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COLLEGE OF NATURAL SCIENCE

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REMOTE SENSING AND GEOINFORMATICS STREAM

AGRICULTURAL DROUGHT RISK AREA IDENTIFICATION USING NDVI AND LAND SURFACE TEMPERATURE: A CASE STUDY OF EAST ARSSI ZONE, ETHIOPIA

A Thesis submitted to

The School of Graduate Studies of Addis Ababa University In partial Fulfillment of the requirements for the Degree of Masters of Science in Remote Sensing and Geo-informatics

BY: GEZAHEGN BALCHA MOJO

(GSR/5560/10)

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Addis Ababa, Ethiopia

May, 2019

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This is to certify the thesis prepared by Gezahegn Balcha Mojo entitled as **"Agricultural Drought Risk Area Identification Using NDVI and Land Surface Temperature: A Case Study of East Arssi Zone, Ethiopia"** is submitted in partial fulfillment of the requirements for the Degree of Master of Science in Remote Sensing and Geo-informatics compiles with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

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LIST OF ABBREVIATIONS

AVHRR	Advanced Very High-Resolution Radiometer
CHIRPS	Climate Hazard Group Infrared Precipitation with Station
CSA	Central Statistical Agency
CSWB	Crop Soil Water Balance
DEM	Digital Elevation Model
FAO	Food and Agricultural Organization
FEWS-NET	Famine Early Warning System
GIS	Geographic Information System
LEAP	Livelihood Early Assessment and Protection
LST	Land Surface Temperature
MCE	Multi Criteria Evaluation
eMODIS	The EROS Moderate Resolution Imaging Spectroradiometer
MODIS	Moderate Resolution Imaging Spectro Radiometer
NDVI	Normalized Difference Vegetation Index
NGO	Non-Governmental Organization
NOAA	National Oceanic and Atmospheric Administration
OCHA	Office for the Coordination of Humanitarian Affairs
PDSI	Palmer Drought Severity Index
SPI	Standard Precipitation Index
TCI	Temperature Condition Index
VCI	Vegetation Condition Index
WFP	World Food Program
WHC	Water Holding Capacity

WR	Water Requirement
WMO	World Meteorological Organization
WRSI	Water Requirement Satisfaction Index

ACKNOWLEDGMENTS

I am thankful to the Almighty God for his showers of blessings throughout my life. I would like to express my gratitude and appreciation to my advisor, Dr. Tesfaye Korme, School of Earth Sciences, Addis Ababa University, for his interest in my research work, and for his continues advice, guidance and encouragement to accomplish my thesis work successfully.

I am also thankful to Central Statistics Agency of Ethiopia, National Meterological Agency and East Arssi zone Agricultural and natural resource management offices as well as their respective woreda bureau for their cooperation in providing the necessary data and information to carry out this research.

I express my honest and sincere gratitude towards my family for their encouragement to pursue this study. Their constant support and love have given me additional energy to complete my study. Further, I would like to extend my thanks to all Earth Science Department staff members and Remote Sensing and Geo-informatics stream staff members for securing lab facility and unreserved support.

I owe Sincere and earnest thankfulness to my officemate Mulalem Wawaya, Shewaleul Mandefro and Mulgeta Abera for their support and kindness.

Abstract

Agriculture in the East Arssi Zone is the most vulnerable and sensitive sector that is seriously affected by the impact of climate variability and change, which is usually manifested through rainfall variability and recurrent drought.. Thus, in order to adapt and/or mitigate the impact of agricultural drought, agricultural drought risk area has to form one dimension of research to be done whereas the use of remote sensing and GIS techniques provides wide scope in drought risk area detection and mapping. Consequently, this study was conducted in East Arssi zone with the objective of assessing agricultural drought risk area identification and preparing agricultural drought risk area map using satellite data. To assess and examine spatiotemporal variation of seasonal agricultural drought patterns and severity, three drought indices namely, land surface temperature (LST), Standard precipitation index (SPI) and NDVI anomaly are applied. A time series MODIS NDVI AND LST satellite data for the years 2001- 2016 were utilized as input data for the indices while Meteorological data was used to validate the strength of indices in explaining the impact of agricultural drought. The result derived from indices for the study period has shown that the edge of rift valley and low land of Arssi continues mountain have been affected by severe drought, with observed spatial difference in severity level within East Arssi zone. However, the severity level was higher in 2009 and 2016 cropping seasons whereas 2015 being the most severe of all. In order to evaluate the strength of the indices for expressing the existence of agricultural drought, simple regression analysis of indices results with rain fall and NDVI, LST and SPI and NDVI and LST have been computed and can be a good indicator for occurrence of agricultural drought. Agricultural risk map of East Arssi zone was produced by integrating the three drought indices. The result indicates that East Arssi zone is classified into slight, severe and no drought agricultural drought risk area covering 22, 41.5 and 63.50 percent of the total geographical area respectively.

Thus, this agricultural drought risk mapping can be useful to guide decision-making process in drought monitoring and to reduce the risk of drought on agricultural production and productivity.

***Keywords**: Agricultural drought, East Arssi, GIS, NDVI, Remote Sensing, SPI, LST,*

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the Study

Drought a natural hazard, defined as "severe water shortage". It adversely affects ecosystem, environmental productivity and socioeconomic conditions. Its effect on vegetation condition causes severe impacts on agriculture, ecosystem, food security, human health, water resource and economy (Wilhite et al., 2000). Drought could be defined contextually in different disciplines in relation to the parameters that it affects the most. Drought is a regional phenomenon and its characteristics will vary from one climate regime to another (Iglesias et al., 2009). Eastern lowlands of Ethiopia are vulnerable to drought and there have been notable droughts in this part of the country throughout human history (Webb and Braun, 1994). Previous droughts and the frequency of rainfall deviation from the average suggested that drought occur every 3-5 and 6-8 years in the arid and semi-arid regions of Ethiopia and every 8-10 years for the whole country (Haile, 1988).Although drought could be characterized from the perspective of meteorological, hydrological, agricultural and socio-economic drought context, the proposed study was focus on agricultural drought in eastern Arssi zone. Due to its cumulative impacts and widespread over large geographical areas, drought is stronger than other natural disasters (Tadesse et al., 2004). Again, drought is pointed out as dangerous natural phenomena that occur when precipitation is lower than normal period thereby characterized by causing insufficiency for human practices and the natural activities (WMO, 2006). Drought in developing countries is very disastrous causing suffering, population displacement, food shortage, loss of life, death of animals, reduction of agricultural output, diminishing of rivers and lakes, deteriorations of water conditions, wildfires and permanent vegetation failure (FAO, 2011; Huang et al.,2013; Kapoi and Alabi,2013). Ethiopia, one of the sub-Saharan African countries that highly vulnerable to natural hazards that have been recorded. However, drought has remained the leading cause of disaster and human sufferings in Ethiopia in terms of frequency, area coverage and the number of people affected. The severity and persistence of the latest droughts has produced a wide range of impacts across the country (Sara Abebe, 2010; Defferew Kebede, 2011. Agricultural drought defined by a reduction in soil moisture availability below the optimal level required by a crop during the different growth stages, resulting in impaired growth and reduced yields. Agricultural drought happens, when moisture in the soil is insufficient to ensure optimal crop growth (Gizachew, 2010). It occurs typically after meteorological drought but before hydrological drought (Flood and Climate Basics, 2004). Hydrological drought results when precipitation deficiencies begin to reduce the availability of natural and artificial surface and subsurface water resources. Hydrological drought occurs when there is substantial deficit in surface runoff below normal conditions or when there is a depletion of ground water recharge. Socioeconomic drought occurs when human activities are affected by reduced precipitation and related water availability. Even though it is difficult to clearly monitor the beginning and the end of drought occurrence, it is possible to monitor and analyze its characteristics such as intensity using different drought indices. This can be done either through climatic drought indices from meteorological data sets or modern remote sensing-based drought indices (Palmer, 1965; Abbas et al., 2014; Himanshu et al., 2015). In comparing with conventional weather data, remote sensing approaches are relatively better suited for monitoring vegetation conditions, agricultural drought and crop yield assessment (Domenikiotis et al., 2004).

In 2015, eastern Ethiopia had experienced a severe drought. The drought had caused low crop production for both Belg and Meher harvests, poor livestock health and low water availability. It was erratically distributed and punctuated by several long dry spells. The Kiremt rains started at a typical time, and there were fairly normal amounts of rainfall in the middle of June. However, the remaining period of the Kiremt was characterized by quite low rainfall, and as a result, cumulative June to September Kiremt rainfall was well below average, with particularly low rainfall. As a result of the dry conditions, pasture and water availability were very low in eastern Oromia. A vulnerability assessment is the process of identifying, quantifying, and prioritizing (or scoring) the vulnerabilities in a system. Vulnerability from the perspective of drought planning means “assessing the threat from potential drought hazards to various sectors across social, economic, environmental and political fields” (CWCB, 2013). GIS and Remote sensing techniques are being widely used for analysis of drought monitoring and assessment using various drought indices (Alemayehu Kassa, 1999; Jeyaseelan, 2004; Chopra, 2006, Amare Degefaw, 2007; Beyene Ergogo, 2007).

1.2. Problem Statement

East Arssi Zone is, one of the Eastern regions of Ethiopia, some area affected by the recurrent drought, for the last many years. In this region of the country, drought is manifested by the irregularity of rainfall. The regional risks associated with rainfall variability and the consequential drought generally, characterized by late beginning and early endings of the rainy seasons. This results in temporally and spatially inadequate amount of moisture to support crop growth. The amount and distribution of rainfall during the short period was so unsatisfactory that had rendered crops vulnerable to moisture deficit, leading to reduced yields. Agriculture is vulnerable to climate change. The sector is sensitive and it is seriously affected by the recurrent drought which is mostly related to climate change. These prominent realities clearly emphasize the degree of vulnerability of agricultural sector products of the zone to sever drought hazards. Drought is currently more pronounced in the study area which results in yield reduction and crop failure. Several studies have been carried out to monitor agricultural drought using remote sensing and GIS techniques including Huang et al. (2013) and Abbas et al. (2014) in China, Kapoi and Alabi (2013) in Kenya, Biranu (2014) in Tigray, Gizachew and Suryabhagavan (2014) in East Shewa Zone, Wondewsen Negesse in west Hararge zone. However, none of them conducted the study on drought using NDVI and Land Surface temperature in East Arssi zone. Therefore, by applying NDVI and LST, the most drought–vulnerable areas will be identified in East Arssi zone, Ethiopia

1.3. OBJECTIVES

1.3.1. General Objective

The general objective of the study is to identify and assess the most drought vulnerable areas using satellite image and ground truth data.

1.3.2. Specific Objectives

- To analyze the advantages of the different drought indices and identify an appropriate index that can be used for monitoring drought in the region.
- To identify the most drought–vulnerable areas in the Region
- To investigate the impact of drought on agricultural production using remote sensing-based drought indices.

1.4. Significance of Study

This study is expected to provide quantified information regarding drought. This will be valuable information to take pre, and post–drought risk management plans by decision and policy makers. The most drought–vulnerable area was delineated based on the livelihood class of the zone, which will be important for Regional State Government and the Federal Government of Ethiopia to identify the most drought–prone areas to save the life of communities in the Arssi zone.

1.5 Scope of The Study

This study focuses on identification of drought risk area using Normalized difference vegetation index and Land surface temperature. The scope of the study is limited to East Arssi zone, Ethiopia.

1.6. Limitation of Study

Among the various drought measuring indices, the study focused on one of the indices which combines two datasets solely extracted from satellite imagery. The information extracted from this satellite imagery signifies the condition of temperature on soil and leaf canopy and the behavior of vegetation as variable to monitor drought.

The study was conducted with all possible efforts in collecting required inputs for both primary and secondary data. However, required quantitatively and temporally appropriate meteorological information and high-resolution data for Water Requirement Satisfaction Index (WRSI) were not available.

1.7. Organization of The Thesis

This thesis is organized into six (6) chapters. Chapter one contains the introduction describing the problem and gives a highlight of the significance of the study as well as the goals and scope of the study. Chapter two review of related literature, Chapter three deals with data and methodology. Chapter four provides information on the results. Chapter five contain discussion on the results. Chapter six gives conclusion and recommendations

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Drought

Drought is dangerous natural phenomena that occur when precipitation is lower than normal period there by characterized by causing insufficiency for human practices and the natural activities (WMO, 2006).

2.2. Types of Drought

2.2.1. Meterological Drought

Meteorological drought refers to a decline of precipitation, as compared to average conditions, over an extended period of time. It basically originates from the deficiency of precipitation and focuses on the physical characteristics of drought (Mokhtari, 2005) rather than impacts associated with shortage of precipitation. Meteorological drought leads to depletion of soil moisture and has always an impact on crop production.

2.2.2. Agricultural Drought

Agricultural drought is defined to a situation in which the moisture in the soil is no longer sufficient to meet the needs of crops growing in the area. The reduction in soil moisture availability below the optimal level required by a crop during the different growth stages, resulting in impaired growth and reduced yields. It is typically occurred after meteorological drought but before hydrological drought (Flood and Climate Basics, 2004). Focus is placed on precipitation shortages reduced ground water/reservoir levels differences between actual and potential evapotranspiration and so on.

Drought is a protracted period of deficient precipitation resulting in extensive damage to crops and loss of yield. A good definition of agricultural drought should be to able to account for variable susceptibility of crops during different stages of crops development from emergence to maturity. Deficient to topsoil moisture at plating may hinder germination leading to low plant population per hector and reduction of final yield. The demand of crops depends on weather condition (such as temperature, relative humidity), its biological make up, what stage of growth the crops is in and the physical/chemical makeup of the soil. This drought does not depend only on the amount of rainfall but also the correct use of that water.

2.2.3. Hydrological Drought

Hydrological drought results when precipitation deficiencies begin to reduce the availability of natural and artificial surface and subsurface water resource that means, it is persistently low discharge and/or volume of water in streams and reservoirs, lasting months or years. It occurs when there is substantial deficit in surface runoff below normal conditions or when there is a depletion of ground water recharge. This perception agrees with the fact that hydrological drought is closely related with long term absence of precipitation increased evapotranspiration.

2.2.4. Socioeconomic Drought

Socio-economic drought is associated with failure of water resources systems to meet water demands and thus associating droughts with supply of and demand for an economic good (water). Socio-economic drought occurs when the demand for an economic good exceeds supply as a result of a weather-related shortfall in water supply. Otherwise, it is the effect of elements of the above droughts on supply and demand of economic goods and human well-being. Some scientists suggest that the time and space processes of supply and demand are the two basic processes that should be included in an objective definition of drought (WMO, 2006).

2.3. Impacts of Drought

The impacts of a drought can be economic, environmental or social. Drought produces a complex web of impacts that spans many sectors of the economy and reaches well beyond the area experiencing physical drought. This complexity exists because water is integral to society's ability to produce goods and provide services. Impacts are commonly referred to as direct and indirect. Direct impacts include reduced crop, rangeland, and forest productivity, increased fire hazard, reduced water levels, increased livestock and wildlife mortality rates, and damage to wildlife and fish habitat. The consequences of these direct impacts illustrate indirect impacts. For example, a reduction in crop, rangeland, and forest productivity may result in reduced income for farmers and agribusiness, increased prices for food and timber, unemployment, reduced tax revenues because of reduced expenditures, foreclosures on bank loans to farmers and businesses, migration, and disaster relief programs. Assessing the threat of from potential drought impacts to various sectors across agricultural, social, economic, environmental and political fields (CWCB, 2013)

2.3.1 Agricultural Drought Impact on Agricultural Sector

Agricultural drought produces a complex web of impacts that span many economic sectors. Among, agriculture is the primary economic sector affected by agricultural drought and particularly, short term agricultural drought at the critical growth stages has severe impacts on agriculture (Wu and Wilhite, 2004 cited in Mokhtari, 2005).

Agriculture is the largest consumer of water and, therefore, the most sensitive to agricultural drought. Moisture deficit is often the most limiting factor for crop production. In Ethiopia, rainfall in main rainy season (Kiremt) is the most important for agricultural activities as nearly 95 percent of crop production is in this season (Workneh Degefu, 1987). Thus, the occurrence of agricultural drought during the main rainy season has greater impact on country's food production. This impact is largely prominent in dryland semiarid areas. Agricultural drought has either direct or indirect impact on agricultural activities. Direct impact includes reduced crop yield, rangeland and forest productivities. The consequence of these impacts results in reduction of income of farmers and agro based industries, increased price for food and other agricultural products such as forest products. Besides, losses in crop production, agricultural drought is associated with increases in insect infestation, plant disease and wind erosion (Mokhtari, 2005).

Agricultural drought induced physiological stress increases a plant's susceptibility to disease and insects, and reduces crop survival. Furthermore, the loss of soil organic matter can lessen cropland productivity and facilitate for wind erosion. On the other extreme, agricultural drought has also social impact particularly on farmers that drive the agricultural sectors. It involves food shortage and migration to urban areas. This makes drought migrants increase pressure on social infrastructure of the urban areas and leads to increased poverty.

2.3.2. Agricultural Drought Impact on Environmental Sector

Environmental losses are the result of damages to plant and animal species, wildlife habitat, and air and water quality; forest and range fires; degradation of landscape quality; loss of biodiversity; and soil erosion. Some of the effects are short-term and conditions quickly return to normal following the end of the drought. Other environmental effects linger for some time or may even become permanent. Wildlife habitat, for example, may be degraded through the loss of wetlands, lakes, and vegetation. However, many species will eventually recover from this temporary aberration. The degradation of landscape quality, including increased soil erosion, may lead to a more permanent loss of biological productivity of the landscape. Although environmental losses are difficult to quantify, growing public awareness and concern for environmental quality has forced public officials to focus greater attention and resources on these effects. Environmental impacts realized through the hydrological effects where the water sources like water pans, rivers dry up and the reporting of reduced levels of water by flowing springs and drying up of the available boreholes. The loss of biodiversity natural habitat, degradation of landscapes increased soil erosion leading to permanent loss of land productivity and the loss of wetlands impacts negatively on plant and animal species and eco-systems.

2.3.3. Agricultural Drought Impact on Economic Sector

Many economic impacts occur in agriculture and related sectors, including forestry and fisheries, because of the reliance of these sectors on surface and subsurface water supplies. In addition to obvious losses in yields in crop and livestock production, drought is associated with increases in insect infestations, plant disease, and wind erosion. Droughts also bring increased problems with insects and diseases to forests and reduce growth. The incidence of forest and range fires increases substantially during extended droughts, which in turn places both human and wildlife populations at higher levels of risk.

The massive loss of livestock and significant loss of grassland and pasture marked a record observation on stock population changes. The effects of drought are clearly manifested by reduced crop production, loss of agriculture, land degradation, livestock population deaths, unemployment and health problems, Murad et al, (2011).

Drought most common economic impacts are wasted animal body condition, reduced milk production, direct loss of browse and pasture, predation of small ruminants by Hyena and baboons as well as crop failures are common.

2.3.4. Agricultural Drought Impact on Social Sector

Social impacts involve public safety, health, conflicts between water users, reduced quality of life, and inequities in the distribution of impacts and disaster relief. Many of the impacts identified as economic and environmental have social components as well. Population migration is a significant problem in many countries, often stimulated by a greater supply of food and water elsewhere. Migration is usually to urban areas within the stressed area, or to regions outside the drought area. Migration may even be to adjacent countries. When the drought has abated, the migrants seldom return home, depriving rural areas of valuable human resources. The drought migrants place increasing pressure on the social infrastructure of the urban areas, leading to increased poverty and social unrest.

Social impacts as a result of drought includes the conflict and public safety, health and nutrition affecting quality of life, population migration and increased poverty. For the case of study area, the malnutrition levels have been reported to the declining as stated in office for the coordination of Humanitarian Affairs (OCHA) Emergency unit for Ethiopia (EUE),2003, field assessment mission. The loss of human lives through protracted drought impacts occasional by increased heat stress and declining purchasing power in Ethiopian's arid and semiarid areas has been a key cause of water and management conflicts among the pastoral and agropastoral livelihood zones. In general, the sequence of drought impact on social, economic and environmental sector with meteorological, agricultural and hydrological drought were illustrated in the following Figure

Source: -National drought mitigation center. Centre, http://enso.unl.edu/ndmc/enigma/ def2.htm)

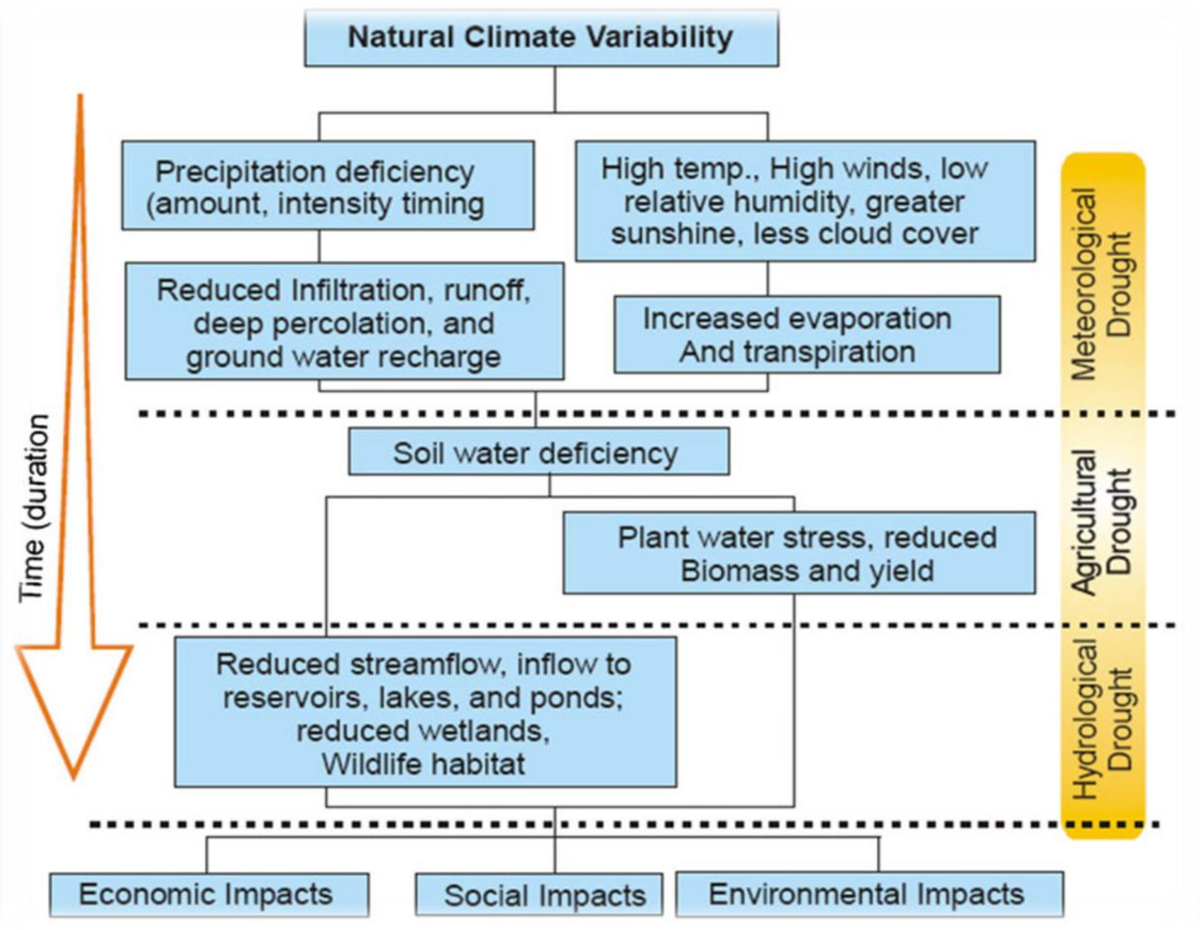

Figure 2.3.1. Categories of drought impact

2.4. Current Drought in Ethiopia

The worst drought in decades gripped north and central Ethiopia in 2015, affecting nearly 10 million people. The dry conditions left hundreds of thousands of farmers with failed crops and weakened or dead livestock. The resulting food scarcity meant more than eight million people in the parched country needed emergency food aid, according to the United Nations (UN).

The magnitude of the devastation to Ethiopia led the UN's Allahoury Diallo to declare that the "drought is not just a food crisis – it is, above all, a livelihood crisis." Signs of trouble began to surface early in the year. Farmers waited for the *belg* rains that generally occur between February and May in the central and eastern parts of the country. About 10% of the Ethiopian population is completely dependent on this season to provide rainfall for crops and pastures. But in 2015, after a false start, the *belg* rains came a month late in northern and central Ethiopia. What also arrived was a particularly strong El Niño, associated with the warming of equatorial waters in the Pacific Ocean. The effects of El Niño play out in different ways across the planet. In Ethiopia, El Niño can lead to drier conditions, mainly in the north-western part of the country, affecting the rainy season known as *kiremt* that occurs in June–September. In a normal year, the *kiremt* rains account for 50–80% of annual rainfall. But in 2015, the *kiremt* season was delayed and the rains were erratic and below average. From February to August 2015, the northern-central and some eastern parts of the country received only 500 mm of rainfall, a deficit of 167 mm from the long-term average (Climate Hazards Group Infrared Precipitation with Stations, CHIRPS). Only half to three quarters of the rainfall expected was received from February to September. In a world warmed by human-induced climate change, droughts are expected to become more common and more severe in some parts of the world. The observed 2015 drought was an extremely rare event that is expected to happen in the central to north-eastern parts of Ethiopia only about once every few hundred years.

2.5. Role of Remote Sensing and GIS In Drought Identification

The mitigation of the effects of disasters requires relevant information regarding the disaster in real time. Also, the possible prediction and monitoring of the disaster requires rapid and continuous data and information generation or gathering. Since disasters that cause huge social and economic disruptions normally affect large areas or territories and are linked to global change, it is not possible to effectively collect continuous data on them using conventional methods. The space technology or remote sensing tools offer excellent possibilities of collecting this vital data. This is because the technology has capability of collecting data at global and regional scales rapidly and repetitively and the data is collected in digital form. The technology further provides an excellent communication medium.

The satellite or remote sensing techniques can be used to monitor the current situation- before, during or after disaster. They can be used to provide baseline data against which future changes can be compared while the GIS techniques provide a suitable framework for integrating and analyzing the many types of data sources required for disaster monitoring. In recent years, the ever-increasing population and overstress on natural resources, soil degradation, decrease in water resources, and future projected climate change scenarios have become important areas of concern. The main goal of global agriculture is to feed 6 billion people, a number likely to double by (Kogan 2000). The first requirement of living creature is food, and a setback in agricultural and fodder production leads to socio-economic unrest especially in developing countries. Therefore, management of natural resources in developing as well as developed countries requires information on the state and changes in a range of biophysical variables. Droughts has been viewed as such a disaster where in a shortfall in precipitation has led to substantial reduction in production levels thereby leading to conditions which causes large scale migration and death of men and animals. Therefore, there is a need for proper quantification of drought impacts and monitoring and reporting of drought development in economically and environmentally sensitive areas. The impact of drought on society and agriculture is a real issue but it is not easily quantified. Reliable indices to detect the spatial and temporal dimensions of drought occurrences and its intensity are necessary to assess the impact and also for decision-making and crop research priorities for alleviation (Seiler and Kogan et al. 1998). The development and advancements in space technology, to address issues like drought detection, monitoring and assessment have been dealt with very successfully and helped in formulation of plans to deal with this slow onset disaster. With the help of environmental satellite, drought can be detected 4-6weeks earlier than before and delineated more accurately, and its impact on agriculture can be diagnosed far in advance of harvest, which is the most vital for global food security and trade (Kogan ,1990).

2.6. Land Surface Temperature (LST)

Land Surface Temperature denotes the temperature on the surface of the earth or it is the skin temperature of the earth surface phenomena (Kayet *et al.*, 2016). Land surface temperature also defined as, the monitoring of surface temperature based on pixel derived observation through RS

(Paramasivam, 2016). From the satellite's point of view the 'surface 'looks different for different area at different times (Kumar and Singh, 2016). Remote Sensing and geospatial tools play crucial role in quantifying and estimating LST. Land Surface Temperature can be derived from geometrically corrected Landsat Thermal Infrared (TIR) band 6 and Landsat 8 thermal infrared (TIR) band 10 and 11 (Khin *et al.*, 2012) and also from MODIS Terra and aqua sensor. Land surface temperature of a given area can be determined based on its brightness temperature and the land surface emissivity, which is calculated through applying the split window algorithm (Rajeshwari and Mani, 2014). According to Kerr *et al.,* (2004) LST gives information about the difference of the surface equilibrium state and vigorous/vital for many applications. The characteristics of urban land surface temperature is depending up on its surface energy balance, which is governed by its properties such as orientation, sky and wind, openness to the sun and radioactive ability to reflect solar and infrared and also ability to emit infrared availability of surface moisture to evaporate and roughness of the surface (Voogt, 2000). Land-use/land-cover changes due to changes in surface temperature (ST) which makes both urban and rural managers to estimate the urban ST and its surrounding rural area for urban planning as well land management in general (Becker *et al.*, 1990).

LST is a very important variable required for a wide variety of applications for instance climatological, hydrological, agricultural, biochemical and change detection studies, Prasanjit Dash (2005). The LST as a climatic variable is related to surface energy balance and integrated thermal state of atmosphere, Jin, (1999). it acts as an indicator of climate change due to its upward terrestrial radiation influencing sensible latent heat flux exchange of air. Yin, (2007).

Land surface temperature therefore can provide information about surface physical properties and climate which plays a role in environmental processes, Javed *et al*, (2008). The LST research shows that land surface temperature varies with surface soil water content and vegetation cover, Weng *et al* (2003) that the higher latent heat exchange is found with vegetated areas while the sensible heat exchange found in sparsely vegetated and urban areas.

The land surface temperature is sensitive to vegetation and soil moisture and it can therefore be used to detect land use, land cover changes, Javed *et al*, (2008).

2.7. Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index is the difference of near infrared and visible red reflectance values normalized over reflectance and calculated from reflectance measurements in the near infrared (NIR) and red portion of the spectrum (Burgan and Hartford, 1993). The NDVI values range from -1 to 1, the negative values are indicative of water, snow, clouds, non-reflective surface and other non-vegetated, while the positive value expresses reflective surfaces such as vegetated area (Burgan and Hartford 1993). Vegetation has a direct match/correspondence with thermal, moisture and radioactive properties of the earth's surface that determine LST (Weng, 2004). In addition to NDVI, Normalized Difference Moisture Index (NDVI) also used as an alternative indicator of surface urban heat island effects in Landsat imagery by investigating the relationships between land surface temperature and NDVI. The index is expressed as NDMI= (NIR-IR)/ (NIR+IR), it evaluates the different content of humidity from the landscape elements, especially in soils, rocks and vegetation's and it is an excellent indicator of dryness. Values greater than 0.1 are symbolized light colors and they signal high humidity level, whereas values close to -1 symbolized by dark colors represents low-level humidity level (Mihai, 2012). Previously, different researchers outside Ethiopia did researches in relation to the impact of LU/LCCs on LST. However, in Ethiopia there are some papers related to the proposed title. For example, (Gebrekidan, 2016) studied modeling land surface temperature from satellite data, the case of Addis Ababa, which presented in Africa hall, United Nations conference center Addis Ababa; Ethiopia (ESRI Eastern Africa Education GIS conference which held from 23−24 September, 2016). The study mainly focuses on modeling LST of Addis Ababa city, which acquired Landsat 5 and 8, from 1985 and 2015. Finally, the results show that negative correlation was found between NDVI and LST and the study indicates the need for urban greening and plans to increase vegetation's covers to sustain the ecosystem of the city and to minimize urban heat island effect. According to Streutker (2003), one of the promising of studying urban surface temperature is using remote sensing or air born technology. Evaluation of land surface temperature from remotely sensed data is common and typically used in studies of evapotranspiration and desertification processes. Further, (Walsh *et al*., 2011) stated that urban area such as buildings and roads and infrastructures or anthropogenic factors contribute to increase atmospheric temperature. The wide use of land surface temperature for environmental studies, have made remote sensing of land surface temperature important academic issue during the last decades. Indeed, one of the most important parameters in all surface atmosphere interactions and fluxes between the land and the atmospheric is land surface temperature (Buyadi *et al*, 2013).

2.8. The Needs of Remote Sensing Data for Drought Identification

Agricultural drought has been recurrent phenomenon in dryland semi-arid rift valley of Ethiopia. It occurs when soil moisture and rainfall are inadequate during the growing season to sustain successful crop growth to maturity and cause extreme crop stress and wilt posing a challenge to rainfed cropping system (Murali et al., 2008).

Consequently, rainfed agriculture failed most of the Meteorological data from the ground stations can be a good source of information that can be used for agricultural drought assessment. However, the poor density of weather stations makes it difficult to acquire sufficient spatial and temporal data to make reliable assessment and risk mapping. Furthermore, the data collected from existing meteorological stations are incomplete and not available timely. Besides, it is also difficult to monitor large areas using conventional methods. In order to alleviate those problems, remote sensing data is an ideal option (Jeyaseelan, 2004; Thenkabail et al., 2004) and is currently utilized worldwide (Anyamba and Tucker, 2005; Mokhtari, 2005; Murali et al., 2008). Moreover, observation from space provides permanent data archive, extra visual information, and enables one to have regular and repetitive view of nearly the earth's entire surface (Kogan, 1997) as well as the region.

Technique make possible to acquire information rapidly over large areas by means of sensors operating in several spectral bands mounted on satellites. Even though weather satellites such as NOAA were first designed to help weather forecasts, they are found useful for addressing vegetation status in the earth surface (FEWS-NET). According to Kogan (1997), since the late 1980.s, they have also been used for drought detection, monitoring and impact assessment in agriculture.

2.9. Drought Indices and Their Application in Drought Assessment

Different types of drought require different indices that can be used to quantify the moisture condition of a region and thereby detect the onset and measure the severity of drought events, and to quantify the spatial extent of a drought event thereby allowing a comparison of moisture supply condition between regions (Quiring and Papakryiakou, 2003; Beyene Ergogo, 2007).

It has become clear that no single indicator or index is adequate for monitoring drought on regional scale. Instead, a combination of monitoring tools integrated together is preferable for producing regional or national maps (Martini et al., 2004). Thus, spatiotemporal patterns of seasonal drought can be detected using meteorological, vegetative as well as crop performance indices among others.

2.10. Index of Drought

2.10.1 Meterological Drought Index

2.10.1.1 Standard Precipitation Index (SPI)

Assessment of rainfall is used to identify the pattern and the intensity of drought. SPI developed by McKee et al. (1993), is the most widely used index for understanding the magnitude and duration of drought events. According to Thavorntam and Mongkolsawat (2006), SPI is used to examine the severity and spatial patterns of drought in the given region. Besides, it offers a quick, handy and simple approach with minimal data requirements (Komuscu, 1999). It is designed to quantify the impacts of precipitation deficit on groundwater, reservoir storage, soil moisture, and stream flow for multiple time scales. Soil moisture conditions respond to precipitation anomalies on a relatively short scale. Whereas ground water stream flow and reservoir storage reflect the longer-term precipitation anomalies.

(URL:http://**drought**.unl.edu/monitor/spi)

Guttman (1998) has made comparison of Palmers Drought Severity Index (PDSI) and SPI, and recommend SPI as drought index, as it is easy to determine and has greater spatial consistence.

Moreover, it can be used in risk assessment analysis and making decisions with special ability for adjustments to time periods for which the users are interested, for example, short time periods in life cycle of crops or longer periods regarding water resources. According to McKee et al. (1993), conditions of soil moisture are reacting to precipitation anomalies in relatively short time period and appearance of drought is happening every time when SPI is negative and its intensity comes to -1.0 or lower, while drought stops when SPI is positive.

2.10.2 Vegetation Based Drought Index

The conventional drought indices that utilize point measurement uses station based meteorological data. However, they could not reflect spatial details particularly where station density is poor. Reed et al. (2002) cited in Beyene Ergogo (2007) indicated that the major drawback of station-based drought indicators is their lack of spatial detail affecting the reliability of drought indices. Thus currently, Vegetative based drought indices have been developed and utilized widely to study drought.

2.10.2.1 Normalized Difference Vegetation Index (NDVI)

In satellite image, vegetation appears very different at different light spectrum particularly in the visible and near infrared wavelengths. Healthy or dense vegetation absorbs most of the visible light that reached on it and reflects a large portion of the near infrared light. Unhealthy or sparse vegetation reflects more visible light and less near infrared light. By comparing visible and near infrared light, scientists measure the relative amount of vegetation and its vigor using vegetation Index. NDVI is an index of vegetation health and density and computed from the satellite Image using spectral radiance in red and near infrared reflectance using the formula:

$$NDVI= (NIR-R) / (NIR+R); \ldots\ldots\ldots\ldots\ldots \text{ equ [1]}$$

Where NIR= near infrared band, R= Red band

NDVI is a powerful indicator to monitor the vegetation cover of wide areas, and to detect the frequent occurrence and persistence of droughts (Thavorntam and Mongkolsawat, 2006). It provides a measure of the amount and vigor of vegetation at the land surface. The magnitude of NDVI is related to the level of photosynthetic activity in the observed vegetation. In general, higher values of NDVI indicate greater vigor and amounts of vegetation. Tucker first suggested NDVI in 1979 as an index of vegetation health and density (Thenkabail et al., 2004) and it has been considered as the most important index for mapping of agricultural drought (Voogt, 2000 cited in Mokhtari, 2005).

The Moderate Imaging Spectrometer (MODIS) onboard Terra satellite collects the data that are used to produce NDVI. The scanning radiometer is used primarily for weather forecasting. However, there are an increasing number of other applications, e.g., drought monitoring (FEWSNET). NDVI is a nonlinear function that varies between -1 and +1 and values of NDVI for vegetated land generally range from about 0.1 to 0.7, with values greater than 0.5 indicating dense vegetation (FEWSNET).

NDVI is good indicator of green biomass, leaf area index and patterns of production (Thenkabail et al., 2004). Furthermore, NDVI can be used not only for accurate description of vegetation vigor, vegetation classification and continental land cover but is also effective for monitoring rainfall and drought, estimating net primary production of vegetation, crop growth conditions and crop yields, detecting weather impacts and other events important for agriculture, ecology and economics (Ramesh et al., 2003).

2.10.3. Crop Performance Index

2.10.3.1 Water Requirement Satisfaction Index (WRSI)

WRSI is a geospatial model that was developed by Food and Agricultural Organization (FAO) for use with satellite data to monitor water supply and demand for rainfed crop throughout the growing season (Free and Popov, 1986). It is also a crop performance index based on the availability of water in the soil. In Ethiopia, crop yields are too large extent predicted by the amount of available water compared to water requirement. Taking this into account, new software environment for drought indexing, namely Livelihood Early Assessment and Protection (LEAP) was designed specifically for Ethiopian context commissioned by World Food Program (WFP) in 2006 (Hoefsloot, 2008). One of the goals of LEAP is as a platform for calculation of weather-based indices starting out with the calculation of a crop water balance indicator, WRSI. In addition, it uses relevant soil information from FAO digital soil map and topographical parameters derived from the GTOPO30 digital elevation model (DEM) (Gesch et al., 1999).

The performance of the crop during the growing season is one of the indicators of agricultural drought. Currently, crop moisture stress on grain crop can be monitored using satellite-based crop performance index, WRSI (Victor et al., 1988; FEWS NET, 2009). This index indicates the extent to which the water requirement of the crop has been satisfied in the growing season (Hoefsloot, 2008). WRSI can be related to crop production using a linear yield reduction function specific to a crop (FAO, 1977; FAO, 1979) and the reduction of crop yield due to water deficit is simulated from it. WRSI is currently operational as monitoring and forecasting tool for regionwide food security analyses in drought prone countries in Sub-Saharan Africa. Furthermore, Senay and Verdin (2002) evaluated the performance of the model using district level crop yield data from Ethiopia. Historical yield data from 1996-1999 were used to evaluate the performance of a seasonal WRSI for sorghum. WRSI values and reported district yield data were significantly correlated (r=0.77) and the model was particularly found successful in capturing the response of the crop during a relatively dry year.

2.11. Satellite Indices Based Drought Assessment Studies

The Earth observation satellites which include both geostationary and polar orbiting provide comprehensive and multi temporal coverage of large areas in real time and at frequent intervals and thus, have become valuable for continuous monitoring of atmospheric as well as surface parameters related to droughts and floods (Jeyaseelan, 2004). Due to lack of spatial detail from station-based drought indicators, satellite based derived indices widely used for drought assessment. Many satellite-based droughts assessment studies are conducted worldwide and 15 most of them uses vegetation indices calculated from long term records of remote sensing data (Nageswara et al., 2005; Murali et al., 2008). According to Seiler et al. (1998), the AVHRR-based Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) have been developed and successfully used for monitoring drought in the USA, the Former Soviet Union, Zimbabwe, and China.

This research was designed to apply and validate those indices for drought detection and impact assessment on agricultural yields in Cordoba province of Argentina. They concluded that those indices were useful to assess the spatial characteristics, the duration and severity of drought, and were in good agreement with precipitation patterns.

Drought risk assessment and monitoring can also be conducted using the relationship of NDVI and rainfall. Alemayehu Kassa (1999) used regression techniques in order to monitor drought and verify whether there is a correlation between NDVI and rainfall in Sudan. The result showed that there is strong positive relationship of NDVI to rainfall in Sudan with regression coefficient between 0.74 and 0.8. In another study in East Africa by Eklundh (1997), the possibility of using NDVI data for crop and natural vegetation monitoring has been analyzed by measuring the cross-correlation between time series of NDVI and vegetation indicators such as rainfall for the area where rainfall is a limiting factor. The result has shown that there is good correlation between NDVI and rainfall with coefficients of correlation 0.7 and 0.9. Rainfall is one of the climatic variables that largely determine the occurrence of drought. The severity of drought is considered to be a function of rainfall. In many research studies, the relationship between rainfall and satellite-based vegetation indices have been analyzed in order to see the pattern between them (Pavel et al., 2006; Alemayehu Kassa, 2007). As vegetation indices derived from AVHRR are directly related to plant vigor, density and growth conditions they may also be used to detect natural hazards such as drought. According to Li et al. (2002) cited in Chopra (2006), Vegetation amount and condition are a function of environmental variables such as rainfall.

Consequently, a strong relationship, involving a brief time lag (1 to 12 weeks) in the vegetation response to rainfall, would be expected between vegetation indices such as NDVI and rainfall.

Herrmann and Anyamba (2004) have investigated temporal and spatial patterns of vegetation greenness and explored relationships between rainfall and vegetation dynamics in the Sahel, based on the analyses of NDVI time series and gridded precipitation estimates at different spatial resolutions. They assumed that rainfall is the most important constraint to vegetation growth in this semi-arid zone, which justify the attempt to predict vegetation greenness from rainfall estimates through linear regression. Moreover, Anyamba and Tucker (2005) analyzed seasonal and inter-annual vegetation dynamics in Sahel using NOAA-AVHRR NDVI. The study focused only on NDVI patterns in growing season, which was defined by examining the long-term patterns of both rainfall and NDVI. Year to year variability in NDVI patterns was examined by calculating yearly growing season anomalies. The correlation between NDVI and rainfall anomaly time series was found to be positive and significant, indicating the close coupling between rainfall and land surface response patterns over the region. The correlation between NDVI anomaly and grain yield anomaly were also used to conduct agricultural drought risk assessment (Chopra, 2006; Beyene Ergogo, 2007). Moreover, the correlation between grain yield and NDVI is important to quantify the impact of drought on the crop production. Alemayehu Kassa (1999) also addressed that NDVI can be used for the assessment of weather impact on vegetation, and evaluation of vegetation health and productivity. Besides, as satellite based radiative indices are good indicators of leaf area index, which are good indicators of yield potential. Rainfed agriculture is always characterized by significant fluctuation in yield due to variation in moisture availability. Agricultural drought in general and extended intra-seasonal dry spell in particular, as moisture deficit can lead to crop failure. Agricultural drought is a permanent constraint to agricultural production in many developing countries, and an occasional cause of losses of agricultural production in developed ones. Application of satellite derived indices for assessment of crop growth conditions using geospatial rainfall estimate is well known in semiarid countries. Tracking the spatial and temporal patterns of rainfall data from satellite with respect to crop and soil characteristics can reveal situation of yield reduction due to water deficits (Senay and Verdin, 2002).

CHAPTER THREE

3.DATA AND METHODOLOGY

3.1. Description of Study Area

3.1.1 Location

This present study was conducted in eastern Arssi zone which is located in the Eastern Ethiopia, Oromia Region. The northern part of the study area is located at about 120 km from Addis Ababa and 20694kilometer square area coverage.The study area is bounded by Latitude 7°10'34"–8° 42'46"N'and Longitude 38°41'14"–40°43'58"E. The area is entirely found in tropical zone having its associated climate. With respect to its relative location the zone has physical contact on North by Adama special zone, on the South by Bale, on the South West by the West Arssi zone, on the North West by East Shewa and on the East by West Hararghe. The notable mountains in eastern Arssi zone are mounts Chilalo, Kaka and Guge. Among these mountains, mount Chilalo is the highest peak in eastern Arsi zone. The administrative center of this zone is Asalla and the other towns which was found in eastern Arsi zone are Abomsa, Asasa, Bokoji, Sagure Kersa, Dera, Etaya, Sire, Arsi Robe and Huruta.

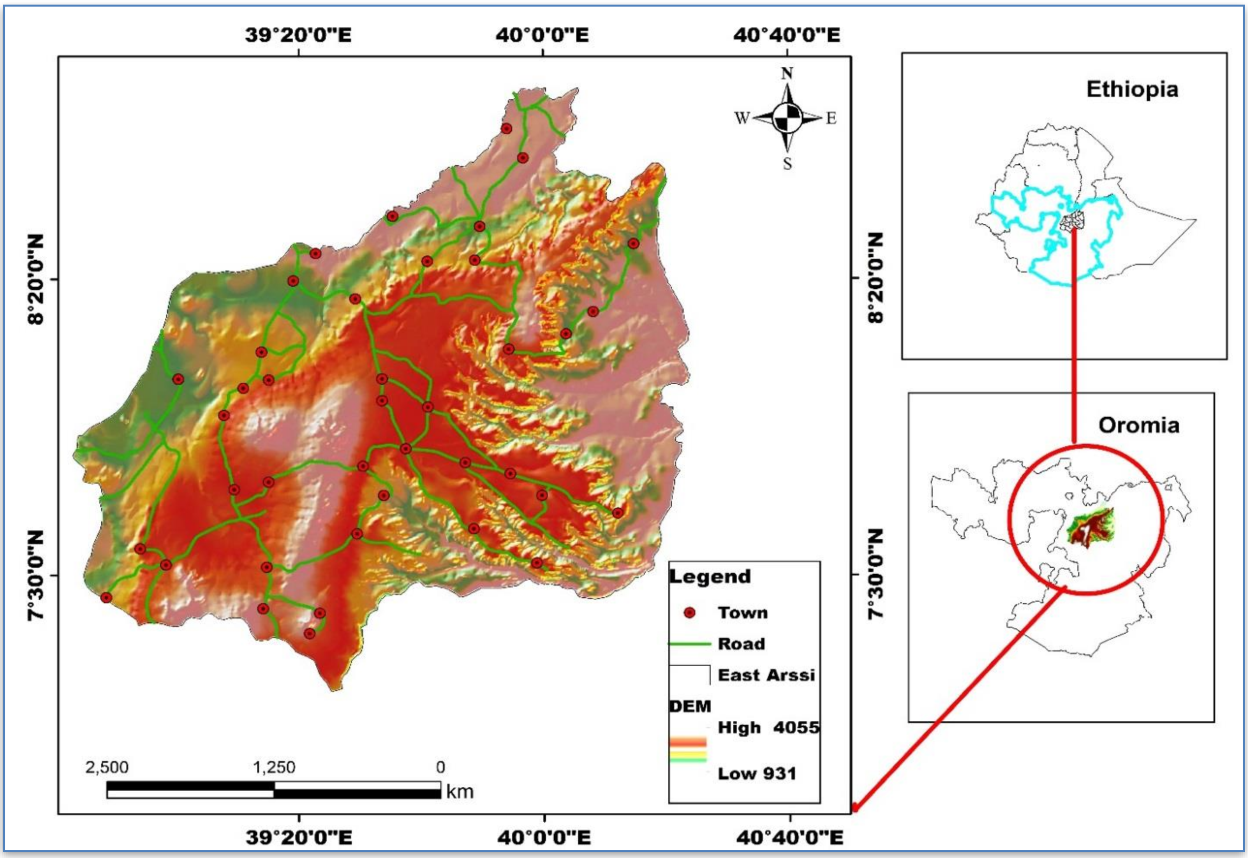

Figure 3. 1.1.Location map of the study area.

3.1.2 Population

According to Central Statistics Agency (CSA, 2007) national census report is the total population of eastern Arssi zone was 2,637,657 of among which 1,323,424 were men and 1,314,233 women with spatial area of 20694.41 km$^{2.}$ Easter Arssi zone has a population density of 133.05 % while 305,701 or 11.59 % are urban inhabitants, a further 7,098 or 0.27% were pastoralists. A total of 541,959 houses hold found in this zone, which results in average of 4.875 persons to a household, and 523,342 housing units and the detail information is presented in below Figure 3.1.2

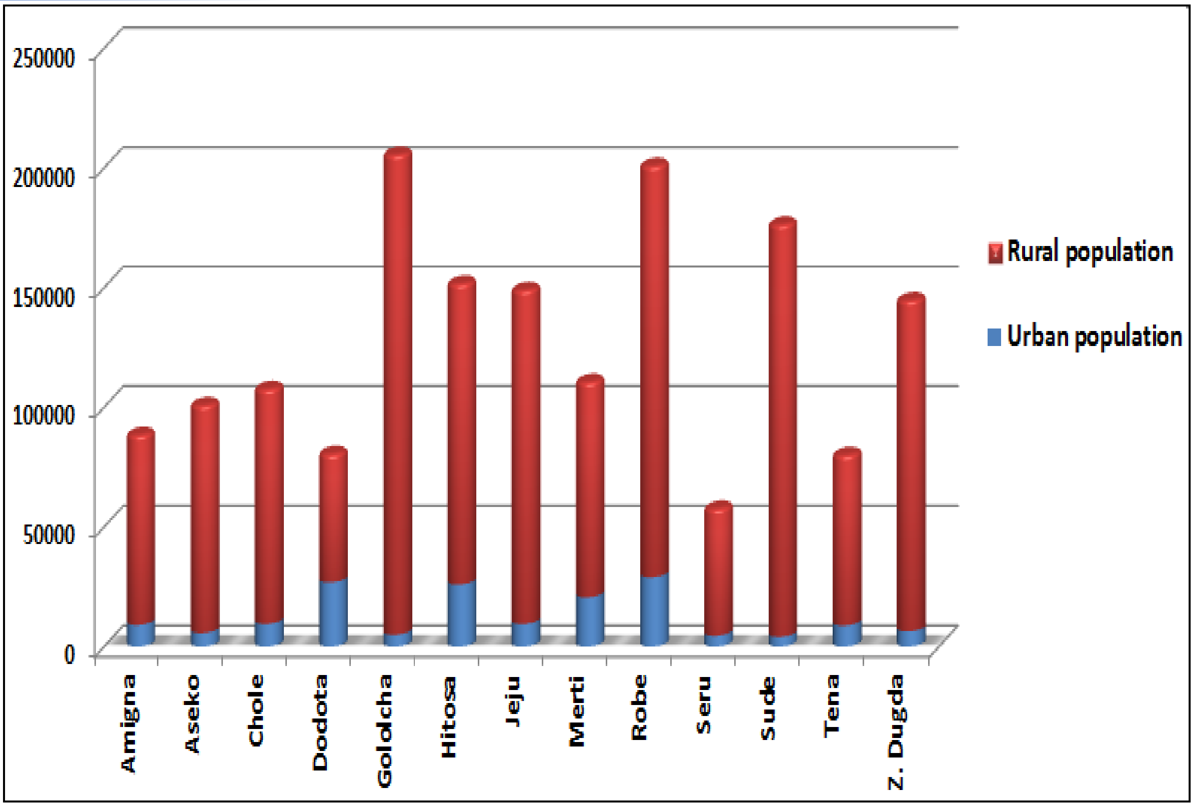

Figure 3. 1.2. Population projection values of Arssi zone at woreda level

3.1.3. Topography

The altitude variation of eastern Arssi zone ranges from 931 to 4055 m a.s.l. From of the total land sizes of the zone, the land form types in the study areas is classified into seven major physiographic classes. These are smooth plain, irregular plain, escarpments, hills, breaks, low mountains and high mountains (Deep Canyons) classes. The elevation of the study area is indicated in the following Figure 3.1.3.

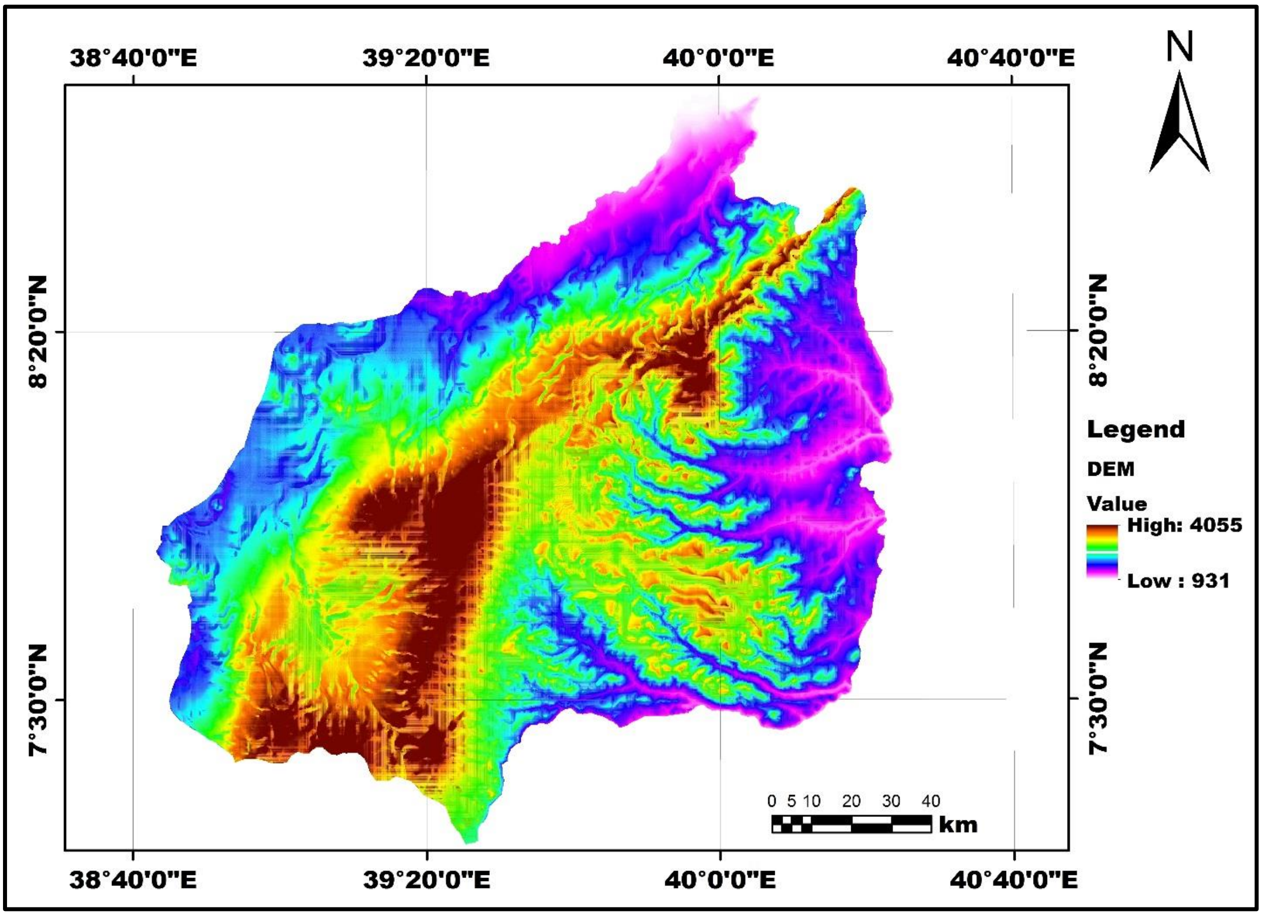

Figure 3.1.3. Digital elevation map (DEM) of the study area.

3.1.4. Slope

The slope was derived from a preprocessed DEM 90m. According to the FAO slope classification which depend on land surface percentage rise (Sheng,1993) the study areas is classified into seven slope zones, which extends from nearly level (less than 1%) to extremely steep (greater than 35%) follows: Slope classification of the study area (FAO class)

Table 3.1.4. slope class of study area

NO.	Slope (%)	Slope Category
1	0-1	Nearly Level
2	1-3	Very gentle sloping
3	3-8	Gently sloping
4	8-15	Moderately sloping
5	15-30	Steep sloping
6	30-35	Very steep sloping
7	>30	Extremely steep

3.1.5. Soil

Soil plays a vital role in the survival of living things on the earth. Healthy soil is the foundation of the food system. It produces healthy crops that in turn nourish people. Soils provide readily available nutrients to plants and animals by converting dead organic matter into various nutrient forms. According to Food and Agricultural Organization (FAO) cited in Finance and Economic Development Bureau of Oromia (2007), Eutric Fluvisols, chronic cambisols, Lithosols and Eutric Nitosols are the dominant soil type found in East Arssi zone as shown in the Figure 3.1.5

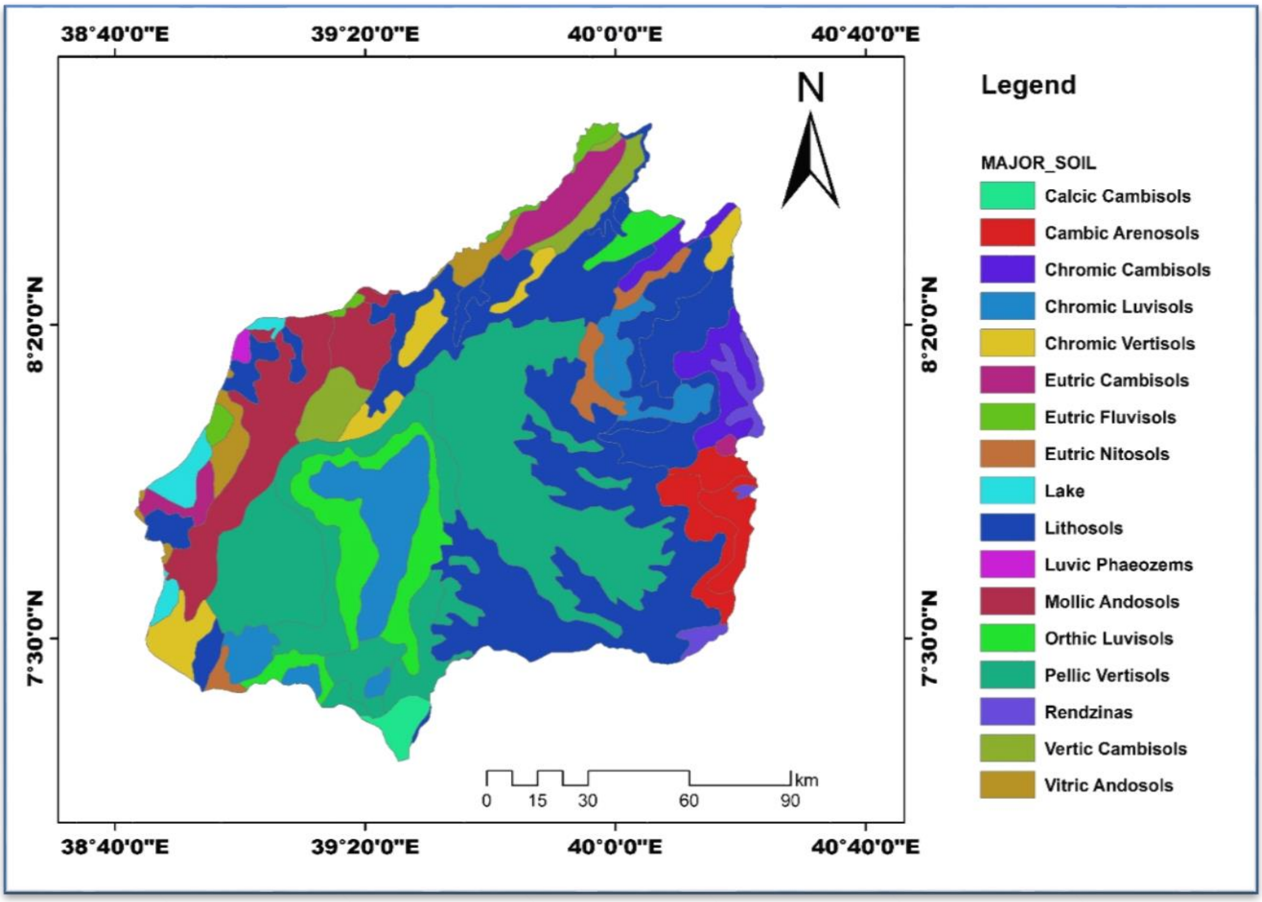

Figure 3.1.4. Soil Types of Study Area

3.1.6. Climate and Vegetation

3.1.6.1 Rain Fall

The main rainfall season for determining the drought risk area for Arssi zone starts from June to September. Spatial interpolation technique was carried out by estimating and evaluating regionalized value of National Metrological Agency (NMA) rain gauge station records. In order to evaluate mean annual precipitation of the study area, the general formula for spatial interpolation is as follow:

$$Zg= \sum_{i=1}^{ns} \lambda_i zs_i \text{.. ....equ [2]}$$

Where, Zg is the new estimated value at the required points,$ZS\acute{\imath}$ is the recorded known value at point$i$,ns is the total number of observed points and $\lambda = (\lambda\acute{\imath})$ is the weight contributing to the interpolation. From other interpolation techniques, an Inverse Distance Weighted (IDW) deterministic, nonlinear interpolation algorithm is preferable technique for rainfall data interpolation by most scholars, which was selected for interpolating precipitation data for the entire study area. This algorithm estimates cell values by averaging the values of nearby sample data points. The closer a point is to the center of the cell that is being estimated, the more weight it is given. It was calculated as follows:

$$\hat{V}\imath = \frac{\sum_{i=1}^{n} \frac{1}{d_i^p} v_i}{\sum_{i=1}^{n} \frac{1}{d_i^p}} \text{..equ[3]}$$

Where, $\hat{V}i$ is a value of the unknown points to be estimated V_i is known sampled points values dpi and dpn is the distances from then value points to the power of p of the points that estimated and the results of interpolated centers are shown in following Figure 3.1.6

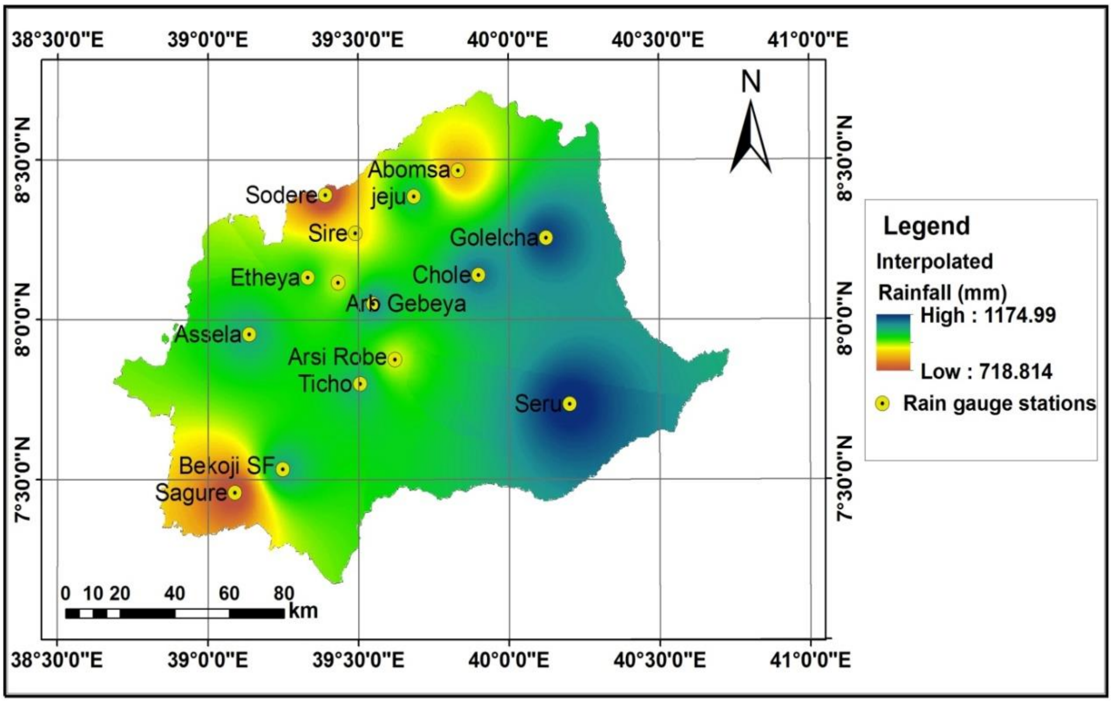

Figure 3.1.5. Interpolated mean annual rain fall (mm) stations records.

3.1.6.2. Climate

According to NMA, the average minimum and maximum temperature of eastern Arssi zone is 10 to 26 respectively. The rainfall of the zone characteristic by bimodal pattern. The annual average rainfall in eastern Arssi zone is 1000mm with a different seasonal distribution. The main rainy season, these accounts approximately 60% of the annual precipitation, covers the period between the beginning of June and end of September, while the short rainy season is during March and May. The following figures shows the main seasonal rain fall that have bimodal rainfall pattern distribution that means begging of June to end of September.

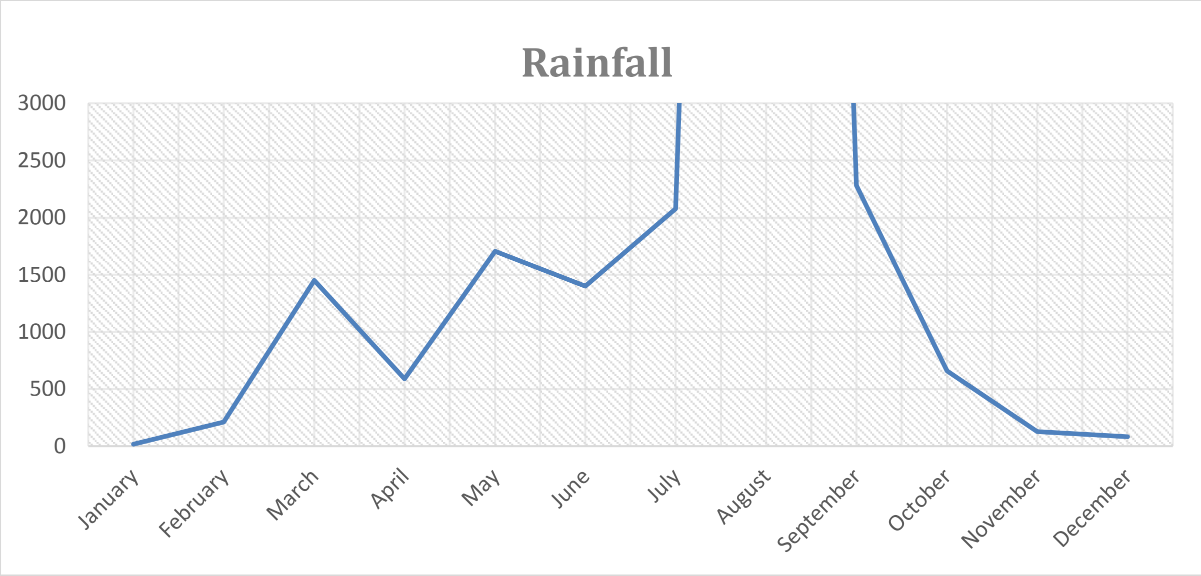

Figure 3.1.6. Rainfall pattern of study Area

3.1.6.3. Vegetation

The vegetation distribution of the area is mainly dependent on the climate condition of the area. The climate condition of the study area is characterized as tropical. On these types of climate, vegetation is scarce and typical example that is found in the area is shrub, Acacia and scattered trees of Eucalyptus. Eucalyptus trees, which is, grown by local communities in soil conservation program that is applied in the main Ethiopian rift to protect soil from erosion. Agriculture is the main stake in Arssi zone and, the types of crops cultivated in the area are Teff, Wheat, Barley, Maize and Sorghum. The harvesting season is between October and December during which the long rain season recedes.

3.2. Data Acquisition And Software Package

3.2.1. Satellite Images

A time series Moderate Resolution Imaging Spectro radiometer (MODIS) NDVI and LST Terra satellite data were used in this study.

3.2.1.1. NDVI Data

The EROS Moderate Resolution Imaging Spectroradiometer (eMODIS) NDVI data of East Africa is used. The U.S. Geological Survey's (USGS) Earth Resources Observation and Science (EROS) Center is generating one product called "eMODIS" (U.S. Geological Survey, 2012) based on Moderate Resolution Imaging Spectroradiometer (MODIS) data acquired by the National Aeronautics and Space Administration's (NASA) Earth Observing System (EOS). eMODIS NDVI data of East Africa are 16-day composites at 250-meter spatial resolution in Geographic Lat/Long (WGS 84) projection. This global data is obtained in the GEOTIFF format and generate vegetation surface reflectance and corrected for molecular scattering, ozone absorption, and aerosols using MODIS Science Team algorithms.

3.2.1.2. LST Data

The MODIS instrument derived MOD11A2 Level 3 Land Surface Temperature (LST) data is used. MODIS Land Surface Temperature and Emissivity (LST/E) products provide per-pixel temperature and emissivity values. This level-3 MODIS global Land Surface Temperature (LST) and Emissivity data are composed from the daily 1-kilometer LST product (MOD11A2) with a spatial resolution of 1km and temporal resolution of 8 days in sinusoidal projection represented as the average values of clear-sky LSTs during 8-day period.

LST of the study area for the years 2001, 2006, 2011 and 2016 were calculated from the MOD11A2 data. In this data, temperatures were extracted in Kelvin with a view-angle dependent algorithm applied to direct observations. This method yields accurate Land Surface Temperature data. To derive the actual LST data and converted to degree Celsius the following formula is used.

Temperature = (DN * 0.02) - 273.15 ^{o}c………………………… …………………equ [4]

3.2.2. Meteorological data

The Meteorological Data were acquired for the period of the main rainy season (June- September) from 2001 to 2016 rainfall satellite data were collected from National Meteorological Agency (NMA), which includes mean annual precipitation and temperature for all 12 meteorological stations located in the study the areas for 2 decades records (2001-2016) as shown in the figure below the station data were used in validation and verification of drought risk area in the Arssi zone. Other data like Demographic characteristics, geological topographic and other data were gathered from geological surveys of Ethiopia.

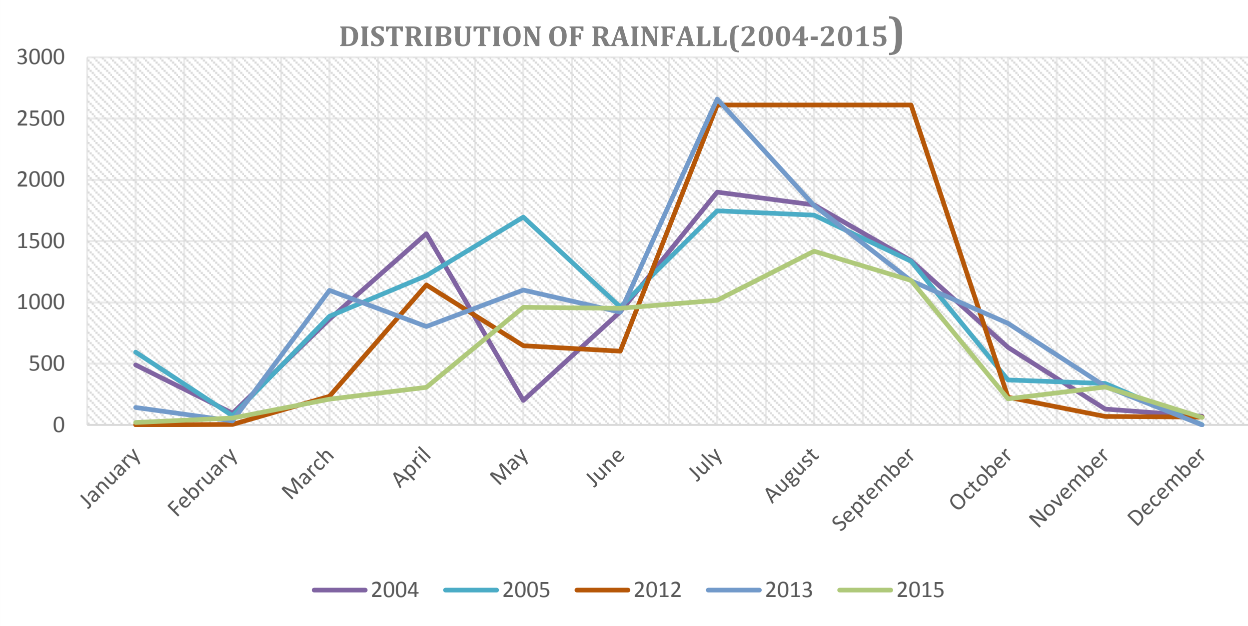

Figure 3.2.7.Rainfall Distribution of Study Area.

3.2.4. Software package

ArcGIS 10.5, ERDAS IMAGIN 2014, SPI Software program and Google Earth software were used for data analyses.

Table 2.3. Types of software packages used

Type	Version	Data Type	Purpose
ArcGIS	10	NDVI, SPI, LST	Image processing, statistical analysis, Graphical display, and map preparation
ERDAS IMAGINE	2014	LULC	Image processing, land use land cover classification
Spi software		SPI	Calculation of SPI

3.3. Methodology

3.3.1. Data processing and analysis methods

The primary and secondary data that were identified as criteria and constraint factors for analysis were collected from different sources. Primary data and information were generated from analysis of satellite images, field observation, and the secondary data were obtained from different sources surveys and mappings that have already been conducted in the area for different purpose. Digital Elevation Model (DEM) data was used in mapping the elevation and slope of the study area.

Table 3.3. Data source

			Resolution			
Data set	Variable	Description	Spacial	Temporal	Period	Source
eMODIS	NDVI	Satellite	250m	16 days	2001-2016	USGS Earth explorer
eMODIS	LST	Satellite	1km	8 days	2001-2016	USGS Earth explorer
Meteorological Data	SPI	Ground Data	Average mean	2001-2016	2001-2016	ENMA
Agricultural Data	Yield	Ground Data				CSA
LULC		Ground Data			2019	
Elevation	DEM	Satellite	90m			USGS Earth explorer

3.3.2. Preprocessing of Satellite Image

As the MODIS NDVI satellite images are radiometrically corrected, geometric corrections were done. All images were imported in generic binary format and information related to image dimension (number of rows, columns and bands), projection parameters (Spheroid name, datum name, latitudes of standard parallels, longitudes of central meridian, latitudes of origin of projection, false easting at central meridian and false northing at origin) were incorporated in the row images. In order to transform the imported raw data into -1 to 1 range of NDVI, the formula (NDVI= raw data *0.0001) which is provided with row data by MODIS was applied to each NDVI images. Thereafter, the study area was extracted and became ready for further analysis. For this study, June to September seasonal NDVI for 2001 to 2016 images were analyzed and used as an input data for NDVI anomaly drought index.

NDVI=DN*0.0001……………………………………………………………………equ [5]

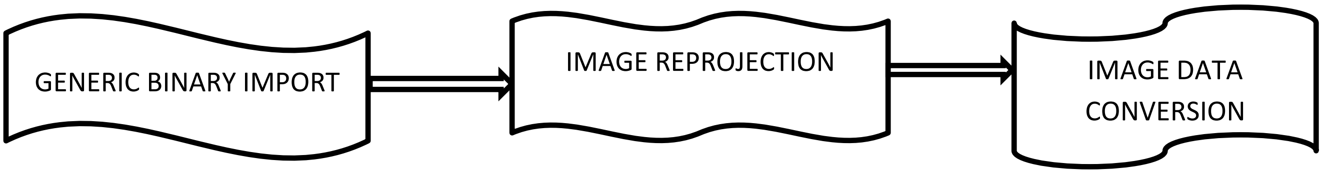

Figure 3.2.8. Image preprocessing process

3.3.3. Land use land cover map

Land-use/land-cover classification result of east arssi zone in 2017 image showed that farmland, shrub land and the forest are the largest proportion of land in the study area with the value of 8,961.04 km^2 (43.30 %), 7,639.60 km^2 (36.91 %) and 2,684.02 km^2 (12.97%) accounted respectively. Other LU/LC classes such as grassland, bare land, settlement and wetland and water body together accounted for 1409.77 (6.83%) of the total area. In 2017 water body covered the smallest area than all other classes. However, the extent of farmland increased year to year due to population increase. Farmland is the major LU/LC of the study area in relation to area coverage, followed by shrub land and forest.

Table 3.4. Land-use/land-cover distribution and of 2017.

No	**LU/LC classes**	**2017**	
		Area (km^2)	**Area (%)**
1	Farm land	11961.04	58.0
2	Shrub land	4639.60	22.41
3	Forest	2684.02	12.97
4	Grass land	935.21	4.52
5	Bare land	293.90	1.43
6	Settlement	117	0.57
7	Wet land	51.68	0.25
8	Water body	11.98	0.06
9	Total	20694.43	100

Table 3.5 .Statistical information of accuracy assessment for the year 2017

Class Name	**2017**			
	Producers accuracy	**Users accuracy**	**Overall classification accuracy**	**Overall Kappa statistics**
Farm land	85.12%	84%	85.15%	0.82
Shrub land	85%	85.12%		
Forest	85%	85%		
Grass land	80%	80.20%		
Bare land	85.10%	85.10%		
Settlement	90.50%	90.50%		
Wet land	90.52%	90.32%		
Water body	80%	80%		

The accuracy assessment of LU/LC for the classification was 85.15%. The classification Kappa statistics values was 0.82.

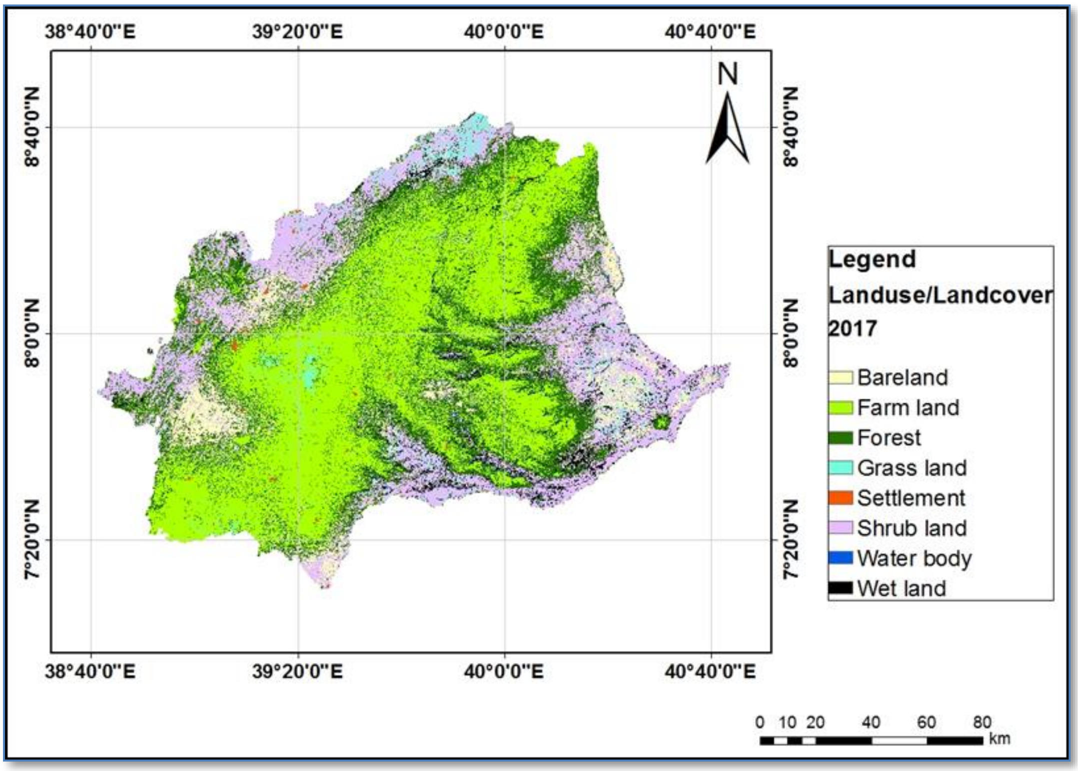

Figure 3.2.9. Land use land cover of Study Area

3.3.4. Analysis of Agricultural Drought Risk Area Using Various Drought Indices

3.3.4.1. Normalized Difference Vegetation Index (NDVI)

MODIS_NDVI (Moderate Resolution Imaging Spectroradiometer) images that were computed from the MODIS Terra Image using spectral radiance in red and near infrared reflectance were used for time series analysis of vegetation dynamics. The highest value shows healthy vegetation

3.3.4.2. Normalized Difference Vegetation Index Anomaly

NDVI can be used as an index to assess crop condition through analysis of NDVI anomaly (Murali et al., 2008). Vegetative drought index has been calculated using NDVI values. Maximum NDVI and long term mean maximum NDVI in the growing season (June to September) were computed in order to derive seasonal NDVI anomaly. NDVI anomaly percentage was then derived using the following formula for each grid cell in the study area:

NDVI Anomaly i= [(NDVI max i - Mean NDVI max)/ (Mean NDVI max)] *100…. …….Equ [6]

Where NDVI maxi=Maximum NDVI in the growing season in ith year and Mean NDVI max=long term mean maximum NDVI in the growing season. The resulting NDVI anomaly percentage assigned to respective grid cell was reclassified into four drought severity classes.

Table 3.6. NDVI anomaly-based drought severity class.

NDVI Anomaly (%)	Drought severity class
Above 0	No drought
0 to -10	Slight drought
-25 to -50	Severe drought

3.3.4.3. Land Surface Temperature (LST)

The daytime MOD11A2 product is a level-3 product, which consists of 12 Science Data Sets (SDSs), including 8-day composite LST, quality of each LST pixel. The LST values in Kelvin are encoded in 16-bit unsigned integer. To derive the actual value of temperature it was multiplied by a factor of 0.02 as stated in MODIS product manual. The quality information was used as criteria for LST pixel data to be included in the analyses. The quality information is stored in 8 bits, in which each of 2-bit combination (i.e. bit fields) represents different quality information. Criteria used to select the best quality pixel were; from 1 and 0 bits we selected good quality; from 3 and 2 bits we used 00(good data quality); from 5 and 4 bits we used Emissivity error flag less than 0.02; and LST error flag less than 2 kelvins as described in Science Data Sets (SDS). The LST data in two 24 consecutive periods were averaged to generate composite LST for the same periods as the NDVI to match the 16-days NDVI composite product.

3.3.4.4. Standard Precipitation Index (SPI)

SPI is an index that was developed to quantify precipitation deficit at different time scales, and can also help assess drought severity. The SPI was calculated using the following equation:

$$SPI = (Xij - Xim) / ó \quad \text{......[7]}$$

Where, *Xij*= is the seasonal precipitation and, *Xim* is its long-term seasonal mean and *ó* is its standard deviation. SPI was used to quantify the precipitation deficit in the growing season and analyze the impact of rainfall deficiency on drought development. SPI results computed from seasonal rainfall data were assigned to each grid cell of the study area, and reclassified based on drought severity classless.

Table 3. 7. SPI based drought severity class.

SPI Value	Drought severity class
Above 0	No drought
0.0 to -0.99	Slight drought
-1.5 to -1.99	Severe drought

3.3.4.4. Agricultural Drought Risk Map

Final result risk map was obtained by integrating SPI, LST and NDVI biophysical parameters of identification of drought indices which indicate the areas were facing a combined drought. By using time series climate data and satellite-based drought monitoring system, the agricultural drought risk area can be depicted from extreme temporal and spatial variability of rainfall, temperature and vegetation status, can be used for area that mostly affected by drought in the eastern Arssi zone. As shown in the following schematic flow chart 3.3.4.4.

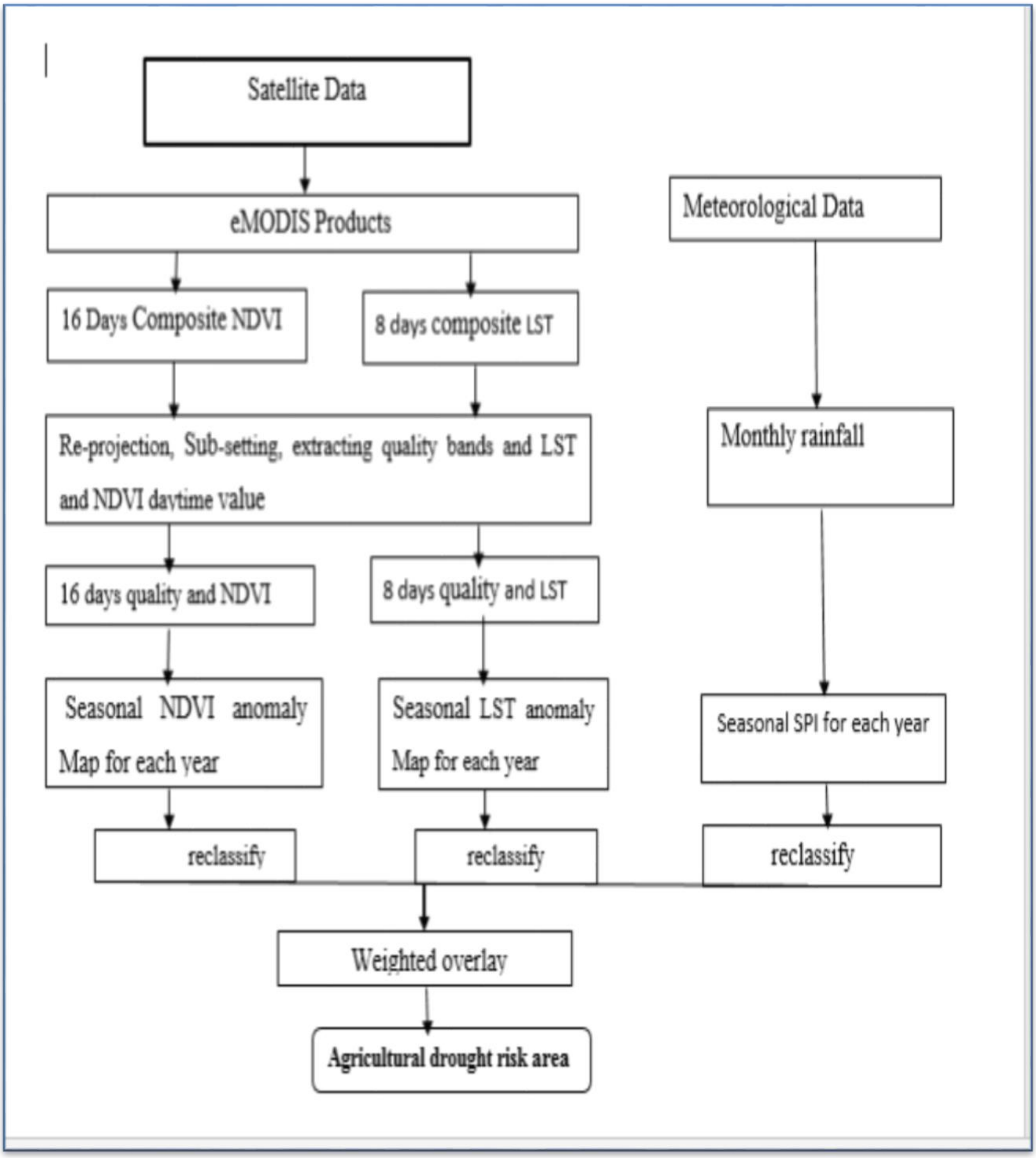

Figure 3.3.10. Schematic flow chart of the study.

CHAPTER FOUR

4. RESULTS

4.1. Relationship Between Seasonal Rain Fall And NDVI

Seasonal Rainfall and NDVI analysis result showed that there was good correlation in between rainfall and NDVI during the years (2001- 2016) in the eastern Arssi zone as shown in Fig 4.1 below. There was considerable year to year variation in precipitation and NDVI. It revealed that, there was increasing trend both in rainfall and NDVI. Also, they have better association that indicating within 16 year's data, 51 % percent of NDVI variability can be explained by seasonal rainfall (R2 value 0.6656). The result of this study lines with the findings of Aynamba and Tucker (2005), Beyene (2007) and Gizachew and Suryabhagavan (2014) who have reported the strong correlation between NDVI and seasonal rainfall.

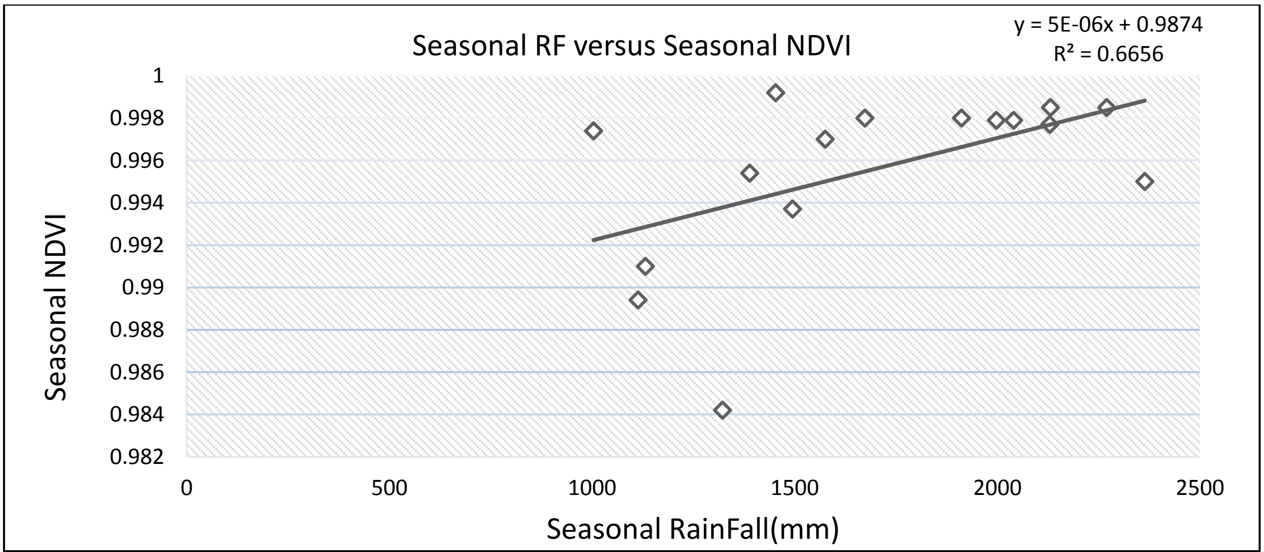

Figure 4.1.1..Seasonal (June-September) Patterns of Rainfall and NDVI (2001_2016)

4.2. Influence of Rain Fall on Vegetation Growth And Deveopemnt

Rainfall is an important climatic variable that influence the growth and development of vegetations, which is reflected by NDVI. According to the study Henericksen (1986) cited in Beyene Ergogo (2007), it has been shown that NDVI was highly sensitive to an extended rainfall anomaly. In this regard, simple linear regression analysis between rainfall and NDVI were carried out for different lag time periods so as to better understand the influence of rainfall on vegetation growth and development. The rainfall had highest influence on the growth and development of vegetation that the variability of NDVI is highly explained by one-month preceding rainfall. The obtained result is in concurrence with the finding of Chopra (2007) that states the time interval between rainfall event and the time when rainfall water might reach a plant root and induce subsequent plant growth can occur in one-month time period in semi-arid areas. Therefore, the influence of rainfall on vegetation growth and development occurs at one-month time. That means the vegetation growth in each month is influenced by rainfall in the preceding month, and change in soil moisture and vegetation development are significantly observed during this period. In addition, correlation and simple regression analysis were made to see the strength of association between normalized difference vegetation index and rainfall.

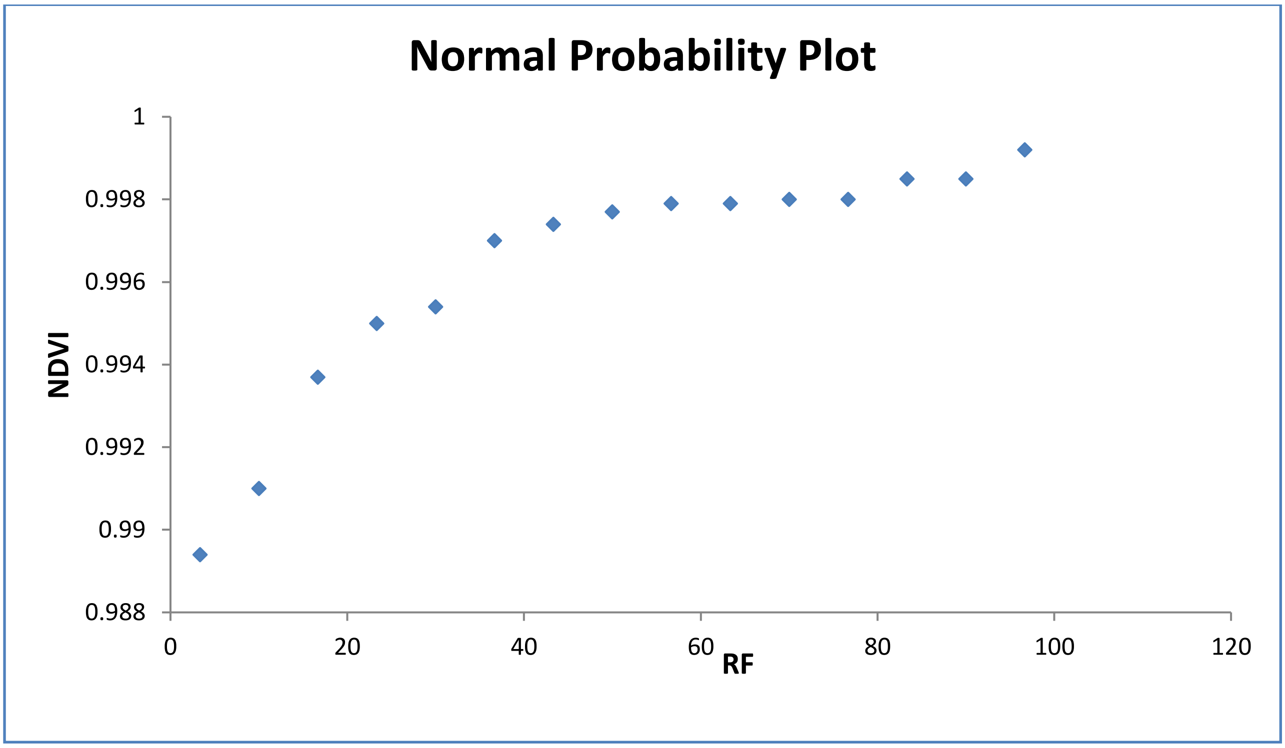

Figure 4.1.2. Normal Probability Plot of NDVI Versus Rainfall

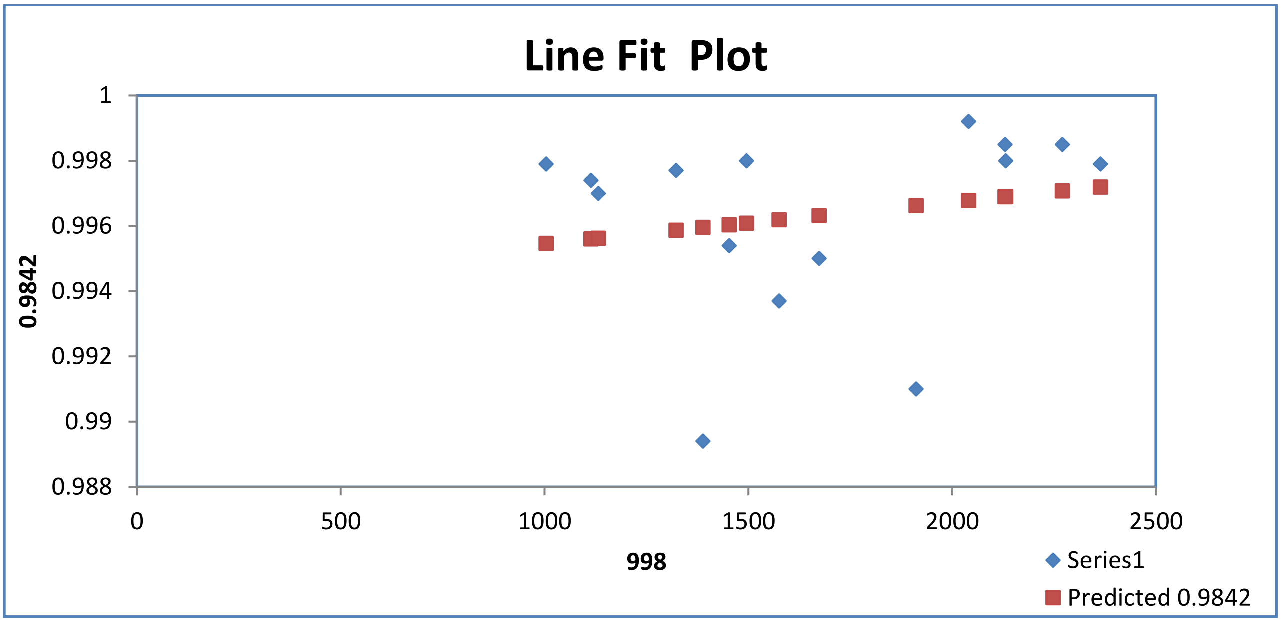

Figure 4.2.3. Simple regression between Rainfall and Normalized Difference Vegetation Index (2001_2016).

4.3. Normalized Difference Vegetation Index(NDVI) Anomaly And Agricultural Drought

NDVI for the year 2001, 2006, 2011 and 2016 was calculated using ArcMap 10.5 on the basis of main agricultural season and vegetation cover classes were derived and trend in their shift was also identified from June to September. When consider year 200l main season there was great changes in variation of NDVI. The NDVI is useful indicator as a measure of agricultural drought when compared to normal plant health. It is reflected through NDVI anomaly. NDVI anomaly is one of agricultural drought index that shows the severity level. Based on this index, spatial pattern of agricultural drought for wet years (2001 and 2006) and drought years (2011 and 2016) was computed for agricultural production area to determine the risk of agricultural drought in the eastern Arssi zone. The result provided the spatial patterns of agricultural drought events, and the level of drought occurred ranges from moderate to slight drought in 2001-2016 years. However, the extent of moderate drought covers small pocket areas which account for less percent of the total area. The result showed NDVI generally has different pattern from June to September in 2001, 2006, 2011 and 2016. Figure 4.3 shows the NDVI values calculated for 2001-2016.

The majority of the study area was stricken by slight agricultural drought. The following Figure 4.3.4 shows that NDVI anomaly of main seasonal period of agricultural drought starting from June to September with respective year of study that categorized in the five year (2001-2016).

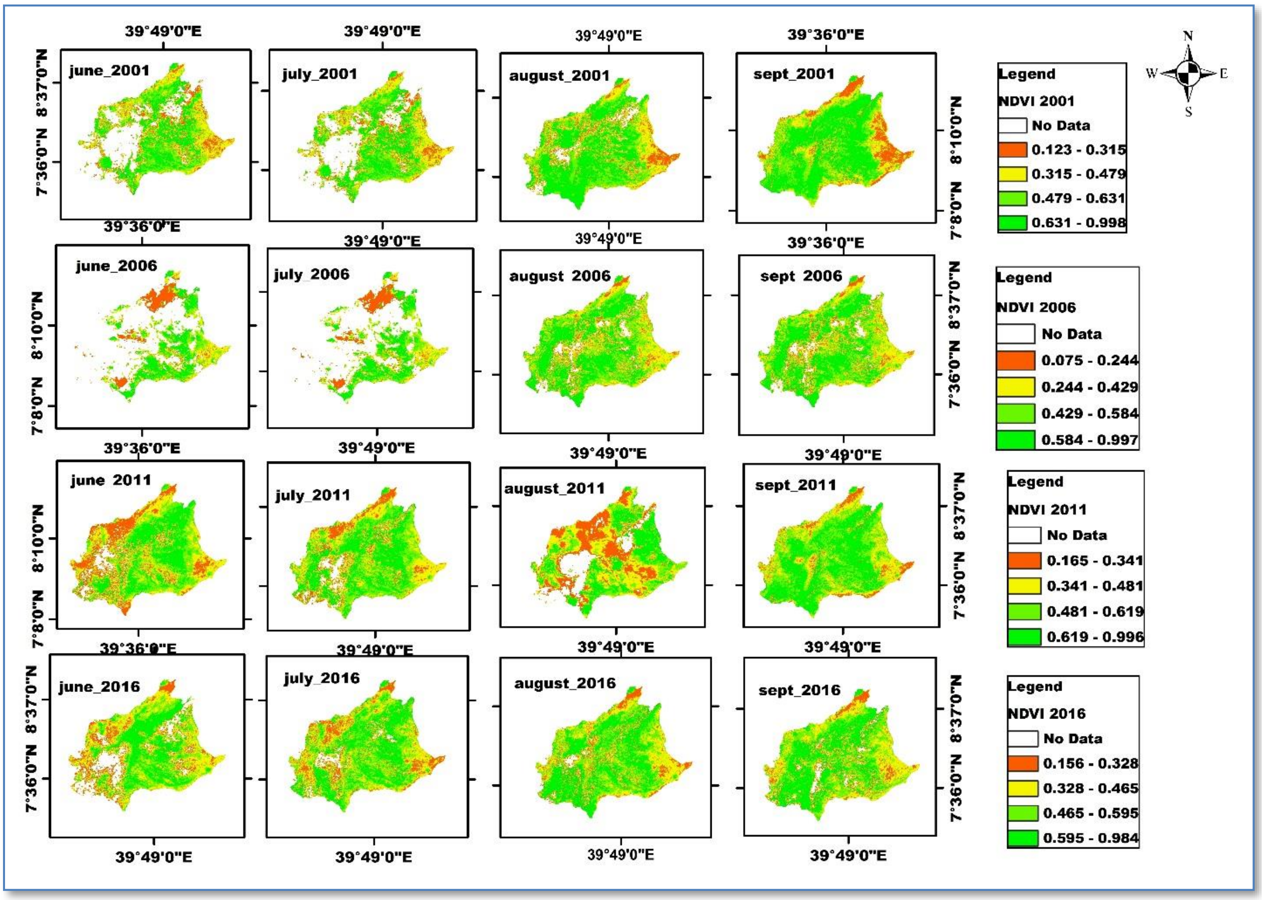

Figure 4.3.4. Seasonal normalized difference vegetation index anomaly (2001-2016)

4.4. Relationship Between NDVI Anomaly And LST Anomaly

The result showed NDVI and LST generally have different pattern from June to September in 2001, 2006, 2011 and 2016. Figure 4.4 below shows the NDVI values calculated for 2001-2016 (June-September). The figure shows that the vegetation cover density decreased and the land surface temperature increased in the regions faced drought. The area where NDVI is low and LST is high was area that have been affect by drought of different severity starting from moderate to slight drought. The LST when correlated with the vegetation index it can be used to detect the agricultural drought of a study area. The edge of rift valley and low land of arssi zone have faced drought in the shown figure below. The results indicate that all remote-sensing indices used in this study NDVI and LST were complementary and found to be sensitive indicators of drought conditions which is recommended for future drought monitoring in case of the Study area. A negative correlation, which indicated a trend for drought, was observed between LST&NDVI during a sixteen -year -period. Based on these findings, we can conclude that NDVI and LST is useful for identifying agricultural drought risk area and are being used for the development of a regional drought monitoring by considering the spread and frequency of droughts in the region.

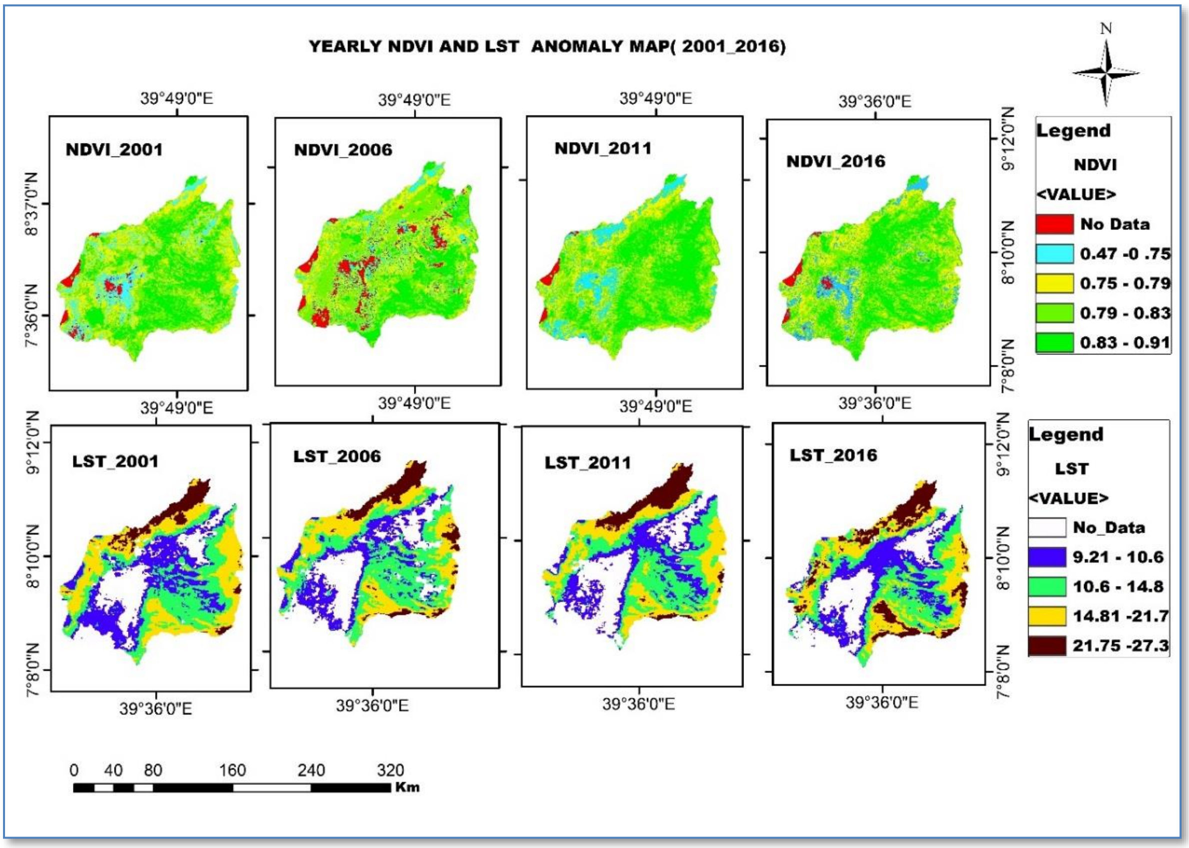

Figure 4.4.5. Normalize difference vegetation index and Land Surface Temperature (2001-2016)

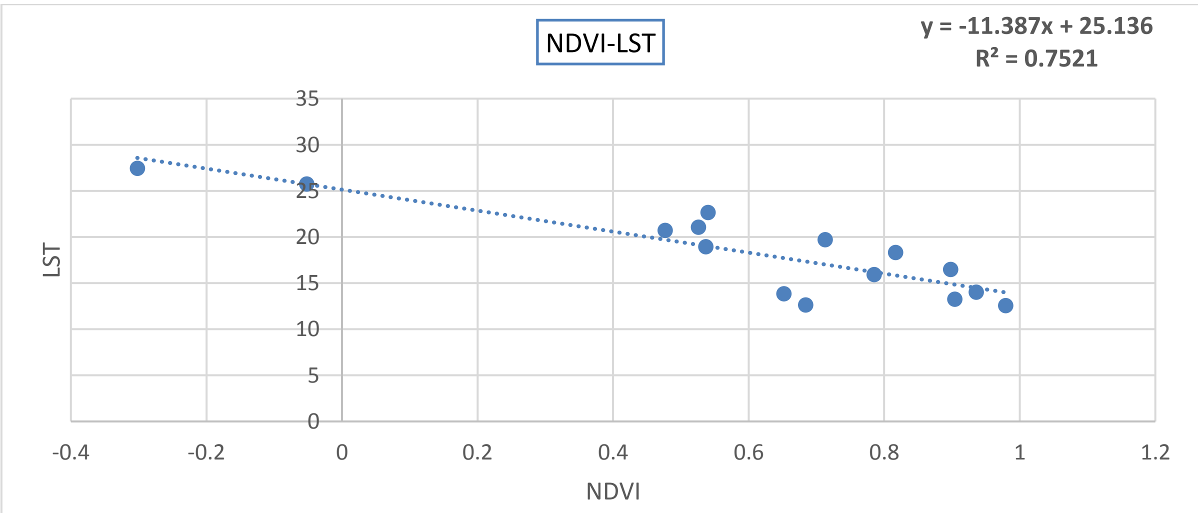

Figure 4.4.6. Scatter plot of NDVI and Land Surface Temperature

The use of temperature and vegetation index provides adequate means for mapping drought extend over the agricultural fields and Use of time series data offers potentials to establishing long term mean average for vegetation moisture levels that shows effective agricultural drought risk area. As shown in the figure 4.3.1 the edge of rift valley and some back of continuous Arssi mountain indicates slight agricultural drought.

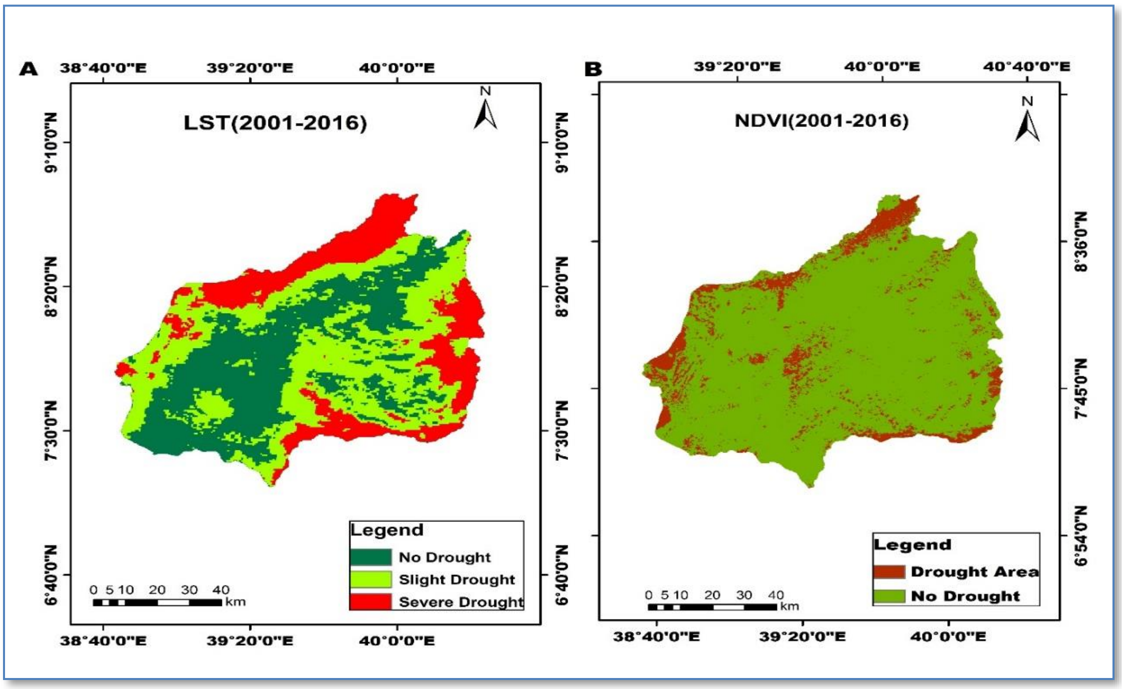

Figure 4.4.7. Land surface temperature (A) and normalized difference vegetation index(B)

4.5. Spacial and Temporal Patterns of SPI And Drought Severity

SPI is analyzed for growing season (June, July, August and September) of East Arssi zone. The analysis of SPI (Figure 4.4) revealed that drought has occurred at different level of severity in the study area from 2001 to 2016 cropping season. The drought that happened in year 2009 and 2015 was severe one compare to other years as explained by the SPI mean values that range from -1.2716 to -1.51583 respectively. The result indicates that during those years, there was rainfall deficit in the growing season and it, therefore, was the worst dry seasons. Time series analysis of SPI indicated decrease in SPI values during 2001-2016 reflecting the increase in dry conditions in the study area.

Positive mean SPI have indicated no drought whereas negative mean SPI indicates drought that have different severity. Considering two of the most severe droughts years (2009 and 2015), drought risk area and extent was illustrated for the eastern Arssi Zone.

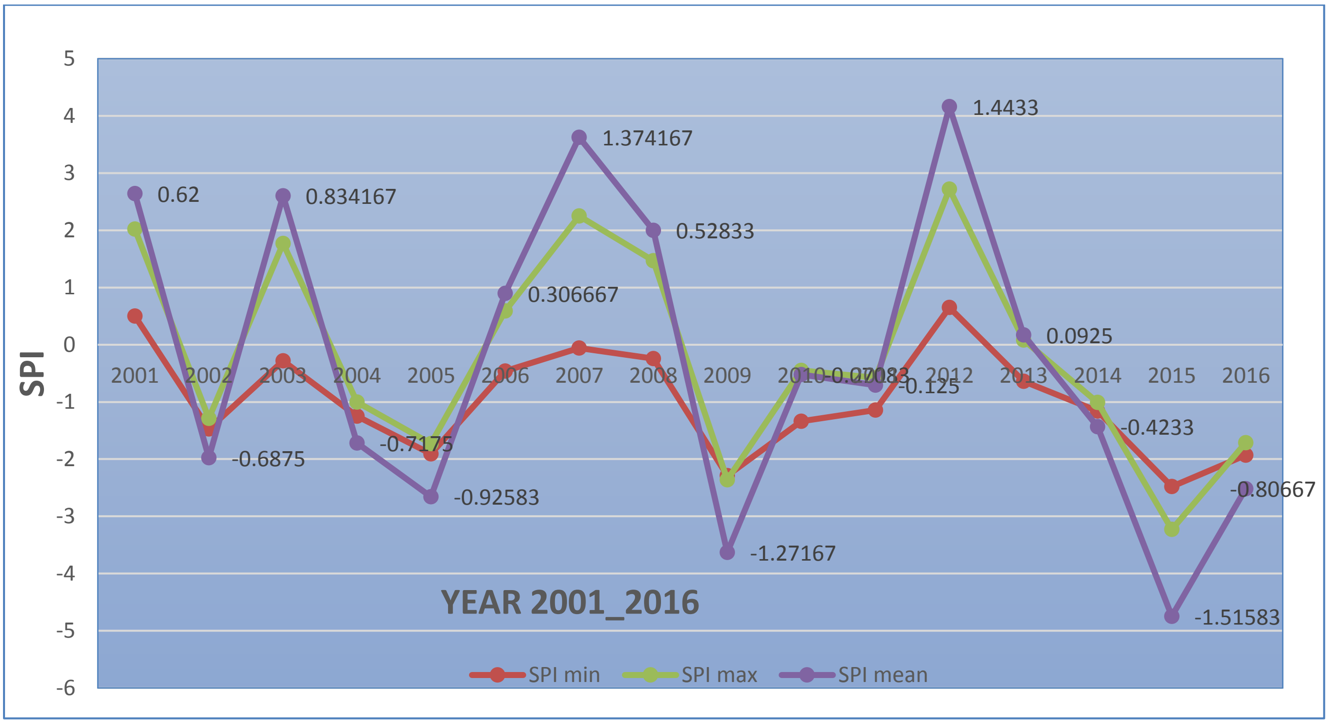

Figure 4.5.8. Temporal pattern of Seasonal (June - September) SPI (2001 - 2016)

Standard precipitation Index was computed for growing season of East Arssi zone. The results of the analysis revealed that droughts have occurred at different levels of severity from 2001 to 2016 cropping seasons. The drought that occurred in edge of rift valley was the severe compared to other as explained by the SPI pattern shown in (Fig 4.4.1). The result indicates that at back of Arssi continuous mountain and near Bale mountain there was area like Seru woreda that have risk of agricultural drought. Spatial patterns of SPI for drought years (2002, 2004, 2005, 2009, 2014 ,2015 and 2016) and wet years (2001, 2003, 2006, 2007, 2008, 2012 and2013) analyzed and reclassified to show spatial trends of drought severity at different rainfall station in study area. Standard precipitation index (SPI), which is a measure of drought and assessed from meteorological data was used to verify remote sensing results.

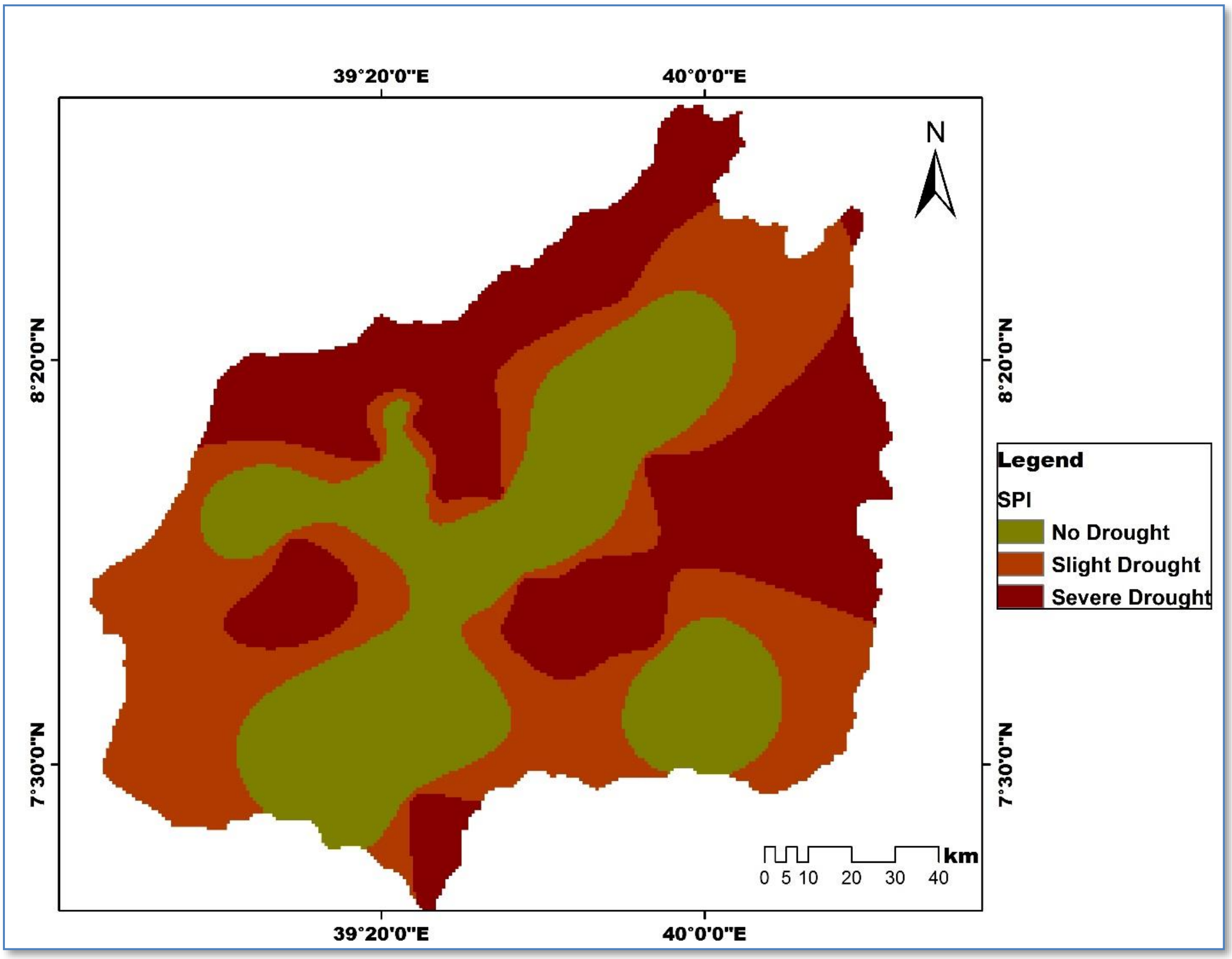

Figure 4.5.9. Spatial pattern of drought risk area by SPI in the study area (2001-2016).

4.5. Standard Precipitation Index (SPI) And NDVI Anomaly

The use of precipitation and vegetation index provides adequate means for identifying drought risk area in the study area extend over the agricultural fields and use of time series data offers potentials to establishing long term mean average for vegetation moisture levels that will provide adequate monitoring for effective early warning system to the farmers. The two biophysical parameters have potential to shows agricultural drought risk areas when SPI increase NDVI have also increase the same for vice versa while considering there spacial pattern as shown in the Figure 4.5.

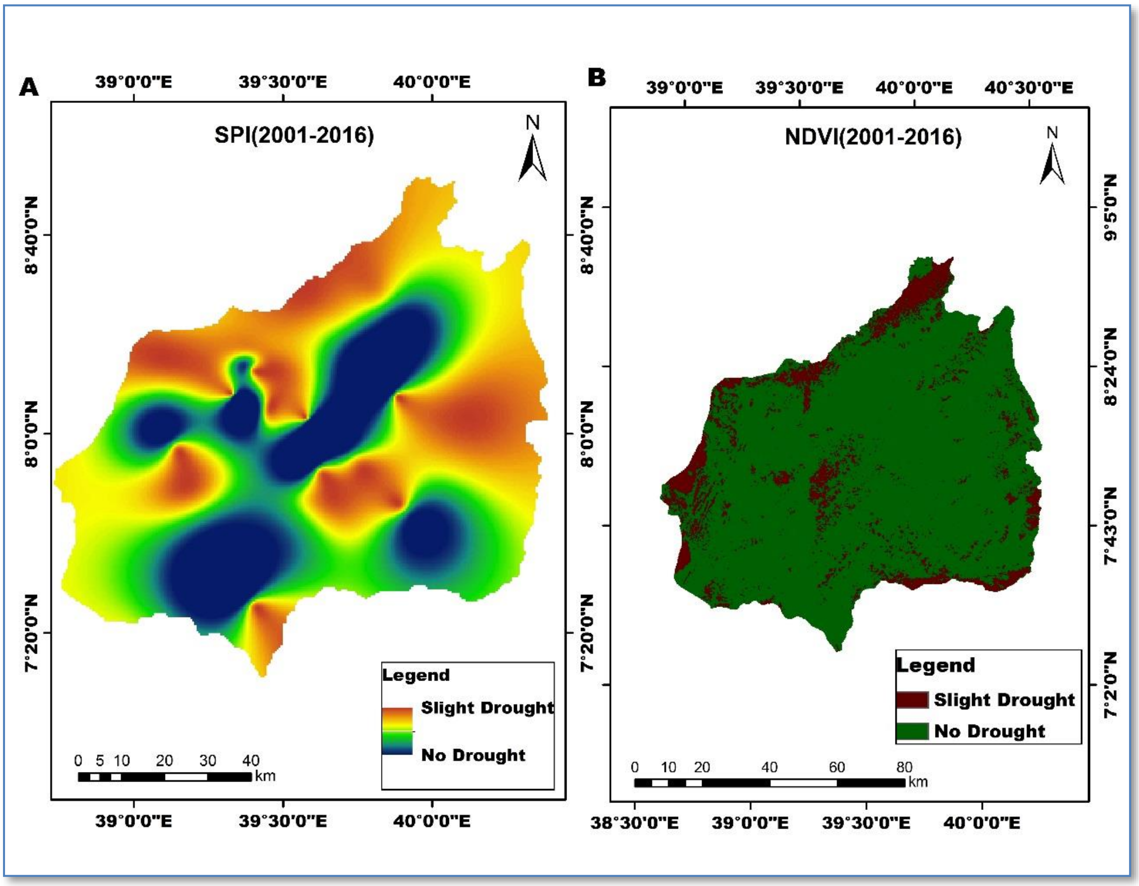

Figure 4.5.10.Standard Precipitation Index and Normalized Difference Vegetation Index (2001-2016)

4.6. Standard Precipitation Index (SPI) Land Surface Temperature (LST)

The two biophysical parameter namely SPI and LST that indicate drought risk area were inversely proportional to each other as shown in the following figure 4.6 was that area that have slight drought and have temperature value 21-27.3ºc were area that frequently drought occur in the eastern arssi zone.SPI was computed for growing season of eastern arssi zone starting from June to September of different rain fall station placed in the area where as also LST. The number of stations occur in the study area was limited in number, by interpolation them using IDW interpolation technique's the drought prone area can be depicted in the study area. The results of the analysis revealed that droughts have occurred at different levels of severity in edge of rift valley and low land of eastern Arssi from 2001 to 2016 cropping seasons.

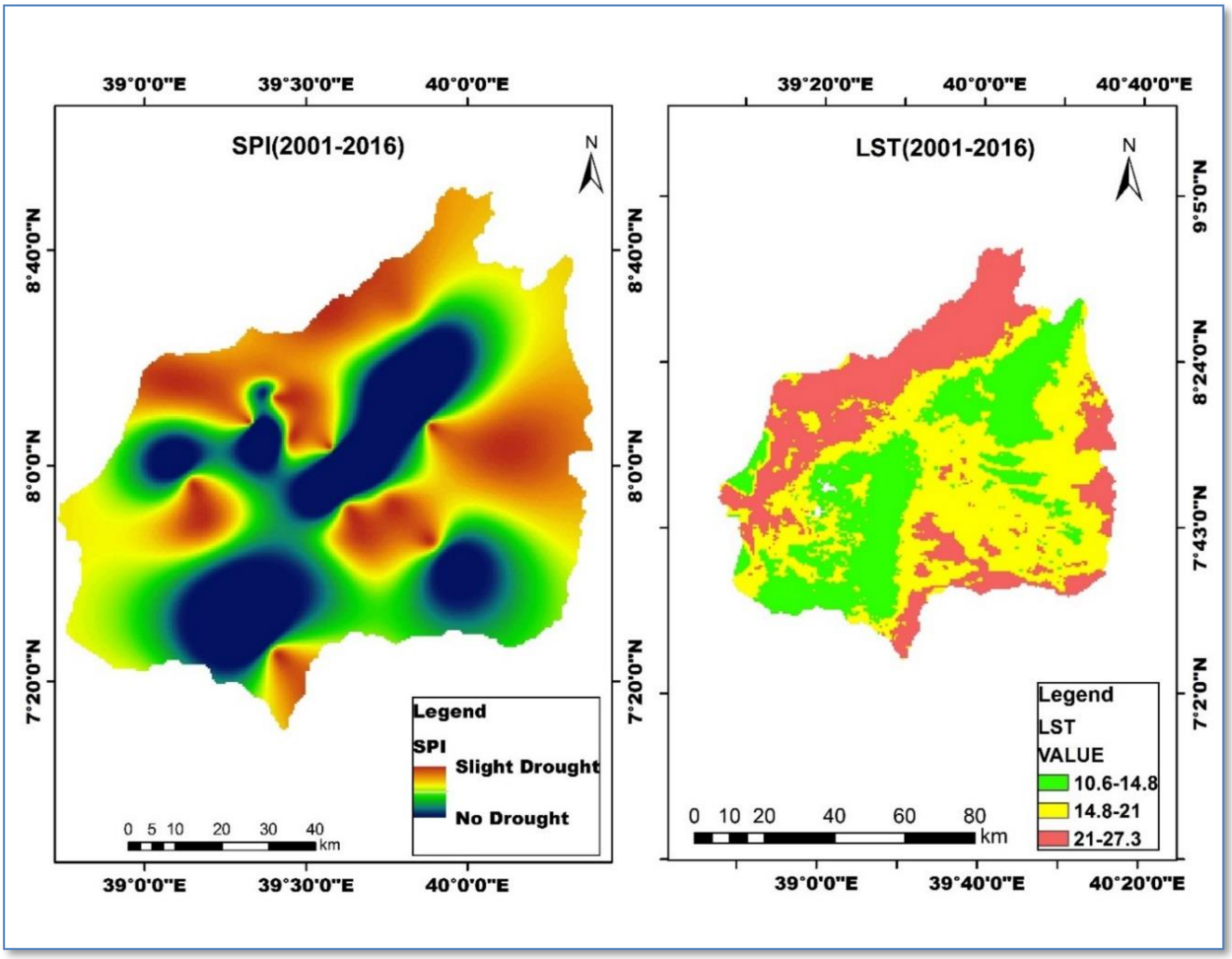

Figure 4.6.11. Standard Precipitation Index and Land Surface Temperature

4.7 Land Surface Temperature Anomaly And Agricultural Drought

Increasing temperature and altered precipitation patterns, leads to the extreme weather events like Drought which drastically affects the agricultural production. Agricultural drought is nothing but the decline in the productivity of crops due to irregularities in the rainfall as well as decrease in the soil moisture, which in turn affects the economy of the country. As the surface temperature increase from time to time there is the change of production on agricultural production. Monitoring of land surface temperature enables critical assessment of the influence and how the surface is influenced by weather and climate Patters. LST for the year 2001, 2006, 2011 and 2016 was calculated using ArcMap 10.5 on the basis of main agricultural season and trend in their shift was also identified from June to September. Consider June 2001 and September 2016 there is clear difference in temperature pattern that is the area of of red part is small in the year June 2001 when compared with September year 2016.The lowland of arssi have no longer hot in 2001 where as in 2016 the temperature increase. When temperature increase it alters the precipitation and makes climate change that makes agricultural drought. The following figures shows the main seasonal temperature shift of study area and also area that drought frequently occur as determined by SPI and NDVI anomaly.

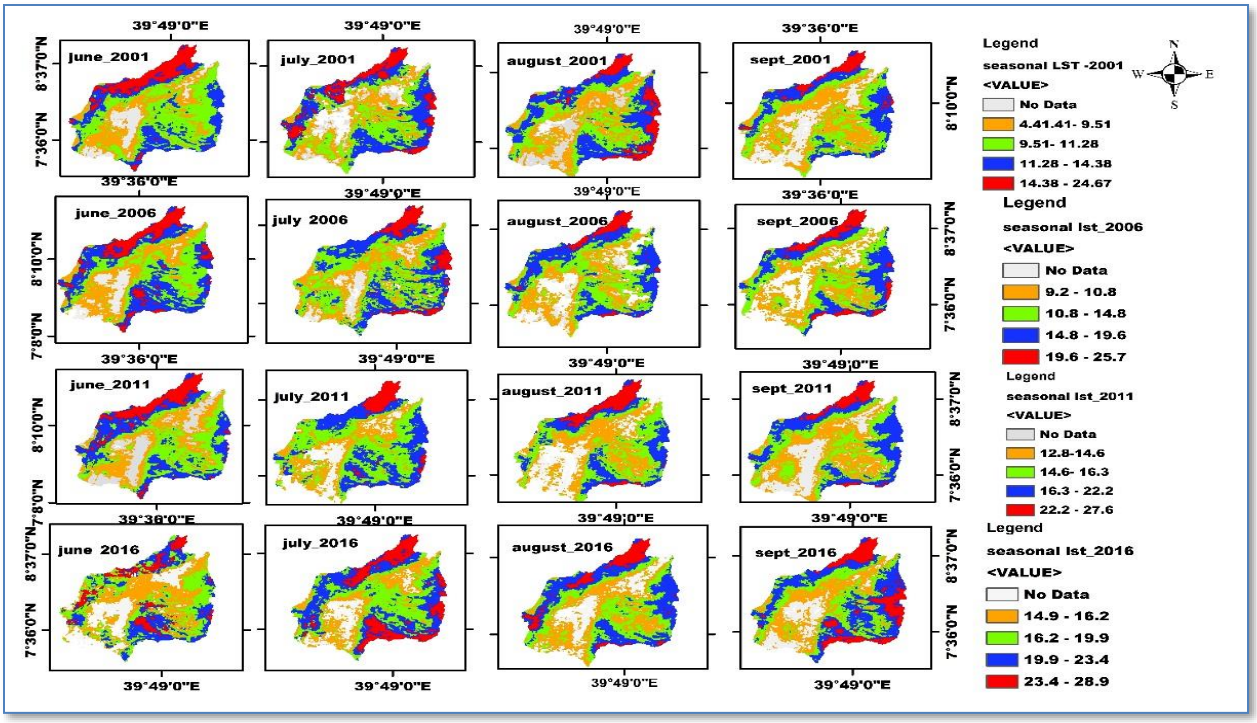

Figure 4.7.12. Land Surface Temperature anomaly (2001-2016)

4.8. Classifiation Of Agricultural Drought Risk Area.

The agricultural drought risk map has been prepared by integrating all drought indices, SPI, LST and NDVI anomaly (Fig.4.8). The three layers representing drought indices were prioritized according to their degree of influence using pair-wise comparison. According to the result derived from the integration of all drought indices, East Arssi zone is classified into no drought, slight drought and severe agricultural drought, as shown in the figure. 4.8.

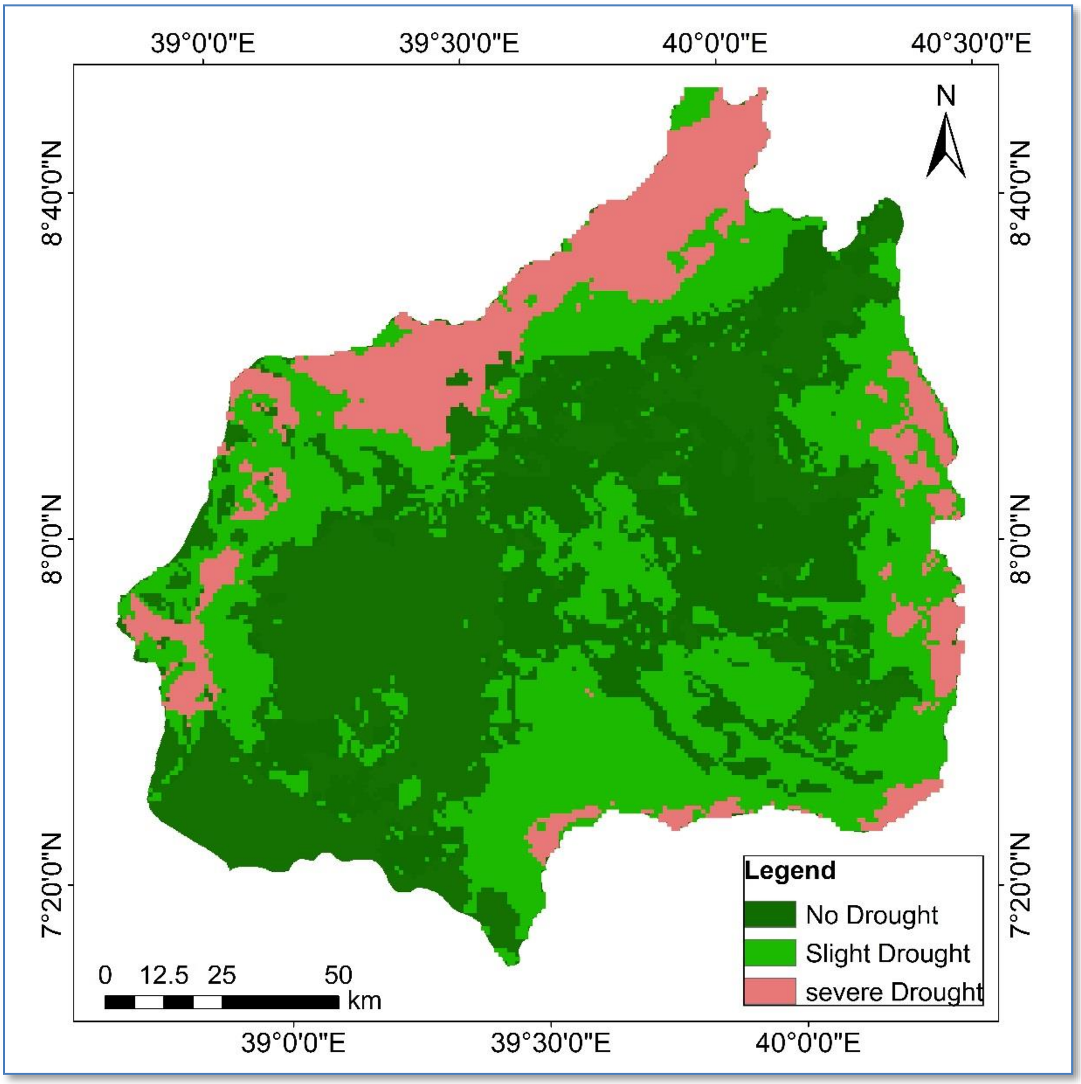

Figure 4.8.13. Agricultural drought risk map

Table 3. 8. Percentage area affected by different agricultural drought risk levels

Agricultural drought severity level	**Area(km²)**	**Area (%)**
No Drought	13197	63.5
Slight Drought	4494	22
Severe Drought	3003.4	14.5
Total	20694.4	100

CHAPTRE FIVE

5. DISCUSSION

5.1. Normalized Difference Vegetation Index (NDVI)

NDVI is a measure of greenness of vegetation. Kabo-bah et al., (2013) showed the effectiveness of the SPOT vegetation NDVI for monitoring the vegetation cover in northern Ghana. Belal et al., (2012) have also found that inter-annual variations in the magnitude and evolution of the NDVI for particular location governed by meteorological variables such as precipitation, temperature and relative humidity. It was also noted that interpretation of NDVI values was spatially dependent as more productive ecosystems have different radiometric properties than less productive ones due to difference in climate, soil and topography. The findings of this study also revealed that NDVI increased from highlands of Arssi to low lands. The NDVI and rainfall relationship was evaluated in this study as r = 0.81, which indicated a good correlation. Gizachew and Suryabhagavan (2014) showed good relationship between rainfall and NDVI in East Shewa Zone, Ethiopia. Gaikwad et al., (2015) also concluded in their review that the mean seasonal NDVI indicating greenness of the vegetation and seasonal rainfall has strong relationship and also concluded that NDVI can be used as an indicator for drought. This study also revealed that the NDVI responded to the rainfall variation seasonally and spatially. Therefore, NDVI is found to be a relatively good indicator of drought in East Arssi Zone, Ethiopia.

5.2. Standard Vegetation Index (SPI)

Standardized Precipitation Index is useful for identifying spatiotemporal extent of long-term historical droughts. Different studies across the world used SPI as a drought indicator, particularly meteorological drought. This study incorporated SPI to assess meteorological drought in East Arssi Zone, Ethiopia. Results indicated occurrence of meteorological drought in different years in the Zone. Shah et al., (2015) and Dutta et al., (2015) have also used SPI for drought risk assessment. Farahmand and Aghakouchak (2015) derived SPI using 33 years of precipitation data and concluded that the result obtained was realistic and more reliable. Similarly, Dodomani et al., (2015) carried out SPI in their research on Agricultural drought modeling using Remote Sensing. This study correlated SPI with normalized difference vegetation index (r = 0.72), that revealed statistically significant positive relationship. Similarly, Li et al., (2014) conducted Index based assessment of agricultural drought in semi-arid region of Inner Mongolia and found significant correlation between SPI and crop yield. In other parts of the world, particularly in the Sub- Saharan

Sudan, Elagib, (2013) had come up with an impressive correlation between SPI and crop yields. Therefore, the result of this study agrees with the available information and as effective for drought assessment in the dry and semi-arid areas.

5.3. Land Surface Temperature (LST)

As the surface temperature increase from time to time there is the change of production on agricultural production. Monitoring of land surface temperature enables critical assessment of the influence and how the surface is influenced by weather and climate Patters. LST for the year 2001, 2006, 2011 and 2016 from MOD11A2 was calculated using ArcMap 10.5 on the basis of main agricultural season and trend in their shift was also identified from June to September. Consider June 2001 and September 2016 there is clear difference in temperature pattern that is the area of red part is small in the year June 2001 when compared with September year 2016.The lowland of arssi have no longer hot in 2001 where as in 2016 the temperature increase. When temperature increase it alters the precipitation and makes climate change that makes agricultural drought. Agricultural drought is nothing but the decline in the productivity of crops due to irregularities in rainfall, increase in the temperature rate etc., which causes a decrease in the soil moisture. LST is a good indicator of the energy balance at the Earth's surface which can provide important information about the surface physical properties and climate. Negative correlation between LST and NDVI, (fig 4.4.1) was largely due to changes in vegetation cover and soil moisture, and indicted that the surface temperature can rise rapidly with water stress. Thus, it can be noticed that the ratio of LST/NDVI increases during times of drought. Analysis of vegetation stress caused by the lower precipitation, higher temperature, indicates agricultural drought risk area in the Easter Arssi zone.

CHAPTER SIX

6. CONCLUTION AND RECOMMEDATION

6.1. Conclusion

Agriculture is the most vulnerable and sensitive sector that is seriously affected by the impacts of climate variability and climate change. In a country where the impact of agricultural drought is increasing, detailed identification of drought risk area and early monitoring are required to trigger responses that allow mitigating the drought effect. Therefore, a thorough understanding of the drivers of agricultural drought are needed even when detailed field observations are lacking, and reliable meteorological stations are scarce, as is the case of Ethiopia, Agricultural drought risk mapping can be constructive to guide decision-making process in drought monitoring and to reduce the impact of drought on agricultural production and productivity, while identifying appropriate sites for specific adaptation and mitigation measures have taken. This result makes remote sensing datasets for identification of agricultural drought risk area for a particular study as a powerful tool for understand drought prone area. It is clear that, no single indicator or index is sufficient to monitor drought on a zonal scale; instead, a combination of integrated monitoring tools was preferable to producing drought maps. The results of remotely-sensed indices for the years 2001 to 2016 showed that most of the region experienced no drought and the edge of rift valley area and the back of Arssi continues mountain area have experience drought in those year of study as quantifying from SPI, LST and NDVI. Analysis of vegetation stress caused by the lower precipitation, higher temperature, indicates agricultural drought risk area in the Easter Arssi zone. It was also observed that the SPI values indicating magnitude and spatial extents drought condition varies in accordance with elevation and on the type of land use/ land cover in the region. Based on the precipitation drought analysis, it was illustrated that there is significant correlation between the rainfall anomalies and NDVI over the region. This is a good indicator that NDVI can as drought identification tool where is no sufficient rainfall information. To investigate the impact of drought on agricultural production using remote sensing-based drought indices data from central statistics agency (CSA) have not provide full information. Persistent drought was observed on the edge of rift valley areas of the eastern arssi and in the bare soil land cover type while, the sparse vegetation showed extreme variation in the time series. The zonal based analysis of SPI the variation over the mean for the past 16 years drought was not constant. In some year it can be severe drought, slight drought and in other year no drought. It is an indication that the drought can happen at any given time with different magnitude and extent over Eastern Arssi zone. It could further indicate that the characteristics of vegetation and the surface temperature may not be the only factor that influences the condition of drought.

In Ethiopia, there is low spatial resolution of meteorological station as a whole very sparsely gauging at the study area. Continuous measurement of drought measurement variables like rainfall, soil moisture, discharges are impossible even if the National Meteorological Agency accepted SPI as a standard index of drought measurement. As result, where there is low spatial density of stations, the use of indices derived from remotely sensed data could be very useful to identify risk area of agricultural drought using indices like LST and NDVI which require data from remotely sensed, could led the basis for completely understand of drought and its manifestations over larger areas.

This paper indicates that theirs is the area affected by drought in the eastern Arssi zone even though arssi zone have good name in agricultural production. This will have great implication for planner, NGOs and policy makers who are actively engaged in the drought risk area identification and make preparedness. Therefore, our study partially demonstrated the use of land surface temperature, normalized difference vegetation index and standard precipitation index for identifying agricultural drought risk area in the Eastern Arssi in particular and Ethiopia at large.

6.2. Recommendation

Conventional methods of drought monitoring and early warning system using only station point data is time consuming and tedious. Similarly, the data are often incomplete and inconsistent so using remote sensed data to identify drought risk area and forecast effectively the occurrences of drought in study area requires satellite data products characterized by higher spacial resolution is recommended. Even though satellite data employed in this study is eMODIS NDVI having 250m and for land surface temperature having 1km spacial resolution.

Drought has been observed as a recurrent phenomenon in the area. It is recommended that an operational service for drought forecast be put in place. So that the measure of mitigation strategy be put in place.

Agricultural drought risk mapping can be constructive to guide decision-making process in drought monitoring and to reduce the impact of drought on agricultural production and productivity, while identifying drought risk area appropriate adaptation and mitigation measures like drought tolerance crops, the type of crop variety and soil moisture conservation practices should be made to fit into the agricultural drought risks.

The study could be more meaningful if effects of drought on human and livestock population would be assessed. Therefore, it is recommended to include the socioeconomic data to better understand the vulnerable factors. Prioritization and implementation of site-specific adaptation and mitigation projects should be made based on the drought severity levels of specific locations.

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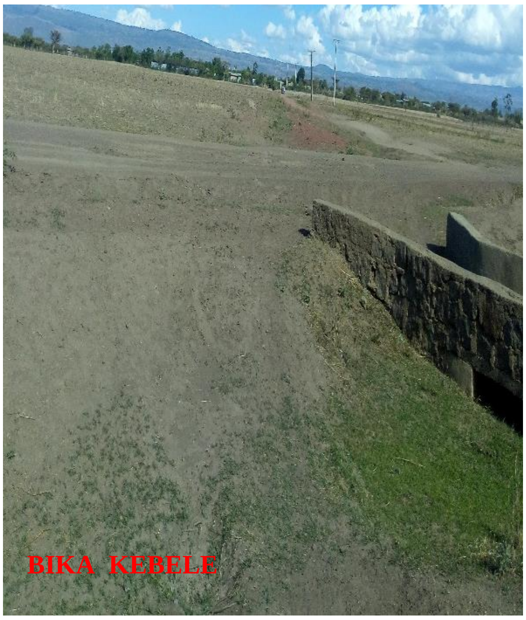
Appendices

Appendix 1: Partial view of the study are



Appendix 2: Simple linear regression between Seasonal (June-September) rainfall and NDVI

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.867258498
R Square	0.752137302
Adjusted R Square	0.73307094
Standard Error	0.063772558
Observations	15

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	234.42231	234.4223	39.44839	2.8296E-05
Residual	13	77.252578	5.942506		
Total	14	311.67489			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*upper 95.0%*
Intercept	25.13628551	1.2666202	19.84516	4.19E-11	22.399919	27.87265	22.39992	27.87265
X Variable 1	-11.38709947	1.8130027	-6.2808	2.83E-05	-15.3038538	-7.47035	-15.3039	-7.47035

Appendix 3: Simple linear regression between Seasonal (June-September) SPI and NDVI

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.08007285
R Square	0.006411661
Adjusted R Square	-0.070018211
Standard Error	0.932346464
Observations	15

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.072922591	0.072922591	0.083889467	0.776662007
Residual	13	11.30050909	0.86926993		
Total	14	11.37343168			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.15764965	0.484438792	-0.325427386	0.750035949	-1.204216032	0.888916733

X Variable 1	0.200837447	0.693411396	0.289636785	0.776662007	-1.297186798	1.698861692

Appendix 3: Simple linear regression between Seasonal (June-September) SPI and NDVI

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.132349387
R Square	0.01751636
Adjusted R Square	-0.058059304
Standard Error	0.927121706
Observations	15

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.199221127	0.199221127	0.2317725	0.638215278
Residual	13	11.17421055	0.859554658		
Total	14	11.37343168			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.425075374	0.986964185	0.430689766	0.6737487	-1.707131116	2.557281863
X Variable 1	-0.025282312	0.052515299	-0.48142756	0.6382153	-0.138734719	0.088170094

Appendix 4: Simple linear regression between Seasonal (June-September) LST and NDVI

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.867258
R Square	0.752137
Adjusted R Square	0.73307
Standard Error	2.4377
Observations	15

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	234.4223073	234.4223073	39.44839215	2.8296E-05
Residual	13	77.25257807	5.942506006		
Total	14	311.6748853			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	25.13628551	1.266620169	19.845164	4.1896E-11	22.39992	27.8726520
X Variable 1	-11.38709947	1.813002743	-6.2807955	2.8296E-05	-15.303854	-7.4703452

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NAME OF STUDENT	Gezahegn Balcha Mojo
STREAM	Remote sensing and Geo-informatics
ID No	GSR/5560/10
THESIS TITLE	Drought Risk Area Identification Using NDVI And Land Surface Temperature: Case Study of East Arssi Zone
Online site used for originally test	http://www.paperrater.com/plagiarisim_checker

FORMAT FOR THESIS ORIGINALITY TEST REPORT

No	Particular	Test 1		Test 2		Test 3		Test 4		Test 5		Average
		Oringi (%)	Plagia- (%)	Oringi (%)	Plagia - (%)	Oringi (%)	Plagia- (%)	Oringi (%)	Plagia- (%)	Oringi (%)	Plagia- (%)	
1	Abstraction	100	-	-	-	-	-	-	-	-	-	100
2	Introduction	94	4	96	2	97	3	99	1	100	-	100
3	Literature	98	2	98	2	98	2	98	2	98	2	98
4	Methodology	100	-	-	-	-	-	-	-	-	-	100
5	Results	100	-	-	-	-	-	-	-	-	-	100
6	Discussion	100	-	-	-	-	-	-	-	-	-	100
7	Conclusion	100	-	-	-	-	-	-	-	-	-	100
	Overall thesis											98

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DECLARATION

I hereby declare that this thesis is my original work and has not been presented for a Degree in any other university and that all sources of materials used for the thesis have been duly acknowledged.

Gezahegn Balcha

Signature __________________________ Date_________________________

School of Earth Science

May, 2019

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

Advisor:

Dr. Tesfaye Korme

Signature __________________________ Date _____________________