) from the rivers. Thereafter, all maps were reclassified into 5 classes (1, 2, 3, 4, & 5) except Soil type map which was divided into two classes (1 & 3). These class numbers represent areas containing specific categories (range or type) of the factor. For example, for soil type map, class 1: represent area containing **Clay-Loam** type of soil while class 3: represent area containing **clay soil** in the study area. The higher factor class number such as 5 indicates factor categories that have the highest influence on the occurrence of landslides based on basic understanding and literature reviews.

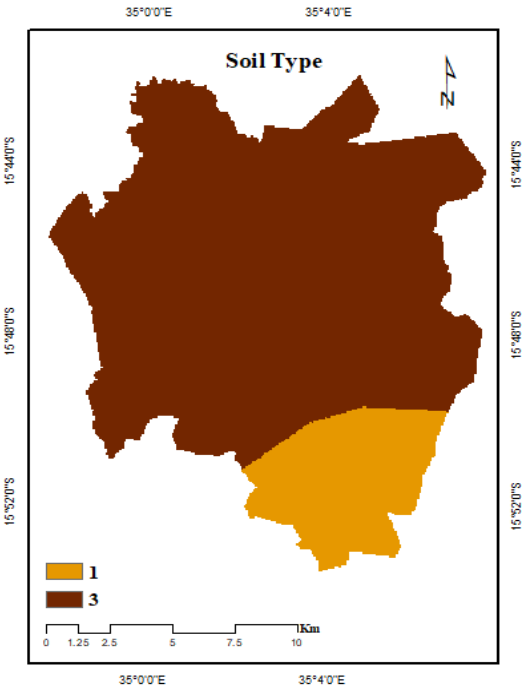
Table 1. Class Numbers with their Respective Categories

FACTOR MAP	CLASS	CATEGORY
Slope Angle (degree)	1	0 - 4.9
	2	4.9 - 9.3
	3	9.3 - 15.9
	4	15. 9 - 25.2
	5	25.2 - 62.4
Geology	1	Charnockitic Granulites
	2	Perthite gneiss & perthosite
	3	Calc-silicate granite
	4	Garnet hypersthene
	5	Pyroxenite & Dolerite
Elevation (m)	1	780 - 953.4
	2	953.4 - 1059.4
	3	1059.4 - 1139.7
	4	1139.7 - 1261.8
	5	1261.8 - 1599
Soil type	1	Clay-loam
	3	Clay
Land use/cover	1	Vegetation
	2	Crops
	3	Water
	4	Built up and range land
	5	Bare land
Distance to Rivers (km)	1	2
	2	1.5
	3	1
	4	0.5
	5	0.2


Slope Angle
35°0'0"E
35°4'0"E
15°44'0"S
15°48'0"S
15°52'0"S
N
1
2
3
4
5
0 1.25 2.5 5 7.5 10
Km


Elevation
35°0'0"E
35°4'0"E
15°44'0"S
15°48'0"S
15°52'0"S
N
1
2
3
4
5
0 1.25 2.5 5 7.5 10
Km


Geology
35°0'0"E
35°4'0"E
15°44'0"S
15°48'0"S
15°52'0"S
N
1
2
3
4
5
0 1.25 2.5 5 7.5 10
Km


Soil Type
35°0'0"E
35°4'0"E
15°44'0"S
15°48'0"S
15°52'0"S
N
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Km

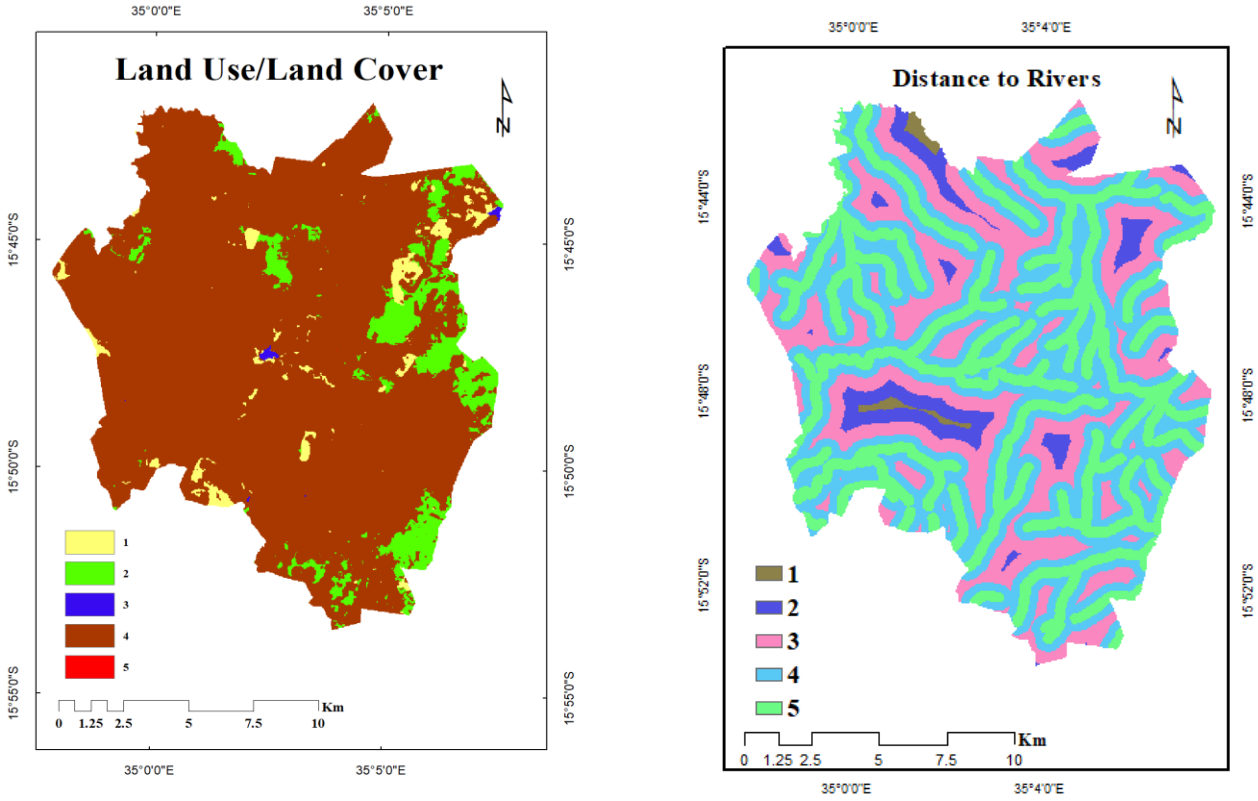


Figure 4. Conditioning Factor Maps

3.4. Data Analysis

3.4.1. Susceptibility Analysis

The projections and pixel sizes of all reclassified and rasterized factor maps were converted into WGS_1984__UTM_Zone_36S and 30m × 30m respectively. Generally, when factor maps have different projections, it can lead to misalignment of features resulting in inaccurate analysis. Furthermore, different pixel sizes can give undue weight to certain areas. For example, a factor with larger pixels might overestimate the influence of a specific factor compared to one with smaller pixels. Using the rasterized training landslide data set, tabulated area analysis was carried out using ArcGIS for all factor maps to calculate the number of pixels containing landslides in each factor class using a field calculator. The formula below was applied.

Number of Factor Class Pixels (containing landslides) = Factor Class Area/ (30m × 30m), where Factor Class Area is obtained after doing tabulated area spatial analysis in Arc tool box, and (30m × 30m) is pixel size for all factors.

Thereafter, the FR for all factor classes/intervals and LSI for all the factor maps were calculated in Microsoft excel using the following formulas;

FR = $\frac{\%\ of\ landslide\ pixels}{\%\ of\ class\ pixels}$, where **% of landslide pixels** represents ratio of number of pixels with landslides in each factor class or interval to the total number of pixels containing landslides within the factor multiplied by 100 while **% of class pixels** represents the ratio of number of pixels for the specific factor class or interval to the total number of pixels containing the whole factor multiplied by 100 (Park et al., 2012).

LSI = $FR_1 + FR_2$ ..... FRn, where $\mathbf{FR_n}$ represents Frequency Ratio for a specific factor interval (n).

Thereafter, using calculated LSI Values, all maps were combined to develop landslide susceptibility map using Raster Calculator in arc toolbox as shown below;

("Soil Map" * 1.17) + ("Geology Map"*4.28) +("Cover Map"*4.91) +("Rainfall Map"*5) +("Slope Map"*8.08) + ("River Map"*3.24) +("Elevation"*8.67).

The map has been reclassified into five classes indicating susceptibility levels (Very Low, Low, moderate, high, and very high).

3.4.2. Validation of the Landslide Susceptibility Map

Landslide susceptibility maps will be useless without validation. In light of this, Landslide susceptibility mapping requires validation of the predictive model (Bui et al., 2012). Basically, validation helps to assess the performance of the model used to create the Map. In addition to that, a validated map with robust scientific backing is more credible and trustworthy for stakeholders. In this study, the susceptibility map was validated by overlying testing landslide locations on the map to see how well these landslides align with the areas classified as highly susceptible on the map. From the results, it is observed that a large portion (approximately,

99%) of testing landslides fall within the high landslide-susceptible zones as shown in Figure 6 (b).

Furthermore, The Blantyre City Risk Atlas information, specifically the landslide risk section has also been used to validate the susceptibility classes on the map (https://blantyreriskatlas.must.ac.mw/#/). The areas designated as susceptible on the susceptibility map were visually compared with the locations designated as hazard zones in the atlas. Despite some few discrepancies, there is agreement between the two maps regarding high, medium, and low susceptibility zones. The discrepancies might have been caused by differences in relevant factors used.

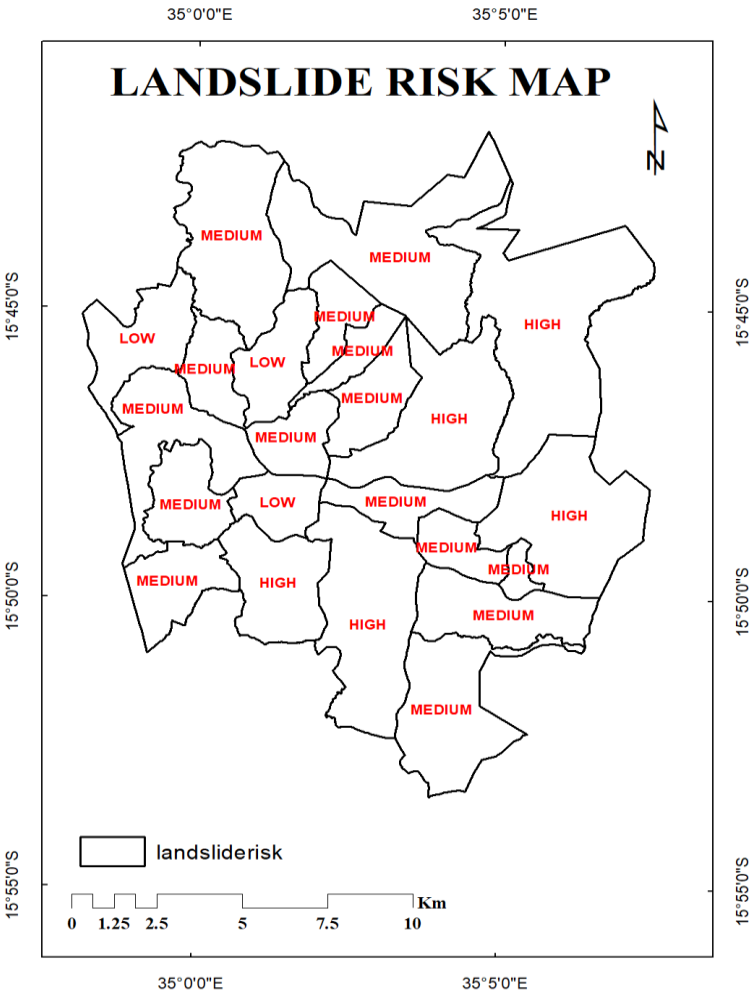


Figure 5. Landslide Risk Map Generated from Blantyre City Risk Atlas

3.4.3. The Conceptual Framework of Early Warning System (EWS)

The conceptual framework for the Territorial Early Warning System (TEWS) for rainfall-induced landslides has been developed considering the Landslide Susceptibility Map and a comprehensive review of relevant literature (including published and unpublished books, reports, and articles). Areas identified on the map as highly susceptible to landslides are the ones prioritized for the deployment of a sensor network. Furthermore, Communities located in these zones will be actively engaged in public awareness campaigns and education programs to ensure that they are well prepared to respond effectively after phased warnings.

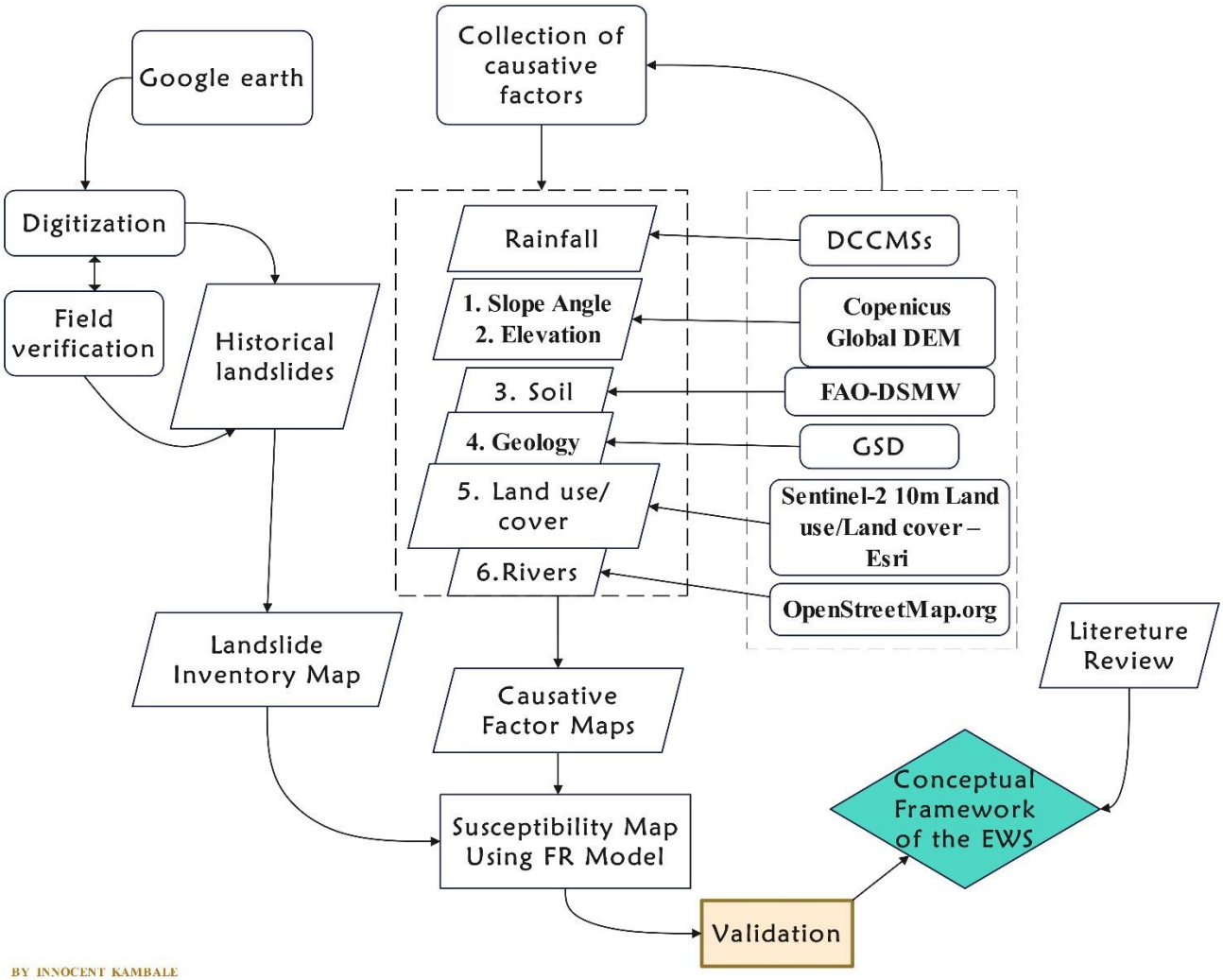


Figure 6. A Simplified Flow Chart for the Methodology (developed using Wondershare EdrawMax App)

4.0. CHAPTER FOUR: RESULTS AND DISCUSSIONS

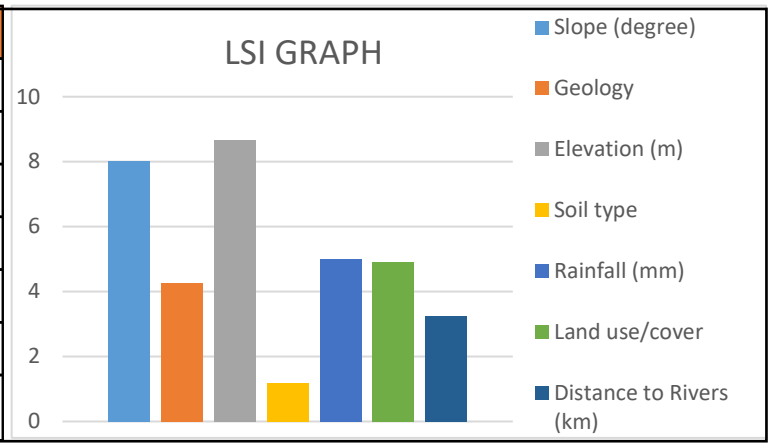
4.1. Results

Table 2. Frequency Ratio Values

Data Layers	Class	Class Pixels	% of Class pixels	Landslide pixels	% Landslide pixels	FR
Slope Angle	1	40140	15.34603121	0	0	0
	2	60956	23.30425208	3	0.70754717	0.0304
	3	88000	33.64351636	96	22.64150943	0.673
	4	58359	22.31138604	208	49.05660377	2.1987
	5	14111	5.394814311	117	27.59433962	5.115
Total		261566		424		8.017
Geology	1	23716	9.079667227	0	0	0
	2	142290	54.47570626	390	92.19858156	1.6925
	3	96	0.036753586	0	0	0
	4	89454	34.24745118	10	2.364066194	0.069
	5	5643	2.160421747	23	5.437352246	2.5168
Total		261199		423		4.2783
Elevation	1	32159	12.25749156	0	0	0
	2	67175	25.60393655	2	0.471698113	0.0184
	3	86142	32.83326091	96	22.64150943	0.6896
	4	64646	24.64000122	208	49.05660377	1.9909
	5	12240	4.665309763	118	27.83018868	5.9653
Total		262362		424		8.6643
Soil type	1	37410	14.29914687	0	0	0
	3	224214	85.70085313	424	100	1.1668
Total		261624		424		1.1668
Rainfall	1	30084	11.48121575	11	2.594339623	0.226
	2	85350	32.57285481	192	45.28301887	1.3902
	3	71847	27.41958875	56	13.20754717	0.4817
	4	54132	20.65886089	110	25.94339623	1.2558
	5	20615	7.867479811	55	12.97169811	1.6488
Total		262028		424	100	5.0024
Land use/cover	1	72183	2.763601308	10	2.358490566	0.8534
	2	222719	8.527028796	67	15.80188679	1.8532
	3	4801	0.183811284	1	0.235849057	1.2831
	4	2312135	88.52249573	346	81.60377358	0.9218
	5	80	0.003062883	0	0	0
Total		2611918		424		4.9115
Distance to Rivers	1	1860	0.70826384	0	0	0
	2	14614	5.564821373	0	0	0
	3	66992	25.50968341	126	29.78723404	1.1677
	4	99789	37.998355	158	37.35224586	0.983
	5	79359	30.21887637	139	32.86052009	1.0874
Total		262614		423		3.2381

Table 3. Landslide Susceptibility Index Values

FACTOR	LSI
Slope (degree)	8.01
Geology	4.28
Elevation (m)	8.67
Soil type	1.17
Rainfall (mm)	5
Land use/cover	4.91
Distance to Rivers (km)	3.24



(a) (b)

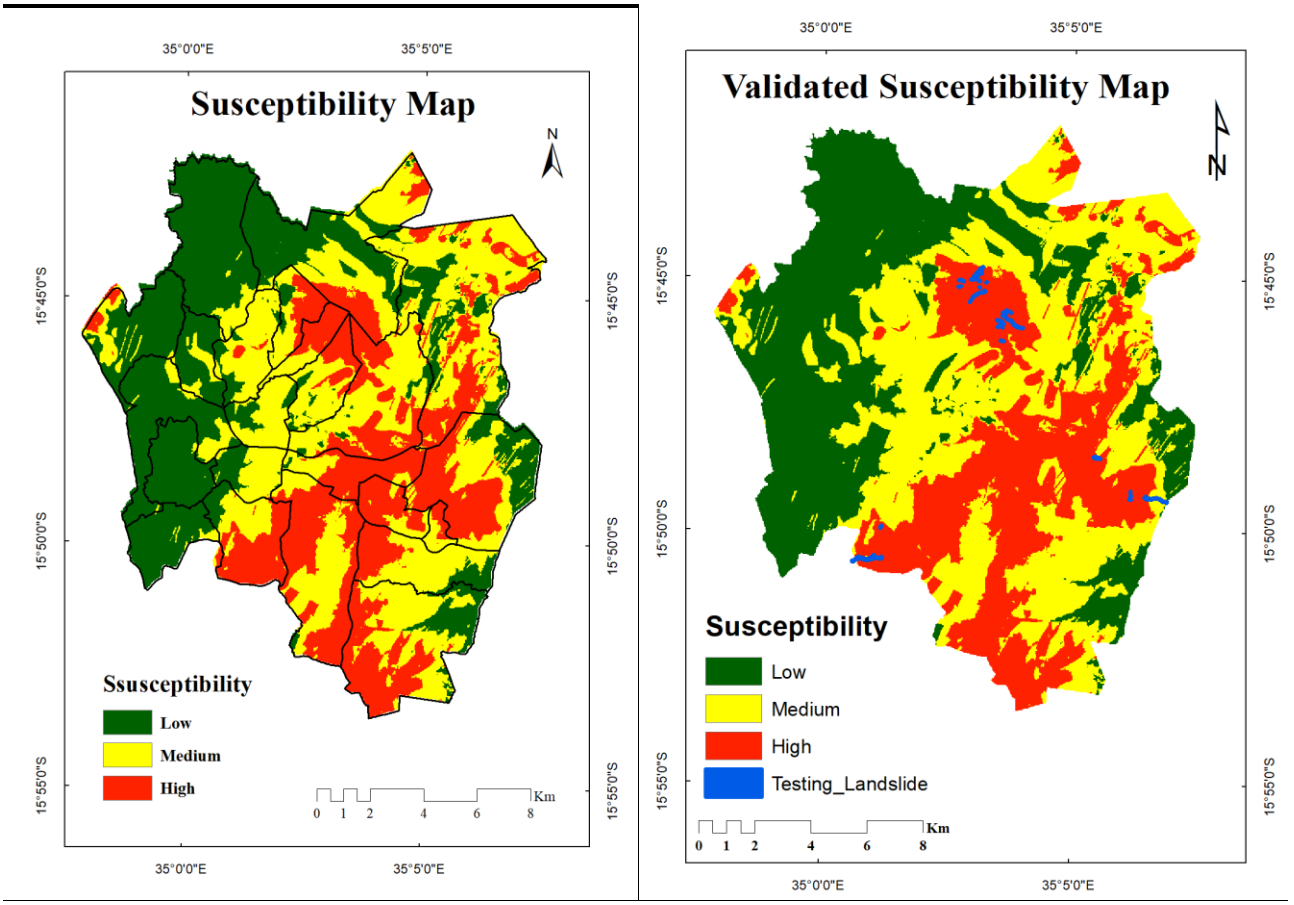


Figure 7. Landslide Susceptibility Map (a), and Validated Map (b)

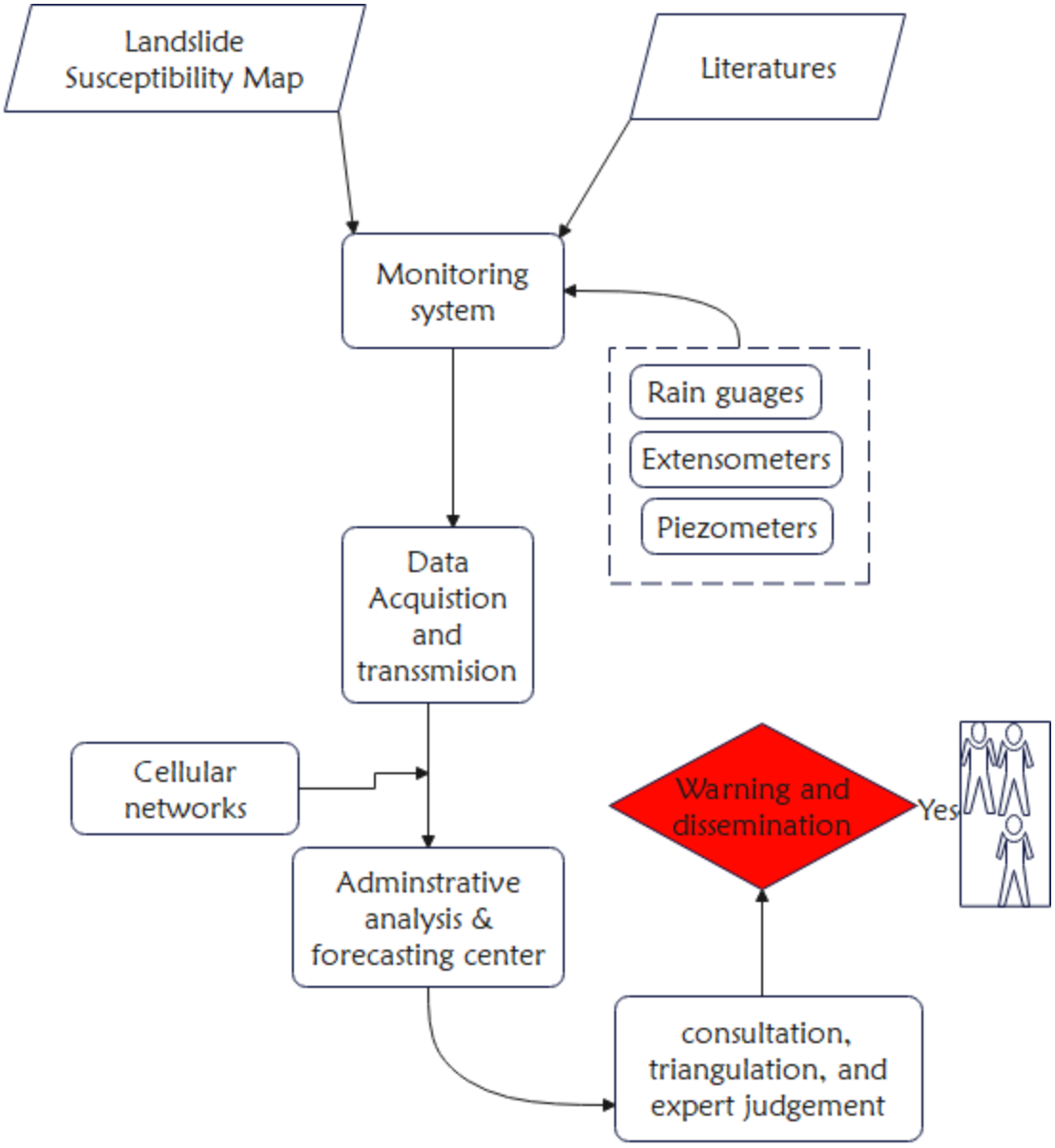


Figure 8. Flow Chart for the Conceptual Framework of Early Warning System

4.2. Discussions

4.2.1. Frequency Ratio

The importance of each causative factor class can be inferred from its landslide frequency ratio. For slope angle, the FR values progressively increase from class 1 (flattest slopes) to class 4 (steepest slopes), indicating a strong correlation between steeper slopes and landslide occurrence. Particularly, the area in slope class 5 ($25.2^0 – 62.4^0$) is the most landslide-prone area while the area in class 1 ($0^0 – 4.9^0$) is the least landslide-prone area. This aligns with the understanding that steeper slopes are inherently less stable & more prone to failure. The same applies to elevation, where the FR values increase with the increase in area's height. Elevation class 5 with height ranging from 1261.8m to 1599m contributes strongly to the landslides followed by class 4 (1139.7m – 1261.8m). In the case of geology, class 5 (Pyroxenite & Dolerite rocks) has the highest FR value compared to the other classes, suggesting a strong association with landslides. This could be due to factors like, their susceptibility to weathering and erosion, and less mechanical strength.

Based on collected data for this study, the area contains only two types of soil, class 1(Clay-Loam) and class 3(Clay). It has been observed that only the clay soil contributes to the occurrence of landslides making the area in that class 3 susceptible to Rainfall-Induced landslides. The fact that clay soil has high water-holding capacity due to its composition (very fine particles) which makes it highly plastic when saturated with water causing it to lose its shear strength may support the result. In the case of rainfall, class 5(1823.8mm – 1913.4mm) has a relatively strong relationship with landslides followed by class 2(1678.3mm - 1727.7mm). Despite the basic understanding that as rainfall increases the FR values would also be increasing (increasing landslide susceptibility), class 2 has high FR value compared to classes 3 and 4, which have relatively high amounts of rainfall. The geology, soil and land use/cover characteristics of those areas might have contributed to this scenario.

For Land Use/ Land Cover, Class 2 (crops) is more susceptible to landslides. When the soil is cultivated, its strength is compromised and can easily get eroded by heavy rains. While class 5 which contains Bare land is irreverent to the occurrence of landslides. The fact that there is

a very small area (80 pixels) containing bare land might have contributed to its irreverence. In the case of distance to rivers, Classes 3, 4 & 5 have high susceptibility for landslides. Basically, decrease in distance from the rivers increases the probability of landslide occurrence. In general, some of the classes have a zero frequency ratio value, meaning there have not been any recorded landslides within those specific categories of the factors. This doesn't necessarily mean that landslides are impossible in those categories, but based on the collected data, there is no evidence of the past landslides having occurred there. Hence, it can be inferred that these factor classes are irreverent to the occurrence of landslides in this area.

4.2.2. Landslide Susceptibility Index Values

The landslide frequency ratios of the causative factor classes were accumulated and transformed into weights to represent landslide susceptibility. The resulting landslide susceptibility Index values range from 1.17 to 8.67. The high values indicate factors with relatively high susceptibility for landslide occurrence. From the results, elevation has the highest LSI followed by rainfall. Soil Type has the least LSI. Hence, it can be concluded that the landslide occurrence in this study is highly contributed by Elevation and slope angle.

4.2.3. Conceptual Framework of the EWS

Because of the multidisciplinary characteristic of landslide forecasts, cooperation among government departments is essential to ensure the system is effective (SHEAR Knowledge Brokers Team, 2021) . For example, the system can be run by DCCMs in collaboration with geological, and disaster risk management departments. Other relevant stakeholders include, Researchers, media, local government and communities. The system consists of the following components:

4.2.3.1. Monitoring System

The system has adopted a ground-based kind of monitoring which includes a network of automated sensors; Extensometers, Piezometers and rain gauges. These are a bit cheaper than Aerial-Based sensors. Based on the susceptibility map (after overlaying it with Blantyre city ward boundaries), areas that are susceptible to landslide include Soche West Ward, Misesa Ward, Bangwe Ward, Bangwe Mthandizi Ward, Mzedi Ward, Chigumula Ward,

Nyambadwe Ward, South Lunzu Ward, Ndirande Gamulani Ward, Ndirande Makata Ward, Ndirande Matope Ward, Mkolokoti Ward, Mapanga Ward, Limbe Central Ward and Chilomoni Ward. These sensors would be deployed along slopes (in hills/mountains) present within these susceptible areas. For Example, Sensors installed in Soche mountain will cover Soche West Ward and Misesa Ward. The sensors will continuously monitor slope movement, pore water pressure, and rainfall which are key indicators of rainfall induced landslides. Specifically, Extensometers measure ground tilt and deformation, indicating slope movement. Piezometers measure changes in pore water pressure within the soil while rain gauges' measure rainfall amounts and intensity. The sensors use power supply from batteries connected to solar panels for recharging in remote areas. Below are some of the Images of the sensors.

(a) (b) (c)

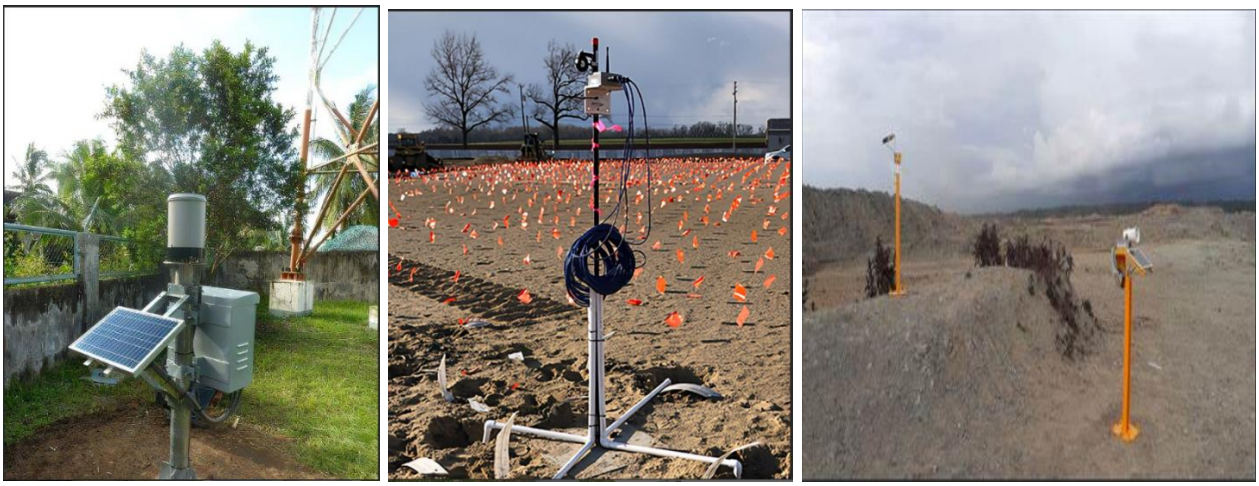


Figure 9. Rain gauge (a), Piezometer (b), and Extensometer (c)

4.2.3.2. Data Acquisition and Transmission

Each Sensor is connected to a Data Acquisition Unit (DAU), a small computer that acts as a local data collection point. The DAU collects and stores sensor data (tilt, rainfall and pore pressure), and performs preliminary data processing (filtering and calibration) to ensure data quality. In addition to that, DAU also manages power supply.

The slope movement, pore water pressure, and rainfall data is transmitted in real-time to administrative processing & analysis center using telemetry systems; cellular networks. Basically, DAUs are equipped with cellular modems that connect to a cellular network providing wireless data transmission capabilities. The cellular network infrastructure consisting of cell towers and a core network, facilitates data transfers across the network. Message Queuing Telemetry Transport (MQTT) should be incorporated to optimize data transmission.

4.2.3.3. Administrative Analysis & Forecasting Center

The center has a central server which receives data streams from all DAUs connected to the sensors deployed in the field. Using the specialized software algorithms, the sensor readings and historical landslides data are analyzed. Expert knowledge is incorporated to define critical thresholds for each monitored slope. These thresholds represent levels of ground movement, pore pressure, or rainfall that indicate high risk of landslide occurrence.

4.2.3.4. Warning Generation and Dissemination

When the values reach or exceed the predefined thresholds, phased warnings will be manually triggered, informed by a process of consultation, triangulation, and expert judgment. The landslide forecast information will be re-packaged into a warning map where the level of landslides warning is classified by an established scale (high/medium/low) and illustrated using color coding (Red/Orange/Green). The warning map is provided with administrative boundaries and location of key towns to guide the interpretation. The information will be disseminated to the individuals and key institutions/stakeholders through multi-channel approach including TVs, Radios, email bulletin, SMS or APP alert and online through website platforms.

4.2.3.5. Community preparedness and Response

All communities situated in high-susceptibility zones will be actively involved in preparedness activities like evacuation drills, establishing safe evacuation routes, and identifying temporary shelters hence ensuring effective response plans. Additionally, awareness campaigns and education programs would be offered to these communities to make sure they understand everything and also to avoid issues of vandalism since some of the sensors are installed in the

field. Local authorities will have predefined emergency response plans in place for different landslides scenarios.

5.0. CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

The study successfully designed a contextualized Te-EWS for rainfall induced landslides in Blantyre city. The system leverages a susceptibility map generated through a Frequency Ratio Model analysis of historical landslides data and causative factors including recent rainfall patterns. This map identifies areas with high landslide risk, such as those surrounding Soche Chigumula Bangwe, Bangwe Mthandizi, Mpingwe, Nyambadwe, Michiru and Ndirande hills/mountains. The proposed EWS consists of five main interconnected components which are; Monitoring system (comprises a network of sensors), Data Acquisition and transmission, Administrative analysis and forecasting center, Warning generation and Dissemination, and community preparedness and response. By providing sufficient lead time for effective evacuation and mitigation strategies, this EWS has potential to significantly reduce the risk of casualties from Rainfall-induced landslides in Blantyre City.

5.2. Limitations

While the proposed EWS is promising, the study itself faced some challenges/limitations due to its theoretical nature. To begin with, the study solely relied on historical data which does not account for the potential impact of the future climate scenarios on landslide Frequency and Intensity. Hence, it might happen that some of the areas that have been established as low susceptible to landslides will also experience fatal landslides. Another limitation is insufficient rainfall data. Only data from three stations (Mpemba, Ndilande, and Chichiri) were given for rainfall analysis and mapping. Insufficient rainfall data, especially when limited to just a few stations, can significantly affect the accuracy of a Susceptibility Map. This is one of the factors that might have caused few discrepancies of the susceptibility map with the Blantyre City landslide risk.

Resources constraints can also be pinpointed as one of the major challenges in this study. Generally, the study had no access to enough funding and other relevant instruments to conduct extensive physical testing of sensor networks and account for optimal placements of sensors. Additionally, the study did not engage any key stakeholders like government agencies, emergency response teams, and potentially affected people during this designing

phase. This has made the study not to account for the capacity and expertise of existing proposed administrative analysis center and personnel respectively. This could lead to challenges during implementation, affecting the effectiveness and sustainability of the System.

5.3. Recommendations

- Enough financial resources and further physical studies and feasibility analysis are crucial for effective implementation of the Early Warning System (EWS).
- Refine the landslide susceptibility map by incorporating relevant factors mentioned in the atlas
- Develop a robust system maintenance plan to ensure the functionality and effectiveness of the EWS. This includes regular sensor calibration, data quality checks, and system upgrades as needed.
- Conduct further research to explore the integration of advanced monitoring technologies, such as satellite imagery and real-time weather forecasting models, to enhance the accuracy and lead time of the EWS.
- Additionally, investigate the potential for incorporating early intervention measures like slope stabilization works in high-risk areas.

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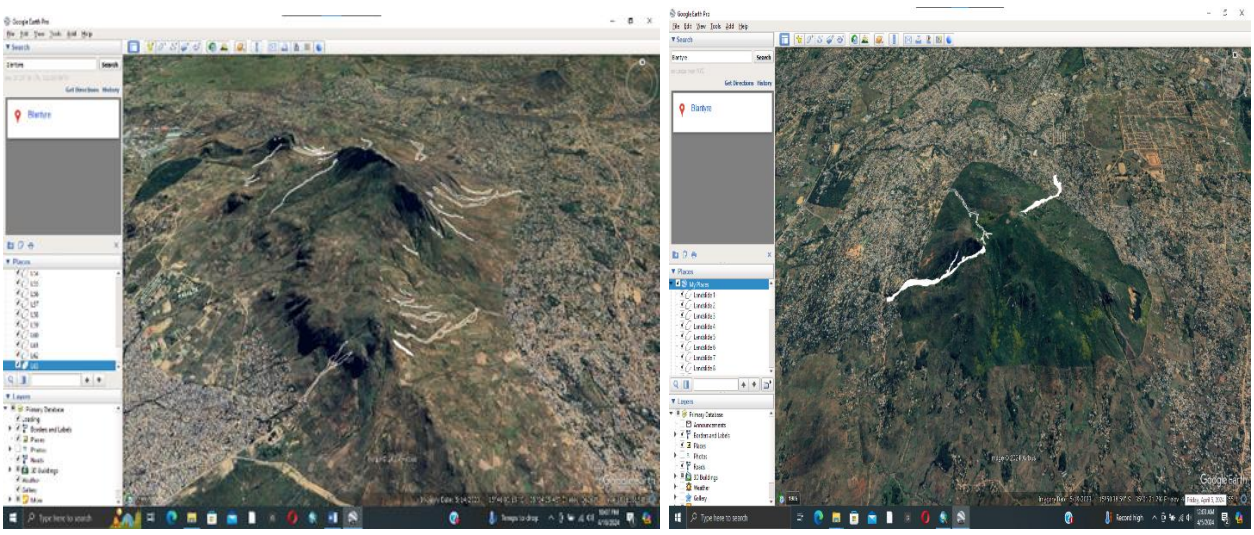
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APPENDICES

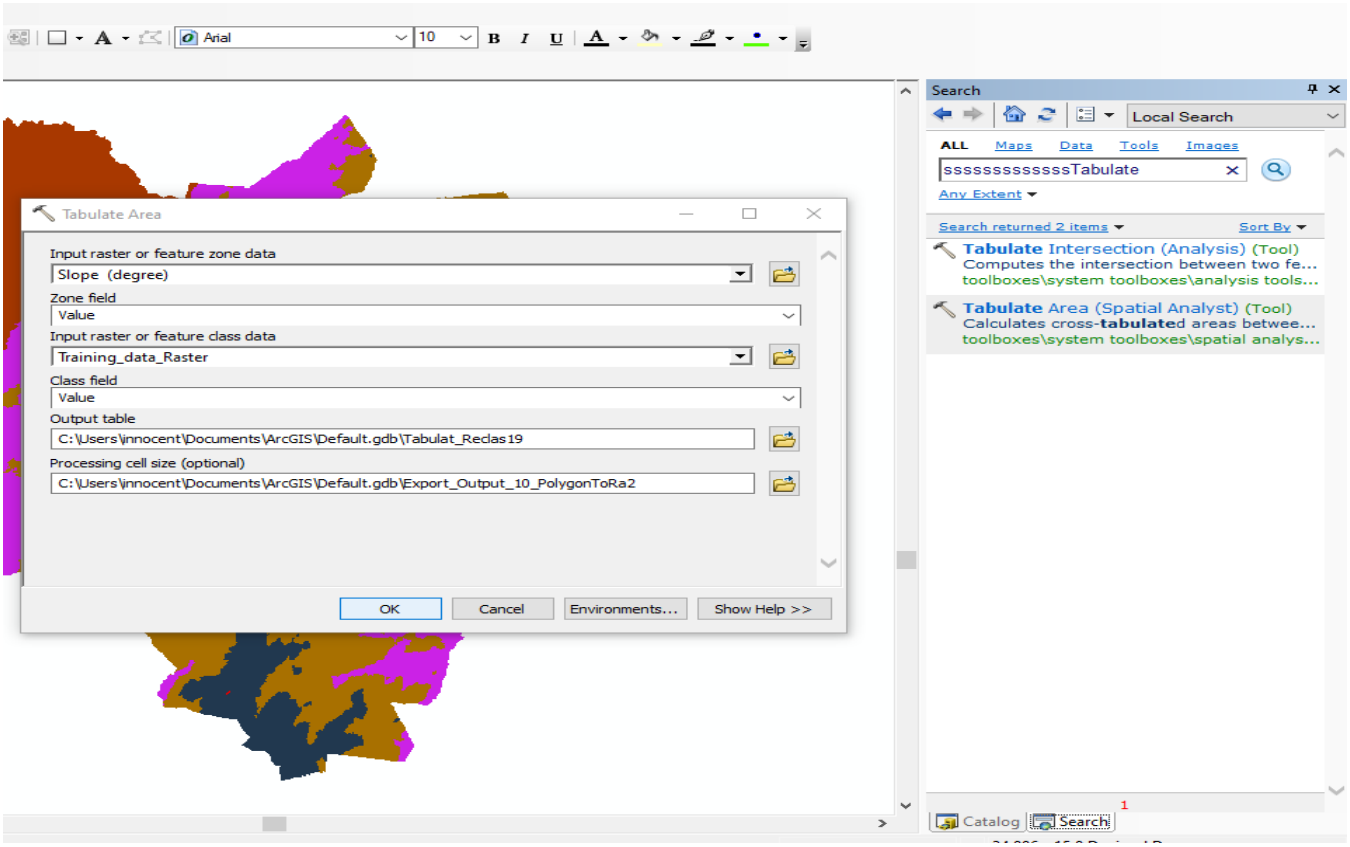


Appendix A. Images taken during field visit in Soche (3 ways area)

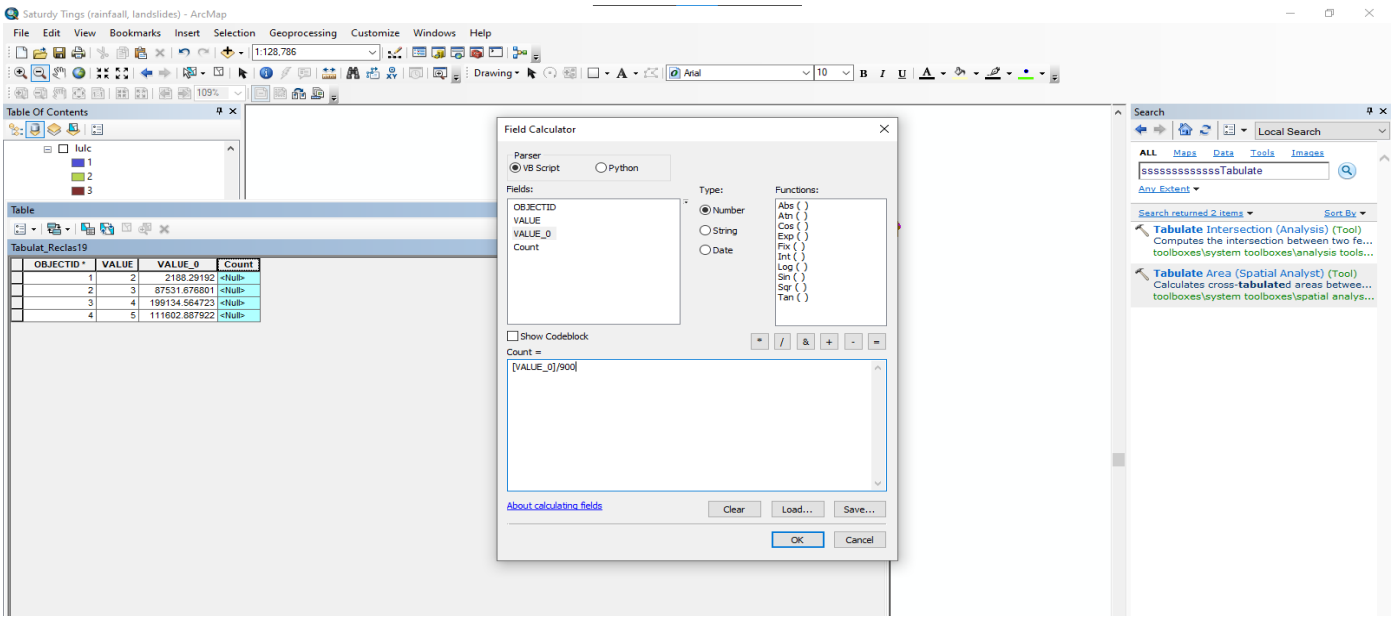


(a) (b)

Appendix B. Images showing some of the digitized landslides in (a) Ndirande and (b) Soche mountains



Appendix C. Image showing how area containing landslides in each factor class were calculated using field calculator in ArcGIS



Appendix E. Image showing how number of pixels containing landslides in each factor class were calculated using field calculator in ArcGIS