

**GIS-BASED LANDSLIDE SUSCEPTIBILITY MODELING USING
WEIGHT OF EVIDENCE AND LOGISTIC REGRESSION METHODS
IN BICHENA AND YED WIHA AREA, EAST GOJAM, CENTRAL
ETHIOPIA**



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GIS-BASED LANDSLIDE SUSCEPTIBILITY MODELING USING
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BICHENA AND YED WIHA AREA, EAST GOJAM, CENTRAL ETHIOPIA

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Declaration

I declare that this thesis entitled “GIS-based Landslide susceptibility modeling using the Weights of Evidence and Logistic Regression Methods in Bichena and Yed Wiha area, East Gojam, Central Ethiopia” is my work and has been submitted to any university for a similar purpose. The references used in this thesis are duly recognized by proper citations.

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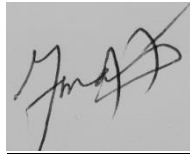
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Table of Contents

Declaration.....	i
Recommendation of Advisors	ii
Approval sheet of the Thesis	iii
Acknowledgments	iv
Table of Contents.....	v
List of Figures.....	ix
List of Tables.....	xi
List of Plates	xii
List of Abbreviations and Acronyms.....	xiii
<i>ABSTRACT</i>	xiv
CHAPTER ONE.....	1
INTRODUCTION	1
1.1 Background of the Study.....	1
1.2 Statement of the Problem	3
1.3 Objective of the Research	4
1.3.1 General Objective.....	4
1.3.2 Specific objectives.....	5
1.4 Significance of the Study	5
1.5 Limitations of the Study	6
1.6 Organization of the Thesis	6
CHAPTER TWO.....	7
LITERATURE REVIEW	7
2.1 Definition of Landslide and Their Impact.....	7
2.2 Landslide hazards controlling factors in Ethiopia, particularly in the highlands of Ethiopia ..	7
2.2.1 Influence of Geological (Lithological and Structural) Settings	8
2.2.2 Influence of slope gradients on landslides.....	8
2.2.3 Influence of Slope Shapes (Curvature) on Landslides	9
2.2.4 Influence of Slope Modification on Landslides	9
2.2.5 Influence of Vegetation Cover on Landslides	10
2.2.6 Influence of Hydrological Condition on Landslide.....	11

2.2.7 Seismic Hazard.....	12
2.2.8 Influence of Soil Properties.....	13
2.2.9 Influence of Manmade Factors.....	14
2.9.9.1 Manmade factors	14
2.3 Classification of Landslide	14
2.3.1 Falls	15
2.3.2 Topples	15
2.3.3 Rotational slides	15
2.3.4 Translational slide	16
2.3.5 Spread.....	16
2.3.6 Creep	16
2.3.7 Earth flows	16
2.3.8 Complex	17
2.4 Different Types of Landslide Maps.....	17
2.4.1 Landslide Inventory Map	18
2.4.2 Landslide Susceptibility Map.....	19
2.4.3 Landslide Hazard Map	19
2.5 Landslide Susceptibility Mapping Techniques	20
2.5.1 Qualitative Approaches	21
2.5.2 Quantitative techniques	22
2.5.3 Probabilistic Approaches.....	26
2.6 Previous Landslide Studies in Ethiopia.....	26
2.7 Previous Landslide Studies and Gaps in the Study Area	29
CHAPTER THREE	31
DESCRIPTION OF STUDY AREA, METHODS, AND MATERIALS	31
3.1 Overview of the Study Area.....	31
3.1.1 Location of the Study Area	31
3.1.2 Physiography	32
3.1.3 Drainage Network	33
3.1.4 Climate and Vegetation.....	33
3.2 Materials and Methods	36
3.2.1 Data Collection and Preparation.....	36
3.2.2 Landslide Susceptibility Mapping Methods or Models.....	38
3.2.3 Materials.....	41
3.2.4 Methods.....	41

CHAPTER FOUR	43
GEOLOGY OF THE AREA	43
4.1 Previous Work.....	43
4.2 Regional Geology.....	44
4.2.1 Lithology of the Area	45
4.3 Local Geology	54
4.3.1 Lithology of the study area.....	55
4.3 Structure of the Study Area.....	57
4.3.1 Lineament.....	57
4.3.2 Joints and fractures.....	58
CHAPTER FIVE	61
LANDSLIDE INVENTORY AND CAUSATIVE FACTOR EVALUATION	61
5.1 Distribution of Landslide in the Study Area	61
5.2 Landslide Causative Factors in the Study Area.....	64
5.2.1 Aspect.....	64
5.2.2 Curvature.....	65
5.2.3 Slope.....	66
5.2.4 Land Use and Land Cover (LULC).....	66
5.2.5 Distance to Stream	67
5.2.6 Distance to Lineament.....	68
5.1.7 Lithology	68
5.2.8 Rainfall	69
Chapter Six	73
Result and Discussion.....	73
6.1 The Relationship between Landslide and Causative Factors	73
6.2 Landslide Susceptibility Mapping Using WoE and LR Methods	81
6.2.1 Application of WoE Method	81
6.1.2 Application of LR Method	84
6.2 Validation of the Models.....	88
6.2.1 Validation of the Model Using ROC.....	88
6.2.2 Validation of the Model Using Landside Density Index (LDI).....	90
6.3 Comparison of Models	93
Chapter Seven.....	95
Conclusion and Recommendation	95

7.1 Conclusion.....	95
7.2 Recommendation.....	96
Reference	99
Appendix 1.1 Annual rainfall of nine stations Average (rf = Rainfall).....	105

List of Figures

Fig 2.1 Source: USGS landslide hazard report (Oita Expressway, which was buried by a massive landslide in Japan seven years ago).	10
Fig 2.2 Seismic hazard map of Ethiopia for 100 years return period (EBCS, 1995).	12
Fig 2.3 Google Earth showing the study area distance from the Main Ethiopian Rift (MER)	13
Fig 2.4 Types of landslides (Cruden & Varnes, 1996).	17
Fig 2.5. Flow chart showing the taxonomy of the LSZ Map approaches (Kanungo et al., 2009).....	21
Fig. 2.6 Landslide distribution map from (Woldearegay, 2013).	30
Fig. 3.1 Location map of the study area.	31
Fig 3.2 (3D) Physiographic map of the study area.	32
Fig 3.3 Stream order of the study area.....	33
Fig 3.4 Total yearly Rainfall (A), Average maximum monthly rainfall (B) (Source: Ethiopian Meteorological Agency).	35
Fig 3.5 Landslide Inventory Training and testing dataset	37
Fig 3.6 Flow chart of the methodology.	42
Fig 4.1 Regional Geological Map obtained from the Geological Survey of Ethiopia (Scale = 1: 250,000) (GSE).....	47
Fig. 4.2 World Soil Data downloaded from USGS and converted into Arc GIS 10.8 to check the area coverage and distribution of Eluvial sediment, alluvial sediment, and Slope deposits particularly in the current study area.	50
Fig 4.3 Lithological map from geological mapping at a scale of 1: 50,000 was carried out from 2006 through the work of Matebie Meten (Ph.D.).	54
Fig. 4.5 The main Structural map of the study area.	58
Fig. 5.1 Percentage of each lithology area coverage in the study area.....	69
Fig. 5.2 Landslide causative factor maps, (A) LULC Map, B) Slope, C) Aspect, D) Curvature, E) Distance to Stream, F) Distance to Lineament, G) Lithology and H) Rainfall map.	72
Fig. 6.1 Percentage of Landslide frequency distribution against (A) Slope angle, (B) Rainfall, (C) Stream, (D) Aspect, (E) Curvature, (F) Lineament, (G) LULC, and (H) Lithology.....	73
Fig 6.4 Landslide susceptibility map produced using Weight of Evidence Model.....	83
Fig 6.5 Landslide susceptibility map produced using Logistic Regression Model.	87
Fig 6.6 Success and Predictive rate curves of models (LR and WoE).	89

Fig 6.7 The landslide density for both the training and validation datasets using logistic regression (LR) and Weight of Evidence (WOE) 92

Fig 6.8 A) Bar diagram displaying the landslide in various landslide susceptibility classes for validation and B) bar diagram shows an illustration of the distribution of landslide susceptibility classes. 93

List of Tables

Table 2.1 Classification of landslide according to (Cruden & Varnes, 1996).....	15
Table 4.1 Stratigraphy of Lithological units in the study area.	48
Table 5.1 Lithological units and their area coverage.....	69
Table 6.1 Data used in the analyses and results obtained from the WoE method (Nslide = 206550 and Nmap = 1473101).	74
Table 6.2 Data Used in LR Analysis and the Result Obtained.....	75
Table 6.3. Landslide susceptibility class index and training landslide pixels of WoE Model	82
Table 6.4 The distribution of landslide in the classes of LR	86
Table 6.6 Validation of the Model Using Landslide Density Index Method	91

List of Plates

Plate 2.1 Google Earth image showing the impact of water on slope stability in the study area (Lat. 10° 13' 58.34" N, long. 38°21'33.31" E).	11
Plate 4.1 Mesozoic Limestone east of Kutkwat village (Bichena area)	52
Plate. 4.2 Paleozoic Sandstone at Abay River.....	52
Plate 4.3 Fossiliferous Limestone (fossils of bivalves are visible)	55
Plate 4.4 Columnarly jointed Aphanitic basalt at Dejen – Abay Road southern part of the study area.	56
Plate 5.1 A) Forest area affected by different types of landslide, B) Planar (left side) and concave (on the right side) type of Landslide (Google Earth Pro Image) showing the direction of sliding. .	62
Plate 5.2 A) Rock fall (10°11'33.86"N 38°17'30.05"E,) B) Gypsum unit sliding down to the Suha River (Lat. 10°11'8.82"N, Long. 38°17'7.92"E) Google Earth Pro.....	63
Plate 5.3 Different colors of farmland images in the study area, Plate (A and B).	66
Plate 7.1 Unplanned land use initiating new landslide from the older one (Google Earth Pro).....	97

List of Abbreviations and Acronyms

Arc GIS	Aeronautical Reconnaissance Coverage Geographic Information System
AUC	Area under the Curve
DEM	Digital Elevation Model
ERDAS	Earth Resource Data Analysis System
ENVI	Environment for Visualizing Images
GERD	Grand Ethiopian Renaissance Dam
GIS	Geographic Information System
GPS	Global Positioning System
IDW	Inverse Distance Weight
LDI	Landslide Density Index
LSI	Landslide Susceptibility Index
LSM	Landslide Susceptibility Map
LULC	Land Use Land Cover
LR	Logistic Regression
M (m)	Meter
MER	Main Ethiopian Rift
NR	Not Recorded
ROC	Receiver Operating Characteristic
SPSS	Statistical Package for the Social Science
WoE	Weights of Evidence

ABSTRACT

Landslide distribution and susceptibility mapping are fundamental steps for landslide-related hazard and risk management activities. This is especially crucial in a country like Ethiopia. It has mountainous terrain, heterogeneous rock units with varying degrees of weathering, and complex hydrology that contribute to landslide initiation. Landslides can result in loss of life, property damage, and infrastructure disruption. The primary purpose of this study is to prepare a landslide susceptibility map for the Bichena and Yed Wiha area using the Weight of Evidence (WoE) and Logistic Regression (LR) methods that use continuous and discrete variables efficiently. Data were collected from different sources to delineate landslide susceptibility zones in the study area to produce better results of a landslide susceptibility map. Eight triggering factors were considered namely; Aspect, Slope, Curvature, Distance from Stream, Distance from Lineament, Lithology, Land Use, and Rainfall. Rainfall-induced landslides of different types frequently affect the hilly and mountainous terrains of the highlands of Ethiopia and are weighted using the weight of Evidence. The weight of each factor will be calculated and assigned in Aeronautical Reconnaissance Coverage Geographic Information System (Arc-GIS). To add these factors in Arc-GIS spatial analyst tools raster calculator, and produce a landslide susceptibility map, the weighted contrast linear combination and coefficient of regression were used between training landslide and landslide causative factors. To establish the relational statistical correlation of various causative factors with past landslides in the area, landslide inventory were made through Google Earth image interpretation. Further, the weight of evidence and logistic regression, bivariate, and multivariate statistical analysis methods were used to prepare the model. Statistical Package for the Social Science (SPSS) software and MS Excel were used to check the validation of the overlay maps using Receiver Operating Characteristic (ROC) and Landslide Density Index (LDI). Finally, a landslide susceptibility map was prepared and classified into five classes: Very Low, Low, Medium, High, and Very High. Finally, landslide mitigation measures were recommended for susceptible areas.

Keywords: Bichena, Logistic Regression, Susceptibility mapping, Weight of evidence, Yed Wiha.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The Earth's surface is constantly undergoing dynamic changes, primarily due to various mass-wasting processes. These changes are particularly prominent in mountainous terrains characterized by diverse geological units and structures. One such mass-wasting process is landslides, which pose a recurring natural hazard with global prevalence, especially in mountainous regions where different degrees of weathering in rock formations can result in substantial harm to human life, property damage, and infrastructure (Mersha and Meten, 2022). Therefore, the study of landslides has garnered global attention, primarily to raise awareness about their socioeconomic impacts and the mounting pressure of urbanization in mountainous regions. However, it is widely acknowledged that landslides are predictable hazards, and their economic losses can be significantly reduced. In recent years, there have been advancements in understanding the triggers of landslides and techniques for assessing, predicting, and mitigating slope instability hazards. Despite these advancements, landslides continue to occur in both developed and developing countries, resulting in higher casualties in developing nations and substantial economic losses in industrialized nations.

Given these factors, worldwide efforts are expected to persist in the 21st century due to the following reasons: (a) increased urbanization and development in areas prone to landslides, (b) ongoing deforestation in landslide-prone regions, and (c) rising precipitation patterns attributed to changing climatic conditions (Woldearegay, 2013). A landslide, a geological phenomenon involving ground movement, is influenced by various factors such as the type of movement (fall, topple, spread, flow, slide, and slope deformation), the type of material involved (rock, earth, debris), and the speed of the movement. It is important to note that gravity serves as the primary driving force behind landslide (Woldearegay, 2013). There are other factors triggering landslides such as earthquakes, Hydrogeology, or human interaction (Mebrahtu et al., 2021). Landslide hazard, without any doubt, is one of the crucial environmental problems for the development of Ethiopia. It represents a limiting factor for urbanization and infrastructure projects and, generally, for all activities conducted on or at the foot of slopes (Abebe et al., 2010). The damage caused by landslides in Ethiopia from 1993 to 1998 alone revealed that over 200 houses were destroyed, more than 500 km of roads were interrupted, and approximately 300 people lost their lives (Ayalew, 1999). Ethiopia's landslide activities are primarily associated with the northern, northwestern, central, southern, southwestern, and rift escarpments. This is due to the presence of complex

geomorphological, hydrological, and geological settings, active geodynamic processes, and unplanned land use practices (Woldearegay, 2013). Preparing a landslide susceptibility map of a certain area is a useful tool in landslide hazard control as it shows the degree of susceptibility of the area to landslide occurrence. Landslide susceptibility maps can be generated based on the assumption that future landslides will occur under the same conditions as in the past and present (Mersha and Meten, 2022). Due to the lack of remote sensing data and advancements in GIS tools, landslide susceptibility mapping has been a difficult task in the past. However, today, with the advancement of computers, remote sensing, and GIS, preparing landslide susceptibility maps has become easier. Although several approaches have been developed for landslide susceptibility mapping, they can generally be categorized into different methods. Researchers have used similar techniques for assessing landslide susceptibility mapping, which can be classified as heuristic, statistical, deterministic, and a combination of statistical and deterministic methods. Statistical approaches, such as multivariate and bivariate statistical techniques, are widely used worldwide and provide reliable results (Wubalem, 2021). This approach includes bivariate statistical models, such as weights of evidence and frequency ratio, as well as multivariate statistical techniques, such as logistic regression. Additionally, nonlinear methods like support vector machines and artificial neural networks are also utilized in landslide susceptibility mapping (Goyes-Peñafiel & Hernandez-Rojas, 2021).

The use of statistical models in producing susceptibility maps has seen significant improvements, which can serve as a basis for hazard risk management (Ayalew et al., 2004). This research utilized a GIS-based statistical method using bivariate (Weight of Evidence) and multivariate (Logistic Regression) techniques. The Weight of Evidence (WoE) method, based on Bayesian theorem and probability concepts, was employed to assess the importance of evidential variables by analyzing their spatial relationship with landslide-affected areas and known landslide locations (Goyes-Peñafiel & Hernandez-Rojas, 2021). The weights of evidence modeling used the Bayesian probability approach and were originally designed for mineral potential assessment. This method has also been applied in landslide susceptibility mapping in the past three decades (Meten, Bhandary, et al., 2015b). Nowadays, the weight of evidence model is the most commonly applied method for landslide susceptibility mapping as the model is simple, easy to use, and less time-consuming. Logistic regression is the most commonly used multivariate method as it can be used for various purposes. To predict a result measured by a binary variable such as the presence or absence of landslides

based on a set of one or more independent variables, it does not require the variables to be normally distributed; the independent variables can be non-linear, continuous, categorical, or a combination of both continuous and categorical. It helps form a multivariate regression analysis between the dependent and several independent variables (Meten & Prakash Bhandary, 2020). This method has also been widely used for landslide susceptibility concerning triggering factors. This method is useful when the result-dependent variables are binary or dichotomous (Wang et al., 2022). The presence or absence of a landslide is the dependent variable in this analysis. As the dependent variable is dichotomous and the relationship between the dependent variable and independent variables is nonlinear, a logistic multiple regression model was constructed based on the causative factors for landslides (Meten & Prakash Bhandary, 2020).

The study area falls in the Central Ethiopian highland Amhara Regional State. The present study area is a part of the Ethiopian highlands, having a complex geological setting severely affected by landslide incidences in recent years and has not been studied particularly. The primary objective of this landslide susceptibility modeling is to provide realistic data and information on critical landslide causative factors discussed earlier to ensure that more or less the unstable areas are to be identified and propose remedial measures for its stabilization. These can be done through Remote sensing technology, which provides up-to-date geographic information and is the primary source of input data for assessing and monitoring landslides. For proper and strategic planning, it is required to evaluate and delineate landslide-prone areas using landslide susceptibility modeling techniques like weights of evidence and logistic regression models, which are bivariate and multivariate statistical models.

1.2 Statement of the Problem

Landslide-generated hazard is one of the major geo-environmental problems that cause considerable damage to houses, infrastructures, and the natural environment. It poses a threat to society's well-being; in particular, locals who live close to the bottom of steep slopes are highly affected by active landslides. There are active landslides along road sections and nearby with various degrees and ways of collapse. The main factors of land sliding in the Ethiopian highlands include the high relief (on average between 2000 and 3000 m), induced by the large-scale Pliocene-Quaternary uplift, and the resulting rugged morphology, characterized by very deep valleys and gorges with high steep slopes. Energetic river incision is tremendous and causes further slope steepening and instability. Hydrological triggering mechanisms of landslides, both antecedent rainfall, and a critical intensity of rainfall are also

important factors in triggering landslides. A review of various studies on landslides in the highlands of Ethiopia revealed that most of the reported rainfall-induced landslides have occurred during prolonged and heavy rainfalls, mainly in the period mid-August and mid-September. Moreover, anthropogenic activities such as deforestation, overgrazing, intensive farming, and cultivation on a steep slope can initiate slope instability. As the Google Earth map show, the study area is part of the Ethiopian highlands.

In the study area, landslide-generated problems are becoming serious concerns for local people. In general, the Ethiopian highlands, as the study area, consist of a very deep valley, gorges with steep slopes, active river incision, different geological settings, etc., and have a very complex geological and hydrogeological framework and more complicated surface and subsurface water interaction. They are also associated with weak structures like faults, fractures, and others. Moreover, the study area is highly susceptible to landslides due to the presence of weak geological material effects. Geological effects such as the presence of tributary rivers that feed the Abay River, drainage density pore water pressure generated due to excessive precipitation, etc., geomorphology, and different lithologies like Mesozoic sedimentary (alluvial deposits, limestone, sandstones, marl, and gypsum) and weathered or incompetent igneous rock mainly basalt (Paleozoic glacial tallies, post-glacial sediments, and shales). These complex phenomena living around this area extremely difficult unless a detailed landslide susceptibility study is conducted and proper remedial measures are provided. Proper land use planning development and management of landslide-prone regions are conducted. Although investigations on landslide problems were conducted in many parts of the Ethiopian highlands, no research was done in this particular study area. Since a landslide is a complex geological phenomenon, it requires a suitable method to identify the causative factors for landslide occurrence using a suitable method. This research work is therefore intended to fill these gaps.

1.3 Objective of the Research

1.3.1 General Objective

The general objective of this research is to prepare a landslide susceptibility map of the study area using bivariate (Weight of Evidence) and multivariate (Logistic Regression) statistical approaches with the aid of GIS-based techniques.

1.3.2 Specific objectives

- To identify the type of landslides occurring in the study area based on the materials involved.
- To understand the processes and factors leading to slope failure and prepare the landslide causative factors and landslide susceptibility maps.
- To validate the resulting landslide susceptibility models.
- To recommend possible remedial measures based on the results of the current study.

1.4 Significance of the Study

This study will help to:

- Upgrade the information to create better awareness of landslide impacts, particularly for rural people who live and farm near the toe of hill slopes.
- Provide information that helps the community settle there to minimize landslide impacts and thereby reduce casualties (deaths and injuries), suffering, and natural environmental destruction.
- Acquire tangible data/information that demonstrates how human activities can facilitate and increase landslide hazards, and based on which it will be possible to educate them on how to minimize socio-economic losses and natural environmental damage due to landslides in the area.
- Obtain data and develop possible recommendations to reduce the impact of landslides.

In general, the study will have the utmost significance for the local community in the study area. As the study area is located in a landslide-prone region of the country's central highland, fertile soils are being eroded, and families and animals are being lost. Not only that, it is also a critical issue for the country as landslides mainly occur at the tributaries of the Blue Nile River, which increases siltation in the Grand Ethiopian Renaissance Dam (GERD) reservoir. Additionally, small towns are emerging rapidly, such as Bichena.

Therefore, detailed landslide susceptibility mapping is needed before grand projects and infrastructure facilities are installed in the study area. Moreover, the results obtained from this study will also be used as a reference for other related hazards that may be conducted in similar areas by different researchers.

1.5 Limitations of the Study

No existing roadways connect all areas of the study area, making it usually hard for motor vehicles to enter the area. Traversing various parts of the research area is challenging due to the type of soil and its landscape. A limitation in obtaining the necessary database for this investigation was the unavailability of previous landslide records in all parts of the current study area. The dense vegetation in some areas, deep gorges, and steep rocky slopes made it difficult to access data such as spring locations for detailed analysis of groundwater conditions during the investigation of landslide areas. Political instability is another challenge, especially along the border between the Oromia and Amhara regions. Therefore, in inaccessible locations, the use of Google Earth photos and different office data interpretation was necessary to generate a map of the study area's landslides.

1.6 Organization of the Thesis

The current study is divided into seven chapters. The first chapter introduces landslides, describes the study area, presents the problem statement, outlines the objectives of the investigation, discusses the significance of the study, and addresses the limitations of the study. The second chapter examines extensive literature on landslides, landslide controlling factors and their impacts particularly in the northern part of Ethiopia, classification of landslides, landslide components, types of landslide maps, landslide susceptibility mapping techniques, regional geology of the area, and previous landslide studies in Ethiopia, as well as previous landslide studies and gaps in the study areas. The third chapter provides an overview of the study area, methods, and materials used for data collection and processing, and the preparation of the landslide inventory dataset of the study. The fourth chapter focuses on the geology of the area. Chapter Five discusses the causative factors of landslides and the distribution of landslides in the study area. The sixth chapter examines the relationship between landslide occurrence and causative factors, presents the landslide susceptibility map utilizing the WoE and LR approach, and validates the anticipated model. Finally, chapter seven presents the conclusion and recommendations of the study.

CHAPTER TWO

LITERATURE REVIEW

2.1 Definition of Landslide and Their Impact

Scholars have provided different definitions for the term "landslide". Geologists, engineers, and other professionals often rely on unique and slightly differing definitions, reflecting the complex nature of studying landslide phenomena (Mersha and Meten, 2022). This study established a widely accepted definition of landslide: the movement of a mass of rock, soils, debris, and organic materials down a slope under the effects of gravity (Nohani et al., 2019). Landslides are recurrent natural hazards that occur worldwide, particularly in mountainous and weak geological areas. They cause significant injury, loss of human life, and damage to properties and infrastructures (Atta-ur-Rahman et al., 2011). Rock slope failures, which are geological activities controlled by natural physical processes, are a major contributor to economic losses, property damage, maintenance costs, and injuries (Hoek and Marinos, 2000). These failures occur when driving forces exceed resisting forces, where gravity represents the main driving force and shear strength represents the resisting force. (Pantelidis, 2010). Therefore, conducting a detailed and systematic study, starting from defining the term, extending to mapping and providing appropriate preventive, and mitigation measures for different types of landslides, is of paramount importance. (Hamza and Raghuvanshi, 2017).

2.2 Landslide hazards controlling factors in Ethiopia, particularly in the highlands of Ethiopia

Landslide controlling/influencing factors are those factors that make the slope susceptible to movements without actually initiating it and thereby tend to place the slope in a marginally stable state. The factor that initiates the movement of the slope, which was on the verge of failure, is the triggering factor. For instance, in low-relief areas, landslides occur as cut-and-fill failures (roadway and building excavations), river bluff failures, the collapse of mine-waste piles (especially coal), and a wide variety of slope failures associated with quarries and open-pit mines. Landslides commonly occur in conjunction with other natural hazards such as storms, floods, earthquakes, volcanic eruptions, or tsunamis. Water pressure reduces the normal pressure on the discontinuity, lowering the shear strength. Rainfall-induced slope failures are common in hilly and mountainous terrains of Ethiopia characterized by a variety

of topographical, geological, hydrological (surface and groundwater), and land-use conditions (Woldearegay, 2013). A review of previous studies on rainfall-triggered landslides in the highlands of Ethiopia revealed that most slope failures occurred in areas with specific geological (lithological and structural) settings, slope shapes, slope gradients, drainage lines (stream incisions/gullying), artificial excavations (cuts), and vegetation cover. From 2004 to 2016, over 55,000 people lost their lives due to landslides, not including deaths caused by seismically triggered landslides. Overall losses were estimated to be USD 20 billion annually (Sim et al., 2022). The same is true for the Ethiopian highlands. There is no significant association of landslides with seismicity and geological structures compared to the MER region, which is prone to landslides due to tectonic structures and seismic activities. The Ethiopian Plateau is dominated by an active drainage system, including the Blue Nile and its tributaries, leading to active landslides (Gani and Abdelsalam, 2006).

2.2.1 Influence of Geological (Lithological and Structural) Settings

Factors inherent like the materials and discontinuities may influence the engineering characteristics of slopes. As it causes a marked anisotropy in the permeability, strength, and deformation characteristics of soil/rock masses. The presence of filling material between the rock units can also affect the stability of the rock when the water washes away the rock easily fails toward the free face. Though different rock types rarely represent the highlands of Ethiopia, most of the reported landslides took place in areas that are underlain by: (a) incompetent rocks (Paleozoic glacial tallies, post-glacial sediments, and Shales), and (b) competent rocks (basalt flows) which are associated with volcanic ash/lacustrine deposits. According to (Woldearegay, 2013) the prevalence of landslides in areas underlain by Paleozoic glacial tallies, post-glacial sediments, and shale (in northern Ethiopia) is attributed to the fact that these slope masses are associated with (a) low shear strength behaviors, (b) low permeability characteristics, which enhance the development of seepage forces within the overlying slope masses, and (c) high susceptibility to weathering, erosion, and lubrication (softening). The landslides in the rift margins of the highlands of Ethiopia are associated with deep-seated, structurally controlled deformations that require a comprehensive understanding of the geological and structural settings to clearly define the failure mechanisms and mitigation options

2.2.2 Influence of slope gradients on landslides

It is known that gravity is the primary force that generates movements on slopes. Several published and unpublished papers have reported that most debris/earth slides/flows and

rockslides occur in areas with slope angles ranging from 15° to 45°. The low likelihood of landslides occurring in low slope gradients is due to the corresponding increase safety factor and a higher water table required to initiate failure. Conversely, major debris/earth slides and debris/earth flows are absent in terrains with slope gradients greater than approximately 50 degrees, as these terrains typically lack significant thickness or even absence of unconsolidated deposits. Landslides can occur when slightly to moderately weathered rocks dominate most steep slopes. Moderately steep terrains are often covered by vulnerable unconsolidated deposits, which are prone to rainfall-triggered slope failures as water percolates between cracks and easily undergoes weathering, applying pressure due to increased water volume as it cools to ice, ultimately initiating landslides.

2.2.3 Influence of Slope Shapes (Curvature) on Landslides

Slope geometry is an important factor that affects slope stability. Slope shapes influence the susceptibility of landslides by governing the distribution of water (surface/subsurface) within a slope. Positive plan curvature values (convex) indicate divergence and negative plan curvature values (concave) indicate the concentration of flow. Concave plan terrains promote the concentrated flow of water, while convex plan terrains cause divergence of flow curvature and regulate converging/diverging flow and soil-water content. No systematic comparison of slope forms and reported landslides was done for all of the landslides in Ethiopia, however according to (Woldearegay, 2013), many of the landslides occurred in concave locations, with some occurring on planar terrains. These authors claim that the high susceptibility of concave areas to rainfall-induced landslides is related to the fact that such terrains are connected to many factors. Such factors are (a) convergent water flows (surface and subsurface), which cause an increase in water pressure, (b) high susceptibility to subsurface erosion (piping) because the subsurface water flow is concentrated along previous layers, and (c) greater thickness of unconsolidated deposits, as these areas are typically zones of material deposition.

2.2.4 Influence of Slope Modification on Landslides

The majority of rainfall-triggered landslides in the highlands of Ethiopia have taken place in areas close to streams/topographic breaks or where there is active gully erosion. The association of landslides with drainage lines, which are affected by stream/river incisions and gullying, indicates the effects of land degradation and associated erosional processes on the initiation of slope failures in the highlands of Ethiopia. Some landslides have occurred along road cuts. Different authors have reported the association of landslides with road cuts.

This implies that there is a need for proper site investigation and remedial measurements before, during, and after road cuts (the maximum safest angle should be known before the slope cut) to mitigate landslides Fig 2.1.



Fig 2.1 Source: USGS landslide hazard report (Oita Expressway, which was buried by a massive landslide in Japan seven years ago).

2.2.5 Influence of Vegetation Cover on Landslides

The influence of vegetation cover on landslides is mainly associated with land use activities. The effects of vegetation on slope stability appear to be complex, depending on local conditions such as soil depth, slope, and type of vegetation. Vegetation cover can promote stability in some ways but may also impose a load on soil stability and cause landslides if the vegetation has short roots. The effects of vegetation cover on the hydrological processes of shallow landslides can be divided into three categories: interception of precipitation, removal of soil moisture through evapotranspiration, and effects on hydraulic conductivity. If the vegetation types in an area have significant weight and shallow roots located above the slip surface of the landslide mass, the presence of vegetation may increase the infiltration rate. This, in turn, increases water accumulation and decreases slope stability due to increased pore water pressure and unit weight of the sliding mass. However, as suggested by various authors, vegetation covers with deeper and broader roots have a positive influence on shallow debris/earth slides. These types of vegetation improve soil strength through root reinforcement and anchor slope masses into the underlying bedrock. A review of the behavior of vegetation on slope stability indicates that forests reduce the impact of climatic agents on natural masses, favoring slope stability (Dewitte and Dumoulin, 2005) and (Kanungo et al., 2013). Generally, to reduce soil erosion, an active policy of reforestation of

the steepest slopes has taken place to decrease soil erosion rates, suggesting that increased infiltration on these reforested hillslopes (i.e., enclosures) locally decreases slope stability.

2.2.6 Influence of Hydrological Condition on Landslide

Landslides often occur after heavy rainfall for a long time (Guzzetti et al., 2008). Most failures are caused by the effects of water in the ground, including pore pressures, and erosion of the slope materials. Water is considered the worst enemy of slope stability and human actions where excavations are carried out without adequate geotechnical care. The presence of water in a slope reduces stability by decreasing ground strength and increasing forces, which favor instability (Plate 2.1). On the other hand, the lowering of a lake or reservoir due to rapid withdrawal by water supply wells or the lowering of the groundwater table can cause slope failure when the buoyancy offered by the water declines and seepage gradients occur (B. Beyene et al., 2016). The main effect of water is a reduction in the shear strength of failure surfaces as the effective normal stress (σ_n) decreases (Wubalem, 2021). Water as a lubricant decreases the cohesion between geological units and exposes them to failure. In order to estimate sediment discharge, the Monthly Weighted Average Method needs to be utilized with hydrometric data, encompassing sediment concentration and flow discharge (Lin et al., 2008). This is another impact of surface water on human economic activities for small and mega projects like the GERD, which is affected by sediment accumulation in the reservoir area due to landslides occurring at Gojam and different parts of the northern Ethiopian highland.



Plate 2.1 Google Earth image showing the impact of water on slope stability in the study area (Lat. 10° 13' 58.34" N, long. 38° 21' 33.31" E).

2.2.7 Seismic Hazard

Earthquakes in steep terrain prone to landslides significantly increase the chance of landslides due to ground shaking alone or shaking caused by the deformation of soil elements, allowing for rapid water infiltration. Landslides caused by earthquakes frequently occur in tectonically active mountain ranges. Most of these slope failures, like rock or soil, falls, are reported of minor size, and just a few of them are claimed to have caused significant amounts of soil or rock material damage. Landslides caused by earthquakes have the same shape and internal dynamics as landslides not caused by earthquakes. However, they occur more frequently and abruptly. The most frequent types of earthquake-induced landslides are rock falls and slides of rock fragments on steep slopes Shao and Xu, (2022). Rock falls, disturbed rockslides disrupted earth slides, and avalanches of rock, earth, or debris are among the most frequent types of earthquake-induced landslides; nevertheless, earth flows, debris flows, and avalanches of rock, earth, or debris frequently transport the most material the farthest. Liquefaction failure is a type of landslide frequently occurring during earthquakes and can cause ground fissuring or subsidence. Sands and silts temporarily lose their strength due to liquefaction, which makes them behave more like viscous fluids than soils. In an earthquake, this might have disastrous results. The seismic hazard map of the whole country given by EBCS (1995) was used in this study to attempt estimate the study area's seismic hazard rating.

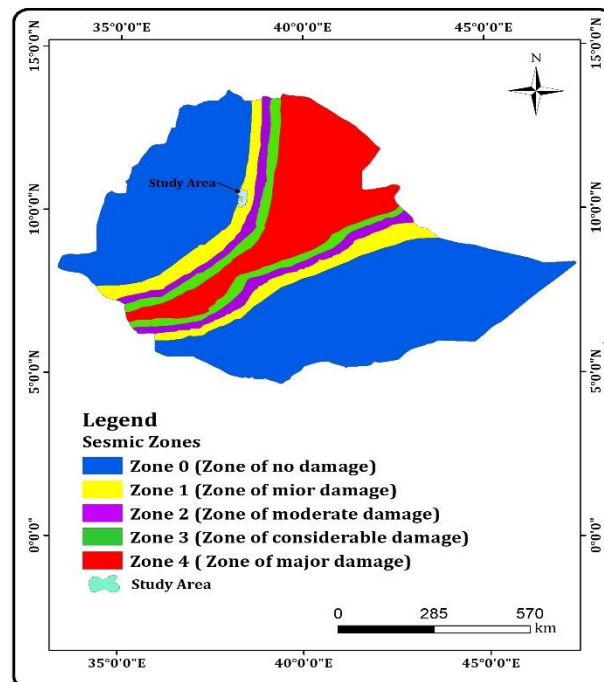


Fig 2.2 Seismic hazard map of Ethiopia for 100 years return period (EBCS, 1995).

This map was produced based on the magnitude of ground acceleration during a period of one hundred years. Based on the known history of devastating earthquakes, this map (Fig. 2.2) divides the country into five seismic risk zones. These zones range from earthquake-free zones (Zone 0), less destructive zones (Zone 1), moderate damage zones (Zone 2), and danger zones (Zone 3), to high-risk zones (Zone 4) (Fig 2.2). Zone 0 is regarded as seismically free, while Zones 1, 2, 3, and 4 are given constant bedrock acceleration rates of 0.03, 0.05, 0.07, or 0.1, respectively. The study area is located in the Southeast of the Choke mountain escarpment, which is part of the Ethiopian highland. It is about 225 km from the Main Ethiopian Rift (MER), an active seismic risk zone (Fig 2.3). This indicates that the study area is not close to active seismic zones. It falls partly in the Zero seismic zone (Zone of no damage) and the major parts of the area are in seismic zone 3 (Zone of minor damage) (Fig 2.2).

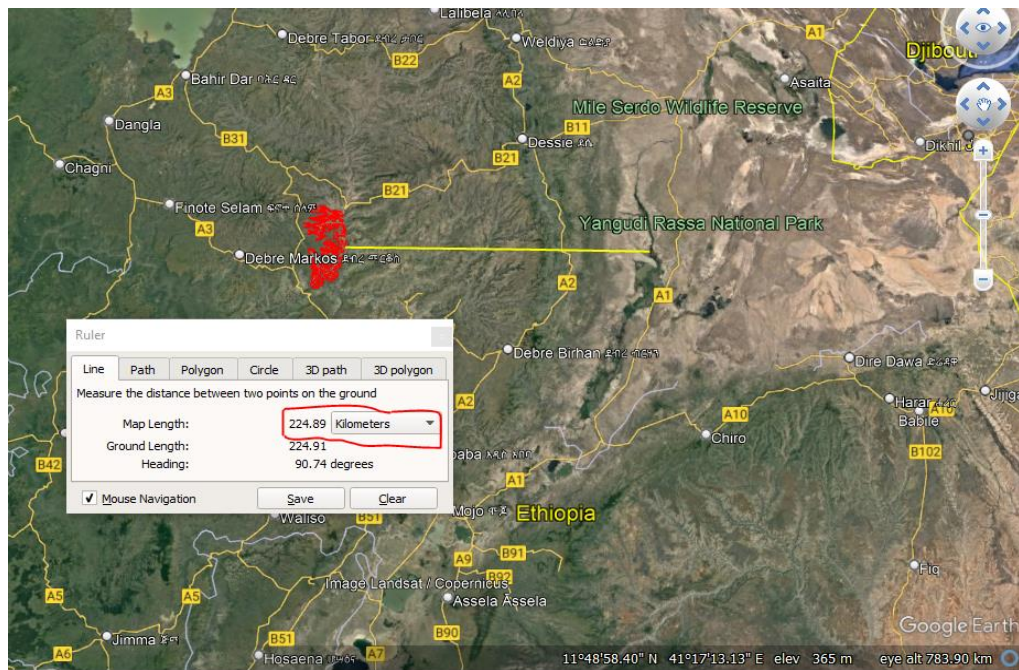


Fig 2.3 Google Earth showing the study area distance from the Main Ethiopian Rift (MER)

2.2.8 Influence of Soil Properties

The existence of soils with a high concentration of clay mineral smectites, also known as montmorillonite, is another supposed effect. These clay minerals enlarge when they are wet because water seeps into the crystal structure and expands the mineral's volume. Such clays shrink or compress as a result of water loss when they dry out (DiFonzo & Bordia, 1998). The soil influences landslides. I might occur if the field's soil moisture content exceeds the liquid limit. Since the Earth looks to be solid but has the potential to unexpectedly separate

when strained, this phenomenon has major and perhaps disastrous effects. By reducing capillary cohesiveness, increased soil moisture content affects the soil (Maiti & Bidinger, 1981).

2.2.9 Influence of Manmade Factors

The anthropogenic factor is another landslide influencing factors in Ethiopia.

2.9.9.1 Manmade factors

Land use and land cover change: Modifications in land use such as deforestation, agricultural activities, resource extraction, and changing vegetated slopes to built-up areas may cause landslides to occur (Kanungo et al., 2006; Manderso, 2021).

Vegetation: It is essential in limiting the activities that cause erosion on the slopes. Due to the natural anchorage provided by the tree roots, a heavily vegetated slope decreases the effects of erosion, whereas barren slopes are typically more susceptible to erosion activity, which leads to unstable slopes (Mersha, 2022).

Unplanned construction: Human intervention overloading or lateral support loss is a major concern for slope instabilities in many regions. Land-use change, such as deforestation, agricultural activity, exploitation of natural resources, conversion of vegetated slopes into built-up areas, etc. may result in landslide occurrences (Kanungo et al., 2006)

2.3 Classification of Landslide

Individuals performing landslide mapping must utilize uniform nomenclature to categorize moreover, characterize landslides. The characteristics of the movement and the type of earth material involved serve to distinguish the many types of landslides. Due to the complexity of movement, landslides can be divided into a variety of categories (Mersha and Meten, 2022). However, the (Cruden & Varnes, 1996) classification system is by far the most popular and is now acknowledged as the approved method of describing the nature of landslides. According to their classification, landslides were defined as the various types of movement experienced on one hand, and the kinds of materials involved on the other. In brief, material in a landslide mass is either rock or soil (or both); the latter is described as the earth being mainly composed of sand-sized or finer particles and debris if composed of coarser fragments. The type of movement, such as fall, topple, slide, spread, or flow, reflects the actual internal mechanics of how the landslide mass moves. Thus, rock fall, debris flow, and other identities that refer to material and movement, respectively, are used to characterize landslides (Table 2.1). In this section, specific descriptions of the various types of landslides that have occurred around the world are provided.

Table 2.1 Classification of landslide according to (Cruden & Varnes, 1996)

Types of movement		Types of materials		
		Bedrock	Engineering soils	
			Predominantly coarse	Predominantly fine
Rock fall		Rock fall	Debris fall	Earth falls
Topples		Rock topple	Debris topple	Earth topple
slides	Rotational	Rockslide	Debris slide	Earth slide
	Translational			
Lateral spreads		Rock spread	Debris spread	Earth spread
Flows		Rock flow	Debris flow	Earth flow
Complex's		A combination of two or more principal types of movement		

2.3.1 Falls

Falls are the sudden movement of a mass of geologic materials, such as rocks, boulders, or soils, which separate from steep slopes or cliffs along joints, beds, or weak areas Fig 2.4D. The dislodged masses fall, bounce, and free fall as they slide downward (Mersha, 2022). Undercutting slopes by streams and rivers or differential weathering, excavation during road building, loosening by rain, plant root wedging, expanding ice, and seismic shaking are some of the factors that cause falls.

2.3.2 Topples

Topples are similar to falls, except that the initial action involves a forward rotation of the mass. Toppling failures happen when the blocks roll over instead of sliding Fig 2.4E. They are found in columnar jointed volcanic terrain as well as along streams and river systems with steep banks. Topples can be comprised of rock, debris (coarse materials), or soil (fine-grained materials) (Ayele, 2019). Gravity, water, or ice in fractures within the mass, vibrations undercutting, differential weathering, excavation, or stream erosion are the mechanisms that cause topples. They can be exceedingly damaging, especially if the failure is quick or the velocity is high (Cruden & Varnes, 1996).

2.3.3 Rotational slides

Rotational slides can occur only in very weak rock masses, often under the surcharge of a stronger cap rock Fig 2.4A. Most rotational slides in rock proceed at slow to moderate speeds, in part because the rotating mechanism is self-stabilizing as gravitational driving forces decrease with increasing displacement. Rock rotational slide ("rock slump"): The

uncontrolled sliding of a collection of weak rock on a cylindrical or another rotational rupture surface. A strong primary scarp characterizes the morphology, a distinctive back-tilted bench at the head, and small internal deformation typically slow to moderately slow. Furthermore, under shear stress, a weak rock mass tends to fail ductility (Hung, 2005).

2.3.4 Translational slide

This type of movement often occurs along structural characteristics, such as a bedding plane or the contact between resistant bedrock and weaker overlaying material Fig 2.4B. The sliding surface is inclined and usually fails when it encounters geologic features like faults, joints, bedding surfaces, or rock-soil contact (Ayele, 2019). A block slide occurs when the underlying material slides as a single, less-deformed mass (Cruden & Varnes, 1996).

2.3.5 Spread

In flat terrain, lateral spreads are more common than other types of landslides. This movement occurs when a stronger rock or soil top layer extends and travels over a softer, weaker layer beneath it. Such breakdowns are typically accompanied by widespread sinking into the underlying weaker unit (Highland & Bobrowsky, 2008).

2.3.6 Creep

Internal shear stress causes this movement, as it is powerful enough to generate deformation but not strong enough to cause failure. Creeps can cause fence posts, telephone poles, power lines, and retaining walls to tilt (Fig 2.4 I) (Cruden & Varnes, 1996). It also shifts the trunks of trees on slopes. Creep is the slowest mass movement compared to other types, moving at a rate ranging from a few millimeters to several centimeters each year.

2.3.7 Earth flows

Earth flows occur on mild to moderate slopes with fine-grained soils, most often clay and silt, as well as weathered clay-bearing bedrock. The mass of an earth flow moves as a viscous flow with significant internal deformation. The susceptible coastal clay (fast clay) loses all shear strength with a change in its natural moisture content and abruptly liquefies, potentially damaging enormous regions and flowing for several meters. The failure depth might range from a few meters to many tens of meters (Cruden & Varnes, 1996). Common triggering mechanisms for earth flows include saturation of soil due to prolonged or intense rainfall, sudden lowering of adjacent water surfaces causing rapid drawdown of the groundwater table, stream erosion at the bottom of a slope, excavation and construction activities,

excessive loading on a slope, earthquakes, or human-induced vibration (Highland & Bobrowsky, 2008) Fig 2.4H.

2.3.8 Complex

Landslides are not listed as a separate category type, but the user of the classification can create composite types by combining two or more type names if advantageous (Hung, 2005). Sometimes a combination of two or more types of failures will occur in a single slope. This combination failure could occur simultaneously or during the lifetime of a slope failure (Cruden & Varnes, 1996). It is also difficult to directly identify from Google Earth, as it is a combination of different types of landslides.

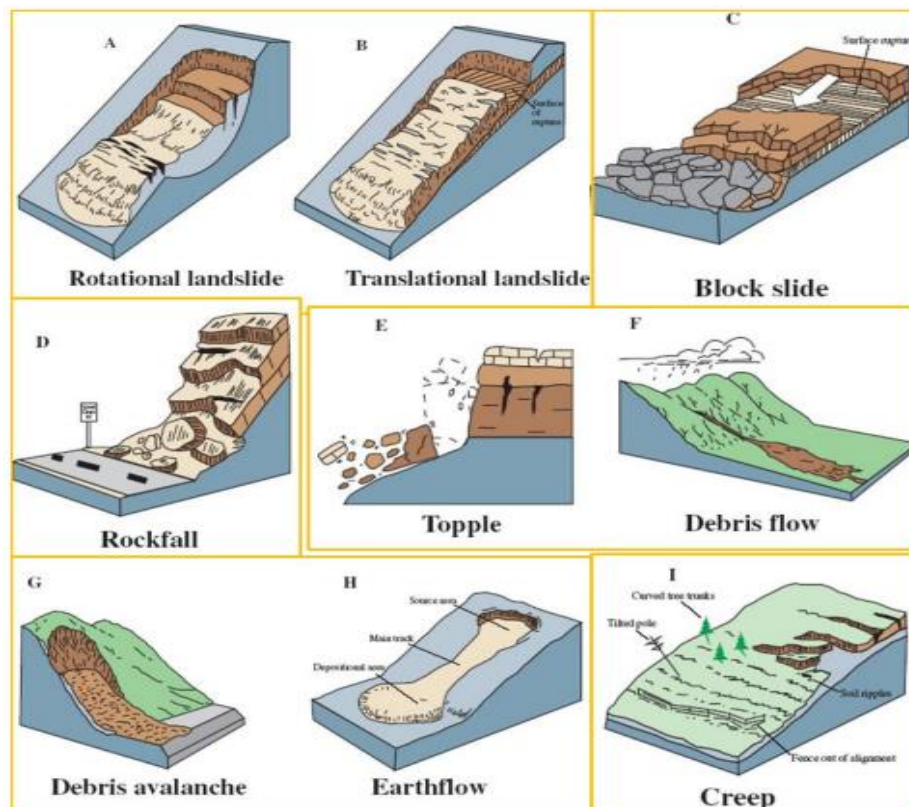


Fig 2.4 Types of landslides (Cruden & Varnes, 1996).

2.4 Different Types of Landslide Maps

Different kinds of maps are used to predict the danger of a landslide. The following types of maps are used to describe and depict landslide hazards: The threat of a landslide is projected using a variety of maps (Mersha and Meten, 2022). The information on landslide effects or damage can be very useful for both the government and communities living close to the landslide-prone area to conserve their environment and to make decisions for remedial measures.

The impact of landslides was explained increasingly from landslide inventory to risk mapping. The following map formats are used to explain and show the hazards posed by landslides:

2.4.1 Landslide Inventory Map

Landslide inventory is an essential first step in improving hazard mapping since it demonstrates previous landslides' distribution, types, and trends. It is based on the assumption that future landslides will occur under similar conditions as past landslides (Getachew & Meten, 2021). These slope failures are caused by climatic, topographical, and geological factors. As a result, they often make it easier to predict where and how future landslides may occur. The systematic mapping of landslides in a region using a variety of methods, such as field surveys, interpretation of satellite and air photograph images, and literature searches for records of previous landslides, is known as landslide inventory mapping (Ayalew, 1999; Mersha and Meten, 2022). Depending on the target, the scope of the research region, the scale of the base maps and aerial photographs, and the resources available to complete the task, various techniques can be used to generate landslide inventory maps (Getachew & Meten, 2021).

A landslide inventory map is also collected using Google Earth image interpretation. Field investigations, past landslide occurrences, and satellite image analysis created a GIS-based landslide inventory map. Field surveys and Google Earth imagery can also be used to create landslide inventory maps (Wubalem, 2021). Maps showing the locations and distributions of landslides that have moved in the past and present are the focus of landslide inventory maps. Geological, topographical, or climatic factors can cause a slope collapse. They can therefore frequently provide predictable potential landslide sites and situations (Blais-Stevens et al., 2011). The primary purpose of landslide inventory maps is to show the location (spatial distribution), type, and abundance of landslides in a region, to highlight the effects of significant landslide-triggering events like heavy rainfall, earthquakes, and so forth, to calculate the frequency-area statistics of landslide areas. In addition, it provides accurate data for creating landslide susceptibility and hazard models, thereby assisting in landslide risk assessment. The validity of these models, as well as the resultant landslide susceptibility and hazard maps, may be confirmed by inventory maps (Galli et al., 2008). The collected landslide inventory may be recorded either by the locality name or by landslide types depending on the data collector's interest or the compatibility of data for the organization.

2.4.2 Landslide Susceptibility Map

Landslide susceptibility map is created based on an appropriate selection of elements that significantly influence a site's slope stability. It depicts the relative likelihood of a future landslide occurrence in an area. The map takes into account various factors such as topographic features, geological conditions, climatic factors, and hydrogeological circumstances. To create a landslide susceptibility map, several essential steps are followed. Firstly, a landslide inventory map is created, which records past landslide occurrences in the area. Next, landslide-controlling factor maps are generated, identifying and analyzing the influencing factors such as slope angle, soil type, vegetation cover, rainfall patterns, etc. The next step involves determining the weightage or importance of each factor in contributing to landslide susceptibility. This is done through various statistical or analytical techniques to assess the significance of each factor. Finally, a GIS (Geographic Information System) procedure integrates the landslide inventory data, controlling factor maps, and weightage information to generate the landslide susceptibility map. It's important to note that the accuracy of the landslide susceptibility map can be influenced by several factors, including the selection of causative factors, their distribution in the area, and the model used for mapping. (Getachew and Meten, 2021). Therefore, landslide susceptibility is described as a quantitative evaluation of the type, amount, area, and spatial distribution of landslides that are present or potentially could occur in a region (Flentje et al., 2007; Ayele, 2019). Therefore, careful consideration and validation of these factors are necessary to ensure the reliability and usefulness of the resulting map for landslide hazard zonation, risk management, and further analysis

2.4.3 Landslide Hazard Map

The 'Slide' category Susceptibility maps that were previously described have been improved with more information about each landslide site and averages per zone, allowing them to be considered 'Slide' category Hazard maps. Hazard and susceptibility zones are linear. Even though significantly different types and levels of detail accompany the maps. Each landslide location is defined and tagged with its distinct location reference code on the Susceptibility and Hazard maps. Each landslide is also identified on the Hazard Maps with its unique frequency, volume, and "profile" angle (Flentje et al., 2007). According to Getachew & Meten (2021), the landslide is defined as "the process of categorizing the land surface into areas and ranking these areas according to the degree of actual or potential hazard from landslides or other mass movements". An essential phase in landslides' research

and risk management is the zonation of landslide hazards. A landslide hazard map shows the likelihood of landslides occurring in a specific location at a particular time or frequency. It can range from a basic map that indicates possible instability based on historical landslide locations to a more complex map that incorporates probabilities using variables such as rainfall thresholds, slope angle, soil type, and earthquake shaking levels. Landslide hazard maps often divide the research area into zones based on the degree of hazard to slope movement. Remote sensing techniques are commonly used for the detection, monitoring, and classification of landslides. Several studies have been conducted to explore the capabilities of available satellites and advancements in digital image processing technology to aid in landslide mapping and prevention. Various factors are associated with landslide occurrences, including lithology, curvature, aspect, slope, drainage system, precipitation, vegetation cover, and human-made factors such as road systems, structures, and deforestation. These variables are considered in the process of creating landslide hazard maps (Ayele, 2019).

2.5 Landslide Susceptibility Mapping Techniques

The term “landslide susceptibility mapping techniques” and landslide hazard zonation (LHZ) mapping techniques are used interchangeably. In the past, researchers have utilized different techniques with GIS (Geographic Information System) to assess landslide susceptibility mapping and identify susceptibility zones in various regions worldwide. However, there is no universally accepted technique for efficiently evaluating landslide hazards (Ibrahim, 2011) unpublished paper; (Pardeshi et al., 2013; Ayele, 2019). Kanungo et al. (2009) categorized various landslide hazard zonation methods into qualitative and quantitative approaches. Geomorphological analysis and inventory techniques are examples of qualitative methodologies. These rely more on the judgment of experts and are more specific than quantitative approaches. Quantitative procedures like deterministic analysis, probabilistic approaches, and statistical techniques all heavily rely on mathematical models, which have quite less personal bias but still need the skills to develop and operate Fig 2.5. It should be noted that while these various approaches have been used, no single technique has emerged as the standard for assessing landslide hazards (Mersha and Meten, 2022) The following is an explanation from Kanungo et al. (2009) of the various methods for landslide hazard zonation mapping.

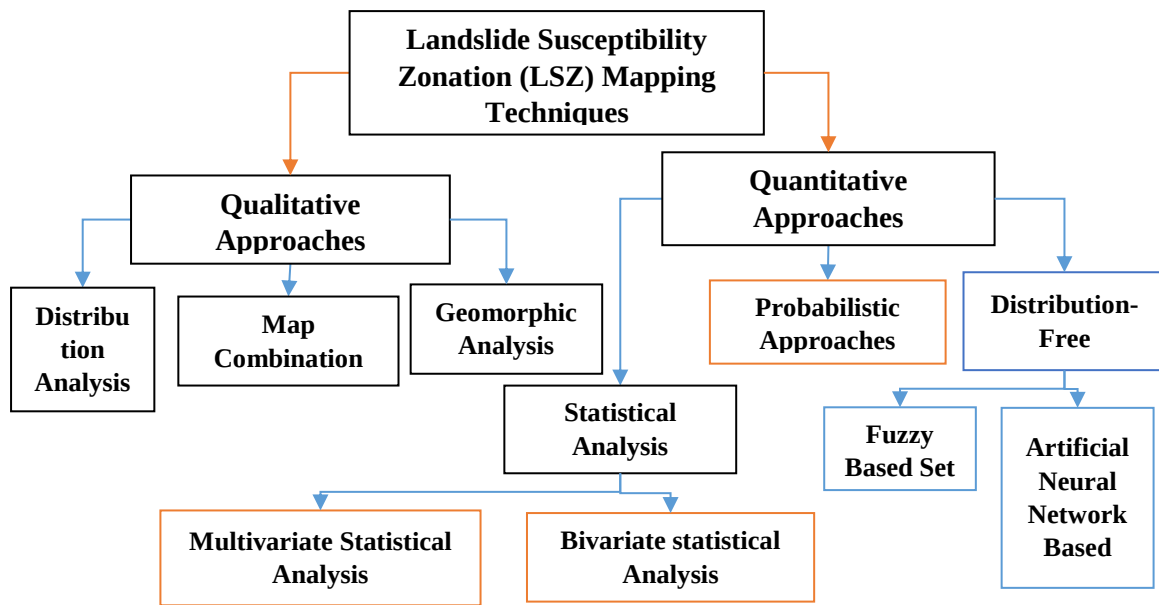


Fig 2.5. Flow chart showing the taxonomy of the LSZ Map approaches (Kanungo et al., 2009)

2.5.1 Qualitative Approaches

The qualitative method, which is an expert-based technique, has a problem with subjectivity when ranking weights for conditioning factors. Although this is based on personal judgment and the quantitative approach slope stability analysis employs mathematical formulas rather than descriptive ones (Wubalem and Meten, 2020). Geomorphological analysis and direct field mapping are examples of qualitative procedures since they rely more on judgment and personality than quantitative approaches and are based on observation. The primary drawback of the qualitative approach is that accuracy depends on the researchers' knowledge. Typically, the input data come from observations made during field visits, possibly supplemented by the interpretation of aerial photographs. These procedures are also known as expert evaluation. (Ayele, 2019).

2.5.1.1 Field Geomorphological (Heuristic) Approaches

It is probably the most straightforward kind of qualitative technique and is applied directly in the field. Earth scientists can assess the actual and potential slope failure based on their experience. The fundamental shortcomings of this approach are the subjectivity involved in choosing the information and regulations that control a slope's capacity or the risk of instability.

It is tough to compare because the results from different researchers in the same field vary, and the use of implicit rather than explicit principles makes it difficult to analyze the results critically and makes it challenging to update the assessment as new data becomes available (Aleotti & Chowdhury, 1999; Ayele, 2019).

2.5.1.2 Distribution Analysis

One of the easiest qualitative LHZ mapping techniques is distribution analysis. It is sometimes referred to as a "landslide inventory." This research generates landslide inventory maps that show the spatial and temporal distribution of landslides, their types, rates, and types of displaced material (earth, rock, debris, etc.). Field survey mapping, historical records, interpretation of satellite pictures, and aerial photo analysis gather data *about* landslides. Other landslip susceptibility methods are based on maps of landslide distribution and density (Pardeshi et al., 2013; Ayele, 2019) As it has an advantage over other approaches, there is also some drawback to these approaches. The primary limitations are as follows: (a) Inventory Mapping does not consider the connection between the landslide and its fundamental causative factors. (b) They exclude the temporal variations in landslide distribution. (c) They do not offer details on how susceptible future landslide activity will be. The main benefit is that they can be used to present landslide densities quantitatively. They help offer personal information about the local landslide activity.

2.5.1.3 Map Combination Approaches

This method for mapping the likelihood of landslides necessitates the creation of thematic data layers referring to various causal elements. The lithology, lineament, slope, aspect, land use, land cover, drainage, etc., are frequently included in this list. Combining this LSZ map is created in a GIS system using thematic layers with weights based on their relative value. However, in this method, the weights are allocated based on the expertise of the subject- and study-area experts. From expert to expert and from region to region, the weight may change. The main drawback of this strategy is how weights are subjectively assigned to each thematic data layer and its categories (Mersha and Meten, 2022; Ayele, 2019)

2.5.2 Quantitative techniques

Quantitative techniques for assessing slope failure include field geomorphological approaches, which rely on the experience of earth scientists, and distribution approaches that analyze the spatial and temporal distribution of landslides. Map combination approaches involve creating thematic data layers and assigning weights based on expert knowledge. Quantitative methods, such as deterministic analyses, probabilistic approaches, and

statistical methods, use mathematical models to assess landslide hazards and susceptibility. (Shano et al., 2020; Mersha and Meten, 2022; Ruxton & Neuhäuser, 2013)

2.5.2.1 Deterministic Method

Deterministic methods consider factors such as slope angle, strength of slope material, moisture content, and depth of the groundwater table. On the other hand, heuristic methods, rely on field observation and expert knowledge to identify landslides. To calculate the safety factor, deterministic methods employ a physical model equation that considers the slope's angle, the cohesion and internal friction angle of the slope material, and its structural characteristics such as rock discontinuities and soil stratification. Additionally, these methods consider the moisture content, depth of the groundwater table, and pore-water pressure of the slope material. Decision rules are then developed or weighted values are assigned to the classes of index maps. These maps are subsequently combined to create a landslide susceptibility map (Meten, Bhandary, et al., 2015b). Engineering slope instability principles that provide hazard in absolute values in the form of a factor of safety are the basis of deterministic techniques. These techniques involve a quantitative evaluation of the many forces that contribute to instability and stability. The quantitative data for landslide hazards provided by the deterministic approach can be directly applied to engineering design. If determined by various experts, the landslide susceptibility and risk assessed by the heuristic approach for a given location may differ significantly. However, the ease of use of these techniques is what makes them so well-liked. Methods are well supported by the expertise and judgment of an evaluator and are based on facts, particularly field data. (Shano et al., 2020). These methods can only be used at large scales due to the requirement for comprehensive geotechnical data from individual slopes (Mersha and Meten, 2022). These types of methods were used for large-scale (1: 2000 to 1: 10 000) study areas, as it is difficult to survey a large study area. In addition, the method is not recommended for an area with extremely rugged topography, which is difficult to reach everywhere.

2.5.2.2 Statistical Method

Based on the relationship between previous landslide activities and landslide causative elements, statistical methods are indirect techniques that are used to assess spatial landslide instability. These methods have been used for landslide susceptibility mapping studies to reduce the subjectivity in weight assignment processes associated with qualitative approaches. GIS tools are categorized as bivariate and multivariate approaches in this analysis and are very useful (Zhou et al., 2002; Wubalem, 2020; Mersha and Meten, 2022).

To determine locations that would be susceptible based on landslide inventory, statistical tools systematically use mathematical functions. The statistical techniques can be successfully used for regional LSM by calibrating them with the spatial knowledge of landslide presence and non-presence (i.e., absence) (Mahalingam et al., 2016). To reduce subjectivity in the weightage assignment process and create more objective and reliable outcomes, the approach to LHZ has recently been changed from a heuristic (knowledge-based) approach to a data-driven (statistical) approach (Mahalingam et al., 2016). This method is broadly categorized into Bivariate and Multivariate statistical methods.

I) Bivariate Statistical Method

Bivariate analysis is a statistical technique for analyzing the relationships between two separate variables. The bivariate analysis aims to identify whether there is a statistical relationship between the two variables, and if so, how significant and in which direction it is. Bivariate statistical analysis compares the present landslide distribution with each data layer of the causative element to assess landslide hazard zonation. Weights for components causing landslides are allocated based on landslide density. The Weight of Evidence model is a log-linear Bayesian probability model that uses incidence of landslides as training data to predict landslide susceptibility. It calculates the probability of landslide hazards under unconditional and conditional circumstances. This model uses weight calculations to determine the spatial correlation between landslide occurrence and explanatory variables. The Weight of Evidence model has been widely used since the 1990s to determine landslide susceptibility based on various combinations of causative factors. (Pardeshi et al., 2013). There are several significant bivariate statistical techniques used in LHZ maps, including the frequency ratio method, Information Value Model (IVM), Weights of Evidence model, and Weighted Overlay Model (Kanungo et al., 2009; Pardeshi et al., 2013; Mersha and Meten, 2022). In addition, there is also a new improved bivariate statistical method called the Shannon Entropy (SE) model. According to (Sarkar et al., 2022), The frequency ratio model has been improved by Shannon's entropy model, which gauges system's instability, disruption, or uncertainties. Shannon's entropy provides a framework for calculating the major factors among the active factors contributing to an objective weight for the index system. However, bivariate statistical methods have a fundamental drawback in that they involve a certain amount of subjectivity, particularly in the weighting methods used to assign distinct causative factors. In this study, a landslide susceptibility map was generated using

the Weight of Evidence (WoE) method, along with multivariate logistic regression. The selection of WoE over other methods is justified by the following points:

- 1) WoE consistently generates outstanding landslide susceptibility maps, which are essential for this study.
- 2) WoE has demonstrated remarkable accuracy, as shown by previous research conducted by (Lee & Pradhan, 2007).
- 3) In areas with rugged and difficult-to-access terrain, where geotechnical data is scarce, the WoE model becomes particularly crucial. Deterministic methods cannot be applied effectively in study areas with such geomorphology and extensive coverage, as noted by (Meten et al., 2015; Mersha and Meten, 2022).
- 4) The input and output of the WoE model are simple and easy to understand.

II) Multivariate statistical method

Landslide susceptibility analysis often utilizes the quantitative statistical logistic regression (LR) technique, which predicts the likelihood of landslides occurring based on predictor variables. These variables can be continuous, discrete, or a combination of both, and they are not required to follow a normal distribution (Goyes-Peñafiel & Hernandez-Rojas, 2021). Logistic regression allows for predicting of a binary response variable, such as the presence or absence of landslides, using categorical and continuously scaled predictors (Shano et al., 2022). These techniques provide a layer of data indicating the presence or absence of landslides, determine the percentage of the area affected, and then reclassify the hazard level for a given area using a multivariate statistical method. In multivariate statistical analysis for landslide susceptibility zoning, each thematic data layer's contribution to the total landslide susceptibility is taken into consideration (Kanungo et al., 2009; Pardeshi et al., 2013; Mersha, 2022). These techniques provide a layer of data showing the presence or absence of landslides, determine the percentage of that region, and then reclassify the hazard level for a given area using a multivariate statistical method (Graddy & Wang, 2007).

Pardeshi et al. (2013) state that statistical analysis, artificial neural networks (ANN), multiple regression models, discriminant analysis, and logistic regression models commonly use multivariate landslide hazard zone mapping techniques. However, (Mersha and Meten, 2022) classify ANN under a separate distribution category (inventory) rather than as a statistical method. The limitations of the multivariate statistical approach include the following. These procedures require the analysis of large amounts of data and take a

considerable amount of time to complete; they require data from a population with a regular distribution, which is often violated. The combination of continuous (e.g., slope, curvature, aspect) and categorical (e.g., lithology, land use, land cover) elements can lead to inaccurate results; and some factors may have a weak physical connection to landslide occurrence, making their analysis challenging when combined with other factors (Mersha and Meten, 2022). For this research, logistic regression (LR) was selected as the preferred method among other multivariate statistical analysis techniques.

2.5.3 Probabilistic Approaches

Probabilistic approaches are used to assess landslide susceptibility and hazard zonation by converting the degree of association between previous landslide distribution and causative factors into values based on probability distribution functions (Pardeshi et al., 2013). These methods involve assessing the spatial, temporal, and amount probabilities of landslides using probabilistic techniques, comparing the spatial distribution of landslides with assumed causative factors within a framework of probability theory (Shano et al., 2020; Pardeshi et al., 2013). Terms such as favorability function, certainty factor, and Bayesian probability are used in these methods. The degree of association between each thematic data layer and the landslide distribution is converted into a value using probability distribution functions. It should be noted that while this method is quantitative, assigning weights involves some subjectivity (Pardeshi et al., 2013).

2.6 Previous Landslide Studies in Ethiopia

Landslide hazard is a significant environmental issue in Ethiopia, particularly in the country's northern, western, and southern highlands. These areas have rough morphology, complicated geology, unstable soil cover, high rainfall, high relief energy, and unpredictable hydrologic and hydrogeological conditions, all contributing to the wide distribution of landslides. These highlands are located away from the main Ethiopian Rift System and are not affected by landslides caused by seismic activity. However, there is a high association of landslides with seismic activity in the central part of the country along the main rift system and at the margin of the Ethiopian Rift (Ayalew, 1999; Abebe et al., 2010; Mersha and Meten, 2022; Wubalem, 2020; Woldearegay, 2013). Increased landslides have also been observed in Ethiopia's highlands due to recent increases in man-made activities such as road and construction projects (Ayalew, 1999; Woldearegay, 2013). Numerous studies have been conducted using various qualitative and quantitative techniques to determine the causes and

triggers of landslides in different parts of the country's highlands. One such study was conducted by (Getachew & Meten, 2021) in the Kabi-Gebro locality of the Gundomeskel area, located in the Abay Basin in the Dera District of North Shewa Zone in the central highlands of Ethiopia. The researchers conducted field evaluations and interpreted Google Earth images, identifying various types of landslides, including earth slides (rotational and translational slides), debris slides, debris flows, rock falls, topples, rock slides, creeps, and complicated landslides. They created a landslide susceptibility map for the research area using nine landslide causative elements, including lithology, slope, aspect, curvature, land use/land cover, distance to stream, distance to lineament, distance to spring, and rainfall. Recommendations to mitigate the impact of landslides in this area included implementing afforestation strategies on bare land, constructing surface drainage channels and ditches, providing engineering reinforcements like gabion walls, retaining walls, anchors, and bolts when necessary, and removing hazardous zones when possible.

Shano et al. (2022) studied the Shafe and Baso catchments area in the Gamo highland, Ethiopia's southern nation and nationality. He considered lithology, groundwater conditions, distance to faults, morphometric factors (slope, aspect, and curvature), and land use/land cover as landslide predisposing/influencing factors while using precipitation as the triggering factor integration with GIS-based statistical Logistic regression method. This conclusion states that the landslide influencing elements, such as distance to fault, distance to stream, groundwater zones, lithological units, and aspect, have shown the greatest effect on the incidence of landslides as they demonstrated larger than a unit odds ratio. The investigation by Mulatu et al. (2011) was conducted in South Western Ethiopia along the recently built route from Fofa town to Gilgel Gibe-II powerhouse. Their analysis has made an effort to provide details on the landslide hazard zones present along the proposed route. The landslide hazard evaluation factor rating scheme (LHEF) suggested by Anbalagan, (1992) has been used to define dangerous zones. He has used data on the main intrinsic causes of slope instability, including geology, slope morphometry, relative relief, land use and land cover, and groundwater conditions, which have been gathered for the LHEF rating method. The study area's slopes have been divided into three categories based on their landslide potential: High, Moderate, and Low. According to his study's findings, 54% of the slopes in the study region are classified as High Hazard, 34% as Moderate Hazard, and 12% as Low Hazard. Therefore, the Landslip Hazard Zonation demonstrates that there is a high likelihood of slope failures in the study area. In the Blue Nile Gorge in central Ethiopia,

Meten et al. (2015) discussed the impact of landslide factor combinations on the predictability of landslide susceptibility maps. The results of this study demonstrate that 595 landslides, including rockslides, rock falls, mudflows, and debris slides, have been located using Google Earth and field observation. Eight landslide factors were chosen to create a map of the region's landslide susceptibility using the frequency ratio model. The combination of four landslide factors (slope, lithology, land use, and distance from lineament) and seven landslide components (apart from distance from the river) had the same forecast accuracy of 87.7%. This demonstrated that these four landslide causes tend to have more of an impact on triggering landslides. Ayenew and Barbieri, (2005) conducted landslide studies and susceptibility mapping in the Dessie area, 22 distinct active landslide locations as well as 4 general landslide susceptibility zones were found in this investigation. The results of this study indicate that there may have been a variety of landslides in the area, including complicated, rock and debris falls, earth and soil slumps, and debris slides. These landslides were mostly caused by hydrological circumstances linked to gravity movements that were supported by the geotechnical properties of the soil and rock.

Ayele, (2009) investigated remote sensing and GIS to identify landslide hazard zones in central Ethiopia's Abay Gorge, particularly from Gohatsion to Dejen. He took into account a variety of potential causes, such as geology, groundwater quality, land use, land cover, drainage, structure, aspect, and slope. In this study, a comparison between the area's actual landslide incidents and the landslide danger map was made. He discovered that the maximum hazard zone encompasses 67% of the region. Woldearegay, (2013) reviewed the occurrences and influencing elements of landslides in Ethiopia's highlands and the implications for the construction of infrastructure. This work's review reveals that landslides caused by rainfall frequently damage Ethiopia's hilly and mountainous regions. These landslides resulted in fatalities, the collapse of engineering marvels, the destruction of agricultural areas, and harm to the ecosystem. Finally, he concluded that because Ethiopia is currently engaged in extensive infrastructure development, attention must be paid to landslides and ground failures caused by landslides to minimize losses from these hazards and create safe geoenvironments. Many more authors in different parts of the country have studied similar issues related to landslide problems (Abbate et al., 2015; Manderso; Wubalem, 2021; Hamza & Raghuvanshi, 2017; Meten & Prakash Bhandary; Shano et al., 2020; 2021; Mulatu et al., 2011).

2.7 Previous Landslide Studies and Gaps in the Study Area

Even though several scholars recognized landslide issues, particularly in Ethiopia's highland regions in the north, northwest, south, and southwest, they only looked at a small area of the entire country Fig 2.6. According to many researchers, most Ethiopia is made up of rugged terrain is vulnerable to landslides. This shows that further research is needed to cover every region of the nation, as Ethiopia is now investing extensively in infrastructure development. According to Woldearegay, (2013) to decrease losses from such risks and create a safe geoenvironmental, landslides and landslide-generated ground failures need to be given sufficient attention. For instance, except for a few localities like Selelkula (Meten, Bhandary, et al., 2015a), and Dejen (Addis, 2023) on the entire Abay (Blue Nile) Basin (Meten, Bhandary, et al., 2015a), and many more authors, there is no published or unpublished work about landslide investigations in the entire current study region by a combination of these two methods before the present study. The majority of researchers who conducted the landslide studies in the Central Highlands of Ethiopia (Aby George) were around Dejen to Gohatsion following the road from Addis Ababa to Bahir Dar only. However, landslide issues have severely affected the region in recent years. People have been forced to leave their homes permanently due to house losses, animal deaths, and damage to agricultural fields and crops. The current work was done to close this gap because of how serious this issue is in the area and to a large extent. Many researchers in Ethiopia focus on the impact of landslides only on the community in and around the risk area rather than global and the whole country impacts. Landslides can impose damage either directly or indirectly for both communities living around and far apart from the area. For instance, the boundary of the current study area was connected to the Blue Nile (Abay River) to the north, northeast, east, south, and southeast. The sediments that feed the Abay River originate more from Gojam. Then they are transported long distances to the Grand Ethiopian Renaissance Dam (GERD) reservoir following their drainage system. The drainage basin of the Nile, the longest river on Earth, along with its major tributaries, the Blue Nile, is one of the Nile basins in the northwest Ethiopian plateau that has periodically lost at least 93,200 km³ of rocks (siltation). (Gani et al., 2007). This siltation problem will be a great headache for such a gigantic project therefore, the current work was done to close this gap and the local effects Problems.

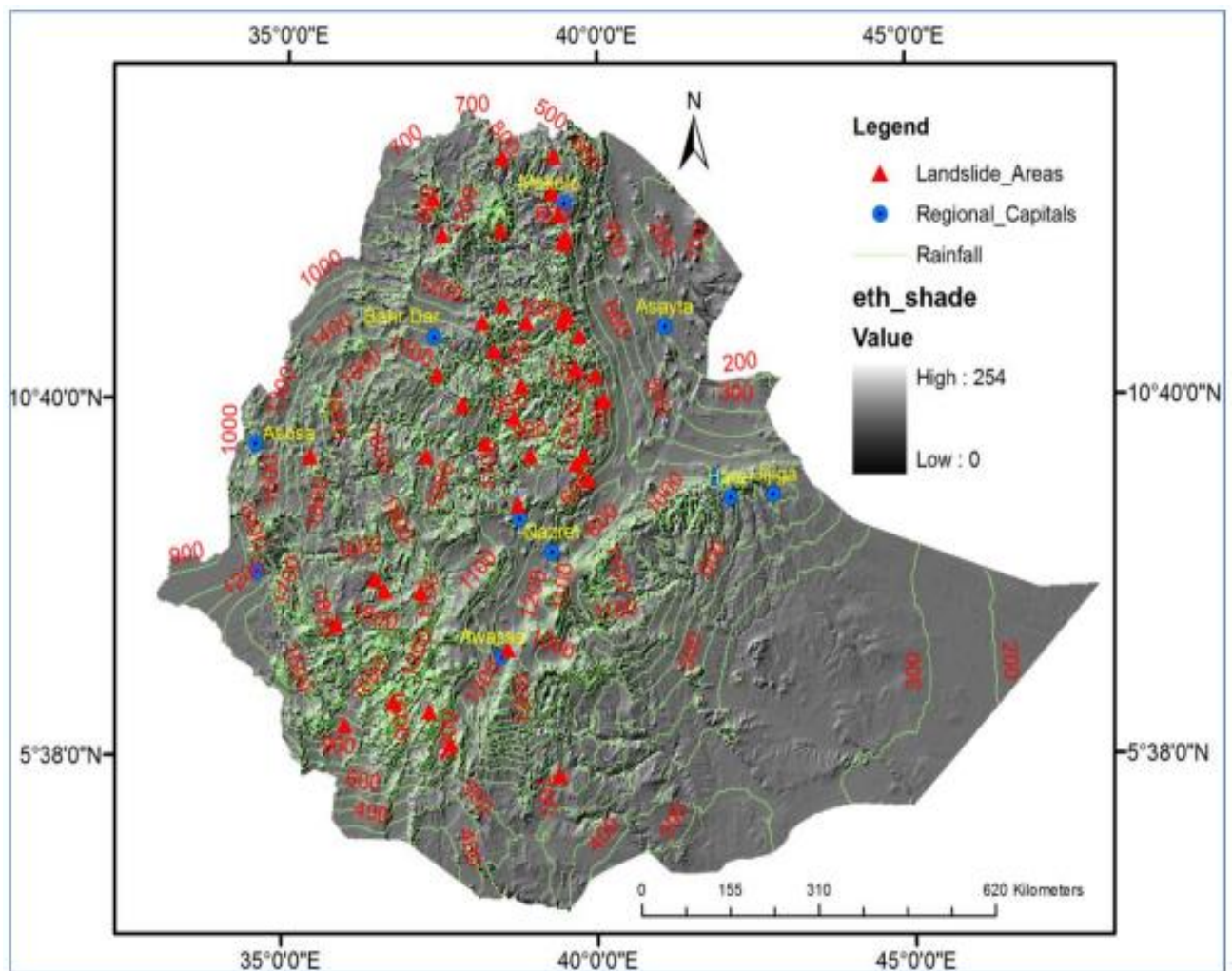


Fig. 2.6 Landslide distribution map from (Woldearegay, 2013).

CHAPTER THREE

DESCRIPTION OF STUDY AREA, METHODS, AND MATERIALS

3.1 Overview of the Study Area

3.1.1 Location of the Study Area

The study area is in the Amhara regional state in the central Ethiopian highlands part of the Blue Nile Basin (the Abay River and its tributaries). It is elongated 62.18 km from north to south and is 174 km from Addis Ababa, the capital city of Ethiopia. The study area is geographically bounded between 10° 8' 0" N to 10° 40' 0" N and 38°10'0" E to 38°35'30" E, covering an area of 1325.7 km². The Abay River (Blue Nile) bounds the study area to the south, southeast, east, and northeast.

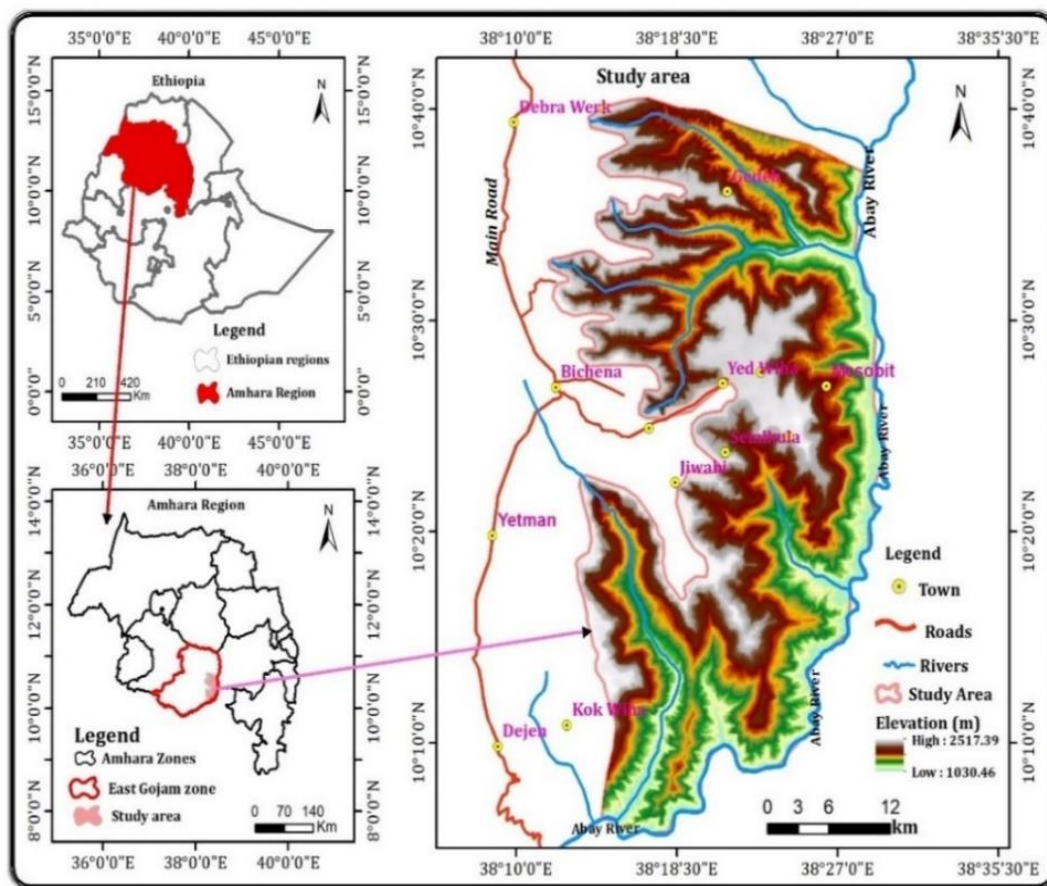


Fig. 3.1 Location map of the study area.

3.1.2 Physiography

The physiography of the study area was mapped using Surfer 25 software (Figure 3.2). The research area's physiography mainly belongs to the northwestern Ethiopian highlands, below Choke Mountain, with a peak elevation of 2500 meters above mean sea level and a lowest elevation of 1100 meters above mean sea level in the deep river valley. The presence of steep scarps, cliffs, sharp ridges, rugged slope faces, deep gorges, and valleys generally indicates that the area is prone to active surface processes and landslide activities. The study area can be divided into two main parts: a small plateau at the center and the dominant rugged morphology. The main physiographic zones that make up the study area include rough terrain, with a few kilometers of the plateau region in the central part (around Yetemen) formed by different flood lava flows of the tertiary age and quaternary eluvial sediments. The escarpments are cliffs formed from the Mesozoic limestone unit and the tertiary lava flows or basaltic lava. Deep gorges and sloping topography are due to the deep cuts of the major rivers and their tributaries.

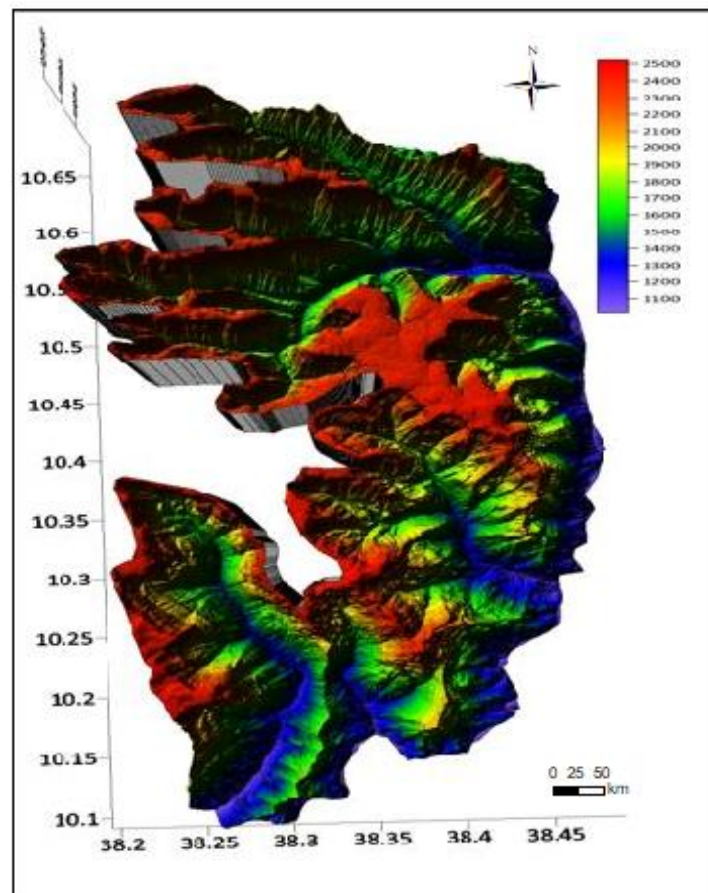


Fig 3.2 (3D) Physiographic map of the study area.

3.1.3 Drainage Network

The drainage patterns in the area are characterized by at least three patterns (Figure 3.1.3). Near the northern and northeastern part of the study area, the drainage pattern is dendritic, possibly due to the thick alluvial sediments developed on top of the basalt lava flows and down flow gully erosions from Mount Choke escarpment towards the tributary rivers, finally joining the Blue Nile (Abay) River and are the major pattern in the study area. The radial drainage pattern has been developed study area's peripheral north and northwestern parts. The dendritic drainage patterns are dominantly developed on highly weathered basalt and sedimentary rocks. The trellis drainage pattern developed due to the effect of folds, faults, and joints developed in the study area.

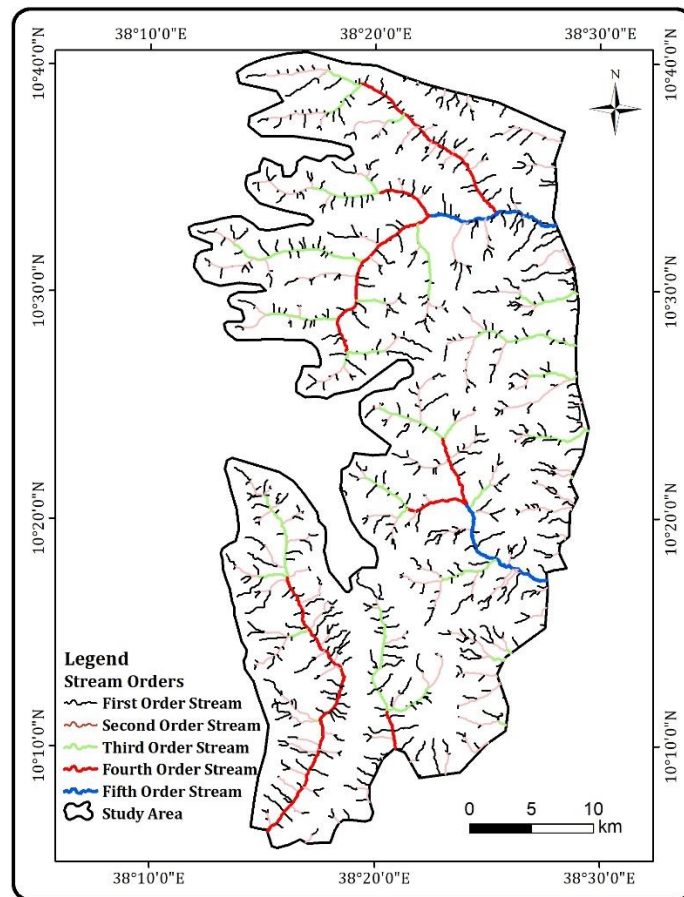


Fig 3.3 Stream order of the study area.

3.1.4 Climate and Vegetation

3.1.4.1 Climate

The geomorphology of Ethiopia is classified into three main parts. The Afar depression, Main Ethiopian Rift (MER), and Ethiopian plateaus all formed before Ethiopia's current morphology. The intrusion of one or more mantle plumes beneath the Afro-Arabian plate is

the cause of these episodes. The Ethiopian plateaus (high morphology) are the product of extensive volcanic buildup and subsequent uplift (Abbate et al., 2015). The diverse landscape of Ethiopia, along with the yearly migration of the Intertropical Convergence Zone (ITCZ) that tracks the position of the sun around the Earth and is associated with atmospheric circulation, has a significant role in regulating the temperature of the country (E. G. Beyene & Meissner, 2010). There are various classification way for Ethiopia's climatic systems (Haregeweyn & Yohannes, 2003). The traditional classification system (four seasons: Summer = Kiremt = Gana, autumn = Belg = Bira, winter = Bega = Bona) and spring = Tseday = Arfasa) in English, Amharic, and Afan Oromo respectively. Different researchers in the country primarily considered the height and temperature of the area (Wurch, Dega Weyna-dega, and Kola) in the Amharic language, from highland to lowland which is frequently used. Except for the lowlands which experience hot daily temperature (25-30°C), most parts of the area (about 75%) experience slightly warm temperature (18-22°C) and has an elevation above 2000m.a.s.l. Consequently, the area belongs to the Weyna-dega climatic zones (warm subtropical climatic conditions) and has a mean annual daily temperature of 20°C (National Atlas of Ethiopia, 1981).

‘Kiremt’ and ‘Belg’ rainfall accounts for the annual precipitation of the area. However, the June-September (Kiremt) rainfall makes up most of the rainfall in the region. Except for dense vegetation cover at the mountain summit, poor vegetation cover and diversity characterize the area. The climate in the study area falls under warm subtropical climatic conditions. The area receives rainfall twice a year, heavy precipitation from mid-June to mid-September (Kiremt or Gana) (Fig 3.4B), and light to moderate precipitation from mid-February to mid-March (Belg). The maximum mean seasonal rainfall is between 6000mm and 8000mm, which is the maximum rainy month in June, July, August, September, and October (Fig 3.4B). According to the data obtained from the meteorological agency, the area around Bichena gets moderate to high rainfall. However, the overall precipitation was situated more in the northern and northeastern parts of the study area, especially around Yetemen. Dejen also has high precipitation records (between 1997 and 2004) (Fig 3.4A). As for rainfall, data indicates June to August is the main wet season. The amount of rainfall varies greatly, with the highest months for rainfall being July and August during the rainy season, which goes from June to September (Fig 3.4B)

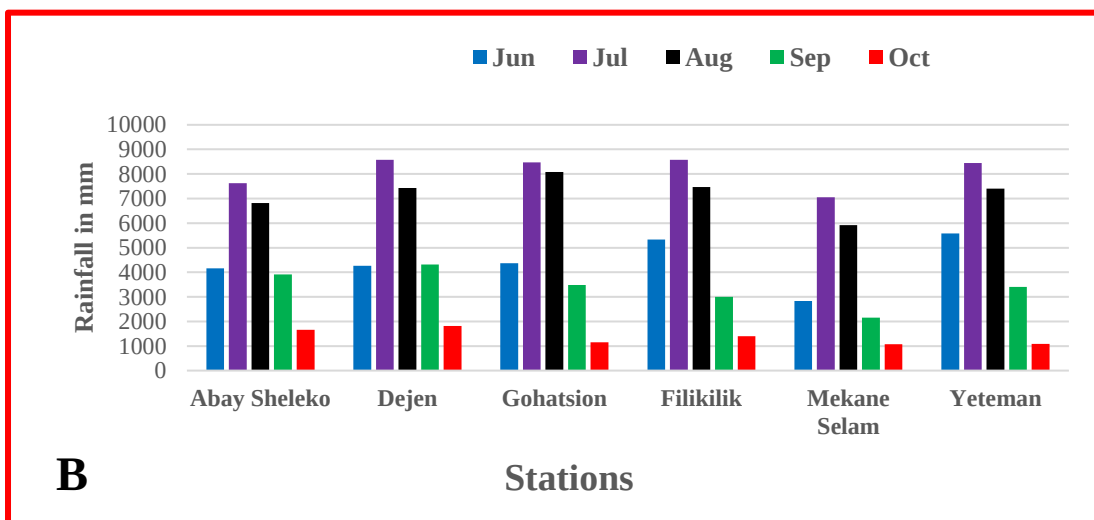
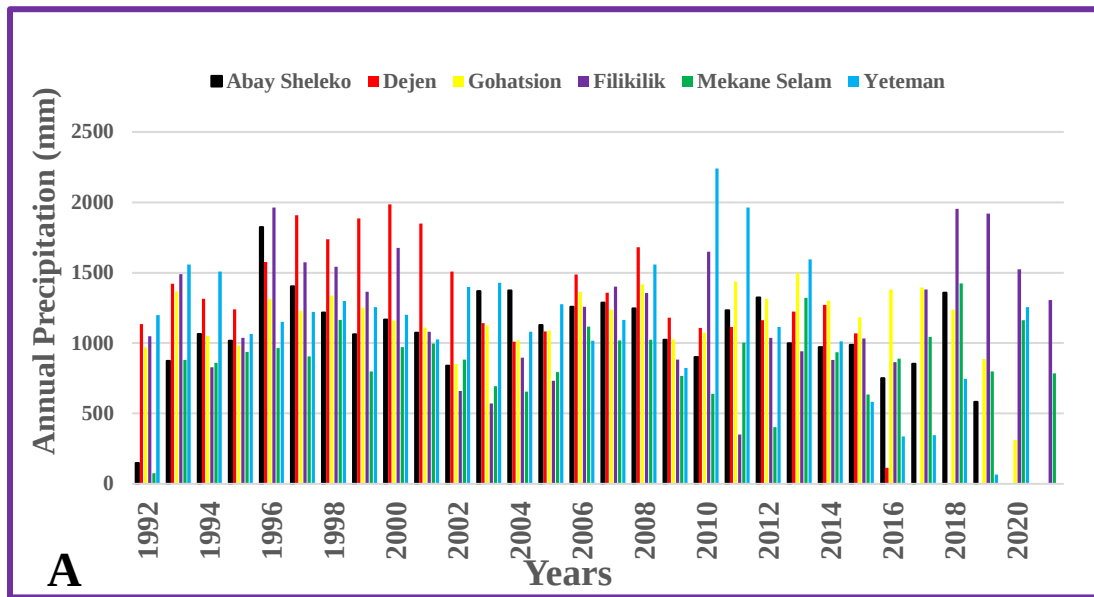


Fig 3.4 Total yearly Rainfall (A), Average maximum monthly rainfall (B) (Source: Ethiopian Meteorological Agency).

3.1.4.2 Vegetation

The presence of vegetation on slopes is essential for reducing erosional activity. A slope with dense vegetation has less erosion because of the natural anchoring provided by the tree roots. In contrast, bare slopes are more likely to have erosional activity, which leads to instability (Beck et al., 1996). In another way, vegetation with short roots may impose a load on the soil stability by itself and may cause landslides. Some of the vegetation encountered during traverses are woodlands, rangelands, and scrubs. The woodlands consist of eucalyptus and junipers.

3.2 Materials and Methods

3.2.1 Data Collection and Preparation

The data acquisition part of this research work involved primary and secondary data collected from different sources. Secondary data includes a comprehensive literature review of both published and unpublished papers. Regional geological maps, topographic maps, and meteorological data were obtained from the Geological Survey of Ethiopia, the Ethiopian Space Science and Geospatial Information Agency, and the National Metrology Agency of Ethiopia, respectively. Digital Elevation Model (DEM) with a spatial resolution of 30×30 m was used to generate topographic parameters such as slope, aspect, and curvature. The primary data, including landslide inventory maps, land use/land cover (LULC), and lineaments, were prepared using Google Earth Pro. The relationship between the factor classes and landslides in the study area was analyzed using the Weight of Evidence and Logistic Regression models of the triggering factor maps and landslide inventory map. Finally, validation was conducted based on the grid data map of the susceptibility index obtained from the two models. The Random Point tool were created through ArcGIS 10.8, and non-landslide points with the same number of geological hazard points was created and imported into SPSS software. The accuracy of the results of the two models was evaluated through the Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) analysis tools.

3.2.1.1 Landslide Inventory Dataset Preparation

Using Google Earth image interpretation, landslide distribution datasets were prepared, consisting of 4506 inventory polygons and 267,472 pixels representing landslides. In the Abay (Blue Nile) Basin, the frequency of landslides is attributed to previous tectonic changes that have led to extensive river incision and the formation of steep-walled cliffs, tabular ridges, and deteriorated masses (Ayalew & Yamagishi, 2005; Meten et al., 2015a). The study area exhibits various types of local landslides, including rockslides, rock falls, debris slides, and mudflows. The predominant types of landslides in the study area are debris slides and rock falls associated with river incisions. Landslides are concentrated in areas with high slopes and weathering, particularly in tertiary lower basalt and Mesozoic limestone units. The percolation of excess rainwater along fissures in weathered lower basalt and bedding planes of limestone and gypsum is a common trigger for rock slides and topples in this region. For landslide susceptibility mapping, there are training and validation datasets in the form of polygons. The validation dataset is used to predict the model's performance, while

the training dataset is used to construct the model. The exact dates of landslide occurrences are not well known for this investigation. Therefore, the landslide polygons were randomly divided into two classes, with 75% (3741 inventory polygons and 206550 pixels) and 25% (765 inventory polygons and 60922 pixels) being used for training and validation, respectively. Landslides primarily affect study area's southern, northern, southwestern, and eastern parts. These regions exhibit rugged topography with high relative relief, weathered rocks, steep slopes, and deep valleys leading towards the Blue Nile (Abay) and its tributaries, with different types of soil and rock groups.

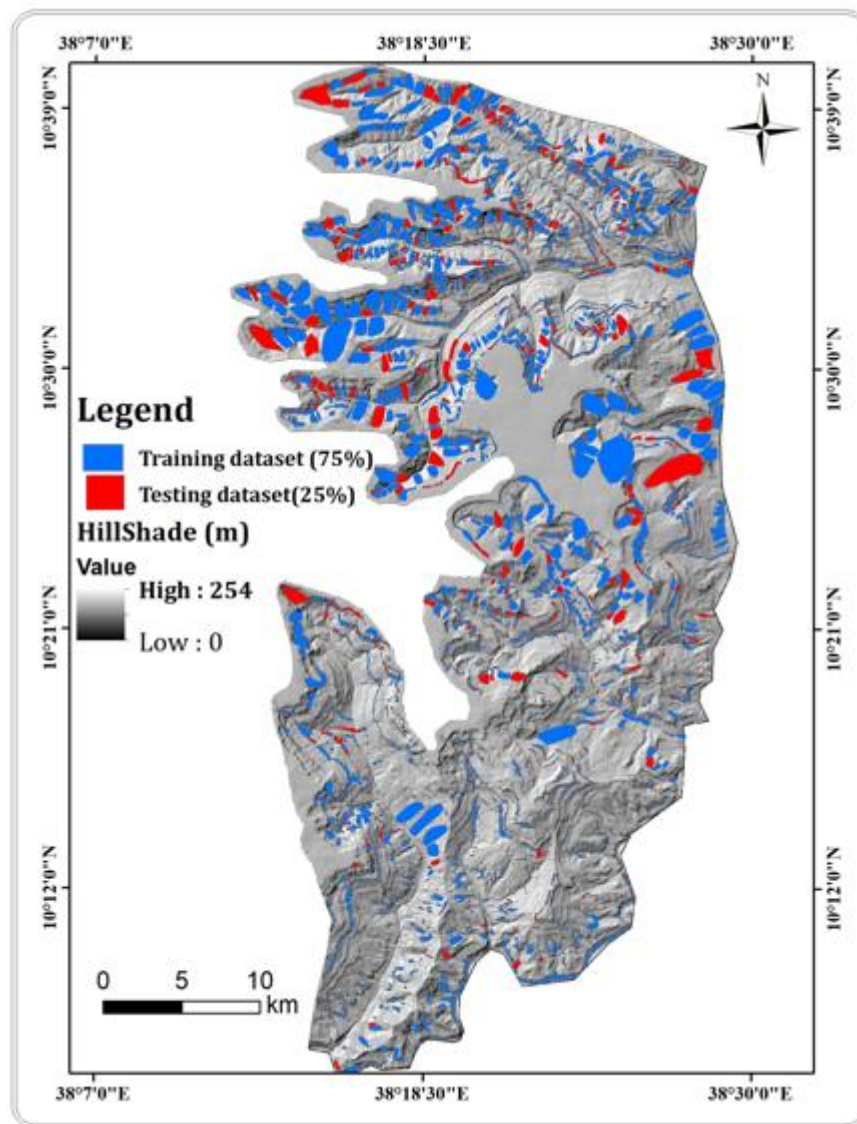


Fig 3.5 Landslide Inventory Training and testing dataset

3.2.1.2 Construction of Landslide Causative Factors Dataset

The ArcMap 10.8 software package, and spatial analytical tools in the GIS framework were, used for analysis. Eight landslide causative factors, including slope, aspect, curvature,

distance to stream, distance to lineament, lithology, and land use/land cover (LULC), as well as landslide inventory for training and validation, were included in the database. Raster maps of all causative factor maps were created using the projected WGS 1984 UTM Zone 37N coordinate system and a pixel size of 30m x 30m. The ArcGIS tool was used to determine the values of all factor classes for Weight of Evidence (WOE) and Logistic Regression (LR) models using the rasterized training (75%) landslide map and all causative factor maps. The spatial relationship between these landslide parameters and the occurrence of landslides in the study area was evaluated. The results were then validated using an analysis of these techniques based on the relationship between landslides and causative factors. Regarding various statistical techniques for landslide mapping, there are no formal standards for triggering factors. In some areas, one parameter could be a significant controlling factor for landslide occurrence, while not in others (Ayalew & Yamagishi, 2005). The selection of landslide causative factors requires considering the accessibility of data and the nature of the study. For example, areas without structural discontinuities do not require constructing distance to fault, and flat terrains do not need to consider slope, aspect, and curvatures. A Digital Elevation Model (DEM) downloaded from USGS was used to generate topographically governed characteristics associated with landslide activity. Slope angle, aspect, curvature, and distance to stream maps were produced from this DEM with a cell size of 30m x 30m. Lithology and land use maps were produced using geological data obtained from GSE and the interpretation of Google Earth images, respectively. Meteorological data obtained from the Ethiopian Meteorological Agency, using nine rain gauge stations (Abay Sheleko, Dejen, Mekane Selam, Filikilik, Debre Worke, Mertolemariam, Yejube, and Bichena) (Annex 1.1), were used to create a rainfall map using the Inverse Distance Weighting (IDW) interpolation method in the Spatial Analyst tool.

3.2.2 Landslide Susceptibility Mapping Methods or Models

Depending on the research region's target, scope, scale of base maps and aerial photographs, and available resources, various techniques can be used to generate landslide inventory maps (Getachew & Meten, 2021). Landslide susceptibility models, based on regional geological, geomorphological, and other physical factors, define locations where landslides are likely to occur. There are numerous approaches for modeling landslide susceptibility, and in the current study, WOE and LR methods are employed.

3.2.2.1 Weight of Evidence (WoE) method

In this research, landslide susceptibility mapping was conducted using a bivariate statistical method known as the Weights of Evidence (WoE) model. The WoE model is a data-driven Bayesian model that utilizes prior and conditional probabilities. Initially designed for assessing mineral potential sites (Ayalew & Yamagishi, 2005). It calculates the likelihood of landslide hazards in both unconditional and conditional situations. This approach solely calculates the prior probability. The prior probability is computed by dividing the number of pixels on the landslide map by the total number of pixels in the study area (Getachew & Meten, 2021)

$$Pp = \frac{\text{Number of pixels in the Area of landslide}}{\text{Total number of pixels in the area of study}} \quad \dots \text{Eqn (1)}$$

To determine the level of spatial correlation between landslide occurrences and each explanatory variable class, this method calculates positive and negative weights (Mersha and Meten, 2022; Pardeshi et al., 2013). Positive weights (w^+) indicate the occurrence of an event, while negative weights (w^-) indicate its absence. The following parameters need to be calculated according to (Ag et al., 1991).

- ❖ $N_{pix2} = N_{slide} - N_{SLclass}$
- ❖ $N_{pix1} = N_{SLclass}$
- ❖ $N_{pix3} = N_{class} - N_{SLclass}$
- ❖ $N_{pix4} = N_{map} - N_{slide} - N_{class} + N_{SLclass}$

Then, the weights are calculated using the following formula:

$$W^+ = \ln \frac{\frac{N_{pix1}}{N_{pix1}+N_{pix2}}}{\frac{N_{pix3}}{N_{pix3}+N_{pix4}}} \quad \dots \text{Eqn (2)}$$

$$W^- = \ln \frac{\frac{N_{pix2}}{N_{pix1}+N_{pix2}}}{\frac{N_{pix4}}{N_{pix3}+N_{pix4}}} \quad \dots \text{Eqn (3)}$$

Where:

N_{pix1} represents the number of pixels with landslides in a given factor class, N_{pix2} represents the number of landslides pixels not present in a given factor class, N_{pix3} represents the number of pixels in a given factor class without landslides, and $npix4$ represents the number of pixels without landslides or the given factor. Using the calculated

weights, a contrast value (c) can be generated for the specific susceptibility variable (Ag et al., 1991).

$$C = W^+ - W^- \quad \dots \text{Eqn (4)}$$

The calculated difference in weight (c) indicates the degree of association between landslide causes. A positive contrast value (c) indicates a positive spatial link, while a negative contrast value indicates a negative spatial association. By combining the weighted maps (Wmap) of each factor using a raster calculator in the spatial analyst tools of map algebra, the final Landslide Susceptibility Index (LSI) map is produced.

3.2.2.2 Logistic Regression (LR) Method

Logistic regression is the most commonly used multivariate method as it can be used for various purposes. It is used to predict a result measured by a binary variable, such as the presence or absence of landslides, based on one or more independent variables. It does not require the variables to be normally distributed; the independent variables can be non-linear, continuous, categorical, or a combination of both continuous and categorical. Logistic regression helps form a multivariate regression analysis between the dependent (Meten & Prakash Bhandary, 2020). This method has also been widely used for assessing landslide susceptibility concerning triggering factors. It is particularly useful when the dependent variables are binary or dichotomous (Wang et al., 2022). In this analysis, the presence or absence of a landslide is the dependent variable. Since the dependent variable is dichotomous and the relationship between the dependent variable and independent variables is nonlinear, a logistic multiple regression model was constructed based on the causative factors for landslides (Meten & Prakash Bhandary, 2020). The target variable, which represents the distribution of landslides, is represented by dichotomous variables in the LR model. "1" denotes the presence of landslides in the region, while "0" denotes their absence. Several conditioning factors that may affect landslide stability represent the independent variables. Statistical techniques are usually considered the best regional landslide susceptibility mapping options because they are accurate, predictable, and simple to update (Chen et al., 2021). It is better to use a combination of both to overcome the weaknesses of bivariate and multivariate methods. Equation (5) can be used to define the relationship between the occurrence of landslides in the area and its dependence on a variety of variables (causative factors).

$$P = \frac{1}{1+e^{-z}} \quad \dots \text{Eqn (5)}$$

Where "P" is the predicted likelihood that a landslide will occur and ranges from 0 to 1 on an "S-shaped" curve. 'Z' stands for a linear combination. The logistic regression uses the data set fitted to an equation (6).

$$z = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \dots + b_nx_n \quad \dots \text{Eqn (6)}$$

"Where 'b₀' represents the intercept of the model, 'b_i' denotes the coefficient of the logistic regression model's causative factors (i = 0, 1, 2, ..., n), and 'x_i' (i = 0, 1, 2, 3.....,n) represents the independent variable (Ayalew & Yamagishi, 2005; Shao & Xu, 2022).

3.2.3 Materials

3.2.3.1 Software

1) Google Earth Pro: used to prepare lineament, land use land cover, and inventory maps, as well as identify the geomorphology of the entire study area, anthropogenic activity, and distribution of landslides. 2) ArcGIS 10.8: utilized for preparing inventory, study area, drainage, and all causative factors maps, analyzing data, performing data calculations, and preparing landslide susceptibility maps for both WoE and LR models. 3) Microsoft Office Word 2016: employed for writing the entire thesis. 4) Microsoft Excel 2016: used to organize rainfall, inventory, and landslide pixel data calculations, as well as produce graphs. 5) Surfer 25: utilized to prepare the 3D physiographic map of the study area. 6) SPSS: employed to organize landslide-modeling data for the LR model and produce validation and training graphs of AUC for both models.

3.2.4 Methods

As shown in the flow chart below (Fig. 3.6), the main steps of this study are: (a) Literature review (detailed review of each activity that is related to the thesis), (b) data collection and preparation, (c) landslide susceptibility modeling using Weight of Evidence (WoE) and Logistic Regression (LR), and (d) validation and selection of the optimal models.

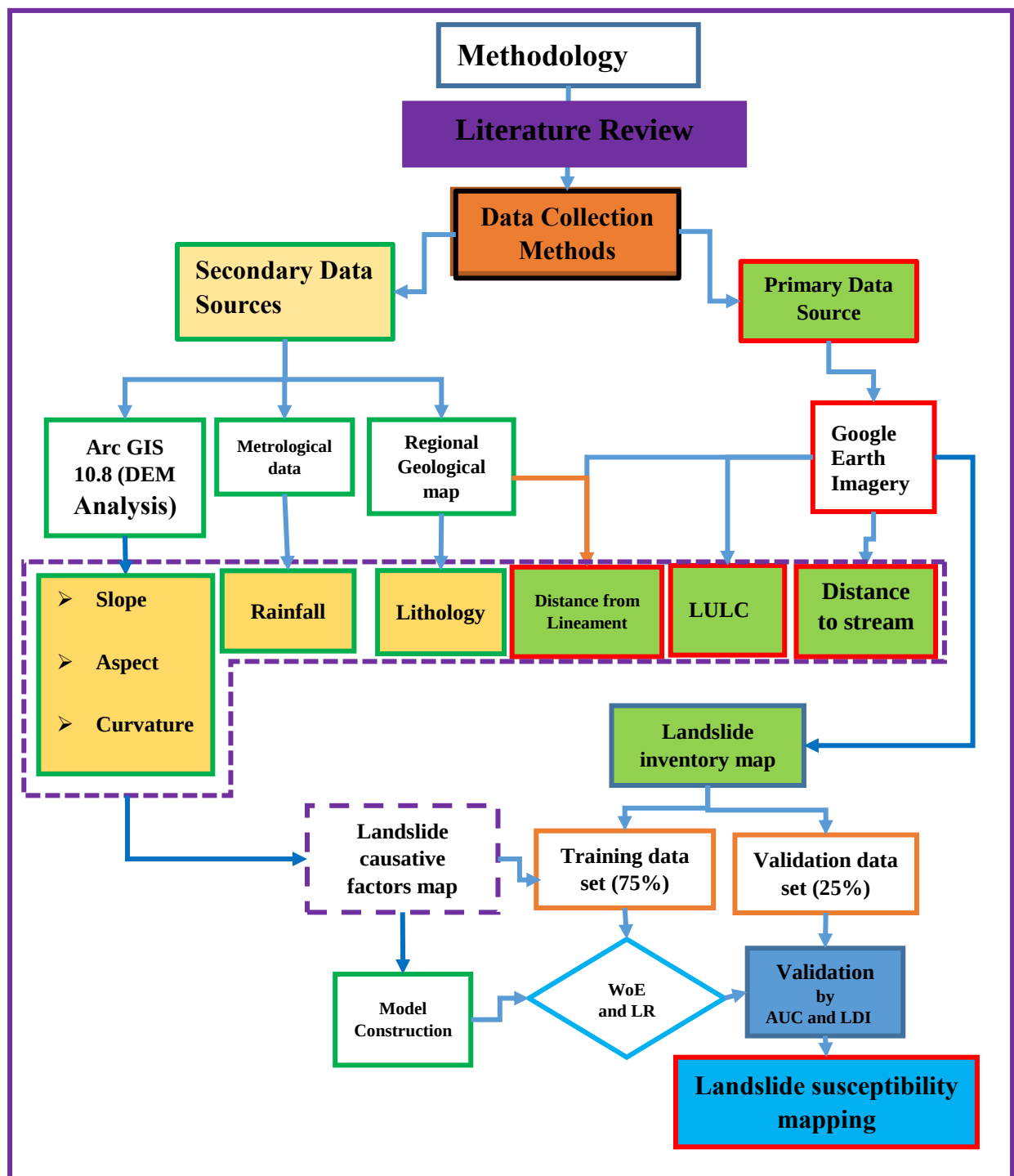


Fig 3.6 Flow chart of the methodology.

CHAPTER FOUR

GEOLOGY OF THE AREA

4.1 Previous Work

A comprehensive field investigation and literature review prepared the study area's geology. The various rock types discovered in the research area and their locations. Researchers, with field reconnaissance operations by Kazmin (1972), which were revised subsequently by Mengesha et al (1996), did not extensively explore the area. On the country's geological map at a scale of 1: 2,000,000, Kazmin (1972) sheds light on the general geology of the area. He claimed that the Mesozoic ages saw the deposition of sedimentary rocks such as the Adigrat sandstone, Abay beds, Antalo limestone, and Upper sandstone. He also stated that young Quaternary plateau basalt was deposited in the area and that the Ashange and Termaber Gussa formations are the first in the sedimentary succession overlaying the volcanic succession in central Ethiopia.

The present study area is part of the Debremarkos-Blue Nile George, which was the subject of research by Dainelli in 1970. He identified three formational groupings: II, the trap series; III, the Mount Choke volcanic series and I, the Mesozoic sedimentary section. The upper surface of the Mesozoic sedimentary rocks was peneplained before the extrusion of the trap basalts, and they are dipping towards the NNE. Although the trap series are horizontal, the surface exhibits signs of leveling caused by erosion before the extruded Choke volcanic. The Choke Series demonstrates the features of a core eruption. Zanetin, B., et al. (1978) investigated volcanic succession, tectonics, and magmatology in central Ethiopia. As a result, the three main volcanic and tectonic stages of Ethiopia's Tertiary volcanism are divided between intervals of quiescence and erosion. The evolution of the latter two phases followed a comparable pattern, with transitional (tholeiitic) flood basalts emitting first, then ignimbritic alkaline rhyolites, and finally alkali basalts. The accompanying extensional movement's strength determined the basaltic magma's chemistry. The structural setting controlled of the fissural silicic volcanism, which was linked to the genesis of the Afar and Ethiopian rift. The uplift movements that initially afflicted the northern regions and then spread to the southern regions are associated with the aging population.

4.2 Regional Geology

The research area, which is a part of the Tertiary flood basalts and the Blue Nile Basin, is situated in Ethiopia's central plateau (Tefera et al., 1996; Wolela, 2002). According to Kazmin (1972) and Getaneh (1991), Ethiopia's Precambrian basement comprises a range of sedimentary, volcanic, and intrusive rocks that have undergone varied metamorphism. In the most Ethiopia during the upper Paleozoic, the basement rock was buried. According to previous research, the Horn of Africa's sedimentary history probably began between the late Carboniferous-Ordovician and Early Triassic periods (Getaneh, 1991), when grabens with NNE and NW trending accumulated continental sediments began to form. Marine sediments started to accumulate after these grabens in the Late Triassic. Early Jurassic sea transgression swept most of Ethiopia from the southeast to the western and northern parts. By laying down regressive continental sediments at the end of the Jurassic, epigenetic rising started to cause the sea to retreat from the area. Following the Paleozoic deposits, vast amounts of Mesozoic Sediments (mostly carbonates and evaporates) were deposited throughout the Horn of Africa. The outcrops in the Abay Basin, Mekele Basin, and Danakil Alps show how much of Ethiopia was covered by Mesozoic sedimentation. Additionally, they outcrop over a sizable portion of the plateau's southeast. Deep boreholes were drilled into the Ogaden Basin's Mesozoic deposits in addition to these locations. In the majority of the Abay Basin, channel-filling Paleozoic sediments are unconformably overlain by the basement rocks, which are unconformably overlain by Triassic-Early Jurassic Adigrat sandstone. However, according to Beicip (1998), the pre-Triassic sedimentation, did not reach the Abay area, and the basin primarily comprises Jurassic sediments. Africa is greatly warped downward, and the sea extends from the southeast.

The Triassic- Jurassic time resulted in the deposition of fluvial sandstone in the region known as Adigrat Sandstone. The transgression was widespread over most parts of Ethiopia, reaching its maximum limit in western and northern Ethiopia during the Kimeridgian (Beyth, 1972). As the transgression advanced shallow marine to lagoonal and deltaic rocks of the Hamanlei in the Ogaden Basin and Gohatsion formation and Antalo limestone in the Abay Basin and Antalo limestone and Agulashale in the Mekele Basin were deposited. During this time, Organic rich shale and carbonates with evaporates were deposited in the Ogaden Basin. Shales alternating with gypsum of the Gohatsian Formation, the lateral equivalent of Middle Hamanlei, may have a source potential in the Abay Basin deposited

during this time. During the Early Cretaceous, a general uplifting of the northern part of Ethiopia took place and regression began, while, subsidence of the Ogaden Basin continued, depositing Gorrahei, Mustahil, Ferfer, and Beltune Formation. Clastic sediment (Amba Aradom Formation in the Abay and Mekele Basins) represents this regression, but the lateral equivalent sediments in the Ogaden Basin are neritic carbonates and evaporites (Gebreyohannes, 1989). Development of the East Africa Rift, in the Early Miocene, is associated with volcanism resulting in the outpouring of vast quantities of lava chiefly represented by basalt, masks the Mesozoic strata in most parts of the country including the Abay Basin. Therefore, Mesozoic sediments in the Abay Basin are exposed only in deep valleys and in the Canyon of Abay River itself. The processes of uplifting and unwarmping control the general evolution of Tertiary volcanism in central Ethiopia. At the beginning of each stage, the volcanism occurred within a large, elongated basin (Zanettin, 1974). During the pre-Oligocene stage, Ashangi Formations erupted. Basalts with transitional, tholeiitic affinities and/or alkaline basalt have erupted in this stage. Extensive crustal extension resulted in the fracturing of the 'peneplain of Ashangi' and the outpouring of fissural Aiba basalts whose composition is transitional between tholeiitic and alkaline basalt. The fissural volcanism then continued with the emission of large quantities of ignimbrites (Alaji rhyolites). Afterward, the volcanism of the plateau changed its mode of eruption to central type (Termaber basalts). This basalt is different from the older ones by its association: phonolites (Mt. sale phonolites), tuffs, ultramafics, and paleosoils. After a period of erosion, another cycle of basalts (Fursa basalts) and/or ignimbrites (Balchi rhyolites) were deposited unconformably over the older volcanics. The Pleistocene movements, which slightly tilted and severely faulted the original Balchi plain, reduced the Ethiopian rift to its present dimension. Since then, volcanism has taken place almost exclusively in the Afar Rift, and the floor of the Ethiopian Rift. Emission of basalts called "Bishoftu", in the zone to the south of Addis Ababa and, locally, in the plateaus (Mts. Salale, Choke, and Amba Farit) are documented (Source: Geological Survey of Ethiopia GSE).

4.2.1 Lithology of the Area

A comprehensive field investigation and literature review were used to prepare the study area's geology. The various rock types discovered in the research area and their locations. The lithological units of the study area are Paleozoic-age sedimentary rocks, Mesozoic-age sedimentary rocks, Tertiary-age volcanic rocks, and Quaternary-age superficial deposits. The Paleozoic sedimentary rocks are Abay Sandstone unit, the sandstone at its top part

alternates with siltstone and/or shale and mudstone; the siltstone and/or shale and mudstone sediments occupy the topmost part while the sandstone occupies the lower part in terms of the stratigraphic position (Pssen). The Mesozoic sedimentary rocks from the oldest to the youngest are; (1) Upper Sandstone unit (Adigrat Sandstone), sandstone with lenses of conglomerate and siltstone or shale (Mst), (2) Mudstone unit mudstone alternates with shale and/or siltstone and thin layers of sandstone (Mms), (3) Gypsum unit; gypsum beds alternate with limestone, blue shale, dolomite and minor sandstone (Mgb), (4) Limestone unit; fossiliferous limestone occasionally alternates with black shale, impure limestone and very minor sandstone (Mis), (5) Upper sandstone unit; sandstone alternates with shale (Must).

The Tertiary dominated by basalt lava flows (eight major lava flows) with their unconformities and from the oldest to the youngest are (1) Arero Gidabo basalt (Tvl) (with overlying occasional thin layers of carbonate mudstone and basaltic agglomerate), (2) Weylu Gidabo basalt (Tv2) (with overlying occasional thin layers of carbonate mudstone), (4) Sandstone, carbonate mudstone and anhydrite-gypsum unit (Tscg). (5) Hacho basalt (Tv4), (6) Carbonate mudstone unit (shale and claystone) (Tem), (7) Selelkula basalt (TV5), (8) Siltstone, carbonate t mudstone, very fine-grained limestone unit (Tsel), (9) Basaltic coarse ash to lapilli lithic tuff (Tpr), (10) Borobor basalt (Tv6), (11) Sandstone unit (Tss), (12) Lumame basalt (TV7) with overlying occasional thin layers of basaltic agglomerate, and (13) Adelge basalt (Tv8).

The transitional rock unit is composed of mainly shales, sandstones, siltstones, limestone, and dolostones and evaporates. The alteration of marine facies and continental facies reflects source area variation and change of environment from the continental environment to the marine environment and, dated as Upper Jurassic at northern Ethiopia and Lower Jurassic at eastern Ethiopia, Ogaden Basin. The Early Jurassic Hamanlei Limestone Formation represents the main transgressive phase of Mesozoic sediments in Ethiopia and attains a maximum thickness of 750m in the Blue Nile Basin, 800m in the Mekele Outlier, 1558m in the Ogaden Basin, and 1480m in the Danakil Alps. In the Early Jurassic time a major transgression, probably related to the drift phase and major sea level high stand occurred over the Whole of Eastern Africa, with the downing (downward bending) of the craton as documented by the deposition of the Antalo Limestone Formation. The Middle Hamanlei Limestone Formation represents the Middle Jurassic time shale-gypsum sequences with interbeds of limestone. The alternative sequences of gypsum and shale indicate a restricted marine or lagoonal environment that could allow for rhythmic or periodic sedimentation deposition. The Upper Hamanlei (Antalo) Limestone Formation covers extensive areas in the Ogaden Basin, the Blue Nile Basin, and the Mekele Outlier. A transitional facies is developed between the Upper Hamanlei

Formation and the Mugher Mudstone Formation. Regionally, the Upper Hamanlei Limestone Formation and the overlying Mugher Mudstone Formation contact is gradational, where thin beds of limestone, claystone, gypsum, and sandstone alternate. In the Late Jurassic to Early Cretaceous, the sea began to withdraw from northern and central Ethiopia, resulting in the deposition of meandering river deposits and braided river-dominated deposits of the Debre Libanose Sandstone Formation. At the end of the Cretaceous, probably all of the Ethiopian landmass except the Ogaden Basin had emerged above sea level. The regression of the sea gave way to the development of the fluviatile mudstone and sandstone formations. The highly fractured and jointed Trap volcanics of the Tertiary overly the Debre Libanose Sandstone Formation, are the youngest Mesozoic sedimentary rocks of the Blue Nile Basin. The Palaeozoic and Mesozoic rocks are exposed mostly to deeply eroded surfaces (Georges). A large part of the Palaeozoic and Mesozoic sediments in terms of the aerial extent in the Blue Nile Basin are buried under thick Cenozoic volcanics as the deeply eroded surfaces indicate in the studied area. The K/Ar dates for the Mugher Plateau basalts range from 20-28Ma (Geological Survey of Ethiopia GSE).

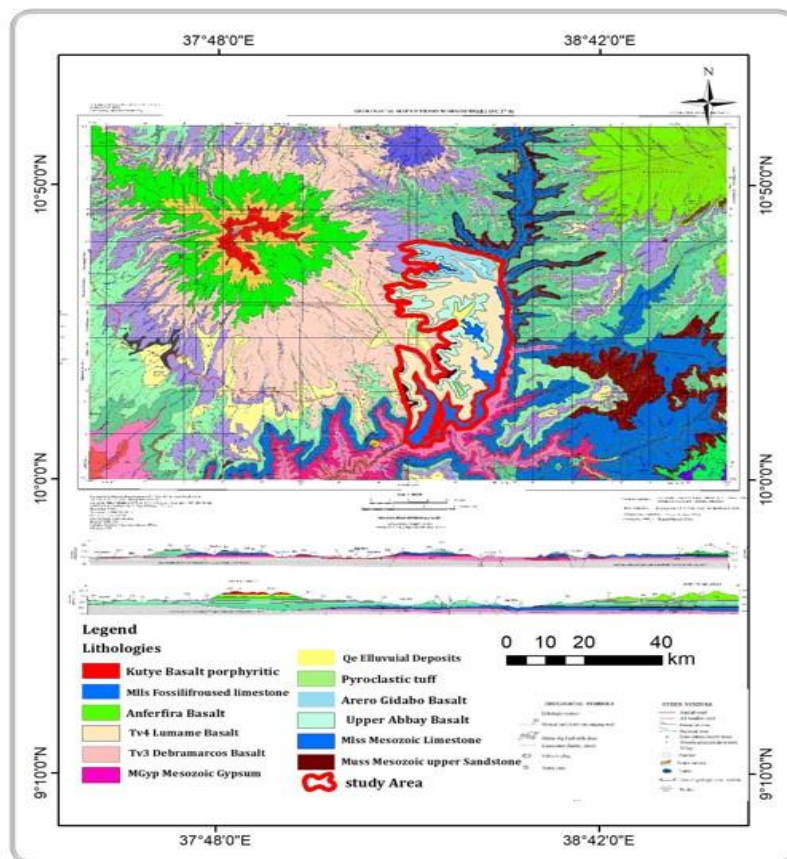


Fig 4.1 Regional Geological Map obtained from the Geological Survey of Ethiopia (Scale = 1: 250,000) (GSE).

Two major lithological units namely Mesozoic sediments and Cenozoic volcanic rocks associated with superficial deposits are observed in the study area; respectively (Table 4.1) Major litho-stratigraphic units are indicated.

Table 4.1 Stratigraphy of Lithological units in the study area.

Age	Major litho-stratigraphic unit	Map unit	
Cenozoic	Superficial Deposits	-Alluvium (Qa) -Elluvium (Qe) -Slope Deposit (Qs)	
	Tertiary Volcanic rocks	-Mertolemariam Trachite (Tv5) -Bichena-Keraniyo Basalt (Tv4) -Debrework-Gundewayn Basalt (Tv3) -Upper Abay Basalt (Tv2) -Lower Abay Basalt (Tv1)	
Mesozoic Sediment	Mesozoic Sediments	-Sandstone	Abay Sandstone(Pass)
			Adigrat or lower sandstone (Mlsst)
			Upper Sandstone (MUsst)
		-Antalo Limestone (Mlst) -Gypsum (MGyp)	

I) Superficial Deposits

World Soil data were downloaded from (USGS) and converted into ArcGIS 10.8. The area coverage and distribution of superficial deposits (Elluvial sediment, alluvial sediments, and Slope deposit) in the study area have been calculated and they occupy 48.9%, 51%, and 0.1% respectively (Fig 4.2).

1) Elluvial Sediments (Qe)

The eluvial sediments in the study area developed from all rock types from the incipient alteration of the bedrocks with a variety of thicknesses. A mappable unit of these sediments covers about 48.9% of the study area (Fig 4.2) and is exposed to the left side of the study area in the northwestern, north-central, and southwestern parts of the area. The eluvial sediments appear in reddish, reddish-brown, brown, dark brown, and dark colors depending on the composition of the rock where they have derived, the addition of the organic matter, land topography, and other factors. The soil size varies from sand-silt-clay, silt-clay, and clay-size particles.

2) Alluvial sediments (Qa)

These sediments occur along stream or river channels. As mappable units, these sediments cover about 51% of the study area (Fig 4.2) and are exposed in the southwestern and northeastern parts of the area. The mappable alluvial sediments are along the Blue Nile River and Muga River. These sediments vary in size clay, silt, sand, pebble, cobble, and boulder. The alluvial sediments form bedding and lamination at the banks of these Rivers. The sediments are brown, sand-granule size, and friable. At the base, surrounded basalt fragments dominate the gravelly layer. The spaces between the gravels are filled with sand-sized particles. The loose conglomerate and sandstone layers are observed along the downstream of the Muga River. Basalt boulders dominate the boulders along the riverbed. The alluvial sediments from the bank of the Jema River, along the Ejere-Selelkula all-weather road, along the Jema River bank are bedded. The principal bedding surface dips 5° into N40E and the cross-beds plunge 40° to the west (N90°W). In this area, the Jema River drains into the south. The riverbank deposits represent the sandy conglomerate layers and the conglomerate layers. The rocks are friable or loose. The pebbles, cobbles, or boulders originated from sandstone, gypsum, limestone, and basalt and have angular, sub-angular, sub-rounded, and rounded shapes. The gravel layer in this area is overlaid and underlain conformably respectively by sandy gravel layers.

3) Slope deposit (Qs)

The moderate slope and steep slope topography are susceptible to slope deposits and later exposed to landslide hazards. The slope deposits cover about 0.1% of the study area. The slope deposits are friable and vary from massive to locally layered sediments with white tints. These sediments vary in size from clay, silt, sand, pebble, and cobble to boulder. The boulders developed from basalt, gypsum, and limestone.

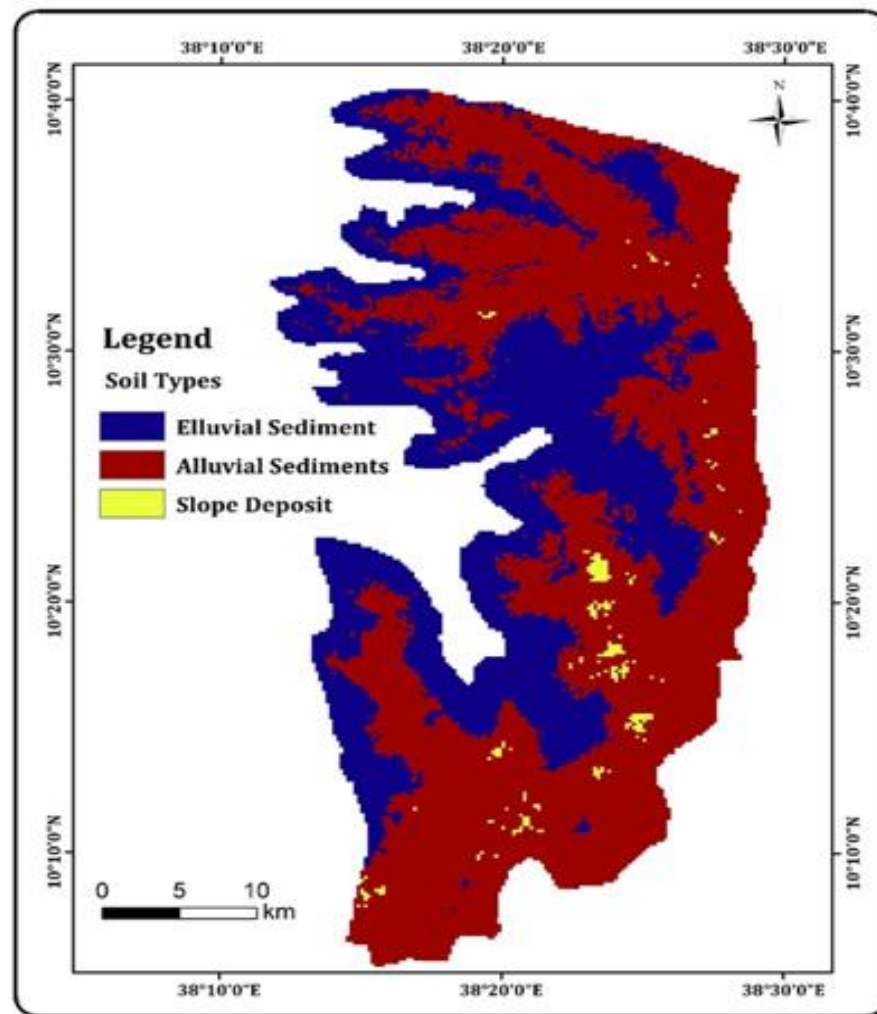


Fig. 4.2 World Soil Data downloaded from USGS and converted into Arc GIS 10.8 to check the area coverage and distribution of Elluvial sediment, alluvial sediment, and Slope deposits particularly in the current study area.

II) Mesozoic sedimentary rocks

These rocks are stratified sediments of the Mesozoic age, which cover some areas in the region. The maximum thickness of these rocks is about 875m. Based on the composition, texture, color, and morphology they form, the Mesozoic sediments are classified into three units the Gypsum unit, Limestones, and sandstone.

In most parts of the area, the sandstone pinches out. The tertiary basalt is seen to overlie unconformably on the sandstone and the limestone, whereas between the sediments and the basalt is a parallel unconformity.

Gypsum unit (MGyp)

The gypsum unit is composed of predominantly white and gray, rarely pinkish, thickly bedded rarely nodular, which attains a maximum of 5 cm long and 2 cm wide showing a chicken wire structure. Gypsum unit exposed at the eastern and western part of Abay River at Yed Wiha and Soma sub sheet. The thickness of this unit is 425m. It covers 3.74% of the total mapped area. A petrographic study of gypsum shows, that gypsum comprised 96% gypsum crystals, 2% anhydrite, 1% opaque, and, 1% iron oxide (hematite). Clay minerals cement the Gypsum. They are also altered. It shows an anhedral shape (sutured). The gypsum grains are altered to clay minerals and dehydrated to anhydrite.

Limestone (Antalo limestone)

The limestone unit outcrops the southeastern and northeastern parts of Yed Wiha and the soma area covers about 5.9% of the study area. This unit overlies with the gypsum unit and underlies upper sandstone, Lower Abay basalt (Tv1), and upper Abay basalt (Tv2). The contact is marked by a gradational change in composition from pure limestone to sandy limestone and calcareous sandstone. The exposed section has a thickness of about 400m. Some are thinly bedded (Plate 4.1). Limestone is light gray to yellowish tint in color, fine to medium-grained, sub-horizontal, and very thickly bedded with abundant fossils that are observable. The fossils observed in the limestone are brachiopods, corals, gastropods, and bivalves. Occasionally the fossils are replaced with secondary calcite. Compositionally and mineralogically, it is mainly biomicritic with oolites, cherty and karstic, some spray calcite, and a trace amount of quartz which filled sub-spherical to elliptical cavities superficially (see appendices 4 and 5). In some places, the microcrystalline limestone that is fine-grained with a small proportion of calcite crystal, (grain) and minor fossil fragments are observed. The limestone unit forms cliffs, and gentle to moderate slope topography. Some are thinly bedded.



Plate 4.1 Mesozoic Limestone east of Kutkwat village (Bichena area) (Matebie Meten (Ph.D.)).

Sandstone unit (PSst)

This unit consists of sandstones with minor siltstone layers covering 0.74% of the total area. It occupies the lower stratigraphic positions in the Blue Nile (Abay) gorge and is overlain unconformably by Mesozoic Lower sandstone. Sandstone is the most dominant rock type of the unit. It is reddish brown, light gray, fine to medium, and sometimes very fine-grained faintly cross-bedded, highly weathered forming gentle morphology Plate 4.2. The rock weathers to dull brown and dull gray colors. The maximum observed thickness in the area is 143m.



Plate. 4.2 Paleozoic Sandstone at Abay River (Matebie Meten (Ph.D.)).

III) Tertiary volcanic rock

Lower Abay basalt (Tv1)

This unit outcrops mainly along Alet River bank, one of the Abay River's major tributaries, in the Northern and central parts of the area. It forms a cliff with a maximum thickness of about 125m. It covers about 1.89% of the study area. The rock is unconformably underlain by sandstone and limestone units and unconformably overlain by the Upper Abay basalt (Tv2). The rock is dark gray, columnar jointed, and amygdaloidal; the amygdules are filled by silica, which is green and yellow secondary minerals.

Upper Abay basalt (Tv2)

This unit exposed most of the Mertolemarium part of the study area, the western part of the Soma and Yed Wiha area, and the northern part of the Keraniyo and Gundawayne area of the study area. It covers 28.13% of the mapped area. It forms a gentle slope to the cliff. The Upper Abay basalt is the thickest in the area with an overall thickness of about 1700m (plate 5a). It is highly enriched with opaline material. The rock is unconformably underlain by the lower Abay basalt and limestone unit and unconformably overlain by Debrework-Gundawayne basalt (TV3) at different places throughout the area. Lacustrine sediments (fine siltstone) mark the contact between TV1 and TV2, it is white and friable. This unit exhibits vertical compositional variations

This basalt has a dark-gray color and it shows dark brown and reddish brown color upon weathering. Composition varies vertically. The basalts are stratified with pyroclastic layers interbedded in between. About four layers of pyroclastic materials were observed interbedded with basalt. The lower pyroclastic material is agglomerated with coarse-grained lithic fragments cemented by ash matrix. The rest are ignimbritic in composition. Their thickness ranges from 2-5m.

Bichena-Keraniyo basalt (Tv4)

This unit outcrops the western part of Debrework and Mertolemarium, the southern part of Keraniyo, and the north and south of the study area in Bichena. It occurs as linear ridges and covers about a very small part of the study area. The maximum exposed thickness measured is about 125m and has different lithological variations below it. The rock is dark fine to medium-grained porphyritic with dominant plagioclase phenocrysts and some proportion of olivine.

Mertolemariam Trachyte basalt (TV5)

This unit is exposed in the northern part of the study area. It covers 1.19% of the study area and occurs as it extends from the dome part of the Mertolemariam area. The rock is dark gray to dark green, with extensive and elongated ridges forming. It is also sheeted and can easily be cleaved along the sheeted surface.

4.3 Local Geology

The geological formation significantly affects the probability of landslides occurrence (Ayalew and Yamagishi, 2005; Getachew and Meten, 2021). Since each class of materials has a specific shear strength and permeability characteristic, lithology is one of the factors that impact the most slope instability (Yalcin & Bulut, 2007; Mersha and Meten, 2022). Various rock types' composition and structure vary, adding to the material's strength. When compared to the softer/weaker rocks, the stronger rock units provide more resistance to the driving force, which can lead to landslides. A detailed geological map 1:50,000 scale of six sub-sheets of the study area which include (Soma, Debrework, Dejen, Selekula, Bichena, and Yed Wiha) prepared by Matebie Meten (Ph.D.) where mosaicked and digitized on Arc GIS software 10.8 (Fig. 4.3). Additionally an existing regional geological map (obtained from Geological Survey of Ethiopia GSE) also used to create the lithological map (Fig.5.1G) of the research area. Six lithological units, including highly weathered lower Abay Basalt (Tv2), Weathered Debrework-Gundewayn Basalt (Tv3), Upper Sandstone (MUst), Gypsum (MGyp), Antalo Limestone (Mlst), and Elluvium Deposits (Qel) are present in the studied region (Fig. 5.1G).

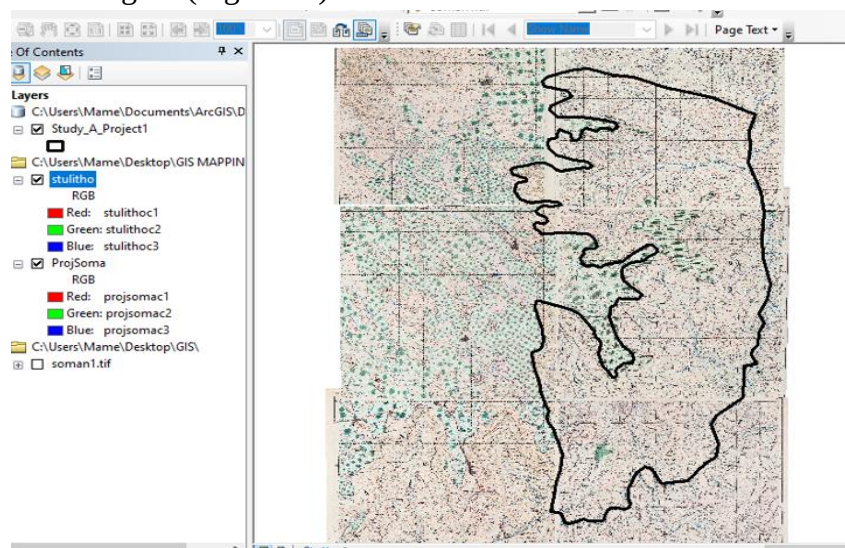


Fig 4.3 Lithological map from geological mapping at a scale of 1: 50,000 was carried out from 2006 through the work of Matebie Meten (Ph.D.).

4.3.1 Lithology of the study area

Mesozoic Limestone (MLst)

This unit is found in the study area's eastern, central, and southern parts, covering 26.8% of thickens to the east and thins out to the Southwestern part of the area. It is mostly exposed in the Alel, Gedeb, and Abay Rivers. The unit comprises the dominant limestone together with minor intercalations of mudstone and shale. The limestone is yellowish gray, light gray, sometimes black colored, mostly fossiliferous, sometimes massive, medium to thickly bedded, occupying gentle cliffs. The limestone forms a bed thickness of 0.25 – 0.5 m sometimes reaching up to 1 m. Brachiopod, bivalve, and Ooid fossils are encountered in most of the limestone rocks Plate 4.3.



Plate 4.3 Fossiliferous Limestone (fossils of bivalves are visible) (Matebie Meten (Ph.D.)).

Debrework-Gundawayne basalt (Tv3)

This unit is exposed in the southwest of the Keraniyo area, the central part of the Gundawayne area, and central and southeast of the Debrework area of the study area. It covers 4.9% of the study area (Fig 4.5). TV, unconformably underlain by TV2. It has a dark gray color; fine to medium-grained plain to gentle slope. The rock also contains amygdols, which are white. Sometimes it intercalated with aphyric basalt, which is dark gray, extensive, and elongated ridge forming one. The thickness of this unit is 200m. The contact between Tv2 and Tv3 marked by white color, friable and weighted, gentle slope forming pyroclastic material (ignimbrite to ash), and reworked travertine.

Lower Abay Basalt (Tv1)

The Lower basalt forms a steep morphology above the Upper Sandstone or the limestone units with a total area coverage of 28.06% (Fig. 4.7). It is dark gray, fine to medium-grained, aphanitic basalt, plagioclase phyric and olivine - plagioclase phyric basalts. The basalt in Goha Tsion – Dejen Road, Hamusit – Sens River, Selelkula – Jema River, and Merto Lemaryam – Abay River sections show spectacular columnar jointing. Among these, the latter section is triggering a critical landslide problem in the study area in the northern part.



Plate 4.4 Columnarly jointed Aphanitic basalt at Dejen – Abay Road southern part of the study area (Matebie Meten (Ph.D.)).

From south to north, there is a progressive increment in the elevation the unit is exposed. For example in the northern part (Mekane Selam – Abay River section), the lower elevation is 1580 m; in the extreme southwestern part, it starts at 2040 m. It weathers to dull gray color. The lowest thickness is 232 m at the May Angetam – Wintern River section and the highest thickness is 810m at the Mekane Selam – Abay River section.

Elluvial Sediments (Qel)

The eluvial sediments are widespread over most of the study area and they are developed from all rock types, the incipient alteration of the bedrocks with a variety of thicknesses. A mappable unit of these sediments is exposed in the central flat area, peripheral of northeastern and southeastern parts of the study area (Fig.4.7). The eluvial sediments appear in reddish, reddish-brown, brown, dark brown, and dark colors depending on the composition of the rock where they have derived, the addition of the organic matter, land

topography, and other factors. The soil size varies from sand-silt-clay, silt-clay, and clay-size particles. Moreover, they overly on lower Abay Basalt and other lithology in the study area.

Gypsum (MGyp)

The gypsum unit was exposed at the southeastern western, and southern parts of the study area (Fig.4.10). The thickness of this unit is 425m. It covers 18.35% of the total study area. The Gypsum is cemented by clay minerals. They are also altered. Stratigraphically surrounded by limestone. It shows an anhedral shape (sutured). The gypsum grains at places are altered to clay minerals and dehydrated to anhydrite.

Upper Sandstone (MUst)

This unit is exposed in the central part of the study area toward the east from the major eluvial deposit (Fig.4.10). It covers a small part of the study area next to Debre worke Gundawayne basalt, which is 0.8%. It is reddish brown, light gray, fine to medium, and sometimes very fine-grained faintly cross-bedded, highly weathered forming gentle morphology. The rock weathers to dull brown and dull gray colors. The maximum observed thickness in the area is 143m.

4.3 Structure of the Study Area

The area is tectonically simple and dominated by NE structures. Locally there are also NW, NS, and EW structures. These structures occur in the area as photo-lineaments. Joints and fractures are also widely observed in the area. The primary structures include bedding planes, stylolites, and karsts for sedimentary rocks; and flow banding and/or layering for volcanic rocks. Irregular stylolite structure also develops sporadically within the limestone.

4.3.1 Lineament

The NW under NE structures crosscut in the area. From the crosscutting relationship, it is obvious that the NE structures are relatively younger than the NW structures. The NW structure tectonically controls young volcanic rocks like the Lower Abay basalt (Tv1 and this indicates that the old NW structures are reactivated in the area. Thus, the NW structures control the occurrence and formation of the area's sedimentary and volcanic rock. The NS structure, on the other hand, controls only the formation of the sedimentary basin and the placement of the Abay River, which is trending in the NS direction. The EW structures control the orientation of streams, which are tributaries of the Abay River. Lineaments generally in the area manifested in the form of linear ridges, straight valleys, streams and

ivers, and aligned hills. The length of lineaments varies from a few meters to a maximum of 10 km.

4.3.2 Joints and fractures

Joints are widely observed both in sedimentary and volcanic rocks. The joints occur as vertical and oblique joint sets. At places, the joints are observed to be filled with iron oxide in the case of sandstone units. Columnar joints are also widely observed in the area. It is particularly common in the Lower Abay basalts (Tv1). On the other hand, virtually all rocks in the area are affected by fracture, and the Lower Abay basalt especially is highly fractured. Structural map over the geological map.

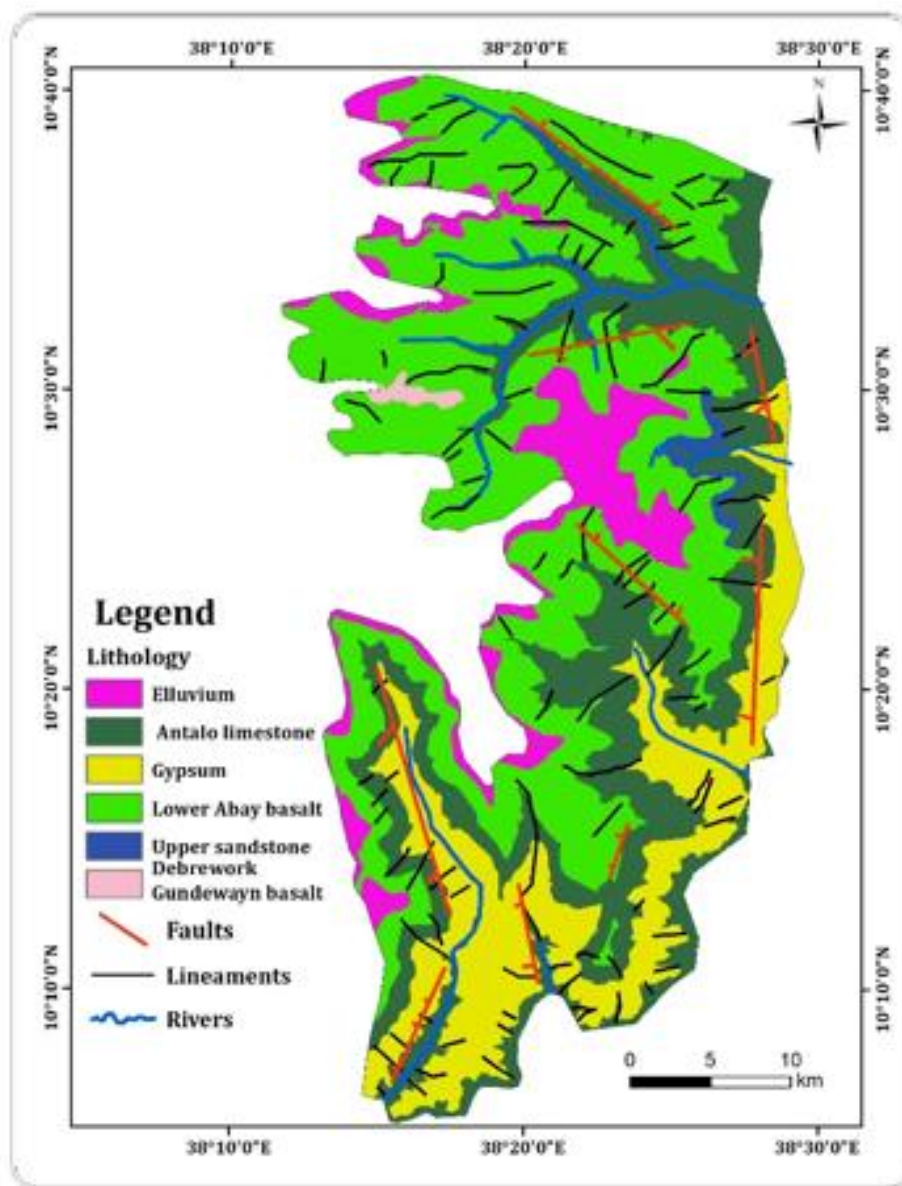


Fig. 4.5 The main Structural map of the study area.

4.4 The Effects of Groundwater

Even though we encounter difficulties in collecting spring locations due to the steepness of the slope and rugged topography it is easy to identify the presence of Groundwater based on the geological formation of the study area and precipitation data obtained from the meteorological agency of Ethiopia. Since the area receives moderate to high precipitation annually during the summer, there is a presence of groundwater as the water from precipitation is percolated to the ground. The rock units that can facilitate groundwater accumulation are Quaternary alluvium, sedimentary deposition, and Cenozoic volcanic rock associated with geological structures such as faults, joints, and lineaments during and after their formation. The Quaternary alluvium could also be an important reservoir for groundwater. The presence of few productive drill holes along these valleys indicates that they are good reservoirs. Hence, deep drilling along some valleys and plains can be conducted to get more groundwater. In addition, fractured limestones may contain perched groundwater. Alluvial deposits may be sought for groundwater during the dry season. (Report from Geological Survey of Ethiopia GSE).

Water is the most crucial need of the people and the cattle (Haji et al., 2018). However, Groundwater has a negative response against the stability of rock and soil in many ways. Raising Groundwater or pore pressure can lead to land sliding as it applies force on geologic material above it. In another way, if the groundwater is lost from the area due to prolonged drought or different manmade activities, the area may collapse as the space occupied by water becomes empty. The shallow groundwater is also highly responsible for lubrication during seismic shaking of soil material and resulting in mudflow types of landslide, which can damage large areas.

4.5 Geologic History

An attempt has been made to reconstruct the geologic history of the map area as follows.

1. The Gypsum Formation, which is exposed at the base of the Abay River valley, is the oldest rock unit in the area. It is presumed to have been deposited in the Yed Wiha environment in the Lower Jurassic period.
2. Then gradually marine invasion changes the environment of deposition from continental to near-shore and then to marine. Limestone begins to deposit in Upper Jurassic times in an environment ranging from the continental shelf to near-shore open marine environment, under high to low tidal energy conditions.

3. Marine regression is followed by the deposition of sandstone, which has a gradational contact with limestone formation and is deposited in an environment where fluvial action is prevalent. Moreover, it is presumed to have been deposited in a braided river system during the Upper Cretaceous period.
4. After a period of erosion, volcanic activity prevailed in the region, and uplifting followed by a massive outpouring of fissural basalts deposited the Lower and Upper Abay sandstone, which are presumed to be the oldest volcanic rock in the map area, during Middle to Upper Oligocene. The lower Abay basalt overlies the sandstone unit unconformably.
5. Fissural volcanism continues and emits large quantities of basalt; consequently, Debrework-Gundeweyne basalts were deposited in the Upper Oligocene to Miocene period.
6. Then reactivation of the older NW structure took place and allowed the outpouring of highly porphyritic Bichena-Keranio basalts, which form ridges oriented in the NW direction towards Mt. Choke to the northeastern study area.
7. Volcanism in the area changed progressively from fissural type to central. In addition, the Mertolemariam trachyte was deposited during this time. This unit is believed to be the youngest in the area and deposited most probably in the early quaternary.
8. Lastly, Quaternary sediment and soil deposited in the area (Geological Survey of Ethiopia GSE)

CHAPTER FIVE

LANDSLIDE INVENTORY AND CAUSATIVE FACTOR EVALUATION

5.1 Distribution of Landslide in the Study Area

One of the essential components of landslide susceptibility mapping is landslide inventory mapping, which can be created using a variety of methods, including the interpretation of aerial photographs or Google Earth images, the assessment of archived data, and the use of GIS tools (Van Westen et al., 2008; Wubalem, 2021). Landslide inventory is the most significant part of slope stability analysis in landslide susceptibility mapping. By analyzing the relationship between the current landslide event and landslide causative factors, the landslide inventory map is used as a framework for future landslide prediction (Wubalem, 2021). A landslide inventory map was produced using GIS by (van Westen et al., 2008) based on fieldwork, a study of past landslides, and satellite image analysis. Field surveys and Google Earth imagery can also generate inventory maps of the landslides that have already occurred (Meten et al., 2015b; Wubalem & Meten, 2020; Wubalem, 2021). However, for large study areas like this one, it is difficult to access areas such as; rugged topography, political instability, and dense forests Google Earth time series is the most appropriate as it can reach everywhere within a short period entire the study area to identify the landslide.

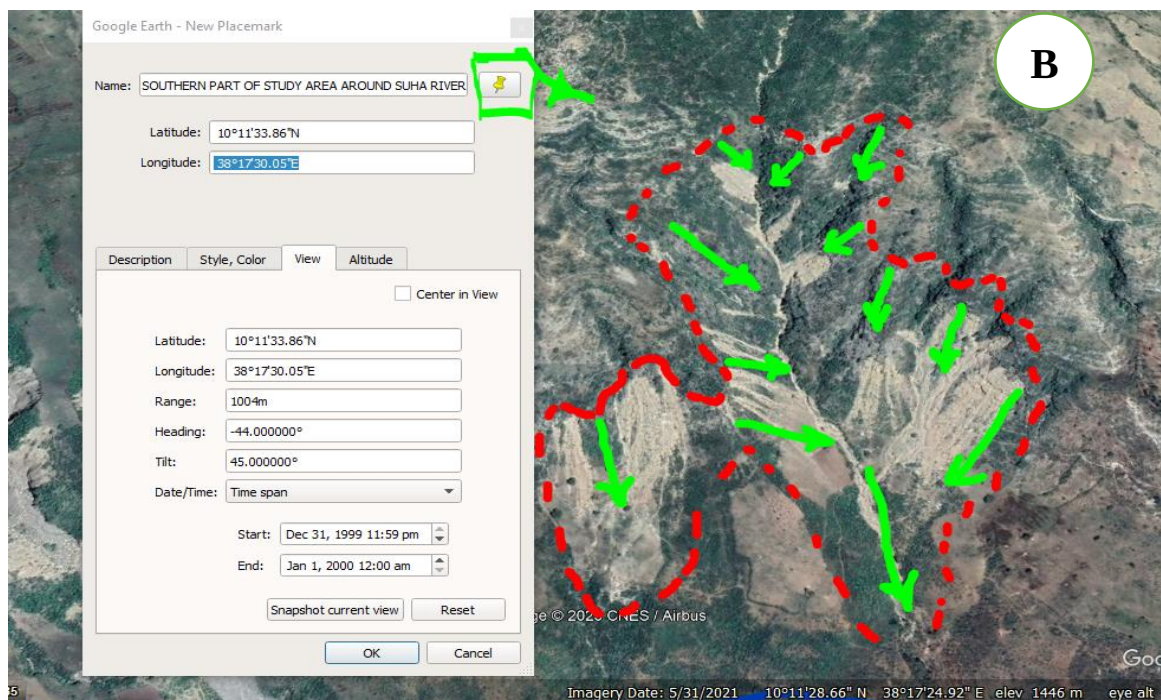
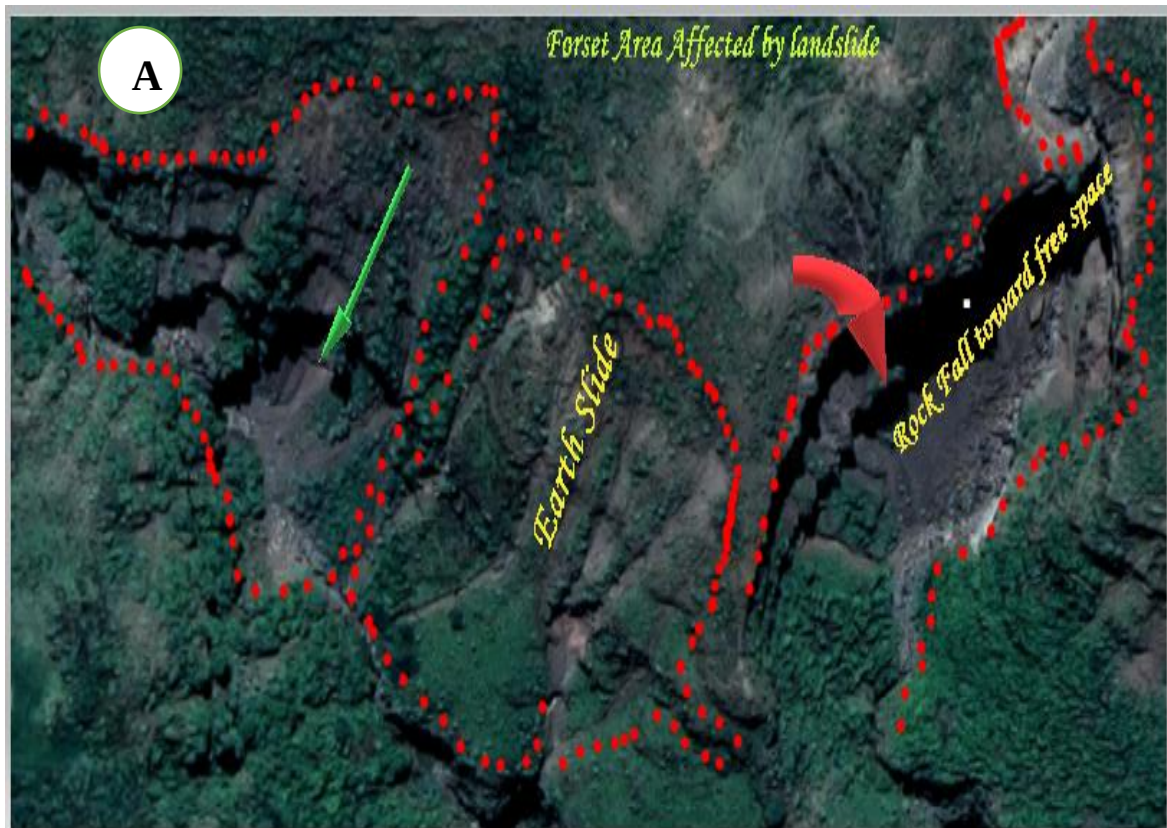


Plate 5.1 A) Forest area affected by different types of landslide, B) Planar (left side) and concave (on the right side) type of Landslide (Google Earth Pro Image) showing the direction of sliding.

In the current study, a thorough field survey and the analysis of Google Earth images were used to identify 4506 landslides that covered an area of 1325.7 km² and comprised both the

past scarps and present slides. By taking into account their spatial distribution, the landslide inventory was randomly divided into training (3741 number of inventory polygon and, 206550 pixels) and testing (765 number of inventory polygon and, 60922 pixels) datasets. The study region has several kinds of slides, including rockslides, soil slides, debris flows, earth flows, mudflows, rock falls, and rock toppling (Plate 5.3).

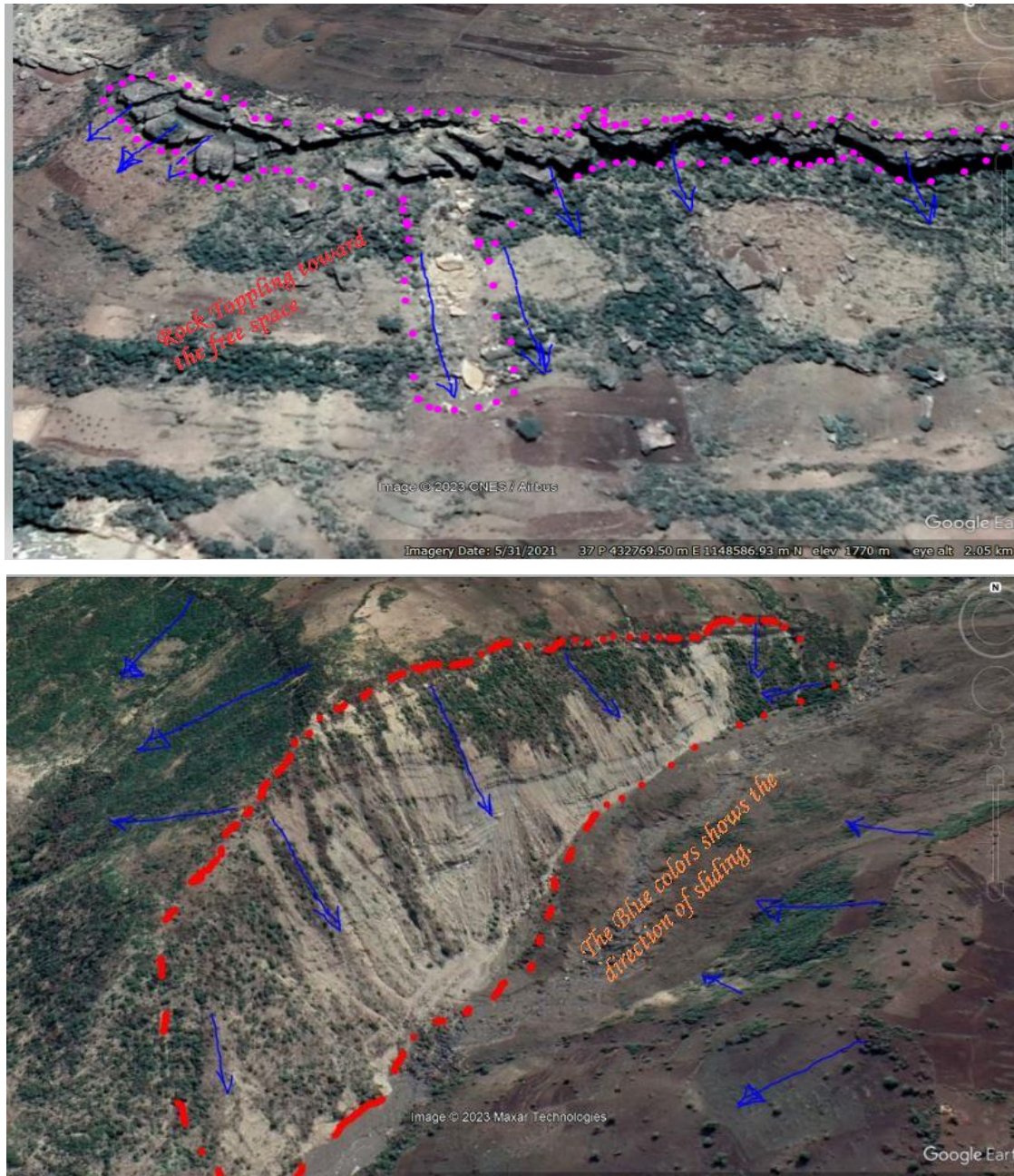


Plate 5.2 A) Rock fall ($10^{\circ}11'33.86''\text{N}$ $38^{\circ}17'30.05''\text{E}$,) B) Gypsum unit sliding down to the Suha River (Lat. $10^{\circ}11'8.82''\text{N}$, Long. $38^{\circ}17'7.92''\text{E}$) Google Earth Pro.

Among these types of landslide Debris slide is the dominant type of slope instability in the study area due to the high degree of weathering of basalt and the thick overlay of eluvial and deposits. Since the study area coverage is large, landslides were not collected by local name

instead they depended on Cruden and Varnes, (1996) classification, which is a type of movement and material, involved in the entire study area.

According to reports made by local people and analysis of the time series Google Earth Imagery, the study area was often affected by landslide occurrence because of the following reasons. The major landslide in the study area is due to rugged topography with steep slopes and the occurrence of high-density lineaments, particularly in northern and northwestern parts of the study area including Debre worke, Bichena, and Soma. In the Abay (Blue Nile) basin, the frequency of landslides is due to previous tectonic change that favors extensive river incision and the construction of steep-walled cliffs, tabular ridges, and deteriorated masses (Ayalew & Yamagishi, 2005; Meten et al., 2015a). In addition, due to the steep slope and rugged morphology, the common, heavy rains during the summer season highly affected the area specifically in the southern part of the study area. The variation of lithology, especially the existence of unconsolidated soil deposits, sedimentary rock interaction with both surface and subsurface water, and highly fractured (Lower Abay basalt) rock units.

5.2 Landslide Causative Factors in the Study Area

Geology, weather, landscape, anthropogenic factors, and land use/land cover all significantly affect where landslides occur and how frequently they appear. To understand how the landslides operate and after that create a map of landslide susceptibility, it is important to assess how these causal factors affect the geographic distribution of the landslides. In this study area, the eight causative factors that have been employed to create landslide susceptibility maps are slope angle, aspect, curvature, distance to stream (from DEM 30x30m) using different classification systems in spatial analyst tools like Natural Break or Jenks, Equal Intervals, into different groups. Land use/land cover, distance to lineament (from Google Earth Pro), lithology, and rainfall were prepared based on the data obtained from the Geological Survey of Ethiopia GSE and Ethiopian Space Science and Geospatial Agency respectively. Below are detailed explanations of each of these causal elements' functions.

5.2.1 Aspect

Aspect is the term for slope orientation, which is typically stated as a degree between 0 and 360. The aspect (slope orientation) influences how much sunlight, wind, and precipitation are exposed to the area, subsequently impacting other elements that cause landslides such as soil moisture, vegetation cover, and soil thickness (Meten et al, 2015). In disaster

management, such information can help to identify potential landslides, avalanches, or flood-prone areas based on the terrain's slope and orientation. For this research area, an aspect map (Fig. 5.2C) with nine classes was used to categorize the aspect as, Flat, North, northeast, east, southeast, south, southwest, west, and northwest using the “Natural breaks (Jenks)” in the spatial analyst’s tool using Arc GIS 10.8. Aspect or slope facing towards S (187.5 to 202.5), SE (112.5 to 157.5), and NW (292.5 to 337.5) are showing a positive contrast (C) value.

5.2.2 Curvature

According to (SONG et al., 2008) Curvature can be classified as plan and profile curvature. Profile curvature: The inclination of the vertical plane concerning the slope. It gauges the slope's rate of change, which affects the speed at which water drains off the surface and, in turn, erosion and sediment movement. Positive values indicate convex-upward surfaces. Plan curvature: A contour line's curvature is created by crossing a horizontal plane at an angle with the surface. In a downhill flow, plan curvature affects the convergence or divergence of water. In another way (Meten, et al., 2015a) explained plan and profile curvatures: For hillslope and landslide analysis, profile and plan curvatures are used. Plan curvature and its impact on hillslope stability in areas with a high prevalence of earth flow and earth slide. It is the arc created by the intersection of an idealized horizontal plane and the ground surface; alternatively, it is the curvature of topographic contours. Hillslopes can be separated into hollows, noses, and generally planar parts according to the plan curvature. Surface water would congregate in hollows, areas where the contours' plan is concave in the downslope direction. Noses or coves are areas where surface water will diverge because the plan curvature of the contours is convex in the downslope direction. The curvature along a line created by the junction of a hypothetical vertical plane and the ground surface is known as a profile curvature. The concavity or convexity of the curve can be determined by looking at the sign of the curve. Both profile and plan curvatures will impact the vulnerability to landslides. Concave curvature surfaces and convex are represented by their corresponding positive and negative values. The driving and resisting pressures within a landslide are impacted by profile curvature in the direction of motion. Plan curvature regulates whether water and landslide debris converge or diverge in the path of landslide motion. For this study curvatures are classified into three classes as: concave (-ve), plan (0) and convex (+ve) (Fig. 5.2D). Concave (-ve) and convex (+ve) are showing the positive result showing landslide occurrence.

5.2.3 Slope

A landslide susceptibility map is often prepared using the slope angle, which is an essential measurement for landslide analysis and is directly related to landslides. The shear stress in the soil or rock increases as the slope angle increases. Unconsolidated matter typically gets bigger. Because low gradients are associated with reduced shear forces, gentle slopes are predicted to have a low frequency of landslides. In contrast to moderate and moderate slopes, steep slopes are more likely to experience landslides (Meten, et al., 2015a). In this study, slope angle ranges from 0° – 74° were classified based on the Natural Breaks (Jenks) method into five classes $(0 - 8)^{\circ}$, $8^{\circ} - 16^{\circ}$, $(16 - 25)^{\circ}$, $(25 - 36)^{\circ}$, and $>36^{\circ}$ and the last three classes are responsible for the occurrence of landslides as they have positive C value and regression coefficients (Fig. 5.2B).

5.2.4 Land Use and Land Cover (LULC)

When the research area is so large and the users are unfamiliar with the area, creating a land use map using the supervised classification of satellite imagery could be the best option (Wubalem, 2021). Even though the study area is large, Google Earth digitization preferred to classify the land use land cover as the result of its high spatial resolution and direct control over the classification process, Land use categorization of Google Earth imagery has been proven to be successful. The software can classify only the area that directly correlates with the one that is given to it as a training sample. For instance, the two figures below (Plate 5.3 A) both depict the farmland, which can be identified manually and may be absent for supervised classification, as their colors are different unless the training samples are taken from both places.



Plate 5.3 Different colors of farmland images in the study area, Plate A.

Digitizing Land use/land cover manually on Google Earth and then again on Arc GIS is difficult and time-consuming for large study areas. Even though it is time-consuming and boring, LULC in this study was digitized by hand on Google Earth Pro then converted to Arc GIS 10.8 and digitized again into five classes (Bare land, Water body, Farmland, Forest, and Settlement) after checking different supervised and unsupervised classification using a variety of software products such as ERDAS and ENVI are less satisfactory. This barren land (hilly areas, cliffs, shrubs, and grasslands or any land cover free from Engineering Geological activities) covers the major parts of the study area (fig. 5.2A)

5.2.5 Distance to Stream

The area's slope evolution is significantly influenced by its proximity to the stream course, which also predicts of landslides and related erosional characteristics. Landslides are more likely to occur in rivers with numerous drainage networks. Occurs as they erode the slope's base and soak the material that makes up the slope underwater (Akgün and Türk, 2011; Mersha and Meten, 2022). Active River or stream incision significantly affects slope instability through toe erosion and saturation of the materials that make up the slope, leading to increased instability and steepening of the slope (Getachew and Meten, 2021). The proximity to the river increases the probability of landslide occurrences. However, Landslides can occur even at long distances from Stream River. The combined influence of other conditions that favored the development of landslides may be the cause of the high density of landslides at a greater distance to the stream class (Ayalew et al., 2004; Getachew and Meten, 2021).

Many landslides happened close to the Suha River, Wagra River, Alel River, Taga River, and Bela Medab River because numerous streams in the research area run into Abay or Blue River. Thus, this parameter was taken into account as one of the primary factors in the analysis of landslide susceptibility. The probable landside sites are located in areas with parallel drainage patterns on steep hillslopes. According to (Mersha and Meten, 2022) as pore-water pressure develops, having an impact on decreasing the shear strength of rocks and soils, drainage is frequently a key component of land-slide occurrence. The stream map was prepared from the DEM 30m pixel size downloaded using USGS, and the distance to the stream map was calculated using Euclidean distance buffering with a 100m buffer distance. The stream map was then divided using a spatial analyst tool into five classes using

the Natural Breaks (Jenks) method: 0 to 100m, 100 to 200m, 200 to 300m, 300 to 400m, and more than 400m (fig. 5.2E).

5.2.6 Distance to Lineament

The number of landslides is governed by lineaments, which are localized linear scarps of ridges. Without any evident indication of displacement, such as a topographic break, including tectonic structures and a linear arrangement of geomorphological elements particularly sedimentary bedding planes that may be continuous or interrupted. Due to extensive Pliocene quaternary disruption, the Ethiopian highland is characterized by high relief and severe topography (deep valleys and gorges with steep slopes). As a result, various structures like fault scarps, tectonic depressions, and horst spanned the Ethiopian highlands. The current study region is a portion of the highlands in northwest Ethiopia, which are home to a variety of geological structures such as faults, fractures, and escarpments. Faults, breaks, and escarpments are all included in the term "lineament." The likelihood of slope failure typically rises as the distance to the lineament decreases. This metric is a crucial factor in determining a region is susceptibility to landslides. (Getachew and Meten, 2021).

The degree of weathering and fracturing rises with an increase in the quantity and concentration of geological structures, suggesting a decline in the strength of slope materials. These structures can be used as a water movement conduit and slip-and-failure surface. For this research, lineaments are digitized manually using Google Earth Pro software after checking the Regional Geological Map obtained from GSE to compare the lineaments mapped before with newly collected ones. Euclidian distance analysis was performed using Arc GIS 10.8 on the entire lineament map at a distance of 50 m intervals, and the results were divided into five classes using the Natural Breaks (Jenks) method: 0 - 50 m, 50 - 100 m, 100 - 150 m, 150 - 200 m, and >200 m. The lineaments were more situated in the Southeast, northern, and northeastern parts of the study area (Fig. 5.2F).

5.1.7 Lithology

The geological formation significantly affects the probability of landslides occurrence (Ayalew and Yamagishi, 2005; Getachew and Meten, 2021). Each class of materials has a specific shear strength and permeability characteristic depending on each unit's geological structures and formation. Lithology is one of the factors that have the greatest impact on slope instability (Yalcin & Bulut, 2007; Mersha and Meten, 2022). The composition and structure of various rock types vary, resulting in addition to the material's strength. When

compared to the softer/weaker rocks, the stronger rock units provide more resistance to the driving force, which can lead to landslides. Six lithological units, including highly weathered lower Abay Basalt (Tv2), Weathered Debrework-Gundewayn Basalt (Tv3), Upper Sandstone (MUst), Gypsum (MGyp), Antalo Limestone (Mlst), and Elluvium Deposits (Qel) are present in the studied region. The dominant rock unit which covers the study area is Lower Abay Basalt (Tv2), followed by Antalo limestone (Mlst), and Gypsum (MGyp). Debrework Gundewayn basalt (Tv3) covers a very small portion of the study area to the northwest direction Table 5.1, Fig 5.1 and Fig 5.2G.

Table 5.1 Lithological units and their area coverage.

Lithology	Area in Km ²	Percentage area
Gypsum (MGyp)	243.2246	18.34640949
Antalo limestone (Mlst)	355.3008	26.80030491
Upper sandstone (MUst)	10.5979	0.799398363
Elluvium (Qel)	121.6044	9.172609114
Lower Abay basalt (TV1)	589.0356	44.43090716
Debrework Gundewayn basalt (Tv3)	5.970721	0.45037096
Total	1325.734	100

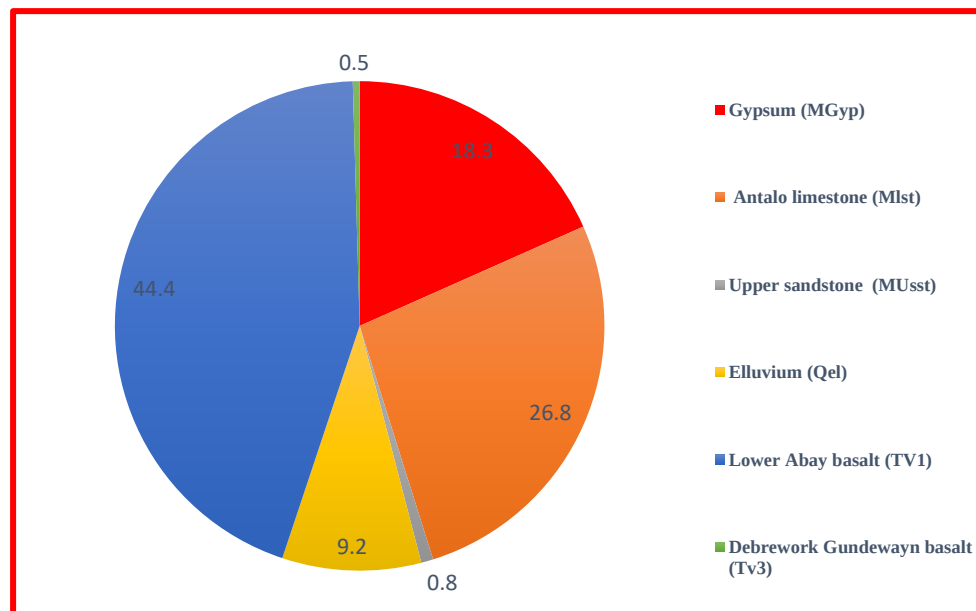


Fig. 5.1 Percentage of each lithology area coverage in the study area

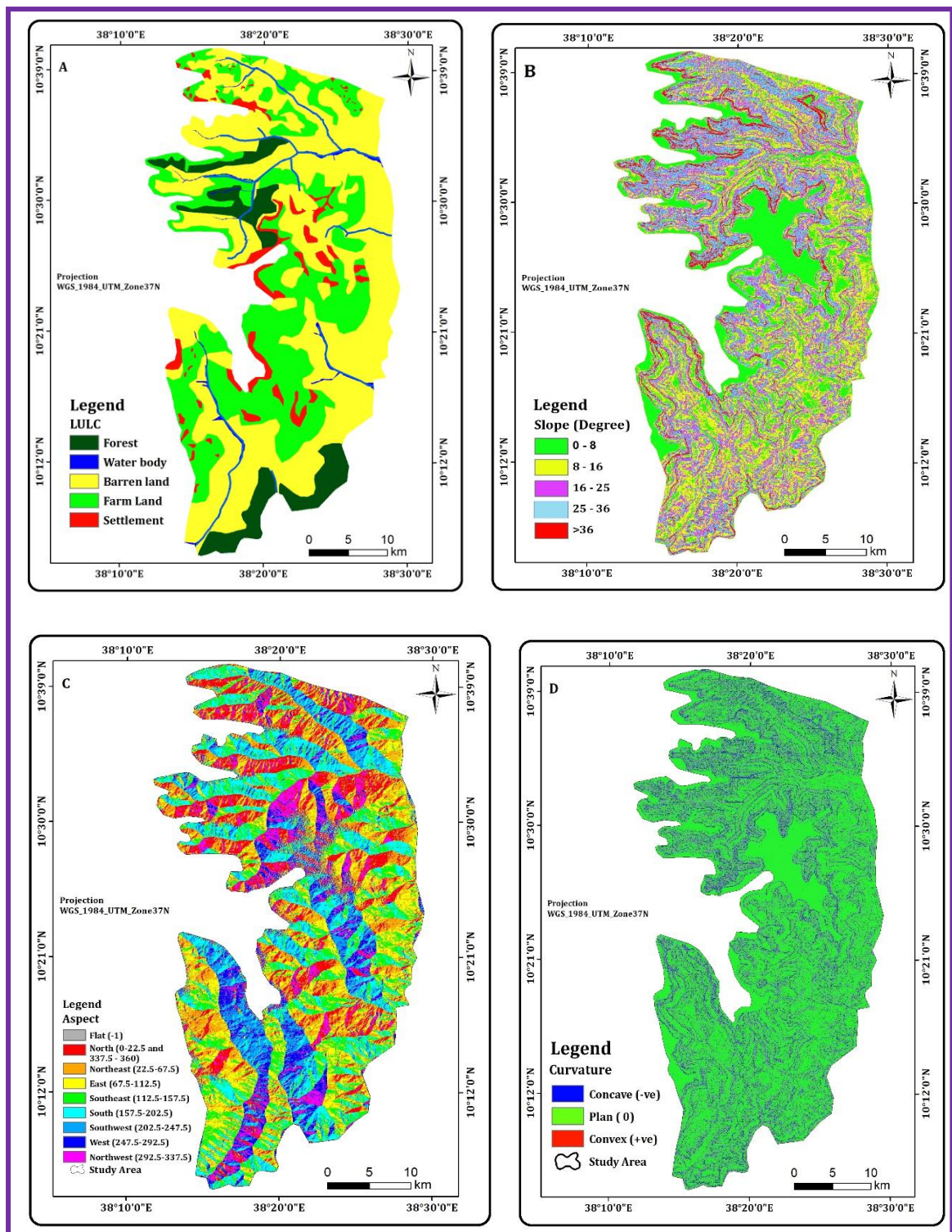
5.2.8 Rainfall

Heavy rain is the primary cause of slope failures (Ayalew, 1999; Getachew & Meten, 2021). Although it is generally known that rainfall influences the stability of subsurface materials, it

is difficult to assess the significance of rainfall considering the other variables that might also have an impact on the process of landslide formation. While in some areas, considerably lower hills with moderate relief may fail after relatively small amounts of rain over several days, very irregular chains of mountains with steep slope angles may maintain their stability regardless of the amount of precipitation (Ayalew, 1999). For instance, the continuous chain of Bale Mountains in the southeast of the country received a high amount of rainfall but they are not subjected to landslide at all.

In a particular area, rainfall plays a significant role in the prevalence of slope instability. Rainfall (in particular, sudden and intense downpours) is a controlling factor that can cause landslides by supplying moisture, raising the pore water pressure and the hydrostatic level below the Earth. Such pressure variations in the soil cause the water there to build up negative or upward pressure since it cannot immediately drain (Getachew and Meten, 2021). The shearing resistance of the material decreases and the material fails when the pore water pressure equals the upper pressure. The nine stations' rainfall data obtained from the Ethiopian Metrological Agency were used to generate the rainfall map of the study area using the IDW method in the Arc GIS Spatial analyst tool. IDW is used because Kriging requires intricate statistical modeling and variation of analysis and is more complex and harder to understand than IDW, which is simpler and more basic. IDW is easier for non-experts to understand and makes fewer assumptions. It can be used to calculate the unknown spatial rainfall data from the known sites' around known sites' data.

Additionally, it gives the user more freedom and flexibility to change variables, like the power or exponent value, that may impact on the interpolation results. This can be useful when you have prior knowledge or unique needs for the interpolation process. However, some data records were missing for some months in the gauging points and they are considered non-record (NR) (Appendix 1.1). The interpolated rainfall of the study area was classified into five classes of (1157 – 1184), (1184 – 1200), (1200 – 1214), (1214 – 1230), and (1230 – 1253), rainfall in mm (using the Natural Breaks (Jenks) method, the fourth class of (1214 – 1230mm) is the dominant rainfall in the study area Fig 5.2H.



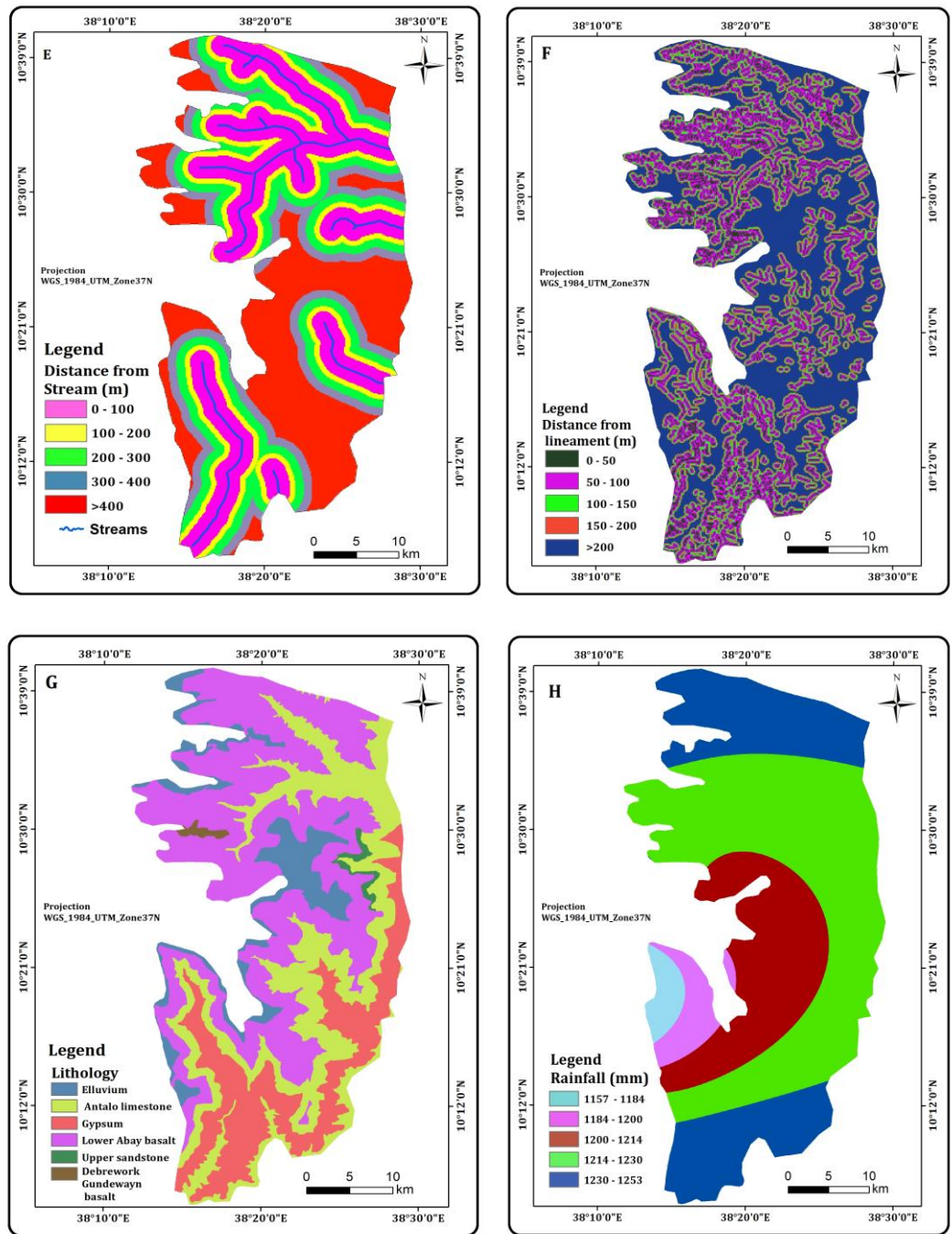


Fig. 5.2 Landslide causative factor maps, (A) LULC Map, B) Slope, C) Aspect, D) Curvature, E) Distance to Stream, F) Distance to Lineament, G) Lithology and H) Rainfall map.

CHAPTER SIX

RESULT AND DISCUSSION

6.1 The Relationship between Landslide and Causative Factors

Relationship between the percentages of landslide distribution with each causative factor class calculated using the landslide training dataset (75% of landslide inventory) in the spatial analyst tool of Arc GIS 10.8.

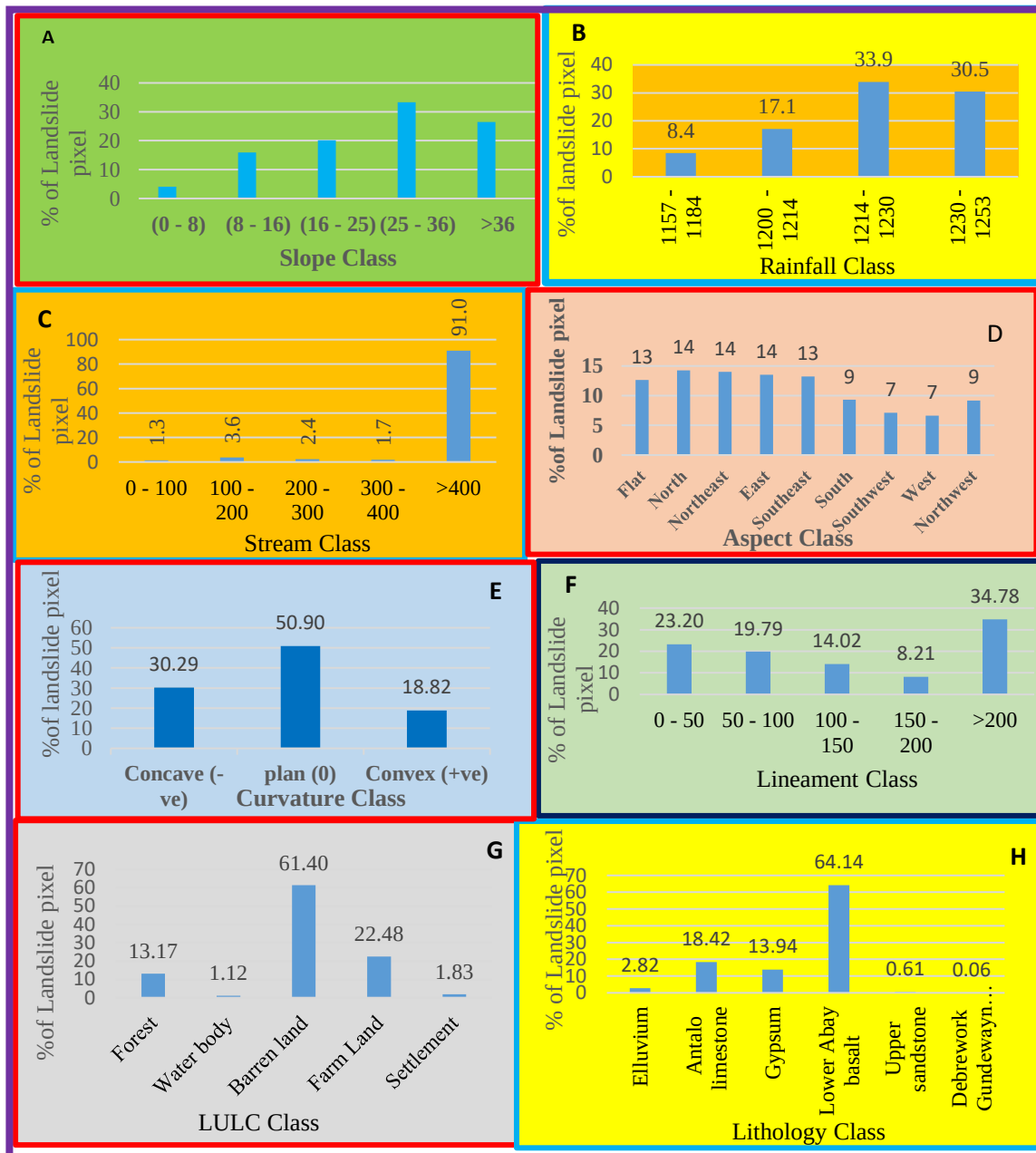


Fig. 6.1 Percentage of Landslide frequency distribution against (A) Slope angle, (B) Rainfall, (C) Stream, (D) Aspect, (E) Curvature, (F) Lineament, (G) LULC, and (H) Lithology.

This study examined the relationships between eight causative factors and the likelihood of landslides. The contrast weight and regression coefficient values have been calculated using the WoE and LR models and are shown in Tables 6.1 and 6.2.

Table 6.1 Data used in the analyses and results obtained from the WoE method (Nslide = 206550 and Nmap = 1473101).

Factors	Class	Nclass	Npix1 (Nslide)	Npix2	Npix3	Npix4	W+	W-	C
Slope (Degree)	(0 - 8)	344168	9554	196996	334614	931937	-1.743	0.259	-2.002
	(8 - 16)	429603	33189	173361	396414	870137	-0.667	0.200	-0.867
	(16 - 25)	350541	53766	152784	296775	969776	0.105	-0.035	0.140
	(25 - 36)	246725	68992	137558	177733	1088818	0.867	-0.255	1.123
	>36	102064	41025	165525	61039	1205512	1.416	-0.172	1.588*
Rainfall in (mm)	1157 - 1184	142645	12474	194076	130171	1136380	-0.532	0.046	-0.578
	1184 - 1200	294842	26076	180474	268766	997785	-0.519	0.104	-0.623
	1200 - 1214	565725	84639	121911	481086	785465	0.076	-0.049	0.125
	1214 - 1230	280401	47276	159274	233125	1033426	0.218	-0.056	0.274
	1230 - 1253	189488	36061	170489	153427	1113124	0.365	-0.063	0.428
Stream in (m)	0 - 100	17046	2121	204429	14925	1251626	-0.138	0.002	-0.139
	100 - 200	46741	6293	200257	40448	1226103	-0.047	0.002	-0.049
	200 - 300	33307	4607	201943	28700	1237851	-0.016	0.000	-0.016
	300 - 400	24471	3571	202979	20900	1245651	0.047	-0.001	0.047
	>400	1351536	189933	16617	1161603	104948	0.003	-0.030	0.032
Aspect	Flat	179447	24851	181699	154596	1111955	-0.014	0.002	-0.016
	North	210082	26263	180287	183819	1082732	-0.132	0.021	-0.153
	Northeast	206250	27075	179475	179175	1087376	-0.076	0.012	-0.088
	East	199380	26759	179791	172621	1093930	-0.051	0.008	-0.058
	Southeast	194888	32030	174520	162858	1103693	0.187	-0.031	0.218
	South	136872	20724	185826	116148	1150403	0.090	-0.010	0.099
	Southwest	105278	13270	193280	92008	1174543	-0.123	0.009	-0.132
	West	97288	13612	192938	83676	1182875	-0.002	0.000	-0.003
	Northwest	143615	21942	184608	121673	1144878	0.101	-0.011	0.112
Curvature	Concave (-ve)	234672	55100	151450	179572	1086979	0.632	-0.157	0.789
	plan (0)	1043962	112863	93687	931099	335452	-0.297	0.538	-0.835
	Convex (+ve)	194467	38563	167987	155904	1110647	0.417	-0.075	0.492

Lineament	0 - 100	158906	54726	151824	104180	1162371	1.170	-0.222	1.392*
	100 - 200	403660	85662	120888	317998	948553	0.502	-0.247	0.748
	200 - 300	237577	27093	179457	210484	1056067	-0.237	0.041	-0.278
	300 - 400	115960	9675	196875	106285	1160266	-0.583	0.040	-0.623
	>400	556998	29369	177181	527629	738922	-1.075	0.385	-1.460
LULC	Forest	128840	27190	179360	101650	1164901	0.495	-0.057	0.552
	Waterbody	21519	2310	204240	19209	1247342	-0.305	0.004	-0.309
	Barren land	787433	126806	79744	660627	605924	0.163	-0.214	0.377
	Farm Land	463563	46433	160117	417130	849421	-0.382	0.145	-0.527
	Settlement	71746	3786	202764	67960	1198591	-1.074	0.037	-1.111
Lithology	Elluvium	135176	5834	200716	129342	1137209	-1.285	0.079	-1.364
	Antalo limestone	394816	38045	168505	356771	909780	-0.425	0.127	-0.552
	Gypsum	270261	28785	177765	241476	1025075	-0.313	0.061	-0.375
	Lower Abay basalt	654435	132468	74082	521967	744584	0.442	-0.494	0.936*
	Upper sandstone	11772	1266	205284	10506	1256045	-0.303	0.002	-0.305
	Debrework Gundewayn basalt	6641	127	206423	6514	1260037	-2.124	0.005	-2.129

Table 6.2 Data Used in LR Analysis and the Result Obtained

Independent variables	Variables in the Equation				Collinearity Diagnostics		Hosmer and Lemeshow Test	Model Summary	
	B	S.E.	Sig.	Exp(B)	TOL	VIF		Chie Square (x2) 0.605	Cox & Snell R Square 0.181
Stream	- 3.675	.102	.009*	.003	0.107	1.014			
Aspect	0.186	.070	.000	.071	0.628	1.717			
Curvature	0.467	.010	.000	1.500	0.692	1.920			
Lineament	1.027	.002	.000	4.298	0.701	1.966			
Lithology	0.678	.013	.000	.187	0.683	1.876			
Lulc	0.257	.073	.000	.013	0.671	1.579			
Rainfall	1.070	.000*	.000	2.000	0.621	1.646			
Slope	6.955	.001	.000	8.403*	0.9428	1.1376			
Constant	-6.04	.013	.000	2.022					
Variable(s) entered in step 1: Stream, Aspect, Curvature, Lineament, Lithology, Lulc, RF, and Slope. B = LR Coefficient, SE = Standard Error, Exp(B) = Represent Odd Ratio, Sig = Significance of the Model, VIF = Variance Inflations factors, TOL = Tolerance.									

As shown in Tables 6.1 and 6.2, the causative factors were divided into various classes and given weights for both the WoE and LR models. W^+ and C factors, describe the correlation and spatial linkage of the landslide with components in the WoE model based on weight contrast C and regression coefficients B respectively.

Landslide Relationships with Causative Factors based on LR

The regression coefficients obtained from the logistic regression analysis with the eight significant independent variables indicate the strength and direction of the relationship between each independent variable and the likelihood of landslide occurrence. These coefficients can be used to interpret the impact of each variable on the probability of landslides. Positive coefficients indicate that an increase in the corresponding independent variable is associated with an increased likelihood of landslides, while negative coefficients suggest a decrease in the likelihood of landslides with an increase in the independent variable. The magnitude of the coefficient represents the strength of the relationship. Larger coefficients indicate a stronger influence on the probability of landslides, while smaller coefficients suggest a weaker influence.

In this scenario, all factors are strongly correlated to the probability of landslide occurrences except for distance to stream. The significance level of 0.000 indicates that the p-value associated with the coefficient is very small, suggesting that the relationship between aspect and landslide occurrence is statistically significant. In this case, the significance level of all causative factors is very small except for the distance from the stream, which shows a high value compared to other classes suggesting less contribution to landslide occurrence Table 6.2. The $\exp(b)$ value of 0.71 represents the odds ratio. It indicates that for every one-unit increase in aspect, the odds of landslide occurrence increase by a factor of approximately 0.71. The standard error of 0.070 indicates the precision of the estimated coefficient and the same is true for all factors in Table 6.2. A smaller standard error suggests a more precise estimate.

Landslide Relationships with Topographic Parameter Based on WoE

Landslides are more likely to occur when the C factor is positive, and vice versa for a negative C factor. A greater degree of influence on the probability of landslides is described by the WoE model's higher contrast (C) value. The study area's slope was divided into five classes, and each class's contribution was calculated according to Table 6.1. The probability of a landslide occurring increases directly with the slope's steepness (Lee and Min, 2001,

Getachew and Meten, 2021). According to (Mahdadi et al., 2018), when the slope angle increases, the pushing force of the slope mass also rises while the resistive force falls. This assertion was supported by the studies in this research findings as well. According to the information obtained from WoE data in Table 6.1, there is a negative weight contrast for slope angles between (0 – 8), and (8 – 16), which means that because the terrain is flat and has minimal or no inclination, there is a lower probability of having landslides in these slope classes. On the other side, the 3rd and 4th ((16 – 25) and (25 – 36)) classes are affected by landslides due to moderate to gentle slope prevalence which is suitable for settlement and other different anthropogenic activities. The fifth slope class (>36°) with the highest significance over all eight causative factors used in the research with a “C” value of 1.588 (Table 6.1) enhances the probability of landslides. Landslides appear to be the most frequent in this slope class due to the steepness of the angle up to a maximum of 74° dominantly in northern parts of the study area, which increases the driving force and decreases the resistive force due to gravity and interaction of surface and subsurface water.

Aspect classes, with SE, S, and NW slope faces have each exhibited a positive relationship between the landslide and each factor class with C = 0.218, 0.099, and 0.112, respectively. According to this result, there is a significant chance of landslides occurring on most slopes facing toward the Southeast since stream erosion and geological formations (lineaments), and facing toward sunlight are the main causes. The remaining six classes of aspects demonstrate a negative correlation toward landslide Table 6.1. The main element groundwater and surface water flow is curvature. This study classifies curvature into three classes: Concave, flat, and convex. Concave classes displayed a relatively more favorable connection with the occurrence of landslides with C = 0.789 as slopes frequently collect and keep water, especially during severe rainfall. Concave land surfaces make it challenging for water to drain properly, which causes the soil to be saturated. This extra moisture can weaken the soil and raise pore pressure, which increases the probability of landslides on the concave slope. This may be due to high groundwater discharge and most streams are flowing in this direction from the top parts of Choke Mountain to the (Abay) Blue Nile River across the study area. The weight of this class also suggested a high probability of landslide occurrence. The third convex curvature class also shows a positive weight contrast of C = 0.492. The shallow soil depths on convex slopes are frequently caused by weathering and or erosion. The shear strength of this thin soil layer may have decreased, causing it more to be prone to failure. Reduced shear strength and increased pore water pressure during

rainfall can cause landslides and slope instability in both concave and convex slope curvature.

According to Table 6.1, the second class (flat) displayed a negative connection ($C = -0.8$). Compared to higher slopes, flat or moderately sloping terrain typically offers more stable conditions. The lack of major slope variations lessens the gravitational forces operating on the earth's surface, which lowers the probability of slope failure and landslides. When compared to steep slopes, flat terrain frequently offers better natural drainage. Water may flow off the ground surface freely and easily because there are no large inclines, reducing the amount of extra water that collects. Inadequate drainage lowers the risk of landslides by maintaining soil strength and stability. Finally, the probability of dense vegetation cover is higher in flat places. By strengthening soil structure, increasing root cohesion, and catching rainwater, vegetation plays a critical role in slope stabilization by lowering soil erosion and improving slope stability.

Landslide Relationships between Lithology, Land Use, and Rainfall Based on WoE

High percentages of landslides have been observed in the highly weathered lower Abay basalt (Fig 5.2A, G, H), indicating a higher probability of landslides in these areas. The highly weathered lower Abay basalt class exhibited the highest contrast value ($c = 0.936$) Table 6.1. The remaining classes showed negative contrast values and a negative association with landslides. This can be attributed to the presence of geological structures like lineaments and faults in the northern parts of the study area where the highly weathered lower Abay basalt is located. The negative contrast values and negative association with landslides in the other classes could be due to various factors. These factors may include different geological characteristics, such as soil composition, slope gradient, vegetation cover, or land use practices. These factors may not favor landslide occurrence or are less conducive to landslide formation compared to the highly weathered lower Abay basalt class.

Steeper slope gradients increase the likelihood of landslides due to greater gravitational force. If the other classes have lower slope gradients compared to the highly weathered lower Abay basalt class, it could explain the lower landslide occurrence and negative contrast values. Similarly, high rainfall can saturate the soil and decrease its shear strength, increasing the likelihood of landslides. As the other classes have lower rainfall amounts compared to the highly weathered lower Abay basalt class, it could explain the lower landslide occurrence and negative contrast values.

With a decreasing order of the weights of contrast, the classes of forest ($C = 0.552$) and bare land ($C = 0.377$) have a larger potential than landslides associated with LULC. Negative C values and negative correlation are indicated in the remaining classes in Table 6.1. This is because steep slopes of highly weathered basalt and limestone are covered in forest and bare land in the northern and a little southern parts (around Selelkula) of the study area (Fig 5.2G). Additionally, the forest region is prone to water saturation and active erosion, which makes it susceptible to landslides. Trees with shallow and disconnected roots can even cause landslides on their own. Landslides are often triggered by heavy rainfall, as the excess water can saturate the soil and reduce its stability (Getachew and Meten, 2021). When the soil becomes saturated, it loses its ability to hold itself together, leading to a higher likelihood of landslides occurring. Therefore, as rainfall intensity increases, the risk of landslides also increases. The current study has also verified a similar situation; however, it is important to note that other factors such as slope steepness, soil type, and vegetation cover also play a significant role in determining the occurrence of landslides. The classes of rainfall exhibit a progressive increase in the probability of landslide occurrence. The first and second classes have negative contrast values, while the last three classes (rainfall ranges of 1200-1214 mm/year, 1214-1230 mm/year, and 1230-1253 mm/year) show high landslide occurrences with contrast values of 0.125, 0.274, and 0.428 respectively Table 6.1.

There are five classes for distance to stream in landslide susceptibility mapping for this study. The first, second, and third classes exhibit negative C values, while the fourth and fifth classes show positive $C = 0.047$ and 0.032 values respectively. Additionally, the fourth class has a higher value than the other classes. fourth class of distance to stream shows a higher positive C value compared to the other classes because this class represents closer proximity to streams, which is known to have a higher likelihood of landslide occurrence than other classes. In this case, the closer the distance to streams, the higher the weight of evidence for landslide susceptibility. Therefore, the fourth class, representing a closer distance to streams, may have a higher positive C value indicating a stronger association with landslide occurrence.

Landslide Relationships between Distance to Lineaments and Streams Based on WoE

The closer a location is to a stream and lineaments, the higher the likelihood of landslide occurrence. The distance to the stream is considered one of the factors influencing landslide susceptibility. This is because streams can erode and weaken the surrounding soil or rock mass, increasing the vulnerability to landslides. However, the result obtained for this study

deviated from this except for lineament. According to the result obtained, the distance to stream classes did not show a strong correlation with landslides as the distance to stream decreased and the value of C was close to zero from both sides. This suggests that the proximity to streams alone may not be a determining factor for landslides. Other factors such as geological conditions, slope gradients, soil properties, and rainfall patterns can also play significant roles in landslide occurrence. It is essential to consider a combination of factors when assessing landslide susceptibility. From the five classes of distance to stream for this study, the fourth and fifth classes of distance show positive contrast values of $C = 0.047$ and $C = 0.032$, respectively. The rest three classes show a negative value. In this particular study, it appears that apart from distance to stream, other seven factors such as slope gradient, geological structures, and topographic and drainage patterns were found to impact the area's landslide susceptibility. This is because these factors are commonly considered in landslide susceptibility mapping as they contribute to the overall stability of slopes.

Slope gradient: Steeper slopes are generally more susceptible to landslides due to the increased gravitational forces acting on the materials. For this study, Google Earth shows the gentle slope for an area close to streams. This reveals that up to a distance of 0–300 m.

Topographic and drainage patterns: The shape of the landscape and the presence of natural drainage patterns can influence the distribution of water and its ability to infiltrate or runoff. Poor drainage can lead to increased soil saturation, reducing its strength and stability. In this case, there is sophisticated drainage and a steep slope, which easily reduces the saturation of riverbanks as the water from the tributary follows the drainage path to join the main river.

Geological structures: Certain geological structures, such as faults, joints, lineament, and bedding planes, can act as potential pathways for water infiltration, leading to increased pore pressure and reduced slope stability.

Next to slope, lineament is the main factor governing the susceptibility of landslides. In this study, the lineaments are overlaid with a landslide susceptibility map, and the high and very high landslide susceptible zones are found in areas with high lineament density dominantly to the North, Northwest, south, and southwestern of the study area. This indicates a strong relationship between lineaments (linear features like faults or fractures) and the occurrence of landslides. Lineaments can act as potential weak points in the Earth's crust, making those areas more prone to landslides. The distance from lineament for the first and second classes, (0 – 100m) and (100 – 200 m) strongly correlates with the probability of landslide occurrence

as their contrast value $C = 1.392$ and 0.748 respectively. As the distance from the lineament increases, the value of contrast C also decreases for the rest of the classes Table 6.1.

In general, the weight values generated from WoE and the regression coefficient from LR techniques illustrate the spatial correlations of the causative factors contributing to the incidence of landslides. Both models show a relatively similar correlation with minimum variation.

6.2 Landslide Susceptibility Mapping Using WoE and LR Methods

6.2.1 Application of WoE Method

The WOE model produced a final map of the study area's susceptibility to landslides based on the weighted results of the eight causal factors and the training landslide (Table 6.1). The weight contrast, or the difference between W^+ and W^- ($C = W^+ - W^-$), represents the total spatial relationship between causative factors and landslides. Based on Equations 2 and 3, each factor class's positive and negative weights were determined. All parameters were assigned weights to contrast values, including lithology, slope, curvature, aspect, land use/cover, rainfall, distance to stream, and distance to lineament. The difference between the positive and negative weights is known as the weight of contrast. To create the LSI map, the weight contrast value (C) of each of the eight causative factors was determined using a raster calculator in the ArcGIS Spatial Analyst tools

$$LSI = C_{lithology} + C_{slope} + C_{aspect} + C_{stream} + C_{lulc} + C_{curvature} + C_{rainfall} + C_{lineament} \dots \text{Eqn. (7)}.$$

Where

- $C_{lithology}$ = weights of contrast value of lithology,
- C_{slope} = weights of contrast value of Slope,
- C_{aspect} = weights of contrast value of Aspect,
- C_{stream} = weights of contrast value of distance to stream,
- C_{lulc} = weights of contrast value of LULC,
- Curvature = weights of contrast value of Curvature,
- $C_{rain\ fall}$ = weights of contrast value of rainfall, and
- $C_{lineament}$ = weights of contrast value of distance to lineaments.

The LSI values were reclassified using the natural breaks classification method into five landslide susceptibility classes: Very Low ($-5.33 - -2.81$), Low ($-2.81 - -0.75$), Medium ($-0.75 - 1.19$), High ($1.19 - 3.29$) Very High ($3.29 - 6.964$) with percent LDI of 9.26, 30.12,

24.78, 21.86, and 13.96 respectively Fig 6.4 and Table 6.3. The research area spans 1326 km², with approximately 64.16 km² classified as having Very low, low and medium landslide susceptibility, accounting for 1.207 % of the total landslide density. Interestingly, 70.14% of historical landslides (35.82 km²) occurred in areas characterized by high and very high landslide susceptibility Table 6.3. These statistics highlight the importance of considering areas with high and very high susceptibility when assessing landslide risk of the study area into different susceptibility classes, allowing for a better understanding of the varying levels of landslide risk and the corresponding area coverage associated with each class. Generally, the study area has been classified into five landslide susceptibility classes based on Landslide susceptibility (LSI) values. These classes range from very low to very high susceptibility. The very low susceptibility class covers a significant area but has a lower level of susceptibility. The low, medium, high, and very high susceptibility classes cover larger areas and indicate higher levels of susceptibility. The classification provides insights into varying levels of landslide risk and their corresponding area coverage.

Table 6.3. Landslide susceptibility class index and training landslide pixels of WoE Model

Classes	Landslide Susceptibility and Classes	Number of Pixels in the Map Classes	% of Pixels in the Map classes (a)	Number of Training Landslide pixels	Landslide Area coverage (Km ²)	% Landslide area covered	% Training Landslide pixels (b)	Landslide Density Index LDI = (b/a)
1	Very Low (-5.33 - -2.81)	136846.4	9.26	1739	89.9	9.26	0.84	0.09
2	Low (-2.81 - -0.75)	442696	30.12	17047	430.52	30.12	8.25	0.27
3	Medium (-0.75 – 1.19)	364190	24.78	42880	343.3	24.78	20.76	0.84
4	High (1. 19 – 3.29)	321297	21.86	66365	295.64	21.86	32.13	1.47
5	Very High (3.29 – 6.964)	205219	13.96	78519	166.66	13.96	38.02	2.72

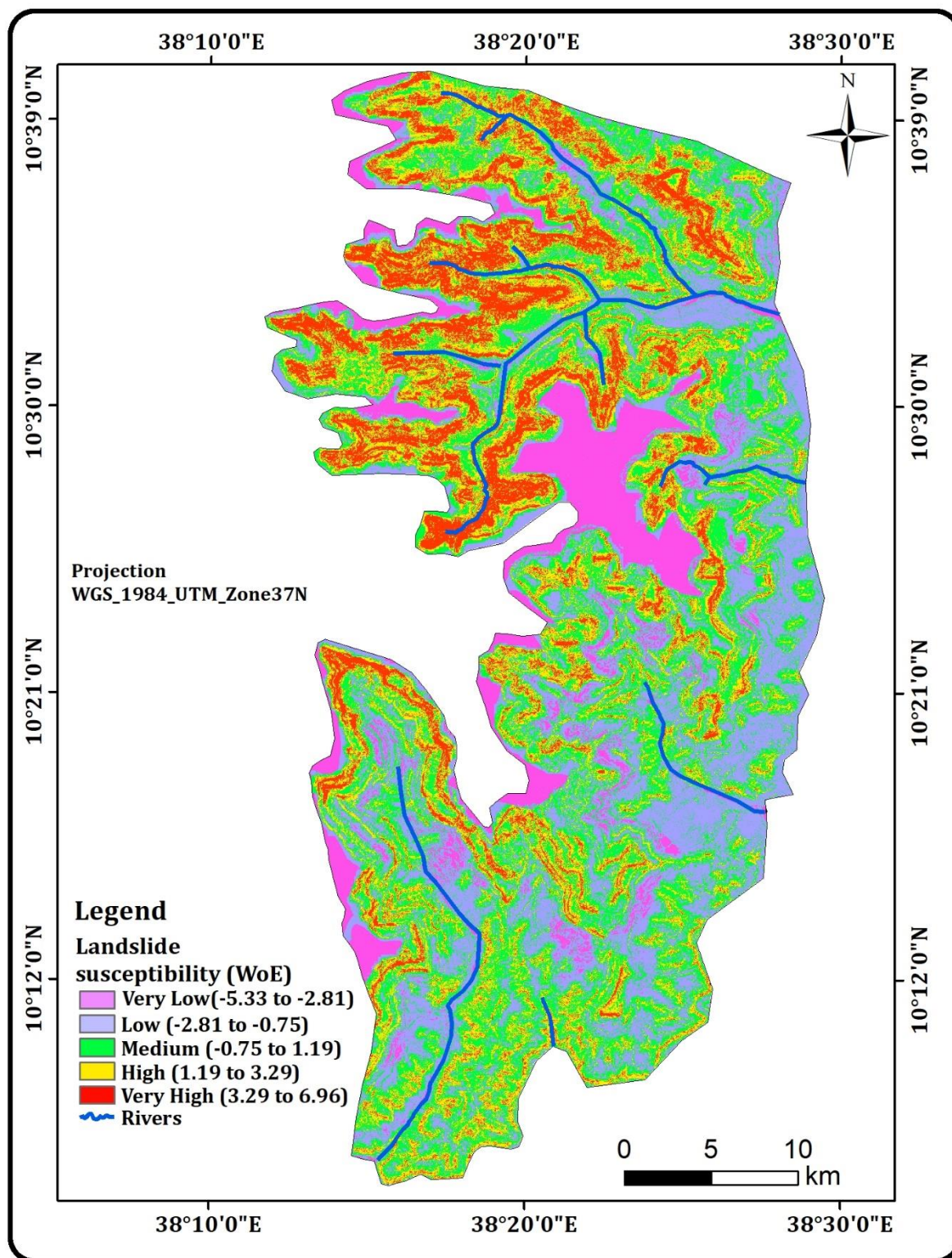


Fig 6.4 Landslide susceptibility map produced using Weight of Evidence Model.

6.1.2 Application of LR Method

Logistic regression is commonly used in multivariate analysis because it allows us to predict a binary outcome, such as the presence or absence of landslides, based on a set of independent variables (Meten, PrakashBhandary, et al., 2015; Bai et al., 2010; Wubalem and Meten, 2020; Goyes-Peñafiel and Hernandez-Rojas, 2021). Unlike linear regression, logistic regression does not assume that the dependent variable follows a normal distribution. This makes it suitable for analyzing non-linear relationships and handling continuous, categorical variables or a combination of both. The challenge in conducting a landslide susceptibility analysis using a logistic regression model is choosing the appropriate sample size for the dependent and independent variables. There are three methods for sampling places with and without landslides. There are three different methods used in this study to handle the uneven proportion of landslide and non-landslide pixels (Bai et al., 2010; Wubalem, 2021):

1. The first method involves using all data from all study areas. However, this approach may result in an uneven proportion of non-landslide and landslide pixels, which can introduce a large volume of data into the analysis. This can potentially affect the reliability of the output.
2. The second method involves using all landslide pixels with an equal number of non-landslide pixels. While this approach can reduce sample size and sampling bias, it may also lead to a less reliable output compared to using all available data.
3. The third method involves using an unequal proportion of landslide and non-landslide pixels. In this particular study, the second method was used by the landslides in the study area were classified into training landslides (75% with 206550 pixels) and (25% with 60922) pixels of testing landslides. This method allows for a more balanced representation of both classes and can help improve the accuracy of the analysis (Bai et al., 2010; Meten et al. 2020). In the training dataset, it is typically advised that the ratio of landslide presence (1)/landslide absence (0) should be equal to 1 (Bai et al., 2010; Nefeslioglu et al., 2008). In addition, since the study area is too large, there are fewer areas of the study region where landslides are present than when they are absent, they are regarded as a rare occurrence.

After converting the dependent variable into a logit variable (the natural log of the probability of the dependent occurring or not), the logistic regression algorithm uses maximum likelihood estimation. This is how logistic regression calculates the likelihood that a specific event (Landslide in this case) will occur (Bai et al., 2010). To create a landslide susceptibility map of the LR the Arc GIS 10.8 and SPSS 26 were used and regression coefficients were obtained for each independent variable in the SPSS software as shown in

Table 6.2. The simplest form of the logistic model for a binary dependent variable representing the presence or absence of landslides can be expressed as Eqn...5 and $(-z)$ represents the linear combination of predictor variables and their coefficients Eqn...6. In the logistic regression model, the coefficients of the predictor variables determine the impact of each variable on the probability of landslides. The logistic function $(1 / (1 + \exp(-z)))$ transforms the linear combination into a probability value between 0 and 1. $P(Y=1) = 1 / (1 + \exp(-(b_0 + b_1 \cdot \text{stream} + b_2 \cdot \text{aspect} + b_3 \cdot \text{curvature} + b_4 \cdot \text{lineament} + b_5 \cdot \text{lithology} + b_6 \cdot \text{lulc} + b_7 \cdot \text{Rainfall} + b_8 \cdot \text{slope})))$

where:

- b_0 represents the constant term (-6.04)
- b_1 represents the coefficient for the "stream" variable (-3.675)
- b_2 represents the coefficient for the "aspect" variable (0.186)
- b_3 represents the coefficient for the "curvature" variable (0.467)
- b_4 represents the coefficient for the "lineament" variable (1.027)
- b_5 represents the coefficient for the "lithology" variable (0.678)
- b_6 represents the coefficient for the "Lulc" variable (0.257)
- b_7 represents the coefficient for the "Rainfall" variable (1.070)
- b_8 represents the coefficient for the "slope" variable (6.955)

The results obtained show that except for distance from stream negative coefficient (-3.675), all factors contribute to the probability of landslide occurrence Table 6.2. This suggests that the distance from the stream has a negative correlation with landslide occurrence (the last class of stream distance >400m has 91% of landslide Fig.6.1. This implies that areas with higher stream values such as increased flow or water volume are less likely to experience landslides. This can be explained by the fact that streams tend to effectively drain water from the surrounding areas, reducing the saturation of the soil and decreasing the likelihood of slope instability.

High stream values may also indicate well-established drainage systems, which can prevent water accumulation and decrease landslide risk. The LSI values were prepared and reclassified using the natural breaks classification method into five landslide susceptibility classes in the Arc GIS spatial analyst tool Very Low (0.07 - 0.3), Low (0.3 - 0.44), Medium (0.44 - 0.59), High (0.59 - 0.74), and Very High (0.74 - 0.96) Table 6.4 and Fig 6.5. From the total research area (1326 km²), about 58.67% area was affected by Medium (0.44 - 0.59),

High (0.59 - 0.74), and Very High (0.74 - 0.96) landslide susceptibility with 0.8, 1.4, 2.1 the value of LSDI Table 6.4. In general, the value of the landslide susceptibility increases the density of the landslide is also increased Table 6.4.

Table 6.4 The distribution of landslide in the classes of LR

Class Number	Landslide Susceptibility Classes and LSI	Number of Pixels in the Map Classes	Landslide Area Coverage (Km ²)	% Landslide Area Coverage (Km ²)	% of Pixels in the Map classes (a)	Number of Training Landslide pixels	% Training Landslide pixels (b)	LDI = (b/a)
1	Very Low (0.07 - 0.3)	309418	133.26	10.05	21.049	24608	11.915438	0.5661
2	Low (0.3 - 0.44)	394874	414.59	31.27	26.850	36435	17.642188	0.6571
3	Medium (0.44 - 0.59)	326468	338.58	25.53	22.206	40827	19.768838	0.8902
4	High (0.59 - 0.74)	265608	270.97	20.44	18.075	52281	25.314979	1.4006
5	Very High (0.74 - 0.96)	173464	168.59	12.71	11.820	52371	25.358557	2.1454

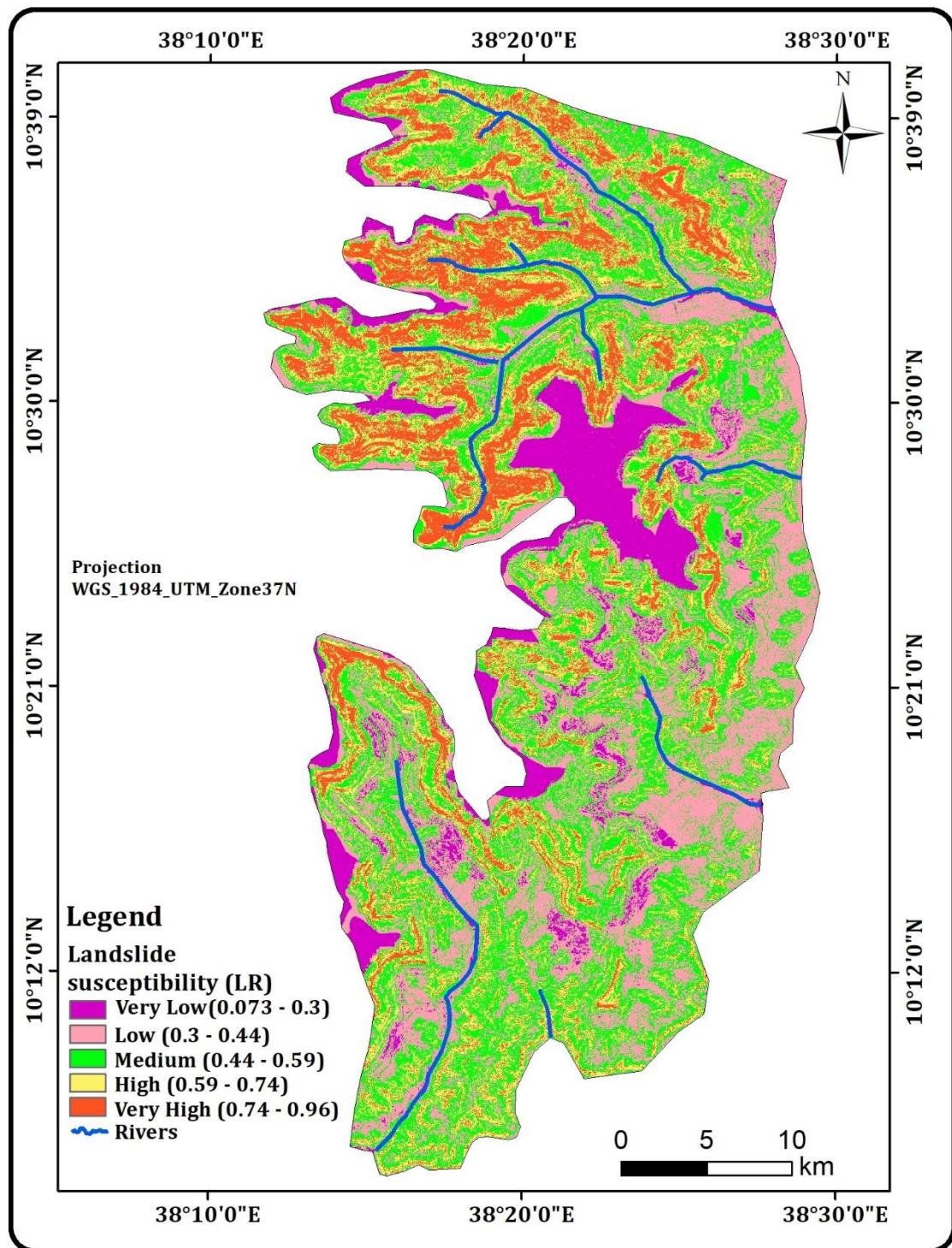


Fig 6.5 Landslide susceptibility map produced using Logistic Regression Model.

6.2 Models Validation

Model validation is a crucial step in the process of creating landslide susceptibility maps. Without validation, the maps may not accurately represent the true susceptibility of an area and can be misleading (Wubalem, 2021). Validation of predictive landslide models involves assessing the performance and accuracy of the model's predictions against independent datasets or real-world observations. This helps determine the reliability and effectiveness of the model in identifying areas prone to landslides. Various validation techniques can be employed, such as splitting the dataset into training and testing subsets, cross-validation, or comparing the model's predictions with actual landslide occurrences. These validation procedures help evaluate the model's performance metrics, such as sensitivity, specificity, accuracy, and area under the curve (AUC). Researchers and practitioners can ensure that the landslide susceptibility maps are meaningful and provide reliable information for land use planning, risk assessment, and mitigation strategies by conducting proper model validation. For this research, the sensitivity of the Area under the Curve of Receiver operating characteristics (AUC of ROC in SPSS 28 software) and Landslide Density Index (LDI in Arc GIS 10.8) were used, and a graph plotted for each using Excel 2016)

6.2.1 Validation of the Model Using ROC

The area under the Receiver Operating Characteristics (ROC) curve is a commonly used metric to evaluate models' performance and predictive accuracy, including logistic regression models. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) for different classification thresholds. In evaluating the success and predictive rates of both training and testing datasets, the area under the ROC curve provides a measure of how well the model can discriminate between positive and negative outcomes. A higher area under the ROC curve indicates better predictive performance, with values closer to 1 indicating higher accuracy (Wubalem and Meten, 2020). A probability of 0.018 indicates a low likelihood of landslide occurrence, while a probability of 0.957 indicates a high likelihood (Bai et al., 2010). The following categories can be used to categorize the quantitative and qualitative correlation between AUC value and prediction accuracy, According to (Mersha, 2022), Poor is 0.5-0.6, average is 0.6-0.7, good is 0.7-0.8, very good is 0.8-0.9, and excellent is 0.9 - 1.

To create a spatially effective landslide susceptibility map, two rules are mentioned: 1) Observed landslide areas should coincide with the areas having high-susceptibility values:

This means that areas, where landslides have occurred, should align with the areas identified as having high susceptibility based on the model (0.8 – 1). If the observed landslides are located in areas with high susceptibility values: 1) It suggests that the model can identify areas prone to landslides. 2) High-susceptibility values should cover only small areas: This rule implies that the areas identified as highly susceptible to landslides should not be widespread but rather localized. If the high-susceptibility values cover only small areas, it indicates a more precise mapping of landslide-prone regions. The result obtained in this research also suggests that high landslide susceptibility areas are localized to the northern (dominantly around Gedeb, Fenteriya, and Dima Georgis Betekiristian) and Southwestern (around Selelkula and Suha) and observed landslide areas coincide with the areas having high-susceptibility values. In this case, the real Statistics in Microsoft Excel is a statistical analysis tool that provides functions and tools to calculate and analyze various statistical measures, including the area under the ROC curve. Based on the information provided, both the logistic regression and Weight of Evidence models seem reliable and accurate (Fig 6.6).

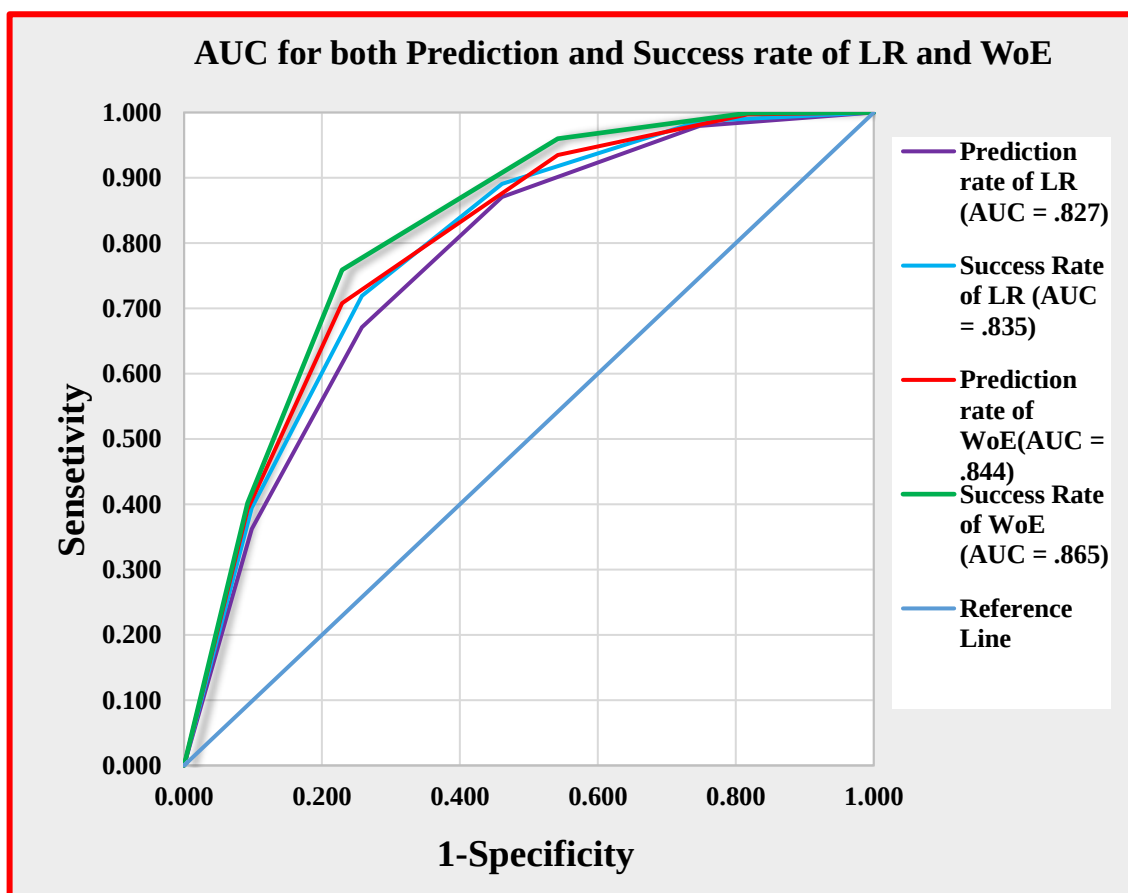


Fig 6.6 Success and Predictive rate curves of models (LR and WoE).

6.2.2 Validation of the Model Using Landside Density Index (LDI)

To validate the landslide susceptibility model, the testing samples (25% of landslide pixels) and the training dataset (75% of pixels) were overlaid onto the landslide susceptibility map of logistic regression and weight of evidence. By comparing the predicted landslide susceptibility values with the actual landslide occurrences in these datasets, the success rate and predictive rate of the model were evaluated. The success rate measures how accurately the model predicts the actual landslide occurrences in the testing samples, while the predictive rate measures its accuracy in predicting landslide occurrences in the training dataset. This validation process helps assess the performance and accuracy of the landslide susceptibility model.

The Landslide Density Index (LDI) was used as a validation metric for the landslide susceptibility model. This index is calculated by dividing the percentage of landslide pixels by the percentage of class pixels in each severity class on the landslide susceptibility map. According to (Ram et al., 2020), if the value of the landslide density index increases from a low level to a very high level of severity, it indicates that the landslide susceptibility map is valid. This means that the model accurately predicts the areas with a higher likelihood of landslides and provides a reliable representation of landslide susceptibility and the same is true for this result (Table 6.6 and Fig 6.7).

By dividing the percentage of landslide pixels by the percentage of area pixels, the LDI provides a measure of how frequently landslides occur in a given area, relative to the total area analyzed Eqn...(8). If the LDI is high, it suggests that landslides are more common in that area, and hence, the susceptibility to landslides is higher. Conversely, a lower LDI suggests that landslides occur less frequently in that region, thus lowering the susceptibility to landslides.

$$\text{LDI} = \text{percentage of landslide pixels} / \text{percentage of area pixels} \dots \text{Eqn (8)}$$

Nominator (Percentage of landslide pixels) refers to the proportion of pixels in the study area that have been identified as having experienced landslides. The denominator (percentage of area pixels) refers to the total proportion of the study area that has been covered by the analysis, usually in the form of a gridded map or raster.

Table 6.6 Validation of the Model Using Landslide Density Index Method

Models	Class Number	Landslide Susceptibility Classes and LSI	Number of Pixels in the Map	% of Pixels in the Map classes (a)	Number of Training Landslide pixels	% Training Landslide pixels (b)	LDI = (b/a)	Number of Validation	% Validation Landslide pixels (c)	LDI = (c/a)
Logistic Regression	1	Very Low (0.07 - 0.3)	309418	21.049	24608	11.915438	0.5661	6755	11.0907	0.527
	2	Low (0.3 - 0.44)	394874	26.850	36435	17.642188	0.6571	10301	16.9127	0.63
	3	Medium (0.44 - 0.59)	326468	22.206	40827	19.768838	0.8902	12156	19.9583	0.899
	4	High (0.59 - 0.74)	265608	18.075	52281	25.314979	1.4006	15783	25.9133	1.434
	5	Very High (0.74 - 0.96)	173464	11.820	52371	25.358557	2.1454	15912	26.1251	2.21
Weight of Evidence	1	Very Low (-5.33 - -2.81)	136133	9.26	1733	0.8391439	0.0906	210	0.3448	0.037
	2	Low (-2.81 - -0.75)	442696	30.12	17041	8.2515011	0.2739	6711	11.0188	0.366
	3	Medium (-0.75 - 1.19)	364190	24.78	42874	20.760217	0.8377	12076	19.8276	0.8
	4	High (1.19 - 3.29)	321297	21.86	66359	32.131997	1.4696	18085	29.6938	1.358
	5	Very High (3.29 - 6.964)	205219	13.96	78513	38.017141	2.7223	23823	39.115	2.801

LDI = Landslide Density Index, TL = Number of Training Landslide pixels, VL = Number of Validation Landslide pixels

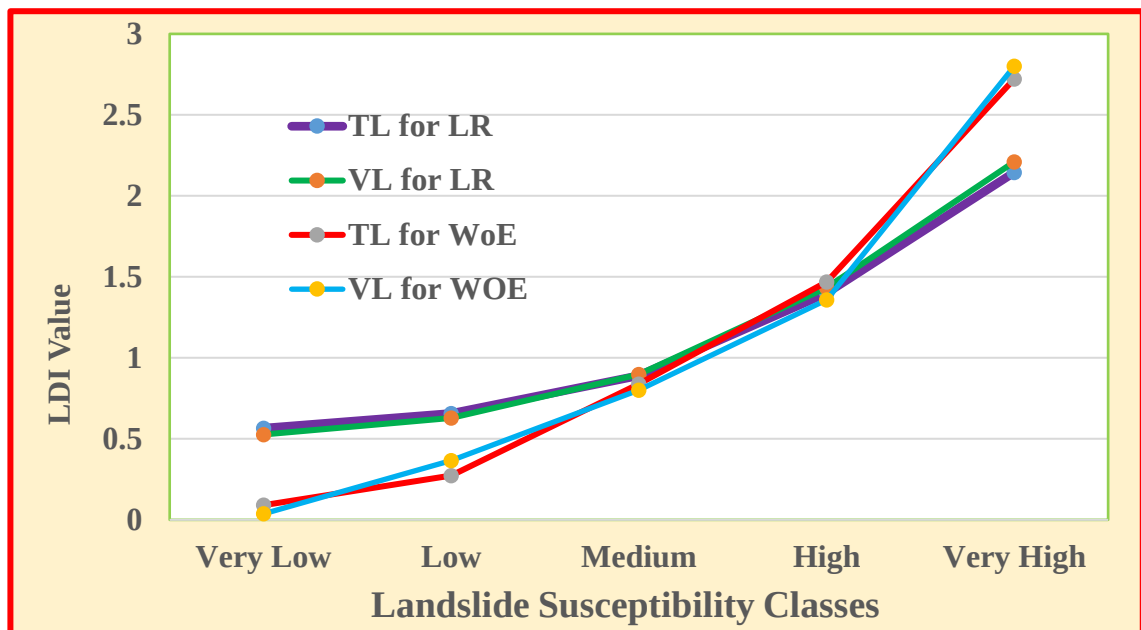


Fig 6.7 The landslide density for both the training and validation datasets using logistic regression (LR) and Weight of Evidence (WoE)

Table 6.6 show that the landslide density values for different susceptibility classes in the study area, specifically focusing on the very high susceptibility classes. The values for the WoE and LR models are 2.801 and 2.21, respectively, notably higher than those for other classes. This indicates that the very high susceptibility zones have a significantly higher density of landslides compared to the other classes. Furthermore, there is a gradual decrease in landslide density values as we go from the very high to very low susceptibility zones, as shown in Fig 6.8A and Table 6.6. This supports the validity of the landslide susceptibility map, suggesting that it accurately represents the varying degrees of susceptibility in the study area. Fig 6.8B likely provide additional information on the characteristics of susceptibility classes for the validation of both the WoE and LR models. These findings are likely consistent with the Landslide Density Index (LDI) method or other approaches used in the study. In general, the analysis indicates that the highest percentage or density of landslides is found in the very high landslide susceptibility zone. This suggests that the landslide susceptibility maps produced from both the WoE and LR models are reliable and provide useful information for understanding the distribution and intensity of landslide susceptibility in the study area.

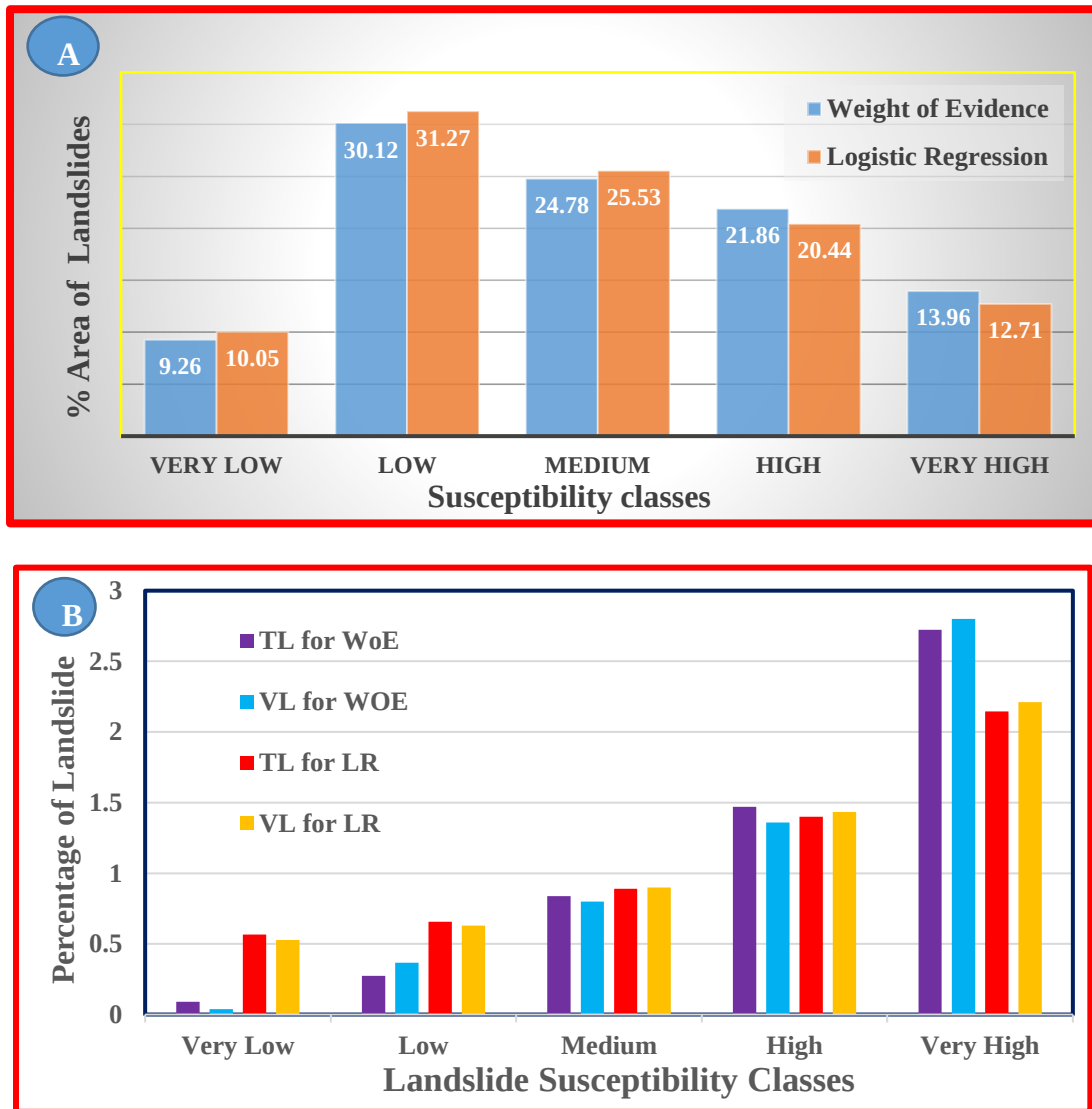


Fig 6.8 A) Bar diagram displaying the landslide in various landslide susceptibility classes for validation and B) bar diagram shows an illustration of the distribution of landslide susceptibility classes.

6.3 Comparison of Models

The WoE method offers several advantages. Firstly, it is easy to use and can be implemented by non-experts due to its simplicity. The resulting landslide susceptibility maps are easily interpretable since they are based on a straightforward weighting of evidence. The WoE method is also computationally efficient, relying on simple arithmetic computations. Furthermore, it can handle both continuous and categorical factors, making it a versatile choice. However, the WoE method has limitations to consider. Its modeling capability is limited as it cannot capture complex relationships between input factors and landslide occurrences. Non-linear relationships cannot be properly handled by the WoE method, which assumes linearity. Moreover, the simplicity of the method contributes to a higher level

of uncertainty in the results. On the other hand, the LR method offers distinct advantages. It can capture non-linear relationships between input factors and landslide occurrences, providing more flexibility in modeling. LR can handle both continuous and categorical factors, broadening its applicability. The method is robust, effectively handling noise and missing data. Moreover, LR is a well-established statistical method, widely used in various research fields. However, LR also has its drawbacks. Model complexity can increase, especially when dealing with large datasets and numerous input factors.

The LR method can be computationally intensive, requiring more computations than WoE, particularly with many input factors. Overfitting is a risk in LR, especially when irrelevant factors are included. Additionally, the results may be less easily interpretable for non-experts, as they are based on a statistical model. In summary, the WoE method excels in simplicity, ease of use, interpretability, and computational efficiency but has limitations in modeling capability and handling non-linear relationships. Conversely, the LR method captures non-linear relationships, handles various factor types, and has robustness, but it can be complex, computationally intensive, carries a risk of overfitting, and may be less interpretable for non-experts. Choosing the appropriate method depends on the specific requirements and constraints of the analysis.

CHAPTER SEVEN

CONCLUSION AND RECOMMENDATION

7.1 Conclusion

Landslide susceptibility mapping was conducted using LR and WoE models in Bichena and Yed Wiha, central Ethiopia. The landslides in these areas had significant impacts on human and animal lives, agricultural lands, settlements, and infrastructures, as well as the social and economic dimensions of the rural society. Therefore, it was crucial to prepare a landslide susceptibility map to effectively develop and manage of these landslide-prone areas. In this study, a landslide inventory map of the study area was created, which included a total of 4506 landslide locations divided into training and validation landslides with proportions of 75% and 25% respectively. Eight landslide causative factors were considered for analysis, including slope, aspect, curvature, lithology, land use, distance to lineament, rainfall, and distance to stream. The spatial relationship between these factors and landslide occurrence was evaluated. From the regression coefficients of LR and WoE models, significant factors and factor classes contributing to landslide occurrence in the study area were identified. Positive regression coefficient (b) values of LR ($b = 6.955$) and positive WoE weight contrast (c) values were observed in factor classes such as slope angle greater than 16 (three respective classes), curvature class of concave (-26 to -0.77) and convex (0.777 to 26), aspect or slope facing towards S (187.5 to 202.5), SE (112.5 to 157.5), and NW (292.5 to 337.5) (three classes), areas near lineaments (0-100) and (100-200) (two classes), land use: bare land, forest (two classes), lithology: highly weathered lower Abay basalt (one class), and rainfall ranges from 1200mm to 1253mm (two classes).

The study found slope was the typical landslide-triggering factor in the study area. The landslide susceptibility index (LSI) map of the study area was prepared based on LR values and WoE contrast values using the spatial analyst tools of ArcGIS 10.8. These LSI maps were reclassified into five susceptibility classes (very low, low, moderate, high, and very high) according to the natural breaks classification method to produce the final landslide susceptibility maps. The performance of the final landslide susceptibility maps produced by the LR and WoE models was validated using the landslide density index (LDI) and AUC values in SPSS 26 and Arc GIS 10.8. The results showed that very low, low, moderate, high, and very high values in the landslide susceptibility map were comparable with the landslide density index. In terms of AUC, rate curves were drawn using the sensitivity of the landslide

on the y-axis and 1-specificity on the x-axis. The results indicated that both models exhibited very good performance. However, the WoE model performed better (success rate of 86.5% and prediction rate of 84.4%) than the LR model (success rate of 85.3% and prediction rate of 82.7%). This study confirmed the effectiveness of LR and WoE models, which are bivariate and multivariate statistical methods, for landslide susceptibility mapping in rugged topographic areas with steep slopes, such as the current study area. With a scale of 1:50,000, the landslide susceptibility map can be utilized by the government, field engineers, geologists, designers, and decision-makers for regional land use planning, engineering structure site selection, and landslide prevention and mitigation.

7.2 Recommendation

Due to the lengthy transit of slide debris materials by the Abay River landslides in the study area have influenced the mega project that is located far from the site and the local people who live nearby. Their homes, farms, and animals all perished, and both social and economic activity was affected. According to the current study, the landslide that occurred in the study area was caused by the interaction of several different causes. Therefore, to mitigate the impact of landslide hazards in the future, it is important to recommend the necessary preventative measures on high and very high susceptibility zones of the mapped geographical area in addition to creating landslide susceptibility maps of the area. By this study's findings, the following broad remedial measurements are recommended.

Resettlement: The results of the current study indicated that 12% of the pixel fell into high landslide susceptibility zones. Future landslide activity is highly probable to occur in these areas. Therefore, it is necessary to move the locals currently residing in these areas, especially those in Kutkuat, Selelkula, and Gedeb Village, all of which are positioned at the bottom of a very unstable slope.

Afforestation and Replant Trees: Most of the research area (61.8%) comprises barren lands with poorly vegetated agricultural fields, which the locals use as grazing land. This causes barren terrain and eventually leads to soil erosion in slope areas. Therefore, by lowering the pore water pressure and tightening the roots of the plants, vegetation cover with terracing can stabilize the underlying slope. Since the study area's extent is large, government and active community participation are highly encouraged to replant more trees to overcome landslides and erosion of the slid debris materials.

Proper Drainage management: There is either no drainage management system or an inadequate one in the studied area. The area's slopes can be stabilized by installing appropriate drainage systems on important slopes. Since surface drainage, structures like ditches and pipelines can stop surface water from entering the failing slopes.

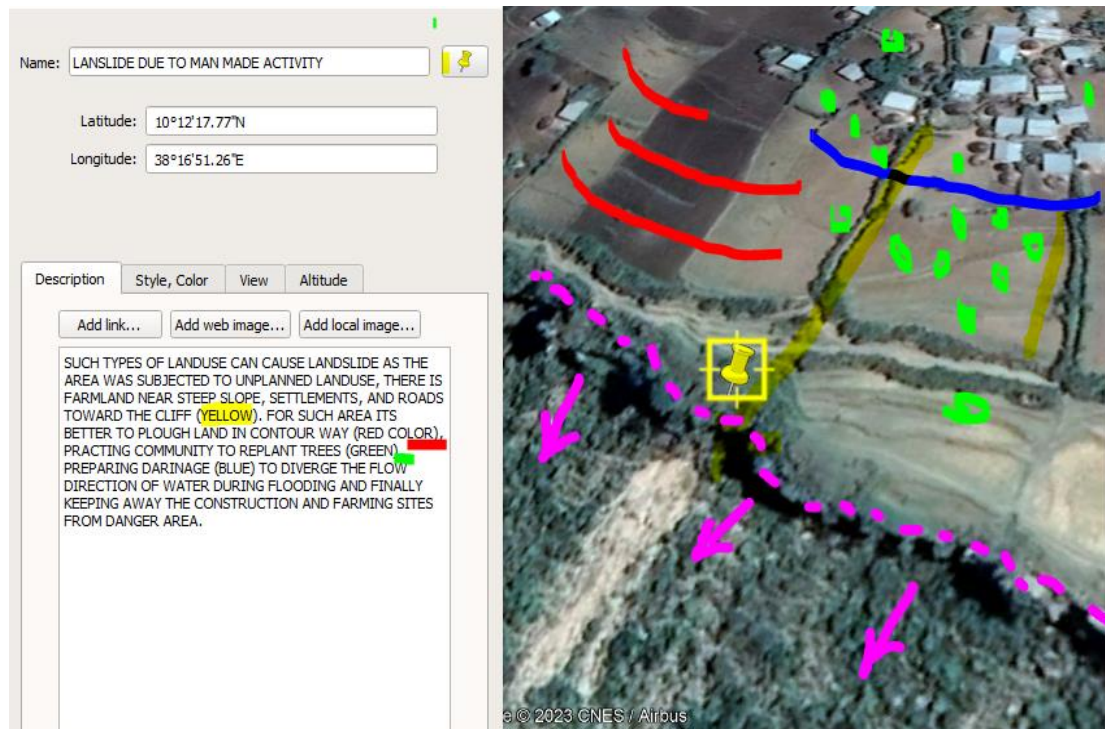


Plate 7.1 Unplanned land use initiating new landslide from the older one (Google Earth Pro).

As observed from Plate 7.1 the yellow pinning symbol, landslide occurrence due to saturation of landslide following the road between the fences constructed along the steepest slope angle. Therefore, it is mandatory to plant more trees across the steepest slope. This stabilization technique is especially advised along the sides of the gravel roads in the study area of the village toward the steep slopes in addition to the plantation. Especially in areas close to the top of hillslopes where percolated water from different ponds and small dams is highly affected by landslides as they are saturated and easily slide down the slope Plate 7.1. Therefore, it needs a proper channel, which takes the water safely from the top to the bottom. Slope instability and slope undercutting are caused by being close to or on the Suha River, Wagra River, Alel River, Taga River, and Bela Medab River and their tributaries, which flow all year into the Abay River. Therefore, to address stream and river undercutting, it is imperative that in addition to all of the above preventive and mitigation measures, gabion wall is also use

Public Awareness and Education: The local population must be aware of the nature of landslide hazards, their possible impact on them and the community, their option for minimizing the damage, and the proper remedial measures to protect unstable slopes. Local decision-makers should also stop people from cutting down trees or engaging in excessive deforestation, farming in hazardous regions, changing the pattern of land use and cover without sufficient consultation with specialists, and removing materials from the soil. To produce future landslide hazard and risk maps, the necessary landslide database needs to be documented at the local, regional, and federal levels.

Finally, decision-makers might use the generated landslide susceptibility map to guide regional and local land use planning, engineering structure site selection, and landslide prevention and mitigation measures.

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Appendix 1.1 Annual rainfall of nine stations Average (rf = Rainfall).

stations	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual rf
Dejen: Latitude, 10.17115, Longitude, 38.15067	1992	0	32.9	32.8	77.5	69.5	154	185	230	186.2	98.6	27.2	0	1094.3
	1993	8.8	11.7	35.7	172	64.4	171	284	240	212	123	0	0	1322
	1994	0	0	60.6	14.2	9.7	97.8	402	364	259	0	1.4	0	1208.7
	1994	0	0	15.2	56.3	87.4	121	330	388	193.1	6	4.7	39.1	1240.1
	1994	5.2	2.3	86.5	130	95.8	153	492	357	98.3	18.3	31.8	7.2	1476.1
	1994	54.8	0	95.9	173	96.1	311	376	335	53.6	201	199	13.9	1909.2
	1994	0.4	13	62.1	3.6	18.1	167	385	472	193.3	255	0	0	1568.4
	1994	4.9	0	0	28.8	161	637	595	129	322.5	2.1	5.5		1886.3
	1994	0	0	0	187	101.9	137	485	559	288	58.8	65.8	3.2	1885.1
	1994	0	9	12.8	87.5	83.7	298	645	362	134.3	101	2.4	6.1	1741.6
	1994	60.9	12.3	77.2	55.1	20.2	168	83	423	200.5	0	0	8.6	1108.5
	1994	0.8	36	13.9	64.1	3.3	124	273	83.3	192.5	0	16.1	9.9	816.8
	1994	6.5	19	46	56.4	12.5	125	266	250	92.3	116	19.6	0	1008.9
	1994	6	0	69.3	49.4	90	151	261	223	139	80.5	13.3	0	1082.2
	1994	7.1	9.2	108	124	72.3	141	337	308	297.4	46.1	4.4	33.7	1487.9
	1994	17.6	68.2	42.8	83.4	17.8	181	335	261	175.5	15.2	0	0	1197.8
	1994	0	0	0	42.6	78.1	307	421	43.7	78.4	33	105	0	1108.6
	1994	0	3	52.2	66.2	19.8	101	332	240	132.4	114	9.9	12	1081.9
	1994	0	4.7	93.3	95.8	174.7	77.6	245	297	79.2	13.7	28.2	0	1108.5
	1994	0	0	10.5	44.8	151.2	19.5	361	49	0	113	0		748.7
	1994	0	0	10.3	44.8	28.7	38	323	294	220.1	1.4	11.8	0	972
	1994	0	0	15.4	14.1	122	172	151	311	118.1	110	9.9	0	1023.7
	1994	0	38.8	19.6	95.6	147.6	52	279	227	143.7	86	38.4	0	1128.4
	1994	0	4.1	10.4	0	185.2	89.9	130	319	166.7	29.9	110	23	1068.6
	1994	6.2	55.6	52.7										114.5
Average annual rf														1215.6
Debre	2007	26.6	20.2	24.2	143	229.2	344	241	191	52.3				NR

	2008	0	0	184.9	193	107.1	56.3	21.5	4					NR
	2009	7.9	38.4	29.7	52.3	298.3	295	31.5	1.2	14.2				NR
	2010	9.1	6.3	39.4	84	161.7	82.9	283	181	241.9	60.8	13	14.9	1178.3
	2011	21.8	5	70.7	33.7	120.9	124	292	198	118	33.7	54.2	0	1071.9
	2012	0	0	68.5	37.4	34	78.9	261	234	105.9	8.5	7.8	10	NR
	2013	11	0	24.7	39.2	38.1	121	324	331	67.8	65.3	444	0	1466
	2014	6.8	12.5	33.7	47.3	134.1	105	168	130	74.4	11.6	26.8	3	NR
	2015	0	11.5	38.6	3.8	78.9	78.7	119	56.4	145.5	0	29	31.2	NR
	2016	6.8	0	16.4	38.8	146.5	66.5	219	203	57.9	40.8	3	0	NR
	2017	0	19.8	12.8	18.6	144	25.6	212	158	78.3	56.7	0	0	NR
	2018	0	18.1	57.4	63.8	45.5	12.9	0.4						NR
	2019	0	12.1	70.2	53.3	63.8	157	130	325	174.7	240	66.2	0	1292.9
	2020	0												NR
	2021	2.5	18.3	4.5	77.9	149	107	394	150	94.3	104	2.1	6.3	1110
Average annual rf														1235.2
Mekane Selam: Latitude, 10.74311 Longitude, 3875669	1992	49.4	25.9											NR
	1993	4.6	35.1	205.3	53.3	98.3	192	97.5	147	37.9	10.4	0		NR
	1994	0	21.9	63.8	44.5	43.9	69.4	276	238	74.2	8.1	19	0	NR
	1995	0	26.4	58	109	98.6	18.7	320	226	55.4	0.4	0	24.5	NR
	1996	32.8	1.6	63.8	103	83.1	135	244	195	78.2	0.2	23.3	6.5	NR
	1997	48.9	2.2	62.5	73.9	49.4	94.7	165	138	43	110	100	17	NR
	1998	23.2	3.7	102.8	48	70.2	70.9	319	265	123.7	118	19.3	0	1163.6
	1999	8	0	2.4	63.9	24	33.1	265	220	80.7	90.1	0	9.8	NR
	2000	0	0	12.5	128	43.8	84.1	286	185	111.3	74.7	36.5	9	NR
	2001	0.4	27.3	133.9	55.1	58.4	105	319	169	45.2	62.2	0.9	20.8	NR
	2002	55.3	14.8	60.3	38.6	41.5	57.1	277	213	91	0	7.1	28.1	NR
	2003	15.2	47.1	77.8	55	8.8	80.2	245	151	0	4	9.3		NR
	2004	0.8	0.9	29.4	44.6	21.3	95.9	184	182	51.7	41	3.4	0	NR
	2005	12.2	0	61	55.2	86.3	60.2	207	151	122.4	32.9	5	0	NR
	2006	3	0	60.5	67.5	86.7	222	231	252	115	40.6	21.1	18.1	1116.4

	2007	4.4	66.9	71.2	58.1	79.8	224	241	152	108.5	14.1	0	0	NR
	2008	19.6	0	0.4	32.5	62.6	101	278	210	90.9	148	80.3	0.4	1023.7
	2009	7	7.1	71.8	21.6	11.1	32.4	266	204	26.2	71	10	38	NR
	2010	14.3	9.7	35.8	112	54.3	56.8	254	85.9	1.5	10.5	4.6		NR
	2011	40.7	0	177	51.8	60	104	200	217	114.8	0	37.7	0	NR
	2012	0	0	74.1	225	95	6.2	0	2.1					1223.82
	2013	20.9	2.8	26.9	36.9	33.8	124	453	418	102.5	84.4	17.4	0	1320.6
	2014	0	54.6	35.3	72	121.6	60.6	187	230	143.6	19.5	9.8	0	NR
	2015	0.2	4.1	37.1	12.7	138.9	48.9	0.2	241	79.6	16	13.3	42.3	NR
	2016	10.8	6.2	0	101	154.5	123	176	229	80.7	8.5	0	0	NR
	2017	0	23.6	71.8	33.7	165.8	37.2	261	282	126.3	31	11.6	0	1044.3
	2018	0	20.5	7.6	69.9	40.6	209	298	629	32.3	46.9	69.2	0	1423.9
	2019	0	28.7	69.3	84	56.6	73.9	274	168	13.9	18.9	10.6		NR
	2020	27.8	38.1	124.6	55.2	34.7	266	271	124	199.8	10	10		1161.2
	2021	0	36.8	0.8	92.8	142.7	53.7	459						NR
Average annual rf														1184.7
Yejube: lat. 10.1533, long. 37.7488	2013	0	44.3	0	172	69.1	19.7	0						304.9
	2014	8.3	13.6	26.8	80.1	163.7	149	372	392	242.8	5.5	9.7	0	1463.5
	2015	0	0	33.1	53.6	35.5	44	391	253	19.1	59.5	5.7		893.6
	2016	0.4	11.7	2.6	28.2	157.9	155	157	67.8	380.6	114	0	0	1075.4
	2017	0	0	14.7	11.7	126.9	0	518	310	18.5	33.4	12.6	0	1045.9
	2018	0	20.2	14.9	0	88.2	348	40.7	384	131.8	10	10.3	0	1047.4
	2019	0	1.3	14.1	131	157.8	277	515	407	284.6	11	76.6	9.3	1884
	2020	0												0
	2021	0	18.2	0.4	44.6	157	119	350	643	157.8	99.4	11.8	1	1602.3
Average annual rf														1184.7
Gohatsion: Latitude, 10.006Longitude, 20.24E	1992	20.9	23.4	36.2	51.1	79.8	93.1	158	292	128.5	43.6	43.1	0	969.2
	1993	190.8	172.1	104.6	469	233.2	174	24.6	0	0				NR
	1994	0	0	37.7	48.4	101.9	98.2	282	262	221	0	0	0	1050.6
	1995	0	40.7	72.9	117	96	273	243	88.6	0	3.2	48		982.1

	1996	10.3	2	135.3	150	123.7	179	293	275	86.5	9.2	48.8	0	1313.2
	1997	32.8	0	23.8	115	57.9	110	300	269	46.4	106	158	9.3	1228.8
	1998	11.7	5	80.8	30.5	135.3	178	270	324	154.8	136	11.2	0	1337.1
	1999	5	0	2	25.6	25.9	121	454	407	39.4	165	0	5	1250.4
	2000	0	0	3	64.6	64.7	123	397	291	158.4	58.8	0		1160.6
	2001	0	69.7	87	59.5	60.6	151	309	257	79.7	6.3	8	22.8	1110.1
	2002	28.6	5.2	45.5	31.1	4.1	117	194	323	72.8	0	0	28.4	849.7
	2003	6	41.8	51.7	31.9	0	151	404	313	123	0	3	0	1125.4
	2004	5.1	8.3	45	66.9	43.2	120	288	324	108.9	10.1	0	0	1018.8
	2005	20.5	0	49.1	30	70.4	165	288	251	124.6	75.2	16	0	1088.6
	2006	5	27.4	136.9	29	76	125	354	345	174.9	79	7.5	3	1363.2
	2007	0	38	0	29.6	125.8	202	295	323	217.4	8	0	0	1238.1
	2008	0	0	0	51.7	226.5	218	379	320	139.3	18.7	62.7	0	1416
	2009	0	3.2	23.4	42.4	20.5	69.2	275	407	83	100	0	2.1	1026
	2010	7.1	0	20.2	40.4	106.4	119	336	274	163.8	1.1	0	6	1073.6
	2011	0	0	71.8	40.4	127.2	139	217	439	283.8	0	120	0	1438.5
	2012	0	0	14.5	58.6	35.3	93.7	457	378	264	0	6.3	7.2	1314.8
	2013	11	0	14.5	27.8	80.4	193	365	430	213.4	126	34.5	0	1495.7
	2014	0	25.9	11.3	74.6	161.2	101	389	313	193.9	23.3	7.6	0	1301.5
	2015	0	0	3.2	0	166.8	196	225	310	142.3	33.3	56.4	48.2	1182.1
	2016	0	26.6	10.2	83.8	275.5	141	423	301	89.1	16.4	14.5	0	1381.2
	2017	0	35.8	13.3	28.1	187.6	73	464	384	137.7	71.4	0	0	1395.1
	2018	0	34.4	36.3	245	413.1	451	19.7	15.6	22.6	0			1237.7
	2019	0	18.6	40.5	75.9	61	83	370	158	18.5	61.3	1.2		887.9
	2020	0	0	0	12.9	187.5	111							NR
	2021	0	0											NR
	Average annual rf													1193.9
Filikilik Latitude , 10.056 Longitude 20.25	1992	21.9	25.5	12.6	63.9	65.6	95	152	351	116.7	112	31.4	0	1048
	1993	0	19.5	21.4	241	159.6	530	270	202	47	0	0		NR
	1994	3	0	60.8	27.5	259.5	298	180	0	0	0			828.2

Merto Lemarian	1995	0	4.1	26	42.1	71.9	66.2	320	361	85.8	6.2	6.5	47.3	1037.5
	1996	12	2	133.3	278	163.5	271	462	480	100.8	8.7	51.4	0	1962.1
	1997	41.5	0	35.6	180	90	243	478	204	55.6	104	119	24	1573.4
	1998	0	0	101.7	15.7	80.2	103	293	457	242.6	248	0	0	1541
	1999	23	0	2.2	20.9	6.4	87.3	410	460	69.9	266	14.4	4.1	1363.9
	2000	0	0	0	18.4	34.8	152	386	378	279.3	232	193	4.6	1677.4
	2001	0	21.4	59	59.5	61.7	226	440	147	37.1	27.1	0	2.1	1080.1
	2002	40.7	0	11.8	33.3	10.1	130	121	189	75.7	0	0	49.8	660.7
	2003	0	13.6	17.2	17	0	333	191	0	0	0	0		571.3
	2004	0	0	4	8.2	33.3	162	224	236	191.7	36.5	0	0	895.1
	2005	0	1.8	24.1	22.6	33.7	89.4	308	178	35.1	14.3	24.8	0	731.8
	2006	3.2	24.5	78.1	84.8	59.3	87.5	353	330	188.7	23.5	26	0	1258.8
	2007	13.8	100.1	17.6	28.1	84.1	264	327	351	211.9	2.4	0	0	1400.2
	2008	0	0	0	32	165.2	229	398	410	14	68.9	39.1	0	1355.9
	2009	0	0	16.1	45.3	26.8	130	406	225	0	33.6	0	0	883
	2010	0	0	60.7	96.8	214.6	253	398	271	218.6	0	50.1	86.3	1648
	2011	0	0	131.9	32.3	186.4								NR
	2012	61.1	103.3	56.3	210	235.6	213	157	0	0	0			1036.2
	2013	0	0	0	0	126	134	313	253	70.8	45.1	0	0	942.6
	2014	0	20.7	0	90.2	131.3	0	163	285	165.2	0	25.7	0	880.2
	2015	0	0	9.3	0	114.5	195	165	289	171	18.8	70.2	0	1031.9
	2016	0	22.9	18.7	79.3	107.6	185	267	126	57.5	0	0		863.9
	2017	0	0	16.7	37.2	162.7	93.1	457	354	155	53	53		1381.6
	2018	22.8	69.7	194.8	595	858.1	74.2	48.8	86.6	5.3				NR
	2019	1.4	41.8	64.5	98.2	144.9	331	443	442	253	15.3	81.9	2.5	1919
	2020	48.6	43	118.3	519	519.3	277							NR
	2021	0	0	0.6	25.8	117.4	87.1	440	406	148.2	81.2	0		1305.9
	Average annual rf													1193.9
Merto Lemarian	1970	69.2	19.2	3.6	22.6	235.6								NR
	1987	74.7	208.3	283.1	49.5	56.6	5.5	1.4						NR

	1988	10.5	84.1	0	96.8	8.1	85.6	963	228	172.2	153	0	0	1801.9
	1989	0	0	88.2	57.3	34	97.4	217	181	43.9	15.8	0	111	NR
	1990	0	50.9	28.8	68	13.2	34.7	178	202	121.2	20.9			NR
	1991		17.5	3.5	0									NR
	2014	9.6	62.2	184.9	54.5	169.1	256	150	26.4	32.4	14.1			NR
	2015	1.1	1.4	33	3.7	136	140	100	114	102.9	31.6	56.1	26.8	NR
	2016	2.7	6.8	41.8	78.4	177.3	85.4	290	299	109.2	54.9	0	0	1145.5
	2017	0	30.2	22	53.4	90.3	71.8	215	196	104.6	23.1	22.4	0	NR
	2018	0	21.6	6.8	21.4	25.4	161	313	255	46.5	96.6	246	1.7	1194
	2019	0	33.6	38.2	32.4	121.7	194	225	92.7	22.2	49.3	0		NR
	2020	0												NR
	2021	0	10.2	2	108	124.7	23.4	323	79.6	21.5	0.6	2.2		NR
Average annual rf														1380.5
Bichena: Lat.10.445 Long. 38.2035	2014	0	18	29.5	38.6	126.2	27.8	350	213	123	33.6	21.1	3.5	NR
	2015	0	14.8	25.2	33.5	193	125	148	190	94.8	8	40.8	15.9	NR
	2016	19.7	0	13.8	163	326.9	222	111	7	1	0			NR
	2017	33.7	13.1	33.6	23.8	161.5	67.8	313	421	69.7	32.4	8.9	0	1179.2
	2018	0	44.9	47.8	59	62.8	227	468	206	22.1	10.2	86.3	0	1233.5
	2019	18.3	2.1	65.5	96.2	107.4	147	252	319	105	30.3	40.7	12.3	1195.4
	2020	9.1	0	47.5	37.7	94.6	140	272	178	20.3				NR
	2021	0	0	0	115	110.8	146	307	47.9	0	5.2			NR
Average annual rf														1202.7
Abay Sheleko: Latitude, 10.1125 Longitude, 38.1567	1992	0	11.3	12.1	11.6	17.9	27.2	30.5	20.5	15.2	2	0		148.3
	1993	4.6	0.8	4.9	64.3	100.9	123	274	184	21.5	96.2	0	0	874.1
	1994	0	0	36.1	24.6	137.7	64.8	361	273	167.6	0	0	0	1064.3
	1995	0	12.3	30.1	73.5	130	122	195	235	128.3	65	7.4	17.4	1016.7
	1996	4.1	1.5	96.4	130	239.9	233	424	459	135	44.9	56.7	0	1824.4
	1997	65.8	0	111.8	179	139.7	354	255	92.3	113.5	78.5	14.2		1403.2
	1998	0	2.9	57.4	4.5	80.5	80.1	261	326	191.2	213	0	0	1216.2
	1999	5.2	0	3	16.3	19.7	96.3	373	336	42.1	165	0	6	1063

2000	0	0	0	64.7	60.1	96.9	296	359	192.7	58.8	39.1	0	1167.3
2001	0	8.9	38.8	36.4	60.9	223	356	187	60.5	96.8	0	4.1	1072.5
2002	17.3	0	34.3	172	263.1	254	82.1	0	0	17.5			840.5
2003	0	5.7	26.6	12.8	2.4	184	479	289	351.7	2.1	0	16.1	1369.7
2004	0	1.7	29.6	30.1	19.1	140	239	742	124.5	48.1	0	0	1374.1
2005	7.9	0	32.2	0	90.4	106	237	172	328.1	132	22.3	0	1128.6
2006	10.1	8.8	79	64.6	57.8	99.1	365	287	206.5	51.2	0	28.4	1257.7
2007	4.3	73.3	11.3	27.6	145.9	157	334	300	212.2	20.7	0		1286.6
2008	0	1	0	48.9	150.1	251	260	221	139	50.4	126	0	1247.4
2009	0	0	32.6	59.1	2.3	54.8	329	274	126.4	128	16.6		1023.5
2010	3.1	2.1	47.7	83.5	115	112	168	369					901
2011	7.4	0	59.7	27.5	138.9	153	220	277	187.4	0	162	0	1232.7
2012	0	0	58.5	69.7	33.9	199	368	348	201.8	37.2	8.7	0	1324.1
2013							216	288	223.8	266	5.4	0	NR
2014	0	11.6	0	76.4	117.7	64.5	195	233	215.3	30.5	27.5	0	971.6
2015	0	10.5	0	0	163.6	131	132	269	157.4	0	123	0	986.3
2016	0	0	8.2	28.2	97.3	69.5	195	204	111.4	38.1	0	0	751
2017	0	13.5	0	146	65.6	261	256	70.6	40.4	0	0		852.1
2018	0	27.6	3.2	16.2	76.4	314	531		225.7	13.5	151	0	1357.8
2019	0	13.7	52	61.9	69	195	191						NR
Average annual rf													1106

stations	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual rf
Dejen: Latitude, 10.1715, Longitude, 38.15067	1992	0	32.9	32.8	77.5	69.5	154	185	230	186.2	98.6	27.2	0	1094.3
	1993	8.8	11.7	35.7	17.2	64.4	171	284	240	212	123	0	0	1322
	1994	0	0	60.6	14.2	9.7	97.8	402	364	259	0	1.4	0	1208.7
	1994	0	0	15.2	56.3	87.4	121	330	388	193.1	6	4.7	39.1	1240.1

	1994	5.2	2.3	86.5	130	95.8	153	492	357	98.3	18.3	31.8	7.2	1476.1
	1994	54.8	0	95.9	173	96.1	311	376	335	53.6	201	199	13.9	1909.2
	1994	0.4	13	62.1	3.6	18.1	167	385	472	193.3	255	0	0	1568.4
	1994	4.9	0	0	28.8	161	637	595	129	322.5	2.1	5.5		1886.3
	1994	0	0	0	187	101.9	137	485	559	288	58.8	65.8	3.2	1885.1
	1994	0	9	12.8	87.5	83.7	298	645	362	134.3	101	2.4	6.1	1741.6
	1994	60.9	12.3	77.2	55.1	20.2	168	83	423	200.5	0	0	8.6	1108.5
	1994	0.8	36	13.9	64.1	3.3	124	273	83.3	192.5	0	16.1	9.9	816.8
	1994	6.5	19	46	56.4	12.5	125	266	250	92.3	116	19.6	0	1008.9
	1994	6	0	69.3	49.4	90	151	261	223	139	80.5	13.3	0	1082.2
	1994	7.1	9.2	108	124	72.3	141	337	308	297.4	46.1	4.4	33.7	1487.9
	1994	17.6	68.2	42.8	83.4	17.8	181	335	261	175.5	15.2	0	0	1197.8
	1994	0	0	0	42.6	78.1	307	421	43.7	78.4	33	10.5	0	1108.6
	1994	0	3	52.2	66.2	19.8	101	332	240	132.4	114	9.9	12	1081.9
	1994	0	4.7	93.3	95.8	174.7	77.6	245	297	79.2	13.7	28.2	0	1108.5
	1994	0	0	10.5	44.8	151.2	19.5	361	49	0	113	0		748.7
	1994	0	0	10.3	44.8	28.7	383	323	294	220.1	1.4	11.8	0	972
	1994	0	0	15.4	14.1	122	172	151	311	118.1	110	9.9	0	1023.7
	1994	0	38.8	19.6	95.6	147.6	529	279	227	143.7	86	38.4	0	1128.4
	1994	0	4.1	10.4	0	185.2	89.9	130	319	166.7	29.9	110	23	1068.6
	1994	6.2	55.6	52.7										114.5
	Average annual.rf													1215.6
Debre Worke: Latitude, 10.6506 Longitude, 38.1623	2007	26.6	20.2	24.2	143	229.2	344	241	191	52.3				NR
	2008	0	0	184.9	193	107.1	56.3	21.5	4					NR
	2009	7.9	38.4	29.7	52.3	298.3	295	31.5	1.2	14.2				NR
	2010	9.1	6.3	39.4	84	161.7	82.9	283	181	241.9	60.8	13	14.9	1178.3
	2011	21.8	5	70.7	33.7	120.9	124	292	198	118	33.7	54.2	0	1071.9
	2012	0	0	68.5	37.4	34	78.9	261	234	105.9	8.5	7.8	10	NR
	2013	11	0	24.7	39.2	38.1	121	324	331	67.8	65.3	44	0	1466
	2014	6.8	12.5	33.7	47.3	134.1	105	168	130	74.4	11.6	26.8	3	NR

	2015	0	11.5	38.6	3.8	78.9	78.7	119	56.4	145.5	0	29	31.2	NR
	2016	6.8	0	16.4	38.8	146.5	66.5	219	203	57.9	40.8	3	0	NR
	2017	0	19.8	12.8	18.6	144	25.6	212	158	78.3	56.7	0	0	NR
	2018	0	18.1	57.4	63.8	45.5	12.9	0.4						NR
	2019	0	12.1	70.2	53.3	63.8	157	130	325	174.7	240	66.2	0	1292.9
	2020	0												NR
	2021	2.5	18.3	4.5	77.9	149	107	394	150	94.3	104	2.1	6.3	1110
Average annual.rf														1235.2
Mekane Selam: Latitude, 10.74311 Longitude, 3875669	1992	49.4	25.9											NR
	1993	4.6	35.1	205.3	53.3	98.3	192	97.5	147	37.9	10.4	0		NR
	1994	0	21.9	63.8	44.5	43.9	69.4	276	238	74.2	8.1	19	0	NR
	1995	0	26.4	58	109	98.6	18.7	320	226	55.4	0.4	0	24.5	NR
	1996	32.8	1.6	63.8	103	83.1	135	244	195	78.2	0.2	23.3	6.5	NR
	1997	48.9	2.2	62.5	73.9	49.4	94.7	165	138	43	110	100	17	NR
	1998	23.2	3.7	102.8	48	70.2	70.9	319	265	123.7	118	19.3	0	1163.6
	1999	8	0	2.4	63.9	24	33.1	265	220	80.7	90.1	0	9.8	NR
	2000	0	0	12.5	128	43.8	84.1	286	185	111.3	74.7	36.5	9	NR
	2001	0.4	27.3	133.9	55.1	58.4	105	319	169	45.2	62.2	0.9	20.8	NR
	2002	55.3	14.8	60.3	38.6	41.5	57.1	277	213	91	0	7.1	28.1	NR
	2003	15.2	47.1	77.8	55	8.8	80.2	245	151	0	4	9.3		NR
	2004	0.8	0.9	29.4	44.6	21.3	95.9	184	182	51.7	41	3.4	0	NR
	2005	12.2	0	61	55.2	86.3	60.2	207	151	122.4	32.9	5	0	NR
	2006	3	0	60.5	67.5	86.7	222	231	252	115	40.6	21.1	18.1	1116.4
	2007	4.4	66.9	71.2	58.1	79.8	224	241	152	108.5	14.1	0	0	NR
	2008	19.6	0	0.4	32.5	62.6	101	278	210	90.9	148	80.3	0.4	1023.7
	2009	7	7.1	71.8	21.6	11.1	32.4	266	204	26.2	71	10	38	NR
	2010	14.3	9.7	35.8	112	54.3	56.8	254	85.9	1.5	10.5	4.6		NR
	2011	40.7	0	177	51.8	60	104	200	217	114.8	0	37.7	0	NR
	2012	0	0	74.1	225	95	6.2	0	2.1					1223.82
	2013	20.9	2.8	26.9	36.9	33.8	124	453	418	102.5	84.4	17.4	0	1320.6

	2014	0	54.6	35.3	72	121.6	60.6	187	230	143.6	19.5	9.8	0	NR
	2015	0.2	4.1	37.1	12.7	138.9	48.9	0.2	241	79.6	16	13.3	42.3	NR
	2016	10.8	6.2	0	101	154.5	123	176	229	80.7	8.5	0	0	NR
	2017	0	23.6	71.8	33.7	165.8	37.2	261	282	126.3	31	11.6	0	1044.3
	2018	0	20.5	7.6	69.9	40.6	209	298	629	32.3	46.9	69.2	0	1423.9
	2019	0	28.7	69.3	84	56.6	73.9	274	168	13.9	18.9	10.6		NR
	2020	27.8	38.1	124.6	55.2	34.7	266	271	124	199.8	10	10		1161.2
	2021	0	36.8	0.8	92.8	142.7	53.7	459						NR
Average annual.rf														1184.7
Yejube: lat. 10.1533, long. 37.7488	2013	0	44.3	0	172	69.1	19.7	0						304.9
	2014	8.3	13.6	26.8	80.1	163.7	149	372	392	242.8	5.5	9.7	0	1463.5
	2015	0	0	33.1	53.6	35.5	44	391	253	19.1	59.5	5.7		893.6
	2016	0.4	11.7	2.6	28.2	157.9	155	157	67.8	380.6	114	0	0	1075.4
	2017	0	0	14.7	11.7	126.9	0	518	310	18.5	33.4	12.6	0	1045.9
	2018	0	20.2	14.9	0	88.2	348	40.7	384	131.8	10	10.3	0	1047.4
	2019	0	1.3	14.1	131	157.8	277	515	407	284.6	11	76.6	9.3	1884
	2020	0												0
	2021	0	18.2	0.4	44.6	157	119	350	643	157.8	99.4	11.8	1	1602.3
Average annual.rf														1184.7
Gohatsion: Latitude, 10.006Longitude, 38.245	1992	20.9	23.4	36.2	51.1	79.8	93.1	158	292	128.5	43.6	43.1	0	969.2
	1993	190.8	172.1	104.6	469	233.2	174	24.6	0	0				NR
	1994	0	0	37.7	48.4	101.9	98.2	282	262	221	0	0	0	1050.6
	1995	0	40.7	72.9	117	96	273	243	88.6	0	3.2	48		982.1
	1996	10.3	2	135.3	150	123.7	179	293	275	86.5	9.2	48.8	0	1313.2
	1997	32.8	0	23.8	115	57.9	110	300	269	46.4	10.6	15.8	9.3	1228.8
	1998	11.7	5	80.8	30.5	135.3	178	270	324	154.8	13.6	11.2	0	1337.1
	1999	5	0	2	25.6	25.9	121	454	407	39.4	16.5	0	5	1250.4
	2000	0	0	3	64.6	64.7	123	397	291	158.4	58.8	0		1160.6
	2001	0	69.7	87	59.5	60.6	151	309	257	79.7	6.3	8	22.8	1110.1
	2002	28.6	5.2	45.5	31.1	4.1	117	194	323	72.8	0	0	4	849.7

	2003	6	41.8	51.7	31.9	0	151	404	313	123	0	3	0	1125.4
	2004	5.1	8.3	45	66.9	43.2	120	288	324	108.9	10.1	0	0	1018.8
	2005	20.5	0	49.1	30	70.4	165	288	251	124.6	75.2	16	0	1088.6
	2006	5	27.4	136.9	29	76	125	354	345	174.9	79	7.5	3	1363.2
	2007	0	38	0	29.6	125.8	202	295	323	217.4	8	0	0	1238.1
	2008	0	0	0	51.7	226.5	218	379	320	139.3	18.7	62.7	0	1416
	2009	0	3.2	23.4	42.4	20.5	69.2	275	407	83	100	0	2.1	1026
	2010	7.1	0	20.2	40.4	106.4	119	336	274	163.8	1.1	0	6	1073.6
	2011	0	0	71.8	40.4	127.2	139	217	439	283.8	0	120	0	1438.5
	2012	0	0	14.5	58.6	35.3	93.7	457	378	264	0	6.3	7.2	1314.8
	2013	11	0	14.5	27.8	80.4	193	365	430	213.4	126	34.5	0	1495.7
	2014	0	25.9	11.3	74.6	161.2	101	389	313	193.9	23.3	7.6	0	1301.5
	2015	0	0	3.2	0	166.8	196	225	310	142.3	33.3	56.4	48.2	1182.1
	2016	0	26.6	10.2	83.8	275.5	141	423	301	89.1	16.4	14.5	0	1381.2
	2017	0	35.8	13.3	28.1	187.6	73	464	384	137.7	71.4	0	0	1395.1
	2018	0	34.4	36.3	245	413.1	451	19.7	15.6	22.6	0			1237.7
	2019	0	18.6	40.5	75.9	61	83	370	158	18.5	61.3	1.2		887.9
	2020	0	0	0	12.9	187.5	111							NR
	2021	0	0											NR
Average annual.rf														1193.9
Filiklik Latitude , 10.056 Longitude, 38.25	1992	21.9	25.5	12.6	63.9	65.6	95	152	351	116.7	112	31.4	0	1048
	1993	0	19.5	21.4	241	159.6	530	270	202	47	0	0		NR
	1994	3	0	60.8	27.5	259.5	298	180	0	0	0			828.2
	1995	0	4.1	26	42.1	71.9	66.2	320	361	85.8	6.2	6.5	47.3	1037.5
	1996	12	2	133.3	278	163.5	271	462	480	100.8	8.7	51.4	0	1962.1
	1997	41.5	0	35.6	180	90	243	478	204	55.6	104	119	24	1573.4
	1998	0	0	101.7	15.7	80.2	103	293	457	242.6	248	0	0	1541
	1999	23	0	2.2	20.9	6.4	87.3	410	460	69.9	266	14.4	4.1	1363.9
	2000	0	0	0	18.4	34.8	152	386	378	279.3	232	193	4.6	1677.4
	2001	0	21.4	59	59.5	61.7	226	440	147	37.1	27.1	0	2.1	1080.1

	200 2	40.7	0	11.8	33. 3	10.1	13 0	12 1	189	75.7	0	0	49. 8	660.7
	200 3	0	13.6	17.2	17	0	33 3	19 1	0	0	0	0		571.3
	200 4	0	0	4	8.2	33.3	16 2	22 4	236	191. 7	36. 5	0	0	895.1
	200 5	0	1.8	24.1	22. 6	33.7	89. 4	30 8	178	35.1	14. 3	24. 8	0	731.8
	200 6	3.2	24.5	78.1	84. 8	59.3	87. 5	35 3	330	188. 7	23. 5	26	0	1258.8
	200 7	13.8	100. 1	17.6	28. 1	84.1	26 4	32 7	351	211. 9	2.4	0	0	1400.2
	200 8	0	0	0	32	165. 2	22 9	39 8	410	14	68. 9	39. 1	0	1355.9
	200 9	0	0	16.1	45. 3	26.8	13 0	40 6	225	0	33. 6	0	0	883
	201 0	0	0	60.7	96. 8	214. 6	25 3	39 8	271	218. 6	0	50. 1	86. 3	1648
	201 1	0	0	131. 9	32. 3	186. 4								NR
	201 2	61.1	103. 3	56.3	21 0	235. 6	21 3	15 7	0	0	0			1036.2
	201 3	0	0	0	0	126	13 4	31 3	253	70.8	45. 1	0	0	942.6
	201 4	0	20.7	0	90. 2	131. 3	0	16 3	285	165. 2	0	25. 7	0	880.2
	201 5	0	0	9.3	0	114. 5	19 5	16 5	289	171	18. 8	70. 2	0	1031.9
	201 6	0	22.9	18.7	79. 3	107. 6	18 5	26 7	126	57.5	0	0		863.9
	201 7	0	0	16.7	37. 2	162. 7	93. 1	45 7	354	155	53	53		1381.6
	201 8	22.8	69.7	194. 8	59 5	858. 1	74. 2	48. 8	86. 6	5.3				NR
	201 9	1.4	41.8	64.5	98. 2	144. 9	33 1	44 3	442	253	15. 3	81. 9	2.5	1919
	202 0	48.6	43	118. 3	51 9	519. 3	27 7							NR
	202 1	0	0	0.6	25. 8	117. 4	87. 1	44 0	406	148. 2	81. 2	0		1305.9
	Average annual.rf													1193.9
Merto Lenariam: Latitude, 10.833 Longitude, 38.233	197 0	69.2	19.2	3.6	22. 6	235. 6								NR
	198 7	74.7	208. 3	283. 1	49. 5	56.6	5.5	1.4						NR
	198 8	10.5	84.1	0	96. 8	8.1	85. 6	96 3	228	172. 2	15 3	0	0	1801.9
	198 9	0	0	88.2	57. 3	34	97. 4	21 7	181	43.9	15. 8	0	11 1	NR
	199 0	0	50.9	28.8	68	13.2	34. 7	17 8	202	121. 2	20. 9			NR
	199 1		17.5	3.5	0									NR
	201 4	9.6	62.2	184. 9	54. 5	169. 1	25 6	15 0	26. 4	32.4	14. 1			NR
	201 5	1.1	1.4	33	3.7	136	14 0	10 0	114	102. 9	31. 6	56. 1	26. 8	NR
	201 6	2.7	6.8	41.8	78. 4	177. 3	85. 4	29 0	299	109. 2	54. 9	0	0	1145.5

	2017	0	30.2	22	53.4	90.3	71.8	215	196	104.6	23.1	22.4	0	NR
	2018	0	21.6	6.8	21.4	25.4	161	313	255	46.5	96.6	246	1.7	1194
	2019	0	33.6	38.2	32.4	121.7	194	225	92.7	22.2	49.3	0		NR
	2020	0												NR
	2021	0	10.2	2	108	124.7	23.4	323	79.6	21.5	0.6	2.2		NR
Average annual.rf														1380.5
Bichena: Lat.10.445 Long. 38.2035	2014	0	18	29.5	38.6	126.2	27.8	350	213	123	33.6	21.1	3.5	NR
	2015	0	14.8	25.2	33.5	193	125	148	190	94.8	88	40.8	15.9	NR
	2016	19.7	0	13.8	163	326.9	222	111	7	1	0			NR
	2017	33.7	13.1	33.6	23.8	161.5	67.8	313	421	69.7	32.4	8.9	0	1179.2
	2018	0	44.9	47.8	59	62.8	227	468	206	22.1	10.2	86.3	0	1233.5
	2019	18.3	2.1	65.5	96.2	107.4	147	252	319	105	30.3	40.7	12.3	1195.4
	2020	9.1	0	47.5	37.7	94.6	140	272	178	20.3				NR
	2021	0	0	0	115	110.8	146	307	47.9	0	5.2			NR
Average annual.rf														1202.7
Abay Sheleko: Latitude, 10.1125 Longitude, 38.1567	1992	0	11.3	12.1	11.6	17.9	27.2	30.5	20.5	15.2	2	0		148.3
	1993	4.6	0.8	4.9	64.3	100.9	123	274	184	21.5	96.2	0	0	874.1
	1994	0	0	36.1	24.6	137.7	64.8	361	273	167.6	0	0	0	1064.3
	1995	0	12.3	30.1	73.5	130	122	195	235	128.3	65	7.4	17.4	1016.7
	1996	4.1	1.5	96.4	130	239.9	233	424	459	135	44.9	56.7	0	1824.4
	1997	65.8	0	111.8	179	139.7	354	255	92.3	113.5	78.5	14.2		1403.2
	1998	0	2.9	57.4	4.5	80.5	80.1	261	326	191.2	213	0	0	1216.2
	1999	5.2	0	3	16.3	19.7	96.3	373	336	42.1	16.5	0	6	1063
	2000	0	0	0	64.7	60.1	96.9	296	359	192.7	58.8	39.1	0	1167.3
	2001	0	8.9	38.8	36.4	60.9	223	356	187	60.5	96.8	0	4.1	1072.5
	2002	17.3	0	34.3	172	263.1	254	821	0	0	17.5			840.5
	2003	0	5.7	26.6	12.8	2.4	184	479	289	351.7	2.1	0	16.1	1369.7
	2004	0	1.7	29.6	30.1	19.1	140	239	742	124.5	48.1	0	0	1374.1
	2005	7.9	0	32.2	0	90.4	106	237	172	328.1	132	22.3	0	1128.6
	2006	10.1	8.8	79	64.6	57.8	99.1	365	287	206.5	51.2	0	28.4	1257.7

2007	4.3	73.3	11.3	27.6	145.9	157	334	300	212.2	20.7	0		1286.6
2008	0	1	0	48.9	150.1	251	260	221	139	50.4	126	0	1247.4
2009	0	0	32.6	59.1	2.3	54.8	329	274	126.4	128	16.6		1023.5
2010	3.1	2.1	47.7	83.5	115	112	168	369					901
2011	7.4	0	59.7	27.5	138.9	153	220	277	187.4	0	162	0	1232.7
2012	0	0	58.5	69.7	33.9	199	368	348	201.8	37.2	8.7	0	1324.1
2013							216	288	223.8	266	5.4	0	NR
2014	0	11.6	0	76.4	117.7	64.5	195	233	215.3	30.5	27.5	0	971.6
2015	0	10.5	0	0	163.6	131	132	269	157.4	0	123	0	986.3
2016	0	0	8.2	28.2	97.3	69.5	195	204	111.4	38.1	0	0	751
2017	0	13.5	0	146	65.6	261	256	70.6	40.4	0	0		852.1
2018	0	27.6	3.2	16.2	76.4	314	531		225.7	13.5	151	0	1357.8
2019	0	13.7	52	61.9	69	195	191						NR
Average annual.rf													1106