ADDIS ABABA UNIVERSITY
COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES
SCHOOL OF EARTH SCIENCES

GEO-SPATIAL APPROACH FOR FOREST COVER DYNAMICS AND ITS RELATIONSHIP WITH LAND SURFACE TEMPERATURE AND RAINFALL IN AWI ZONE, ETHIOPIA

A Thesis Submitted to the School of Graduate Studies of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree of Masters of Science
In Remote Sensing and Geo-Informatics

By

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Addis Ababa, Ethiopia
JUNE, 2020

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School of Graduate Studies

This is to certify that thesis prepared by **SAMSON TSEGAYE MEKASHA**, entitled: "**Geo-spatial approach for forest cover dynamics and its relationship with land surface temperature and rainfall in Awi zone, Ethiopia**" and submitted in partial fulfillment of the requirements for the degree of Masters 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.

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DECLARATION

I here by declare that the dissertation entitled “Geo-spatial approach for forest cover dynamics and its relationship with land surface temperature and rainfall in Awi zone, Ethiopia” has been carried out by me under the supervision of Dr. K. V. Suryabhagavan and Dr. Tibebu Kassawmar, School of Earth Sciences, Addis Ababa University, Addis Ababa during the year 2018−2020 as a part of Master of Science programme in Remote sensing and Geo-informatics. I further declare that this work has not been submitted to any other University or Institution for the award of any degree or diploma.

Place: Addis Ababa
Date: June, 2020

(Samson Tsegaye)

Acknowledgments

First and for most, I would like to thank "**Almighty GOD**" who made it possible and for the strength and patience that he gave me to complete my study successfully.

I wish to express my deepest gratitude to my advisors Dr. K.V.Suryabhagavan and Dr. Tibebu Kassawmar for their constructive comments, generous support, continuous guidance and feedback throughout the thesis process made this study possible.

I also wish to thank Dr. Balemwal Atnafu, Head, School of Earth Sciences, Addis Ababa University, Addis Ababa for permitting me to use the Remote sensing lab facilities for the analysis of thematic layers. I would like to express my special acknowledgments to Dr. Binyam Tesfaw and Dr. Ameha Atnafu for their kindly support and encouragement.

I also want to thank Ethiopian Environment, Forest and Climate Change Commission (EFCCC) and Addis Ababa University College of natural and computational science Remote sensing and Geo-informatics stream to give me this opportunity.

I am also would like to thank Awi Zone administration officers for supporting in field data collection and National Metrological Agency (NMA) for providing the historical methodological data.

I am greatly indebted to all my family members for their helpful nature throughout my assignment and financial support throughout my study.

Samson Tsegaye

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Acronyms and Abbreviations

AD	Activity Data
ACZ	Agro-climatic zone
CHIRPS	Climate Hazards Infrared Precipitation with Stations
DEM	Digital Elevation Model
EF	Emission Factor
ENSO	El Niño and La Niña
EVI	Enhanced Vegetation Index
FAO	Food and Agricultural Organization
FCC	False Color Composite
FRA	Forest Resources Assessment
FRL	Forest Reference Level
GDP	Gross Domestic Product
GFOI	Global Forests Observation Initiative
GHG	Greenhouse Gas
GPS	Global Positioning System
GTPs	Ground Truthing Points
HDF	Hierarchical Data Format
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Inter-tropical Convergence Zone
LST	Land Surface Temperature
LULC	Land-Use Land-Cover
LULCC	Land-Use Land-Cover Change
MODIS	Moderate Resolution Imaging Spectro-radiometer
MK	Mann-Kendall
NDVI	Normalized Deference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
OLI-TIRS	Operational Land Imager and Thermal Infrared Sensor
REDD+	Reducing emissions from deforestation and forest degradation
SVM	Support Vector Machines
TLUs	Tropical Livestock Units
TM	Thematic Mapper
UNFCCC	United Nations Framework Convention on Climate Change
USGS	United States Geological Survey
WGS	World Geodetic System

Geo-Spatial approach for forest cover dynamics and its relationship with land surface temperature and rainfall in Awi Zone, Ethiopia
Samson Tsegaye Mekasha, MSc. Thesis
Addis Ababa University, May 2020

Abstract

In Ethiopia, the population number was increasing continuously with agricultural land expansion and urbanization for the last five decades. The present study aimed to assess the changes in land use patterns in Awi Zone during the last 34 years and its relation with land surface temperature (LST) and rainfall using digital change detection approaches. Multi-temporal Landsat imageries (1985, 2000, 2009 and 2019), MODIS and CHIRPS were used combined with Google Earth and field data for this study. Support vector machine classification technique was used to produce LULC maps. Likewise, Mann-Kendall test for LST (2000–2019) and rainfall (1981–2019) was used to compute non-parametric trend analysis. The analysis revealed that 47255.5 ha of forest and 24674.9 ha of other land were increasing from 1985 to 2019. In contrast, agriculture and bare land were decreased by 16819.9 ha and 55110.5 ha, respectively. In addition, in Dega agro-climatic zone mean and minimum LST trend analysis result revealed a significant decrease with p-value of 0.015 and 0.035 (α=0.05), respectively. The Sen's slope show mean, minimum and maximum Dega LST decreasing trend with 0.13C°/yr., 0.12C°/yr. and 0.1C°/yr., respectively. Whereas, in Woyna Dega and Kolla LST trend analysis result show decreasing and increasing trend from 2000 to 2019. Additionally, in winter season, declining trend of LST was shown while in dry season except maximum value mean and minimum LST revealed decreased trend. Mann-Kendall trend test analysis for annual and dry season rainfall show increasing trend from 1981 to 2019. Coefficient of determination (R^2) for forest cover and mean LST for Dega, Woyna Dega and Kolla zone revealed that 0.98, 0.81, and 0.2, respectively. Likewise, coefficient of determination (R^2) for forest cover with winter and dry season mean LST and showed that 0.025 and 0.86, respectively. Also, forest cover with annual and dry season mean rainfall result revealed that R^2=0.066 and R^2=0.0001, respectively. Accordingly, the result indicates the study area was under continually spontaneous LULCC for the last thirty four years. Based on the findings the effect of forest cover increase in Dega ACZ has a significant decreasing LST trend in central and eastern part of the study area. The reason is probably recently appeared plantation forest expansion by the local community or else uprising of the integrated watershed development campaign by the government body since 2000. However, the natural forest was decreasing continuously. In conclusion, the area was highly influenced by anthropogenic factors such as deforestation, afforestation and urbanization. Those activities have their own effect on the LST of the study area. In the future, community-based land-use land-cover planning and sustainable forest management system is recommended to protect, conserve and rehabilitate the remaining natural environment.

Key words: Awi zone; Landsat;Mann-kandell test; land surface temperature; rainfall

CHAPTER ONE

1. INTRODUCTION

1.1. Background and Justification

Land-use and land cover-change has a significant impact on climate condition at local, regional and global level (Jiang and Tian, 2010; Alemayehu *et al.*, 2017; Li *et al.*, 2018b; Dagnachew and Tesfaye, 2019). Land-cover is the observed bio-physical cover on the outer earth's surface. Land-use is all about human interaction with the environment and is characterized by the interference of people on certain land-cover type. Change on land-use land-cover is the human modification in quantitative and/or qualitative of LULC types (FAO, 2016). According to United Nations Framework Convention on Climate Change (UNFCCC) definition "Climate change" means alteration of climatic conditions which affect directly or indirectly to human activity that modifies the composition of the global atmosphere and which is in addition to natural climate variability observed over a given time period. Ethiopia is ranked 11th in terms of its vulnerability to physical climate impacts and 9th in terms of overall vulnerability from the world (MEFCC, 2016).

Humans have been altering land to get food, shelter and other basics for thousands of years which cause abnormal changes in ecosystems and environmental processes at local, regional and global level (Ellis, 2015; Tibebu *et al.*, 2018; Stévart *et al.*, 2019). Therefore, the major reason for alteration of land-use land-cover is anthropogenic factors (Helmut *et al.*, 2001; Turner *et al.*, 2009). Due to inappropriate use of natural resources such as agricultural land expansion, unplanned settlements, illegal logging, mining investment, building massive infrastructure construction like dams and road have a significant impact on the qualitative and quantitative decline of natural environment.

Forest is a very complex and constantly changing natural resource which contains different types of living and nonliving things having a strong integration (Joseph, 2005). According to IPCC Land Category description 'Forest Land is all land with woody vegetation consistent with thresholds used to define Forest Land in the national GHG inventory, sub-divided into managed and unmanaged, and also by ecosystem type' (GFOI, 2016). According to global forest resources assessment report 2015, from the year 1990 upto 2015 the world's forest area has declined from 4.1 billion ha to just under 4 billion ha, a decrease of 3.1% due to a continued growth in human populations and a high demand for forest products. The amount of forest cover in East African is declining dramatically (FAO, 2017). In Ethiopia, deforestation and forest degradation is driven by forest clearance for small-scale agricultural expansion, large-scale agricultural investment adjacent to the forest, illegal use of forest products (fuel wood collection and charcoal making), human settlements, artificially occurred forest fires and expansion of infrastructure (REDD+, 2015).

Climate and vegetation interaction is majorly affected by anthropogenic factor (Alemayehu *et al.*, 2017; Hou *et al.*, 2018; Li *et al.*, 2018b). This could be expressed by deforestation, reforestation, afforestation, urbanization, agricultural land expansion and so on. For instance, two major bio-physical climatic effects are evaporation (Li *et al.*, 2018b) and Albedo (Adams, 2007). Thus, as the vegetation cover is changing the incidence of climate variability that mostly expressed by fluctuation of rainfall and temperature is expected. It is clear that the current trend of climate change leads to significant economic fail in countries like Ethiopia whose economy is mainly dependent on climate sensitive activities like small scale agriculture (MFCC, 2016; Alemayehu *et al.*, 2017). Ethiopia is vulnerable for climate change impact as livelihoods are extremely sensitive to changes in precipitation and temperature. Rainfall variability and the rising temperature are responsible for the frequent droughts that at times lead to famine, affecting the people's livelihood (MFCC, 2016). Extreme maximum temperature events have been rising in Ethiopia for the last three decade, which is directly affecting agricultural and livestock activities (Suryabhagavan, 2017). Therefore, understanding the trend of climate variability with LULC dynamics play a very important role in a country's future economic development (Ahmad *et al.*, 2015; Yitea and Bethel, 2015).

Hence, this study investigate the amount of LULCC, specifically forest cover conversion for the past three decades and analyze its relation with land surface temperature and rainfall by using updated and advanced remote sensing and GIS technology in Awi zone, Amhara region, Ethiopia. The study is provides timely and scientifically backed information for policy and decision makers and also will be used as information for future resource management.

1.2. Statement of the Problem

Land-use land-cover; mostly social and economic importance for humans globally include cultivation in various forms, livestock grazing, urbanization and construction, reserves and protected lands, and timber extraction (Turner *et al.,* 2009). In Ethiopia, land-use land-cover conversion is common problem due to an increase of population growth, expansion of small scale agriculture, over grazing, large scale agricultural investment, urbanization etc. Many research papers indicate that most of the reason for this conversion is man-made (Mengistie *et al.,* 2013; Obang *et al.,* 2017). According to FRL, in Ethiopia the annual forest loss was around 92 thousand ha $yr.^{-1}$ and annual forest gain of around 19 thousand ha $yr.^{-1}$ from year 2000 to 2013 (MEFCC, 2017). This report indicate that the country loss a vast amount of forest cover every year and if this trend continuous loss of bio diversity, soil erosion, flood, desertification, shortage of timber, dam and lake sediment problem, climate variability and other social, political and economic challenge will increase in the future. Vegetation cover change cause environmental, economic and social damage as a result of strong relationship the change in one feature affect the others such as rainfall and temperature (Alemayehu *et al.,* 2017; Temesgen *et al.,* 2018). Rainfall and temperature are common parameters of climate variability, which have direct or indirect interaction with land-use land-cover change (Hu *et al.,* 2010; Temesgen *et al.,* 2018).

In Ethiopia, around 85% of the total population and 75% of the livestock live in highland area which is greater than 1500 m a.s.l covers 43% of the overall territory (Aklilu and De Graaff, 2006). Hence, the natural environment is highly affected by human activity. The major environmental issues of the country are deforestation, soil erosion, recurrent droughts, desertification, land degradation, and loss of biodiversity including both fauna and flora (MEF, 2015). Currently, Northwestern Ethiopia specifically Awi zone has a large coverage of natural forest. However, due to expansion of agriculture and large scale investment it is shrinking down (REDD+, 2015) whereas secondary forest (man-made forest) is increasing from time to time in Awi zone (Abiyot, 2017). Therefore, this forest cover dynamics could have direct and/or indirect relationship on land surface temperature and rainfall. This makes the local community vulnerable for climate change impact due to heavily dependent on rain-fed agricultural activities (MFCC, 2016).

Therefore, in the study area land-use land-cover change and its relationship with land surface temperature and rainfall have not been well studied except few studies like Abiyot,

(2017) and Abyot *et al.* (2014). Therefore, these studies fill this gap and open future doors by providing clear and advanced information about the past and present LULC dynamics, forest cover transition and its relationship land surface temperature and rainfall in the study area.

1.3. Objectives

1.3.1. General objective

The general objective of this research is to quantify the forest cover change and its response to land surface temperature and rainfall in Awi Zone, Ethiopia using remote sensing and GIS technology.

1.3.2. Specific Objectives

- To investigate the rate of land-use and land-cover change for the past three decade since 1985.
- To quantify the amount of forest cover dynamics for the last three decades during the study time.
- To analyze the trends of land surface temperature and rainfall, their relationship with forest cover change.
- To analyze the effect of forest cover change on land surface temperature and rainfall.

1.4. Research Question

- What is the rate and amount of land-use and land-cover change occurred for the last 34 years?
- How much is forest cover change for the past thirty four years?
- What is the trend of land surface temperature and rainfall their relationship with forest cover change during study period (1985 –2019)?
- What is the of effect forest cover change on land surface temperature and rainfall?

1.5. Significance of the Study

Land-use and land-cover dynamics in northwestern Ethiopia remain spontaneous which needs detail scientific research for present and future land-use planning and management. Furthermore, the relationship between forest cover change with land surface temperature and rainfall remain unpredictable due to lack of advanced scientific research. Hence, this study provides useful data and information about the rate and trend of land-use land-cover change especially forest cover conversion and its relationship with land surface temperature and rainfall for the past three decades in Awi zone. In addition, LST and rainfall trend were analyzed to recognize its historical variability, that is significant for highly dependent on agricultural activity. Therefore, the result of this study can be used by policy and decision makers, natural resource managers, climatologists, environmental experts, development agents, foresters, researchers and other stakeholders.

1.6. Scope of the study

The scope of this research paper was spatially limited only in Awi Zone, Amhara Regional State of Ethiopia. The study focused on investigating forest cover change and analyzes its relationship with land surface temperature and rainfall for the past thirty four years. Besides, it was also evaluate the trend of land surface temperature (2000–2019) and rainfall (1981–2019) in the study area.

1.7 Organization of the thesis

This thesis is organized into six chapters: chapter one is introduction, where the background, statement of the problem, objectives of the study, research questions and significance of the study discussed. In chapter two, review of related literatures is presented. Chapter three provides necessary background information about the study area in terms of location, topography, climate, geology, soils, vegetation cover and population of the studied. This section also elaborates the source of the data and software used and methodologies applied to achieve the desired objectives with details of the data sources and relevant parameters. In the fourth chapter, results are provided. In the fifth chapter interpretation and discussion of the results of the research from land-use/land-cover classification, assessment of forest cover status, Land surface temperature trends and Rainfall trend analysis are given. Finally, in section; six, conclusions, recommendations and suggestions for further research work in the study area are provided.

CHAPTER TWO

2. LETRITURES REVIEW

2.1. Land-use and Land-cover change

Land-use and land-cover is a vigorous constituent in the interfaces of human activities with environmental understanding. Human activities on land to fulfill different needs can be defined as land-use (Obang *et al.*, 2017). Whereas land-cover is observer (bio) physical cover on the earth's surface (FAO, 2016). A quantitative and qualitative alteration of LULC mostly with the interference of humans is called Land-use and land-cover changes. It is a prime environmental issue at local, regional and global level (Letchumy *et al.*, 2012). Human beings modifies the structure and functioning of ecosystems at a different levels by activities like farming expansion, and influence the interaction between ecosystem and its surrounding environment (Asmamaw, 2013; Dinku and Suryabhagavan, 2019). Globally, land-use and land-cover changes play a major role in controlling fundamental aspects of earth system functioning such as influence biotic diversity worldwide and contribute to local and regional climate variability and change (Chase *et al.*, 2000; Sala *et al.*, 2000). Also, soil degradation, desertification, deforestation, global warming, flooding, landslide collectively affect climatic, economic or socio-political integration.

Ethiopia is endowed with various biodiversity resources due to different agro-ecological patterns. The country can be classified into 15 land-use patterns, 19 livestock patterns, 48 cropping patterns and at least six farming systems. The dominant land-use patterns are grazing land, browsing, agriculture land, forest land and woodlands. In AFOLU (Agriculture, Forestry and Land-Use) release of CO_2 is estimated from the land-use change as a result of deforestation, expansion of cultivation land, forest fires and biomass burning in grasslands (MEF, 2015). However, around 85% of the population and 75% of the livestock of Ethiopia live in the highlands which is greater than 1500 m elevation, covers 43% of the overall territory (Aklilu and De Graaff, 2006). Many research papers shows LULC change is mainly driven by uncontrolled high population growth, the rapid expansion of urbanization, high demand for production, land shortage. Land-use land-cover change respond to social, demographic, political, cultural, economic and environmental status and forces which are highly characterized by high human populations (Masek *et al.*, 2000; Ayele *et al.*, 2014)

In north-western part of Ethiopia, natural resource is influenced by human intervention mainly by agricultural expansion and illegal settlements. More recent evidence (Abiyot, 2017) which studies in forest patches of Guangua-Illala and Kahtasa forests in Awi Zone shows that for the last four decades natural forest cover experienced significant negative change. As a result, more than 80% of the primary forest was dramatically converted into other lands with a high rate of deforestation. Hence, this change threatened the remaining forest patches and a significant number of endemic and other species in the study area. He recommends that reversing the change by using integrated land-use planning and restoration measures using priority species is very critical. Likewise, Asmamaw (2013) the land-use and land-cover of the Gilgel Abbay watershed area were changed considerably from 1986 to 2001. Agricultural land significantly changed from 9% in 1986 to 55% in 2001 which create redaction of the amount of forest cover. The dynamic shift within LULCs on the area was due to uncontrolled population growth which creates high pressure on the forest and other lands to expand cultivated land.

Similarly, Mengistie *et al.* (2013) have been performed on LULC change analysis in Munessa Sheshemene district. The study shows a continuous increase of croplands observed but natural forests, grasslands and woodlands were declining as the result of deforestation and grassland decline. Besides, increases in tree patches along the study landscape show the fast forest fragmentation over the last four decades and the significant transformation into monoculture agricultural systems. The result shows that about 60% of the land-use land-cover is changing dramatically from 1974 to 2013. About 75% of the plantation forest land was altered from natural forest. In developing countries like Ethiopia, a rapid increase in population which causes high demand for raw materials and production (food, fuel-wood, cloth, shelter, forage) leads us continuous change of land-use land-cover pattern of our natural environment.

The population of Ethiopia has increased for the last few decades; from 42.6 million in the 1984 census to 53.5 million in the 1994 census and 73.8 million in the 2007 census, and to a projected 91 million in 2013 (CSA, 2013). More than 80% lives in rural areas and about 16 percent of the population living in urban areas. Rapid population growth in the county for the last decades therefore turns out to be deterioration and over-exploitation on the natural resources (MEF, 2015). Due to high percent of the population depends on agriculture for their livelihood well-being the problems became serious.

2.1. An overview of forest cover in Ethiopia

Vegetation cover is essential natural resources that serves as a bond among many earth's bio-physical components such as soil, atmosphere and hydrological cycle (Tadesse *et al.*, 2020). Ethiopia is one of the most essential bio-diversity hotspots in the world. Potential vegetation types of Ethiopia has been studied in detail by Friis *et al.* (2010), map indicates the distribution of twelve categories that can be mapped using environmental parameters and GIS-methodology. Therefore, these vegetation types have been described and further classified into a number of subtypes. The types are *Desert and semi-desert scrubland, Acacia-Commiphora woodland and bushland, Wooded grassland of the western Gambela region, Combretum-Terminalia woodland and wooded grassland, Dry evergreen Afromontaneforest and grassland complex, Moist evergreen Afromontane forest, Transitional rainforest, Ericaceous belt, Afroalpine belt, Riverine vegetation, Fresh-water lakes and Salt lake.* According to MEFCC (2017) definition, forest is 'land spanning more than 0.5 ha with trees higher than 2 meter and a canopy cover of more than 10%, or trees able to reach these thresholds in situ'. Forest is a very essential category of vegetation used for environmental protection and socio-economic development. However, deforestation, forest degradation and forest fragmentation is still a problem for the remaining natural forest in Ethiopia (Mengistie et al., 2013; MEFCC, 2017; Obang *et al.*, 2017).

Over the past 25 years the world's forest area has decreased from 4.1 billion ha to under 4 billion ha which means a decrease of 3.1% (FAO, 2015). Forestry sector play an important role in social, economic, environmental and cultural development for a country. In Ethiopia, about 4% total GDP (Gross Domestic Product) (9% of agricultural GDP) is obtained from forestry sector. Forest and woodlands have a significant national economic value for the country. Informal forest based activities estimated to contribute more than 30% of per capita income in some areas (CRGE, 2011). Forests also give benefits for food security, health, employment and support ecosystem services which in turn offer economic benefits. For instance, Ethiopia was produced 42,000t of honey in 2010/11. The second largest national GHG (Greenhouse Gas) source is from forest sector, currently accounting for 55 $MtCO_2eyr.^{-1}$, and is predicted to increase up to 90 $MtCO_2e$ by 2030 under a business as usual scenario. Deforestation is the major reason caused by pressure for agricultural land and fuel-wood and charcoal demand (CRGE, 2011). Therefore, for Ethiopia protecting and conserving the forest is very important task through sustainable forest management plan.

2.2. Forest cover change

Deforestation is a total conversion of forest land into other land-use such as agriculture or infrastructure. This conversion of forest land is mainly due to human activities. Natural disasters like volcano and forest fire may cause deforestation and when the area is unable to regenerate naturally; it is converts to other land (MEFCC, 2017). Globally, the extent of the forest cover continues to decline as human populations continue to grow and high demand for food and land increases, the rate of net forest loss has been change by over 50 percent (FAO, 2015). According to the report, there was a net loss of 129 million ha of forest between 1990 and 2015, covers the size of South Africa, with 0.13 percent net loss every year. The largest forest area loss occurred in the tropics, spatially in Africa and South America, although the rate of loss in those areas has decreased significantly in the past five years. About 93 percent of the world's forest is covered with natural forest or 3.7 billion ha, in 2015. Unfortunately, from the year 2010 to 2015 the natural forest area decreased by a net 6.5 million ha annually.

According to Global Canopy Program report in 2015 indicates that about half of the world tropical rainforest has been lost within the last 50 years (Bregman, 2015). From the total annual global greenhouse gas emissions 16−19% is caused by deforestation on tropical forest. Furthermore, forests are used for environmental and social values including biodiversity reserve, water reservoir, climate regulation, pollination, seed dispersal, natural pest control, cultural values and tourism. Hence, deforestation brings the imbalance within and between environmental and social integration.

The country forest cover was declined from 40% to 1% for the last four decades since 1950 (Gore, 1992). Ethiopia proposes a forest reference level (MEFCC, 2017) based on average annual emissions and removals over the period 2000 to 2013 assessed by multiplying activity data (AD) with emission factor (EF) nationally. The result shows 17.9 mln tCO_2eyr^{-1} was emitted from deforestation and 4.8 mln tCO_2yr^{-1} was removed from the atmosphere in afforestation. The prime reason for climate change is the uprising of global temperature due to release of carbon dioxide in to atmosphere. In tropical regions, deforestation has long term impact on soil resource. When the vegetation cover is removed from the land, the soil is exposed to slash erosion and expand into gully erosion though time. In addition, increase its compaction, deterioration of organic material, leeching out its few nutrients available, aluminum toxicity of soils increase and reduction of organic material are other impact of deforestation and forest degradation on soil (FAO, 2007).

2.3. Causes of deforestation in Ethiopia

Deforestation has been attributed to socio-demographic factors, such as population growth and the political economy of class structure, and specific exploitation activities like illegal logging, farming forest, fuel wood collection, and pasture clearance for cattle production (FAO, 2007). Causes of deforestation can be divided into two categories: proximate/direct causes and underlying/indirect causes.

Proximate or direct drivers of deforestation and forest degradation are human activities and actions that directly impact the forest cover and result in quantitative and qualitative loss of forest biomass. In Africa, (sub) tropical Asia and Latin America, agriculture remains the dominant proximate cause of deforestation and forest degradation. Urbanization, mining investment, infrastructure, (commercial) timber extraction and logging activities, Fuel wood collection, charcoal production, and livestock grazing in forests are the most important proximate or direct drivers of deforestation and forest degradation around the world. Underlying or indirect drivers are complex interactions of economic, social, political, cultural and technological processes that affect the proximate drivers to cause deforestation and forest degradation. Population growth, domestic markets, national policies, governance are some of the indirect cause at national and subsistence and poverty at local level (Kissinger *et al.*, 2012).

In Ethiopia, deforestation and forest degradation to be driven mainly by free livestock grazing, fodder use and fuel wood collection/charcoal production in all the regions followed by farmland expansion, land fires and construction wood harvesting. The underlying causes of deforestation and degradation based on framework analysis were identified to be population growth, unsecure land tenure and poor law enforcement. South-eastern wood land areas of the county are affected by free grazing. In Gambella, Benishangul-Gumuz and Afar regional states, large-scale agricultural investment remain a significant driver of deforestation (MEFCC, 2017).

2.4. Climate change and variability

Climate change can be characterized by an increasing temperature and a set of other alterations to the recent climate regime such as GHG, rainfall, radiation that can strongly disturb natural terrestrial (Zhou *et al.*, 2019). Many research papers show that the earth's climate is changing dramatically as a result of the increasing amount of GHG in the atmosphere that is released largely from anthropogenic activities (EFDR, 2007). Climate change is generally considered to be a threat to ecosystem health in highland areas (Mukwada and Manatsa, 2018). The climate of Ethiopia is governed by two major topographic factors: the closeness of the Equator, with the southern part of the country and the different type of the relief. The topography of country is extremely important for the climate (Liljequist, 1986). In general, two different seasons characterize the Ethiopia's climate, the dry season "Bega" (from October to May) and rainy season "Keremt" (from June to September). An increasing trend in temperatures (+0.3°C $yr.^{-1}$) and a descending trend in precipitation (0.4 mm $month^{-1}$ $yr.^{-1}$) has been detected since 1948 and is projected to remain up to 2050 (Jury *et al.*, 2013).

Historic climatic Variability, extreme events (temperature and rainfall) and natural hazards have caused negative impact on economic growth in agricultural sector. The economic impact depends on the amount of the climate variability and extreme events but only droughts can decrease total GDP from 1% to 4%, whereas soil erosion has been estimated to decrease agricultural GDP by 2% or 3% in Ethiopia. Shortage of rainfall and its variability had led to considerable shortages in agricultural production, which can lead to famine (EFDR, 2007). In addition, climate change and variability also can affect the productivity of pastoral herds by reducing water availability, forage production and quality (Bekele *et al.*, 2014). Arragaw and Woldeamlak (2016) reported that in central highlands of Ethiopia climate variability has a significant influence on agricultural production and it has been a considerable threat for a local community for the future. Thus, agricultural livelihoods are also susceptible to climate variability and stresses. The impact to agricultural livelihoods is influenced by livelihood type and region of the country. Recurrent droughts are the most visible of these hazards and the impact are all livelihood types (CRGE, 2011).

In Ethiopia, future climate change remains indeterminate with scenarios of change show the range of possible outcomes. There is a possibility of uncertainty to forecasts how global climate change will affect precipitation and temperature patterns in the country. While projections evidently indicate temperatures increasing, there is disagreement on the exact degree, with a range of projections indicating between 0.5°C to 2°C by the 2050s relative to today. Due to the complexity of our climate condition, the projections of future precipitation are indeterminate. However, many studies project that current precipitation variability will continue with future annual rainfall range from +25% to +30% by the 2050s (CRGE, 2011). As a consequence of high population growth, the expansion of agriculture onto marginal dry lands, and unproductive and environmentally degrading cropland and grazing practices, the direct dependency on rain-fed agriculture makes the nation directly vulnerable to climate variability. The hazards and uncertainty clearly related with climate variability contribute meaningfully to both temporary and long-lasting poverty and food insecurity (EPA, 2007). Therefore, Kirsty (2017) suggested that unless the food system experiences transformational adaptation, food insecurity issue will be remain.

2.5. The relationship between forest, land surface temperature and rainfall

The relationship between vegetation cover and climate variability was studied by many researchers elsewhere (Chuai *et al.*, 2013; Leilei *et al.*, 2014; Yitea and Bethel, 2015; Temesgen *et al.*, 2018; Tenaw and Habte, 2018). A study conducted in Gojam zone from 2000 to 2008 reported that the relationship between rainfall and vegetation cover is very strong and predictable when observed at the appropriate spatio-Temporal scale. The study confirms phenology of vegetation in all formations closely reveals the seasonal cycle of rainfall and the yearly correlation coefficients between vegetation and rainfall are very high, whereas the correlation between vegetation and temperature are low in their study area (Yitea and Bethel, 2015). Likewise, seasonality of daytime vegetation greenness patterns was negatively related with land surface temperature in the region of horn Africa (Temesgen *et al.*, 2018). According to their research finding Comparison of land surface temperature before and after forest loss in three selected areas in the region shown average increase of LST with 0.7°$Cyr.^{-1}$, 1.8°$Cyr.^{-1}$, and 0.2°$Cyr.^{-1}$(2001–2016). Tadesse *et al.* (2020) conducted a research in northwest lowland of Ethiopia which revealed that rainfall and woodland have strong relationship. Their report show there was significantly contribution of vegetation for the occurrence of climate variability in the area. The spatial variation of land surface temperature is highly affected by the existence of different land-use land-cover types (Dagnachew and Tesfaye, 2019).

In Ethiopia, rainfall is depends predominantly on the prevailing winds, which are governed by the movement of the inter-tropical convergence zone (ITCZ). However, the rainfall is considerably influenced by local relief. Two complementary wind systems exist, depending upon the position of the ITCZ which is summer from May to Oct north of the Equator and the usual wind over most of south-westerly. Whereas, in the winter months, from Nov to Apr, the ITCZ is well to the south and the usual winds are north-easterly, carrying only little moisture relative to summer. Therefore, the highest rainfall is in the south-western part of the country which is related to the passage of the ITCZ in northern and southern direction (Friis *et al.,* 2010). At the national level, temperatures have increased by an average of around 1°C since the 1960s. This increase has been touched all regions of the country. Precipitation at national level is subjected to high variability between years, seasons and regions. Yearly variation around mean rainfall levels is 25 percent and can increase to 50 percent in some parts of the region. Nevertheless, there are many research papers which show 20% decreases in rainfall in the south central regions of the country (CRGE, 2011). 'Land Surface Temperature (LST) is the radioactive skin temperature of the land surface of land surface processes from local through global scales or it can be defined as an average temperature of features of the exact surface of the Earth calculated from measured radiance' (Kayet *et al.*, 2016).

2.6. Role of Remote Sensing and GIS for forest cover change and climate variability analysis

Remote sensing defined as data on the characteristics of the earth surface are acquired by a device that is not in contact with the objects being measure (Bakker *et al.,* 2001). Remote sensing helps to detect the extent and magnitude of deforestation and forest degradation problem. Multi-temporal data which is very important to study LULC change analysis is provided remote sensing technology. Advanced relevant information about the LULC dynamics could be extracted from different sources of remote sensing. It serves as a monitoring tool to ensure companies are following cut guidelines and specifications (CCRS, 2000).

Remote Sensing provides a unique opportunity to assess and monitor deforestation, afforestation and climate parameters variability for a number of reasons. First, with remote sensing we can work at multiple scales ranging from few meters to several kilometers. This included detailed study at local level to global forest resources assessment. Second, remotely sensed data can be acquired repeatedly (e.g. daily, monthly) that helps us monitor forest resources and climate variability in a regular basis. Third, these measurements can be made in near real time basis which is quite useful for monitoring events such as forest fire and extreme temperature. Fourth, remote sensing data has synoptic coverage and information can be acquired in places where accessibility is an issue and missing metrological station data occurred. Fifth, we could use wavelengths that are not visible to human eye. Thus, remote sensing is the most effective means of assessing and monitoring natural resources. It is important to understand that remote sensing does not replace field survey but provides complimentary information (FAO, 2007).

CHAPTER THREE

3. MATERIALS AND METHODS

3.1. Description of the study area

3.1.1. Location and description

Awi Zone is found in Amhara National Regional State, northwestern Ethiopia, approximately 480 km northwestern of Addis Ababa, the capital city and 120 km south west of Bahir Dar, the capital town of Amhara Regional State of Ethiopia. Geographically its absolute location extends between the coordinates of 10°31'46"–10°41'32"N latitude and 36°36'18"–36°59'33"E longitude covering a total area of 634,510 ha. Awi Zone is bordered on the south by Metekel zone, on the west by north Gonder Zone and on the east by Gojam Zones (Figure 1).

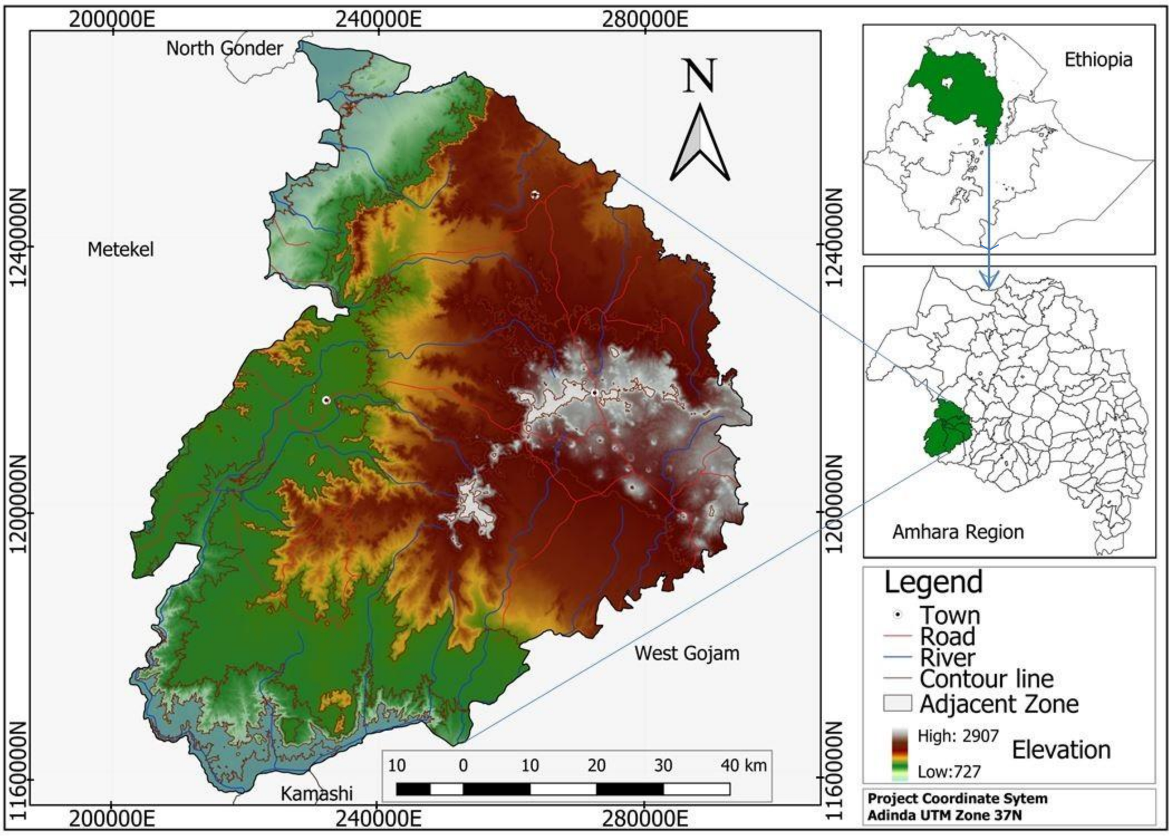

Figure 1: Location map of the study area

3.1.2. Physiography

Topography

The topography consists of areas with gentle to steep slopes. The landscape is composed of agricultural and grazing areas, settlements, rivers valleys, hills and small to medium sized mountains (at the northern side of the study area). The slope of the largest part of the study area (69%) ranges from 0 to 25% and the remaining has slopes above 25%. Flat land and steep slopes each account to about 7% of the study area. Flat land and gentle slopes are mostly utilized for agriculture, settlement and grazing lands; whereas moderate and steep slopes above 25% slope gradient usually consists of primary/high forests, although in some areas of Bradi, Degera and Khatasa forests the steep slopes are utilized for growing crops and settlement. A number of perennial rivers and small streams cross the study area (Abiyot, 2017)

Geology and soils

The bulk of the plateau where the Afromontane vegetation occurs consists of volcanic rocks. Accordingly, the northeast (Khatasa forest), east, southeast and southern (Ambiqi forest) parts of the study area are dominated by pre-Cambrian rocks; the north and northwestern parts (Askunabo forest) are of early tertiary volcanics while the central part (Bradi, Degera and Kidamaja) is dominated by late tertiary volcanics. Generally, the soils of the study area belong to five textural classes. Most of the soil samples fall in the clay and clay loam textural classes; while few of them are silty clay loam, silt loam and sandy clay loam (Abiyot, 2017).

Climate

Friis *et al*. (2010) classified the rainfall pattern of the study area as unimodal. Based on meteorological data from four stations, most of the study area gets rain at least eight months with variable intensity. The annual precipitation ranges from 1685–1870 mm. According to the metrological stations of NMA (national metrology agency), the study area receives erratic average rainfall from 1305.4–3055.75 mm of rainfall per year while 31.3 °C and 9.9 °C of average maximum and minimum air temperatures per month, respectively (Figure 3 and 4). The months of July and August receive the highest amount of rainfall that reaches above 350 mm per month at the peak periods (Figure 2).

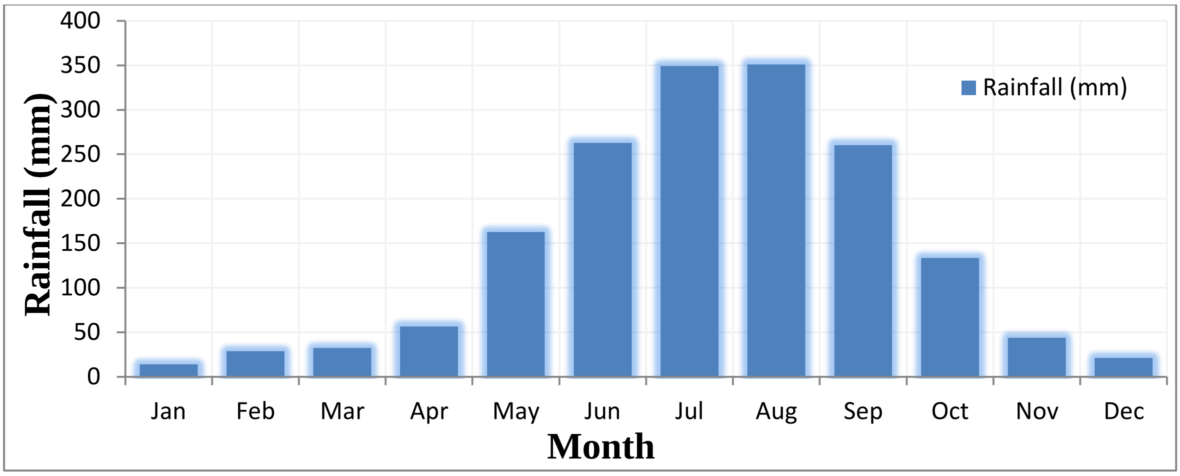

Figure 2: Mean monthly rainfall distribution (1987-2019)

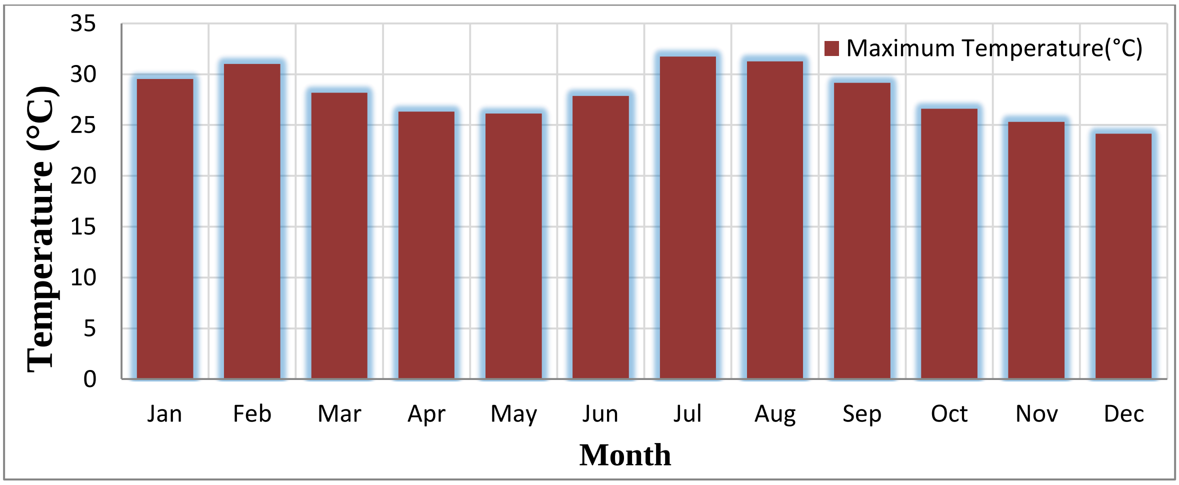

Figure 3: Mean maximum monthly temperature distribution (1987-2019)

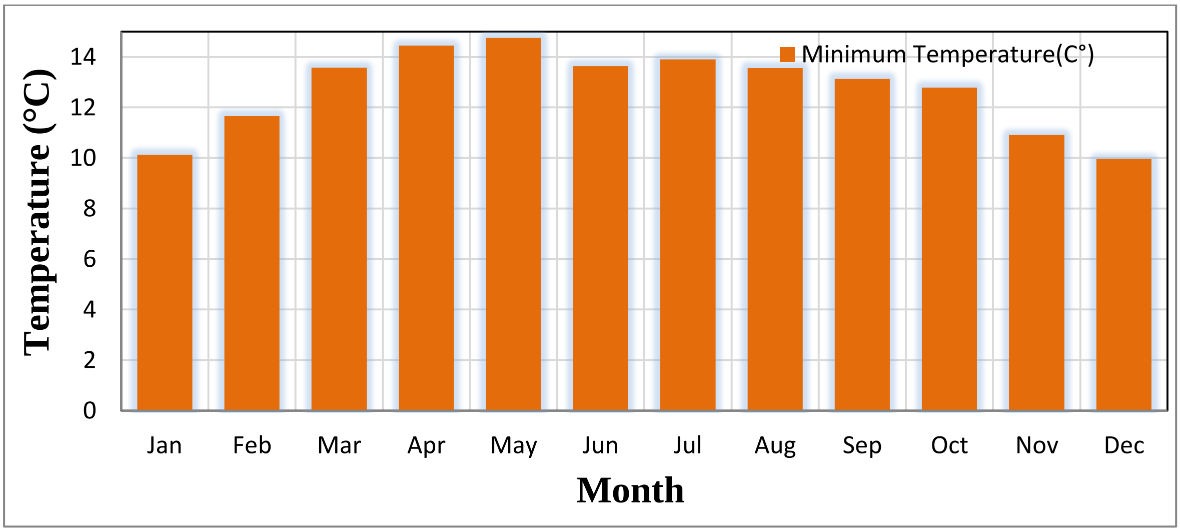

Figure 4: Mean minimum monthly temperature distribution (1987-2019)

Agro-climatic zone

In Ethiopia, traditional agro-climatic zone classified from Bereha to Worch, ranging from below 500 m to over 3700 m a.s.l. in altitude and from below 500 mm to over 1400 mm annual rainfall. Agro-climatic zone of the area is classified into three which is Dega, Woyna Dega and Kolla (Figure 5).

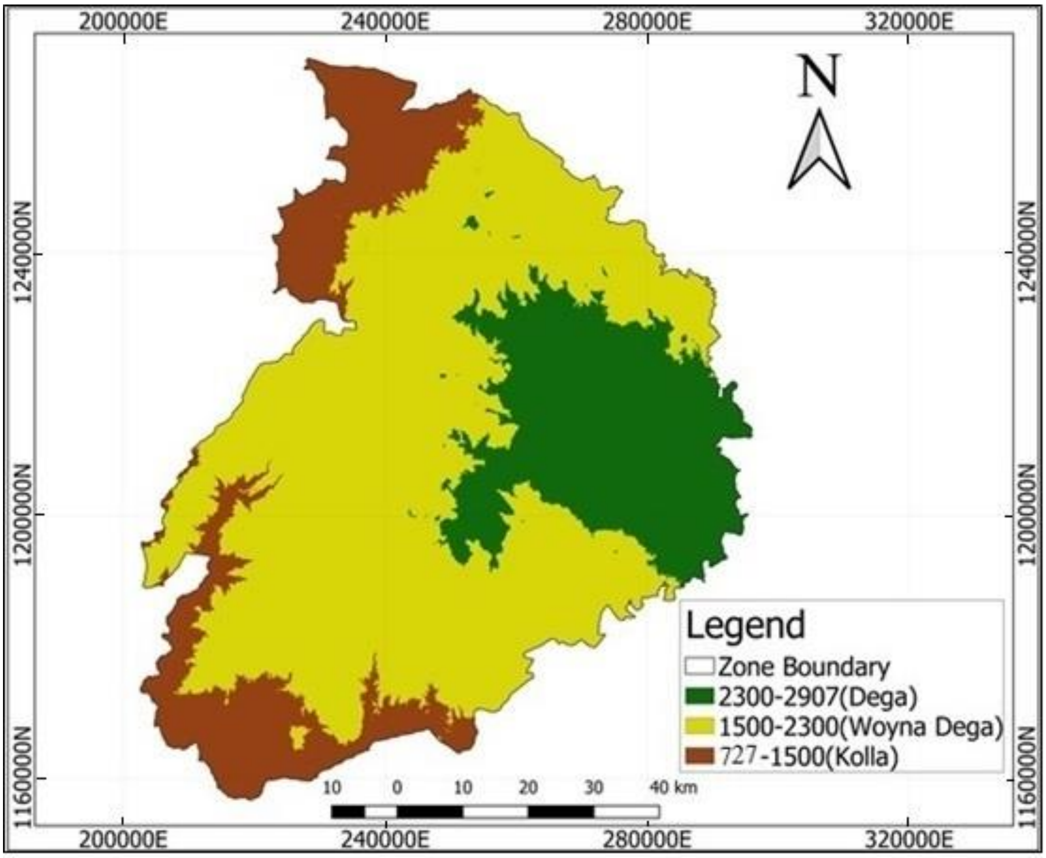

Figure 5 Agro-climatic Zone of the study area (Source: Azene, 1993)

Vegetation

The vegetation of north, northwest, west and southwest lowlands of Awi Zone belongs to *Combretum-Terminalia* woodland and wooded grassland; whereas the northeast, central and southeast highlands contain fragmented forests of the Dry evergreen Afromontane forest and grassland complex vegetation type (Figure 6). Few wetlands and crater lakes are found scattered in northeast. Significant portion of primary forests exist in Awi Zone, while the study area for land-use land-cover changes includes most of the primary forests of the zone. The primary forests of the forest patches are generally categorized under the *Dry evergreen Afromontane* forest and grassland complex vegetation and Riverine vegetation types (Friis *et al.*, 2010).

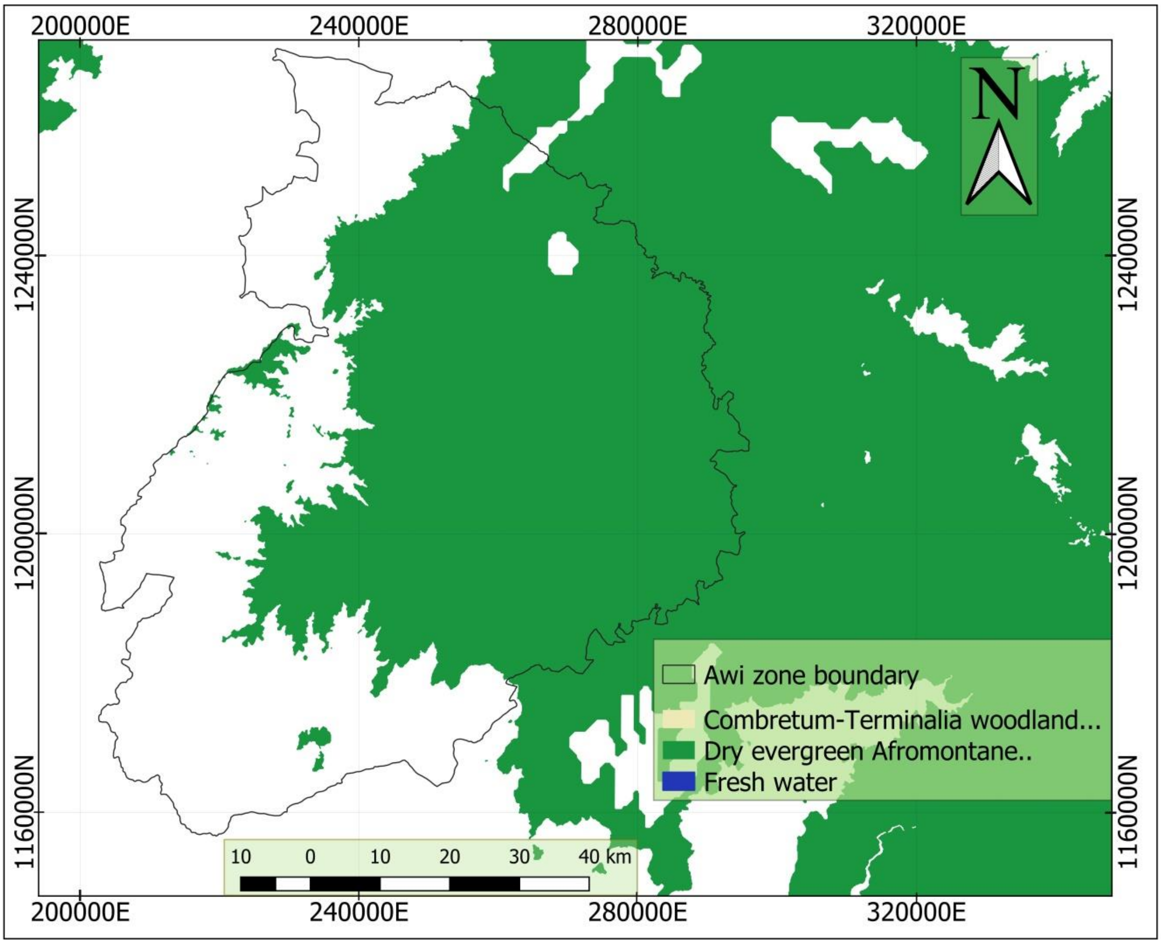

Figure 6: Potential vegetation types of Awi zone (Source: Friis *et al.*, 2010)

Population

The human population of Awi Zone is projected to be 1,143,639 heads with a density of 16 heads/ km^2 in the years 2014 – 2017 (Table 1). Among the total population, 84% live in rural areas, while the remaining 16% live in urban areas. The majority of the population is Agaw (60%), followed by the Amhara (38%); all other ethnic groups made up 1.7% of the population. On the other hand, the livestock (cattle, sheep, goats, horses, mules and donkeys) population is projected to be 635,448 Tropical Livestock Units (TLUs) with a density of 64 TLUs/km^2 in the years 2014–2017 (CSA, 2013).

Table 1: Population data in the years 2014–2017

Gender	Total population			Urban population			Rural population		
	Male	Female	Total	Male	Female	Total	Male	Female	Total
Total	571,821	571,818	1,143,639	93,370	88,845	182,215	478,451	482,972	961,423
Percent	50	50	100	8	8	16	42	42	8

3.2. Data Acquisition

3.2.1. Satellite imagery

Primary and secondary data were collected and used from different data sources. Remote sensing and Geographic Information System was used in this study to produce information on the trend and the amount of change taking place over the last three decades in both bio-physical and climatic condition. All remote sensing dataset were obtained from free data sources.

Landsat TM, ETM+ and OLI-TIRS from USGS Earth Resources Observation Systems (http://www.earthexplorer.usgs.gov) of the year 1985, 2000, 2009 and 2019 were selected to be employed to produce adequate information to meet the major problems and objectives of the research. The Landsat images were selected as much as possible in the same vegetation season which is January and February. All the Landsat images were referenced and projected using UTM WGS 84 Zone 37N. The Landsat image has spatial resolution 30 m which is commonly used for land-use land-cover change detection and geo-spatial analysis purpose (Tibebu *et al.*, 2018) (Table 1).

CHIRPS (Climate Hazards Infrared Precipitation with Stations) was used for obtaining rainfall dataset provided by National Oceanic and Atmospheric Administration's (NOAA's). Spanning 50°S−50° N (and all longitudes), starting in 1981 up to present year, CHIRPS incorporates 5 km resolution satellite imagery with in-situ station data to make gridded precipitation time series for trend analysis and seasonal drought monitoring (Tenaw and Habte, 2018; Agenagnew and Assefa, 2019). It was used to obtained annual and dry season rainfall data from 1981 to 2019 of the study area.

MODIS (Moderate Resolution Imaging Spectro-radiometer) is a well-known vital instrument aboard the Terra (originally called EOS AM-1) and Aqua (originally called EOS PM-1) satellites. Terra's orbit around the Earth is timed then it passes from north to south direction across the equator in the morning, while Aqua passes from south to north direction over the equator in the afternoon time. Terra MODIS and Aqua MODIS are viewing the entire Earth's surface every 1 to 2 days, obtaining data in 36 spectral bands, or groups of wavelengths. Land surface temperature and emissivity of the study area was obtained from MODIS LST with 1km resolution (MOD11A2) since 2000 (https://modis.gsfc.nasa.gov/about/). It was used to analyses the land surface temperature trend of the study area for the last twenty years (Klein *et al.*, 2017; Temesgen *et al.*, 2018).

Table 2: Description of the satellite images used in this study

Image Type	Path and Row	Resolution	Observation Date
Landsat TM	170/52 and 170/53	30 m	02/17/1985
Landsat TM	170/52 and 170/53	30 m	02/11/2000
Landsat ETM+	170/52 and 170/53	30 m	02/11/2009
Landsat OLI-TIRS	170/52 and 170/53	30 m	01/14/2019
CHIRPS		5 km	1981–2019
MODIS LST	MOD11A2	1 km	2000–2019
DEM	AP_07582_FBD_F0200_RT1 AP_07582_FBD_F0190_RT1 AP_07334_FBD_F0190_RT1 AP_07334_FBD_F0200_RT1 AP_07334_FBD_F0210_RT1	12.5 m	09/09/2019

3.2.2. Ground truth data

Data acquired from satellite sensors should be supported and checked with reality by using solid ground truth information. Hence, in the present study ground truth data were collected from the field using handheld Global positioning system GPS for training data (Region of Interest) and accuracy assessment. Training data that was used to produce land-use land-cover map was collected from the field to have a correct spectral value for each class. However, Google Earth (high resolution image) also used to collect information from areas where impossible to accesses.

The software packages used in this study were: ERDAS Imagine 2015, ArcGIS Desktop 10.3, ENVI 5.3, QGIS (Quantum GIS) 3.3, R Shiny and Microsoft Excel (XLSTAT) to make the LULC change detection, mapping and analyzing both satellite and field data.

3.3. Methodology

3.3.1. Image pre-processing

Digital image pre-processing is the improvement of digital image for human interpretation (Bakker *et al.*, 2001). After downloading and extracting the Landsat image (Level 1), pre-processing activities have taken place. These include layer stacking/merging, atmospheric correction, gap filling (Landsat 7), image mosaic (Appendix 7) and to improve the quality and interpretability of the image so that the image become applicable and ready for further analysis.

3.3.1.1. Image classification

Image classification is the process used to produce thematic maps from the satellite images. The themes can vary from general categories to detail descriptions of specific classes (Robert and Schowengerdt, 2007). In the present study, different classes from a pre-processed image were identified through support vector machine (SVM) algorithm to produce primary LULC map. This map was used to collect training data to have a clear understanding of the features and locations of classes during fieldwork. Subsequently, training data was collected from the field with the help of local experts and elder peoples who live in the area over a long time. However, high-resolution satellite imagery (Google Earth) was used to collect necessary data for areas that is difficult to address. In the present study, a total of 220 Ground Truthing Points (GTPs) (Agriculture land, forest and other land collected 60 points for each class and 40 for bare-land) were collected. Finally, the last land-use land-cover classification map was performed using support vector machine (SVM). This method is selected because it gives the best classification result and offers better certainty for land-use land-cover classification (Avalos *et al.*, 2018). Land-use and Land-cover classes and its description are presented in Table 3.

Table 3: Land-use and land-cover types

LULC Class	Description
Forest	It represents both natural and fragmented plantation forest areas that are stoked with trees capable of producing timber or other wood products.
Agriculture	Lands covered with agricultural activities.
Bare land	represents an areas under degraded grassland and with some area that are bare grounded (rocky).
Other land	LULC that contains built up, water body, scrubland and shrub land.

Based on the result of the classified land-use land-cover data the rate of LULC change was calculated and analyzed based on the formula of (Suleiman *et al.*, 2017) as follows:

$$Annual\ change\ rate(ha/yr) = \frac{(a_2 - a_1)}{N} \quad (1)$$

where annual change rate is the change in LULC (a_2–a_1) a_2 is recent year land-use land-cover in ha, a_1 is initial year land-use land-cover in ha and N is the number of years between the initial and the final of study period.

To compute percentage changes in each land-use land-cover for the study area, targeted land-use land-cover was segmented into two change periods of image analysis. From Eq. (1), a relationship for estimating percentage change of targeted land-use land-cover for the change detection periods under study was established (Suleiman *et al.*, 2017) Eq. (2).

$$\%\Delta inl = \frac{(a_2 - a_1)}{A} \times 100 \qquad (2)$$

where Δinl is change in the targeted land-use land cover under study, a_1 and a_2 are the areas (image-based estimated areas) of the targeted land-use land cover at the beginning and end of the change detection analysis and A is the sum total area.

3.3.1.2. Image reclassification

One of the objectives of this study was to quantify the amount of forest cover change for the last thirty four years. Therefore, the raster map which was produced as four LULC classes were reclassified into forest and non-forest. Forest was already classified as a forest but non-forest contains agriculture land, bare land and other land. Those thematic maps were used to assess and analyze forest cover transition and the relationship with land surface temperature and rainfall in the study area.

3.3.1.3. Normalized Difference Vegetation Index (NDVI)

Spectral band ratio is the most important mathematical operations applied to multispectral data to obtain useful spatio-temporal information. NDVI is the most common used in many research papers to understand vegetation dynamics and statues. The absolute value of NDVI for vegetation change analysis ranges from -1 to +1 (Tucker, 1979). It is computed as indicated in equation below:

$$NVDI = \frac{NIR - R}{NIR + R} \qquad (3)$$

where *NDVI* is normalized difference vegetation index, *NIR* is near infrared reflectance and *R* is red reflectance.

3.3.2. Accuracy assessment

Accuracy assessment was conducted to obtain better data from sample points (ground control points) using Global positioning system (GPS) and comparing this data with the map classification to improve the uncertainty. The importance of accuracy assessment using GCP for improving the uncertainty of classification is emphasized (FAO, 2016). Stratified random sampling was used to determine the GCP for each LULC class. This sampling technique is selected because to sample each LULC individually, each pixel element is assigned only in one particular class and no pixel element is left to assign (FAO, 2016 and GFOI, 2016). The sample was distributed in proportional allocation technique; the number of samples was allocated based on the size of area within the classes. The smallest number of sample was 8 per class. Overall accuracy is the proportion of area classified, and thus refers to the probability that randomly selected samples on the LULC map is classified correctly Eq. (4). Users accuracy is the proportion of the area classified as class i that is also class i in the reference data (ground data) Eq. (5). It provides users with the probability that a specific area of the map of class i is also that class on the ground. Producer's accuracy is the proportion of area that is reference class j and is also class j in the LULC map Eq. (6). It is the probability that class j on the ground is mapped as the similar class (FAO, 2016).

$$A = \sum_{j=1}^{q} P\mathrm{jj} \tag{4}$$

$$Ui = \frac{Pii}{Pi.} \tag{5}$$

$$Pj = \frac{Pjj}{P.j} \tag{6}$$

where A is overall accuracy, Pjj and Pii diagonal values, Ui is users accuracy, Pj is producers accuracy, P.j is column total and Pi is row total. In addition to overall accuracy, kappa coefficient was also computed as follows:

$$\mathrm{k} = \frac{N\sum_{i}^{r} Xii - \sum_{i}^{r}(Xi{*}X{+}i)}{N^2 - \sum_{i}^{r}(Xi{+}{*}X{+}i)} \tag{7}$$

where N is the total number of samples in the matrix, r is number of rows in the matrix, x_{ii} is the number in row i and column i, x_{+i} represent the total for row i, and x_{i+} represent the total for column i.

3.3.3. Land Surface Temperature analysis

MODIS dataset originally found in sinusoidal (SIN) mapping grid and provided in the form of HDF (Hierarchical Data Format). Therefore, HDF format should be changed into Geotiff format to carry out further analysis. MODIS Land Surface Temperature/Emissivity (LST/E) data with 1 km spatial resolution with a data type of 16-bit unsigned integer to get the temperature data in degree Celsius (°C) (Sruthi and Aslam, 2015). The pixel value (PV) of LST data is converted to degree Celsius by using the following empirical formula.

$$LST(°\mathrm{C}) = (PV \times 0.02) - 273.15 \tag{8}$$

Where, *LST(C°)* is land surface temperature in degree centigrade and *PV* is pixel value of MODIS data. After conversion, the eight days MODIS image (MOD11A2) for each month were added and divided by number of image to get LST data for each month during study period (2000–2019). Then, seasonal land surface temperature were computed by adding monthly MODIS LST (°C) from May to September divided by five for winter season LST and from October to April divided by seven for Dry season LST by using ArcGIS Desktop 10.3.

3.3.4. Trend analysis for land surface temperature and rainfall

Different statistical test methods are used to detect trends in climatological time series; these are classified as parametric and non-parametric tests. Parametric tests are more powerful but require that data be independent and normally distributed, which is rarely true for climatological time series data. For non-parametric tests, data need to be independent, but outliers are better tolerated. The Mann-Kendall (MK) test is the most common and widely used by several researchers to study temperature and rainfall time series trends (Negash *et al.* 2013; Ahmad *et al.*, 2015; Alemayehu *et al.*, 2017; Tesfay *et al.*, 2018; Abebe and Arega, 2019; Worku *et al*, 2019). Before MK trend analysed, all the data used was checked whether or not autocorrelation was presented. So, there is no autocorrelation exist between dataset. The magnitude of the slope in data time series was computed using sen's slope method. In Mann-Kendall test, the null hypothesis (H_0) was that there has been no trend in land surface temperature and rainfall over time; the alternate hypothesis (H_1) was that there has been a trend (increasing or decreasing) over time. The mathematical equations for calculating MK Statistics as follows: The MK statistic (S) is computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sig(yj - yi) \qquad (9)$$

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

$$sign(yj - yi)\begin{cases} 1, if(yj - yi) > 0, \\ 0, if(yj - yi) = 0, \\ -1, if(yj - yi) < 0, \end{cases} \qquad (10)$$

Here yj and yi are the sequential data values, and n is the length of the data set.

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

$$f(t) = Q(t) + B \quad (11)$$

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

$$B1 = Median\left[\frac{(yj-yi)}{(yj-yi)}\right] \quad (12)$$

For all j > i and i = 1, 2, …, n-1 and j = 2, 3…, n; in other words, calculating the slope for all pairs of data that were used to compute S in Eq. (9). The median of the slopes is the Sen slope estimator (Rahman and Begum, 2013).

3.3.5. Correlation analysis

A correlation analysis describes the liner relationship between two or more variables (land surface temperature and rainfall). A Pearson correlation coefficient is a numerical indicator that shows the relationship between tow variables. As linear regression, closeness relationships of LST and rainfall by a positive and negative correlation trend (Li *et al.*, 2018a).The empirical relation to calculate the Pearson correlation coefficient value (r) were calculated as follows:

$$r_{xy} = \frac{\sum_{i=1}^{n}(xi-xm)(yi-ym)}{\sqrt{\sum_{i=1}^{n}(xi-xm)^2 \sum_{i-1}^{n}(yi-ym)^2}} \quad (13)$$

Where, r_{xy} is the correlation coefficient between the monthly value of two variables *x* and *y*, and *xm* and *ym* are the means of the two variables. The correlation values are classified as weak, low, moderate and strong with (0<|r|≤0.3), (0.3<|r|≤0.5), (0.5<|r|≤0.8) and (0.8<|r|≤1) range values, respectively. In the present study, Land surface temperature and rainfall is dependent variable whereas forest cover is independent variable. Overall methodological framework and data analysis is presented in Figure 7.

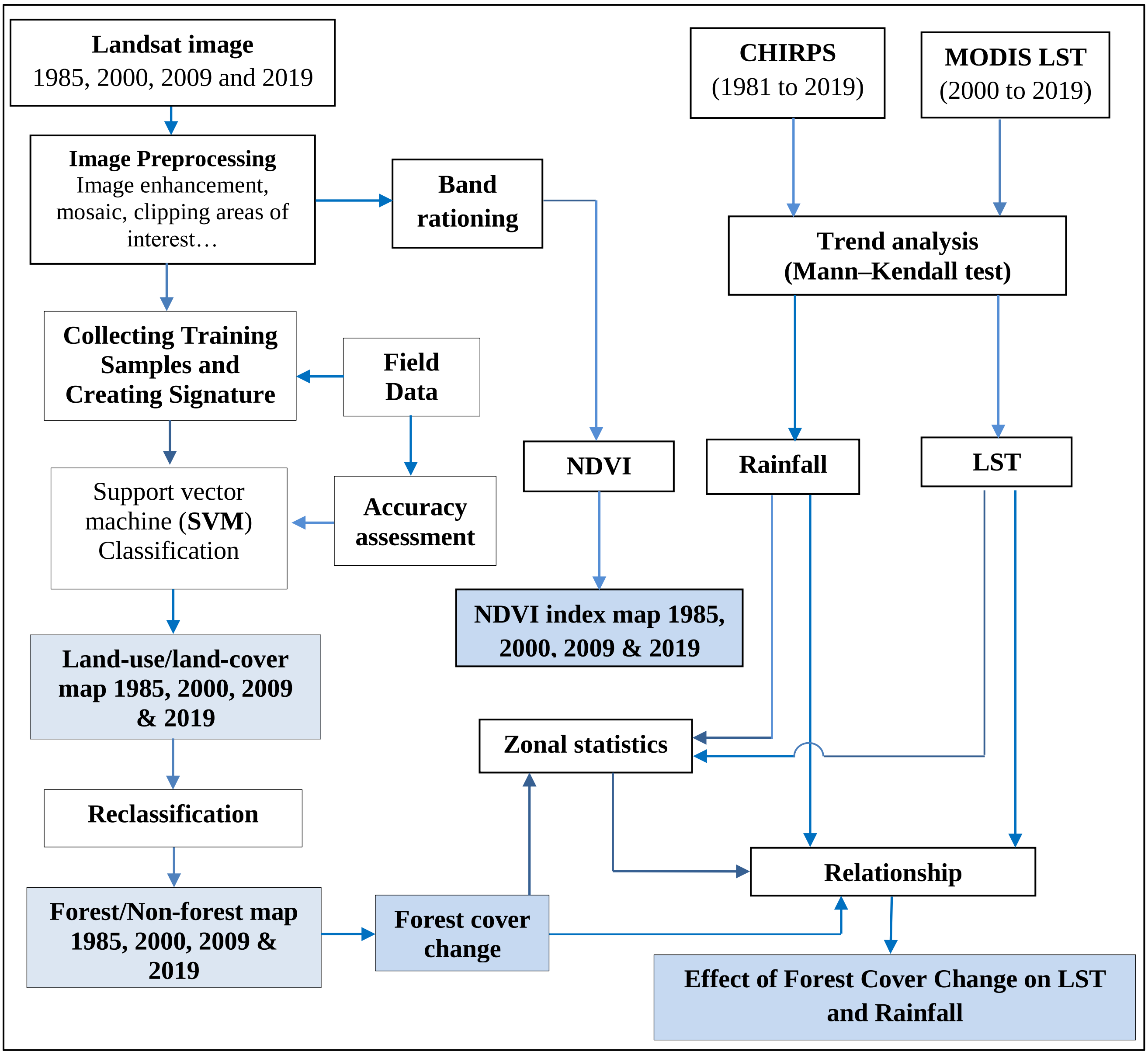

Figure 7: Methodological flow chart

CHAPTER FOUR

4. RESULTS

4.1. Land-use and land-cover

Figure 8 and 9 presents the spatial and temporal pattern of various land-use and land-cover cover types for 1985 to 2019. The spatial extent for land-use land cover types are shown in Table 4. The results reveal that the dominant LU/LC classes were agriculture and other land in 1985. These classes accounted for 78% of the overall area coverage. From the total area of 634510 ha, agriculture accounted for 318303.4 ha (50.2%) and other land accounted for 175935.7 ha (27.73%). The remaining LULC classes forest and bare land cover about 22% from the total coverage with 42741.8 ha (6.74%) and 97529 ha (15.4%), respectively. The smallest LULC was dense natural forest land found mainly in the middle part of the study area with a large extent. In 2000, from the total land coverage agriculture land was accounted for about 369935.64 ha (58.3%). Forest, bare land and other land take the share of 36887.3 ha (5.8%), 73884.4 ha (11.64%) and 153802.7 ha (24.2%), respectively. Bare land was found in northern and southern lowland of the study area. The results were shown that there has been a significant decrease in the area of forest with one percent, particularly in the boundaries of the natural forest.

The classified map of 2009 showed that agriculture land coverage units was about 347678.7 ha or 54.8% of the total area whereas the remaining LULCs took around 45%. The second largest class was other land with 181052 ha (28.5%). Bare land and forest was 60548.4 ha (9.5%) and 45229.05 ha (7.2%), respectively. Like previous years forest was the smallest LULC class but the area was increasing with 1.3% from the last study year. Results from the classified image of 2019 illustrate that more than 47.5% of the area was covered by agriculture land, whereas forest area share was 89997.3 ha (14.2%), other land and bare-land was covering 200610.6 ha (31.6%) and 42418.5 ha (6.7%), respectively.

Table 4: Land-use and land-cover areas during 1985–2019

LULC Type	1985		2000		2009		2019	
	Area(ha)	**Area(%)**	**Area(ha)**	**Area(%)**	**Area(ha)**	**Area(%)**	**Area(ha)**	**Area(%)**
Forest	42741.81	6.74	36887.31	5.81	45230.85	7.13	89997.30	14.18
Agriculture	318303.45	50.17	369935.64	58.30	347678.73	54.79	301483.53	47.51
Bare land	97529.04	15.37	73884.42	11.64	60548.40	9.54	42418.53	6.69
Other land	175935.69	27.73	153802.71	24.24	181052.01	28.53	200610.63	31.62
Total	**634510**	**100**	**634510**	**100**	**634510**	**100**	**634510**	**100**

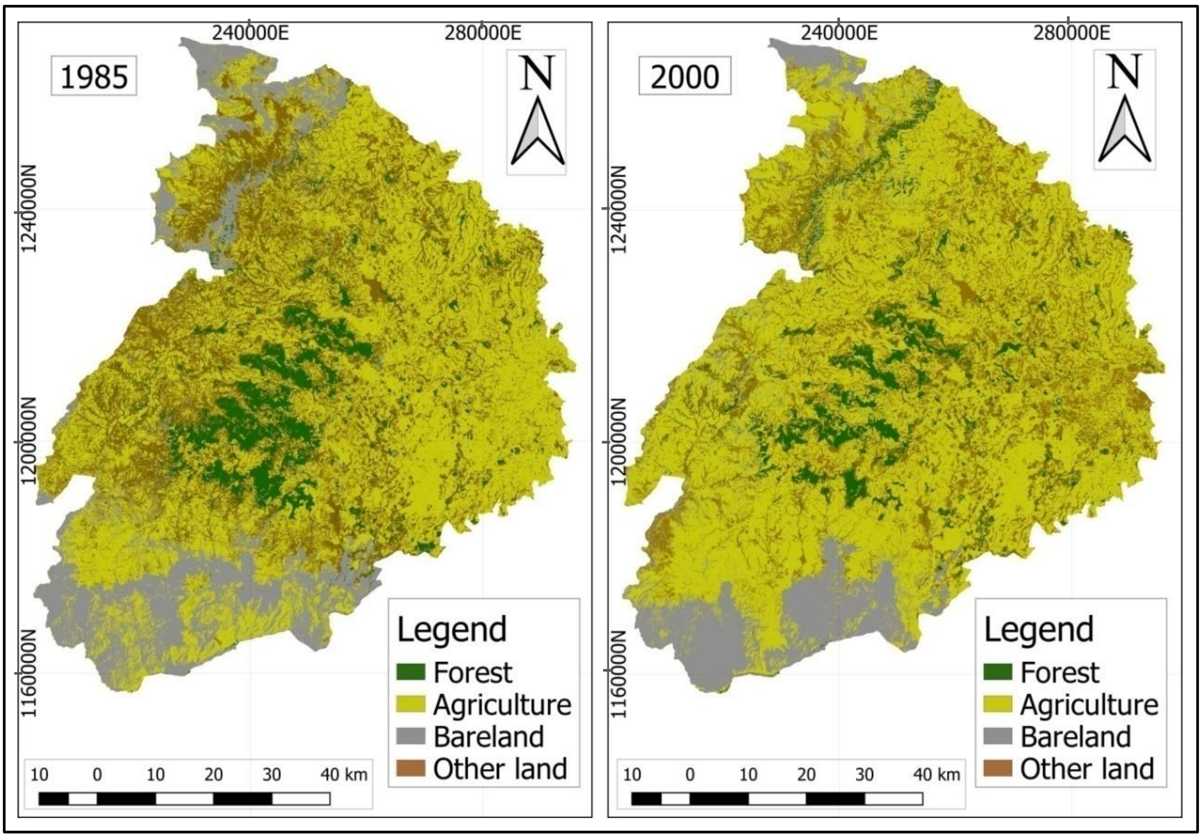

Figure 8: Land-use and land-cover map of 1985 and 2000

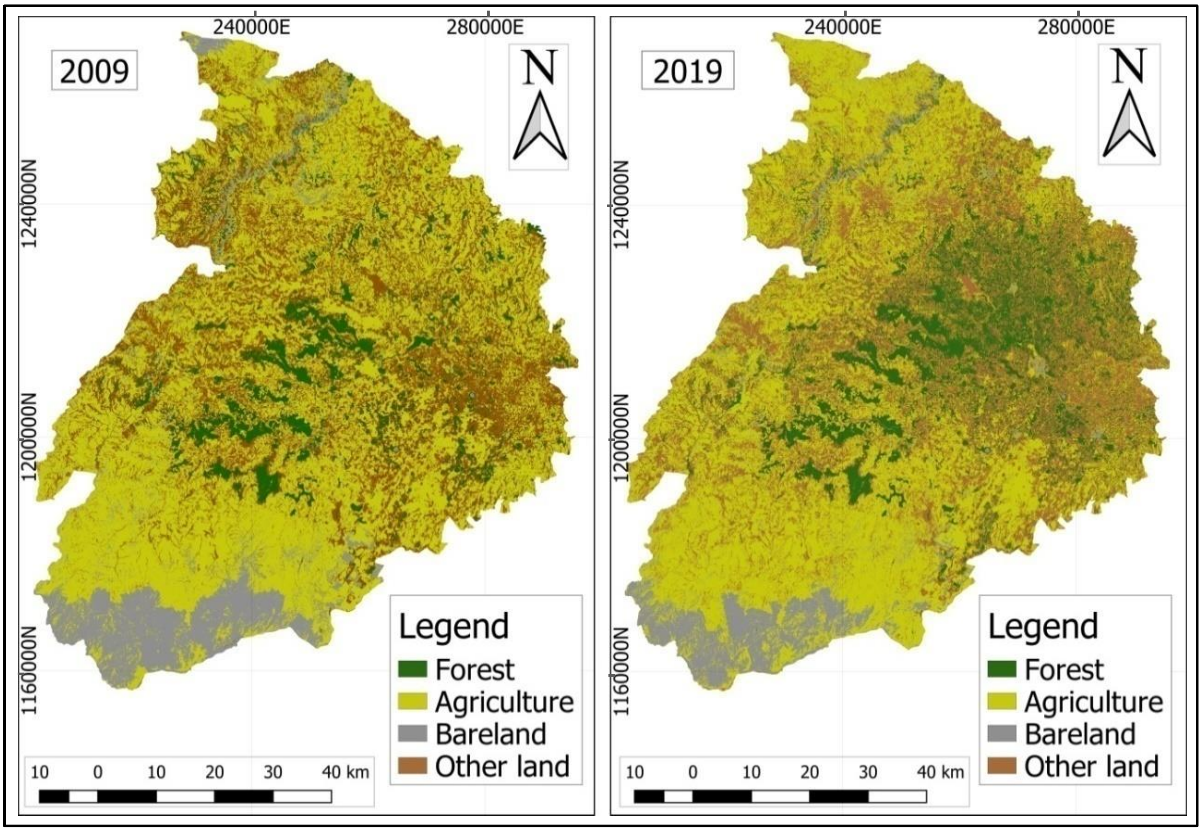

Figure 9: Land-use and land-cover map of 2009 and2019

4.2. Trend and rate of land-use and land-cover change

Land-use and land-cover trend of the study area shows a significant change from 1985 up to 2019. The results further revealed that forest land, bare land and Other land from the year 1985 to 2000 have declined by 5854.5 ha (0.9%), 23644.6 ha (3.72%) and 22132.9 ha (3.4%), respectively. However, agricultural land increased by 51632.2 ha (8%) during the first period, respectively. In the next study period (2000–2009), the extents of forest and other land have increased by 8343.5 ha (1.3%) and 27249.3 ha (4.3%) whereas agriculture land and bare land have decreased by 22256.9 ha (3.5%) and 13336.02 ha (2.1%), respectively. In the final period (2009–2019), forest and other land have increased with 44766.4 ha (7%) and 19558.6 ha (3%), respectively. Agriculture land and bare land have decreased by 46195.2 ha (7.3%) and 18129.8 ha (2.8%), respectively. Land-use and land-cover trend from the baseline up to the final year shows increase in forest and other land by 47255.49 ha (7.4%) and 24674.94 ha (3.8%), respectively. In contrast, agriculture and bare land show decreased by 16819.92 ha (2.6%) and 55110.51 (8.6%) ha, respectively. The land-use and land-cover change during 1985–2000, 2000–2009, 2009–2019 and 1985–2019 shown in Figure 10.

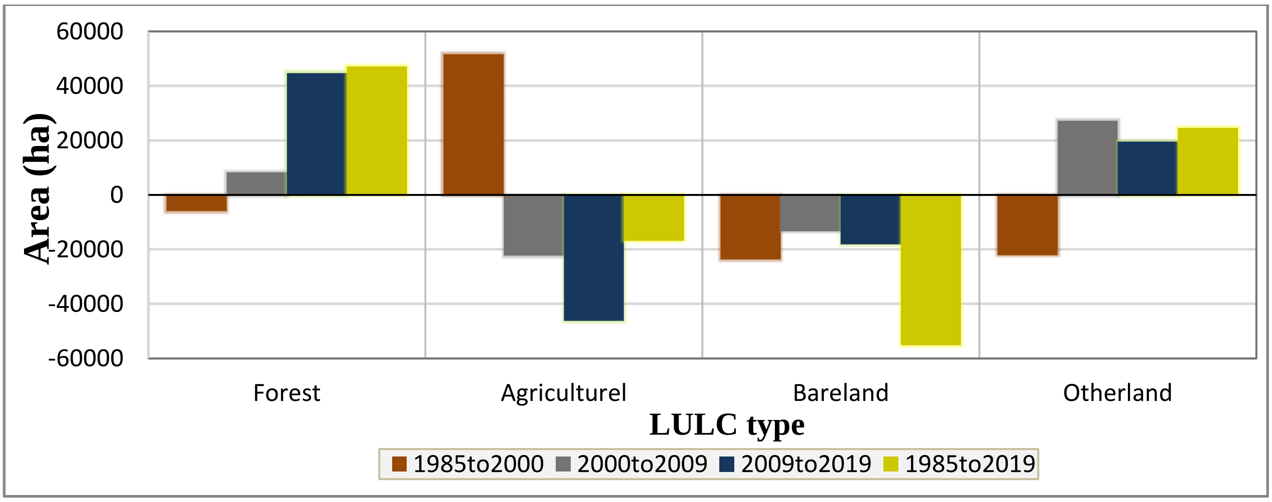

Figure 10: Extent and trend of land-use and land-cover changes

The rate of land-use land-cover change was continually spontaneous for the last thirty four years since 1985 (Appendix 2). Agriculture land in the first periods show a significant increase with 3442.1 ha yr.$^{-1}$ but in the second and final period it decreases with 2473 ha yr^{-1} and 4619.5 ha yr.$^{-1}$, respectively. This result indicates the demand for agricultural land was very high in 1985–2000. Contrary to expectations agriculture land was replaced by newly emerged forest in most middle part of the study area. Forest shows decreasing rate in the first period with 390.3 ha yr.$^{-1}$, but in the second and third period it shows continuous increasing rate with 927.1 ha yr.$^{-1}$ and 4476.6 ha yr.$^{-1}$, respectively. A continuous decreasing rate throughout the study period was recorded in bare land with 1576.3 ha yr.$^{-1}$, 1481.7 ha yr.$^{-1}$ and 1812.9 ha yr.$^{-1}$, respectively. Other land shows a decreasing rate in the first period with 1475.5 ha yr.$^{-1}$, but for the second and third periods it increase with 3027.7 ha yr.$^{-1}$ and 1955.8 ha yr.$^{-1}$, respectively. Specifically, in the third period forest area was increasing with extreme amount. This result indicates during 2009–2019 agricultural and bare land has been shifting into forest land (afforestation and/or reforestation) which shown in central and northeastern part of the study area.

4.3. Forest cover change

Forest non-forest result revealed that a high amount of forest cover was observed in 2019 with 89997.3 ha and the smallest coverage was in 2000 with 36886.86 ha. However, in the initial year 1985 and 2009 relatively similar forest cover was shown with 42731.37 ha and 45229.05 ha, respectively. The result of forest/non-forest change statistics and map shows in the first period 17770.9 ha (2.8%) of forest area was changed into non-forest while 24970.78 ha (3.9%) stay unchanged. Likewise, in the same period 11916.41 ha (1.8%) non-forest areas were changed to the forest and 579851.78 ha (91.4%) stay unchanged. In the second period (2000–2009) 10057.9 ha (1.5%) of forest was changed into non-forest area which shows a significant decrease compared with the previous one. In contrast, the change from non-forest to forest show increase by covering 18404.7 ha (2.9%) while stable forest and stable non-forest cover 26826.2 ha (4.2%) and 579221 ha (91.3%), respectively. Furthermore, the amount of change from forest to non-forest was 11819.25 ha (1.8%) and from non-forest to forest covers 56317.4 ha (8.8%) in the final period (2009–2019). In this period stable non-forest show a significant decrease by covering 532693 ha (83.9%) while the stable forest was 33679.9 ha (5.3%) (Figures 11, 12 and Table 5).

Table 5: Forest/non-forest change statistics (1985– 2019)

	1985 to 2000		**2000 to 2009**		**2009 to 2019**		**1985 to2019**	
	Area(ha)	**Area(%)**	**Area(ha)**	**Area(%)**	**Area(ha)**	**Area(%)**	**Area(ha)**	**Area(%)**
Stable Forest	24970.90	3.93	26826.2	4.22	33679.9	5.31	27596.3	4.35
Forest to Non forest	17770.91	2.81	10057.9	1.585	11819.3	1.86	15480.1	2.44
Non forest to Forest	11916.41	1.87	18404.7	2.91	56317.4	8.87	62400	9.83
Stable Non-forest	579851.78	91.3	579221	91.28	532693	83.95	529034	83.37
	634510	100	**634510**	100	**634510**	100	**634510**	100

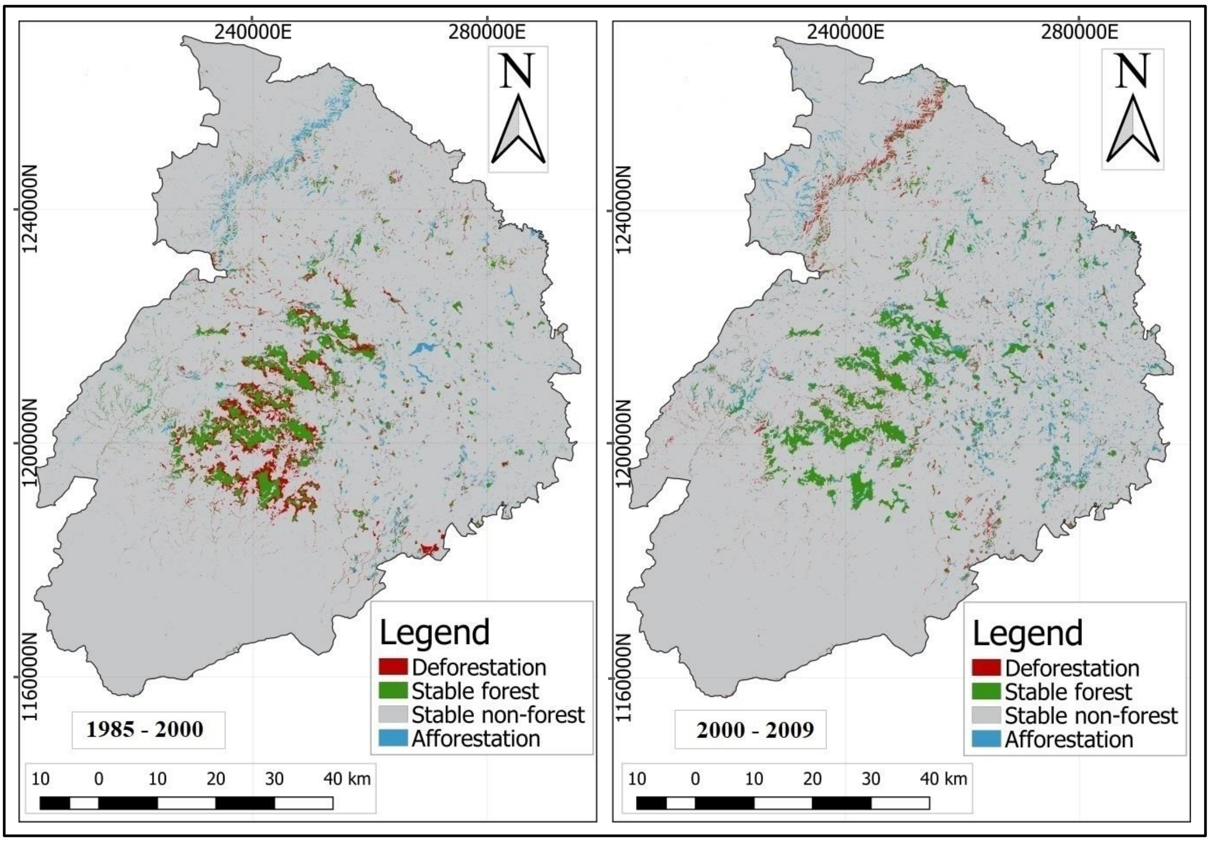

Figure 11: Forest cover change of 1985 to 2000 and 2000 to 2009

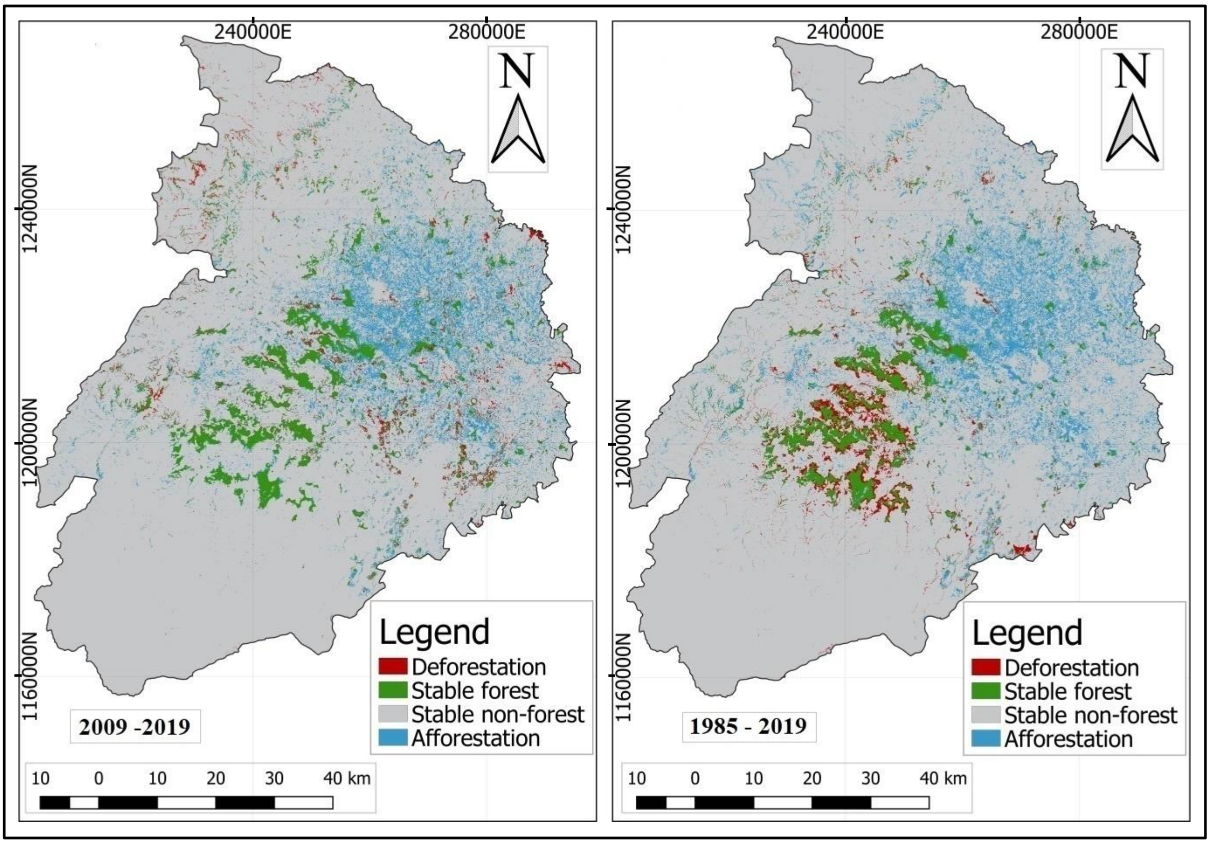

Figure 12: Forest cover change of 2009 to 2019 and 1985 to 2019

4.4. Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) results revealed that there was fluctuation in vegetation coverage for the last three decade. As it is shown on Table 5, NDVI value ranged from 0.71 to -0.35 and from 0.59 to -0.16 in 1985 and 2019. As a result, vegetation cover show declined for the net change (1985–2019). The highest and lowest maximum NDVI value was observed in 2000 and 2019 with 0.85 and 0.59 NDVI values, respectively. The maximum NDVI value from 1985 to 2000 increased from 0.71 to 0.85 whereas for recent two study years (2009 and 2019) were decreased with 0.64 and 0.59, respectively (Table 6).

Table 6: Normalized Difference Vegetation Index value of years 1985, 2000, 2009 and 2019

Years	Minimum	Maximum	Mean	STD
1985	-0.35	0.71	0.14	0.1
2000	-0.67	0.85	0.16	0.1
2009	-0.44	0.64	0.05	0.1
2019	-0.16	0.59	0.21	0.08

Figure 13 and 14 illustrated that in central, northeastern and some southeastern part of the study area show a high NDVI value, whereas in south and northern areas had lowest NDVI values. In 1985, high NDVI value show deep green color areas were observed in central part of the study areas. This indicated that high amount of vegetation cover closely existed in this area until it was fragmented through time. In contrast, in 2019 dense deep green color areas were scatted into a small patch of vegetation cover dispersed in most eastern part. This show there was deforestation/forest fragmentation and afforestation/reforestation was taken place for the last thirty four years. However, Normalized Difference Vegetation Index maps show not only forest cover but also other vegetation types like shrub land and bush lands.

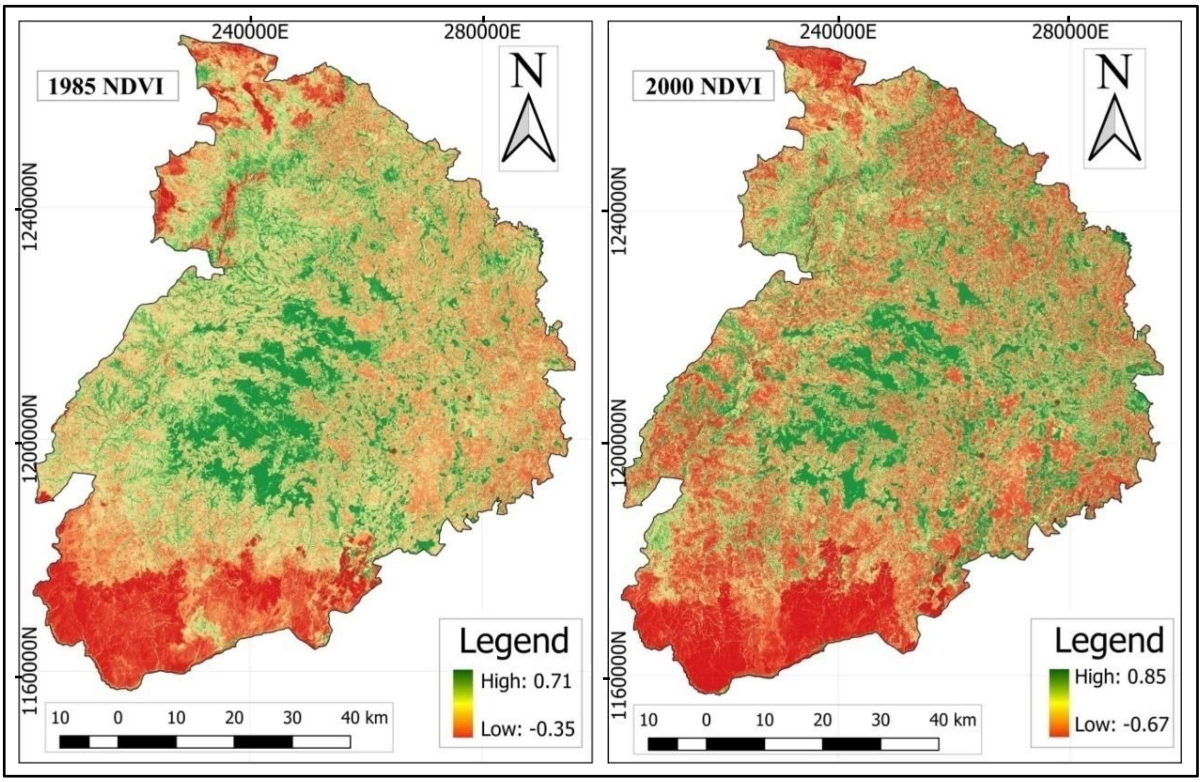

Figure 13: NDVI map of 1985 and 2000

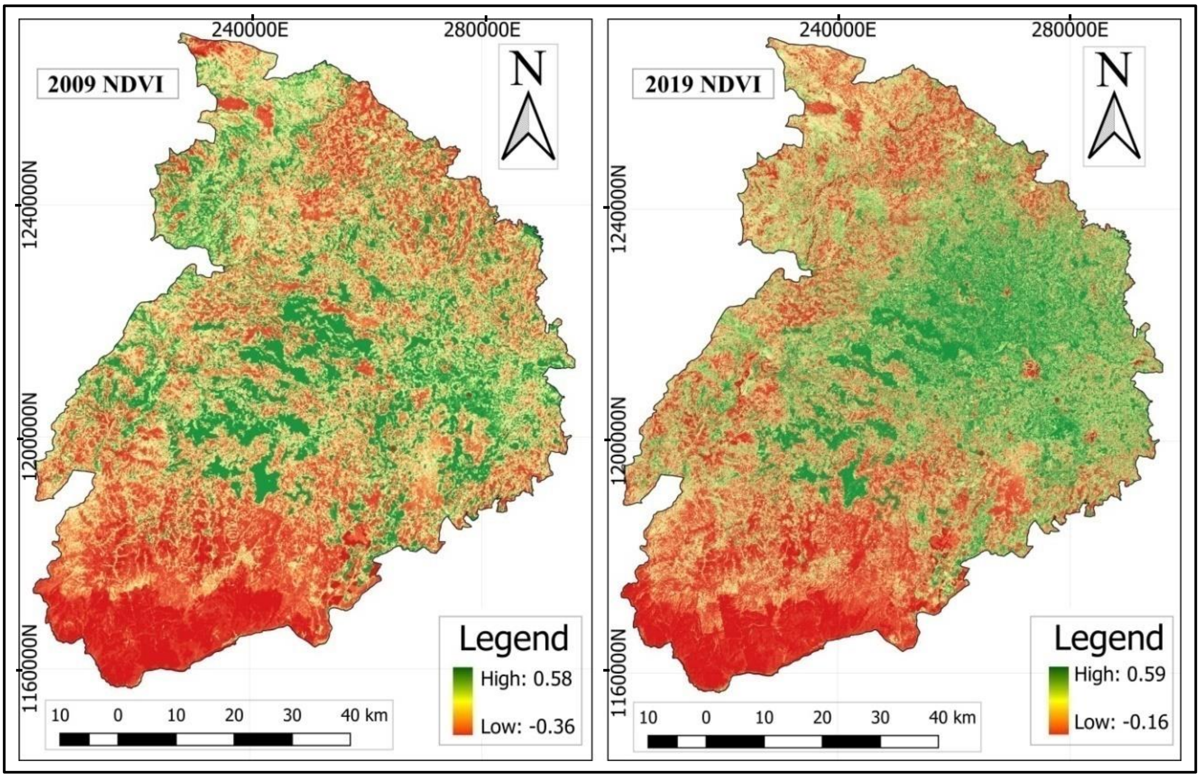

Figure 14: NDVI map of 2009 and 2019

4.5. Accuracy assessment

Accuracy assessment result for land-use and land-cover shows that, for 1985, overall accuracy was 85.42% with Kappa equal to 0.78. For 2000, Overall accuracy 89.11%, Kappa equal to 0.83. In 2009, the overall accuracy was 91.58%, Kappa equal to 0.86. Overall accuracy result of 2019 was 92.55% with Kappa equal to 0.88, respectively (Appendix 1). According to (Anderson *et al.*, 1976), the result of overall accuracy is 85% and above then the map accuracy is acceptable.

4.6. Land Surface Temperature trend

4.6.1 Trend of Land Surface Temperature *vs* agro-climatic zone (ACZ)

The land surface temperature on three agro-climatic zones has shown that a dynamic result from 2000 to 2019 in the study area. In Dega zone, Land Surface Temperature show significant decreasing trend of mean and minimum LST with a changing factor of -0.15, -0.14 whereas maximum LST show insignificant decreasing trend with -0.1 changing factor. However, other two ACZ results revealed insignificant trend of mean, minimum and maximum LST result. Hence, Woyna Dega zone mean, minimum and maximum LST result has shown changing factor by -0.022, -0.043 and 0.007, respectively. Likewise, in Kolla zone mean, minimum and maximum LST changing factor was 0.018, -0.006 and 0.038, respectively. Accordingly, the result show that mean, minimum and maximum LST for Dega zone were ranges from 27.11°C–32.37°C, 21.49ºC–26.32ºC and 31.35ºC–35.99ºC, respectively. Likewise, the result of mean, minimum and maximum LST for Woyna Dega zone were ranges from 32.01 °C–34.57°C, 23.63ºC–26.42ºC and 36.59ºC–40.52ºC, respectively. In Kolla zone, the result revealed that mean, minimum and maximum LST ranges from 33.59 °C–36.26 °C, 29.59ºC–32.48ºC and 37.62ºC–39.24ºC, respectively (Figure 15 and Table 7).

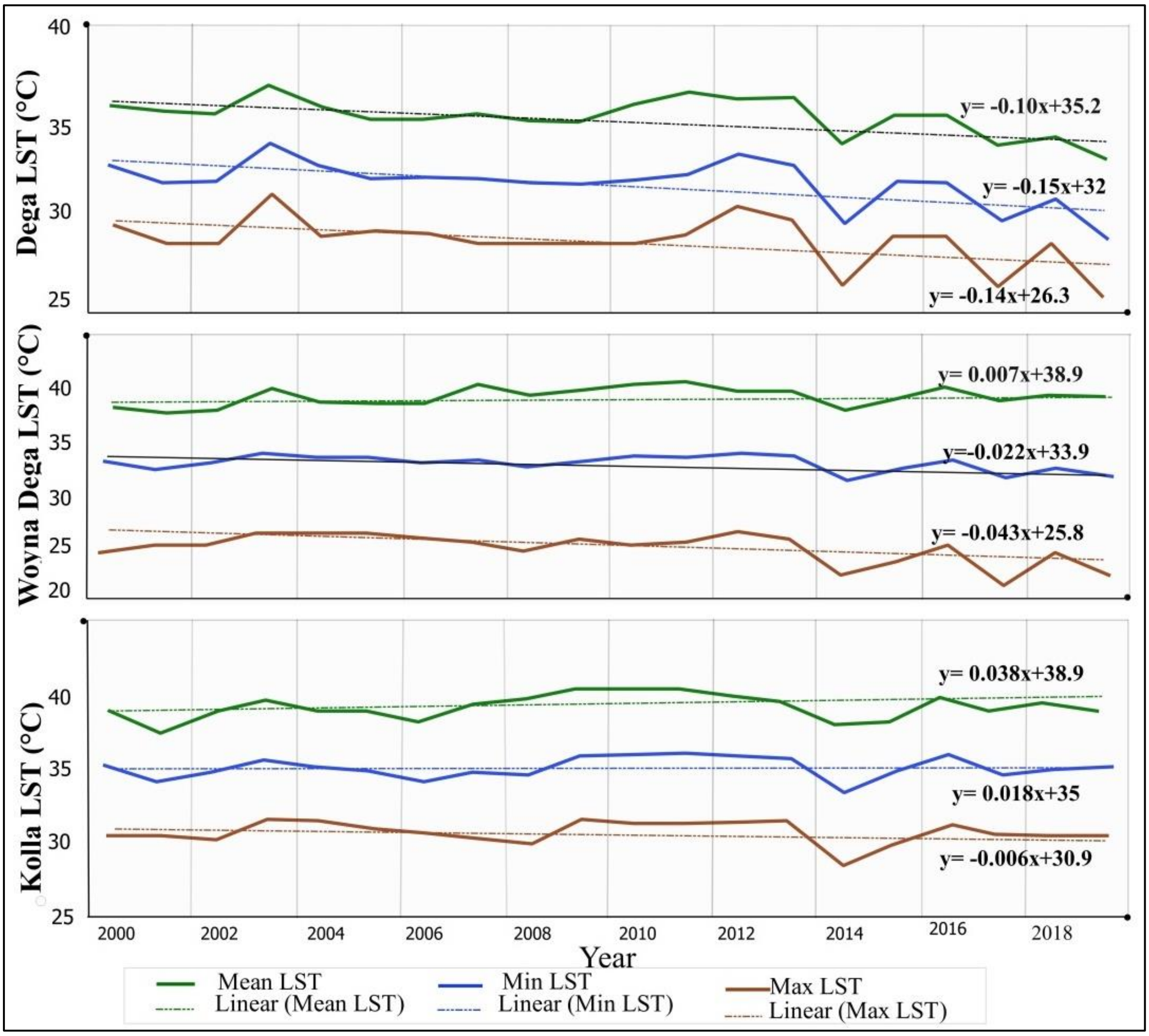

Figure 15: Trend line minimum, maximum and mean LST of Dega, Woyna Dega and Kolla

Table 7: Mann-Kendall and Sen's slope of mean, minimum and maximum LST for ACZ, at a significance level of α=0.05

Variables	Dega			Woyna Dega			Kolla		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
Kendall's tau	-0.4	-0.34	-0.27	-0.08	-0.22	0.10	0.10	0	0.13
P-value	**0.015**	**0.035**	0.09	0.62	0.18	0.53	0.53	1.00	0.41
Min	27.11	21.49	31.35	32.01	23.63	36.59	33.59	29.59	37.62
Max	32.37	26.32	35.99	34.57	26.42	40.52	36.26	32.48	40.64
Mean	30.33	24.8	34.1	33.72	25.42	39.06	35.13	31.59	39.24
Sen's slope (C°/yr.)	-0.13	-0.12	-0.10	-0.12	-0.17	0.083	0.093	0.008	0.087

When the result indicates p-value greater than the significance level α = 0.05 then null hypothesis H_0 cannot be rejected and vice versa. However, mean and minimum LST of Dega zone revealed that statistically significant decreasing trend with P-value (<0.05) of

0.015 and 0.035 but maximum LST show insignificant decreasing trend with p-value of 0.09. Therefore, the risk to reject the null hypothesis Ho while it is true is 9% for maximum Dega zone LST. However, in Woyna Dega zone the mean, minimum and maximum LST shows statistically insignificant LST trend with p-value (>0.05) of 0.62, 0.18 and 0.53, respectively. Accordingly, the risk to reject the null hypothesis H_0 while it is true is 62%, 18% and 53% for the mean, minimum and maximum of Woyna Dega zone LST. Likewise, in Kolla zone the mean, minimum and maximum result of LST show insignificant LST trend with a p-value (>0.05) 0.53, 1.00 and 0.41, respectively. Thus, the risk to reject the null hypothesis H_0 while it is true for the mean, minimum and maximum of Kolla LST is 53%, 100% and 41%, respectively.

The Sen's slope estimator result indicated that mean, minimum and maximum LST of Dega zone similarly decreased with 0.13ºC yr. $^{-1}$, 0.12ºC yr. $^{-1}$ and 0.1ºC yr.$^{-1}$, respectively. In Woyna Dega zone, the Sen's slope revealed that mean and minimum LST decreasing with 0.12ºC yr.$^{-1}$ and 0.17ºC yr.$^{-1}$ whereas maximum LST increasing with 0.083ºC yr $^{-1}$. Although, Kolla zone mean, minimum and maximum LST Sen's slope value show increased with 0.093ºC yr. $^{-1}$, 0.008ºC yr.$^{-1}$ and 0.087ºC yr.$^{-1}$ respectively .

4.6.2. Trend of Seasonal Land Surface Temperature

The Mann-Kendall trend test result revealed that mean, minimum and maximum land surface temperature for winter season decreasing trend with a change factor of 0.063, 0.057 and 0.044, respectively (2000–2019). In dry season Land Surface Temperature show insignificant decreasing trend of mean and minimum LST with a changing factor of 0.043 and 0.138 while maximum LST value show increasing trend with changing factor of 0.034. The Mann-Kendall trend test show that mean, minimum and maximum LST for winter season were ranges 24.03°C–28.05°C, 17.29ºC–21.31ºC and 29.98ºC–33.91ºC, respectively. Likewise, the result of mean, minimum and maximum LST for dry season were ranges 31.46°C–34.22°C, 21.49ºC–26.32ºC and 37.63ºC–40.64ºC, respectively (Figure 16 and Table 8).

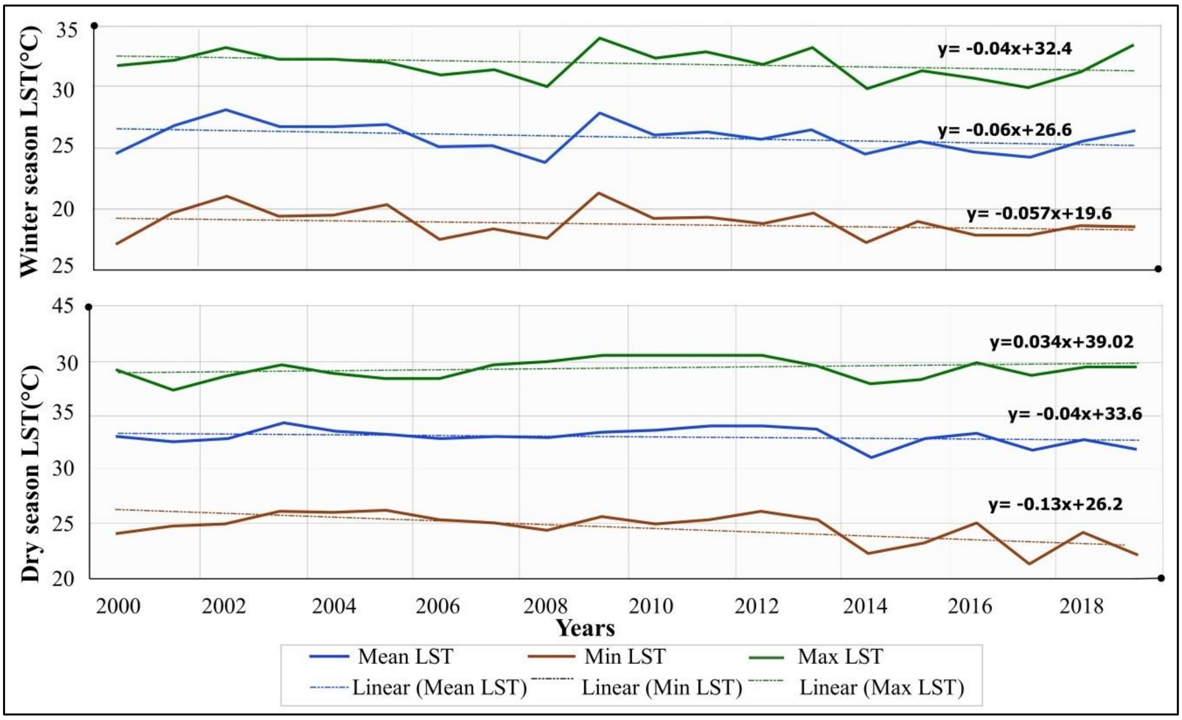

Figure 16: Trend line of mean, minimum and maximum LST for winter and dry season

Table 8: Mann-Kendall and Sen's slope of mean, minimum and maximum LST of winter and dry season, at a significance level of α=0.05

Variables	Dry season			Winter season		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**
Kendall's tau	-0.16	-0.316	0.137	-0.232	-0.221	-0.168
P-value	0.347	0.056	0.42	0.163	0.183	0.315
Min	31.46	21.49	37.63	24.03	17.29	29.98
Max	34.22	26.32	40.64	28.05	21.31	33.91
Mean	33.24	24.77	39.38	26	19.04	31.94
Sen's slope(C°/yr.)	-0.114	-0.126	0.1135	-0.0925	-0.1225	-0.0786

In addition, the result revealed that mean, minimum and maximum LST of winter season revealed that statistically insignificant decreasing trend with P-value of 0.163, 0.183 and 0.315, respectively. Therefore, the p-value is greater than significant level 0.05 then the null hypothesis is accepted. Accordingly, the risk to reject the null hypothesis while it is true is 16.3%, 18.3% and 31.5% for the mean, minimum and maximum of winter season LST. Similarly, in dry season mean, minimum and maximum LST result show statistically insignificant change with p-value 0.347, 0.056 and 0.42, respectively. So, the risk to reject the null hypothesis Ho while it is true for the mean, minimum and maximum of dry season LST is 34.4%, 5.6% and 42%, respectively.

The Mann-Kendall trend analysis Sen's slope result indicated that mean, minimum and maximum LST of winter season decreased with 0.093ºC yr.$^{-1}$, 0.12ºC yr.$^{-1}$ and 0.078ºC yr.$^{-1,}$ respectively. In dry season the Sen's slope revealed that mean and minimum LST decreased with 0.114ºC yr.$^{-1}$ and 0.13ºC yr.$^{-1}$ whereas maximum LST increased with 0.113 ºC yr.$^{-1}$. In addition, linear regression trend and 5-year moving average line for mean and dry season land surface temperature data series was computed. The 5-year moving average line is a very useful trend indicator showing variations of the long study periods in short bands. The seasonal land surface temperature shows high inter seasonal variability. This variability is tracked by the periodic fluctuations between consecutive wet years and consecutive dry years as shown in Figure 17.

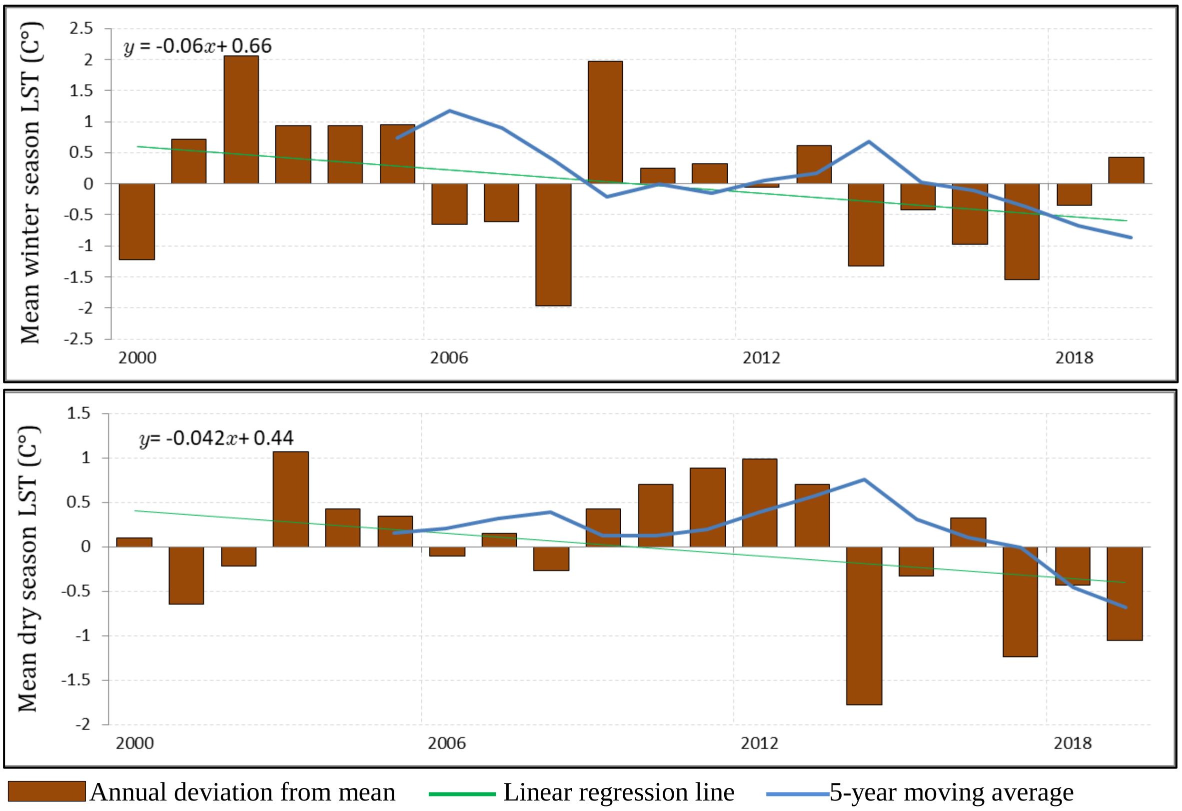

Figure 17: Dry and winter season LST and equivalent linear regression trend line and 5-year moving average line plotted (2000–2019)

4.7. Rainfall trend

Mann–Kendall test result for annual and dry season rainfall show a statistically insignificant trend in the study period (1981–2019). Nevertheless, there was an increasing trend of mean, minimum and maximum annual and dry season rainfall in the study area. The trend line indicated that a positive insignificant increasing value of annual mean, minimum and maximum rainfall changed with the factor of 0.96, 0.34, and 1.12, respectively. Similarly, the dry season rainfall mean, minimum and maximum trend line show positive insignificant increasing value with a factor of 0.78, 0.47 and 0.84, respectively (Figure 18).

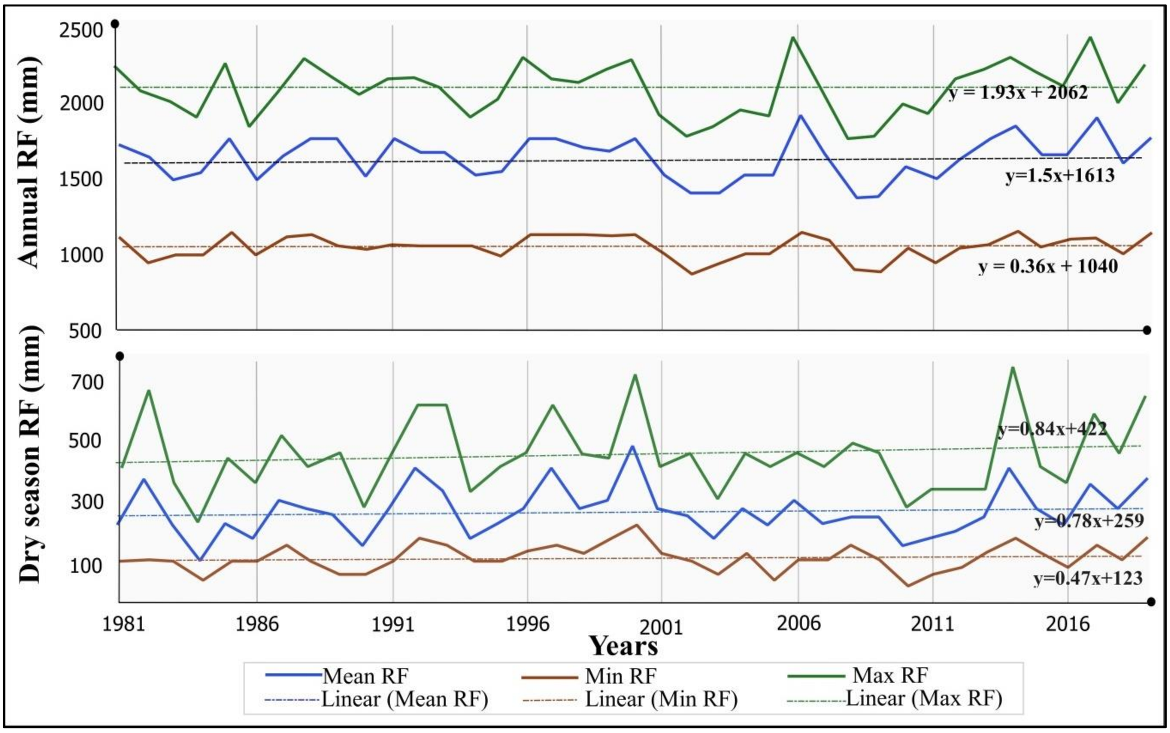

Figure 18: Annual and dry season rainfall trend from 1981 to 2019

Table 9: Mann-Kendall and Sen's slope of mean, minimum and maximum of annual and dry season rainfall, at a significance level of α=0.05.

Variables	**Annual rainfall**			**Dry season rainfall**		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**
Kendall's tau	0.085	0.077	0.085	0.063	0.117	0.053
P-value	0.45	0.49	0.45	0.578	0.298	0.646
Min	1394.3	884.5	1780.23	137	63.59	246.32
Max	1918.6	1152.3	2451.03	458.58	231.7	681.97
Mean	1644.8	1047.5	2101.7	274	132.6	439.62
Sen's slope (mm /decade)	0.003	0.005	0.003	0.005	0.015	0.003

As the computed p-value is greater than the significance level (α=0.05), one cannot reject the null hypothesis. The risk to reject the null hypothesis Ho while it is true is 45%, 49% and 45% for annual mean, minimum and maximum annual rainfall, respectively. Similarly, risk to reject the null hypothesis Ho while it is true is 57.8%, 29.8% and 64.6% for mean, minimum and maximum dry season rainfall, respectively. Therefore, for both results p-value is greater than alpha value that show scientifically there is no significant trend of rainfall annually as well as dry season for the last thirty nine years in the study area (Table 9).

In addition, annual rainfall Sen's slope estimator result indicated that there was a very slight increasing trend of annual mean, minimum and maximum annual rainfall by 0.003 mm, 0.005 mm and 0.003 mm per decade, respectively. The maximum annual rainfall was 2451.03 mm in 2006 and minimum annual rainfall 884.5 mm has been observed in 2009. In dry season, the Sen's slope estimator result show increasing trend of mean, minimum and maximum rainfall with 0.005 mm, 0.015 mm and 0.003 mm per decade, respectively. Moreover, linear regression trend and 5-year moving average line for annual and dry season rainfall data series was computed to understand inter seasonal and inter annual rainfall variability. The dry season rainfall indicates inter seasonal and annual rainfall show inter annual rainfall variability. This variability is tracked by the periodic fluctuations between consecutive annual years and consecutive dry season rainfall. Hence, as shown in Figure 19 higher inter annual rainfall variability was observed in the study area.

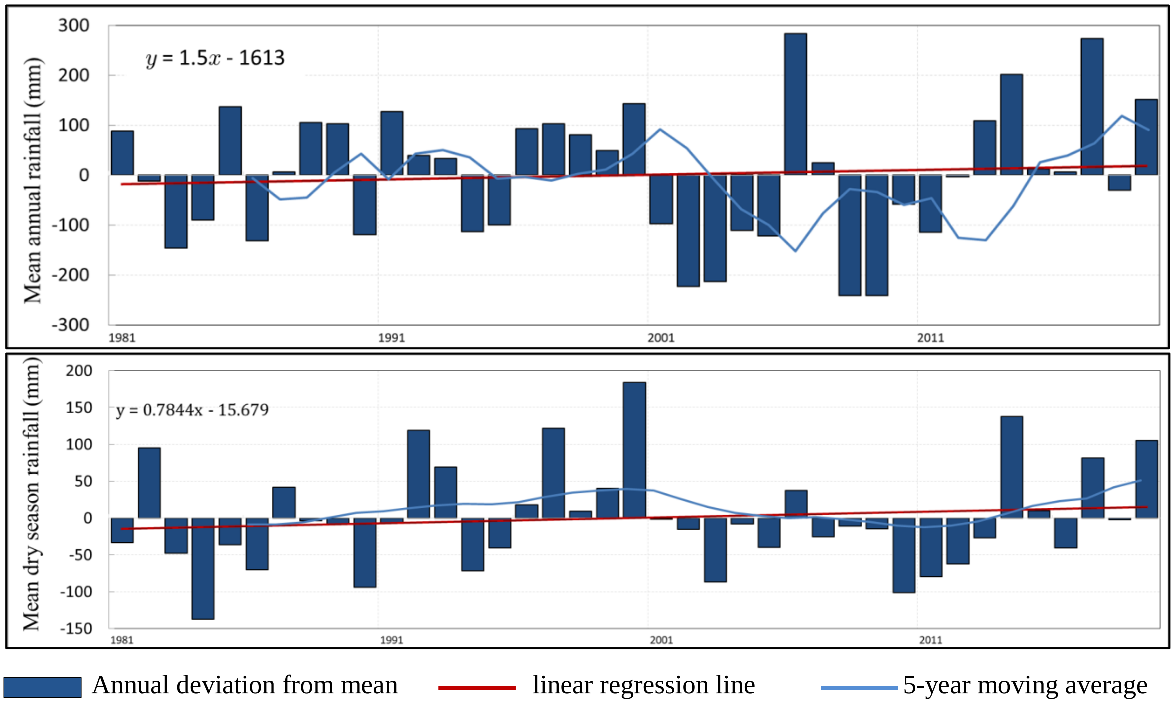

Figure 19: Mean annual and dry season rainfall and equivalent linear regression trend line and 5-year moving average line plotted (1981–2019)

4.8. Relationship of forest cover change with land surface temperature along agro-climatic zones

The correlation between mean LST and forest cover across agro-climatic zone (Appendix 4) is computed in the study area. The correlation coefficient obtained between Dega, Woyna Dega and Kolla land surface temperature and forest cover change is -0.99, -0.90 and -0.43 and p-value 0.07, 0.28 and 0.7, respectively. This is clearly indicating that LST show a strong negative correlation with forest cover change in Dega and Woyna Dega zones. Figure 20 and 21 showed that in central and northeastern areas was cooler LST value while in non-forest areas southern, northern and western part revealed higher LST value (Table 10).

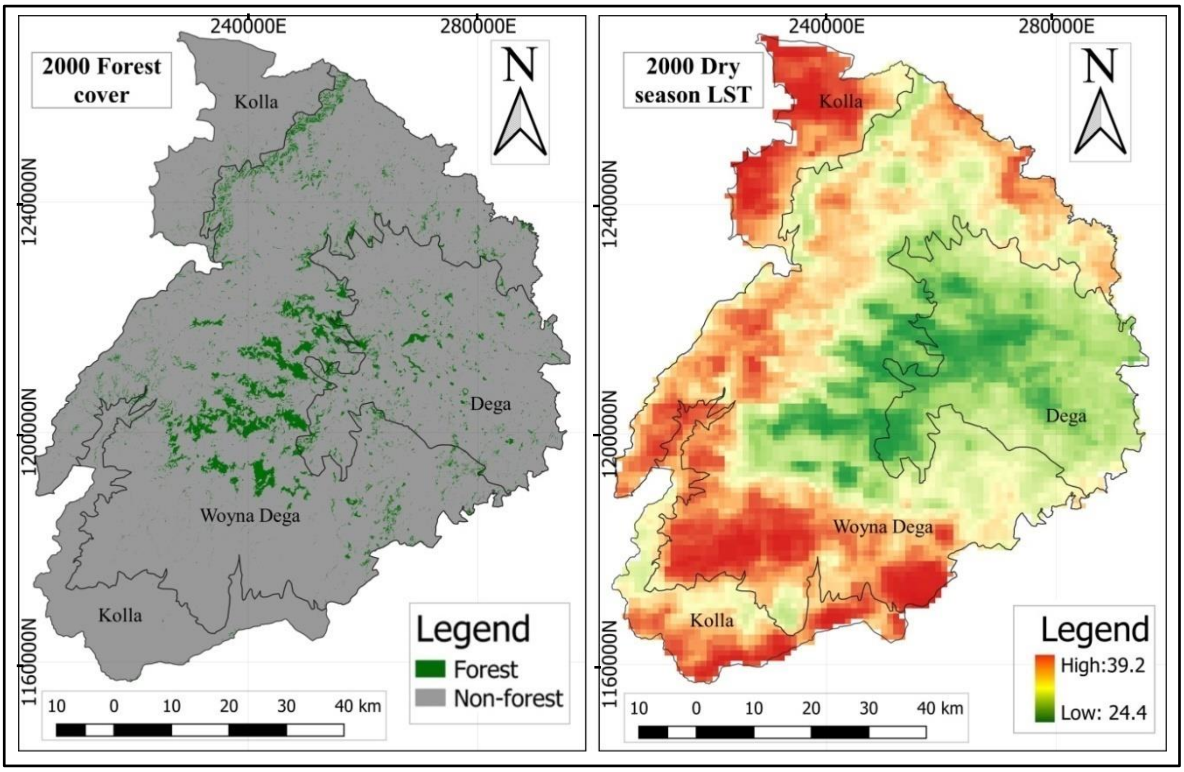

Figure 20: Forest cover and dry season LST map with ACZ of 2000

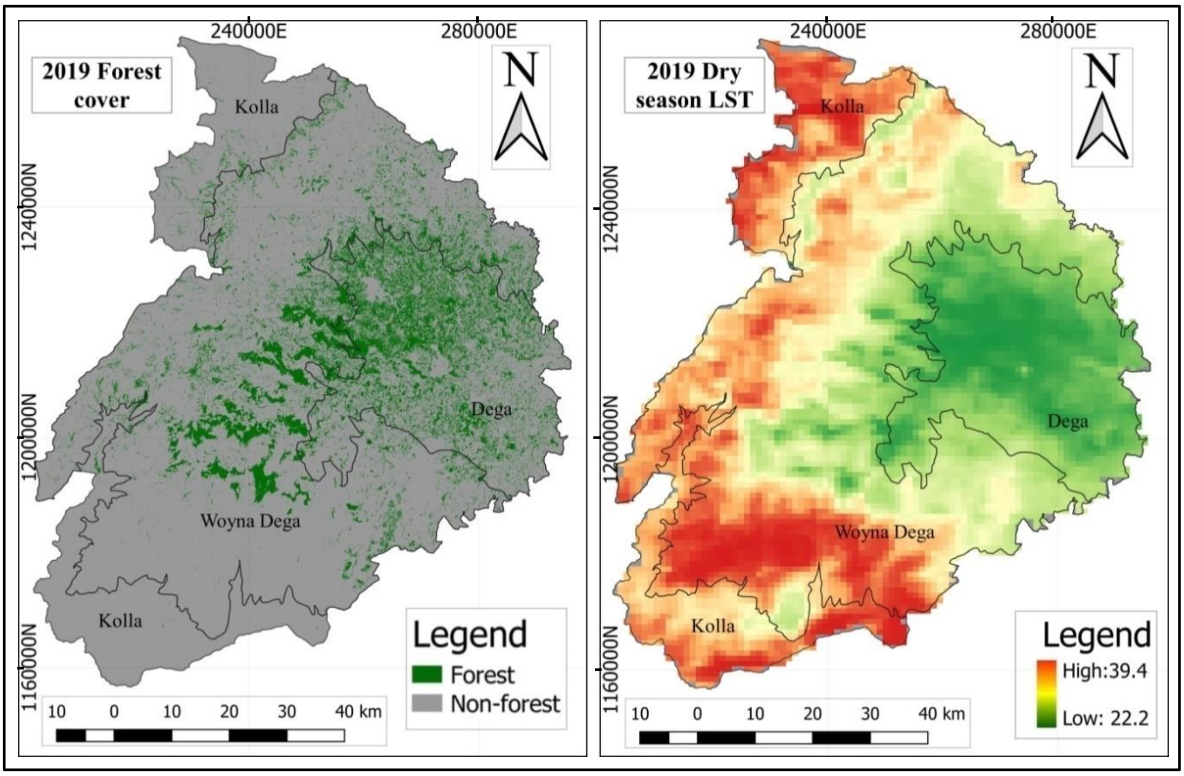

Figure 21: Forest cover and Dry season LST map with ACZ of 2019

Table 10: Relationship of forest cover with zonal LST (agro-climatic zones), at a significance level of α=0.05

	P	r	R^2
Forest cover *vs* Dega LST	0.07	-0.99	0.98
Forest cover *vs* Woyna Dega LST	0.28	-0.90	0.81
Forest cover *vs* Kolla LST	0.7	-0.43	0.2

4.9. Relationship of forest cover and land surface temperature with seasonal variation

The correlation between dry season mean LST and forest cover showed that forest cover and dry season mean LST have a strong and negative correlation (r=–0.93). On the other hand, the correlation between winter season mean LST and forest cover showed weak and positive correlation (r=0.16) (Table 11). From the analysis, it was observed that the forest cover had shown a considerably low land surface temperature over the study years. This is because high forest cover can reduce the amount of heat stored in the soil and surface structures through transpiration. The forest cover and LST map indicated that areas with high forest cover had shown lower LST, whereas, non-forest areas had shown higher land surface temperature. Figure 22 and 23 indicated that higher forest coverage with cooler LST have been observed in the central, east and northeastern of the study area over the study period. On the other hand, in non-forest areas higher LST has been observed in the south low land areas and northwestern part of the study area during the study period.

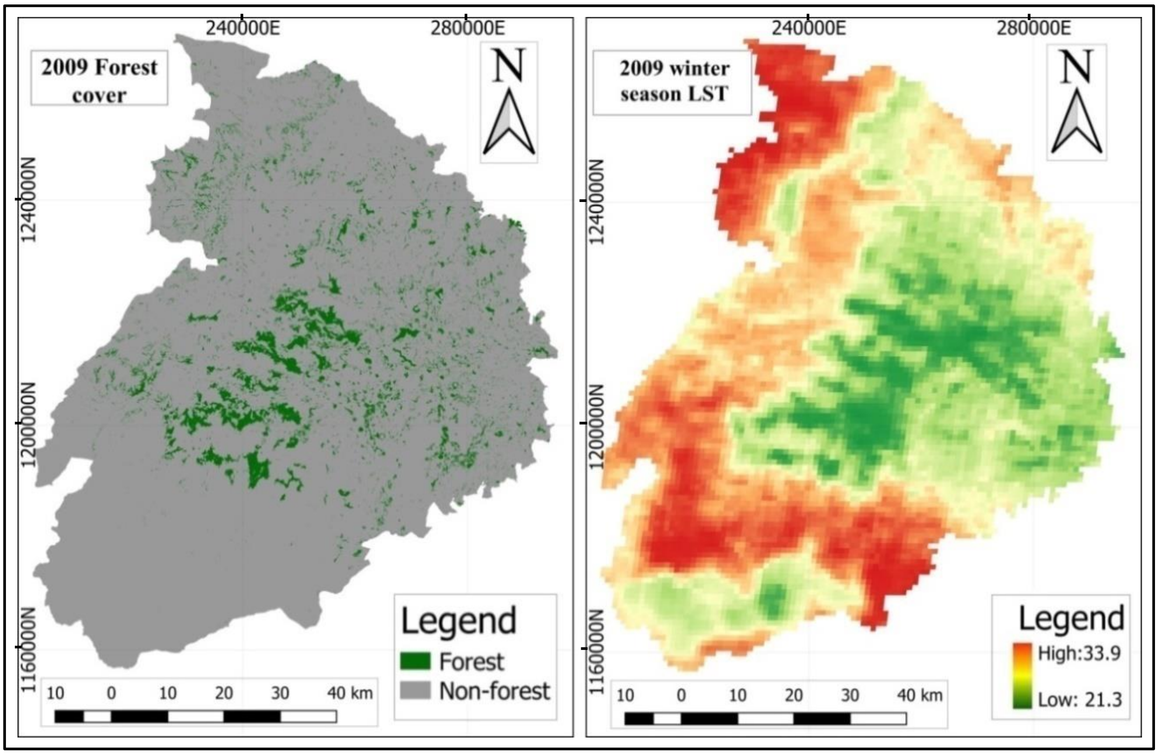

Figure 22: Forest cover and winter season land surface temperature map of 2009

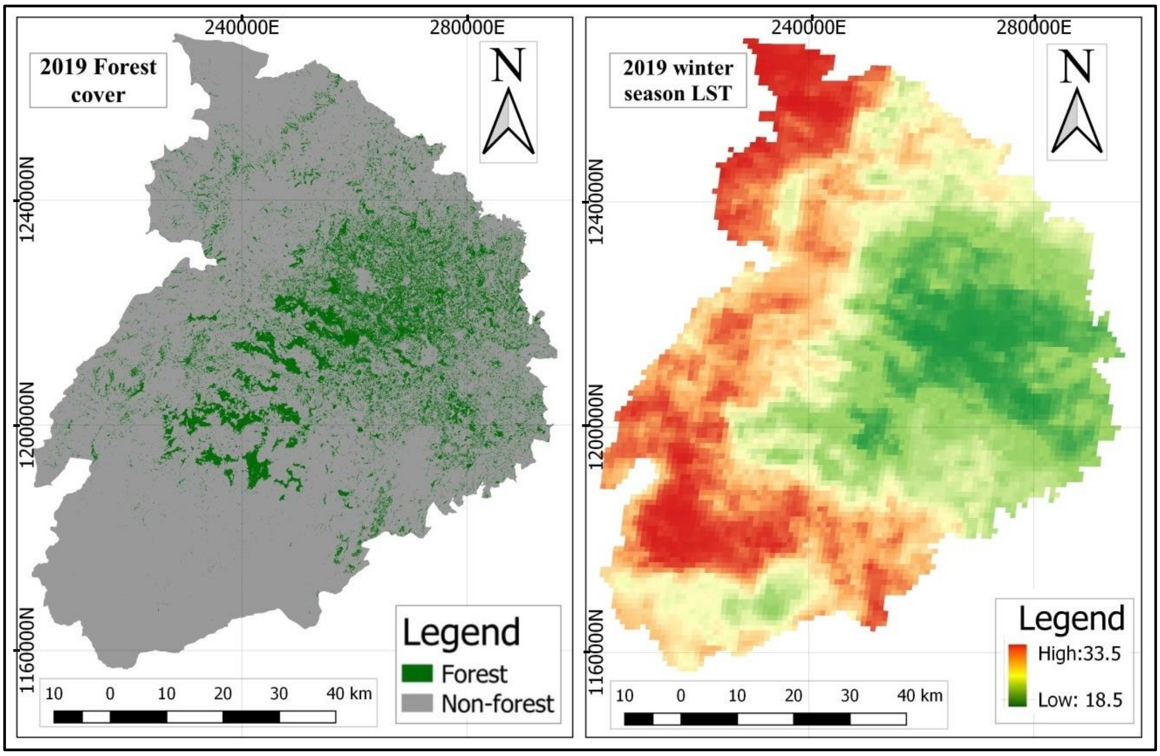

Figure 23: Forest cover and winter season land surface temperature map of 2019

Table 11: Relationship of forest cover with seasonal Land Surface Temperature, at a significance level of α=0.05

	P	r	R^2
Forest cover *vs* Winter LST	0.9	0.16	0.025
Forest cover *vs* Dry season LST	0.23	-0.93	0.86

4.10. Relationship of forest cover and rainfall

The correlation result of forest cover with annual and dry season rainfall revealed that mean annual rainfall and forest cover have weak and positive correlation (r=0.01). But, dry season mean rainfall and forest cover have weak and negative correlation (r=–0.27) (Table 12). The results have shown that there is no significant relationship between forest cover with annual and dry season rainfall as p-value 0.74 and 0.99 which is higher than significant level alpha 0.05. Forest cover and rainfall map Figure 24 and 25 showed that an area which has high forest and rainfall value have been observed in the centeral, East and wastern part of the study area. The result has shown that areas with high forest cover have shown high rainfall value, whereas an area with low forest cover has shown low rainfall over the study area. This indicates that an area which has high forest cover had relatively high rainfall. On the other hand, an area with low foret cover had shown low rainfall.

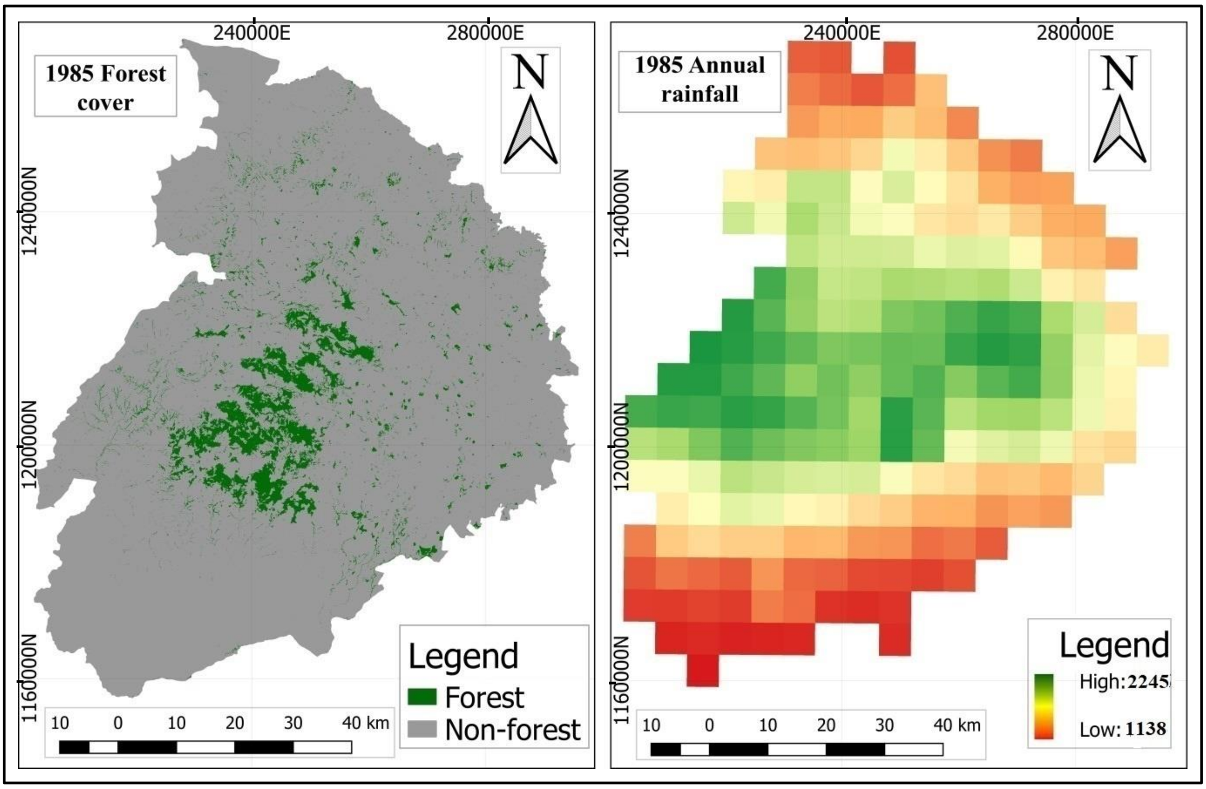

Figure 24: Forest cover and Annual rainfall 1985

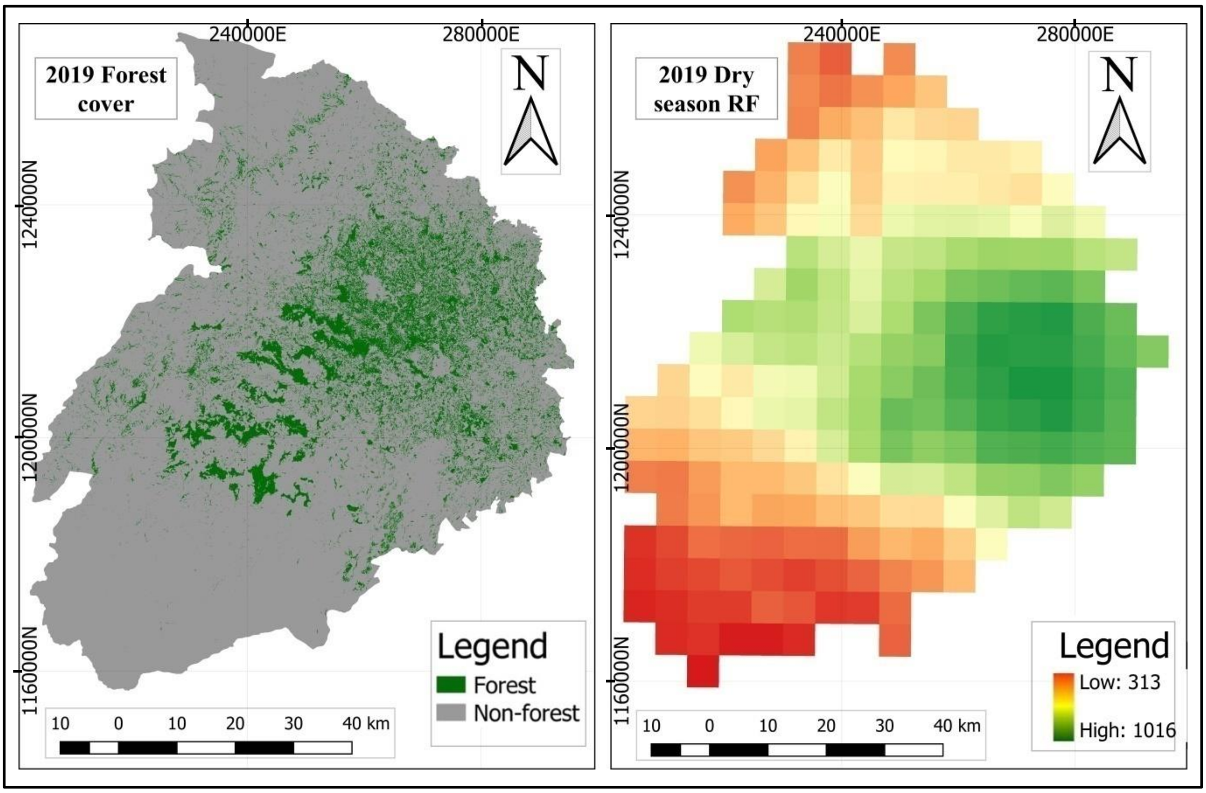

Figure 25: Forest cover and dry season rainfall 2019

Table 12: Relationship of forest and vegetation cover with annual and dry rainfall, at a significance level of α=0.05

	P	r	R^2
Forest cover *vs* Annual RF	0.74	0.01	0.0001
Forest cover *vs* Dry season RF	0.99	-0.27	0.073

4.11. Effect of forest cover dynamics on Land Surface Temperature

The Pearson correlation result indicated that there was a negative correlation between forest cover and land surface temperature (ACZ) in the study area. The correlation coefficient and coefficient of determination for Dega zone mean LST and forest cover revealed strong negative relationship by -0.99 and 0.98 with p-value of 0.07. Likewise, forest cover and Woyna Dega zone LST show a strong relationship with correlation coefficient -0.90 and coefficient of determination 0.81 (P-value= 0.28). Moreover, the correlation coefficient and coefficient of determination for Kolla zone mean LST and forest cover show low negative relationship by -0.43 and 0.2 (P-value= 0.7). The coefficient of determination (R^2) indicated that 98%, 81% and 20% of the variability in Dega, Woyna Dega and Kolla dry season LST is caused by the forest cover change over the study area. The analysis of Pearson correlation result revealed that correlation coefficient and coefficient of determination for winter season LST and forest cover change show a weak positive relationship by 0.16 and 0.025 with p-value of 0.9. In contrast, dry season LST and forest cover change show strong negative relationship with correlation coefficient -0.93 and coefficient of determination 0.86. The coefficient of determination (R^2) indicated that 86% variability in dry season LST is caused by the forest cover change over central, northern and south eastern parts of Awi Zone during the study period. In winter season LST, only 2.5% variability was caused by forest cover dynamics.

Forest cover and mean seasonal LST zonal statistics result revealed that mean dry season LST show moderate decreasing trend as the forest cover increased for the selected study years (2000, 2009 and 2019). This result is aligned with the previous result of Person correlation. In contrast with Mann-Kendall test result, zonal statistics result indicated that as the forest cover increasing mean winter season LST in declining in the first period (2000–2009), but it was increasing in the second period (2009–2019) (Figure 26 and Table 13).

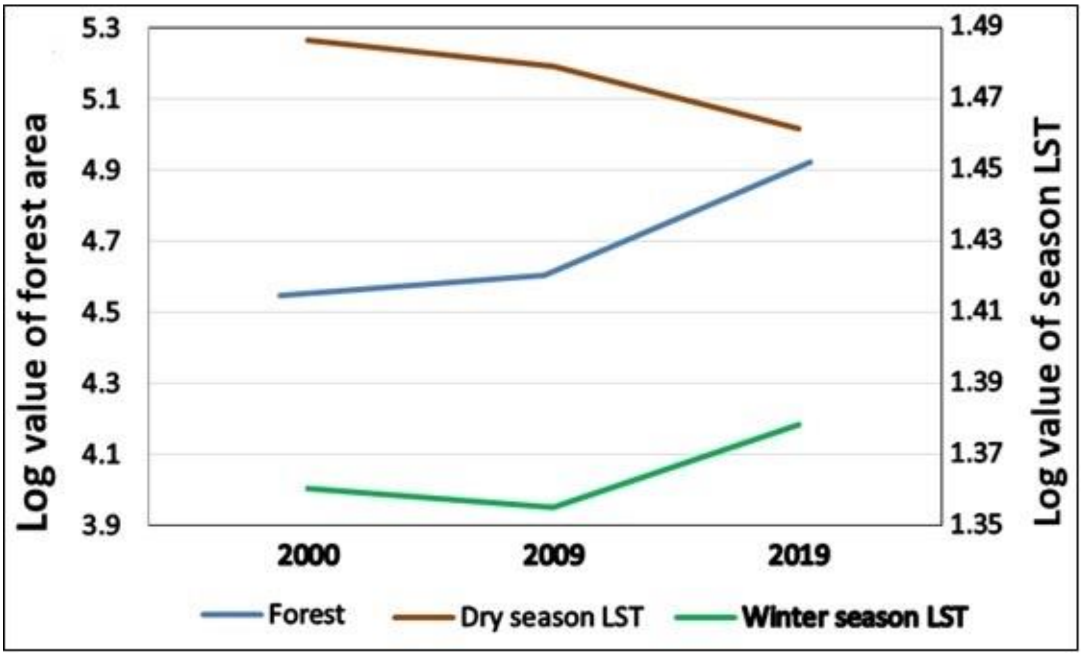

Figure 26: Log value of forest cover and mean seasonal LST

Table 13: Zonal statistics of forest/non-forest areas with minimum, maximum and mean seasonal LST

Year	LULC	Area(ha)	Dry season LST			Winter season LST		
			MIN	MAX	MEAN	MIN	MAX	MEAN
2000	Forest	36887.86	24.48	36.46	30.60	17.68	29.01	22.90
	Non-forest	597622.14	25.05	39.19	33.50	17.30	31.80	24.89
2009	Forest	45230.85	25.79	38.16	30.09	18.09	29.22	22.63
	Non-forest	589279.15	25.70	40.65	33.85	18.63	30.32	24.13
2019	Forest	89997.3	22.29	36.99	28.90	18.54	31.93	23.87
	Non-forest	544512.7	22.52	39.47	32.71	18.79	33.58	26.83

4.12. Effect of forest cover dynamics on rainfall

Pearson correlation result indicated that there was a weak positive correlation of forest cover with annual rainfall in the study area. The correlation coefficient and coefficient of determination for forest cover change and annual rainfall show weak relationship by 0.01 and 0.06 with p-value of 0.74. The coefficient of determination (R^2) indicated that only 7.3% variability in dry season rainfall is caused by the forest cover change in the study area. Likewise, forest cover change and annual rainfall show weak negative relationship with correlation coefficient -0.27 and coefficient of determination 0.0001 (P-value= 0.99). Although zonal statistics result revealed that as the forest cover increases the mean annual rainfall increase/decrease in the study years (1985, 2000, 2009 and 2019). In contrast, zonal statistics result indicated that as the forest cover increasing mean dry season rainfall is increasing in the study areas for the selected years (1985, 2000, 2009 and 2019) (Figure 27 and Table 14).

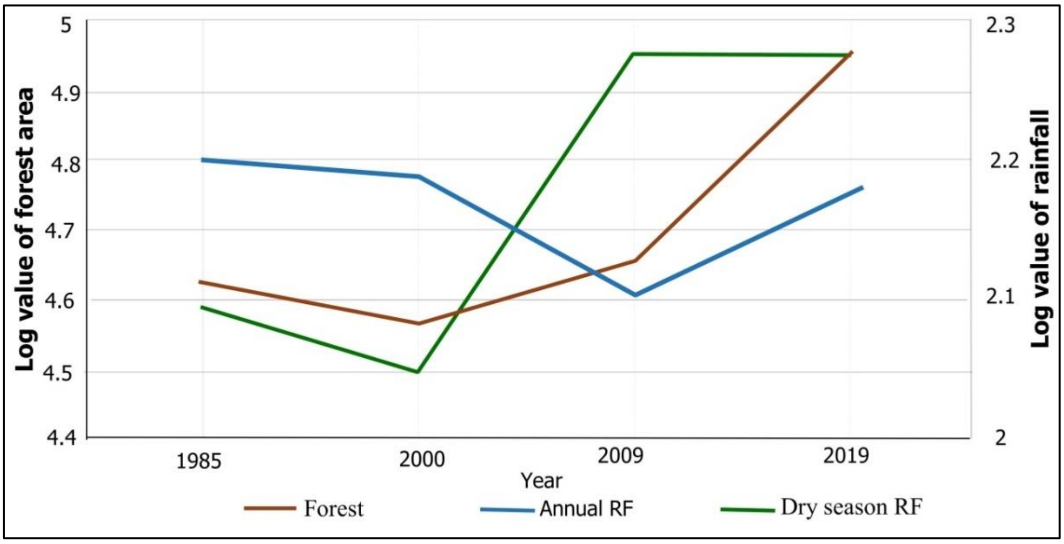

Figure 27: Log value of forest cover with annual and dry season rainfall

Table 14: Zonal statistics of forest/non-forest areas with minimum, maximum and mean annual and dry season rainfall

Year	LULC	Area(ha)	Dry season rainfall			Annual rainfall		
			Min	Max	Mean	Min	Max	Mean
1985	Forest	42741.87	312	726	447	1685	2111	1916
	Non-forest	591768.13	209	721	408	1138	2132	1744
2000	Forest	36887.36	575	993	773	1530	2199	1857
	Non-forest	597622.14	397	1167	786	1131	2174	1752
2009	Forest	45230.85	405	752	508	1293	1739	1515
	Non-forest	589279.15	210	762	447	885	1769	1371
2019	Forest	89997.3	395	985	726	1376	2092	1813
	Non-forest	544512.7	313	1016	591	1056	2025	1619

CHAPTER FIVE

5. DISCUSSION

5.1. Land-use and land-cover change

Understanding the past land-use land-cover dynamics is essential to know the main reason of local climate variability (Jiang and Tian, 2010; Li *et al.*, 2018b). In the present study land-use land-cover change was examined by using remote sensing and GIS technology and the result reveals that there was a decline of agriculture and bare-land whereas forest and other land increase in average. However, land-use land-cover change was continually spontaneous for the last thirty four years since 1985 (Appendix 2). Hence, agricultural land increasing in the first period then decline in the second and last study period. Unlike, bare-land shows a continuous decrease in the study area since 1985. Forest and other land indicate a moderate decline in the first period but increasing for the next two study periods. This indicates the study area was highly influenced by local people with poor land use planning system.

These results are in good agreement with Letchumy *et al.* (2012); Asmamaw (2013); De Mûelenaere *et al.* (2014) which have shown that the land-use land-cover trend was multi-directional. Hence, one LULC type (e.g. bare-land) was changed into other LULC types (e.g. cropland) and vice versa. This is due to lack of appropriate land-use land-cover planning, which is very important for protecting and conserving the surrounding natural environment. Mengistie *et al.* (2013) reported a continuous increase in agricultural lands was observed at the expense of decreasing natural forests, grasslands and woodlands. The study implies increasing land-use land-cover types were the result of grassland conversion and deforestation. The agricultural land was increased by nearly 50%, while bare-land shows high decline in Holeta watershed, central Oromia from 1984 to 2006 (Ayele *et al.*, 2014). Mekonen and Muluberhan (2019) conducted a research in Eritrean refugee settlements in the north-western Tigray that land-use land-cover has changed dramatically with farmlands and settlements were increasing at the expense of the forest land.

5.2. Forest cover change

Forest non-forest result of this study revealed that high amount of forest cover was observed in 2019 with 89997.3ha (14.18%) and the smallest coverage was in 2000 with

36887.3ha (5.8%). The forest coverage was declined in the first period but increasing in the next two study periods. In1985 and 2009 the presentation seems relatively similar but the position of the forest cover relocated (distributed) in most central areas. Accordingly, it shows dramatic transition from one to other study period. Hence, deforestation was occurred in central boundaries of the dense natural forest and its surrounding area is shrinking down. While, conversion from non-forest to forest (afforestation/reforestation) occurred in the western and central part with several smaller patch of forest. This indicated that forest cover change in Awi zone is due to anthropogenic factor as reveled in earlier studies (Berhanu and Suryabhagavan, 2014; Qamer et al., 2016).

Significant differences were found from the result of rate of forest cover change during three study periods. The major finding of the present study is the alarming rate of reduction of natural habitats during the period 1985 to 2000. Almost 17770.9 ha of the forest area decreased with the expense of other land-use land-cover classes during this period. This result is consistent with De Mûelenaere *et al.* (2014); Jacob *et al.* (2015); Abiyot (2017) that shows the most significant decline of natural forest whereas plantation forest was increasing. One question still unanswered is the exact reason for afforestation/reforestation. The first possible reason could be an opening of integrated watershed management and natural resource protection as a nationwide campaign by the government since 2000. In the early 2000s, community based integrated watershed development was introduced to achieve wider integrated natural resource management and livelihood improvement (Gebrehaweria *et al.*, 2016).

The second reason could be the recent findings of a large plantation forest potential by the local community with two major species *Eucalyptus spp.* and *Acacia decurrens* established in the study area. Moreover, cropland show that decreasing trend in the second and third study periods with 22256.9 ha (1.32%) and 46195.2 ha (7.28%). This is probably the spread of plantation by converting from other LULC into forest land in recent years. Tesfa *et al.* (2016) reported the major reasons have been positively contributed to the increase of the share of forest coverage such as afforestation, community and private level tree plantation of *Sesbania susban*, tree *Lucerne* and *Eucalyptus* trees. The result of this conversion from agriculture land to forest can be the quantitative and qualitative decline of soil fertility of the area. Birhanu *et al.* (2014) contacted a research to evaluate the status of soil acidity of the Fagtalekoma district, Awi Zone. Their result shows cropland and grazing land contains strongly acidic value with pH<5.5. In contrast, the bamboo dominated natural forest which is found in the central part of the study seems to decrease dramatically. Ethiopia is one of the four regions in Africa that are highlighted with a high proportion (greater than 40%) of potentially threatened species existed (Stévart *et al.*, 2019). Tibebu *et al.* (2018) reported their is revegetation process occurred in rain-fed agriculture areas of the country from 1986 to 2010. The causes of deforestation might be due to the habits of the local community and their extreme poverty, which led them too dependent on forest resources and despite attempts to implement a management transfer system, the illegal exploitation remained considerable (Dinku and Suryabhagavan, 2019).

5.3. Trend of land surface temperature and rainfall

Mann–Kendall test revealed a statistically significant decreasing trend of mean and minimum land surface temperature in Dega agro-climatic zone from the year 2000 to 2019. The result also indicated that in Dega (maximum), Woyna Dega and Kolla zones land surface temperature show insignificant decreasing/increasing trend. Moreover, the result of mean, minimum and maximum seasonal LST analysis have shown insignificant trend for the last twenty years since 2000. A similar pattern of results was obtained by Hou *et al.* (2018) show decreasing annual minimum temperature trend. On the other hand, Tekleab *et al.* (2013) conducted a research in Abaya/upper Blue Nile basin reported that increasing trends in temperature at different weather stations was observed for the mean annual, rainy, dry and small rainy seasons. Abebe and Arega (2019) and Baoa *et al.* (2019) also exhibited decadal minimum, maximum and average temperature has shown increasing trend.

Mann–Kendall test revealed that mean, minimum and maximum annual and dry season rainfall trend analysis result show insignificant increase over the last three decades in Awi zone. In dry season, mean, minimum and maximum rainfall amount ranged in 137–458 mm, 63.6–231 mm and 246–682 mm, respectively. This result indicates that annual and dry season rainfall is rising insignificantly in the study area from 1981 to 2019. This result is in line with Worku (2016) that rainfall show statistically non-significant increasing trend in annual mean rainfall time from the year 1983 to 2014 in western Tigray region, Ethiopia. According to Tenaw and Habte (2018) western, central rift valley and eastern area of Ethiopia indicated an increasing trend of rainfall. In contrast, Negash *et al.* (2013) reported that annual and dry season rainfall data show significant decreasing trends in northern, northwestern and western parts of the Ethiopia, whereas a few areas in eastern areas show increasing annual rainfall trends. In most other parts of the country (approx.

77% of the area) the annual rainfall series shows no significant trend during 1951–2000. Many studies near to Abay basin and other areas of the country have also found insignificant trends at different spatial and temporal scales (Tesfay *et al.*, 2018).

5.4. Relationship between forest cover with land surface temperature and rainfall

Pearson Correlation coefficient result of mean LST along agro-climatic zone and forest cover revealed that -0.99 for Dega, -0.90 for Woyna Dega and -0.43 for Kolla zone, respectively. This result indicates that the reason for negative correlation in Dega and Woyna Dega Zone is expansion of afforestation/reforestation in the study area. Likewise, dry season LST revealed strong negative correlation (r) -0.93, whereas winter season show weak positive correlation (r=0.16) with forest cover for the last twenty years. The reason could be in winter season (rainy) the LST is not influenced by forest as compared to dry season. This shows forest plays a vital role in dry season surface temperature cooling. According to forest transition result, around 21,877 ha (3.44%) of non-forest was converting into forest cover during 2000 to 2019 in central and eastern part of the study area. The result is in line with Temesgen *et al.* (2018) that the vegetation cover (EVI) is negatively correlated with land surface temperature both in winter and dry season. In contrast, Chuai *et al.* (2013) reported that temperature and coniferous and broadleaf forest areas exhibited positive correlation.

The analysis of Pearson Correlation result showed that forest cover and rainfall have showed weak correlation coefficient(r) with annual and dry season value of 0.01 and -0.27, respectively. The result indicates that forest cover have insignificant low correlation with annual and dry season rainfall. This result is in line with Alemayehu *et al.* (2017) that conducted a study in Central Rift Valley reported there is insignificant correlation between long-term rainfall with forest and woodland cover change in the area. In contrast, Hou *et al.* (2018) reported a forest cover dynamics have a significant variability on the local climatic condition.

5.5. Effect of forest cover dynamics on land surface temperature and rainfall

Coefficient of determination between forest cover and land surface temperature for different agro-climatic zones is computed. Accordingly, the result revealed that Dega zone R^2 = 0.98 (r =-0.99 and p-value 0.07), Woyna Dega zone R^2 = 0.81 (r =-0.9 and p-value 0.28) and Kolla zone R^2 = 0.2 (r =-0.43 and p-value 0.7), respectively. This indicates that

98%, 81% and 20% variability in Dega, Woyna Dega and Kolla zone is caused by the forest cover dynamics. The reason for this result could be in Dega and Woyna Dega zones watershed conservation and rehabilitation program and/or dramatic expansion of plantation forest by the local community with two major species *Eucalyptus spp*. and *Acacia decurrens*. Forest cover change has critical contributions for climate variability (Hou *et al.*, 2018; Liu *et al.*, 2018). Alemayehu *et al.* (2017) reported that increase in maximum and daily temperature in rift valley floor was well correlated with forest and woodland cover change (R^2 =0.62). Nevertheless, their study minimum daily temperature show poor correlation in valley floor.

In addition, coefficient of determination (R^2) between forest cover and winter season mean LST was 0.025. This result shows that 2.5% in winter season but 86% in dry season mean LST variability is caused by the forest cover dynamics in the study area. The reason for this result could be in dry season LST is highly controlled by the existence of forest cover. Therefore, the effect of forest cover change on LST in dry season is higher than winter season. Worku *et al.* (2019) reported in North Gonder zone (2000–2017) vegetation cover and dry season land surface temperature negatively strong correlation by r = –0.89 (p-value=0.29 and R^2 = 0.8). Additionally, forest cover with annual mean rainfall showed weak correlation by r= 0.01 (p-value=0.74) and forest cover with dry season mean rainfall showed weak correlation by r = –0.27 (p-value=0.99). This means the effect of forest cover on rainfall variability is negligible. According to Yitea and Bethel (2015) exhibited that in Gojam zone the forest cover change show correlation with rainfall (R^2 = 0.45). In contrast, Hou *et al.* (2018) reported both reforestation and deforestation contribute to significant decline in dry season runoff, while climate variability yielded positive effects in their studied watersheds. Alemayehu *et al.* (2017) reported remnant forests had a significant effect on rainfall observed for two exceptional years (2012–2013).

CHAPTER SIX

6. CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

North-western part of the country has been under continual LULC changes for the last fifty years. The finding of this study showed that there is a substantial transition of LULC types in the study area since 1985. Expansion of agricultural land due to high rate of population growth has been shifting bare-land, other land and slightly forest land in the first study period (1985–2000). In the second and third period, agriculture and bare-land declined while forest and other land increased. This alteration has its own positive or negative impact on the climatic condition of the study area. Therefore, it is possible to conclude that the reason for the alteration of the land-use land-cover was anthropogenic because the rate of land-use land-cover change was continually spontaneous for the last three decade. More interestingly, the forest coverage shows unpredicted change throughout the study period. As indicated in the result, it was decreased only in the first period but in the second and third period increases recorded since 2000. However, in the central part large area of compound forest reduction was found in 1985 which shrink down in 2019. However, most part of central, eastern and northeastern part of the study area show expansion of small patch of forest land which could be afforestation and/or reforestation. Therefore, it is possible to conclude that the existence of forest change implies that there was a high amount of natural forest resource decline followed by social, environmental and economic problems in the study area. In contrast, a recent year's expansion of plantation and/or reforestation gives a chance to minimize anthropogenic pressure for the remaining natural forest to conserve and protect flora and fauna of the study area. Further experimental investigations are needed to understand the reason for this change and the opportunity potential behind it.

Land surface temperature trend line across agro-climatic zones shows different patterns in the study area. In Dega zone, the LST trend analysis result revealed scientifically significant decreasing trend of mean and minimum LST with a p-value of 0.015 and 0.035 (α=0.05), respectively. However, Woyna Dega and Kolla zones LST show insignificant decreasing/increasing trend. Here, it is possible to conclude that in moist highland part of the study area was under a significant decrease of LST by mean value 0.13C°/yr. and by minimum value 0.12C°/yr. for the last twenty years. In addition, winter season mean, minimum and maximum LST trend analysis result show scientifically insignificant decrease. Furthermore, dry season mean and minimum decreased while maximum LST was increased. One reason for winter season land surface temperature decline could be an increasing of annual rainfall as the greenness is high at rainy period. Furthermore, MK test result for annual and dry season rainfall show a statistically insignificant increasing trend in the study period (1981–2019). Annual and dry season mean, minimum and maximum rainfall values increasing trend with similar pattern. Rainfall trend was rising insignificantly with 0.003 mm/decade and 0.005 mm/decade in mean annual and dry season rainfall for the last four decade since 1981. In conclusion, the effect of forest cover on annual and dry season rainfall is negligible in the study area.

The correlation coefficient and coefficient of determination for Dega zone LST and forest cover revealed a strong negative relationship. Likewise, Woyna Dega zone LST and forest cover show a strong relationship. While, the correlation coefficient and coefficient of determination for Kolla zone LST and forest cover show weak negative relationship. The coefficient of determination (R^2) indicate that 98%, 81% and 20% variability in Dega, Woyna Dega and Kolla LST is caused by the forest cover change in the study area since 2000. Therefore, in Dega and Woyna Dega zones land surface temperature is highly influenced by anthropogenic factor afforestation and/or reforestation mostly in eastern, central and north eastern part of Awi zone. In addition, correlation coefficient and coefficient of determination for winter season LST and forest cover show a weak positive relationship by 0.16 and 0.025 (p-value 0.9). In contrast, dry season LST and forest cover change show strong negative relationship with correlation coefficient 0.93 and coefficient of determination 0.86 (p-value 0.23). The coefficient of determination (R^2) indicated that 86% variability in dry season LST and 2.5% winter season LST is caused by the forest cover change over central, eastern and north eastern parts of the study area. Hence, in dry season land surface temperature variability is highly influenced by forest cover rather than winter season. This is because forests cover regularly balance the temperature of an area over the year. The coefficient of determination (R^2) indicated that 6.6% variability in annual and 0.01% dry season rainfall is caused by the forest cover change in the study area. In conclusion, the effect of forest cover dynamics in annual and dry season rainfall is negligible in the study period (1985–2019).

6.2. Recommendations

- As the population number is increasing obviously scarcity of natural resources occurred. As a result, people always explore the natural resources found in their surroundings to survive which causes damage. Thus, it is highly recommended to implement sustainable land-use land-cover planning, promoting agricultural intensification systems with irrigation and applying integrated watershed management system should carry out to control the decline and deterioration of entire natural resource in the study area.
- Awi Zone areas including have a very wide potential of bamboo forest the so-called the new green gold. Hence, it is recommended to introduce participatory forest management (PFM) that the community can be economically benefited as well as the natural environment will be conserved.
- It is recommended that the effect of forest cover dynamics on land surface temperature and rainfall and this impact in livelihood level should be considered for further analysis in the study area.

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Appendices

Appendix 1: Statistical information of accuracy assessment for the year 1985, 2000, 2009 and 2019.

LULC Type	1985 Producers Accuracy (%)	1985 User's accuracy (%)	2000 Producers Accuracy (%)	2000 User's accuracy (%)	2009 Producers Accuracy (%)	2009 User's accuracy (%)	2019 Producers Accuracy (%)	2019 User's accuracy (%)
Agriculture	87.27	90.57	97.92	85.45	92.16	94	92.16	95.12
Bare land	63.64	63.64	92.31	85.71	100	100	100	66.67
Forest	100	72.73	87.50	87.50	63.64	87.5	63.64	88.24
Other land	86.36	90.48	88.89	100	100	86.21	100	96.67
Overall accuracy (%)	**85.42**		**89.11**		**91.58**		**92.55**	
kappa statistics	**0.78**		**0.83**		**0.86**		**0.88**	

Confusion matrix for LULC map of 1985.

Map Data	Reference Data: Agriculture	Bare land	Forest	Other land	Grand Total	User accuracy
Agriculture	**48**	3	0	2	**53**	**90.57**
Bare land	3	**7**	0	1	**11**	**63.64**
Forest	2	1	**8**	0	**11**	**72.73**
Other land	2	0	0	**19**	**21**	**90.48**
Grand Total	**55**	**11**	**8**	**22**	**96**	
Producer accuracy	**87.27**	**63.64**	**100**	**86.36**	**85.42**	

Confusion matrix for LULC map of 2000.

Map Data	Reference Data: Agriculture	Bare land	Forest	Other land	Grand Total	User Accuracy
Agriculture	**47**	0	3	5	**55**	**85.45**
Bare land	0	**12**	0	2	**14**	**85.71**
Forest	1	0	**7**	0	**8**	**87.50**
Other land	0	0	0	**24**	**24**	**100**
Grand Total	**48**	**13**	**8**	**27**	**101**	
Producer Accuracy	**97.92**	**92.31**	**87.50**	**88.89**	**89.11**	

Confusion matrix for LULC map of 2009.

Map Data	Reference Data: Agriculture	Bare land	Forest	Other land	Grand Total	User Accuracy
Agriculture	**47**	0	3	0	**50**	**94**
Bare land	0	**8**	0	0	**8**	**100**
Forest	1	0	**7**	0	**8**	**87.5**
Other land	3	0	1	**25**	**29**	**86.21**
Grand Total	**51**	**8**	**11**	**25**	**95**	
Producer Accuracy	**92.16**	**100**	**63.64**	**100**	**91.58**	

Confusion matrix for LULC map of 2019.

Map Data	Reference Data: Agriculture	Bare land	Forest	Other land	Grand Total	User Accuracy
Agriculture	**39**	0	2	0	**41**	**95.12**
Bare land	2	**4**	0	0	**6**	**66.67**
Forest	1	0	**15**	1	**17**	**88.24**
Other land	1	0	0	**29**	**30**	**96.67**
Grand Total	**43**	**4**	**17**	**30**	**94**	
Producer Accuracy	**90.70**	**100**	**88.24**	**96.67**	**92.55**	

Appendix 2: Land-use land-cover transition matrix.

Land-use land-cover transition matrix (1985–2000)

Land-Use Land-Cover (1985)		Land-Use Land-Cover (2000)					
		Forest	Agriculture	Other-land	Bare land	Total	Class change
	Forest	**24970.90**	4907.90	12250.92	612.13	**42741.85**	**-5854.81**
	Agriculture	2171.49	**249417.44**	43776.54	22937.91	**318303.38**	**51632.28**
	Other-land	5169.17	79105.83	**87300.20**	4361.20	**175936.40**	**-22132.9**
	Bare land	4575.49	36504.48	10475.08	**45973.20**	**97528.25**	**-23643.81**
	Total	**36887.04**	**369935.66**	**153802.74**	**73884.44**	**634510**	

Land-use land-cover transition matrix (2000–2009)

Land-Use Land-cover(2000)		Land-Use Land-Cover (2009)					
		Forest	Agriculture	Other-land	Bare land	Total	Class change
	Forest	**26826.20**	1494.15	5557.29	3009.61	**36887.24**	**8343.53**
	Agriculture	2354.65	**282331.38**	72183.56	13066.03	**369935.61**	**-22256.9**
	Other-land	14639.36	37348.29	**99788.62**	2026.46	**153802.73**	**27249.33**
	Bare land	1410.57	26504.90	3522.58	**42446.29**	**73884.34**	**-13335.96**
	Total	**45230.78**	**347678.71**	**181052.06**	**60548.38**	**634510**	

Land-use land-cover transition matrix (2009–2019)

Land-Use Land-Cover (2009)		Land-Use Land-Cover (2019)					
		Forest	Agriculture	Other-land	Bare land	Total	Class change
	Forest	**33679.90**	2967.08	8071.02	513.20	**45231.20**	**44766.05**
	Agriculture	27824.24	**231294.05**	80247.98	8312.52	**347678.79**	**-46195.17**
	Other-land	26527.34	42991.37	**110361.07**	1172.56	**181052.34**	**19558.40**
	Bare land	1965.77	24231.12	1930.67	**32420.33**	**60547.90**	**-18129.8**
	Total	**89997.25**	**301483.62**	**200610.74**	**42418.61**	**634510**	

Land-use land-cover transition matrix (1985–2019).

Land-Use Land-Cover (1985)		Land-Use Land-Cover (2019)					
		Forest	Agriculture	Other-land	Bare land	Total	Class change
	Forest	**27596.30**	5793.48	8738.88	613.31	**42741.82**	**47255.48**
	Agriculture	36534.17	**171723.21**	97735.76	12310.30	**318303.45**	**-16819.92**
	Other-land	22152.18	68536.36	**83090.82**	2156.19	**175935.56**	**24675.07**
	Bare land	3714.80	55430.52	11045.30	**27338.52**	**97529.13**	**-55110.59**
	Total	**89997.3**	**301483.53**	**200610.63**	**42418.53**	**634510**	

Appendix 3: Mean, minimum and maximum LST with agro-climatic zones (2000−2019).

Year	Dega LST			Woyna Dega LST			Kolla LST		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
2000	30.66	24.48	34.35	33.68	25.05	38.98	35.41	32.46	39.19
2001	30.33	24.89	33.78	33.30	25.20	38.43	34.10	30.45	37.63
2002	30.81	25.20	34.23	33.30	25.20	38.43	34.64	31.05	38.66
2003	32.37	26.22	35.99	34.58	26.42	39.73	35.63	32.36	39.28
2004	31.25	26.17	34.94	33.97	26.20	38.51	35.39	31.70	38.92
2005	31.62	26.33	34.79	33.82	26.32	38.23	35.04	31.62	38.78
2006	31.09	25.87	34.02	33.46	25.40	38.62	34.35	31.04	38.06
2007	30.78	25.32	34.51	33.91	25.69	39.91	34.59	31.25	38.77
2008	30.26	24.72	33.71	33.38	24.72	38.96	34.66	31.35	39.96
2009	30.57	25.79	34.24	34.07	25.70	39.57	35.86	32.44	40.65
2010	30.83	25.18	34.65	34.46	26.09	40.07	35.73	32.34	40.43
2011	30.91	25.48	35.32	34.58	25.82	40.53	36.27	32.48	40.58
2012	31.92	26.20	35.54	34.57	26.28	40.46	35.67	32.47	40.44
2013	31.24	25.51	34.86	34.35	25.63	39.47	35.62	32.10	39.76
2014	27.98	22.35	32.08	32.01	23.63	36.59	33.59	29.59	38.18
2015	29.67	23.54	33.19	33.42	25.05	38.42	34.93	30.93	38.42
2016	30.19	25.03	34.41	34.01	25.71	39.98	35.90	31.76	39.76
2017	27.78	21.50	32.49	33.33	24.96	38.92	34.63	31.10	38.84
2018	29.25	24.08	33.59	33.33	24.96	38.92	35.33	31.80	39.56
2019	27.11	22.29	31.36	32.95	24.42	38.63	35.33	31.67	38.94

Appendix 4: Mean, minimum and maximum LST for winter and dry season (2000−2019).

Year	Winter season LST			Dry season LST		
	Mean	Min	Max	Mean	Min	Max
2000	24.77	17.30	31.80	33.33	24.48	39.19
2001	26.72	19.82	32.46	32.60	24.89	37.63
2002	28.06	21.18	33.19	33.02	25.20	38.66
2003	26.93	19.64	32.35	34.31	26.22	39.73
2004	26.93	19.64	32.35	33.66	26.17	38.92
2005	26.95	20.51	32.23	33.58	26.32	38.78
2006	25.35	17.78	31.02	33.13	25.40	38.62
2007	25.38	18.46	31.45	33.39	25.32	39.91
2008	24.03	18.09	30.32	32.97	24.72	39.96
2009	27.97	21.31	33.92	33.67	25.70	40.65
2010	26.25	19.21	32.53	33.94	25.18	40.43
2011	26.33	19.25	32.97	34.12	25.48	40.58
2012	25.94	19.04	31.99	34.22	26.20	40.46
2013	26.62	19.74	33.26	33.94	25.51	39.76
2014	24.68	17.37	29.99	31.46	22.35	38.18
2015	25.58	18.99	31.29	32.91	23.54	38.42
2016	25.02	18.06	30.93	33.56	25.03	39.98
2017	24.46	18.18	29.99	32.00	21.50	38.84
2018	25.65	18.83	31.28	32.81	24.08	39.56
2019	26.42	18.54	33.58	32.19	22.29	39.47

Appendix 5: Mean, minimum and maximum rainfall for winter and dry season (2000−2019).

Year	Annual rainfall			Dry season rainfall		
	Mean RF	**Min RF**	**Max RF**	**Mean RF**	**Min RF**	**Max RF**
1981	1722.65	1113.10	2235.99	241.23	110.04	391.50
1982	1622.73	934.21	2059.40	370.02	136.83	641.57
1983	1489.60	985.72	2018.67	226.83	110.28	348.05
1984	1545.07	974.31	1910.30	137.34	64.88	246.32
1985	1772.12	1138.16	2245.92	238.34	122.05	423.83
1986	1503.14	999.63	1858.64	204.46	112.09	343.04
1987	1641.97	1103.12	2073.11	316.35	174.73	500.23
1988	1740.65	1129.35	2280.25	270.85	121.72	395.64
1989	1737.78	1031.87	2160.00	266.78	105.06	445.72
1990	1515.68	1026.36	2056.53	180.94	98.50	274.55
1991	1762.63	1064.09	2159.26	267.53	121.39	442.03
1992	1674.78	1046.11	2165.96	393.97	184.93	597.06
1993	1668.29	1048.29	2087.41	343.98	172.76	586.34
1994	1522.11	1034.28	1912.08	203.15	123.24	335.59
1995	1534.89	973.97	2018.30	233.95	106.42	411.29
1996	1727.73	1111.92	2300.81	292.63	151.83	453.21
1997	1737.32	1127.07	2157.90	396.99	177.06	609.18
1998	1715.46	1134.48	2128.92	283.83	141.93	437.07
1999	1684.28	1130.68	2218.70	315.12	187.95	424.34
2000	1778.69	1131.74	2283.99	458.58	231.71	681.24
2001	1538.4	994.72	1923.97	273.27	136.73	403.85
2002	1412.71	886.90	1783.27	259.19	110.50	445.30
2003	1422.03	930.76	1827.40	188.39	92.29	323.54
2004	1524.69	1006.39	1954.31	266.53	136.67	443.38
2005	1513.18	994.87	1912.82	234.83	70.59	409.51
2006	1918.67	1140.51	2451.03	311.95	132.21	452.11
2007	1659.89	1102.27	2086.43	249.51	127.56	410.80
2008	1767.60	1090.92	2287.08	263.72	149.79	452.04
2009	1394.05	884.47	1780.23	260.48	122.90	444.60
2010	1577.40	1011.73	1998.57	173.93	63.59	288.81
2011	1520.29	938.77	1934.76	195.45	87.60	337.19
2012	1631.84	1034.23	2150.27	212.86	103.77	344.81
2013	1743.86	1061.50	2225.12	247.93	145.13	338.57
2014	1836.67	1152.33	2293.64	412.92	189.73	691.97
2015	1648.01	1031.76	2204.08	284.44	146.63	407.11
2016	1641.93	1097.20	2122.88	234.03	106.79	346.65
2017	1908.11	1106.15	2443.17	356.40	163.12	565.33
2018	1604.90	1009.11	1997.80	272.55	134.46	438.09
2019	1787.05	1141.38	2253.55	380.22	197.39	613.69

Appendix 6: Forest cover area statistics along agro-climatic zones.

Year	Dega	Woyna Dega	Kolla
	Area (ha)	Area (ha)	Area (ha)
2000	6683.4	29173.9	1029.9
2009	11522.7	31006.2	2701.9
2019	39829.7	47589.5	2578.1

Appendix 7: Two False Color Composite (FCC) scenes of Landsat 5(1985) and Landsat 8(2019) (A&C) and after mosaic clipped FCC image of Awi zone for 1985(B) and 2019(D).