



ADDIS ABABA INSTITUTE OF TECHNOLOGY

**LANDSLIDE SUSCEPTIBILITY AND SLOPE INSTABILITY MODELING
USING GIS BASED ANN AND MTINSAR TECHNIQUES**

**(A CASE STUDY: ALONG THE SAWLA TO LASKA ROAD CORRIDOR
AND SURROUNDING AREA, SOUTHERN REGIONAL STATE,
ETHIOPIA)**

A Thesis in Geomatics and Geodesy (specialization in Geomatics)

By

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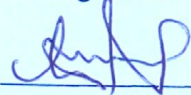
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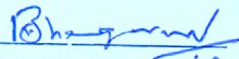
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List of Abbreviations

ANN	Artificial Neural Network
AUC	Area under the Curve
DEM	Digital Elevation Model
DInSAR	Differential Synthetic Aperture Radar Interferometry
EMA(EGA)	Ethiopian Geospatial Information Agency/Ethiopian Mapping Agency
ESA	European Space Agency
EO	Earth Observation
GNSS	Global Navigation Satellite System
GW	Generalized Weight
InSAR	Interferometric Synthetic Aperture Radar
LS	Landslide Susceptibility
LOS	Line of sight
LR	Logistic Regression
MLP	Multi Layered Perception
MT-InSAR	Multi Temporal InSAR
ML	Machine Learning
NDVI	Normalized Difference Vegetation Index
OPM	Open Street Map
PS	Persistent Scatterer
PSC	Persistent Scatterer Candidate
PSI	Persistent Scatterer Interferometry
RF	Random Forest
ROC	Receiver Operating Characteristic Curve
SAR	Syntethic Aperture Radar
SLC	Single Look Complex
SRTM	Shuttle Radar Topography Mission

TWI	Topographic Wetness Index
TOPS	Terrain Observation with Progressive Scans
QPSI	Quasi PSI
SVM	Vector Support Machine

Abstract

Landslides are common known natural hazards that lead to infrastructure destruction (road failure), property damage, and human loss. Current study area located in southwestern Ethiopian highlands near rift margin and prone to landslide. Spatial and temporal landslide susceptibility studies are important for predicting, preventing, and mitigating landslide-derived threats. This study was aimed to analysis role of landslide causative factors (weight determination), predict spatial landslide susceptibility and model slope instability based on spatial coherence preliminary result. GIS based ANN Landslide susceptibility was performed through the identification and analysis of hill slope instability factors and landslide inventory. A total of 195 polygons and twelve thematic raster pixels were intersected from which 1482 training and 513 testing pixels were extracted to train the model. Simultaneously, the ANN model was trained to achieve an optimum standard error between the predicted and observed dataset by adjusting weights and NN structures. The generalized weight result revealed the factors effect on the landslide occurrence positively, negatively and neutrally. The LSS result showed that 213.6 (86.7%), 3 (1.2%), and 29.4 (11.9%) areas fall into low, medium, and highly susceptible zones, respectively. In other side, cumulative displacement was modeled based on the preliminary interferometric coherence result. freely available 20 sentinel-1A SLC imageries from 2017 to 2021 were processed for this purpose. Spatial coherence test revealed that it is impossible to monitor and model slope instability (cumulative displacement) entire the landslide prone area. Attempt was made to model cumulative displacement at partially coherent landslide susceptible sample area. The result showed that there was cumulative displacement rate ranging from -6 mm/yr to +6 mm/yr. ROC and AUC are important tools to test training and predicting capability of machine learning model the model achieved training and testing performance of 94% and 88% respectively. This indicated that the model had successfully learned the existing problem and predicted it for the future. Therefore, the susceptibility result can be used to plan future development activities. Spatial coherence revealed, there is need of using high resolution SAR datasets to monitor slope instability entire the study area.

Keywords: Landslide, Artificial Neural Network, Landslide Inventory, Spatial Coherence, Synthetic Aperture Radar

CHAPTER ONE

1. INTRODUCTION

1.1. Background

Landslides are common known natural hazards that lead to infrastructure destruction (road failure), property damage, and human loss (Martínek et al., 2021; Shano et al., 2021). As per the Emergency Events Database, landslides have killed 66,438 people globally and cost the economy around 10.8 billion dollars between 1900 and 2020 (Emberson et al., 2020; Fang et al., 2021). Usually, it is a significant burden for areas under the rugged topography and diverse climate conditions such as the Alpine–Himalayan Mountain tectonic belt (Froude and Petley, 2018; Petley, 2012). Also, Geo-hazards like landslide are the common events in the Ethiopian northern, southern, and western highlands, as well as areas near rift margins are. In such areas, landslide is one of the severe geo-hazards that are precondition for slope instabilities, road failures, and other impacts.

A landslide is complex and non-linear in a nature; its occurrence varies from place to place. It has occurred when the driving force exceeds the resistance force due to the destabilization of natural soil or rock slopes. Landslide hazards can be caused by a variety of factors, including geological, topographical, ground water conditions, rainfall, earth quack, and illegal and legal human activities (Getachew and Meten, 2021). Aside from natural landslides, improper land use planning and infrastructure development along mountainous terrains are also major slide derivivers.

Landslide studies like landslide susceptibility assessment and slope instability monitoring are important tools for disaster management and development activities. Landslide susceptibility is the possibility of a slope failure, given the right set of geo-environmental parameters (Shano et al., 2021). Due to the landslide's complex and nonlinear nature, various methods have been developed and applied for landslide susceptibility. In general, these methods can be qualitative or bivarite and parametric multivariate statistical methods (Cherie and Ayele, 2021; Getachew and Meten, 2021; Meten, 2020; Shano et al., 2021; Wubalem, 2021). Due to their lower subjectivity and simplicity, these statistical methods are the most popular in landslide

susceptibility modeling. Such methods, however, cannot account for the landslide's complex and non-linear nature.

As a result of development in computing power and remote sensing, more advanced machine learning approaches and their ensembles are also in use for landslide susceptibility modeling. Since these methods can understand and model complex and nonlinearly related problems, they are becoming promised techniques in landslide susceptibility modeling studies (Mohamed and Reza, 2021; Yang et al., 2020). There are many ML algorithms developed and applied for landslide susceptibility modeling such as artificial neural networks (Bragagnolo et al., 2020; Lee et al., 2004; Melchiorre et al., 2008), random forest (RF) (Mohamed and Reza, 2021), vector support machine and logistic regression (Chen et al., 2018; Lin et al., 2017).

Nowadays, earth observation (EO) techniques are also playing important role in landslide, monitoring. In this regard, high-resolution optical remote sensing datasets such as IKONS, SPOT, Google maps and others have significant role in landslide inventory collection and mapping. Also, active remote sensing products such as Synthetic Aperture Radar (SAR) datasets have made easy slope instability monitoring. Accordingly, Landslide investigation is becoming easy since these datasets can easily update landslide inventory, optimize fieldwork and enable investigating hazardous or inaccessible areas (Westen et al., 2008; Zêzere et al., 2017).

In addition to spatially mapping landslide, temporal monitoring is also a great concern of landslide studies. Various Interferometric SAR (InSAR) techniques have been developed for the purpose of monitoring slope instability based on the pair of SAR images utilized and connection between them. Accordingly, the differential InSAR (DInSAR) which was limited only to exploit single pair images was first introduced for land surface deformation monitoring (Jan, 2019). Following the defects in DInSAR approach, advanced algorithms was developed with capability of exploiting phase change from time series images. The most familiar multi temporal InSAR approaches include Persistence Scattered InSAR (PSInSAR (Cherie and Ayele, 2021; Endashaw Debru, 2020; Mengistu et al., 2019), and quasi-InSAR (QInSAR) methods (Perissin and Wang, 2011; Razi et al., 2018).

Conducting integrated landslide studies that incorporate aspects of space and time is essential for understanding the threats and for predicting, preventing, and mitigating landslides. In addition,

analyzing landslide conditioning factors and mapping inventories are curtail tasks in landslide susceptibility studies. Thus, this study aimed to model landslide susceptibility and slope instability along the Sawla-Laska road corridor and surrounding areas using GIS-based ANN and QPINSAR techniques.

1.2.Statement of the Problem

Landslides remain a severe disaster throughout the world due to its complex nature and nonlinear relationship. Generally, it has not uniform characteristics everywhere since its nature and cause factors vary from place to place. Thus, according to Ac et al.(2017),landslide deriving factors should be studied in a systematic way before conducting landslide susceptibility studies.

Ethiopia's northern, southern, and western highlands and areas nearby rift margins are vulnerable to various geo-hazards like landslides, seismicity (earthquake), and ground fissuring/cracking and flooding landslides. Landslides are becoming a common events, challenging infrastructure development and living in a mountainous and steep terrain environment, leading to loss of life, extra construction costs, repair costs, costly delays, and subsequent maintenance costs both during and post construction periods (Meten, 2020; Wubalem, 2021). Therefore, in order to mitigate further hazards in the future, there is a need to analysis landslide controlling factors role and conduct landslide studies.

Although many landslide researches have been carried out in the south western highlands and other parts of Ethiopia, no studies were investigated in the current study area. Bivariate and multivariate parametric (predefined equation based) statistical methods are becoming popular in landslide studies, due to less subjectivity and simplicity. However, according to the (Senise et al., 2013; Won, 2003), these methods cannot understand non linear interaction between landslide and conditioning factors. In this regard, machine learning models like ANN has got attention due to their capability of modeling non-linear problems. Besides, coherence based slope instability modeling is applied in this study which can optimize the desired results (Gonnuru, 2018; Perissin and Wang, 2011).

Even though various studies were carried out for landslide susceptibility modeling, machine learning (non-parametric algorithms) based studies are not common in Ethiopia. This study was intended to optimize landslide susceptibility modeling by GIS based ANN and model slope

instability using the coherence based QPSI technique. ANN was applied to filter out generalized weight relationships between conditioning factors and landslides so as to optimize final landslide susceptibility modeling. It has the capability to understand nonlinearly related problems and model landslide susceptibility with better performance. On the other hand, QPSI modeled the cumulative displacement based on spatial coherence which can optimize the result. It has the ability of detecting less coherent targets. In addition, the study presents all the available existing landslide distributions, which can be used as a basis for further studies. Eventually, the findings of the study will be the basis for safer land use planning and developmental activities.

1.3.Objectives of the Research

1.3.1. General Objective

The main objective of this study is to model landslide susceptibility and slope instability using ANN and coherence based QInSAR techniques along the Sawla-Laska road corridor and surrounding areas in South-Western Ethiopia.

1.3.2. Specific Objectives

To achieve a general objective, some specific objectives have been conducted in this study. Accordingly, the following sub objectives were carried out:

1. To determine generalized weight for landslide conditioning factors, training GIS based ANN model.
2. To model landslide susceptibility of the study area optimizing ANN model.
3. To test the possibility of slope instability monitoring using the S1AC dataset and InSAR technique in the current study from 2017 to 2021.

1.4.Research questions

Based on the specific objectives, the following research questions are expected to be answered.

1. Which factors have the highest general weight relationship with training (response) variable?
2. Which factor is the most influential for landslide occurrence in the study area?

3. Which parts of the study areas are highly susceptible to landslide?
4. Is it possible to monitor slope instability using the S1A SLC datasets and QInSAR technique in the current study area?

1.5. Significance of the Study

Conducting landslide susceptibility and slope instability studies has many significant benefits. The information emanating from this research study is hoped to be of great importance in assisting the improvement of the decision making processes in the project area related to land-use planning and other design options for developmental activities.

Such susceptibility maps help planners in determining the best areas for development initiatives like building and road construction. Even if hazardous places cannot be completely avoided, recognizing them early in the planning process can aid in the implementation of appropriate preventative measures. Besides, through these delineated susceptibility maps, environmental restoration programs can be started with the right mitigating measures in place..

Moreover, through the present study recommendations, future research directions are also forwarded, which can be used as a research gap for future researchers.

1.6. Scope of the Study

Conducting landslide susceptibility studies over large study has great importance to decision makers, urban planners, and engineers to take early mitigation measures. However, there are constraints related to time, money and processing machine over large area considerations.

Therefore, in the context of past, present, and future landslide patterns, this research aimed to model landslide susceptibility and slope instability along the Sawla-Laska road corridor and surrounding areas. Among the available landslide susceptibility and slope instability modeling techniques, GIS based ANN and multi InSAR methods were applied in this study. For the sake of susceptibility mapping, twelve landslide causative factors were derived from various thematic areas: topographic theme (slope, DEM, aspect, plane, and profile curvature), proximity theme (proximity to road, proximity to fault/lineament, and proximity to drainage), and hydrologic theme (topographic wetness index and drainage density). Besides, landslide inventory was

extracted from Google Earth scars and field investigation, which was used as a dependent variable for this research. Slope instability was monitored from 2017 to 2021 using freely available sentinel 1SLC data sets. Therefore, the scope of this study was to model landslide susceptibility and slope instability along Sawla-Laska and surrounding areas using freely available datasets..

1.7.Limitations of the Study

This study was achieved successfully using all possible resources and available processing techniques. However; various challenges were encountered during the data collection and processing. The following issues were the main challenges:

1. Due to the rugged and complex topography of the study area, it was not possible to include large study area.
2. Effect of decorrelation on PSC signals availability.
3. Resource limitations while downloading and processing Sentinel1A (S-1A) imageries.

1.8.Organizations of the thesis

This thesis was organized in five chapters. The first chapter was aimed to introduce about background of landslide, described statement of the problem, and stated the objectives, scopes and limitations of the study. In second chapter broad literature reviews were explained related to landslide deriving factors, various landslide susceptibility and slope instability monitoring approaches, methodological procedures of landslide susceptibility and slope instability monitoring modeling are presented in chapter three. In this chapter input data preparation and analysis strategies presented in detail. In chapter four, the revealed results and consecutive discussions were presented in detail. Finally, this thesis was closed by reflective conclusions and recommendations in chapter five.

CHAPTER TWO

2. LITERATURE REVIEW

2.1.Overview of Landslide

Following the most severe geo-hazards, like earth quakes, tsunamis, floods, and landslides, it is also a shocking hazard that usually leads to enormous destruction of infrastructure, loss of life, and property throughout the world (Petley, 2012). In particular, it is a common burden for those nations characterized by rugged topography followed by climate changes like high rainfall intensity (Getachew and Meten, 2021). According to the global landslide susceptibility model, the highest class is distributed mainly around the major structural mountains; where transportation corridors and other linear structures are most susceptible to it. This severe hazard is always present in the Alpine–Himalayan Mountain tectonic belt, the Pacific Rim, and the Great Rift (Embersen et al., 2020; Froude and Petley, 2018; Petley, 2012; Pradhan et al., 2010).

The event landslides have been explained and defined in different earth science studies. In a common way, a downward mass soil or rock movement is controlled by gravity, geology, the presence of water, and morphology (Getachew and Meten, 2021; Wubalem, 2021). Besides this definition, it is also used to express as a processes that leads to the downward and outward movement of slope forming materials, including artificial fill, soil, rock and integration of them. As reviewed from different sources, the materials may move by flowing, falling, sliding, toppling or spreading. Also, the movement of materials may be slow or rapid and can vary widely in terms of width, ranging from several meters to a kilometer.

In landslide researches, there are various terms commonly used in landslide studies, such as landslide hazard, landslide susceptibility, and landslide risk (Catani and Casagli, 2005; Dikshit et al., 2007). Even though, these terms have various stages of study, own applications, mapping scales and data types, they commonly used in many landslide studies. According to (Shano et al., 2021) landslide susceptibility deals with possible occurrence of slope failure providing a set of geo-environmental factors. Landslide hazard study includes “where” landslides are likely to occur (susceptibility component) and also estimates the time “when” the landslide occurs as well as how frequently it occurs.

2.2.Landslide Deriving Factors

Landslide occurrence and causative factors vary from place to place, which makes it more complex. In general, it can be imitated through one or more combined effects of the factors, which can be either internal or external factors.

2.2.1. Internal Factors

The internal factors are intrinsic factors that represent the inherent attributes of the ground that encourage the slopes susceptible to landslides. These include geological materials and structures, hydrology, lithology, and geomorphology that allow external factors to trigger a landslide.

Litho-logical units and structural discontinuities such as joints and faults are considered basic geologically contributing factors that affect slope stability (Getachew and Meten, 2021; Kumar et al., 2015). Fault zones increase landslide potential by creating steep slopes and sheared and weak zones. Slope materials can be soil; rock, or both soil and rock. Its composition, fabric, texture, and other properties of slope material influence its shear strength.

Slope geometry is an important intrinsic landslide controlling factor that describes the relative relief and morphometry of the slope (Kumar et al., 2015; Vojteková and Vojtek, 2020). The steepness of the slope is described by landform morphology. The slope will be prone to instability when the slope morphology is steep as relative relief is higher.

Hydrologic contributors such as ground water intensity have also been identified as a main contributing factor for slope instability. Saturation of groundwater in a slope degrades the shear strength of the material and also creates pore water pressure, which plays an important role in slope instability conditions (Chimidi et al., 2017; Wubalem, 2021). Groundwater within jointed rock masses and in soil masses weakened the shear capacity of slope material by developing joint water and pore water pressure.

2.2.2. External Triggering Factors

There are various external landslide controlling factors, including rainfall, volcanic activity, seismic vibration, and manmade activities.

Among the external landslide control factors, rainfall is a primary cause of landslides and worsening slope stability problems. According to Neaupane and Achet(2004)rainfall intensity and duration play an important role in triggering landslides like debris flows, mudflows, and medium-to large-scale rockslides, though it depends on climatic conditions, topography, land cover, the geological structure of slopes, and the permeability of material. It plays a vital role in decreasing the shear force of the material by saturating the slope material. Rainwater can also cause slope instability by increasing the weight on the slope, especially in areas where the slope material is soil (Mersha and Meten, 2020)

Seismicity Earthquakes are a major cause of landslides, imitated through ground shaking, liquefaction of susceptible sediments, or shaking-caused dilation of soil materials (Guo, 2015). Ground shaking decreases the shear resistance of slope material and generates a high excess pore water pressure, which adds to the slope instability condition.

Besides, human-caused activities such as poor land use practice are also important landslide-deriving factors (Chimidi et al., 2017; Pradhan et al., 2010; S and Panhalkar, 2019). The demand for new land for agriculture, infrastructure, and settlement are the primary causes that contribute to slope instability conditions caused by human interference. Man made activities are changing or disturbing drainage patterns, destabilizing the slopes, removing vegetation, overstepping by undercutting the bottom of slopes, loading the upper part of the slope, and irrigation may result in directly or indirectly initiating the slope instability condition (Chimidi et al., 2017; Vojteková and Vojtek, 2020).

2.3.Landslide Overview in Ethiopia

Ethiopia's rugged topography and landscape, climate conditions, and complex geological settings are preconditions for slope instabilities. Landslides are most common in Ethiopia's highlands and near rift margins (Mengistu et al., 2019; Shano et al., 2021; Wubalem, 2021). This frequently leads to infrastructure destruction, loss of life, and property damage. Accordingly, geo-hazards like earthquakes, ground cracking, landslides, and flooding frequently challenge the road sector in Ethiopia (Meten, 2020; Wubalem, 2021)

Every year, landslides and related hazards destroy wide areas of fertile agricultural lands, natural forests, and infrastructure, including roads, bridges, and urban and rural settlements, and also lead to a significant number of fatalities. The consequences of these phenomena are reflected in many places in the country and are already accepted as major sources of challenges faced during the development of roads and other infrastructure in the northern, central, southwestern, and southeastern highlands, as well as at the borders of the Ethiopian Rift Valley (Martínek et al., 2021; Shano et al., 2021).

In many parts of the country, landslide mass movement occurs due to heavy rain fall, particularly from July to September, and, in some cases, from April to May, as well as poor land use practice and population growth (Chimidi et al., 2017; Kumar et al., 2015; Wubalem, 2021). It is a more severe challenge for the transportation corridor over the step topography following heavy rainfall. As a result, it causes life losses, additional construction costs, repair costs, costly delays, and subsequent maintenance costs both during and after construction. Frequently subjected to landslide destruction include: Dejen-Gohatsion, Sawla-Laska-Salayish, Harer-Diredawa, Kombolcha-Desssie, Ambo to Gedo, DebrebirhanTarmaber-Shewarobit, AlamataKorem, Bonga-MizanTepi, Chelenko-Dengego-Diredawa, Jimma-Bonga, Shire-Maitsebri, Abomsa-Aseko-Cheleleka, Mertolemariam-Mekanselam, Arbaminch-Gidole, Shire-Adiremets and others . Landslides along these and other route sections have been challenging the transport sector for years (Mengistu et al., 2019; Mewa et al., 2018). The Figure 2.1 illustrates the recorded distribution of the landslides in Ethiopia.

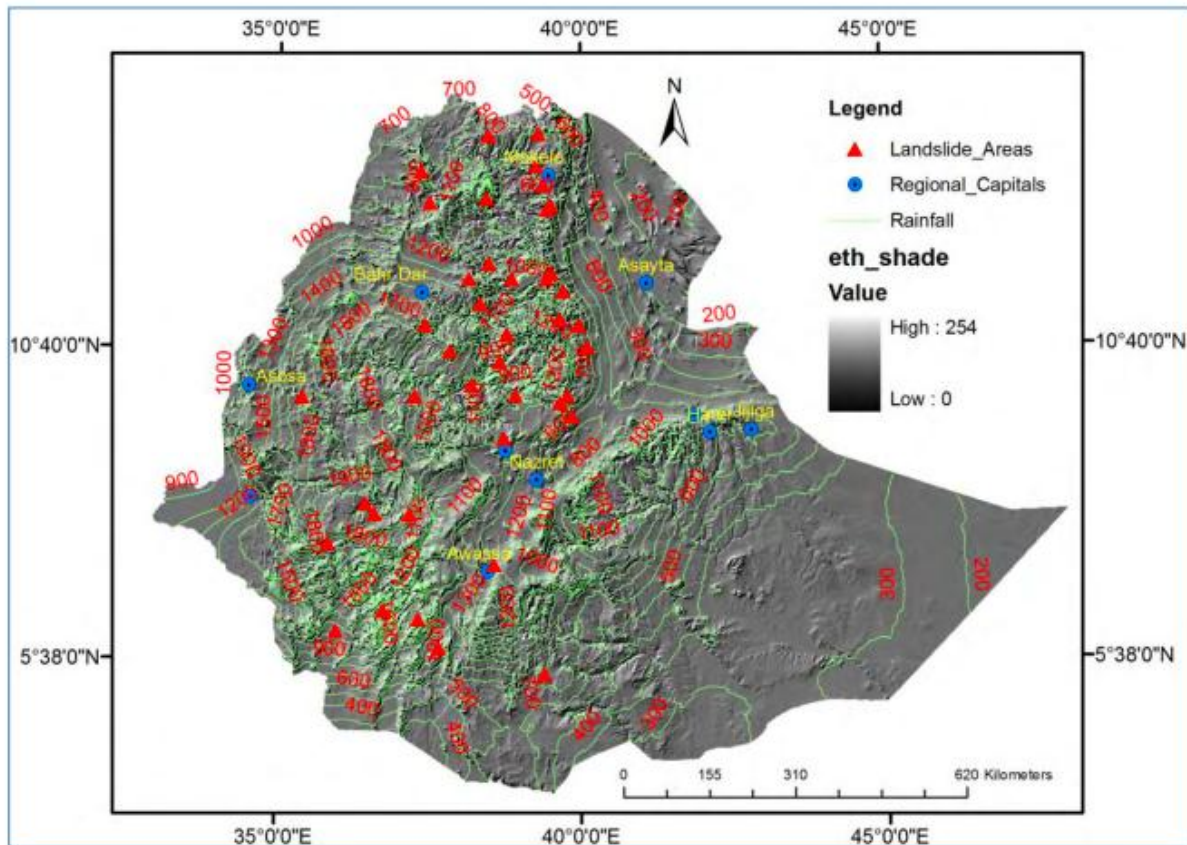


Figure 2.1: Landslide distribution in Ethiopian highlands(Woldearegay, 2019)

2.4.Landslide Susceptibility Modeling Approaches

Following the complex characteristics of landslides, different landslide susceptibility mapping techniques have been designed and applied for landslide studies. Generally, these methods can be grouped as qualitative and quantitative approaches to landslide mapping. Qualitative approaches are subjective to geoscientists' involvement in factors' importance assigning. These include landslide inventory mapping and knowledge-driven techniques, such as the analytic hierarchy process (Abay et al., 2019). Quantitative methods are methods based on numerical expressions between landslide controlling factors and landslides. Quantitative approaches include statistical methods and deterministic methods. Deterministic methods depend on physical laws to detect slope instability (Ermini et al., 2005), while statistical methods are based on functional expressions between inferred contributing factors and landslide occurrence such as

logistic regression (Meten, 2020; Mousavi et al., 2011), linear regression (Tang et al., 2021) and multi-criteria decision analysis (Chandio et al., 2013).

However, as discussed in an interesting researcher's work by Shano et al. (2020), there is no best accepted method for landslide susceptibility mapping. The researchers also highlighted that the landslide mechanism is not similar place to place due to its complex and non-linear nature. They concluded that the choice of the susceptibility modeling methods depends on the scale of the processing, data availability, accessibility to the study area, objective of the study, and background of the researcher.

2.4.1. Landslide Inventory Mapping

Data-driven methods primarily depend on landslide inventory data (Ermini et al., 2005; Senise et al., 2013). It is used as the dependent variable to build a model and is crucial to validating any landslide susceptibility map. Landslide inventory data is crucial in order to have reliable landslide susceptibility maps. Since previous and present landslide progress is the key to future events in the same environmental conditions, landslide inventory mapping needs great care and less subjectivity. In data-driven landslide susceptibility mapping methods, inventory data is used to train and test the developed model (Althuwaynee et al., 2012; Chen et al., 2018; Mohamed & Reza, 2021).

Different methods have been applied for landslide inventory mapping. Most often, landslide inventory has been captured by traditional field survey investigations, which are tedious, time-consuming, and difficult in harsh environments. Despite these limitations, such techniques are the most reliable for landslide susceptibility mapping, especially in small areas. However, these days, even automatic landslide capturing is possible following the advancement of remote sensing approaches like high resolution satellite imagery and aerial photo interpretation techniques (Mersha and Meten, 2020). In this regard, high resolution remote sensing imageries such as IKONOS, Quick Bird, Spot, DEMS, SAR imageries, LiDAR topographic data, and other products have been successfully applied in landslide susceptibility studies (Westen et al., 2008; Zêzere et al., 2017). Such methods have many advantages over the large study area: rapid inventory updating, optimizing field investigation and monitoring.

Zêzere et al. (2017) noted that landslide inventory representation is another issue in landslide susceptibility analysis where it can be either point or polygon based mapping. Accordingly, there are preconditions which guide us to choice point or aerial landslide representation, such as the positional accuracy, the scale of the study, the landslide mapping objective, the limitation of the cost, and the limitations of software and hardware. According to Zêzere et al.(2017), where there are large slides, areal (polygon) inventory based landslide susceptibility analysis can generate better predictions than point representation.

However, most of the high-resolution remote sensing images are not available freely and it is a big challenge in landslide studies in order to achieve accurate results. On the other hand, Google Earth is a very important product applied in many landslide susceptibility studies. For this reason, in addition to extensive field investigation, Google earth imagery has been used to capture landslide inventories (Mengistu et al., 2019; Mersha and Meten, 2020; Shano et al., 2021; Wubalem, 2021).

2.4.2. Landslide Susceptibility mapping units

Zêzere *et al.* (2017); Shano, Raghuvanshi and Meten (2020) highlights that selection of a suitable mapping unit is a basic requirement for landslide susceptibility studies. A mapping unit is a section of land that comprises a set of surface conditions that differ from neighboring cells across specified borders. A mapping unit represents a domain at the scale of the analysis that optimizes internal uniformity and in between variability. Accordingly, commonly used landslide mapping units have been suggested that the terrain be partitioned for landslide susceptibility mapping. They are Grid-cells, Slope-units, Unique-condition units, terrain units

Grid-cells based approach is primarily preferred by the raster-based GIS users in which the terrain splitted into regular squares of pre-determined size which serve as the mapping unit. In this system, each grid cell has a value assigned to it based on morphological, geological, land-use, and other factors.

Slope-units, which are generated automatically from high-quality DTMs, divide the land into hydrological zones between drainage and divide lines. Depending on the type of instability to be investigated, the mapping unit may correspond to the sub-basin or the main slope-unit on the right or left side of the sub-basin. Each slope-instability factor is divided into a few categories

that are recorded in a single map, or layer, is referred to as unique-condition units. Homogeneous domains (unique conditions) are identified by sequentially covering all layers. Their number, size, and type are determined by the criteria used in classifying the input factors prepared (Ermini et al., 2005). Terrain units are also founded on the idea that in natural environments, the interrelationships between materials, shapes, and processes result in boundaries that frequently represent geomorphological and geological variations (Ermini et al., 2005). The land-system classification approach, which has been used in numerous land resource analyses, is based on terrain units.

2.4.3. Statistical Approach

Statistical methods based on a statistical relationship between a landslide event and conditioning factors. Most of the statistical landslide susceptibility methods fall into either bivariate or multivariate statistical categories.

2.4.3.1. Bivariate Statistical Analysis

These are the most common landslide susceptibility mapping techniques where individual contributing factors are compared with landslide distribution (Shano et al., 2020). In these methods, landslide susceptibility analysis is based on the landslide density derived from the weights of landslide conditioning. There are bivariate statistical methods successfully applied for landslide susceptibility analysis: information value (Mengistu et al., 2019), frequency ratio (Meten, 2020; Shano et al., 2021), weights of evidence (Getachew & Meten, 2021; Meten, 2020) and certainty factor functions (Wubalem, 2021). Thus, by combining landslide contributing factors with the spatial distribution of previous and present landslides, future landslide occurrence can be predicted under the same geological, geo-morphological, and environmental conditions.

Despite simplicity and lower subjectivity, (Shano et al., 2020) also explain that these methods need a complete data set in order to achieve an accurate landslide susceptibility result. But in reality, having such a complete data set is difficult for different reasons. Getachew and Meten (2021) and Zêzere et al. (2017) highlighted that the interdependency of predictive variables cannot be considered where susceptibility maps result from combining all conditioning factors.

This is also the main drawback of such methods, which allow the development of multivariate statistical approaches.

2.4.3.2. Multivariate Statistical Approaches

These are landslide susceptibility mapping methods where all relevant landslide casual factors are treated together with a dependent variable (Zêzere et al., 2017). In this method, the model evaluates the combined relationship between the dependent variable (landslide distribution) and a set of independent variables (landslide predisposing factors).

Multivariate methods are further classified as having a parametric or nonparametric relationship between dependent and independent variables. Parametric approach, the relationship between dependent and independent parameter is formed based on the regression equation. In such parametric equation based models, the generated coefficients maximize the predictive capability of the model. The most commonly used regression analysis methods include; logistic regression (Meten, 2020; Mousavi et al., 2011), linear regression (Tang et al., 2021), and random forest (Youssef & Pourghasemi, 2021).

Non-parametric landslide susceptibility modeling approaches use non-linear function approximations to model complex and nonlinear events. These methods include machine learning algorithms such as ANN, SVM, etc., where generic inherit nonlinear function approximators are used to model landslide events that are complex and nonlinear in nature. In these approaches, landslide and deriving factors are assumed to be not linearly related, hence there is no need for equations to combine dependent and independent variables (Senise et al., 2013; Won, 2003).

2.4.4. Machine Learning Approaches

Promising landslide modeling approaches have emerged over time as a result of technological developments in computing power and remote sensing (Fang et al., 2021). ML algorithms have an important role in modeling complex problems (nonlinearly related in nature) in earth science studies such as landslides (Mohamed and Reza, 2021; Yang et al., 2020). Basically, Machine learning helps computers to learn by experience in the same way that humans do. That is, instead

of depending on a predefined equation as a model, machine learning algorithms employ mathematical methods to "learn" information directly from data. To do so, two techniques of learning strategies are: Unsupervised learning finds hidden patterns and relationships in input data while supervised learning learns a model on existing input and output data to predict future outcomes.

ML approaches were successfully applied for landslide prediction modeling due to their modeling capability of nonlinear and complex relations between landslide events and conditioning factors. ML methods introduced with better performance in landslide susceptibility mapping include, artificial neural network (ANN), adaptive neuro fuzzy inference system (ANFIS), , support vector machine (SVM), decision trees, linear regression, deep learning neural networks and support vector regression (SVR).

However, the performance of these models significantly varies from place to place based on the required scale, environmental conditions, data, and others. As a result, Chen et al.(2017) and Mohamed and Reza (2021) and Shano et al. (2020) all agree that conducting comparative studies in specific areas is critical.

2.4.4.1 Vector Support Machine (SVM)

The SVM was first created for classification applications in the early 1990s, and later extended its use to regression analysis (Lin et al., 2017). The SVM performs classification tasks by employing classifier functions that may create hyper planes in multidimensional space, allowing distinct groups of training data to be separated (Ayalew, 2021).

The SVM was used to analyze landslide susceptibility, and its prediction ability was found to be superior to that of traditional approaches (Chen et al., 2017; Kanungo et al., 2006; Lin et al., 2017; Mohamed and Reza, 2021). A fitting kernel function, such as, polynomial (PL), a sigmoid, a radial basis function (RBF), a linear (LN), is used to transfer the SVM's input vector into a Feature space with a higher dimensionality.

2.4.2.2 Random Forest (RF)

The RF method is a type of ensemble learning generating many classification trees that are aggregated to compute a classification. The RF is a classification algorithm that based on multiple tree predictors. For landslide susceptibility mapping, the RF is a prominent machine learning approach (Chen et al., 2018).

RF is the preferred method by many researchers due to its resistance to keep over learning. It also avoid over-fitting since it resists growing many number of RF. Data in RF algorithm does not need to be transformed, rescaled, or modified. Also it has capability of predictors that are resistant to outliers and correctly manage null values (Mohamed & Reza, 2021). However, even if RF is popular in classification, it hidden patterns in large data.

2.4.4.3. Logistic regression (LR)

This method is the most practiced multivariate statistical method applied in a spatial landslide susceptibility prediction (Chen et al., 2018; Lin et al., 2017). This method predicts a binary response parameter like absence or presence of landslides by continuously scaled and predictors.

Logistic regression method can be applicable using continuous or discrete or combination of both. This is the main advantage of this method. As a shortcoming, this method cannot identify the influence of different classes on landslide occurrence (Shano et al., 2020).

2.4.4.4. ANN Learning Algorithm

Artificial neural networks are generic non-linear function approximators that attempt to mimic the parallel-information processing features of the human brain it's been used a to various applications in different subject areas, such as pattern recognition and classification (Neaupane and Achet, 2004). It was applied to modeling non-linear multivariate problems in earth science fields, such as landslide susceptibility studies (Ermini et al., 2005; Neaupane and Achet, 2004; Senise et al., 2013; Won, 2003). It works on the supervised learning algorithm principle, in which a given output is compared to a predicted output. Thus, through training procedures, learning algorithms fit neural networks to the data and predict the output over the entire area.

2.4.4.4.1. Structure of ANN

As discussed in previous sections, ANN is a data-driven multivariate statistical method based on organized inputs and observed outputs in order to train the network. Feeding such basic data sets to developed ANN algorithms, the model forecasts the required outcomes from input over the study area. While training ANN models, various GIS thematic layers (geological, hydrological, geomorphological, and anthropogenic factors) have been used to train ANN models as input datasets, in addition to the landslide inventory as an output dataset.

There are different ANN network structures developed for training the ANN model, such as multilayer perception (MLP) and probabilistic neural networks (PNN). The MLP network is the most widely used ANN in landslide susceptibility studies (Ermini et al., 2005; Lee et al., 2004), where basic processing units called neurons are arranged in a layered feed-forward topology. Since it is a multi-layer structure, it can separate data that is non-linear, such as landslide conditioning factors, because it is multi-layer. There are also PNN classifiers developed to model various earth science applications Ermini et al , (2005), which primarily lack the capability of a back propagation algorithm to achieve a minimum error between observed and predicted output values by adjusting weights.

Various MPL topology structures were developed and applied for landslide susceptibility studies (Neaupane and Achet, 2004; Senise et al., 2013; Won, 2003). The MLP network may have two or more layers, such as input, hidden, and output layers, where each node in the network is interconnected to the nodes in both the preceding and following layers. In its simplest network, MLP consists of only two layers: input and output layers, but the network becomes complex with the addition of internal hidden layers. In these layered structures, the input layer represents nodes of the independent variables, (such as slope, DEM), while the output layers are the dependent variables that represent output data (landslide sample).

2.4.4.4.2. Advantage of the ANN

As discussed in Neaupane and Achet(2004), the ANN method is popular in landslide susceptibility due to its modeling capability of nonlinear and complex relationships between landslides and conditioning factors. This nonlinear function learning capability makes the

problem of clustering landslide prone areas easy. Regarding statistical methods, the artificial neural network has a lot of importance where either the absence of correlation between variables or the distribution of input variables does not require any statistical assumptions (Lee et al., 2004). Accordingly, the ANN method is applicable even when conditioning factors are not attaining a normal distribution approximation and are strongly correlated variables. Additionally, with uncertain and noisy spatial data, ANN can predict good results. As assured by susceptibility studies, ANN can achieve accurate results even in data-limited conditions with fewer training samples.

2.4.4.4.3. Weight Determination

(Lee et al., 2004) noted that there are no common values for weight and rating for causative factors of the landslide. In a landslide-susceptibility analysis, determining the weight and rating value is critical, as the weight and rating should be based on objective assessment rather than subjective expert judgment. As mentioned in (Ermini et al., 2005; Melchiorre et al., 2008), various techniques have been applied to weight determination of landslide causative factors and applied to landslide susceptibility mapping. In many landslide susceptibility studies (Mohamed and Reza, 2021; Neaupane and Achet, 2004), the ANN approach was identified as the promised method since it is independent of expert subjectivity and reduces noisy factors that affect model performance.

2.5. Multi Temporal Interferometric Synthetic Aperture Radar(MTInSAR)

In this section background of SAR remote sensing and principle of InSAR slope instability modeling discussed.

2.5.1 Synthetic Aperture Radar (SAR)

(SAR) is a microwave imaging system that uses a radar antenna mounted on an airborne or satellite-based platform to transmit and receive electromagnetic (EM) waves (Bu et al., 2000; Samsonov and Oreya, 2012; Goudarzi, 2013). It operates in the microwave EM spectrum range of 1 mm to 1 m. The capability of transmitting their own energy makes SAR sensors observe the earth's surface day and night. Their operation in the lower frequency and longer wavelength portions of the microwave spectrum makes them penetrate clouds and operate irrespective of

whether conditions prevail. Some of the most common SAR satellite sensors used in various earth science studies are Sentinel 1A, Envista, Radarsat1_2, TerraSAR X, COSMO-SkyMed, and ERS1_2 (Goudarzi, 2013).

Based on the intended purpose, the imaging radar sensors emit signals over a specific portion of the electromagnetic spectrum and operate at different microwave frequencies and wavelengths. The SAR sensor's main frequencies and wavelengths are: X-band (9.6GHz, 3cm), L-band (1.3GHz, 23.6cm), C-band (5.3GHz, 5.6cm), and P-band (0.44GHz, 74cm)(Goudarzi, 2010; Greif & Vlcko, 2012; Zhang et al., 2019; W. Zhu et al., 2013). These specifications show that the X-band exhibits higher spatial resolution and the P-band have greater penetration power (Nassir, 2019). Besides, there are four SAR signals transmitting and receiving orientations where the electric field associated with each radar pulse lies in a specific plane (Nassir, 2019). The simple polarizations are vertical (VV), where the phase signal is transmitted and received in the same vertical plane, and horizontal polarization (HH), where transmitted and received phase signals are oriented through the horizontal plane. The other two polarizations; (HH, HV) or (VH, VV), operate in dual orientation mode. Currently, complete-polarization systems are in uses which are designed to transmit two orthogonal polarizations and record both received polarizations (HH, HV, VH, and VV). (Nassir, 2019) also highlights that SAR systems that are equipped with complete polarization can provide a complete scattering matrix to extract substantial information from the image. It is also better to separate surface scattering from dihedral scattering in more vegetated areas than single polarization systems.

2.5.2. SAR Satellite Missions

There are different satellite missions launched for SAR remote sensing applications. Organizations launched satellites with SAR sensors for Earth's surface monitoring. These include ERS1/2, ENVISAT, and Sentinel-1 by the European Spatial Agency, ALOS by the Japan Aerospace Exploration Agency, RADARSAT by the Canadian Spatial Agency, and COSMOSkymed by the Italian Spatial Agency (Samsonov & Oreye, 2012). They are designed to follow sun-synchronous near-polar orbits that are slightly inclined with respect to Earth's meridians. These satellites orbit the Earth at an altitude ranging from 500 to 800 km above the Earth's surface. The full description of radar satellites is presented in Table 2.1

Table 2.1:Description of Radar data set for interferometry (ESA, 2012)

Satellite Mission	Life Span	Band	Revisit Time [Days]	SwathWidth [Km]	Resloution [M]*
ERS-1	1991-2000	C	35	100	30*30
ERS-2	1995-2011	C	35	100	30*30
ENVISAT	2002-2012	C	35	35 5-400	(30-150) x (30-150)
RADARSAT-1	1995-2013	C	24	24 45 – 500	(8-100) x (8-100)
RADARSAT-2	2007-present	C	24	18 – 500	(1-100) x (1-100)
SENTINEL 1A	2014-present	C	12	20-400	(5-20) x (5-40)
ALOS	2006-2011	L	46	30-350	(10-100) x (10-100)
TERRASAR-X	2007-present	X	11	10-100	(1-16) x (1-16)
COSMOSKYMED	2007-present	X	16	10-200	(1-100) x (1-100)

2.5.3. Slope Instability Detecting Using Interferometry SAR Technique

INSAR is a technique for measuring ground surface subsidence, structural deformation, and slope movement by combining two or more SAR scenes over time (Bhattacharya et al., 2015; Greif and Vlcko, 2012; Mengistu et al., 2019). It is based on the superposition of two images to generate a new image that displays changes in topography and ground levels with millimeter-level precision. That means InSAR processing aims to combine two SAR scenes of the same area, acquired at different periods of time (Borghero, 2017).

2.5.4. Interferometric Phase Measuring Principle

Synthetic Aperture Radar (SAR) is a microwave imaging system that uses a radar antenna mounted on an airborne or satellite-based platform to transmit and receive electromagnetic (EM) waves (Borghero, 2017; Goudarzi, 2010; Nassir, 2019). The standard InSAR processing technique combines two SAR scenes of the same area, acquired at different times. Calculating the difference in phase component ($\Delta\phi$) of the reflected signal is known as radar interferometry,

and the image of the for all pixels is called an interferogram. The data is collected along the line of sight (LOS) direction, from the antenna to the earth's surface. If the effect of topography is removed, then it can provide an accurate measure of the change in elevation of the land surface. Because of the cyclic nature of the phase, it will only be known in 2π radians, which is called the wrapped phase. The process of estimating and adding the unknown correct integer multiple of 2π is called phase unwrapping (Borghero, 2017; Liu et al., 2019; Mengistu et al., 2019).

Most often, the measured difference in the phase of the two signals is the sum of six parts (Reeves, 2013).

$$\Delta\phi = \Delta\phi_{def} + \Delta\phi_{topo} + \Delta\phi_{orb} + \Delta\phi_{ip} + \Delta\phi_{atm} + \Delta\phi_n \quad 2.1$$

where $\Delta\phi_{def}$ is the phase change due to the deformation of the ground surface, $\Delta\phi_{topo}$ is the phase change due to topography, $\Delta\phi_{ip}$ is the phase change due to integer phase ambiguities, $\Delta\phi_{orb}$ is the phase change due to orbital errors, $\Delta\phi_{atm}$ is the phase change due to atmospheric phase effects and $\Delta\phi_n$ is the phase change due to random phase noise. The different components can be considered signal or noise in different applications; however for this study we are interested in the phase change due to the deformation of the ground surface as shown in Figure 2.2 below. $\Delta\phi_{def}$ is related to the deformation (Δd) by

$$\phi_{def} = \frac{2\pi}{\lambda}(\Delta d) = \frac{4\pi}{\lambda}(\Delta d) \quad 2.2$$

where λ , is the wavelength of the radar system. The noise components $\Delta\phi_{topo}$ and $\Delta\phi_{orb}$ must be removed and the noise components $\Delta\phi_{ip}$, $\Delta\phi_{atm}$ and $\Delta\phi_n$ must be mitigated in order to accurately determine ϕ_{def}

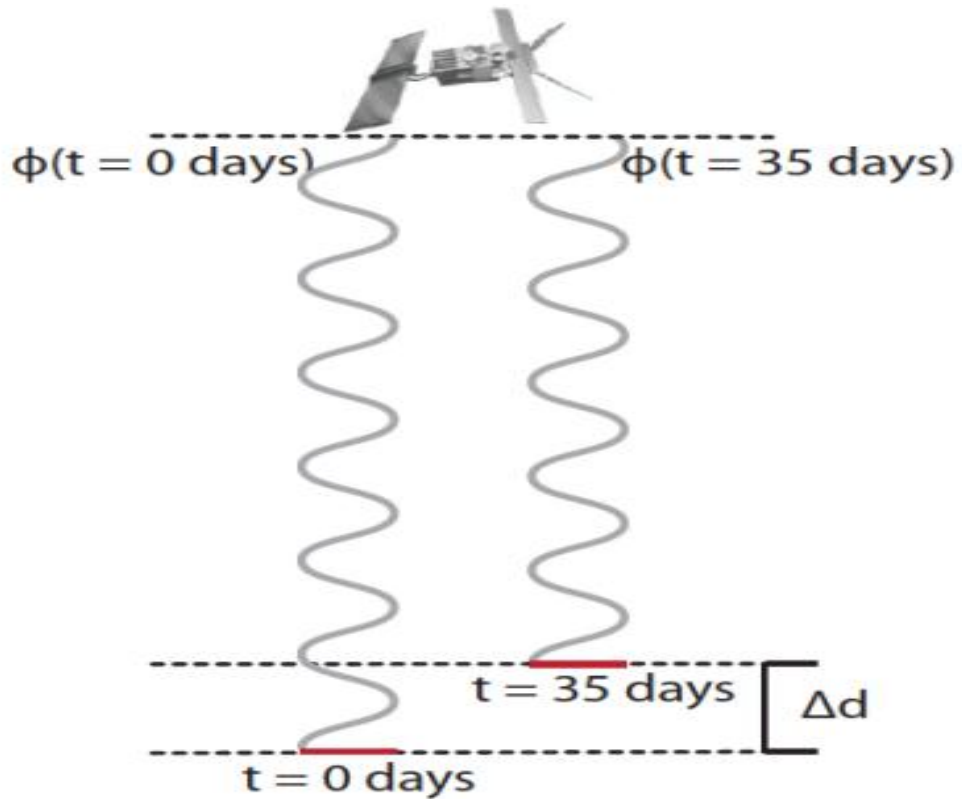


Figure 2.2: Principle of InSAR deformation measuring ; Source : (Reeves, 2013)

2.5.5. InSAR Slope Instability Monitoring Approaches

Slope instability can be modeled using various techniques. In this section various slope instability modeling approaches will be described.

2.5.5.1. Differential InSAR (DInSAR) Technique

It is the first technique to use radar data for monitoring land surface subsidence, such as landslides, earthquakes, and other geological instability. On its first attempt to estimate deformation rate, its capability was limited to using only two SAR image acquisitions, which led to the creation of a few interferograms (Jan, 2019). Only atmospheric and topographic errors were introduced to the interferograms. This technique uses different modes of computing to determine the deformation rate. The first one is the two-pass DInSAR technique, which uses an external elevation model to remove atmospheric errors. The other mode is the three-pass DInSAR technique, which determines deformation based on three images, where all images are paired to the same master image and differentiated to generate deformation without an external elevation model (Greif and Vlcko, 2012; Tantiaparp et al., 2013).

2.5.5.2.Multi Temporal INSAR techniques

MTINSAR is a technique developed so as to overcome limitations introduced in the differential interferometric synthetic aperture method of measuring deformation. The most common methods developed under MTINSAR approaches include the Permanent Scatterers technique (PSInSAR), Quasi PSI, Small Baseline Subset (SBAS) InSAR, and the Stanford Method for PSs (StaMPS) (Mengistu et al., 2019)

2.5.5.3.PS InSAR Technique

It is a pioneer in multi-temporal InSAR processing, proposed by the Polytechnic of Milan. In early 2000, this technique was introduced so that one could analyze multibaseline and temporal SAR data stacks of inteferograms. It enables us to get inteferograms over long spatial and temporal baseline acquisitions, in which the DInSAR technique failed. In the PS InSAR technique, there are algorithms to overcome atmospheric errors introduced to interferograms by topographic residuals through statistical filtering algorithms. This technique has been used by different researchers (Greif and Vlcko, 2012; Tantanuparp et al., 2013)to detect ground deformation due to geo-hazards such as landslides and volcanoes. Most studies have achieved good results in urban areas where permanent and stable structures like buildings and bridges are available.

Recently, the Quasi-PS (QPS) MTINSAR approach presented by (Perissin and Wang, 2011) has been promised capability in slope monitoring applications (Razi et al., 2018). The basic difference from the previous methods is that they utilize multimaster interferograms, looking for a more coherent one. Such multimaster inteferograms have the capability of extracting information from distributed and decorrelating targets (Parizzi et al., n.d.; Razi et al., 2018).

2.6. Previous Studies

GIS-based ANN and MTINSAR approaches have been successfully applied in landslide susceptibility and slope instability modeling studies. This section aims to highlight some similar researchers' works and draw current research directions.

Many researchers have confirmed the better capability of ANN for LS mapping. Won(2003)successfully applied the AAN method for landslide susceptibility in Korea using seven input parameters (slope, curvature, soil texture, soil drainage, soil effective thickness, timber age, and timber diameter) from a spatial database and a landslide training inventory from aerial photographs and field survey. Researchers Lee et al. (2004)applied ANN for weight determination of landslide slide conditioning factors in order to avoid subjectivity. They evaluated the efficiency the of LS results with and without introducing weights for factors. The study revealed that the accuracy of LS prediction can be increased through the determination of weights using ANN. Besides, it optimizes the model capability by identifying the importance of the factors.

Also, seeking better accuracy, two or more methods have been evaluated over the same area using the same dataset. Chen et al.(2017) and Fang et al.(2021) and Kanungo et al.(2006) and Thi Ngo et al. (2021) and Yang et al. (2020) and Pourghasemi and Youssef (2021) and A. X. Zhu et al.(2018) conducted comparative landslide susceptibility studies applying two or more techniques in order to test the best performed one over the same study area and data. For instance, in a research work by Youssef and Pourghasemi (2021), seven ML techniques such as, Random Forest (RF), Quadratic Discriminant Analysis (QDA) Support Vector Machine (SVM) Artificial Neural Network (ANN), Multivariate Adaptive Regression Spline (MARS) and Naive Bayes (NB) were applied for landslide susceptibility mapping using 12 causative factors and 243 training samples in an open source R and GIS environment. Their performance was evaluated by AUC results of, 93.0%, 91.6%, 95.1% , 91.8% and 89.0% for RF, ANN, SVM, MARS, NB, and QDA, respectively. This assures that all the models can be applicable for environmental planning since $AUC > 70\%$ is sufficient performance. The researchers also stressed that comparative studies are important since the performance of the models can vary from place to place.

Besides, various studies have been conducted on slope instability detection and monitoring. In this regard, there are a lot of researchers conducted using different methods and data sets. The researchers, Cusson et al. (2018) and Dai et al. (2018) and Fiorentini et al. (2020) and Jan (2019), successfully conducted the InSAR technique to detect slope instability (displacement) along different high-way corridors. Zhang et al. (2019) successfully used space borne InSAR to detect ground movement trends along the railway corridor. Their research reveals that the InSAR technique can monitor landslide-induced ground deformation to millimeter accuracy. Additionally, the InSAR approach has been used to other linear infrastructures (power lines, pipe lines, etc.) for monitoring against geo-hazards (Liu et al., 2019).

Some local researchers have successfully combined GIS and InSAR techniques to assess landslide hazard and landmass movement (Bhattacharya et al., 2015; Mengistu et al., 2019). Along the Ethiopian road corridors, there is some published research (Mulatu et al., 2011) conducted to assess slope instability and landslide hazard using GIS multicriteria and geological approaches. There are also some unpublished studies along the road corridors based on MCDM, geological and field-based geophysical approaches (Woldegiorgis et al., 2014).

In general, these empirical reviews revealed that advancement in model development and datasets acquisition is on track of change continuously. Current researcher interested to integrate the most two advanced landslide susceptibility modeling method for this study. ANN and MInSAR techniques have applied in such studies independently. Even if such methods were applied before, in current study they integrated with some optimization techniques.

CHAPTER THREE

3. MATERIALS AND METHODS

3.1. Description of the area

The current area is located in SW Ethiopia, SNNP, Semen Omo Zone, within Geze Gofa Woreda. The study area was selected following the main road corridors passing through Sawla-Bulki to Bedro, as well as Bulki to Laska. The area accessed from capital of Addis Ababa travelling to Wolayita Sodo, Sawla town and Bulki-Laska routes. As shown in Figure 3.1 the area bounded on the south by Oyda, on the west by Basketo woreda, on the north-west Melokoza to the west and DembaGofa to the east. Geographically, the study area is bounded approximately by UTM coordinates 243,000–251,300 m E longitude and 695,600–700,100 m N latitude and covers total area of 246 km². The area known with complex and rugged topography which falls under the main Ethiopian Rift Valley in the western margin. It forms a part in the Southern Ethiopian plateau and is bounded by the Rift from the west. The altitude over the study area shows significant change around a maximum of nearly 2600m (at north Bulki), the elevation drastically declines and reaches a minimum of 1200m above mean sea level (on the Irgina course) river.

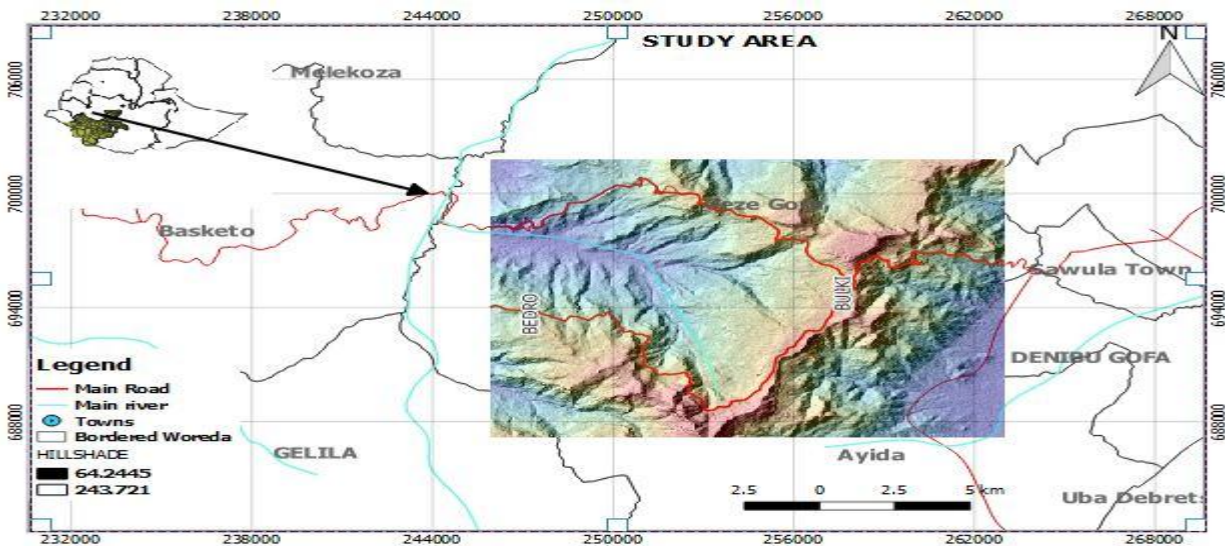


Figure 3.1: Location map of the study area

3.2.Drainage Condition

As the area gets quite excess rainfall surface and groundwater are quite abundant resources in the area. The Irigine River and Meto are the main rivers in the area, and many small rivers branch from them. Besides, the chained mountains in the north-eastern part of the area create favorable conditions for the formation of springs, which is a big challenge for the road infrastructure passing through such steep topography.

Such emerging springs that drain towards the roadside suggests the presence of a barrier at a shallow depth. Hence, the availability of excess water together with the steepness of surface morphology formed by colluvial deposits (silt, clay with some gravel) has created an environment where earth materials easily slide whenever triggered by water and aggravated by other anthropogenic factors. Overall condition of the drainage pattern has mapped in the Figure 3.2.

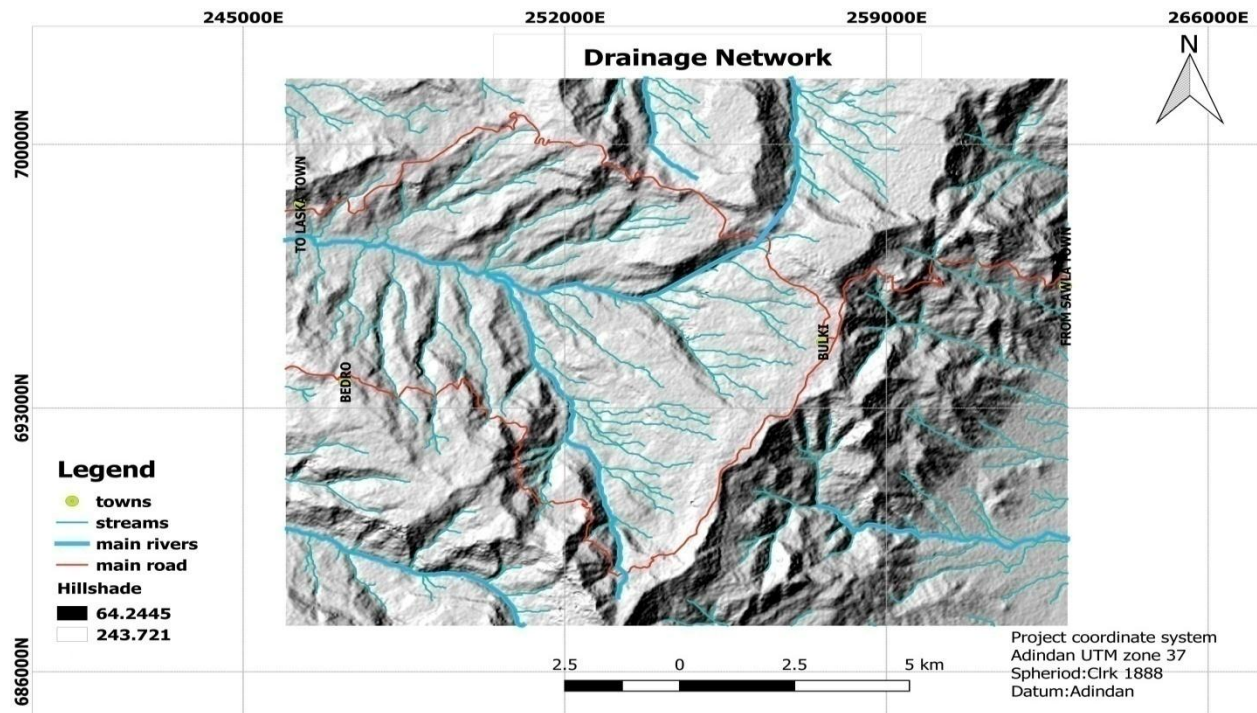


Figure 3.2: Drainage pattern of the study area

3.3. Climate Condition

There are five climatic zones in Ethiopia based on elevation, temperature, and rainfall variation. As a result, Wurch (> 3200), Daga (2300–3200), Woyna Daga (1500–2300), Kola (500–1500), and Barha (500) are the highest altitudes (Ermias, 2017). Therefore, the area is bounded to an elevation range of 2874–1244 m from sea level and falls into three climate zones: Daga, Woyna Daga, and Kola due to the complex and variable topography. The rain fall pattern in the area is bimodal, i.e., the area gets rain fall twice a year; the first one in March, April, and May and the other in July, August, and September.

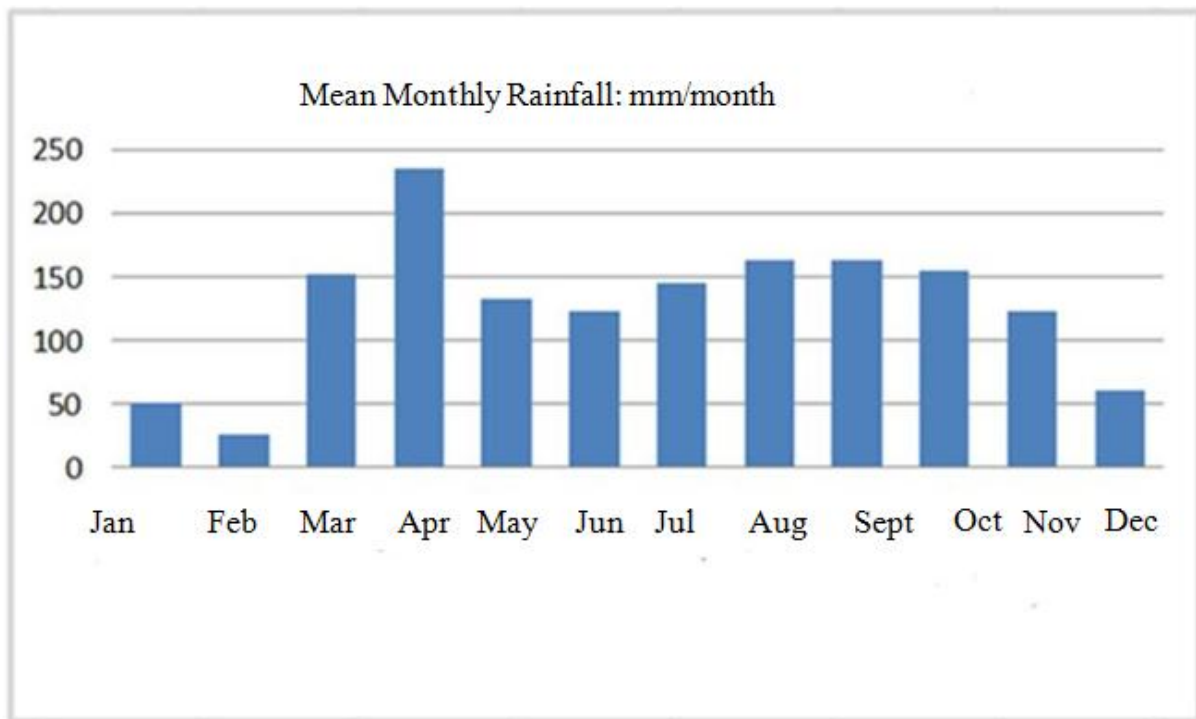


Figure 3.3: Mean monthly rainfall for 20 years (2001_2021):source:Ethiopia metrological agency

3.4. Geology

The research area is located in the south-western Ethiopian highlands and associated lowlands, just east of the Ethiopian Rift. The geology along the road corridors and various area are

primarily composed of a huge lava flows, representing the Jima basalts that have built up to an altitude of more than 2400m.

Colluvial deposits, consisting of variable sizes of rock materials (cobbles to boulder sizes) mixed with silt, clay, and gravel, are highly distributed along the road sections. Such materials are moved by gravity from higher grounds and cover the upper parts of the geological sections. These formations, which are found almost all over the road corridors, are poorly sorted and, due to their coarser grain sizes, highly porous. The colluvial deposits are very susceptible to landslides, particularly because they easily lose their shear strength when they occupy steeply dipping topographies, as whenever they get saturated.

3.5.Data Collection and Sources

In this research, landslide susceptibility and slope instability were modeled using various datasets from different sources. Accordingly, freely available satellite and other supportive datasets were collected and described in this section.

In this research, landslide susceptibility and slope instability were modeled using various datasets from different sources. Accordingly, freely available satellite Achieve and other ancillary datasets were collected and described in this section.

3.5.1. Satellite Imagery extraction

There are commercial and freely available satellite datasets extensively used for landslide susceptibility analysis and slope monitoring. For this research purpose, only freely available datasets such as sentinel 2A, sentinel1ASLC, DEM, and Google satellite map are used. Accordingly, ALOS PALSAR DEM was acquired to extract topographic and hydrological factors. The Sentinel two images and an online-based Google satellite map were used to extract land cover alternatively and NDVI. Besides, sentinel 1AC was captured to model slope instability. More information about the datasets is presented in Table 3.1.

Table 3.1: Satellite data sets description

Satellite datasets	Source	Format	Purpose
Sentinel 1AC data	Search.asf.alaska.edu	10*5	To detect slope instability
Sentinel 2A	Earthexplorer.usgs.gov	raster	To extract NDV
ALOS PALSAR	Search.asf.alaska.edu	raster	To extract topographic and hydrologic derivatives
Google-Satellite Map	http://www.google.satellite	vector	To capture landslide polygon and land cover
GPS point data	Handled GPS	.gpx	To collect new landslide locations and mark points

3.5.2. Ancillary Data

Besides the satellite Achieve data sets, secondary data sets were also collected for this study accomplishment. The ancillary datasets collected for this study include soil maps, topographical maps, and road networks. Also, landslide locations were collected as primary data from existing inventory and intensive field investigation. Different ancillary data sets with their respective sources are represented in Table 3.2.

Table 3.2: Ancillary Data description

Data type	Source	Format	Purpose
Soil map	Ethio GIS soil database	Vector	To extract soil classes
Road network	OPM	Vector	To prepare road proximity
Topographic map	EMA(EGA)	Vector	To extract features

3.6. Software Packages Description

To accomplish landslide susceptibility mapping, different open source software packages were used. QGIS utilized to prepare testing and testing data, which was used to train the landslide susceptibility model. Besides, QGIS is also applied to map thematic landslide conditioning factors. Final landslide susceptibility was modeled in QGIS, built in the R software environment. Overall compilation of the research paper was managed using Microsoft Office Packages (2010). Over all software descriptions are presented in Table 3.3 below.

Table 3.3: Softwares used description

No	Software to be used	Purpose
1	QGIS 2.18	To prepare thematic layers To model landslide grid analysis To prepare training and testing data
2	RStudio	To build and train ANN model To determine weight of conditioning factors To model landslide susceptibility
3	Google earth pro	To extract landslide polygons
4	Sarproz licensed software	To detect interferometric coherence and slope instability

3.7.General Workflow

This study was aimed in modeling spatial and temporal aspect of landslide susceptibility. The left side procedures in

Figure 3.4 represents ANN based LS mapping procedures. Right side Regard to temporal aspect, cumulative displacement was modeled.

Landslide susceptibility studies usually predict the potential occurrence of a slope failure, given a set of geo-environmental conditions and previous events (Shano et al., 2021). These datasets were basic inputs for the current model. Therefore, the methodology designed adopted comprised five major steps: input data acquisition, data sets preparation, extracting training and testing dataset, model training, and model validation and prediction phases.

Accordingly, twelve thematic layers were extracted from topographic, hydrologic, geological (soil and lineament/fault) and environmental schemas (land cover and NDV) and proximity (road, lineament and drainage). Thematic layers prepared from the topographic and hydrologic schemas were extracted from ALOS PALSAR DEM .These input layers were dem, slope, aspect,

plane and profile curvature from topographic schema and TWI and drainage from hydrologic schema. Besides, previous and recent inventory datasets were collected from Google earth scars supported with GPS and analyzed to prepare training and testing datasets. All these input datasets were prepared and analyzed in QGIS and ArcGIS environment.

In the third phase, training and testing datasets were extracted using landslide with in grid analysis in QGIS model builder environment. In the fourth phase, ANN model was developed and trained to the datasets up to achieving optimum root mean square error between predicted and observed output (landslide and non slide). Consequently the model outputs were compared based on various model structural arrangements. Neural networks contain two important elements: different neural interconnections and the types of algorithms used to set the weight of the connections. Each neural net arrangement has three layers: input-hidden-output layers. The input layer (independent variable) represents the landslide conditioning thematic raster training datasets; the hidden layer represents internal processing functions; output layer represents the landslide training datasets (response variable). In model validation stage, the model training and testing performance were validated using ROC and AUC. Finally, landslide susceptibility entire the study area was modeled using full datasets. The detail steps of the study presented in the subsequent sections.

The right side workflow in

Figure 3.4 presents the procedures followed to process the InSAR data. The slope instability work flow was achieved passing through four main steps: data set collection, preprocessing, processing and cumulative displacement detection.

There were preprocessing tasks which should be done, including Interferometric wide swath (IW) sub swath selection (TOPSAR split), orbital information and weather information retrieval, master image selection, and co-registration.

The next important preprocessing was providing orbital information to the datasets acquisition. There are three orbital data acquiring options; precise, restitute, and built-in, where precise orbital data is the most accurate. Precise orbital information is recommended since it determines the quality of the whole processing, such as co-registration and InSAR processing (Braun,

2020b). Accordingly, precise orbital information is provided for 20 acquisition positions using sarproz software. Co registration is also important step used for georeferncing or aligning the corresponding pixels between the master and slave images using the application of an orbital file or DEM (Braun, 2020b). That means it creates aligned stacks of images from which phase-exploiting is possible. Other operation in this phase was preliminary geocoding SAR images using orbital datasets and DEM. Following the preprocessing, main InSAR processing were analyzed including inteferogram generation, interferomeric coherence estimation and PSC analysis. These analyses were conducted in sarproz software environment and described in detail in the subsequent sections.

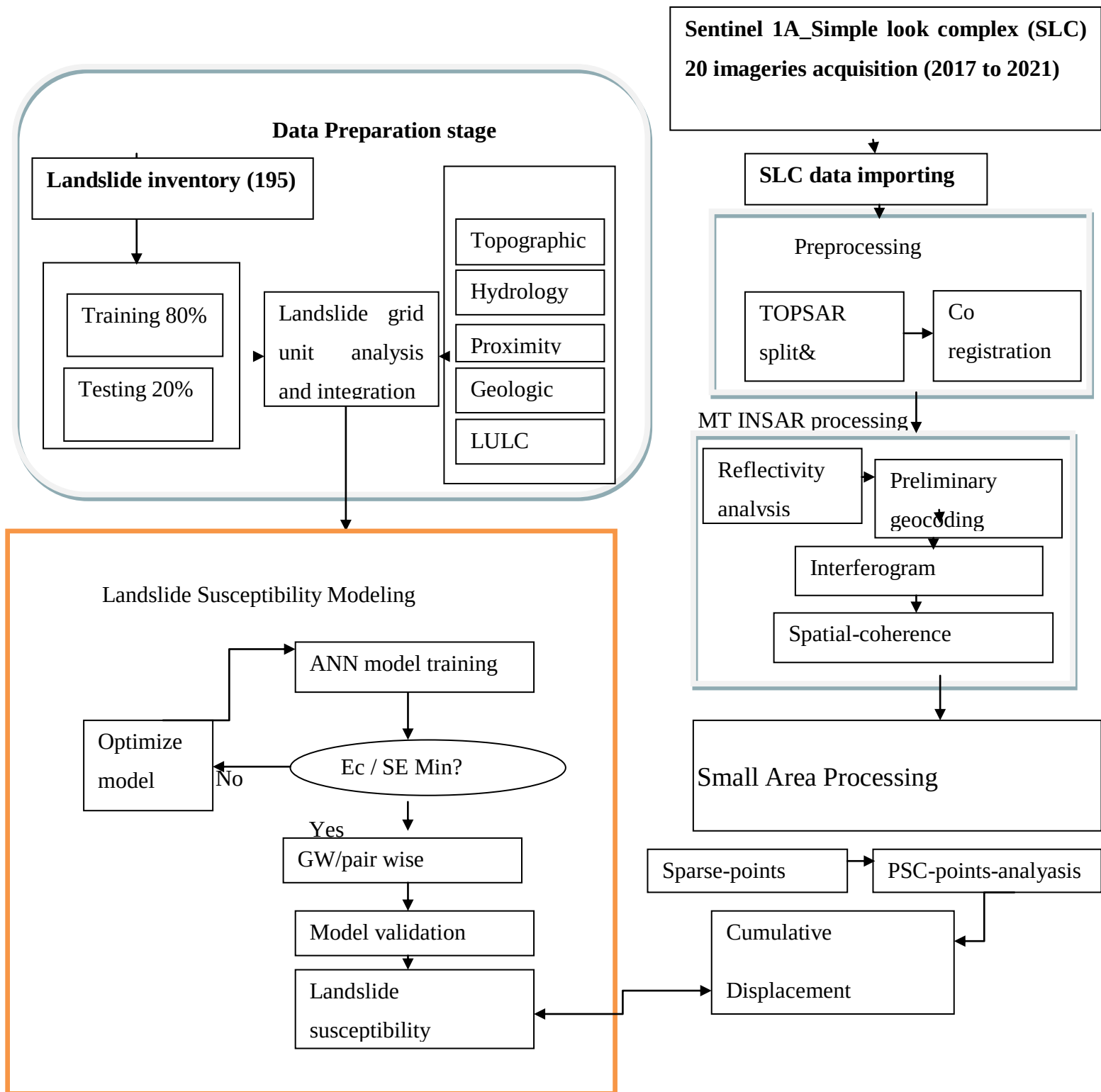


Figure 3.4: Work flow of the research

3.8.Landslide Inventory Mapping and Thematic Layers Preparation

Landslide inventory and different landslide conditioning thematic layers are basic data sets for landslide susceptibility mapping. In this study, landslide polygons and various slide deriving factors were prepared for this purpose.

3.8.1. Landslide Inventory Mapping

For GIS-based ANN landslide susceptibility modeling, landslide inventor (location) data is the backbone of the model. Therefore, the first step in ANN-based landslide susceptibility analysis is preparing a landslide inventory, which is used for testing and training the model. Accordingly, from previous landslide evidences, field survey investigation, and Google Earth scars, a total of 195 landslide polygons were captured for this research purpose. Area statistics shows that maximum, mean and minimum landslide polygon covers $406m^2$, $6995.7m^2$ and $657004 m^2$ areas respectively.

Among the inventories, most of the slides were collected following the road corridors that pass through steep topography. Besides, following the landslide event that incidences on September 11, 2021, many slides were collected from different sites in the area. These occurred due to the heavy rainfall incidence on 11, September, 2021. These slides were the worst events in the region, which brought damage to farm lands and property and forced people to leave their settlements. Around 20 recent slides that damaged large cultivation and settlements, property, and human lives were recorded from the Bulki-Tsire Keble region. Also, in the Yongi area of the region, 20 landslides, which mainly damaged cultivation lands, were recorded using handheld GPS. Following the geological and hydrological effects, cultivation practices and road construction along the slope terrain have made the region vulnerable to landslide events. Besides, the remaining slides were collected from various parts of the area, such as river corridors. The existing landslide distributions are presented in Figure 3.5 below.

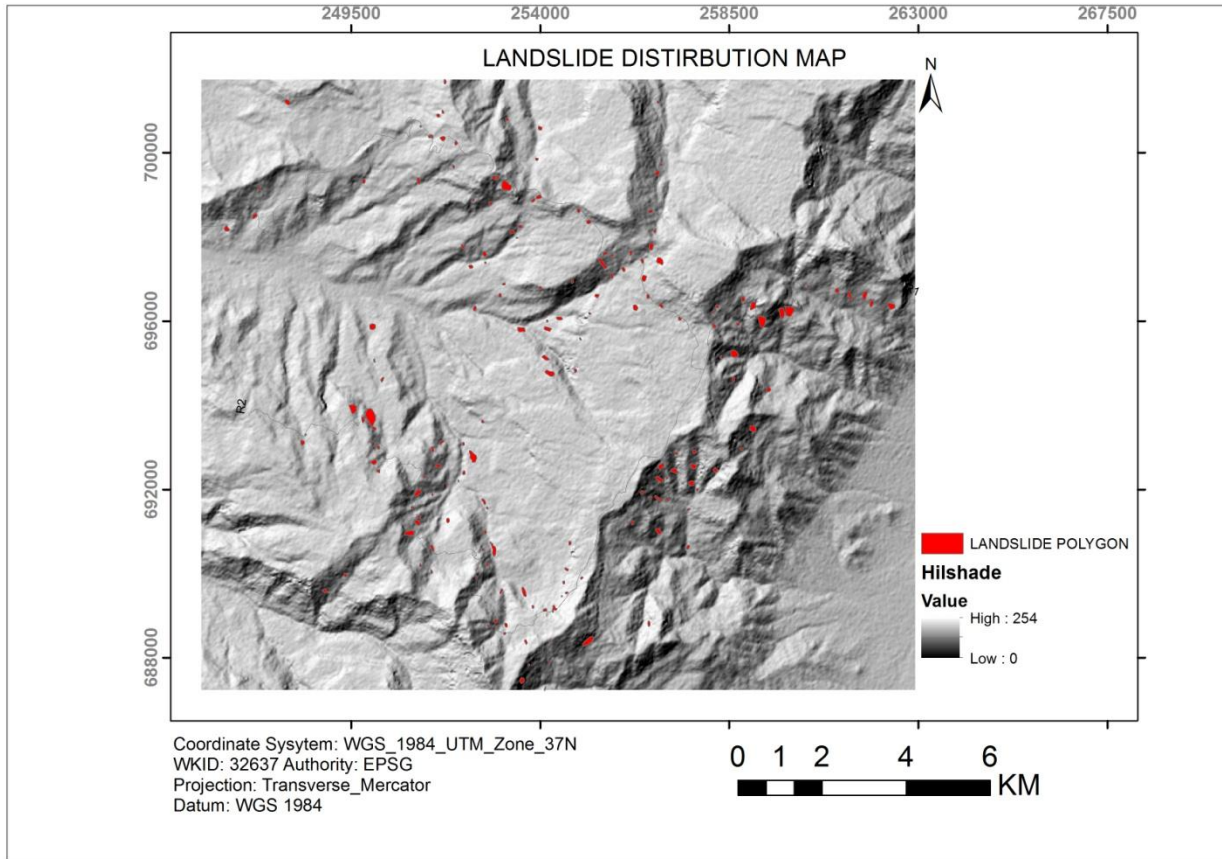


Figure 3.5: landslide distribution in the study area

3.8.2. Landslide Susceptibility Conditioning Factors Mapping

For landslide susceptibility analysis, there is a need to prepare thematic input data sets. Based on the previous studies and study area conditions, different landslide deriving factors have been identified from various thematic schemas such as, topographic, hydrologic, geological, proximity, environmental, and triggering factors.

3.8.2.1. Topographic Factors

Geomorphologic parameters are the main factors contributing to landslide occurrence. The important landslide controlling primary topographic (DEM) derivatives include: slope, altitude, aspect, profile curvature and plan curvature.

Slope is very often utilized in susceptibility studies due to the fact that land sliding is immediately associated with slope perspective. It is the one influential factor that directly affects soil formation,

erosion potential, soil water content and slope stability (Shano et al., 2021). The slope instability tendency increases as the slope angle increases, leading to higher shear stress. Altitude is another important factor regarding landslide occurrence because weather and climate conditions vary greatly at different elevations. It has an indirect impact on slope instability by affecting the rainfall amount and vegetation coverage. Furthermore, it is influenced by a variety of geomorphologic, geological, and meteorological factors such as lithological units, weathering, wind action, and precipitations (Mohamed & Reza, 2021). Also aspect been considered as a landslide controlling factor in many studies. It represents the direction of the slope face (0 to 360°) and affects the moisture content of the soil by reducing the sunlight to effectively heat the ground. Thematic layers of these topographic factors were presented in Figure 3.6.

Plane and profile curvatures are another important DEM derivative for landslide occurrences. They show the effect of slope shape and terrain morphology on landslide susceptibility processes. In plan curvature, positive curvature denotes convex, zero curvature denotes flat, and negative curvature denotes concave. It influences erosion processes by either diverging or converging diverging water during downhill flow (Senise et al., 2013). The plane curvature map of the area has shown in Figure 3.6.

The profile curvature is depicts the flow velocity, erodibility (negative values), and sedimentation (positive values) and controls the change in velocity of mass flowing down a slope. All the topographic derivates were derived from ALOS DEM with a resolution of 12.5m, which resembled latter by 20 m.

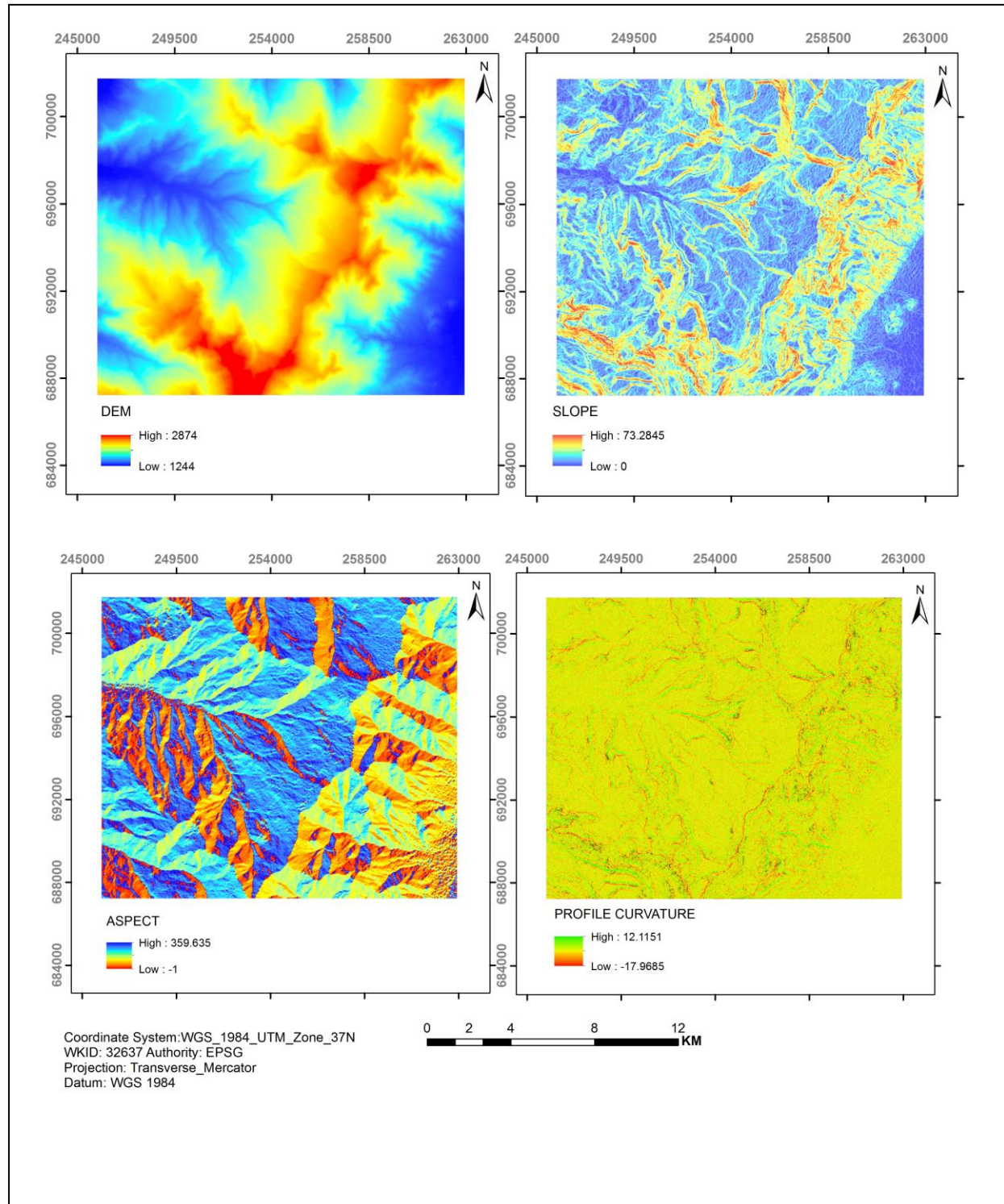


Figure 3.6: Topographic factors map

3.8.2.2. Hydrological Factors

Hydrology has a great role in landslide occurrences. Among the landslide influencing hydrological factors such as drainage density, ground water, and precipitation distribution, TWI and most often considered as landslide deriving factors. However, groundwater information has been used rarely in landslide studies due to data limitations. Due to uniform distribution in a specific study area, rainfall distribution (precipitation) parameters are rarely used in landslide studies, although they are the main landslide triggering factors. Accordingly, these two factors were skipped in this work and are represented by their derivatives, which indirectly influence landslide occurrence.

Drainage density and TWI are secondary DEM derivatives which facilitate conditions for landslide occurrence. Most often, landslides occur along drainages because erosion and excavation near rivers provide the accumulation of the necessary potential energy and the potential for landslide occurrence.

TWI is widely used parameter for modeling the runoff process (Althuwaynee et al., 2012; Chen et al., 2018). In general, it indicates the conditions of soil moisture, ground water flow and accumulation. It can be calculated using a slope gradient and catchment area. Built on a steady state assumption, for uniform soil conditions, the TWI was computed using Eq. 3.1, as follow.

$$TWI = \ln \frac{(\alpha)}{(\tan \beta)} \quad 3.1$$

where, α is cumulative upslope, $(\tan \beta)$ is slope angle at the point

3.8.2.3. Geological factors

Geological factors also play a great role in landslide conditioning and most often include soil types, lithology, and geological structures such as faults or lineaments and cracks. Since uniform lithology units are found in the area, only available soil categories and proximity to faults are used for this research purpose.

Soil categories based on various parameters (texture, erodibility index) have different roles in deriving landslide susceptibility. According to (Cherie & Ayele, 2021), soil based on their erodibility index value has linear effect on landslide occurrence. In this study, three soil types were extracted include Humic Alisol, Humic Nitosol and dystic Leptosol from EthioGIS soil database. Their respective texture types and erodibility values are Loam (0.12330), Loam (0.1273) and sandy loam (0.15).

3.8.2.4. Anthropogenic Factors

Anthropogenic factors are human activity-related factors and other living things that affect the environment. The anthropogenic factors are essential factors that bring the slope stability, which includes improper land use planning.

Land-use and land-cover have a significant impact on the occurrence of landslides. The areas that have good vegetation density can remain stable, whereas improper land-use planning leads to slope instability. In the current study area, unplanned cultivation activities are dramatically expanding under the steep terrain and road corridors.

Alternative land over map of the present area was extracted by using sentinel 2A imagery and real time Google satellite map. Since Google satellite maps are HR satellite images and under the control of the user, they have gotten reasonable results and suitable for extracting training and testing datasets. The land-cover was also prepared using Sentinel 2 imagery, but for the developed model analysis, Google satellite results found the best one. In addition to machine learning models preference, in the small area where the user is familiar with the study area, using Google satellite maps is more convenient. In particular, this is especially advantageous in rural areas where there are complex land cover types that generate similar signature problems (Mersha

& Meten, 2020; Meten, 2020; Shano et al., 2021; Wubalem, 2021). Accordingly, seven land cover classes were mapped such as agriculture, settlements, sparse vegetation, forest, range land, river and barren land.

NDVI also has a significant role in landslide occurrences. The NDVI is vital for immobilizing huge volumes of water and enhancing the lithological mass's shear capacity and soil cohesion. (Mohamed and Reza, 2021). NDVI was derived from sentinel 2A imagery with acquisition date Dec/27/2020 in QGIS environment using semi automatic classification plug in. For this purpose, spectral values of the sentinel 2 bands red band and near infrared utilized due to their green reflectance capability on that wavelength spectrum (Ayalew, 2021). It was extracted using the equation 3.2 below.

$$NDVI = \frac{B_{nir} - B_{red}}{B_{nir} + B_{red}} \quad 3.2.$$

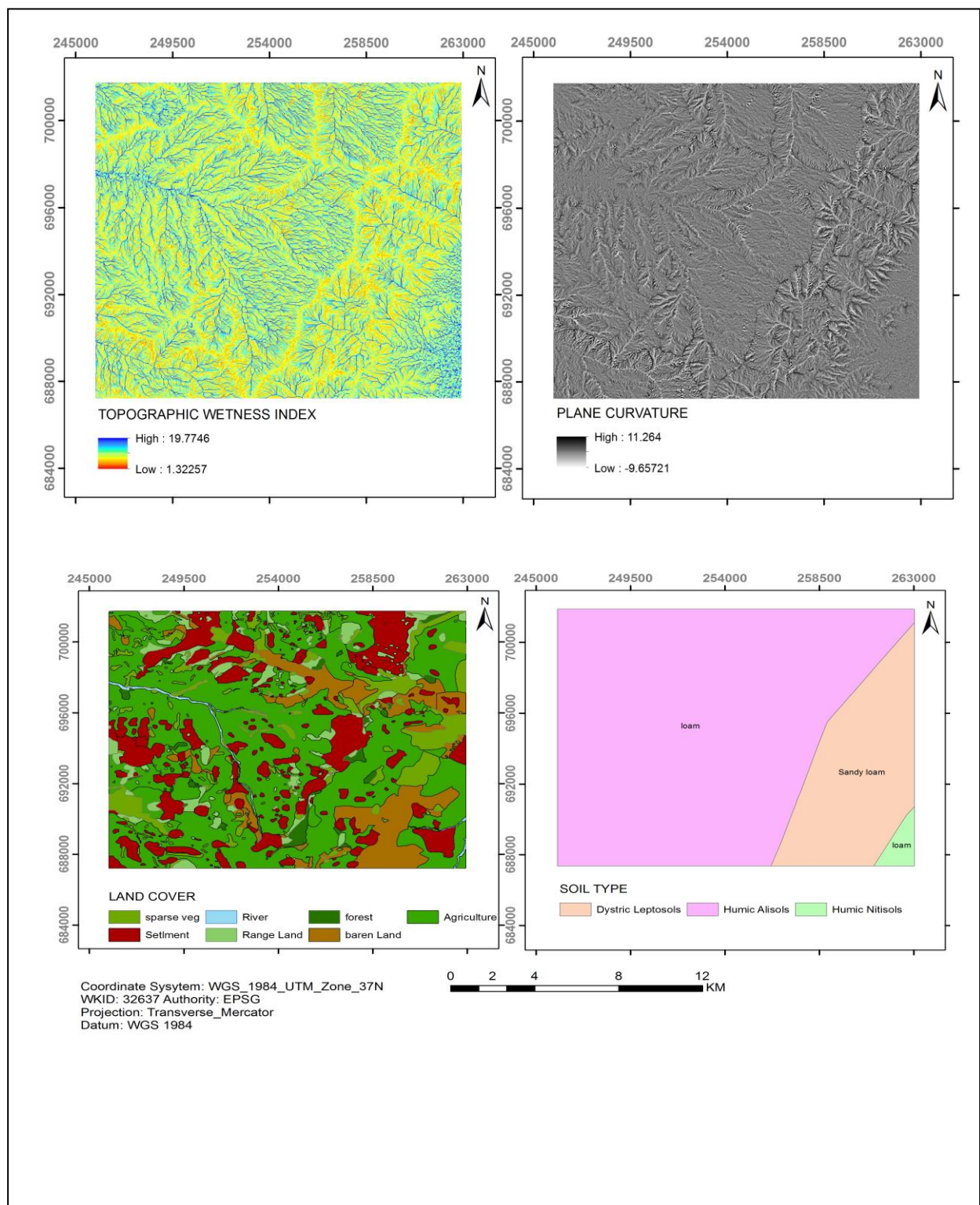


Figure 3.7: Topographic wetnes, plane curvature, landcover and soil maps

3.8.2.5. Proximity Factors (Location factors)

These are geographical factors linked to human development and environmental fragility that can be determined using distances to roads, faults, and rivers. These factors can also influence landslide occurrence in various circumstances. Landslides frequently occur along road corridors following construction excavations and human activities. In particular, this condition is particularly severe in mountainous terrain corridors. Drainage density is another proximity factor that contributes to landslide susceptibility. The area becomes more prone to landslide susceptibility as distance from streams decreases where erosion and water transportation processes increase.

Besides, the creation of structural discontinuities, which are tectonic breaks such as faults, folds, fractures, joints, and shear zones, is critical in weakening rock masses (reducing rock strength) and producing landslides (Shano et al., 2021). As a result, the distance from faults could be used to predict landslide susceptibility. The proximity factors, proximity to streams/rivers, and faults are extracted from the ALOS DEM. Various hill shade view angles (315,200,150,90) were used to extract lineaments and proximity to roads were extracted from the open street map shape file. They were all mapped to the minimum to maximum distance range as presented in Figure 3.8.

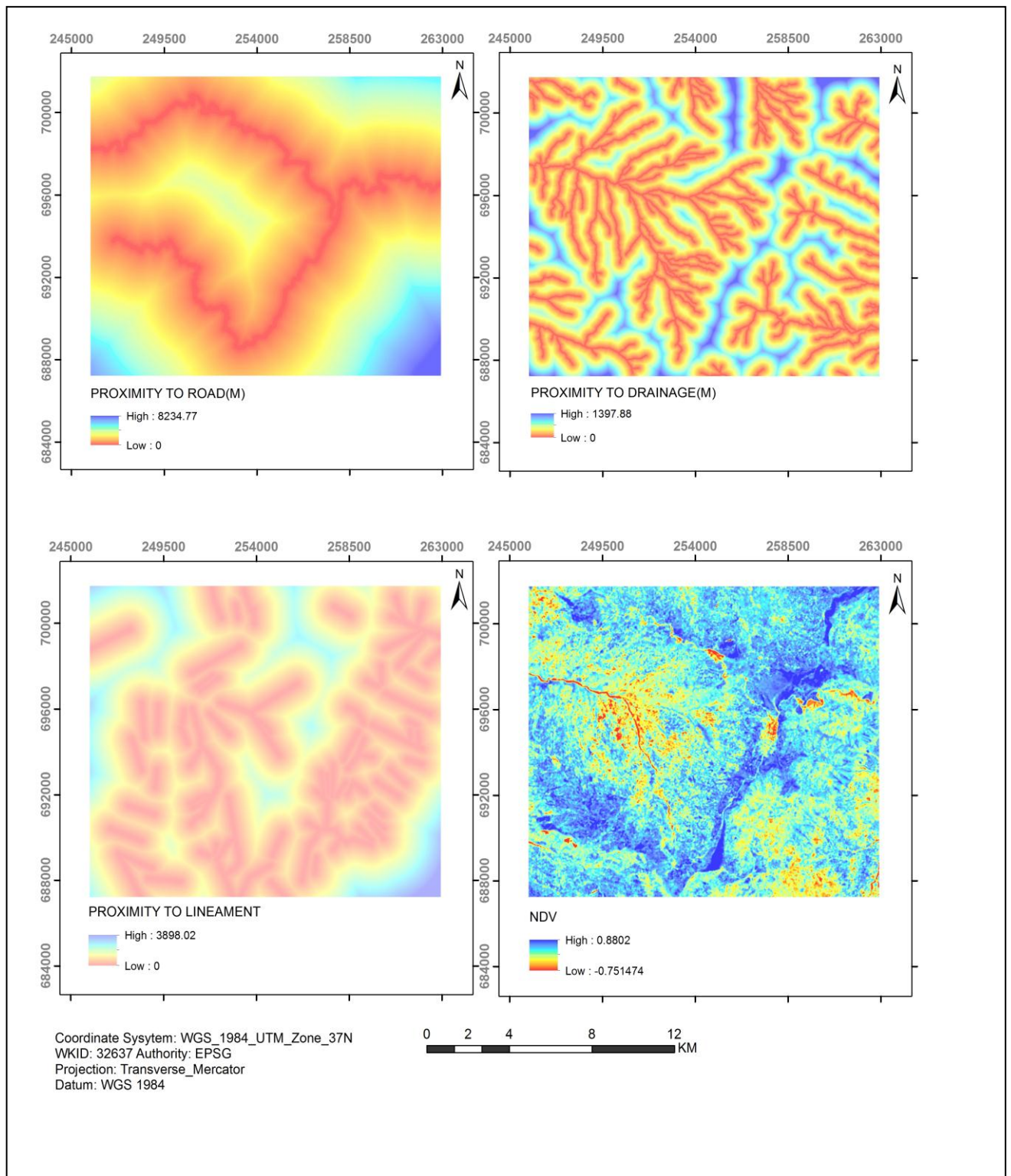


Figure 3.8: Vegetation and proximity maps

3.9.Dataset preparation for Interferometry Analysis

There are different SAR data retrieval sensors which provide time series datasets for InSAR processing. For this purpose, such as COSMO-SkyMED, sentinel 1A, TERRASAR-X images and others, however, due to some inconveniences in getting such datasets, current research is limited only to sentinel 1A as it is freely available and has global coverage. Accordingly, 20 S1A SLC data sets were retrieved from descending orbit and VV polarization mode. The datasets were acquired for the temporal period 2017 to 2021 with the acquisition parameters including incidence angle of 39.45, IW tracking mode with 12m spatial resolution, and an orbital path of 1571. The appendix 1 represents over all description of the Sentinel 1A datasets.

The Figure 3.9 below presents geometrical and statistical information about the images. The figure to the left presents the statistical distribution of the datasets graphically, such as normal baseline, acquisition data, temperature condition, and Doppler centroid. The right side figure shows the strength of the full graph coherence for consecutive dataset pairs.

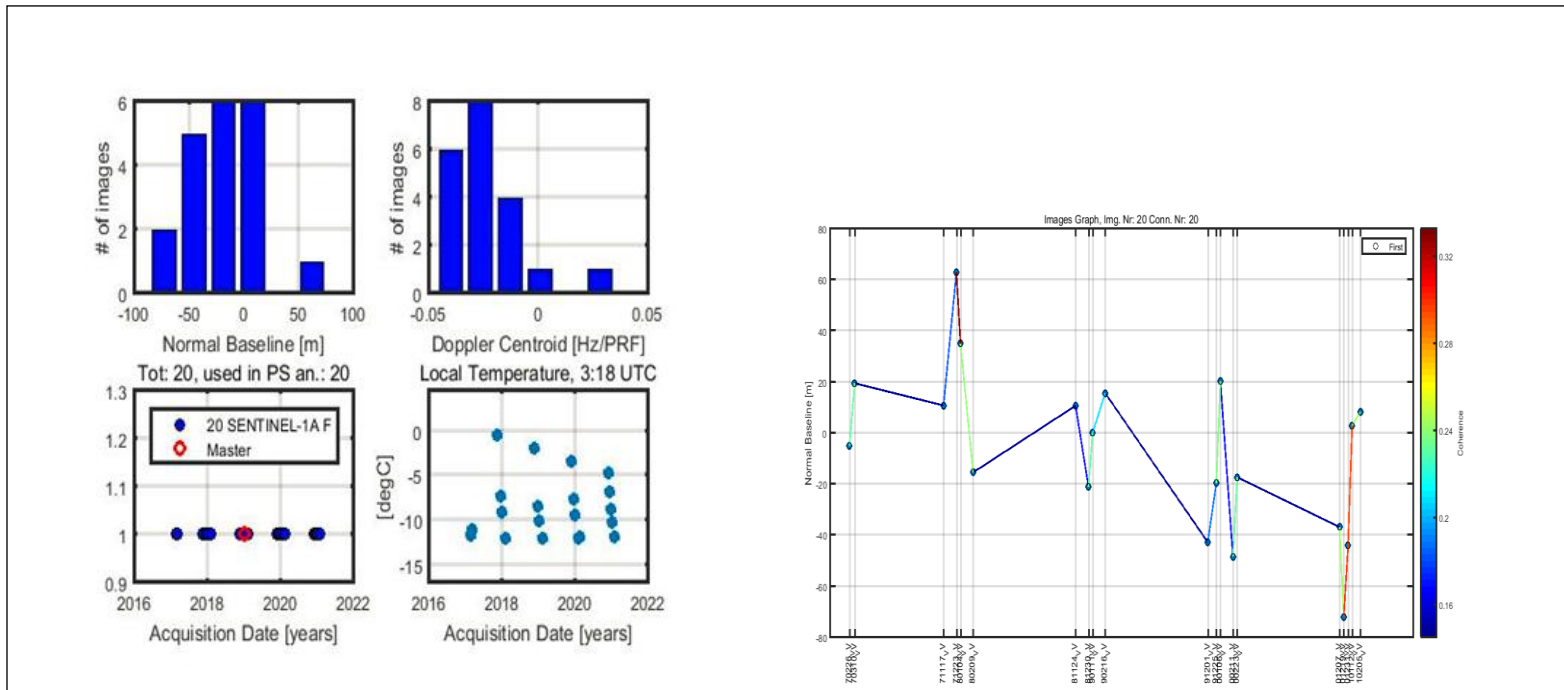


Figure 3.9: Statistical description of the acquired Sentinel dataset

3.10. Data Analysis

Before proceeding with landslide susceptibility modeling, the entire thematic layer should be in a compatible (common) format, projection, and cell size. Accordingly, all thematic layers in vector format, such as soil types and road networks, were converted to raster format since the model is raster pixel based. Also, all thematic layers were scaled and resampled to a common pixel size of 20m. This is to compensate for factors with coarse resolution, such as soil and road network. Finally, all the input layers assure that they are in the common projection system of the UTM 37N zone.

3.10.1. Extracting Training and Testing Landslide grid units

As mentioned in the previous section, grid cell terrain units have been mentioned as one of the landslide susceptibility mapping units. Grid cell terrain units split the region into uniform areas of predetermined size and shape (typically squares) to which each landslide inducing factor is given a value. That means landslide polygons intersect with thematic raster pixels from which landslide grid cells can be extracted to prepare model testing and training datasets.

Predicting models such as ANN need training and testing datasets in order to model LS maps. Preparing for testing and training datasets requires two basic datasets called landslide inventory and thematic raster layers of landslide initiating factors. As described in section (3.4.1), 195 landslide were prepared to prepare training and testing datasets. For this purpose, the landslide inventory dataset was divided into testing and training datasets, where 80 percent (156) and 20 percent (39) were used for training and testing model performance, respectively. In addition to landslide events, landslide conditioning factors are the important data sets for landslide susceptibility analysis. Consequently, 12 thematic conditioning factors were prepared and intersected with landslide polygons to extract landslide grid cells.

Multivariate machine learning algorithms like ANN model landslide susceptibility based on binary classification; 1 and 0 each represent landslide occurrence and non-slide, respectively (Mohamed and Reza, 2021; Senise et al., 2013; A. X. Zhu et al., 2018). Accordingly, a total of 1482 binary points were extracted for building the model, of which 225 represent landslide areas and 1257 non landslide areas. Similarly, 448 non-landslide (zero) and 65 slide pixels were extracted from the 39 testing datasets based on landslide grid unit analysis in QGIS environment.

Based on the nature of the dataset, there are continuous raster pixels such as elevation, slope, curvature, TWI, and categorical raster pixels such as land cover, aspect, and soil. Therefore, for training and testing datasets, the mean and mode of the raster values were extracted for continuous and categorical raster cells, respectively. Finally, landslide (1) and non landslide (0) pixels were generated to train the model and validate the dataset.

3.10.2. Training Artificial Neural Network Model

The training phase is the first step of the ANN application in modeling landslide susceptibility as a function of different network structures and classifying algorithms. ANN is the refined method for forecasting landslide susceptibility, providing training and testing data sets of independent and dependent inputs.

Neural networks contain two important elements: various types of neural interconnection arrangements and the types of algorithms used to set the strength of the connections. Through this structural arrangement, the outputs of one node (neuron) are fed to another neuron in the succeeding layer or to the same neuron and other neurons, which may or may not allow the outputs of one node to be feedback to other nodes in the preceding layer or to the same node. This structural arrangement can be either unidirectional flow or bidirectional (back and forth) flow of signals, which are called feed-forward networks and recurrent network structures, respectively. Various supervised algorithms distinguish a number of neural networks and determine the weight of the inter node connections.

Each neural net arrangement has three layers: input-hidden-output layers. The input layer (independent variable) represents the landslide conditioning thematic raster training datasets; the hidden layer represents internal processing functions; and the output layer represents the landslide training datasets (response variable). Figure 3.10 clearly shows network arrangements with thematic inputs, one hidden layer, and a training output layer that represents slide and non-slide binaries (0, 1). As input training dataset, 12 independent variables from topographic, hydrology, proximity, geological, land cover, and vegetation index factors were used in this study. Including categorical classes for land cover, aspect and soil a total of 26 input training

datasets were used for model training. In other hand, training datasets containing the presence and absence of landslide events are used as output training datasets.

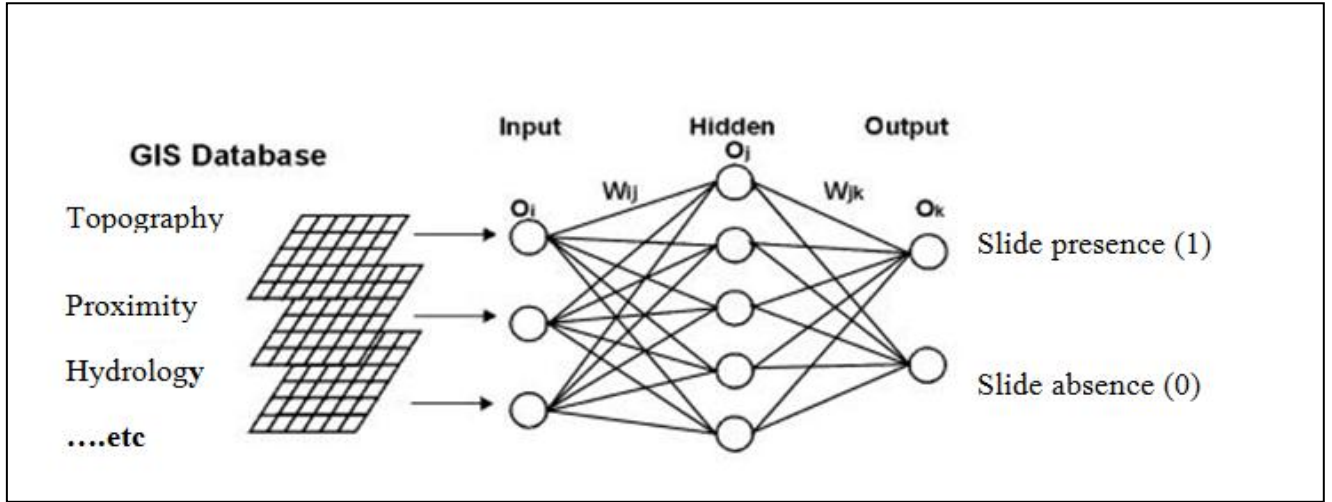


Figure 3.10: Modified Neural Network model structure: (Lee et al., 2004)

The model trained itself to classify grid unit pixels in either the presence or absence of landslides, which are found in binary form as 1 and 0 respectively. In order to train the model, the training datasets should be numeric data types and scaled to the range between 0 and 1. Accordingly, nominal (categorical) training inputs such as land cover, aspect, and soil were converted to numeric data format and all inputs were normalized between 0 and 1 in the R software environment. The seven land cover classes were assigned by numbers 10, 11, 12, 13, 14, 15 and 16 for agriculture, settlement, sparse vegetation, forest, range land, river and barren land respectively. The aspect classes were also categorized into eight classes in which letters, 'a' b, c, d, e, f, g and h were assigned for aspect ranges 0° - 45° , 45° - 90° , 90° - 135° , 135° - 180° , 180° - 125° , 125° - 270° , 270° - 315° and 315° - 360° degree respectively. Finally, the three soil classes were assigned by letters M, N and P for Dystric Leptosols, Humic Alisols and Humic Nitisols respectively.

3.10.3. Weight determination strategies

The hidden and output layer neurons process their inputs by multiplying each by the associated weights, summing the product, and afterwards computing the sum with a non-linear transfer

function to give an output. Synaptic weights, w_{ij} between neurons i and j , determine the connections between neurons. In general, the higher the value of w_{ij} , the more powerful the parameters connected with it. Positive values of w_{ij} show a positive relationship between the parameter and the degree of susceptibility, whereas negative values show a negative relationship.

$$net_j = \sum_i w_{ij} * o_i \quad 3.3$$

where w_{ij} represents the weight between node i and node j , and o_i is the output from node i

After the synaptic weights have been given to the neurons, an activation function is used to keep the amplitude of each neuron's output value between -1 and 1. The S-shaped sigmoid function is a transfer function that exhibits a balance of linear and nonlinear behavior, and is defined by Equation 3.4.

$$f(x) = \frac{1}{1 + e^{-x}} \quad 3.4$$

where, x represents weight summation at hidden layers

The back propagation procedure is used by ANN to train it, and it comprises of determining the weight values by evaluating the error between the response acquired through propagation and the known real value of the output. The goal of the back propagation algorithm is to change the synaptic weights during the training process so that the error function E approaches a minimum. As a result, there is a corresponding output k for each example presented during the training, which is compared to the reference output, O_k , yielding the error function:

$$E = \frac{1}{2} \sum_K (p_k - o_k)^2 \quad 3.5$$

Where, p_k represent predicted output and o_k observed output.

Finally, the model was trained applying four alternative NN input-hidden layers-output structure strategies. In the first cycle, the model was trained through 12-2-2 or (26-2_2 including categorical classless for aspect, soil and land cover) network structure using model default

weight values. Simultaneously, ANN was learned the second, third, and fourth training phases using 12_5_2, 12_10_2, and 11_15_2 or respectively. The representative model structures and learning results are attached in appendix 4.

Finally, the model was trained applying four alternative NN input-hidden layers-output structure strategies. In the first cycle, the model was trained through 12-2-2 or (26-2_2 including categorical classless for aspect, soil and land cover) network structure using model default weight values. Simultaneously, ANN was learned the second, third, and fourth training phases using 12_5_2, 12_10_2, and 11_15_2 or respectively. The representative model structures and learning results are attached in appendix 4.

3.10.4. Model Optimization

Because there may be some noisy elements that decrease the LS forecasting performance of models, selecting landslide conditioning factors is a key step (Lee et al., 2004). So, before choosing a final landslide susceptibility model structure, there is a need to identify the effect of landslide deriving factors on landslide occurrence.

The model performance was optimized by increasing internal learning capacity, filtering some inputs based on the generalized weight and pair wise analysis. During the first and second training phase, some factors were found less predictive and reduced from the final model analysis. Finally the model was trained based on the highly predictive inputs and hidden layers. Accordingly, the optimized model structure was once again adjusted, consist of 12-2-2, 12_5_2, 12_10_2, and 12_15_2 or 16-2-2, 16_5_2, 16_10_2, and 16_15_2 input-hidden-output NN structure. For further understanding, these NN structures and model training outputs are attached under the appendix 4 section.

3.10.5. Landslide Susceptibility Modeling

The end goal of the developed model above is not only to train the model for the training dataset but also to predict events throughout the study area. Thus, it is the most important step after training and validating the model on the target dataset.

In the model training phases, only pixels of the landslide polygons were extracted from each thematic raster, i.e., the entire raster pixels were not included during the model training stage. Thus, landslide susceptibility modeling requires integrating both trained models and entire raster pixels. For this purpose, the trained model results were combined with entire stacked raster cells so as to predict the event across the study area. Finally, landslide susceptibility was predicted using optimized model structure where some factors reduced due to their less significant role in landslide occurrence.

3.10.6. Multi Temporal InSAR Analysis

Interferometry synthetic aperture radar (InSAR) models earth surface displacement by exploiting the phase difference between two or more complex radar SAR measurements sensed from relatively different satellite positions in the same area. The SAR signal contains both amplitude and phase information.

3.10.6.1. Interferometric Coherence Estimation

Interferometric coherence determines the strength of the backscattered signal phases overtime, whether readable or not. Also, it reveals the impact of the decorrelation factors on the interferometric phase, which can bias proper parameter determination. The area under investigation can be subject to temporal reflectivity variations such as, decorrelation due to vegetation, human activities, and others. Therefore, interferometric coherence estimation is a crucial step to indicate the reliability of the interferometric phase for displacement and other parameter detection. An interferometric coherence map can be generated by averaging all the possible interferograms using the following formula (Perissin, 1988):

$$\gamma_{i,k} = \frac{E[Img_i Img_k^*]}{\sqrt{E[|Img_i|^2]} \sqrt{E[|Img_k|^2]}} \quad 3.3$$

where E denotes the expected value, the absolute value of $\gamma(i,k)$ is called interferometric coherence. Values of the coherence close to 1 indicate high correlation between the two images and thus a readable interferometric phase. Conversely, low coherence identifies decorrelation as a noisy and unreliable phase.

3.10.6.2. Multitemporal InSAR Processing

Multi-temporal InSAR processing techniques were developed to follow the limitations of basic InSAR processing (Razi et al., 2018). As explained early, PSI and QPSI are the main MTInSAR approaches, where the former is best for dealing in strongly coherent areas (urban areas) and the latter is developed to compensate for the number of PSC points in less coherent areas (rural areas). These techniques were developed on the premise that by utilizing long series of SAR images, it is possible to identify targets whose electromagnetic signature does not change throughout the dataset. Targets that are not affected by temporal or geometrical decorrelation, such as vegetation cover, steep slopes, or poor co-registration, can be revealed through the operation of the reflectivity strength of an averaged scene over time. For MTInSAR processing the optimal coherence and amplitude stability index (reflectivity strength) threshold value is 0.8 and above (Perissin & Wang, 2011). However, in this study, coherence and amplitude stability index threshold value of 0.65 is applied considered the above decorrelation and other effects.

For those PSC targets which remain coherent throughout the dataset (interferograms), the interferometric phase has been analyzed so that displacement and height can be estimated. But, these interferometry phases from respective interferograms consist of different contributing factors which affect the required displacement result. Therefore, there is a need for modeling and removing such biases from the interferometric phase. For this case, sarproz allows different analyses, such as APS processing for atmospheric correction and DEM for topographic phase correction (Gonnuru, 2018). Interferometric phase of the targeted point p along with contributing factors represented by the following equation (Perissin, 1988; Reeves, 2013).

$$\Delta\phi_{i,k}(p) = \Delta\phi_{i,k}^{flat}(p) + \Delta\phi_{i,k}^{height}(p) + \Delta\phi_{i,k}^{disp}(p) + \Delta\phi_{i,k}^{atmo}(p) + \Delta\eta_{i,k}(p) \quad 3.4$$

where, Indexes i, k denote interferometric couples, with k being the master image and i the generic image of the dataset. For each of the above biases, different measures were applied so that only the displacement phase remained. The term flat terrain was removed by applying orbital data. The s term, the topographic phase, was removed using DEM. The term "atmospheric delay" is neglected in the case of this research since its effect is small in small area processing. The last term $(p) i, k$, noise will be estimated from the model residuals, and it will tell us the

stability and reliability of the target at hand. Surface changes relating to all PSC targets account for the remaining variation in the inteferometric phase.

CHAPTER FOUR

4. RESULTS AND DISCUSION

4.1.ANN Model Training and Testing Results

During the NN training phase, 12 input variables containing 1482 training and 513 testing pixels was fed to the developed model. Four model training steps have been applied, altering model network structure, parameters, and filtering input variables. The model was trained up to achieve an optimum (minimum) root mean square error (cross entropy) between observed and predicted values by adjusting weight. Based on this preliminary model training result, the relation between covariates and the dependent (landslide) was determined. Besides, pair wise results were also generated as preliminary outputs before generalized weights determination. Finally, landslide susceptibility was modeled after achieving optimum model prediction and performance validation results.

4.1.1. Model Training Results

Thus, the outcomes of the learning phase are usually represented by error functions (such as the sum squared error or cross entropy error functions), which give a measure of how the network fits the training set of the observed data. As presented in Table 4.1, four learning steps were applied using various network structures. Consequently, learning error between observed and predicted outputs was achieved from which model structure with the optimum RMSE isselected.

Table 4.1: Model training results

Phase	Network structure	RMS
1	12_2_2 (26-2-2)	2.356866e+02
2	12_5_2 (26_5_2)	1.169658e+02
3	12_10_2 (16-10-2)	2.770010e+01
4	12_15_2 (16_15_2)	5.677242e-02=0.056

4.1.2. Generalized weight vs variables

The first important result of the NN model was the weight relationship between landslide factors and the landslide itself. It was determined based on the above preliminary network results. The acquired generalized weight between response and explanatory variables displayed below.

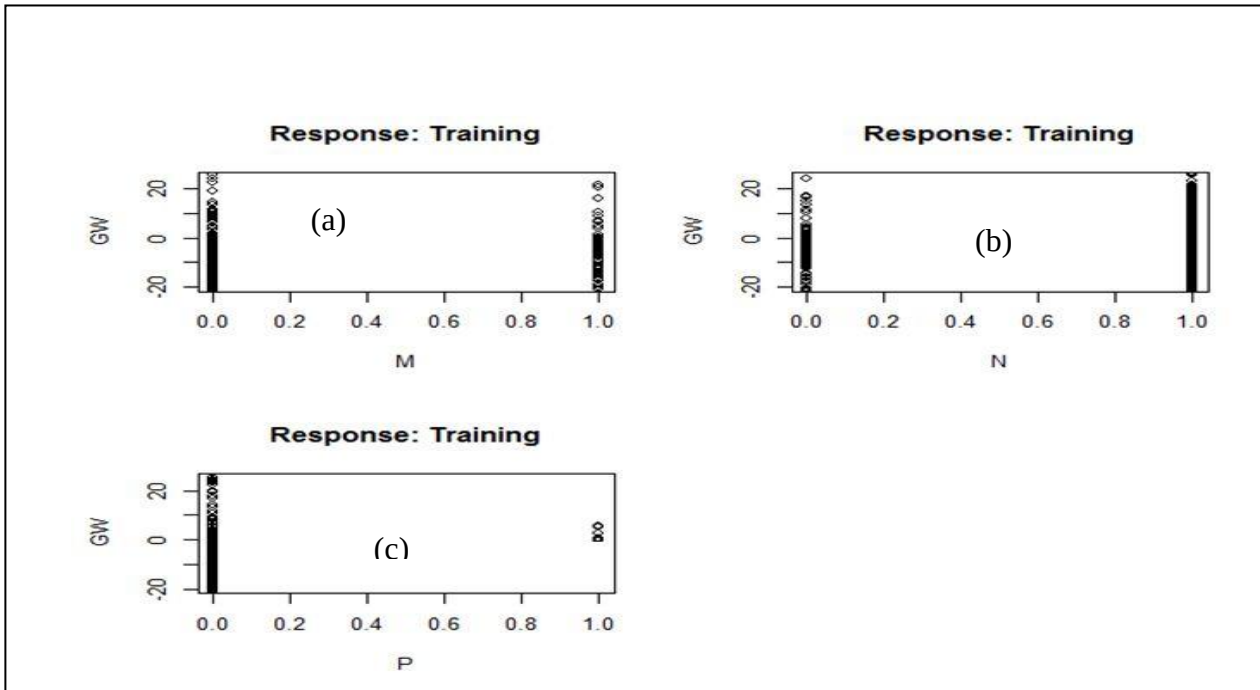


Figure 4.1: Plot GW between landslide and soil classes, M(DysticLeptosolls, N(Humic Alisols), (Humic Nitosols)

In each plot, scaled input datasets are distributed horizontally and their respective weight ranges are assigned vertically. According to the resulted weight versus input plots, input datasets are distributed in three ways. Some datasets are distributed above zero weight, others below zero, and some input datasets are populated along zero weight ranges. That means, if the datasets distributed above the zero weight, there is positive relationship between landslide and input variables and vice versa.

The Figure 4.1 represents GW for soil groups. As a result revealed, the first two groups achieved weight values greater than zero with positive and negative contributions respectively. Also clearly seen that third soil group found weightless which can be removed for model optimization.

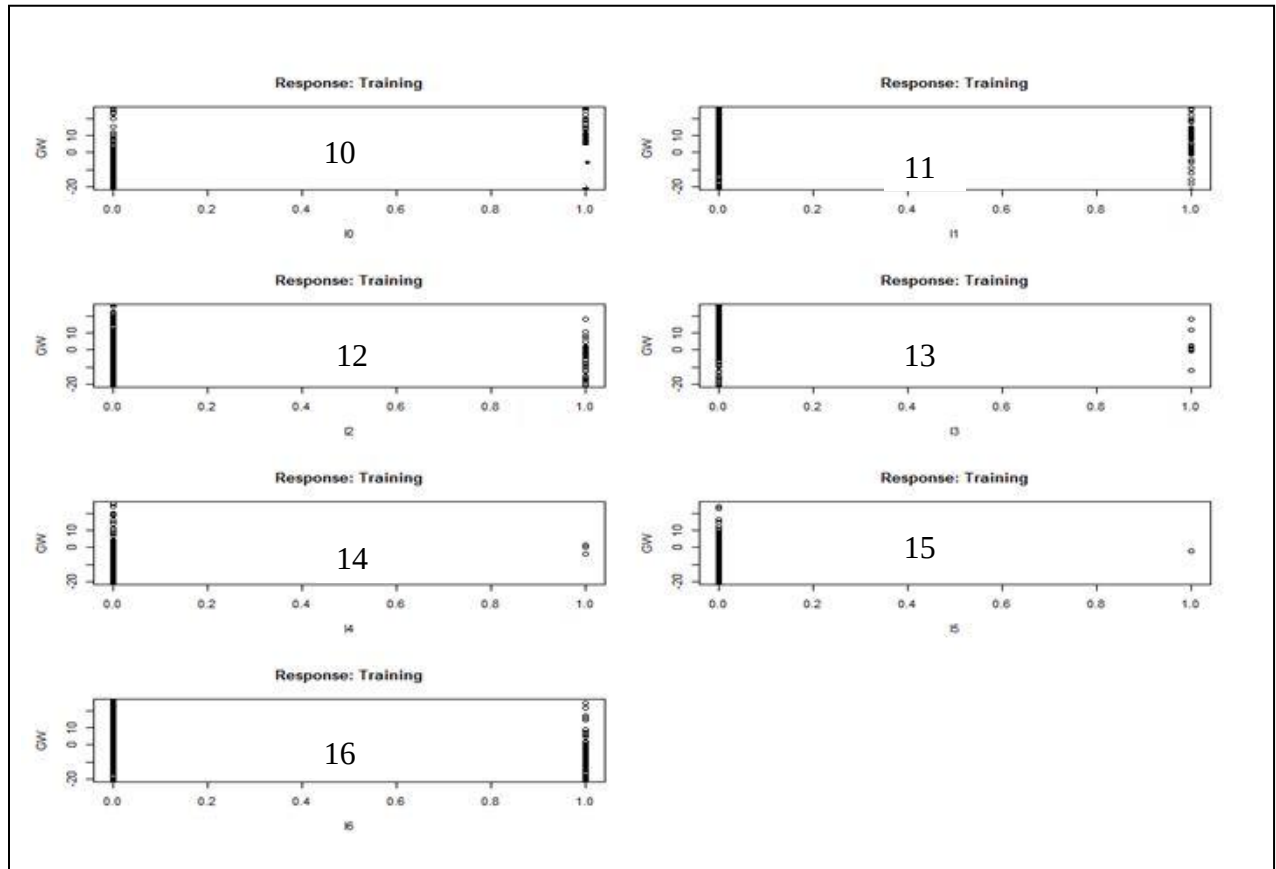


Figure 4.2: Generalized weight for landcover classes: 10(agriculture, 11(settlement),12(sparse veg), 13(forest),14(range land), 15(river) and 16(barren land)

The above Figure 4.2 represents the GW values for various land cover classes. The result revealed that agriculture, settlement, sparse vegetation and barren land are contributing to landslide occurrence positively and negatively. That means they achieved weight values greater than zero below or above it. In other side, forest, rangeland and river remained neutral without landslide weight. Since these factors found weightless, they were removed from landslide susceptibility prediction so as to optimize model performance.

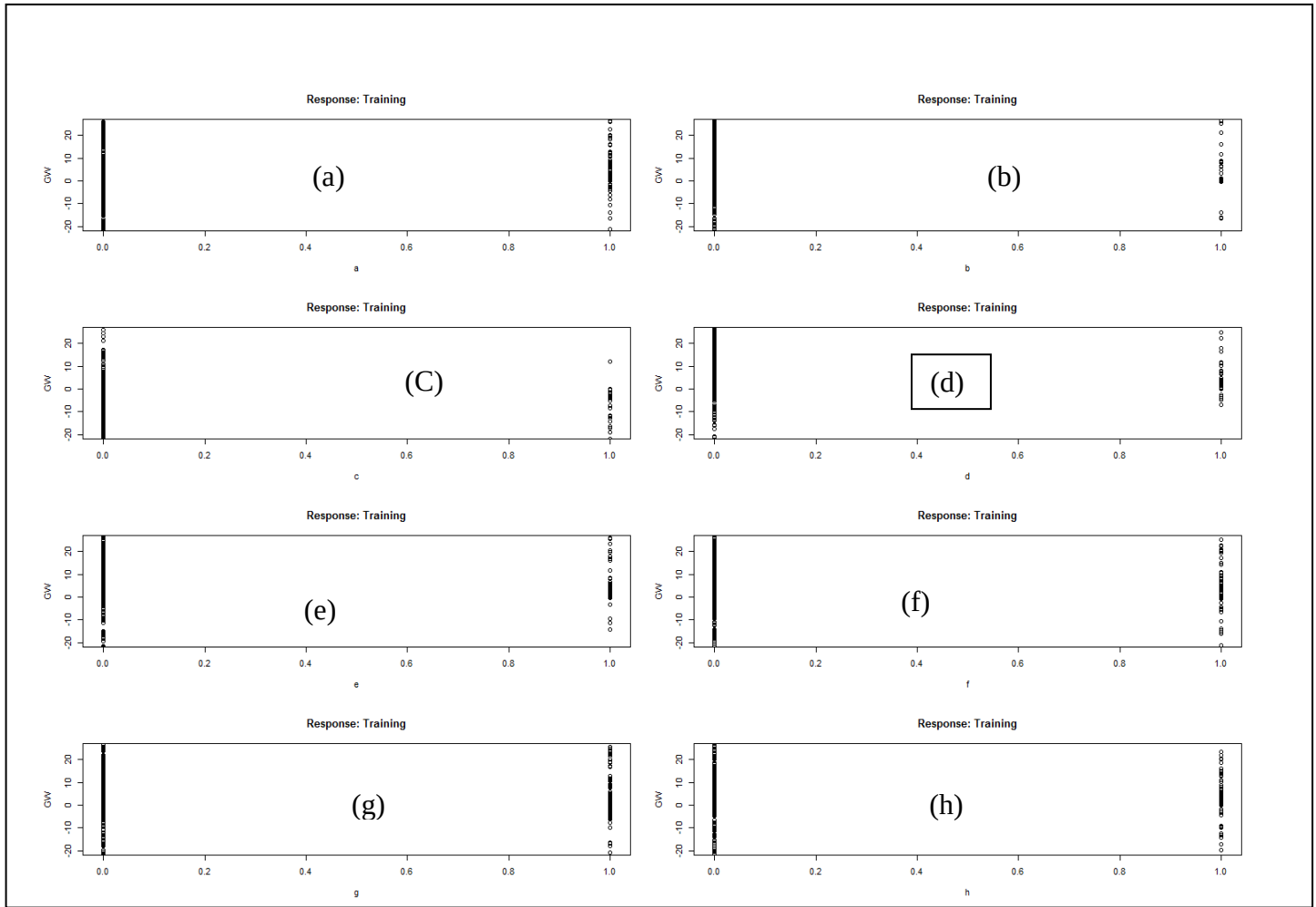


Figure 4.3: Aspect classes and landslide weight relation: a(0^0 - 45^0), b(45^0 - 90^0), c(90^0 - 135^0) d(135^0 - 180^0), e(180^0 - 225^0), f(225^0 - 270^0), g(270^0 - 315^0), and h(315^0 - 360^0)

The Figure 4.3 also represents the GW between each aspect classes and response variable. As the result showed, aspect classes (90^0 - 135^0) (135^0 - 180^0) and (180^0 - 225^0) were experienced with GW values greater than zero. That means the aspect classes below and above zero weight values are contributing negatively and positively for landslide occurrence. All other aspect classes have got weak or near zero weight relationship. These factors were considered as less important for LS modeling and were reduced.

The Figure 4.4 also represents similar result description for GW relationship between response and causative factors. The revealed results indicated that all the factors are important and can predict landslide susceptibility. The three proximity factors, slope and plane curvature were experienced positive and others positive and negative relationship with response variable. Also

effect of each factor classes was revealed. According to the slope classes, the 10^0 - 21^0 , 40^0 - 45^0 slope classes were found the most landslide contributing intervals.

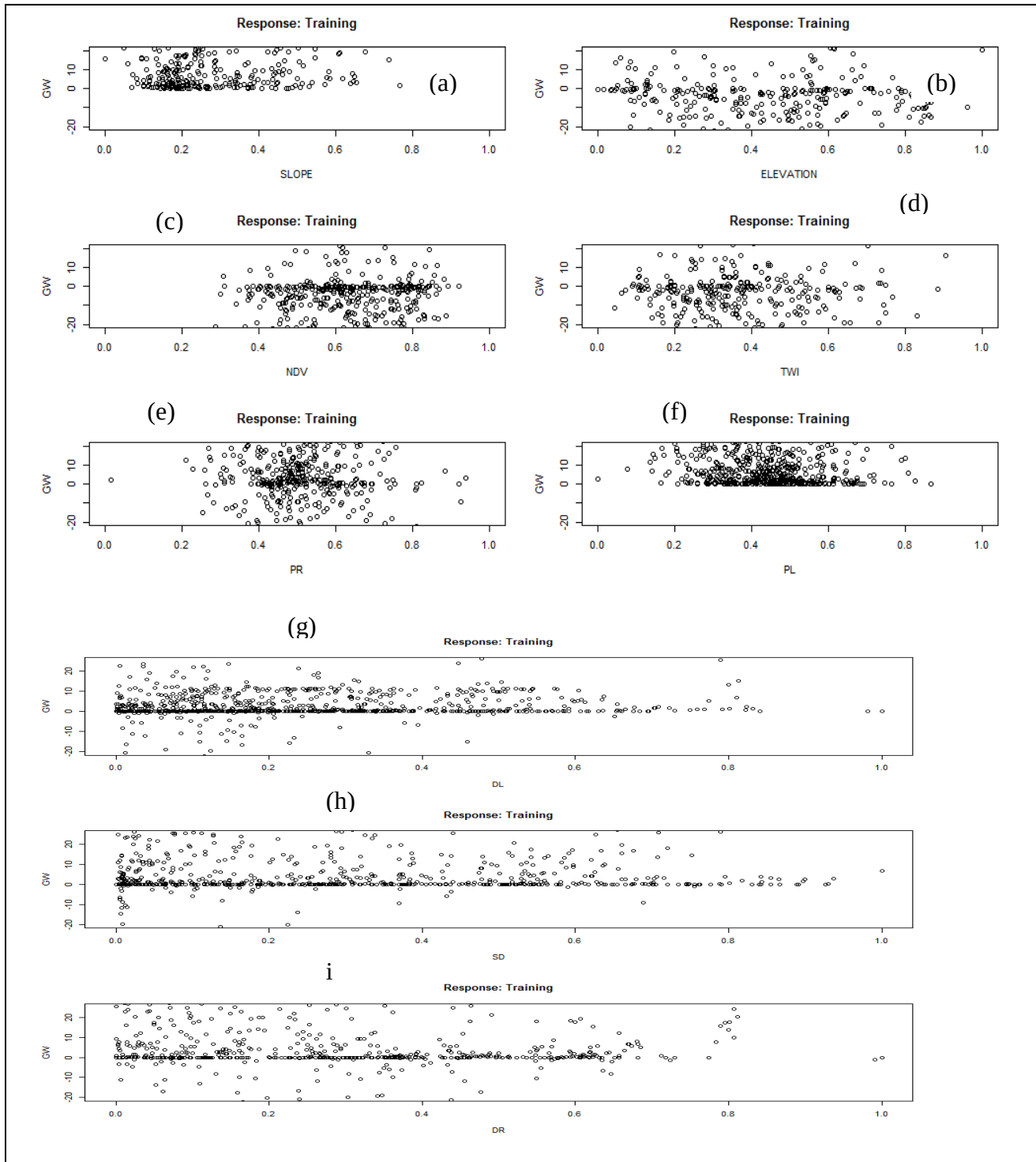


Figure 4.4: GW relationship between landslid and 9 cauastive variable (a)Slope,(b) Dem, (c) NDV, (d) TWI,(e)PR ,(f)PL, (g) lineament, (h) drainage and (i) road proximity factors

4.1.3. Relationship among covariates (landslide conditioning factors)

During generalized weight analysis, weight relationships between covariates were also generated. It was a preliminary result showing role each of factors and relationship between factors. In the right side, last column of the pair wise matrix table below, generalized weight represented which indicated the significant role of the each covariate. All the covariates represented along the diagonal, significant ranks between covariates represented above it and below graphically.

As revealed from the pair wise result, slope found the controlling factor having high significant rank value 0.72^{***} alone. Following slope proximity factors, NDV, agriculture, settlement, barren land also identified as the main controlling factors. Besides, strong relationship found between slope and TWI, slope, NDV, road proximity, lineament, agriculture, barren land, two aspect classes, two soil classes; TWI and plane curvature, drainage proximity, profile curvature and elevation.

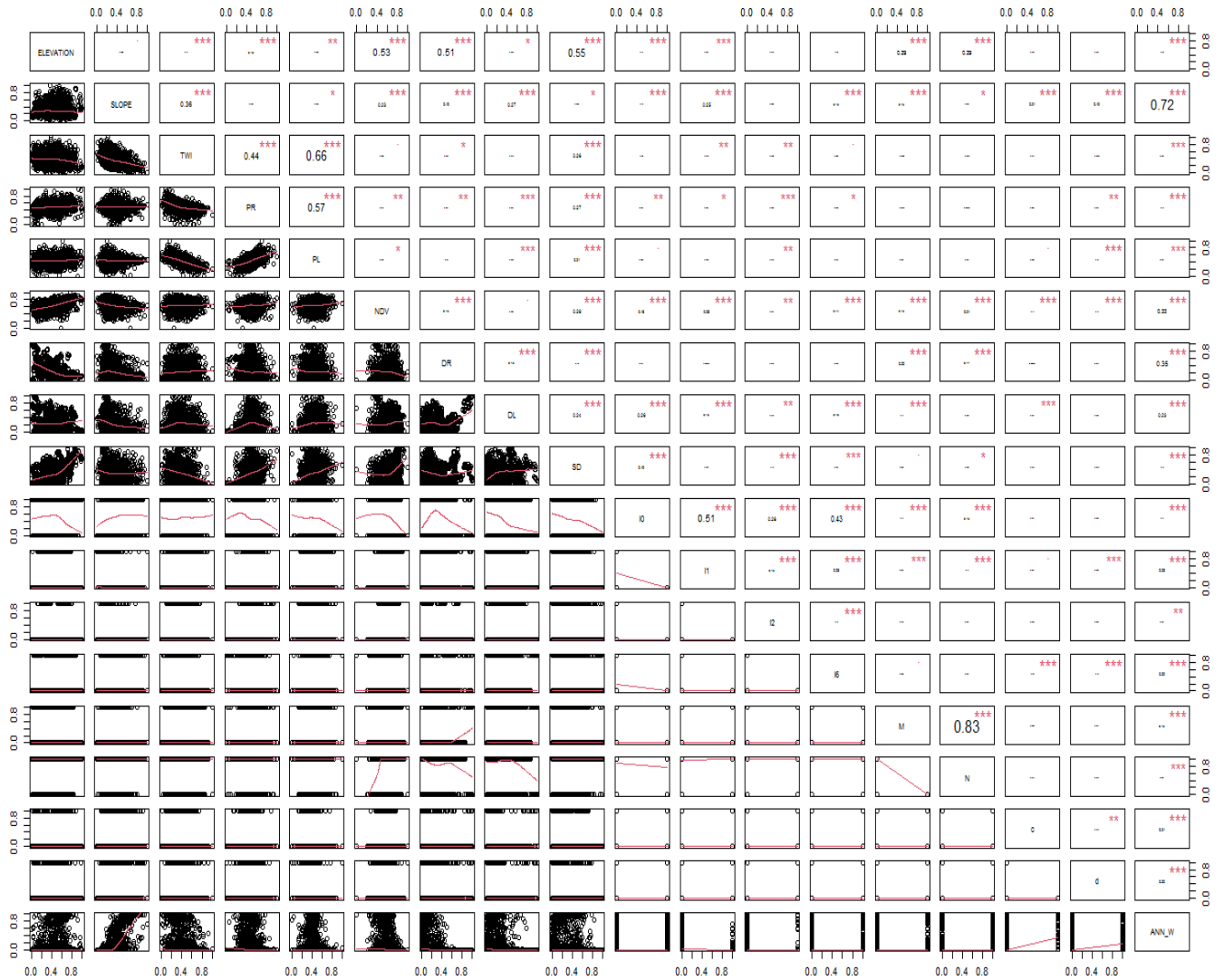


Figure 4.5: GW between covariates

4.2. Model performance evaluation

ANN-based landslide susceptibility modeling requires two validation tests: model learning success and prediction performance. The first assessment pertains to the model's learning success on the imputed dataset. It measures the capability of the model to classify provided landslide and non-landslide binaries correctly. The second validation is to check the prediction capability of the model using testing datasets that were not used during the modeling process.

Both model learning success and prediction performance were assessed using the receiver operating characteristic curve (ROC) curve and area under the curve (AUC) methods. ROC curve and AUC are the widely used methods in various landslide susceptibility studies for this purpose (Chen et al., 2018; A. X. Zhu et al., 2018). ROCK curves examine the probability of the landslide and non-landslide cells being classified correctly. In the ROCK plot, the positive rate represents the possibility that a landslide pixel is correctly categorized and plotted on the Y-axis. On the other hand, the true negative rate is the probability that a non-landslide cell is correctly classified. Finally, AUC quantitatively summarized the performance of the developed model for predicting landslide susceptibility. The following table summarizes model testing and training performance statistics.

In the Figure 4.6 , left side represents training pixels (slides and non slides), ROC curve and AUC. According to the training pixels summary, over the 1257 non slide pixels, 1201 pixels are correctly classified and only 65 pixels misclassified. Similarly, from the 225 landslide pixels (1), 175 pixels correctly classified and only 50 pixels misclassified. Quantitatively, the model achieved learning success rate of 94%. In other hand, right side of the Figure 4.6 represents testing pixels (slides and non slides), ROC and AUC plots. The model testing pixels showed that 385 pixels correctly classified as non slide and 63 pixels misclassified from total 448 non slides (0) participated. Similarly, 50 slides classified correctly as 1 and 15 slides misclassified as 0. The ROC and AUC assures that the model has achieved predictive performance of 88% using testing dataset (20%) which were no participated during training phase.

a) Model training performance

	FALSE	TRUE
0	1201	56
1	50	175

b) Model testing performance

	FALSE	TRUE
0	385	63
1	15	50

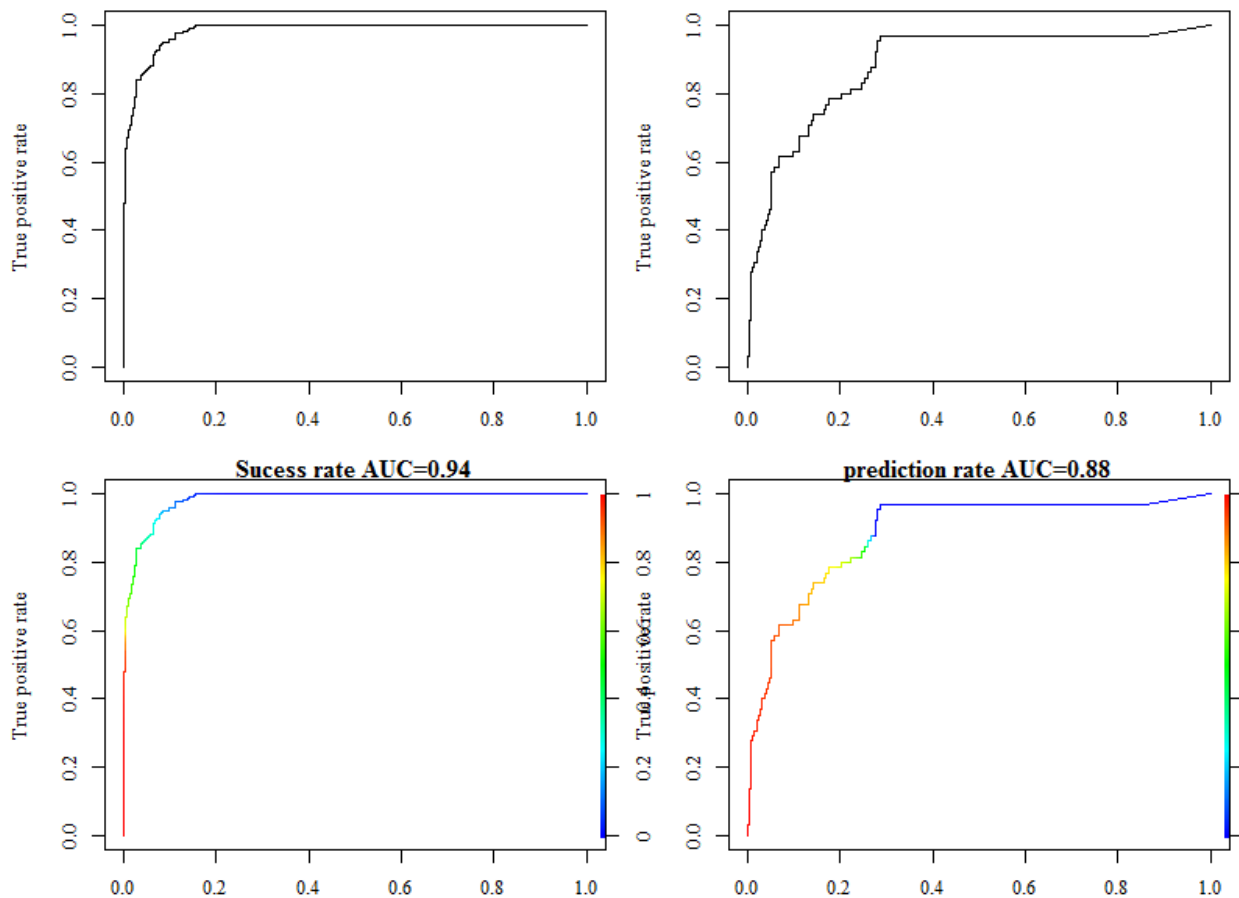


Figure 4.6: ROC and AUC success of the model learning and prediction rates

4.2.1. Landslide susceptibility map

In the model training phase, the model was trained on the existing landslide problems. The achieved model learning and predicting outputs indicated that the model is applicable and can predict the entire study area. Thus, land slide susceptibility was modeled for the whole study area

by integrating model learning results with all thematic raster values. Finally, a landslide susceptibility map, which shows probable landslide occurrences in the future, was generated.

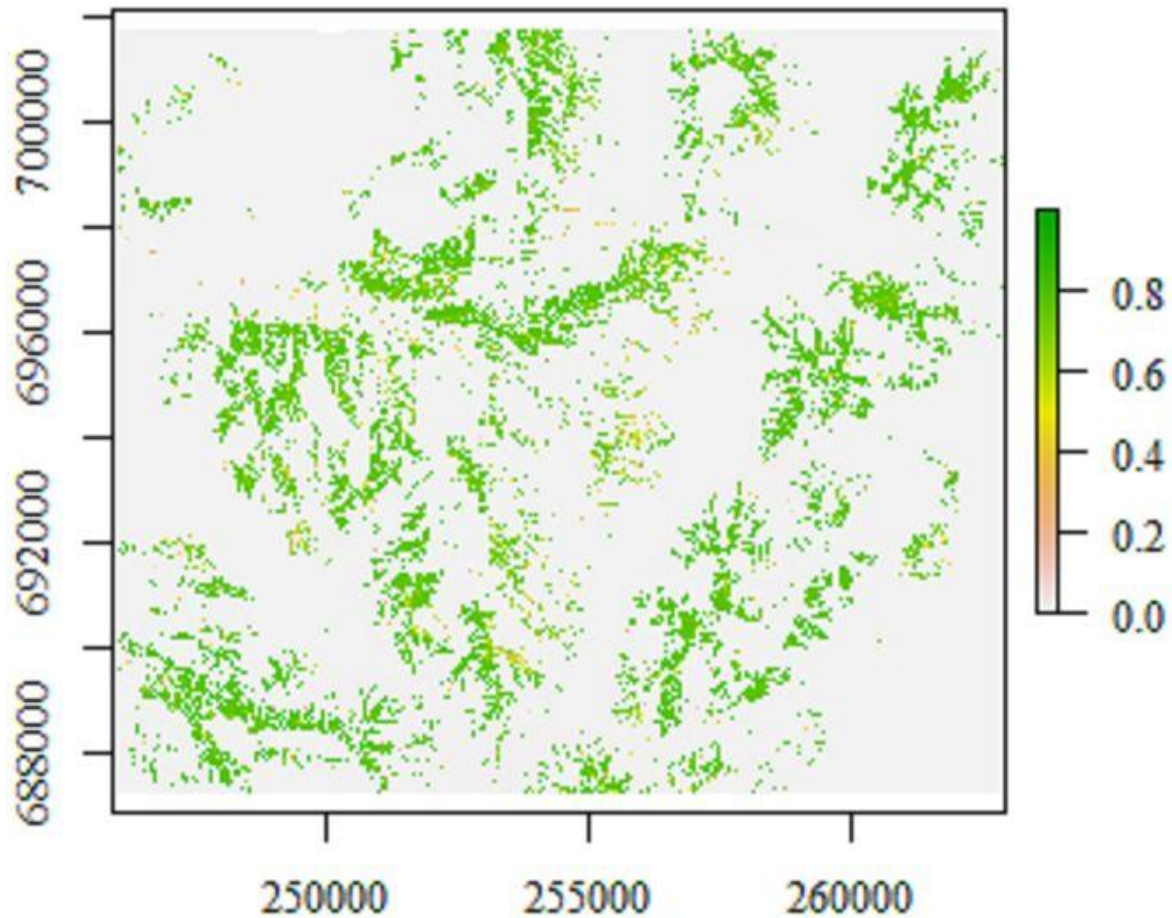


Figure 4.7: Landslide susceptibility map: model output

The landslide susceptibility in Figure 4.7 ranged from 0 to 1 since the model was trained using a scaled dataset between 0 and 1. Values of 1 and near to 1 indicate that the possibility of landslide incident is high and it decreases as the value goes to 0. The final ANN susceptibility map was exported to a GIS environment for better visualization and interpretation. There, the map was classified into three susceptibility zones, such as low (0-0.30), medium (0.30-0.60) and high (0.60-0.99).

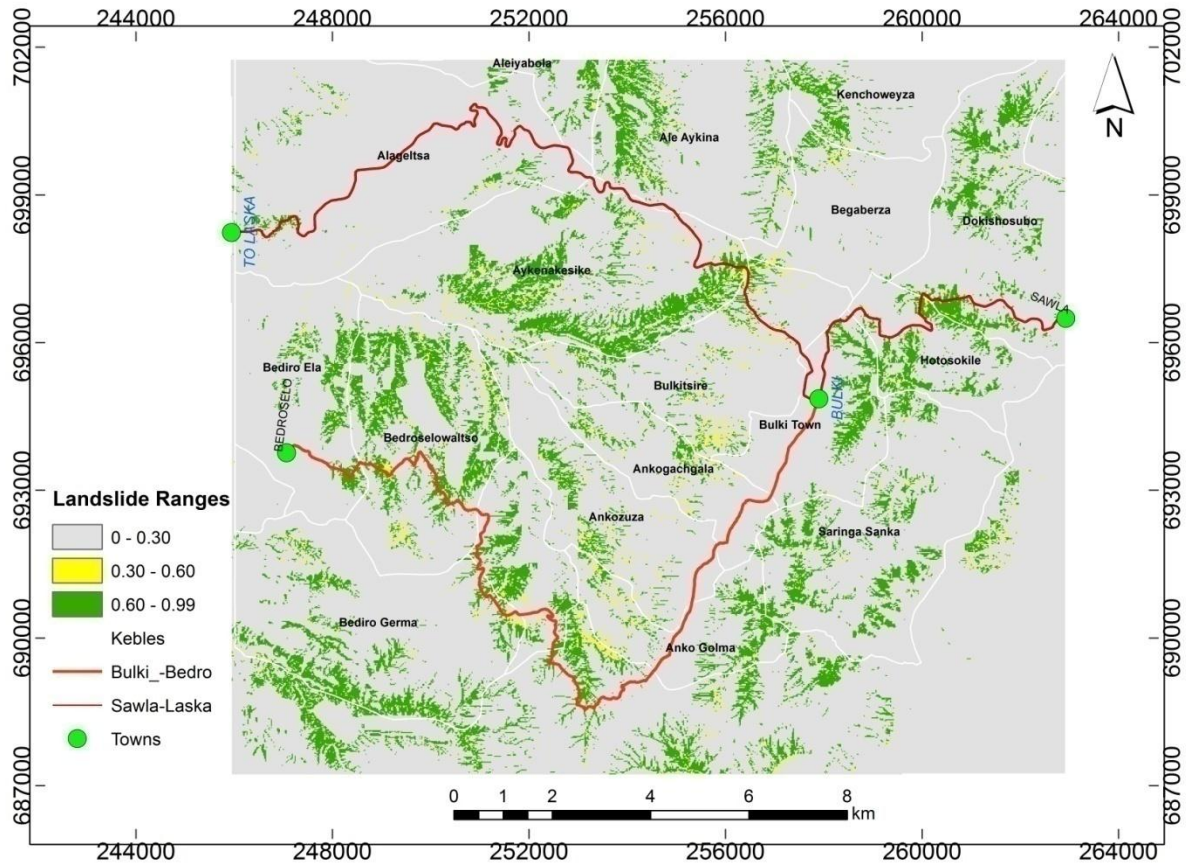


Figure 4.8: Landslide susceptibility map of the study area

The table 4.2 shows the reclassified landslide intensity throughout the entire study area. Accordingly, the susceptibility range was classified into three zones based on the pixels value distribution. Most of the area is classified into lowly susceptible zones, which cover 183.85 km^2 (75%), 14.55 km^2 (6%) falls into moderately susceptible zones and, 47.6 km^2 (19.34%) falls into a highly susceptible zone. The result shows that high landslide susceptibility concentrated on the central part of the study areas following slope. Also road and river corridors found highly susceptible along the road corridor. Besides, as seen from the above spatial landslide susceptibility distribution map, Aykenaksike, Bedroselowaltso, Bedrogerma, and Aleaykina kebeles found the most susceptible in future. In other hand, other part of the study areas following flat terrain found less susceptible.

Table 4.2: landslide susceptibility intensity ranges

ID	Susceptibility range	Area (km ²)	Area (%)
1	0-0.30 (low)	183.85	75
2	0.30-0.60 (medium)	14.55	6.
3	0.60-0.990 (highly)	47.6	19
Total		246	100

4.2.2. Landslide susceptibility along the Road Corridors

A LS map of the entire area is already presented in Figure 4.8. It is also useful to characterize the landslide intensity with respect to important elements at risk. Accordingly, landslide susceptibility intensity along the road corridor, which is the most affected element in the area, was extracted. The Figure 4.9 reveals shows landslide intensity along various road sections.

Accordingly, around seven road sections were identified passing through Sawla-Bulki, Bulki-Satconcamp, Satconcamp-Geltsa1, Geltsa1- Geltsa2, Geltsa2-Laska, Bulki-Anko and Anko-Bedro villages. As the clearly shown in Figure 4.9, Sawla-Bulki, Bulki-Satconcamp, Geltsa2-Laska and Anko Bedro road sections were found highly susceptible to slope instability. In other hand, the remaining road sections remained more or less stable.

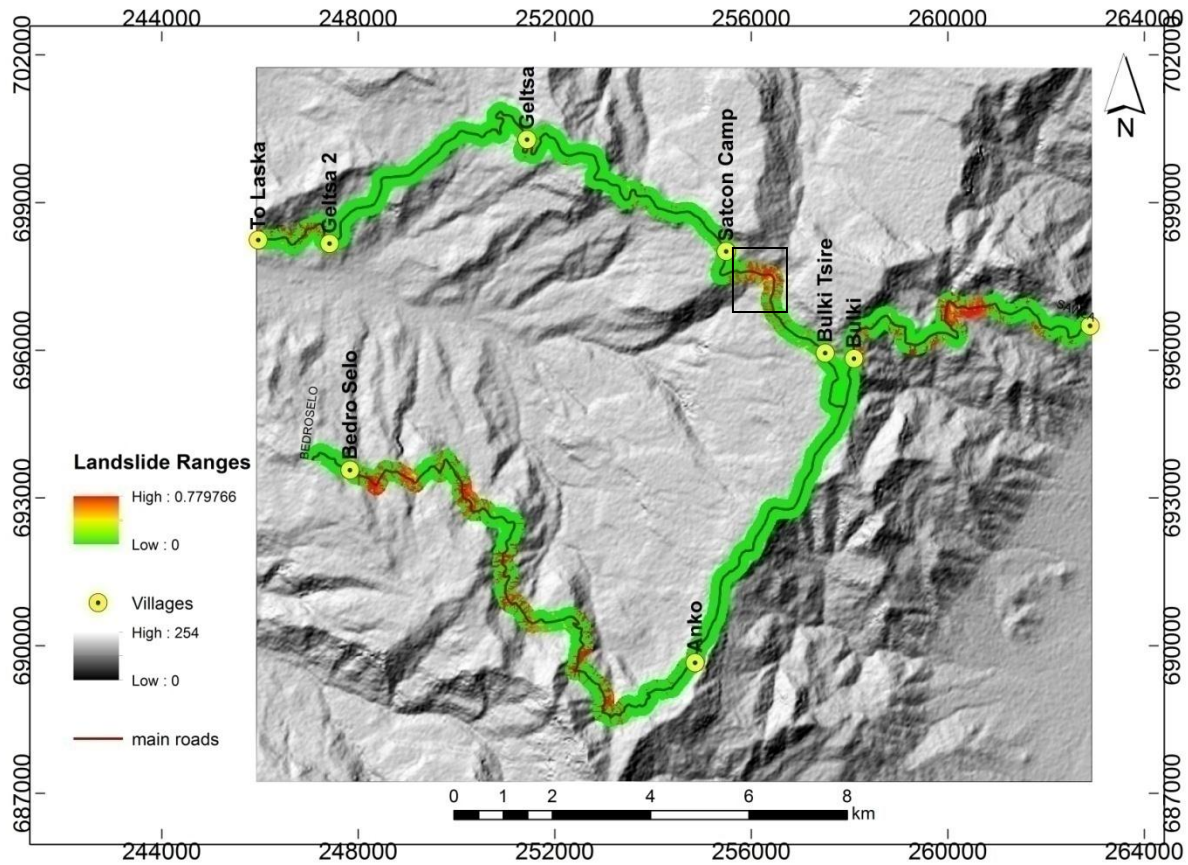


Figure 4.9: Landslide susceptibility intensity along the road corridors.

4.3.MTINSAR processing results

In this study, 20 multi temporal S1A SLC SAR images from 2017 to 2021 were utilized to determine cumulative displacement (slope instability) using a full graph QPSI processing approaches. Besides, the preliminary results such as spatial coherence maps were generated. Finally, based on the spatial coherence result, cumulative displacement was analyzed using the small area MTInSAR processing module in sarproz software.

4.3.1. Spatial coherence map generation

Spatial (interferometric coherence) map is the important preliminary output of the multi-temporal INSAR analysis. It was generated by averaging intensities interferogram pairs. It gives us good clues toward strength of backscattered phase signals over time.

According to the generated spatial coherence map, different areas are identified with various phase stability strengths. As shown in Figure 4.10 Coherence legend bar below, most of the area resulted in low interferometric phase coherence except for reflectivity values starting from 0.4 uniquely visible in different parts of the areas like road corridor and towns.

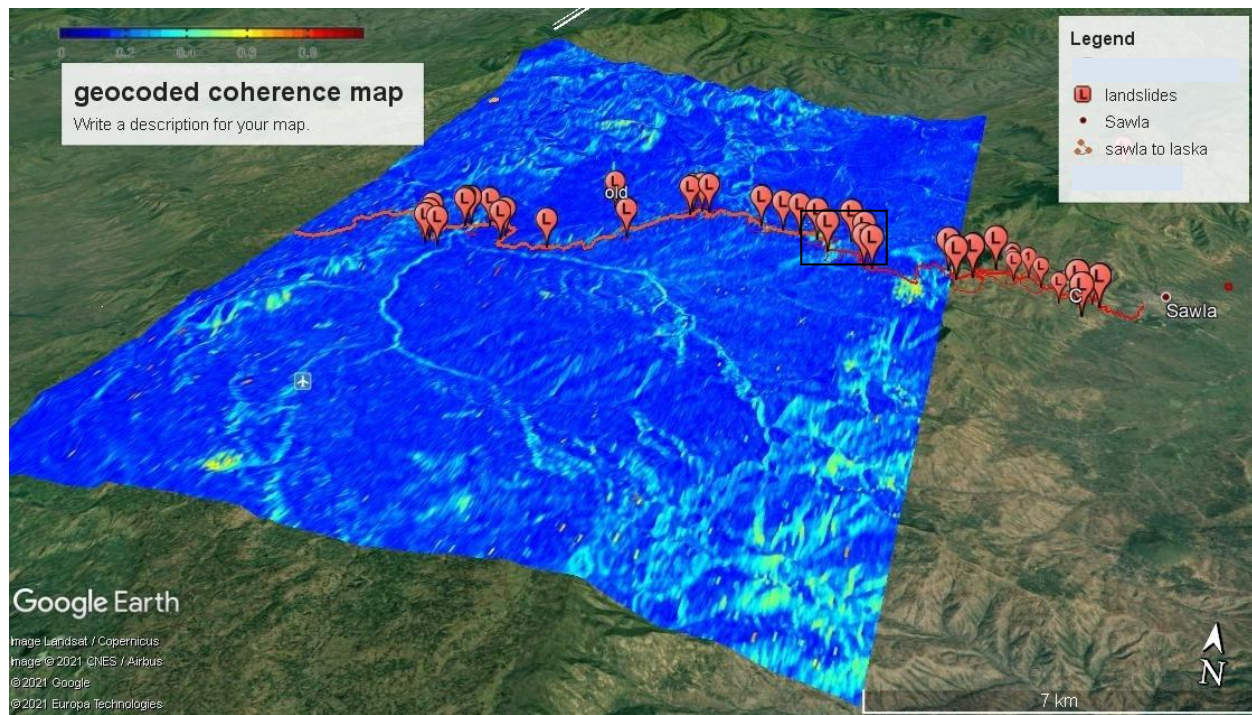


Figure 4.10: Geocoded Coherence map of the study area

4.3.2. Cumulative displacement

Based on the coherence map result above, a small area MT INSAR analysis module was applied over the landslide affected partially coherent area, labeled by rectangle in road corridor above. As a result, the Bulki-Satcon road corridor (labeled as LS 2 AREA above) is designated as a coherent case study area. From the sparse (PSC) analysis, about 1200 coherent PSC points were gained, posing an amplitude stability index threshold of 0.65 (Perissin and Wang, 2011). Finally, through interferometric phase analysis slope instability was estimated as a cumulative

displacement. As presented in Figure 4.11 cumulative displacement estimated ranged to -6 mm/yr and +6 mm/yr. the positive observations indicated there is a deposition and negative observations show there is mass movement or erosion process.

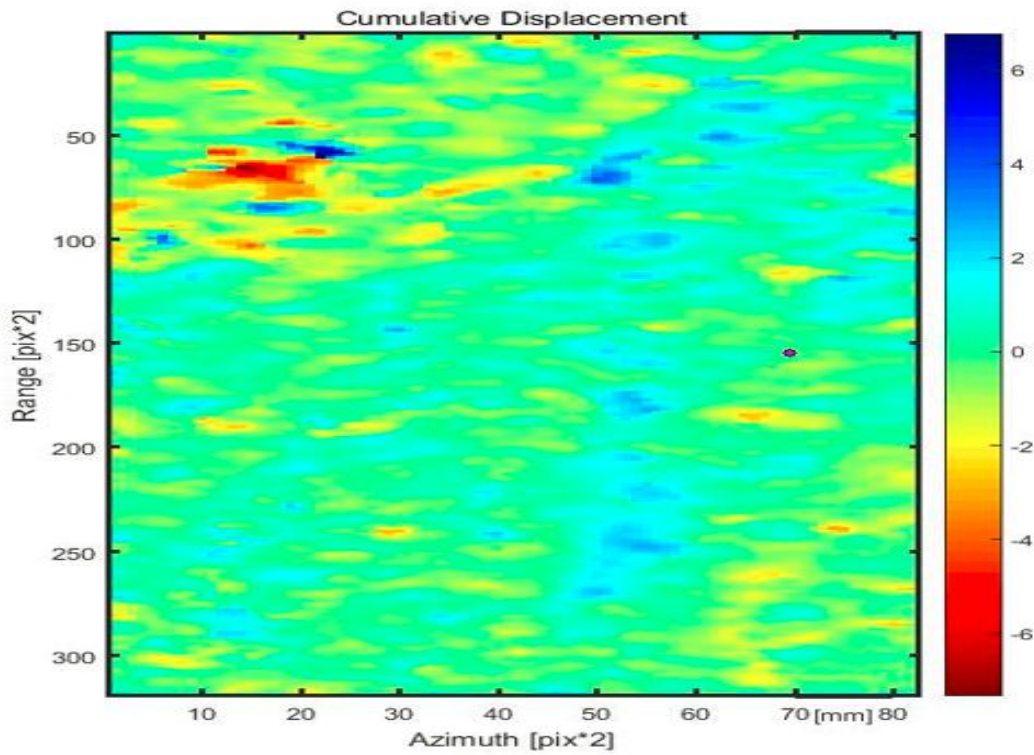


Figure 4.11: commulative displacement of sample area

4.4.DISCUSION

In present study, GIS and SAR RS based landslide susceptibility was mapped using ANN and InSAR technique. Along with landslide susceptibility modeling generalized weights and role landslide contributing factors were also analyzed. Besides, multi temporal InSAR analysis was performed seeking to monitor slope instability in the study area. This section aimed to add further interpretations for the revealed results.

First it is important to discuss model training strategies and respective model outputs. As presented in

Table 4.2 the model was achieved best learning results from 12_15_2 (16_15_2) input-hidden-output NN structure. This shows that the network learning capability was increased by applying two strategies, increasing hidden numbers and reducing those input variables suspected to reduce learning capacity. Increasing the hidden layer may improve model predicting performance, but the system becomes so complex that limits the capability of the processing machine (Neaupane and Achet, 2004; Senise et al., 2013).

The generalized weight plots between response and each explanatory variables showed that all the input variables, except the reduced ones, were contributing for landslide occurrence (Bragagnolo et al., 2020). This indicated that these factors can predict LS in the research area. GW results between covariates revealed that, the slope is the most landslide controlling factor in the study area. This is due to the landslide condition of the area where human activities such as road construction and poor land use practices (agriculture) are dominated over the slope areas. This is also revealed by the GW of the proximity factors, agriculture, and soil.

In addition, weak soil properties following intensive rainfall incidents have made such slope areas unstable and vulnerable to erosion, runoff, and ground water accumulation. As an integrated generalized weight indicated, such effects were revealed through TWI, Profile curvature, plane curvature, and drainage proximity factors. Most of the results are agree the previous studies conducted in Southwestern Ethiopian highlands (Endashaw Debru, 2020; Mengistu et al., 2019; Shano et al., 2021). Generally, all the conditioning factors are important for landslide occurrence, but their significance varies from place to place (Lee et al., 2004).

Therefore, there is a need for systematic factor selection so as to optimize the performance of the developed model.

The LS prediction by ANN model was evaluated using ROC plot and AUC methods. Current model was achieved training and testing performance of 94% and 88% respectively. This shows that the model was successfully learned to the dataset. The result also indicated, it is acceptable and enough to classify landslide and no landslide binaries successfully (Chen et al., 2018; Thao et al., 2021; A. X. Zhu et al., 2018).

Based on the model performance result, LS was modeled entire the study area. The result indicated that three LS zones generated: low 183.85km^2 (75%), medium 14.55 km^2 (6%) and highly 47.6 km^2 (19.34%). From the areas following road corridors, areas in the central part and high altitudes are highly susceptible in the future. This is due to poor land use planning practices and uncontrolled hydrology along the steep terrain. Most of the existing road corridors are unstable due to the integrated effect of poor soil, hydrology, rugged topography, and unmanaged construction work. Besides, areas with flat topography remain stable since there is less human activity and people are migrating toward mountainous and unstable areas for living and agricultural activities.

Even if no previous studies have been conducted in current study area, studies in Southwestern Ethiopian highlands and near rift margin mentioned similar conditions (Endashaw Debru, 2020; Mengistu et al., 2019; Shano et al., 2021).

From the MTINSAR analysis, two results were obtained: spatial coherence and cumulative displacement maps. As revealed by coherence map in Figure 4.10 the study area is highly affected by decorrelaton (vegetation coverage) effect which consequently, influence cumulative displacement modeling (Gonnuru, 2018). In such circumstances it is somehow difficult to generate time series results since these analyses need capability of vegetation penetrating using high resolution SAR sensors and best applicable in coherent urban areas. Therefore, estimating slope instability over the study area is somehow not important as there are many human activities and decorrelation effects that significantly affect the result (Gonnuru, 2018; D. Perissin and Wang, 2011). Thus, it is a wise decision to estimate slope instability over the coherent landslide

affected areas. Accordingly, slope instability analysis applied along the 5km road corridor and surrounding areas resulted in a -6mm/yr to 6mm/year cumulative displacement rate.

The result shows that there are slope instability problems in the specified study area, which agrees with the landslide inventories and the generated susceptibility map. Locally some studies have been conducted using similar datasets over large area coverage. For instance, (Endashaw Debru, 2020; Mengistu et al., 2019) applied PSI analysis at Arbaminch area and Gidole using 16 and 7 S1SLC images and resulted in, +5 mm/yr. to -5.4 mm/yr and -9 mm/yr +15 mm/yr. Recently also (Cherie and Ayele, 2021) achieved -19 mm/yr to 27 mm/yr deformation rates using 23 S1SLC images in Debresena area. The current study result is a little bit underestimated. This might be due to the different processing strategies and small area processing effect. In other hand, mentioned researchers achieved larger value. This also may be due study area characteristics and terrain changes due to human activities like construction works over large scenario.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This study was aimed at modeling landslide susceptibility and slope instability along the Sawla-Laska road corridor and surrounding areas. GIS based ANN model was applied for landslide susceptibility modeling and analyzing landslide controlling factors using training and testing dataset. Coherence based MTInSAR was also processed for preliminary spatial coherence and cumulative displacement modeling using S1A SLC datasets for 2017 to 2021. Based on the achieved results, added discussions and designed objectives, the following conclusions were drawn.

Based on the complex and nonlinear nature of landslide, this study was interested to analyze landslide conditioning factor behaviors and their role. Consequently, the role of the landslide conditioning factors also is not uniform place to place. The current study revealed that all the landslide causative factors were not important for landslide susceptibility mapping. Therefore, applying systematic analysis is so curtail to filter out significant role of each landslide conditioning factors. In this regard the capability of the ANN model was assured in optimizing landslide susceptibility mapping.

Accordingly, landslide susceptibility was modeled for the entire study area based on the training phase results and thematic raster pixels. The result indicated that the model successfully understood the existing landslide distribution and predicted entire the study area. This shows that machine learning methods have complex problem solving capability as long as we fed reliable dataset to the model. Accordingly, this landslide susceptibility map depicts probable landslide distribution in the study area and can be used as a footprint for further studies and to plan future development activities such as proper land use planning, engineering projects, site selection etc.

As revealed by the spatial coherence map, slope instability could not be monitored entire the study area even if there was many landslide affected sites. This shows that freely available SAR sensors like S1SLC images signals are not enough strong in challenging such problems deccorelated environment.

In conclusion, ANN model was learned to the existing problems and predicted throughout the study area successfully. This shows that its robust model can be used for other similar problems, providing a proper dataset. However, for better decision making there is need of comparative studies integrating two or more techniques(Chen et al., 2017; Fang et al., 2021; Mohamed & Reza, 2021). On the other hand, the temporal effect of the slope instability was not successfully monitored throughout the study area. This assures that low resolution SAR dataset like sentinel 1A signals cannot challenge decorrelation effect due to vegetation coverage. Even though slope instability was not monitored throughout the study area; attempt was made to model only cumulative displacement in partially coherent target. Finally, this study revealed the capability machine learning methods, specifically ANN in understanding natural problems and predicting for future.

5.2.Recommendations

Current study was focused on the modeling of landslide susceptibility and slope instability along the Sawla-Laska and surrounding. Besides, the study also analyses the role of various landslide conditioning factor. The study depicts that important factors considered in this analysis are contributing to landslide occurrence positively. Also landslide susceptibility result revealed many predicted many areas are at risk unless mitigation works not done. Therefore, from the study work, the following recommendations were passed.

As the study revealed, most of the landslide calling factors are positively contributing landslide occurrence. The field investigation also revealed that activities along the sloppy terrain, such as cultivation, road construction, and poor drainage, are found as the main landslide controlling factors. This also, revealed by the predicted susceptibility map where high landslide susceptibility zones falls along the road corridor, sloppy terrain following agricultural practices. Therefore, Local planners and respective bodies should worry about the problem and work on early mitigation strategies. Therefore, it is recommended that series work has to be done to increase the awareness of local dwellers about deforestation's causing slope instability in the area, and it is important to regenerate the afforestation and reforestation activities in the area.

As revealed by spatial coherence map, the study area has low phase signal strength due to decorrelation. This is most likely due to the weak penetrating strength of S1 C wave length in such an environment. Therefore, I recommend future researchers to use high resolution SAR sensor datasets that can penetrate decorrelated (vegetated) targets and extract phase information to detect slope instability across the study area. Also ground based GPS (GNSS) approaches are strongly recommended.

In addition, conducting comparative landslide susceptibility studies is important since it has complex and nonlinear characteristics that vary from place to place. This influence the performance of models. Therefore, in the future, researchers can conduct comparative studies using well-known ML methods such as Random Forest, Support Vector Machine, and others.

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APENDICES

APPENDIX 1: Sentinel Dataset Description

Num	Data	Acquisition date	Prep_B	Temp_B		Acquisition pass	Orbit track
1	S1-A SLC	20170226_VV	-5.054848	-684	0.082237	Descending	1571
2	S1-A SLC	20170310_VV	19.530158	-672	0.131586	Descending	1571
3	S1-A SLC	20171117_VV	10.826034	-420	-0.003519	Descending	1571
4	S1-A SLC	20171223_VV	62.955221	-384	-0.004846	Descending	1571
5	S1-A SLC	20180104_VV	35.074533	-372	0.043941	Descending	1571
6	S1-A SLC	20180209_VV	-15.387284	-336	0.072707	Descending	1571
7	S1-A SLC	20181124_VV	10.737146	-48	0.045105	Descending	1571
8	S1-A SLC	20181230_VV	-21.069065	-12	0.051163	Descending	1571
9	S1-A SLC	20190111_VV	0.000000	0.0	0.074379	Descending	1571
10	S1-A SLC	20190216_VV	15.697587	36	0.036985	Descending	1571
11	S1-A SLC	20191201_VV	-42.710905	324	0.031515	Descending	1571
12	S1-A SLC	20191225_VV	-19.492709	348	0.027897	Descending	1571
13	S1-A SLC	20200106_VV	20.300098	360	0.016966	Descending	1571
14	S1-A SLC	20200211_VV	-48.432652	396	0.024141	Descending	1571
15	S1-A SLC	20200223_VV	-17.262620	408	0.027087	Descending	1571
16	S1-A SLC	20201207_VV	-36.763156	696	0.063645	Descending	1571
17	S1-A SLC	20201219_VV	-72.071096	708	0.012196	Descending	1571
18	S1-A SLC	20201231_VV	-44.062289	720	0.020178	Descending	1571
19	S1-A SLC	20210112_VV	2.958199	732	0.019018	Descending	1571
20	S1-A SLC	20211126_VV	8.275703	756	0.040005	Descending	1571

APPENDIX 2: Landslide Inventories description

FID	Shape *	OID_	Site	Area(m ²)	xcentroids	ycentroids
0	Polygon ZM	256875	Y2	13676	256875	692548
1	Polygon ZM	257191	Y5	12891	257191	692444
2	Polygon ZM	257528	Y8	3003	257528	691529
3	Polygon ZM	257825	Y9	695	257825	692414
4	Polygon ZM	257872	Y10	407	257872	692502
5	Polygon ZM	256837	Y13	13203	256837	692244
6	Polygon ZM	256812	Y15	10191	256812	691788
7	Polygon ZM	256816	Y16	13064	256816	691013
8	Polygon ZM	255836	Y19	2173	255836	690230
9	Polygon ZM	255142	Y20	29328	255142	688396
10	Polygon ZM	254216	Y22	2571	254216	687921
11	Polygon ZM	254115	Y23	1732	254115	687268
12	Polygon ZM	262352	BS4	18871	262352	696361
13	Polygon ZM	261886	BS5	9793	261886	696419
14	Polygon ZM	261724	BS6	15440	261724	696616
15	Polygon ZM	261845	BS7	2536	261845	696491
16	Polygon ZM	261365	BS8	11764	261365	696611
17	Polygon ZM	261063	BS9	7720	261063	696729
18	Polygon ZM	260370	BS10	2669	260370	696818
19	Polygon ZM	259931	BS11	38562	259931	696240
20	Polygon ZM	259276	BS12	35638	259276	696000
21	Polygon ZM	254331	BB1	7378	254331	689183
22	Polygon ZM	253614	BD2	13892	253614	689567
23	Polygon ZM	253072	BD3	4959	253072	689584
24	Polygon ZM	253659	BD6	4425	253659	688384
25	Polygon ZM	253158	BD7	2459	253158	688587
26	Polygon ZM	251081	BD12	11273	251081	691218
27	Polygon ZM	251150	BD13	2923	251150	690202
28	Polygon ZM	250894	BD14	20467	250894	690966
29	Polygon ZM	252895	bd18	19781	252895	690568
30	Polygon ZM	252660	bd19	6351	252660	691716
31	Polygon ZM	252400	bd21_slope	29679	252400	692780
32	Polygon ZM	250061	bd22	1147	250061	693036
33	Polygon ZM	250146	bd23	4925	250146	693006
34	Polygon ZM	250150	bd24	3637	250150	692441
35	Polygon ZM	248420	bd25	818	248420	693300
36	Polygon ZM	250047	bd26	5299	250047	693452

37	Polygon ZM	249994	bd28	2597	249994	693128
38	Polygon ZM	250047	bd29	10618	250047	692653
39	Polygon ZM	249363	bd30	5309	249363	689974
40	Polygon ZM	248876	bd31	6567	248876	689595
41	Polygon ZM	252171	bd32	2821	252171	693086
42	Polygon ZM	252630	bd33	2854	252630	693614
43	Polygon ZM	252053	bd34	1027	252053	692210
44	Polygon ZM	252182	bd35	4587	252182	692395
45	Polygon ZM	253136	T2	2743	253136	696883
46	Polygon ZM	253996	T3	3048	253996	696790
47	Polygon ZM	254150	T4	1226	254150	696117
48	Polygon ZM	254125	T6	12204	254125	695129
49	Polygon ZM	254233	T7	20577	254233	694762
50	Polygon ZM	253550	T8	15734	253550	695800
51	Polygon ZM	254456	T11_SLOPE	8410	254456	696067
52	Polygon ZM	254175	T12	11368	254175	695816
53	Polygon ZM	254956	T14	1548	254956	695579
54	Polygon ZM	255178	T18	2075	255178	696182
55	Polygon ZM	255350	T20	6482	255350	696604
56	Polygon ZM	254981	T23	1328	254981	696949
57	Polygon ZM	255705	T25	6045	255705	697078
58	Polygon ZM	255485	T27	18901	255485	697367
59	Polygon ZM	252694	T32	1565	252694	697391
60	Polygon ZM	253447	T33	1055	253447	697986
61	Polygon ZM	253967	T36	8864	253967	698949
62	Polygon ZM	251156	T37	1296	251156	700625
63	Polygon ZM	249799	T39	6190	249799	699326
64	Polygon ZM	247206	T40	8777	247206	698498
65	Polygon ZM	246539	T42	10109	246539	698192
66	Polygon ZM	247316	T43	3700	247316	699155
67	Polygon ZM	257013	2	2262	257013	692281
68	Polygon ZM	257029	4	4205	257029	691772
69	Polygon ZM	257598	5	11993	257598	692151
70	Polygon ZM	257664	6	6076	257664	692902
71	Polygon ZM	257647	7	12110	257647	692553
72	Polygon ZM	257738	8	2253	257738	692001
73	Polygon ZM	258618	9	24192	258618	695226
74	Polygon ZM	259057	10	17425	259057	693447
75	Polygon ZM	258789	13	4359	258789	692965
76	Polygon ZM	257516	14	5479	257516	690635
77	Polygon ZM	258168	17	9019	258168	692464

78	Polygon ZM	257238	19	3584	257238	692860
79	Polygon ZM	257109	20	768	257109	692882
80	Polygon ZM	256631	22	2911	256631	691806
81	Polygon ZM	256416	23	4930	256416	691932
82	Polygon ZM	256193	24	4920	256193	691223
83	Polygon ZM	256586	25	5510	256586	688817
84	Polygon ZM	254225	28	1811	254225	688395
85	Polygon ZM	253730	30	2121	253730	687838
86	Polygon ZM	253567	31	11423	253567	687466
87	Polygon ZM	252941	36	5679	252941	688874
88	Polygon ZM	252768	37	2476	252768	688763
89	Polygon ZM	253183	38	4966	253183	688783
90	Polygon ZM	252815	42	811	252815	690748
91	Polygon ZM	252692	44	4233	252692	690991
92	Polygon ZM	252741	45	1538	252741	691565
93	Polygon ZM	254835	47	4423	254835	694828
94	Polygon ZM	254167	48	1493	254167	696006
95	Polygon ZM	252444	49	6031	252444	696305
96	Polygon ZM	253043	50	4350	253043	696611
97	Polygon ZM	254764	53	3506	254764	696938
98	Polygon ZM	254704	55	3913	254704	690729
99	Polygon ZM	254560	57	2602	254560	689796
100	Polygon ZM	254513	58	617	254513	689469
101	Polygon ZM	254112	60	4210	254112	689140
102	Polygon ZM	254301	62	706	254301	689098
103	Polygon ZM	254628	63	2478	254628	689548
104	Polygon ZM	254987	64	2477	254987	689899
105	Polygon ZM	254629	65	3715	254629	690106
106	Polygon ZM	253826	66	2618	253826	689214
107	Polygon ZM	253158	68	1265	253158	689193
108	Polygon ZM	252947	70	1418	252947	688756
109	Polygon ZM	252691	71	1381	252691	689320
110	Polygon ZM	252319	72	1151	252319	689437
111	Polygon ZM	252405	74	1117	252405	689541
112	Polygon ZM	252502	76	1470	252502	689652
113	Polygon ZM	252479	77	2619	252479	689922
114	Polygon ZM	252744	79	4207	252744	690231
115	Polygon ZM	252642	80	2224	252642	690577
116	Polygon ZM	251431	81	6497	251431	690615
117	Polygon ZM	251415	84	2530	251415	690048
118	Polygon ZM	251805	85	6110	251805	691270

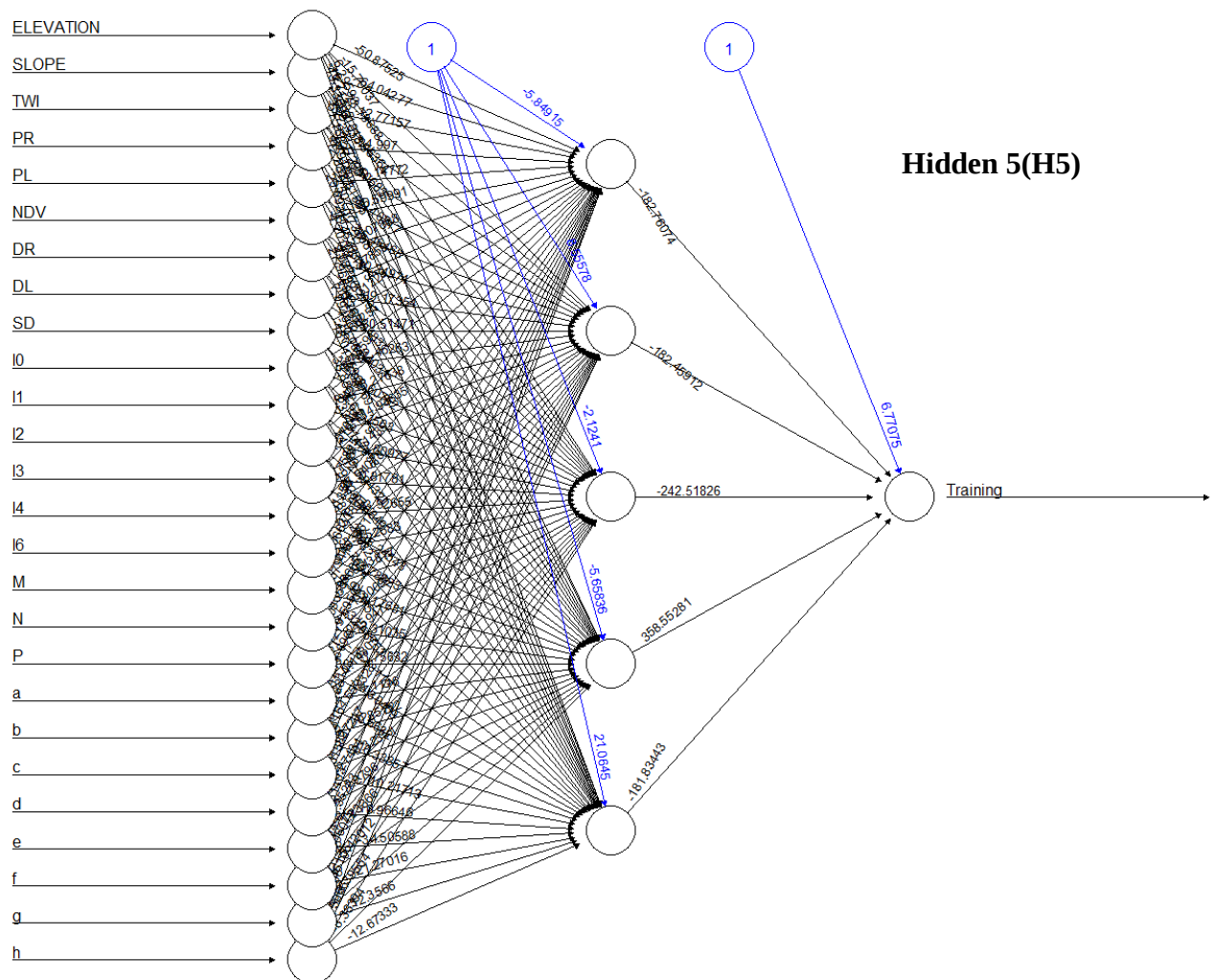
119	Polygon ZM	251118	86	3961	251118	691347
120	Polygon ZM	250955	87	2452	250955	691576
121	Polygon ZM	250930	88	591	250930	691791
122	Polygon ZM	251433	90	1690	251433	691886
123	Polygon ZM	251784	92	2085	251784	692132
124	Polygon ZM	249967	bd27	65704	249967	693733
125	Polygon ZM	249547	94	26009	249547	693922
126	Polygon ZM	249785	96	6730	249785	693660
127	Polygon ZM	249912	97	1696	249912	693578
128	Polygon ZM	251086	98	15643	251086	691920
129	Polygon ZM	255711	100	3204	255711	697567
130	Polygon ZM	256638	102	12733	256638	697776
131	Polygon ZM	256567	103	1257	256567	697653
132	Polygon ZM	255980	106	5529	255980	697234
133	Polygon ZM	256264	108	11529	256264	696323
134	Polygon ZM	256563	109	4336	256563	696584
135	Polygon ZM	256470	110	12314	256470	697022
136	Polygon ZM	256159	111	5289	256159	697626
137	Polygon ZM	256427	112	4832	256427	697433
138	Polygon ZM	256876	116	6111	256876	696369
139	Polygon ZM	257318	117	4528	257318	696059
140	Polygon ZM	255545	118	5615	255545	697611
141	Polygon ZM	255154	119	6844	255154	698358
142	Polygon ZM	254911	120	5596	254911	698628
143	Polygon ZM	253836	124	4769	253836	698870
144	Polygon ZM	253701	125	944	253701	699061
145	Polygon ZM	253191	126	38095	253191	699211
146	Polygon ZM	252986	127	3878	252986	699407
147	Polygon ZM	252907	128	6077	252907	699410
148	Polygon ZM	252408	129	2751	252408	698883
149	Polygon ZM	253917	130	2970	253917	699847
150	Polygon ZM	253995	131	6397	253995	700580
151	Polygon ZM	256807	133	2559	256807	701200
152	Polygon ZM	256873	133	2977	256873	699716
153	Polygon ZM	256781	134	8813	256781	699510
154	Polygon ZM	256628	136	5828	256628	698606
155	Polygon ZM	256729	139	3680	256729	698141
156	Polygon ZM	256847	140	18636	256847	697430
157	Polygon ZM	251681	141	2926	251681	700970
158	Polygon ZM	251571	142	4804	251571	700883
159	Polygon ZM	251994	143	4364	251994	700230

160	Polygon ZM	251684	144	9299	251684	700340
161	Polygon ZM	251425	145	2393	251425	700393
162	Polygon ZM	251373	147	3379	251373	700376
163	Polygon ZM	251934	149	2945	251934	699672
164	Polygon ZM	251107	150	7452	251107	699335
165	Polygon ZM	253563	152	587	253563	698480
166	Polygon ZM	253494	153	628	253494	698378
167	Polygon ZM	253521	154	4928	253521	698247
168	Polygon ZM	253330	155	7263	253330	698125
169	Polygon ZM	252676	156	8656	252676	697599
170	Polygon ZM	252348	158	5358	252348	697294
171	Polygon ZM	252160	159	4882	252160	697767
172	Polygon ZM	252820	160	4974	252820	698803
173	Polygon ZM	247987	161	10974	247987	701201
174	Polygon ZM	251735	163	4183	251735	701685
175	Polygon ZM	253204	164	4015	253204	700792
176	Polygon ZM	258299	165	3178	258299	695146
177	Polygon ZM	259433	166	8800	259433	694375
178	Polygon ZM	258598	167	5484	258598	694618
179	Polygon ZM	258137	169	5765	258137	695896
180	Polygon ZM	258116	170	3169	258116	696218
181	Polygon ZM	258209	171	4671	258209	696351
182	Polygon ZM	258376	172	1167	258376	696199
183	Polygon ZM	258829	173	7307	258829	696527
184	Polygon ZM	258707	175	4531	258707	695932
185	Polygon ZM	259063	156	18169	259063	696367
186	Polygon ZM	259751	178	22734	259751	696203
187	Polygon ZM	251248	179	3355	251248	692306
188	Polygon ZM	248341	180	7630	248341	693116
189	Polygon ZM	250010	181	15764	250010	695870
190	Polygon ZM	250242	181	4840	250242	694616
191	Polygon ZM	250054	182	2273	250054	695065
192	Polygon ZM	251576	183	8698	251576	692571
193	Polygon ZM	251650	184	5509	251650	693124
194	Polygon ZM	251439	185	5324	251439	692958

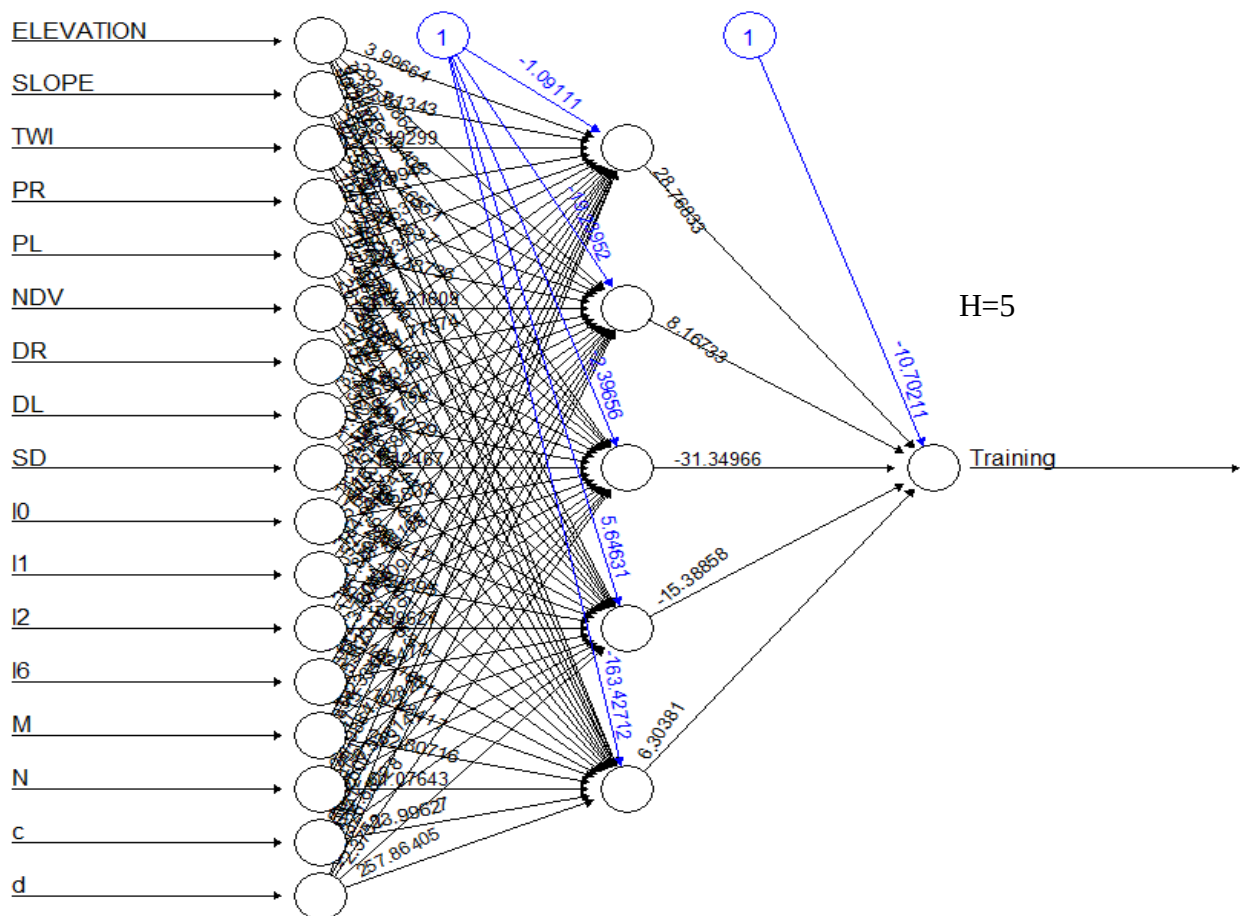
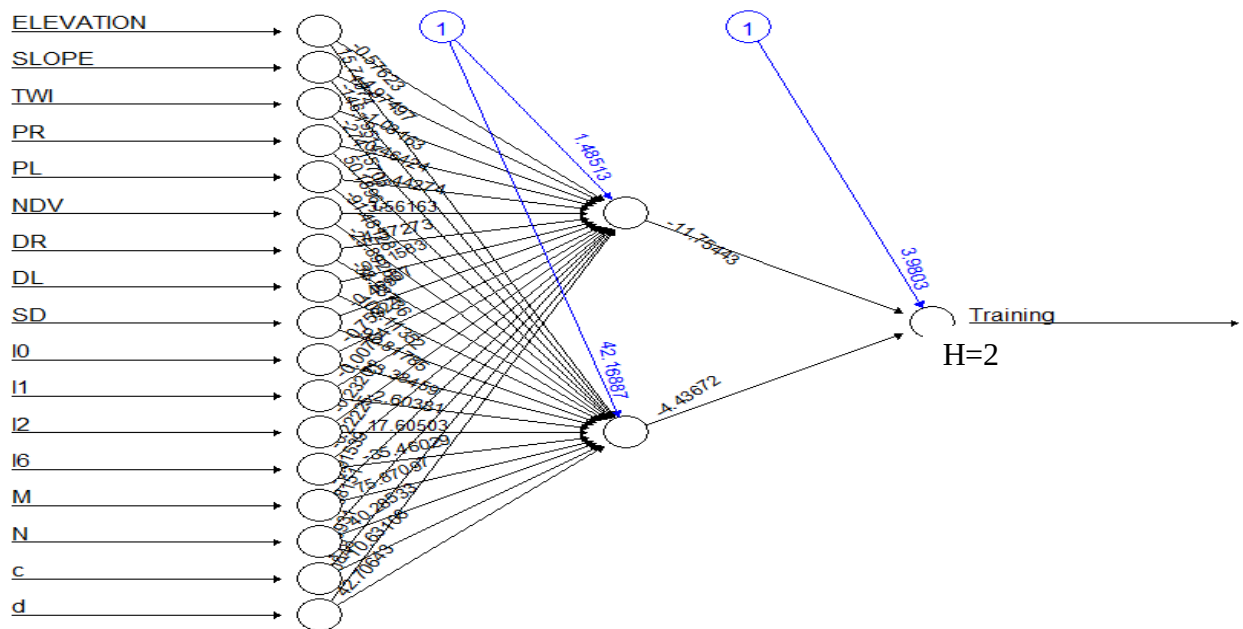
NOTE= abbrevations representation: Y=yongi area, T=tsire area, bd=along bedro road corridor, sb=along sawla bulki,

APPENDIX 3: ANN Training phase Model Outputs

A) First phase model structure output: Training with all input datasets



B) After optimization



A) First and second Phase Model Training Results: **Training with all input datasets**

Hidden 5 processing weight result	
error	1.169658e+02
Reached. threshold	9.914092e-03
steps	6.448760e+05
Intercept.to.1layhid1	-5.849147e+00
ELEVATION.to.1layhid1	-5.087525e+01
SLOPE.to.1layhid1	-6.404277e+01
TWI.to.1layhid1	1.277157e+01
PR.to.1layhid1	2.499700e+01
PL.to.1layhid1	-1.477169e-01
NDV.to.1layhid1	8.059991e+01
DR.to.1layhid1	-9.078682e+00
DL.to.1layhid1	8.278589e+00
SD.to.1layhid1	2.571223e+01
10.to.1layhid1	-8.662507e+00
11.to.1layhid1	-1.248590e+01
12.to.1layhid1	9.421542e-01
13.to.1layhid1	7.578475e+00
14.to.1layhid1	7.575825e+01
16.to.1layhid1	2.313584e+00
M.to.1layhid1	-2.566310e+00
N.to.1layhid1	1.257944e+01
P.to.1layhid1	2.309059e+01
a.to.1layhid1	5.037279e+01
b.to.1layhid1	-4.420920e-01
c.to.1layhid1	-1.546826e+01
d.to.1layhid1	-5.288619e+01
e.to.1layhid1	3.394707e+00
f.to.1layhid1	-4.502502e+01
g.to.1layhid1	-3.798505e+01
h.to.1layhid1	-9.699473e+00
Intercept.to.1layhid2	8.555777e+00
ELEVATION.to.1layhid2	-1.570037e+01
SLOPE.to.1layhid2	-2.373688e+01
TWI.to.1layhid2	-3.396364e+01
PR.to.1layhid2	5.506828e+00
PL.to.1layhid2	-1.040747e+01
NDV.to.1layhid2	1.546468e+01
DR.to.1layhid2	1.024974e+01

DL.to.1layhid2	-1.917354e+01
SD.to.1layhid2	-3.051471e+01
10.to.1layhid2	2.246263e+01
11.to.1layhid2	1.627638e+01
12.to.1layhid2	-7.149364e+02
13.to.1layhid2	-7.143511e-01
14.to.1layhid2	8.754078e+01
16.to.1layhid2	1.810995e-01
M.to.1layhid2	1.193461e+01
N.to.1layhid2	8.560491e-01
P.to.1layhid2	-1.059592e+01
a.to.1layhid2	-6.669624e+00
b.to.1layhid2	-2.281484e+00
c.to.1layhid2	1.731598e+00
d.to.1layhid2	2.451589e+01
e.to.1layhid2	2.261403e+01
f.to.1layhid2	6.594448e+00
g.to.1layhid2	1.191796e+01
h.to.1layhid2	7.866666e+02
Intercept.to.1layhid3	-2.124099e+00
ELEVATION.to.1layhid3	6.295926e+00
SLOPE.to.1layhid3	-3.618176e+00
TWI.to.1layhid3	7.272984e+00
PR.to.1layhid3	-8.315846e+00
PL.to.1layhid3	-7.375808e-01
NDV.to.1layhid3	1.815130e+00
DR.to.1layhid3	9.328967e+00
DL.to.1layhid3	5.354834e+00
SD.to.1layhid3	1.440308e+00
10.to.1layhid3	-2.607521e+00
11.to.1layhid3	2.150301e+00
12.to.1layhid3	-3.809765e+00
13.to.1layhid3	8.178072e-01
14.to.1layhid3	4.392655e+01
16.to.1layhid3	2.526827e+00
M.to.1layhid3	4.387656e-01
N.to.1layhid3	-1.200912e+00
P.to.1layhid3	-1.594730e-01
a.to.1layhid3	-1.430508e-01
b.to.1layhid3	-4.652316e+00
c.to.1layhid3	3.272170e+00

d.to.1layhid3	-3.274338e+00
e.to.1layhid3	-4.352230e+00
f.to.1layhid3	-3.060752e+00
g.to.1layhid3	-1.861065e+00
h.to.1layhid3	-4.759661e+00
Intercept.to.1layhid4	-5.658363e+00
ELEVATION.to.1layhid4	-1.071335e+01
SLOPE.to.1layhid4	1.573311e+01
TWI.to.1layhid4	4.791801e+01
PR.to.1layhid4	-2.507771e+00
PL.to.1layhid4	1.846363e+01
NDV.to.1layhid4	9.087560e+00
DR.to.1layhid4	-1.626810e+01
DL.to.1layhid4	-2.005440e+01
SD.to.1layhid4	-1.604769e+01
10.to.1layhid4	-4.612786e+00
11.to.1layhid4	-1.470382e+00
12.to.1layhid4	-2.594321e+01
13.to.1layhid4	2.158494e+00
14.to.1layhid4	-6.352454e+02
16.to.1layhid4	-3.788230e+00
M.to.1layhid4	-3.176813e+00
N.to.1layhid4	3.310349e+00
P.to.1layhid4	-3.756322e+00
a.to.1layhid4	-1.111600e+00
b.to.1layhid4	-8.572213e-01
c.to.1layhid4	-3.235072e-01
d.to.1layhid4	1.279603e+00
e.to.1layhid4	1.233661e+00
f.to.1layhid4	-5.420124e+00
g.to.1layhid4	-3.395536e+00
h.to.1layhid4	-8.383940e+00
Intercept.to.1layhid5	2.106450e+01
ELEVATION.to.1layhid5	-4.333692e+01
SLOPE.to.1layhid5	-5.116837e+01
TWI.to.1layhid5	-1.288771e+01
PR.to.1layhid5	2.369211e+01
PL.to.1layhid5	-4.701436e+00
NDV.to.1layhid5	2.796694e+01
DR.to.1layhid5	7.994986e+00
DL.to.1layhid5	-1.801659e+01

SD.to.1layhid5	3.885620e+01
10.to.1layhid5	8.334809e+00
11.to.1layhid5	1.439600e+01
12.to.1layhid5	-9.623073e+00
13.to.1layhid5	8.012093e+02
14.to.1layhid5	5.975940e+01
16.to.1layhid5	4.947149e+00
M.to.1layhid5	-3.258751e+01
N.to.1layhid5	-1.668113e+01
P.to.1layhid5	-2.430459e+01
a.to.1layhid5	-6.631986e-01
b.to.1layhid5	1.033357e+01
c.to.1layhid5	-7.102171e+02
d.to.1layhid5	1.096646e+01
e.to.1layhid5	-3.450588e+01
f.to.1layhid5	2.127016e+01
g.to.1layhid5	1.235660e+01
h.to.1layhid5	-1.267333e+01
Intercept.to.Training	6.770747e+00
1layhid1.to.Training	-1.827607e+02
1layhid2.to.Training	-1.824591e+02
1layhid3.to.Training	-2.425183e+02
1layhid4.to.Training	3.585528e+02
1layhid5.to.Training	-1.818344e+02

B) Third Phase Model Training Results: After optimization(factors reduction and hiddens increased)

Hidden 10 processing weight result	
error	2.770010e+01
Reached. threshold	8.323873e-03
steps	7.094100e+04
Intercept.to.1layhid1	1.548771e-01
ELEVATION.to.1layhid1	-1.858725e+00
SLOPE.to.1layhid1	-4.841118e+00
TWI.to.1layhid1	-1.505318e+00
PR.to.1layhid1	8.601995e-01
PL.to.1layhid1	1.529116e+00
NDV.to.1layhid1	3.415386e+00
DR.to.1layhid1	-7.083727e-01
DL.to.1layhid1	4.653875e+00
SD.to.1layhid1	-1.291082e+00
10.to.1layhid1	-4.935995e-01
11.to.1layhid1	-9.818926e-01
12.to.1layhid1	-1.310160e+00
16.to.1layhid1	-1.196493e+00
M.to.1layhid1	4.768319e-01
N.to.1layhid1	-5.024700e-01
c.to.1layhid1	3.544654e+00
d.to.1layhid1	-1.358794e+00
Intercept.to.1layhid2	-9.427451e-01
ELEVATION.to.1layhid2	7.777958e+00
SLOPE.to.1layhid2	9.150959e+00
TWI.to.1layhid2	3.693580e+00
PR.to.1layhid2	-6.844425e+00
PL.to.1layhid2	4.418975e+00
NDV.to.1layhid2	-4.500024e+00
DR.to.1layhid2	-1.501728e+01
DL.to.1layhid2	4.760875e+00
SD.to.1layhid2	-7.966070e+00
10.to.1layhid2	-7.742171e-01
11.to.1layhid2	6.219155e+00
12.to.1layhid2	3.629621e+00
16.to.1layhid2	-4.921972e+00
M.to.1layhid2	5.210142e+00
N.to.1layhid2	-2.431392e+00

c.to.1layhid2	6.079564e+00
d.to.1layhid2	-1.169216e+00
Intercept.to.1layhid3	-3.372070e+00
ELEVATION.to.1layhid3	-1.988210e+00
SLOPE.to.1layhid3	1.132311e+01
TWI.to.1layhid3	4.005947e+00
PR.to.1layhid3	4.787823e+00
PL.to.1layhid3	-2.503690e+00
NDV.to.1layhid3	2.176258e+00
DR.to.1layhid3	-6.023105e+00
DL.to.1layhid3	-2.042471e+01
SD.to.1layhid3	6.451127e+00
10.to.1layhid3	-1.707261e+00
11.to.1layhid3	5.526911e+01
12.to.1layhid3	5.051849e+00
16.to.1layhid3	3.247788e+00
M.to.1layhid3	-1.176230e+00
N.to.1layhid3	-6.229221e-01
c.to.1layhid3	3.080540e+00
d.to.1layhid3	1.322716e-01
Intercept.to.1layhid4	-3.242975e-01
ELEVATION.to.1layhid4	-1.262855e+01
SLOPE.to.1layhid4	-2.091144e+01
TWI.to.1layhid4	9.703049e+01
PR.to.1layhid4	-2.584483e+01
PL.to.1layhid4	1.459021e+01
NDV.to.1layhid4	-4.208797e+01
DR.to.1layhid4	7.552757e+01
DL.to.1layhid4	-3.118795e+01
SD.to.1layhid4	-2.997378e+02
10.to.1layhid4	2.387732e+00
11.to.1layhid4	1.666244e+02
12.to.1layhid4	-7.833905e+02
16.to.1layhid4	-4.889748e+00
M.to.1layhid4	-4.378689e+01
N.to.1layhid4	3.664732e+01
c.to.1layhid4	-2.037975e+02
d.to.1layhid4	-5.194634e+01
Intercept.to.1layhid5	5.865943e-01
ELEVATION.to.1layhid5	8.073647e+01
SLOPE.to.1layhid5	1.684918e+02

TWI.to.1layhid5	4.389489e+02
PR.to.1layhid5	-2.550633e+02
PL.to.1layhid5	-5.615247e+01
NDV.to.1layhid5	2.450825e+01
DR.to.1layhid5	-2.975327e+02
DL.to.1layhid5	4.741608e+02
SD.to.1layhid5	1.034029e+02
10.to.1layhid5	1.956058e+01
11.to.1layhid5	-2.263765e+02
12.to.1layhid5	-2.471210e+02
16.to.1layhid5	-6.617674e+01
M.to.1layhid5	5.457844e+01
N.to.1layhid5	-4.370205e+00
c.to.1layhid5	-6.577750e+01
d.to.1layhid5	-4.250937e+01
Intercept.to.1layhid6	-1.423646e+00
ELEVATION.to.1layhid6	4.325898e+00
SLOPE.to.1layhid6	-3.195525e+00
TWI.to.1layhid6	-9.313381e+00
PR.to.1layhid6	-6.187683e+00
PL.to.1layhid6	5.312284e+00
NDV.to.1layhid6	-3.702573e+00
DR.to.1layhid6	5.456840e+00
DL.to.1layhid6	2.578988e+00
SD.to.1layhid6	1.887105e+00
10.to.1layhid6	1.307205e+00
11.to.1layhid6	4.291363e+00
12.to.1layhid6	7.072412e+00
16.to.1layhid6	9.606464e-01
M.to.1layhid6	-2.267415e-02
N.to.1layhid6	1.001330e+00
c.to.1layhid6	-7.097323e+02
d.to.1layhid6	-1.654190e+00
Intercept.to.1layhid7	2.946195e-01
ELEVATION.to.1layhid7	-1.490024e+01
SLOPE.to.1layhid7	2.134072e+00
TWI.to.1layhid7	1.407678e-01
PR.to.1layhid7	-2.060231e+00
PL.to.1layhid7	8.875004e+00
NDV.to.1layhid7	1.284919e+01
DR.to.1layhid7	1.574953e+00

DL.to.1layhid7	-1.754597e+01
SD.to.1layhid7	8.030145e-02
10.to.1layhid7	-4.687927e+00
11.to.1layhid7	7.241730e+00
12.to.1layhid7	-1.754956e+00
16.to.1layhid7	2.187894e+00
M.to.1layhid7	-7.141432e+02
N.to.1layhid7	1.546416e+00
c.to.1layhid7	1.072825e+01
d.to.1layhid7	6.442955e-01
Intercept.to.1layhid8	1.063679e+01
ELEVATION.to.1layhid8	-9.035351e+00
SLOPE.to.1layhid8	3.878724e+01
TWI.to.1layhid8	-7.239658e+01
PR.to.1layhid8	4.335567e+01
PL.to.1layhid8	2.383027e+01
NDV.to.1layhid8	1.845405e+01
DR.to.1layhid8	-3.127298e+01
DL.to.1layhid8	-4.067347e+01
SD.to.1layhid8	-6.638214e+00
10.to.1layhid8	-1.070038e+01
11.to.1layhid8	-8.966094e+00
12.to.1layhid8	6.679218e+01
16.to.1layhid8	-1.148940e+00
M.to.1layhid8	-1.841019e+01
N.to.1layhid8	1.003980e+01
c.to.1layhid8	1.055297e+01
d.to.1layhid8	-1.923821e+01
Intercept.to.1layhid9	-1.163310e+02
ELEVATION.to.1layhid9	3.335875e+02
SLOPE.to.1layhid9	-1.606538e+02
TWI.to.1layhid9	1.650349e+02
PR.to.1layhid9	9.123019e+01
PL.to.1layhid9	1.524419e+02
NDV.to.1layhid9	-1.364787e+01
DR.to.1layhid9	-3.223823e+01
DL.to.1layhid9	-2.074978e+02
SD.to.1layhid9	2.750510e+02
10.to.1layhid9	7.926087e+01
11.to.1layhid9	-8.450876e+01
12.to.1layhid9	-1.550148e+01

l6.to.l1ayhid9	-4.993058e+01
M.to.l1ayhid9	-8.155607e+01
N.to.l1ayhid9	-6.121184e+01
c.to.l1ayhid9	-1.977635e+01
d.to.l1ayhid9	1.801537e+02
Intercept.to.l1ayhid10	3.355817e+00
ELEVATION.to.l1ayhid10	1.060785e+02
SLOPE.to.l1ayhid10	1.597189e+01
TWI.to.l1ayhid10	-4.339686e+00
PR.to.l1ayhid10	-5.849527e+01
PL.to.l1ayhid10	-8.083786e+01
NDV.to.l1ayhid10	-8.374011e+00
DR.to.l1ayhid10	1.439967e+02
DL.to.l1ayhid10	-2.726828e+01
SD.to.l1ayhid10	-5.657958e+00
l0.to.l1ayhid10	-1.005277e+01
l1.to.l1ayhid10	2.485557e+01
l2.to.l1ayhid10	-9.833322e+01
l6.to.l1ayhid10	-6.597503e+01
M.to.l1ayhid10	4.787015e+01
N.to.l1ayhid10	-1.481261e+01
c.to.l1ayhid10	-7.444466e+02
d.to.l1ayhid10	8.213678e+01
Intercept.to.Training	-5.784784e-01
l1ayhid1.to.Training	-5.283730e+02
l1ayhid2.to.Training	2.953148e+02
l1ayhid3.to.Training	-3.042140e+02
l1ayhid4.to.Training	-1.606390e+02
l1ayhid5.to.Training	7.746477e+01
l1ayhid6.to.Training	-3.139433e+02
l1ayhid7.to.Training	2.014299e+02
l1ayhid8.to.Training	1.454576e+02
l1ayhid9.to.Training	5.393460e+01
l1ayhid10.to.Training	-8.654271e+01

C) Fourth Phase Model Training Result: After optimization(factors reduction)

Hidden 15 weight results	
error	5.677242e-02=0.056
Reached. threshold	9.712077e-03
steps	7.422000e+03
Intercept.to.1layhid1	-1.315389e+00
ELEVATION.to.1layhid1	-1.200353e+00
SLOPE.to.1layhid1	6.492282e+00
TWI.to.1layhid1	-2.572681e+00
PR.to.1layhid1	-4.952027e+00
PL.to.1layhid1	4.100143e+00
NDV.to.1layhid1	-8.173508e-01
DR.to.1layhid1	2.752917e+01
DL.to.1layhid1	-1.375110e+00
SD.to.1layhid1	-6.852522e+00
10.to.1layhid1	1.788509e+00
11.to.1layhid1	-5.751242e+02
12.to.1layhid1	4.904985e+01
16.to.1layhid1	5.924457e+00
M.to.1layhid1	-1.209698e+01
N.to.1layhid1	-2.229270e+00
c.to.1layhid1	-2.570301e+00
d.to.1layhid1	7.971766e-01
Intercept.to.1layhid2	-5.460750e-01
ELEVATION.to.1layhid2	-2.246737e-01
SLOPE.to.1layhid2	6.729082e-01
TWI.to.1layhid2	4.917479e+00
PR.to.1layhid2	-1.988125e+00
PL.to.1layhid2	-5.670858e+00
NDV.to.1layhid2	2.890401e+00
DR.to.1layhid2	4.379080e+00
DL.to.1layhid2	-2.389813e+00
SD.to.1layhid2	1.148042e-02
10.to.1layhid2	-1.687416e+00
11.to.1layhid2	4.471461e+01
12.to.1layhid2	-3.801311e+00
16.to.1layhid2	-2.873823e-01
M.to.1layhid2	-1.358374e+00
N.to.1layhid2	-1.665786e+00
c.to.1layhid2	-1.851301e+00

d.to.1layhid2	1.439503e+00
Intercept.to.1layhid3	6.450257e-01
ELEVATION.to.1layhid3	-2.552253e+00
SLOPE.to.1layhid3	-3.825641e+00
TWI.to.1layhid3	4.009246e+00
PR.to.1layhid3	5.533871e+00
PL.to.1layhid3	1.445444e+00
NDV.to.1layhid3	-4.775162e+00
DR.to.1layhid3	-1.042136e+00
DL.to.1layhid3	-5.483225e+00
SD.to.1layhid3	-5.058064e-01
10.to.1layhid3	-1.127355e+00
11.to.1layhid3	-3.952349e+00
12.to.1layhid3	-1.188188e+00
16.to.1layhid3	-1.356709e+00
M.to.1layhid3	1.142948e+00
N.to.1layhid3	7.520791e-01
c.to.1layhid3	4.583451e+00
d.to.1layhid3	4.111211e+00
Intercept.to.1layhid4	-1.371560e+00
ELEVATION.to.1layhid4	7.993931e+00
SLOPE.to.1layhid4	4.047548e+01
TWI.to.1layhid4	2.023342e+00
PR.to.1layhid4	5.118435e+00
PL.to.1layhid4	1.059619e+01
NDV.to.1layhid4	-1.036028e+01
DR.to.1layhid4	-9.807522e+01
DL.to.1layhid4	-2.445206e+01
SD.to.1layhid4	2.526057e+01
10.to.1layhid4	-8.288978e+00
11.to.1layhid4	-1.114468e+01
12.to.1layhid4	-2.076959e+01
16.to.1layhid4	5.063170e+00
M.to.1layhid4	-1.114611e+01
N.to.1layhid4	1.295914e+00
c.to.1layhid4	9.064322e+00
d.to.1layhid4	4.653517e+01
Intercept.to.1layhid5	8.336702e-01
ELEVATION.to.1layhid5	-1.363730e+01
SLOPE.to.1layhid5	2.280631e+00
TWI.to.1layhid5	-1.596374e+01

PR.to.1layhid5	2.893454e+00
PL.to.1layhid5	2.976561e+00
NDV.to.1layhid5	8.985814e+00
DR.to.1layhid5	8.658534e+01
DL.to.1layhid5	1.517023e+01
SD.to.1layhid5	-8.468478e+00
10.to.1layhid5	8.096895e+00
11.to.1layhid5	-2.113778e+02
12.to.1layhid5	-1.048889e+01
16.to.1layhid5	-8.624849e-01
M.to.1layhid5	-1.340614e+01
N.to.1layhid5	7.411533e-01
c.to.1layhid5	4.843945e+00
d.to.1layhid5	-1.378569e+01
Intercept.to.1layhid6	6.509341e-01
ELEVATION.to.1layhid6	-1.243048e+00
SLOPE.to.1layhid6	3.032379e+00
TWI.to.1layhid6	1.950761e+01
PR.to.1layhid6	-6.698839e+00
PL.to.1layhid6	-2.964050e+00
NDV.to.1layhid6	-1.294461e+00
DR.to.1layhid6	-2.215696e+01
DL.to.1layhid6	-2.413489e+01
SD.to.1layhid6	-8.416469e-01
10.to.1layhid6	4.974104e+00
11.to.1layhid6	-2.368020e+00
12.to.1layhid6	3.145355e+00
16.to.1layhid6	1.378810e+01
M.to.1layhid6	1.693913e+00
N.to.1layhid6	1.540115e+00
c.to.1layhid6	5.601753e+00
d.to.1layhid6	-4.190035e+00
Intercept.to.1layhid7	-7.586336e-01
ELEVATION.to.1layhid7	1.751089e+01
SLOPE.to.1layhid7	-5.387446e+00
TWI.to.1layhid7	-3.367113e-01
PR.to.1layhid7	2.454501e-01
PL.to.1layhid7	-2.185266e+00
NDV.to.1layhid7	-1.187928e+01
DR.to.1layhid7	-1.711931e+01
DL.to.1layhid7	2.035421e+01

SD.to.1layhid7	-6.456125e+00
10.to.1layhid7	-8.133263e+00
11.to.1layhid7	5.334299e-01
12.to.1layhid7	1.223625e+01
16.to.1layhid7	4.783155e+00
M.to.1layhid7	-2.568973e+01
N.to.1layhid7	2.734017e+00
c.to.1layhid7	1.131423e+01
d.to.1layhid7	6.396736e+00
Intercept.to.1layhid8	-4.024727e-01
ELEVATION.to.1layhid8	-2.689937e-01
SLOPE.to.1layhid8	7.580129e+00
TWI.to.1layhid8	-9.942016e-01
PR.to.1layhid8	6.190548e+00
PL.to.1layhid8	4.131973e+00
NDV.to.1layhid8	-6.825757e+00
DR.to.1layhid8	-2.099587e+01
DL.to.1layhid8	1.294841e+01
SD.to.1layhid8	2.570079e+00
10.to.1layhid8	9.929440e-01
11.to.1layhid8	-1.299898e+01
12.to.1layhid8	-1.019926e+00
16.to.1layhid8	-1.035626e+01
M.to.1layhid8	-2.337204e+00
N.to.1layhid8	3.840962e+00
c.to.1layhid8	6.362314e+01
d.to.1layhid8	-6.715783e+00
Intercept.to.1layhid9	1.581645e+00
ELEVATION.to.1layhid9	6.968826e+00
SLOPE.to.1layhid9	7.596259e-01
TWI.to.1layhid9	1.440083e+01
PR.to.1layhid9	-2.595121e+00
PL.to.1layhid9	-8.635980e-01
NDV.to.1layhid9	-3.852835e+00
DR.to.1layhid9	-2.374810e+00
DL.to.1layhid9	1.005229e+01
SD.to.1layhid9	-2.017563e+01
10.to.1layhid9	2.263217e+00
11.to.1layhid9	-6.334703e+00
12.to.1layhid9	-9.762949e+00
16.to.1layhid9	-1.170997e+00

M.to.1layhid9	-2.459333e+00
N.to.1layhid9	-2.252277e+00
c.to.1layhid9	-3.970420e+00
d.to.1layhid9	6.592027e+00
Intercept.to.1layhid10	-7.995244e-01
ELEVATION.to.1layhid10	-1.018752e+00
SLOPE.to.1layhid10	8.252512e-01
TWI.to.1layhid10	-6.498046e+00
PR.to.1layhid10	7.671151e-02
PL.to.1layhid10	-6.071385e+00
NDV.to.1layhid10	4.470794e+00
DR.to.1layhid10	-1.101631e+00
DL.to.1layhid10	1.343660e+00
SD.to.1layhid10	2.755894e+00
10.to.1layhid10	-4.750431e-01
11.to.1layhid10	-4.907175e+02
12.to.1layhid10	1.087644e+00
16.to.1layhid10	5.070050e+00
M.to.1layhid10	1.873256e+00
N.to.1layhid10	1.258669e+00
c.to.1layhid10	-2.905077e+00
d.to.1layhid10	-6.879815e-01
Intercept.to.1layhid11	-2.947681e-01
ELEVATION.to.1layhid11	-1.635652e+01
SLOPE.to.1layhid11	-3.049943e+01
TWI.to.1layhid11	-5.993082e+00
PR.to.1layhid11	4.550187e+00
PL.to.1layhid11	5.286332e+00
NDV.to.1layhid11	-1.657747e+00
DR.to.1layhid11	2.272791e+02
DL.to.1layhid11	5.464653e+01
SD.to.1layhid11	-2.340130e+01
10.to.1layhid11	1.173644e+01
11.to.1layhid11	-2.222693e+01
12.to.1layhid11	-5.147771e+01
16.to.1layhid11	1.083601e+01
M.to.1layhid11	-3.203689e+00
N.to.1layhid11	2.617690e+00
c.to.1layhid11	3.767683e+00
d.to.1layhid11	6.244576e+00
Intercept.to.1layhid12	1.385401e+00

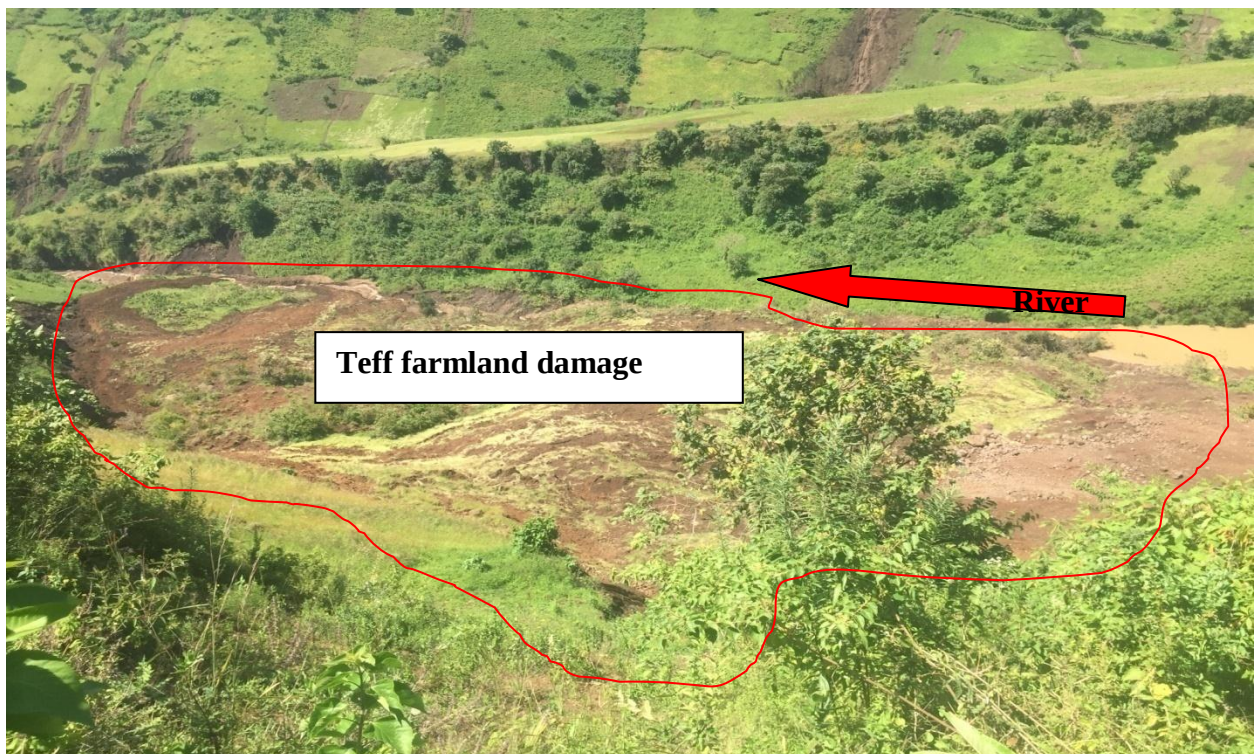
ELEVATION.to.1layhid12	1.769004e+01
SLOPE.to.1layhid12	-7.442629e+00
TWI.to.1layhid12	-5.499302e+00
PR.to.1layhid12	8.048972e-01
PL.to.1layhid12	-9.555144e-01
NDV.to.1layhid12	2.617817e+00
DR.to.1layhid12	-8.806891e-01
DL.to.1layhid12	5.116155e+00
SD.to.1layhid12	-6.306964e+00
10.to.1layhid12	9.718953e-01
11.to.1layhid12	-4.754703e+00
12.to.1layhid12	8.904207e+00
16.to.1layhid12	-2.400100e+00
M.to.1layhid12	-6.315609e+00
N.to.1layhid12	-3.591257e+00
c.to.1layhid12	-4.954616e+00
d.to.1layhid12	-1.046425e+01
Intercept.to.1layhid13	-1.480048e+00
ELEVATION.to.1layhid13	1.713484e+00
SLOPE.to.1layhid13	2.560050e+00
TWI.to.1layhid13	-1.304463e+00
PR.to.1layhid13	-8.194628e-01
PL.to.1layhid13	-1.082222e+00
NDV.to.1layhid13	-2.656483e+00
DR.to.1layhid13	-2.051526e+00
DL.to.1layhid13	7.441260e+00
SD.to.1layhid13	7.821979e+00
10.to.1layhid13	-3.674891e-01
11.to.1layhid13	-2.482197e+00
12.to.1layhid13	-1.989215e+00
16.to.1layhid13	-1.365740e-01
M.to.1layhid13	5.421833e-02
N.to.1layhid13	-4.545700e-01
c.to.1layhid13	-1.595509e-01
d.to.1layhid13	-7.157616e+02
Intercept.to.1layhid14	1.968610e-01
ELEVATION.to.1layhid14	1.013856e+01
SLOPE.to.1layhid14	-1.047997e+01
TWI.to.1layhid14	-3.169287e-03
PR.to.1layhid14	2.428228e+01
PL.to.1layhid14	-3.197509e+00

NDV.to.1layhid14	-6.271271e+00
DR.to.1layhid14	-1.864185e+01
DL.to.1layhid14	-1.514808e+00
SD.to.1layhid14	-6.319639e+00
10.to.1layhid14	4.414075e+00
11.to.1layhid14	-7.565265e+00
12.to.1layhid14	-3.046064e+01
16.to.1layhid14	-9.532111e+00
M.to.1layhid14	-2.337704e+00
N.to.1layhid14	-1.297106e+00
c.to.1layhid14	6.684159e+00
d.to.1layhid14	3.270213e+01
Intercept.to.1layhid15	1.318893e+00
ELEVATION.to.1layhid15	2.084140e+00
SLOPE.to.1layhid15	2.852236e+01
TWI.to.1layhid15	9.263582e-01
PR.to.1layhid15	1.025891e+00
PL.to.1layhid15	-1.245887e+01
NDV.to.1layhid15	5.436678e-01
DR.to.1layhid15	2.782045e-02
DL.to.1layhid15	-1.600922e+01
SD.to.1layhid15	-6.298760e+00
10.to.1layhid15	-2.251495e+00
11.to.1layhid15	-5.608067e+00
12.to.1layhid15	-8.371817e+00
16.to.1layhid15	1.422752e+01
M.to.1layhid15	1.170825e+00
N.to.1layhid15	2.149993e+00
c.to.1layhid15	-1.077637e+01
d.to.1layhid15	-1.331369e+01
Intercept.to.Training	4.451005e-01
1layhid1.to.Training	3.493375e+01
1layhid2.to.Training	-1.008534e+02
1layhid3.to.Training	-6.799536e+01
1layhid4.to.Training	3.694332e+01
1layhid5.to.Training	-2.285493e+01
1layhid6.to.Training	2.420155e+01
1layhid7.to.Training	3.952603e+01
1layhid8.to.Training	-3.594303e+01
1layhid9.to.Training	3.569713e+01
1layhid10.to.Training	-9.738648e+01

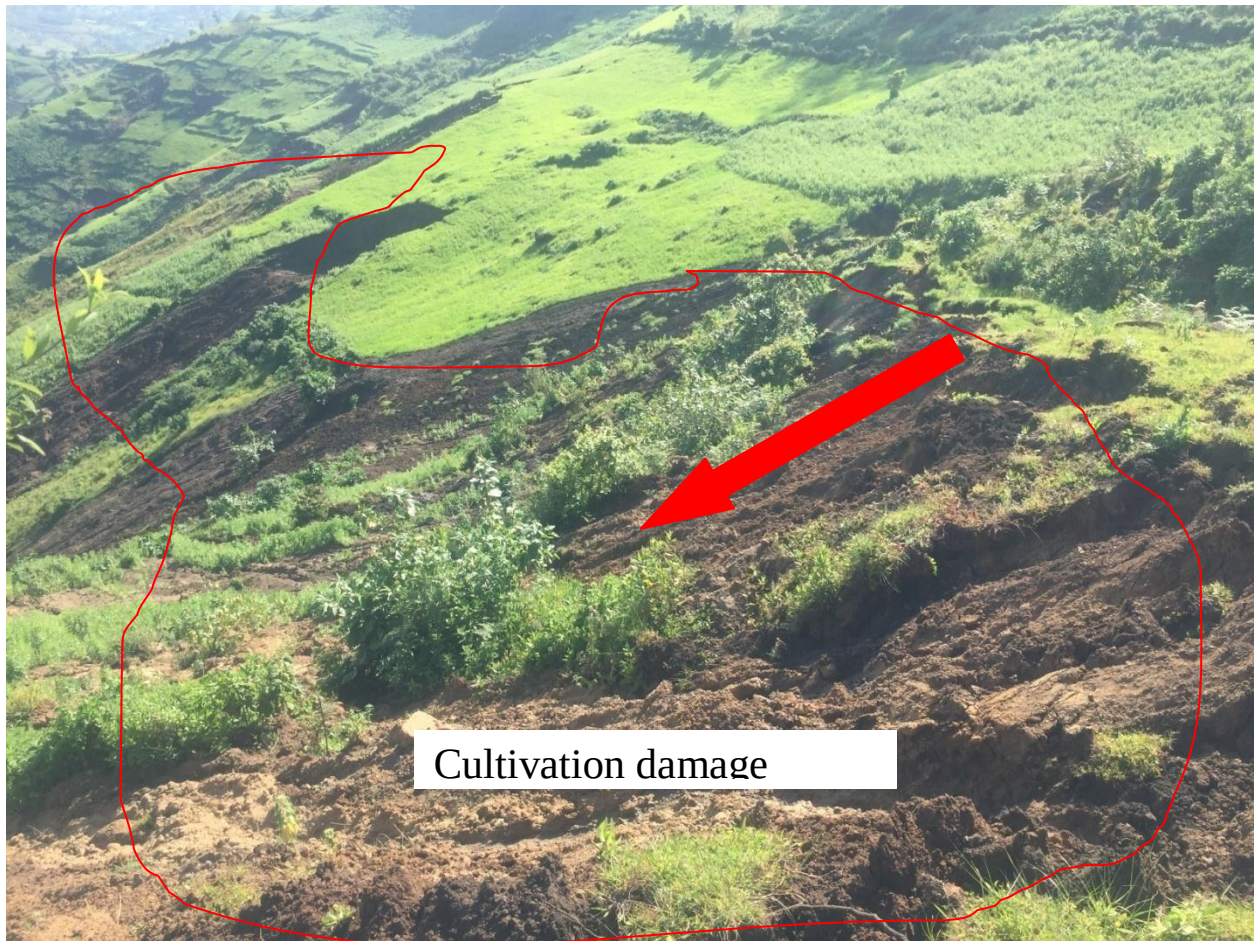
1layhid11.to.Training	-2.957483e+01
1layhid12.to.Training	-5.575448e+01
1layhid13.to.Training	3.924239e+01
1layhid14.to.Training	3.893315e+01
1layhid15.to.Training	3.908993e+01

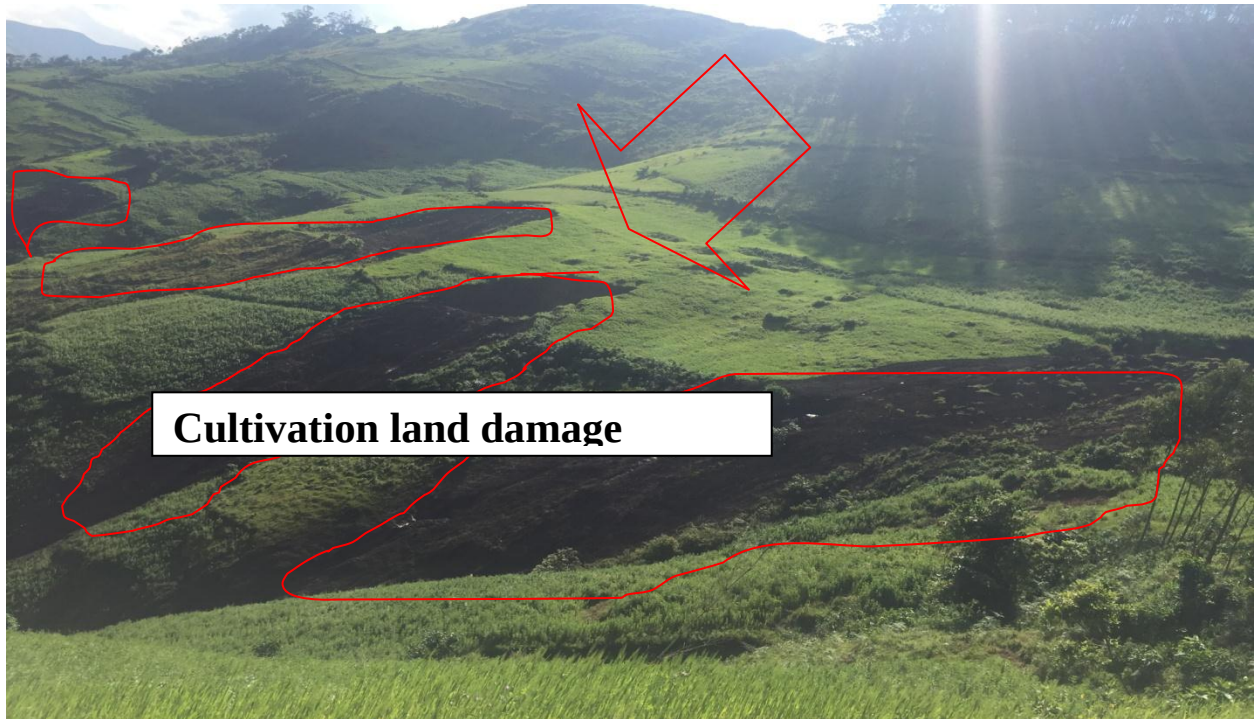
APPENDIX 5: Sample Landslide affected areas Photos

A) Bulki Tsire Site



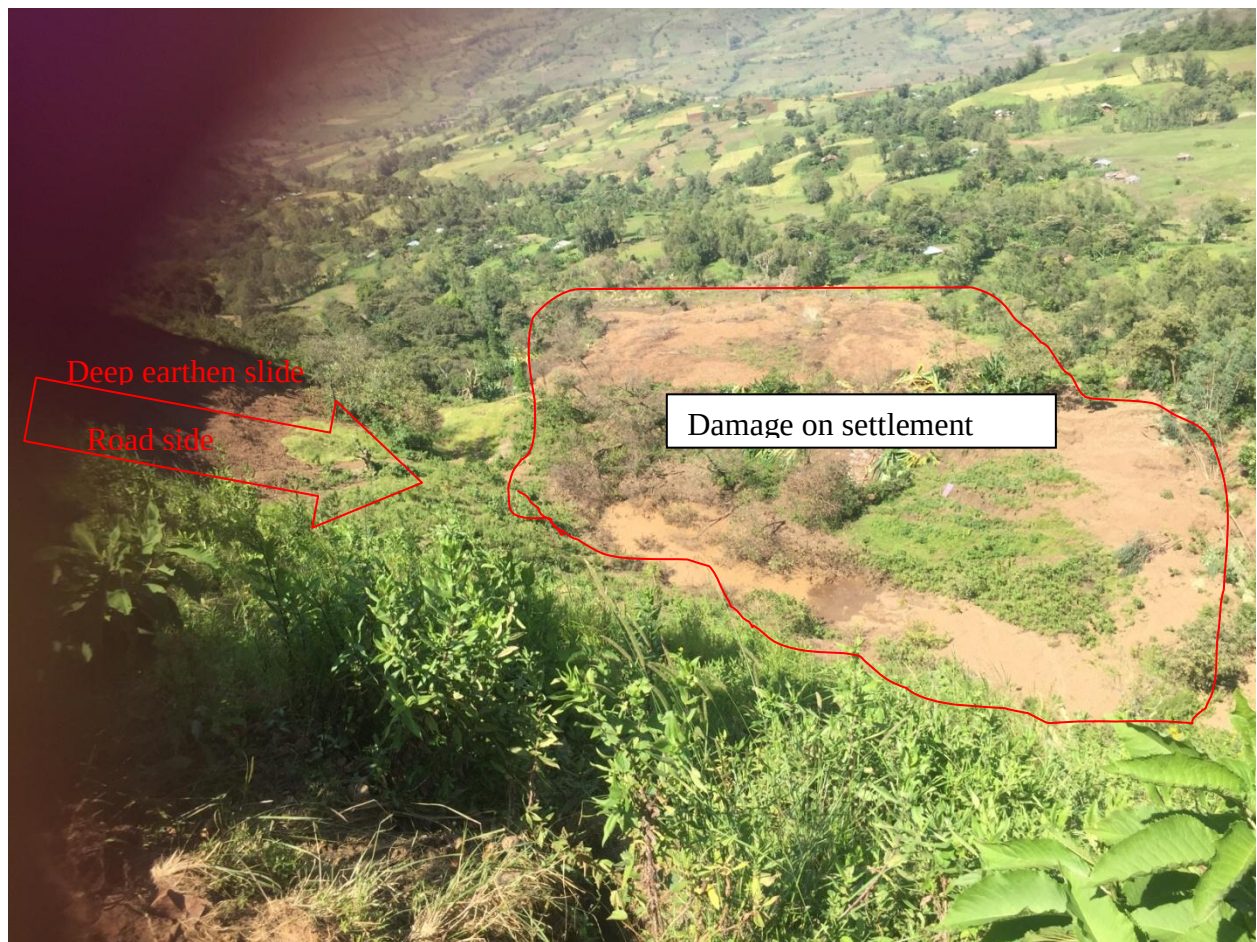
B) Yongi Village : damage on cultivation lands





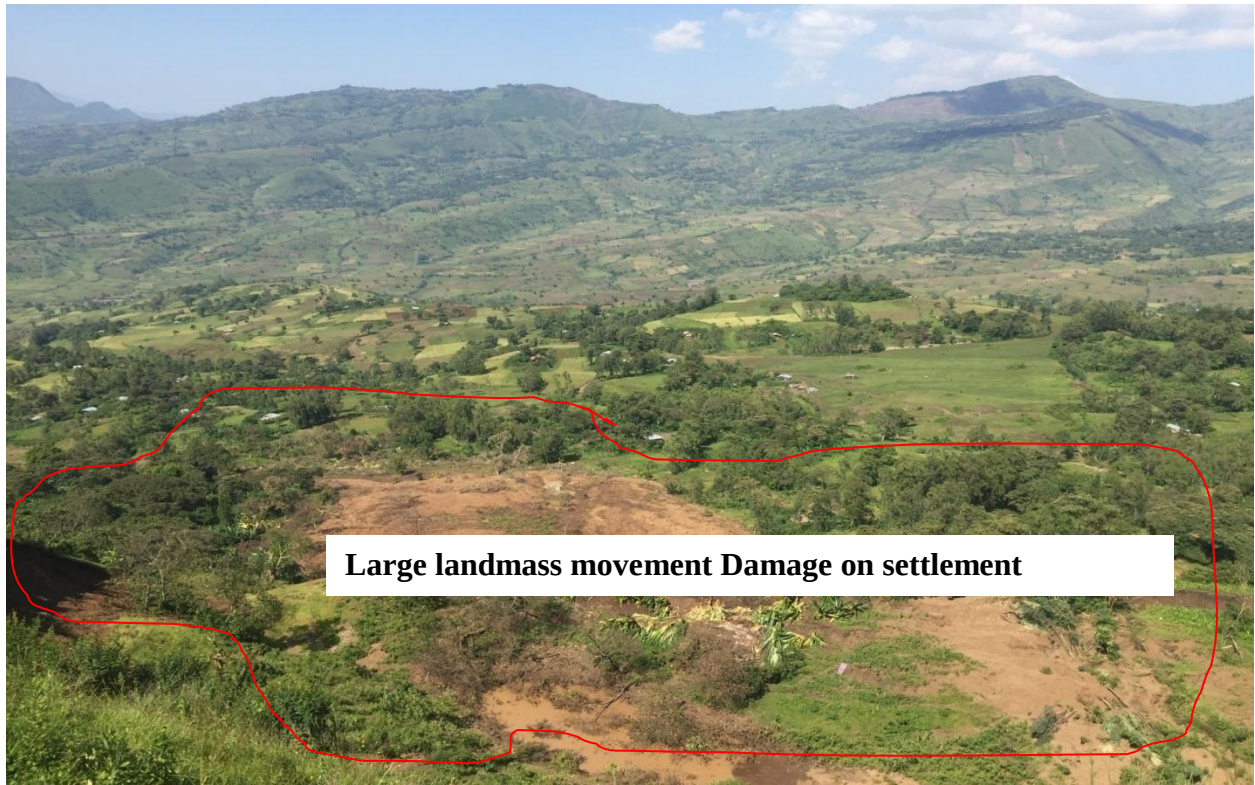
C) BedroSelo Site_Bulki To Bedro Road corridor











Large landmass movement Damage on settlement