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COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES

SCHOOL OF EARTH SCIENCES

THE IMPACTS OF VEGETATION COVER CHANGE ON RAINFALL AND LAND SURFACE TEMPERATURE USING REMOTE SENSING: A CASE STUDY OF NORTH GONDAR ZONE, ETHIOPIA

By:

WORKU NEGA

GSR/6454/09

ADVISOR: DR. BINYAM TESFAW

CO-ADVISOR: DR. ARAMDE FETENE

A THESIS SUBMITTED TO

SCHOOL OF GRADUATE STUDIES OF ADDIS ABABA UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN REMOTE SENSING AND GEO-INFORMATICS

Addis Ababa, Ethiopia

June, 2018

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Addis Ababa University
School of Graduate Studies

This is to certify that a Thesis prepared by **Worku Nega**, entitled: “The impacts of vegetation cover change on rainfall and land surface temperature using remote sensing: A case study of North Gondar zone, Ethiopia” and submitted in partial fulfillment of the requirements for the degree of Master of Science in Remote sensing and Geo-informatics complies with the regulations of the University and meets the accepted standards with respect to the originality and quality.

Signed by the Examining committee:

Examiner

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Abstract

Remote Sensing has a great importance for vegetation cover change analysis specifically deforestation and its impacts on climatic parameters, biodiversity, fertility of soil and land productivity. However, there is a gap on quantifying and analyzing the impact of change in vegetation cover on the change of climatic variables such as: fluctuation of rainfall and Land Surface Temperature (LST). Therefore, this study aims to assess of vegetation cover change and its impacts on rainfall and land surface temperature using remote sensing data and statistical methods. The study was conducted in North Gondar which is characterized by high deforestation, expansion of agriculture and high rate of population growth. The data were i) satellite images from Landsat 5 Thematic Mapper Sensor(TM) (1985, 2000, 2010) and Landsat 8 Operational Land Imager/ Thermal Infrared Sensor (OLI/TIRS) (2017): to analyze the vegetation cover change using NDVI threshold method by using Ground truth and google earth data, and previous studies. ii) Climate Hazard Group InfraRed Precipitation (CHIRPS) and Moderate Resolution Imaging Spectroradiometer (MODIS): to evaluate rainfall and LST using Mann-Kendall Trend Test (iii) field observation and google earth to verify remotely sensed data. Pearson Correlation coefficient was conducted to quantify and to analyze the relationship of vegetation cover with rainfall and LST. The result showed that vegetation cover occupied an area of 210,177 ha (4.7%), 173,971 ha (3.9 %), 141785 ha (3.2%) and 117,019 ha (2.6%) in 1985,2000, 2010 and 2017, respectively where 2.1% of vegetation cover has been lost in the last 32 years in in the study area. The Mann-Kendall trend test result revealed that annual and dry season rainfall increases however no significant trend in mean annual and dry season rainfall with p-value = 0.09 and 0.54 from 1981 to 2017. The trend test result also shows no significant trend in mean dry season LST with p-value= 0.35. According to the pearson correlation coefficient result, the relationship of vegetation cover with rainfall and LST was not statistically significant (p-value=0.68 and R^2=0.23 with alpha 0.05) and (p-value=0.29, R^2=0.80 with alpha 0.05), respectively. The findings from the zonal statistics result, this study concluded that mean annual rainfall was decreased with declined vegetation cover in central, northern and southeastern part of North Gondar zone. On the other hand, mean LST was increased with declined vegetation cover in the area. LST.

Keywords: North Gondar zone, Vegetation Cover, Land Surface Temperature, Rainfall.

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Acronyms and Abbreviations

CFS	Climate Forecast System
CHIRPS	Climate Hazards Group Infrared Precipitation with Stations
CHPClim	Climate Hazards Precipitation Climatology
CSA	Central Statistics Agency
DEM	Digital Elevation Model
DN	Digital Number
ERDAS	Earth Resources Data Analysis System
EROS	Earth Resources Observation and Science
EVI	Enhanced Vegetation Index
FAO	Food and Agricultural Organization
GCPs	Ground Control Points
GHG	Green House Gas
GIS	Geographic Information System
GPS	Global Positioning System
Ha	Hectare
HDF	Hierarchical Data Format
LC	Land Cover
LST	Land Surface Temperature
LULC	Land Use/Land Cover
LULCC	Land Use/Land Cover Change
MoA	Ministry of Agriculture
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NCDC	National Climatic Data Center
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
OLI	Operational Land Imager
RDE	Rural Development of Ethiopia
RF	Rainfall
RS	Remote Sensing
SRTM	Shuttle Radar Topography Mission
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TRMM	Tropical Rainfall Measuring Mission
USGS	United States Geological Survey
XLSTAT	Statistical software for Microsoft Excel

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

Forest cover is affected by Land Use/Land Cover Change (LULCC) (Solomon, 2016)**.** Land Use/Land Cover (LULC) has become one of the major issues for natural resource management and environmental change monitoring. LULCC has impacts on terrestrial ecosystems including forestry, biodiversity and agriculture that have been recognized as high priority issues in global, national, and regional levels. Thus, land productivity could be declined because of LULC change under continuous cultivation, overgrazing and soil erosion (Solomon, 2016)**.** LULC contributes to climate change in Ethiopia (Sisay *et al*., 2016). Climate change causes wide-ranging effects on the environment, and on socio-economic and related sectors, including water resources, agriculture and food security, human health, terrestrial ecosystems and biodiversity (Belay and Getaneh, 2016).

In Ethiopia, deforestation is a continuous process that is causing changes to climatic conditions, loss of biodiversity, desertification, and displacement of people (Tigabu, 2016). Deforestation is the destruction of forests followed by a change in the land use that prevents the forest from regenerating (Belay and Getaneh, 2016). Deforestation and forest degradation in the country have resulted in heavy soil erosion and land degradation and consequently, decline in annual yield for crop particularly in the highlands of Ethiopia (Mulatie *et al*., 2016). Moreover, deforestation has negative impact on rainfall (Hanif *et al*., 2016**).** The other consequence of deforestation is that the carbon originally held in forests is released to the atmosphere, either immediately if the trees are burned, or more slowly as un-burned organic matter decays (Archana, 2013). Forest degradation lead to the destruction and erosion of biodiversity of both plants and animals (Fekadu, 2015).

Population growth and demand of population creates a pressure on LULC. This pressure results in unplanned and uncontrolled changes in LULC. The LULC alterations are generally caused by mismanagement of agricultural, urban, and forest land. The main underlying causes of deforestation and forest degradation includes the presence of increasing in population growth, promotion of agricultural investment, lack of sense of ownership and lack of clear legal policy framework (Tigabu, 2016).

Mapping, quantifying and monitoring of LULC is essential to generate information for planning and for making the land more productive. The accurate quantification of vegetation cover change is therefore critically important for reducing uncertainties in carbon emission estimates, and for evaluating the effectiveness of environmental policies aiming at reducing emissions from deforestation and forest degradation (Xiao, 2014). Quantification of vegetation cover is also important to prevent soil erosion, preserve biodiversity, maintain agro-ecological zone and increase the productivity of the land.

Normalized Difference Vegetation Index (NDVI) is an index that provides a standardized method of providing information about vegetation greenness between satellite images. It is an alternative measure of vegetation amount and condition. It can also be associated with vegetation canopy characteristics such as biomass, leaf area index and percentage of vegetation cover (Babalola and Akinsanola, 2016). NDVI has relation with Vegetation cover that indicates the presence of dense vegetation cover or bare/lower vegetation cover.

There is a strong relationship between NDVI and rainfall (Martiny *et al*., 2006). Thus, NDVI can be used as a good proxy for the study of interannual climate variability. Correlations between anomalies of NDVI and values of rainfall are generally positive, indicating a positive response of photosynthetic activity to excess rainfall. Rainfall is the most important climatic factor that closely correlates with NDVI (Richard & Poccard, 2010). A simple linear relationship between NDVI and rainfall with positive correlation has been found in many studies (Li *et al*., 2004; Richard & Poccard, 2010; Lamchin *et al*., 2015).

Land Surface Temperature (LST) plays an important role in many environmental processes. It can provide primary information on the surface physical properties and climate (Kayet *et al*., 2016). The LST is highly influenced by the LULC, and very sensitive to vegetation and soil moisture; specifically, the amount of vegetation was discovered to be the main factor on the relationship between vegetation cover and LST. For example, high LST has been seen in areas with less vegetated LULC and vice versa (Rasul and Ibrahim, 2017). Babalola and Akinsanola (2016) in their study reported that forest cover had shown a considerably low radiant temperature in all the years considered, because dense vegetation can reduce amount of heat stored in the soil and surface structures through transpiration. There is strong negative correlation between LST and NDVI values (Rehman *et al*., 2015**;** Chaithanya *et al*., 2017; Suresh and Mani, 2017). Vegetation with dense cover has the lowest mean LST and highest mean NDVI; while non-vegetated areas have the highest LST and lowest mean NDVI (Sun et al., 2011) which implies that lower LST is usually measured in areas with higher NDVI values (Sundara *et al*., 2012).

In the present study, the impacts of vegetation cover change on climate parameter variability (rainfall and LST) in the North Gondar zone is investigated by remote sensing approach ***(***Eunice, 2013**).** Remote sensing data is widely used in environmental and climatic studies. The use of satellite-based remote sensing data has been widely applied to receive cost-effective Land Cover (LC) data over large geographic regions. The mapping, quantifying and monitoring of (LC) is essential to understand the current state of landscape. In recent years, remote sensing data is useful for assessing vegetation cover change through time (Batool *et al*., 2015). Moderate Resolution Imaging Spectroradiometer (MODIS) LST is the skin temperature of the earth surface. It gives information on the heat of the earth which depends on different LULC type. It provides information on time to time variation of earth surface energy change. It is an important factor for monitoring vegetation and climate change (Kayet *et al*., 2016).

1.2 Statement of the Problem

Ethiopia is endowed with diverse natural resource in general and vegetation resource in particular. However, due to unwise use of the vegetation resource in the country, which has been taking place for centuries, the remaining vegetation coverage is extremely very small and is confined in southwestern part of the country (Amogne, 2013). Destruction of the natural vegetation of Ethiopia results directly in the loss of unaccounted plant and animal species. It also leads to more aggravated soil erosion, deterioration of the water quality, drought and flooding, reduction of agricultural productivity, species extinction and to an ever-increasing poverty of the rural population (Fekadu, 2015).

The depletion of vegetation resources contributes to climatic and physical changes of the environment. Climate change is a major threat to sustainable growth and development in Africa (Fekadu, 2015). Climate change is attributed directly or indirectly to human activity. It alters the composition of the global and/or regional atmosphere and natural climate variability observed over comparable time periods. Agricultural expansion and deforestation are major contributors to climate change. Climatic variability is the types of changes (temperature, rainfall); in magnitude and rate of climate change (Belay and Getaneh, 2016).

Natural vegetations are diminishing from time to time due to firewood collection, conversion to farmland, overgrazing, and use of wood from the forest for building materials. Rapid deforestation that has been fueled by ever increasing of population growth, vegetation clearing for agricultural use, overgrazing, exploitation of existing vegetation for fuel wood has been resulted in depletion of productivity both at the natural and working landscapes (Amogne, 2013; Srinivasan, 2014).

Vegetation cover change has a long history in Amhara Region where subsistence farming and settlements have been changing the entire landscapes. Vegetation degradation in Amhara Region is increases from day-to-day due to population growth and overgrazing pressure (Dessalew, 2016). Vegetation cover change in the region have resulted in heavy soil erosion and land degradation and consequently, decline in annual yield for crop and grass in particular in the highlands of the region (Mulatie *et al*., 2016). Today, very few remnants of natural vegetation are found exclusively in the southern and southwestern parts of the country (Abineh *et al*., 2015). In the study area, there has been trends of deforestation for different land use purposes. However, there has not been comprehensive study related to the rate of deforestation and its impacts on the climatic variables particularly on the rainfall and the land surface temperature. Understanding such relationships would benefit to put in place effective conservation plan for informed decision making. On way of analyzing the relationship of vegetation cover change with the rainfall and land surface temperature is using site specific Normalized Difference Vegetation Index (NDVI) from the red and infrared bands of electromagnetic spectrum. Suresh and Mani (2017) reported that there was strong negative correlation between NDVI and LST. On the other hand, Martiny *et al*. (2006) reported that NDVI and rainfall has strong positive relationship with each other. More importantly, the relationships that could exist among these interrelated components have to be identified in order to make accurate and realistic predictions on the changing conditions of vegetation and its relationship with climatic parameters (for example, rainfall and LST).

The other important parameter to be considered related to vegetation cover change is the land tenure situation which has expected to have impact on vegetation cover change and vegetation degradation. Land tenure is a social construct which defines the relationships between individuals, groups of individuals and the state with respect to land. Therefore, a given land tenure system determines who can use which resources for how long, and under what conditions (Achamyeleh, 2014). Local people with some environmental awareness living in an area usually take better care of their landscape than the people, who come from outside with economic interests only. There is no organized land tenure system in the study area especially in lower 'kola' areas (Amogne, 2013). 'Kola' is traditional climatic zone in Ethiopia with elevation between 500 masl-1500 masl, warm semi-arid climate of mean annual temperature (20–27.5^{o}C) and mean annual rainfall (200–800 mm). Because of this miss-land management, any farmer who come far from different locality able to use the land unwisely. Additionally, Sesame and Cotton are the two main cash crops which are produced in some parts of North Gondar zone with the expense of vegetation land use change. Therefore, in the area, the vegetation is cleared because of expansion of agriculture, and charcoal production. As a result, most of the natural vegetation land is converted into agricultural land.

Moreover, like in many other parts of the country, the problem of vegetation cover change is a very serious environmental problem in North Gondar zone and extensive areas of vegetation cover have been deforested. However, as mentioned earlier, the rate and areal extent of the vegetation cover change have not yet been well studied in the study area. In addition, the LST and rainfall variability was not assessed. Thus, for a sustainable vegetation resource management and analysis of climate, it is necessary to estimate for vegetation cover change and climate variability on large spatial and temporal scales. In this regard, this study was conducted using Landsat imageries, CHIRPS and MODIS LST to accommodate large spatial and temporal changes of vegetation cover, rainfall and LST of the study area. Therefore, the aim of this study was to assess the spatial and temporal vegetation cover change and its impacts on selected climate variabilities (rainfall and LST) in the study area.

1.3 Objectives

1.3.1 General Objective

The general objective of this study was to assess the impacts of vegetation cover change on rainfall and land surface temperature.

1.3.2 Specific Objectives

- To analyze vegetation cover change of the study area (1985-2017).
- To study the trends of rainfall and land surface temperature of the study period.
- To examine the relationship of vegetation cover with rainfall and land surface temperature during the study period.

1.4 Significance of the Study

This study would provide information which is important to maintain the agro-climatic condition, assure sustainability in resource utilization and proper land use planning and decision making for policy makers, agricultural experts, foresters, non-governmental organizations (i.e., forest management stakeholders), planners and land administrators.

Besides, the present study will provide firsthand information for the other researchers who have an interest to conduct further study related to landscape change and landscape disturbance from remote sensing data. Finally, investors and stakeholders will be informed about the vegetation cover change and its impacts on climate so that they could take care and utilize their natural resources in a sustainable way.

1.5 Scope of the Study

The scope of the study was spatially limited in the Amhara National Regional State, North Gondar zone, Ethiopia. It covers an area of 4476421 ha. The study focused only on quantifying vegetation cover change, assessing trend of rainfall and evaluating land surface temperature in North Gondar zone. The study was also focused on only vegetation and non-vegetation classes during the study period. To conduct this study, satellite imagery, ground truth data and google earth were used.

1.6 Limitation of the study

The study was limited by lack of high resolution remote sensing data for analyzing vegetation cover in the study area.

1.7 Organization of the Study

This study is organized into six chapters. The first chapter elaborates the background of the study, statement of the problem, general and specific objectives, significance and scope of the study. The second chapter describes literature review which focuses on concepts of vegetation cover change, deforestation in Ethiopia, cause of climate variability, and impacts of vegetation cover change on rainfall and LST. The third chapter provides an overall description of data sets and how the research is conducted. The fourth chapter deals with the results. The fifth chapter describes discussion and the final chapter elaborates conclusion and recommendation.

CHAPTER TWO

2 LITERATURE REVIEW

2.1 Concepts of Vegetation Cover Change

Human beings are the major contributors to land cover changes and are the ones experiencing the consequences of these changes, it is important to understand the interaction between human beings and the terrestrial environment. This need becomes more imperative as changes in land use become more rapid affecting the livelihoods of societies (Kahsay, 2004). Analyzing Land Use/Land Cover (LULC) change is focused on understanding the processes, patterns and dynamics of land use transitions and driving forces of change of LULC (Worku, 2016). In the twenty-first century, Land cover dynamic has the global concern with the dramatic implication for human survival. Land cover change is the change in biological as well as physical characteristics of land which is attributable to management including conversion of vegetation into grazing land, farming land, built-up land (Tesfa *et al*., 2016). LULC changes are temporally and spatially dynamic (Eunice, 2013). It has been recognized as an important driver of environmental change on all spatial and temporal scales. It also affects forest cover, and biodiversity. Analyzing LULC change is useful for environmental change monitoring and natural resource management (Habtamu, 2011). Land use/cover change detection is very essential for better understanding of landscape dynamic during a known period of time having sustainable management. Understanding landscape patterns, changes and interactions between human activities and natural phenomenon are essential for proper land management and decision improvement (Rawat and Manish, 2015). Land cover mapping and monitoring can serve as important indicators of landscape and environmental status, distributions, and patterns. A common and an effective way to better understand temporal changes, as well as the spatial variability of an area, is through the study of land cover change.

Normalized Vegetation Index (NDVI) can indicate the existence of vegetation cover besides fractional vegetation cover (Rasul and Ibrahim, 2017). NDVI is widely used for vegetation cover monitoring. It is also an indicator of vegetation growth and coverage which has been widely employed to describe the spatiotemporal characteristics of LULC (Nurhussen, 2016). NDVI is a numerical indicator of vegetation cover which is derived from the Visible and Near

Infrared bands of the electromagnetic spectrum used in remote sensing to assess the concentration of green vegetation. It is also widely used index in characterization and assessment of vegetation cover change. NDVI is widely accepted as a good indicator for providing vegetation properties and associated changes for large spatial scale (Lamchin *et al*., 2014). The NDVI derived from satellite-based optical sensor images allow to monitor the development of green vegetation in land surfaces over wide areas. NDVI is a quantitative indicator of the relative abundance and activity of green vegetation cover.

Vegetation cover has a great role to maintain local climate change and climate variability (Nurhussen, 2016). Vegetation has an important role to conserve the natural environment and to improve the living environment of human beings. Thus, assessing spatiotemporal deviations of vegetation cover is a key indicator to realize natural environmental changes (Lamchin, 2014). Forest covers change is a dynamic, widespread and accelerating process (Dessalew, 2016). Forests can minimize the impacts of soil erosion and can absorb rainfall. Forests are useful to preserve water shades, improve water quality and quantity, prevent soil erosion, serve as habitat for wild animals, and prepare medicines. Another critically important function of forests increasingly and widely acknowledged now is that they help to protect the planet from climate change by absorbing carbon dioxide (CO2), a major greenhouse gas. Therefore, forests play a critical role in protecting the earth from climate change and regulating climate patterns (Archana, 2013).

2.2 Causes of Vegetation Cover Change

The fundamental causes of vegetation cover change emanated from poverty, limited opportunities for alternative livelihoods, expansion of resettlement, inadequate policy support, improper investment and inadequacy of law enforcement (Worku, 2016). The primary causes of natural vegetation destruction are agricultural expansion, both through shifting cultivation, large-scale investment and the spread of agriculture; the demand for increasing amounts of construction material, fuelwood and charcoal; as well as expansion of livestock grazing (Amogne, 2013). In most parts of the world, particularly in developing countries agriculture is the livelihoods of the population in turn primarily the most driver of land use change (Tesfa *et al*., 2016).

Forest-related drivers of forest degradation and deforestation are usually illegal and conducted by persons who are less aware of environmental consequences of their actions. The worst kinds are the illegal timber cuttings in the last remaining forests which one can blame a number of wood traders. In more developed regions of Ethiopia charcoal is illegally produced from natural forests and woodland trees, and most of the charcoal end up to be used in regional. A main cause of vegetation degradation and destruction is the expansion of population growth of recent years which results socio-economic imbalances because landless farmers are increasing as the population is increasing in rural parts of the country and unsustainable shifting cultivation is increased which aggravate forest degradation (Amogne, 2013). Anthropogenic activities such as agriculture, mining, deforestation and construction influence on shifting patterns of land use are a primary component of many current environmental concerns as LULC change is a key driver of environmental change. Changes in LULC are widespread and increasingly rapid, at local, regional and global scales (Batool *et al*., 2015). All the factors of deforestation such as the prevalence of various types of agricultural activities, firewood and charcoal production, cutting trees to fulfill the demand of constructional materials, and settlement expansion are directly or indirectly related to population growth and new settlements. The absence of applicable forest policy is cited as a contributing factor for deforestation in different parts of the world including Ethiopia (Solomon, 2016).

There are two main causes of vegetation cover change. These are: proximate and underlying causes (Solomon, 2016). Proximate causes are immediate actions of local people in order to fulfill their needs from the use of the land. Proximate causes directly affect vegetation cover such as wood extraction or clearing land for agriculture, infrastructure expansion and others that change the physical state of land cover. Underlying causes are the fundamental forces that trigger the proximate causes, including demographic pressure, economic policy, and technological development that influence LULC. In addition to this, lack of appropriate land use and forest policies and the absence of corresponding laws are responsible for decline of forests in Ethiopia (Tesfa *et al*., 2016).

2.3 Impacts of Vegetation Cover Change

Vegetation cover change affects biodiversity, hydrological cycle, productivity of land and the sustainability of natural resources (Tesfa *et al*., 2016). Forest and generally biomass degradation, as well as consequent land degradation, lead to the destruction and erosion of biodiversity of both plants and animals (Fekadu, 2015). From 75% to 80% of global emissions greenhouse gas is caused by industrial sources, specifically the burning of fossil fuels. The remaining 20% to 25% is caused by deforestation (Archana, 2013). Deforestation has an impact on climate change. Climate change is a major threat to sustainable growth and development in Africa. Africa is particularly vulnerable to climate change because of its overdependence on rain-fed agriculture (Kahsay, 2004**).** The main long impacts of climate change include: changing rainfall patterns affecting agriculture and reducing food security; worsening water security; decreasing fish resources in large lakes due to rising temperature, and shifting vector-borne diseases (Fekadu, 2015). The impact of climate change on Ethiopia is more pronounced by alarming loss of forest resource (Archana, 2013). There is a better understanding that forests burnt in certain parts of the world are contributing to greenhouse gases and contributing to climate change. Overall these changes affect the livelihoods of societies (Kahsay, 2004**)**.

Vegetation cover is converted to different other land use type that results soil erosion. Soil erosion is increased because of vegetation removal, over-grazing, and continuous cultivation. Large forest areas of the country are now exposed to heavy soil erosion resulting in a massive environmental degradation and serious threat to sustainable agriculture and forestry (Kahsay, 2004**).** The reduction of forest cover has resulted in decreased water preservation potential, increased frequency and intensity of flooding and landslides, loss of soil fertility and agricultural productivity, soil erosion. Generally, deforestation has many negative consequences such as loss of biodiversity; which in turn results in declines in ecosystem integrity, and also genetic losses that may impede future scientific advances in agriculture, climate change, degradation of soils, disruption of hydrological cycles, desertification, economic loss and social conflicts (Fekadu, 2015).

2.4 Impacts of Vegetation Cover Change on Rainfall and Land Surface Temperature

2.4.1 Impacts of Vegetation Cover Change on Rainfall

There was a positive relation between vegetation cover and rainfall through time. It was identified that rainfall pattern is decreased due to vegetation cover declined (Batool *et al*., 2015). There was positive correlation between rainfall and forest cover, which showed high correlation. In the correlation the vegetation was taken as an independent variable and rainfall as dependent one. The rainfall pattern changed on temporal basis as change in vegetation cover (Nathaniel, 2014). There is a high correlation between rainfall and NDVI (vegetation cover) which proved that vegetation cover change can give accurate indication of rainfall change (Batool *et al*., 2015).

Vegetation removal, which usually accompanies the process of urbanization, is responsible for the reduction of rainfall interception and storage. The depletion of forest resources contributes significantly to the climatic and physical changes of the environment (Fekadu, 2015). Vegetation is affected the local climate and rainfall (Batool *et al*., 2015). Studies have indicated that the LULC change is also related to hydrological and climate changes at global, regional and local scale (Amare, 2015). In addition, deforestation can also impact on hydrological processes, leading to localized declines in rainfall (Kahsay, 2004).

2.4.2 Impacts of Vegetation Cover Change on Land Surface Temperature

The temperature is greater in areas which has low vegetation cover. The correlation of vegetation cover and LST is negative. it can be clearly noticed that vegetation cover can reduce LST (Sruthi and Mohammed, 2015). Land Surface Temperature (LST) is sensitive to vegetation cover. There is strong negative correlation between LST and NDVI values (Chaithanya *et al*., 2017). The LST of each LULC class therefore depends on its particular characteristic. The LST was highly influenced by the LULC, and very sensitive to vegetation cover and soil moisture; specifically, the amount of vegetation cover was the main factor on the relationship of vegetation cover and LST (Rasul and Ibrahim, 2017). The present study raises the possibility that a rapid decrease in vegetation cover areas may lead increased the LST. A large number of scholars studied the relationship between vegetation cover and LST in various districts with remote sensing images. The results show that vegetation cover and temperature have a significant negative correlation, meaning that the lower the vegetation coverage, the higher the temperature, and vice versa (Zhang *et al*., 2010; Hanif, 2016).

Counting indirect emissions from LULC changes through deforestation, and urbanization accounted GHG release which also contribute to increase the atmospheric temperature (Belay and Getaneh, 2016). The releasing of greenhouse gases to the atmosphere and increases the releasing of carbon dioxide to the atmosphere is caused by deforestation, especially by the expansion of agriculture (Amare, 2015). Deforestation would increase the amount of CO2 in the atmosphere, because when forests (which act as major carbon store) are cleared and the trees are burnt the stored carbon is released as CO2 in the atmosphere. Generally, remove of the vegetation cover is leading to global warming. Agriculture and land-use change (deforestation) are major contributors to climate change. Climate change causes the frequency and severity of weather events. Some indirect effect of climate change includes, changes in soil moisture, land and water condition, and the distribution of diseases (Belay and Getaneh, 2016). Vegetation cover has negative impact on land surface temperature. It can reduce land surface temperature in a certain area (Khasay, 2004).

2.5 Deforestation in Ethiopia

Deforestation is the permanent conversion of forests to some other LULC (Fekadu, 2015). Deforestation has become one of the major phenomena impacting the climate over Ethiopia. Many debates have focused on the impact of deforestation on rainfall spatial-temporal variability by the changes in vegetation cover (Dessalew, 2016). Natural resource degradation in Ethiopia has been decreasing for centuries. The country faces different problems in relation to natural resource management. From this, vegetation cover change is one of the most serious environmental problems (Abineh *et al*., 2015**).** The country's forest coverage is estimated to be 40% over a century ago and now to less than 3% (Temesgen *et al*., 2014).

Table 2.1: Annual deforestation from 1955-1979

Year	Annual Average Deforestation (ha)
1955–1967	697,000
1967–1976	293,000
1976–1979	205,000

Source: (Sisay *et al*., 2016).

The annual loss of natural forest cover has been estimated to be 150,000 to 200,000 ha per year and in 1989 forest cover was estimated at only 2.7% of the Ethiopian land mass (Kahsay, 2004). About 141,000 ha of forest have been lost annually between 1990 and 2010. The average annual deforestation rate, based on forest cover change from 2005-2010, amounts to 1.11% of total forest cover. This significant decrease of vegetation cover is due to the expansion of cultivated land (Temesgen *et al*., 2014). Over the period of 1972- 2014, there is a significant change in LULC as evidenced by a significant increase in size of cropland of about 53% and a net loss of over 61% of woodland area.

The period 2000-2014 has shown a sharp increase of cropland and a sharp decline of woodland areas. Woodland has shown the highest loss compared to other land use types (Worku, 2016). The loss of dry land vegetation, mainly due to deforestation is becoming a concern of environmental safety. The trend in shift of vegetation cover is continuing as a major threat to the dynamic dryland ecosystems. As loss in dryland vegetation is prevalent in arid and semi-arid regions, it could be a significant contributor for the degradation of drylands of the country (Worku, 2016). In Ethiopia, agricultural practices and deforestation are increased from time to time. As mentioned previously, among the land use changes occurring, the most significant historical change in land cover has been the expansion of agricultural lands (Kahsay, 2004**)**.

2.6 Causes of Climate Variability and Change

Climate variability is the fluctuation between the normally experienced climate conditions and a different or unusual fluctuation of climatic elements in an area (Getahun and Shefine, 2012). Climatic variabilities are the types of changes (temperature, rainfall) in magnitude and rate of the climate change that causes the impacts on the area of public health, agriculture, food security, biodiversity, forest and water resources (Amogne, 2013). The rainfall is highly variable both in amount and distribution across regions and seasons in Ethiopia. Historical climate analysis for Ethiopia indicates that mean annual temperature has increased by 1.3°C between 1960 and 2006, an average rate of 0.28°C per decade (Belay and Getaneh, 2016). In Ethiopia, climate variability and change in the country is mainly manifested through the variability and decreasing trend in rainfall and increasing trend in temperature. Besides, rainfall and temperature patterns show large regional differences. Ethiopia has been identified as one of the most vulnerable countries to climate variability and change, and is frequently faced with climate-related hazards, commonly drought and floods. The variability of rainfall and the increasing temperature were a cause for frequent drought and famine and putting disastrous impact on the livelihood of the people. The most vulnerable sectors to climate variability and change in the country are agriculture, water and human health (Temesgen *et al*., 2014).

Human beings had been altered the environment for thousands of years to satisfy their basic needs. In the past two centuries the impact of human activities on the land has grown enormously, altering entire landscapes, and ultimately impacting the earth's nutrient and hydrological cycles as well as climate. LULC changes are local and place specific, occurring incrementally that often escape our attention. However, collectively, they add up to one of the most important facets of global environmental change (Yetnayet, 2017). Human interactions with the environment are identified as one of the leading causes of climate change and variation. Modification, conversion and maintenance of land cover are all forms of anthropogenic interactions with the environment that result in a variety of vital changes to the environment that either positively or negatively feedback to the environment and climate *(*Eunice, 2013). The major activities contributing to GHG emissions in forestry were deforestation for agricultural expansion, forest degradation for fuelwood (Sisay *et al*., 2016). Changes in land cover and land use are bound to influence meteorological parameters including precipitation, humidity and temperature. Land surface properties are also affected. Land Surface Temperature (LST) is one of the land surface properties that is affected by LULC changes and is measurable continuously over space using remote sensing methods *(*Eunice, 2013). There are various climatic changes that occur as a result when an area of forest is cut down. Deforestation leads to CO2 emissions, and is mostly caused by the conversion of forested areas to agricultural land (Belay and Getaneh, 2016). Vegetation is an important factor in global climatic variability and plays a key role in the complex interactions between the land surface and the atmosphere (Eric, 2017). Human activities such as deforestation, burning of fossil fuels from vehicles, plane travel, heavy industries are some of the activities which are acknowledged to catalyze climate change by emission of carbon dioxide (Martine, 2017). Simultaneously, LULC change is an important parameter contributing to local and regional climate change. Temperature and precipitation are assumed to be one of the important climatic parameters that represent climate change on a long-term basis. Therefore, several explorations on climatic trends have been conducted by analyzing precipitation and temperature data at different periods of records throughout the world (Soni, 2017).

2.7 Rainfall and Land Surface Temperature

Climate variability observed over comparable time periods in the types of changes of temperature and rainfall. Land use change alters the thermal environment; the Land Surface Temperature (LST) is a proper change indicator to show the thermal changes in relation with land use changes (Youneszadeh, 2015). LST is a good indicator of the energy balance at the earth's surface which can provide important information about the surface physical properties and climate (Sruthi and Mohammed, 2015). LST is a property of the land surface and refers to the temperature of the interface between the earth's land surface and the atmosphere. It is therefore an important variable in land-atmosphere interactions and a climate change indicator which varies over space and time as a function of vegetation cover, surface moisture, soil types, and topography (Eunice, 2013). LST is the skin temperature of earth surface phenomena. It is an indicator of how much hot the surface of the earth. It depends on different LULC types. LST is entirely related to the physical process of surface energy. It provides information on time to time variation of earth surface energy change (Kayet *et al*., 2016). The changes of LST is related to many factors, including changes in land use, land surface parameters, seasonal variation, climatic condition and economic development. In other words, the change of land use is the important reasons leading to increase in LST (Jing and Guangjin, 2010). Changes in rainfall pattern are also likely to lead to severe water shortages and/or flooding (Belay and Getaneh, 2016). Expected worldwide climate-change trends are likely to introduce shifts in the frequency and intensity of extreme climatic events, including increase in mean annual temperature and increase/decrease in mean annual rainfall, depending on the region (Jing and Guangjin, 2010).

2.8 Remote Sensing for Analyzing Vegetation Cover, Rainfall and Land Surface Temperature

Remote sensing is the technique of obtaining information about an object or feature through the analysis of data acquired by a device that is not in contact with the object or feature under investigation. Planners and resource managers need a reliable mechanism to assess the consequence of the changes resulted by the stress imposed on natural resource by detecting, monitoring and analyzing land use changes quickly and efficiently (Zhang *et al*., 2010). Remote sensing technology however can play a vital role in providing accurate and reliable information with cost-effective and less time compared to other methods. It provides a source of data from which updated land cover information can be extracted efficiently and cheaply in order to inventor and monitor these changes effectively. Thus, change detection has become a major application of remotely sensed data because of repetitive coverage at short intervals and consistent image quality (Habtamu, 2011).

Remote Sensing is the most modern technology which has been widely used in the field of natural resource management and monitoring. This technology provides a very powerful tool to observe and collect the information on natural resources and dynamic phenomenon on the earth surface, and ability to integrate different data and present the data in different formats. It provides a tool to monitor and to model climatic and environmental change with the ability to observe the earth in spatially and temporally. By monitor the changes in climate, the impacts and effects from climate change can be analyzed (Zhang *et al*., 2010).

There are many successful applications of satellite monitoring of forest cover change Such as: protect soil erosion, maintain biodiversity and keep water resources (Xiao, 2014). Remote sensing can determine spatiotemporal changes in vegetation and urban land cover. With the development of remote sensing, it is possible to get more information from multi-date and multi-spectral remote sensing data, which provide effective methods to study the vegetation distribution and interannual and seasonal changes (Mingjun *et al*., 2007). Landsat images are able to provide information necessary for monitoring ecosystem dynamics at adequate spatiotemporal resolution using vegetation index such as NDVI. For this reason, the Landsat can be employed in the quantification of green biomass and vegetation cover (Hussein *et al*., 2017). NDVI due to its simple calculation is largely used for the vegetation studies in a regional as well as global level (Sruthi and Mohammed, 2015). Today, data from satellites are very applicable and useful for forest cover change detection studies. Monitoring of forest cover change is one of the main applications of remote sensing-based change detection (Abyot *et al*., 2014).

Remote Sensing (RS) and Geographic Information System (GIS) have found wide application areas in climate change analyses and adaptation. For climate change analysis, RS is required for up-to-date environmental data acquisition both at local and regional levels (Nathaniel, 2014). The use of satellite imagery allows the observation of states and processes of the atmosphere, land and ocean at several spatiotemporal scales. For instance, it is one of the most effective approaches for monitoring land cover and its changes through time over a variety of spatial scales. Satellite data are frequently used with climate models to simulate the dynamics of the climate system and to improve climate conditions. Satellite data also contribute significantly to the improvement of meteorological analysis products that are widely used for climate change studies (Jun *et al*., 2013). Satellite remote sensing provides an excellent, cost-effective and time-saving methodology to analyze spatially and temporally distributed of LST (Abyot *et al*., 2014). Remote sensing is extremely useful for understanding the spatiotemporal land cover change in relation to the basic physical properties in terms of the surface radiance and emissivity data. There is a range of recent studies in developed and developing countries, focused on the application of Moderate Resolution Imaging Spectroradiometer (MODIS) to model trends in vegetation patterns and to assess land surface temperature (Hussein *et al*., 2017). In this study, remote sensing techniques were used to retrieve the land surface temperature (LST) by using the MODIS Terra (MOD11A2) Satellite imagery product (Youneszadeh, 2015).

Remote Sensing provides information about the changes occurring on the earth's surface and carry out change detection analysis. Further, it enables the detection of vegetation cover, differentiation by type or nature and analysis of the state of the vegetation (Eunice, 2013). For preparing accurate land cover map and for monitoring changes at regular intervals of time, satellite remote sensing techniques are useful. RS technique for change detection of forest cover monitoring has been used to assess the forest cover change over two or more time periods caused by environmental conditions and human actions which is used in estimating and validating ecosystem changes arising from forest use and forest management interventions (Batool *et al*., 2015).

The potential of remote sensing and GIS in the field of forestry become established over many years through the use of aerial photos and satellite image interpretations in vegetation cover change detection analysis, for the generation of vegetation cover map and inventory analysis of vegetation cover (Eunice, 2013). Multi-temporal satellite data provides information for change detection analyses and remote sensing can analyze the extent and the rate of deforestation or vegetation cover change by comparing images of earlier years to recent years. Satellite image data can be used to effectively monitor the status of existing vegetation cover and can give updated information about the vegetation cover change. Therefore, remote Sensing is a powerful technique for surveying, mapping and monitoring earth resources (Workaferahu, 2015). This study applies remote sensing data for quantifying and analyzing of vegetation cover change, examining the relationship of vegetation cover with rainfall and LST in the study area (Rehman *et al*., 2015). Remote sensing technique is used to detect the land use changes, its impact on LST and rainfall (Kayet *et al*., 2016).

CHAPTER THREE

3 MATERIALS AND METHODS

3.1 Description of the Study Area

3.1.1 Location

North Gondar zone is one of the largest zones in Amhara National Regional State. It has 23 administrative woreda boundaries and it covers a total area of 4,476,421 ha. The study area is geographically located in 35°16'36" to 38°44'54" Longitude and 11°37'31" to 13°54'9" Latitude (Figure 3.1).

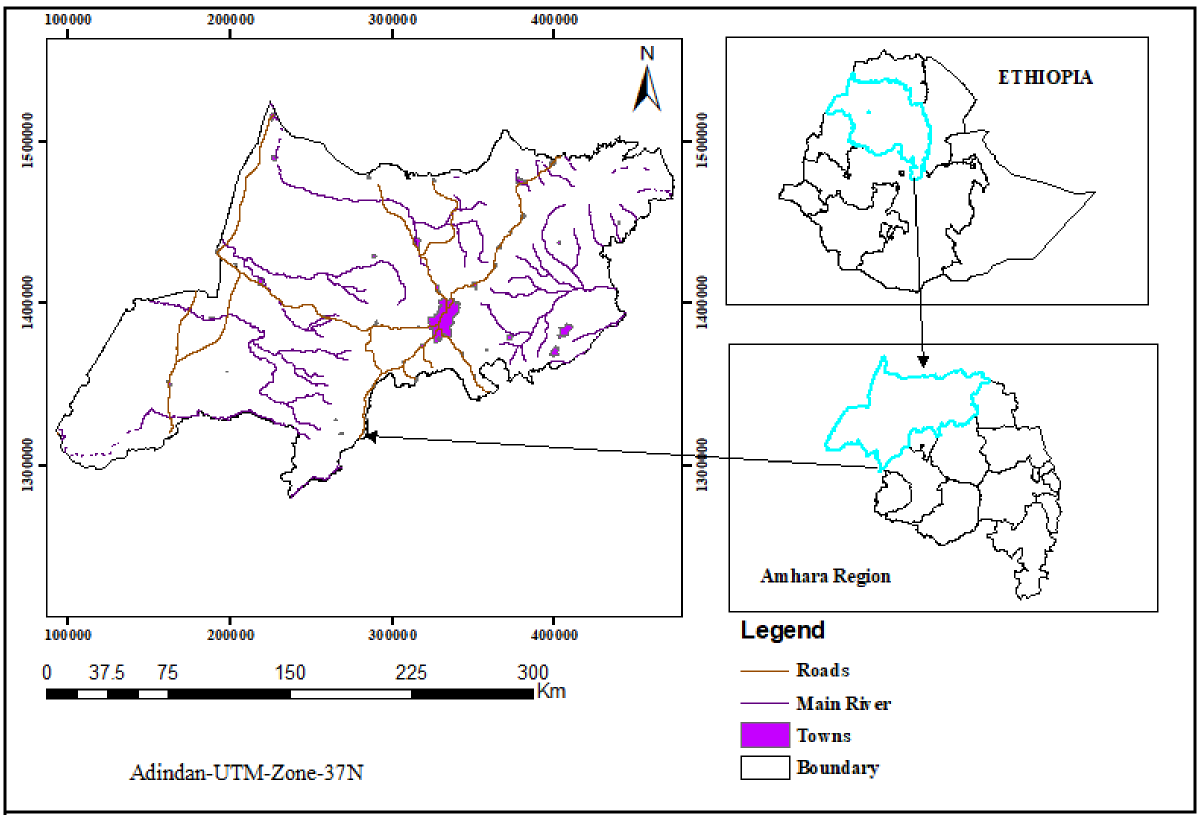


Figure 3.1: Location map of the study area.

North Gondar zone is bordered by Lake Tana, West Gojam zone, Awi zone and Benshangul Gumz Region in the south; Sudan in the west; Waghimra zone in the east; Tigray Region in the north and South Gondar in the south-east direction. The study area is located topographically between 448 m to 4540 m. The elevation map of the study area is given in Figure 3.2.

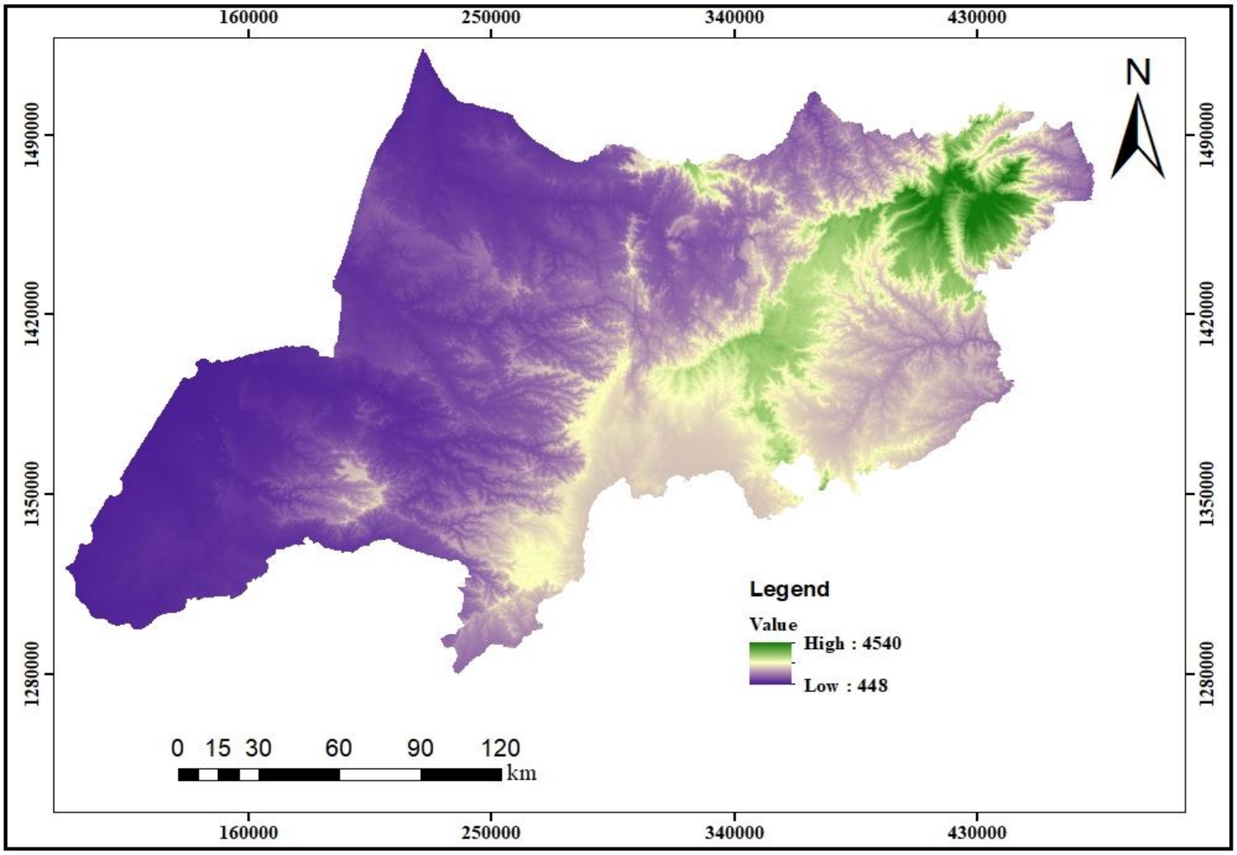


Figure 3.2: Elevation map.

3.1.2 Soil

The major soil types found in North Gondar zone are Chromic Luvisols, Chromic Vertisols, Eutric Cambisols, Dystric Cambisols, Eutric Nitosols, Orthic Luvisols, Lithosols, Eutric Fluvisols, Chromic Cambisols, and Lake. Chromic Luvisols are the major soil types in the study area and covered about 26.36% of the study area. Chromic Vertisols are the second dominant soil types that covered 22.48% of the study area. The third major soil type is Eutric Cambisols which covered 15.03% of the study area (FAO, 1974). The major soil type map is shown below in Figure 3.3.

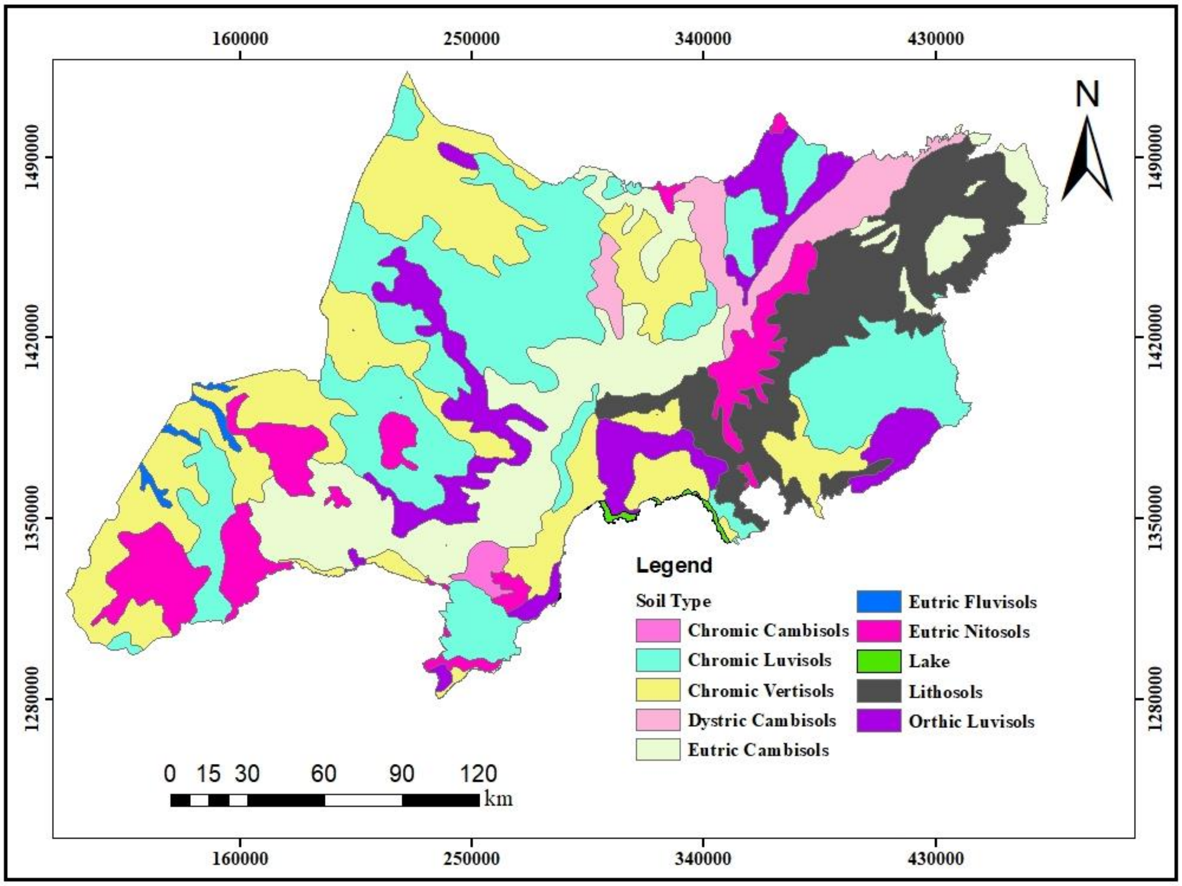


Figure 3.3: Soil type map.

3.1.3 Population and Socio-Economic Activity

According to CSA (2007), the total population of North Gondar zone was 2,929,628. The people in the rural area are engaged in the farming activity. They are engaged in the mixed types of farming activities both ploughing and animal raring. On the central parts of the area and Tana lowland, teff, millet, barley, maize, beans, and peas are cultivated. They also produce spices and sorghum, especially in the Tana lowland. In addition, tomato, onion, and potato are cultivated in the study area. Sorghum and Sesame cultivations are very common in the western areas. Some people are also engaged in fishing activity. For instance, those living around Lake Tana and big rivers depend partly on fishing activity. Production of livestock such as cattle, sheep, and goats are also the dominant human activity in North Gondar zone. Pack animals such as horses, donkeys, and mule are also common (North Gondar zone Agricultural office, 2012).

3.1.4 Climate and Vegetation

North Gondar zone generally belongs to subtropical climate. The temperature is hot during winter and cold during summer and reaches up to 40ºc. Mean seasonal temperature is between 20 and 25ºc. The central parts of the area and the Tana lowland areas are generally humid, but the western lowland is hot and humidity is very less. The western lowland is very hot and dry (North Gondar Zone Agricultural Office, 2012). The rainy season is normally summer as it is the case for the major parts of the country. The rainy season is from June to September. Maximum and minimum annual rainfall for the map area is 2,185 mm and 433 mm.

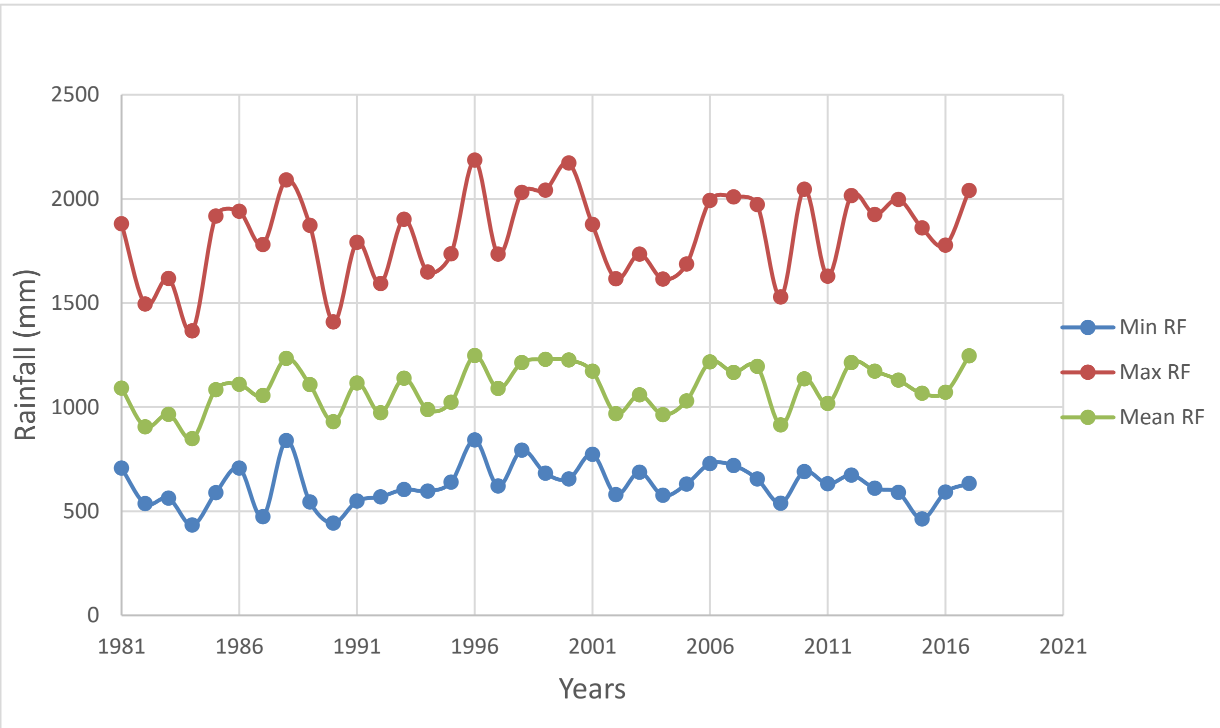


Figure 3.4: Annual minimum, maximum and mean rainfall from 1981 to 2017.

North Gondar zone is categorized in six agroecology zones. Most of the study area is upper Kol1a. It covers 33% of the study area. Lower Kolla is the second major agroecology zone which covers 31% of the study area. About 27% of North Gonder zone is categorized under Weyena Dega. About 7% and 0.9% of the study area is categorized Dega and upper Dega. Kur covers 0.4% of the study area. Negade-Bahir, Shehdi, Metema and Gelegu areas belong to Kola type of climate. Kur type of climate occurs to the northeastern part extending to Rasdashen (MoA and RDE,2005).

Vegetation in the area varies from place to place. The southern part of the area is characterized by grassland with the bush formation. Evergreen scattered woods are existing in central, south and north of the study area. Plantation such as eucalyptus trees are common around Gondar town and other major towns of the area. The west low land areas and east of the study area are covered by deciduous woody vegetation (North Gondar Zone Agricultural office, 2012).

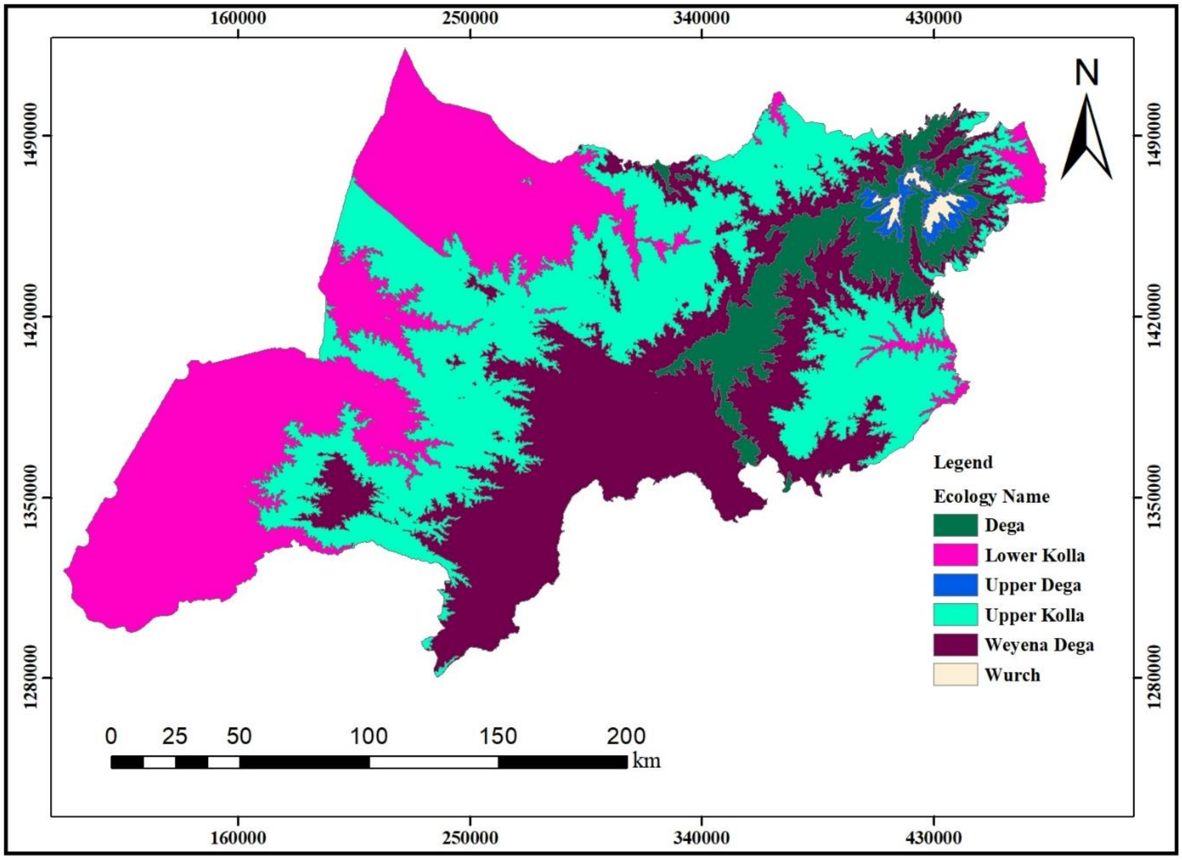


Figure 3.5: Agroecology map.

3.1.5 Drainage

The major rivers in the area are Shinfa, Atbara, Ayma (Dinder) and Guang. All of them flow to the west to form the Abay drainage basin. Some rivers towards the northern part flow to Angreb and form Tekeze drainage basin. Thus, extreme northeastern part of the study area rivers belongs to Tekeze Basin and much of the westerly flowing rivers belong to Abay Basin. To the southeast of the study area, rivers flow to Tana and this form Tana sub-basin (North Gondar Zone Agricultural office, 2012).

3.2 Data and Software

3.2.1 Remote Sensing Data

3.2.1.1 Landsat Data

Landsat images are medium-resolution remote sensing data's that are mainly used for land use and land cover change analyses. They are digital files comprising pixels (picture elements) that represent measured local reflectance (emission or backscatter) values in some designated part of the electromagnetic spectrum (Sisay *et al*., 2016). The selection of the Landsat satellite image dates was influenced by the quality of the image especially for those with limited or low cloud cover. Dry season and cloud-free images were used in this study. Since this study focused on the impacts of vegetation cover change on rainfall and LST, dry season images help to separate evergreen vegetations from rainfall dependent vegetations like grass and other agricultural crops. The satellite imagery used for this study consists of multispectral Landsat data that includes Landsat 8 OLI 2017 and Landsat 5 TM for the year 1985, 2000, and 2010 (Table 3.1). Landsat 8 OLI and Landsat 5TM were used for land use land cover classification in order to know the extent of deforestation in North Gondar zone for the last 32 years. The Landsat TM was carried on Landsat 4 and Landsat 5 images that have seven spectral bands with a spatial resolution of 30 meters for bands 1 to 5 and 7. Landsat 8 OLI/TIRS images have eleven spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9. The resolution for Band 8 (panchromatic) is 15 meters. Thermal bands 10 and 11 are useful in providing more accurate surface temperatures and are collected at 100 meters (https://landsat.usgs.gov).

3.2.1.2 Moderate Resolution Imaging Spectroradiometer

Moderate Resolution Imaging Spectroradiometer (MODIS) flies onboard the Terra and Aqua satellite platforms, which were launched on 18 December 1999 and 4 May 2002, respectively. These satellites, which are sun-synchronous polar orbiting, pass from north to south across the equator at 1030 Land Surface Temperature(LST) (Terra) and at 1330 LST (Aqua). MODIS provides 44 global data products for land, ocean, and atmospheric variables. MODIS has been designed for the needs of global change research with improved capability for terrestrial satellite remote sensing (Hong and Lakshm, 2007). The study was used MODIS/Terra Land Surface Temperature and Emissivity 8-Day L3 Global 1 km Grid SIN V006 (MOD11A2). The

MOD11A2 version 6 products provide an average, 8-day, per-pixel LST. Each pixel value in the MOD11A2 is a simple average of all the corresponding MOD11A1 LST pixels to be collected within that 8-day period (Patel *et al*., 2009).

3.2.1.3 Climate Hazards Group Infrared Precipitation

In order to assess trends in the temporal variation of precipitation, the monthly product of Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) time series data from 1981 to 2017 was used. CHIRPS was created in collaboration with scientists at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center in order to deliver reliable, up to date, and more complete datasets for a number of early warning objectives (Moctar and Sander, 2016). The data inputs used for CHIRPS creation are: (1) the Climate Hazards Precipitation Climatology (CHPClim); (2) quasi-global geostationary TIR satellite observations from two NOAA sources, Climate Prediction Center (CPC)and the National Climatic Data Center (NCDC); (3) atmospheric model rainfall fields from the NOAA Climate Forecast System, version 2 (CFSv2); (4) the TRMM 3B42 product from NASA; and (5) in situ precipitation observations obtained from a variety of sources including national and regional meteorological services (Moctar & Sander, 2016). The reason why CHIRPS data were selected from other satellite-based rainfall estimation product is that the CHIRPS product corresponds best to the rain gauge values (Carolien *et al*., 2015; Yared *et al*., 2017).

Table 3.1: Description of satellite data

	Sensor	**Spatial Resolution**	**Path**	**Row**	**Date of Acquisition**			
					1985	**2000**	**2010**	**2017**
Landsat 5 and Landsat 8	TM/OLI	30 m	169	051	15/04/1985	04/02/2000	30/01/2010	02/02/2017
	TM/OLI	30 m	169	052	15/04/1985	04/02/2000	14/01/2010	02/02/2017
	TM/OLI	30 m	170	051	17/02/1985	11/02/2000	23/12/2010	24/01/2017
	TM/OLI	30 m	170	052	17/02/1985	11/02/2000	23/12/2010	24/01/2017
	TM/OLI	30 m	171	050	13/04/1985	02/02/2000	28/01/2010	31/01/2017
	TM/OLI	30 m	171	051	13/04/1985	02/02/2000	30/12/2010	31/01/2017
	TM/OLI	30 m	171	052	13/04/1985	02/02/2000	14/12/2010	31/01/2017
CHIRPS		5 km			1981-2017			
MODIS LST		1 km			2000-2017			

3.2.2 Google Earth and Ground Truth Data

Ground truth data has been collected through a hand-held GPS. Ground truth data and Google Earth data were used in exploratory data analysis, validation and threshold of the NDVI value in the study area. Accordingly, 200 GPS points and 300 Google Earth points were used to threshold and to validate the result of 2017 Landsat images and total of 500 Google Earth points were taken for 1985, 2000 and 2010 Landsat images.

Table 3.2: Description of data and source.

GIS and RS Data Layer	Description	Data Source
Raster	Satellite Image ▪ 1985 Landsat5 TM ▪ 2000 Landsat5 TM ▪ 2010 Landsat5 TM ▪ 2017 Landsat8 OLI/TIRS	USGS 1985,2000, 2010 and 2017
Raster	CHIRPS (1981-2017)	USGS Earth Resources and Observation Science (EROS)
Raster	MODIS LST (2000-2017)	USGS
Raster	Elevation	DEM 30 m SRTM
Vector (Point)	Major Town	Ethio-GIS
Vector (Line)	Roads and Rivers	CSA, 2008
Vector (Polygon)	Zone Boundary	CSA, 2008
Vector (Polygon)	Soil Type	FAO, 1974
Vector (Polygon)	Agroecology	MoA and RDE, 2005
Ground and Google Earth points	Field Survey and Google earth	Field survey 2017, Google Earth 1985, 2000, 2010 and 2017.
Attribute Table	Population	CSA, 2007

3.2.3 Software

Software packages used for this study were ArcGIS 10.3, ERDAS (Earth Resources Data Analysis System) Imagine 2015 and Statistical Software for Microsoft Excel (XLSTAT) software. ArcGIS 10.3 was used to preprocess MODIS LST, calculate LST and rainfall. It has also used for the analysis of zonal statistics, identify the threshold of NDVI and prepare all maps. ERDAS imagine 2015 were used for preprocessing of Landsat (Layer stack, Top of atmospheric correction, sun angle correction, mosaic, and subset) and NDVI calculation. Trend analysis of rainfall and LST, correlation of vegetation cover with rainfall and LST were processed using XLSTAT 2018 software.

3.3 Methods of Data Analysis

3.3.1 Landsat Images Pre-processing

The purpose of image preprocessing is to correct distorted or degraded image data to create a more faithful representation of the original scene. This typically involves the initial processing of raw image data to correct radiometric and atmospheric corrections, to minimize geometric distortions. Layer stacking, resampling, image enhancement of the image dataset, mosaicking and subsetting which are of utmost importance for LULC analyses.

3.3.1.1 Atmospheric and Radiometric Correction

The raw satellite image is with errors and is not directly utilized for features identification and any applications. Pre-processing was done before the main data analysis and extraction of information. It aims to correct distorted data in order to create a more realistic representation of the original scene. This typically involves the initial processing of raw image data to correct for geometric distortions, to calibrate the data radiometrically, and to eliminate noise present in the data (Habtamu, 2011). Preprocessing of satellite images prior to perform LULC is essential to remove noise and increase the interpretability of image data. Radiometric correction of remote sensing data normally involves the process of correcting radiometric errors or distortions of digital images to improve the quality of satellite images (Yichun *et al*., 2007).

Radiometric correction is mainly performed for normalization of differences among scenes of imagery taken at different time periods. Top of Atmosphere reflectance (TOA), surface reflectance, bi-directional reflectance distribution, viewing angle normalization, and terrain normalization are among the commonly applied radiometric correction methods to improve the information obtained from satellite imagery (Worku, 2016). Sun angle and earth-sun distance adjustment can be made mainly using the calculation of top of atmosphere reflectance. In this study, haze and noise reduction, top of atmospheric correction and sun angle correction were performed on the original Landsat imageries. This correction was applied to the whole scene as there is no separate Landsat solar geometry supplied for each pixel and hence there is no distinctive variation in TOA adjustment per each pixel within a scene. TOA calibration is significant for normalization of differences between imagery taken at different time intervals in order to cross-calibrate sensor radiometry (Kayet *et al*., 2016).

Cloud cover affects not only the ability to sense what is beneath the clouds using certain bands but can also increase the Digital Number (DN) values of adjacent pixels. Clouds scatter light, thereby increasing brightness measured from ground features. Consequently, adjacent pixels can be affected because clouds often have gradations of vapor and moisture leading to the cloud center (Rehman *et al*., 2015). The study was based on multi-temporal satellite image analysis; Satellite images used were Landsat 5 TM and Landsat 8 OLI, all with cloud cover less than 10%. The images were pre-processed to remove radiometric errors prior to further processing. In order to remove scene variation due to atmospheric scattering, the atmospheric correction was employed in all Landsat imagery to have a common radiometric scale. The digital numbers were recalculated to top of atmosphere radiance (Worku, 2016).

3.3.1.2 Layer Stacking

Layer stacking is a method to build a new multiband file from geo-referenced images of various pixel sizes, extents, and projections. The input bands were re-sampled and re-projected to a common user-selected output projection and pixel size. The output file usually has a geographic extent that either encompasses all of the input file extents or only the data extent where all of the files overlap (Sisay *et al*., 2016). The original satellite imagery of Landsat 8 OLI and Landsat 5 TM have eleven and seven bands respectively. Those bands are existed separately each other and have their own information about the earth's features. To have good spectral information about the earth surface, each band were stacked together and produce a single multispectral image. Band-six in Landsat 5 TM and band ten and band eleven in Landsat 8 OLI are thermal bands which are used to detect surface temperature. Due to this, to prepare vegetation cover map of the study area, from band 1 to band 7 except band 6 were stacked in the case of Landsat 5 TM and from band 2 to band 7 were stacked in the case of Landsat 8 OLI/TIRS.

3.3.1.3 Mosaicking and Subsetting

After radiometric and atmospheric corrections were done in all satellite images, all scenes from the same year were mosaicked together in their spatial sequence to get a single image that covers all parts of the study area. From the mosaicked image, the portion that fell within the study area was extracted (subsetted) to limit the size of the mosaicked image to the size of the study area boundary for preliminary classification, field verification, and the processing work to take place at a later stage

3.3.2 Image Enhancement

Image enhancement was used to increase the detail of the image by assigning the image maximum and minimum brightness values to maximum and minimum display values, and it was conducted on pixel values, and this makes visual interpretation easier by increasing the visual discrimination between features in a scene and assists the human analyst (Habtamu, 2011). The goal of image enhancement is to improve the visual interpretability of an image by increasing the apparent distinction between features in the image. For the improvement of image interpretability, image enhancement is important. It makes a raw image readily interpretable for a particular application (Sisay *et al*., 2016). There are several image enhancement techniques among those techniques; false color composite and Normalized Vegetation Index (NDVI) were used for this study.

3.3.3 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) has been widely used for remote sensing of vegetation for many years. This image enhancement technique has a function to determine vegetation class from other types of classes (Badamasi *et al*., 2012). NDVI is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum and is adopted to analyze remote sensing measurements and assess whether the target being observed contains live green vegetation or not. The NDVI is an index that provides a standardized method of comparing vegetation greenness between satellite images over seasons and years. It is an alternative measure of vegetation amount and condition. It can also be associated with vegetation canopy characteristics such as biomass, leaf area index and percentage of vegetation cover (Babalola and Akinsanola, 2016). NDVI is one of the most widely used indexes of which applicability in satellite analysis and in the monitoring of vegetation cover was sufficiently verified in the last two decades (Lamchin *et al*., 2014; Nurhussen, 2016). The NDVI value of the pixels varies between -1 and +1. Higher values of NDVI closest to +1 indicate the richer and healthier vegetation (Sundara *et al*., 2012), whereas values closet to 0 & -1 indicate water body or non-vegetation (bare lands). In the present study, NDVI was calculated to identify vegetated area from non-vegetated area in the study area and was calculated from the red and near infra-red using the following formula:

$$NDVI = \frac{NIR-R}{NIR+R} \quad (1)$$

Where, NDVI = Normalized Difference Vegetation Index, NIR = Near Infra-Red and R= Red

3.3.4 Thresholding

Thresholding is the process of identifying the minimum and maximum threshold values from the processed NDVI image to classify the NDVI value to vegetation and non-vegetation class. Threshold values are scene-dependent and should be calculated dynamically based on the image content (Ahmed and Ahmed, 2013). A threshold value is required to separate vegetation and non-vegetation classes from NDVI image. In this study, threshold values were determined based on data collected from google earth and ground survey and the previous studies such as (Badamasi *et al*., 2012; Zaidi *et al*., 2017). Therefore, NDVI images were reclassified into two classes (vegetated and non-vegetated) based on the NDVI threshold value i.e. 0.45.

3.3.5 Land Cover Change Detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Essentially, it involves the ability to quantify temporal effects using multi-temporal data sets. Many change detection methods have been developed and used for various applications. For example, there are a post-classification comparison, image differencing, image rationing, NDVI differencing, image regression, principal component analysis. From these methods, image differencing was used in many studies such as Habtamu, (2011), Almutairi and Warner, (2010), Tripathi *et al*., (2015) and has also been used in the present study. The land cover/use change detection involves the application of multi-temporal datasets to quantify the rate and magnitude of change extracting information from images (Amare, 2015). It also involves the use of multi-temporal data sets to differentiate areas of land cover change between dates of imaging. This kind of change detection method identifies where and how much change has occurred (Abyot *et al*., 2014).

3.3.6 Image Differencing

Image differencing is the subtraction of two spatially registered imageries, pixel by pixel. The pixels of the changed area is expected to be distributed in the two tails of the histogram of the resultant image, and the unchanged area is grouped around zero (Aldoski *et al*., 2013). Image differencing change detection technique was performed by subtracting the digital number (DN) value of a pixel in one date for a given band from the DN value of the same pixel for the same band of another date. The results of the image differencing technique are simply the pixels that changed between the two acquisition dates (Tripathi *et al*., 2015). This method was applied in this study on the classified image to determine the changed area. In the differenced image, spectral changes are highlighted as relatively high positive or negative values. Unchanged pixels are associated with values close to zero. It is a relatively simple approach and therefore is commonly used (Almutairi and Warner, 2010).

3.3.7 Accuracy Assessment

In this study, the accuracy assessment was carried out using ground control points from field observations as the major sources of reference data and google earth points generated to assess accuracy (Amare, 2015). About 500 reference points were used from field survey and google earth to check the accuracy assessment. The accuracy of classification was carried out by means of overlaying of the classified maps and the test samples. The image classification accuracy was further assessed by calculating the Kappa coefficient ‘k’. The kappa statistics is an estimate of measure of overall agreement between image data and the reference (ground truth) data. Its coefficient falls typically on a scale between 0 and 1, where the latter indicates complete agreement and is often multiplied by 100 to give a percentage measure of classification accuracy.

$$K = \frac{N\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(xi+*x+i)}{N^2 - \sum_{i=1}^{r}(xi+*x+i)} \quad (2)$$

Where, k is kappa statistics, n is totals samples, xii is the number in row i and in column i, xi+ is row total. X+I is column total.

Kappa values are also characterized into 3 groupings: a value greater than 0.80 (80%) represents strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement, and a value below 0.40 (40%) represents poor agreement (Yetnayet *et al*., 2017). One of the most important final steps in classification process is accuracy assessment. The aim of accuracy assessment is to quantitatively assess how effectively the pixels were sampled into the correct land cover classes. (Sophia *et al*., 2017). The accuracy is essentially a measure of how many ground truth pixels were classified correctly. When looking at the land cover map, it is important to remember that no map is a perfect representation of reality. There are always errors in maps. It is important to keep in mind that the map will be most accurate for viewing geographic patterns over larger areas. The result of an accuracy assessment provides an overall accuracy of the map based on an average of the accuracies for each class in the map (Habtamu, 2011).

$$OA(\%) = \frac{SCC}{TS} * 100 \tag{3}$$

Where, OA is overall accuracy, SCC is sum of correctly classified, TS is total sample. A set of reference pixels representing geographic points on the classified image is required for the accuracy assessment.

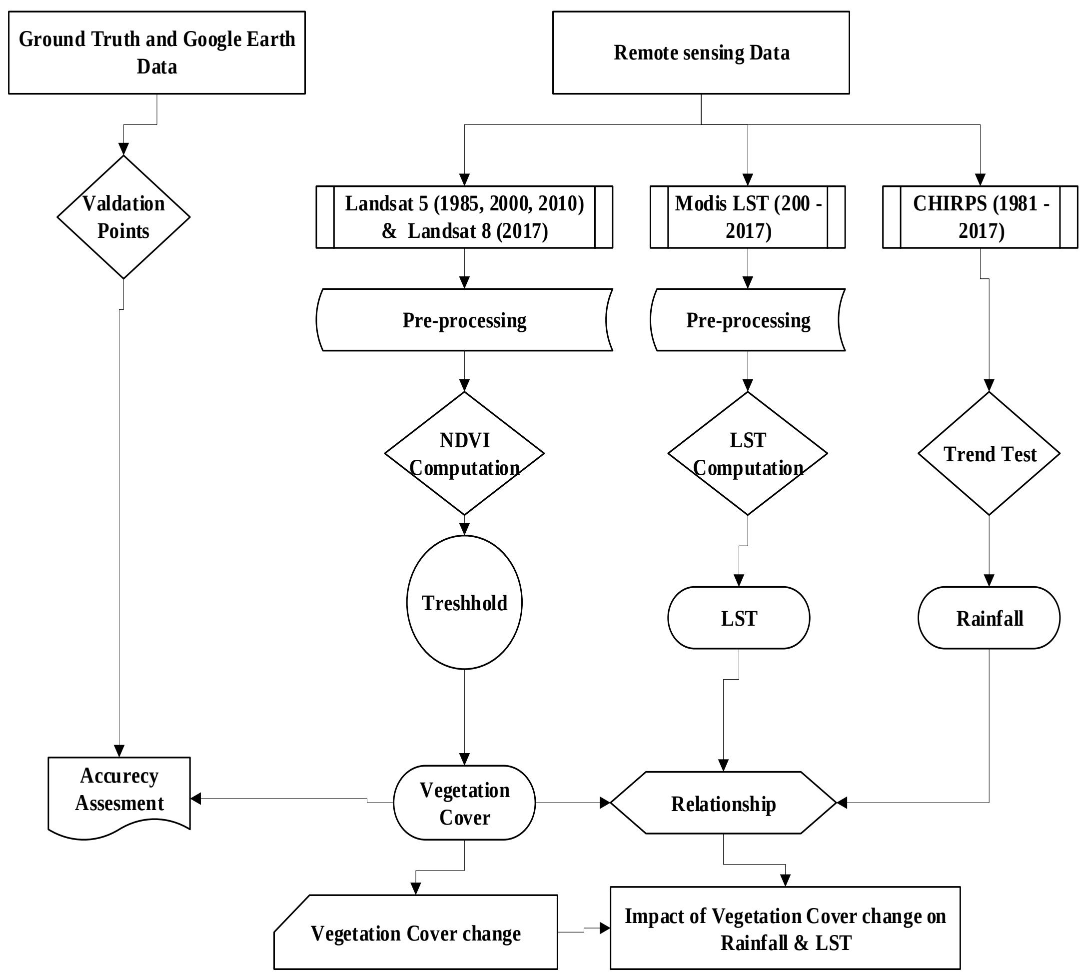


Figure 3.6: General workflow.

3.3.8 Preprocessing of MODIS Data

All MODIS datasets are originally found in sinusoidal (SIN) mapping grid and provided in the form of HDF (Hierarchical Data Format) which is not compatible to use and make an analysis. Therefore, the original data has been projected to the appropriate projection system and formatting using ArcGIS. The HDF format of MODIS data was converted to tiff format using extract sub-dataset tool in ArcGIS.

3.3.9 Computation of Land Surface Temperature

MODIS Land Surface Temperature/Emissivity (LST/E) data with 1 km spatial resolution with a data type of 16-bit unsigned integer was multiplied by a scale factor of 0.02 to obtain the temperature data in the form of degree Celsius (°C) (Sruthi and Aslam, 2015). The digital numbers (DN) of LST data is converted to degree Celsius by using the following formula.

$$Temperature(°c) = (DN * 0.02) - 273.15 \quad (4)$$

To get the mean monthly LST for each year, in the study period (2000-2017), four 8-days composite images of each year were added and divided by 4 in raster calculator. After that operation, the mean LST of dry season for each year in the study period were calculated using raster calculator by adding the mean monthly LST for every month in the year and dividing the sum by 7. The number 7 indicates the number of dry season months (October- April).

3.3.10 Trend Analysis

The trend is a significant change of variable over time detectable by statistical non-parametric and parametric procedures (Soni, 2017). Trend analysis is used for detection of a statistically significant trend in variables like rainfall and temperature. These is extremely important parameters for analyzing climate change and variability in the long term for any region (Ganguly *et al*., 2015). Precipitation and temperature data can show a long-term change of data or some pattern changes in the given temporal scale series. Hence, to describe a trend of a time series of rainfall and LST, Mann-Kendall trend test was used to see whether there is a decreasing or increasing trend or not change. It is one of non-parametric statistical test used for detecting trends of climatic variables (Prasada and Solomon, 2013). It also used to assess the significance of trends in climatic time series data such as precipitation and temperature. Non-parametric tests are thought to be more suitable for non-normally distributed data which are encountered in climatic time series (Soni, 2017).

Mann-Kendall test is distribution-free trend test, which considers the positive or negative course of successive values. It is also for identifying trends in time series data. One of the benefits of this test is that the data need not conform to any particular distribution (Sithranjan, 2012). The Mann-Kendall test analyzes the sign of the difference between later-measured data and earlier-measured data. Each later-measured value is compared to all values measured earlier; resulting in a total of $n(n-1)/2$ possible pairs of data, where n is the total number of observations (Mondal *et al*., 2012). According to this test, the null hypothesis H0 assumes that there is no trend (the data is independent and randomly ordered). This is tested against the alternative hypothesis *H*a, which assumes that there is a trend. If the p-value is greater than the level of confidence alpha, there is no significant trend. On the other hand, if the p-value is less than the level of confidence alpha, there is a significant trend (Thenmozhi and Kottiswaran, 2016). The Mann-Kendall statistic (S) is computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sign}(yj - yi) \tag{5}$$

The trend test is applied to a time series y_i, which is ranked from i = 1,2,3, ... n – 1 and y_j, which is ranked from j = i + 1, i + 2, i + 3, ... n. Each of the data points y_j is taken as a reference point, which is compared with the rest of the data points y_i, so that,

$$\mathrm{sign}(yj - yi) = \begin{Bmatrix} 1, & \mathrm{if}(yj - yi) > 0 \\ 0, & \mathrm{if}(yj - yi) = 0 \\ -1 & \mathrm{if}(yj - yi) < 0 \end{Bmatrix} \tag{6}$$

Here y_j and y_i are the sequential data values, and *n* is the length of the data set (Wani *et al*., 2017).

3.3.10.1 Sen’s Slope Estimator Test

To estimate the true slope of an existing trend such as the amount of change per year, Sen’s slop nonparametric method is used. The Sen's method can be used in cases where the trend can be assumed to be linear such as:

$$f(t) = Q(t) + B \tag{7}$$

Here Q is the slope, and B is a constant. Therefore, the Sen slope estimator is computed as follows:

$$B1 = \mathrm{median}\left[\frac{(yj - yi)}{xj - xi}\right] \tag{8}$$

For all j > i and i = 1, 2, …, n-1 and j = 2, 3…, n; in other words, computing the slope for all pairs of data that were used to compute S. The median of those slopes is the Sen slope estimator (Rahman and Begum, 2013).

3.3.11 Statistical Analysis

Relationship of vegetation cover with rainfall and LST was analyzed using Pearson Correlation Coefficient for each pixel to test the strength of the linear relationship of vegetation cover with rainfall and LST (Lamchin *et al.*, 2015). Pearson's correlation coefficient is a statistical measure of the strength of a linear relationship between paired data (http://www.statstutor.ac.uk).

It is the test statistics that measure the statistical relationship, or association, between two continuous variables and known as the best method of measuring the association between variables of interest. It gives information about the magnitude of the association, or correlation, as well as the direction of the relationship (http://www.statisticssolutions.com). Coefficient values can range from +1 to -1, where +1 indicates a perfect positive relationship, -1 indicates a perfect negative relationship and 0 indicates no relationship exists (http://www.statisticssolutions.com). The absolute value of the correlation coefficients (r) is divided into a weak correlation ($0<|r|\leq 0.3$), a low correlation ($0.3<|r|\leq 0.5$), a moderate correlation ($0.5<|r|\leq 0.8$), and a strong correlation ($0.8<|r|\leq 1$) (Li *et al.*, 2014).

$$r_{xy} = \frac{\sum_{i=1}^{n}(xi-xm)*(yi-ym)}{\sqrt{\sum_{i=1}^{n}(xi-xm)^2 \sum_{i=1}^{n}(yi-ym)^2}} \qquad (9)$$

Where, rxy is the simple correlation coefficient of variables X and Y, xi is NDVI or vegetation cover of the i^{th} year/month, Yi is climatic elements (rainfall or LST) of the i^{th} year/month; Xm is the average NDVI or vegetation cover for all years/month, Ym is the average rainfall or LST for all years/month (Li *et al.*, 2014).

CHAPTER FOUR

4 RESULTS

4.1 Normalized Difference Vegetation Index Results

The Normalized Difference Vegetation Index results of the study area have ranged from +1.00 to -0.51 and +0.53 to -0.22 in 1985 and in 2017, respectively (Table 4.1). This indicates the fact that the amount of vegetation has decreased in 2017 as compared to the 1985. The maximum values of the vegetation index reduced from 1.00 in 1985 to 0.53 in 2017. The NDVI value result shows that vegetation cover was decreased from 1985 to 2017. The maximum and the minimum NDVI values were observed in 1985 and in 2017, respectively in the study area. The maximum NDVI value of 1.00 in 1985 decreased by 0.67 in the year 2000. The maximum NDVI value of 2010 and 2017 were 0.63 and 0.53, respectively. This reduction in NDVI values revealed that the loss of vegetation covers in North Gondar zone.

Table 4.1: Statistical Normalized Difference Vegetation Index value of years 1985, 2000, 2010 and 2017.

Years	Minimum	Maximum	Mean	Std
1985	-0.51	1.00	0.14	0.07
2000	-0.56	0.67	0.13	0.09
2010	-0.53	0.63	0.08	0.07
2017	-0.22	0.53	0.07	0.05

The mean values decreased from 0.14 in 1985 to 0.07 in 2017 as shown in Table 4.1. This means the highest mean value of NDVI shown in 1985 image revealed the highest level of vegetation cover whereas the lowest mean value of NDVI in 2017 satellite images indicates the lowest vegetation coverage. Hence, the status of vegetation cover was better in 1985 than 2017 satellite images in the study area.

The mean NDVI value was reduced from 0.14 in 1985 to 0.13 in 2000 and 0.08 in 2010. The least mean NDVI value occurred in 2017. This reduction trend of mean NDVI value indicated that vegetation cover decreased through time in the study area. As shown in Figure 4.1, the darker green color in the image revealed the highest NDVI values and the highest vegetation cover. The darker red color showed the lowest NDVI value and the lowest vegetation cover. This comparison result shows that highest vegetation cover was observed in 1985 whereas lowest vegetation cover was observed in 2000.

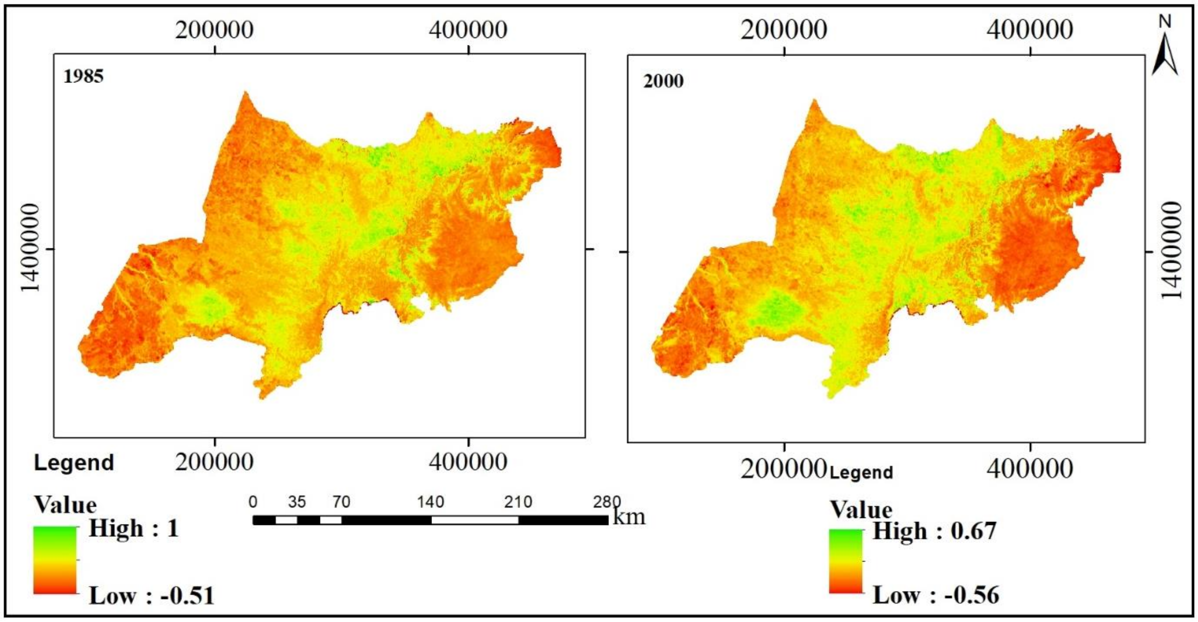


Figure 4.1: Normalized Difference Vegetation Index map of 1985 and 2000.

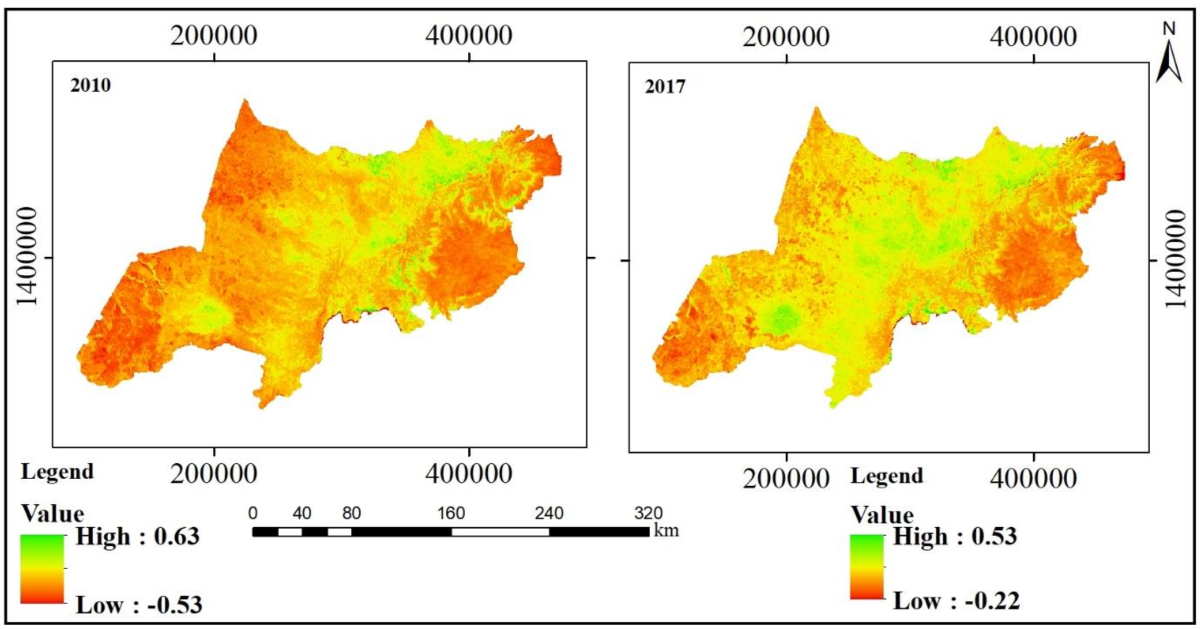


Figure 4.2: Normalized Difference Vegetation Index map of 2000 and 2017.

The outcomes of the maximum and the mean NDVI values indicated that there was a decrease in vegetation cover over the last 32 years. Based on the NDVI value results, vegetation cover decreased through time in the study area. NDVI value results have shown that vegetation cover is observed in central, northern and southeastern part of the study area (Figure 4.1 and 4.2).

Vegetation and non-vegetation cover changes have been observed in the north, southeastern and central part of the area. However, low vegetation cover has been seen in the western low land areas and eastern part of the study area over the study period.

4.2 Vegetation Cover Mapping

According to the study threshold classification, there are two main Land-use/Land-cover classes. These are vegetation and non-vegetation. The vegetation cover of the study area was 210,177 hectors (ha) (4.7%) of the total study area and the non-vegetated area was 4,266,244 ha (95.3%) of the study area in1985. Vegetation cover decreased in 2000 which had covered an area of 173,971 ha (3.9 %). About 36,206 ha (0.8%) of vegetation cover has been lost in 2000 from 1985. On the contrary, the non-vegetated area increased from 4,266,244 ha (95.30%) to 4,302,450 ha (96.1%) in 2000 which increased by 36,206 ha (0.8%).

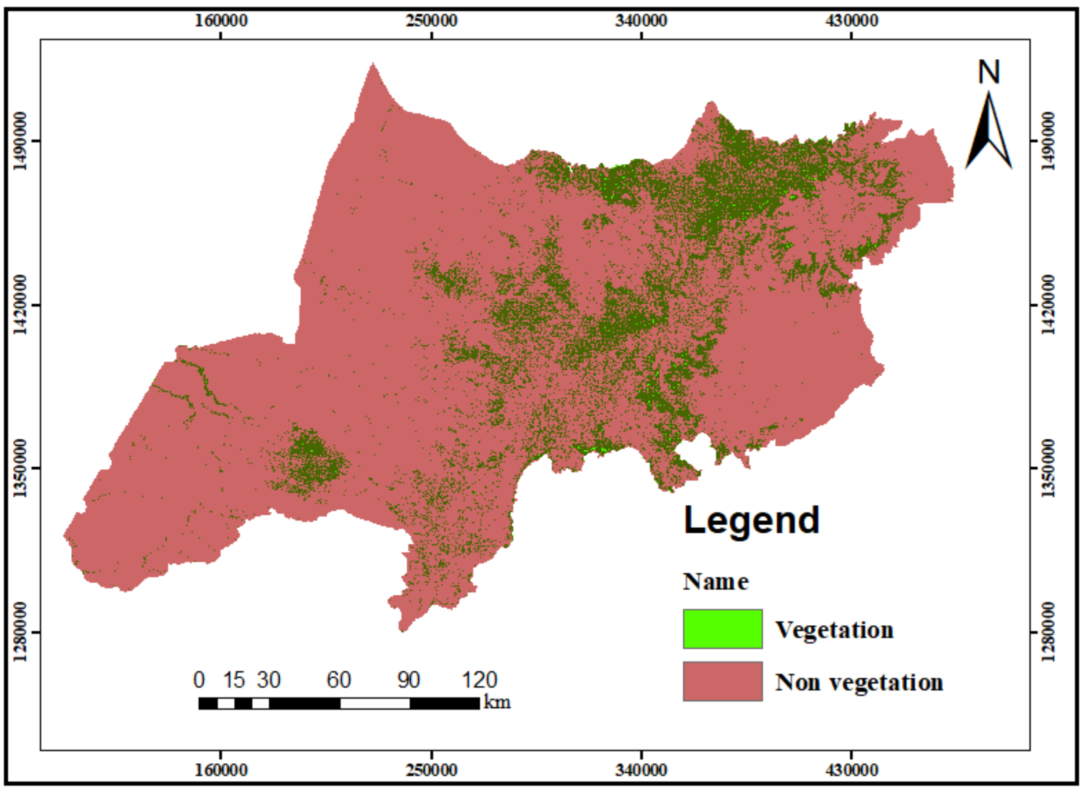


Figure 4.3: Land use/land cover map of 1985.

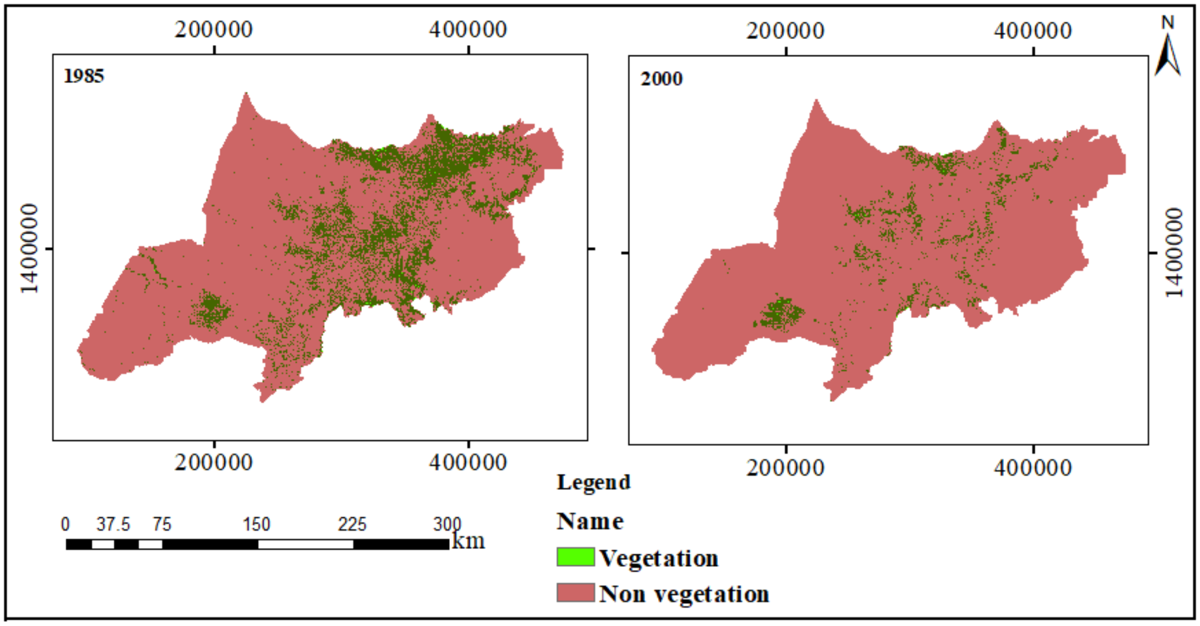


Figure 4.4: Land use/land cover map of 1985 and 2000.

Table 4.2: Land use/land cover showing the area in ha for the year 1985, 2000, 2010 and 2017.

LULC Classes	1985	2000	2010	2017
Vegetation	210,177	173,971	141,785	117,019
Non-vegetation	4,266,244	4,302,450	4,334,636	4,359,402
Total	4,476,421	4,476,421	4,476,421	4,476,421

The vegetated and the non-vegetated areas were 141,785 ha (3.2%) and 4,334,636 ha (96.8%), respectively, in 2010. The vegetation cover decreased by 32,186 ha and the non-vegetated area increased by 32,186 ha in 2010. The vegetation and the non-vegetation cover, in 2017, was 117,019 and 4,359,402 ha, respectively. From 1985 to 2000 a large area of vegetation cover has been lost. However, a small area of vegetation has been lost from 2010 to 2017. The analysis of land-use land-cover change for 32 years from 1985 to 2017 of the study indicated that 93,158 ha (2.1 %) of vegetation cover land has been lost. Therefore, the analysis of the result clearly indicated that vegetation covers decreased over the study period while non-vegetation covers increased.

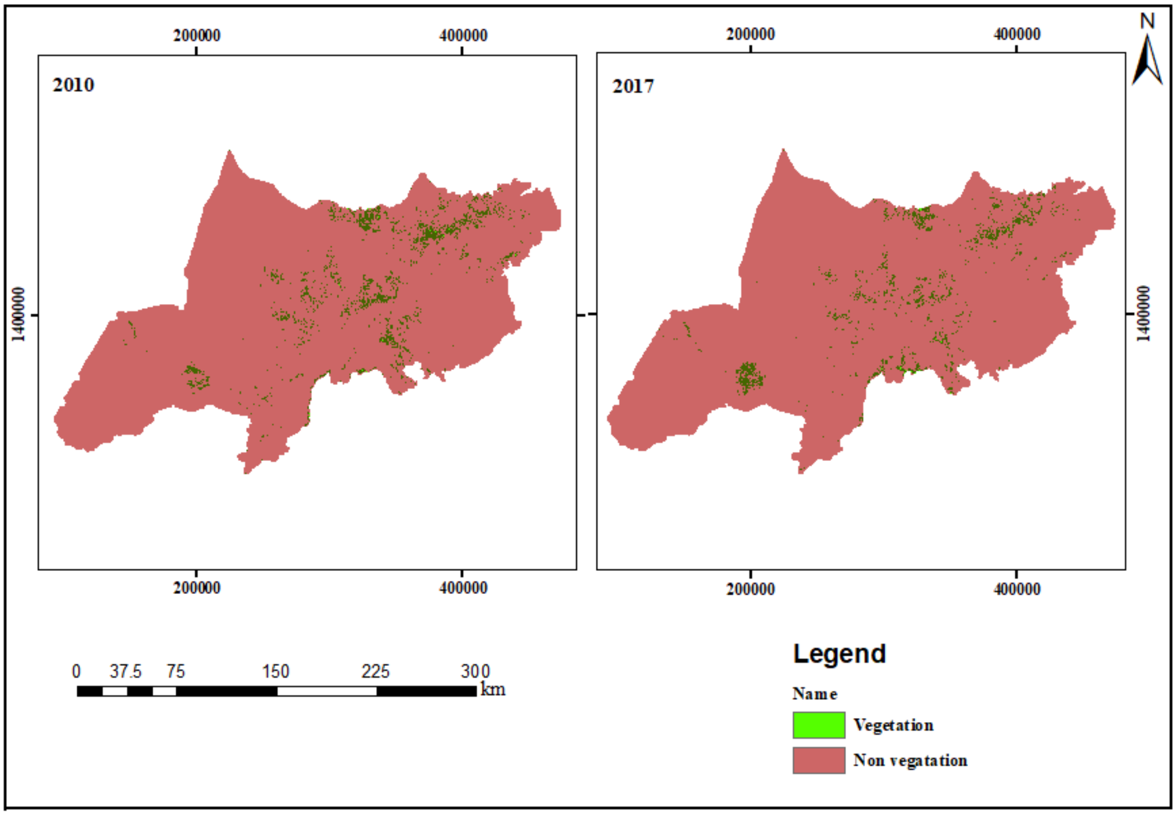


Figure 4.5: Land use/land cover map of 2010 and 2017.

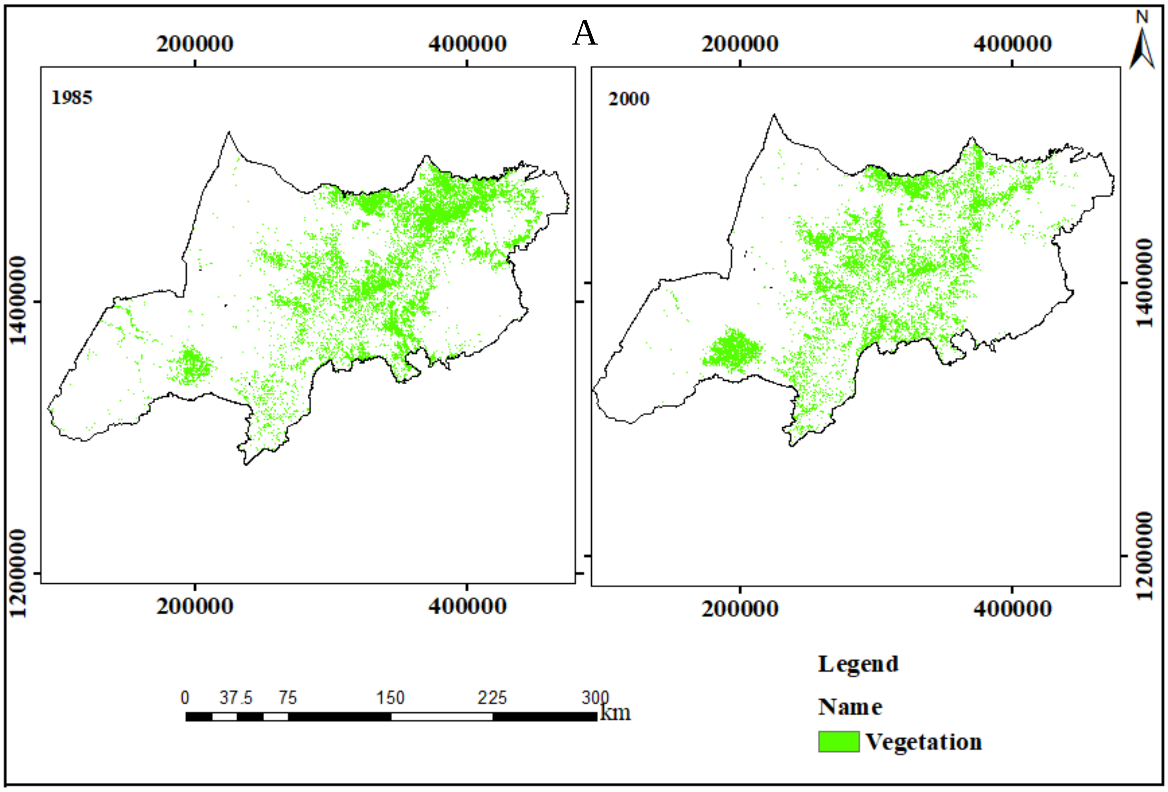
4.3 Vegetation Cover Change

The area covered by vegetation was 210,177 ha in 1985 and 173,971 ha in 2000 which indicated removal of 36,206 ha vegetation cover within a span of 15 years. The vegetation covers was141,785 and 117,019 ha in 2010 and in 2017, respectively.

Table 4.3: Vegetation cover change (area in ha) from 1985 to 2017.

	Change (1985 to 2000)	**Change (2010 to 2017)**
Vegetation	-36,206	-24,766

Negative (-) sign indicates decreasing


A
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2000
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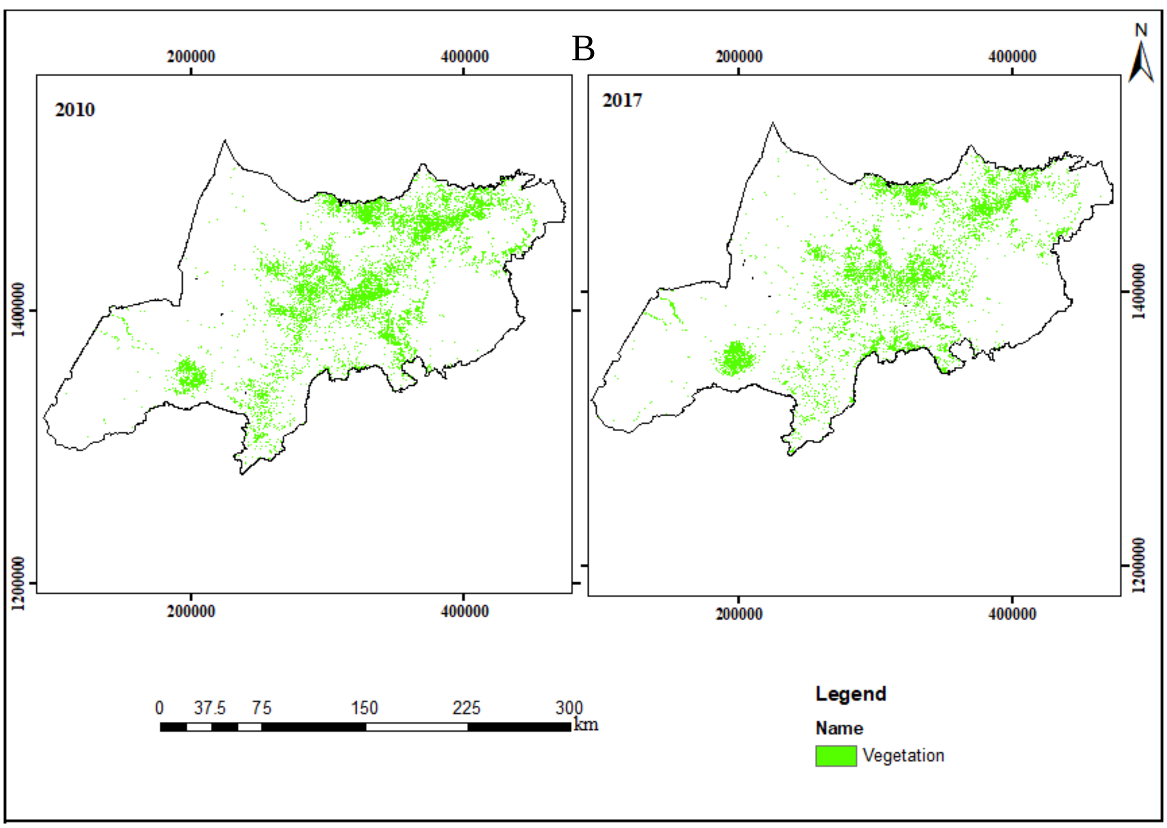
Legend
Name
Vegetation
0 37.5 75 150 225 300
km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km

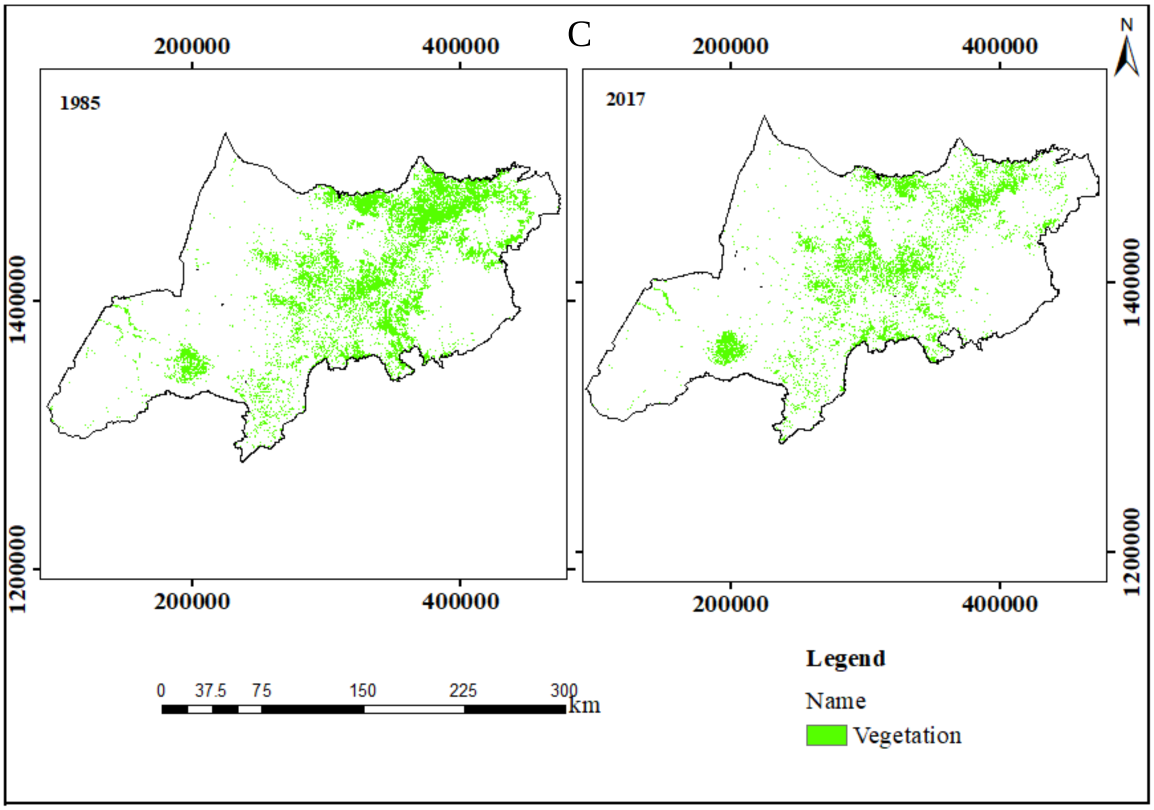

Figure 4.6: (A) Vegetation cover map of 1985 and 2000 (B) Vegetation cover map of 2010 and 2017 (C) Vegetation cover map of 1985 and 2017.

During the last three decades, the vegetation cover in the study area decreased from 210,177 ha in 1985 to 117,019 ha in 2017 accounting for 2.6% of the total study area, 2.1% of vegetation cover has been converted to the non-vegetated area. The image differencing of threshold results between 1985 and 2017 show that NDVI indicated greater degradation in vegetation cover than regeneration in vegetation cover (Table 4.4). The results of vegetation cover change detection between 1985 and 2017, 1985 and 2000, 2000 and 2010, 2000 and 2017, 2010 and 2017 are presented in Table 4.4:

Table 4.4: Change detection of vegetation cover change (area in ha).

	Years	**1985 to 2017**	**1985 to 2000**	**2000 to 2010**	**2000 to 2017**	**2010 to 2017**
Vegetation Cover	Increased	55,459	108,670	83,671	56,068	59,963
	Unchanged	4,272,345	4,222,875	4,276,893	4,307,333	4,331,709
	Decreased	148,617	144,876	115,857	113,020	84,739

The image differencing result indicated that there was a greater vegetation degradation

(144,876 ha) than the area of vegetation restoration (108,670 ha) in 1985 to 2000.This result implies that from the period of 1985-2000, afforestation area occupied 2.4% of the research area, while deforested area occupied 3.2% of the study area. The major change was detected between 1985 and 2000, showing that about 0.8% of total vegetation cover of the study area was lost. The extent of afforestation was covered an area of 83,671 ha (1.9%) between 2000 to 2010. Change detection analysis of image differencing showed that 59,963 ha area were afforested, and 84,739 ha were deforested between 2010 and 2017. During the period of 2000 to 2017, the afforestation covered 1.3% of the total area and deforestation was reported as 2.5% of the total area of the study site. Similarly, between 1985 and 2017 the result has shown that an increase of vegetation cover by 55,459 ha (1.2%) and a decrease by 148,617 ha (3.3%) of the total area.

The differences between vegetated and un-vegetated areas can clearly be seen in Figure 4.7. The changed area on the map is assigned as red and blue colors, while regions with little or no changes are shown in light sienna color. Likewise, red areas are regions that have lost vegetation and blue areas represent a gain in vegetation from 1985 to 2017. The main negative changes or decrease in vegetation cover between 1985 and 2017 are in the central and northern parts of North Gondar zone. The area shows an overall decrease in the amount of vegetation, again, in the northern, central and southeastern parts of the study area.

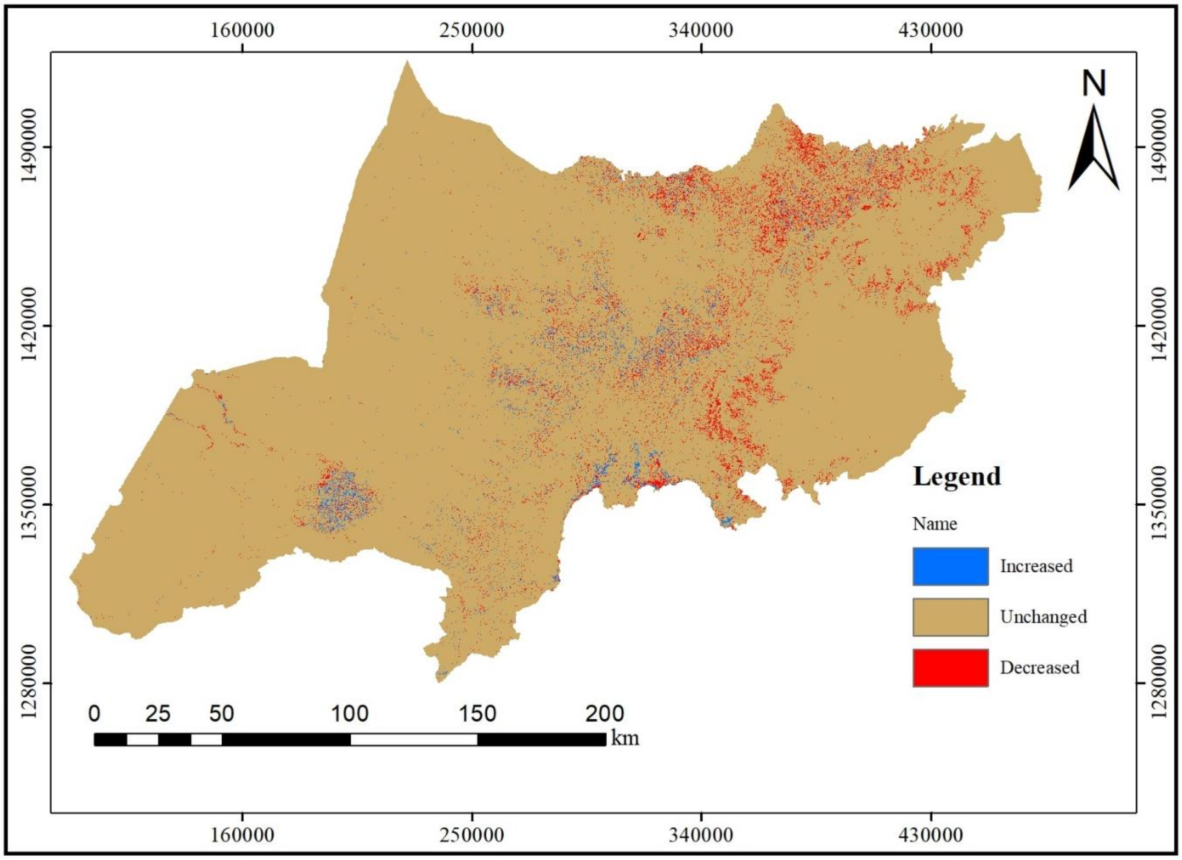

Figure 4.7: Change detection map from 1985 to 2017.

4.4 Accuracy Assessment

The accuracy of LULCC along with the overall accuracy and the Kappa coefficient was summarized in Table 4.5. The overall accuracy and kappa analysis were used to perform a classification accuracy assessment. The producer 's accuracies of both classes were consistently high, ranging from 80.3% to 95.6%. The user 's accuracies for both classes were precisely high, ranging between 86.8% and 95%, respectively. The accuracy assessment result showed that the overall accuracy was 86.4% with kappa statistics 0.72 for 1985. The overall accuracy of classification image was 92.2% and the Kappa coefficient was 0.84 in the year 2017.

Table 4.5: Accuracy assessment for the year 1985, 2000, 2010 and 2017.

	1985		**2000**		**2010**		**2017**	
	Vegetation	**Non-veg.**	**Vegetation**	**Non-veg.**	**Vegetation**	**Non-veg.**	**Vegetation**	**Non-veg.**
Users accuracy (%)	87.5	85.7	89	87.3	86	93.3	88.5	95
Producers accuracy (%)	80.3	91.1	82.4	92.3	89.6	90.9	92.2	95.6
Overall accuracy (%)	86.4		88		90.4		92.2	
Kappa statistics (%)	0.72		0.82		0.84		0.84	

4.5 Trend Analysis of Annual Mean, Maximum and Minimum Rainfall

The Mann-Kendall trend test has shown that the mean, minimum and maximum annual rainfall changes were not statistically significant over the study period (Table 4.6). However, there was an increasing trend of mean, minimum and maximum annual rainfall during the study period. The slope of the trend line in annual mean, minimum, and maximum rainfall graph were a positive value which explained the increase of insignificant value across the three decades time series analysis. The annual mean, minimum and maximum rainfall have been changed by the factors of 3.2679, 1.0579 and 5.5132 as per the trend line indicated in Figure 4.8

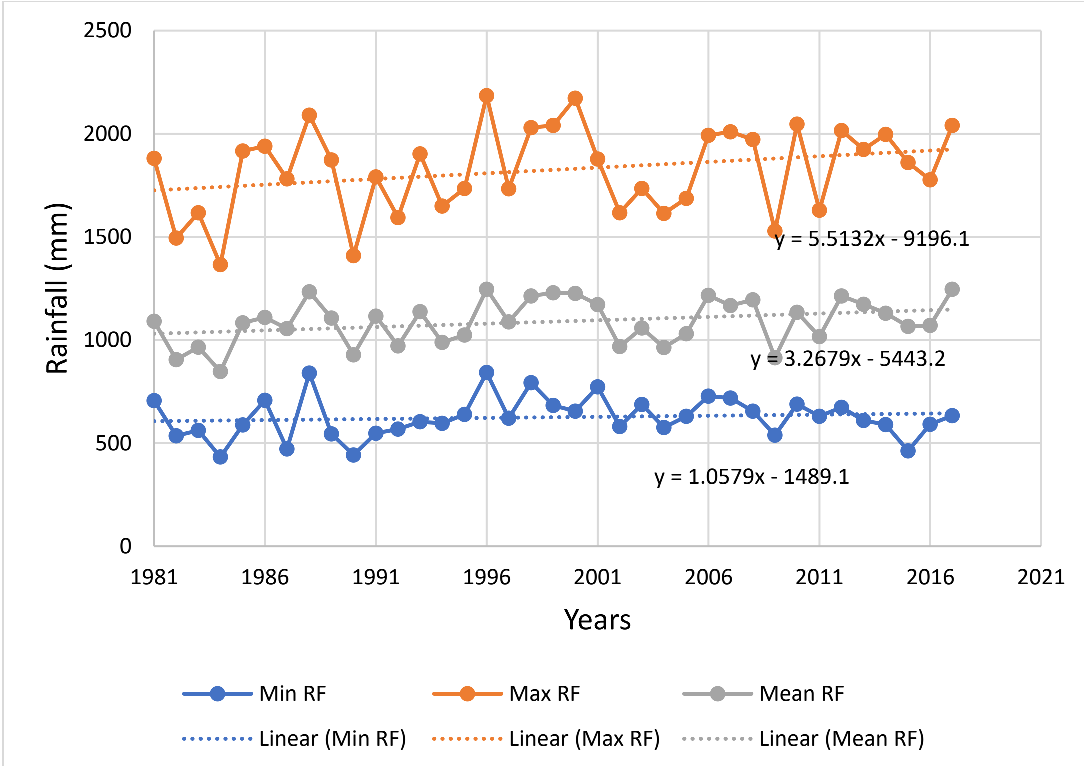

Figure 4.8: Result of the trend line of minimum, maximum and mean annual rainfall.

Table 4.6: Mann-Kendall Trend Test of Annual Mean, min and max rainfall.

Variables	Mean RF	Min RF	Max RF
Obs.	37	37	37
Obs. Without missing data	37	37	37
Kendall's tau	0.2	0.13	0.17
Alpha	0.05	0.05	0.05
P-value	0.09	0.28	0.15
Min	847.47	432.68	1,364.98
Max	1,246.59	842.07	2,185.03
Mean	1,089.23	625.65	1,824.78
Std	0.14	0.5	0.92
Sen's slope	3.56	1.41	4.88

H_O, there is no trend in the time series analysis of 37 years annual mean, min and max rainfall.

Ha, there is a trend in the time series analysis of 37 years annual mean, min and max rainfall.

As the computed p-value is greater than the significance level alpha = 0.05, one cannot reject the null hypothesis Ho. The risk to reject the null hypothesis Ho while it is true is 9%, 28% and 15.4% for mean, minimum and maximum annual rainfall respectively. Therefore, Mann-Kendall trend test indicated that p-value of annual mean, minimum and maximum rainfall were

0.09, 0.28 and 0.15 with level of confidence 0.05. In all cases, p-value is greater than the alpha value. This means that there is no significant trend of mean, minimum and maximum annual rainfall change for the last three decades.

Annual minimum, maximum and mean rainfall variability has been observed in the study area. The result revealed that there was no uniformly increased annual minimum, maximum and mean rainfall throughout the study period. The analysis of Mann-Kendall trend test result showed that there was no a significant change in trend of minimum, maximum and mean rainfall from 1981 to 2017 in North Gondar zone. However, the upward increased of annual minimum, maximum and mean rainfall have been observed over the study area. The result of Sen's slope estimator indicated that there was upward increased trend of minimum, maximum and mean annual rainfall by 1.41 mm, 4.88 mm and 3.56 mm per year, respectively. The analysis of the result revealed that within 37 years the maximum annual rainfall (2,185 mm) has been seen in 1996, while the minimum annual rainfall (432 mm) has been observed in 1984.

4.6 Trend Analysis of Mean, Maximum and Minimum Rainfall of Dry Season

The result of Mann-Kendall trend test and trend line indicate that seasonal mean, maximum, and minimum rainfall were increased from 1981–2017 over the study area. The results of the analyses indicate that the seasonal minimum, maximum and mean rainfall from 1981–2017 periods have shown an increasing trend at a 95% confidence level, although it is not statistically significant. Dry season maximum, minimum and mean rainfall were changed by the factors of 0.609, 0.3077 and 0.6929, respectively.

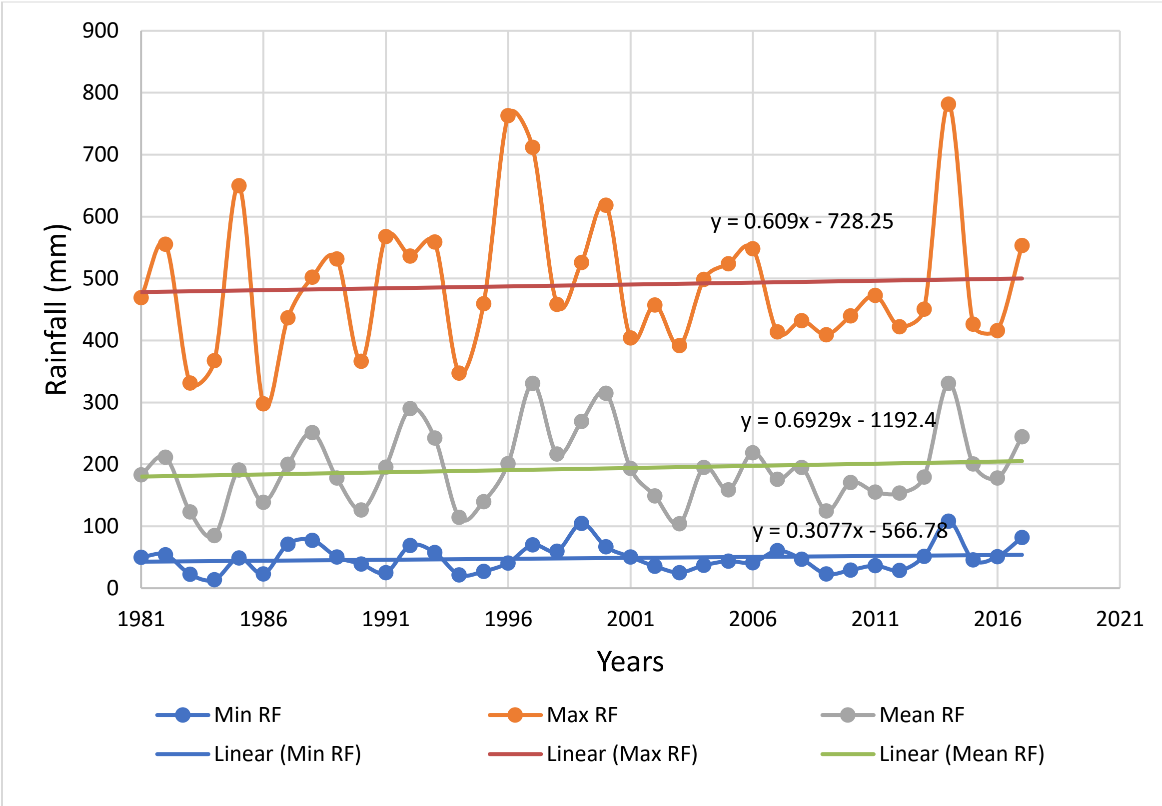

Figure 4.9: Result of the trend line of minimum, maximum and mean of dry season rainfall.

Table 4.7: Mann-Kendall trend test of minimum, maximum and mean rainfall of the dry season.

Variables	Mean RF	Min RF	Max RF
Obs.	37	37	37
Obs. Without missing data	37	37	37
Kendall's tau	0.07	0.08	0.03
Alpha	0.05	0.05	0.05
P-value	0.54	0.47	0.82
Min	84.74	13.73	297.52
Max	330.86	108.45	781.49
Mean	192.71	48.35	489.11
Std	0.41	0.17	0.87
Sen's slope	0.03	0.02	0.03

H_O, there is no trend in the time series analysis of 37 years min, max and mean of dry season rainfall.

Ha, there is a trend in the time series analysis of 37 years min, max and mean of dry season rainfall.

As the computed p-value is greater than the significance level alpha = 0.05, one cannot reject the null hypothesis Ho. The risk to reject the null hypothesis Ho while it is true is 47%, 82% and 54% for minimum, maximum and mean of dry season rainfall. According to the result of rainfall data analysis, the minimum seasonal rainfall ranges from 13.73 mm to 108.45 mm in the study area. The dry season minimum rainfall shows a positive increasing trend with Kendall's tau value 0.08 and significance level of 0.05. The minimum dry season rainfall has increased by 0.02 mm per year, although it is not statistically significant (p-value=0.47 with alpha 0.05). Based on the rainfall data analysis result, maximum dry season rainfall was ranged from 297.52 mm to 781.49 mm. The Mann- Kendall trend analysis result indicated that dry season of maximum rainfall has been increased by 0.03 mm per year with Kendall's tau of 0.03. The results of the analysis indicate that the dry season maximum rainfall from1981–2017 periods have shown an increasing trend at a 95% confidence level, although it is not statistically significant (p-value=0.82 with alpha 0.05). Although the trend of mean rainfall was not significant (p-value=0.54 with alpha 0.05), the results clearly indicated that changes are occurring in the mean rainfall in the study area. Therefore, the results of the study reveal that there are signs of increasing trend of mean dry season rainfall in the study period. The mean dry season rainfall has shown an increasing trend by 0.03 mm per year.

4.7 Analysis of Dry Season Land Surface Temperature

The analysis of Mann-Kendall trend test result revealed that the range of minimum, maximum and mean of Land Surface Temperature (LST) were from 17.88°C -20.13°C, 45.37ºC -48.88ºC and 37.16ºC -39.13ºC respectively, from 2000 to 2017 (Table 4.8). According to the trend line as shown in Figure 4.10, the minimum, maximum and mean LST were changed by the factors of 0.016, 0.0317, and 0.0239 over North Gondar zone, respectively. The Mann-Kendall trend test result indicated that there was no significant trend of LST in the study area in the study period. Since p-value is greater than the significant level for all minimum, maximum and mean LST.

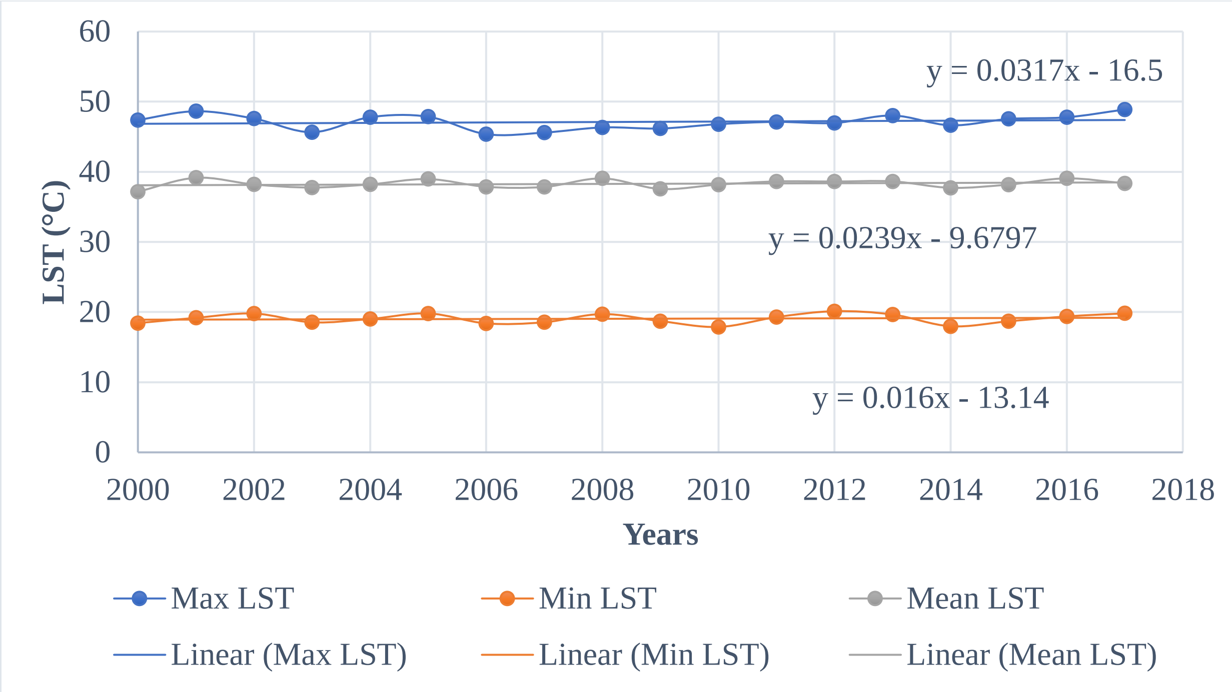

Figure 4.10: Result of the trend line minimum, maximum and mean LST of the dry season.

Table 4.8: Mann-Kendall trend test of minimum, maximum and mean LST of the dry season.

Variables	Mean LST	Min LST	Max LST
Obs.	18	18	18
Obs. Without missing data	18	18	18
Kendall's tau	0.13	0.14	0.16
Alpha	0.05	0.05	0.05
P-value	0.35	0.45	0.36
Min	37.16	17.88	45.37
Max	39.15	20.12	48.88
Mean	38.28	19.05	47.12
Std	0.57	0.68	0.67
Sen's slope	0.03	0.02	0.09

Ho, there is no trend in the time series analysis of 18 years min, max and mean of dry season LST

Ha, there is a trend in the time series analysis of 18 years min, max and mean of dry season LST

As the computed p-value is greater than the significance level alpha = 0.05, one cannot reject the null hypothesis Ho. The risk to reject the null hypothesis Ho while it is true is 45%, 36% and 35% for the minimum, maximum and mean of dry season LST. Although there was no statistically significant change of LST in the study period, there is LST variability. The Sen's slope result showed that the minimum, maximum and mean LST were increased by 0.02ºC, 0.09ºC and 0.03ºC per year with significant level 0.05 and p-value 0.45, 0.36 and 0.35, respectively.

The mean, minimum and maximum LST for 2000 were 37.16ºC, 18.42ºC, and 47.39ºC. For 2017, 38.36ºC, 19.82ºC and 48.88ºC were mean, minimum and maximum of LST, respectively. This represents 1.4ºC and 1.5ºC increases in minimum and maximum LST (Table 4.9). The mean LST was increased by 1.2ºC in the same year. The minimum, maximum and mean LST values 18.68ºC, 47.9ºC and 37.16ºC in 2010 were increased to 19.82ºC, 48.88ºC, and 38.36ºC in 2017, respectively.

Table 4.9: Minimum, maximum and mean LST of 2000, 2010 and 2017.

Years	Min LST(ºC)	Max LST(ºC)	Mean LST(ºC)
2000	18.42	47.4	37.16
2010	18.68	47.9	37.54
2017	19.82	48.88	38.36

4.8 Relationship of NDVI and Vegetation Cover with Rainfall

Although the results of the Pearson Correlation show no significant relationship existing between vegetation index of mean NDVI of the dry season and annual mean rainfall, there was a moderate positive linear relationship existing between NDVI and rainfall. The correlation coefficient R between mean NDVI of the dry season and mean annual rainfall was 0.76. The correlation between mean annual rainfall and the vegetation index mean NDVI of the dry season is presented in Table 4.10. The results have shown that there is no significant relationship between mean annual rainfall and mean NDVI of dry season as the p-value 0.45 is higher than significant level alpha 0.05.

Table 4.10: Relationship of Normalized Difference Vegetation Index and vegetation cover with rainfall.

NDVI *vs* Rainfall				Vegetation cover *vs* rainfall			
P	R	R^2	Alpha	P	R	R^2	Alpha
0.45	0.76	0.58	0.05	0.68	0.48	0.23	0.05

The analysis of Pearson Correlation result showed that there was no significant relationship between vegetation cover in (ha) and rainfall in the central, northern and southeastern parts of the study area. The correlation result indicated that the mean annual rainfall was positively correlated with vegetation cover in (ha). The correlation coefficient of mean annual rainfall with vegetation cover in (ha) was 0.48 with significant level alpha and p-value 0.05 and 0.68 respectively. Therefore, the analysis of the Pearson Correlation result indicated that low correlation has been observed between the variables in the study area.

The NDVI and rainfall map Figure 4.11 indicated that an area which has high NDVI and rainfall value have been observed in the central, northern and southeastern part of the study area. The result has shown that areas with high NDVI values have shown high rainfall value, whereas an area with low NDVI value has shown low rainfall over the study period in the study area. This indicates that an area which has high vegetation cover had relatively high rainfall. On the other hand, an area with low vegetation cover had shown low rainfall.

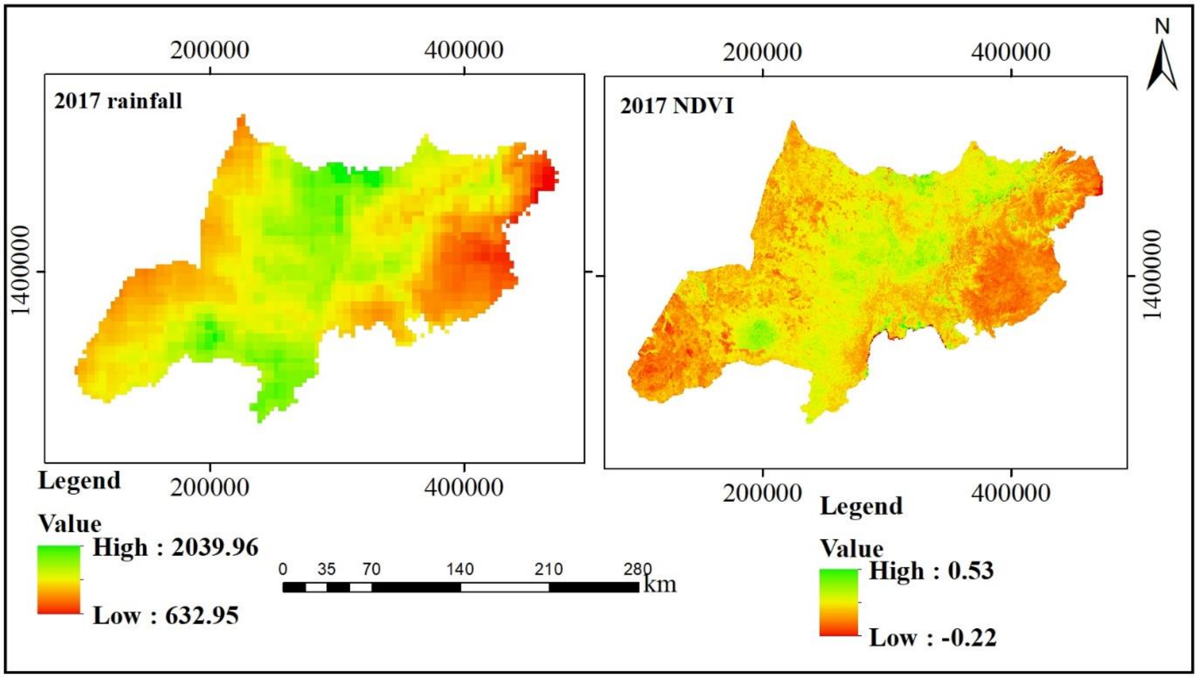

Figure 4.11: Rainfall and Normalized Difference Vegetation Index map of 2017.

4.9 Relationship of NDVI and Vegetation Cover with Land Surface Temperature

Land Surface Temperature (LST) is sensitive to vegetation cover. Table 4.11 shows the correlation between mean LST and mean NDVI of the dry season in the study area. The correlation coefficient obtained between LST and NDVI is found as -0.98 with significant level alpha 0.05 and p-value 0.14. This is clearly indicating that the LST is strongly and negatively correlated with NDVI. Hence, areas with least vegetation cover are experiencing more land surface temperature. Although the results of the Pearson Correlation showed strongly negative relationship existing between vegetation index of mean NDVI and mean LST of dry season, there was no significant negative linear relationship existing between the variables. Since p-value (0.14) is greater than alpha (0.05).

The result of correlation analysis also revealed that there was no significant relationship between vegetation cover (ha) and mean LST of dry season during the study period over central, northern and southeastern parts of the study area. However, there was a strong and negative correlation between vegetation cover in (ha) and mean LST with significant level and p-value (0.29, 0.05), respectively. In this case, the correlation coefficient was -0.89.

Table 4.11: Relationship of Normalized Difference Vegetation Index and vegetation cover *with* Land Surface Temperature.

NDVI *vs* LST				**Vegetation cover *vs* LST**			
P	R	R^2	Alpha	P	R	R^2	Alpha
0.14	-0.98	0.95	0.05	0.29	-0.89	0.80	0.05

From the analysis, it was observed that the vegetation covers had shown a considerably low land surface temperature in all the years. This is because high vegetation cover can reduce the amount of heat stored in the soil and surface structures through transpiration. The vegetation coverage and land surface temperature map (Figure 4.12) indicated that areas with high vegetation cover had shown low land surface temperature, whereas, areas with low vegetation cover had shown high land surface temperature. According to the result analysis, high vegetation coverage and low LST have been observed in the central, north and southeastern of the study area over the study period. On the other hand, low vegetation cover and high LST has been observed in the west low land areas and eastern part of the study area during the study period.

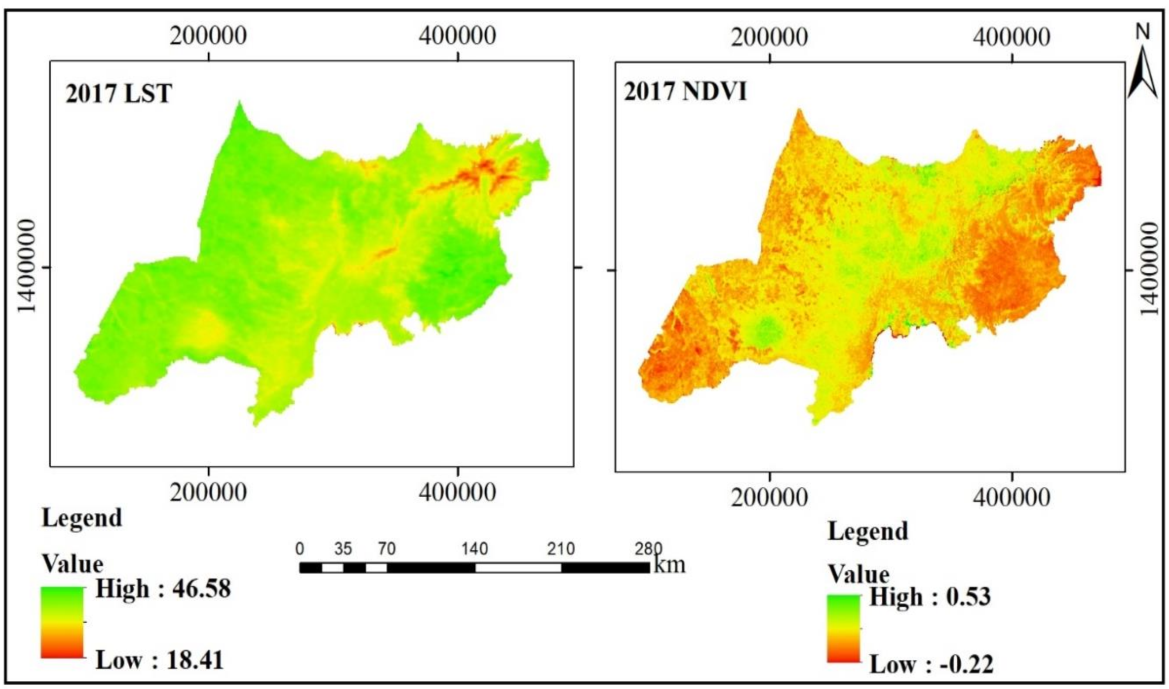

Figure 4.12: Normalized Difference Vegetation Index and Land Surface Temperature map of 2017.

4.10 The Impacts of Vegetation Cover Change on Rainfall and Land Surface Temperature

4.10.1 The Impacts of Vegetation Cover Change on Rainfall.

The analysis of Pearson Correlation result indicated that there was a positive correlation of vegetation cover with annual mean rainfall in the central, northern and southeastern parts of North Gondar zone. The correlation coefficient and coefficient of determination with significant level=0.05and p-value= 0.68 were 0.48 and 0.23, respectively. Although there was a positive relationship between vegetation cover with mean annual rainfall, the relationship between the variables is not statistically significant for the p-value is greater than alpha (level of significance). Areas with higher vegetation cover have shown high mean annual rainfall in the study area during the study period, whereas areas with low vegetation cover have shown low mean annual rainfall (Figure 4.13). This indicates that the vegetation cover has a positive impact on local rainfall.

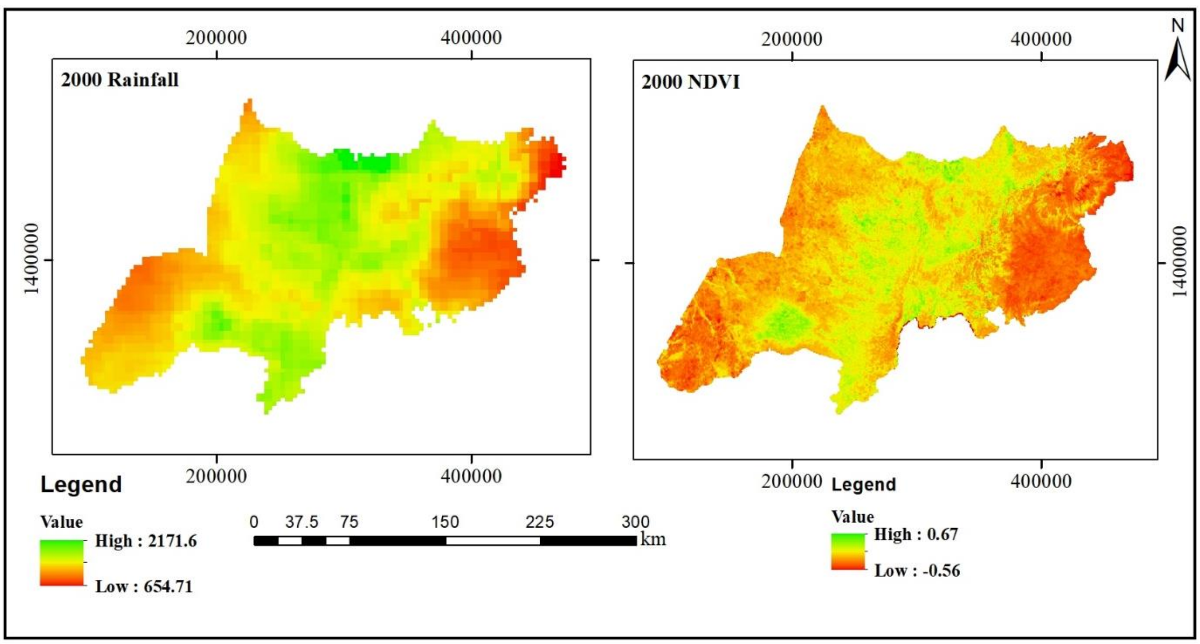

Figure 4.13: Rainfall and Normalized Difference Vegetation Index map of 2000.

The coefficient of determination R^2 indicated that 23% of the variability in rainfall is caused by the vegetation cover change over central, northern and south eastern parts of North Gondar zone during the study period. The result of zonal statistics of vegetation coverage with rainfall in Figure 4.14 indicated that vegetation cover and mean annual rainfall were reduced during the study period (200, 2010 and 2017). The Mann-Kendall trend test of result indicated that there was an increased trend of mean annual rainfall over North Gondar zone during the study period. However, zonal statistics of vegetation cover with mean annual rainfall indicated that the mean annual rainfall was reduced as the vegetation cover decreased in the selected years (2000, 2010 and 2017) over the central, northern and southeastern of the study area.

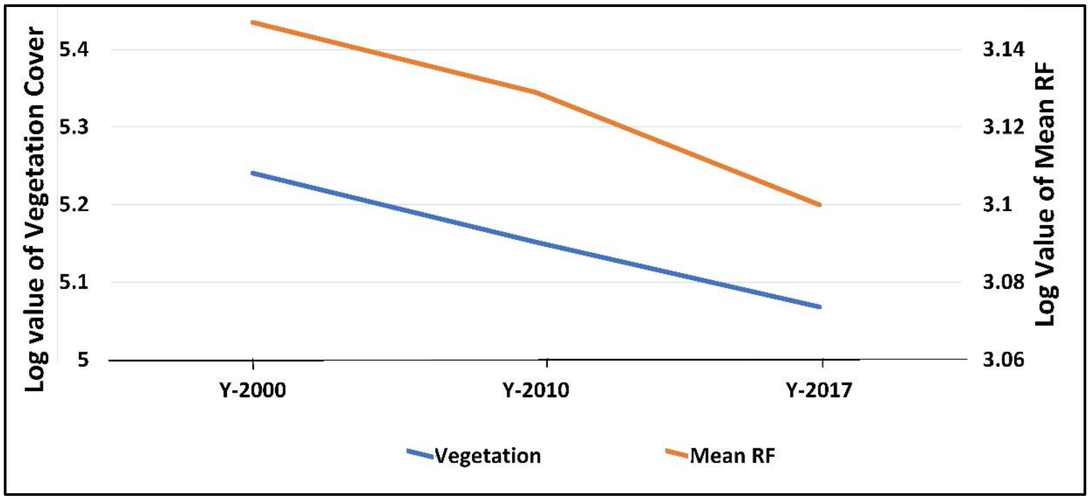

Figure 4.14: Log value of vegetation cover with log value of mean rainfall.

Table 4.12: Zonal statistics of vegetated and non-vegetated areas *with* minimum, maximum and mean rainfall.

	Years	2000	2010	2017
Vegetation	Area (ha)	173,971	141,785	117,019
	Max RF (mm)	2,171.60	2,046	1,912.5
	Min RF (mm)	888.7	857.9	843.6
	Mean RF (mm)	1,402.7	1,345.6	1,258.8
Non-vegetation	Area (ha)	4,302,450	4,334,636	4,359,402
	Max RF (mm)	1,876.6	1,722.9	1,634.25
	Min RF (mm)	689.7	654.7	633
	Mean RF (mm)	1,243	1,219.1	1,160.6

Zonal statistics result showed that the minimum, maximum and mean rainfall of vegetated area is greater than the minimum, maximum and mean rainfall of non-vegetated area. Vegetation and non-vegetation cover has occupied an area of 173,971 and 4,302,450 ha in 2000. The mean annual rainfall of vegetated and non-vegetated areas was 1,402.7 mm and 1,243 mm, in 2000 respectively. By the year 2010, the mean annual rainfall was reduced to 1,345.6 mm and 1219.1

mm on vegetated and non-vegetated areas. Since the vegetation cover and non-vegetation cover were decreased and increased in 2010, respectively. The non-vegetated areas have increased with decreased mean annual rainfall in 2017.

Table 4.13: Zonal statistics of vegetation cover *with* minimum, maximum and mean rainfall.

	Years	**2000**	**2010**	**2017**
Vegetation	Area (ha)	173,971	141,785	117,019
	Mean RF (mm)	1,402.7	1345.6	1,258.8
	Max RF (mm)	2,171.60	2,046	1,912.5
	Min RF (mm)	888.7	857.9	843.6

Vegetation cover and annual mean rainfall Table 4.13 clearly indicated that the highest mean annual rainfall and the highest vegetation cover have been seen in 2000, while the lowest mean annual rainfall and the lowest vegetation cover have been observed in 2017. According to zonal statistics of vegetation cover with mean annual rainfall, from 2000 to 2010, vegetation cover has been reduced by 32,186 ha. The mean annual rainfall has been also decreased by 57.1 mm from 2000 to 2010. Vegetation cover has been reduced by 24,766 ha and the mean annual rainfall decreased by 86.8 mm from 2010 to 2017. The mean, maximum and minimum annual rainfall has been decreased through time with declined vegetation cover in the central, northern and southeastern parts of the study area. Therefore, the result of the study showed that vegetation cover has a positive impact on local rainfall.

4.10.2 The Impacts of Vegetation Cover Change on Land Surface Temperature

The analysis of Pearson Correlation result showed that there was a negative correlation between mean NDVI of the dry season and vegetation cover with mean LST of the dry season in the study period. The coefficient of determination (R^2) of mean NDVI with mean LST of the dry season and vegetation cover with mean LST were 0.95 and 0.8, respectively. The analysis of this result revealed that NDVI and vegetation cover (ha) has a negative impact on LST because areas with higher vegetation cover have shown relatively lower LST than areas with lower vegetation cover (Figure 4.15).

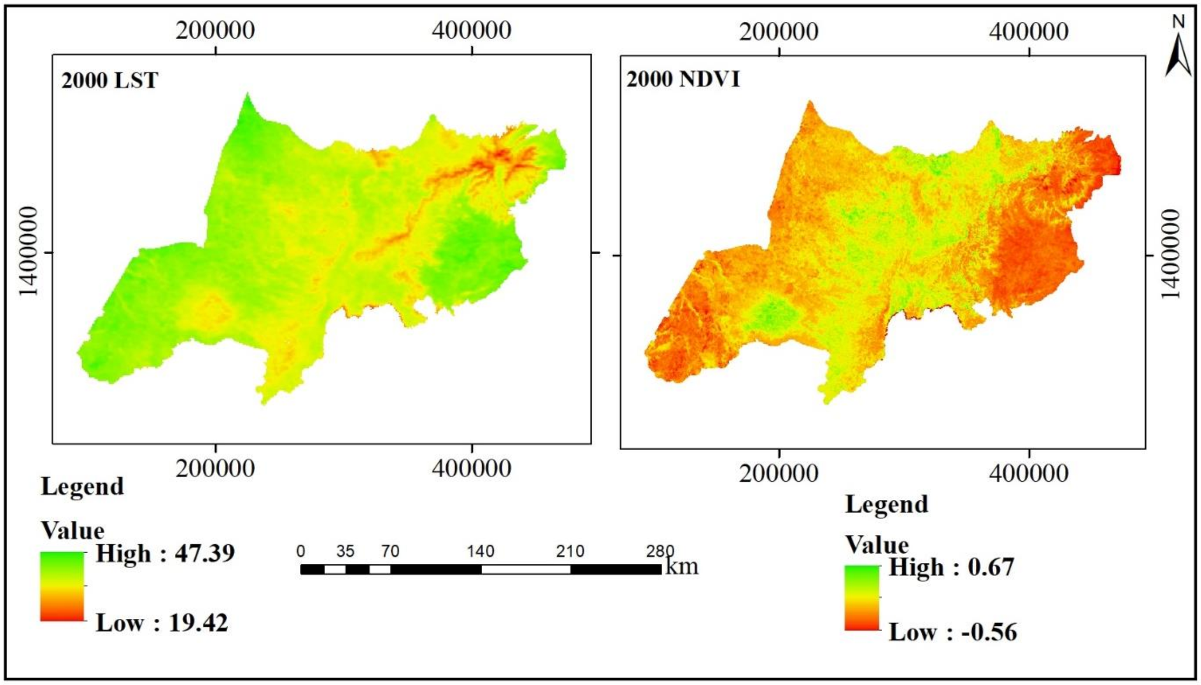

Figure 4.15: Land Surface Temperature and Normalized Difference Vegetation Index map of 2000.

The coefficient of determination, R^2, indicated that 80% of the variability in LST is explained by a change in vegetation cover in the central, northern and southeastern parts of North Gondar zone over the study period. The LST of vegetated and non-vegetated areas for three years 2000, 2010 and 2017 are presented in Table 4.14.

Table 4.14: Zonal statistics of vegetated and non-vegetated areas *with* minimum, maximum and mean land surface temperature.

	Year	2000	2010	2017
Vegetation	Area (ha)	173,971	141,785	117,019
	Max LST (°C)	38.04	40.73	42.63
	Min LST (°C)	19.49	20.22	22.14
	Mean LST (°C)	32.64	33.22	34.23
Non-vegetation	Area (ha)	4,302,450	4,334,636	4,359,402
	Max LST (°C)	46.58	46.79	47.39
	Min LST (°C)	21.42	23.88	25.41
	Mean LST (°C)	37.30	38.30	38.47

The result of Vegetation cover and LST indicated that vegetation cover was reduced over the study period while LST was increased. The mean and maximum LST of the non-vegetated area is higher than the mean and maximum LST of vegetated area.

The maximum LST value of 38.04°C in 2000 increased to 40.73°C in 2010. However, the vegetation cover 173971 ha in 2000 reduced to 141785 ha in 2010. On the other hand, the non-vegetated area has been increased from 4302450 to 4334636 ha and the maximum LST of the non-vegetated area was also increased from 46.58°C to 46.79°C in 2010. The vegetation cover has been reduced to 117019 ha and maximum LST of vegetation cover has been increased to 42.63°C in 2017. The non-vegetated area and the maximum LST of the non-vegetated area were increased from 4334636 ha to 4359402 ha and 46.79°C to 47.39°C, in 2017 respectively.

Table 4.15: Zonal statistics of vegetation cover with minimum, maximum and mean land surface temperature.

	Year	2000	2010	2017
Vegetation	Area (ha)	173,971	141,785	117,019
	Mean LST (°C)	32.64	33.22	34.23
	Max LST (°C)	38.04	40.73	42.63
	Min LST (°C)	19.49	20.22	22.14

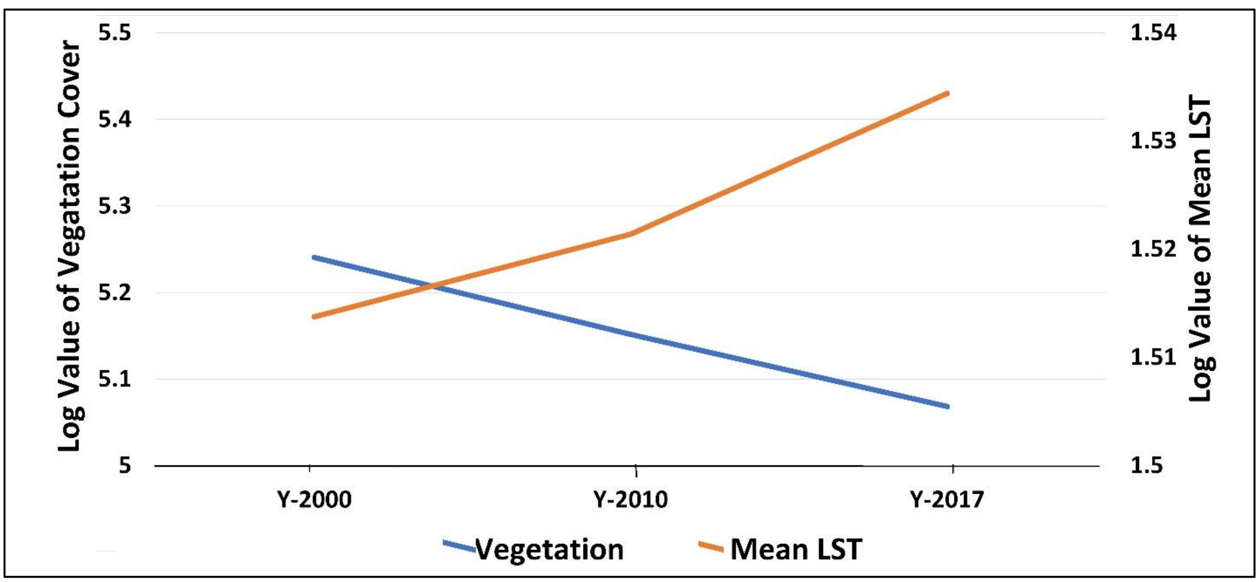

Figure 4.16:Log value of vegetation cover with log value of mean land Surface temperature.

The maximum and the mean LST was increased over the study period. The mean LST was

32.64°C and 37.30°C on the area of vegetation cover (173,971 ha) and non-vegetation cover (4,302,450 ha) in the year 2000. Mean LST on vegetation cover area was increased to 33.22°C in 2010. This is because the extent of vegetation cover in 2010 was lower than the extent of vegetation cover in 2000. The mean LST of vegetation cover was reached to 34.23°C in 2017.

The result of this study indicated that the vegetation cover and LST have negative relationship of each other over the study period. The vegetation cover reduced by 32,186 ha in 2010 from 2000 while the mean and the maximum LST increased by 0.58°C and 2.69°C in this year respectively. The non-vegetated area increased by 32,186 ha and mean and maximum LST increased by 1.00°C and 0.21 in 2010. The mean LST and the maximum LST of vegetation cover also increased by 1.01°C and 1.9°C in 2017 because the vegetation cover in the year 2017 was lower than the vegetation cover in 2010. From the analysis of this result mean, maximum and minimum LST increased with reduced vegetation cover during the study period.

CHAPTER FIVE

5 DISCUSSION

In the present study, NDVI technique was used to assess vegetation cover change from 1985 to 2017 in North Gondar zone. It was used by many researchers to assess vegetation cover change in wide area (Pu et al., 2008; Nusrath, 2010; Nath, 2014; Aly et al., 2016 and Zaidi et al., 2017). NDVI was calculated for Landsat images of 1985, 2000, 2010 and 2017 to assess the extent of vegetation cover change over time and to analyze the impacts of vegetation cover change on rainfall and LST in North Gondar zone. According to the analysis of NDVI value threshold results, vegetation cover has been detected in central, northern and southeastern of North Gondar zone. The analysis of NDVI threshold value result indicated that the vegetation cover was high in 1985 which accounts 4.7% of the study area. The vegetation cover has been reduced to 3.9% in 2000 from 1985. About 3.2% and 2.6% of the study area was covered by vegetation in the year 2010 and 2017, respectively. A total of 2.1% of vegetation has been lost in the past 32 years in North Gondar zone. This indicates that vegetation cover has decreased through time. It is reduced due to the increase of population growth and agricultural activity. Similar results were found in the study of Solomon (2016). His findings reported that the major factor for the depletion of vegetation in Ethiopia is due to high deforestation rate which is greater than the rate of afforestation and it is clear that as the population increases in a particular area there need to have additional land for agriculture and settlement purposes also increases. This can be only possible to meet by cutting vegetations in general and natural forests in particular. Nurhussen (2016) also reported that due to increasing population growth rates, there have been increasing rates of conversion of forest and woodlands to other land uses in line with the present study.

The trend of Mann-Kendal test of CHIRPS data analysis revealed that significant trend of minimum, maximum and mean annual rainfall have not observed in the study area. However, there was an increasing in annual minimum, maximum and mean rainfall over the study period. In similar way, the minimum, maximum and mean of dry season rainfall was not significant in the study period of 1981 to 2017. However, the mean, maximum and minimum of dry season rainfall were also rising in the study area. The result of this study indicates that annual and dry season rainfall variability is seen over the study area. This result, in line with that of

Gebremicael et al. (2017). They did their study on temporal and spatial changes of rainfall and streamflow in the Upper Tekeze–Atbara river basin. Their findings reported that the selected stations have not shown significant trend of rainfall in upper Tekeze- Atbara river basin which is part of my study. Belay and Getaneh (2016) also reported that the rainfall is highly variable both in amount and distribution across regions and seasons in Ethiopia. According to their study result, there was no significant trend of rainfall which is confirmed to the present study.

The results of LST analysis have shown that the dry season minimum, maximum and mean LST have shown an increasing trend for the periods of 2000-2017 although it is not statistically significant. According to this study, the minimum, mean and maximum LST ranged in 17.88°C -20.13°C, 37.16ºC -39.15ºC and 45.37ºC -48.88ºC respectively in the study period of 2000 to 2017 in the study area. Therefore, there was LST variability in the area. Similar result is reported in Belay and Getaneh (2017). According to their study, seasonal and annual temperature is variable in Ethiopia. Their study reported that though there was no significant trend of temperature, the increased trend of temperature is observed in their study area Ethiopia.

The analysis of Pearson Correlation result showed that NDVI and rainfall were moderately correlate with correlation coefficient (R) 0.76. Although there is no statistically significant relationship between NDVI and rainfall, there was a positive relationship between these variables. According to the present study, NDVI was considered as an independent variable while rainfall was dependent variable. NDVI and rainfall data were used in dry season to show the impacts of vegetation cover change on rainfall as in the dry season only rainfall independent vegetations are existed. Other grasses and crops do not exist in this season. This helps to assess the impacts of vegetation cover (evergreen vegetation) change on rainfall. Many researchers have conducted study on relationship of NDVI with rainfall using rainfall and NDVI data time series by considering NDVI value as dependent variable on rainfall (Martiny et al., 2007; Bakri & Suleiman, 2010 and Yan et al., 2017). Their findings revealed that there is strongly positive relationship of NDVI with rainfall where NDVI value positively increased with respect to rainfall variability. Their findings indicate that rainfall is useful for vegetation growth and this study is also in line with the same as the findings of the above researchers. However, in the present study, NDVI (vegetation cover) is independent variable. As a result, in the present study, weakly positive relationship of vegetation cover with rainfall was reported. However, it was not statistically significant. The correlation coefficient and coefficient of determination were 0.48 and 0.23. The coefficient of determination R^2 indicated that 23% of rainfall change is due to the change of vegetation cover in central, northern and southeastern parts of the study area. Therefore, this study indicated that vegetation cover has positive impact on local rainfall. Zonal statistics of vegetation cover with rainfall indicated that the highest mean annual rainfall and vegetation cover was seen in the year 2000. However, the lowest mean annual rainfall and vegetation cover was observed in 2017. Based on the Mann-Kendal test, mean annual rainfall has been increased in the study area during the study period. However, zonal statistics result reported that mean annual rainfall decreased by 143.9 mm from 2000 to 2017 in the central, northern and southeastern of the study area because vegetation cover decreased by 56952 ha in the same year. Annual minimum and maximum rainfall was also decreased as the mean annual rainfall. Therefore, the analysis of this study clearly revealed that minimum, maximum and mean annual rainfall were declined with declined vegetation cover which implies that vegetation cover has a positive impact on local rainfall. Batool et al. (2015) in their study on forest cover change detection and its impact on rainfall in Pakistan reported that vegetation cover is positively correlated with rainfall. In their study, vegetation cover was considered as independent variable whereas rainfall was dependent variable. The findings of this study revealed that rainfall reduced with decreased vegetation cover which is in line with the present study though it is not significant statistically. Hanif et al. (2016) also reported that deforestation has negative impact on local rainfall at Perak, Malasia which is confirmed to the current study.

Land surface temperature plays an important role in many environmental processes. It can provide primary information on the surface physical properties and climate. LST is highly influenced by vegetation cover and it is negatively correlated with vegetation cover (Zia et al., 2015; Chaithanya et al., 2017; Suresh and Mani, 2017). According to the analysis of Pearson Correlation result, in this study, NDVI was negatively correlate with LST. In the same way, vegetation cover was negatively correlated with LST over the central, northern and southeastern of the study area with significant level of 0.05, coefficient of determination 0.8, p-value 0.29 and correlation coefficient -0. 89. The coefficient of determination R^2 indicated that 80% of LST change is caused by vegetation cover change in the area which implies that vegetation cover has a negative impact on LST. Similar results are reported in Chaithanya et al. (2017) where areas with high vegetation cover has low LST. According to this study, vegetation cover and LST are negatively correlate and their study reported that vegetation cover can reduce LST in the area. The result of the present study also in agreement with the study made by Rasul and Ibrahim (2017) and Rehman et al. (2015) where their findings revealed that vegetation cover has negative impact on LST. According to the present study, vegetation cover was high in the year 2000. The minimum, maximum and mean LST were relatively lower in 2000 than 2017. However, vegetation cover has been decreased in the year 2017 while LST was increased which implies that increasing vegetation cover can reduce LST in the area.

CHAPTER SIX

6 CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

Based on the NDVI value of threshold results, vegetation cover has been observed in the central, northern and southeastern parts of the study area. The analysis of threshold result indicated that vegetation cover was covered an area of 4.7% in 1985 and 2.6% in 2017 which revealed that 93158 ha (2.1%) of vegetation cover was lost in the last 32 years in North Gondar zone. Although there was no significant trend of minimum, maximum and mean annual and dry season rainfall, there was an increasing trend of minimum, maximum and mean annual and dry season rainfall in North Gondar zone from 1981 to 2017. Annual minimum, maximum and mean rainfall was increased by 1.41mm, 4.88 mm and 3.56 mm per year during the study period over the study area. The analysis of Mann-Kendall Trend Test also revealed that the trend of minimum, maximum and mean LST were not statistically significant (p-value 0.45,0.36 and 0.35 with alpha value 0.05). However, minimum, maximum and mean LST were increased by 0.01 ºC, 0.09ºC and 0.03ºC per year, respectively in the area during the study period. According to the Pearson Correlation coefficient result, the relationship of vegetation cover with rainfall was not statistically significant (p-value=0.68 and R^2=0.23 with alpha 0.05). However, there was low positive correlation of vegetation cover with rainfall. The analysis indicated that 23% of rainfall variability is caused by vegetation cover change in the central, northern and southeastern parts of the study area.

The NDVI and rainfall map has indicated that areas with high vegetation cover has shown high rainfall which are observed in central, northern and southeastern parts of the study area. NDVI and LST map has also shown that areas with high vegetation cover has collated with low LST in the study area. Even though there was an increasing trend of rainfall in the study area over the study period of 1981 to 2017, zonal statistics of vegetation cover with rainfall indicated that annual rainfall was declined with reduced vegetation cover in the central, northern and southeastern of the study area during the selected years of 2000, 2010 and 2017. This implies that vegetation cover has negative impact on local rainfall. On the other hand, Pearson Correlation coefficient result revealed that there was no statistically significant relationship (p-value=0.29, R^2=0.80 and with alpha 0.05) between vegetation cover and LST. However, the relationship between vegetation cover and LST was negative. Therefore, the analysis of this result showed that 80% of LST change is because of vegetation cover change in the central, northern and southeastern parts of the study area. This indicates that vegetation cover can reduce LST. Zonal statistics result revealed that mean annual rainfall and mean dry season LST reduced by 144 mm and 2°C with decreased vegetation cover by 56952 ha from year 200 to 2017. Therefore, based on the zonal statistics result, the findings of this study concluded that mean annual rainfall was decreased with declined vegetation cover in central, northern and southeastern part of North Gondar zone. On the other hand, mean LST was increased with declined vegetation cover in the area. This indicated that vegetation cover has positive impact on local rainfall and negative impact on LST.

6.2 Recommendations

Based on the findings of this study, the following recommendations are suggested.

- ✓ Overall, results of this study indicated that vegetation cover was declined in North Gondar zone over the study period. This declined of vegetation cover has shown negative and positive impact on local LST and rainfall respectively. Therefore, the concerned body should have taken afforestation and protect vegetations in the area.
- ✓ Societies should have use the vegetations properly.
- ✓ North Gondar zone is a large area in Amhara region. It has different topography, soil types and agroecology. Because of this, the same LULC has different reflectance in the satellite image. As a result, it is very difficult to do detail LULC of North Gondar zone once. Therefore, it is suggested that LULC has to be done in woreda level using high resolution images.
- ✓ In east and west low land areas of the study area, vegetation cover as well as vegetation cover change has not detected throughout the study period. Because eastern parts of the area and west low land areas have been covered by deciduous woody vegetation. They shade their leave in dry season. Since the satellite imagery is downloaded in dry season, the vegetation cover is not detected by NDVI in dry season. As a result, the vegetation cover change is not quantified in west low land areas and east of North Gondar zone. Therefore, farther study is needed in those areas.

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Appendices

Appendix1. Partial view of western low land areas of North Gondar zone

Figure 1.1: Deciduous woody vegetation in western low land areas.

Appendix2. Confusion matrix of Land-use/land cover classification accuracy Assessment

Table 2.1: Confusion matrix of Land-use/land cover Classification in 1985.

		Reference Data			
		Vegetation	Non-vegetation	Total	Users accuracy (%)
Classification Data	Vegetation	175	25	200	87.5
	Non-vegetation	43	257	300	85.7
	Total	218	282	500	
	Producers accuracy (%)	80.3	91.1		

Table 2.2: Confusion matrix of Land-use/land cover Classification in 2000.

		Reference Data			
		Vegetation	Non-vegetation	Total	Users accuracy (%)
Classification Data	Vegetation	178	22	200	89
	Non-vegetation	38	262	300	87.3
	Total	216	284	500	
	Producers accuracy (%)	82.4	92.3		

Table 2.3: Confusion matrix of Land-use/land cover Classification in 2010.

		Reference Data			
		Vegetation	Non-vegetation	Total	Users accuracy (%)
Classification Data	Vegetation	172	28	200	86
	Non-vegetation	20	280	300	93.3
	Total	192	308	500	
	Producers accuracy (%)	89.6	90.9		

Table 2.4: Confusion matrix of Land-use/land cover Classification in 2017.

		Reference Data			
		Vegetation	Non-vegetation	Total	Users accuracy (%)
Classification Data	Vegetation	177	23	200	88.5
	Non-vegetation	15	285	300	95
	Total	192	298	500	
	Producers accuracy (%)	92.2	95.6		

Appendix3. GPS and google earth points

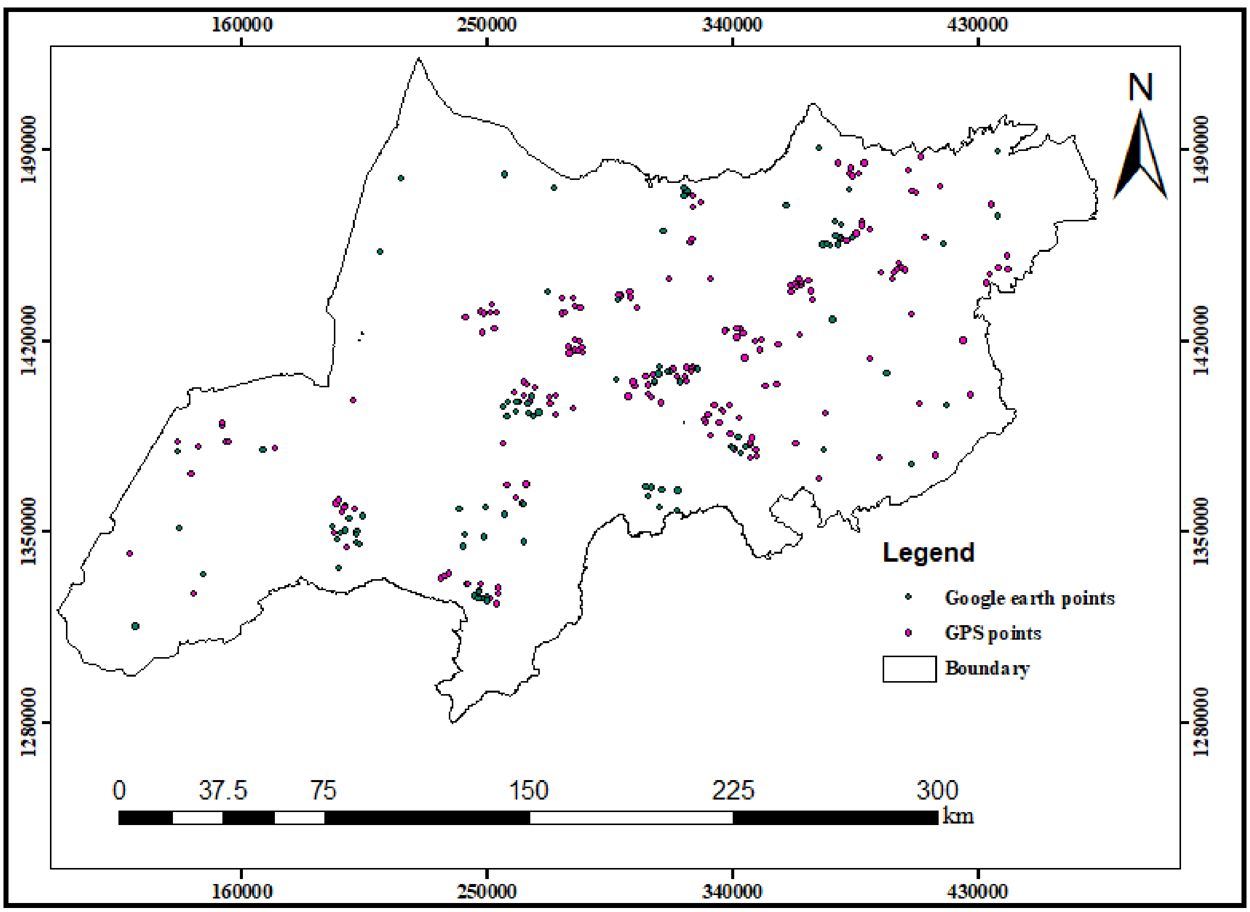

Figure 3.1: GPS and Google Earth points.

Appendix4. MODIS LST and CHIRPS data were used to evaluate LST and rainfall in the study period.

Table 4.1: Minimum, maximum and mean of LST from 2000 to 2017.

Year	Max LST	Min LST	Mean LST
2000	47.3867	18.424	37.1623
2001	48.6347	19.1767	39.1488
2002	47.591	19.7931	38.1953
2003	45.6462	18.541	37.7552
2004	47.7869	19.014	38.2068
2005	47.8521	19.8071	38.9627
2006	45.3671	18.3871	37.8576
2007	45.5898	18.5481	37.8415
2008	46.3247	19.7128	39.0604
2009	46.174	18.714	37.5518
2010	46.7917	17.8774	38.1739
2011	47.1188	19.2788	38.6261
2012	46.9612	20.1245	38.6111
2013	48.0243	19.6479	38.6345
2014	46.6281	17.9793	37.7172
2015	47.5364	18.6857	38.17934
2016	47.7731	19.379	39.0624
2017	48.8814	19.8179	38.3589

Table 4.2: Minimum, maximum and mean annual rainfall (1981 −2017).

Year	Min RF	Max RF	Mean RF
1981	706.716	1880.492	1091.284
1982	535.601	1494.496	905.354
1983	562.292	1617.124	965.271
1984	432.678	1364.978	847.468
1985	587.846	1916.463	1083.67
1986	707.216	1939.711	1109.046
1987	472.617	1780.872	1055.376
1988	839.032	2090.73	1233.849
1989	544.390	1872.391	1107.023
1990	442.693	1408.635	928.769
1991	548.367	1790.944	1115.491
1992	568.849	1593.016	971.764
1993	604.121	1901.735	1138.171
1994	596.471	1648.868	988.018
1995	639.516	1735.176	1023.661
1996	842.069	2185.033	1246.59
1997	620.857	1733.766	1088.459
1998	792.547	2030.228	1214.111
1999	682.729	2041.076	1228.454
2000	654.709	2171.601	1225.454
2001	773.555	1877.097	1171.593
2002	579.916	1616.288	968.420
2003	687.171	1734.31	1058.136
2004	575.547	1614.004	963.829
2005	630.221	1686.136	1030.04
2006	728.395	1992.702	1216.944
2007	719.399	2009.167	1166.694
2008	654.992	1972.057	1194.488
2009	538.569	1528.634	913.450
2010	689.671	2045.945	1134.828
2011	630.835	1628.756	1016.476
2012	673.184	2015.406	1214.229
2013	609.444	1924.358	1172.584
2014	589.852	1997.429	1129.665
2015	462.539	1860.405	1065.771
2016	591.572	1776.92	1070.667
2017	632.953	2039.958	1245.921

Table 4.3: Minimum, maximum and mean of dry season rainfall (1981 −2017).

Year	Min RF	Max RF	Mean RF
1981	50.002	468.951	183.272
1982	54.17	555.425	211.295
1983	22.4568	331.189	123.302
1984	13.730	367.225	84.74
1985	48.848	650.119	190.986
1986	23.219	297.519	138.702
1987	71.141	436.567	200.142
1988	77.505	502.28	251.121
1989	50.479	531.836	177.702
1990	39.089	366.668	126.529
1991	24.930	567.816	195.690
1992	68.971	536.498	289.902
1993	57.617	559.071	242.699
1994	21.632	347.358	114.37
1995	27.208	459.52	139.975
1996	40.842	763.118	201.257
1997	69.761	711.891	330.551
1998	59.906	458.512	216.552
1999	104.376	526.078	269.171
2000	66.752	618.615	314.992
2001	50.388	403.882	193.679
2002	35.317	457.397	149.008
2003	25.292	391.496	103.906
2004	37.029	498.646	194.988
2005	43.652	524.012	158.664
2006	41.3507	548.1211	218.726
2007	60.5703	413.6876	176.090
2008	46.8876	432.0395	194.94
2009	22.8875	409.4855	124.696
2010	29.2929	439.8258	170.691
2011	36.3486	472.7676	155.283
2012	28.7601	421.9467	153.457
2013	51.6572	450.3793	179.700
2014	108.4544	781.486	330.876
2015	45.6038	426.0933	200.674
2016	51.1592	416.2095	177.764
2017	81.7565	553.41	244.311

DE C L A R A T I O N

I the undersigned declare that this thesis is my original work and has not been presented for a

Degree in any other university and that all sources of materials used for the thesis have been duly

acknowledged.

Worku Nega Adugna

Signature __________________________ Date_________________________

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June, 2018

This thesis has been submitted for examination with my approval as university advisor.

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