LANDSLIDE SUSCEPTIBILITY MODELING USING WEIGHT OF EVIDENCE AND LOGISTIC REGRESSION MODELS IN HALILA CATCHMENT, GAMO ZONE, SOUTH ETHIOPIA

Dame Tekalign Tefera

A Thesis Submitted To the Department of Applied Geology

School of Applied Natural Science

Presented In Partial Fulfillment of the Requirement for the Degree of

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Office of Graduate Studies

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Landslide Susceptibility Modeling Using Weight Of Evidence and Logistic Regression Models in Halila Catchment, Gamo Zone, South Ethiopia

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Declaration

I hereby declare that this Master Thesis entitled "Landslide Susceptibility Modeling using Weight of Evidence and Logistic Regression Models in Halila Catchment, Gamo Zone, South Ethiopia" is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All sources of materials used for this thesis have been duly acknowledged through the citation.

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Recommendation

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled **"Landslide Susceptibility Modeling using Weight of Evidence and Logistic Regression Models in Halila Catchment, Gamo Zone, South Ethiopia"** prepared under our guidance by **Dame Tekalign Tefera** submitted in partial fulfillment of the requirements for the degree of Master of Science in Applied Geology. Therefore, we recommend the submission of revised version of the thesis to the department following the applicable procedures.

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Approval Page

We, the advisors of the thesis entitled **"Landslide Susceptibility Modeling using Weight of Evidence and Logistic Regression Models in Halila Catchment, Gamo Zone, South Ethiopia"** and developed by Dame Tekalign Tefera, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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We, the undersigned, members of the Board of Examiners of the thesis by Dame Tekalign Tefera have read and evaluated his thesis entitled **"Landslide Susceptibility Modeling using Weight of Evidence and Logistic Regression Models in Halila Catchment, Gamo Zone, South Ethiopia"** and examined the candidate during open defense. This is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirement of the Degree of Master of Science applied Geology.

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List of Abbreviations and Acronyms

ArcGIS Aeronautical Reconnaissance Coverage Geographic Information System

AUC Area under the Curve

C Contrast weight

CRED Centre for Research on the Epidemiology of Disasters

DEM Digital Elevation Model

GIS Geographic Information System

EBCS Ethiopian Building Code Standard

IV Information Value

FAO Food and Agriculture Organization

FR Frequency Ratio

LDI Landslide Density Index

LHZ Landslide Hazard Zonation

LR Logistic Regression

LSI Landslide Susceptibility Index

LSM Landslide susceptibility Mapping

LULC Landuse Landcover

MER Main Ethiopian Rift

NDVI Normalized Difference Vegetation Index

ROC Receiver Operating Characteristics

SE Standard Error

VIF Variance Inflation Factor

SSEP Slope stability susceptibility evaluation parameter

STRM Shuttle Radar Topography Mission.

UTM Universal Transverse Mercator

WGS World Geodetic System

WoE Weight of Evidence

ABSTRACT

Landslides are one of the most harmful natural phenomena that devastate both property and human lives. Geology, topography, surface and subsurface water condition, land use/land cover are the main causative factors which are highly associated with the most landslide occurrence in study area. This study is aimed at identifying the areas which are most vulnerable to landslides and the important factors related to landslides throughout the Halila catchments of the Gamo zone using statistical methods. Seven landslide influencing factors were chosen for landslide susceptibility mapping, including Slope, Aspect, Curvature, distance from Stream, distance from Lineament, Lithology and Landuse landcover were considered, using 592 landslide inventories. These factors were selected based on the environmental characteristics and data availability. Their contrast weight and regression coefficient were determined from Weight of Evidence and Logistic Regression respectively and added using raster calculator on a spatial analysis tool of ArcGIS. The final landslide susceptibility map was reclassified as very low, low, moderate, high and very high susceptibility classes. Distance from lineament is the major factor concerning landslide occurrence as can be seen from its weights and regression coefficient. This susceptibility map was validated using landslide density index and area under the curve (AUC). The result from Weight of Evidence and Logistic regression model validation showed a validation rate accuracy of 82.4% and 83.4% respectively. This study conclude that the effectiveness of weight of evidence and Logistic regression model for landslide susceptibility map. Finally, implementing afforestation strategies on bare land, constructing surface drainage channels & ditches, providing engineering reinforcements such as gabion walls, retaining walls, anchors and bolts whenever necessary and prohibiting hazardous zones can be recommended in order to lessen the impact of landslides in this area.

Keywords

Halila Catchment, Weight of Evidence, Logistic Regression, Gamo, Ethiopia

CHAPTER ONE

1. INTRODUCTION

1.1 Background

The Earth's surface is constantly changing-dynamically. These changes are more pronounced in mountainous terrains as a result of different mass wasting processes (Nakileza and Nedala, 2020). In many steep and mountainous terrains, landslides are one of the frequent geoenvironmental risks. A landslide can be defined as the down slope movement of rock and soil near the earth's surface under the influence of gravity (Cruden and Varnes, 1996).

Every year, both in the developed and developing worlds, landslides are one of the most harmful natural phenomena that devastate both property and human lives. Increasing awareness of landslides' socioeconomic effects and the pressure that urbanization is placing on the mountain environment has both increased interest in the study of landslides worldwide (Aleotti and Chowdhury, 1999). Landslides are afterwards listed as one of the most significant natural hazards in the entire planet (Crozier and Glade, 2005). According to the 2006 data from the UNISDR and the Centre for Research on the Epidemiology of Disasters (CRED), landslides are the third most common natural disaster among the top 10 natural hazards (Ramakrishnan, 2002).

The landscape of Ethiopia is extremely diverse, ranging from sparsely vegetated deserts to densely wooded highlands and volcanoes. Approximately two-thirds of the country lies on high plateaus at an altitude above 1600m, divided into several distinct geographical regions by mountain ranges and rivers. These altitudes mean that there are climatic differences between the lowlands and highlands; the highlands experience higher levels of rainfall than the lowlands, resulting in humid and cooler temperate climates in comparison to dry heat in the lower areas. The country's diverse landscapes and landforms, which include tall mountain ranges covered in snow, lush green valleys, large regular grasslands, lakes, rivers, wetlands, coastal lagoons, and thermal springs, are largely due to the difference in temperature and precipitation levels. As a mountainous nation, Ethiopia is also characterized by its steep slopes, deep gorges, frequent faulting along the escarpment, highly worn rock, unconsolidated colluvium deposits, residual soil deposits, and heavy and persistent rains (Woldearegay, 2013).

Geology, topography, surface and subsurface water condition, land use/land cover and intense rainfall are the main causative factors which are highly associated with the most landslide occurrence in highlands of Ethiopia (Woldearegay, 2013).

It's important to assess the causes of landslides in order to reduce the harm they cause. These elements are influenced by geology, geomorphology, land use and land cover, rainfall, seismicity, man-made activities, etc. (Anbalagan, 1992, Raghuvanshi et al., 2014a ;). It is typically considered for landslide studies that the interaction of these factors could potentially result in landslides in a certain location. Therefore, evaluating these variables and how they relate to previous landslides in a region may serve as the foundation for predicting future landslides. (Raghuvanshi et al., 2015; Girma et al., 2015; Chimidi et al., 2017). The southern nation is particularly susceptible to landslide threats (shano et al., 2020). In Ethiopia's southern and western highlands, numerous types of landslides have occurred in recent decades. This area is the most populous in the nation and has various topographies (Woldaregay, 2013, Shano et al., 2020). The specific geological and climatic conditions of southern Ethiopia significantly affect the economic and socio-demographic development of this region. The geomorphological and geological character of the area creates favorable conditions for triggering geological processes that negatively influence human activities and the local environment (Kryštof and Leta, 2018).

A variety of approaches have been developed for landslide hazard analysis. They can be grouped into inventory analysis, heuristic analysis, deterministic analysis and statistical analysis (Soeters and van Westen, 1996). Not every one of the approaches indicated above is appropriate for analysis at every size. Because it is feasible to gather enough data for landslide analysis, statistical analysis is typically regarded as the most suitable method for landslide hazard mapping at regional scales (Naranjo et al. 1994).

The study focuses on the application of Geographic Information System (GIS), and statistical calculations for landslide susceptibility modelling of Halila catchment, Gamo Zone, Southern Ethiopia. Here, landslide susceptibility models have been successfully applied for the study area. The weight of evidence method is a statistical technique that uses prior and posterior probabilities to estimate the relative importance of spatial predictors. It is a data-driven approach that uses known landslide locations as training sites to create maps from weighted continuous or categorical input variables. This method was originally developed for mapping mineral potential but has also been applied to landslide susceptibility mapping. By using statistical means, the weight of evidence method helps to identify and prioritize the factors that contribute to landslide occurrence, allowing for better-informed decision-making and risk assessment (Poli and Sterlacchini, 2007). Logistic regression is a statistical model that is used to analyze the relationship between a binary outcome (such as landslide occurrence or non-occurrence) and a set of predictor variables. Logistic regression is one of the multivariate statistical approaches which is often used for landslide hazard zonation or modelling (Meten et al., 2015; Wubalem and Meten, 2020; Sujatha, E, 2021; Sun. D., et al., 2021 shano et al., 2022).

Preparation of landslide susceptibility zoning map serves as an input to delineate areas according to their importance to various developmental activities and helps to identify risk potential ones that demand more evaluations and implementation of mitigation measures before major problems. Large-scale landslide inventory, landslide investigation, and susceptibility mapping for landslide occurrence all require the application of GIS and remote sensing. To extract topographical data such slope, aspect, and elevation, a digital elevation model (DEM) of the study area is needed. This study provides a landslide susceptibility map of the Halila catchment located in Southern nation, nationality, and people Regional State of the southern Ethiopian highland; using remote sensing and GIS applications.

1.2 Statement of Problem

Broadly, the Ethiopian landmass is divided into highlands and lowlands. According to (FAO 1986), the Ethiopian highlands (which include areas with altitude over 1500m a.m.s.l) cover about 44% of the Ethiopian landmass. These areas are threatened by desertification and deforestations (Virgo and Munro, 1978; FAO, 1986; Hurni and Perich, 1992; Billi and Dramis, 2003).

The previous studies showed that landslide is common in northern, southern, and western highlands and partly rift escarpment of Ethiopia due to different natural & man-made influencing factors (Ayalew and Yamagishi, 2004; Ayalew et al., 2004; Ayenew and Barbieri, 2005; Woldearegay, 2013; Raghuvanshi et al., 2014; Meten et al., 2015). Landslide hazards have historically caused damage to infrastructure and loss of life around the world (Raghuvanshi et al., 2014a). The hilly and mountainous highlands of Ethiopia are characterized by diverse topography, geology, hydrology (surface and groundwater) and land use conditions, and are frequently affected by rainfall-induced slope failures, but not earthquakes. It has been argued that landslides are rarely reported (Woldearegay, 2013).

The study is located in the Main Ethiopian Rift (MER), where active extensional tectonics and the intense volcanic activity associated with the East African Rift system are one of the main causes of frequently occurring hazardous geological phenomena (Chorowicz, 2005; Agostini et al., 2011;). In particular, this is because the study area belongs to the western Ethiopian plateau which is characterized by old geological formations. Geological age greatly affects the characteristics of rock and soil formations in a given area. Geological age of an area can determine the type and strength of rocks and soils present. Older geological formations can undergo extensive weathering over time, which can lead to the development of weak or unstable slope materials that are more prone to landslides. In areas where rock uplift or erosion has occurred over an extended period of time, there may be weak material that is susceptible to movement during precipitation or saturation due to the potential for water infiltration from nearby streams or creeks. Such changes in material composition can have a direct impact on the stability of slope landforms and increase the occurrence of landslides in the study area.

The study area is tectonically active, recorded by young faults affecting Quaternary volcanic rocks and outcrop deposits (Verner et al., 2018 c). Geological structure can destabilize slopes by influencing slope angles, and therefore soil strength and infiltration rates, which in turn affect rainfall runoff and lead to increased erosion. In addition, faults increase water pressure on slopes and regulate seepage, which increases the incidence of various types of creep and ultimately leads to sliding.

The currently identified study area is located in the highlands of southern Ethiopia and is prone to landslides due to its steep mountainous terrain, weak geological formation, strong influence of geological structure, and high rainfall twice a year. The area is known for landslide activity that causes significant damage to infrastructure and agricultural land. Therefore, mapping, forecasting, and monitoring of landslide susceptibility is necessary to inform the public and governments of the geographic probability of landslides, enable safer land use planning and development activities, and reduce the impact of eruptions. This study is therefore necessary to generate information that contributes to current spatial planning reforms and to provide local governments with insights into the management of current and future land use practices.

1.3 Research Question

This study is expected to answer the following research questions:

- What are the causative factors for a landslide occurrence in the study area?
- Which causative factors highly contribute to landslides in the study area?
- Which area is vulnerable and at-risk due to landslides?
- What are the possible remedial measures to minimize landslide occurrences?

1.4 Objectives

1.4.1 The General Objective

The main objective of this research is to model landslide susceptibility using two statistical techniques in the Halila catchment, South Ethiopia

1.4.2 The Specific objectives:

This study is going to achieve the following specific objectives:

- ✓ To produce landslide inventory map from past and current landslide records
- ✓ To assess the causative factors that are responsible for landslides in the study area
- ✓ To characterize landslide occurrence with respect causative factors and their classes
- ✓ To check validation of results based on the available and anticipated conditions
- ✓ To propose remedial and mitigation measures in order to mitigate landslides hazards

1.5 Significance of the Study

Ethiopia is one of developing countries in which massive infrastructural development (including roads and railways), urban development and extensive natural resources management are ongoing. In this whole socio-economic development, landslides and landslide generated ground failures needs attention in order to reduce losses from such hazards and create safe environment. The present study focuses on the most susceptible places to landslide hazards and to produce valuable facts on landslide hazards which is a common environmental problem in Ethiopian highlands.

The study area's landslide hazard map can be used to identify the locations where landslides are most likely to occur and to better plan future construction projects. This could aid in choosing suitable locations for farming, building, and other development activities in this research area. Additionally, by giving crucial information to concerned organizations and the local government for controlling current and future land utilization, it will also help to lessen the impact in landslide-prone areas.

1.6 Limitation of the study

The inability to physically reach specific locations of landslide in the study area may result in incomplete mapping or an underestimation of landslide occurrences, as not all affected areas can be surveyed adequately. To overcome this accessibility issue Landslide Inventory map was prepared by collecting past landslides from Google Earth image.

1.7 Organization of the Thesis

The current research is divided into six chapters. The first chapter provides a basic introduction to landslides, a description of the research region, an introduction to the study's problem statement, the objectives of the investigation, the relevance of the study and scope of the study, and the constraints of the study. The second chapter provides extensive literature on landslides and landslide susceptibility mapping. The third chapter describes the description of the area, methods, and materials used: data collection, and data processing, of the study. The fourth chapter focuses on the inventory of landslides and examines causal factors, discusses the outcome of relationship between Landslide Occurrence and Causative Factors, the landslide susceptibility map using weight of evidence and Logistic Regression approaches, and the validation of the anticipated model. The study's conclusion and Recommendations are discussed in Chapter five.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Introduction

Landslides are the most hazardous phenomena throughout the world, where they cause extensive damage for both property and human life (Lee et al., 2004). Geomorphology includes gradient of slope, steepness of the slope, aspect and elevation of the area which has an influence on the stability of the slope. The relationship between gradient of the slope to strength of slope forming material, and also slope aspect are very important and may in turn affect slope stability. Not only this but also, hydrologic (movement, amount and pressure of water) and climatic (temperature and precipitation) conditions also influences the stability of slopes (Varnes, 1984).

In Ethiopia, slope failure occurs in most of the region that possess characteristic earth materials, topographic setting and geologic structures (Ayalew and Yamagishi, 2004). Due to the hilly nature of Ethiopia with improper planning, landslide hazard will continue to challenge road constructions, houses and other infrastructural developments of the country unless it has to be properly addressed in time (Woldaregay, 2013). From the instability point of view, hilly terrains of Ethiopian highland remain highly fragile. Natural causative factors with increasing man-made activities have resulted in increased landslide activities in Ethiopian highland (Raghuvanshi et al., 2014a). The artificial manmade activities (developmental activity) in hilly terrain, especially road constructions, cover large area of the slopes therefore it requires a raped slope stability analysis technique (Raghuvanshi et al., 2014a). Before any developmental planning and construction activity Landslide hazard assessment and risk analysis is advisable (Woldaregay, 2013).

According to several studies, many landslides prone areas have been reported in the Ethiopian highlands. Therefore, in Ethiopia, landslide hazards are becoming serious problem for both public and the government decision makers at various levels (Woldearegay, 2013). Northern Ethiopia has long history of landslide activity especially hill side and road cutting of most rugged regions (Ayenew and Barbieri, 2004). For safer strategic planning and proper mitigation, delineating landslide hazard prone areas is essential. Therefore, to classify lands in to different degree of susceptibility, LHZ technique can be employed (Anbalagan, 1992). In the past, different techniques of LHZ were developed. Those techniques are classified into three groups; expert evaluation, statistical methods and deterministic approach (Leroi, 1997; Guzzettiet et al., 1999).

2.2 Classification of landslides

Landslide may be classified into various categories based on mode of movement, material involved, speed of movement and other. According to (Varnes, 1978) landslide is classified based on the types of material involved (Rock, Earth, Soil, Mud and Debris) and types of movement (fall, topple, slide, spread, flow) and complex class of movement which contains two or more different mode movement acting downslope movement of the landslide mass.

Table 2. 1. Classification of slope movement (Varnes, 1978)

Type of Movement			Type of Material		
			Bedrock	Soils	
				Predominantly course	Predominantly fine
Falls			Rock fall	Debris fall	Earth Fall
Topples			Rock Topple	Debris topple	Earth Topple
Slides	Rotational	Few units	Rock Slump	Debris slump	Earth slump
	Translational	Many units	Rock block slide Rock slide	Debris block slide Debris slide	
Lateral Spreads			Rock spread	Debris spread	Earth spread
Flows			Rock flow (deep creep)	Debris flow (soil creep)	Earth flow
Complex			Combination of two or more principle type of movements		

2.2.1 Fall

A fall begins with the detachment of soil or rock, or both, from a steep slope along a surface on which little or no shear displacement has occurred. The material subsequently descends mainly by falling, bouncing, or rolling. Falls are abrupt, downward movements of rock or earth, or both, that detach from steep slopes or cliffs. The falling material usually strikes the lower slope at angles less than the angle of fall, causing bouncing. The falling`` mass may break on impact, may begin rolling on steeper slopes, and may continue until the terrain flattens (Highland and Bobrowsky, 2008).

2.2.2 Topple

Topple failure is a forward rotational movement of huge masses of soil, rock or debris and earth from a slope (Varnes, 1984). It is usually caused by cracks or fracture in the bedrocks. The rate of movement ranges from extremely slow to extremely rapid and it can be destructive especially when failure is sudden (Highland and Bobrowsky, 2008).

2.2.3 Slide

A slide is a downslope movement of a soil or rock mass occurring on surfaces of rupture or on relatively thin zones of intense shear strain. Movement does not initially occur simultaneously over the whole of what eventually becomes the surface of rupture; the volume of displacing material enlarges from an area of local failure. Slide can be classified as Rotational and Translational slides (Highland and Bobrowsky, 2008).

1. Rotational Landslide

A landslide on which the surface of rupture is curved upward (spoon-shaped) and the slide movement is more or less rotational about an axis that is parallel to the contour of the slope. The displaced mass may, under certain circumstances, move as a relatively coherent mass along the rupture surface with little internal deformation (Highland and Bobrowsky, 2008). The head of the displaced material may move almost vertically downward, and the upper surface of the displaced material may tilt backwards toward the scarp. If the slide is rotational and has several parallel curved planes of movement, it is called a slump (Highland and Bobrowsky, 2008).

2. Translational Landslide

The mass in a translational landslide moves out, or down and outward, along a relatively planar surface with little rotational movement or backward tilting. This type of slide may progress over considerable distances if the surface of rupture is sufficiently inclined, in contrast to rotational slides, which tend to restore the slide equilibrium. The material in the slide may range from loose, unconsolidated soils to extensive slabs of rock, or both. Translational slides commonly fail along geologic discontinuities such as faults, joints, bedding surfaces, or the contact between rock and soil (Highland and Bobrowsky, 2008). According to (Vernas, 2013) translational landslide is structurally controlled and has little or no internal deformation. Also, he stated that planar sliding mechanism is not self-stabilizing and sliding is rapid when compared to rotation sliding and lead high damage to properties and natural environment.

2.2.4 Lateral spreads

These types of landslides usually occur on very gentle slopes or flat terrain. These are distinctive and its dominant mode of movement is lateral extension accompanied by shear or tensile fractures. The failure is result of liquefaction, the process of saturated, loose, cohesion less sediment (usually sands and silts) is changed from a solid into a liquefied state. This Failure is usually triggered by rapid ground motion, such as that of experienced during an earthquake, but can also be artificially induced. Either bedrock or soil which is coherent material, rests on liquefied materials, the upper units may undergo fracturing, extension and then subside, translate, rotate, disintegrate, or liquefy and flow off. Lateral spreading in fine-grained materials on shallow slopes is usually ongoing. Lateral spreads typically damage pipelines, utilities, bridges, and other structures having shallow foundations (Highland and Bobrowsky, 2008).

2.2.5. Flows

A flow is a spatially continuous movement in which the surfaces of shear are short-lived, closely spaced, and usually not preserved. The component velocities in the displacing mass of a flow resemble those in a viscous liquid. Often, there is a gradation of change from slides to flows, depending on the water content, mobility, and evolution of the movement (Cruden & Varnes, 1996)

2.2.5.1 Debris Flows

It is form of rapid mass movement in which loose soil, rock and sometimes organic matter combine with water to form a slurry that flows downslope. They have been informally and inappropriately called “mudslides” due to the large quantity of fine material that may be present in the flow. Occasionally, as a rotational or translational slide gains velocity and the internal mass loses cohesion or gains water, it may evolve into a debris flow. Dry flows can sometimes occur in cohesionless sand (sand flows). Debris flows can be deadly as they can be extremely rapid and may occur without any warning (Highland and Bobrowsky, 2008).

2.2.5.2 Earthflow

Earthflows can occur on gentle to moderate slopes, generally in fine-grained soil, commonly clay or silt, but also in very weathered, clay-bearing bedrock. The mass in an earthflow moves as a plastic or viscous flow with strong internal deformation (Highland and Bobrowsky, 2008).

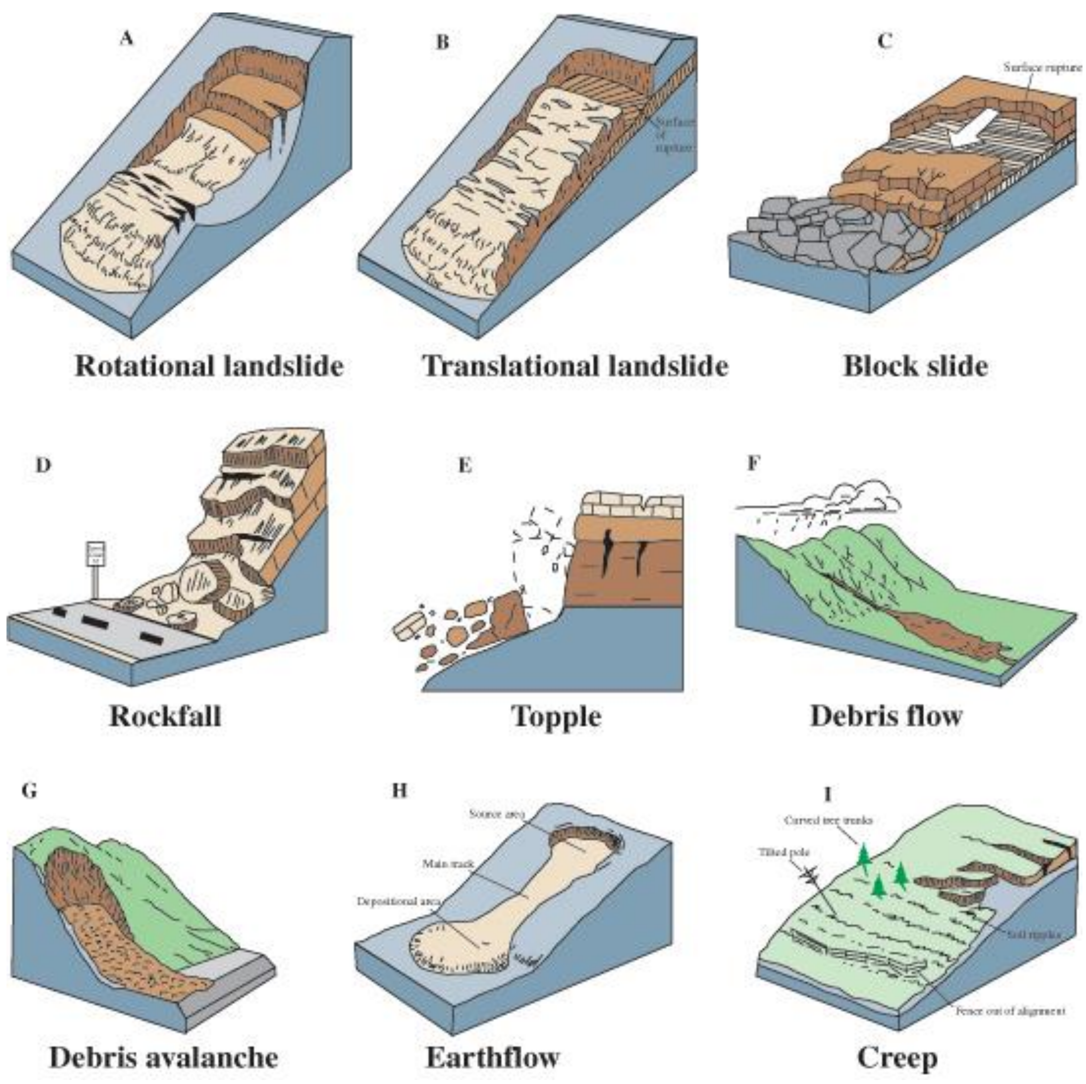


Figure 2. 1. Types of landslides (Highland, 2004)

Susceptible marine clay (quick clay) when disturbed is very vulnerable and may lose all shear strength with a change in its natural moisture content and suddenly liquefy, potentially destroying large areas and flowing for several kilometers. Size commonly increases through headscarp retrogression. Slides or lateral spreads may also evolve downslope into earthflows. Earthflows can range from very slow (creep) to rapid and catastrophic. Very slow flows and specialized forms of earthflow restricted to northern permafrost environments are discussed elsewhere (Highland and Bobrowsky, 2008).

2.2.6 Slow Earthflow (Creep)

Creep is the slowest mass movement, moving at a rate ranging from a few millimeters to several centimeters each year. It is distinguished by a slow, steady downhill flow of slope forming soil or rock. Movement is caused by internal shear stress sufficient to cause deformation but insufficient to cause failure. Generally, there are three types of creep: (1) seasonal, where movement is within the depth of soil affected by seasonal changes in soil moisture and temperature; (2) continuous, where shear stress continuously exceeds the strength of the material; and (3) progressive, where slopes are reaching the point of failure for other types of mass movements (Highland and Bobrowsky, 2008).

2.2.7 Complex type of movement

Sometimes a combination of two or more types of failure happens in a single slope. This type of combination of failure may happen at the same time or during the life time of a slope failure (Cruden and Varnes, 1996).

2.3 Factor Influencing Landslide

2.3.1 Intrinsic Factors

According to Anbalagan, (1992) and Raghuvanshi et al., (2014), intrinsic parameters are the inherent or static causative parameters that define the favorable or unfavorable stability conditions within the slope. These parameters include slope geometry, slope material, structural discontinuities, land use and land cover, and groundwater (Raghuvanshi et al., 2014)

2.3.1.1 Geomorphic Factors

Geomorphic factors are factors related to the gradient of the slope, slope aspect and others. These data can be derived from digital elevation model (DEM). Geomorphic factors are dependent on slope parameters (Endalamaw, 2010). This intrinsic parameter combines the slope morphometry and relative relief (Raghuvanshi et al., 2014). The slope's steepness is expressed by its morphology, which also leads to instability on the slope itself (Hoek and Bray, 1981). When the slope morphometry is steep, the slope will be vulnerable to instability, according to (Hoek and Bray, 1981; Varnes,1984) outlined how, despite the fact that landslides can occur on any slope, their likelihood to occur rises as a slope becomes steeper. The difference between a facet's maximum and minimum elevation is indicated by the relative relief. The slope is more unstable as the relative relief increases (Bekele et al., 2010; Raghuvanshi et al., 2014).

2.3.1.2 Slope Material

Soil, rock, or combined soil and rock can make up a slope (Varnes, 1984). Shear strength, permeability, and susceptibility to chemical and physical weathering of slope material are all influenced by the composition, fabric, texture, and other features of the slope material. The strength and stability of the slope material is also influenced by the cement type, quantity, and sorting of the grain size. Because they have higher infiltration rates and less cohesion and friction than consolidated slope materials, unconsolidated slope materials are more prone to instability (Varnes, 1984).

The type of internal landslide is determined by the slope's material and morphometry. Rock falls, toppling, and rockslides/avalanches are frequent in regions with steep slope morphometry and slope materials covered by hard bed rock such as basalt, welded ignimbrite, limestone, and sandstone (Varnes, 1978; Temesgen et al., 1999). When the slope material deeply weathered volcanic rocks like pyroclastic rocks, rapid landslides mostly involving the eluvial-colluvial cover (debris slides and avalanches, debris flows, earth flows and mudflows) happen. In the banks of deeply incised rivers and gullies the rapid collapse phenomena like topples and slumps frequently occur (Varnes, 1978). When the slope material is like alluvial and colluvial deposits at the foot of the steep slopes, and thick weathered layers on volcanic bed-rock the rotational slides, sometimes passing to earthflows or mud-flows are often produced. Rapid translational slide is probable in slope where hard competent layer overlain by soft clayey bed that dipping downslope. In thick alluvial and colluvial deposits slow translational slides may happen (Varnes, 1978; Cruden and Varnes, 1996).

2.3.1.3 Structural Discontinuities

According to Bell (2007), a discontinuity, is a weak point inside a rock mass where the rock material is structurally discontinuous. Primary and secondary discontinuities like bedding, joints, foliation, cleavage, schistosity, folds, and faults are potentially weak planes in a slope that have a significant impact on the slope's stability, particularly if their inclination makes the slope where they occur more prone to sliding downhill (Blyth and de Freitas, 2005). The strength of joints and other geological surfaces is frequently lower than that of the complete rock they bind; as a result, they are frequently the weakest part of slope geology. It is crucial to understand how they are oriented, spaced, continuous, rough, separated, and what kind of infill material they are in connection to the slope's angle, direction, and strength along such possible weak planes (Blyth and de Freitas, 2005). By forming steep slopes sheared, weak zones and fault zones increase the likelihood of landslides (Wachal and Haduk, 2000). The rock mass could fail along one or more discontinuity plane (Raghuvanshi et al., 2014).

2.3.1.4. Land Use and Land Cover

Slope stability is influenced by land use and land cover. By enhancing shear strength and the impact of climatic factors on natural mass, vegetation tends to promote slope stability. Soil erosion is decreased by intercepting and shielding the bulk from the effects of sunlight, wind, and rain. Although it depends on the soil depth, slope, and type of vegetation, vegetation cover also stops excess water from seeping into the slope. By tying together, the soil bulk, plant roots help strengthen the slope's ability to withstand shear. It has been shown that areas with thick vegetation are less likely to experience slope instability than areas with sparse vegetation, agriculture, and urbanization. Because the type of ground cover influences the stability, places with sparse or no vegetation are more vulnerable to erosion and weathering (Varnes, 1987; Turrini and Visintainer, 1998; Temesgen et al., 1999; Wachal and Haduk, 2000; Abebe et al., 2010; Woldearegay, 2013; Raghuvanshi et al., 2014)

2.3.1.5 Groundwater

Saturation of groundwater in slope reduces the shear strength of the material and also creates pore water pressure which plays important role in slope stability condition (Waltham, 2009; Highland and Bobrowsky, 2008). Groundwater with in jointed rock mass, and in soil mass reduces the shear strength of slope material by developing of joint water and pore water pressure (Waltham, 2009).

2.3.2. External Factors

Rainfall, volcanic activity, seismic vibration, and human-made activities are only a few examples of the external causal elements that are transient, varied, and imposed by new events (Varnes, 1984; Dai and Lee, 2001, and Raghuvanshi et al., 2014).

2.3.2.1 Rainfall

Landslides and more severe slope stability issues are primarily brought on by rainfall (Temesgen et al., 1999; Ayalew et al., 2004; Collision et al., 2000; Dai and Lee, 2001; Dahal et al., 2006). Although it depends on climatic conditions, topography, the geological structure of slopes, and material permeability (Varnes, 1984; Espizua and Bengochea, 2002; and Woldearegay, 2013) contend that rainfall intensity and duration play a significant role in causing landslides like debris flows, mudflows, and medium- to large-scale rockslides. By soaking the slope material, it plays a crucial function in lowering the shear strength of the material. By lubricating the surface of the discontinuities and creating pore water pressure in the rock slope, it also causes the rock to slide along the discontinuities plane (Highland and Bobrowsky, 2008). The rainwater can cause the slope instability by increasing the weight on slope especially in areas where the slope material is soil mass (Hoek and Bray, 1981).

2.3.2.2 Seismicity

One of the factors that might induce a landslide is earthquake shaking (Keefer, 2000; Highland and Peter, 2008). This is because the ground shakes, sensitive sediments liquefy, or soil components expand due to shaking. According to Highland and Bobrowsky (2008), intense seismic ground motion due to ground shaking and shaking caused by the quick penetration of water is the cause of major landslides. Slope instability is caused by ground shaking, which also produces high excess pore water pressure and reduces the shear resistance of slope material (Highland and Bobrowsky, 2008).

The acceleration caused by an earthquake acting on a slope causes a transient shift in tension, disrupting the equilibrium. The external influence of seismic activity increases shear stresses while decreasing shear strength by raising pore water pressure (Chowdhury *et al.,* 2009). As a result, measuring earthquake characteristics is critical for landslide prediction, especially in seismically active locations. The most common forms of earthquake-induced landslides include rock falls, disturbed rock slides, and disrupted earth and debris slides, however, earth flows, debris flows, and avalanches of rock, earth, or debris often move the most material the farthest. One form of a landslide that is common during earthquakes is liquefaction failure, which can result in ground fissuring or subsidence. Liquefaction is the temporary loss of strength of sands and silts, causing them to behave like viscous fluids rather than soils. This can have disastrous consequences during earthquake shaking.

As a result, an attempt was made in this study to estimate the seismic hazard rating of the study area using the seismic hazard map of the country provided by EBCS (1995). This map is based on the estimated amplitude of ground acceleration during 100 years. This map divides the country into various seismic risk zones based on the known history of destructive earthquakes.

These zones vary from earthquake-free zones (zone 0) to fewer damaging zones (zone 1), moderate damage zones (zone 2), risk zones (zone 3), and high-risk areas or zone 4. Zones 1, 2, 3, and 4 are assigned a constant bedrock acceleration ratio, 0 of 0.03, 0.05, 0.07, or 0.1, respectively, whereas Zone 0 is deemed seismic-free. The study area is in zone 0, zone of no damage

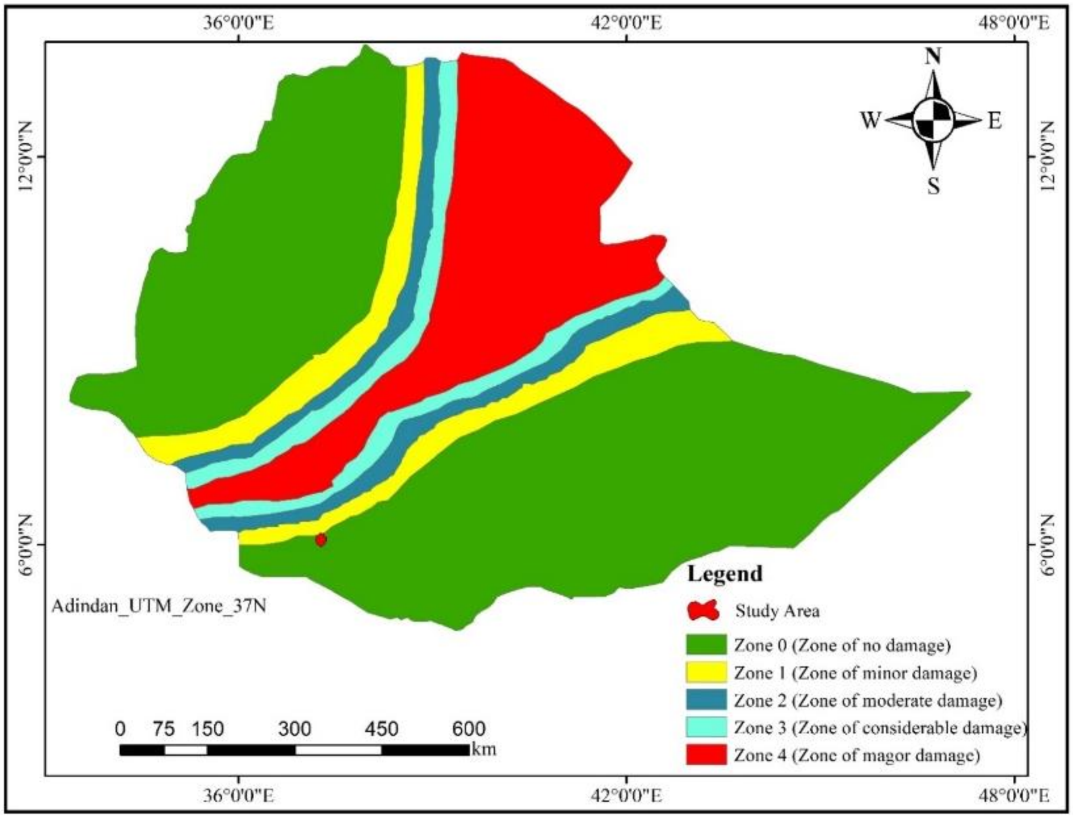


Figure 2. 2. Seismic hazard map of Ethiopia for 100 years return period (EBCS, 1995).

2.3.2.3 Volcanic activity

The most destructive kind of slope failures can result from volcanic activity. Volcanic lava may melt snow, forming a deluge that destroys all in its path, and it can also melt rock, soil, and water. Volcanic lava may melt snow quickly, forming a flood of rock, soil, ash, and water that travels quickly on the steep slopes of volcanoes, which is what produces the most destructive sorts of landslides (Highland and Bobrowsky, 2008).

2.3.2.4 Man-made factors

Human activities triggering landslides are mainly associated with construction and involve changes in slope and in surface-water and ground-water regimes. Terracing for agriculture, cut and fill highway construction, building and railroad construction, and mining operations all change the slope. These activities and facilities may raise slope angle, reduce toe or lateral support, or burden the head of an existing or possible landslide if they are ill-conceived, incorrectly designed, or constructed (Long, 2008).

2.4 Landslide Hazard Mapping Techniques

An essential phase in landslide inquiry and landslide risk management is landslide hazard zonation. The definition of "zoning" given by (Varnes and IAEG, 1984) is "the process of dividing the land surface into zones and rating these areas according to the degree of existing or anticipated hazard from landslides or other mass movements." The definition of landslide hazard given by (Courture, 2011) was "division of land into somewhat homogeneous sections or domain and their ranking according to the degrees of actual or possible landslide susceptibility, hazard or risk, or applicability of specific landslide related rules."

Several approaches have been developed for LHZ mapping such as inventory based mapping, heuristic approach, probabilistic assessment, deterministic approach, statistical analysis and multi criteria decision making approach (Pardeshi, 2013). Broadly, all these techniques or approaches may be further classified into qualitative and quantitative approaches. The qualitative approaches include distribution analysis or inventory, geomorphic analysis and the expert (heuristic) evaluation techniques which are based on the knowledge and experience of the evaluator (Corominas et al. 2014; Raghuvanshi et al., 2014a). The quantitative approaches mainly include statistical, deterministic, and probabilistic and distribution free techniques (Kanungo et al., 2006; Raghuvanshi et al., 2014a).

2.4.1. Distribution (inventory) approach

One of the easiest qualitative LHZ mapping techniques is distribution analysis. It's 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.). The mapping of field surveys, historical records, satellite pictures, and aerial photo interpretation are used to gather data about landslides. Other landslide susceptibility methods are based on maps of landslide distribution and density. The shortcoming of this method is that it shows susceptibility only for those areas where landslides have been observed; however, it may not provide information on landslide susceptibility for those areas which may have potential for future landslide activities (Casagli*et al.,* 2004).

2.4.2. Statistical approach

In last few years the approach towards LHZ has been changed from heuristic (knowledge based) approach to data driven approach (statistical approach) to minimize subjectivity in weightage assignment procedure and produce more objective and reproducible results (Kanungo et al., 2009). The statistical approach is made by rule that is how the individual causative factors contribute to the instability of the active landslide (Van Westen, 1994). The statistical methods for LHZ can be grouped into two. Bi-variate statistical analysis and multi-variate statistical analysis.

2.4.2.1. Bi-variate statistical analysis

The bi-variate statistical analysis for landslide hazard zonation compares each data layer of causative factor to the existing landslide distribution (Kanungo et al., 2009). Weighs to the landslide causative factors are assigned based on landslide density. Frequency Analysis approach, Information Value Model (IVM), Weights of Evidence Model, Weighted overlay model etc. are important bivariate statistical methods used in LHZ mapping (Pardeshi, 2013).

2.4.2.2. Multi-variate statistical analysis

Multi-variate statistical analysis for landslide hazard zonation considers relative contribution of each thematic data layer to the total landslide susceptibility (Kanungo et al., 2009). These methods calculate percentage of landslide area for each pixel and landslide absence - presence data layer is produced followed by the application of multivariate statistical method for reclassification of hazard for the given area. Logistic regression model, Discriminant analysis, multiple regression models, conditional analysis, Artificial Neural Networks (ANN) are commonly used methods for LHZ mapping (Pardeshi, 2013).

2.4.3. Probabilistic approach

The degree of correlation between the historical distribution of landslides and their causes is translated into a value based on a probability distribution function in order to assess landslide susceptibility and hazard zonation. A probabilistic technique aids in the prediction of the geographical and temporal landslide distribution probability in the given area (Lari et al. 2014; Guzzetti et al. 2005b). The probabilistic approach though considered quantitative however it has certain degree of subjectivity in assignment of weights to various causative factors (Kanungo et al. 2006). Thus, probabilistic approach may be considered as semi quantitative.

2.4.4. Deterministic approach

This method generate hazard in absolute value in the form of safety factor (Raghuvanshi et al., 2014a). These techniques primarily rely on the physical laws that are responsible in defining the stability of slope (Guzzetti et al., 2000). Since the deterministic techniques require detailed data on geotechnical parameters therefore collecting such detailed data over large areas make these techniques limited to small areas, effectively limited to individual slopes (Aleotti and Chowdhury, 1999; Fall et al., 2006; Kanungo et al., 2009; Raghuvanshi et al. 2014a, 2014b).

2.4.5. Multi-criteria decision analysis methods

These methods are semi-quantitative approaches which are mostly used for landslide susceptibility evaluation (Erener et al., 2016 and hazard zonation studies (Bera et al., 2019). The methods which are categorized under multi-criteria decision analysis are analytical hierarchy process (AHP), fuzzy set-based analysis, weighted linear combination and ordered weighted average (Feizizadeh and Blaschke, 2012; Ahmed, 2015; Bera et al., 2019).

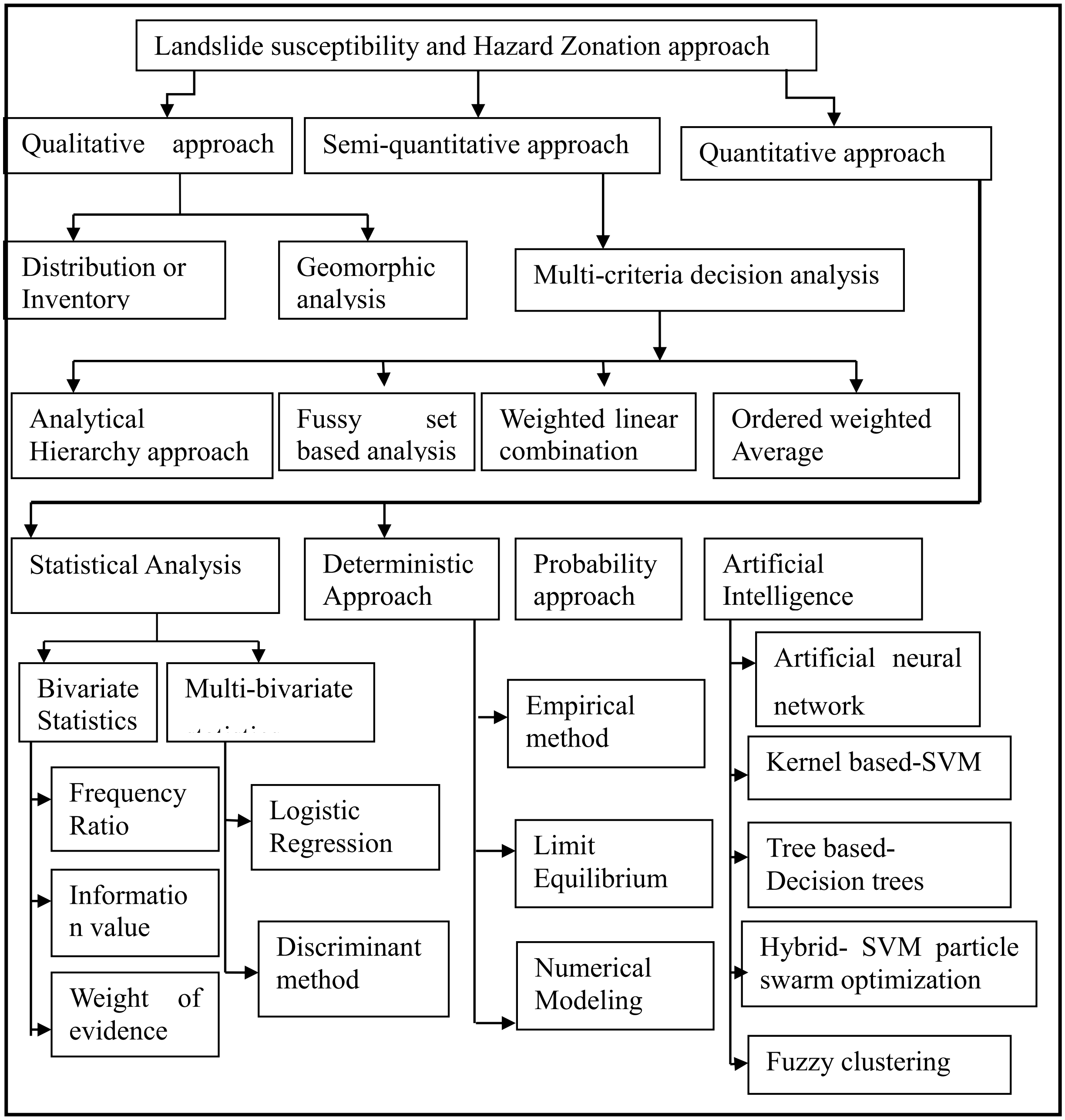


Figure 2. 3. Landslide susceptibility and hazard zonation techniques (Shano et al., 2020).

2.5 Geology

Ethiopia's geology is underpinned by rock types ranging in age from Precambrian to Cenozoic. Precambrian rocks, Paleozoic-Mesozoic sedimentary rocks, Cenozoic volcanic rocks, and related sediments are the geological formations to which these rocks belong (Tefera *et al.*, 1996). On a regional scale, the study area rests in the East African Rift System (EARS), which is an intra-continental rift separating the western African (Nubian), eastern Somalian and northern Arabian lithospheric plates. The axial zone of the rift consists of several depressions (rift valleys) separated by uplifted blocks. The EARS is comprised of three separated domains – the Western branch, the Eastern branch and the Main Ethiopian Rift (MER) to the north. The latter extends to the north towards the Afar Depression where it splits through a triple junction into NW and ENE trending oceanic ridges in the Red Sea and the Gulf of Aden, respectively. The rift separation is attributed to slips along transform faults, perpendicular to the rift axis. The Orientation of these faults reflects ~ NW-SE direction of crustal spreading (Chorowicz, 2005). The MER is divided geographically into three sectors: northern, central, and southern MER (Woldegabriel *et al.*, 1990; Bonini *et al.*, 2005; Corti, 2009). From these three segments were interpreted by Hayward and Ebinger (1996), the early rifting in the Southern MER to more evolved stages in the Central and Northern MER before the incipient seafloor spreading in Afar. However, the ages of the beginning of faulting and volcanism for the three rift segments indicated above indicate varied time space evolution and progression of the continental rifting process and the MER.

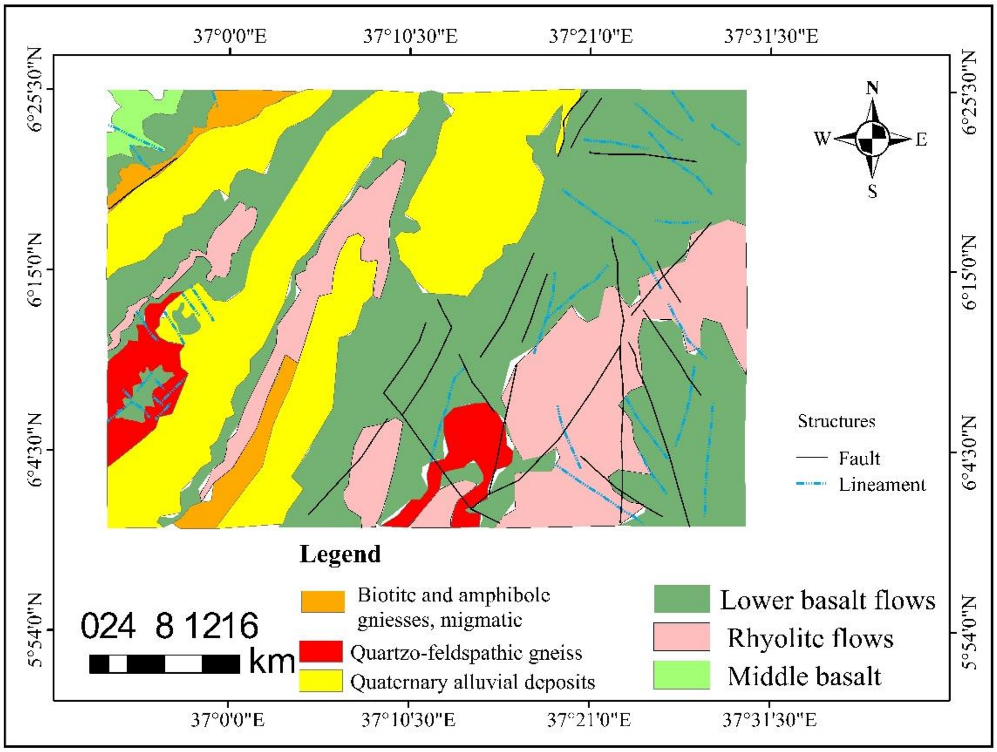
2.5.1 Regional geology of the area

Southwestern Ethiopia metamorphic terrain is comprised of both high-grade gneissic units of the Mozambique Belt and low-grade met volcano-sedimentary sequences of the Arabian-Nubian Shield. The Precambrian basement of south and southwestern Ethiopia was traditionally divided into three complexes (Kazmin et al., 1978): the Lower complex, Middle complex and Upper complex. The Lower complex (considered to be Archaean age) included various gneisses and migmatites, mainly granitic composition. The rock consisted of mainly biotite and amphibole-bearing gneisses. The Lower complex, believed to be a direct northward continuation of the Mozambique Belt (Kazmin et al., 1978), occurs in the south and southwest (Konso, Alghe, Awata and Yavelo gneisses), in the west (Baro and Alghe gneisses) and partially in the east (high-grade gneisses and migmatites). Alghe Group gneisses exposure found in the southern part of Dime map area. The Middle complex was usually represented by psammitic and politic metasediments. On the other hand, the upper complex included low-grade, tightly folded rocks including ophiolitic assemblages, metavolcanics and clasts.

The Paleozoic sediments exposed in the northwest part of Southwestern Ethiopia were terrestrial sediments, consolidated, non-metamorphosed sedimentary rocks, mainly sandstone with conglomerate and intercalated siltstone (Davidson, 1983), which were classified into three units. These were the Gilo, Kari and Meti sandstones. These sandstones showed certain lithological similarities, and occurred above the unconformity between the crystalline basement and its Tertiary volcanic cover. Fossils were not evident, but palynological analysis had proven a Permian age. Mesozoic sediments equivalent to the thick marine succession of East, North and Central Ethiopia were not exposed Southwestern parts of the country.

The Broadly Rift Zone of Southern and Southwestern Ethiopia represented the northern continuation of the Kenya Rift. Like the Southern sector of the MER, the Kenya Rift became bifurcated into at least four half-grabens and a fully developed rift basin within Southern Ethiopia. These structures disappeared into the West-Central Ethiopian highlands. The Chew Bahir rift, located along the eastern part of the Broadly Rift Zone, was characterized by well-defined rift margins and an arrow rift system (10-20 km thick) with more than 300 km length. To the West of the Chew Bahir rift, the Omo, Usno, Kibish half-grabens occupied the rest of the Broadly Rifted Zone. These rift basins were characterized by singular, well-defined rift margins and tilted rift floors. The half grabens later filled by volcano-clastic sediments and mostly devoid of recent volcanic centers and flows except for a few sediment-bound distal ashes erupted from the Main Ethiopian Rift.

The rift basins in Southern and Southwestern Ethiopia were filled with fluvial and lacustrine sediments of Pliocene-Pleistocene ages. These sedimentary deposits were represented by Omo Group units, composed of four formations. These include: Mursi, Nkalabong, Usno and Shungura Formations. The basalt unit of the Mursi Formation extended Northwards from Hana Salamago town in the Southwestern part of Dime map area. This flood basalt composed of columnarly jointed dark gray basalt. The Nkalabong formation placed on faulted, weathered Mursi basalt, and consisted of gray to brown fluvial clastics overlain by Aeolian sands and water lain tuffaceous sediments.



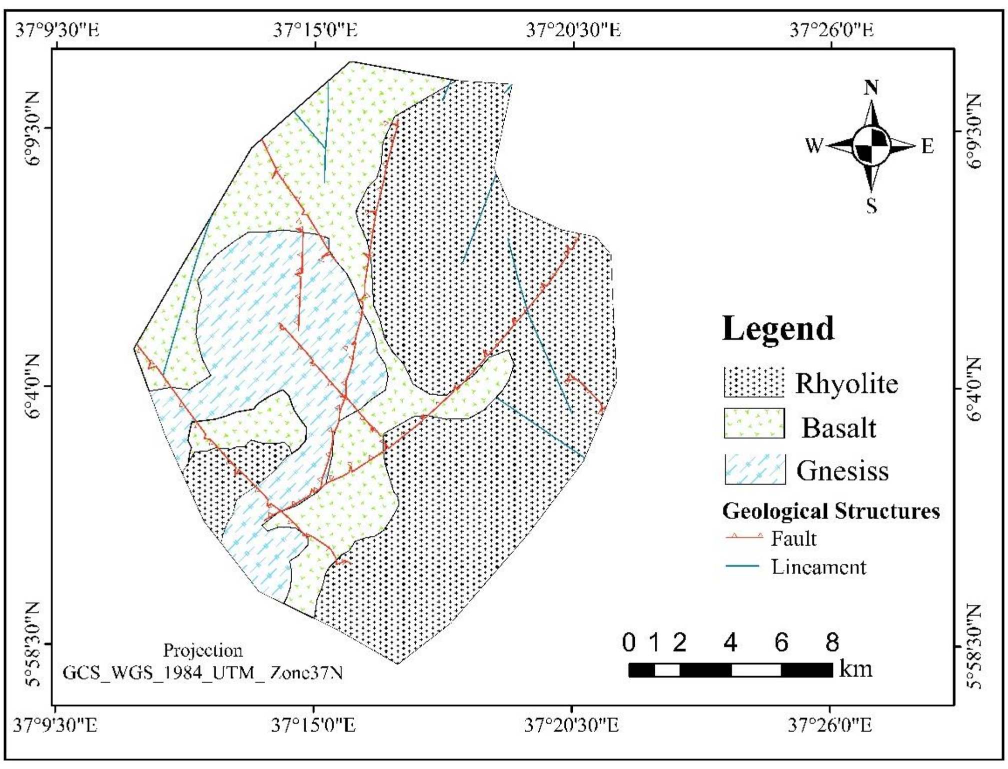


Figure 2. 4. (A) Regional geologic Map of the study area (Adopted from GSE, 2012) and B) study areas geology.

2.6 Landslide overview in Ethiopia

Landslide hazard is, one of the crucial environmental problems for the development of Ethiopia (Abebe et al., 2010). In Ethiopia, landslide-generated hazards are becoming serious concerns to the general public and to the planners and decision-makers at various levels of the government. Community living within mountainous environment may be at risk due to a wide variety of geoenvironmental processes, which include geological, meteorological and human factors. As defined by (Woldearegay, 2013), landslide is the downslope movement of soil and rock under the influence of gravity without the primary assistance of a fluid transporting agent. Landslide hazard is becoming serious environmental constraints for the developmental activities in the highlands of Ethiopia.

The Ethiopian highlands are highly populated and the area is highly characterized by variable topography like steep hill slope and incised valleys and gorges (Woldaregay, 2013) which shows past geological and erosional process. The steepness of the slopes in the highlands of Ethiopia is enough to aggravate instability. In addition to this, external factors like rainfall and manmade activities in the area initiate the instability of slope. As many studies suggest that the highlands of Ethiopia have high variable rainfall intensity. To identify the nature, type, cause and consequence of the landslide in different parts of the country, many researchers have tried to study and recommend preventive and mitigation measures. Some of them are discussed below.

Rainfall-induced landslides of different types and sizes are common in hilly and mountainous terrains of the highlands of Ethiopia. The major types of landslides reported which is a result of heavy rainfalls include debris/earth slides, debris/earth flows and, and medium to large-scale rockslides. Though rock falls are common in the Ethiopian highlands no association is made with rainfalls (Woldearegay, 2013).

Temesigen et al. (2001) conducted research by using GIS and Remote sensing methods for natural hazard assessment to the landslide in the Wondo-Genet area. In their work they evaluated the occurrences of landslides and their relationships with various event controlling parameters using GIS and Remote Sensing techniques. Finally, a landslide hazard zoning prepared done through the statistical relationships of the parameters with landslide occurrence that were converted into risk susceptibility priority numbers.

Ayenew and Barbieri, (2004) have conducted a landslides inventory and susceptibility mapping in the Dessie area. During this study, four broad landslide susceptibility zones and 22 specific active landslide sites were identified. According to this research, the most important landslide types were complex earth and debris slides and flows in silty clay soils associated with alluvial and colluvial deposits overlying highly weathered basalts.

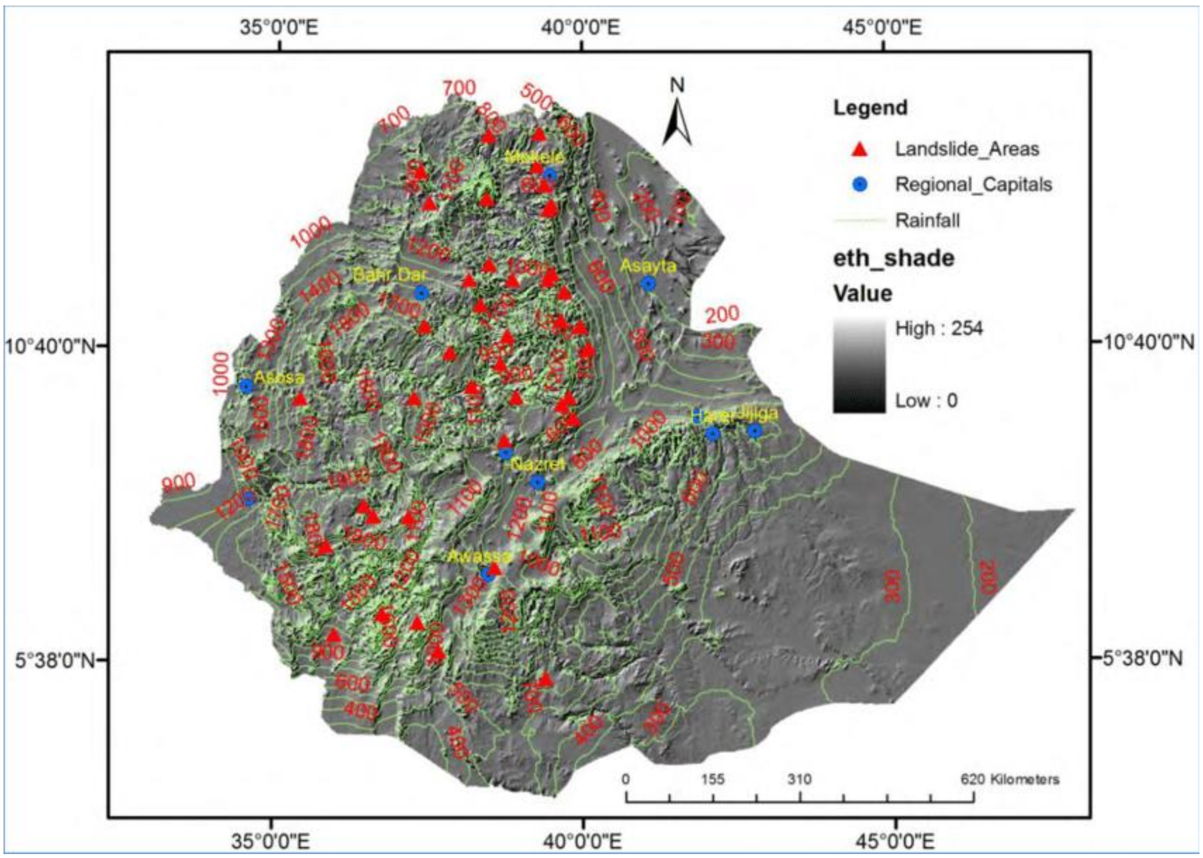


Figure 2. 5. . Location of landslide affected areas in the highlands of Ethiopia (Woldearegay, 2013).

Mulatu *et al.* (2009), Landslide hazard zonation mapping was carried out near Gilgel-Gibe II in Southwestern Ethiopia. In their study, they divided landslide potential locations into high, moderate, and low danger categories. The results indicate that 54% of the slopes in fall in High Hazard, 34% in the Moderate Hazard and 12% in the Low Hazard zone the area.

Abebe et al. (2010) conducted a review of landslide occurrences on the Ethiopian highlands and rift margins. They emphasized on the man-made triggering factors, which include increasing settlement on slope sides due population growth and expanding infrastructure, scarcity of agricultural area and construction material.

Raghuvanshi et al., (2014a) made study on landslide hazard zonation using Slope stability susceptibility evaluation parameter (SSEP) expert approach in the area around Wurgessa Kebelle of North Wollo Zonal Administration, Amhara National Regional State in northern Ethiopia. The results obtained indicates that 8.33% of the area fall under Moderately hazard and 83.33% fall within High hazard whereas 8.34% of the area fall under Very high hazard.

Meten et al. (2015) carried out a study in Debresina GIS-based frequency ratio and logistic regression modeling for landslide susceptibility mapping of Debresina area central Ethiopia. To prepare landslide susceptibility mapping landslide inventory and nine causative factors including lithology, land use, distance from river and fault, slope, aspect, elevation, curvature and annual rainfall were considered. After various rasterization of causative factor thematic maps and landslide inventories for both LR and FR model the success and prediction rates 75.7%, 74.5% and 74.8%, 73.5% were produced respectively. The prediction rate and therefore the validation rates are almost similar, therefore based on this they concluded that the model is acceptable.

Chimidi *et al.* (2017), investigated landslide hazard evaluation and zonation in and around Gimbi town, western Ethiopia Using a GIS-based statistical technique. This research investigated nine parameters for LHM preparation, including slope material, elevation, slope, aspect, curvature, land-use/land-cover, groundwater, and distance to road and stream. This analysis identified five hazard zones and fifty historical landslide locations. They determined that 75% of previous landslides occurred in extremely high and high hazard zones; as a result, future urban planning and development should take this into account.

Demessie (2018), conducts a study in the area in Dilbe and its surrounding area around Northwestern Central Ethiopia by integrating of Geographic Information Systems (GIS) based grid overlay and statistical approach. The author defines the area in terms of vulnerability and assesses the causal characteristics. The statistical method was used to create LHZ maps of the research region. The validation of the produced hazard zone map found that 74% of historical landslides occur inside the produced LHZ map's extremely high and high hazard zones.

Firomsa and Abay (2019), conducted research on landslide assessment and susceptibility zonation in the Ebantu district Oromia region of western Ethiopia. Five landslide causative factors are investigated and incorporated into the study to create a susceptibility map of the area. The statistical index approach is used to assess the spatial relationships between landslide occurrences and each landslide-related causal factor.

Berhane et al. (2020), use a GIS-based frequency ratio model with multi-class spatial data sets to undertake research in the Adwa-Adigrat Mountain ranges in northern Ethiopia.

Mersha and Meten (2020), conducted a study on a GIS-based landslide susceptibility assessment and mapping using bivariate statistical approaches in the Simada region of Northwest Ethiopia. The predictive rate of the FR and WoE models was 88.2 percent and 84.8 percent, respectively. The validation revealed that the LSM created by the WoE model performs better. Finally, the LSM generated by the FR model had a significant geoengineering impact on landslide hazard prevention and mitigation in the study area.

Getachew and Meten (2021), applied, weights of evidence modeling for landslide susceptibility mapping in the Kabi-Gebro locality, Gundomeskel region, Central Ethiopia. The research area's landslide susceptibility map was created 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. The landslide density index and area under the curve were used to validate this susceptibility map.

Genene and Meten (2021), studied landslide susceptibility mapping using GIS-based information value and frequency ratio methods in Gindeberet, West Shewa Zone, Oromia Region, Ethiopia. According to these authors, 580 landslides were randomly chosen into two datasets, with (80%) 460 landslides used for modeling and (20%) 116 landslides used for validation. To create LSMs, conditioning elements (slope, aspect, curvature, distance from stream, distance from lineaments, lithology, rainfall, and land use) were merged in an ArcMap with a training landslide dataset. Finally, the Area under (ROC) curve was used to validate the

LSMs for the IV and FR models, yielding a success rate of 0.836 and 0.835, respectively, and a prediction rate of 0.817 and 0.818

2.8 Previous studies around the study area

Certain previous studies that have been conducted around the study area reveal that it is one of the most susceptible sites to landslide hazards. There has been no prior research on landslides in the current study area.

Feleke (2021), conducted a study on Landslide Hazard Zonation around Ameya town Konta special Woreda S/N/N/P/Region, Ethiopia is carried out by applying Slope Stability Susceptibility Evaluation Parameter (SSEP) rating scheme. Relative relief, slope morphometry, Slope material, land use land cover, Aspect, Elevation, Ground water, and external parameter (Rain fall + Seismicity + Man made activity) are selected conditioning and triggering factors of landslide. The research showed that landslides vary in severity and magnitude at different locations, necessitating different and site-specific engineering remediation activities for different locations that are appropriate for the defined slope segment, material type, depth to groundwater, soil property, and other factors. As a result, light gabions, retaining walls, and strong drainage systems, as well as networking systems with one another, appear to be needed in some areas.

Shano *et al.,* (2021), carried out a study on landslide susceptibility mapping using the frequency ratio model: the case of Gamo highland in South Ethiopia. This study chose eight predisposing variables for the frequency ratio model. The causal elements chosen for landslide susceptibility mapping were slope, aspect, curvature, elevation, proximity to a stream, proximity to lineament, lithology, and land use/land cover. According to the frequency ratio model, all elements have a demonstrated effect on the occurrence of landslides. As a result, the authors concluded that it is preferable to take action on these issues or remove the local inhabitants to reduce the incidence of landslides in the area.

Shano *et al.* (2022), conducted a study on Fuzzy set theory and pixel-based landslide risk assessment in the Shafe and Baso catchments in Southern Ethiopia's Gamo high land. According to this study, both methodologies' risk assessment maps designated separate danger zones with more or less identical geographical coverage. The risk was divided into five categories on the landslide risk map: very high risk (6.86 %), high risk (21.15%), moderate (43.26 %), low (10.97 %), and very low risk (10.97 %) (17.76 %). Based on the findings, appropriate biological and mechanical remedial actions are recommended to reduce the landslide hazard in the studied area.

Shano *et al.* (2022), conducted landslide hazard zonation using a logistic regression model for Shafe and Baso catchments in Gamo Highland, Southern Ethiopia. Landslide predisposing/influencing factors considered in this study include lithology, groundwater conditions, distance to faults, morphometric parameters (slope, aspect, and curvature), and land use/land cover, whereas precipitation was a triggering factor. The statistical analysis of this research found that landslide affecting elements such as distance to fault, distance to stream, groundwater zones, lithological units, and aspects had the most significant influence on landslide occurrence.

Tefera (2022), Conducted a Thesis on Landslide susceptibility mapping using Bivariate statistical methods: In the case of Sile and Elgo catchments, Gamo Highland, Southern Ethiopia. Elevation, slope, aspect, plan curvature, profile curvature, road distance, river distance, fault distance, lithology, vegetation coverage index, and topographic wetness index are chose as influencing factors for the study area's landslide susceptibility based on geological data, field surveys, and landslide information. The IV, FR, and WoE approaches were used to develop the landslide susceptibility model, verified using the ROC curve and the Landslide Density Index (LDI).

2.8 Treatment and Mitigation Measures for Landslides

Different measures for landslide treatment depend on the features identified or mapped that are causing problems. The following are specific techniques for addressing various problems in landslides and general recommendations for treating the various zones of landslides.

1. Land use improvement: Techniques include conservation plantation, grass plantation, on-farm conservation, agro-forestry, safe water drainage, and runoff harvesting ponds or dams in the catchment.
2. Drainage management: Ground water probably is the most important single contributor to landslide initiation. Not surprisingly, therefore, adequate drainage of water is the most important element of a slope stabilization scheme, for both existing and potential

landslides. Drainage is effective because it increases the stability of the soil and reduces the weight of the sliding mass (L.M and Peter, 2008). To prevent runoff from flowing into landslides and to drain the excess water from landslides, drainage management is essential. Drainage management may be surface and subsurface drainage management.

- Surface drainage management: Techniques applied include construction of diversion waterways, sealing of tension cracks so that rainwater cannot get inside and build up pore water pressure, rip-rap (stone or vegetative or combined) of the waterways. These techniques are appropriate for controlling shallow slides.
- Sub-surface drainage management: Techniques applied include sub-surface drainage trenches filled with gravel, perforated drainage pipes (vertical and horizontal), which are appropriate for reducing pore-water pressure along failure planes (Popescu, 2001).
- Conservation ponds to store and divert excess run-off.

3. Reducing the height of the slope: Reducing the height of a cut bank reduces the driving force on the failure plane by reducing the weight of the soil mass and commonly involves the creation of an access road above the main road and the forming of a lower slope by excavation. Also, it is possible to excavate deeply and lower the main road surface if the right- of-way crosses the upper part of a landslide (L.M and Peter, 2008).
4. Internal slope reinforcement: This method can be done by inserting a controlling mechanism to a slope face that resists the movement of materials by attaching of materials together that going to fails.

2.9 Validation of Landslide Susceptibility Assessment

Validation implies a comparison between the maps obtained from the models and the independent dataset. Landslide susceptibility maps can be verified by comparing the susceptibility maps with both the training data with the test data. For this purpose, success rate and prediction rate curves are calculated where the values provide the base for testing the model compatibility and prediction capacity. The success rate curve is derived by comparing the predicted model and the landslides data used in the modeling, and this indicates how well the resulting landslide susceptibility maps have classified the areas of existing landslides (Tien et al. 2012). Whereas the prediction rate curve illuminates how well the model and predictor variables predict the results.

2.9.1 Area under the Curve (AUC)

AUC is one type of accuracy in statistics for prediction models (probabilities) in the assessment or analysis of natural disaster events. Mathematically, AUC is a graph of varying index numbers usually between a maximum value of 1 or equal to 100% and 0.5 Or equal to 50%. In an ideal model, AUC is very close to 1.0 which means the model is perfect fit whereas in a random prediction model, AUC is close to 0.5 (Swets, 1988). AUC is used as measurement to determine the comprehensive quality of the model. When the area of the curve is large, it represents the best performance of the model over whole area of potential cutoffs (Hanley and McNeil, 1982). AUC measure the quality of the prediction of model regardless of what distribution threshold is chosen.

CHAPTER 3

MATERIALS AND METHODS

3.1 Description of the study area

3.1.1 Location and accessibility of the study area

It is located in the Gamo Zone, South Ethiopia about 500 kilometers south of Addis Ababa. Geographically lies between 5°58’8.26” to 6°10’58” N and 37°11’7.968” to 37°21’24.8” E with an area extent of about 296 km^2. It lies in the Main Ethiopian Rift Valley at the foot of the western Ethiopian volcanic plateau. The area is accessible by a road from Addis Ababa to Arba Minch, from Arba Minch about 40km to south west. The altitudes of the area reach up to a maximum of 3250m.

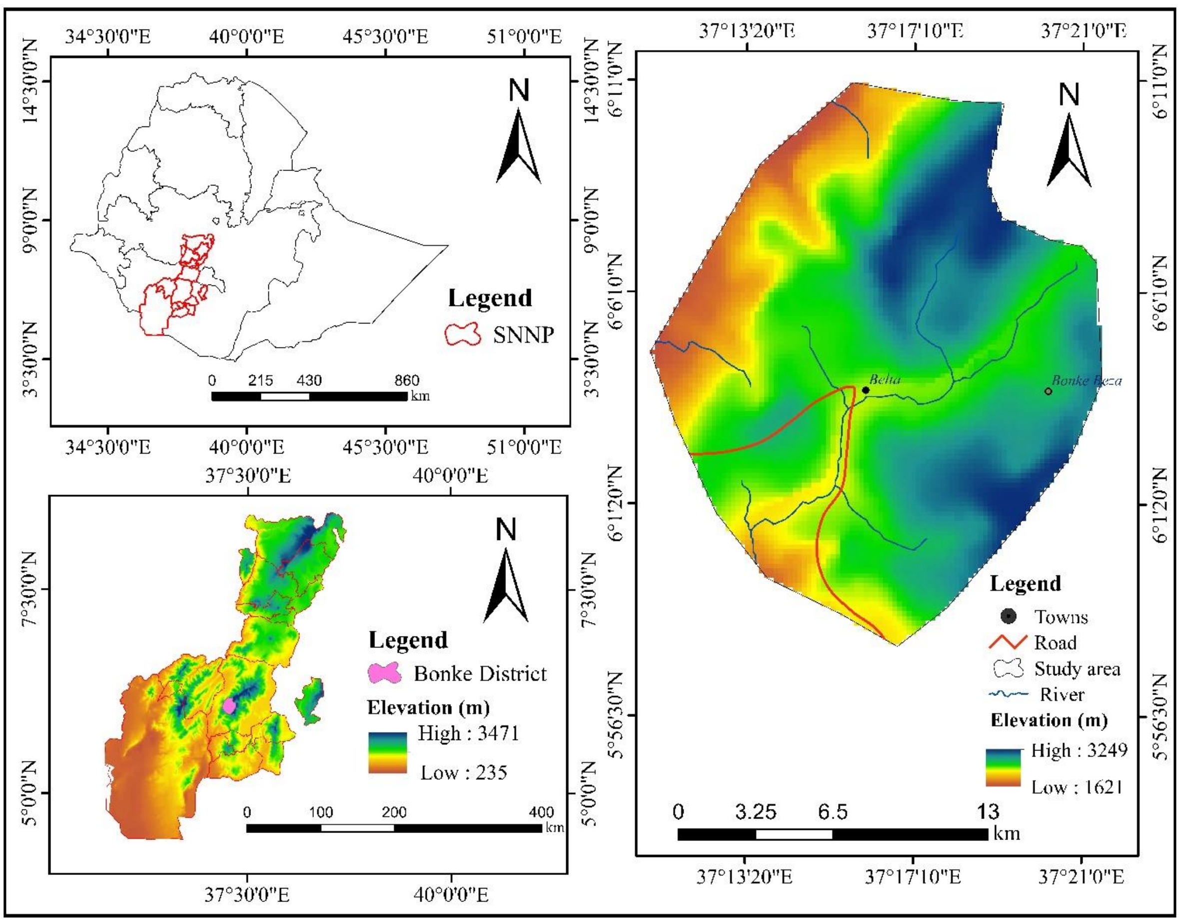


Figure 3. 1. Location map of the study area

3.1.2 Physiography

The Physiography Ethiopia, the geological setting has played a significant role in shaping its diverse and varied landscape. One of the most prominent geological features of Ethiopia is the East African Rift System. The East African Rift passes through Ethiopia, creating a complex network of rift valleys. This tectonic activity has led to the formation of deep valleys, escarpments, and volcanic features. The physiography of Ethiopia, with its diverse topography and geological features, reflects the dynamic geological processes that have shaped the region over past of years. The topography of the area is characterized by the rugged topography and mountainous landscape that shows various geomorphic features, ecological zones, and steep to very steep slopes. Study area belongs to western Ethiopian plateau with a peak elevation of 3378 meters above mean sea level and a lowest elevation of 1608 meters above mean sea level in the deep river valley. In general, the presence of deep gorges, valleys, steep scarps, cliffs, sharp ridges, and rugged slope faces suggests that the area is vulnerable to landslide activities and active surface processes.

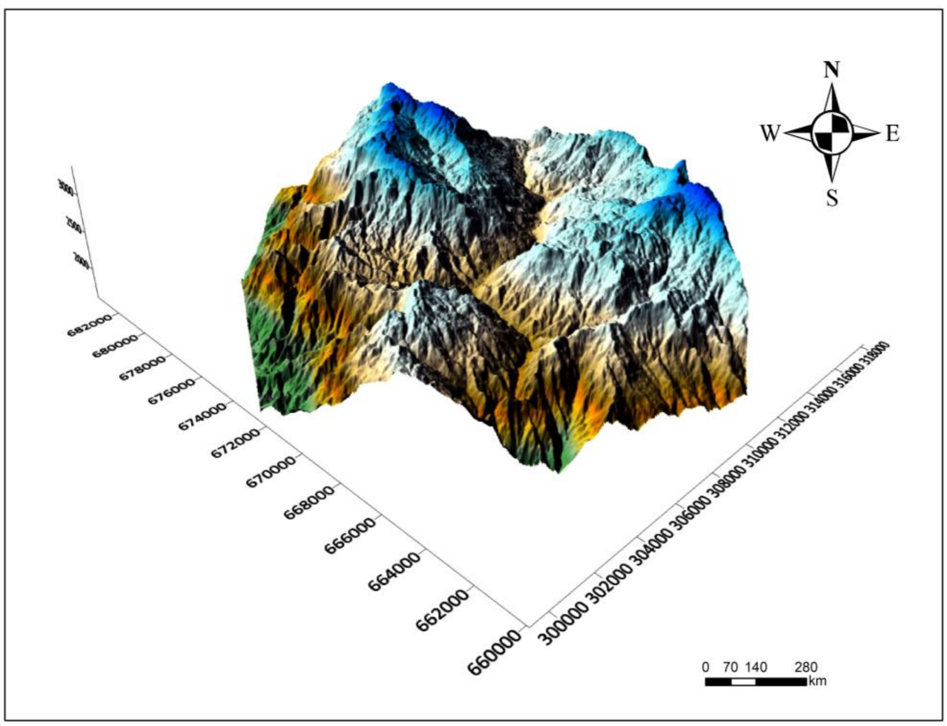


Figure 3. 2. Physiography map of the study area

3.1.3 Drainage pattern

The drainage patterns in the area are characterized by dendritic as shown in figure 8. In a dendritic drainage pattern, the river channels form a network of interconnected streams resembling the branching patterns of tree limbs. This type of drainage system is common in study area because the area is characterized with homogeneous rock or soil types where there is little variation in resistance to erosion.

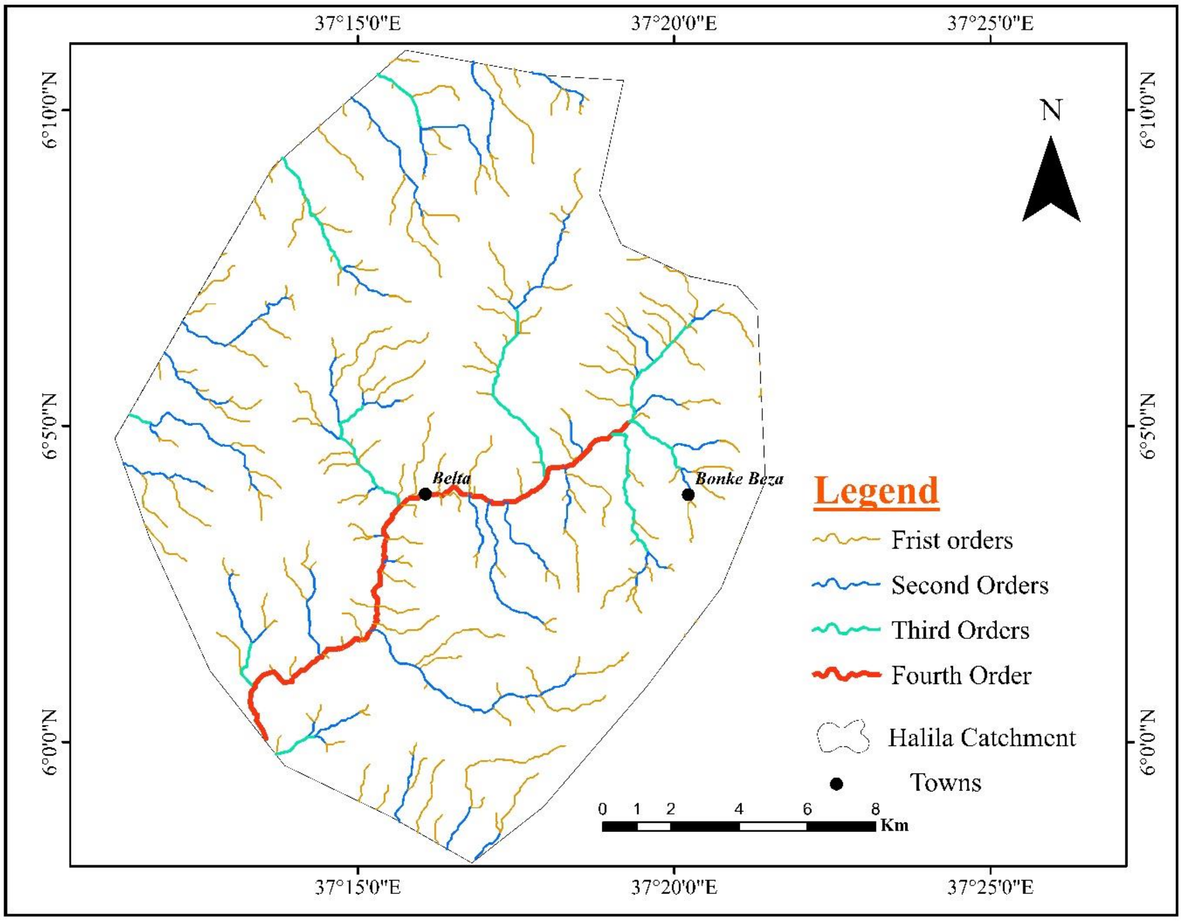


Figure 3. 3. Drainage network of the study area

3.1.4 Climate and Vegetation cover

Ethiopia's varied topography has given rise to three distinct climatic zones, namely the Cool zone (Dega), situated at elevations mostly exceeding 2400 meters, experiencing daily temperatures ranging from nearly freezing to 16°C; the Temperature zone (Weina Dega), found at altitudes between 1500 meters and 2400 meters; and the Hot zone (Kolla), encompassing areas below 1500 meters altitude. Consequently, the study area is situated within Dega and Weigna Dega climatic zones, each characterized by its unique temperature and elevation attributes. The rainfall varies greatly, with the highest rainfall happening and the heaviest rain falling. The rainfall data around the study area from 1992 to 2022 were obtained from meteorological agency.

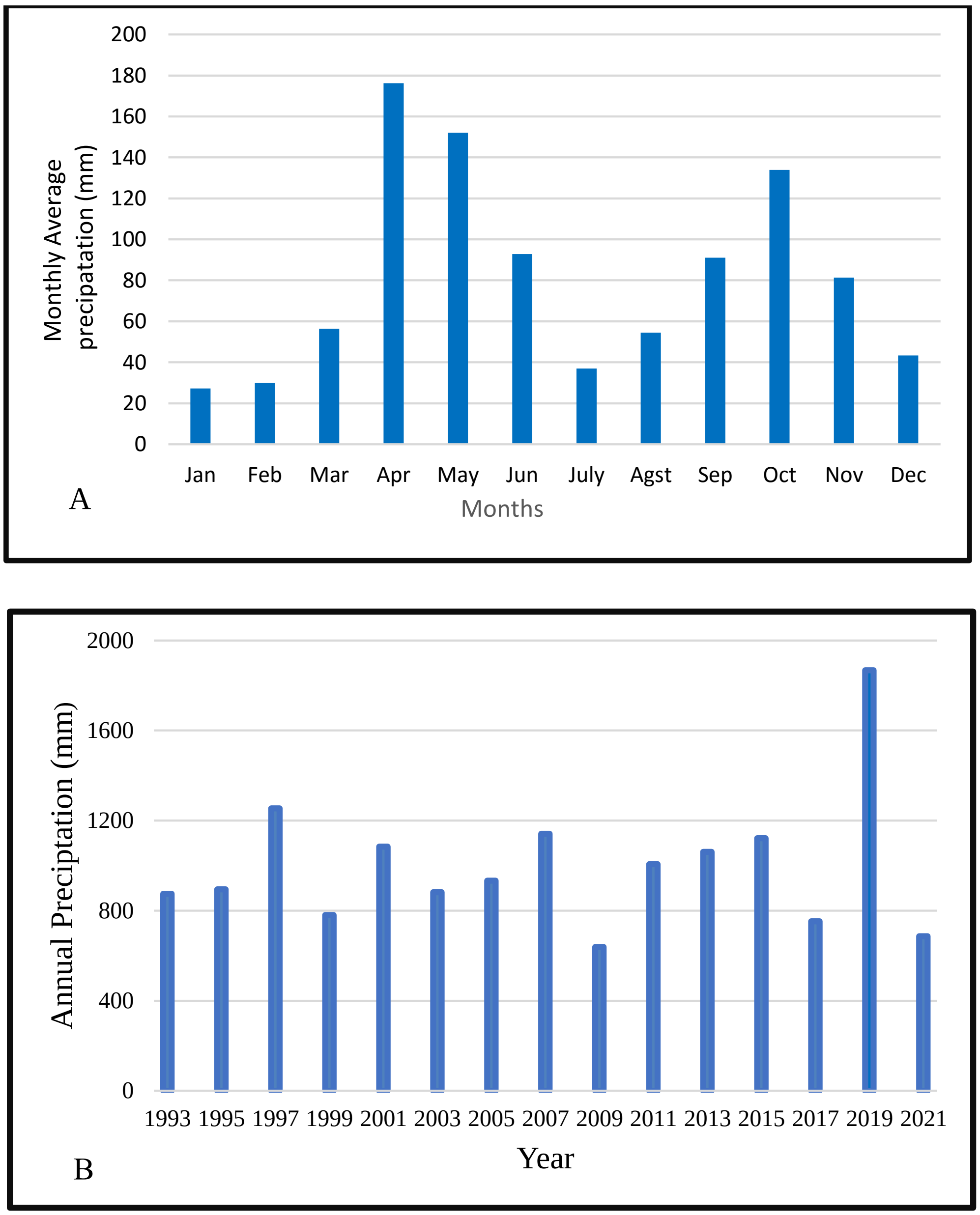


Figure 3. 4. (A) Average monthly precipitation, (B) yearly annual precipitation summarized data gathered from Ethiopian Meteorological Agency.

Having vegetation on slopes plays a crucial role in mitigating erosional activity. Slopes covered with dense vegetation experience reduced erosion due to the natural anchoring provided by tree roots. In contrast, slopes devoid of vegetation are more susceptible to erosional processes, contributing to instability (Ayalew & Yamagishi, 2004). The research locale manifests a heterogeneous topography characterized by both sparse and dense vegetation. Meager plant and shrubbery cover are discernible, the latter being particularly limited in extent. Predominantly, the central part of the area is occupied by cultivated and fallow lands. Inhabitants are principally engaged in agrarian pursuits, compelled by the challenging and precipitous terrain to cultivate areas characterized by moderately gentle slopes. Grazing is confined to demarcated regions. Notably, the arboreal landscape in the northern precinct is dominated by eucalyptus (bahirzaf) and bamboo trees.

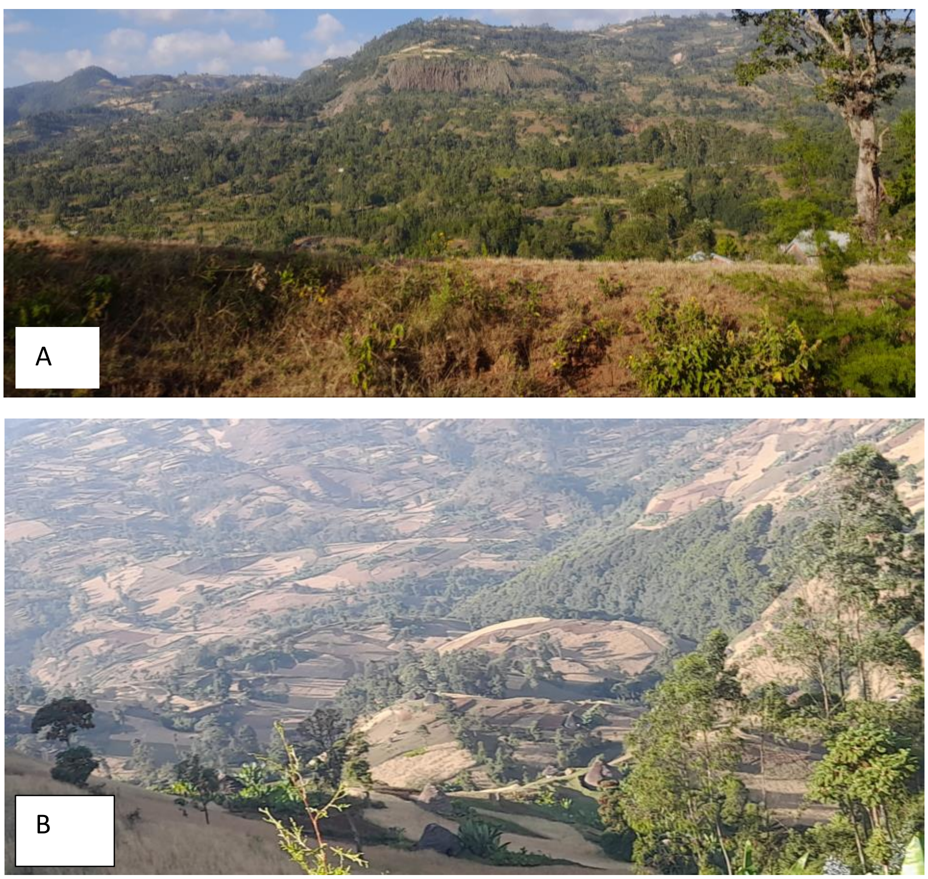


Figure 3. 5. (A) Some vegetation covers of the area and (B) cultivated lands

3.2 Methods

3.2.1 Data Collection and Preparation

This phase will see the completion of a number of tasks that formed the basis for achieving the goal of the current study. During this phase, secondary data and the required materials will be acquired from different organizations and sources. Literatures, articles and websites related to landslide and landslide hazard zonation, both unpublished and published written materials, maps and graphs were collected and studied in order to have a general background and a conceptual framework about the subject. Metrological data will be collected from metrological agency to acquire good understanding about climatic conditions of the study area. In order to verify the causal factor maps that were created using secondary data sources and to gather various forms of primary data, field research will be undertaken.

With the use of Arc GIS 10.8, aspect, slope, and curvature maps will be created using the DEM (Digital Elevation Model with 30 m x 30 m resolution from Shuttle Radar Topography Mission (SRTM). The precision of mapping landslide susceptibility is influenced by the chosen resolution. In a comparative study by Lee et al. (2004) that assessed landslide susceptibility at various spatial resolutions, it was determined that a 30-meter pixel size is recommended as the maximum for achieving acceptable predictive capacity. Satellite images are used to prepare the landuse and landcover of the area, while fieldwork and Google Earth are used to confirm the information. Landslide polygons from the past and lineaments can be gathered using Google Earth Pro and converted to shape file using Arc GIS 10.8 for Analysis.

3.2.2 Landslide Inventory Dataset Preparation

Landslide inventory mapping is thought to be simple and necessary for the majority of susceptibility and hazard zonation techniques (Dai and Lee, 2002), either to validate the predicted model or to develop general guidelines for hazard prediction. Landslide inventory maps display the locations and features of landslides that have occurred in the past, but evaluations do not identify the mechanism or mechanisms that caused them. The locations and circumstances of future slope failures are frequently inferred from the geology, topography, and climate factors that contributed to previous slope failures. Thus, inventory maps offer important information regarding the likelihood of landslides in the future. Understanding the type of landslide can also help with the scope and design of geotechnical investigations relevant to the site and can direct plans for slope restoration. Using Google Earth image interpretation landslide distribution datasets were prepared, consisting of 592 inventory polygons (21834 pixels). Field investigation was conducted to validate the collected polygons.

For landslide susceptibility mapping, landslide polygons can be separated into training and validation datasets. The model is built using the training dataset, and it is predicted using the validation dataset. In this investigation, the precise date of the landslide's occurrence is unknown. In landslide susceptibility mapping, for the validation of the maps, landslide locations must be split into training and validation data sets (Chen et al. 2017). As a result, the landslide polygons were divided into two classes at random with 75% (16397 pixels) or 444 landslides and 25% (5437 pixels) or 148 landslides for training and validation, respectively (Rabby.Y et al., 2022). In the study area, landslides were found mostly in the Western, southwest, and southern regions. This region is made up of rugged, hilly terrain with steep slopes, deep gorges, and weathered rocks that are fractured and have a high relative relief.

3.2.3 Landslide causative factors preparation

For analysis, the ArcMap 10.8 software package and spatial analytical tools in the GIS framework were used. The database included seven landslide causative factors, including slope, aspect, curvature, distance to stream, distance to lineament, lithology, and land use/land cover (LULC), as well as a landslide inventory for training and validation. Raster maps of all causative factor maps were created with a pixel size of 30m x 30m and the projected WGS 1984 UTM Zone 37N coordinate system. To determine the values of all factor classes for the LR and WoE models, the rasterized training (75%) landslide map and all causative factor maps were overlaid using the ArcMap tool. After that, an analysis of these techniques based on the connection between landslides and causative factors was used to validate the results. As for the different statistical methods used in landslide mapping, there are no official guidelines for triggering variables. Ayalew and Yamagishi (2005) suggest that a particular parameter may have a significant controlling effect on the occurrence of landslides in certain areas but not in others. To accomplish this, it is necessary to comprehend the physical process, or rather, the mechanism of landslides. In general, studied landslides are presumably caused by precipitation, which may cause landslides when rainfall is intense, soil resistance is low, and slope inclination is high.

3.3.4 Landslide susceptibility modeling using Weight of Evidence and Logistic Regression.

Until now, a number of researchers have worked to improve the accuracy of landslide susceptibility mapping. A variety of methods, including qualitative and quantitative modeling, have been used. Westen et al. (1997) classified general approaches to analyzing landslide zoning using GIS techniques as heuristic, statistical, and deterministic. The most popular techniques for landslide susceptibility and hazard zonation are statistical approaches (Kanungo et al. 2006; Hamza and Raghuvanshi 2017; Mengistu et al. 2019; Girma et al. 2015; Shano et al. 2020). Statistical methods for assessing landslide susceptibility and zonation can be broadly divided into two categories: bivariate and multivariate statistical approaches. The current study applies Weight of Evidence and Logistic Regression models.

3.3.4.1 Weight of Evidence (WoE) method

The weights of evidence modeling used to create the landside hazard map based on the Bayesian probability model (Dahal et al., 2008). This model was first developed and used for mineral potential assessment (Bonham-Carter, 2002). This method has also been applied to landslide susceptibility mapping (Lee et al., 2002; Van Westen et al., 2003, Lee and Choi 2004, Lee et al. 2007; Neuhäuser and Terhorst 2007; Sharma and Kumar 2008). Dahal et al. 2008 used this method for landslide hazard mapping. The method calculates the weight for each landslide causative factor based on the presence or absence of the landslides within the area. It calculates both unconditional and conditional probability of landslide hazards. This method is based on calculation of positive and negative weights to define degree of spatial association between landslide occurrence and each explanatory variables class. The related mathematical relationships are described below.

W_i^+ (Bonham-Carter 2002) and can be expressed as below:

$$W+ = \ln\left(\frac{\frac{Npix1}{Npix1 + Npix2}}{\frac{Npix3}{Npix3 + Npix4}}\right) \quad \text{...Equation (1)}$$

Similarly, negative weights of evidence, W_i^-, as follows:

$$W- = \ln\left(\frac{\frac{Npix2}{Npix1 + Npix2}}{\frac{Npix4}{Npix3 + Npix4}}\right)$$ ……..…….…………………………Equation (2)

A positive weight (W_i^+) indicates that the causative factor is present at the landslide location, and the magnitude of this weight is an indication of the positive correlation between presence of the causative factor and landslides. A negative weight (W^-) indicates an absence of the causative factor and shows the level of negative correlation.

The number of pixels in each class can be calculated as:

i. Npix1= Nslclass
ii. Npix2= Nslide-Nslclass
iii. Npix3= Nclass-Nslclass
iv. Npix4= Nmap-Nslide-Nclass+nslclass

The above variables represent Nslide = Number of pixels with landslides in the map, Nclass = Number of pixels in the class, Nslclass = Number of pixels with landslides in the class and Nmap = Total number of pixels in the map.

Weights of contrast is the difference between positive and negative weights.

$C = W^+ - W^-$ *…………………………………………….…. Equation (3)*

The magnitude of these contrast values reflects the overall spatial association between each causative factor class and the landslides. The positive contrast value indicates positive spatial associations while the negative ones for a negative spatial association. Finally, the landslide susceptibility index (LSI) is produced by combining the weighted map (W*map*) of each factor through summation process using Eq. 4 below. The final landslide susceptibility map was verified based on landslide validation.

$LSI = \sum Wmap$ *…………………………………………….... Equation (4)*

3.3.4.2 Logistic Regression (LR) Method

Among the various multivariate statistical techniques, the most widely used method for spatial prediction of landslide susceptibility and hazard zonation is logistic regression (Wu et al. 2015; Schicker and Moon 2012; Gorsevski et al. 2000). The presence or absence of landslides is typically the dependent variable in the analysis of landslide susceptibility mapping. An ordinary linear regression model, which assumes a normally distributed dependent variable, is unable to model this. A dichotomous dependent variable can be transformed into a logit variable using logistic regression, which has the benefit of allowing the formation of a multivariate regression relationship between the dichotomous dependent variable and a number of independent variables.

Basically, logistic regression analysis relates the probability of landslide occurrence (constrained to fall in the interval between 0 and 1) to the "logit" Z (where $-\infty<Z<0$ for higher odds of non-occurrence and $0<Z<\infty$ for higher odds of occurrence). Since the relationship between the independent variables and the probability is nonlinear in the logistic multiple regression model, an iterative algorithm is required to estimate the parameters. After converting the dependent variable into a logit variable (the natural log of the odds of the dependent occurring or not), the logistic regression algorithm applies maximum likelihood estimation. In this manner, the results of the logistic regression produce a helpful formula for predicting the probability of presence or absence of a characteristic or outcome based on values of a set of predictors (Lee and Pradhan, 2007). Each cell had its representative binary dependent variable in terms of 1 (presence of landslide) or 0 (absence of landslide) as well as the information of the independent variables (the observed values of predictors) (Nandi and Shakoor, 2010). An equation predicting the landslide occurrence was obtained as followed, based on the description that (Hosmer and Lemeshow, 2000) have provided.

Quantitatively, the relationship between the probability of landslide occurrence and its dependency on several variables can be expressed as:

$$p = \frac{1}{(1 + e^{-z})} \quad \text{...Equation (5)}$$

p refers to the estimated probability or 'susceptibility' of landslide occurrence. The value of p is constrained within a range between 0 and 1 on and S-shaped curve, where 0 indicates a 0%

probability of a landslide and 1 indicates a 100% probability. The term z is the linear combination of independent variables.

$$z = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \ldots\ldots + b_nx_n \quad \text{………..…………Equation(6)}$$

b_0 is a constant, xi (i = 0, 1, 2. . . n) are the independent variables, n is the number of independent variables, bi (i = 1, 2. . . n) are the coefficients of the logistic regression model.

3.3.5 Materials

Materials that are used for this study can be categorized as field equipment and software. Field equipment can be used for obtaining and collecting data in the field and software's are used for processing the raw data obtained from the Literature and Google Earth.

Software's used and their functions are listed below

- ArcGIS 10.8, used to create maps of the study area, drainage, and causative factors; to analyze and compute data; and to create maps of the susceptibility of landslides for the WoE and LR models.
- Microsoft office word 2016 to write the entire papers, and Microsoft Excel 2016, used to calculate inventory and landslide pixel data, as well as produce graphs.
- Sulfer 20 used to prepare the 3D map of the study area
- SPSS 26 employed to organize landslide-modeling data for the LR model and produce validation and training graphs of AUC for both models.
- Google Earth Pro used to collect landslide polygons and lineament extractions and validate landcover of the area

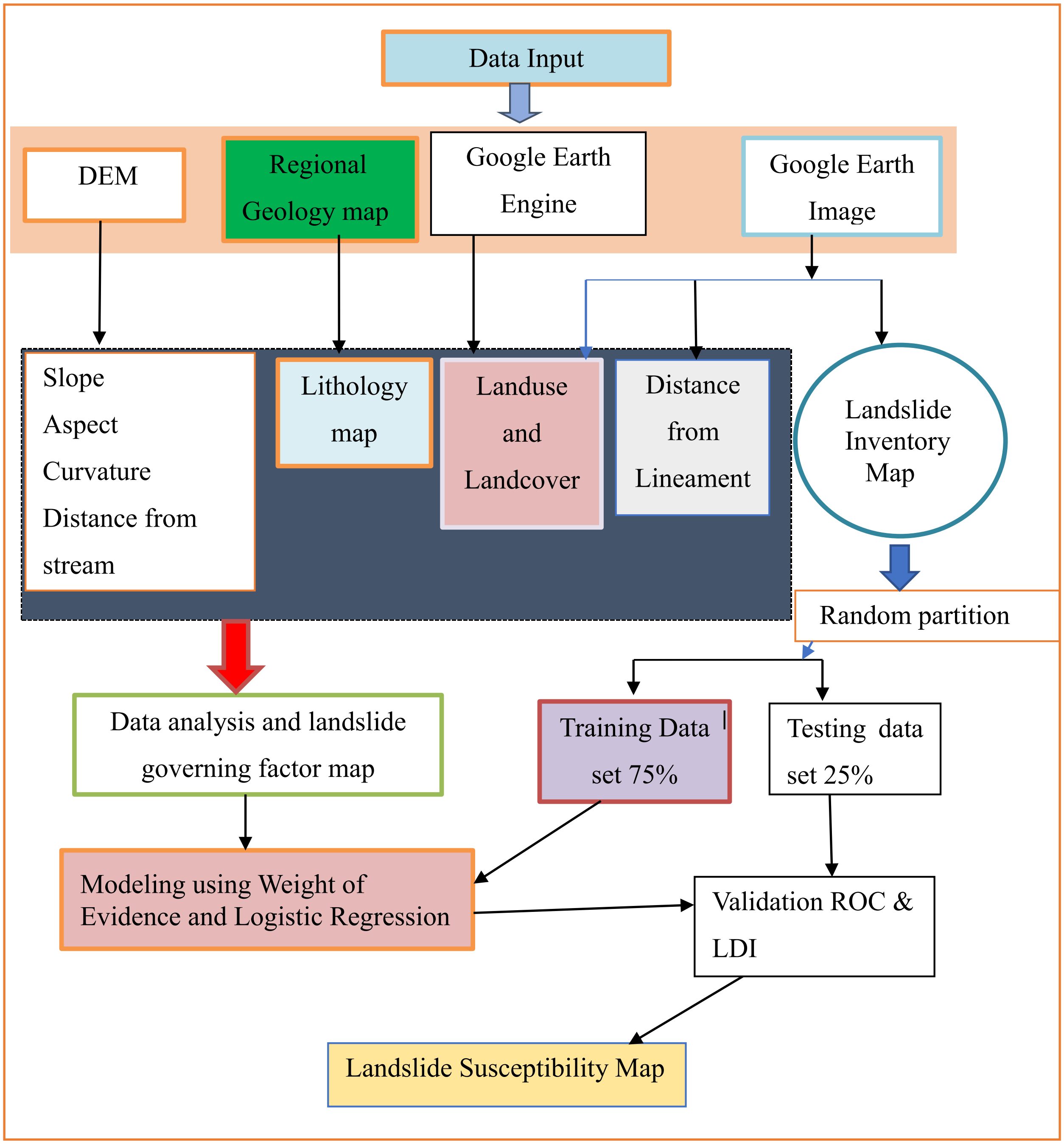


Figure 3.6. General flow chart of methods

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1 Landslide inventory

The foundation for determining landslide risk, hazard, and susceptibility is a landslide inventory (Van Westen et al., 2008). They are necessary for susceptibility models, which forecast landslides based on historical data. In the event that these are insufficiently available, expert assessment and evaluation ought to receive greater attention. For this reason, we must ascertain the locations of previous landslides. Future landslides are predicted by analyzing the conditions that led to previous landslides and combining pertinent variables. We must comprehend the causal relationships that exist between the causative factors and landslides. Since these circumstances vary depending on the type of landslide, landslides should be categorized into various types. Landslide inventories are also used to validate landslide susceptibility, hazard and risk maps.

Preparation of a landslide inventory relies on the following main assumptions. A) Significant indicators are left behind by landslides, the majority of which can be identified, categorized, and charted in the field by interpreting (stereoscopic) aerial photos, satellite images, or digital depictions of the topographic surface (Guzzetti et al., 2000). These signs can include cracks or fissures in the ground, tilting or leaning trees or structures, sudden changes in water flow or quality, and changes in the appearance of the landscape such as scarps or terraces. B) Landslides do not happen at random Slope failures are caused by the interaction of physical processes and mechanical laws that regulate the stability or failure of a slope. The mechanical laws that govern the size, shape, spatial and temporal evolution of landslides can be determined or inferred empirically, statistically, or deterministically (Guzzetti et al., 2002; Turcotte et al., 2002). C) Geomorphologists apply the principle of "the past and present are keys to the future consequence of uniformitarianism" to landslides. The principle implies that slope failures are more likely to occur when the conditions that caused previous instability are present. As a result, identifying recent slope failures is critical for detecting and mapping past landslides.

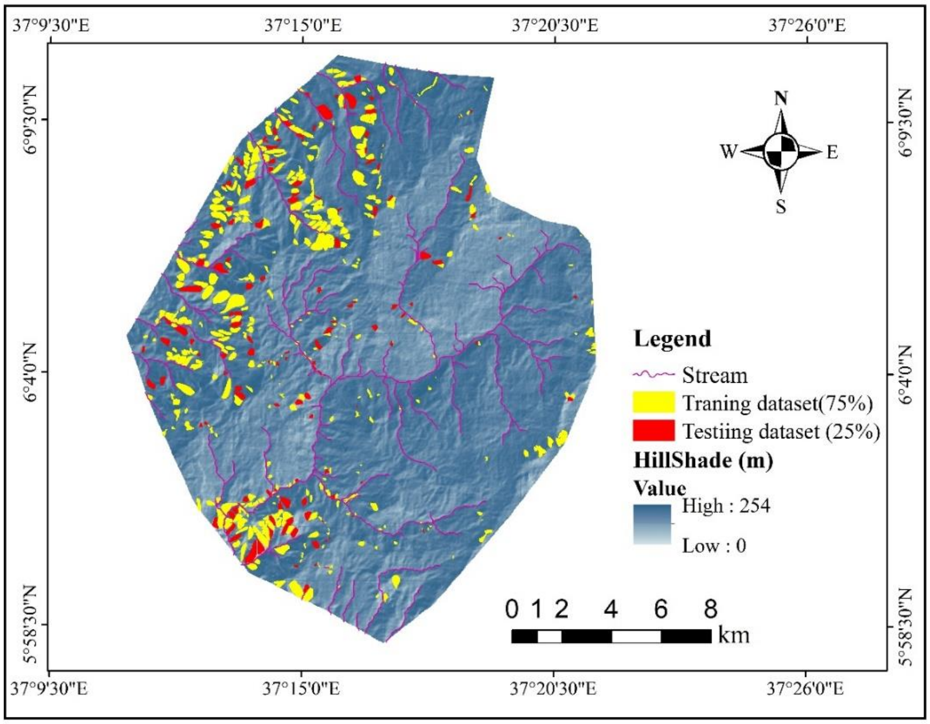
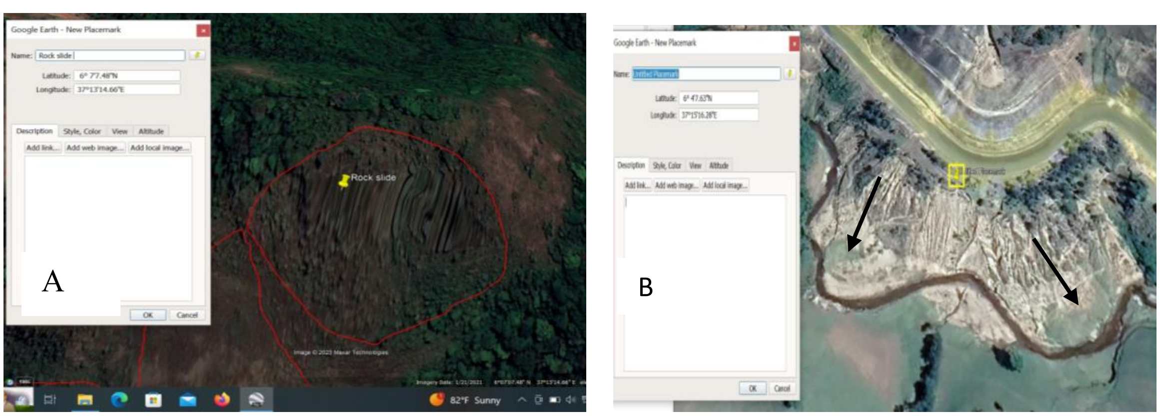


Figure 4. 1. Landslide inventory map of the study area

Data on landslides inventories were gathered form Google Earth image and via field surveys. Through extensive fieldwork and the use of Google Earth imagery, a total of 592 landslides were recorded. ArcGIS was used to create the landslide inventory map, which was used to separate the training and validation data sets for landslides.



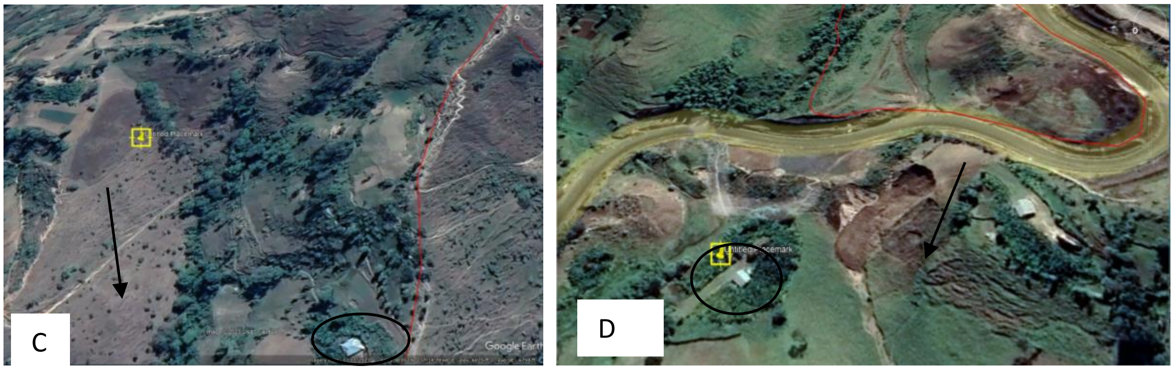


Figure 4. 2. A) Shows Rockslide from Hill of Forest areas, B) shows debris C) and D) Earth slide type of Landslide identified from Google Earth Image

Figure 4. 3. Different field photo of study area affected by landslide (A) Complex, (B) Rock slide, (C) Debris slide (D) Earth slide, (E) Debris slide and (F) Rock slide type of landslides.

4.2 Causative factor evaluation

A landslide can occur as a result of a combination of landslide causative factors and a single triggering factor. There will always be triggering and/or causative factors for every landslide event. The reason why a landslide happens in a specific location is known as a landslide causal factor. These variables are in charge of the slope's susceptibility to collapse. A landslide triggering factor is a single stimulus that sets off a landslide. According to (Gilbert et al., 2000) storms, intense or prolonged rainfall, earthquakes or seismic activity, snow melting, and human activity are well-known landslide triggering factors. Understanding the primary causes of landslides, also referred to as landslide causative factors is crucial for determining landslide susceptibility. The selection of causative factors, characteristics of the study area, kind of landslide, information accessibility, data quality, user experience, and other factors are all determined by the scope of the investigation (Shano *et al.*, 2020). These factors are broadly categorized into four aspects: geomorphological factors (elevation, slope, and slope aspect), geological factors (bedding structure, distance from fault, lithology), hydrological factors (precipitation, distance from water), and environmental factors (NDVI, distance from road, land use). For this study seven different factors are selected to model the Landslide susceptibility map of Halila Catchment. Those factors are discussed in detail below.

4.2.1 Slope

Slope is clearly the primary factor influencing the occurrence of landslides. The risk of a landslide increases with slope because of the increased shears caused by gravity. Slope gradient and slope instability, however, have a complicated relationship. Not all slopes that have the steepest gradients also have the highest risk of landslides. In contrast to relatively gentle slopes of weak material, steep slopes are typically occupied by very resistant/competent rock, making the slopes more stable. The preferential location of landslides at small slope angles is not caused by the slope angel itself but related with complex interaction between slope angle and the Environment.

The slope map of Halila catchment is derived from the DEM using ArcGIS software. The slope map is in the form of a raster map with the same pixel size as the DEM. In this study, slope angle ranges from $0^{o} – 67^{o}$ were classified based on the Natural Breaks (Jenks) method into five classes ($0^{\circ} – 10.37^{\circ}$), ($10.37^{\circ} – 16.87^{\circ}$), ($16.87^{\circ} – 23.93^{\circ}$), ($23.93^{\circ} – 32.92^{\circ}$), and >$32.92^{\circ}$ (Bopche & Rege, 2022) as shown on figure 4.4. (A) below.

4.2.2 Slope aspect

It shows the maximum rate of value change from each cell to its neighbors in a downslope direction (slope direction). Additionally, it can provide precise measurements for the amount of moisture in the soil, evaporation, and the distribution of vegetation that needs a lot of moisture. Furthermore, factors related to it, like sunlight exposure, drying winds, rainfall or saturation level, and discontinuities, may regulate the frequency of landslides (Dai and Lee, 2002). The aspect map of the study area was derived from the DEM of the study area with the same pixel. For the present study the aspect was sub-divided in to all possible geographical directions namely; Flat (-1), North (0-22.50 and 337.5-360), Northeast (22.5-67.50), East (67.5-112.50), Southeast (112.5-157.50), South (157.5-202.50), Southwest (202.5-247.50), West (247.5-292.50), and Northwest (292.5-337.50). The distribution of various aspect classes in the present study area is presented in figure 4.4 (B) below.

4.2.3 Curvature

The curvature of the terrain is another significant factor contributing to slope instability. The rate at which a slope, gradient, or aspect changes in a specific direction is the theoretical definition of curvature, a term used to characterize the morphology of topography. Curvature can be divided into plan and profile curvatures (Wilson and Gallon, 2000). Plan curvature regulates the convergence or divergence of landslide debris and water in the direction of landslide motion. It is defined as the curvature of a contour line formed by intersecting a horizontal plane with the surface. Because the profile curvature affects flow acceleration and deceleration, it also affects erosion and deposition. In relation to the convergence and divergence of flow across a surface, profile curvature influences the flow's acceleration or deceleration (concave and convex). The positive, zero and negative value indicate convexity, flat, and concavity surface, respectively. For this study curvatures are classified into three classes as: concave (-ve), plan (0) and convex (+ve).

4.2.4 Distance to stream

The stability of a slope can be influenced by its distance from a stream. Regions characterized by steep slopes are at a higher risk of experiencing landslides, and the likelihood of slope instability is further heightened when the slope is in close proximity to a stream. This is due to the erosive effects of streams on the surrounding soil and rock, weakening the slope and rendering it more susceptible to landslides. The presence of streams contributes to increased water content in the soil and rock, elevating their weight and making them more prone to sliding. Furthermore, streams can induce soil saturation, diminishing its strength and raising the probability of landslides.

4.2.5 Distance from Lineaments

Lineaments, which are linear features on the Earth's surface, such as faults, fractures, or joints, can indeed have an impact on landslide occurrence. Lineaments often represent zones of weakness in the Earth's crust, where rocks may be fractured or faulted. If a slope is situated close to such a lineament, it may experience increased vulnerability to landslides. The presence of fractures or faults can create planes of weakness along which sliding can occur. Lineaments can influence the drainage patterns of an area. If a lineament intersects with a slope, it might alter the natural drainage pathways. Changes in drainage patterns can affect the stability of the slope, potentially increasing the risk of landslides.

In this research, lineaments were manually digitized using Google Earth Pro software, and the Regional Geological Map obtained from GSE served as a reference for comparing previously mapped lineaments with newly collected ones. The entire lineament map underwent Euclidean distance analysis using ArcGIS 10.8. The resulting data were categorized into five classes (0 - 50 m, 50 - 100 m, 100 - 150 m, 150 - 200 m, and >200 m) through the Natural Breaks (Jenks) method. The study revealed that lineaments were predominantly located in the Southeast, northern, and northeastern regions of the study area. The figure 4.4 (E) illustrates the distance from the lineament map.

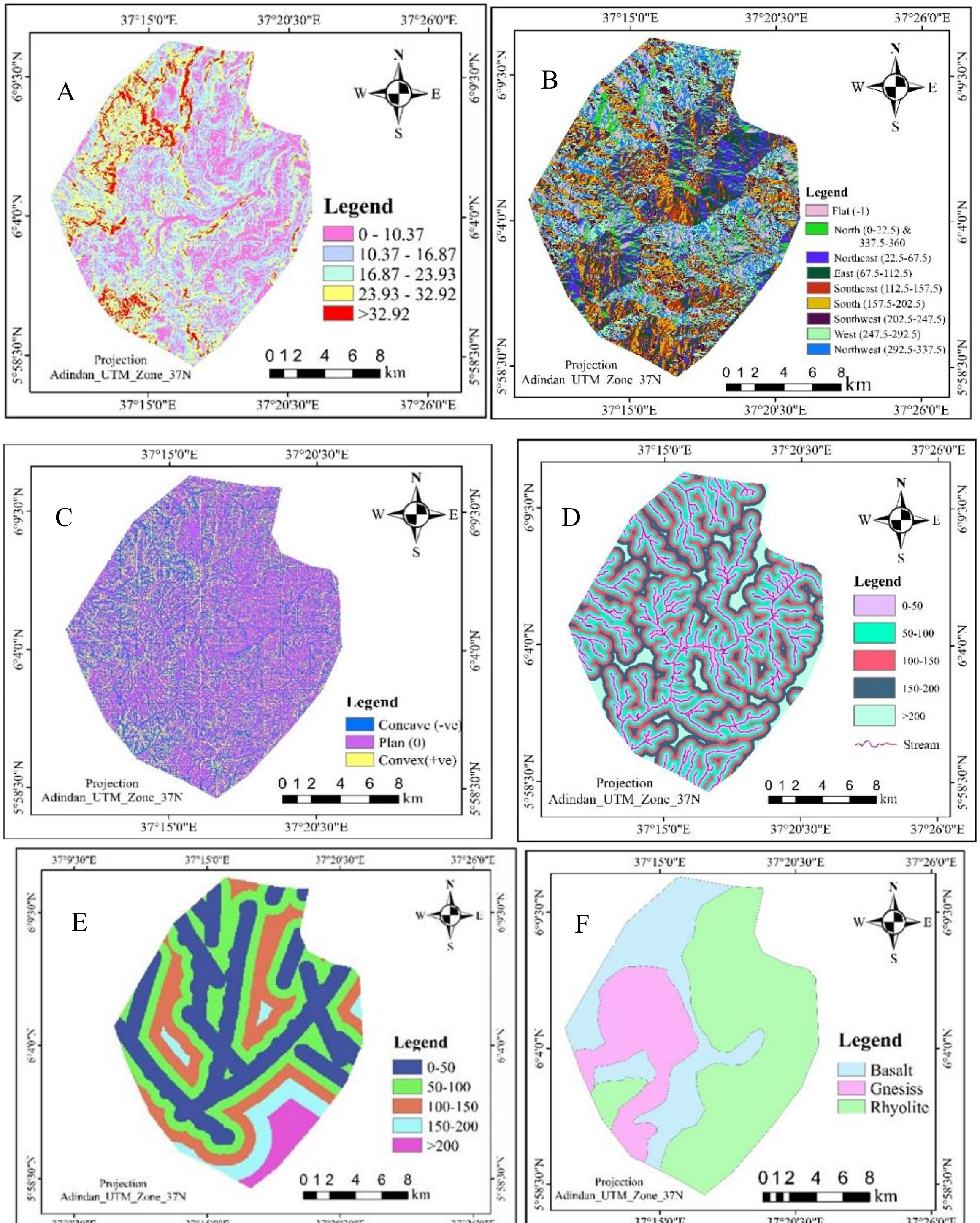
4.2.6 Lithology

Lithology is a key factor influencing slope instability and is closely linked to the characteristics of materials forming the slope, including rock-mass strength and structure, as emphasized by (Bai et al., 2014). This recognition underscores the fundamental role that lithology plays in shaping the landscape and contributing to slope dynamics. Different lithology have varying strengths and stability characteristics. Weaker or more weathered rocks are generally more susceptible to landslides. Since different rock units have different degrees of susceptibility, it effects the slope instability and landslide occurrence (Lee et al., 2002).

The lithological composition influences the ability of rocks to absorb and retain water. Rocks with high porosity or permeability can absorb water, leading to increased weight and reduced stability. Saturation of rocks can contribute to landslides, particularly during periods of heavy rainfall. The presence and orientation of joints, fractures, and bedding planes in lithological formations can create planes of weakness along which landslides may occur. Water infiltration along these discontinuities can further reduce stability. In the study area three common rock types area exposed as shown figure 4.4 (F).

4.2.7 Landuse landcover

Landcover is a factor that influences the likelihood of landslides in both positive and negative ways. The type and intensity of human activities on the landscape can either contribute to slope stability or exacerbate the risk of landslides. Land cover has the strongest correlation with human activity when compared to the other factors. As a result, managing and altering an area's land cover is easier. (Akgun & Türk, 2010). The susceptibility varies amongst different types of land cover. The landuse landcover map of the study area generated using google earth engine and classified into five class using ArcGIS software's for a better comparison as follows: Baren land, Crops, Forest Settlement and Water bodies. Land Use and Land Cover (LULC) mapping using Google Earth Engine (GEE) involves utilizing the extensive satellite imagery and computational capabilities provided by the platform. Google Earth Engine allows you to access a wide range of satellite data and perform analyses on the cloud, making it a powerful tool for remote sensing applications like LULC mapping.


A
Legend
0 - 10.37
10.37 - 16.87
16.87 - 23.93
23.93 - 32.92
>32.92
Projection
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B
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Flat (-1)
North (0-22.5) & 337.5-360
Northeast (22.5-67.5)
East (67.5-112.5)
Southeast (112.5-157.5)
South (157.5-202.5)
Southwest (202.5-247.5)
West (247.5-292.5)
Northwest (292.5-337.5)
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Stream
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37°26'0"E
6°9'30"N
6°4'0"N
5°58'30"N

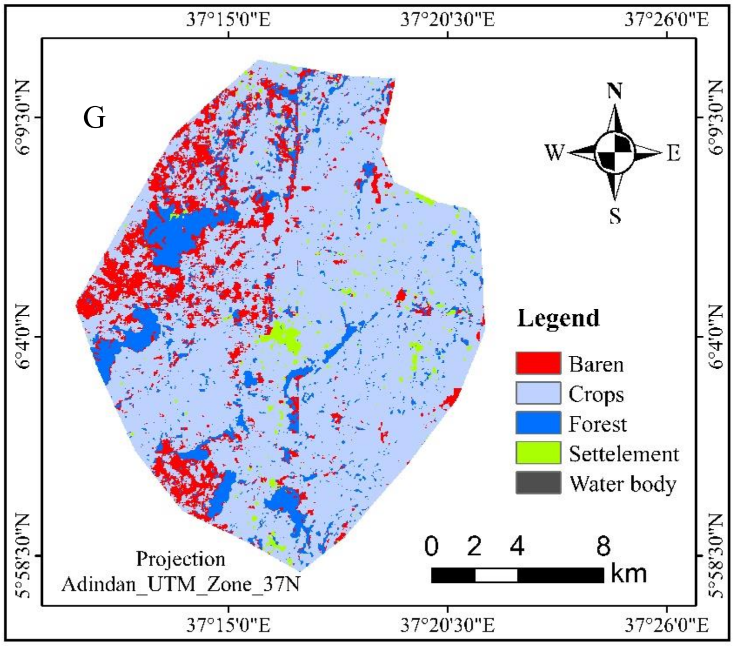

Figure 4. 4. Landslide causative factor maps, (A) Slope map (Degree), (B) Slope Aspect, (C) Curvature, (D) Distance to Stream (m), (E) Distance to Lineament (m), (F) Lithology and (G) Landuse landcover.

4.3 The Relationship between Landslide and Causative Factors

The relationship between the percentages of landslide distribution and causative factors is an essential aspect of understanding the patterns and drivers of landslides. An essential aspect of the application of statistical method is a calculation of density of landslides in each class of input factors. From this calculation, it is possible to express the degree of susceptibility to landsliding in each class of factors. This analysis is typically conducted using a dataset that includes information on both the occurrence of landslides and selected factors that may contribute to landslide susceptibility. The relationship can be calculated using the landslide training dataset (75% of landslide inventory). The spatial analysis tool within ArcGIS is employed to ascertain the quantity of landslides occurring in each classification.

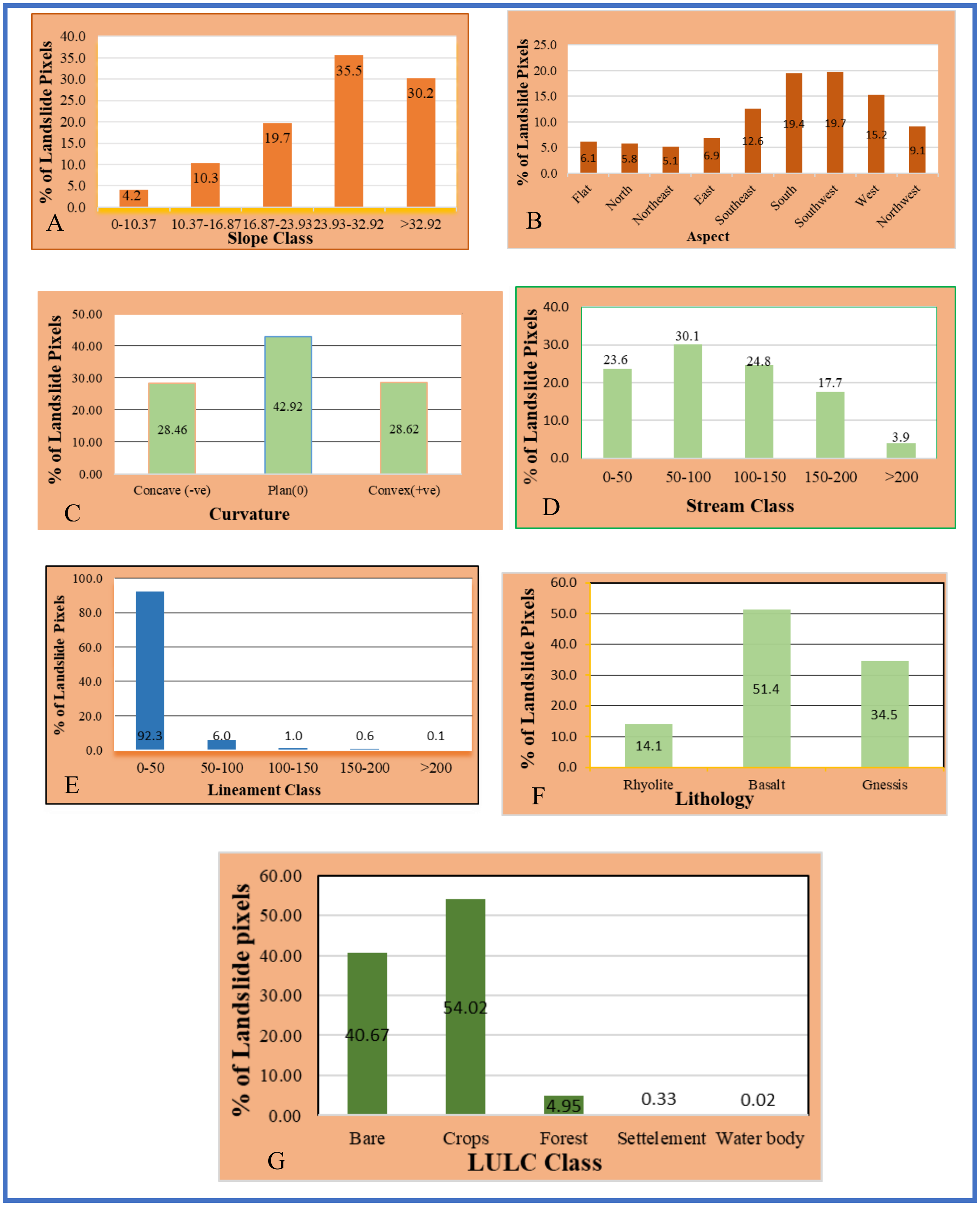

Figure 4. 5. Bar chart that shows the relationship between each causative factor and landslide pixles within each class (A) Slope angle, (B) Slope Aspect, (C) Curvature, (E) Stream, (F), Lineament (G) Lithology, and (H) Landuse landcover

This research examined the relationship between seven selected conditioning factors and occurrence of landslide. The result obtained from each factor using the weight of evidence and logistic regression model can be shown on table 4.1 and table 4.2.

4.4 Landslide susceptibility modeling

4.4.1 Causative Factor Evaluation based on WoE

The computation of WoE starts with calculating the pixel count in each class of the causality factor and landslide pixels in each class. The magnitude of WoE values reflects the strength of the relationship between the predictor variable and landslides. When the C factor is positive, landslides are more likely to occur, and inversely when the C factor is negative.

Slope: The slope angle plays a pivotal role in influencing the occurrence of landslides, with a direct and significant impact on slope stability. As the angle of a slope increases, the gravitational force acting on the mass of soil or rock also intensifies. This heightened gravitational force can surpass the resisting forces within the slope, including the shear strength of the materials and the friction between them (Mahdadi et al., 2018). Consequently, slopes that exceed a critical angle become more susceptible to landslides. Steeper slope are more prone to slope failures (Lee and Min, 2001). The findings of this investigation corroborated this assertion as well. The slope of the study area classified into five class. Slope degree which has lessthan 23.93 indicates an opposite relationship with landslide because they have a negative contrast weight (C) as shown on table 4.1. Slope class above 32.92^{o} has highest contrast weight (2.141) and followed by slope class between (23.93-32.92) which has 1.25 “C” value. This validates as the slope of an area increase its more prone to landslide. Higher slopes are influenced by greater gravitational pulls, which increases the shear stress on the materials that make up the slope. The soil or rock becomes less cohesive and has a lower frictional resistance along potential sliding surfaces due to the gravitational component parallel to the slope

Aspect: The orientation of a slope dictates the amount of sunlight it receives, affecting temperature, soil moisture, and vegetation distribution**.** The amount of moisture in soils, the rate of weathering, and the intensity of rainfall are all influenced by the exposure of a terrain aspect to sunlight, wind, rainfall, and waves (Huang et al., 2015). Southeast, South, Southwest and West aspect class of the study area has a positive coloration within landslide with a contrast weight of 0.295, 0.622, 0.398 and 0.123 respectively. The type of rock or soil on a slope may respond differently to sunlight and temperature variations and the orientation of lineament toward the aspect face can easily slide. From table 4.1 the remaining aspect class has no effect on the landslide.

Curvature: Curvature, referring to the shape or contour of a slope, plays a crucial role in influencing landslide occurrences. The slope's shape has a significant impact on slope instability, which in turn increases the likelihood of landslides (Gadtaula and Dhakal, 2019). The curvature of the study area classified into three class; concave, plan and convex. Concave and convex class curvature has positive relation having 0.272 and 0.526 contrast weight respectively. Convex slopes, with their outward-curving shape, can accumulate water and sediment, increasing the likelihood of saturation and reducing slope stability. In convex slopes, the outer portions may experience increased stress, contributing to tension cracks and potential failure planes. Concave slopes, the central area may be more susceptible to compression, impacting the overall stability of the slope. Concave slopes may channel water more efficiently, potentially creating erosive conditions that compromise the integrity of the slope. The plan curvature has a negative "C" (-0.591) has no effect on the occurrence of landslide in the study area.

Distance from Stream: The distance from a stream is a critical factor that significantly influences the occurrence of landslides. The instability of slopes is notably impacted by the active incision of rivers or streams, leading to toe erosion and saturation of slope materials. This process results in increased slope steepness and heightened instability (Abebe et al., 2010). Streams contribute to the saturation of soil through natural processes such as erosion and sediment transport. As the distance from a stream increases, the potential for soil saturation diminishes, reducing the likelihood of landslides. Conversely, slopes located closer to streams may be more susceptible to landslides due to increased water content in the soil, making them more prone to failure. In this study the stream class has been classified into five classes. The first class (0-50m) has a negative contrast weight (-0.32), this happens as a landslide occurrence depends on the combination of other factors (Raghuvanshi et al., 2014). Distance from stream class of second (50-100m), third (100-150), and fourth (150-200) has a positive coloration with landslide as they a have a contrast weight of 0.18, 0.28 and 0.32

respectively. Distance from stream class >200m has a negative contrast weight, thus it has no effect on the landslide. Because of the stream's close proximity to the water source, the water content is usually higher there, increasing the soil's susceptibility to saturation and decreasing its shear strength. The soil tends to get drier the farther it is from the stream, which helps to restore some of its shear strength and stability.

Distance from Lineament: Lineaments often represent geological structures that can influence the stability of slopes. If a lineament is associated with a fault or a fracture, the proximity to such features may affect the mechanical properties of rocks and soils. Slopes near lineaments might be more prone to instability if the geological structure promotes weaknesses in the subsurface materials. Lineaments may coincide with changes in topography, such as ridges or valleys. Slopes adjacent to lineaments might experience different erosional and depositional processes, affecting the stability of the terrain. The proximity to structural elements, such as active faults, plays a crucial role as a contributing factor in assessing landslide susceptibility. The alignment of discontinuities within weathered rock, relative to the slope angle and direction, significantly influences susceptibility to landslides (van Westen, 2003). This study classifies the distance from lineament into five classes. The first class has high Contrast weight (2.63) which has greater influence on the landslide than the other class. The remaining class of distance from lineament has a negative contrast weight.

Lithology: The physical and chemical attributes of rocks, collectively known as lithology, exert significant control over the stability of slopes. Rocks with varying degrees of strength and cohesion respond differently to the forces acting upon them, impacting their resistance to landslides. This includes factors like the strength and structure of the rock mass. The correlation between lithology and slope forming materials is integral to understanding and assessing the stability of slopes. The properties of the rock mass, including its strength and structural composition, play a fundamental role in determining the susceptibility of slopes to instability and potential landslides (Bai et al., 2014). In the study area Basalt class has high contrast weight followed by Gnessis and Rhyolite as shown on table 4.1. From field investigation the basaltic formation in study area is highly affected by geological structures and weathering. Over time, weathering processes in basalt can break down the mineral grains and change the composition of the rock matrix. When weathering is paired with Geological structures like faulting, jointing the rock can become weaker and more prone to landslides.

LULC: Land Use and Land Cover (LULC) wield a profound influence on the occurrence and susceptibility of landslides. Human activities such as agriculture, logging, and mining modify landscapes, making certain areas more prone to landslides through soil structure weakening. The study area LULC can be classified as Forest, Baren land, settlement, crops and water bodies. The Baren land includes shrubs and grasses in this study it has a high a contrast weight (1.72). The absence of plant roots in bare land leaves the soil less bound and cohesive, making it prone to erosion and instability. The other class of landuse landcover has a negative impacts on the landslide as they a negative contrast weight.

Table 4. 1. Data used in the analyses and results obtained from the WoE method (Nslide = 16397 and Nmap = 329153.

Factor	**Class**	**Nclass**	**Lspix1**	**%of L pixel**	**Lsp2**	**Lsp3**	**Lsp4**	**W+**	**W-**	**C**
Slope(Degree)	0-10.37	71722	683	4.2	15714	71039	241717	-1.70	0.22	-1.91
	10.37-16.87	101229	1695	10.3	14702	99534	213222	-1.12	0.27	-1.40
	16.87-23.93	82790	3237	19.7	13160	79553	233203	-0.25	0.07	-0.33
	23.93-32.92	53312	5829	35.5	10568	47483	265273	0.85	-0.27	**1.13**
	>32.92	20100	4953	30.2	11444	15147	297609	1.83	-0.31	**2.14**
Stream(m)	0-50	99551	3873	23.62	12524	95678	217078	-0.26	0.06	-0.32
	50-100	93085	4929	30.06	11468	88156	224600	0.06	-0.12	**0.18**
	100-150	70363	4060	24.76	12337	66303	246453	0.16	-0.12	**0.28**
	150-200	49269	2896	17.66	13501	46373	266383	0.17	-0.14	**0.32**
	>200	16885	639	3.90	15758	16246	296510	-0.29	0.01	-0.30
Lineament(m)	0-50	159460	15128	92.26	1269	144332	168424	0.69	-1.94	**2.63**
	50-100	90955	979	5.97	15418	89976	222780	-1.57	0.28	-1.85
	100-150	44298	163	0.99	16234	44135	268621	-2.65	0.14	-2.80
	150-200	22766	106	0.65	16291	22660	290096	-2.42	0.07	-2.49
	>200	11674	21	0.13	16376	11653	301103	-3.37	0.04	-3.41
Lithology	Rhyolite	170427	2316	14.12	14081	168111	144645	-1.34	0.62	-1.96
	Basalt	90045	8421	51.36	7976	81624	231132	0.68	-0.42	**1.10**
	Gnessis	68681	5660	34.52	10737	63021	249735	0.54	-0.20	**0.74**
L	Bare	40808	6669	40.67	9728	34139	278637	1.32	-0.41	**1.72**

	Crops	246575	8858	54.02	7539	237717	75059	-0.34	0.65	-0.99
	Forest	35882	812	4.95	15585	35070	277706	-0.82	0.07	-0.89
	Settlement	5904	54	0.33	16343	5850	306926	-1.74	0.02	-1.75
	Water body	4	4	0.02	16393	0	312776	0.00	0.00	**0.00**
Curvature	Concave (-ve)	77416	4666	28.46	11731	72750	240006	0.20	-0.07	**0.27**
	Plan(0)	187144	7038	42.92	9359	180106	132650	-0.29	0.30	-0.59
	Convex(+ve)	64593	4693	28.62	11704	59900	252856	0.40	-0.12	**0.53**
Aspect	Flat	32200	1000	6.10	15397	31200	281556	-0.49	0.04	-0.53
	North	26757	953	5.81	15444	25804	286952	-0.35	0.03	-0.38
	Northeast	32675	839	5.12	15558	31836	280920	-0.69	0.05	-0.74
	East	33687	1132	6.90	15265	32555	280201	-0.41	0.04	-0.45
	Southeast	32355	2065	12.59	14332	30290	282466	0.26	-0.03	**0.30**
	South	39071	3189	19.45	13208	35882	276874	0.53	-0.09	**0.62**
	Southwest	47415	3227	19.68	13170	44188	268568	0.33	-0.07	**0.40**
	West	45420	2499	15.24	13898	42921	269835	0.10	-0.02	**0.12**
	Northwest	39573	1493	9.11	14904	38080	274676	-0.29	0.03	-0.32

The landslide susceptibility index can be computed by assessing the overall spatial correlation among the seven causative factors and the training landslides. The calculation of the weight for each factor class was determined by evaluating the landslide density within each respective factor class. The positive and negative weights of each factor class were calculated based on equation 1 and 2. The weights for contrast values of all factors, encompassing slope, curvature, aspect, lithology, land use/land cover, distance to stream and distance to lineament, were computed. Weight of contrast is the difference between positive and negative weight values. Raster maps for each of the seven causative factors were generated, incorporating the weights of contrast values. These maps were subsequently integrated using a raster calculator within the spatial analyst tool in ArcGIS to generate the landslide susceptibility index (LSI) map.

$$LSI = C_{Slope} + C_{Curvature} + C_{Aspect} + C_{Lithology} + C_{stream} + C_{Lineament} + C_{Lulc}$$

Where, C_{Slope} = weight contrast of slope, $C_{Curvature}$ = weights of contrast value of Curvature, C_{Aspect} = weights of contrast value of Aspect, $C_{Lithology}$ = weights of contrast value of lithology, C_{stream} = weights of contrast value of distance to stream, $C_{Lineament}$ = weights of contrast value of distance to lineaments, C_{lulc} = weights of contrast value of LULC.

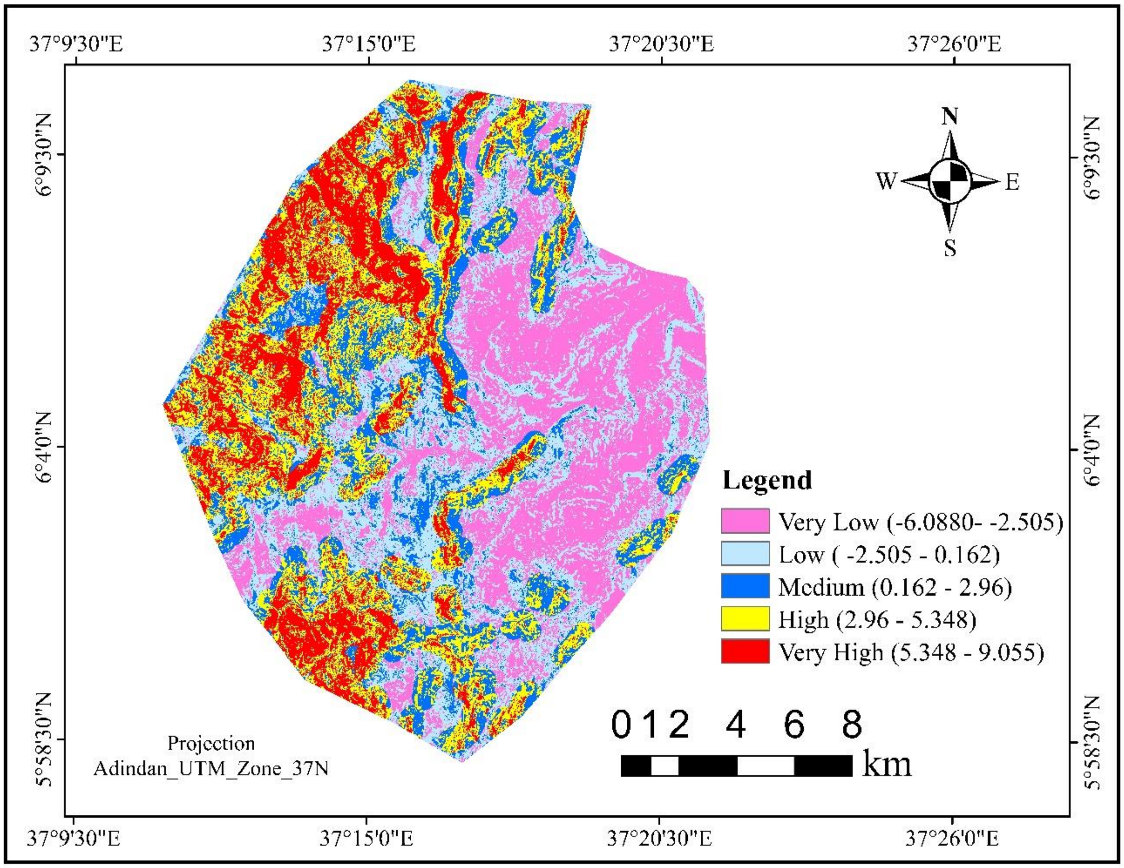

Figure 4. 6. Landslide susceptibility map produced using Weight of Evidence Model

The LSI values range from – 6.088 to 9.055 that were reclassified into five landslide susceptibility classes of very low (− 6.088 - - 2.505), low (− 2.505 - 0.162), moderate (0.162 – 2.96), high (2.96 – 5.348) and very high (5.348 – 9.055) using the natural breaks classification method (Figure 4.6). The study area covered 296km^2 out of which 73.1 km^2 falls to the very low and comprised 0.85% of the landslide density. 64.34 km^2 of the study area categorized under low class and comprised 3.12% of landslide density index. Medium class covers 50.84 km^2 and 7.88% of Landslide density index. High and Very high class covers an area of 58.82 km^2 and 48.45 km^2 with Landslide density index of 20.99% and 67.17% respectively as shown on table 4.2.

Table 4. 2. Landslide susceptibility class index and training landslide pixels of the WoE model

Landslide Susptebility Class	LSP	% LSP	TLP	% TLP	Area (km^2)	% of Area (km^2)	LDI
Very Low (-6.0880- - 2.505)	81401	24.73	199	1.21	73.10	24.73	0.049
Low (-2.505 - 0.162	71654	21.77	639	3.90	64.34	21.77	0.179
Medium (0.162 - 2.96)	56622	17.20	1274	7.77	50.84	17.20	0.452
High (2.96 - 5.348)	65512	19.90	3928	23.96	58.82	19.90	1.204
Very High (5.348 - 9.055)	53964	16.39	10357	63.16	48.45	16.39	3.853

Generally, the causative factors selected for landslide susceptibility map include slope gradient, slope aspect, curvature, distance to lineament, lithology, distance to streams and landuse land cover. In general the result obtained from weight of evidence model can be interpreted based on the derived contrast weight of each class parameters. Positive WoE values suggest that the presence of the corresponding predictor variable is associated with an increased likelihood of landslides. Negative WoE values suggest that the presence of the corresponding predictor variable is associated with a decreased likelihood of landslides. So we can easily understand the computed weight of evidence value for each factor as shown on table 4.1. Thus, areas with higher values of this particular predictor variable are expected to be more susceptible to landslides

4.4.2 Causative Factor Evaluation based on Logistic Regression

Logistic regression identifies the factor effect on the landslide based on the regression coefficient. The regression coefficient plays a crucial role in understanding the relationship between landslide factors and the occurrence of landslides. Each factor contributing to landslides is assigned a regression coefficient that represents the change in the dependent variable (landslide occurrence) for a one-unit change in the independent variable. Positive coefficients indicate a positive association, suggesting that an increase in the factor is associated with a higher likelihood of landslides, while negative coefficients imply a negative association. Larger coefficient signifies a stronger influence on landslide occurrence.

The result obtained from the logistic regression the coefficient of regression for all factor is positive on table 4.3. The positive regression coefficients for the seven landslide factors: slope, aspect, curvature, lithology, distance from stream, distance from lineament, and Land Use and

Land Cover (LULC); The presence of positive coefficients suggests that as the values of the independent variable rise, the likelihood of a landslide increases, assuming that the other variables in the model remain constant (Chen & Wang 2007). The regression coefficient of each factor indicates for a single increase of the factor value, the landslide occurrence will increase by its regression coefficient amount.

Logistic regression proves valuable in assessing the connection between landslide occurrence and associated factors. This method is particularly effective when the outcome variable, or dependent variable, follows a binary or dichotomous pattern. In the context of this analysis, the dependent variable (denoted as y) signifies the absence or presence of a landslide. With regards to P independent variables, denoted as $x_1, x_2, ..., x_p$, influencing landslide occurrences, we establish the vector $X = (x_1, x_2, ..., x_p)$. In this investigation, the independent variables align with the categories found in table 4.2. Each of these variables is binary, taking values of 1 (indicating presence) or 0 (indicating absence).

The conditional probability that a landslide occurs is represented by $P(y = 1/X)$. The logit of the multiple logistic regression model (Hosmer and Lemeshow, 2000) is given on equation 6 and 7. This model has the advantage of using either continuous or discrete variables, and it does not require a normal distribution. The sample size selection of dependent and independent variables for landslide susceptibility analysis is where the logistic regression model's difficulty lies. There are three ways of sampling landslide and non-landslide points (Zhang. et al., 2017). The first way is using all data from all the study areas. However, this leads to an uneven proportion of non-landslide and landslide pixels which incorporate a large volume of data in the analysis (Guzzetti.F et al., 2000). The second method, which can also reduce sample size and sampling bias, applied by Dai and Lee, (2002) involves replacing all landslide pixels with equal non-landslide pixels. This approach also yields a less reliable output. Atkinson and Massari (1998) used the third method an unequal proportion of landslide and non-landslide pixels. In the present work, the landslides of the study area were classified into training landslides (75% with 444 landslides) and as testing landslides (22% with 148 landslides), thus the second method is implemented. SPSS 26 is used to calculate the coefficient of each factor map and ArcGIS is used to concert the coefficient to the landslide susceptibility map.

Table 4. 3. Coefficients and statistical parameters of the logistic regression model

Independent variables	Variables in the Equation				Collinearity Diagnostics	
	B	S.E	Sig.	Exp(B)	Tolerance	VIF
Slope	2.05	0.096	0	7.77	0.943	1.06
Aspect	0.23	0.373	0	1.25	1	1
Curvature	0.01	0.38	0	1.01	0.976	1.024
Stream	1.6	1.035	0	4.95	0.995	1.005
Lineament	2.23	0.349	0	9.299	0.994	1.006
Lithology	0.42	0.002	0.013	1.52	1	1
Lulc	0.12	0.001	0.336	1.12	1	1
Constant	-5.664	0.06	0	0.003		

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 (-(b0 + b1*slope + b2*aspect + b3*curvature + b4*lineament + b5*lithology + b6*lulc + b7*stream))). Where b0 = -5.66 coefficient constant, b1= regression coefficient slope (2.05), b2= is regression coefficient of aspect (0.23), b3= the regression coefficient of curvature (0.01), b4= is the regression coefficient of lineament (2.23), b5= is the regression coefficient of lithology (0.42), b6 = is the regression coefficient of landuse landcover (0.12), b7 = regression coefficient of stream (1.6). As shown on table 4.3 all the factors has a positive cofficient of regression, thus keeping constant other factor each factor has a influence on the occurrence of landslide.

In the context of landslide susceptibility modeling using logistic regression, the Standard Error (SE) associated with the estimated coefficients provides crucial information about the precision and reliability of the model's predictions. A smaller SE indicates that the model's estimates are more precise and have less variability, suggesting greater confidence in the relationships between predictor variables and landslide susceptibility. On the other hand, a larger SE suggests increased uncertainty and less precision in the estimates, which could be due to various factors such as limited data, collinearity among predictors, or inherent complexity in the terrain (Hosmer et al., 2013).

Significance of the model (Sig.) is another parameter in Logistic regression analysis.The assessment of the model's significance is typically conducted through statistical tests with the assumption that the null hypothesis positing that all coefficients associated with predictor variables are equal to zero(or it assume that there is no assossation of landslide and factors). When the p-value associated with the model's significance test is sufficiently low, commonly set at 0.05, it provides evidence to reject the null hypothesis, indicating that the model as a whole has statistical significance and is capable of explaining variations in landslide occurrence based on the selected predictors.

In logistic regression analysis, the term Exp(ß) represents the exponentiation of the coefficient (ß) associated with a predictor variable in the model. Odds ratio (exp(bi)) is alternatively used with the coefficient of independent variables as it has importance with respect to a dependent variable (Hosmer and Lemeshow, 2000; Nattino et al., 2020).

Multi-collinearity is a statistical environment that refers to the numbers of simulated factors in a logistic regression model which is highly correlated in such a way that one can be linearly predicted from the others with a non-trivial degree of accuracy (Shano et al., 2021). According to (Saha, 2017), tolerance is less than 0.10 or variance inflation factor (VIF) is greater than 10 indicates the presence of multicollinearity problems. The result showed that all tolerance values were greater than 0.10 which indicates no collinearity among the seven landslide suscpetibility determining factors. From table 4.3 the values of VIF are less than 10, with no collinearity among the seven independent factors. From this it can be concluded that there is no collinearity problem within independent variables.

Landslide susceptibility map generated using Logistic regression ranges from 0.06 – 0.91 that were classified into five landslide susceptibility classes. Statistical mapping often uses a classification technique known as "natural breaks," and ArcGIS software includes this feature. Natural breaks categorize the data according to the gaps or breaks in the data (Lin, 2013). It develops by increasing the variance value between classes and decreasing the variance value within the classroom (Arif., et al., 2015). These categories were considered sufficient to reveal any existing spatial patterns in the dataset and facilitate map interpretation (Armstrong et al,. 2003; Foote and Crum, 2014).

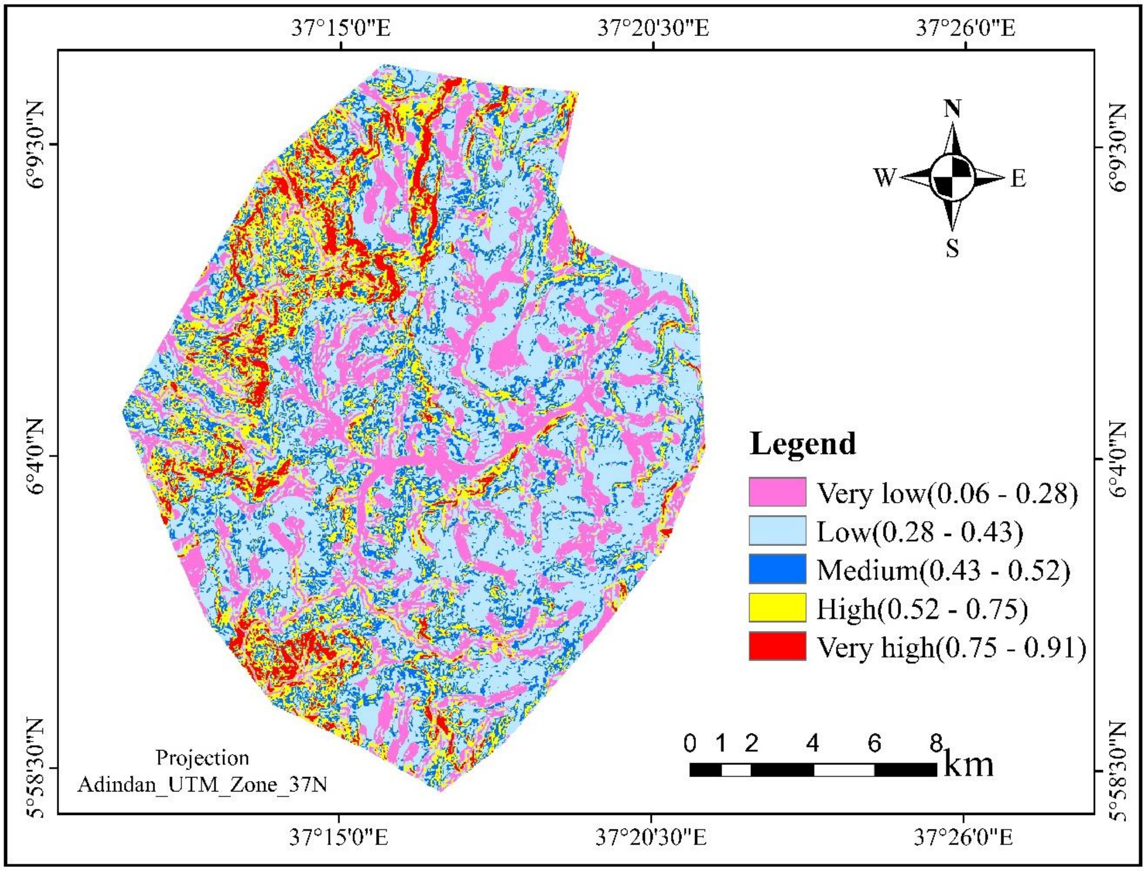

Figure 4. 7. Landslide susceptibility map produced using Logistic regression Model.

This study apply natural breaks (Jenks) classification methods and Categorized as very low (0.06 – 0.28), low (0.28 - 0.43), moderate (0.43 – 0.52), high (0.52 – 0.75) and very high (0.75 – 0.91) using the natural breaks classification method (Figure 4.7). The study area covered 296km^2 out of which 59.13 km^2 falls to the very low and comprised 3.1% of the landslide density. 122.05 km^2 of the study area categorized under low class and comprised 12.59% of landslide density index. Medium class covers 49.01km^2 and 14.55% of Landslide density index. High and Very high class covers an area of 47.89km^2 and 18.05km^2 with Landslide density index of 28.8% and 40.9% respectively as shown on table 4.4.

Table 4. 4. Table Landslide susceptibility class index and training landslide pixels of the LR model

Landslide Susptebility class	LSP	% LSP	TLP	%TLP	Area	% of area	LDI
Very Low (0.06 - 0.28)	98475	29.92	895	5.46	59.13	19.97	0.18
Low (0.28 - 0.43)	66546	20.22	2454	14.97	122.05	41.22	0.74
Medium (0.43 – 0.52)	53981	16.40	2301	14.03	49.01	16.55	0.86
High (0.52 – 0.75)	69357	21.07	5856	35.71	47.89	16.17	1.69
Very High (0.75 – 0.91)	40808	12.40	4891	29.83	18.05	6.10	2.41

Generally, the binary logistic regression model has been interpreted based on the coefficients of independent variables and different parameters as listed on table 4.3. Many studies in the existing literature mention the utilization of odds in logistic regression for interpretation purposes (Shano et al., 2021). However, it's crucial to recognize that various statistical parameters play a significant role in determining the impact of predicting or independent factors on a dependent variable. Solely relying on the odds of logistic regression for model interpretation might lead to overlooking other essential factors. This is because odds are solely contingent on the coefficients of independent variables, and an exclusive focus on odds may result in the neglect of other influential factors in the analysis (Shano et al., 2021). A value of Exp (β) greater than 1 indicates an increase in the odds, suggesting a positive association between the predictor variable and landslide susceptibility. Conversely, a value less than 1 implies a decrease in the odds, indicating a negative association. The magnitude of Exp (β) is essential; larger values signify a stronger influence of the variable on landslide susceptibility. In this study Lineament has higher odd ratio than other parameters. This is because lineament features can weaken the rock or soil mass, creating zones of potential failure, influence hydrological pathways for the movement of water, facilitating the infiltration of rainfall into the subsurface. Increased water infiltration can contribute to changes in pore pressure within the slope, reducing the effective stress and consequently promoting landslide susceptibility.

4.5 Validation of the Model

Validation is an integral part of the modeling process for landslide susceptibility because it ensures the model's accuracy, generalization capability, and reliability in providing valuable information for landslide risk assessment and mitigation. Predictive landslide validation is an essential aspect of the methods for landslide susceptibility mapping (Berhane *et al.*, 2020). The overall model validation is the most important step which is applied before interpretation of the model. A receiver operating characteristic (ROC) curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity). Generally, the sensitivity increases, specificity also increases (Shano et al., 2022). In this study, the research methodology involved assessing the sensitivity of two key metrics: the Area under the Curve of Receiver Operating Characteristics (AUC of ROC) in SPSS 26 software and the Landslide Density Index (LDI) in ArcGIS 10.8. The AUC of ROC was analyzed using SPSS 26, while the LDI was computed using ArcGIS 10.8. To visually represent the results, graphs were generated for both model using Excel 2016.

4.5.1 Validation of the Model Using ROC

The area under the curve (AUC) is a valuable metric employed to evaluate the accuracy of landslide susceptibility maps through the creation of success and prediction rate curves. Essentially, the AUC quantifies the likelihood that a greater number of pixels are correctly classified compared to those that are misclassified (Genene and Meten, 2021). Consequently, higher AUC values indicate a higher degree of accuracy in the resulting susceptibility map. The success rate is a key component of this evaluation, measuring the efficacy with which the susceptibility map captures the locations of landslides predicted by the model. In essence, it serves as a gauge of the model's efficiency in accurately identifying landslide-prone areas (Neuhäuser et al., 2012). The area under the curve (AUC) values and prediction accuracy in the ROC approach can be characterized as follows: 50% – 60% is considered poor; 60% – 70% is considered medium; 70% – 80% is deemed to be good; 80% – 90% is considered very good; and 90% – 100% is considered excellent (Yesilnacar and Topal, 2005). The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) for different classification thresholds. In this study generated using SPSS. In evaluating the success and predictive rates of both training and testing datasets are used.

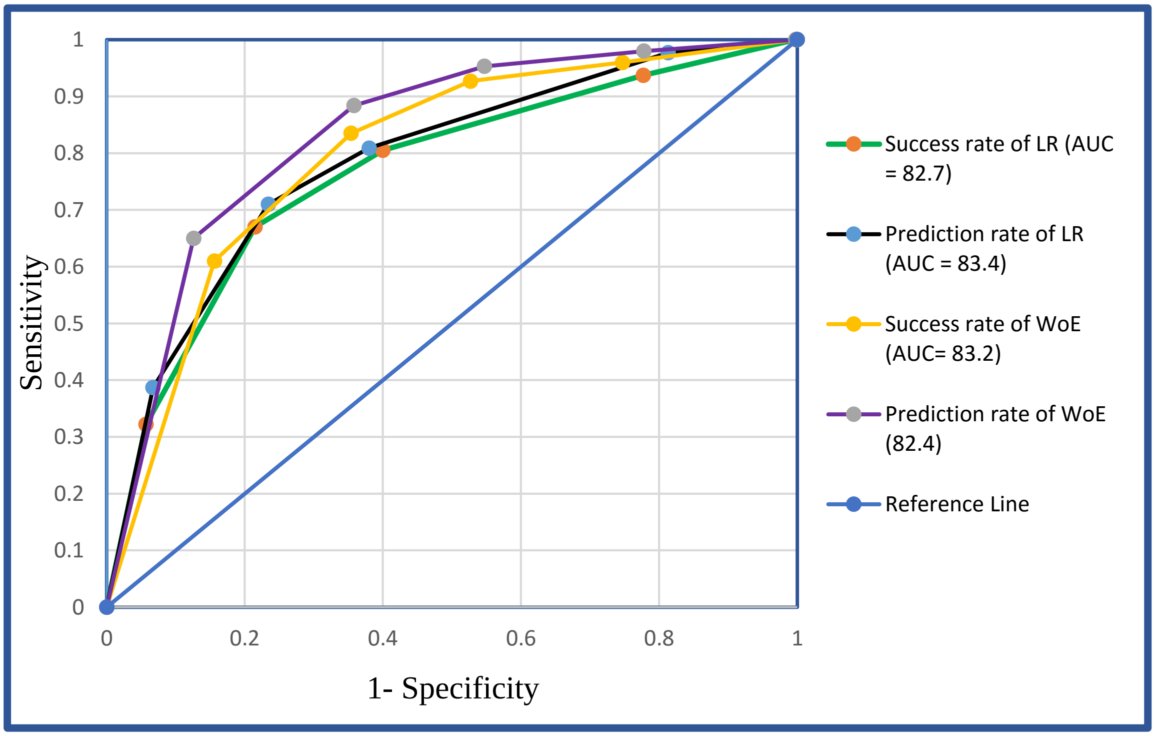

Figure 4. 8. Success and Predictive rate curves of models (LR and WoE).

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

The landslide susceptibility model was validated using the Landslide Density Index (LDI). The landslide susceptibility map's percentage of landslide pixels is divided by the percentage of class pixels in each severity class to get this index. The validity of the landslide susceptibility map is indicated if the landslide density index value rises from a low level to a very high level of severity (Ram et al., 2020). This indicates that the model provides a reliable representation of the susceptibility to landslides and accurately predicts the areas with a higher likelihood of landslides.

$$\text{LDI} = \frac{\textit{Percent of observed landslide}}{\textit{Percent of predicted landslide}} \text{................................equation (7)}$$

The Landslide Density index of Weight of evidence and Logistic regression model is shown on table 4.5. The very high class of landslide susceptibility for the WoE and LR models are 3.7 and 2.59, 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 Figure 4.9.

Table 4. 5. Landslide density index of Weight of evidence and Logistic regression.

Model	Landslide Susptebility class	LSP	% LSP (a)	TLP	% TLP (b)	LDI (b/a)	VLP	% VLP (d)	LDI (d/a)
WoE	Very Low (-6.0880- -2.505)	81401	24.7	199	1.2	0.0	220	4.0	0.2
	Low (-2.505 - 0.162	71654	21.8	639	3.9	0.2	182	3.3	0.2
	Medium (0.162 - 2.96)	56622	17.2	1274	7.8	0.5	501	9.2	0.5
	High (2.96 - 5.348)	65512	19.9	3928	24.0	1.2	1224	22.5	1.1
	Very High (5.348 - 9.055)	53964	16.4	10357	63.2	3.9	3309	60.9	3.7
Logistic Regression	Very Low (0.06- 0.28)	98475	29.9	895	5.5	0.18	340	6.3	0.21
	Low (0.28 - 0.43)	66546	20.2	2454	15.0	0.74	784	14.4	0.71
	Medium (0.43 – 0.52)	53981	16.4	2301	14.0	0.86	672	12.4	0.75
	High (0.52 – 0.75)	69357	21.1	5856	35.7	1.69	1893	34.8	1.65
	Very High (0.75 – 0.91)	40808	12.4	4891	29.8	2.41	1747	32.1	2.59

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.

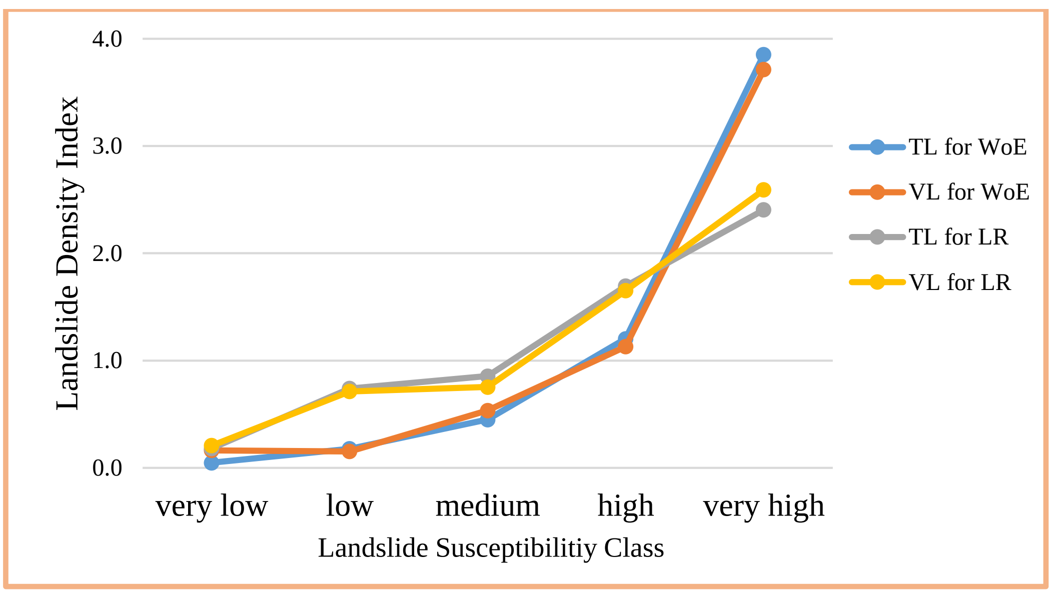

Figure 4. 9. The landslide density for both the training and validation datasets using logistic regression (LR) and Weight of Evidence (WOE).

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The landslide susceptibility map of Halila Catchment, Gamo Zone, South Ethiopia was conducted using Logistic Regression and Weight of Evidence models. Landslides are one of the most geoenvironmental hazards in the study area. Landslides in these places influence human and animal life, agricultural lands, settlements, and infrastructure, as well as the rural society's social and economic dimensions. As a result, creating a landslide susceptibility map for the area is critical for the effective development and management of disaster areas.

A landslide inventory map of Halila catchment was prepared and consist of a total of 592 polygons that classified randomly into training (75%) and validating (25%) data set. Seven conditioning landslide factors are selected namely Slope, Aspect, Curvature, Distance from Stream, Distance from Lineament, Lithology and landuse. All factors are reclassified to class and their relationship with landslide is identified. From Weight of evidence model the contrast weight of each class is calculated and those class having positive contrast weight has a direct relationship with landslide and the negative contrast weight indicates as they have no effect on the landslide occurrence. The regression coefficient determined from SPSS for all factor has positive value thus the selected factor has effect on landslide occurrence. This study found that a distance from lineament was major conditioning landslide factor in the study area.

The landslide susceptibility map prepared from Weight of Evidence and Logistic Regression was classified in to very low, low, medium, high and very high class using ArcGIS. The model can be validated using AUC and Landslide Density Index. AUC of Weight of Evidence and Logistic Regression model showed the predictive rate accuracies of 82.4% and 83.4% respectively. This confirms that both model has a very good performance. The landslide density index showed that the percentage of landslides progressively increased from very low to very high landslide susceptibility classes which proved the validity of the landslide susceptibility map. Finally, the model applied in this study was found to be reliable and effective in assessment of numerous causative factors with landslides. Hence, the final landslide susceptibility map from both model in this study area can provide firsthand information for decision makers in infrastructure development and land use planning at district, zonal, regional and federal levels.

5.2 Recommendation

A landslide has impact on residents who live nearby in the area. Their animals died, and their homes and agricultural lands were devastated, resulting in major social and economic losses for the government and the local people. As a result, in addition to creating a landslide Susceptibility Zone map for the study area, identifying relevant remedial and preventative actions for significant slopes would be extremely beneficial in reducing the area's economic and social concerns. This study recommend the following points

- Implement strict land-use planning and zoning regulations to restrict construction in high-risk landslide areas. Avoiding development in vulnerable zones can reduce the potential for damage and loss of life.
- Enforce and update building codes and construction standards to ensure that structures are designed to withstand potential landslide impacts. This includes proper foundation design and slope stabilization measures.
- Design and retrofit critical infrastructure, such as roads and bridges, to enhance resilience against landslide impacts. This includes the construction of retaining walls and other structural measures to mitigate the effects of slope failure. From field investigation in study area roads and bridge failures are a commonly affected by landslide.
- Promote the preservation and restoration of natural vegetation, which helps stabilize slopes and reduce the risk of landslides. Planting trees and vegetation on vulnerable slopes can enhance stability
- Install effective drainage systems to manage surface water runoff and prevent water from infiltrating slopes. Proper drainage can reduce soil saturation and mitigate the risk of landslides. During the fieldwork, it was observed that most of the springs emanated on the failed slope section.
- Promote the preservation and restoration of natural vegetation, which helps stabilize slopes and reduce the risk of landslides. Planting trees and vegetation on vulnerable slopes can enhance stability.

- Conduct public awareness campaigns to educate communities about the risks of landslides, the early warning signs, and appropriate response measures. This can include the development of emergency plans and evacuation procedures.
- Implementing these general recommendations requires collaboration among government agencies, local communities, engineers, and scientists. A holistic and proactive approach is essential to minimize the impact of landslides and build resilience in landslide-prone areas.

References

A. Basofi, A. Fariza, A. S. Ahsan and I. M. Kamal, "A comparison between natural and Head/tail breaks in LSI (Landslide Susceptibility Index) classification for landslide susceptibility mapping: A case study in Ponorogo, East Java, Indonesia," *2015 International Conference on Science in Information Technology (ICSITech)*, Yogyakarta, Indonesia, 2015, pp. 337-342, doi: 10.1109/ICSITech.2015.7407828.

Abebe, B., Dramis, F., Fubelli, G., Umer, M., & Asrat, A. (2010). Landslides in the Ethiopian Highlands and the Rift margins. *Journal of African Earth Sciences*, *56*(4-5), 131-138.

Abija, F. A., Nwosu, J. I., Ifedotun, A. I., & Osadebe, C. C. (2019). Landslide susceptibility assessment of Calabar, Nigeria using Geotechnical. *Remote Sensing and Multi-Criteria Decision Analysis: Im-plications for urban planning and development*, 774-788.

Agostini, A., Bonini, M., Corti, G., Sani, F., & Manetti, P. (2011). Distribution of quaternary deformation in the central Main Ethiopian Rift, East Africa. *Tectonics, 30*(4).

Atkinson, P.M., Massari, R., 1998. Generalized linear modeling of susceptibility to landsliding in the central Apennines, Italy. Computers and Geosciences 24, 373 – 385

Armstrong MP, Xiao N, Bennett DA (2003) Using genetic algorithms to create multicriteria class intervals for choropleth maps. Ann Assoc Am Geogr 93(3):595–623. Doi: 10.1111/1467-8306.9303005

Ahmed B (2015) Landslide susceptibility mapping using multi-criteria evaluation techniques in Chittagong metropolitan area, Bangladesh. Landslides 12(6): 1077– 95

Akgun, A. & Türk, N. Landslide susceptibility mapping for Ayvalik (Western Turkey) and its vicinity by multicriteria decision analysis. Environmental Earth Sciences 61, 595–611 (2010).

Ayalew, L. (1999). The effect of seasonal rainfall on landslides in the highlands of Ethiopia. Bulletin of Engineering Geology and the Environment, 58(1), 9-19.

Ayalew, L., Yamagishi, H., & Ugawa, N. (2004). Landslide susceptibility mapping using GIS-Based weighted linear combination, the case in Tsugawa area of Agano River, Niigata Prefecture, Japan. Landslides, 1(1), 73-81.

Ayalew, L., & Yamagishi, H. (2004). Slope failures in the Blue Nile basin, as seen from Landscape evolution perspective. Geomorphology, 57(1-2), 95-116.

Ayenew, T., & Barbieri, G. (2005). Inventory of landslides and susceptibility mapping in the Dessie area, northern Ethiopia. Engineering Geology, 77(1-2), 1-15.

Aleottsi, P., & Chowdhury, R. (1999). Landslide hazard assessment: summary review and new perspectives. *Bulletin of EngSineering Geology and the environment*, *58*(1), 21-44

Anbalagan, R. (1992). Landslide hazard evaluation and zonation mapping in mountainous terrain. Engineering geology, 32(4), 269-277.s

Bai, S., Wang, J., Thiebes, B., Cheng, C., & Yang, Y. (2014). Analysis of the relationship of landslide occurrence with rainfall: a case study of Wudu County, China. *Arabian Journal of Geosciences*, *7*, 1277-1285.

Bekele Abebe, Dramis, F., Fubelli, G., Mohammed Umer, Asfawossen Asrat (2010). Landslides in the Ethiopian highlands and the Rift margins. *Journal of African Earth Sciences*. **56**:131-138.

Bera A, Mukhopadhyay BP, Das D (2019) Landslide hazard zonation mapping using multi-criteria analysis with the help of GIS techniques: a case study from eastern Himalayas, Namchi, South Sikkim. Nat Hazards 96(2):935–959

Beutel, E., van Wijk, J., Ebinger, C., Keir, D., & Agostini, A. (2010). Formation and stability of magmatic segments in the Main Ethiopian and Afar rifts. *Earth and Planetary Science Letters*, *293*(3-4), 225-235.

Billi, P., & Dramis, F. (2003). Geomorphological investigation on gully erosion in the Rift Valley and the northern highlands of Ethiopia. Catena, 50(2-4), 353-368.

Blyth, F. G. H., & De Freitas, M. H. (2005). A geology for engineers. 7th. *Great Britain: Butterworth-Heinemann London, 227-239*

Bonham-Carter, G. F., & Bonham-Carter, G. (1994). *Geographic information systems for geoscientists: modelling with GIS* (No. 13). Elsevier.

Bonini, M., Corti, G., Innocenti, F., Manetti, P., Mazzarini, F., Abebe, T., & Pecskay, Z. (2005). Evolution of the Main Ethiopian Rift in the frame of Afar and Kenya rifts propagation. *Tectonics*, *24*(1).

Bopche, L., Rege, P.P. Landslide Susceptibility Mapping: An Integrated Approach using Geographic Information Value, Remote Sensing, and Weight of Evidence Method. *Geotech Geol Eng* **40**, 2935–2947 (2022). https://doi.org/10.1007/s10706-022-02070-4

Casagli, N., Catani, F., Puglisi, C., Delmonaco, G., Ermini, L., & Margottini, C. (2004). An inventory-based approach to landslide susceptibility assessment and its application to the Virginio River Basin, Italy. Environmental and Engineering Geoscience, 10(3), 203-216.

Chau, K. T., & Chan, J. E. (2005). Regional bias of landslide data in generating susceptibility maps using logistic regression: Case of Hong Kong Island. Landslides, 2(4), 280-290.

Chen, Z., & Wang, J. (2007). Landslide hazard mapping using logistic regression model in Mackenzie Valley, Canada. Natural hazards, 42(1), 75-89.

Chimidi, G., Raghuvanshi, T. K., & Suryabhagavan, K. V. (2017). Landslide hazard evaluation and zonation in and around Gimbi town, western Ethiopia—a GIS-based statistical approach. Applied Geomatics, 9(4), 219-236.

Chorowicz, J. (2005). The east African rift system. *Journal of African Earth Sciences*, *43*(1-3), 379-410

Corominas, J., van Westen, C., Frattini, P., Cascini, L., Malet, J. P., Fotopoulou, S., ... & Smith, J. T. (2014). Recommendations for the quantitative analysis of landslide risk. *Bulletin of engineering geology and the environment*, *73*, 209-263.

Chowdhury, R., Flentje, P., & Bhattacharya, G. (2009). *Geotechnical slope analysis*. CRC Press.

Couture, R. (2011). Landslide terminology-national technical guidelines and best practices on landslides. *Geological Survey of Canada*, *12*.

Corti, G. (2009). Continental rift evolution: from rift initiation to incipient break-up in the Main Ethiopian Rift, East Africa. *Earth-Science Reviews*, *96*(1-2), 1-53.

Cruden, D. M., & Varnes, D. J. Landslides Types and Processes in Turner, AK and Schuster, RL (eds.), 1996, Landslides Investigation and Mitigation, Special Report 247. *Transportation Research Board, National Research Council, Washington, DC*.

Crozier, M. J., & Glade, T. (2005). Landslide hazard and risk: issues, concepts and approach. *Landslide hazard and risk*, 1-40.

Dai, F. C. and Lee, C. F., 2001. Terrain-based mapping of landslide susceptibility using a geographical information system: a case study. *Canadian Geotechnical Journal* **38:**911 – 923.SS

Dai, F. C., & Lee, C. F. (2002). Landslide characteristics and slope instability modeling using GIS, Lantau Island, Hong Kong. *Geomorphology*, *42*(3-4), 213-228.

Dahal, R. K., Hasegawa, S., Nonomura, A., Yamanaka, M., Dhakal, S., & Paudyal, P. (2008). Predictive modeling of rainfall-induced landslide hazard in the Lesser Himalaya of Nepal based on weights-of-evidence. Geomorphology, 102(3-4), 496-510

Davidson, A. (compiler) (1983). The Omo River project, reconnaissance geology and Geochemistry of part of Illubabor, Kefa, Gemu Gofa and Sidamo, Ethiopian. Inst. Geol.Surv, Minist. Of Mines, 2, 1-89.

Davidson, A., & Rex, D. C. (1980). Age of volcanism and rifting in southwestern Ethiopia. *Nature*, *283*(5748), 657-658.

Delacourt, C., Allemand, P., Berthier, E., Raucoules, D., Casson, B., Grandjean, P., ... & Varel, E. (2007). Remote-sensing techniques for analysing landslide kinematics: a review. Bulletin de la Société Géologique de France, 178(2), 89-100.

Demessie, S. (2018). Landslide hazard zonation and evaluation in Dilbe and its surrounding area Northwestern central Ethiopia an integrated GIS-based Grid overlay and statistical approach, Unpublished MSc Thesis, Addis Ababa University.

EBCS. (1995). Standard, Ethiopian Building Code-8: design of structures for earthquake resistance. *Addis Ababa: Ministry of Works and Urban Development*.

Ebinger, C. J., Yemane, T., Woldegabriel, G., Aronson, J. L., & Walter, R. C. (1993). Late Eocene–Recent volcanism and faulting in the southern main Ethiopian rift. *Journal of the Geological Society*, *150*(1), 99-108.

Ebinger, C. J., Yemane, T., Harding, D. J., Tesfaye, S., Kelley, S., & Rex, D. C. (2000). Rift deflection, migration, and propagation: Linkage of the Ethiopian and Eastern rifts, Africa. *Geological Society of America Bulletin*, *112*(2), 163-176

Erener, A., Mutlu, A., & Düzgün, H. S. (2016). A comparative study for landslide susceptibility mapping using GIS-based multi-criteria decision analysis (MCDA), logistic regression (LR) and association rule mining (ARM). *Engineering geology*, *203*, 45-55.

Espizua, L. E., & Bengochea, J. D. (2002). Landslide hazard and risk zonation mapping in the Rio Grande Basin, Central Andes of Mendsoza, Argentina. *Mountain Research and Development*, *22*(2), 177-185.

Fall M, Azzam R, Noubactep C (2006) A multi-method approach to study the stability of natural slopes and landslide susceptibility mapping. Eng Geol 82: 241 – 63

FAO, 1986. Ethiopian highlands reclamation study, Final Report (Volume I and II). Food and Agriculture Organization of the United Nations (FAO), Rome.

Feizizadeh, B., & Blaschke, T. (2012). Uncertainty analysis of GIS-based ordered weighted averaging method for landslide susceptibility mapping in Urmia Lake Basin, Iran. In *Seventh International Geographic Information Science Conference, September* (pp. 18-21).

Firomsa, M., & Abay, A. (2019). Landslide assessment and susceptibility zonation in Ebantu district of Oromia region, western Ethiopia. Bulletin of Engineering Geology and the Environment, 78(6), 4229-4239

Foote KE, Crum S (2014) Issues of statistical generalization. Cartographic communication, section 6. Colorado, The Geographer's Craft Project, Department of Geography. The University of Colorado at Boulder.

Gadtaula A, Dhakal S (2019) Landslide susceptibility mapping using weight of evidence method in Haku, landslide susceptibility mapping using weight of evidence method in Haku, Rasuwa District, Nepal, vol 0–10. https://doi.org/10.3126/jngs.v58i0.24601

Genene, A., & Meten, M. (2021). Landslide Susceptibility Mapping Using GIS-based Information Value and Frequency Ratio Methods in Gindeberet area, West Shewa Zone, Oromia Region, Ethiopia.

Getachew, N., & Meten, M. (2021). Weights of evidence modeling for landslide susceptibility mapping of Kabi-Gebro locality, Gundomeskel area, Central Ethiopia. Geoenvironmental Disasters, 8(1), 1-22.

George, R., Rogers, N., & Kelley, S. (1998). Earliest magmatism in Ethiopia: evidence for two mantle plumes in one flood basalt province. *Geology*, *26*(10), 923-926.

George, R., & Rogers, N. (2002). Plume dynamics beneath the African plate inferred from the geochemistry of the Tertiary basalts of southern Ethiopia. *Contributions to Mineralogy and Petrology*, *144*(3), 286-304.

Girma, F., Raghuvanshi, T. K., Ayenew, T., & Hailemariam, T. (2015). Landslide hazard zonation in Ada Berga District, Central Ethiopia–a GIS based statistical approach. J Geom, 9(i), 25-38.

Gorsevski PV, Gessler PE, Foltz RB (2000) Spatial Prediction of Landslide Hazard Using Logistic Regression and GIS. In: Proceeding 4th International Conference on Integrating GIS and Environmental Modeling (GIS/EM4): Problems, Prospects and Research Needs, Banff, Alberta, Canada. J Environ Manage 57(4):296 https://doi.org/10.1016/s0301-4797(99)90317-1

Guzzetti F, Reichenbach P, Cardinali M, Galli M, Ardizzone F (2005b) Probabilistic landslide hazard assessment at the basin scale. Geomorphology 72(1–4):272–99

Guzzetti, F., Cardinali, M., Reichenbach, P., & Carrara, A. (2000). Comparing Landslide Maps: A Case Study in the Upper Tiber River Basin, Central Italy. *Environmental management*, *25*(3).

Hamza, T., & Raghuvanshi, T. K. (2017). GIS based landslide hazard evaluation and zonation–A case from Jeldu District, Central Ethiopia. *Journal of King Saud University-Science*, *29*(2), 151-165.

Hanley, J., & McNeil, B. (1982). The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology, 143(1), 29-36.

Hayward, N. J., & Ebinger, C. J. (1996). Variations in the along- axis segmentation of the Afar Rift system. *Tectonics*, *15*(2), 244-257.

Highland, L., & Bobrowsky, Peter. (2008). *the landslide handbook: a guide to understanding landslides* (p. 129). Reston: US Geological Survey

Hurni, H., & Perich, I. (1992). Towards a Tigray environmental and economic strategy (TREES): A contribution to the Symposium on Combating Environmental Degradation in Tigray, Ethiopia.

Huang J, Zhou Q, Wang F (2015) Annals of GIS mapping the landslide susceptibility in Lantau Island, Hong Kong, by frequency ratio and logistic regression model. Ann GIS 21(3):191–208. https://doi.org/10.1080/19475683.2014.992373

Hoek, E., & Bray, J. D. (1981). *Rock slope engineering*. CRC Press.

Kanungo, D. P., Arora, M. K., Sarkar, S., & Gupta, R. P. (2006). A comparative study of conventional, ANN black box, fuzzy and combined neural and fuzzy weighting procedures for landslide susceptibility zonation in Darjeeling Himalayas. *Engineering geology*, *85*(3-4), 347-366.

Kanungo, D. P., Arora, M. K., Sarkar, S., & Gupta, R. P. (2009). A fuzzy set based approach for integration of thematic maps for landslide susceptibility zonation. *Georisk6*, *3*(1), 30-43.

Kanungo D, Arrora M, Sarkar S, Gupta R (2009) Landslide Susceptibility Zonation (LSZ) mapping-a review. J South Asia Disaster Stud 2:81 –105

Kazmin V. (1979). Stratigraphy and correlation of Cenozoic volcanic rocks in Ethiopia. Ethiopian Institute of Geological Survey, Addis Ababa, Ethiopia, 106, 1-26.

Kazmin, V., Berhe, S. M., Nicoletti, M., & Petrucciani, C. (1980). Evolution of the northern part of the Ethiopian rift: Atti Convegni Lincei, v. 47.

Kazmin V., Shifferaw A., and Balcha T. (1978). The Ethiopian basement: stratigraphy and possible manner of evolution. International Journal of Earth Sciences (Geologische u Rndschau), 67, 531-546.

Keefer, D. K., 2000. Statistical analysis of an earthquake-induced landslide distribution the 1989 Loma Prieta, California event. *Eng. Geol*. **58**:231 –249

Keranen, K., & Klemperer, S. L. (2008). Discontinuous and diachronous evolution of the Main Ethiopian Rift: Implications for development of continental rifts. *Earth and Planetary Science Letters*, *265*(1-2), 96-111

Kryštof, V., & Leta, M. A. (2018). Explanatory notes to the thematic geoscientific maps of Ethiopia at a scale of 1: 50,000. *Map Sheet*, 0637-D3.

Lari S, Frattini P, Crosta GB (2014) A probabilistic approach for landslide hazard analysis. Eng Geology 182:3– 14

Lee, S., & Choi, J. (2004). Landslide susceptibility mapping using GIS and the weight-of evidence model. *International Journal of Geographical Information Science*, *18*(8), 789-814.

Lee, S., Choi, J., & Min, K. (2002). Landslide susceptibility analysis and verification using the Bayesian probability model. *Environmental Geology*, *43*(1), 120-131.

Lee S, Min K (2001) Statistical analysis of landslide susceptibility at Yongin, Korea. Environ Geol 40:1095–1113

Lee, S., & Pradhan, B. (2006). Probabilistic landslide hazards and risk mapping on Penang Island, Malaysia. *Journal of Earth System Science*, *115*, 661-672.

Lee, S., & Pradhan, B. (2007). Landslide hazard mapping at Selangor, Malaysia using frequency ratio and logistic regression models. *Landslides*, *4*(1), 33-41.

Lee, S., Ryu, J. H., & Kim, I. S. (2007). Landslide susceptibility analysis and its verification using likelihood ratio, logistic regression, and artificial neural network models: case study of Youngins, Korea. *Landslides*, *4*(4), 327-338.

Lee, C. T. (2015). Review and perspectives on methodology for landslide hazard analysis. In *Proceedings of 10th Asian regional conference of IAEG*.

Mahdadi F, Boumezbeur A, Hadji R, Kanungo DP, Zahri F (2018) GIS-based landslide susceptibility assessment using statistical models: a case study from Souk Ahras province, N-E Algeria

Mengistu, F., Suryabhagavan, K. V., Raghuvanshi, T. K., & Lewi, E. (2019). Landslide Hazard zonation and slope instability assessment using optical and InSAR data: a case study from Gidole town and its surrounding areas, southern Ethiopia. *Remote Sensing of Land*, *3*(1), 1-14.

Merla G., E. Abbate, A. Azzaroli, P. Bruni, M. Fazzuoli, M. Sagri, and P. Tacconi (1979). A Geological Map of Ethiopia and Somalia (1973): 1:2.000.000, and Comment, with a map of major landforms, 95 pp., Cent. Stampa, Florence

Mersha, T., & Meten, M. (2020). GIS-based landslide susceptibility mapping and assessment using bivariate statistical methods in Simada area, northwestern Ethiopia. Geoenvironmental Disasters, 7(1), 1-22.

Meten, M., PraskashBhandary, N., & Yatabe, R. (2015). Effect of landslide factor combinations on the prediction accuracy of landslide susceptibility maps in the Blue Nile Gorge of Central Ethiopia. Geoenvironmental Dissasters, 2(1), 1-17.s

Meten, M., Bhandary, N. P., & Yatabe, R. (2015). GIS-based frequency ratio and logistic regression modelling for landslide susceptibility mapping of Debre Sina area in central Ethiopia. *Journal of mountain science*, *12*(6), 1355-1372.

Mohr, E. C. J., Van Baren, F. A., & Schuylenborgh, J. V. (1972). Tropical Soils. A Comprehensive Study of Their Genesis. *Tropical Soils. A Comprehensive Study of Their Genesis.*, (Ed. 3).

Mulatu, E., Raghuvanshi, T. K., & Abebe, B. (2009). Landslide hazard zonation around Gilgel Gibe-II hydroelectric project, Southwestern Ethiopia. SINET: Ethiopian Journal of Science, 32(1), 9-20.

Nakileza, B.R., Nedala, S. Topographic influence on landslides characteristics and implication for risk management in upper Manafwa catchment, Mt Elgon Uganda. *Geoenviron Disasters* **7**, 27 (2020). https://doi.org/10.1186/s40677-020-00160-0

Naranjo, J. L., Van Westen, C. J., & Soeters, R. (1994). Evaluating the use of training areas in bivariate statistical landslide hazard analysis-a case study in Colombia. *ITC journal*, (3), 292-300.

Nelson, S. (2010). Slope stability, triggering events and Mass wasting hazards.

NeuShäuser, B., & Terhorst, B. (2007). Landslide susceptibility assessment using “weights-of-evidence” applied to a study area at the Jurassic escarpment (SW-Germany). *Geomorphology*, *86*(1-2), 12-24.

Pardeshi, S. D., Autade, S. E., & Pardeshi, S. S. (2013). Landslide hazard assessment: recent trends and techniques. *SpringerPlus*, *2*(1), 1-11.

Poli, S., & Sterlacchini, S. (2007). Landslide representation strategies in susceptibility studies using weights-of-evidence modeling technique. *Natural Resources Research*, *16*, 121-134.

Popescu M.E. (2001). ‘‘A Suggested Method for Reporting Landslide Remedial Measures.’’ IAEG Bulletin, 60, 1:69–74

Schicker R, Moon V (2012) Comparison of bivariate and multivariate statistical approaches in landslide susceptibility mapping at a regional scale. Geomorphology 161:40–57

Schilling, J. G., Kingsley, R. H., Hanan, B. B., & McCully, B. L. (1992). Nd‐ Sr‐ Pb isotopic variations along the Gulf of Aden: Evidence for Afar mantle plume‐ continental lithosphere interaction. *Journal of Geophysical Research: Solid Earth*, *97*(B7), 10927-10966

Shano, L., Raghuvanshi, T. K., & Meten, M. (2020). Landslide susceptibility evaluation and hazard zonation techniques–a review. Geoenvironmental Disasters, 7(1), 1-19.

Shano, L., Raghuvanshi, T. K., & Meten, M. (2021). Landslide susceptibility mapping using frequency ratio model: the case of Gamo highland, South Ethiopia. *Arabian Journal of Geosciences*, *14*(7). https://doi.org/10.1007/s12517-021-06995-7

Shano, L., Raghuvanshi, T. K., & Meten, M. (2022). Fuzzy set theory and pixel-based landslide risk assessment: the case of Shafe and Baso catchments, Gamo highland, Ethiopia. *Earth Science Informatics*, 1-14.

Shano, L., Raghuvanshi, T. K., & Meten, M. (2022). Landslide Hazard Zonation using Logistic Regression Model: The Case of Shafe and Baso Catchments, Gamo Highland, Southern Ethiopia. *Geotechnical and Geological Engineering*, *40*(1), 83-101.

Sharma, M., & Kumar, R. (2008). GIS-based landslide hazard zonation: a case study from the Parwanoo area, Lesser and Outer Himalaya, HP, India. *Bulletin of Engineering Geology and the Environment*, *67*(1), 129-137.

Shirzadi, A., Saro, L., Hyun Joo, O., & Chapi, K. (2012). A GIS-based logistic regression model in rock-fall susceptibility mapping along a mountainous road: Salavat Abad case study, Kurdistan, Iran. *Natural hazards*, *64*(2), 1639-1656.

Soeters, R., & Van Westen, C. J. (1996). Slope instability recognition, analysis and zonation. *Landslides: investigation and mitigation*, *247*, 129-177.

Sujatha, E. R., & Sridhar, V. (2021). Landslide susceptibility analysis: A logistic regression model case study in Coonoor, India. *Hydrology*, *8*(1), 41.

Sun, D., Xu, J., Wen, H., & Wang, D. (2021). Assessment of landslide susceptibility mapping based on Bayesian hyper parameter optimization: A comparison between logistic regression and random forest. *Engineering Geology*, *281*, 105972

Swets, J. (1988). Easuring the accuracy of diagnostic systems. Science, 240(4857), 1285-1293

Tarekegn Dure, Abebe Misge, Melese Tute, Erko Kebede, Dimberu Besifat and Temesgen Demissi. (2018). Geology, Geochemistry and Gravity Survey of Dime Map Sheet. (Nb 37-5). GSE. Addis Ababa, Ethiopia.

Tefera, M., Chernet, T., & Haro, W. (1996). *Explanation of the geological map of Ethiopia*. Geological Survey of Ethiopia

Temesgen, B., Umer, M., Asrat, A., Berakhi, O., sAyele, A., Francesco, D., & Demissie, M. (1999). Landslide hazard on the slopes of Dabicho Ridge, Wondo Genet area: the case of June 18, 1996 event. *SINET: Ethiopian Journal of Science*, *22*(1), 127-140.

Tefera, S. (2022). Landslide susceptibility mapping using bivariate statistical methods: the case of Sile and Elgo catchments, gamo highland, southern Ethiopia Unpublished MSc Thesis, Adama Science and Technology University

Tiranti, Davide, and Roberto Cremonini. "Landslide hazard in a changing environment" *Frontiers in Earth Science* 7 (2019): 3.

Thanh, L. N. (2008). Landslide susceptibility mapping of the mountainous area in A Luoi district Thua Thien Hue province, Vietnam.

Turcotte, D. L., Malamud, B. D., Guzzetti, F., & Reichenbach, P. (2002). Self-organization, the cascade model, and natural hazards. *Proceedings of the National Academy of Sciences*, *99*(suppl_1), 2530-2537.

Turrini, M. C., & Visintainer, P. (1998). Proposal of a method to define areas of landslide hazard and application to an area of the Dolomites, Italy. *Engineering geology*, *50*(3-4), 255-265.

Rabby, Y. W., Hossain, M. B., & Abedin, J. (2022). Landslide susceptibility mapping in three Upazilas of Rangamati hill district Bangladesh: application and comparison of GIS-based machine learning methods. *Geocarto International*, *37*(12), 3371-3396.

Raghuvanshi, T. K., Ibrahim, J., & Ayalew, D. (2014a). Slope stability susceptibility evaluation parameter (SSEP) rating scheme–an approach for landslide hazard zonation. Journal of African Earth Sciences, 99, 595-612.

Raghuvanshi TK, Kala PM, Singh M (2014b) Landslide Disaster Management and Reduction- An approach through Remote Sensing and GIS. In: Singh M, Singh RB, Hassan MI (eds) Landscape Ecology and Water Management, Proceedings of International Geographical Union (IGU) Rohtak Conference, Vol-2, Advances in Geographical and Environmental Sciences. Springer, Japan, pp 33–40

Raghuvanshi, T. K., Negassa, L., & Kala, P. M. (2015). GIS based Grid overlay method versus modeling approach a comparative study for landslide hazard zonation (LHZ) in Meta Robi District of West Showa Zone in Ethiopia. The Egyptian Journal of Remote Sensing and Space Science, 18(2), 235-250.

Ramakrishnan, S. K. (2002). Landslide Zonation for Hill Area Development. GIS Development.net Viewed March 19th 2013.

Ram, P., Gupta, V., Devi, M., & Vishwakarma, N. (2020). Landslide susceptibility mapping using bivariate statistical method for the hilly township of Mussoorie and its surrounding areas, Uttarakhand Himalaya. *Journal of Earth System Science*, *129*(1). https://doi.org/10.1007/s12040-020-01428-7

Rooney, T. O. (2010). Geochemical evidence of lithospheric thinning in the southern Main Ethiopian Rift. *Lithos*, *117*(1-4), 33-48.

Wachal, D. J., & Hudak, P. F. (2000). Mapping landslide susceptibility in Travis County, Texas, USA. *GeoJournal*, *51*(3), 245-253.

Waltham, T. (2009). *Foundations of engineering geology*. CRC Press. 3 rd ed. Madison Avenue, New York, 72-74 pp.

Wilson, J. P., & Gallant, J. C. (Eds.). (2000). *Terrain analysis: principles and applications*. John Wiley & Sons.

Woldearegay, K. (2013). Review of the occurrences and influencing factors of landslides in the highlands of Ethiopia: With implications for infrastructural development. Momona Ethiopian Journal of Science, 5(1), 3-31.

Woldegabriel, G., Aronson, J. L., & Walter, R. C. (1990). Geology, geochronology, and rift basin development in the central sector of the Main Ethiopia Rift. *Geological Society of America Bulletin*, *102*(4), 439-458.

WoldeGabriel, G., Yemane, T., Suwa, G., White, T., & Asfaw, B. (1991). Age of volcanism and rifting in the Burji-Soyoma area, Amaro Horst, southern Main Ethiopian Rift: geo-and biochronologic data. *Journal of African Earth Sciences (and the Middle East)*, *13*(3-4), 437-447

Wolfenden, E., Ebinger, C., Yirgu, G., Deino, A., & Ayalew, D. (2004). Evolution of the northern Main Ethiopian rift: birth of a triple junction. *Earth and Planetary Science Letters*, *224*(1-2), 213-228

Workineh Haro, Asamnew Besufikad, Daba Bulto, Fikadu Belete and Mohamed Edris (2015). Geology, Geochemistry and Gravity Survey of Jima Area. GSE, Addis Ababa, Ethiopia. Memoir No.35

Wu LZ, Huang RQ, Xu Q, Zhang LM, Li HL (2015) Analysis of physical testing of rainfall-induced soil slope failures. Environ Earth Sci 73(12):8519–31

Van Westen, C. J. (1994). GIS in landslide hazard zonation: a review, with examples from the Andes of Colombia. *Mountain environments & geographic information systems*, 135-166.

Van Westen, C. J., Rengers, N., & Soeters, R. (2003). Use of geomorphological information in indirect landslide susceptibility assessment. *Natural hazards*, *30*(3), 399-419.

Virgo, K. J., & Munro, R. N. (1978). Soil and erosion features of the Central Plateau region of Tigray, Ethiopia. Geoderma, 20(2), 131-157.

Varnes, D. J. (1978). Slope movement types and processes. *Special report*, *176*, 11-33.

Varnes, D. J. (1981). The principles and practice of landslide hazard zonation. *Bulletin of the International Association of Engineering Geology-Bulletin de l'Association Internationale de Géologie de l'Ingénieur*, *23*(1), 13-14.

Varnes, D. J. (1984). *Landslide hazard zonation: a review of principles and practice* (No. 3).

Varnes, D. J. IAEG (1984) Landslide hazard zonation: a review of principles and practice. *UN Sci Cult Organ, Paris*, 1-6.

Verner, K., Megerssa, L., Hroch, T., Buriánek, D., Martínek, K., Gebremariyam, H., Tadesse, E., Legesse, F., NisraS, E., Abateneh, B., Hejtmánková, P., and Krejčí, Z.: Geological map at a scale of 1:50,000, Geological and thematic maps at a scale 1:50,000 for Mejo, Leku, Arba Minch and Dila areas, SNNPR, Ethiopia, Czech Geological Survey, Prague, Map Sheet 0637-D3 Arba Minch, 2018c.

Y. Lin, "A comparison study on Natural and Head/tail Breaks involving digital elevation models," Student Thesis, University of Gävle, Faculty of Engineering and Sustainable Development, Department of Industrial Development, IT and Land Management., 2013.

Zanettin, B., Nicoletti, M., & Petrucciani, C. (1978). The evolution of the Chencha escarpment and the Ganjuli graben (Lake Abbaya) in the southern Ethiopian rift. *Neues Jahrbuch fur Geologic und Palaontotogie*, *9*, 567-574.

Zhang YS, Igbol J, Yae Y (2017) Landslide susceptibility mapping using an integrated model of information value and logistic regression methods in the Bailongjiang watershed, Gansu Province, China. J Mt Sci 14:249–268

Appendix

Appendix 1. Annual Rainfall data from Arbaminch Station

Name	Year	Jan	Feb	Mar	Apr	Mar	Jun	Jul	Aug	Sep	Oct	Nov	De	Annual
Arbaminch	1992	13	18	27.1	165	140	132	32	43	132.2	173	59.6	29	963.5
	1993	178	121	34.4	94.8	198	52.6	3.1	25	31.4	117	18.2	1.2	874.4
	1994	0.3	4.1	36.4	184	165	59.9	72	83	29.7	70.3	59.6	19	782.6
	1995	0.4	27	54.4	257	140	85.3	22	18	84.7	109	53.6	44	894.5
	1996	0.4	33	52.9	283	124	90.4	23	20	100.6	117	58.3	29	932.4
	1997	16	0.4	18	241	173	27.7	61	28	49.1	215	273	153	1253.8
	1998	67	90	24.3	166	97	41.2	30	28	42	149	58.5	0.8	792.9
	1999	17	0.7	109	137	43	44.2	79	24	68.9	204	9.7	45	780.9
	2000	1.3	0	19.3	92.4	236	40.7	62	39	70.4	186	56	66	868.6
	2001	69	87	56	175	236	52.9	41	45	108.2	124	85.1	5.5	1084.3
	2002	43	22	93.9	112	57	52.2	55	12	87.9	87.7	18.1	167	808.7
	2003	14	11	61.6	201	192	98.1	30	106	39.6	89.4	25.8	14	882.4
	2004	42	31	17.5	165	59	34.8	22	70	81.6	60.9	143	32	758.3
	2005	29	1.4	67.1	311	221	16.3	29	22	77.4	121	33.4	4.3	933.1
	2006	13	84	137	115	130	126	24	75	42.8	159	103	119	1128.4
	2007	63	36	16.9	129	193	107	112	99	246.4	76.3	61.5	0	1141.1
	2008	0.6	9	60.1	135	48	76	34	56	200.8	149	81.7	0	850.5
	2009	45	3.1	28.5	98.5	109	14.9	1.4	16	41.3	162	14.1	104	638.7
	2010	19	50	191	178	222	80.7	40	34	146.1	95.1	4.5	8.3	1068.1
	2011	0	29	18.9	30.7	258	60.8	28	85	154.8	73.8	257	12	1006.3

	2012	0	2.2	30.5	320	68	72.3	28	57	193	130	79.3	34	1013.4
	2013	27	6.9	87.7	241	111	87.8	49	33	78.4	245	86.6	7.7	1061.1
	2014	8.7	44	71.2	70.3	208	73.1	15	77	105.2	132	59.3	1.4	866.2
	2015	0	2.7	57.1	122	178	132	19	19	64.6	202	209	115	1121.3
	2016	3.4	9.4	39.1	263	66	111	7.9	52	25.2	118	95.6	4.3	795.1
	2017	0.6	29	18.6	91.2	188	2.7	27	121	92.6	112	70.3	0	752.6
	2018	0	48	35.5	220	136	75.3	4	36	60.6	87	68.4	17	787.2
	2019	0	7.3	12.4	122	200	817	79	50	55.2	181	205	139	1866.9
	2020	123	23	185	241	127	87	38	115	103.5	139	59.7		1241
	2021	0	38	26	238	190	24.7				136	33.6		686.6
	2022	23		5.1	88	50	11.2	4.7	93	27.7				303.1
Mean Average		27	30	56.4	176	152	92.9	37	54	91.1	134	81.4	43	964.6

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