ADDIS ABABA UNIVERSITY
COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES
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Remote Sensing and GIS-based Agricultural Drought Assessment: The Case of Waghimra Zone, Amhara Regional State, Ethiopia

A Thesis Submitted to

The School of Graduate Studies of Addis Ababa University in Partial Fulfillment of the Requirements for the Award of the Degree of

MASTER OF SCIENCE

In

Remote Sensing and Geo–informatics

By
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Advisor
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REMOTE SENSING AND GIS BASED AGRICULTURAL DROUGHT ASSESSMENT: THE CASE OF WAGHIMRA ZONE, AMHARA REGIONAL STATE, ETHIOPIA

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D E C L A R A T I O N

I hereby declare that the dissertation entitled "**Remote Sensing and GIS based Agricultural Drought Assessment: The case of Waghimra Zone, Amhara regional state, Ethiopia**" has been carried out by me under the supervision of Dr. K. V. Suryabhagavan, Department of Earth Sciences, Addis Ababa University, Addis Ababa during the year 2018/2019 as a part of Master of Science programme in Remote Sensing and Geo-informatics. I further declare that this work has not been submitted to any other University or Institution for the award of any degree or diploma.

Abebe Senamaw

Signature:——————————
Date:——————————

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LIST OF ABBREVIATIONS

AMS	American Meteorological Society
AVHRR	Advanced Very High Resolution Radiometer
AWC	Available Water Content
CMI	Crop Moisture Index
CSA	Central Statistics Agency
DRMFSS	Disaster Risk Management and Food Security Sector of the Ministry of Agriculture
ETM^+	Enhancement Thematic Mapper Plus
eMODIS	Enhanced/expedited/expandable MODIS data
ENVI	Environment for Visualizing Image
ERDAS	Earth Resource Data Analysis System
EROS	Earth Resource Observation and Science
FAO	Food and Agricultural Organization
FEWS NET	Famine Early Warning Systems Network
GeoTIFF	Geo-refenced Tagged Image File Format
GIS	Geographic Information System
GPS	Global Positioning System
HDF-EOS	Hierarchical Data Format - Earth Observing System
IDW	Inverse Distance Weight
LULC	Land Use Land Cover
MODIS	Moderate Resolution Imaging Spectro radiometrer
NDVI	Normalized Difference Vegetation Index
NDVImax	Normalized Difference Vegetation Index Maximum
NDVI min	Normalized Difference Vegetation Index minimum
NGO	Non-Governmental Organization
NIR	Near Infrared band,
NMSA	National Meteorological Service Agency
NOAA	National Oceanic and Atmospheric Administration

PET	Potential Evapo-Transpiration
R	Red band
r	Coefficient of Correlation
RS	Remote Sensing
SPEI	Standard Precipitation and Evapotranspiration Index
SPI	Standard Precipitation Index
SWSI	Surface Water Supply Index
TCI	Temperature Condition Index
UNISDR	United Nations Secretariat of the International Strategy for Disaster Reduction
UNOCHA	United Nations Office for The Coordination Of Humanitarian Affairs
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
VCI	Vegetation Condition Index
VHI	Vegetation Health Index
WGS	World Geodetic System
WMO	World Meteorological Organization
WZLFRD	Waghimra Zone Livestock and Fisheries Resource Department

Abstract

Remote Sensing and GIS-based Agricultural Drought Assessment: The Case of Waghimra Zone, Amhara Regional State, Ethiopia

Abebe Senamaw Kebede, MSc. Thesis
Addis Ababa University, June, 2019

In Ethiopia drought is the most prominent hazard affecting economy of the country. Agricultural drought has been a recurrent phenomenon in many part of the country. GIS and Remote Sensing plays an important role for near real time monitoring of agricultural drought condition over large areas. This study was conducted to assess agricultural drought condition in Waghimra Zone using Remote sensing and GIS techniques. Enhanced/expedited/expandable MODIS (eMODIS) NDVI data and monthly rainfall data from 2000 to 2016 were utilized as an input data while crop yield data were utilized as ground truth data for validate strength of drought indices. Normalized Vegetation Index (NDVI), Vegetation condition index, NDVI anomaly were applied to assess spatiotemporal variation of agricultural drought while Standard Precipitation Index(SPI) which is derived from rainfall data were applied to assess spatiotemporal variation of metrological drought. Drought risk map was prepared by combining agricultural and metrological drought. To validate drought indices crop yield anomaly was calculated by using ground truth data of crop yield. Correlation analysis was computed between NDVI and rainfall, NDVI anomaly and crop yield anomaly, VCI and crop yield anomaly and SPI and crop yield anomaly. Results revealed that year 2009 and 2015 were of drought years while 2001 and 2007 were wet years. The result also shows there is good correlation between NDVI and rainfall (r=0.71), NDVI anomaly and crop yield anomaly (0.53), VCI and crop yield anomaly (0.72), SPI and crop yield anomaly (0.74). Drought risk severity map was computed from 2000 to 2016 by integrating agricultural and metrological drought frequency maps. Combined drought risk map showed that 8%, 56%, and 35% of study area were vulnerable to very severe, severe and moderate drought condition respectively. This figure indicates that study area is high vulnerable to drought. Thus, besides mapping drought vulnerable areas integrating socioeconomic data in order to better understand vulnerable factors were recommended.

Keywords: Agricultural drought, eMODIS NDVI, GIS, Remote Sensing, SPI, Waghimra Zone

CHAPTER ONE

INTRODUCTION

1.1. Background

Drought is a one of the extreme climatic phenomenon that can occur at any given time in all climatic zones with its characteristics varies significantly from region to region. To fight against drought and mitigate the impact of major drought it is important to distinguish between different type droughts. The most prominent types of drought are meteorological, agricultural, and hydrological droughts (Wilhite, 2000; Obasi, 1994). Meteorological drought is usually defined according to the degree of dryness (i.e., in comparison to the "normal" or average amount of precipitation of the region) and the duration of the dry period at a particular place and at a particular time. Hydrological drought is associated with the effects of periods of precipitation (including snowfall) shortfalls on the surface or subsurface water supply (i.e. stream flow, reservoir and lake levels, and ground water). Agricultural drought links various characteristics of meteorological and hydrological drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, and reduced ground water or reservoir levels (Wilhite, 2000). It occurs when there is not enough water available for a particular crop to grow at a particular time.

Droughts are one of the highest natural disasters globally (Paulo *et al.,* 2012; Morid *et al.,* 2006). The events are often associated with severe economic losses, reduction in GDP growth, crop failure and impact livestock rearing and mortality (Kenawy *et al.,* 2016). In addition to these, drought is a period of abnormally dry weather sufficiently prolonged because of a lack of precipitation that causes a serious hydrological imbalance and has connotations of a moisture deficiency with respect to water use requirements (McMahon and Arenas, 1982).The deficiencies have impacts on both surface and groundwater resources and lead to reductions in water supply and quality, reduced agricultural productivity, diminished hydro-electric power generation, disturbed riparian and wetland habitats and reduced opportunities for some recreation activities(Riebsame *et al.,* 1991).

Drought is one of the most frequent climate-related disasters occurring across large portions of the African continent, often with devastating consequences for the food security of agricultural households (Rojas *et al.,* 2011). The effects of droughts are severe particularly in East African countries due to high rainfall variability in space and time (Yared *et al.,* 2017). A catastrophic drought occurred in the region in 1984, which killed an estimated 450,000 people in Ethiopia and Sudan. More recently, a severe drought in Somalia and southern Ethiopia in June 2011 resulted in more than 10 million people seeking humanitarian aid, as well as 380,000 refugees impacting neighboring countries (Vicente-Serrano *et al.,* 2012). Among these countries, Ethiopia encounters frequent droughts (occurring once in every 2-3 years). In support of this finding recently, severe drought events have occurred in Ethiopia in 2011, 2012, 2014 and 2015, with most of them covering the whole country (Desalegn *et al.*, 2010; Viste *et al.,* 2013). In the past two decades, millions of people are affected by drought throughout the country. In line with these Tagel *et al.,* (2011) reported that Ethiopia, a highly populated country whose economy largely depends on rain-fed agriculture, drought is a recurrent climate phenomenon, with a frequency of occurrence approaching one event per decade.

Many countries consider that drought monitoring system is one of most effective ways for reducing drought damages by early drought detection and issuing warnings (Boken *et al.,* 2005). This has been carried out mainly by developing an indicator that allows for detection and evaluation of drought events. There are a number of indicators for drought monitoring and assessment. Meteorological drought indicators assimilate information on rainfall, stored soil moisture or water supply but they do not express much local spatial detail. On the other hand, the derived drought indicators calculated from satellite-derived surface parameters have been widely used to study droughts. Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) are some of the extensively used vegetation indices.

There is a firm conviction that the use of Satellite Remote Sensing data and Geographical Information System (GIS) can effectively facilitate the detection, identification and mapping of drought risk prone areas. Research reports attest that, specially, the use of modern Geo-spatial technology of Remote Sensing (RS) combined with Geographic Information System (GIS), for instance, afford powerful mechanisms, not only to monitor local natural events but also to obtain essential quantitative information at large spatial coverage and frequent temporal intervals (Prenzel, 2004).

1.2. Statement of problem

Ethiopia, irrespective of its abundant potential of water resources, has been facing drought at an increasing frequency throughout the past many decade. The effects of droughts are severe due to high rainfall variability in space and time (Yared *et al.*, 2017). The country encounters frequent droughts (occurring once in every 2-3 years). In the past two decades, millions of people are affected by drought throughout the country. The main livelihood activity of Waghimra Zone is almost fully dependent on rain-fed agriculture and the area is often hit by periodic droughts. This drought causes serious economic, social and environmental problems. Thus, drought management has become an important issue in the drought prone parts of Ethiopia in order to reduce its adverse effects. In order to mitigate the impacts, proper drought monitoring and early warning systems are essential (Desalegn *et al.,* 2010; Yared *et al.*, 2015). This requires information on the extent and severity of drought. However, there was no as such detail studies conducted about its magnitude, frequency and spatial extent in different regions of Ethiopia (Mekonnen and Woldeamlak, 2015) in general and study area in particular. Due to this, there is a gap between the drought and pre awareness about it. To fill this gap, this study was initiated to assess agricultural and metrological drought using Remote sensing and GIS technique in study area.

1.3. Objectives of the Study

1.3.1. General objective

The general objective of this study was Remote Sensing and GIS-based agricultural drought assessment in Waghimra Zone Ethiopia.

1.3.2. Specific objectives of the study are as follows:

i. To identify agricultural drought in study area

ii. To identify meteorological drought in study area

iii. To assess drought by combining agricultural and meteorological drought.

1.4. Significant of study

Identification of drought prone areas and estimation of the probability of drought occurrence are fundamental for the implementation of program that aims to increase food security. Drought characterization at regional and local scales has significant implications for drought management such as early warning system. Thus far, few drought studies have been conducted on drought management using the historic time series of hydro-meteorological variables at a local level (e.g. zones or basins) in Ethiopia (Ramakrishna and Assefa, 2002; Desalegn *et al*., 2010; Tagel *et al*., 2011; Eshetu *et al*., 2017; Gizachew and Suryabhagavan (2014), Eshetu *et al*. (2017)). More specific studies need to be conducted to better describe and characterize drought and to associate its characteristics with temporal and spatial variability of rainfall at a local level (e.g. at sub basin level). According to Ethiopian Government Disaster Risk Management and Food Security Sector of the Ministry of Agriculture (DRMFSS) (2018) report; in Waghimra Zone drought and crop failures have been common and rain-fed agriculture is yet to provide minimum food requirement for rapidly growing population. It is important to identify the extent of the areas prone to severe drought conditions in order to reduce its possible consequences. An improved drought management must rely on an accurate monitoring and forecasting of the phenomenon in order to activate appropriate mitigation measure. In recent years, GIS and remote sensing data which consistently available, cost-effective and can be used to detect the onset of drought, its duration and magnitude has been used to monitor drought conditions of an area. Thus, this study was designed to assessing agricultural and metrological drought by using GIS and remote sensing data. The result of this study would contribute as significant inputs about the extent and severity of drought for local communities, development agents and Non-Governmental Organization (NGO) to identify drought prone areas and its recurrent time to plan drought preparedness and locally adopted mitigation strategies.

1.5. Scope of the Study

This study focused on agricultural and metrological drought assessment using satellite and rainfall data in Waghimra Zone, Amhara regional state Ethiopia from year of 2000 to 2016 which, is frequently affected by drought. Methodologically this study incorporate different drought indices like NDVI, NDVI anomaly, VCI from remotely sensed eMODIS NDVI data it also used SPI from monthly rainfall data.

1.6. Limitation of study

The approach had the following limitation in this study 17 years satellite data were available 2000 to 2016. But for proper drought assessment at least 20 years data are essential. Lack of socioeconomic data like population and livestock numbers affected by drought and their coping strategies used to incorporate in study.

1.7. Thesis organization

This thesis is organized into five chapters. The first chapter presents introduction part of paper deals with the statement of the problem, objectives and organization of the thesis, the second chapter review of literatures, the third chapter methodological issue including description study area, the fourth chapter results and discussion, finally chapter five draws conclusion and makes recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1. Concept and Types of Drought

There is no single universally accepted definition of drought as it is dependent on many climatologically limitations with noteworthy spatial unpredictability (Loukas *et al.,* 2002; Rossi, 2009; Akhtar, 2014). According to Glossary of Meteorology (1959) drought is defined as; "a period of abnormally dry weather sufficiently prolonged for the lack of water to cause serious hydrologic imbalance in the affected area''. Drought is a recurrent climate process which occurs with uneven temporal and spatial characteristics over a broad area and over an extended period of time (Bayarjargal *et al.,* 2006). The concept of drought varies among regions of differing climates (Dracup *et al.,* 1980) and resource base. In general, drought gives an impression of water scarcity resulted from insufficient precipitation, high evapotranspiration, and over-exploitation of water resources or combination of these parameters. Drought is one of the world's costliest natural hazards characterized by a significant decrease of water availability during a prolonged period of time over a large area (Yared, 2018). To facilitate communication, management, and response, drought often is categorized into four general types (AMS, 2013) (1) meteorological or climatological, (2) agricultural, (3) hydrological, and (4) socioeconomic.

I. Metrological Drought

Meteorological Drought refers to short-period droughts or dry spells, when precipitation received is far below the expected normal. Data sets required to assess meteorological drought are daily rainfall information, temperature, humidity, wind velocity and pressure, and evaporation. Therefore, metrological measurements are mainly used to indicate the degree of drought. Definitions of meteorological drought must be considered as region specific since the atmospheric conditions that result in deficiencies of precipitation are highly variable from region to region. There are different types of metrological definition indifferent part of the world for instance United States (1942) reported when rainfall amount is less than 2.5 mm in 48 hours there is metrological drought. There is metrological drought when there is fifteen consecutive days with daily precipitation less than 0.25 mm (Great Britain (1936). Libya (1964) also define metrological drought as When annual rainfall is less than 180 mm. similarly Bali (1964) also express metrological drought as a period of six days without rain. Definitions derived for application to one region usually are not transferable to another since meteorological characteristics differ (Ashenafi, 2016).To compare drought conditions between regions presence different definition and human perception variability should be taken in to consideration (WMO, 2006).

II. Agricultural Drought

When soil moisture is insufficient to ensure optimal crop growth Agricultural drought occurs (Gizachew, 2010). Agricultural drought links various characteristics of meteorological drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced groundwater or reservoir levels, and so on. According to this definition Agricultural drought is related to physiological drought, which is determined from conditions of natural vegetation, crops, livestock, pastures and other agricultural systems. It is defined by measure of the availability of soil water to plants or animals. In this case, radiation (heat), drying wind and evaporation become important factors. This type of drought are very difficult to discriminate from the other meteorological and hydrological drought since there is no easy way to separate water leaving from ground and water leaving from plant leafs. A plant's demand for water is dependent on prevailing weather conditions, biological characteristics of the specific plant, its stage of growth, and the physical and biological properties of the soil.

III. Hydrological drought

When precipitation deficiencies begin to reduce the availability of natural and artificial surface and subsurface water resources there is occurrence of Hydrological drought. Hydrological drought is viewed as the deteriorations in water availability in all its forms (Khana, 2009). This explanation includes stream flow, ground water, surface water, Lake Reservoir and other forms of water that closely associated with hydrological cycle. Hydrological droughts are associated with the effects of seasonal precipitation shortfall on surface or subsurface water supply resulting in deficiencies relative to average conditions at various points in time (UNISDR, 2009). Similarly, according to Getachew *et al*. (2011) hydrological drought is perceived as the event occurring as a result of low rainfall. This perception agree with the fact that hydrological drought is closely related with long term absence of precipitation increased evapotranspiration. However, in hydrological drought there is no direct relationship between precipitation amounts and the status of surface and subsurface water supplies in lakes, reservoirs, aquifers, and streams because these hydrological system components are used for multiple and competing purposes, such as irrigation, recreation, tourism, flood control, transportation, hydroelectric power production, domestic water supply, protection of endangered species, and environmental and ecosystem management and preservation. According to the explanation of Mishra and Singh (2010) hydrological drought is related to a period of inadequate water availability for the use of a given resource management system. They stated that, hydrological drought result from stream flow to catchment properties is usually attributed to geology than climatic factors.

IV. Socioeconomic Drought

The socioeconomic drought happens when human activities at individual level are affected by decreased precipitation (Wilhite and Glantz, 1985). It is associated with the supply and demand of some economic good or service with elements of meteorological, hydrological, and agricultural drought (Fig 1). This implies that the demand for economic goods exceeds its supply. Specifically, very limited supply of food item, forage, water, fish, hydroelectric power and other that are related to daily activities if the communities lead to socioeconomic drought as they are depends on weather conditions (Camaro, 2015). In under developed agrarian society, supply is dependent on the prevailing climate condition and is a function of precipitation, even if the demand remains the same. Thus, the socio economic activities of an agrarian society vary annually as a function of precipitation or water availability.

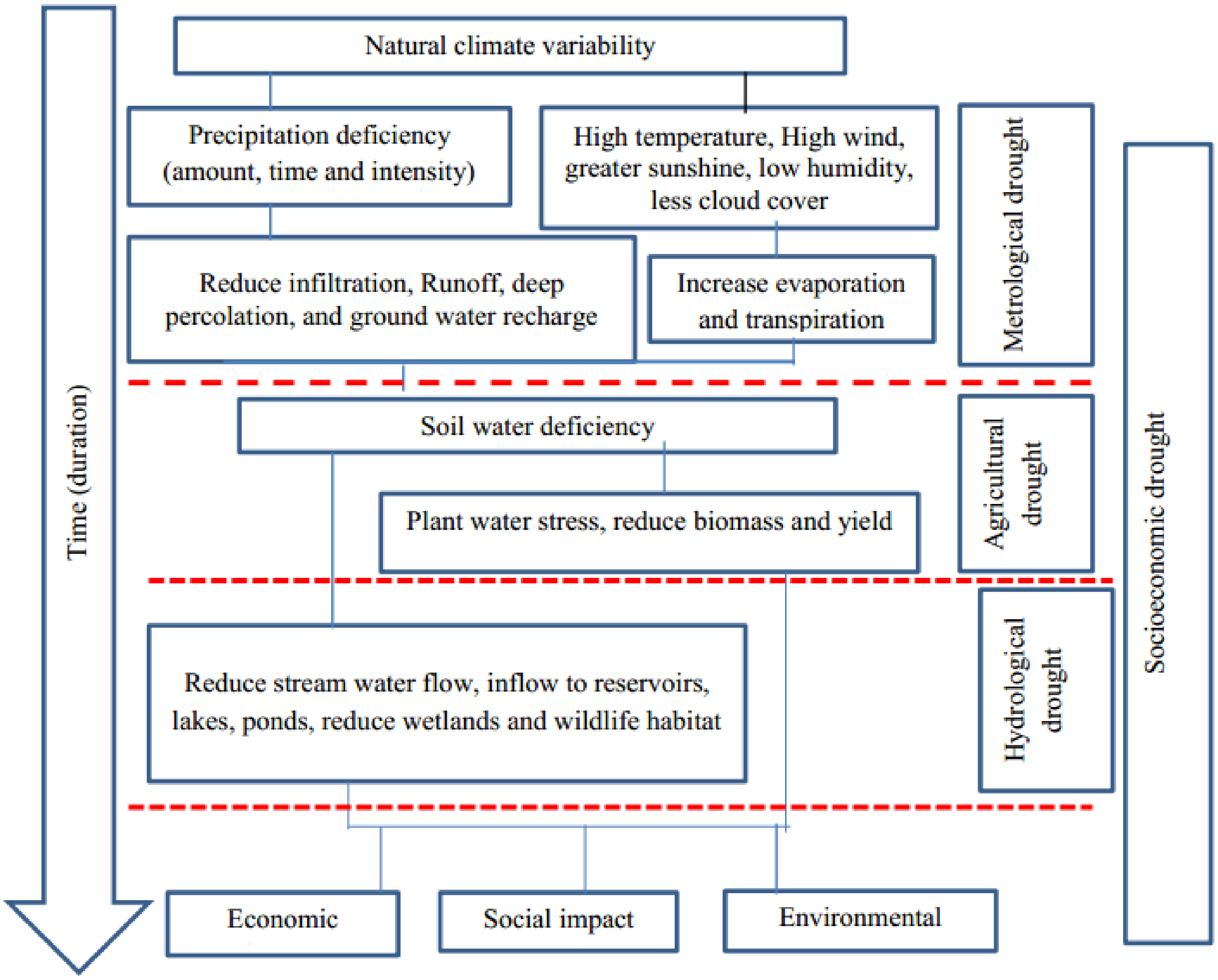

Figure 1. Relation between different types of drought

Source:- National Drought Mitigation Center (2006))

2.2. Drought in Ethiopia

The effects of droughts are severe particularly in East African countries due to high rainfall variability in space and time (Yared *et al.,* 2017). Among these countries, Ethiopia encounters frequent droughts (occurring once in every 2-3 years). In Ethiopia people have lived with recurrent droughts and extreme climatic variability (Meze-Hausken, 2000). According to Segele and Lumb (2005), Ethiopia has been ravaged by severe drought for many of the last 35 years, primarily due to the failure of its main (Kiremt) rainy season. Spring and summer rains in parts of Ethiopia have declined by 15–20 percent since the mid-1970s (FEWS NET, 2012*).* Historical records indicate that drought and Ethiopia have been associated for a long time, as far back as 250 BC (Kiros, 1991; Meze-Hausken, 2000; Block, 2008). Frequency of droughts in Ethiopia has increased during the second half of the twentieth century (Degefu, 1987; Viste *et al.,* 2013). From the 1950s to the 1980s, droughts occurred on average once per decade; presently droughts occur about once every 3 years (Block, 2008). World Bank (2006) indicated that the occurrence of 16 drought events during 1980–2004, which makes Ethiopia the most drought-affected country out of 39 drought-affected countries of Africa. There were severe droughts which have had a substantial impact on the socio-economic and environmental condition of Ethiopia at different times and scales (Table 1). Recently, severe drought events have occurred in Ethiopia in 2011, 2012, 2014 and 2015, with most of them covering the whole country (Viste *et al., 2013*). According to UNOCHA (2015) report the worst drought in decades gripped north and central Ethiopia in 2015, affecting nearly 10 million people.

The agricultural sector on which 85 percent of the population depends is by far the largest sector being affected by drought. Drought episodes in Ethiopia are highly associated with crop damage and food insecurity in drought affected parts (Kiros, 1991; Webb, 1993; Kloos and Lindtjorn 1994; World Bank, 2007). Crop failures and livestock deaths were reported for drought affected regions (Table 1). In line with this World Bank (2003) reported that drought occurrence in Ethiopia can reduce farming output by up to 90% of normal year output. The effects of droughts both on crop and livestock productions are often exacerbated by other drought induced phenomena, such as disease epidemics and insect infestations (Kiros, 1991). Past drought episodes significantly affected rural communities that depend on small-scale rain-fed agriculture (Kloos and Lindtjorn 1994; Meze-Hausken 2000). Drought occurrence usually results in food shortage and malnutrition that lead to human deaths, food aid needs and mass migrations among the rural communities. Drought is the most common form of environmental risk leading to food insecurity (Devereux, 2004). In consistence with this finding FEWS NET(2012) reports that in year 2018, Ethiopia, with a population of 108 million (CIA, 2018) and a population growth rate of 2.83 percent faces increased levels of food insecurity associated with frequent drought and climate change. Since the entire agricultural activity of Ethiopia is rainfall dependent, drought should be given with due attention in achieving food security for all.

Table 1. Major drought years & their effects in Ethiopia for the last 50 years

Year	Region	Impact
1964－1966	Tigray and Wollo	About 1.5 million people were affected and
1972–1973	Tigray and Wollo	Death of about 200,000 people and 30% of livestock population in the area
1978–1979	Southern Ethiopia	1.4 million people were affected
1983–1984	All regions	8 million people affected, 1 million people died
1982	Northern Ethiopia	2 million people were affected
1987–1988	All regions	7 million people were affected
1991–1992	North, east & south Ethiopia	4 million people were affected
1993–1994	Tigray and Wollo	7.6 million people were affected
2000	All regions	About 10.5 million people were affected
2002–2003	All regions	About 13 million people were affected; 1.4 million livestock died
2006	Southern Ethiopia (Borena)	About 7.4 million people affected; 247,000 livestock died
2008	Southern Ethiopia (Borena)	About 26,000 livestock died
2008–2009	All regions	About 5 million people were affected
2011	South-central, southeastern, and eastern part of Ethiopia	About 4.5 million were affected
2015–2016	Northern, Southern and Eastern Ethiopia	About 10.2 million people were affected

Sources: Compiled from Degefu (1987), Meze-Hausken (2000), FAO (2003), Segele and Lamb (2005), Amsalu and Adem (2009), Deressa et al. (2010), Famine Early Warning Systems Network (FEWS NET) (2011), Viste et al. (2012) and FDRE (2016) as cited Yimer *et al.* (2016).

2.3. Application of Remote Sensing and GIS for Drought monitoring

Remote sensing and GIS technologies are capable to cover the earth surface, better than traditional techniques. The detection, monitoring, and mitigation of disasters require gathering of rapid and continuous relevant information that are not effectively collected by conventional methods (Abdel-Aziz *et al.,* 2012). The traditional approaches for drought monitoring that uses ground-based data are laborious, difficult and time consuming (Prasad *et al.,* 2007). Satellite measurements of the biosphere have gained their importance in various aspects of environmental monitoring including the drought monitoring. For drought monitoring, assessment and prediction, Remote sensing and GIS technologies are capable to cover the earth surface, better than traditional techniques (Wilhite, 2002).

Remote sensing is also helpful for Agricultural drought monitoring and assessment. Some of the approaches developed by implementing Remote sensing data are established well enough for Agricultural drought identification and assessment as well. The assessment of drought probability for agricultural areas in Africa has been well shown by Rojas *et al.* (2011) by coarse resolution NDVI and VHI from NOAA AVHRR. Son *et al.* (2012) illustrated the use of monthly MODIS normalized difference vegetation index (NDVI) and land surface temperature (LST) data to monitor Agricultural drought along with integration to Tropical Rainfall Measuring Mission (TRMM) data.

However, Remote sensing derived techniques solely are inefficient for generating a clear picture on drought studies. It needs to be integrated to other field variables like ground-based climate, hydrological, biophysical and surface datasets. Some unique approaches like collaboration of Remote sensing data to other fields have been also developed to take a step towards accuracy in assessment and prediction of Agricultural drought. As Tsegaye *et al.* (2005) reported that integrated AVHRR NDVI 14 day dataset along with Meteorological drought indices from climate data and some biophysical parameters like land cover, eco-regions etc. to predict drought related vegetation stress over U.S. Central Plains. Uniting Remote sensing data with other variables is a significant approach to have potential outcomes.

2.4. Drought Indices

Drought indices are developed and meant for decision making. It is a value representing the extent of drought, which is used for execution of action during drought. Meteorological and Agricultural drought indices or Remote Sensing data derived drought indices are some of drought indices widely used in the world. Martini *et al.,* (2004) confirmed that no single indicator or index is adequate enough by itself for monitoring drought on regional scale. Instead, a combination of monitoring tools integrated together has been found preferable for producing regional or national maps.

I. Meteorological Drought Indices

Meteorological drought indicators assimilate information on rainfall, stored soil moisture or water supply but they do not express much local spatial detail. Also, drought indices calculated at one location is only valid for single location. Thus, a major drawback of climate based drought indicators is their lack of spatial detail as well as they are dependent on data collected at weather stations which sometimes are sparsely distributed affecting the reliability of the drought indices (Brown *et al.,* 2002). There are several indices that measure how much precipitation for a given period of time has deviated from historically established norms. Some of the widely used meteorological drought indices include Palmer Drought Severity Index (PDSI), Crop Moisture Index (CMI), Standardized Precipitation Index (SPI), and Surface Water Supply Index (SWSI), Standardized Precipitation and Evapotranspiration Index (SPEI).

A. Palmer Drought Severity Index (PDSI)

In 1965 Palmer developed Drought Severity Index for the intention of measuring the degree of cumulative departure in surface water balance which is called The Palmer Drought Severity Index (PSDI). Palmer developed this index based on the supply and demand concept of the water balance equation. According to Palmer (1965) the aim of this equation is to measure the departure of moisture supply for normal condition at specific location The PDSI is based on precipitation and temperature data, on the local Available Water Content (AWC) of the soil and other meteorological parameters. The Palmer Drought Severity Index is a standardized measure, ranging from about −10 (dry) to +10 (wet) with values below −3 representing severe to extreme drought (Dai, 2011a)(Table 2). Although, the palmer index has been widely used, it has some limitations. Among them, limitation of identification of drought at shorter time scale, problem of calibration and spatial compatibility, failure to accurately represent the hydrological impact resulting from longer drought are the major ones (Chopra, 2006; Vicente-Serrano *et al.,* 2010b). In addition the index is highly sensitive to the AWC of a soil type and that there are some difficulties in comparing the results obtained in regions with different water balances (Ashenif, 2016).

Table 2. Palmer drought severity index

Palmer drought severity index	Drought Class
4.0 and more	Extremely wet
3.0 to 3.99	Very wet
2.0 to 2.99	Moderately wet
1.0 to 1.99	Slightly wet
0.5 to 0.99	Incipient wet spell
0.49 to –0.49	Near normal
–0.5 to –0.99	Incipient drought
–1.9 to –1.99	Mild drought
–2.0 to –2.99	Moderate drought
–3.0 to –3.99	Severe drought
–4 or less	Extreme drought

B. Crop Moisture Index (CMI)

As complement to PDSI Palmer (1968) develop an index called the Crop Moisture Index (CMI). It measures the degree to which crop moisture requirements are met, is more responsive to short-term changes in moisture conditions and is not intended to assess long-term droughts. According to Heim (2000) CMI depends on the drought severity at the beginning of the week and the evapo-transpiration, soil deficit or soil moisture recharge during the week. It measures both evapo-transpiration deficits (drought) and excessive wetness (more than enough precipitation to meet evapo-transpiration demand and recharge the soil). CMI is designed to monitor short-term moisture conditions affecting a developing crop; therefore CMI is not a good long-term drought-monitoring tool. The CMI’s rapid response to changing short-term conditions may provide misleading information about long-term conditions (Hasan, 2010).

C. Standard Precipitation Index (SPI)

Standard Precipitation Index, developed by Mckee *et al.* (1993) is the most widely used index for calibrating the magnitude and duration of drought events. Compared with PDSI (Palmer drought severity index), SPI is a more simple tool because it just based on rainfall data and less calculation effort. It allows an analyst to determine the rarity of a drought at a given time scale (temporal resolution) of interest for any rainfall station with historic data. It can also be used to determine periods of anomalously wet events. SPI is used to examine the severity and spatial patterns of drought distribution in a given region (Guttman, 1998 and Thavorntam and Mongkolsawat, 2006). 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.in addition SPI 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. SPI was used to quantify the precipitation deficit in the growing season and analyze the impact of rainfall deficiency on drought development. It has been used in many studies to determine the frequency of precipitation distribution like the effect of the time scales on the drought parameters, and the spatial classification of drought patterns. It is defined as:-

$$\mathrm{SPI} = \{(\mathrm{Xij} - \mathrm{Xim}) / \sigma\} \quad (1)$$

Where, (*Xij*= is the seasonal precipitation and, *Xim* is its long-term seasonal mean and σ is it's standard deviation). SPI results computed from seasonal rainfall data were assigned to each grid cell of the study area, and reclassified based on drought severity classes (Table 3). Positive SPI values indicate the rainfall is greater than median rainfall and negative values indicate less than median rainfall.

Standard Perception Index (SPI) which is a probability index that uses monthly rainfall data as an input was used widely to study metrological drought. Standard perception index is recommended as a meteorological drought index by the World Meteorological Organization (Hayes *et al.*, 2011). In Ethiopia few studies very few studies have been conducted in different part of Ethiopia to analyses drought using Standard perception index. Temporal and spatial analysis of metrological and hydrological drought for the Awash Basin of Ethiopia was studied by Desalegn *et al*. (2010). The study showed the potential benefits of SPI for drought assessment and examined the lag time between the hydrological and metrological drought. Similarly Tagel *et al* (2011) evaluated the spatial and temporal variability of drought using SPI and vegetation index for the Tigray zone located in the highland of Ethiopia. The study demonstrated that the large part of the study area is prone to drought. In south Wollo drought magnitude, frequency, trend, patterns and probability of was examined using SPI (Yimer *et al*., 2018). The result showed that most of the studied stations experienced drought episodes in 1984, 1987/1988, 1992/1993, 1999, 2003/2004 and 2007/2008 which were among the worst drought years in the history of Ethiopia. According to the result SPI is a very important tool for quantifying drought and comparing its characteristics over time and space. By applying NDVI, SPI and WRSI indices, the actual impacts of the drought on the agricultural activities of west Hararge Zone's farming communities have been thoroughly investigated and analyzed (Wondwosan, 2017). In line with this result 2005 and 2009 were identified as drought years in East Shewa Zone using SPI as a tool (Hurgesa, 2016). This finding is again in agreement with Gizachew and Suryabhagavan (2014). In the same way, 2012 and 2008 were identified as relatively wet years using SPI result. Generally few study conducted using SPI in Ethiopia shows that SPI is an important index to identify historical drought patterns. In support of this idea Mishra and Singh (2010) SPI is widely used around the world for drought forecasting, frequency analysis, spatial-temporal analysis and climate impact studies

Table 3: Drought classification by standardized precipitation index (SPI) value

SPI values	Drought category
<−2.00 and less	Extreme drought
−1.50 to −1.99	Severe drought
−1.00 to −1.49	Moderate drought
0 to −0.99 Near	Normal or mild drought
Above 0	No drought

D. Standard Precipitation and Evapotranspiration Index (SPEI)

The main factor influencing drought is precipitation; although other factors such as air temperature, ET, wind speed, and soil water holding capacity can also influence drought (Vicente-Serrano *et al.,* 2010b). The SPI can detect wet and dry events occurring simultaneously at different time-scales. However, the main shortcoming of SPI is that it uses only one climate variable (rainfall) for monitoring droughts (Sivakumar *et al.,* 2011; Vicente-Serrano *et al.,* 2012). To overcome the shortcomings of SPI, Vicente-Serrano et al. (2010) develop a new drought index: the Standardized Precipitation Evapo-transpiration Index (SPEI), which depends on the potential evapotranspiration (PET). The Standardized Precipitation Evapo-transpiration Index (SPEI) is a modification of the SPI. Similarly to the PDSI, the SPEI also accounts for the effect of temperature variability in the monitoring of droughts, and like the SPI, it can be computed at different time scales. Therefore the Standardized Precipitation Evapo-transpiration Index can be used to detect the temporal and geographical extension of droughts, and this makes it a good tool for drought analysis and monitoring.

II. Satellite Derived Drought Indices

Remote sensing and GIS technique is increasingly being regarded as a useful drought detection technique, as evidenced by its use across many parts of the world, e.g. Gujarat, India (Chopra, 2006), Western and Central Kansas, USA (Park *et al.,* 2004), Batticaloa District, Srilanka

(Partheepan and Dayawansa, 2008) and Borkhar District, Iran (Moktari, 2005), Ethiopia (Wondwosan, 2017; Gizachew and Suryabhagavan (2014) in East Shewa Zone. With the advancements in Remote sensing technology, the historical drought indices were over powered by the newly developed indices from Remote sensing data. Due to lack of spatial detail from station based drought indicators, satellite based derived indices widely used for drought assessment. Satellite derived drought indicators calculated from satellite-derived surface parameters have been widely used to study droughts. According to Jeyaseelan (2004) 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 . Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), and Temperature Condition Index (TCI) are some of the extensively used vegetation indices.

A. Normalized Difference Vegetation Index (NDVI)

Since 1979 Normalize vegetation index has been considered as the most important index for mapping agricultural drought areas (Sumanta *et al.*, 2013; Nithya and Suja Rose, 2014). Normalized difference vegetation index reflects vegetation vigor (Teillet *et al.,* 1997), green cover percent, Leaf Area Index (LAI) (Baret and Guyot, 1991) and biomass (Thenkabail *et al.*, 2004). As Tucker (1987) reported two characteristics of the NDVI that make it ideal for vegetation monitoring are that no other surface exhibits higher NDVI values than vegetated surfaces and that, when vegetation vigor changes due to the nature of vegetation growth and development or environmental induced stress such as drought, the NDVI also changes. Currently, NDVI is the most commonly used indicator that is sufficiently stable to permit meaningful comparisons of seasonal, inter-annual, and long-term variations of vegetation structure, phenology, and biophysical parameters (Tucker and Sellers, 1986).

The use of NDVI-based indices for monitoring and detecting drought is justified on the basis that vegetation vigor is closely related to moisture condition (Di *et al.,* 1994; Rundquist *et al.,* 2000; Legasse, 2010; Getachew, 2013; Gizachew and Suryabhagavan, 2014). In support of this finding Wang, *et al.* (2003) reported that there is a direct correlation between NDVI and the amount of stress vegetation is experiencing. NDVI is based on Computational result from the satellite image using spectral radiance in red and near infrared reflectance using the formula (Eq2). The 'rationing' properties of the NDVI enable this index to cancel out a large proportion of signal variations attributed to calibration, noise, and changing irradiance conditions that accompany changing sun angles, topography, clouds/shadow and atmospheric conditions (Brown *et al.*, 2008).

$$\text{NDVI} = \frac{NIR-R}{NIR+R} \qquad (2)$$

Where, NIR= near infrared band, R= Red band

Equation 2 illustrates NDVI is a nonlinear function that varies between -1 and +1, and the values of NDVI for vegetated land generally range from about 0.1 to 0.7, with values greater than 0.5 indicating dense vegetation (Sruthi and Mohammed , 2015). The relationship between NDVI and rainfall varies spatially, primarily due to the effects of variation in properties such as vegetation type and soil background, with the sensitivity of NDVI values to fluctuations in rainfall, therefore, showing a notable variation regionally (Tornros and Menzel, 2014). Studies performed in arid and semi-arid regions of east Africa (Nicholson and Farrar, 1990) pointed out that precipitation has the primarily influence on NDVI. In support of this finding Nicholson and Farrar (1990) claim that NDVI responds to rainfall with certain time lag from 1 to 12 weeks (1 to 3 months), reflecting the delay in vegetation development after rain. The lag can vary depending on both climatic and non-climatic factors such as air and soil temperature, evaporation, soil or vegetation type. There are a lot of papers written on the use of NDVI data products for agricultural vulnerability to climate change in Ethiopia Wondwosen (2017) for instance, had assessed the agricultural drought risk zone, using NDVI data products and the results were discussed presence of spatio-temporal variability at zonal level of West Harerga. Likewise Eshetu (2017) assessed the severity of drought using long term mean values of maximum NDVI in North Wollo Zone Ethiopia. Thus, the study results show that NDVI has been confirmed to be the best measure of correlation between rainfall and vegetation growth. Thus, NDVI have a potential in drought detection and climate impact assessment.

B. Vegetation Condition Index (VCI)

Satellite based monitoring can play an important role in vegetation monitoring. Vegetation condition index was first suggested by Kogan (1995). In using NDVI as means of agricultural drought assessment, scientific communities identified two limitations. Firstly, Thomas *et al*. (2004) conclude that different vegetation has different relationship between chlorophyll content and vegetation water condition. Secondly, when there are extensive periods of cloud coverage, the NDVI values tend to be depressed giving a wrong conclusion about drought condition (Tsegaye, 1998). In order to address limitations associated with NDVI, Kogan (1995) suggested Vegetation Condition Index for identifying drought related vegetation stress and impacts of drought on overall vegetation condition Drought monitoring algorithm also considers separation of the short-term weather-related NDVI fluctuations from the long-term ecosystem changes (Kogan,1995). Although the NDVI has been extensively used in the past for vegetation monitoring, it is often very difficult to interpret in relation to vegetation condition, especially when comparing different ecosystems. This is a very important procedure because the weather signal in an NDVI value is weaker than the ecological one. Therefore, weather-related NDVI fluctuations are not easily detectable. The weather-related NDVI, to 100, maximum NDVI for each grid cell and week. The resulting component was named the vegetation condition index (VCI) and was defined by the following expression:

$$\mathrm{VCIj} = \frac{(\mathrm{NDVIj} - \mathrm{NDVImin}) \times 100}{\mathrm{NDVImax} - \mathrm{NDVImin}} \qquad (3)$$

Where, $NDVI_{max}$ and $NDVI_{min}$ are calculated from the long-term record for that month, and j is the index of the current month.

The Vegetation condition index approximates the weather component in NDVI value. It changes from 0 to 100, corresponding to the changes in vegetation conditions from extremely bad to optimal. The range of VCI values appropriate for drought analysis from 0% to 35% was accepted as VCI derived drought indicators (Kogan, 1995). It shows how close the NDVI of the current month or week (j) is to the minimum NDVI calculated from the long-term record (NDVI max and NDVI min) for that month (week). The condition/health of the ground vegetation presented by VCI is measured in percent. A value around 50% reflect fair vegetation conditions, values between 50 and 100% indicate optimal or above normal conditions. Different degrees of Severity are indicated by VCI values below 50% (Kogan, 1995).

The VCI captures rainfall dynamics better than the NDVI particularly in geographically non homogeneous areas. The VCI not only permits the description of land cover and spatial and temporal vegetation change but also allows quantifying the impact of weather on vegetation. Also the VCI makes it possible for one to compare the weather impact in areas with different ecological and economical resources. VCI values indicate easily how much the vegetation has advanced or deteriorated in response to weather and how far vegetation development is from the potential maximum and minimum defined by ecological limits.

C. Temperature Condition Index (TCI)

Temperature Condition Index was developed to reflect vegetation response temperature i.e. higher temperature the more extreme the drought. It is based on the brightness temperature and represents the deviation of the current month's value from the record maximum.it was expressed by the following formula:

$$TCIj = \frac{(YTmax - YTj)}{(YTmax - YTmin)} \times 100 \qquad (4)$$

Where, YT is brightness temperature. Maximum and minimum YT is values are calculated from the long term record of remote sensing image for a particular period j. Low TCI values indicate very hot weather. There for TCI was very useful to assess special characteristics, the duration and severity of drought in Argentina and was a good agreement in precipitation patterns (Seiler *et al*., 1998). In line with this Konga (1998) reported that TCI has been related to recent regional scale drought pattern in South Africa.

CHAPTER THREE

MATERIALS AND METHODS

3.1. Description of Study Area

3.1.1. Location

This study was conducted in Waghimra Zone Easter part of Amhara national Regional state, Ethiopia. It is located 435 km far from Bahir Dar, and 720 km from Addis Ababa Geographically Waghimra Zone is located between 12^{o} $15^{'}$–13^{o} $16^{'}$ N latitude and $38^{o}20^{'}$–39^{o} $17^{'}$ E longitude covering a total area of 9,039.04 km^2(Fig 2).

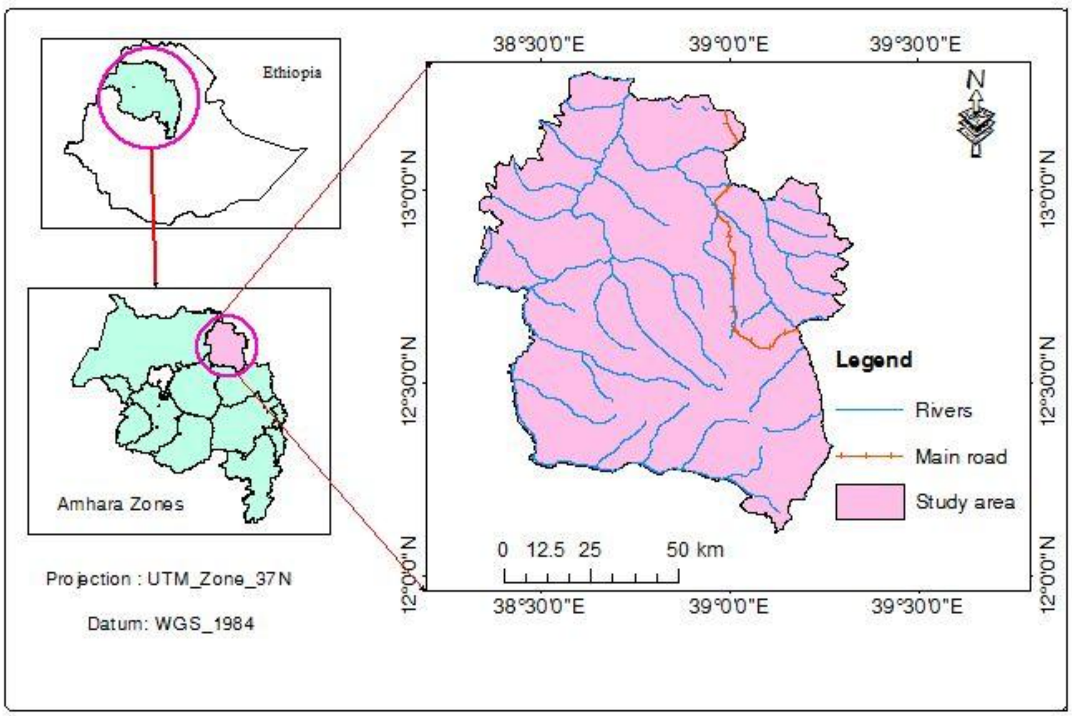

Figure 2. Location map of the study area

3.1.2. Topography and Climate

Study area comprises three major ecological zone: highlands or *dega* (above 2300 masl), midlands or *weina dega* (1500–2300 m asl) and lowlands or *kola* (500–1500 m asl), which constitute 4.6, 66.2 and 29.2 per cent of the total area of the zone, respectively. The most common features of the zone are its rugged topography characterized by mountains, steep escarpments and deeply incised valleys (Berhanu, 2012). The altitudinal range of the agro-climatic zones fall between 989 and 4043 m asl (Fig 3).

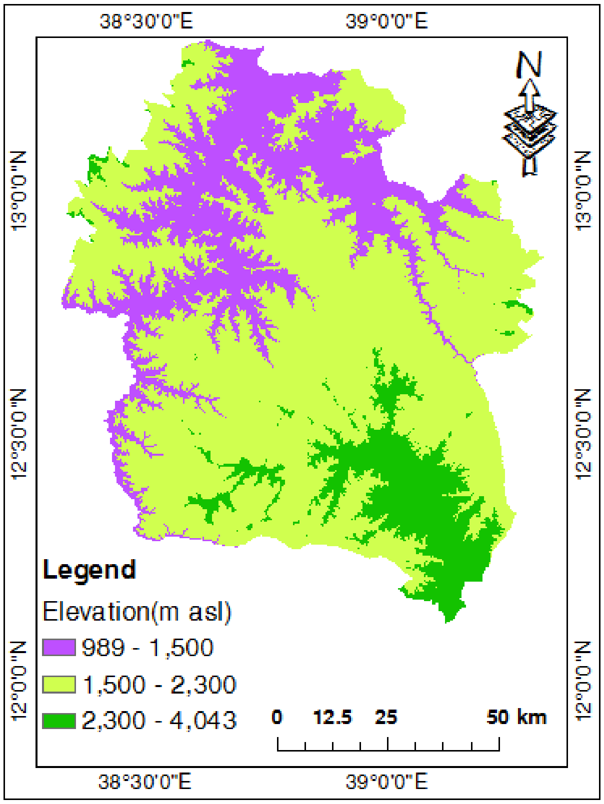

Figure 3. Elevation map

The climate variability of the study area is governed by the topography of the area. The area has a mean annual temperature ranging between 15 to 40°C the bimodal rainfall pattern with a short rainy season “Belg” from February to March and long rainy season “Kiremt” from June to September with peak in August. It has a mean annual rainfall of 150 to 700 mm in which the highest rainfall occur during summer season which starts in mid-June and ends in early September. The rainfall pattern in the area is relatively erratic and unpredictable. Such an erratic nature of rainfall distribution has been contributing factor to the decline in crop production which affects most farmers in study area (NMSA, 1996).

3.1.3. Major Soil Types and Vegetation

According to information obtained from FAO (1997) Ethiopian soil digital data confirm that the major soils of zone are characterized by *Cambisols*, *Luvisols* and *Leptosols* which constituent 19.89, 16.6 and 63.51%, respectively (Fig 4). The wide diversity in climate, topography and vegetation in the area has given rise to marked variation in soils. As shown in (Fig 4) *Leptosls* which is very shallow profile depth and widespread in mountains area is the dominate soil class found in study area (FAO, 1997).

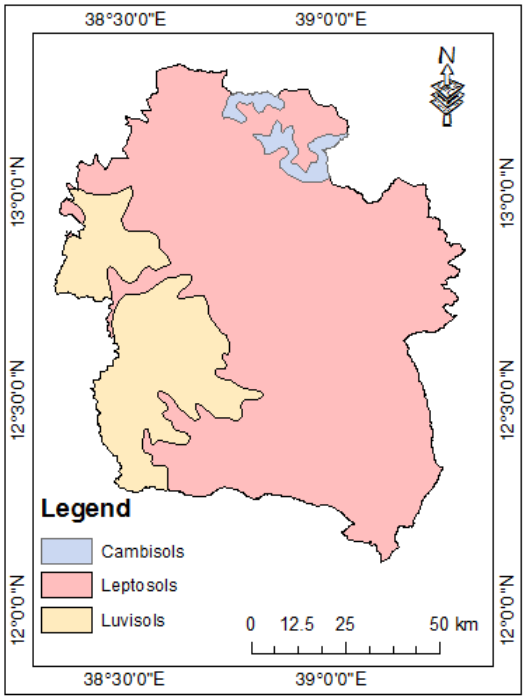

Figure 4. Soil map

Land-use pattern which is an important factor influence agricultural production is closely related to climate and topography. The natural vegetation is diverse and reveals successions of species based on altitude. This is the fact that much of natural vegetation has been destroyed or altered by prolonged cultivation and human settlements. Spare vegetation and mixture of shrub and grassland are found in hilly areas. Cultivated land, grassland, shrub/bush land, forest and water body are the dominant land use land cover types found in study area.

3.1.4. Population

Based on result from central statics agency report of 2013 population projection for year 2017 Waghimra Zone has a total population of 509,897. The sex composition indicts that 254,715 and 255,182 were male and female, respectively of whom 10 and 90 percent are urban and rural inhabitants, respectively. With an area of 9038.04 km^2 this zone has population density of 56 people per km^2. The major ethnic composition of the zone is Kamyr/Agaw (52.92%), Amhara (45.45%), and Tigrayan (1.39%) and all other ethnic groups consist of 0.24% of the total population. The three predominant languages spoken in study area are Amharic (56.27%), Kamyr (41.82%) and Tigrinya (1.67%). population density of study area ranges from 24 to 386 persons per square kilometer (Fig 5).

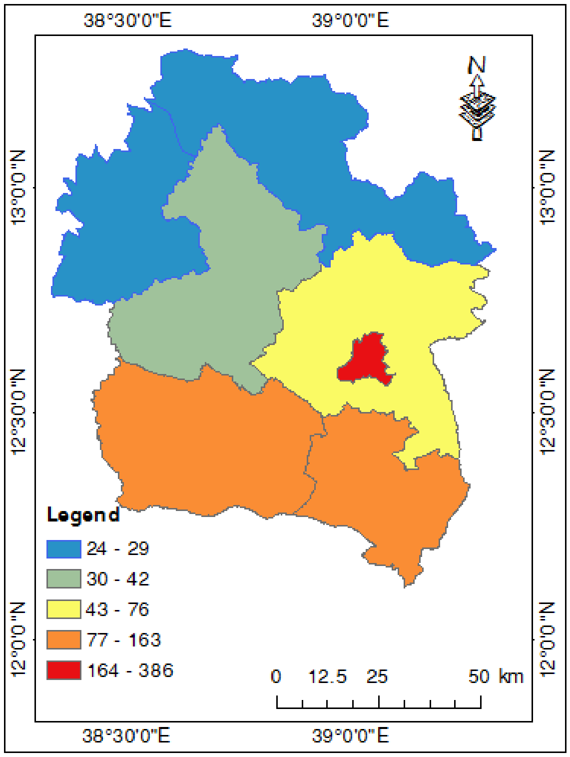

Figure 5. Population density (persons/squ.km) map

3.1.5. Major Economic Activity

The main economic activity of the area is rain fed agriculture, with a subsistence mixing farming system. Like other parts of the region the farming technique used by most farmers are traditional and the dominate farming system are crop livestock mixed farming. Land and livestock are therefore the most important livelihood assets. Cattle, small ruminant, poultry and equines are the major livestock species kept in the Zone (unpublished report of WZLFRD,2016/17) while Barley, Sorghum, Teff , Pea Wheat , Bean Oil crop Cowpea are the major crops produced in large quantity in study area.

3.2. Data acquisition, Source and Software package

3.2.1. Software package

The following software packages were used at different stage of study

Table 4. Software package used

Type	Data type	Purpose
ArcGIS 10.5	NDVI, SPI,VCI	Statistical analysis and graphical display
ERDAS Imagine 2014	LU/LC	Image processing, LULC classification
Microsoft Excel 10	Rainfall, GPS point and crop data	Data processing, graphical display
Google Earth	LULC	Reference or control point collection
SPI version 6	Rainfall	SPI calculation

3.2.2. Data Source and Method of Data collection

Data were collected from both primary and secondary sources to answer the research objective. Primary data were collected from primary sources such as from informal interview and field observation while secondary data were collected from secondary sources such as satellite image, metrological data, journal articles, books and unpublished documents such as extension package manuals and reports from the Zonal office.

Table 5. Data used for this study

			Resolution			
Data sets	**Variable**	**Description**	**Spatial**	**Temporal**	**Period**	**Source**
eMODIS NDVI image	NDVI/VCI	Satellite	250 m	Daily	2000 to 2016	USGS
Agricultural data	Yield	Ground data	Quintal/Ha	Year	2000 to 2016	Zonal
Metrological Data	Rainfall	Ground data	Average mm	Monthly	2000 to 2016	NMSA
Landsat ETM $^{+}$	Land-use /land-cover	Satellite/ground	30 m	Monthly	2016	USGS

3.2.2.1. Satellite Data Acquisition

The Moderate Resolution Imaging Spectro radiometrer (MODIS), launched on NASA's Earth observing system(EOS) terra satellite on December 18,1999 provides a comprehensive series of global observations of the earth's land, ocean, atmosphere and for satellite measurements of global land surface temperature (LST) in the visible and infrared regions of the spectrum (Hasan Murad, 2010). Moderate Resolution Image Spectrometer (MODIS) instrument is operating on both Terra and Aqua spacecraft. It has a viewing swath width of 2330Km and views the entire surface of the earth every one to two days. The sensor acquires data on 36 spectral bands at three spatial resolutions: 250 m, 500 m and 1000 m. It has temporal resolution of 32 days and is available since 2000 till present. The 36 MODIS bands are a compromise of atmospheric, land and ocean studies of which seven bands are considered optimal for land applications (Justice *et al*., 2002).

Moderate Resolution Image Spectrometer (MODIS) data have more frequent repeat cycle than Landsat and higher spatial resolution than the Advanced Very High Resolution Spectro-radiometer (AVHRR) is well suited for vegetation studies. According to Huete *et al*. (2002) report MODIS is more sensitive to changes in vegetation dynamics. It was found to be a more accurate and versatile instrument to monitor the global vegetation conditions than the AVHRR (Gitelson and Kaufman, 1998; Justice *et al.,* 2002).

However, the benefit of MODIS are countered by usability issues with the standard map projection, file format, composite interval, high latitude "bow-tie" effect, and production latency. Enhanced/expedited/expandable MODIS data (eMODIS) respond to a community specific need for alternative packaged MODIS data, addressing each of these factors for real time monitoring and historical trend analysis (Jenkerson *et al*., 2010). In line with this Brown *et al*,(2015) confirm that When "eMODIS" Normalized vegetation index (NDVI) were compared to standard MODIS(MOD/MYD09Q1) it maintained a strong, significant relationship to standard MODIS NDVI, whether from morning(Terra) or afternoon (Aqua) orbits (Table 6). Similarly Jesslyn *et al*. (2015) reported that eMODIS provides rapid MODIS surface reflectance data to operational application in less than 24 hours offering tailored, consistently processed information products that complement standard MODIS products.

For this study an expedited MODIS (eMODIS) NDVI Terra image at 250m spatial resolution were used to monitor vegetation condition. eMODIS product includes either 7 or 10 day composited data sets. The 7 day interval is over continental US and every five day for 10 day product in other areas using the last interval of input (https://www.usgs-eros-archive-vegetation-monitoring). In Africa continent where this study site is located interval of the real time and historical NDVI products were composited in 10 day intervals (every 5 days are available at https://earthexplorer.usgs.gov website) from the period of June to September from 2000 to

2017). Enhanced/expedited/expandable MODIS data (eMODIS) data provides separate Geostationary Earth Orbit Tagged Image File Format (GeoTIFF) for each product in a 10 day interval, allowing the users to download only the files they need. For example, the eMODIS NDVI imagery for the month of June 2015 includes NDVI data from June 1st-10th, 6th-15th, 11th-20th, 16th-25th, 21st-30th, and 26th-July 5th (Eddy, 2016 as cited Munavar *et al*., 2018). In this study 21^{st} to 30^{th} day interval of eMODIS NDVI imagery were taken for analysis purpose in growing season of crops. The NDVI and every reflectance bands have five associated files which are data, quality, metadata, and acquisitions image and acquisition table. These data were directly downloadable free from https://earthexplorer.usgs.gov from the period of June to September from 2000 to 2016 which represent the crop growing season in study area.

Table 6. Selected product Differences for standard Moderate resolution imaging Radiometer (MODIS) and expedited MODIS (eMODIS) NDVI products

Characteristics	Standard MODIS	eMODIS
Product latency	6-10 days	6-10hrs
Image geometric processing	Sinusoidal grid, requires resampling, re-projection	Single resampling , directly from swath
Coverage	Tiled map coverage	Tailord coverage(national or continental)
Composite interval	16 –days composite periods	7/10 day composite period
Format	HDF-EOS	Geotiff

Source: Jesslyn *et al*. (2015).

3.2.2.2. Metrological data

Monthly rainfall data recorded for 17 years (from year of 2000 to 2016) were collected from national metrological agency. In this study 14 stations which are unevenly distributed both within and around study area have been used (Fig 6). Rainfall data was used to analyses relation between NDVI with variability of rainfall and to drive standard precipitation index (SPI). In addition seasonal rainfall map was prepared from latitude/longitude files of those stations (Appendix 2).

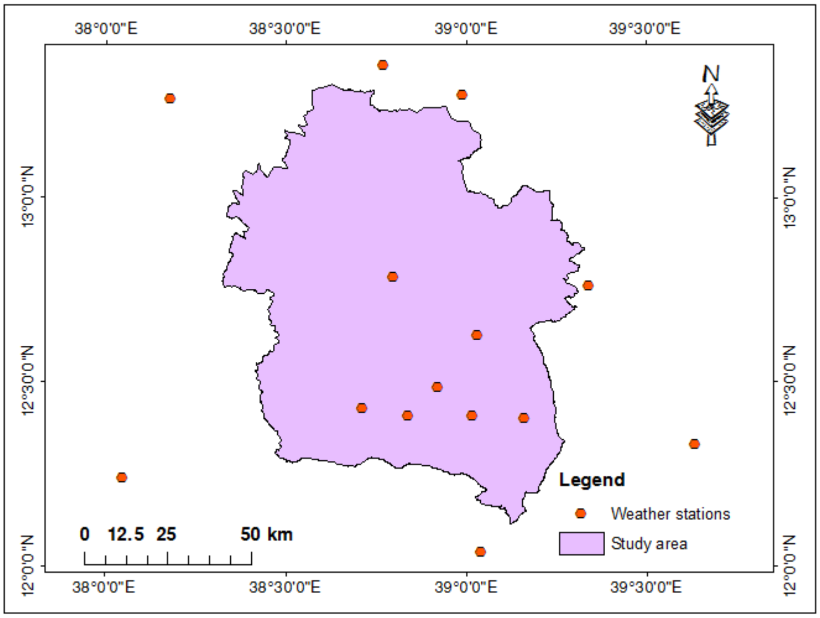

Figure 6. Weather station map

3.2.2.3. Ancillary data

a. Crop yield

To validate satellite derived indices ground truth data was taken. The data that were taken in this study area was agricultural production yield. "Average yield of grain crops for country's administrative regions can be used for validation of satellite-derived droughts" (Kogan, 1997). Because agricultural yields area sensitive to weather fluctuations, it reduces during severe drought periods. For this study agricultural yield data or ground truth data was collected from Waghimra Zone Agricultural office from period of 2000 to 2016. In addition Different information related to agricultural drought hazard and their impacts on agricultural activities as well as cropping practices was collected from different scientific papers, journal, Ministry of Agriculture, Zonal and Woreda agricultural and rural development office, early warning and food security bureaus and informal interview with zonal agriculture office experts.

b. Land-use/land-cover

To understand type and spatial distribution of land-use/land-cover in study area land-use land-cover map were prepared from land sat image of year 2016. Image was classified in to different land-uses. Majority of study area (51%) were covered by cultivated/settlement land. While, forest and bush/shrub land covers 7 and 13.5%, respectively. The rest were occupied by water body, grass and bare land which cover 1%, 21% and 5%, respectively)(Appendix 1). This figure indicates that there is scarce vegetation coverage in study area. As confirmed in field observation and informal interview because of presence of population pressure in the area there rapid land use/ land cover change in addition steep slopes which area unsuitable for cultivation were changed to cultivated land (Fig 7).

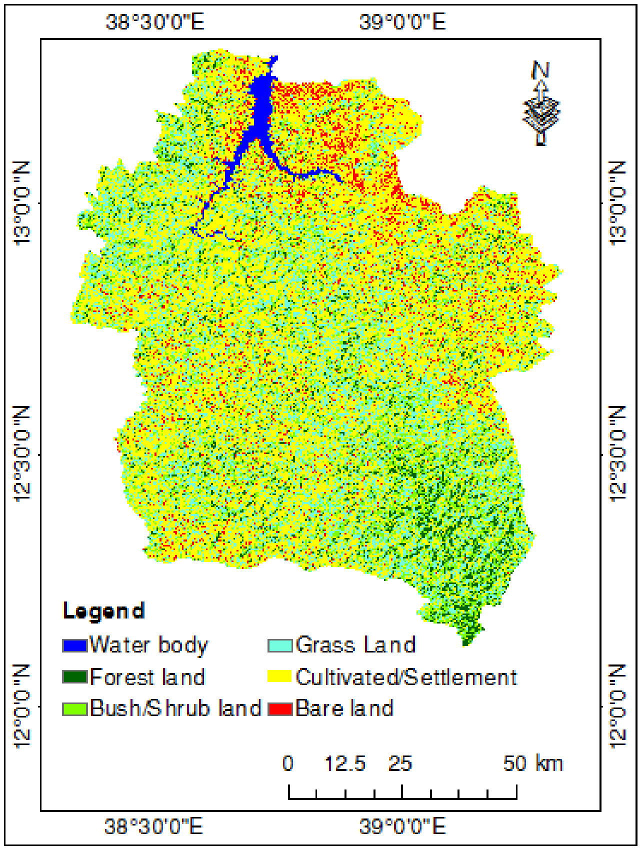

Figure 7. Land-use/land-cover map

3.3. Data Processing and Analysis

3.3.1. Satellite Data Processing and Analysis

The Earth Resource Observation and Science (EROS) moderate resolution imaging spectro-radiometer (eMODIS) NDVI Terra data of African content in a geographic projection which have spatial resolution of 250m were used for this study. Since this study aims to assess agricultural drought only data for crop growing season months from June to September in the 17 years period (2000 to 2016) were downloaded from https://earthexplorer.usgs.gov website. One weekly or 10 day's composite eMODIS data sets include NDVI, quality, acquisition image, and acquisition table and metadata files. In this study NDVI and quality data has been used to calculate NDVI metrics. Quality files have been used to get the reliability of eMODIS NDVI image product which is computed in ArcGIS 10.5 spatial analysis tool in map algebra (Equation 6).

$$\text{Reliable NDVI} = (\text{QC} == 0) * (\text{NDVI} > 2000) * \text{NDVI} \qquad (6)$$

Where, reliable NDVI=reliable NDVI image which have values range from 0 to 10000, QC = quality image which have values from 0 to 10 where 0 is good values and 10 is fill values, NDVI is image which have values ranges from -2000 to 10,000 where -2000 is fill values and -1999 to 10,000 is valid range. After applying scale factor (the scale factor is 0.0001) NDVI values range from –0.2 to 1.0 where valid or normal NDVI ranges from 0.0 to 1.0(Jiang Zhu *et al.*, 2013). (Equation 7)

$$Normal\ NDVI = Reliable\ NDVI * 0.0001 \qquad 7$$

Expedited MODIS (eMODIS) composite are projected to non-Sinusoidal projection that suit the geography in their area of application (Calli Jenkerson *et al.*, 2010). After re-projection eMODIS NDVI image from GCS_WGS_1984 to UTM projection (UTM, Zone 37N) study area were extracted with shape file of study area using extract by mask tool set of ArcGIS 10.5. Time series NDVI variation was derived from the calculation of NDVI using the eMODIS NDVI data set for the year 2000 to 2016 and also used to generate the max, min, average NDVI values of each season for the year 2000 to 2016 using ArcGIS 10.5 environment spatial analysis tool. Based on the threshold value Vegetation Condition Index and Normalized Vegetation Index anomaly was computed. To determine average value of monthly and seasonal composites of NDVI values, float (math) and cell statistics toolset of ArcGIS 10.5 were applied.

I. Vegetation Condition Index (VCI)

Satellite based monitoring can play an important role in vegetation monitoring. The vegetation condition index, which was first suggested by Kogan (1995), reflects the overall effect of rainfall, soil moisture, weather and agricultural practices. According to the author the drought monitoring algorithm also considers separation of the short-term weather related NDVI fluctuations from the long-term ecosystem changes. NDVI has been extensively used in the past for vegetation monitoring; it is often very difficult to interpret in relation to vegetation condition, especially when comparing different ecosystems. The vegetation condition index reflects the overall effect of rainfall, soil moisture, weather and agricultural practices. In area like Waghimra which have different ecosystems and non-homogenous topography VCI is important for one to compare the weather impact in areas with different ecological and economical resources, since the index captures rainfall dynamics better than the NDVI particularly in geographically non homogeneous areas. It permits the description of land cover and spatial and temporal vegetation change, but also allows quantifying the impact of weather on vegetation. The values indicate easily how much the vegetation has advanced or deteriorated in response to weather and how far vegetation development is from the potential maximum and minimum defined by ecological limits.

However, The VCI has been used to estimate the climate impact on vegetation. This index is most useful during the growing season because it is a measure of vegetation vigor. When the vegetation is dormant (not in the summer season), the VCI cannot be used to measure moisture stress or drought. Anything that stresses the vegetation including insects, disease, and lack of nutrients will result in decreases in plant growth and therefore lower VCI values. Also, areas that have significant irrigation may not respond to precipitation deficiencies (Quiring *et al*., 2003). For each monthly and seasonal NDVI image, VCI will be processed from 2000 to 2017 using the ArcGIS raster calculator (Equation 8).

$$\mathrm{VCIj} = \frac{(\mathrm{NDVIj} - \mathrm{NDVImin})*100}{\mathrm{NDVImax} - \mathrm{NDVImin}} \qquad (8)$$

Where, $NDVI_{max}$ and $NDVI_{min}$ are calculated from the long-term record for that month, and j is the index of the current month in ArcGIS cell statistics.

VCI value is being measured in percentage ranging from 1 to 100. The VCI values between 50% and 100% indicates slight or optimal/normal conditions whereas VCI values close to zero percent reflects an extreme dry season (Thenkabail, 2004).The VCI was reclassified into five clusters as shown in (Table 7).

Table 7. Classification of VCI values in terms of drought

VCI value (%)	Category
0 to 20	Very Severe drought
21 to 35	Severe drought
36 to 50	Moderate drought
51 to 60	Slightly drought
61 and above	Optimum/normal

II. Normalize Vegetation Index (NDVI) Anomaly

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

$$NDVI\ Anomaly\ i = \left[\frac{\text{NDVI max i} - \text{Mean NDVI max}}{(\text{Mean NDVI max})}\right] * 100 \qquad 9$$

Where, NDVI max i = Maximum NDVI in the growing season in i^{th} year, Mean NDVI max = long term mean maximum NDVI in the growing season.

To determine the average values of seasonal composites of NDVI value, Float (Math) and cell statistics toolset of ArcGIS 10.5 were applied after computation of major cell statistics (mean, minimum, maximum). NDVI anomaly based drought severity class was reclassified (Table 8).

Table 8. Classification of NDVI anomaly in terms of drought severity

NDVI anomaly (%)	**Drought severity class**
Above 0	No drought
0 to –10	Slight drought
–10 to –25	Moderate drought
–25 to –50	Severe drought
Below –50	Very Severe drought

3.3.2. Crop Yield Anomaly

Agricultural yields area sensitive to weather fluctuations, it will reduce during severe drought periods. NDVI has been extensively used for vegetation monitoring, crop yield assessment and drought detection. Since NDVI takes advantage of the reflective and absorptive characteristics of plants in the red and near –infrared portions of the electromagnetic spectrum and has been used in research on vegetation yield and productivity, crop yield has also been correlated to NDVI. To quantify impact of metrological drought on production of major crops correlation between SPI and zonal level crop yields will be analyzed. Yield trend will be computed to see for the yield trend over last 17 years (2000–2017). Yield anomaly has been calculated in the same way as the computation of NDVI anomaly. Yield anomaly is computed using the following equation (Hasan, 2010)

$$Ya = ((\frac{Yi-Yt}{yt}) * 100) \quad 10$$

Where, Ya is yield anomaly; Yi is yield in a particular year; Yt is yield trend in 17 years

3.3.3. Standardized Precipitation Index (SPI)

In this study the SPI values at two time-scales, i.e. 3 months (SPI-3) was computed. The SPI-3 was used to assess droughts during spring (belg) and summer (kiremt) seasons which represent the shorter and longer rain seasons, respectively. They defined SPI as the number of deviation that the observed value would deviate from the long term mean, for a normally distributed random variable. Seasonal rainfall data have been used as an input to compute the SPI for the periods 2000 – 2016. For this study computer software have been used to compute value of SPI. The software automatically calculates SPI value by using observed monthly rainfall data to detect historical drought at 1, 3, 6, 9, 12, 36 and 48 months' time scale. It is freely available at (https://drought.unl.edu/droughtmonitoring/SPI/SPIProgram.aspx) website. Since the precipitation is not normally distributed, a transformation is first applied so that the transformed precipitation values follows normal distribution. In this case, the positive value of SPI indicates wet conditions while the negative signifies drought condition. The spatial extent of drought in study area were interpolated by inverse distance weight(IDW) method using the spatial analysis tool of ArcGIS 10.5.IDW interpolation explicitly implements the assumption that things that area close to one other are more like than those that are further apart (ArcGIS 10.5). The interpolated maps have been reclassified into different drought severity classes.

3.3.4. Regression analysis of crop yield anomaly with drought indices

After computation of each drought index separately correlation and regression analysis was computed. Since, in this study satellite and metrological data was the main input for processing and analysis of drought in study area. Time series NDVI, VCI and NDVI anomaly were used to detect agricultural drought and SPI indices were applied to analysis metrological drought. Correlation and regression techniques were used to verify if there is a correlation between NDVI and rainfall pattern in Waghimra Zone from 2000 to 2016.VCI and NDVI anomaly was correlated with crop yield. Linear regression between SPI and crop yield for the study area were computed.

3.3.5. Drought Vulnerable Assessment

In this study the seasonal frequency maps derived from agricultural and metrological drought indices were reclassified into common scale based on the frequency of drought occurrence. To generate drought frequency map each drought indices have been reclassified in to binary images for each of the drought severity class. Those maps are added to obtain the frequency of slight, moderate, severe and very severe drought occurrence at each pixel level for both agricultural and metrological drought (Appendix 5 and 6). The resultant severity maps were then added to get agricultural and metrological drought risk maps (Appendix 7).

The probability of drought occurrence in a given area can be classified into high, moderate and low drought probability zones when drought occurs in more than 50 percent, 30 to 50 percent and less than 30 percent of the years, respectively (Lemma (1996) as cited in Gizachew and Suryabhavan (2014)). Based on these criteria, the frequency maps of each drought classes are reclassified into five classes based on the frequency of drought occurrence in study periods: 0-2 classified as no drought; 3-4 as slight drought; 5-8 as moderate drought; 9-13 as severe drought; 13-16 as very severe drought. Finally, maps from agricultural and meteorological drought frequency maps were weighted according to the percentage of influence, and then combined using weighted overly analysis.

A schematic presentation of the methodology that has been followed is mentioned (Fig 8)

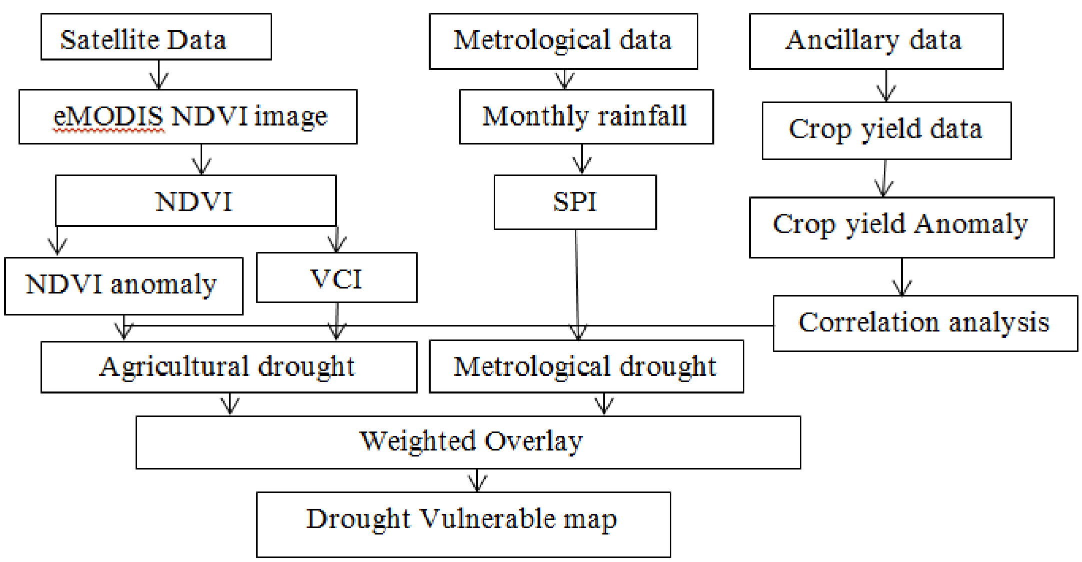

Figure 8. A schematic presentation of the methodology

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1. Relationship between Seasonal Rainfall and Normalized Vegetation Index (NDVI)

Season pattern of rainfall and vegetation condition were analyzed from year of 2000 to 2016 in study area. The results revealed that there is a good correlation (r=0.71) between rainfall and NDVI (Fig 9). The result of this finding is in line with the finding of Eshetu *et al.* (2017) and Hurgasa *et al*. (2016) who have reported that there is a good correlation between NDVI and Season rainfall. In the study period seasonal pattern of NDVI is increased proportional to seasonal rainfall increase (Fig 10). This does not mean that they are exactly increased similar pattern. There were slight year to year variation in both long term NDVI and seasonal rainfall (Fig 10). For instance, in year 2003 and 2012 there is good amount of rainfall however stressed vegetation was observed. The time interval between a precipitation event and the time when precipitated water reach plant root and affect plant growth can vary from 1 to 12 weeks depending on vegetation and soil type (Li *et al*., 2002). This causes existence of variability in relation between two variables. This indicates that it is possible to generalize that in all 17 years 51% of NDVI variability can be explained by seasonal rainfall. Whereas, a study conducted in East Shewa zone by Gizachew and Suryabhagavan (2010) for the period between 1996 to 2008 has reported that 42% of NDVI variability was explained by seasonal rainfall. Accordingly, in study area temporal variation of rain fall distribution is one of the major factors affecting the response of vegetation.

From year of 2000 to 2016 the highest NDVI was observed when seasonal rainfall was in better distribution (Fig11). While, lower NDVI was observed when amount and distribution of rainfall was minimum. Highly rainfall dependent country's like Ethiopia the amount and distribution of rainfall during cropping season are more critical and determinates (Kinde and Walker, 2004). According to the result year 2009 and 2015 were considered as drought year in which minimum NDVI was observed and rainfall was registered. While, in year 2001 and 2007 maximum rainfall and NDVI was observed and considered as wet year (Fig 10). NDVI which indicates greens of vegetation has strong relation with seasonal rainfall thus NDVI can be used as an indicator for drought (Gaikwad *et al*., 2015).

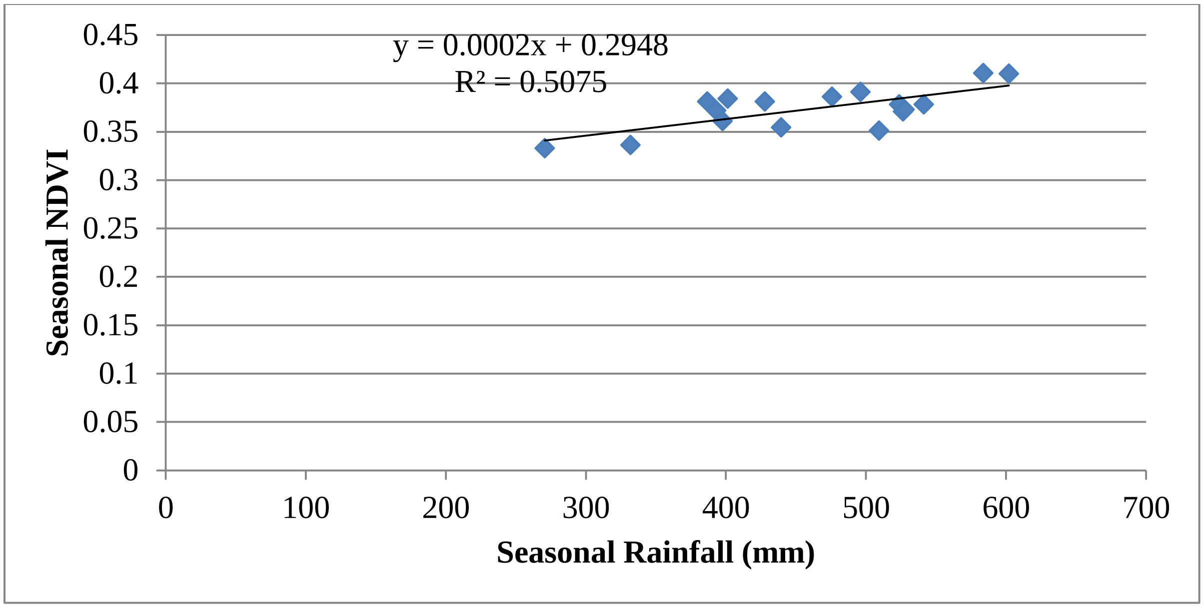

Figure 9.Seasonal (June to September) pattern of Rainfall and NDVI (2000 to 2016)

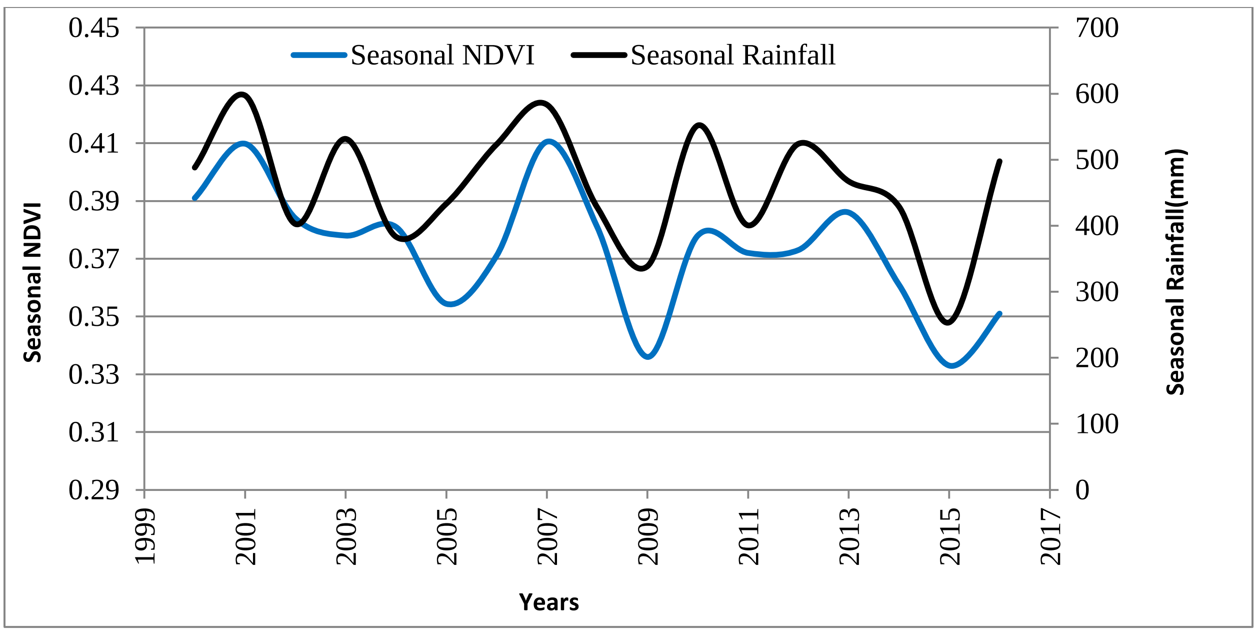

Figure 10. Temporal trend of seasonal Rainfall and NDVI (2000 to 2016)

Long term seasonal NDVI values indicts that there is existence of poor vegetation performance distribution in Zone. There is spatial variation in distribution of vegetation depending on altitude (Fig 11a and 3). In northern part of study area which is lower in elevation good rainfall amount and distribution was observed however, there is presence of poor vegetation coverage as compared to Southern part of the area. This implies there is presence of other environmental factors which influences growth and development/condition of vegetation. Other local factors like soil characteristics, land use land cover pattern and stress in previous years have an influence on vegetation (Abdel-Aziz *et al*., 2012). In support of this finding Chaltu (2017) reported that interpretation of NDVI was spatially dependent as more productive ecosystems have different radiometric properties than less productive ones due to difference in climate, soil and topography. This result indicates in same part of study area rainfall amount and NDVI value were not correlated this is because of presence of other variables like soil, temperature, and topography which, affect growth and development of vegetation. Thus, Rainfall which is an important climate variable that influences the growth and development of vegetation which is reflected by NDVI is not the only factors that influence growth and development of vegetation.

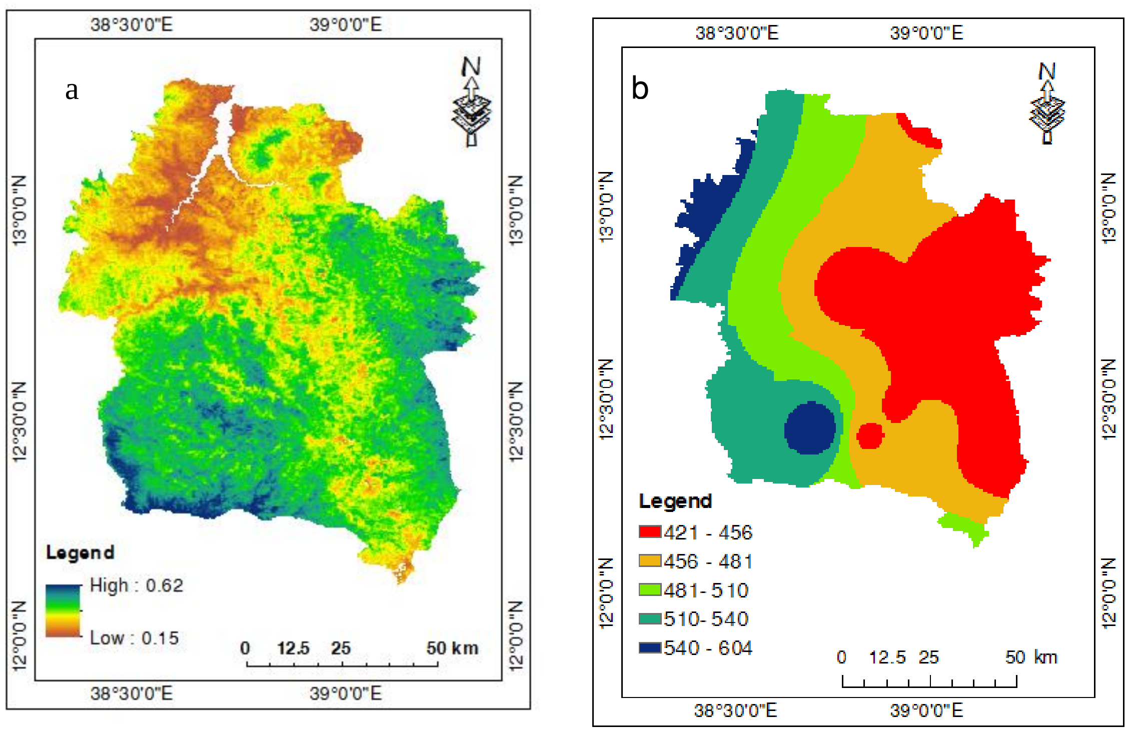

Figure 11.Spatial pattern of long term seasonal (June to September) NDVI (a) and rainfall (b)

4.2. Normalized Difference Vegetation Index (NDVI) Anomaly and Agricultural Drought

Normalized difference vegetation index anomaly is one of agricultural drought index that shows severity of drought. Based on time series analysis of NDVI year 2009 and 2015 were considered as drought year during the main cropping season (Fig 12). Based on NDVI anomaly index spatial pattern of agricultural drought severity for drought years was analyzed. The result revealed that there is spatial variation of drought severity in study area. Majority of the area were stricken by severity to slight drought in drought year of 2009 and 2015 (Fig 12). Table 9 and Figure (12) show the area and their percentage affected by agricultural drought as explained by NDVI anomaly. Accordingly percentage of area stricken by drought during cropping season 2009 was found to be 32.5, 17.6 and 2.27% of the total geographical area for slightly, moderate and sever levels respectively , whereas the corresponding agricultural drought severity for 2015 cropping season was 31.2, 33.3 and 10.3% of the total area were fall under slight, moderate and severe drought class, respectively. In support of this finding a study conducted by Eshetu *et al*. (2017) in North Wollo Zone reported that majority the area were influenced by very severe and severe agricultural drought in year 2015 and 2009.

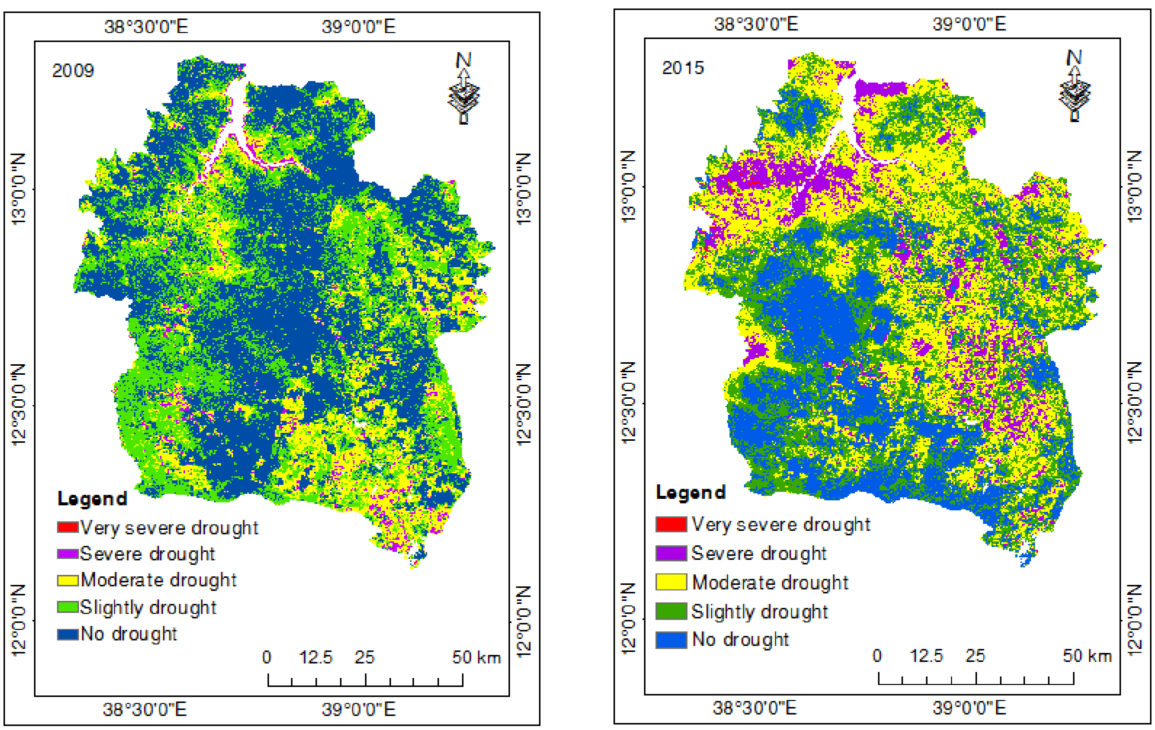

Figure 12. Spatial patter of agricultural drought as expressed in NDVI anomaly in drought year 2009 and 2015

Spatial pattern of Agricultural drought severity were also computed for wet season of year 2001 and 2007 using NDVI anomaly. Only small portion of area were stricken by slightly to moderate drought (Fig13). The percentage range of agricultural drought severity indicts that during cropping season of 2001 3.77 and 21.4 percent of total geographical area of the Zone were stricken by moderate and slightly drought respectively. Similarly in year 2007 5.43 and 19.3 percent of total area were hit by moderate and slightly drought respectively in most central and southern part of study area (Table 9). According to the map (Fig 13) majority area of study area were free from drought.

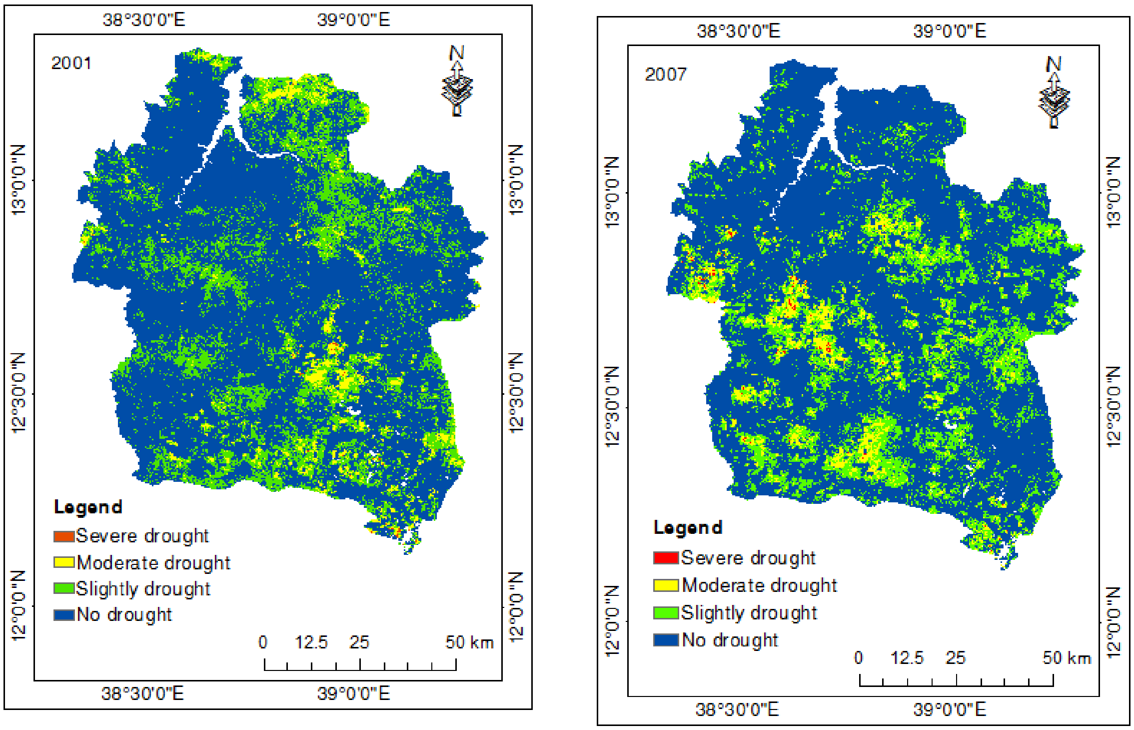

Figure 13. Spatial pattern of agricultural drought expressed by NDVI anomaly during wet year 2001and 2007

Table 9. Agricultural drought severity for drought year 2009 and 2015 and wet year 2001 and 2007 expressed by NDVI anomaly

No	Drought class	Drought year		Wet year	
		2009 Area (%)	2015 Area (%)	2001 Area (%)	2007 Area (%)
1	Very Severe drought	0.04	0.12	-	-
2	Severe drought	2.27	10.3	0.08	0.16
3	Moderate drought	17.6	33.3	3.77	5.43
4	Slightly drought	32.5	31.2	21.4	19.3
5	No drought	47.6	25.1	74.8	75.1
	Total	100	100	100	100

4.2.1. Relation between NDVI anomaly and crop yield anomaly

Relations between NDVI and crop yield anomaly were illustrated (Fig14). The result shows that there is a moderate correlation between NDVI anomaly and crop yield anomaly (r= 0.53). This means 28 percent of crop yield variability can be explained by NDVI anomaly. The result revealed that the relation between two variables is positive; as NDVI anomaly increase so do crop yield anomaly and vise-versa. The highest yield reduction was shown in 2009 and 2015 which was drought year (Appendix 3). There are few studies conducted in other part of Ethiopia on relation between NDVI anomaly and Crop yield anomaly for instance study carried out by Wondwosan (2017) verify that there is good correlation between NDVI anomaly and crop yield anomaly (r=0.77) in West Hararge Zone, similarly, studies conducted by Gizachew (2010), verify that presence of positive correlation between NDVI anomaly and crop yield in studies done in East Shewa zone Ethiopia. Thus, the strength of NDVI anomaly index for explaining spatial temporal condition of agricultural drought is found to be moderate in study area.

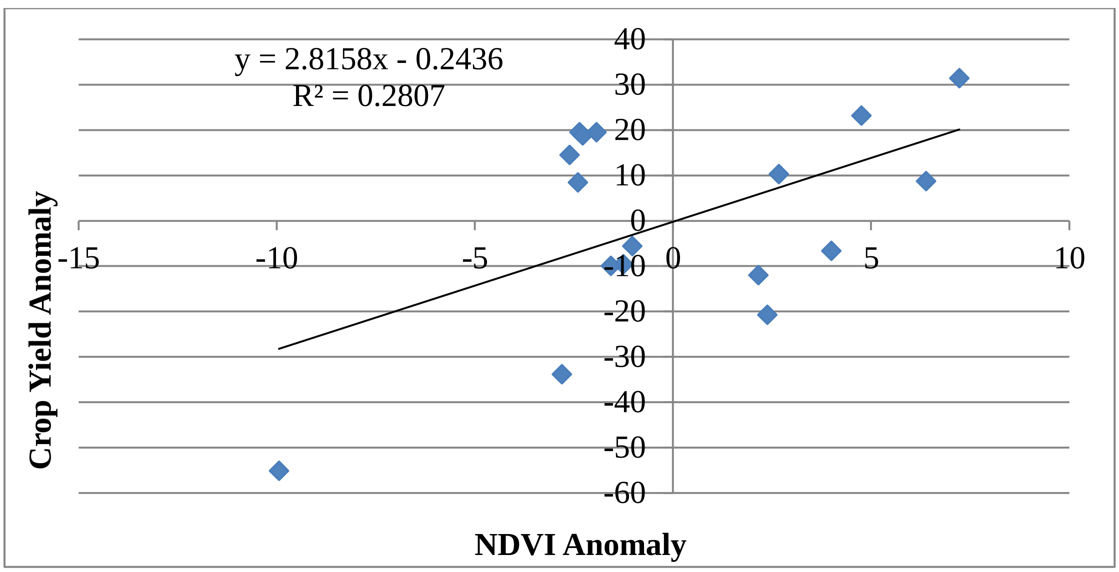

Figure 14. Relation between NDVI anomaly and crop Yield anomaly

4.3. Vegetation Condition Index (VCI) and Agricultural Drought

In this study VCI which was derived from NDVI was computed from 2000 to 2016 to analysis severity of agricultural drought. According to Kogan (1995) report VCI is better indicator of water stress condition than NDVI. The value of VCI ranges from 0 to 100 percent, where 50 to 100% indicts normal or optimal vegetation condition. In this study majority of the area where influenced by drought during drought year of 2009 and 2015. Percentage of areas stricken by very severe, moderate and severe drought during drought year of 2009 (Table 10). Similarly during drought year of 2015 majority of the area were stricken by very severe drought (Table 10). Southern part of study area were not influenced by agricultural drought in 2015 as expressed by VCI, whereas other parts of study area were hit by very severe to slight drought. In support of this finding UNOCHA (2015) reported that in year 2015 there were occurrence of seasonal rainfall failure triggered by ELNio which reduces agricultural production northern part of study area were highly affected by drought in those drought years (Fig 15). This indicated that areas which are low in altitude were sensitive to agricultural drought. VCI below 35 % can be identified as sever and very severe drought condition (Kogan, 1997), which is found in poor vegetation condition. The results of this study also reveal majority of study area were found under poor vegetation condition during cropping season of those drought years. Generally VCI confirm that in the year 2009 and 2015 almost all part of the study area were affected by agricultural drought condition

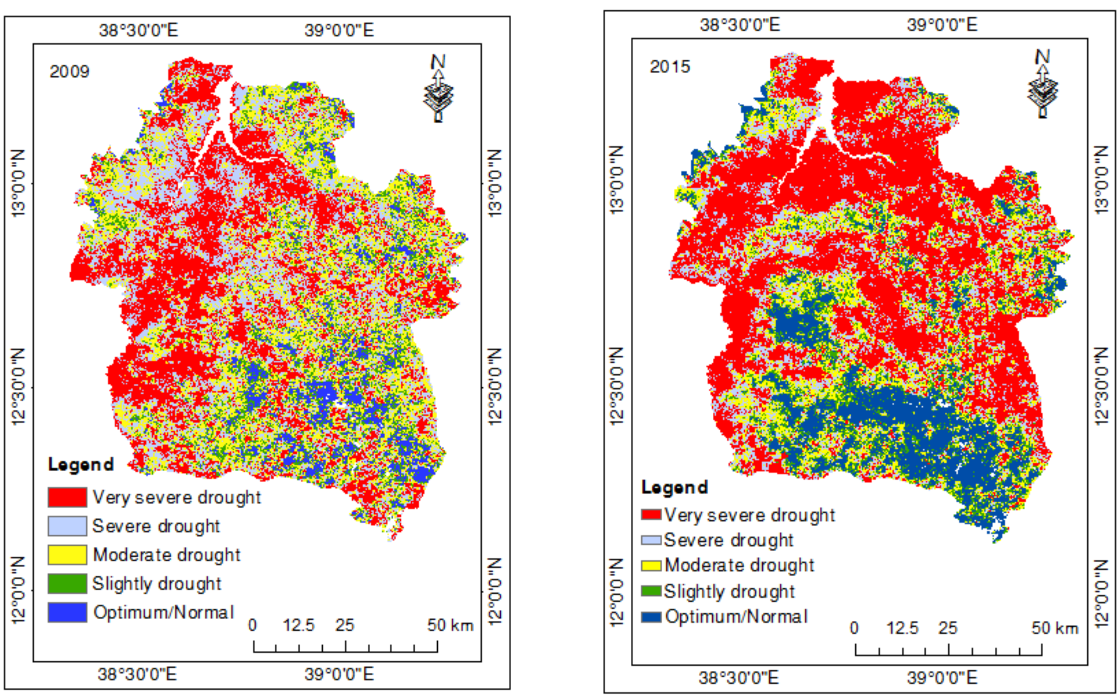

Figure 15.Spatial pattern of agricultural drought expressed by Vegetation condition index during drought year 2009 and 2015

Similarly vegetation condition index for wet years were computed. As shown drought map (Fig16) majority of study area were not under influence of drought in both 2001 and 2007. The value of VCI was above 50% in most of study area. This indicates the value of VCI was above the average indicting good condition of vegetation during cropping season of those years. This mean there is no vegetation stress due to water shortage. During 2001 cropping season the percentage area could not hit by agricultural drought (Table 10) was 83% of total area whereas in year 2007 79% of the total areas were free from drought. Very small areas were hit by very severe to slight drought during cropping season of 2001 and 2007 (Table 10) and (Fig 16).

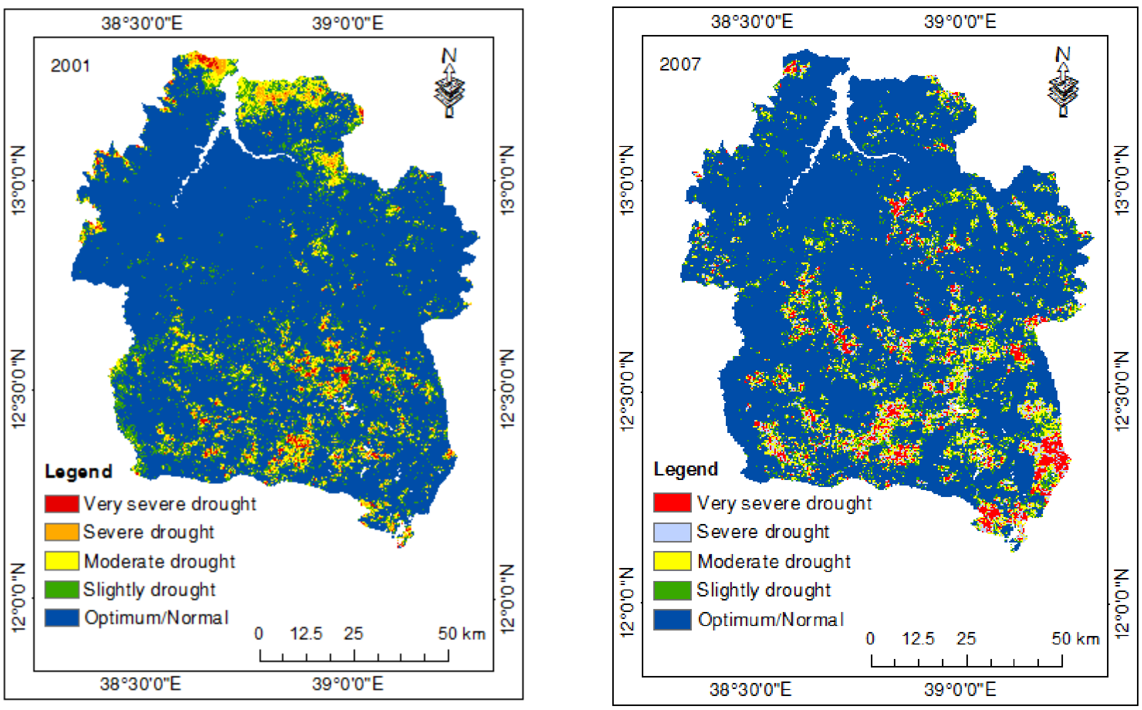

Figure 16.Spatial pattern of agricultural drought expressed as VCI during wet year 2001and 2007

Table 10. Agricultural drought severity for drought year 2009 and 2015 and wet year 2001 and 2007 expressed by VCI

		Drought year		Wet Year	
		2009	2015	2001	2007
No	class	Area (%)	Area (%)	Area (%)	Area (%)
1	Very severe drought	32.2	45.6	1.1	3.8
2	Severe drought	28.3	17.4	2.2	4.1
3	Moderate drought	23.5	14.7	6.0	7.2
4	Slightly drought	9.23	7.38	7.5	6.2
5	Optimum/ normal	6.86	15	83	79
	Total	100	100	100	100

4.3.1. Relation between VCI and Crop Yield Anomaly

To validate the reliability of satellite based agricultural drought indices crop yield data was taken as a ground truth data. The correlation between VCI and crop yield anomaly was positive and it revalued there is good relation between two variables with r=0.72(Fig 17). This indicates 52% of yield variability can be explained by using Vegetation condition index. As vegetation condition index increase crop yield can also increase and vise-versa. This implies higher crop yield reduction was observed in year 2009 and 2015 when the value of VCI was lowest. While, highest yield were found in year 2007 and 2001 when the value of VCI was higher (Appendix 4). The result of this study is consistence with the finding of Seyoum *et al*. (2016) who reported that vegetation condition index is positively correlated with crop yield anomaly in Eastern Amhara with correlation coefficient of (r=0.83). Kogan (1995) also evaluated the relation between corn crop and VCI found good correlation. Thus, study verifies that VCI can explain existence of agricultural drought in a good and reliable manner.

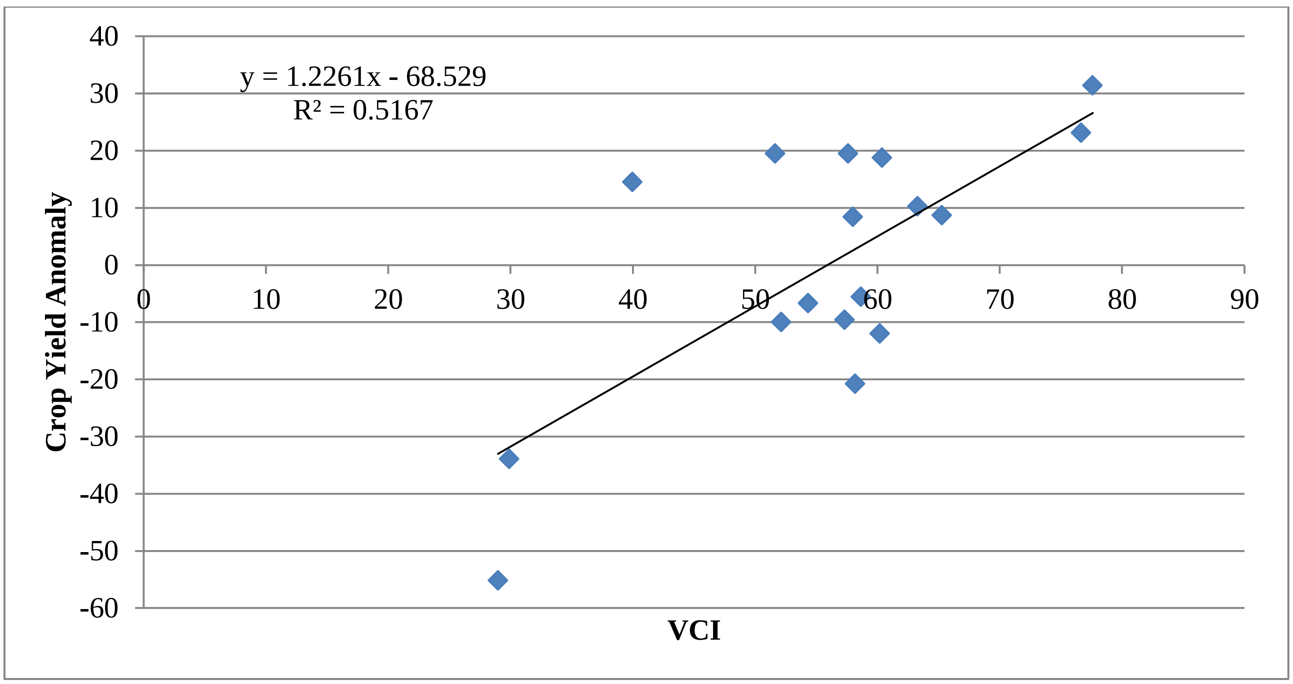

Figure 17. Relation between VCI and crop yield anomaly

4.4. Metrological Drought characterization based on SPI

Standard Precipitation Index (SPI) is an index that was developed to quantify precipitation deficit at different time scales. In this study three month SPI which provides a seasonal estimation of precipitation was computed for 13 stations using monthly data for the period of

2000 to 2016. The three month SPI was used to assess drought during spring (*Belg*) and summer (*Kiremt*) seasons which represents the shorter and longer rainy seasons respectively. Standard Precipitation Index (SPI) value of August month were chosen to be reclassified since August month is moving average of 3 months SPI i.e. June, July and August which is crucial month for crop growth in study area.

The computed SPI value for 3 months timescale during summer revealed that occurrence of negative SPI or drought were observed in the year 2003, 2004, 2005, 2008, 2009, 2011, 2014 and 2015 while in other years positive SPI value was observed in study period (Fig 18). Negative SPI values indicated that the rainfall of the area is less than median rainfall and positive indicate that the rainfall is greater than median rainfall. Every positive SPI value indicates greater than the mean precipitation is wet region and every negative value less than the median across the normal distribution are drier regions (McKee *et al.*, 1993). This finding is coincide with UNOCHA (2015) and FAO (2014) reports as year 2008–2009, 2003, 2011 and 2015 were recent documented droughts of Ethiopia which were all strong ElNino years. This indicated that entire study area is considered as metrological drought prone. However, the lowest SPI value was observed in 2009 next to 2015 which were considered drought year while the highest SPI was observed in 2007 next to 2001 which were considered as wet year using vegetation indices. This is an agreement with results found through analysis of satellite data through NDVI index and rainfall data from metrological stations found in and around study areas. Generally this study conclude that SPI was designed to show that it is possible to simultaneously experience wet conditions in one or more time scales and dry conditions at another time scale.

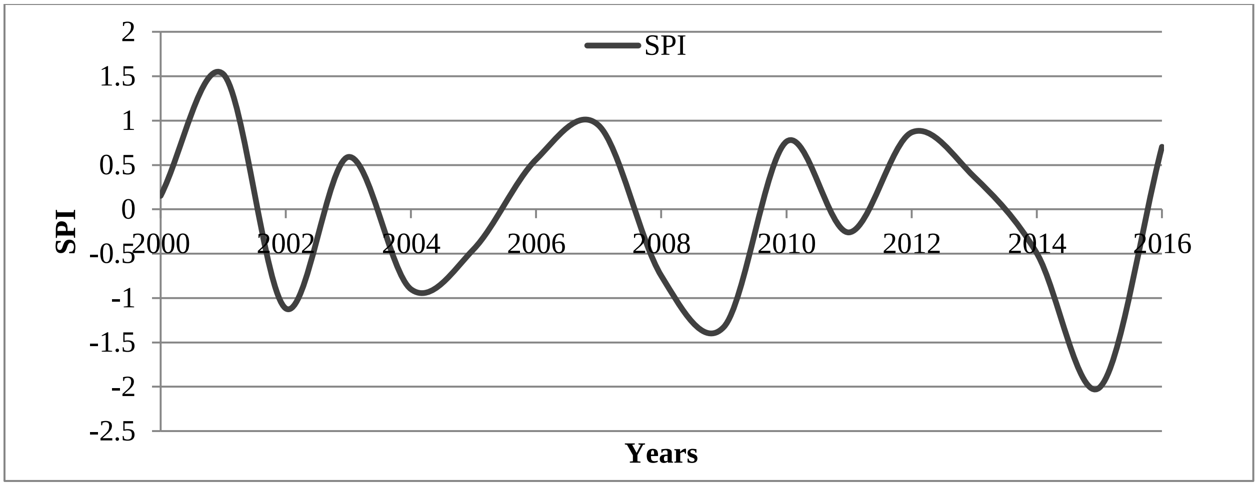

Figure 18.Temporal trend of Standard Precipitation Index (2000 to 2016)

This study examined spatial pattern of metrological drought across the study area using time series (2000 to 2016) SPI value. The analysis of SPI revealed that drought has been occurred at different level of severity across study area during the main cropping season. Standard Precipitation Index (SPI) during selected drought years of 2009 and 2015 and Wet years of 2001 and 2007 have been presented to show the spatial pattern of SPI during these years.

Drought occurred on large spatial extent mainly on summer season of year 2015 and 2009. It can be seen that during the drought year of 2009 and 2015 SPI value was lowest. This indicates that there has been low rainfall in study area during those years. Table 11 majority of the area (99.5%) were stricken by very sever and severe drought in year 2015. Spatial temporal severity map showed that Eastern part of study area was highly strike by very severe drought relative to western part which was strike by severe drought. While, in year 2009 majority of study area (66%) were strike by moderate drought. Northern part of study area was affected by slight drought (Fig 19). This indicted that there was low rainfall distribution during the main crop growing season. Therefore, those years were seen as the worst dry season in study area.

Table 11. Metrological drought during 2009 and 2015 as expressed by SPI

No	class	Drought Year	
		2015	2009
		Area (%)	Area (%)
1	Very severe drought	45	0.2
2	Severe drought	54.5	24.5
3	Moderate drought	0.5	66
4	Slightly drought	-	9.3

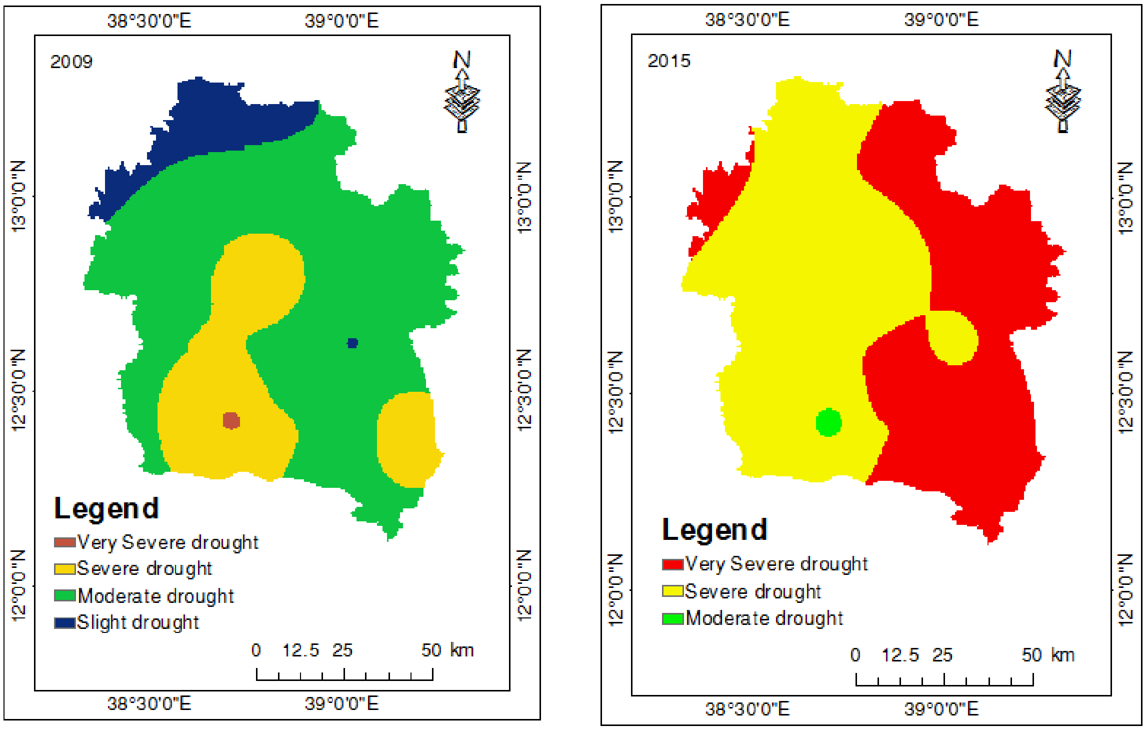

Figure 19. Standard Precipitation Index for drought year 2009 and 2015

According to analysis spatial pattern of SPI were used to identify wet years. In this regard 2001 and 2007 were identified as wet year in study area. Figure 18 the highest SPI value which is above zero was observed in those years. This indicts that there is good distribution of seasonal rainfall. All of areas were not under the influence of drought this implies growing season of 2001 and 2007 were not characterized by water deficit and can be considered as good agricultural time (Fig 20).

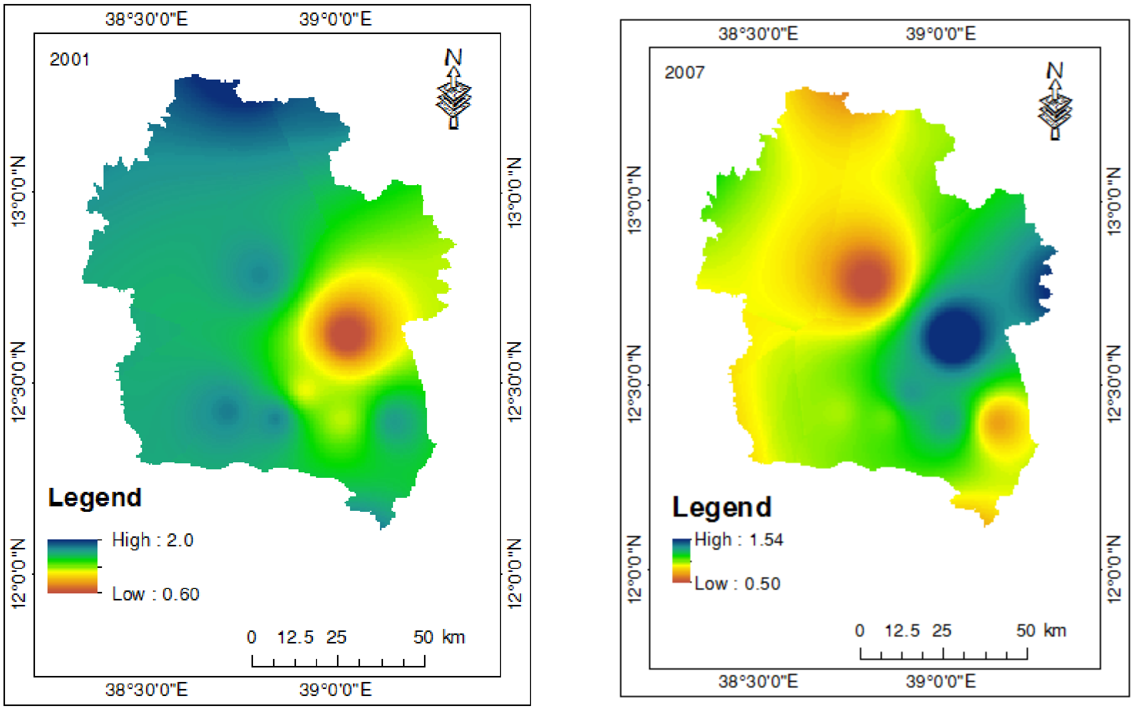

Figure 20.Standard Precipitation Index for wet year 2001and 2007

4.4.1. Standard precipitation index (SPI) and Crop Yield Anomaly

Standard Precipitation Index (SPI) is an index that represents deficiency or excess of water for crops, thus positive SPI indicates presence of excess moisture and negative SPI indicates deficiency of water for the crop. Thus, negative SPI is reflected on crop production through yield reduction. In study area crop failure is most often associated with moisture deficiency during crop growing season. According to Waghimra Zone disaster preparedness and prevention office report late onset and early cessation of the main rainy season, erratic distribution of rainfall and extended dry spells are the main weather related problems that cause drought. These drought periods have series impact on agricultural production. During the same period field observation also confirm that decreasing and erratic rainfall pattern and drought are the most series hazard for agriculture causing decreasing food production and crop failure.

To validate this correlation analysis between SPI and crop yield anomaly was conducted. Figure (21) revealed that there is a positive correlation between two variables with r= 0.74. This implies 55% of crop yield can be explained by SPI. The result of this study is consistence with the finding of Gizachew (2010) who reported a good correlation between SPI and crop yield anomaly in East Shewa Zone. As confirmed from Zonal disaster preparedness and prevention office there were much amount of relief distribution carried out by the government and non-governmental organizations in those drought years. Thus an overall analysis of this can be summed that SPI can be used as an indicator of metrological drought assessment.

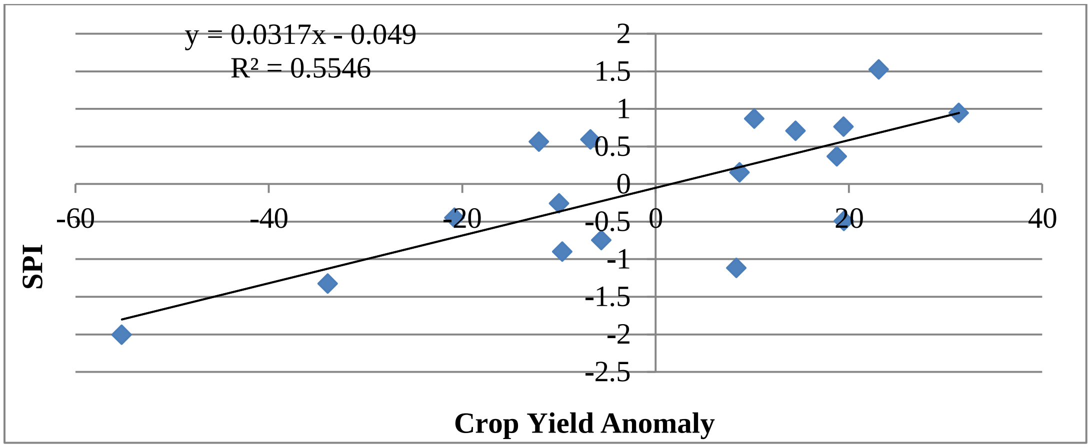

Figure 21. Relation between SPI and Crop yield anomaly

4.5. Combined drought risk map

The final drought severity map was prepared by overlaying agricultural and metrological drought frequency maps (Appendix 7). Weighting overlay tools was used. The weighed was given according to their degree of influence in pairwise comparison. The results reveal that majority of study area were vulnerable with severe drought which covers around 56% of total geographical area which is dominated in northern part of study area. In addition central parts of study area were vulnerable to moderate drought which covers 35% of total geographical area. While, small portion of study are were affected by slight and very severe drought which encompass 0.4 and 8.3% of study area respectively. Figure 22 and Table 12 shows percentage of areas vulnerable to drought. As confirmed from informal interviews of zonal agricultural experts Waghimra Zone is known for prolong and recurring drought features, this study also agree with this fact that the area experienced successive drought events during the last 17 years. From this result we conclude that study area is vulnerable to drought which varies spatially therefore different types of drought adaption and mitigation measures should be applied.

Table 12. Area under different drought severity class

Drought severity class	Area (%)
Slight	0.4
Moderate	35
Severe	56
Very severe	8.3
Total	100

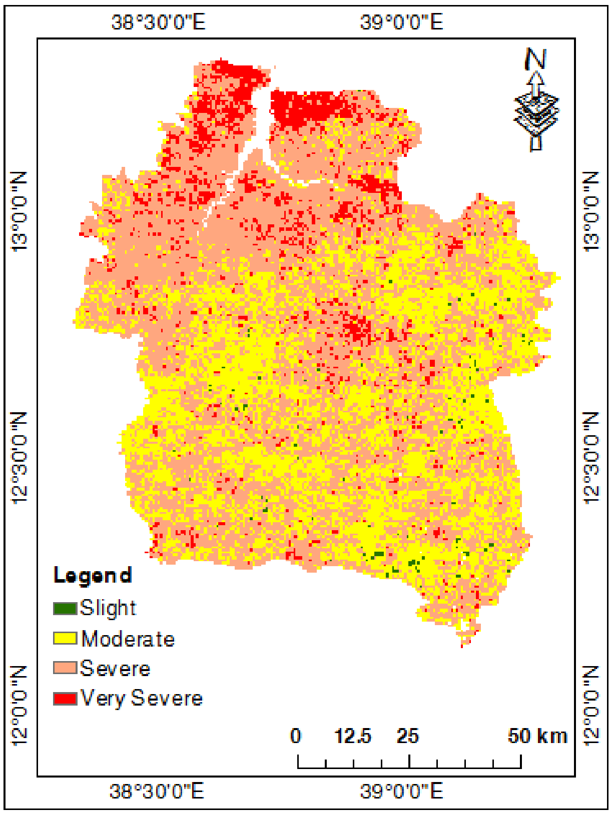

Figure 22.Combined Drought risk map of study area

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

Remote sensing and GIS data which consistently available, cost-effective can be used to detect the onset of drought, its duration and magnitude has been used to monitor drought conditions of an area. Ethiopian in general and Waghimra Zone in particular which depends on rain feed agriculture is frequently affected by drought. In order to map spatio-temporal pattern of agricultural and metrological drought variation and severity from 2000 to 2016 in Waghimra Zone, advanced Remote sensing and GIS techniques was used. Enhanced/expedited/expandable MODIS (eMODIS) NDVI satellite image was used as an input parameter to drought indices like NDVI anomaly and VCI. While, SPI which is derived from metrological data from monthly rainfall was used to assess metrological drought. Ground truth data of crop yield anomaly which is computed from crop yield data was used for validation purpose. This study concluded that spatial temporal variation of NDVI are closely linked with precipitation data and there is strong relation with coefficient of variation r= 0.71. The result reveals that from year 2000 to 2016 Waghimra zone experiences sever and slight severe drought. Year 2009 has been found to be the year of the worst drought next to 2015 while in year 2001 and 2007 the area were wet year which shows good crop yield. In order to evaluate the strength of each drought indices for explain agricultural drought correlation analysis was conducted between indices and crop yield anomaly. The result reveals that there is good correlation between NDVI Anomaly and crop yield anomaly (r= 0.53). Similarly VCI have good correlation with crop yield anomaly with r=0.72. This indicates that VCI is a good indicator of agricultural drought as compared to NDVI anomaly. Standard precipitation index (SPI) which explain occurrence metrological drought was also correlated with crop yield anomaly and the result shows presence of good correlation between two indices (r=0.74). The combined drought risk map showed that 56% of study area was found in severe, 35% in moderate and 8.3% in very severe drought condition. Therefore, using satellite data to assess agricultural drought is a paramount importance in order to assess past and current drought condition which generate baseline information that helps to monitor real time situation in the future for different adaptation options within relatively large geographical area coverage and repetitively time scale

5.2. Recommendations

Based on the finding the following recommendation was forwarded

- In this study eMODIS NDVI satellite image which has spatial resolution of 250m at continental level have been used. However, in order to effectively monitor the occurrence of drought in study area satellite data product characterized by high resolution is essential.
- Besides mapping drought vulnerable areas integrating socioeconomic data like population number, farming system, livestock number and species, livelihood activity and source of income in order to understand vulnerable factors is recommended.
- In this study only 17 years satellite and metrological data analysis were used but for better result long term historical record (more than 20 years) of satellite imaginary and climate data is essential tools in calculating drought severity and to determine drought prone areas.
- In order to obtain more accurate result, it is necessary to have more satellite images collected during different seasons in one year.
- Detail study of drought vulnerable areas in terms of its soil, crop grown, and rainfall, temperature condition, economic importance of area and social condition prevalent can further helps in preparing better management plan.
- Further study is required to quantify impact of drought and its possible site specific drought mitigation/adaption strategies employed in study area

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APENDICES

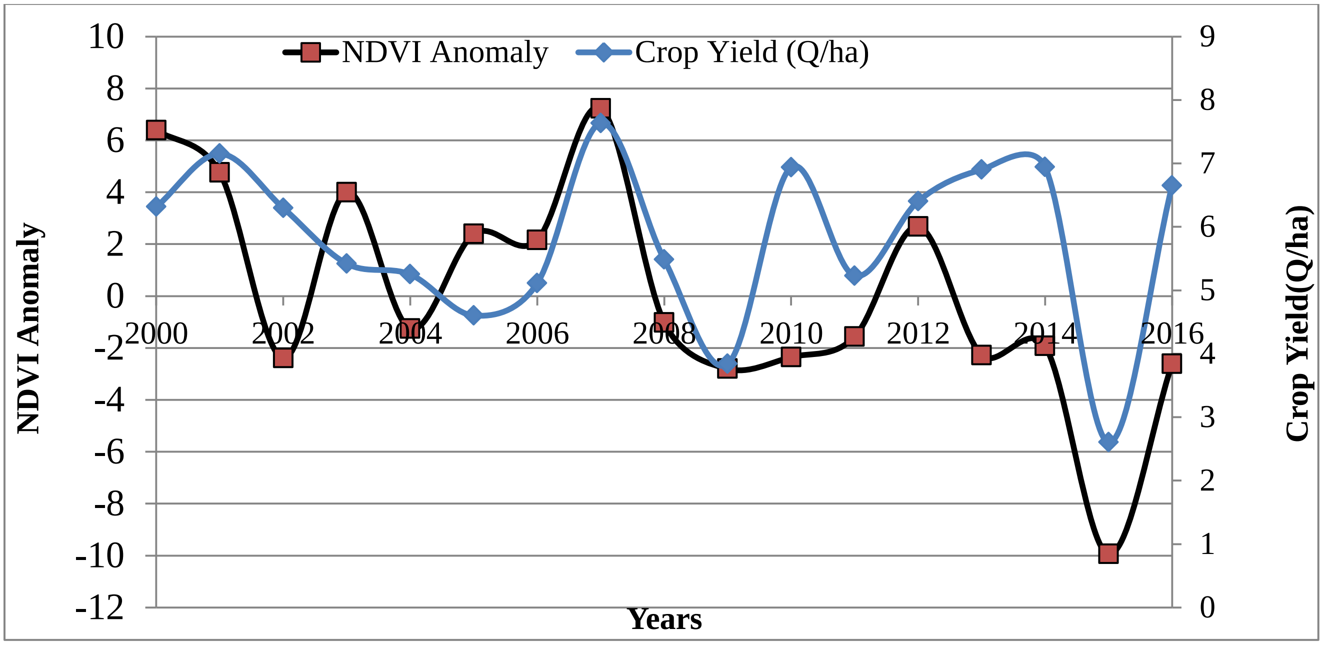
1: Land-use/ land-cover class and there corresponding area cover in study periods

Land use Land cover class	Area (km^2)	Area (%)
Water	122.2848	1.336788
Forest Land	663.6024	7.254343
Bush/shrub Land	1235.2536	13.5035
Grass Land	1936.5795	21.17022
Cultivated/settlement Land	4705.452	51.43888
Bare Land	484.4844	5.296268
Total	9147.6567	100

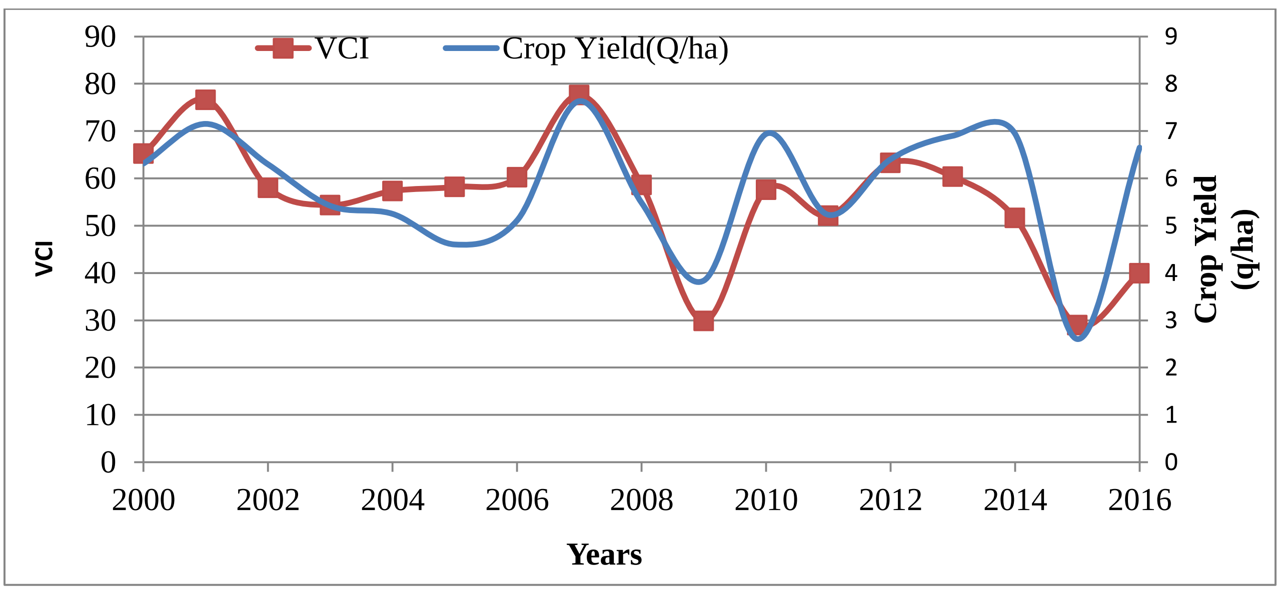
2. List of stations and their geographic coordinate

No	Station Name	Easting	Northing
1	Tsiketema	38.79989	12.78378
2	Amdework	38.71426	12.42758
3	Asketema	39.01782	12.40853
4	Chilla	38.84081	12.40853
5	Kewazba	38.9227	12.48463
6	Lugmura	39.16	12.4
7	Sekota	39.03101	12.62562
8	Yechila	38.99	13.28
9	Tekeza Hydro power	38.77	13.36
10	Wedisemro	39.34	12.76
11	Lalibela	39.04	12.04
12	Guhala	38.05	12.24
13	Chenek/Semen terra	38.1802	13.2663
14	Kobbo	39.633	12.33

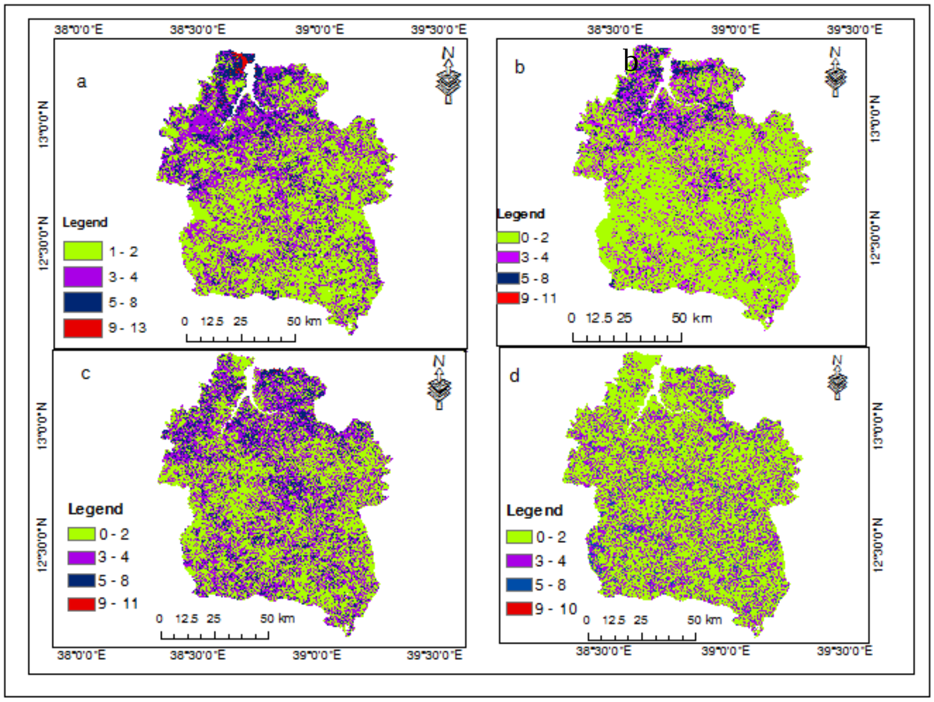
3: Temporal trend of NDVI anomaly and Crop yield data (Q/ha)



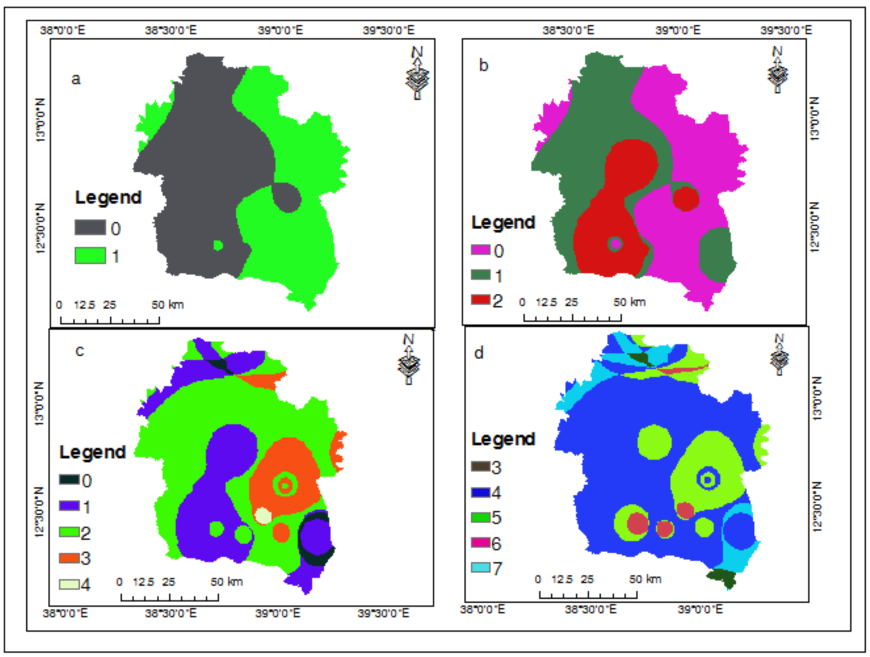
4.Temporal trend of VCI and Crop Yield data (Q/ha)



5. Frequency of Agricultural drought risk in four different severity classes: (a) very severe (b) severe (c) moderate and (d) slight



6. Frequency of metrological drought risk in four different severity classes: (a) very severe (b) severe (c) moderate and (d) slight



7.Frequency of agricultural(a) and metrological (b) drought risk map