Analyzing the Impact of Land Use Land Cover Change on Climate Variability Using Geospatial Techniques. A Case of Wolaita Zone, Southern Region of Ethiopia

Asfaw Anjulo Asaro

A Thesis Submitted to the Department of Geomatics Engineering

School of Civil Engineering & Architecture and Presented in Partial fulfillment of the Requirement for the Degree of Master's in Geo informatics Engineering

Office of Graduate Studies

Adama Science and Technology University

June 2023

Adama, Ethiopia

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DECLARATION

I hereby declare that this Master's entitled "Analyzing the Impact of Land Use Land Cover Change on Climate Variability Using Geospatial Techniques. A Case of Wolaita Zone, Southern Region of Ethiopia" is my own work and has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that were used for this thesis have been duly acknowledged through citation.

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I, the major advisor/supervisor of this thesis, hereby certify that I have read the revised version of the thesis entitled “Analyzing the Impact of Land Use Land Cover Change on Climate Variability Using Geospatial Techniques. A Case of Wolaita Zone, Southern Region of Ethiopia “prepared under my guidance by Asfaw Anjulo Asaro submitted in partial fulfillment of the requirement for the degree of masters of science in Geo informatics. Therefore, I recommend the submission of the revised version of the thesis to the department following the applicable procedures.

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APPROVAL OF BOARD REVIEWERS

I/we, the advisors of the thesis entitled "Analyzing the Impact of Land Use Land Cover Change on Climate Variability Using Geospatial Techniques. A Case of Wolaita Zone, Southern Region of Ethiopia" and developed by Asfaw Anjulo, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

____________________	______________________	_________________
Major Advisor	Signature	Date

We, undersigned members, of the board of Examiners of the thesis by Asfaw Anjulo Asaro have read and evaluated the thesis entitled "Analyzing the Impact of Land Use Land Cover Change on Climate Variability Using Geospatial Techniques. A Case of Wolaita Zone, Southern Region of Ethiopia" and examined the candidates during the open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science degree in Geo informatics.

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AEZ	Agro Ecological Zone
CV	Coefficient of Variation
DEM	Digital Elevation Model
ENVI	Environment for Visualizing Images
ETM^+	Enhanced Thematic Mapper plus
FAO	Food and Agricultural Organization
GCS	Geographic Coordinate System
GIS	Geographic Information System
IDW	Inverse Distance Weight method
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Inter Tropical Convergence Zone
LST	Land Surface Temperature
LULC	Land Use Land Cover
MLC	Maximum Likelihood Classification
MODIS	Moderate Resolution Imaging Spectroradiometer
MSS	Multispectral Scanner
NASA	National Aeronautics and Space Administration
NDVI	Normalize Difference Vegetation Index
NME	National Meteorological Agency
OLI/TIRS	Operational Land Imagery/Thermal Infrared Sensor
SD	Standard Deviation
SPSS	Statistical Package for Social Science
SRTM	Shutle Radar Topography Mission
USGS	United States Geological survey

ABSTRACT

Climate variation refers to long-term shifts in temperatures and rainfall patterns. Climatevariation in Wolaita zone was caused by rapid population growth, improper traditional farming techniques and deforestation of forests. Depending on these causes wolaita zone has been highly impacted by climate variation. Some studies have been conducted in Woliata zone to mitigate the problem of climate variation from several angles. The aim of this study is analyzing the impact of LULC Change on climate variability using Geospatial Techniques in between 1993 to 2022. To achieve the objective, the inverse distance weight interpolation method was used to investigate the spatial pattern of precipitation and temperature while the coefficient of variation was used for trend analysis. Moreover, maximum likelihood supervised classification techniques were used for classifying LULC. Finally, linear regression was used to analyze the correlation between LULC, LST, NDVI and Rainfall data. The long-time recorded climate data, mult-temporal Landsat image, time sires MOD13Q1Normalized difference vegetation Index and survey data collected from key informative persons were used for analyzing the climate variability. The result of the study shown that the mean yearly rainfall of the study area declined by 29.8mm from 1993 to 2022. Similarly, the result shows a reducing trend of rainfall at the seasonal level. Overall amount, it declined by18.1mm and 40.36 mm in kiremt and belg seasons respectively. Furthermore, the study result shows that the average annual maximum and minimum temperature increased by 0.52 ^{0}c and 1.29 ^{0}c respectively between 1993 and 2022. Consequently, the LULC Change result reveals that farm land and buildup land dramatically increased while forest land and bareland declined during the study period. With this regard, mean LST shows an increasing rate of built-up land, farmland, bareland and forest land respectively from 1993 to 2022. In addition to this, the time series MOD13Q1 NDVI result indicates that the forest coverage of the study area declined from 2003 to 2022. This means that the NDVI value declined from 0.934 in 2003 to 0.794 in 2022. Finally, linear regression analyses result shows that there was a strong positive correlation between NDVI and Rainfall while a strong negative correlation with average annual temperature with NDVI. Moreover, there is a strong positive correlation of LST with Built-up land; farm land and bare land while a strong negative correlation with forest land. Generally, the study concluded that the decline in rainfall and the rise of temperature in the study area was caused by the expansion of farmland, built-up land and reduction of forest land. So, concerned body must take remedial measurements to monitor the changing climate condition of the study area.

Key Terms: Climate variability, Geospatial Technology, LULC, LST NDVI

CHAPTER I. INTRODUCTION

1.2 Background of the study

(Foley et al., 2005) The land is the most basic natural resource and the material foundation for human survival and development. LULCC has been identified as a primary driver of global change as well as a critical issue influencing the long-term development of nature, humans, and society (Lambin et al., 2001). Land-use/land-cover Changes generated by natural and human processes have played a significant effect on global and regional-scale patterns of climate and other features of the planet (Ramachandra et al., 2012).

Population growth, urbanization, agricultural expansion, pasturing, and global market dynamics are among the known causes of LULCC (Lambin and Meyfroidt, 2011). Cultural variables such as logging plant cover, exposing soil to erosion, and degrading land may also trigger the LULCC (Lambin et al., 2003). According to (FAO, 2012), deforestation is a major couses of land cover change, and it is the most difficult issue in developing nations, particularly in tropical rain forests, which span around 550 million hectares of the globe and have an annual harvesting rate of more than 2%. As a result, the worldwide forest cover is steadily diminishing, with global environmental consequences.

In most Eastern African countries, LU/LC has been happening due to the increase of both human and livestock populations (Pomeroy et al., 2003). Land-use/land-cover Changes in Ethiopia caused by a combination of various factors though it depends on the conditions of the area (Mohammed, 2011). Most Ethiopian research found that LULCCs were mostly the conversion of natural vegetation to agricultural due to increased demand for agricultural food production (Kibret et al., 2016). Changes in land use/land cover can have an impact on regional and global climates by emitting or sequestering carbon and modifying the overall reflectance qualities of the earth's surface (Houghton and Hackler, 2006).

Land surface temperature is one of the land surface parameters impacted by LULCC (Eunice, 2013). Deforestation and forest degradation accounted for approximately 17% of total global green house gas emissions (Bruno et al., 2011). According to Pielke (2001), deforestation can impact moisture convergence, atmospheric stability, and rainfall changes.

According to the (IPCC,(2009), rising temperatures are caused by deforestation, forest degradation, illegal logging, and settlements and encroachments into forests. In Ethiopia, LULCC has an important role in climate variability by increasing droughts and changing rainfall patterns, generating floods and shrinking lake sizes (Molla, 2014). Woliata zone is also a part of Ethiopia affected by LULCC. Because the area is one of densly populated zone in southern region of Ethiopia. So, the LULCC induced problems resulted the area to climate variability. Therefore, this study was aimed to analyze the impact of land use land cover change on climate variability using geospatial techniques in the case of wolaita zone southern region of Ethiopia.

1.2 Statement of the Problem

Land Use Land Cover Changes affect the overall functioning of the earth system at local, regional, and global levels (Meyfroidt, 2011). This in turn brings global change particularly temperature and rainfall (Woldemichael et al., 2012). In Africa, land-use change accounts for a conversion of 75 million hectares of forest to agriculture and pasture between the years 1990 and 2010 (FAO, 2010). More importantly, in East Africa, nearly 13 million hectares of original forest were lost over the same 20 year period and the remaining forest is fragmented and continued to be under threat (FAO, 2010). Ethiopia is one of east African country that sever to LULCC related problem (Eshetu, 2000).

Wolaita zone is a part of Ethiopia that is currently under stress due to increasing population pressure, severe deforestation, and loss of biodiversity and ecosystem services, land degradation and traditional agricultural practices like cultivating on steep slopes without protective measures According to (WZCCFPO). The loss of forest cover and the LULC Change leads the study area to climate variability Some studies had been done to investigate the climate variation of Wolaita Zone. The study made by (Blen.M, 2021) focused on the climate variability, adaptation strategy and determinat of household food security by using metereological data and household survey.

Anather study conducted by (Befikade et al.,2019) reavls that the climate variability and farmers perception by using gridded metereological data and house hold survey in the case of wolaita zone. However, in the study area, climate variation is still not studied by examining the impact of LULC Change using geospatial technology. The Climate was influenced by land use change.

One research strategy to assess climate variation on the earth's surface is analyzing the impact of land use land cover change and the derivation of the satellite-based vegetation index (Ahl et al., 2006). Terefore, the present research study aimed to analyze LULCC and their impact on climate variability using geospatial techniques in the case of Wolaita zone southern nation nationalities and the Regional State of Ethiopia.

1.3 Objective of the Study

1.3.1 General Objective

The general objective of this study is to examine the influence of Land use land cover change, NDVI and LST on climate variability using Geospatial techniques in the case of wolaita zone, the southern region of Ethiopia.

1.3.2 Specific Objectives

The specific objectives of the study are:

- To investigate the trend and variability of rainfall and temperature of the study area.
- To analyze the temporal and spatial variations of LULCC, LST, and NDVI of the study area.
- To evaluate the statistical relationship between LULC Change, LST, NDVI and Rainfall of the study area.
- To investigate the impact of LULCC on Climate Variability.

1.4 Research question

- How to investigate the trend and variability of rainfall and temperature of the study area from 1993 to 2022?
- How to analyze the temporal and spatial variations of LULCC, NDVI, and LST of the study area?

- How to evaluate the statistical relationship between LULC Change, LST, NDVI, and Rainfall in the study area?
- What are the impact of LULCC on Climate Variability?

1.5 Significance of the Study

The phenomenon of climate variations and change is widely studied around the world. Geospatial technology already plays an important role in managing climate change by inventing and developing software tools that enable reliable geo-data analysis utilized for climate change monitoring, mitigation, and adaptation. Analyzing the spatial-temporal trend of rainfall and knowing the subsequent trends of change will be crucial to the present understanding of the changing nature of the local climate system.

The results of this study will provide important information for policymakers, agricultural experts, farmers, nongovernmental organizations, planners, and land administrators to maintain the agro-climatic condition, ensure sustainability in resource utilization, and proper land use planning and decision-making. Furthermore, the study will provide firsthand information for other researchers who are interested in conducting additional research on climate variability using Geospatial Technology.

1.6 Scope of the Study

Geographically, the study was conducted in Wolaita zone southern region of Ethiopia. The thematic scope of the study is to analyze spatiotemporal climate variability using Geospatial Techniques. From many climate variables, particularly rainfall and temperature were analyzed in this research study. The temporal scope of the study is to examine the trend and variability of rainfall and temperature, to analyze LULC, LST, and NDVI change, and to investigate the effect of forest cover on climate change of the study area from 1993-2022.

1.7 Organization of the Study

The research report was organized into five chapters. The first chapter contains an introduction and statement of the problem. In addition, it briefs the basic research questions, objectives of the study, significance of the study, the scope of the study, organization of research, and limitations of the study.

The second chapter deals with a review of related literature. This part addresses the relevant literature that is very much associated with the research topic.

The third chapter explains the materials and methods. It indicates a brief description of the study area, data sources with a data type, sampling method, data analysis method and the type of methodology used, and the different tools and software. The fourth chapter was indicating the result and discussion of the finding by using a graph, table, chart, or map. Finally, chapter five indicates the conclusion and recommendation.

1.8 Limitations of the study

In this research work various limitations have been identified.

The limitations of this study was the poor availability of metrological data. Some meteorological station of the study area in particular and the country in general, has no long-year recorded climate data. Eventhough there are several meteorological stations in the study area and southern regional state. Most of the stations have limited meteorological data.

The other problem was obtaining data from several different government offices. Some government offices are not willing to give important data related to the present situation.

CHAPTER II. LITERATURE REVIEW

2.1 Concept of Land Use Land Cover Change

Land-use/land-cover changes are fundamental processes on the earth's surface and have significant impacts on human society, climate, biodiversity, hydrological cycles, ecosystems, and many other processes (Lin et al., 2018). Changes in land cover have become key components of global environmental change and represent the impact of human activity (Zhao et al., 2017). Land-use changes modify land cover due to human intrusions, such as cultivation, settlement, transportation, infrastructure, manufacture, recreation, mining, and fishing. In contrast, land cover change converts land cover from one type to another and/or the modification of conditions within a category (Pellikka et al., 2013). These changes alter the accessibility of various biophysical resources including water, vegetation, soil, animal feed, and others (Alemenesh et al., 2020).

Generally, LULCC is driven by natural factors and anthropogenic activities (Bennett and Saunders, 2010) causing the alteration of ecological process and the loss of native biodiversity across different ecosystems (Msofe et al., 2019). LU/LC is constantly changing in response to the dynamic interaction between drivers of change and proximate causes (Leh et al., 2013).

2.2 Factors of Land Use Land Cover Changes

Land-use/land-cover changes occurred due to natural and anthropogenic factors (Geist and Lambin, 2002). As EPA (1999) states there were three main driving causes for LULCC. These are (1) natural processes, such as wildfire, climate, and atmospheric changes, and pest infestation; (2) direct effects of human activity such as deforestation, soil erosion, and reduction of biodiversity which brings land degradation, and construction like road and buildings; and (3) indirect effects of human activities, like depletion or lowering of the water table and contamination of groundwater. Anthropogenic factors are the major driving forces of LULCC (Niamir-Fuller et al., 2012

LULCC is a very complex process due to its causes and impacts are very closely related; for example, land degradation (Abate, 2011). Currently, the human-related causes of LULCC are very serious (Agarwal et al., 2002). For instance, expansion of agricultural land (Bongers and Tennigkeit, 2010; Brink et al., 2014) due to rapid population growth responsible for the massive collapse of natural vegetation, loss of biodiversity, and land degradation (Donato et al., 2016; Sandra et al., 2017). Extreme transformation of forests, grassland, and shrub land brings a reduction of plant species diversity and continuously shrinking of natural wildlife. Intensification of agriculture such as crop and pastoral land towards the natural ecosystem which is related to population growth also contributes to extreme changes of LU/LC and environment (Lambin and Meyfroidt, 2011).

Moreover, rapid population growth reduces forest areas and woodlands (Sandra et al., 2017). This destruction affects biological diversities and functions ecosystems (Peter, 1994) and causes climate change which raises the risk for wildfire (Donato et al., 2016). Yadvinder et al. (2008) also agreed that population expansion causes deforestation and creates pressure on forest resilience. This extreme destruction of forestland is a root for climate change at the local, regional and global levels (Peter, 1994). Deforestation also affects the process of atmosphere and thermodynamics at the earth-atmosphere interface and water storage capacity and soil hydraulic conductivity (Shukla et al., 1990).

Land-use/land-cover change has impacts on hydrology and changes the quality of water and water flows, causing surface water pollution, depletion of groundwater aquifers (Rosell, 2011). Further, LULCC due to urban expansion causes urban heat island (Jianga and Tiana, 2010) that has adverse social, economic and environmental effects both at the local, regional and global scale (Zheng et al., 2014). Thus, higher urban temperatures increase the demand for air conditioning, change urban thermal environments and ultimately lead to thermal discomforts and incidence of heat-related illnesses (Qijiao and Zhixiang, 2015).

2.3 Concept of Climate Variability

Climate change is a change in the state of the climate that can be identified by the changes in the mean and/ or the variability of its properties and that continues for an extended period, normally can take decades or longer (Adugna, 2016). As drawn in the work of (Yilma, 2009) climate is described in terms of the variability of relevant atmospheric variables such as temperature, precipitation, wind, snowfall, humidity, and clouds for long time in a specific area.

Climatic variabilities are various types of variations (in temperature and precipitation) in the rate and magnitude of climate change that affect public health, agriculture, food security, biodiversity, and forest and water resources (Amare, 2017). Almost everywhere, climate variability will rise (Getahun, 2012).

According to (Getahun, 2012), Africa is a continent most vulnerable to climate change and unpredictability due to the combination of "multiple stresses," occurring at different levels. According to (Cooper, 2015), in Many researches on precipitation and temperature change, the African continent is presently warmer than it was 100 years ago, and the rainfall showed higher inter-annual and intra-seasonal variability.

Climate variability over the last three decades of the 20th century led to droughts and famine in various nations of Africa (Conway, 2004). Ethiopia is one of the most sensitive nations in eastern Africa to climate change and variability, and it frequently experiences climate-related hazards, most often drought (Temesgen G., 2014).

The local Ethiopian communities have perceived both an increase in temperature and a decrease in annual total precipitation (Bewket, 2015). According to gathered meteorological data, spring droughts have been more common in all regions of Ethiopia during the past 10 to 15 years, as well as a decrease in rainfall in southern Ethiopia throughout the rainy seasons of February to May and June to September (Viste et al., 2013).

2.4 climate variability in Global and African Context

Many areas of the developing world have changing climates and temperatures, and these areas are predicted to get gradually hotter and drier over time (Collier P., 2008). According to recent studies, the highest temperature extremes, particularly those resulting from low temperatures, have greatly increased during the 20th century and will continue to do so in the 21st century (Anne, 2013). Africa's average temperature is rising faster than the global average and is projected to continue.

According to (Collier P., 2008)., this warming happened at a rate of approximately 0.5^{0}C each decade, with slightly higher warming in crops grown close to the thermal tolerance limits.

Droughts and famines occurred in various African nations as a result of climate variability over the last three decades of the 20th century (Conway, 2004). The International Panel on Climate Change (IPCC) indicated in its Third Assessment Report that developing nations are likely to suffer the worst effects of climate change and climatic variability (Collier P., 2008) This is due to the economic significance of climate-sensitive sectors for these nations as well as their limited institutional, financial, and human capacity to foresee and respond to the direct and indirect effects of climate variability and change,

This is specifically true in Africa, where poverty rates are high and there is a large dependence on the environment for life (Anne, 2013). In particular, climate variability and change harm agriculture in Africa (Conway, 2004). Climate change and variability are anticipated to have a significant negative impact on agricultural production, particularly food access, in the majority of developing countries and many African nations (IPCC, 2007).

Climate variability and change are expected to have an impact on the two most significant direct agricultural production inputs (temperature and rainfall). These climate elements are essential for sustaining livelihoods in Africa, where most people rely on local supply networks vulnerable to climatic change (Deschênes, 2007).

2.5 Climate Variability in the Ethiopian Context

According to (Belay, 2014), Ethiopia has characterized a wide range of climatic conditions, from humid to semi-arid environments.

The average annual rainfall distribution varies from a maximum of more than 2,000 mm throughout the south-western highlands to a minimum of less than 300 mm over the south-eastern and north-western lowlands. The southwest and western regions have a uni-modal rainfall pattern, while the rest regions have a bi-modal pattern (Woldeamlak, 2010).

The mean annual temperature varies significantly, lower than 15°C in the highlands (above 1500 m.s.l.) and above more than 25°C in the lowlands (below 1500 m..s.l.).

According to (Anne, 2013), Ethiopia's food insecurity is a result of climate variability, specifically variations in rainfall. For example, every year, approximately three million Ethiopians are affected by crop production shortfalls, adding to the 7.6 million supported by the Productive Safety Net Program, a social safety net that assists some of Ethiopia's poorest and most food-insecure families (Woldeamlak, 2010).

several studies indicate that future climate change in Ethiopia will increase climate variability. According to UNDP (2008), climate change in Ethiopia could result in extreme temperatures and rainfall events, as well as more severe and continued droughts.

Furthermore, future temperature projections from the IPCC mid-range scenario show that the mean annual temperature in Ethiopia will rise by 0.9 to 1.1^{o}c by 2030, 1.7 to 2.1^{o}c by 2050, and 2.7 to 3.4^{o}c by 2080 when compared to 1961 to 1990 (Emerta, 2013).

Therefore, knowing climate variability, particularly trends and variability in rainfall and temperature, is critical for planning and devising suitable actions.

2.6 Implication of LULC Change on Climate Variability

Land use refers to human activities and the various uses that occur on land, whereas land cover refers to natural flora, water bodies, rock/soil, artificial cover, and other features observed on the land (NRSA, 1989). Land Cover, defined as the assemblage of biotic and abiotic components on the earth’s surface is one of the most crucial properties of the earth system. Land cover is what covers the earth's surface, while land use is how the land cover is changing.. Land cover includes water, snow, grassland, forest, and bare Soil. Land Use includes agricultural land, built-up land, recreation area, wildlife management area, etc.

The land surface is an essential component of the climatic system. Several steps and feedbacks are involved in the interaction of the land surface and the atmosphere. It is widely emphasized that changes in vegetation type can influence the parameters of regional air circulation and large-scale external moisture flows. Thus, changes in surface energy caused by land surface change can have a significant impact on Earth's climate. (WMO, 2005).

The Earth's system is composed of several biogeochemical cycles, all powered by the sun’s energy. These global cycles include the circulation of certain elements, or nutrients, upon which life and the earth’s climate depend. Then, through these cycles, all components of the environment are interrelated and greatly affect each other. Apart from these effects, the presences of drought and hydrological feedback associated with land-use change locally or through teleconnections, have a direct impact on the source/sink capabilities of the terrestrial ecosystem. This feedback, along with other climate forcing and feedbacks, makes climate prediction a difficult problem, over time scales of years. Therefore, biogeochemistry has a significant role in the climate system (Deneke, 2007). Many studies have revealed the extent to which changes in the land surface have affected local and regional climates and it is increasingly clear that some changes in the land surface can have significant impacts on the climate in distant parts of the Earth (Deneke, 2007).

2.7 Implication of Land Surface Temperature on Climate Variability

Land surface temperature is the most important climatic parameter in determining surface radiation and energy exchange (He, 2019). It refers to the skin temperature of the Earth's surface (Kayet, 2016).

LST is also a key variable in land-atmosphere interactions and a climate change indicator that varies over time and space as a function of vegetation cover, surface moisture, soil types, and topography (Eunice, 2013). LST variations are influenced by a variety of factors, including changes in land use, land surface features, seasonal fluctuation, climatic conditions, and economic development (Nega, 2018). In other words, the main reason for an increase in LST is a change in land use

Many scholars throughout the world have used the concept of LST because unexpected rainfall, temperature variations, and vegetation patterns are all factors that affect the LU/LC in a location (Hongjie, 2015). The shifting of this land use/land cover has been linked to anthropogenic activities that change the physical properties of the land surface and rapid changes in temperature in a specific region (Hongjie, 2015).

2.8 Implication of NDVI on Climate Variability

The Normalized Difference Vegetation Index (NDVI) is related to the quantity of photo-synthetically absorbed radiation. It is a measure of the amount and vigor of vegetation on the land surface. Climate plays a major role in vegetation phonological cycles. Vegetation growth is functionally dependent on climate. Consequently, a change in the biophysical parameter of vegetation canopy implies a climate change, accordingly, vegetation is used as a key input into climate change models (Ogunbadewa, 2013). Climate variability is one of the most important factors affecting vegetation conditions. In this regard, remote sensing plays an important role to detect and characterize vegetation dynamics that are affected by climate variability.

Green and healthy vegetation reflects much less solar radiation in the visible part of the electromagnetic spectrum compared to those in the near-infrared part. More importantly, when vegetation is under stress, visible values may increase and near-infrared values may decrease.

The Normalized Difference Vegetation Index (NDVI) is a method used to analyze the vegetation cover of an area. NDVI is calculated from reflectance measured in the visible and near-infrared channels from satellite-based remote sensing. NDVI shows the temporal and spatial change of Vegetation cover. This, vegetation tool sees the entire landscape every day because of its huge field of view and is an important tool for studies of worldwide vegetation (Yohannes, 2012).

2.9 Role of Geospatial Technology in the Assessment of Climate Variability

The issue of climate change is currently an important concept that attracts the attention of several scholars. The problem of climate change is broadly studied from various angles that emanate due to the seriousness of the problem. Among those, the most recent is the application of satellite images which is used to analyze through Geospatial techniques that are developed with the development of Earth Observing satellites.

Reducing the risks caused by climate change is an immense challenge. Scientists, policy makers, developers, engineers, and many others have used geographic information system (GIS) technology to better understand a complex situation and offer some tangible solutions.

A Geospatial Technology based framework helps us to gain a scientific understanding of earth systems at a truly global scale and leads to more thoughtful, informed decision-making. GIS users represent a vast reservoir of knowledge, expertise, and best practices in applying this cornerstone technology to the science of climate change and understanding its impact on natural and human systems (ESRI, 2008).

The same source further explained that the key to understanding our dynamic climate is creating a framework to take many different pieces of past and future data from a variety of sources and merge them into a single system. GIS creates a new framework for studying global climate change by allowing users to inventory and display large, complex spatial data sets. They can also analyze the potential interplay between various factors, getting us closer to a true understanding of how our dynamic climate may change in the coming decades and centuries (ESRI, 2008).

Applications of scientific principles such as GIS and Remote Sensing equipped with GPS in detecting climatic variation are crucial in the world today both in developed and developing countries.

2.10 Empirical Evidence

Climate change is probably the greatest long-term challenge facing the human race. Humanity everywhere in the world is being haunted by multitudes of problems and challenges; and in effect, climate change is one of humanity's most devastating problems. Different research had been conducted to assess the spatial and temporal patterns of climate in different parts of the country. Particularly a few studies have been conducted on the issue of climate variability both in space and time. In this regard, a study made by (Taye et al,.2013) can be mentioned focusing on Climate Variability and Impacts in Central Rift Valley and Adjacent Arsi Highlands Using GIS and Remote Sensing, the finding of the study denoted that temperature is getting increased by 0.37^{o}C in the rift valley and 0.48^{o}C in highlands and by 0.4^{o}C in whole areas per 12 years and rain is constant and shows an insignificant rise.

In addition, another recent study carried out by (Mulugojjam and Ferede, 2012) emphasized Spatio-temporal Variability and Trend of Rainfall and Temperature in Western Amhara: Ethiopia: by using a GIS Approach. The study used 5 meteorological stations with 30 years of daily rainfall, and maximum and minimum temperatures data were used (1979-2008). The study revealed that the contribution of kiremit rainfall to the annual total rainfall was very high in all study stations. Variations of minimum and maximum temperatures were found every month. The long-term recorded rainfall data indicated an increasing trend during 1995-2008 and decreasing trend during 1979-1994, except, for inter-annual fluctuation. Further, late-onset and early cessation of rainfall were noted in all study stations in recent years. The spatiotemporal variability of rainfall, minimum temperature, and maximum temperatures observed in the study stations are alarming.

On the other hand, (Dereje Ayalew, 2012) studied the variability of rainfall and its current trend in Amhara region. In this study, 10 meteorological stations with 30 years of daily rainfall data were employed. Every month, variations in rainfall were observed at all locations. The yearly rainfall distribution ranged from 850 to 1485 mm. Belg ("small rainfall" in March-May) Rainfall contributes significantly to the annual total in the region's central and eastern stations. Annual rainfall showed negative and positive anomalies for much of the 1980s and 1990s, respectively. Furthermore, the long-term movements of rainfall in a time series data did not indicate any increasing or decreasing tendency; however, in recent years, there has been a contraction of the length of the growth period due to early cessation of rainfall.

CHAPTER.III. MATERIALS AND METHODOLOGY

3.1 General Description of the Study Area

3.1.1 Location of the Study Area

The study was conducted in Wolaita Zone, which is located in the Southern Nations and Nationalities People (SNNP) region, 390 km South of Addis Ababa. The absolute location of the Zone is between 6°57´20”-7°04´31” N latitude and 37°35´30”-38°12´02” E longitude. In terms of relative location, Wolaita Zone shares boundaries with Hadiya and Kambata Tambaro Zone in the North, Sidama region in the East, West Arsi zone in North east, Gamo and West Guji Zone in the South and Omo river in the West which separate it from Dawuro zone. the boundary map below shows the location map of the study area. See fig 3.1

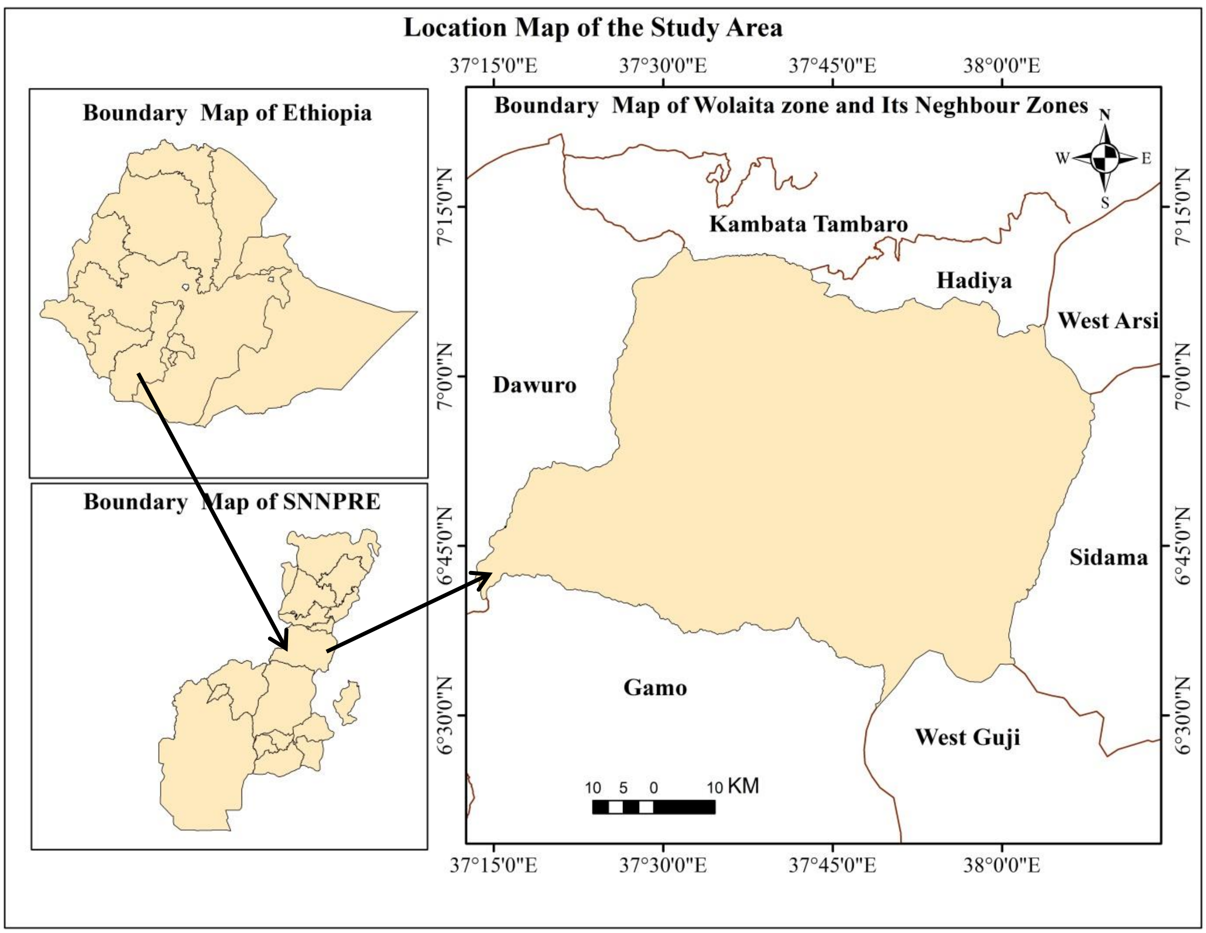


Fig 3.1: Location of the study area

3.1.2 Topography/ Relief of the Study Area

The total area of the zone was 4509.44 km^2 or 450, 944 hectares. The area has generally high land, midland, and low land relief. Most of the study area was covered by mid land relief that cover 2677.59 km^2. The low land and high land relief of the study area covers 1687.26 km^2 and 144.59 km^2 respectively. The altitude range from 648 meters on low land at bilate tena to 2962 meter above sea level at the high land of damota mountain (Gecho et al., 2017). See fig 3.2 below that shows the relief of study area.

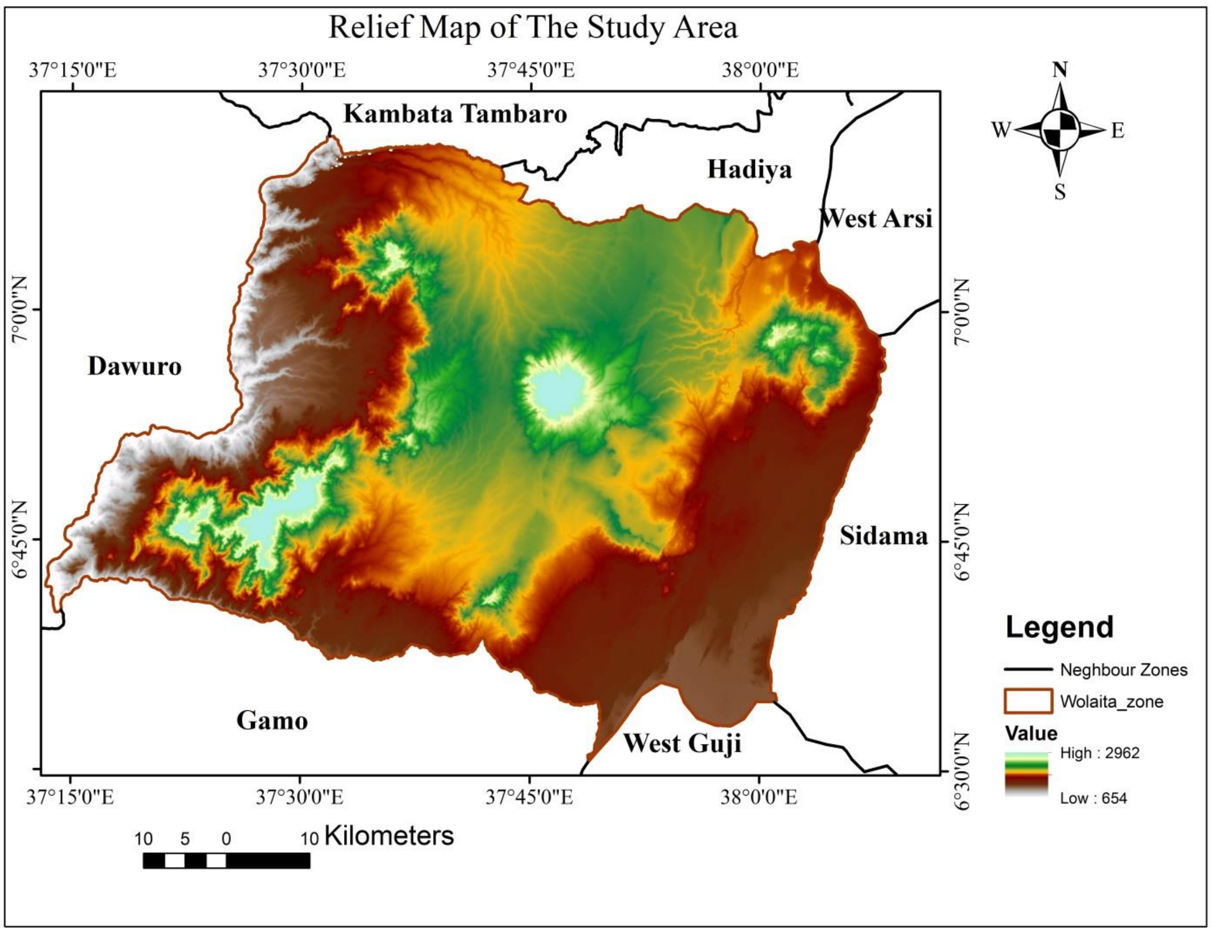


Fig 3.2: Topography of the study area

3.1.3 Agro-Ecological Zone of the Study Area

Woliata zone has been classified into three agroecological zones based on elevation. Depending on this the study area has been classified as kola (low land) woina dega (mid land) and dega (high land) agro-ecological zone.

Table 3.1: Agro-ecological Zones (AEZ)

SN	Name of AEZ	Elevation in (meter)
1	Lowland(kola)	648-1500
2	Midland(Wogna dega)	1501-2300
3	Highland(Dega)	2301-2962

Source: NMA Ethiopia, 2023.

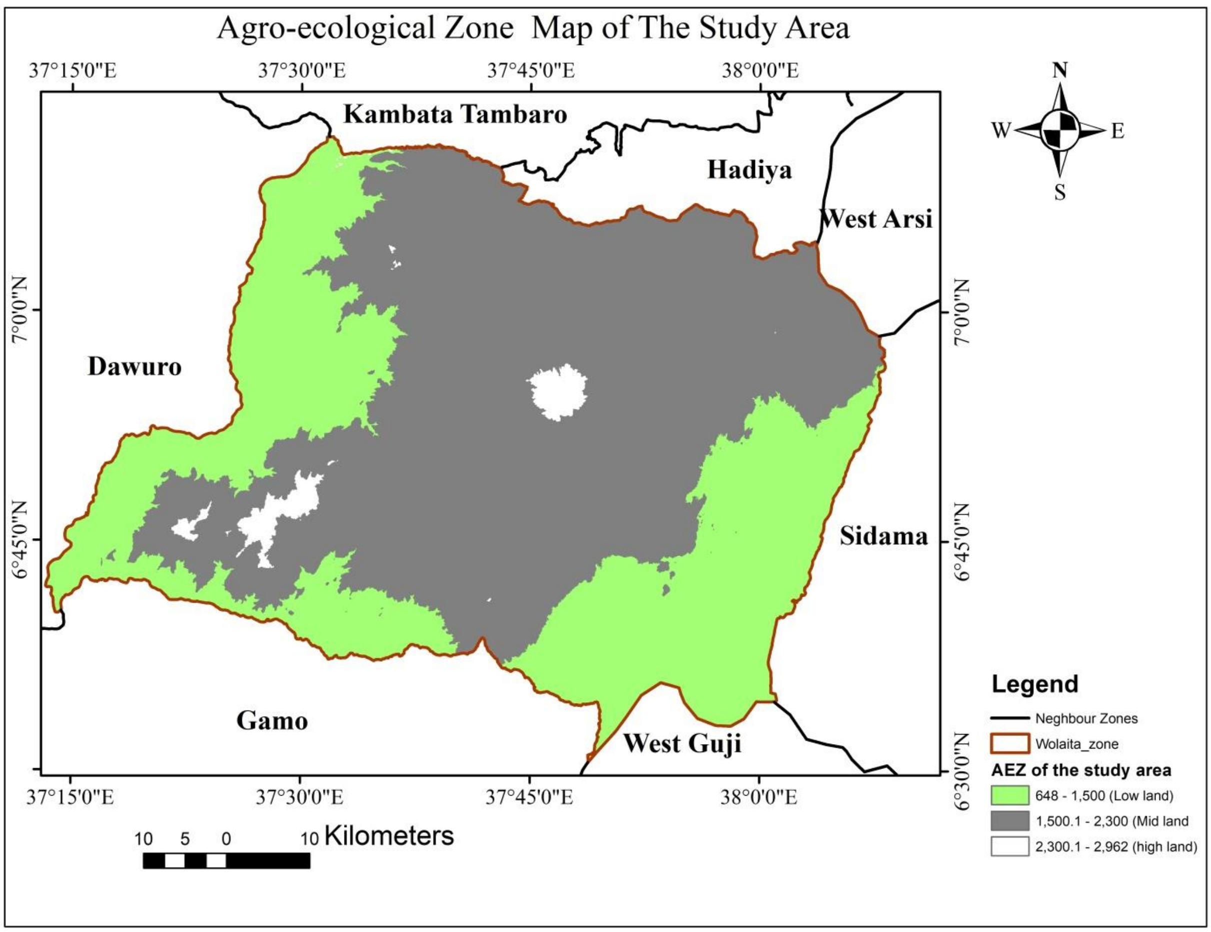


Fig 3.3: Agro-ecological zones of the study area

3.1.4 Climate of the study area

The Wolaita zone climate has a bimodal rainfall pattern that continues from March to August. The first rainy season takes from March to May. The second rainy season lasts from July to August. Over the last 30 years, the average annual rainfall has been 1173.5mm. The average annual temperature was 26.89 ^{0}c.

The year is divided into three seasons: the wet season (balguwa) from June to August, and the dry season (boniya) from September to February. And the third season (Badhesa) from March to May. The dry season is characterized by a strong wind that blows from the east. During the wet seasons, heavy precipitation and violent storms which, at the end of the season can last a full evening or night are common events.

3.1.5 Demography of the study area

Based on the 2020 population projection conducted by the Central Statistical Agency of Ethiopia (CSA), the zone has a total population of 5,385,782 with an area of 450,944 hectares. From the total population of the zone, females count 2,698,261 and males count 2,687,021. The largest ethnic group reported in the zone is the Wolayta (96.31%); all other ethnic groups was 3.69% of the population. Wolayta is spoken as a first language by 96.82% of the inhabitants; the remaining 3.18% spoke all other primary languages reported.(Source:CSA Wolaita sodo district)

3.2 Sources and Types of Data

3.2.1 Source of Data

To analysis the climate variability, both secondary and primary data were collected from different sources. Secondary data such as 30m spatial resolution STRM Digital Elevation Model, 1993 Landsat 5/MSS/, 2002 Landsat 5/MSS/, 2012 Landsat 7/ETM+/ and 2022 Landsat 8/OLI/ and Moderate-resolution imaging spectro-radiometer (MOD13Q1 NDVI 250m resolution) data were downloaded from www.USGS earth explorer website. Long years of gridded climatic data were obtained from the NMA of Hawasa district. The shape file of the study area and published and unpublished written documents related to the current research study was used in this research study. The primary data data were collected from KII.

3.2.2 Types of Data Used

The following type of data was used to conduct this research. First, the long year (1993-2022) daily maximum temperature, daily minimum temperature, and precipitation data were used to analyze the spatial and temporal distribution of the rainfall and temperature of the study area.

Selected Meteorological Station

Three major stations were selected using the latitude and longitude of the some existing stations. These are namely Billate(lowland), boditi (High land), and Wolaita Sodo (Midland) were selected purposely. Because first; this station contains long-year climate data (above 30 years of climate data) compared to other meteorological stations. Second; they are dominant stations and represent all AEZ of the study area. See Table 3.1 illustrates the meteorological stations information.

Table 3.2 illustrates the meteorological stations

SN	Station Name	Latitude	Longitude	Elevation (m)
1	Bilate (Low land)	38^0 05' 16.1" E	6^0 49' 20.3" N	1361
2	Boditi (High land)	37^0 51' 30.7" E	6^0 57' 22.5" N	2043
3	Wolaita Sodo (Midland)	37^0 44' 56.2" E	6^0 49' 17.6" N	1854

Source: NME of Hawassa District

Table 3.3: Types of climate data used

SN	Climate Elements	Purposes
1	Precipitation	For analyzing the variability of rainfall distribution in the study area
2	Temperature	For analyzing the variability of temperature distribution of the study area.

Source: National Metrological Agency (NME) of Hawassa branch

Furthermore, 30m spatial resolution 1993 Landsat 5/MSS/, 2002 Landsat 5/MSS/, 2012 Landsat 7/ETM$^+$/ and 2022 Landsat8/OLI/TIRS was used to analyze LST and Land use land cover change detection of the study area to assess the climate variability

Table 3.4: Satellite image data used

SN	**Image**	**Sensor**	**Path/Row**	**Band**	**Spatial Resolution**	**Acquisition date**
1	Landsat5	MSS	169/055	7	30*30m	10/03/1993
2	Landsat5	MSS	169/055	7	30*30m	15/03/2002
3	Landsat7	ETM^+	169/055	8	30*30m	08/03/2012
4	Landsat8	OLI/TI	169/055	11	30*30m	16/03/2022
	DEM	STRM			30*30	11/3/2015

Source: www.United State geological Survey Earth Explorer.

Moderate-resolution imaging spectro radiometer (MODIS TERA radiometer MOD13Q1 Vegetation index) 250m spatial resolution NDVI data was used.

Table 3.5: NDVI data Used

SN	**Satellite system**	**Sensor**	**Spatial resolution**	**Temporal resolution**	**collected date**	**Source**
1	NASA LPDAAC	MODIS Terra	MOD13Q1 250m NDVI	16 days composite	2003-2022	www.USGS Earth Explorer

3.2.3 Software Used

In ordered to analysis the spatiotemporal climate variability, the following software was used. First Microsoft excel was used to edit, arrange, and organize the long-year gridded temperature and precipitation data before conducting the analysis. Second, Microsoft word was used to write and edit the whole research work. Third, Arc GIS was used to store, manage, analyze, interpret, and display final output such as a map. Fourth, ENVI was used to layer stack and clip Land sat image based on the study area. It is also used to analyze the LULC classification of satellite images of the study area. Google earth was used for visualizing the study area and computing accuracy assessment. SPSS softwares were used for analyzing correlation between variables. See Table 3.6 below that shows types of software.

Table 3.6: Software used

SN	Name of Software	Purposes
1	Microsoft Excel	Used to edit, filter and organize climate element data
2	Arc GIS 10.8	Used to store, manage, interpret, analyze, and display the map It also used to analyze change detection and accuracy assessment
3	ENVI 3.5	Used to layer stack, clip, and analyze LULC Change in the study area
4	SPSS 20	Used to calculate the association between variables
5	Google Earth	Used for visualizing the study area
6	Microsoft Word	Used to write and edit whole research work

Source: Prepared by Researcher, 2023

3.3 Sampling Techniques

Purposeful sampling techniques were employed for the present research study. The study area (Wolaita Zone) was purposefully chosen from other Zones in the southern region of Ethiopia. Because; first, it is one of the most vulnerable and food-insecure Zones in the southern region of Ethiopia (Kuma, 2015). Second, it is one of the most densely populated places in the country, with degraded land and dominated by micro and smallholder farmers (Taye, 2014).

Another reason for choosing Wolayta is that it is the location of the first United Nations Framework Convention on Climate Change (UNFCCC, 2011).

Finally, the same empirical studies were carried out in response to climate variability/change/in different parts of the country. However, analyzing and linking LULC change, and NDVI condition with changing climate in temporal and spatial scale by using a Geospatial techniques perspective was not conducted in the study area.

3.4 Data collection Instrument

3.4.1 Key Informative Interview

According to (USAID, 1996), key informant interviews are qualitative in-depth interviews in which the researcher presents the issue to individuals who know about what is going on in the community. The primary aim of key informant interviews is to get detailed information from a specific group of people, such as community leaders, elder groups, and professionals with actual knowledge of community problems (Othow et al., 2017).

In this study, in addition to Satelite image data and meteorological data, key informant interviews were carried out with individuals who have lived in the study area for a long time and have personal knowledge of the past and current state of climatic variability. Key informant interviews were carried out from farmers, Agricultural experts and climate change and forest preservation experts. Twenty KII participants having more information and knowledge about the climatic condition of the study area were selected purposefully. Purposive questions were asked to obtain useful data regarding the climate variability of the study area.

3.5 Methods of data analysis

To achieve the objective of the research study the following data analysis method was used. The daily maximum temperature, minimum temperature, and rainfall data were entered into Microsoft excel. Then after data quality was verified label possibly wrong values and eliminate them from the investigation. Unrealistic values, such as daily maximum temperature less than or equal to daily minimum temperature, were identified and set to missing values. Then the Data was carefully organized, arranged, and filtered. Daily maximum temperature, minimum temperature, and rainfall data were prepared into seasonal, decadal, and annual ones for each station. Then, the data was imported into Arc GIS software to conduct analysis. Seasonal, decadal, and annual temperature and rainfall data were analyzed using a statistical package available in Arc GIS software. Finally, using this software, the climate variability was analyzed and mapped. To determine the coefficient of variation (CV), the standard deviation was compared to the mean (NMSA, 1996). The following methods/techniques/ were used for achieving the objective of the current research study.

3.5.1 Inverse distance weight (IDW) Method

The estimation of climatological variables at different places can be done using spatial interpolation. So Inverse Distance Weighted (IDW) is a method of interpolation that estimates cell values by averaging the values of sample data points in the neighborhood of each processing cell. Obtaining sample information for the entire region is challenging. So, geo-statistical models forecast values in un sampled locations and quantify the degree of prediction uncertainty. The locations of meteorological stations are typically remote and unattractive to a variety of human pursuits. Only sample points in the area can be used to determine the value of climate elements. In this regard, spatial interpolation could be used to extrapolate values from regions without measurements (Yang et al., 2004). Generally, there are several methods of interpolation method was used to determine the climate element of an unknown location using known sample point data. However, the IDW interpolation method was used in this research to determine the climate element distribution of unknown locations using known location sample data.

3.5.2 Coefficient of Variation for analyzing the trend of temperature and rainfall

Different researchers used different methods for studying spatiotemporal climate variability.

The coefficient of variation (CV) is the ratio of the standard deviation to the mean. The higher the coefficient of variation, the greater the level of dispersion around the mean The CV is useful for comparing the degree of variation from one data series to another.

According to Asfaw (2018), several methods have been created for analyzing temperature and rainfall; these methods typically fall into the categories of variability and trend analysis. The analysis of climate variability only considers the consistency of the data and contains tests for the coefficient of variance (CV), percentage deviation from the mean (anomalies), standard deviation per interval (SPI), and moving average trend. But, for this study rainfall and temperature variability has been calculated by using CV. (Hare, 2003) claims that CV is used to categorize rainfall event variability into three categories: low (CV <20), intermediate (20 < CV < 30), and high (CV > 30). A high value of CV is the indicator of large viability and Vis versa which is computed as

The coefficient of variation calculate as follows $CV = \sigma / N$

Where CV is the coefficient of variation, σ is the standard deviation of temperature and rainfall, and N is the mean of precipitation or temperature.

3.5.3 Land Use Land Cover Analysis

Remote sensing data were used to produce both historical and current information about land cover and land use change for the study area. For this research study, ENVI software was used to create detailed digital picture processing and visual interpretation of satellite images. Land use and land cover of satellite images were analyzed using a supervised classification scheme with maximum likelihood classifier decision techniques. To improve accuracy and reduce classification errors, more than 45 training samples were taken during the time of analyzing LULC classification.

Following that, the final analysis result was imported into the ArcGIS environment to create the maps. Additionally, the change detection map was analyzed in Arc GIS. Essentially, satellite images were used to evaluate changes in land use and cover, with a focus on forest cover change, which has a direct correlation to climate change.

3.5.4 LULC Classification Accuracy Assessment

Accuracy assessment defines the quality of information resulting from remotely sensed data (Cogalton and Green, 2006). Accuracy assessment aims to quantitatively assess how effectively the pixels were sampled into the correct land use land cover classification (Sophia et al, 2017). For the current study, analyzing accuracy assessment was carried out using a ground control point from google earth (Soni, 2017). Using the following method shown below, the image classification was further assessed by calculating the overall accuracy, kappa statistics, producer accuracy, and user accuracy. The kappa statistics is an approximation measure of total agreement between satellite image data and ground truth reference data or points. Its coefficient falls typically on a scale between 0 and 1. Where the final shows complete agreement is often multiplied by hundred (100) to give a percentage measure of classification accuracy (Kamrul *et al,* 2018). Kappa values are categorized into three sets, a value more than 0.80 denote strong agreement, a value between 0.4 and 0.8 denotes moderate agreement, and a value below 0.4 denotes poor agreement (Yetnayet *et al*, 2017).

$$\text{Total accuracy} = \frac{Total\ number\ of\ correctly\ classified\ pixels\ (diagonals)}{Total\ numbers\ of\ referance\ pixels} * 100 \text{………… …..Eq (1)}$$

$$\text{User accuracy} = \frac{Total\ number\ of\ correctly\ classified\ pixels\ in\ each\ catagory}{Totalnumber\ of\ classified\ pixels\ in\ that\ catagory\ (row\ total)} * 100 \text{ ……..…Eq (2)}$$

$$\text{Producer accuracy} = \frac{Total\ number\ of\ correctly\ classified\ pixels\ in\ each\ catagory}{Total\ number\ of\ classified\ pixels\ in\ that\ catagory\ (Column\ total)} * 10..\text{Eq (3)}$$

$$\text{Kappa of coefficient} = \frac{(Total\ sample * Total\ corrected\ sample) - \sum(Column\ total * Row\ total)}{Square\ of\ (Total\ Smple\ ) - \sum(Column\ total * Row\ total)} * 10.\text{Eq}$$

(4)

3.5.5 Land use Land cover Thematic Layer

After the accuracy assessment was accompanied, the final land use land cover thematic layer was identified and mapped for four study periods i.e. 1993, 2002, 2012, and 2022. Therefore the study area was categorized into the following LULC Class. See table 3.7 below the LULC type of the study area.

Table 3.7: Land Use Land Cover Class of the study area

LU/LC Class	**Description**
Farmland	The land is used primarily for the production of food.
Forest land	Natural forests and woodlands with a composition of different tree species
Bare land	Area of land where plant growth may be scarce.
Built up land	The area occupied by houses and buildings includes road network residential, Commercial, transportation, roads, mixed urban and other facilities.
Waterbody	The area covered by Waterbody

Source: Ayele (2017)

3.5.6 Land Use Land Cover Change Detection

Land use land cover change detection was conducted by using satellite images of 1993, 2002, 2012, and 2022. Thematic layers of images were compared using GIS techniques. The post-classification technique is the most widely used method for computing change detection (Chen, 200). The study of land use land cover change detection encompasses procedural ways of integration using Arc GIS software. The first task was to develop a table that direct the area coverage in square kilometers and percentage change for each year 1993, 2002, 2012, and 2022 measured against each land use land cover class. Therefore, to compute the percentage and rate of change for each land use land cover class by using the following formula.

$$\text{Rate of change} = \frac{Area\ kms}{Change\ of\ year} = Y - X/Z \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Eq\ (5)$$

$$\text{Percentage of change} = \frac{Observed\ change\ of\ area}{Total\ area} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots\ldots Eq\ (6)$$

Where, X, indicates the area of the previous LULC class in a square kilometer, Y is the area of the final LULC Class in square kilometers and Z is a time interval between X and Y

3.5.7 Calculating Land Surface Temperature

Calculating LST for Landsat 5 and Landsat 7, band number 6 was used and for Landsat 8, band number 10 was used. So, in this research study Land surface temperature was calculated as follows.

1) Conversion of digital numbers to spectral radiance

$$L\lambda = \left(\frac{LMAX\lambda - LMIN\lambda}{Qcal\ max - Qcal\ min}\right)(Qcal\ max - Qcal) + \text{LMIN}\lambda \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eq(7)}$$

Where

- $L\lambda$-At sensor spectral radiance in (W/(m^2 sr/µm/)
- Q_{cal}-Landsat image (digital number)
- $Q_{cal\ min}$ -Minimum quantized calibrated pixel value corresponding to LMINλ
- $Q_{cal\ max}$ - Maximum quantized calibrated pixel value corresponding to LMAXλ
- LMINλ- Spectral at sensor radiance that is scaled to $Q_{cal\ min}$ (W/(m^2 sr/µm/)
- LMAXλ-Spectral at sensor radiance that is scaled to $Q_{cal\ max}$ (W/(m^2 sr/µm/)

2) Conversion of Radiance to Brightness Temperature in degrees Kelvin

The following equation was used to convert Radiance to Brightness temperature

$$T = \frac{k2}{\ln(\frac{K1}{L\lambda} + 1)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Eq(8)$$

Where

- T -At satellite brightness temperature in (Kelvin)

- Lλ-Spectral radiance in (W/(m^2/sr/μm)
- K1 and K2 =are pre-launch calibration constants. The value of these constants is shown in the table below. See table 3.8 below the thermal band calibration constant of Landsat image.

Table 3.8: indicates TM, ETM+, and OLI/TIRS/ Thermal band calibration constant

Sensor	**Band**	**L_{min}**	**L_{max}**	**$Q_{cal\ min}$**	**$Q_{cal\ max}$**	**K1**	**K2**
Landsat5	6	1.238	15.600	0.0	255.0	607.76	1260.56
Landsat7	6_1	0.00	17.040	1.0	255.0	666.09	1282.71
	6_2	3.200	12.650	1.0	255.0	666.09	1282.71
Landsat8	10	Radiance multiplier(M)		Radiance Add(A)		K1	K2
		0.0003342		0.1		774.89	1201.14

Source: (Febaku etal.,2018)

3) Convert degree kelvin to degree centigrade by using the following formula.

T-273.15……………………………………………………………………………..Eq (9)

Where T is the temperature in degrees in kelvin.

3.5.8 Normalized Difference Vegetation Index (NDVI)

First, MODIS data was displayed as a composite over 16 days. It is essential to convert the data first into both monthly and yearly ones. After that, a statistical algorithm was used to evaluate the time series biomass (NDVI) value.

Finally, by using the raster calculator found in the spatial analyst tool in the ArcGIS environment, the total average annual biomass coverage for the observation period between 2003 and 2022 was determined by adding all yearly average values and dividing the sum by the number of observations. This can be mathematically represented by the following equation:

$$\mathrm{Yi} = \sum_{i=2003}^{2022} (\mathrm{Xi}/\mathrm{N})$$

Where Y_i is the overall mean annual NDVI Value, X_i is the average mean annual NDVI value of a given year and N is the number of total observation years.

The annual mean NDVI of belg and kiremt season was calculated by using the following formula.

$$\text{Xi} = [\textstyle\sum_{j=March}^{May}(\text{K})]/n \qquad\qquad \text{Xi} = [\textstyle\sum_{j=June}^{Augost}(\text{K})]/n$$

Where, Xi is mean NDVI of belg and kiremt season, K is the number of NDVI data and n is observation year.

3.5.9 Linear Regression Descriptive Statistics

The relationship between LULC Change, NDVI, LST, and Rainfall was analyzed using the linear regression analysis method for each pixel to test the strength of the linear relationship between each other. (Lamchin *et al*, 2015). Linear regression analysis is a statistical technique that measures the strength of linear relationships between paired data.

It is a test statistic that measures the statistical relationship or association among two continuous variables. It provides information about the degree of the correlation, association, and as well as direction of the relationship between variables (Worku, 2018).

3.6 Technological Scheme of the Study

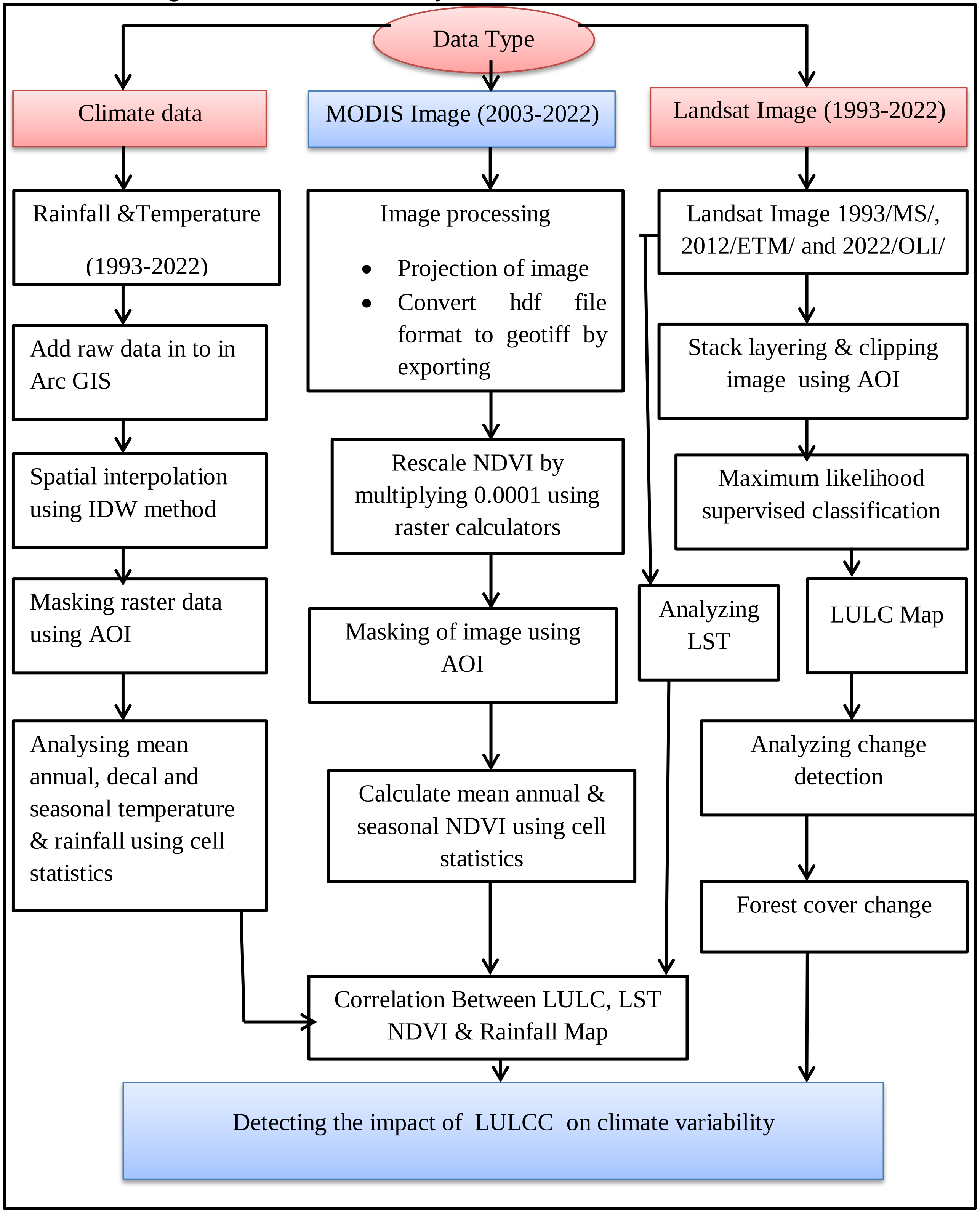


Fig 3.4: Technological scheme of the study

CHAPTER IV.RESULT AND DISCUSSION

4.1 Introduction

This chapter deals with analysis, presentation, interpretation, and discussion of both primary and secondary sources of data. Accordingly, under this chapter, the trends and variability of rainfall and temperature, the spatial and temporal variations of LULCC, LST and NDVI, association of LULCC, LST and NDVI with rainfall as well as the implications of LULCC on climate variability were briefly analyzed, discussed, interpreted, and presented in the form of tables, graphs, maps, and narratives.

4.2 Trend of Rainfall between 1993 and 2022

4.2.1 Annual Rainfall

The mean annual rainfall of the study area was 1185.2mm with standard deviation and coefficient of variation of 104.29 and 0.088 respectively between 1993 and 2002GC. The mean annual rainfall observed between 2003 and 2012 GC was 1179.8 mm with a standard deviation of 110.90 and a coefficient of variation of 0.094. The mean annual rainfall of the last decade, i,e between 2012 and 2022 was 1155.4 mm with a standard derivation of 111.26 and a coefficient of variation of 0.096.

Generally, the result shows that the mean annual rainfall distribution of the three decades relatively shows variation in space and time. The mean decadal rainfall distribution showed that there is declined amount of rainfall during the study period. The mean annual rainfall in the second decade, the intensity of rainfall decreased by 5.4 mm as compared to the first decade observation time. Similarly the mean annual rainfall in the third decade of observation, the intensity of rainfall amount was decreased by 24.4 mm compared to the second decade. See table 4.1 below the decadal rainfall of the study area

Table 4.1: Decadal mean annual rainfall distribution between (1993-2022)

Decade	Mean annual Rainfall in (mm)	SD	CV
1993-2002 1st	1185.2	104.29	0.088
2003-2012 2nd	1179.8	110.90	0.094
2013-2022 3rd	1155.4	111.26	0.096

Based on the resulted indicated in Fig 4.1 below the patterns of the trend over the last three decades, the linear equation of the decadal variation shows declining trend.

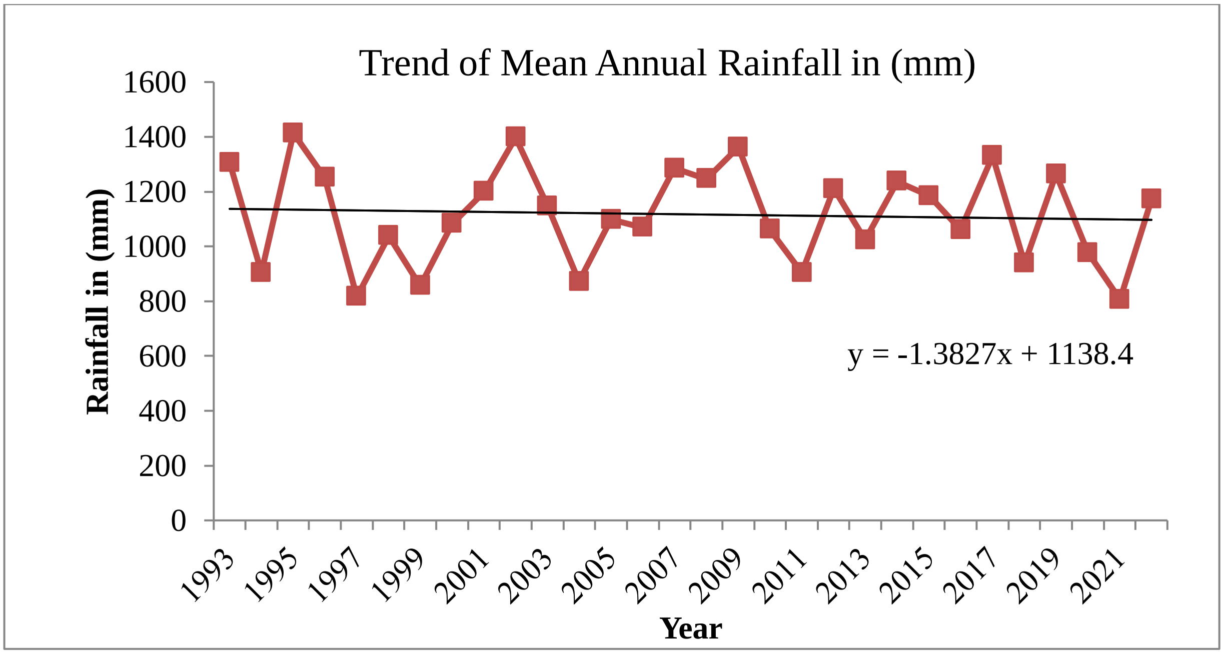


Fig 4.1: Trend of mean annual rainfall distribution of the study area between(1993-2022)

4.2.2 Decadal Rainfall Distribution

A Rainfall Distribution between (1993-2002)

The average annual rainfall of the first decade was 1185.2mm. In this period, the central parts of the study area received high mean annual rainfall (1308.8-1389.8) mm. Some parts of the western and midland of the study area received moderate rainfall (1067.8-1308.7) mm. While the northern, southwestern, and eastern parts of the study area received less rainfall (826.66-1067.7) mm in the first decade. See Fig 4.2 below shows the spatial distribution of mean rainfall between (1993-2002) GC.

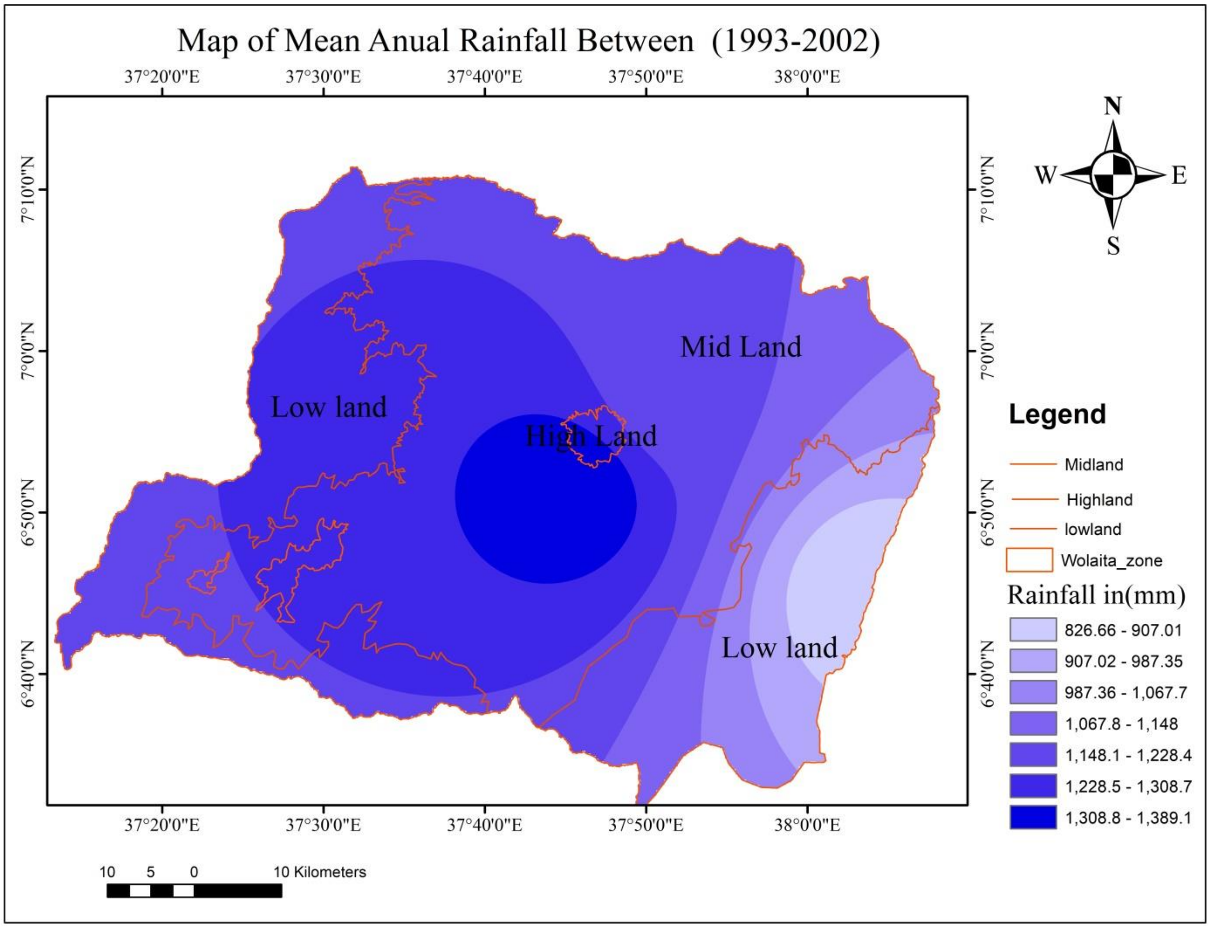


Fig 4.2: First decade mean annual rainfall distribution

B) Rainfall Distribution between (2003-2012)

During the second decade, the mean annual rainfall of the study area was found to be 1179.8mm. in this decade, the central part of the study area received high mean annual rainfall (1265.7-1339)mm. The northern, southern, and western parts of the study area received a mean annual rainfall of (1119.6-1265.7)mm. like the first decade, the eastern part of the study area received less amount of mean annual rainfall(827.5-1119.5)mm. See below fig 4.3 illustrate the spatial distribution of mean annual rainfall distribution between (2003-2012) GC

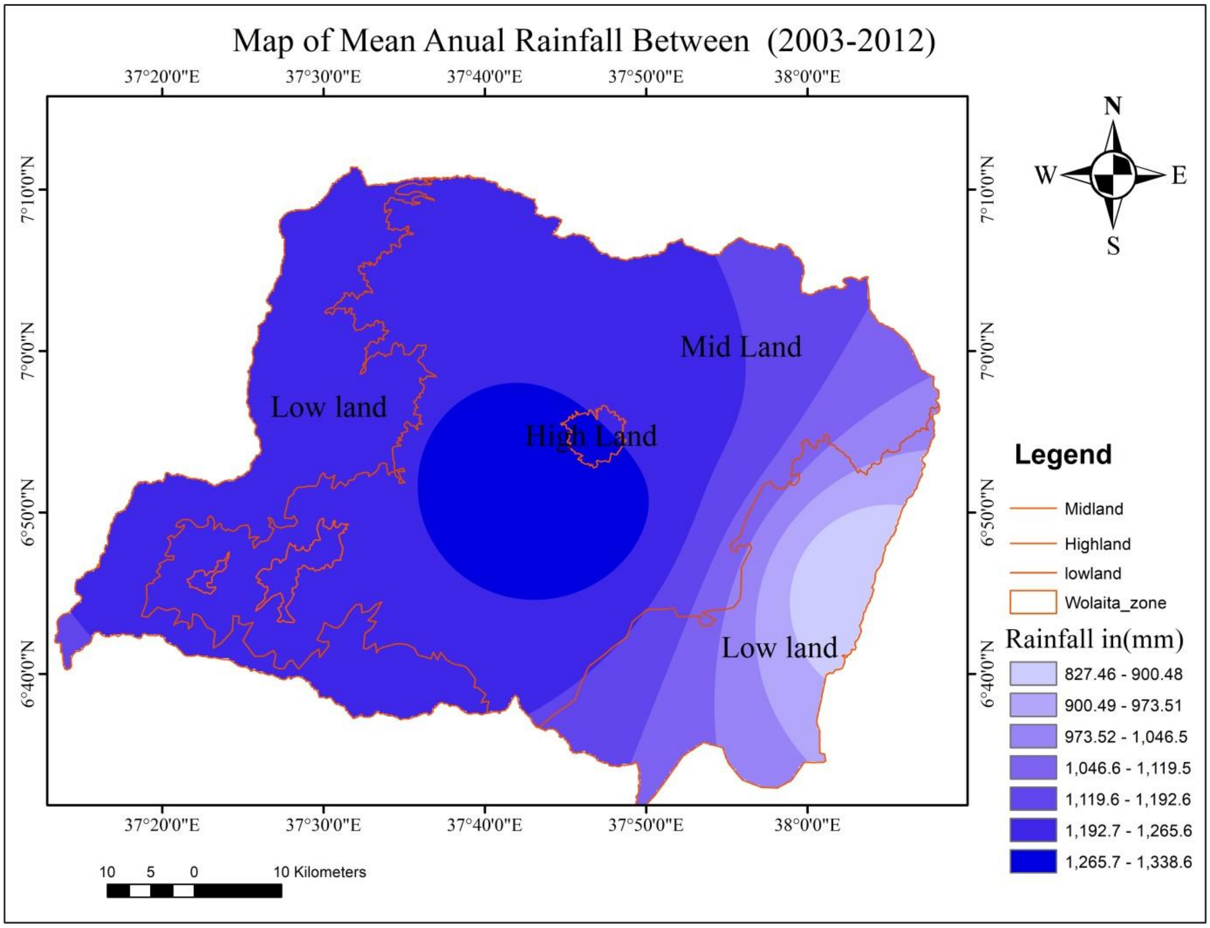


Fig 4.3: second decadal mean rainfall distribution

C) Rainfall Distribution between (2013-2022)

The overall average rainfall recorded in this decade was 1126.24mm. Below fig 4.4 indicates the mean annual rainfall distribution between (2012-2022) GC. In the last decade, the central, and northern parts of the study area received higher mean annual rainfall. However, the western, and southern parts of the study area received moderate mean annual rainfall. Finally, the eastern part of the lowland area received low mean annual rainfall. See below Fig 4.4 illustrates the rainfall distribution of the study area between 2013-2022

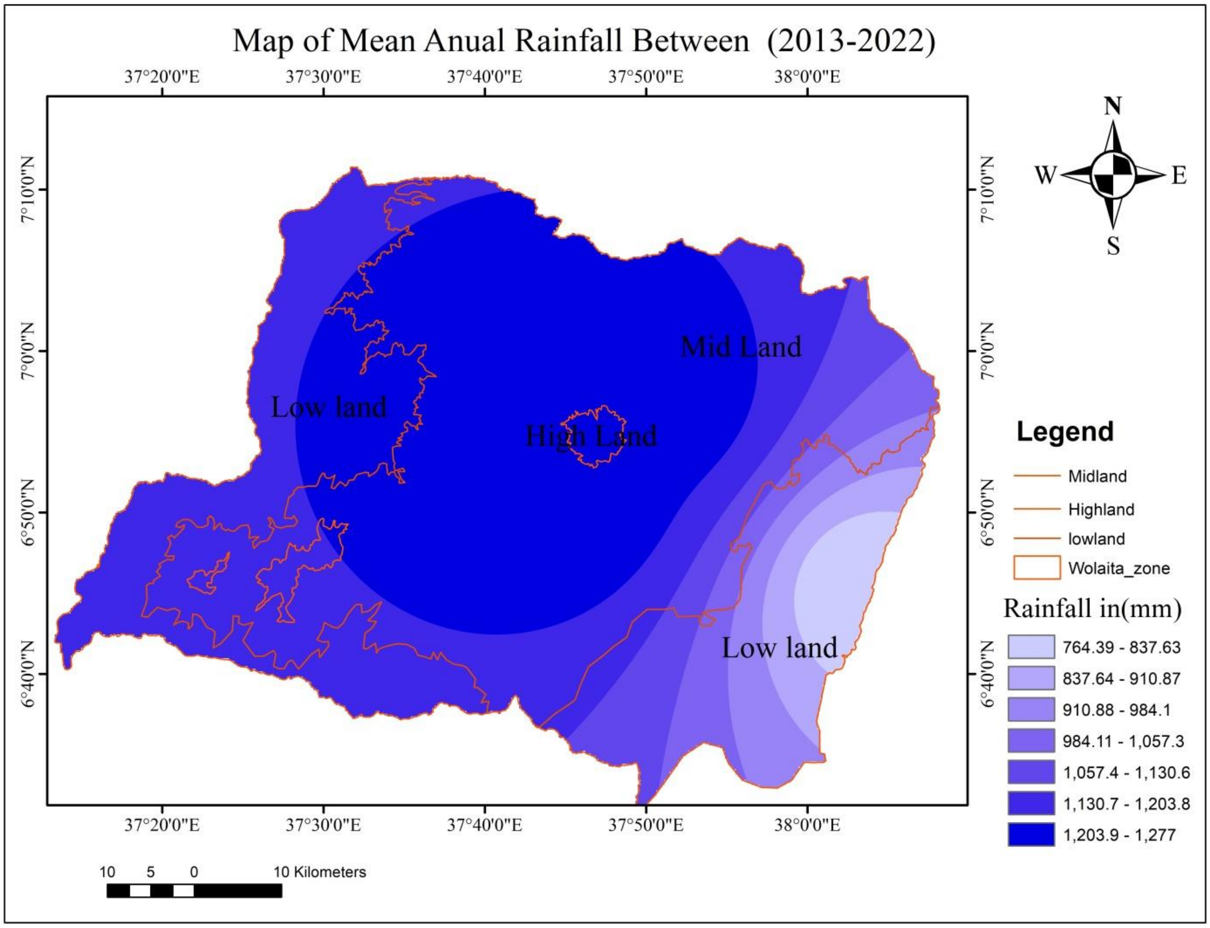


Fig 4.4: Third decade mean rainfall distribution

4.2.3 Seasonal Rainfall Distribution

A) Balguwa(Summer) Season Rainfall Distribution

During the study period, in the balguwa (kiremt) season, the high land or central part of the study area received high rainfall while the eastern part of the study area received low mean annual rainfall. The northern, western, and southern parts of the study area received moderate mean annual rainfall.

During the summer season, the study area received 426.42mm mean annual rainfall with a standard deviation of 51.20 and a coefficient of vitiation of 0.12 between 1993-2022. See Fig 4.5 below shows the summer season mean annual rainfall of the study area during the study period.

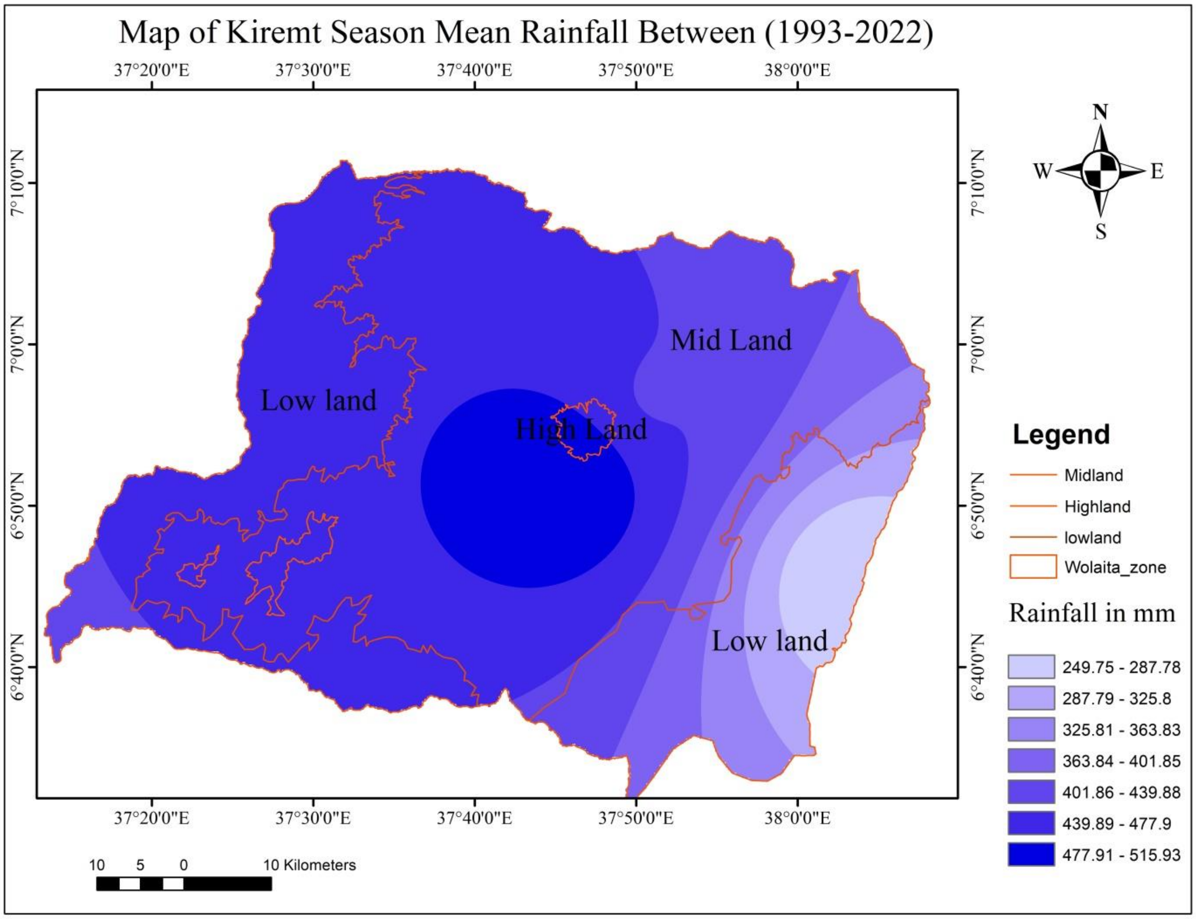


Fig 4.5: kiremt season mean rainfall distribution

B) Badhesa (Belg) Season Rainfall Distribution

Like kiremt season, in the belg season, the central part of the study area received high rainfall while the eastern part of the study area received low mean annual rainfall. The northern, western, and southern parts of the study area received moderate mean annual rainfall.

The mean annual rainfall of the belg (Badhesa) season of the study area was 391.01 mm with standard deviation and coefficient of variation of 33.01 and 0.0846 respectively.

Based on the information obtained from KII, agricultural production of the study area was highly dependent on the Kiremt and Belg season rainfall. See Fig 4.6: below depicts the belg season mean annual rainfall of the study area between 1993-2022.

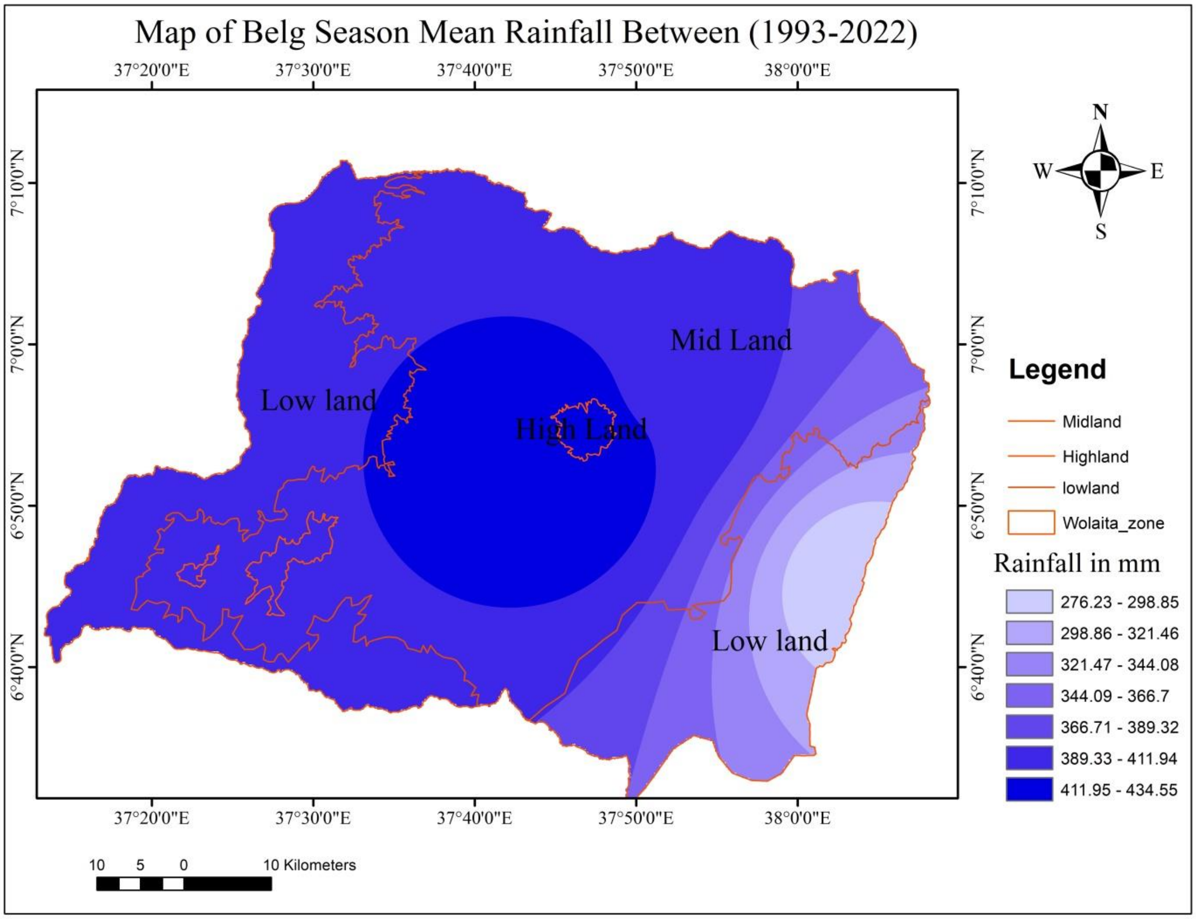


Fig 4.6: Belg season mean rainfall distribution

Table 4.2: Mean annual rainfall of the Belg and Kiremt seasons between (1993-2022)

Decade	Kiremt Rainfall in (mm)	CV	Belg Rainfall In (mm)	CV
1993-2002	433.04	0.13	411.71	0.07
2003-2012	429.25	0.12	392.73	0.1
2013-2022	414.94	0.1	371.35	0.08

Source: Computed by Researcher, 2023

The seasonal rainfall distribution of the kiremt and belg season of the study area at the decadal level was discussed as follows. As the result indicated in Table 4.2 above, the mean annual rainfall of the first decade kiremt season was 433.04 mm with a coefficient of variation of 0.13. The mean annual rainfall of the second decade was 429.25 mm with a coefficient of variation of 0.12. While the third decade, the mean annual rainfall of the kiremt season was 414.94 mm with a coefficient of variation of 0.1. When comparing the trend of rainfall distribution at the seasonal decadal level, the mean annual rainfall distribution was show a declined intensity of rainfall distribution. In this season, the intensity of mean annual rainfall distribution decreased by 3.79 mm and 14.31 mm in the second and third decades respectively. The mean annual rainfall of the first decade Belg season was 411.71 mm with a coefficient of variation of 0.07. During the second decade of the belg season, the mean annual rainfall was 392.73 mm, and the coefficient of variation of 0.1. In the third decade of the belg season, the mean annual rainfall distribution was 371.35 mm with a coefficient of variation of 0.08. When investigating the belg season rainfall distribution at the decadal level, the intensity of the rainfall shows a decreasing trend. The intensity of the belg season rainfall distribution in the second decade was decreased by 19 mm while in the third decade, the rainfall distribution was decreased by 21.38 mm. Generally, the belg season rainfall of the study area declined by 40.36 mm from 1993 to 2022.

4.3 Temperature Variability

Temperature is the most widely reported direct observation of change (Kadir et al.2013). it is a key indicator amongst whole climate elements to show whether the terrestrial or water surface is getting hot or cool. It is due to observable changes recognized in mean temperature in the world that significant emphasis is given to the issues of climate change.

Characterizing and studying temperature data was many advantages such as making helpful decisions about how crops are grown and managing, to estimate crop yield to help the government.

4.3.1 Spatial and Temporal Variability of Maximum Temperature

The results of a thirty-year investigation of temperature variations varied throughout time.

The overall maximum average annual temperature of the study area between the years (1993-2022) was 26.89 ^{0}C with a standard deviation of 0.44 and a coefficient of variation of 0.02.

The average annual maximum temperature of the study area in the first decade (1993-2002) was 26.65^{0}C with a standard deviation of 0.37 and coefficient of variation of 0.014 while the average annual maximum temperature of the second decade (2002-2012) was 26.84 ^{0}C with standard deviation 0.36 and coefficient of variation of 0.013. Finally, the average annual maximum temperature of the third decade (2013-2022) was 27.17 ^{0}C with a standard deviation of 0.44 and a coefficient of variation of 0.016. Depending on this, the result shows a slightly increased average annual maximum temperature during the study period. In this regard, the average annual maximum temperature of the second decade was increased by 0.19^{0}C. In the third decade, the average maximum annual temperature of the study area increased by 0.52 ^{0}C and 0.33^{0}C compared to the first decade and second decade respectively. See Tale 4.3 below the average annual maximum temperature and coefficient of variation at a decadal level.

Table 4.3: Average maximum temperature and CV at the decadal level

Decade	**Average maximum temperature in (^{0}C)**	**CV**
1993-2002	26.65	0.014
2003-2013	26.84	0.013
2013-20222	27.17	0.016

Source: Computed by Researcher, 2023

Generally, the average annual maximum temperature of the study area was increased from 1993 to 2022. It increased by 0.52 ^{o}c from 1993 to 2022.

Higher temperatures increase a variety of disasters, including storms, heat waves, floods, and droughts. A warmer temperature produces an atmosphere that can accumulate, hold, and release more water, altering weather patterns such that wet areas grow wetter and dry ones become drier.

See fig 4.7 below the average annual maximum temperature of the study area during the study period between (1993-2022).

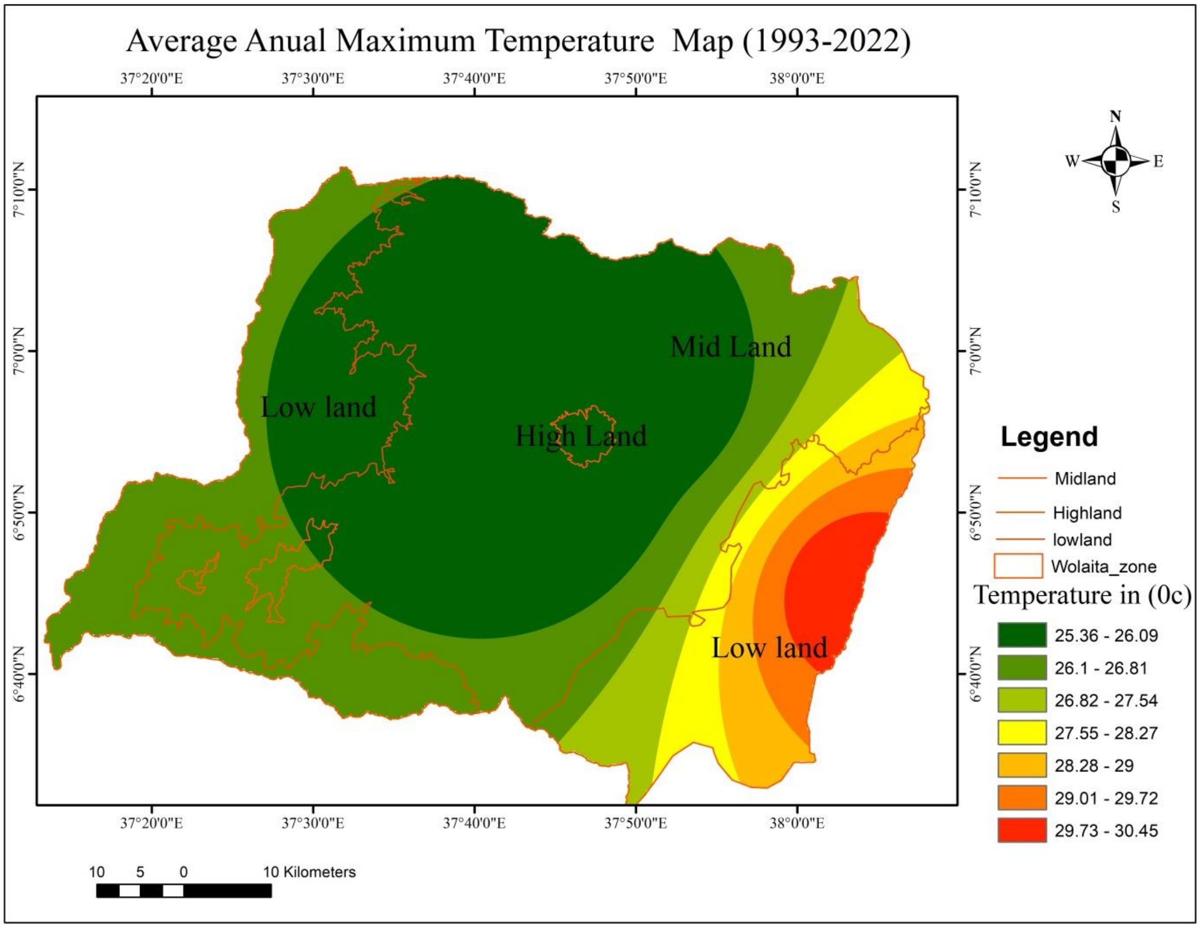


Fig 4.7: Average annual maximum temperature of the study area.

Based on fig 4.7 above the spatial variability of average maximum temperature was discussed as follows. The central and northern parts of the study area were low average annual temperatures (24.76-25.72) ^{0}C. The northwestern, western, and southern parts of the study area obtained the average annual maximum temperature of (25.73-2654) ^{0}C. While the eastern and southeastern parts of the study area obtained high average annual maximum temperature (26.55-30.43) ^{0}C during the study period.

4.3.2 Spatial and Temporal Variability of Minimum Temperature

The average annual minimum temperature of the study area between the years 1993-2022 was 14.89 ^{0}C with a standard deviation of 0.75 and a coefficient of variation of 0.05. The average annual minimum temperature shows variation in time-to-time difference. The average annual minimum temperature of the study area in the first decade was 14.20 ^{0}C with a standard deviation of 0.83 and a coefficient of variation of 0.06. In the second decade, the average annual minimum temperature of the study area was 14.99 ^{0}C with a standard deviation of 0.35 and a coefficient of variation of 0.02. While in the final decade, the average annual minimum temperature of the study area was 15.49 ^{0}C with a standard deviation of 0.28 and a coefficient of variation similar to the second decade. During the study period, the average annual minimum temperature was increased by 0.79 ^{0}C and 0.5^{0}C in the second and third decades. So depending on the result, the average annual minimum temperature of the study area between (1993-2022) showed an increasing trend. See fig 4.8 below illustrates the average annual minimum temperature of the study area between (1993-2022).

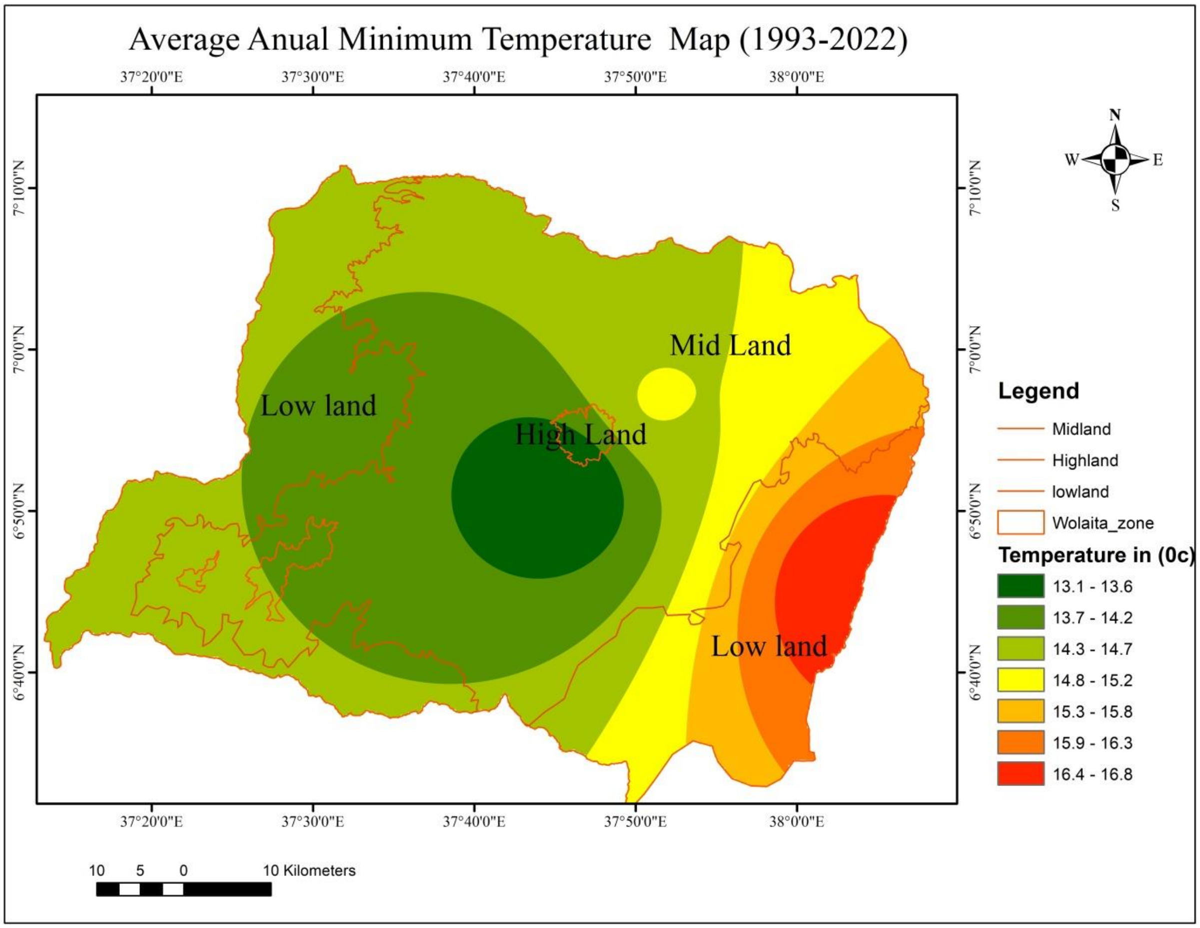


Fig 4.8 Average annual minimum temperature

Based on Fig 4.8 above, the central part of the study area received a low average minimum temperature (13.1-13.9) ^{0}C compared with other parts of the study area. While the northern, western, and southern part of the study area was slightly cold that was received (14-14.5) ^{0}C. But the northeastern part of the study area was relatively hot that was received the average annual minimum temperature of (14.6-15.9) ^{0}C. Finally, the eastern part of the study area was hotter than the other part of the study area during the study period. This part of the study area received the mean annual minimum temperature of (16-16.8) ^{0}C. Tale 4.4 below depicts the average annual minimum temperature, standard deviation, and coefficient of variation at the decadal level.

Table 4.4: Average minimum temperature and CV at the decadal level

Decade	The average minimum temperature in (^{0}C)	CV
1993-2002	14.20	0.006
2003-2013	14.99	0.02
2013-20222	15.49	0.02

Source: Computed by Researcger, 2023

4.4 Land Use Land Cover in 1993, 2002, 2012 and 2022

4.4.1 Land Use Land Cover Classification Analysis

Land cover refers to what covers the earth's surface, whereas land use refers to how the land is used. The Earth's surface contains both natural and man-made geographical landscapes such as ecosystems, landforms, human settlements, and engineering structures. Land use and land cover (LULC) analysis is a general term used to describe Earth's surface cover, whether natural or man-made. For this study, LULC Classification was analyzed as follows.

Four Landsat images namely 1993 /5/MSS, 2002 /5/MSS, 2012/7/ETM+, and 2022/8/OLI /TIRS/ with Spatial resolution of 30m, 30m. 30m and 30 m respectively were used for analyzing land use land cover change in the study area to investigate climate variability. Five major land use land cover class was identified in the study area. These are Farmland, forest land, bareland, built-up land, and water body. As presented in Table 4.6 below, out of the total study area 2617.41km^2 (58.04%), 2005.30km^2 (44.47%), 1953.31km^2 (43.32%), 1293.22km^2 (28.68%) covered with forest land, 1222.05 km^2 (27.09%), 2022.18 km^2 (44.84%), 2142.18 km^2 (47.50%), 2838.37 km^2 (62.95%) covered with farmland, 627.31 km^2 (13.91%), 407.86 km^2 (9.05%), 328..41 km^2 (7.28%), 16.73 km^2 (0.38%) covered with bare land, 15.10 km^2 (0.35%), 58.01 km^2 (1.28%), 70.83 km^2 (1.57%), 269.64 km^2 (5.97%) covered with built-up land, 27.66 km^2 (0.61%), 16.08 km^2 (0.36%), 14.41 km^2 (0.33%), 91.48 km^2 (2.02%) covered with a water body in 1993, 2002, 2012 and 2022 respectively. See table 4.5 below the LULC Class of the study area.

Table 4.5 LULC classes and their area coverage in 1993, 2002, 2012 and 2022

Year	**1993**		**2002**		**2012**		**2022**	
LULC Class	Area in km^2	Area in %	Area in km^2	Area in %	Area in km^2	Area in %	Area in km^2	Area in %
Forest Land	2617.41	58.04	2005.30	44.47	1953.3	43.3	1293.22	28.68
Farm Land	1222.05	27.09	2022.18	44.84	2142.17	47.34	2838.37	62.95
Bare Land	627.31	13.91	407.86	9.05	328..41	7.28	16.73	0.38
Built up land	15.10	0.35	58.01	1.28	70.83	1.57	269.64	5.97
Waterbody	27.66	0.61	16.08	0.36	14.41	0.33	91.48	2.02
Total	**4509.44**	**100**	**4509.44**	**100**	**4509.44**	**100**	**4509.44**	**100**

Source: Computed by Researcher, 2023

LULC Change detection is described as the process of identifying and quantifying the spatial changes of any natural or man-made phenomenon from satellite images collected over time (Singh, 1989).

Information resulting from land use and land cover change detection is essential for land conservation, sustainable development, and water resource management. The aim of change detection is to examine the variability in images recorded during a certain time period related to a specific area.).

Based on the result indicated in Fig 4.9 below, forestland and bare land declined from 1993 to 2022. Also, water bodies decreased from 1993 to 2012 but increased in 2022. However, Built-up land and farmland increased during the study period.

See Fig 4.9 below the Land use land cover classification of the study area of 1993, 2002, 2012, and 2022.

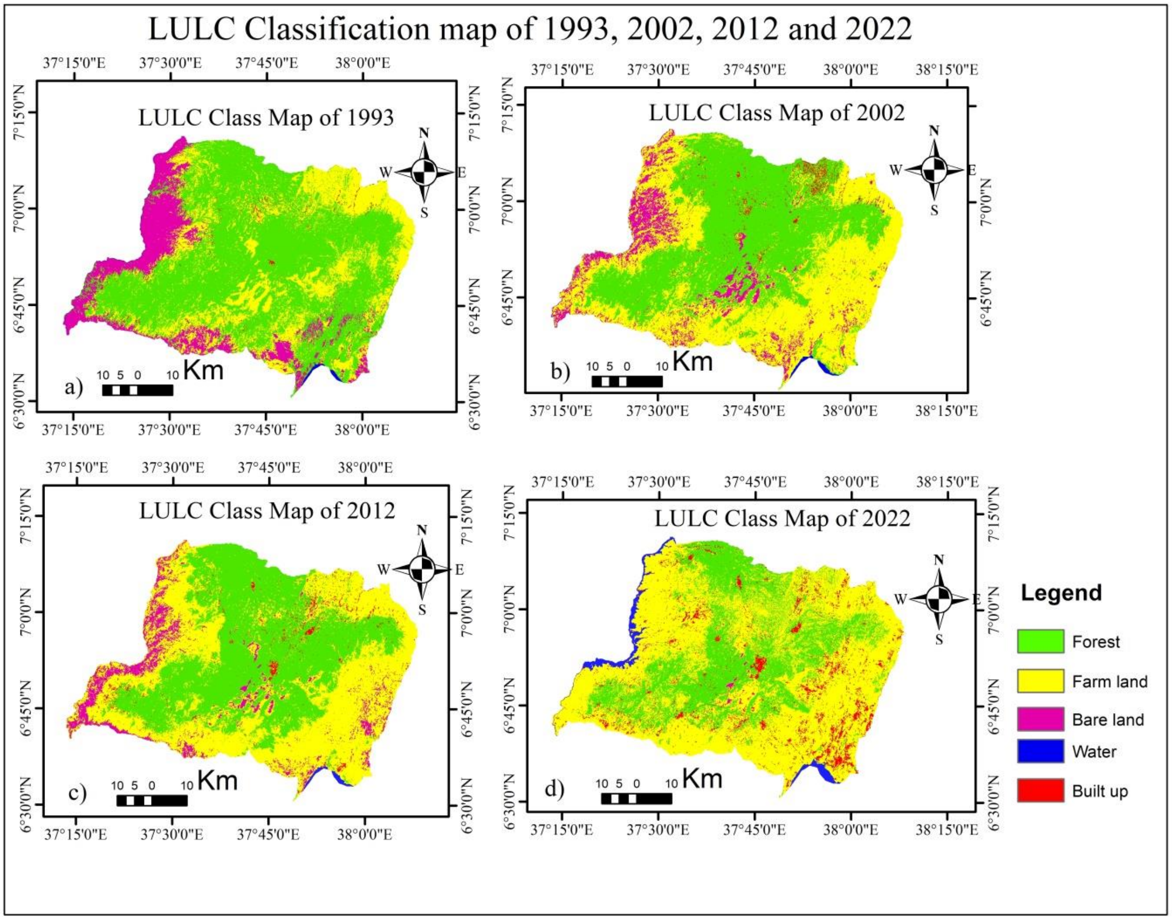


Fig 4.9: a) LULC class of 1993, b) LULC Class of 2002, c) LULC Class of 2012, and d) LULC class of 2022.

4.4.2 Accuracy Assessment of LULC Classification

The aim of accuracy assessment is to identify and quantify map errors. It involves comparing a location on a map ('classified data') to field or photo information ('reference data') for the same location. This work was done on Arc GIS software followed by a classification tab and accuracy assessment tool. First, a random sampling technique was used to collect ground truth reference points (Amit, 2018). these ground truth points were overlaid on the land use land cover classification map and value was extracted (Limited MC, 2014). After that confusion matrix was generated and placed such that class membership was determined by ground truth value along with the x-axis and class membership was determined by image classification along the y-axis(Maitima *et al.* 2012). When placed in this way, correct values fall along the major diagonals of a matrix (Morgado *et al*, 2012). Correctly classified values lie in the diagonal area of the matrix; such that it is apparent to which class they were confused (Mundia, 2009). Field data for validation is not available for 1993, 2002, and 2012. So it was assumed that a similar accuracy was achieved using the same method from the 2022 land use land cover map (Pradesh, 2005). The accuracy result for the land use land cover classification map of 1993, 2002, 2012 and 2022 was presented as follows. See Table 4.6, Table 4.7, Table 4.8 and Table 4.9 below the accuracy assessment of 1993, 2002, 2012 and 2022 respectvley.

Tale 4.6: Accuracy assessment of 1993 LULC map

Classification	Forest land	Farm land	Bare land	Water body	Built up area	Row total	User Accuracy in (%)
Forest land	41	4	0	0	2	47	87.23
Farmland	0	59	3	0	2	64	92.18
Bare land	2	3	41	0	0	46	89.13
Waterbody	2	0	2	77	0	81	95.06
Built up area	2	2	0	0	50	54	92.59
Column Total	47	68	46	77	54	**292**	
Producer accuracy in (%	87.23	89.39	89.13	100	92.59		

Overall classification accuracy=91.21%

Overall Kappa Statistics= 89.29%

Source: Computed by Researcher, 2023

Tale 4.7: Accuracy assessment of 2002 LULC map

Classification	Forest land	Farm land	Bare land	Water body	Built up area	Row total	User Accuracy in (%)
Forest land	51	3	1	0	2	57	89.47
Farmland	2	71	3	0	0	76	93.42
Bare land	3	3	41	0	1	48	85.41
Waterbody	2	2	0	56	0	60	93.33
Built up area	1	2	1	0	61	65	93.84
Column Total	59	81	46	56	64	**306**	
Producer accuracy in (%	86.44	87.65	89.13	100	95.31		
Overall classification accuracy=91.50%							
Overall Kappa Statistics= 89.30%							

Source: Computed by Researcher, 2023

Tale 4.8: Accuracy assessment of 2012 LULC map

Classification	Forest land	Farm land	Bare land	Water body	Built up area	Row total	User Accuracy in (%)
Forest land	64	5	0	0	1	70	91.42
Farmland	3	68	2	0	2	75	90.66
Bare land	0	3	48	3	0	54	88.88
Waterbody	2	0	3	68	0	73	93.15
Built up area	3	2	0	0	60	65	92.30
Column Total	72	78	53	71	63	**337**	
Producer accuracy in (%	88.88	87.17	90.56	95.77	95.23		
Overall classification accuracy=91.30%							
Overall Kappa Statistics= 89.20%							

Source: Computed by Researcher, 2023

Tale 4.9: accuracy assessment of 2022 LULC map

Classification	Forest land	Farm land	Bare land	Water body	Built up area	Row total	User Accuracy in (%)
Forest land	62	3	2	0	2	69	89.85
Farmland	3	59	2	0	1	65	90.76
Bare land	2	2	41	1	0	46	89.13
Waterbody	2	2	0	71	0	75	94.66
Built up area	2	2	0	0	47	51	92.15
Column Total	71	68	45	72	50	**306**	
Producer accuracy in (%	87.32	86.76	91.11	98.61	94		
Overall classification accuracy=91.78%							
Overall Kappa Statistics= 89.60%							

Source: Computed by Researcher, 2023

Depending on the result showed Table 4.6-4.9 above, the highest accuracy of classification was founded in the 2022 LULC map which was 91.78 % accuracy whereas the lowest accuracy of LU/LC classification was founded in 1993, which was 91.21% accuracy. The overall kappa statistics for the LULC map of 1993, 2002, 2012, and 2022 were 89.29, 89.30, 89.20, and 89.60 percent respectively. A kappa statistics value greater than 0.8 indicates strong agreement, between 0.4-0.8 indicates moderate agreement, and less than 0.4 shows poor agreement (Akalu *et al*, 2019).

4.4.3 Magnitude of Land use land covers change

Land use land cover shows degrees of change between successive years. The rate of land use land cover change was shown as follows. In this research study agricultural land and built-up area were indicates an increasing rate of change and forest land, bare land and water body shows a decreasing rate of change from the base year into the next year. For example, in 1993 and 2002 farmland and built-up area positively increased by 80.01 km^2 /year and 4.29 km^2 /year respectively over ten year period. Whereas forest land, bare land, and water body were negatively decreased by 61.21 km^2 /year, 21.94 km^2 /year, and 1.15 km^2 /year respectively over ten year period. Likewise, between 2002 and 2012 farmland and built-up area positively increased by 12 km^2 /year and 1.28 km^2 /year respectively. But forest land, bare land, and water body were negatively decreased by 5.12 km^2/year, 7.94 km^2 /year, and 0.17 km^2 /year respectively. Also between 2012 and 2022 farm land, built-up area, and water body were positively increased by 69.61 km^2 /year, 7.707 km^2 /year, and 19.88 km^2 /year respectively. Moreover, between 1993 and 2022. in the thirty years, farmland, built-up area, and water body were positively increased by 53.87 km^2 /year, 8.48 km2/year, and 2.12 km^2 /year respectively. However, the magnitude of Land use land cover change was changed slowly in the second decade compared to the first and third decades.

4.4.4 LULC Change Detection from 1993-2002

The change detection matrix result in Table 4.10 below indicates that the percentage of forest land decreased in 2002 compared to 1993. Out of total land use 816.87 km^2 (18.11%) of the forest was converted to farmland, 40.35 km^2 (0.89%) of the forest was converted to bare land, and 13.08 km^2 (0.29%) of the forest was converted to build-up land. Due to this reason, the quantity of forest land coverage in the study area was reduced by 612.1 km^2 (13.5%). Similarly, bare land decreased in 2002 compared with the initial year. 393.36 km^2 (8.72%) of bare land was converted into farmland and 1 km^2 (0.02%) of bare land was changed into built-up area in 2002. However, farmland and built-up land increased in 2002 compared with 1993. Specifically, farmland was significantly enlarged by 800.1 km^2 (17.7%). Depending on this, 816.87 km^2 (18.11%) of forest land, 393.36 km^2 (8.72%) of bare land and 2.8 km^2 (0.06%) built-up land was changed into farmland. Also, the built-up area was increased in 2002. It was initially 15.01 km^2 (0.61%) in 1993. However, it increased by 42.92 km^2 (0.93%) in 2002. Out of the total area 13.08 km^2 (0.29%) of forest land, 40.64 km^2 (0.9%) of farmland, and 1 km^2 (0.02%) of bare land were changed into built-up land. See Fig 4.10 below that illustrates the percentage of forest land cover change.

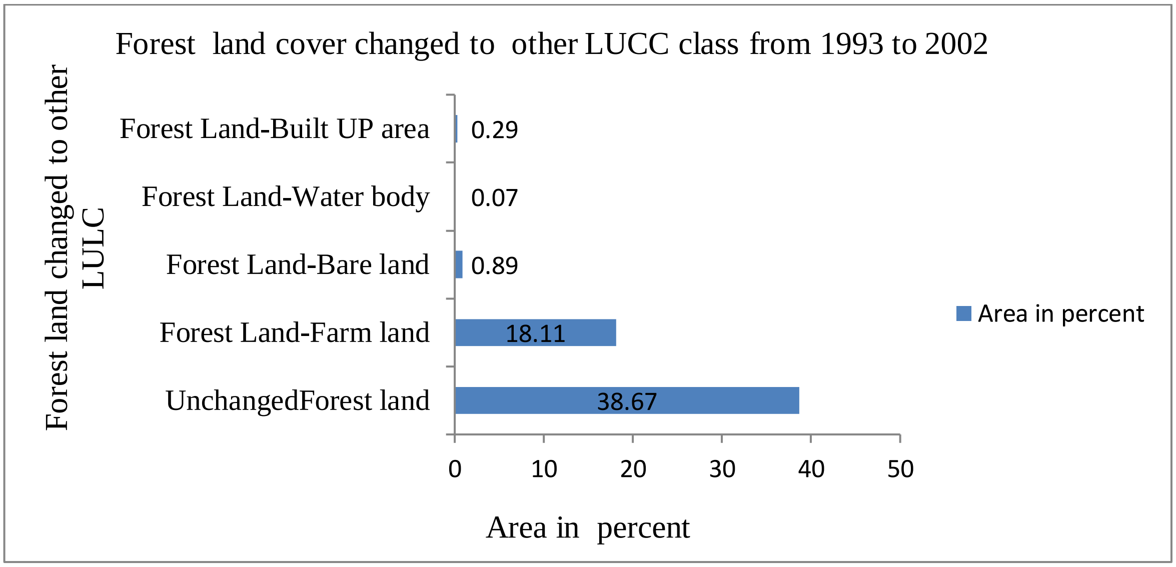


Fig 4.10: Percentage of forest land cover change from 1993 to 2002

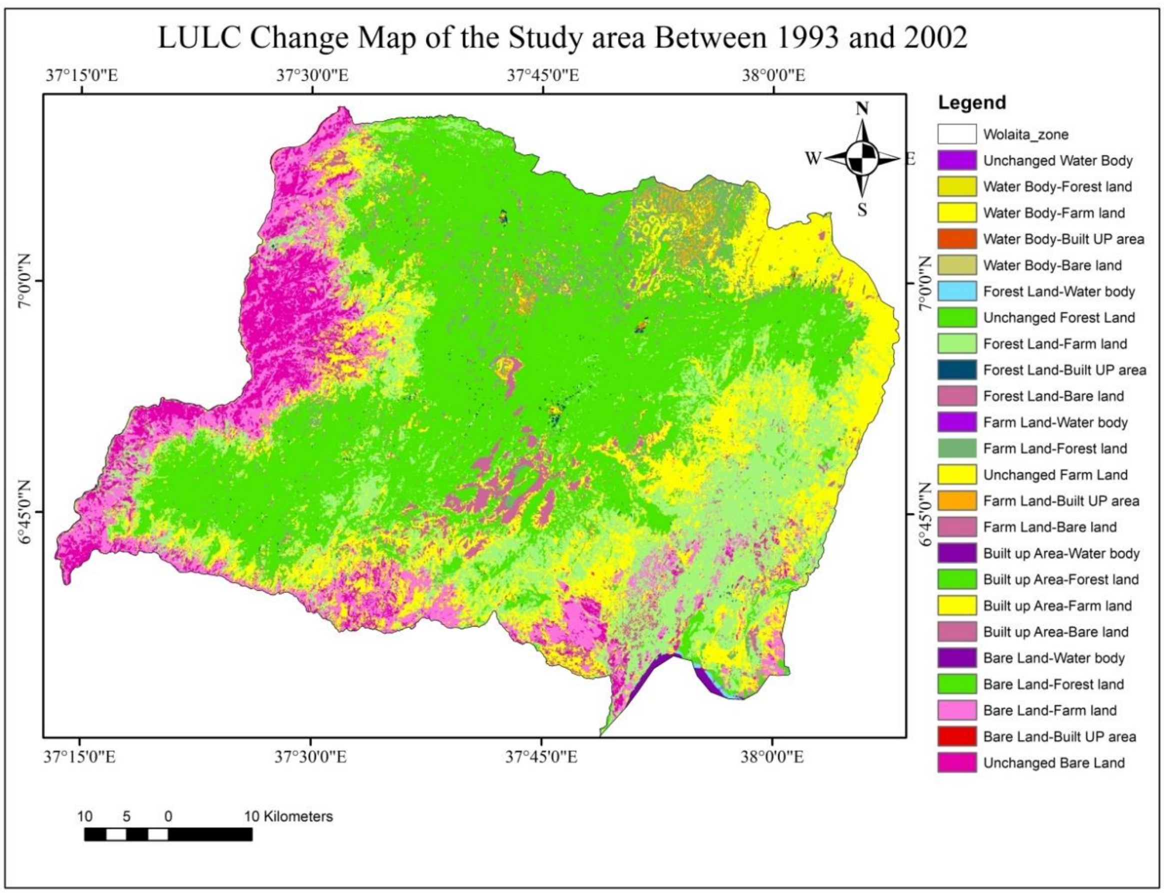


Fig 4.11: LULC Change detection between 1993-2002

Table 4.10: LUCC change detection matrix between 1993 and 2002

		LULC Class for 2002											
	LULC class	Forest land		Farm land		Bare land		Water body		Built up		1993 total	
		Area		Area		Area		Area		Area		Area	
		Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%
LULC Class for 1993	Forest land	**1743.9**	**38.6**	816.87	18.11	40.35	0.89	3.15	0.07	13.08	0.29	2617.41	58.04
	Farm land	249.97	5.54	**793.21**	**17.59**	137.85	3.06	0.37	0.008	40.64	0.90	1222.05	27.09
	Bare land	3.58	0.08	393.36	8.72	**229.15**	**5.08**	0.25	0.006	1	0.02	627.31	13.91
	Water body	7.78	0.17	15.94	0.35	0.41	0.009	**12.1**	**0.27**	0	0.00	27.66	0.35
	built up	0.01	0.00	2.8	0.06	0.1	0.002	0.11	0.00	**3.3**	**0.07**	15.01	0.61
	2002 total Area	2005.31	44.47	2022.18	44.84	407.86	9.04	15.98	0.35	58.02	1.28	**4509.44**	
	Change Km^2	-612.1	-13.5	800.1	17.7	-219.4	-4.87	-11.5	-0.25	42.92	0.93		

LUCC Change detection Matrix from 1993 to 2002

Source: Computed by Researcher, 2023

4.4.5 LULC Change detection from 2002 to1012

The result of change detection analyses in Table 4.11 below indicates that the forest land, bare land, and water body decreased while farmland and built-up land increased in 2012 compared to 2002. The farmland and built-up land were increased by 112.7 km^2 (2.5%) and 12.81 km^2 (0.28%) respectively. However, the area of forest land, bare land, and water body was decreased by 50.9 km^2 (1.15%), 79.4 km^2 (1.77%), and 1.38 km^2 (0.03%) respectively. A massive area of forest land was changed to farmland, bare land, and built-up land in 2012. Out of the total land area 313.18 km^2 (6.94%) forest land was changed to farmland, 6.67 km^2 (0.15%) forest land was changed to bare land and 43.2 km^2 (0.96%) forest land was changed to built-up area. See Table 4.11 and Fig 4.12 below illustrate depicts the LULC change detection from 2002 to 2012.

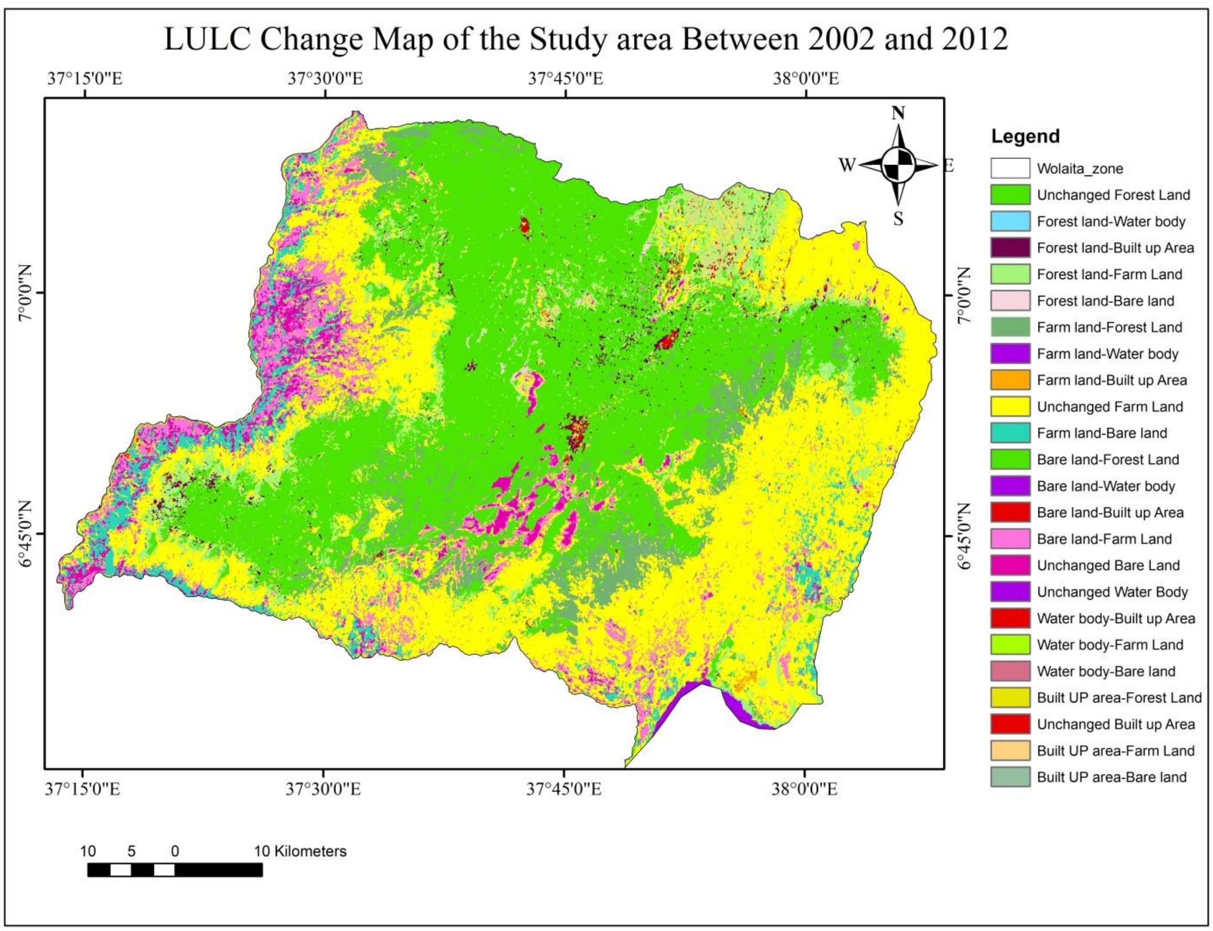


Fig 4.12: LULC change detection from 2002 to 2012

Table 4.11: LULC change detection matrix from2002 to 2012

		LULC Class for 2012											
	LULC class	Forest land		Farm land		Bare land		Water body		Built up		2002 total	
		Area		Area		Area		Area		Area		Area	
		Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%
LULC Class for 2002	Forest land	**1641.61**	**36.4**	313.18	6.94	6.67	0.15	0.63	0.01	43.2	0.96	2005.3	44.5
	Farm land	296.64	6.58	**1514.6**	**33.59**	192.6	4.27	0.37	0.01	17.86	0.40	2022.2	44.8
	Bare land	8.65	0.19	269.93	5.82	**128.4**	**2.85**	0.01	0.00	0.89	0.02	407.86	9.05
	Water body	0	0.00	2.28	0.05	0.01	0.00	**13.7**	**0.30**	0.1	0.00	16.09	0.36
	bulit up	6.42	0.14	42.13	0.93	0.69	0.02	0	0.00	**8.78**	**0.19**	58.02	1.29
	2012 total Area	1953.3	43.32	2394.1	47.34	328.4	7.28	14.71	0.33	70.8	1.57	**4509.44**	
	Change Km^2	-51.9	-1.15	112.7	2.5	-79.4	-1.8	-1.38	-0.03	12.8	0.28		

LULC Change detection matrix from 200 to 2012

Source: Computed by Researcher, 2023

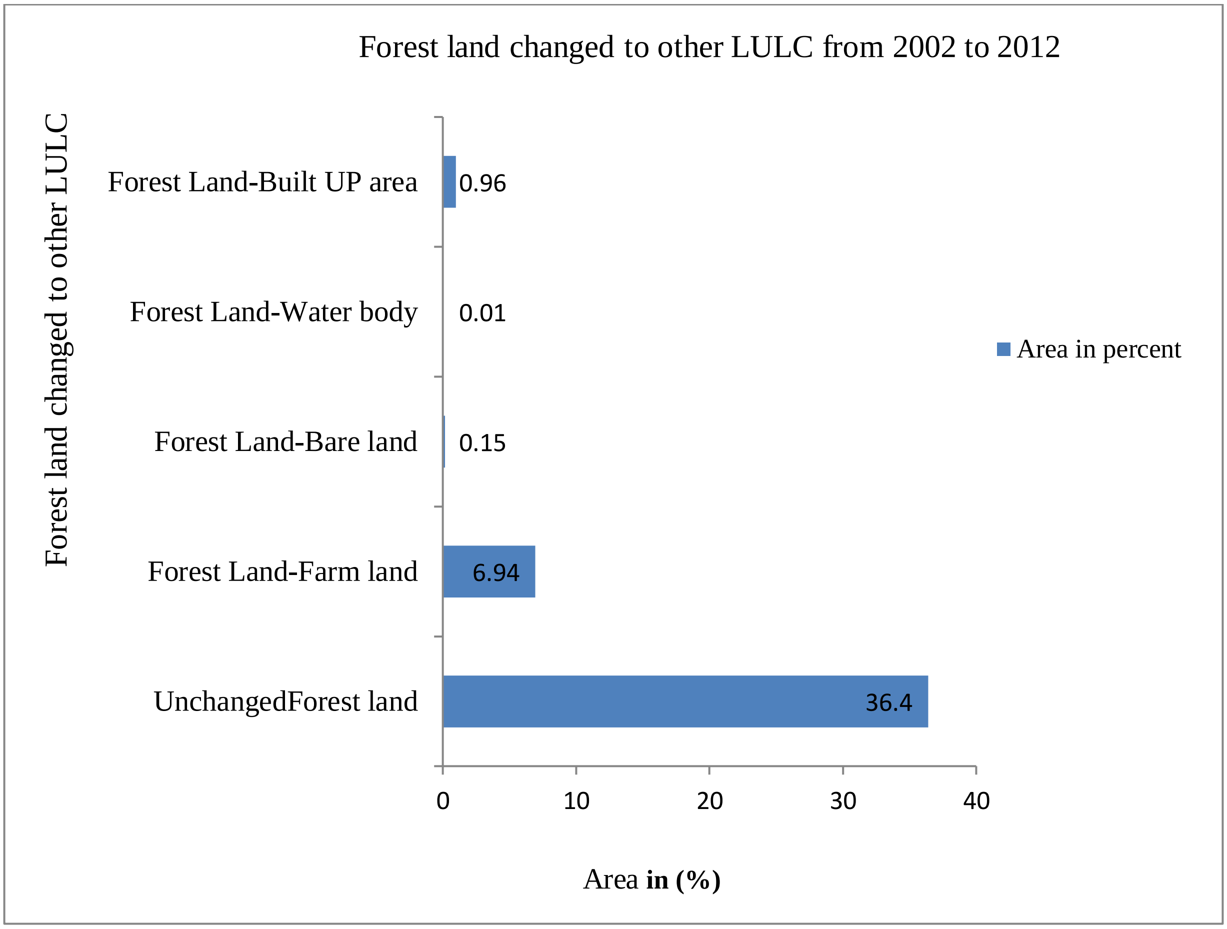


Fig 4.13: Percentage of forest cover converted to other LULC from 2002-2012

4.4.6 LULC Change Detection from 2012 to 2022

Based on the result of land use land cover change detection indicated in Table 4.12 below, the farmland and Built-up area was positively increased while forest land and bare land were negatively decreased in 2022 compared to 2012. Out of the total land area, farmland was increased by 696 km^2 (15.44%), and built-up land was increased by 198.81 km^2 (4.41%). But in the same period, 660 km^2 (14.6%) of forest land and 311.6 km^2 (8.68%) of bare land were decreased. During this period 710.98 km^2 (15.77%) of forest land was transformed into farmland, 1.16 km^2 (0.03%) of forest land was transformed to bare land 2.53 km^2 (0.06%) of forest land transformed into water bodies, and 56.96 km^2 (1.26%) of forest land was changed to settlement land. See Fig 4.14 and Table 4.12 below illustrate the land use land cover change of the study area from 2012 to 2022.

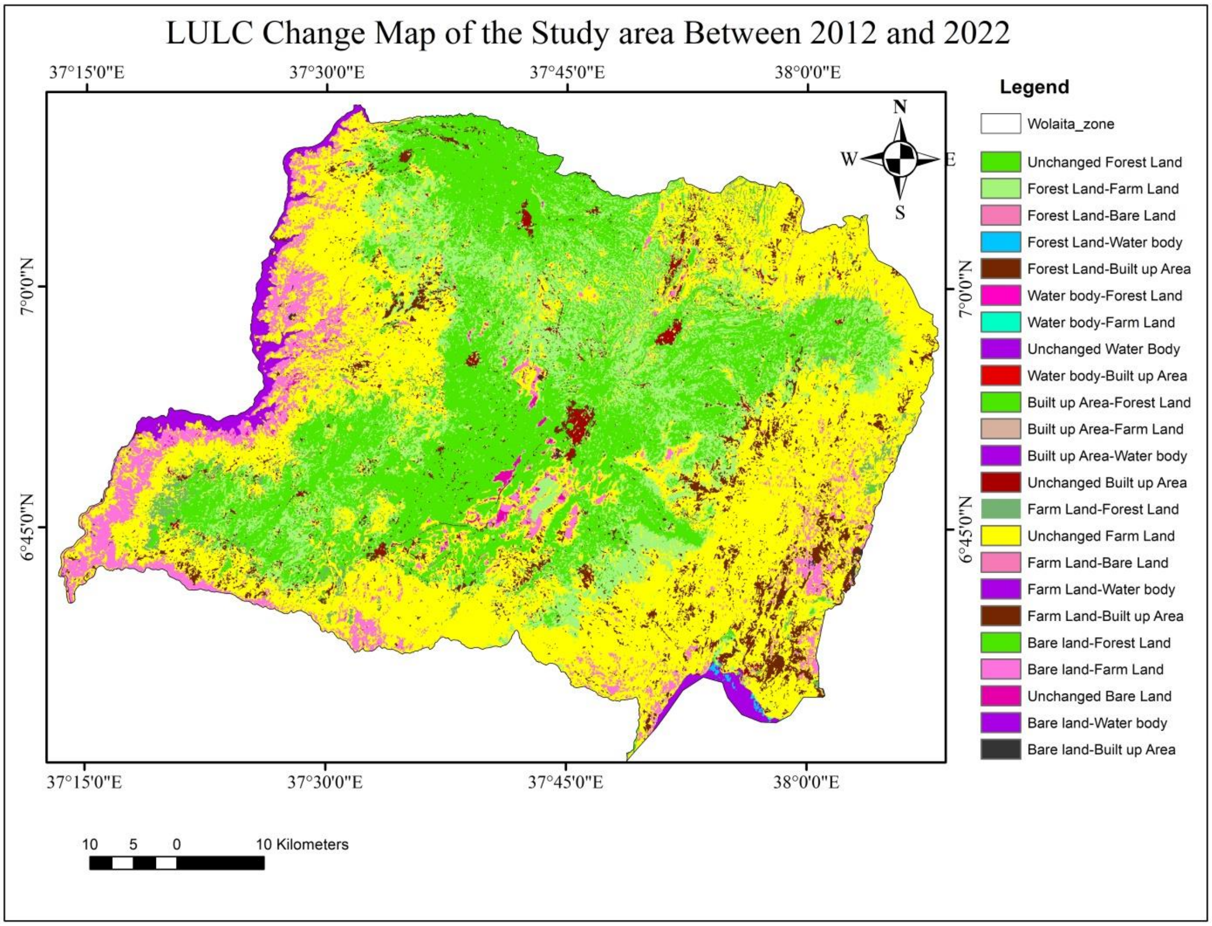


Fig 4.14: LULC Change detection from 2012 to 2022

Based on the information obtained from KII, currently vegetation cover of the study area was highly deforested when compared to last decades. Acording to their information, the main couses of cutting forest was to fulfill the demand of farm land, uses as economy sources, for construction infrastructure such as road and houses and domestic fuel.

The loss of trees and other vegetation can lead to climate change, desertification, soil erosion, less crops, flooding, higher greenhouse gases in the environment. See table 4.12 below the the LULC Change detection matrix between 2013-2022.

Table 4.12: LULC Change Detection from 2012 to 2022

LULC Class for 2012	LULC class	LULC Class for 2022											
		Forest land		Farm land		Bare land		Water body		Built up		1993 total	
		Area		Area		Area		Area		Area		Area	
		Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%
	Forest	**1181.69**	**26.20**	710.98	15.77	1.16	0.03	2.53	0.06	56.96	1.26	1953.32	43.32
	Farm	98.41	2.18	**1813.26**	**40.21**	3.44	0.08	43.24	0.96	183.82	4.08	2142.17	47.50
	Bare	0.84	0.02	277.91	6.16	**12.13**	**0.27**	30.28	0.67	7.25	0.16	328.41	9.05
	Water body	0.01	0.00	0.27	0.01	0	**0.00**	**14.41**	0.32	0.02	0.00	14.41	0.33
	bulit up	12.27	0.27	35.96	0.80	0	0.00	1.01	**0.02**	**21.59**	0.48	70.83	1.57
	2002 total Area	1293.22	28.68	2838.38	62.94	16.73	0.37	91.47	2.03	269.64	5.98	**4509.44**	
	Change in Km^2	-660.1	-14.6	696.21	15.44	-311.6	-8.68	77.06	1.70	198.81	4.41		

LULC Change detection from 2012 to 2022

Source: Computed by Researcher, 2023

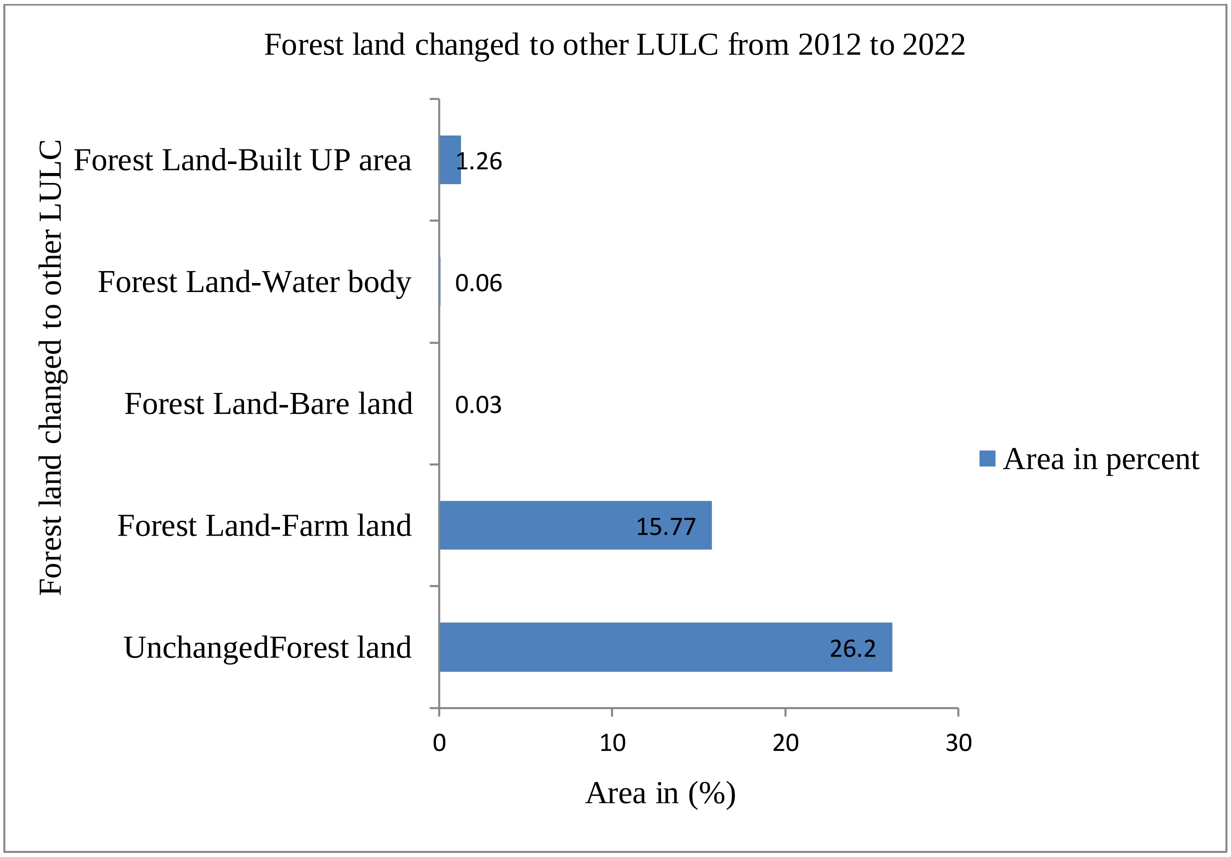


Fig 4.15: Percentage of Forest land cover changed to other land use from 2012 to 2022

Generally, the forest component, namely the amount of forest cover, received special attention in the land use land cover change detection investigation. In the present research study, the classification of land use and the cover result showed that the portion of forest covering fluctuated.

Out of the total area, forest land covers 2617.41 Km^2 (58.04%) in 1993. However, it significantly decreased to 1293.22 Km^2 (28.68%) in 2022. This suggests that during thirty years, the forest cover has decreased by 1,323.92 Km^2 (29.35%) of the total area.

Different explanations could be offered for the local forest resource decline. In this regard, as it is clearly stated in the works of (Netsanet, 2007), the most significant causality of all human-induced factors for land cover change, which are crucial and are currently increasing at an alarming rate; which may be grouped into two major divisions: proximate and driving causes.

The primary drivers of land cover change in Ethiopia are natural forest loss for agricultural expansion, rising demand for building materials, and fuel wood. These factors have a significant impact on the country as a whole and have the potential to significantly alter the climate of a region (Kashay, 2004). Furthermore, climate variability and change can accelerate the conversion of land to unsustainable uses by rendering current land use practices unsustainable and causing land degradation.

Additionally, UNEP (2002) noted in its study that forest ecosystems play many functions at both the local and global levels as sources of commercially valuable products as well as providers of environmental services to humans and other species in general. Further information from the same source stated that woods, particularly natural forests, are used for a variety of ecological and economic functions.

They could manage the hydrological cycle, preserve the local climate, serve as habitats for wildlife, and lessen runoff and soil erosion.

4.5 Spatial and temporal variation of LST and NDVI

4.5.1 Spatial and Temporal Variation of Land Surface Temperature

The spatial pattern of the land surface temperature of Wolaita zone was analyzed from Landsat 5 MSS of 1993, Landsat 5 MSS of 2002, Landsat 7 ETM^+ of 2012, and Landsat 8 OLI/TIRS/ of 2022 thermal band respectively. For Landsat 5 and Landsat 7, band 6 was used and for land sat 8; band 10 was used for analyzing LST. Based on the result indicated in Fig 4.16 below the land surface temperature of the study area ranged between 9.69 ^{0}c and 35.08 ^{0}c from 1993 to 2022. The eastern, southeastern, and some of the western parts of the study area revealed high land surface temperatures. Whereas the northern and central parts of the study area showed medium and low LST during the study period.

See fig 4.16 below shows the LST of different land use land cover classes of the study area during the study period.

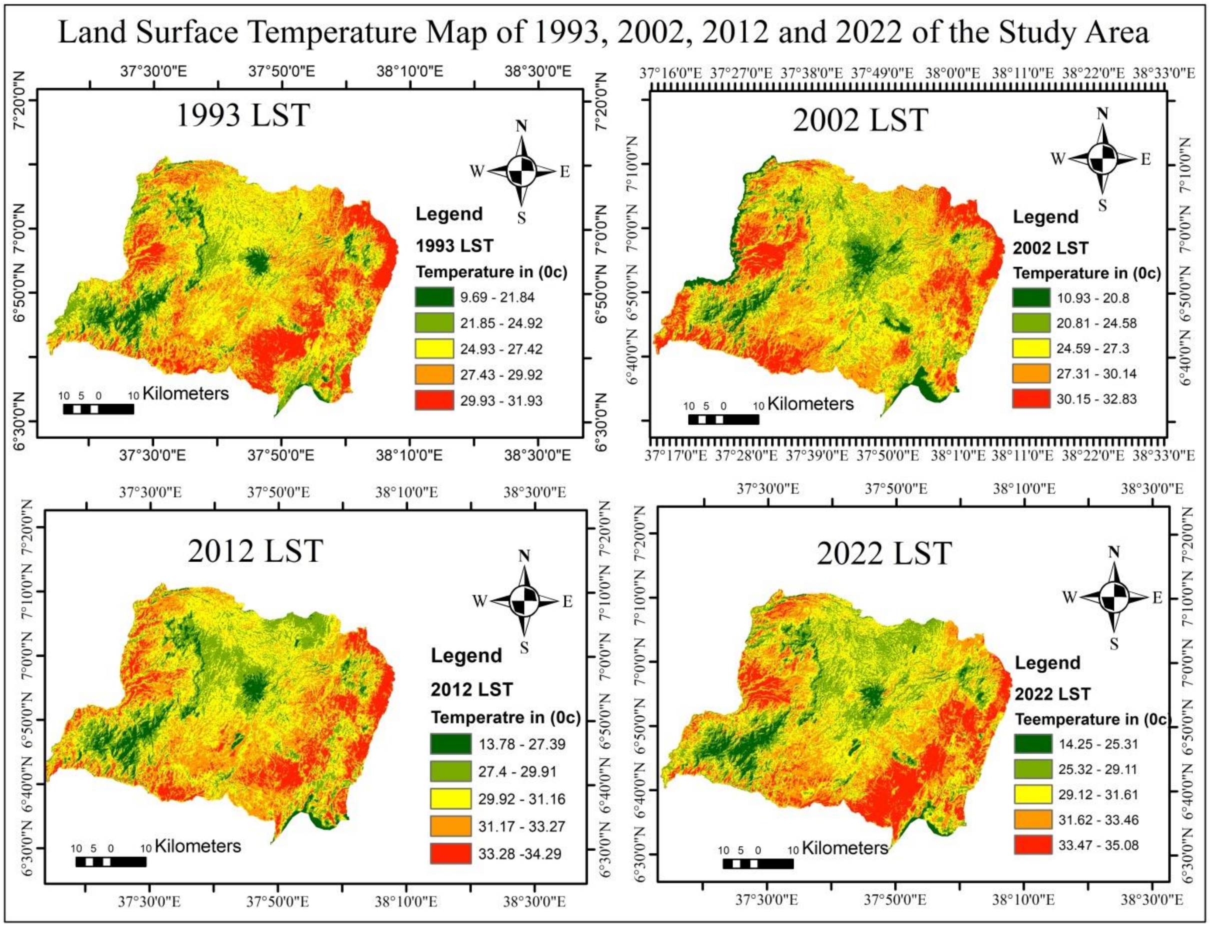


Fig 4.16 LST of the study area of the years 1993, 2002, 2012 and 2022

4.6 Spatial and temporal variation of Mean Annual NDVI Coverage

In this section, the spatial and temporal variation of NDVI for the year 2003-2022 was analyzed on both annual and seasonal bases. The analyses of NDVI were presented as follows.

The result of the quantitative analysis of annual vegetation coverage indicates that the lowest and highest vegetation coverage was identified in the year 2018 and 2003, which was 34.4% and 49.4% respectively. Relating to this, several studies indicate that the temporal and spatial difference in the NDVI was closely related to climate in many places of the world. The time-based change in the NDVI may be descriptive of vegetation response to climate variation. Therefore, vegetation biomass has been commonly used to control and monitor environment dynamics and to identify the spatial scope and temporal changeability of land degradation (Velk et al., 2008).

Depending on USAID (2006) the vegetation condition of an area can be categorized as high vegetation (values above 0.5), medium vegetation (from 0.292 - 0.5), low vegetation (0.166-0.292), no vegetation (from 0.1 -0.166), and water body. Based on the result of quantitative analysis of the mean annual NDVI value, the study area was classified as medium vegetation coverage which ranges between 0.344-0.494 coefficients of variation. See Table 4.13 below illustrates that the quantitative analysis of vegetation coverage of the study area

Table 4.13: Annual quantitative vegetation cover and coefficient of variation

SN	Year	Mean NDVI	CV	Medium Vegetation Coverage in (%)
1	2003	0.930	0494	49.4
2	2004	0.997	0.481	48.1
3	2005	0.798	0.429	42.9
4	2006	0.825	0.396	39.6
5	2007	0.794	0.437	43.7
6	2008	0.749	0.419	41.9
7	2009	0.749	0.386	38.6
8	2010	0.817	0.425	42.5
9	2011	0.760	0.411	41.1
10	2012	0.758	0.421	42.1
11	2013	0.771	0.414	41.4
12	2014	0.792	0.419	41.9
13	2015	0.782	0.421	42.1
14	2016	0.785	0.412	41.2
15	2017	0.847	0.395	39.5
16	2018	0.763	0.344	34.4
17	2019	0.767	0.353	35.3
18	2020	0.752	0.368	36.8
19	2021	0.765	0.351	35.1
20	2022	0.794	0.374	37.4

Source: Computed by Researcher, 2023

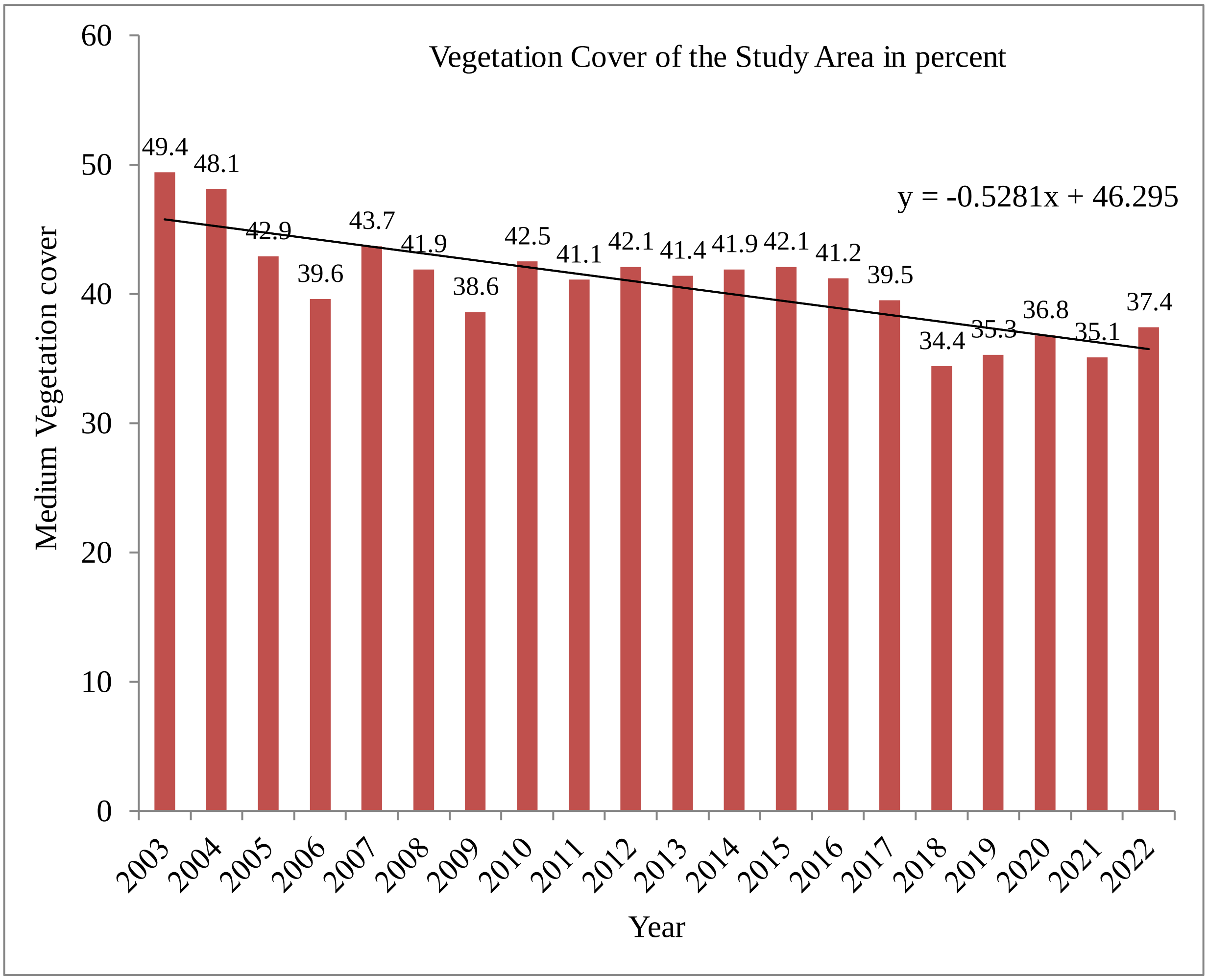


Fig 4.17 Vegetation cover of the study area between (2003-2022)

Based on the result presented in Table 4.13 above, the mean annual NDVI value shows variation from time to time. During the study period, the vegetation coverage of the study area decreased in the second decade compared to the first decade. See fig 4.18 below shows the mean annual NDVI of the study area.

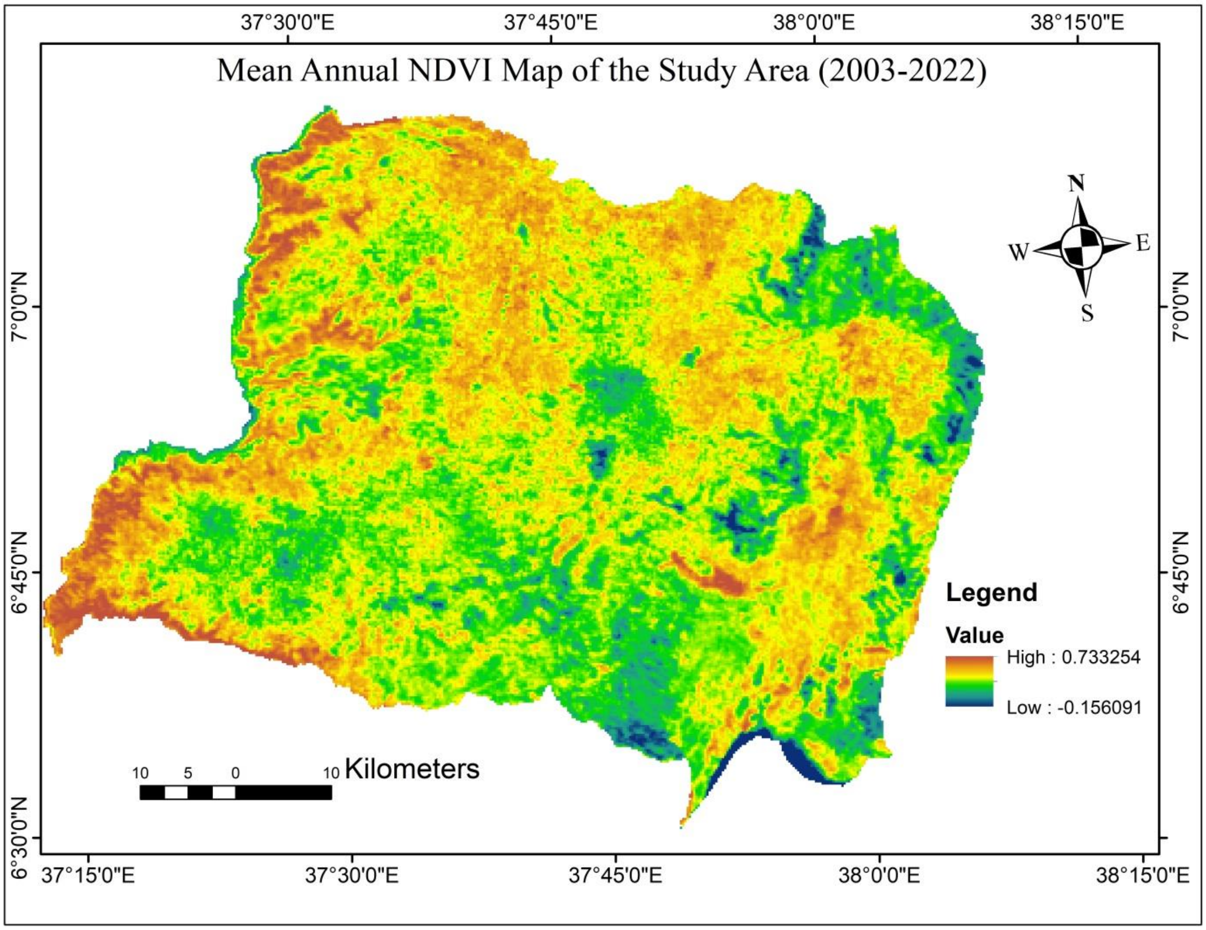


Fig: 4.18 Mean annual NDVI distribution of the study area between 2003-2022

4.6.1 Spatial and temporal variation of Mean Anual NDVI for Belg and Kiremt Season

A) Spatial and temporal variation of NDVI at Kremt season

Mostly, there is high vegetation coverage in the long rainy season (June, July, August) compared to the short rainy season (March, April, and May) of the study area during the study period. Since the period 2003 to 2022 due to the occurrence of a moderately good amount of rainfall which produced a favorable environment for plants or harvest to grow. In the kiremt season, the range of the mean annual NDVI value was (-0.14722-0.79962) maximum and minimum respectively. See Fig 4. 19 below depicts the mean annual NDVI distribution of the study area of the year between 2003-2022.

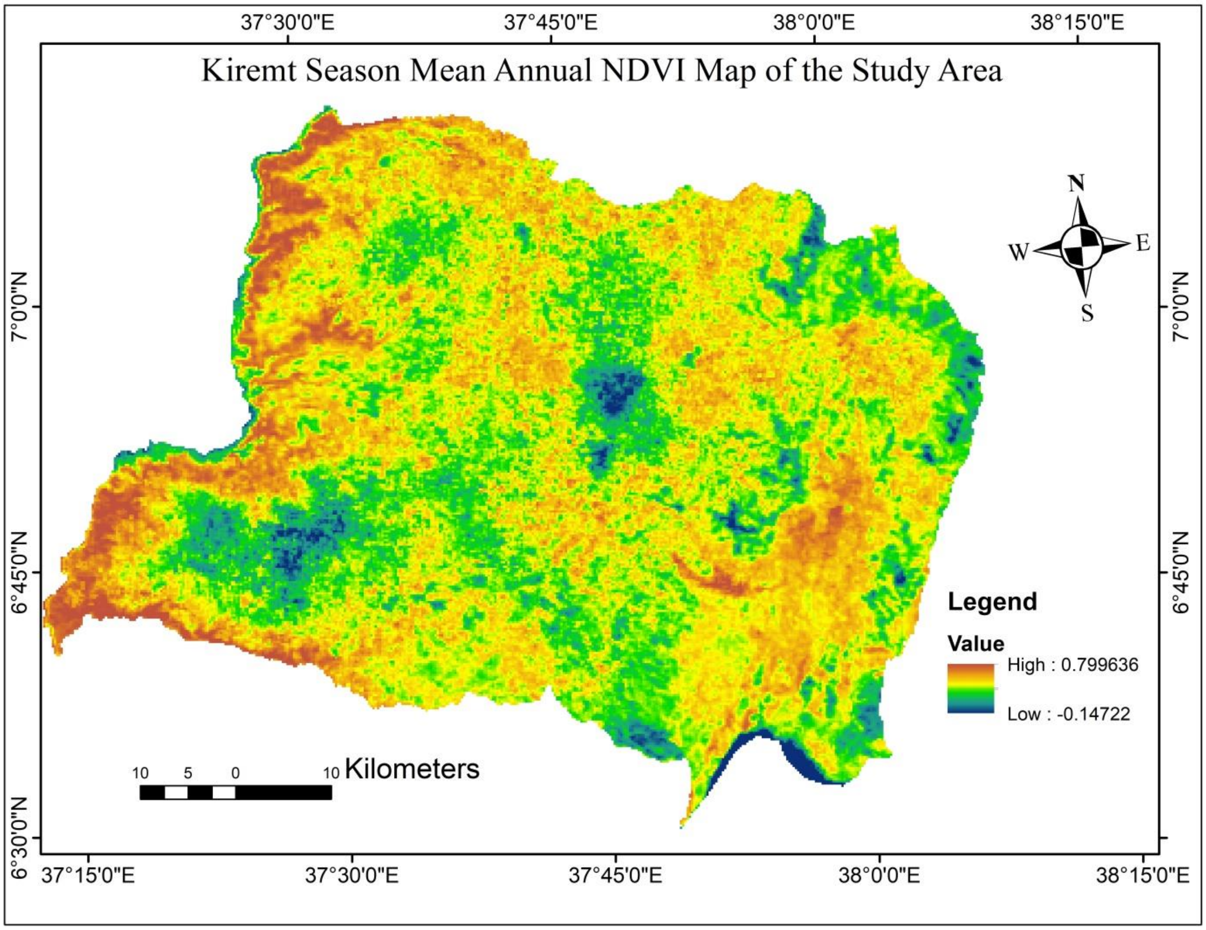


Fig 4.19: Mean annual kremt season NDVI Between 2003-2022)

B) Spatial and temporal variation of NDVI at Belg season.

The result of the quantitative analysis of vegetation cover of the belg season during the study period was presented as follows. In the belg season, the high vegetation cover class year was 2013, which cover 49.8%. However, the low vegetation cover class year was 2018, which cover 33.3%.

See Fig 4.20 below depicts that, the same part of the study area was dry. which means the area was not covered by vegetation in the Belg season.

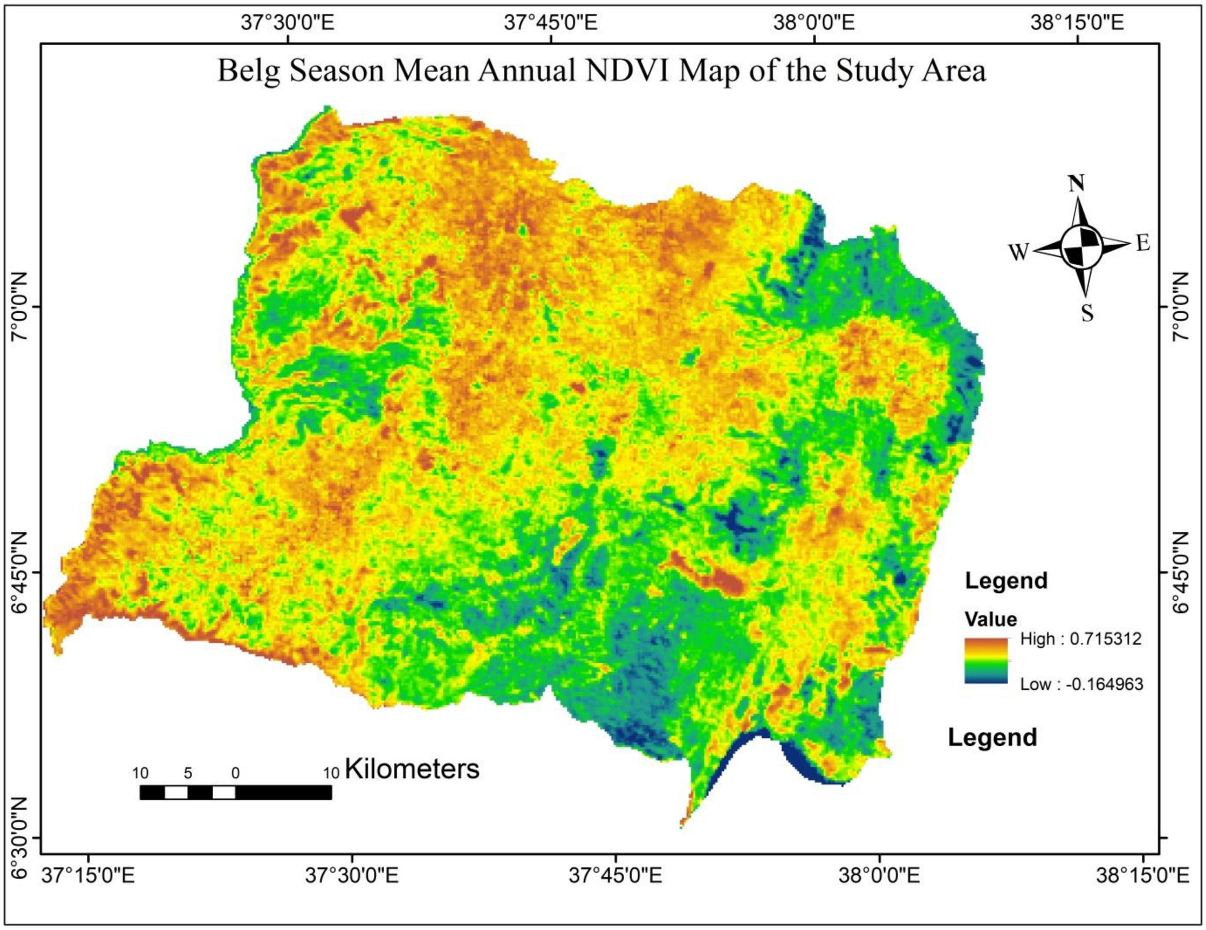


Fig 4.20: Belg season mean annual NDVI Between 2003-2022

4.7 Correlation between LULC Changes, Temperature, precipitation and NDVI

4.7.1 Correlation between LULC Changes with LST

The easiest method to comprehend how LU/LC affects temperature is to look into the relationship between the thermal signatures and each type of land cover (Gupta et al., 2020). According to (Sinha et al, 2015), Land Surface Temperature can be utilized to gather data on multiple LU/LC aspects because it is highly responsive to varied land features. The result showed that from 1993 to 2022, the average surface temperature of the various LU/LC categories within the study area was increased. Based on the result illustrated in Table 4.15 below, the highest land surface temperature was recorded by built-up land and followed by farmland, bare land, forest land, and water body respectively. See table 4.14 below shows the average LST in degree cent grade of different LULC type.

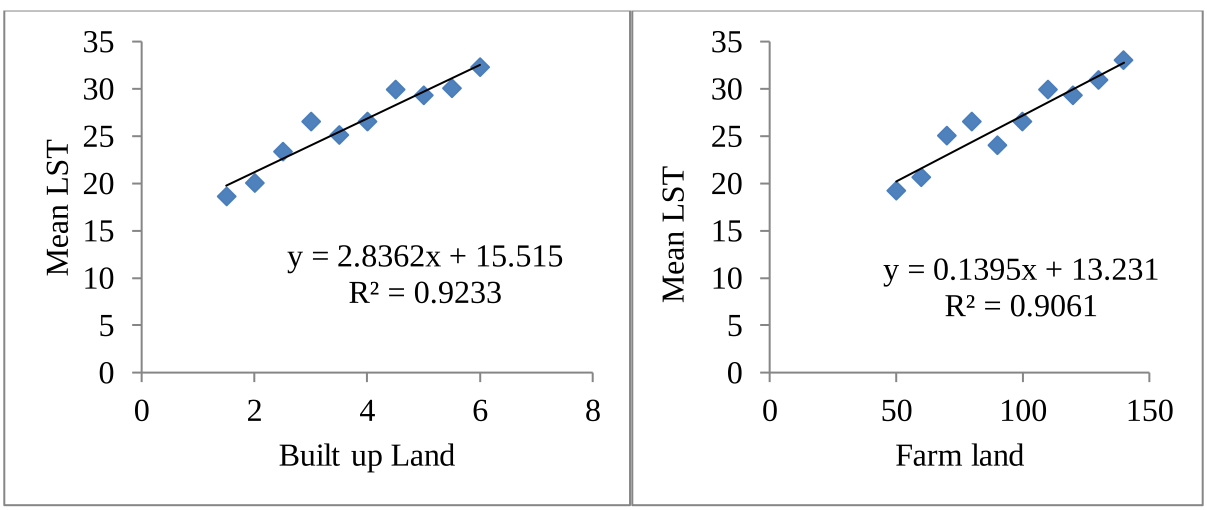
Table 4.14 Average of LST in (^{0}C) and change corresponding to different LULC class

LULC Type	LST in (^{0}C)				Change of LST per LULC type in (^{0}C)			
	1993	2002	2012	2022	1993-2002	2002-2012	2012-2022	1993-2022
Forest land	24.94	25.95	27.4	30.60	1.01	1.45	2.20	5.66
Farmland	27.54	28.78	30.12	33.61	1.24	1.34	3.49	6.07
Bare land	27.07	28.25	30.41	32.97	1.18	2.16	2.24	5.90
Waterbody	19.54	20.83	22.59	23.64	1.29	1.76	2.14	4.1
Built up land	26.17	27.33	29.28	33.45	1.16	1.95	4.17	7.28

Source: Computed by Researcher, 2023

Based on the result presented in Table 4.14 above, the average LST is higher in 2022 than in 1993, 2002, and 2012 for all land use land cover classes. (Fall et al, 2010) noted that when natural vegetation has been transformed into farmland, built-up land, bare land and other uses, the air temperatures and near-surface moisture have been shifting and will continue to change.

As a result, the methods in which the land is used and the types of land covers affect the temperature fluctuation of the study area.



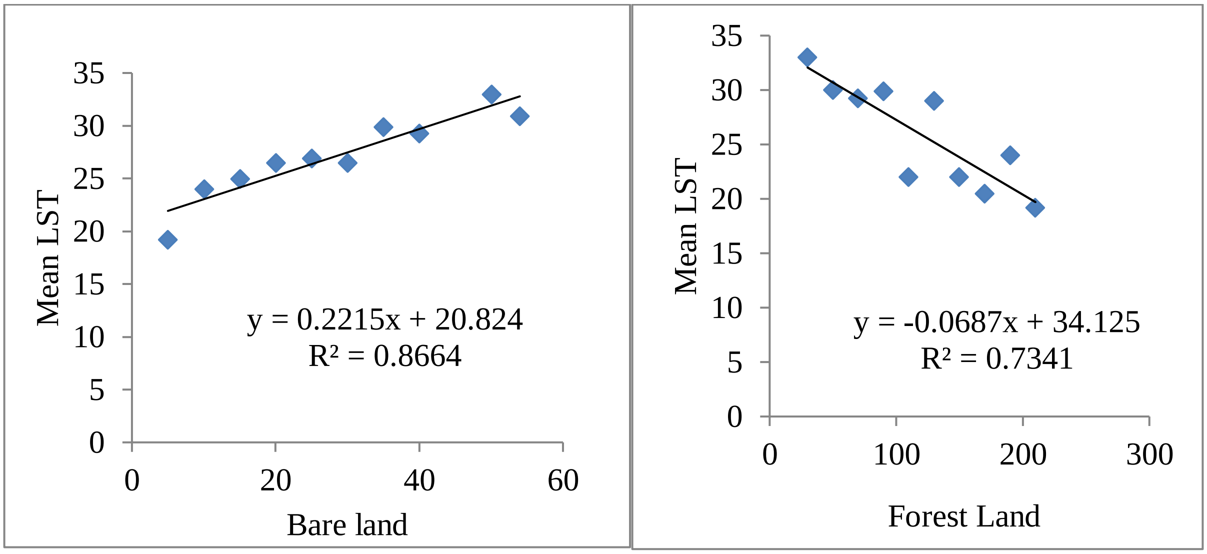


Fig 4.21: Comparison of Mean LST of different land use land covers classes (1993-2022)

Based on the result presented in Fig 4.21 above, LST is highly correlated with built-up land, agriculture, and bare land respectively. However, it was negatively correlated with forest land. The R square value =0.9233, 0.9061and 0.8664 indicates that 92.33% of LST variability was influenced by built-up land, 90.61% of LST variability was influenced by farmland and 86.64% of LST variability was influenced by bare land. The R^2 =0.734 indicates that 73.4% variability of LST was caused by the reduction of forest coverage of the study area. Many factors can either increase or decrease the LST. For example, soil types, geothermal energy, geological setting and altitude are the same factor that increase or decrease the LST. However, this study used a thermal band and examines land surface temperature connected with different LULC Class. According to (Maitima et al,2009), uncontrolled use of land resources and changes in land cover has the potential to raise LST in both rural and urban regions.

4.7.2 Correlation between Mean Annual Rainfall and NDVI Between 2003-2022

In this section, linear correlation was used to determine the degree of relationship between the two variables such as mean rainfall and mean NDVI. During the analysis of the correlation between mean annual rainfall and mean annual NDVI, the 95% confidence level was done. See Table 4.15 illustrates the linear correlation between mean annual rainfall and mean annual NDVI between 2003-2022.

Table 4.15: Correlation between mean annual rainfall and NDVI

Regression statistics	R	R^2	Significance value(Sig)
Value	0.845	0.715	0.00104

Source: Computed by Researcher, 2023

Based on the result presented in Table 4.16 above, R=0.845 indicates that there is a strong positive relationship between mean annual rainfall and mean annual NDVI during the study period. R^2 =0.715, indicates that the 71.5% of rainfall variability of the study area was depend on the vegetation coverage. Sig value =0.00104. The sig value (0.00104<0.05) indicates that the vegetation coverage is most significant for the amount of rainfall distribution of the study area during the study period. See Fig 4.22 indicates that the scatter plot map shows the correlation between mean annual rainfall and mean annual NDVI between 2003-2022. So that the amount of annual rainfall is highly depend on the amount of vegetation cover.

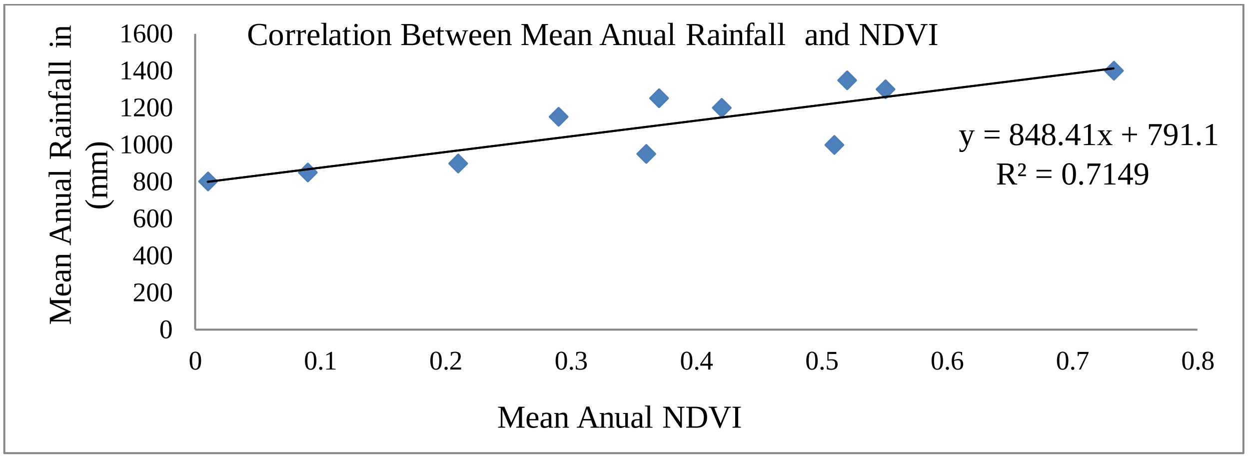


Fig 4.22: Correlation between mean annual rainfall and mean annual NDVI

4.7.3 Correlation Among Kremt Season Mean Annual Rainfall and Kiremt Season Mean Annual NDVI Between 2003-2022

The result of the correlation between mean annual rainfall and mean annual NDVI of the study area in the kremt season was presented in Table 4.16 below.

Table 4.16: correlation of mean annual rainfall and NDVI of kiremt season

Regression statistics	**R**	**R^2**	**Significance (sig value)**
Value	0.894	0.799	0.00048

Source: Computed by Researcher, 2023

Depending on the result presented in Table 4.17 above, the value of R=0894 indicates that there is a strong positive correlation ship between mean annual rainfall and mean annual NDVI in the kremt season during the study period. R^2 =0.799 indicates that 79.9% of rainfall variability of the study area depends on the kremt season vegetation cover. 21.1% rainfall variability of the study area depends on other factors. And P-value =0.00048, indicates that kremt season vegetation cover is most significant for the kiremt season rainfall. See below fig 4.23 indicates the correlation ship between the mean annual rainfall and mean annual NDVI of the study area.

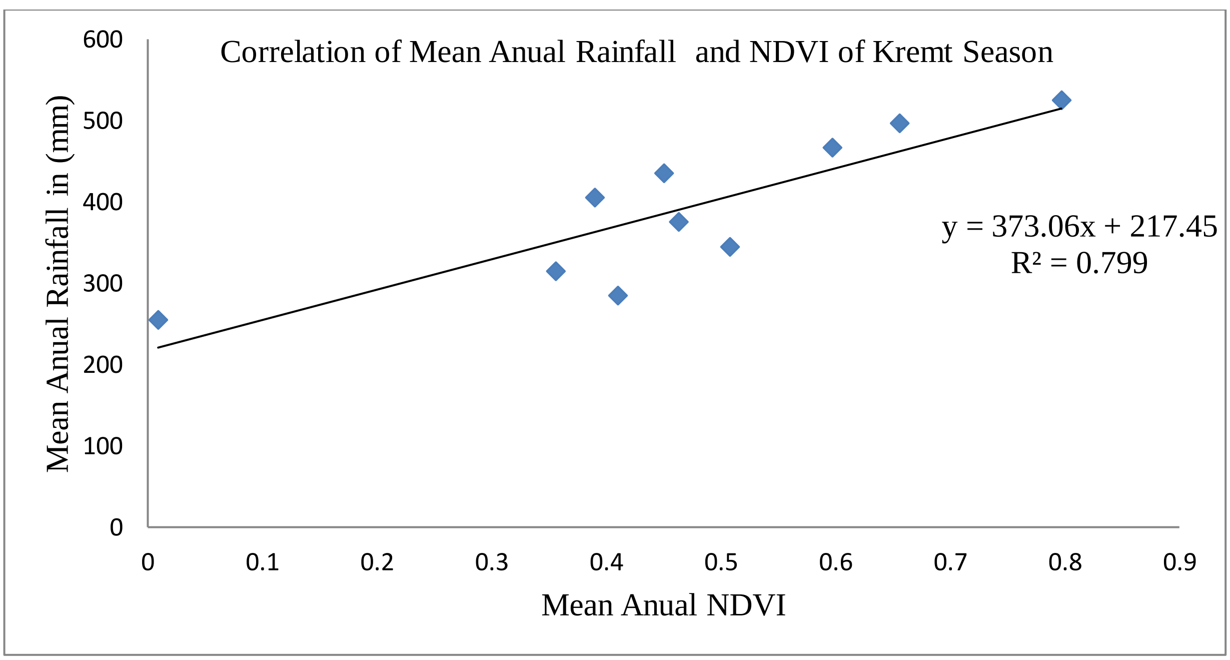


Fig 4.23: Correlation between mean annual rainfall and mean annual NDVI (2003-2022).

4.7.4 Correlation Among Belg Season Mean Annual Rainfall and Belg Season Mean Annual NDVI Between 2003-2022

Based on the result presented in Table 4.17 below, the R-value =0.826 indicates that there is a strong positive correlation ship between mean annual rainfall and mean annual NDVI. The R^2 =0.678 indicates that the 67.8% of rainfall variability of the study area in the belg season depends on the amount of belg season vegetation coverage. The sig value =0.043, indicates that the belg season vegetation coverage is significant for belg season rainfall distribution.

Table 4.17: The correlation between mean annual rainfall and NDVI of Belg season between 2003-2022.

Regression statistics	**R**	**R^2**	**Significance value(Sig)**
Value	0.823	0.678	0.043

Source: Computed by Researcher, 2023

Below Fig 4.25 indicates that the correlation ship between the mean annual rainfall and mean annual NDVI of the study area.

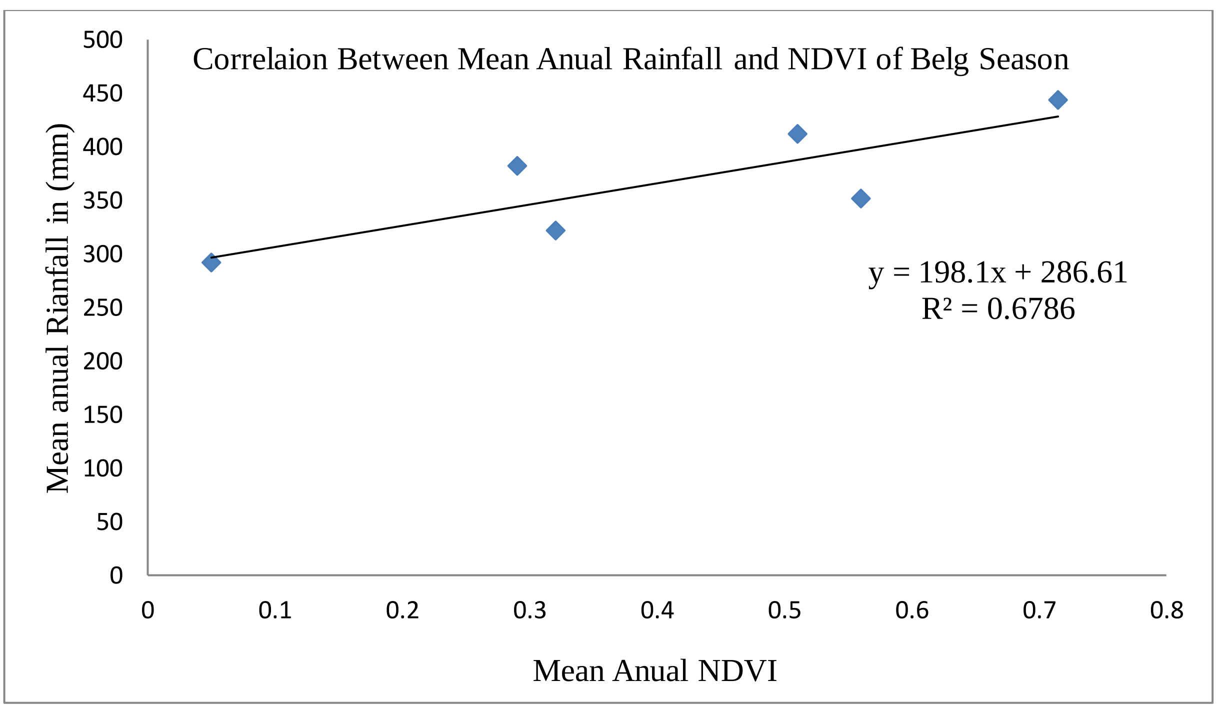


Fig 4.24: correlation between mean annual rainfall and NDVI of the Belg season (2003-2022).

4.7.5 Correlation Between Average annual (Temperature and NDVI) between 2003-2022

Based on the result presented in Table 4.18 below the R =0.868 indicates that there was a strong negative correlation ship between average annual temperature and mean annual NDVI. The R^2 =0.755 indicates that 75.5% of the average annual temperature of the study area was increased due to clearing of forest cover. The sig value =0.0023 indicates that the vegetation cover is very important for controlling the climate variability of the study area. See table 4.19 below shows correlation of temperature with NDVI.

Table 4.18: The correlation between the average annual maximum temperature and mean annual NDVI between 2003-2022

Regression statistics	**R**	**R^2**	**Significance value(Sig)**
Value	0.868	0.755	0.0023

Source: Computed by Researcher, 2023

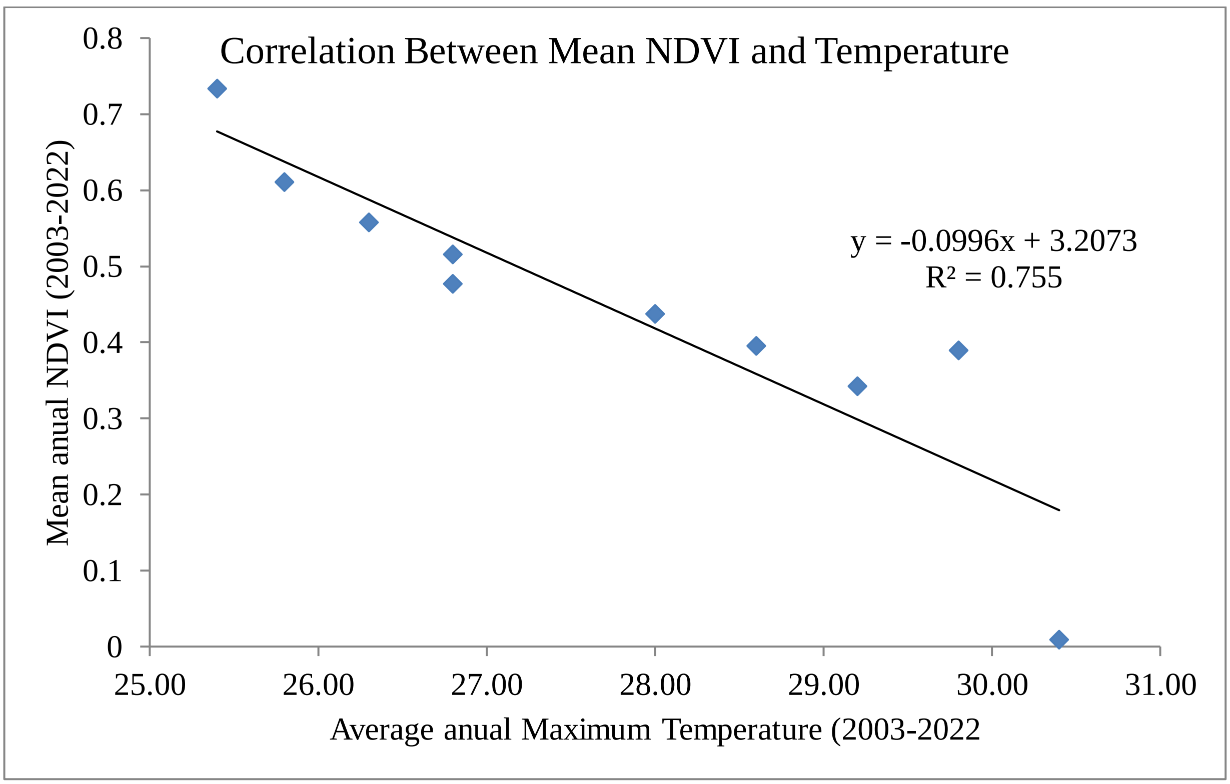


Fig 4.26 Correlation between average annual maximum temperatures with mean annual NDVI between 2003-2022

4.8 Impact of LULCC on Climate Variability

These findings indicated that the demand for agriculture and settlements to increase the population and expand agriculture has led to the clearing of the forest in the study area. In the Wolaita Zone, corresponding to LULCC, there were climate variability and decline trends which was explained by the decrease of rainfall and temperature rise. This was due to the depletion of vegetation covers, which has the potential to affect Temperature and rainfall variability.

Because behind the expansion of settlement and agriculture there is deforestation that attributes to climate variability. In other words, when deforestation increases, rainfall decreases and temperature increases. Then climate variability would happen in the study area, which affects the major categories used for the classification of the land use land cover on the study areas.

Hence, LULCC affects the climate variability directly and indirectly and implies the expansion of drought in the study area. Therefore, the observed LULCC in the study area particularly the expansion of agricultural land and settlements at the expense of vegetation cover forests contributed to affect the climate variability by increased the temperature and decreased seasonal and annual rainfall distributions in WolaitaZone for the last three decades.

4.9 Discussion

Geospatial technology can play a vital role in studying climate change. It is best achieved by mapping the impact of climate variation at the local level through the use of satellite imagery.

Geospatial techniques have been successfully used in a wide range of climate change fields. So, studying climate change by using geospatial techniques was very important for monitoring climate change.

The general objective of this study was to analyze spatiotemporal climate variability using geospatial techniques in the case of the Wolaita zone, the southern region of Ethiopia for the last thirty years (1993-2022). The specific objectives of this research were to examine the trend and variation of rainfall and temperature of the study area, to analyze temporal and spatial variation of LULC Change, LST, and NDVI of the study area, to examine the influence of forest cover on climate change using LULC Change detection analysis and to determine the association between LULC Change, LST, NDVI, and Rainfall.

The study used both primary and secondary data from different sources. The thirty years gridded climate data (temperature and precipitation) were obtained from NME of Hawassa branch. Four temporal cloud-free satellite images (i,e 1993 Landsat 5/MSS/, 2002 Landsat 5/MSS/, 2012 Landsat 7/ETM+/ and 2022 Landsat 8 OLI/TIRS/ were downloaded from the website of www.usgs earth Explorer online imagery portal. Similarly, Moderate-resolution imaging spectro (MOD13Q1 NDVI 250m resolution) data were downloaded from the www.USGS earth explorer website. Finally, the socio-economic data collected from KII was used to cross-check the climate variability of the study area.

The long-year climates data were organized and filtered using Microsoft Excel. The spatial pattern of rainfall and temperature of the study area was analyzed by using the inverse distance weight (IDW) interpolation method in the Arc GIS environment. The trend and variability of climate data such as rainfall and temperature were analyzed using the coefficient of variation (CV). The LULC classification of Landsat image was analyzed through ENVI software through the Maximum likelihood supervised classification method. Simultaneously, the LULC change detection of different years of satellite images was analyzed in the Arc GIS environment through post classification method.

Additionally, LST was analyzed for each LULC class through the Arc GIS environment for the years 1993, 2002, 2012, and 2022 respectively. The association between LULC Class and LST with rainfall and NDVI was examined by using the linear regression analysis method through SPSS software.

The result of climate elements shows considerable variation during the study period. Between 1993 and 2022, the average annual total rainfall in the study area ranged from 806.17 mm to 1334.9 mm. The overall mean annual rainfall of the study area in the last thirty-year period was 1173.5mm. The result of the time series analysis, which was performed at the decadal level, indicates that decreasing trend in rainfall distribution. This means that the average annual rainfall declined by 29.8mm during the study period between (1993-2022).

Similarly, the kiremt and belg season rainfall indicates the declining trend of rainfall distribution from 1993 to 2022. So, the mean kiremt and belg season rainfall of the study area was reduced by 18.1mm and 40.36 mm respectively during the study time. Generally, the result indicates that the amount of annual and seasonal rainfall in the study area decreased from 1993 to 2022. Related to this end, (18) 90% of respondents, responded that there is a variation in rainfall pattern in the study area from time to time.

The coefficient of variation of the mean annual rainfall of the study area was 8.8%, 9.4%, and 9.6% in the first decade, second decade and third decade respectively. Similarly, the coefficient of variation of kiremt and belg season mean annual rainfall was 13%, 12%, 10%, and 7%, 10%, and 8% in the first decade, second decade and third decade respectively. The percentage of CV indicates that there is a variation in the mean annual rainfall distribution of the study area between 1993-2022. According to (Hare, 2003), suggest that the CV<20%, there is low rainfall occurrence variability distribution.

The overall average annual maximum and minimum temperature of the study area was 26.89 ^{0} c and 14.89 ^{0} c respectively between 1993-2022. Both the average annual maximum and minimum temperature of the study area showed an increasing trend. During the last thirty-year period the average annual maximum and minimum temperature of the study area increased by 0.52 ^{0} c and 1.29 ^{0} c respectively from 1993 to 2022. In addition to this, both the average annual maximum and minimum temperature of the study area show an increasing trend in the decadal level. Based on this, the average annual maximum temperature was increased by 0.19 ^{0} c and 0.33 ^{0} c in the second and third decades respectively. While the average annual minimum temperature of the study area increased by 0.79 ^{0} c and 0.5 ^{0} c in the second and third decades respectively.

This research study also deals with analyzing the temporal and spatial variation of LULC change, LST and NDVI of the study area and examines the influence of forest cover change on climate change based on the land use land cover change result.

Based on this, the multi-temporal Landsat image of the study area was categorized into five land use land cover classes. These are namely; forest/vegetation/ cover, farmland, bare land, built-up land and water body. The findings revealed that, during the study period, the agricultural land and built-up land were increased. For instance, from 1993 to 2022, the area of farmland and built-up land increased from 1222.05 km^2 (27.09%) to 2838.37 km2 (62.95%) and 15.1 km^2 (0.36%) to 269.64 km^2 (5.97%) respectively. While forest land and bare land were reduced from 2617.41 km^2 (58.04%) to 1293.22 km^2 (28.68%) and 627.31 km^2 (13.91%) to 16.73 km^2 (0.38%) respectively.

The study also discovered that the size of forest coverage has been decreasing from time to time. Out of the total land area, the forest/vegetation cover of the study area was 2617.41 km^2 (58.04%) in 1993, but due to numerous external factors, it decreased to 1293.22 km^2 (28.68%) in 2022. between 1993-2022, the 1,324.19 km^2 of forest cover was deforested and converted to different types of land use classes.

In this regard, the reduction of forest coverage of the study area was due to increased population may have led to considerable forest removal for agricultural use, overgrazing, and exploitation of existing forests for fuel wood, charcoal, and construction materials (Bishaw, 2001). In addition to this, (17) 85% of respondents, said that the forest coverage of the study area was highly reduced in 2022 compared to 1993.

The study also revealed the impact of LST on climate variability. In this regard, the study's results showed that during the last three decades, the average LST has increased by 7.28^oC in the built-up area, 6.07^oC in farmland area, 5.9^oC in bare land, 5.66^oC in forest land and 4.1^oC in the water body.

This study also intended to examine the statistical association between LULC type with climate parameters, normalized difference vegetation index (NDVI), and surface temperature.

During the study period, LST was positively correlated with built-up land, farmland and bare land but negatively correlated with forest land. Similarly, the mean annual rainfall was a strong positive correlation with forest land but a negative correlation with built-up land, farmland and bare land.

Furthermore, the study showed that there was a strong positive correlation between mean annual rainfalls with mean annual, NDVI. Also, there was a strong positive correlation between kiremt and belg season rainfall with kiremt and belg season NDVI during the study period.

However, the result of the study indicates that there was a strong negative correlation between mean annual NDVI and average annual temperature.

CHAPTER V. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study was carried out aiming at comprehending and figuring out the spatiotemporal climate variability of study area using geospatial techniques. Based on the result obtained, the following conclusions could be developed.

- The mean annual rainfall of the study area declined by 28.9 mm from 1993 to 2022.
- The average annual maximum and minimum temperature of the study area was increased by 0.5^0c and $1.29\ ^0$c from 1993 to 2022.
- The size of forest coverage of the study area declined from 2617.41 km2 (58.04%) in 1993 to 1293.22 km2 (28.68%) in 2022. Based on the result, the study area has a significant rate of deforestation, which is primarily caused by human facctor.
- Farm land and builtup land dramatically increased while forest land and bare land was reduced during the study period. so the expansion of farmland and reduction of forest land have highly impact the distribution of rainfall and temperature of the study area during the stdy period.
- The Mean LST of the study area was increased from 1993 to 2022 for built upland , farm land, bare land, forest land and water body respectively.
- There is a correlation between LULC and NDVI with climate elements such as temperature and rainfall. Based on the result achieved there is a strong positive correlation between LST with Built-up land, bare land and farmland but a negative correlation between forest land and LST.
- Furthermore, there is a strong correlation between time series analysis of mean annual rainfall and mean annual NDVI. While there is a strong negative association between mean annual NDVI and average annual temperature.

5.2 Recommendation

Based on the findings, the following recommendations were made:

- In the study area, the same of meteorological stations have incomplete climate data. Therefore, concerned body must take responsibility to improve the coverage and quality of climate data for all stations of the study area.
- The study area has a high rate of deforestation. As a result, the size of the forest is declining from time to time. Furthermore, continuous forest loss makes people more vulnerable to the impacts of climate change. So, to recover and restore forest resources, the concerned body should pay attention to mitigating the problem by designing appropriate mechanisms that can be implemented, such as tree replanting and large-scale reforestation programs.
- Reporestation and afforestationof forest will be needed for wolaiat Zone to balance the temperature and rainfall condition.
- Improving the present agricultural land management practices through sustainable agricultural intensification, agroforestry, sustainable shifting cultivation, as well as implementing appropriate soil and water conservation measures are needed.

Research Fund Acknowledgement

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Appendix I: Checklist for Key Informative Interview

Dear respondents: The purpose of this checklist was to gather information for conducting the study on the title “Analysis of Spatio Temporal Climate Variability Using Geospatial Techniques in Case of Wolaita Zone Southern Region of Ethiopia”. Therefore, your valid contribution of giving reliable information is extremely valuable in achieving the objective of this study. The information I receive from you will be used only for academic purposes and will be kept confidential. Thus, please fill out the form honestly and truthfully.

Thank You in Advance for Your Cooperation!

Section I: Background Information about the Respondents

Table 1 Respondents Bachground information

SN	Name	Sex	Age	Job
1	Abraham Bobe	Male	48	Agricultural expert
2	Esatu Shure	Male	56	Farmer
3	Baza Tadyos	Male	49	Farmer
4	Adisu Kataro	Male	48	climate change and forest preservation expert
5	Bregene Bajigo	Male	53	Farmer
6	Dasalegn Barana	Male	49	climate change and forest preservation expert
7	Tadyos Dea	Male	65	Farmer
8	Belay madebo	Male	50	Farmer
9	Tamirat Tanga	Male	45	Farmer
10	Kebede Yabago	Male	58	Farmer
11	Dagale Dana	Female	40	Farmer
12	Tadese Lema	Male	46	Farmer
13	Mekuria Habebo	Male	37	Agricultural expert
14	Ejajo Tuka	male	53	Farmer
15	Eshetu Morka	Male	36	Agricultural expert
16	Turunge Gobena	Female	38	Farmer
17	Tadese Zewga	Male	41	climate change and forest preservation expert
18	Duressa Munamo	Male	50	Farmer
19	Dawit Lambebo	Male	40	Farmer
20	Dana Beyene	Male	55	Farmer

Section II: Trend and Variability of Rainfall and Temperature-Related Interview

I. Have you observed any changes in rainfall or temperature in the Wolaita zone?

____

____

II. If you answered "yes" to the above question, how did you see changes in rainfall distribution and temperature in the Wolaita zone between 1993 and 2022? (There are three options based on rainfall distribution and temperature trend: decline, increase, or no change).

____

____

III. Dear interviewee, in the context of the Wolita zone, has changes in LULC types led to variations in rainfall and temperature? Please give your idea with justification.

____

____

Section III: LULC change-related interview

I. Are there any patterns of land use/land cover change in the Woliata Zone?

____

____

II. If you answered "yes" to the above question, how did you see current changes in forest covering, Farmland, built-up land, water body, and bare land use patterns? Which land use type was reduced, expanded, or remained unchanged?

____

____

III. Dear Interviewee, What are the driving causes of LULCC in Woliata Zone? (Options provided: population growth, increased agricultural activity demand, deforestation, settlement expansion and so on.)

____

____

Appendix II: Mean average annual rainfall and temperature of the study area

Table 2: Mean Annual Rainfall and Temperature of the Study Area from 1993 to 2022

year	mean annual rainfall in (mm)	Average Annual Temperature in (0c)
1993	1305.91	25.35
1994	904.17	26.08
1995	1413.13	25.25
1996	1251.40	26.78
1997	815.90	27.18
1998	1038.17	26.47
1999	856.23	26.93
2000	1082.43	26.60
2001	1199.44	26.88
2002	1397.87	27.09
2003	1147.07	26.60
2004	871.23	27.03
2005	1097.37	26.87
2006	1068.87	26.93
2007	1285.10	26.78
2008	1246.30	26.48
2009	1361.97	26.55
2010	1061.77	26.99
2011	903.84	27.73
2012	1209.50	26.45
2013	1023.60	27.28
2014	1237.40	27.51
2015	1183.90	26.64
2016	1060.43	26.91
2017	1330.37	26.75
2018	938.00	27.18
2019	1263.76	27.46
2020	976.87	27.32
2021	806.13	28.00
2022	1171.96	26.51

Appendix III: Kiremt Season Rainfall between 1993-2022

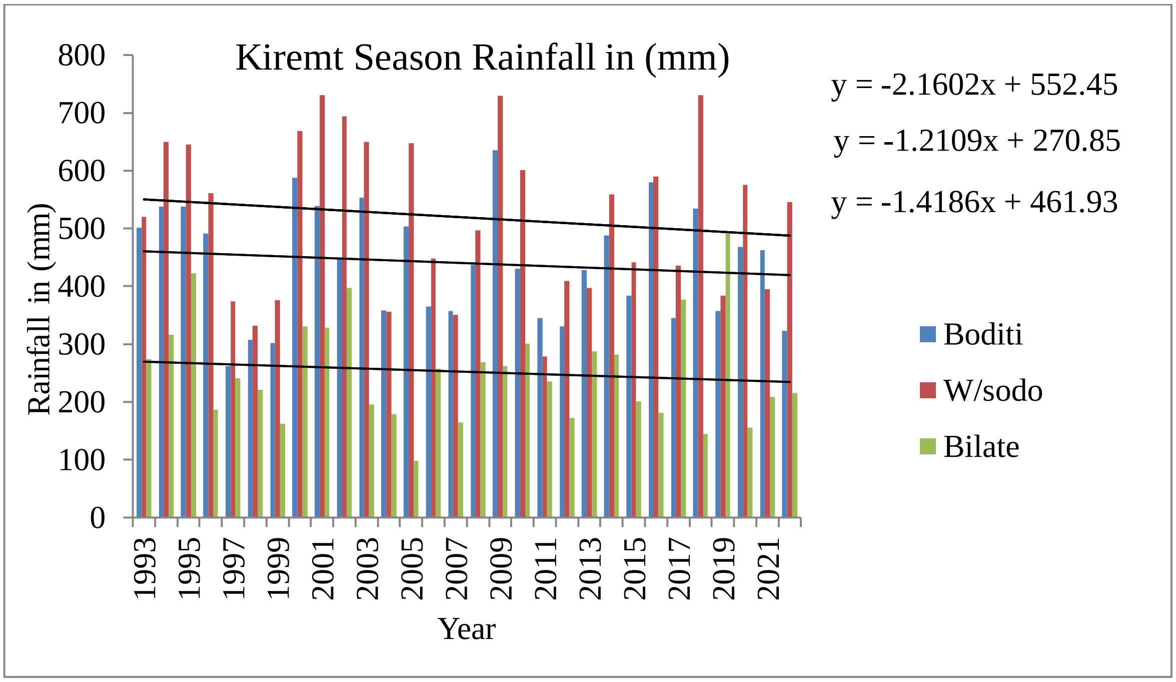


Fig 1:Kiremt Season Rainfall Between 1993-2022

Appendix IV: Annual rainfall in (mm) between 1993-2022

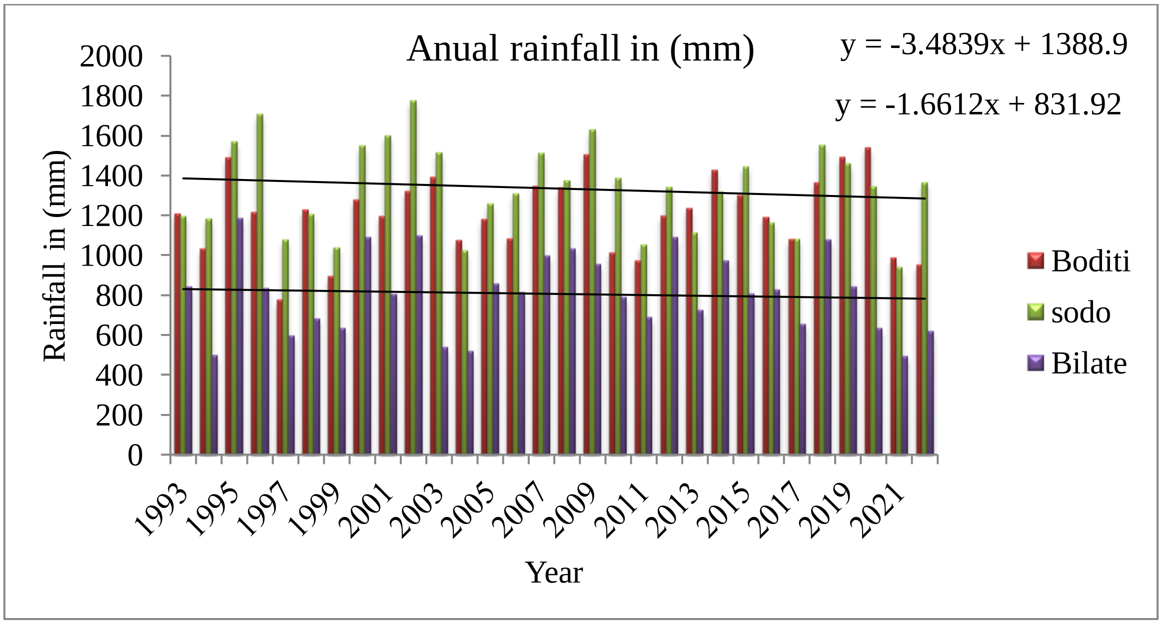


Fig 2: Mean Annual rainfall

Appendix V: Average Annual Maximum Temperature

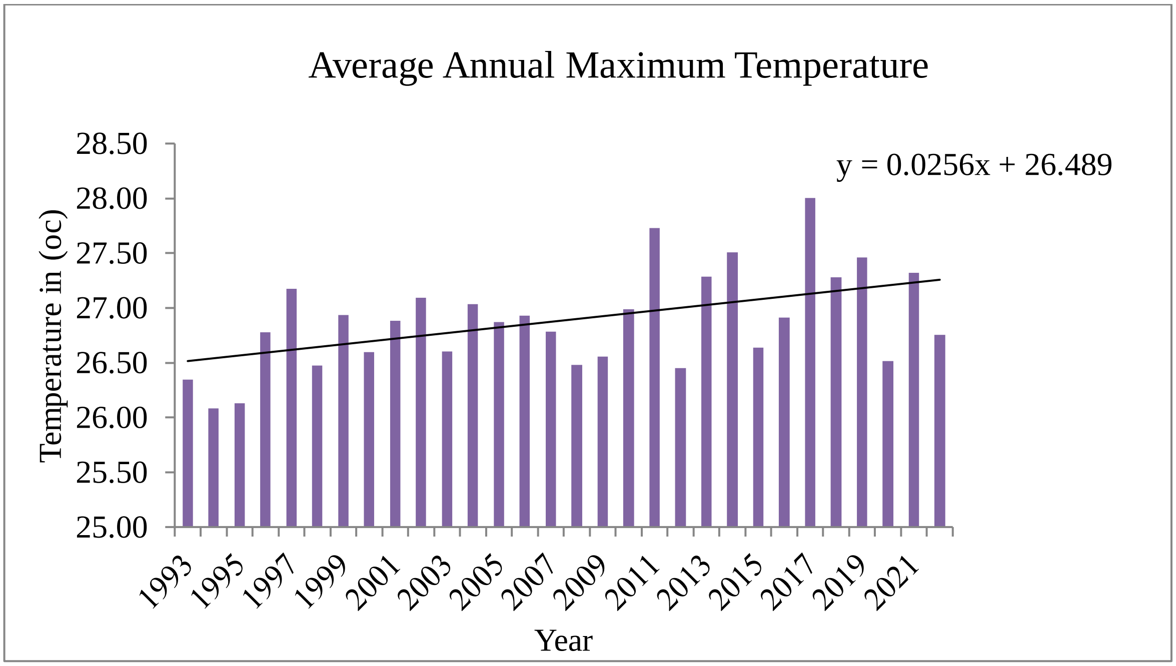
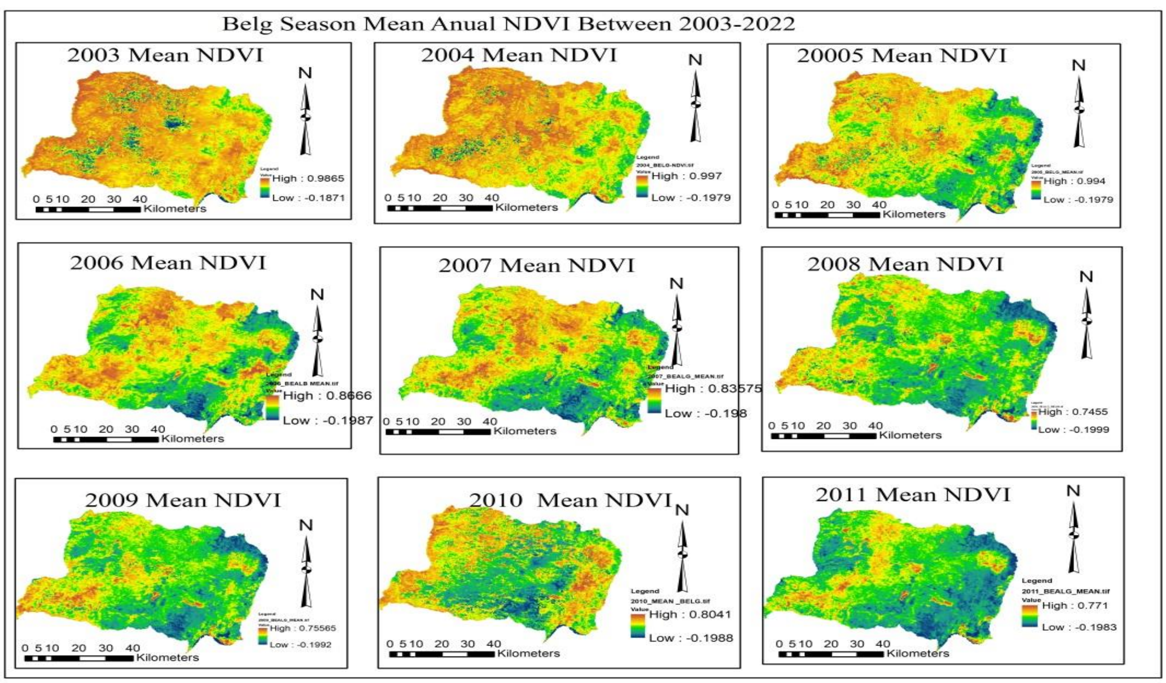


Fig 3: Average Annual Maximum Temperature Between 1993-2022

Appendix VI: Mean annual NDVI

Part I: Belg Season Mean Annual NDVI



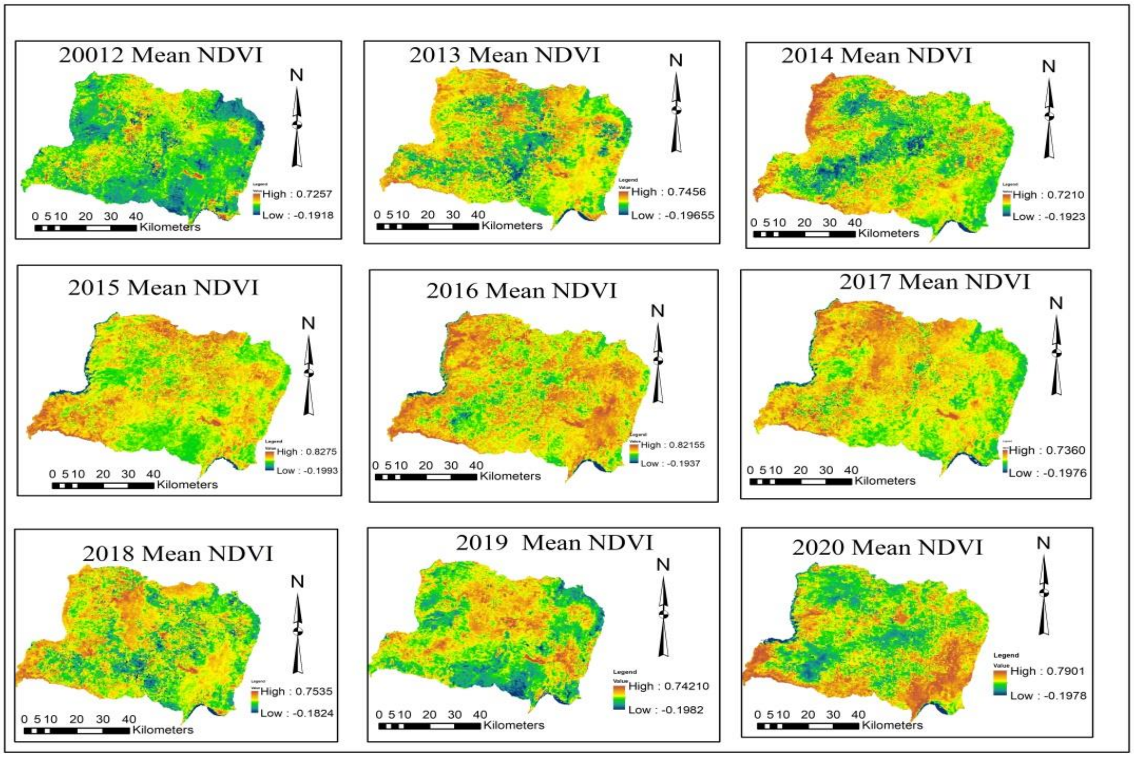
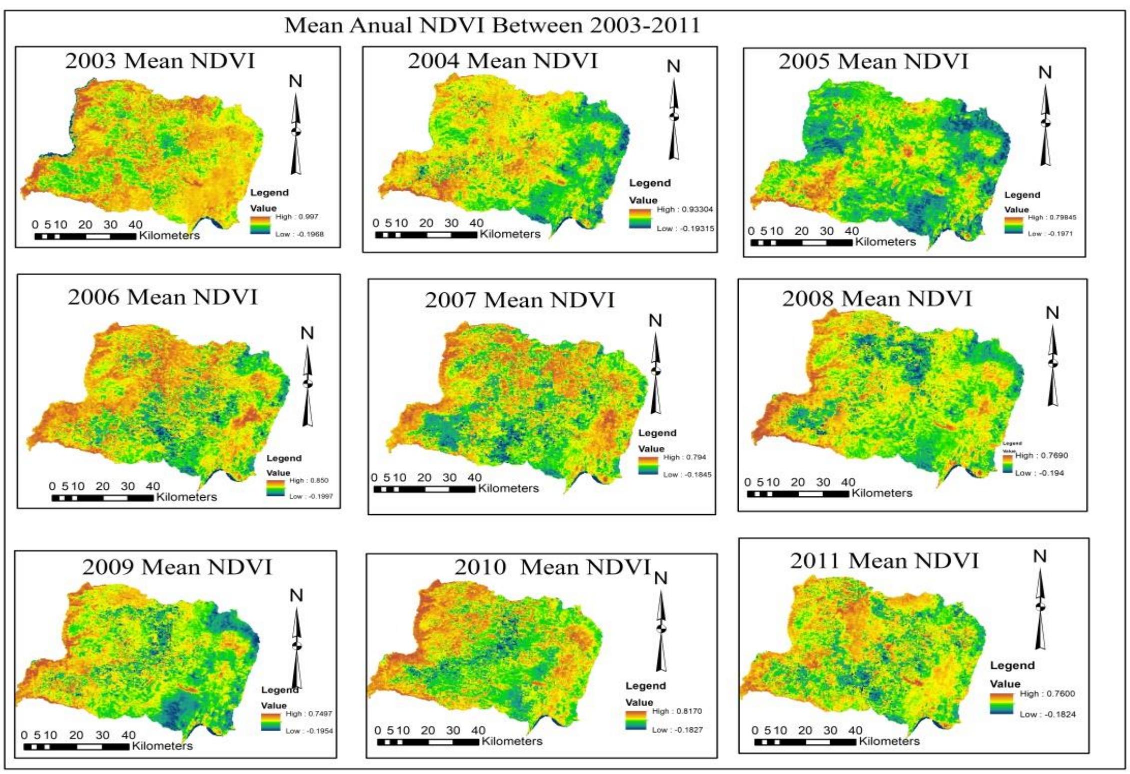


Fig 4: Belg season Mean NDVI

Part II: Mean Annual NDVI



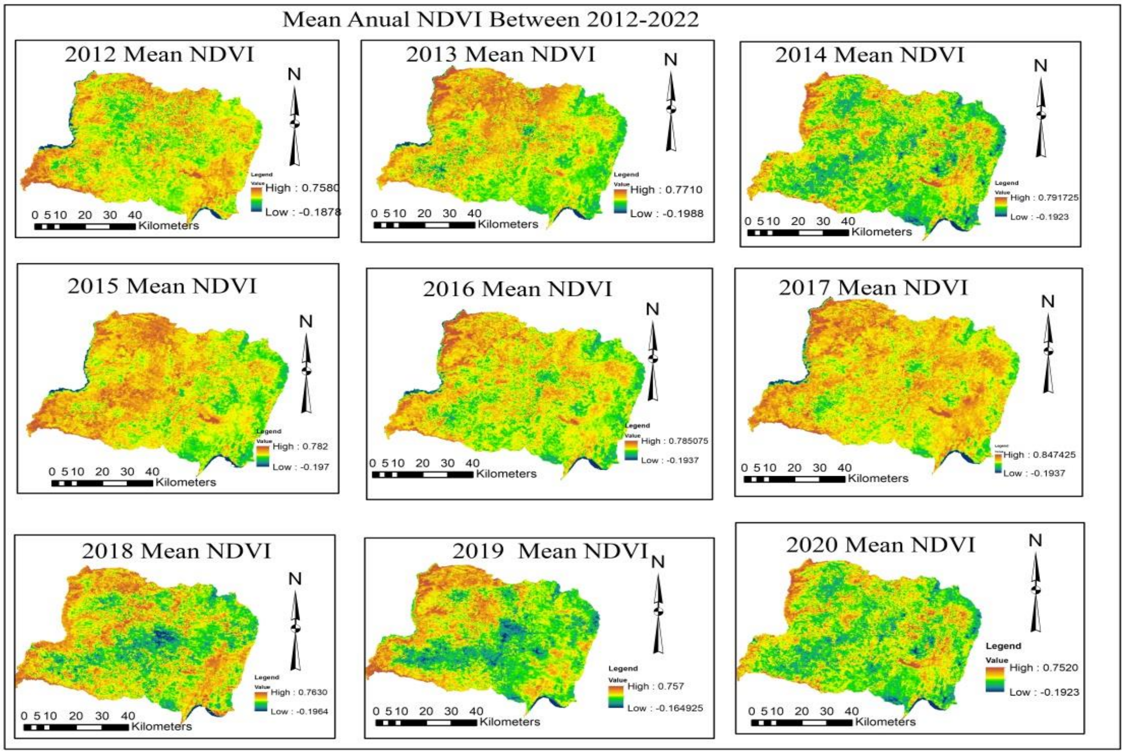
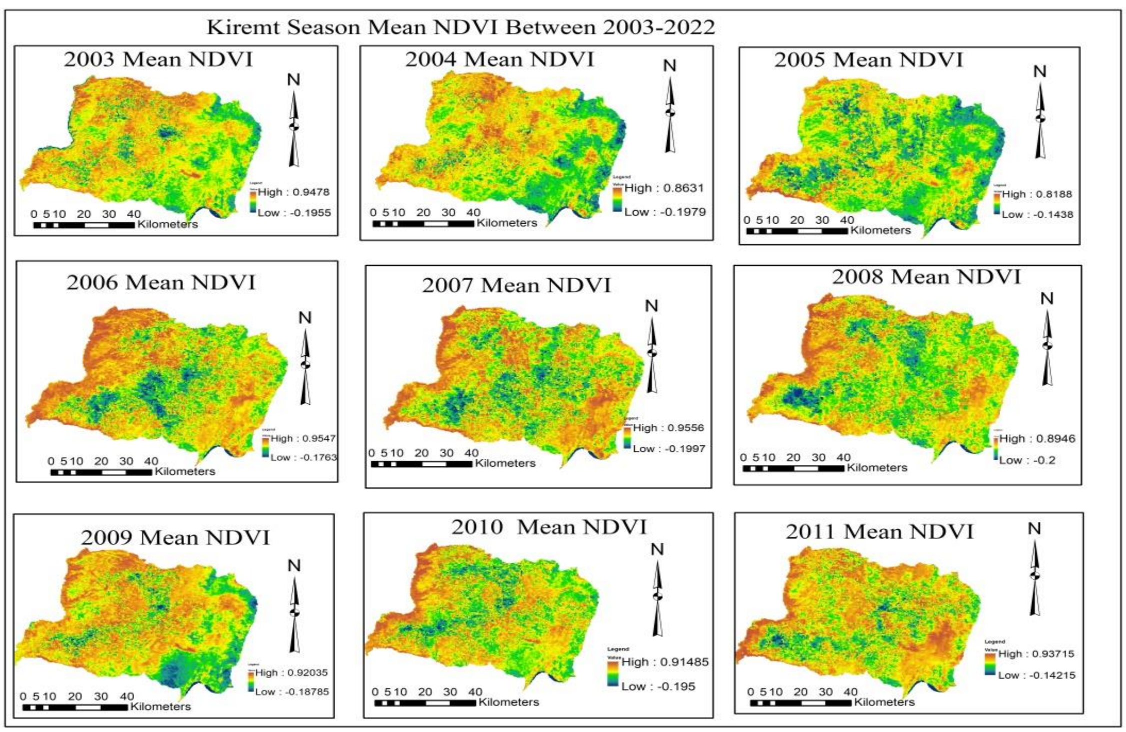


Fig 5: Mean Annual NDVI

Part III: Kiremt season Mean Annual NDVI



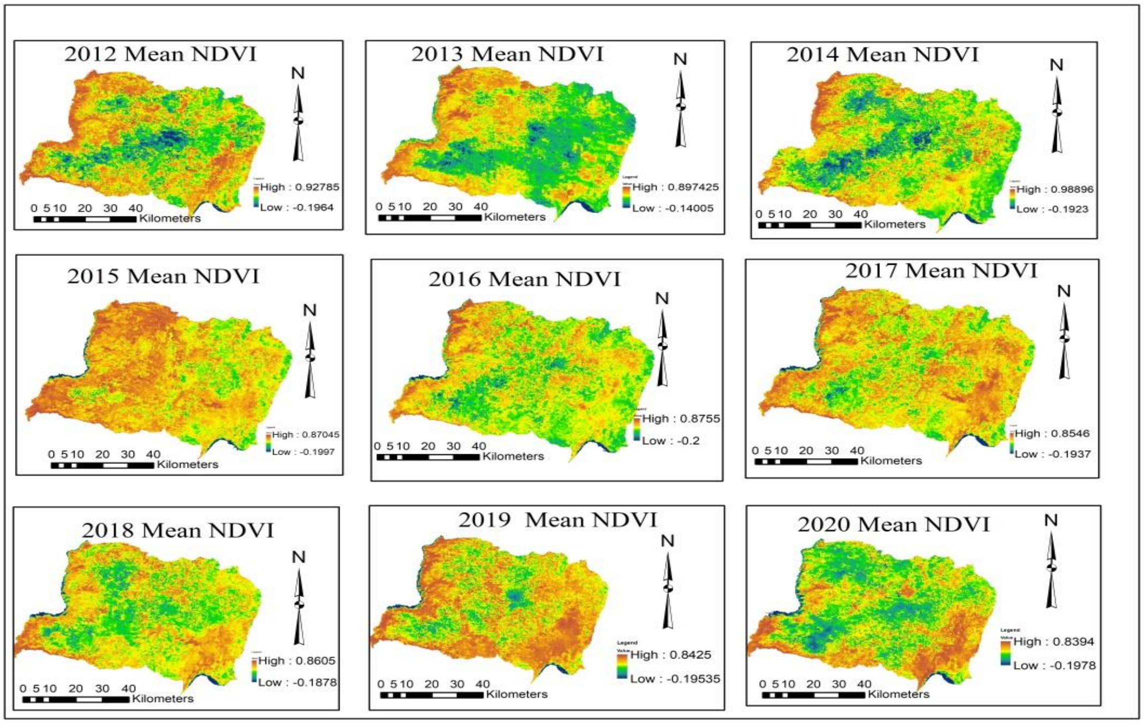


Fig 6: Kiremt Season Mean NDVI

Appendex VII: Change of LST in (^{0}c) Per Different LULC Type