ADDIS ABABA UNIVERSITY

SCHOOL OF EARTH SCIENCES

REMOTE SENSING AND GEOINFORMATICS STREAM

DROUGHT VULNERABILITY ASSESSMENT USING GEOSPATIAL DATA AND MODELING TECHNIQUES: A CASE STUDY OF EAST HARARGE ZONE, ETHIOPIA

A Thesis submitted to

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

BY: CHALTU TADESSE AMANTE (GSR/8405/09)

ADVISOR

DR. TESFAYE KORME

Addis Ababa, Ethiopia

June, 2018

ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

SCHOOL OF EARTH SCIENCE

Drought vulnerability assessment using Geospatial data and Modelling techniques: A case study of East Hararge Zone, Ethiopia

A thesis submitted to

The school of graduate studies of Addis Ababa University in partial fulfillment of the requirements for the degree of masters of science in remote sensing and geo-informatics

By: Chaltu Tadesse Amante (GSR/8405/09)

Advisor

Dr. Tesfaye Korme

Addis Ababa

June, 2018

Addis Ababa University

School of Graduate Studies

This is to certify the thesis prepared by Chaltu Tadesse Amante entitled as "**Drought vulnerability assessment using Geospatial data and Modelling techniques: A case study of East Hararge Zone, Ethiopia**" is submitted in partial fulfillment of the requirements for the Degree of Master of Science in Remote Sensing and Geo-informatics compiles with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

Dr. Dessie Nedaw	___________	_______/______/_______
Chairman	Signature	Date
Dr. Tesfaye Korme	______________	_______/______/_______
Advisor		
Dr. K.V. Suryabhagavan	_______________	_______/______/_______
Examiner	Signature	Date
Dr. Dessie Nedaw	______________	_______/______/_______
Examiner	Signature	Date

Contents

List of Figures

List of Tables

List of Acronyms

AET	Actual Evapotranspiration
AVHRR	Advanced Very High-Resolution Radiometer
CHIRPS	Climate Hazard Group Infrared Precipitation with Station
CSA	Central Statistics Agency
CSWB	Crop Soil Water Balance
DEM	Digital Elevation Model
DN	Digital Number
DPPC	Disaster Prevention and Preparedness Commission
ERDAS	Earth Resource Data Analysis System
EIAR	Ethiopian Institute of Agricultural Research
ERTS	Earth Resource Technology Satellite
EWS	Early Warning System
FAO	Food and Agricultural Organization
FEWS NET	Family Early Warning System
GIS	Geographical Information System
GPS	Global Positioning System
IPCC	International Panel on Climate Change
LEAP	Lively hood Early Assessment Protection
LULC	Land Use/Land Cover
MCE	Multi Criteria Evaluation
MODIS	Moderate Resolution Spectroradiometer
MVC	Maximum Value Composites
NDVI	Normalized Difference Vegetation Index
NGO	Non-Governmental Organization
NMSA	National Meteorological Service Agency
NOAA	National Oceanic and Atmospheric Administration
OWWDSE	Oromia Water Work Design and Supervision Enterprise
PET	Potential Evapotranspiration
PROBA-V	Project On-Board Automation Vegetation
RS	Remote Sensing

SPI	Standard precipitation Index
SPRITS	Software for Processing and Interpreting Remote Sensing Images Time Series
SPOT	Satellite Pour l'Observation de la Terre
USGS	United States Geological Survey
VITO	Vlaamse Instelling voor Technologish Onderzoek
WMO	World Meteorological Organization
WRSI	Water Requirement Satisfaction Index

ACKNOWLEDGMENTS

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

I would also thank Wollega University for this higher education sponsorship and I acknowledge the Ethiopian Metrological Agency for their kindness in providing the necessary data and information to carry out this research.

I express my honest and sincere gratitude towards my family for their encouragement to pursue this study. Their constant support and love have given me additional energy to complete my study.

I am also thankful to my classmates for their constant encouragement and cooperation to finalize the thesis.

Abstract

Drought vulnerability assessment using Geospatial data and Modelling techniques: A case study of East Hararge Zone, Ethiopia

Chaltu Tadesse Amante

Drought is water related natural disaster, which affects a wide range of environmental factors. In 2015, eastern Ethiopia had experienced a severe drought. This drought had caused low crop production for both Belg and Summer harvests, poor livestock health and low water availability. This study investigated the effectiveness of Remote Sensing based drought indices as an indicator for drought assessment in arid and semi-arid areas, examined the relation between rainfall and vegetation indices and identified the most drought–vulnerable areas using geospatial data and modeling techniques in East Hararge Zone, Ethiopia which is a drought-prone area. To assess and examine spatiotemporal variation of seasonal drought patterns and severity, four drought indices namely, Aridity Index (AI), Water requirement satisfaction index (WRSI), Standard precipitation index (SPI) and Normalized difference vegetation Index (NDVI) are applied. SPOT and PROVA-V, MODIS, rainfall data for the years 2005-2015 were utilized as input data for the indices while crop yield data was used to validate the strength of indices in explaining the impact of drought. The result map was produced based on frequency maps of the four indices. This map shows that 40%, 54% and 6% of the total geographical area of the Zone were severe, moderate and mild vulnerable respectively. This result map could be valuable to make pre, and post–drought risk management plans by decision and policy makers.

Keywords: Drought, East Hararge, AI, NDVI, SPI, SPOT, PROBA-V, MODIS, WRSI

CHAPTER ONE

1 INTRODUCTION

Drought is a hydro-climate related and recurrent natural disaster. It adversely affects ecosystem, environmental productivity and socioeconomic conditions. Its effect on vegetation condition causes severe impacts on agriculture, ecosystem, food security, human health, water resource and economy (Wilhite et al., 2000). Drought can be defined contextually in different disciplines in relation to the parameters that it affects the most. Although drought can be characterized from the perspective of meteorological, hydrological, agricultural and socioeconomic drought context. Due to its cumulative impacts and widespread over large geographical areas, drought is stronger than other natural disasters (Tadesse et al., 2004). Again, drought is pointed out as dangerous natural phenomena that occur when precipitation is lower than normal period thereby characterized by causing insufficiency for human practices and the natural activities (WMO, 2006). Drought in developing countries is very disastrous causing suffering, population displacement, food shortage, loss of life, death of animals, reduction of agricultural output, drying of rivers and lakes, deteriorations of water conditions, wildfires and permanent vegetation failure (FAO, 2011). Ethiopia is one of the sub-Saharan African countries that are highly vulnerable to natural hazards. Ethiopia has been ravaged by series of severe drought episodes for most of last many years, primarily, due to the failure of its main (kiremt) rainy season (Segele and Lamb, 2005). Since 250 BC droughts have occurred in different parts of Ethiopia at different times (Webb et al., 1992). Its frequency has increased over the past few decades particularly in the lowlands (NMS, 2007). Therefore, drought has remained the leading cause of disaster and human sufferings in Ethiopia in terms of frequency, area coverage and the number of people affected. The severity and persistence of the latest droughts has produced a wide range of impacts across the country (Sara Abebe, 2010; Defferew Kebede, 2011). There are four major types of draughts namely: Meteorological drought, Agricultural drought, hydrological drought and socio-economic drought. Meteorological drought refers to a deficiency of precipitation, as compared to average conditions, over an extended period of time. It basically originates from the deficiency of precipitation and focuses on the physical characteristics of drought (Mokhtari, 2005) rather than impacts associated with shortage of precipitation. Meteorological drought leads to a depletion of soil moisture and has always an impact on crop production. Agricultural drought is defined by a reduction in soil moisture availability below the optimal level required by a crop during the different growth stages, resulting in impaired growth and reduced yields. It occurs typically after meteorological drought but before hydrological drought (FAO, 2011). Hydrological drought results when precipitation deficiencies begin to reduce the availability of natural and artificial surface and subsurface water resources. It occurs when there is substantial deficit in surface runoff below normal conditions or when there is a depletion of ground water recharge. Socio-economic drought occurs when human activities are affected by reduced precipitation and related water availability. Even though it is difficult to clearly monitor the beginning and the end of drought occurrence, it is possible to monitor and analyze its characteristics such as intensity using different drought indices. This can be done either through climatic drought indices from meteorological data sets or modern remote sensing-based drought indices (Palmer, 1965; Abbasi, 2014; Himanshu et al., 2015). In comparison with conventional weather data, remote sensing approaches are relatively better suited for monitoring vegetation conditions, agricultural drought and crop yield assessment (Domenikiotis et al., 2004). In 2015, eastern Ethiopia had experienced a severe drought. The drought had caused low crop production for both Belg and Meher harvests, poor livestock health and low water availability. It was erratically distributed and punctuated by several long dry spells. The Kiremt rains started at a usual time, and there were fairly normal amounts of rainfall in the middle of June. However, the remaining period of the Kiremt was characterized by quite lower amount of rainfall, and as a result, cumulative June to September Kiremt rainfall was well below average, with particularly low rainfall in eastern Oromia. In East Hararge Zone, nearly a quarter of the land typically used in Meher production remained fallow. Many seeds that were planted failed to germinate. Crops that did germinate, then wilted and dried out from July to September. After failing to germinate or wilting early in the season, significant areas were replanted with short-cycle crops in eastern Oromia. As a result of the dry conditions, pasture and water availability were very low in eastern Oromia. Livestock had migrated as early as June, a time when normally they stay near households, to the river valleys of the Erer, Gobele, Ramis, and Mojo Rivers in East Hararghe zone. Despite ongoing emergency livestock feed support, livestock body conditions have deteriorated and in many cases were poor. Livestock productivity had fallen below average. In September and October, more than 900 livestock deaths were reported in lowland areas of East Hararghe. Much higher number of livestock deaths occurred in the following months of July and August 2015 (FEWS NET, 2015). The vulnerability of agricultural production due to water deficit and the development of regional water distribution systems imply that drought analysis, the investigation of its dynamic meteorological causes, the development of a drought prediction model and the analysis of drought characteristics by drought indices are extremely important. A vulnerability assessment is the process of identifying, quantifying, and prioritizing (or scoring) the vulnerabilities in a system. Vulnerability from the perspective of drought planning means "assessing the threat from potential drought hazards to various sectors across social, economic, environmental and political fields" (CWCB, 2013). GIS and Remote sensing techniques are being widely used for analysis of drought monitoring and assessment using various drought indices (Jeyaseelan, 2004; Chopra, 2006 and Beyene Ergogo, 2007).

1.1 Statement of the problem

In 2011, a severe drought caused severe food crises in Ethiopia that affected southern, southeastern land eastern parts (Viste et al., 2012). East Hararge Zone is one of the Eastern zone of Ethiopia, persistently affected by the recurrent drought, for the last many years. In this Zone, drought is manifested by the irregularity of rainfall. The regional risks associated with rainfall variability and the consequential drought are generally, manifested by late beginning and early endings of the rainy seasons. This results in temporally and spatially inadequate amount of moisture to support crop growth. The amount and distribution of rainfall during the short period was so unsatisfactory that had rendered crops vulnerable to moisture deficit, leading to crop failure and reduced yields. Drought is currently more pronounced in the study area which results in yield reduction and crop failure. Several studies have been carried out to monitor agricultural drought using remote sensing and GIS techniques including Huang et al., (2013) and Abbas, (2014) in China; Kapoi and Alabi, (2013) in Kenya; Biranu et al., (2014) in Tigray; Gizachew and Suryabhagavan (2014) in East Shewa Zone; Wondewosen Negesse, (2016) in West Hararge Zone. However, none of these researchers had conducted the study on drought vulnerability assessment using geospatial data and modeling techniques in East Hararge Zone. Therefore, by applying geospatial data and modeling techniques, the most drought–vulnerable areas will be identified in East Hararge zone, Ethiopia.

1.2 Objective

1.2.1 General objective

The general objective of the study is to identify and assess the most drought vulnerable areas using geospatial data and modeling techniques.

1.2.2 Specific objectives

- To assess and identify the level of drought vulnerability in the Zone
- To analyze the strengths and weaknesses of the different drought indices and identify an appropriate index that can be used for monitoring drought in the Zone with minor customization.
- To identify the most drought–vulnerable areas and to prepare drought vulnerability map of the Zone
- To investigate the impact of drought on agricultural production using remote sensing-based drought indices.

1.3 Significance of the study

This study is expected to provide quantitative and qualitative information regarding drought vulnerability in the study area. This information area valuable to make pre, and post–drought risk management plans by decision and policy makers. The most drought–vulnerable area will be delineated based on the livelihood class of the zone, which will be important for Regional State Government and the Federal Government of Ethiopia to identify the most drought–prone areas to save the life of communities in the zone. It will also provide a baseline information on the most vulnerable areas so that systematic surveillance and monitoring of drought and its effect could be undertaken.

1.4 Scope of the study

This study focuses on the use of Geospatial technology and modeling techniques in drought vulnerability assessment. The scope of the study is limited to East Hararge zone, Ethiopia.

1.5 Limitation of the study

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

1.6 Organization of the Thesis

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

CHAPTER TWO

2 LITERATURE REVIEW

2.1 Drought

Drought is a disastrous natural phenomenon that has significant impact on agricultural, environment and socio-economic conditions of the community. Normally, drought occurrence, as a climate change phenomenon, becomes obvious when there are abnormal dry weather conditions, events of lower rainfalls and insufficient soil moisture in an area. In some cases, it results in decreased water levels of rivers, ponds and lakes with long lasting impacts on agricultural production, livestock and overall economic activities (Shaheen and Baig, 2011; Akhtar, 2014). Drought is a recurring extreme climate event over land characterized by below-normal precipitation over a period of months to years. It is a temporary dry period, in contrast to the permanent aridity in arid areas (Dai, 2011b). In some counties, like Ethiopia, drought occurrence is closely associated with the timing of the rainfall. In other words, the period of rainfall occurrence, the late or early arrival of rain and its duration, in relation to the principal crop growth stages are given greater attention (Lagese Hadish, 2010). It is an insidious hazard of nature and begins from a deficiency of precipitation those consequences in a water deficiency for some activities or some group (WMO, 2006). Accordingly, drought was, conceptually, defined as a protracted period of deficient precipitation causing extensive damage to crops resulting in loss of yields. On the other hand, the operational approach tried to see droughts definition as a means to specifically analyze drought occurrence, frequency, severity, and duration of prevalence for a given return period (Mishra and Singh, 2010).

2.2 Types of droughts

There are four major types of droughts namely: Meteorological drought, Agricultural drought, hydrological drought and socio-economic drought.

2.2.1 Meteorological drought

Meteorological drought is defined as a lack of precipitation over a region for a period of time. This type of drought refers to the degree of dryness specified by deficiencies of precipitation and the duration of the dry period at specific time and place (WMO, 2006). According to Keyatash and Dracup, (2002) it is believed that the duration of meteorological drought can vary due to anomalies, as in large term blocking patterns or a flux in the global wind patterns. Dai (2011b) also observed the duration of meteorological drought as a period of months to years with below-normal precipitation, usually accompanied by above-normal temperature in contrast to the permanent aridity.

2.2.2 Hydrological drought

Hydrological drought refers to a persistently low discharge and/or volume of water in streams and reservoirs, lasting months or years. According to Getachew et al., (2011) hydrological drought is perceived as the event occurring as a result of low rainfall. This perception agrees with the fact that hydrological drought is closely related with long term absence of precipitation increased evapotranspiration.

2.2.3 Agricultural drought

Agricultural drought occurs when moisture in the soil is insufficient to ensure optimal crop growth (Gizachew, 2010). Agricultural drought results in impairment of growth of crops there by reducing yields. According to (Wilhite, 2000) both meteorological and hydrological droughts have significant impact on agricultural drought as insufficient rainfall, soil water deficit and decreased ground water reduces agricultural yields. Agricultural drought is manifested in the form of erratic spatio-temporal distribution of rainfall and insufficient amount of moisture has been claiming life in different parts of the world. In most scanty rainfall dependent agricultural areas like that of Ethiopia, for instance, the scarcity of precipitation and diminished amount of soil moisture have negatively affected crop production and the normal public food supply. In the real sense of the word, agricultural drought has become the biggest threat to life in most developing counties of the world. Agricultural losses from economic terms may be very difficult to assess or compare with some previous episodes since similar patterns of drought may have a different economic impact at various stages of development to the agriculturist (WMO, 2006).

2.2.4 Socio-economic drought

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

2.3 Impacts of Drought

In economic terms, droughts are the costliest natural disaster to strike many other countries (shaheen, 2011). The primary impact of droughts is on food production, as agriculture is by far the largest water user. Droughts may also have severe environmental, economic, and social impacts. The environmental and socioeconomic impacts of droughts are controlled to a large degree by the duration of droughts, rather than their severity, because recovery from the cumulative damage of consecutive drought years is more difficult (Shahen, 2011). The impacts of drought also depend upon human and ecosystem demand for water, available water-resources management capabilities and practices, as well as the meteorological and hydrological characteristics of the drought (Loucks and Gladwell, 1999). Vulnerability to droughts depends in part on the gap between average water use and the safe yield of a system (Lovett, 2005) and the adaptive capacity of the water system and society as a whole. The greatest vulnerability occurs when water supplies are already stretched to meet demands during normal hydrologic conditions. Many regions simply do not have the food, water, and economic resources to overcome multiple-year droughts, particularly in water stressed regions where resources even during normal years may be barely adequate (or inadequate) to meet local needs (e.g., Ethiopia and some other African countries). Vulnerability to droughts is also related to whether the primary water source is groundwater or surface water. Areas dependent on surface water tend to be more vulnerable to droughts because the impacts of reduced precipitation are felt quicker. On the contrary, urban areas that are supplied water primarily by desalination (e.g., many major coastal cities the Middle East), have a very low vulnerability to droughts. The impact of droughts also depends up on the degree of societal development, its per capita GDP, and the density of the rural population (Lovett, 2005). Droughts have also had severe impacts on some ancient cultures, and may have contributed to, or were the primary cause of the cultural collapse. The human and economic impacts of droughts have a strong spatial component. To local communities facing the brunt of drought conditions, the impacts can be catastrophic, including loss of income, malnutrition, starvation, and migration. Droughts have a slow initiation and they are usually only recognized when the drought is already well established. The slow initiation and undefined end of a drought makes it very difficult to take defensive actions (Pereira et al., 2002). A period of drier than normal conditions could be either a dry spell that is about to end, the onset of longer-term drought that will have severe impacts on water users, the beginning of an unrecognized natural climatic fluctuation, or the beginning of a climatic change to increasing aridity. Megadroughts lasting for decades or centuries have been documented in the paleoclimatic record. Similarly, a period of rainfall during a drought may represent either the breaking of the drought condition or just a temporary, short-term event in a continuing.

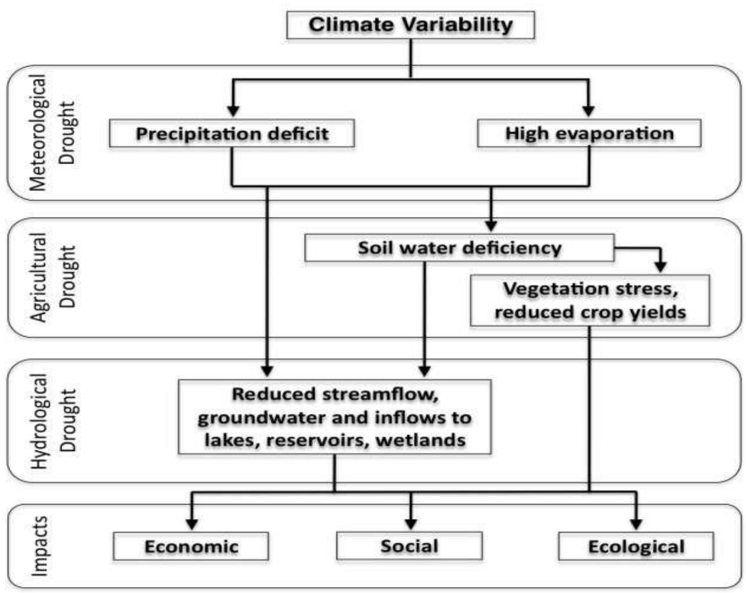

Figure 2.1: Categories of drought impacts.

2.4 Drought in Ethiopia

Ethiopia is a sub-Saharan country that has been affected by drought. Millions of lives have been lost because of recurring droughts in the past several decades. Due to climatic changes, drought occurs every two years in different parts of Ethiopia (NMSA, 1996). In addition, the drought recurrence cycle shortens over time while the affected area is widening, impacting additional parts of the country that were once unaffected (NMSA, 1996). As the overwhelming majority of the country's population depends on rain fed agriculture and related economic activities for its livelihood, agriculture remains by far the most important sector in Ethiopian economy. Yet, because the country's rainfall is significantly scanty, a slight change in it bears drastic negative effects on the agricultural production, in general, and the seasonal crop yields, in particular. According to Stern (2006) the effect of climate variability is felt, even more severely, among the poorer subsistent farming households. Drought is a common occurrence in Ethiopia. Four consecutive years of 1996, 97, 98 and 1999, poor rainfall in Ethiopia had a major impact on rural populations across the country during 2000, leading to drought conditions and minimal harvests. This had a cumulative impact on households in both pastoral and agricultural communities, undermining coping strategies and leading to greater vulnerability to drought. Many households were forced to sell their livestock and other assets and some migrated from their land in search of income and food. On 4 June 2015, Ethiopia's National Meteorological Agency (NMA) declared that the spring B*elg* rains had failed. Soon after, the *kiremt* rains were severely delayed and became erratic. From February through September 2015 the north, central and eastern parts of the country received only 50 to 75%of the rainfall normally expected over this time period. In Ethiopia, rainfall in main rainy season (Kiremt) is the most important for agricultural activities as nearly 95 percent of crop production is in this season. Thus, the occurrence of agricultural drought during the main rainy season has greater impact on country's food production. The 2011 drought year was followed by 2015 drought condition in recent history of Ethiopian drought. That caused over 10.2 million people to require relief food aid in 2016 (Relief Web, 2017). According to The Africa reports, (2015), the drought condition affected areas include southern Tigray, eastern Amhara, Afar, parts of the Somali region, the eastern lowland of SNNP, East and West Hararge, Arsi and West Arsi, and Bale zones of Oromia Regional State. In this area, drought caused loss of over 75% of meher cropping production which accounts for 90% of the country's total grain production and loss of one million livestock have died, and over 1.7 million livestock are reportedly at risk due to poor body conditions (ACAPS, 2016).

2.5 Role of Remote sensing and GIS in Drought Monitoring

The detection, monitoring, and mitigation of disasters require gathering of rapid and continuous relevant information that are not effectively collected using conventional methods. Remote sensing tools and techniques make it possible to obtain and distribute continuous information rapidly over large areas by means of sensors operating in several spectral bands, mounted on aircraft or satellites. A satellite, which orbits the Earth, is able to explore the whole surface in a few days and repeat the survey of the same area at regular intervals while an aircraft can give a more detailed analysis of a smaller area, if a specific need occurs. The spectral bands used by these sensors cover the whole range between visible and microwaves (Legesse Hadish, 2010). Rapid developments in computer technology and the Geographical Information Systems (GIS) help to process Remote Sensing (RS) observations from satellites in a spatial format of maps - both individually and along with tabular data together to provide a new perception - the spatial visualization of information of natural resources. The integration of information derived from RS techniques with other datasets both in spatial and non-spatial formats provides tremendous potential for identification, monitoring and assessment of droughts. The remote sensing monitoring of drought can get frequent and sustained information on the surface characteristics of planar with full using information of ground surface spectrum of time, space, and direction. It can provide macro, dynamic, and real-time monitor data sources for real-time and dynamic monitoring of drought (Zhang et al., 2011). Advancements in the fields of GIS and Remote Sensing (RS) have greatly facilitated the operation of drought risk assessment. Most data required for drought vulnerability assessment have a spatial component and also change over time. Since drought covers large areas, it is difficult to monitor those using conventional systems. The space technology or remote sensing tools offer excellent possibilities of collecting this vital data. This is because the technology has capability of collecting data at global and regional scales rapidly and repetitively and the data is collected in digital form. The technology further provides excellent communication medium. Timely information about the onset of drought, its extent, intensity, duration, and impacts can limit drought-related losses of life, minimize human suffering, and reduce damage to the economy and environment (Kogan, 1997). Weather data is a fairly good source of information that can be used for drought assessment. However, the scarcity of weather stations in some areas make drought monitoring a daunting task. Lack of information about a drought becomes especially acute in areas where the weather station networks is limited (e.g. sub-Saharan Africa). Furthermore, the data is often incomplete for the few available weather stations and/or not available early enough to enable timely drought detection and impact assessment (Johnson et al., 1993). Use of satellite data avoids most of these problems. Moreover, observations from space provide permanent data archive and extra visual information. Also, it is cost effective and enables one to have a regular and repetitive view of nearly the earth's entire surface (Kogan, 1990). Therefore, the use of GIS and RS has become essential. It is evident that GIS has a great role to play in drought vulnerability assessment because natural hazards are multi-dimensional. The main advantage of using GIS for drought vulnerability assessment is that it not only generates a visualization of hazard but also creates potential to further analyze this product to estimate probable damage due to drought hazard. Drought vulnerability assessment requires up-to-date and accurate information on the terrain topography and the use of the land. The remotely sensed images from satellites and aircrafts are often the only source that can provide this information for large areas at acceptable costs (Wang, 2004). A meteorological station can connect to GIS and keep receiving meteorological information directly entered into GIS, and then these data will manage and analyzed uniformly by the system database. GIS transformed the model to its language and analyzes the data by powerful analysis function and then adds drought assessment early warning function into drought assessment system (Tao et al., 2011).

2.6 Drought Indices

Drought indices are important elements of drought monitoring and assessment since they simplify complex interrelationships between many climate and climate related parameters. According to Wilhite et al., (2000) indices make it easier to communicate information about climate anomalies to deserve user audiences allow scientists to assess quantitatively climate anomalies in terms of frequency, intensity, duration and spatial extent. A variety of drought indices have been developed to quantify whether or not a region is experiencing a drought and to categorize the seriousness of the drought. Water resources need to be managed on a continuous basis, so whether or not water shortages cross a specified numerical threshold does not have great operational significance. Drought indices are useful for mapping regional water supply trends, both temporal and spatial. Drought indices are also used to define disaster conditions that qualify for government assistance and where and when emergency water restrictions may be required.

2.6.1 Palmer Drought Severity Index (PDSI)

Palmer Drought Severity Index is important meteorological drought index developed by Palmer (1965) to evaluate drought severity in time and space based on precipitation, evapotranspiration and soil moisture conditions. Using these inputs, PDSI computes four terms in the water balance equation: evapotranspiration, runoff, soil recharge, and moisture (Zargar et al., 2011). The PDSI is a standardized measure, ranging from about −10 (dry) to +10 (wet) with values below −3 representing severe to extreme drought (Dai, 2011b). According to Chopra (2006) and Vicente-Serrano et al., (2010b) 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.

2.6.2 Vegetation Condition Index

The Vegetation Condition Index (VCI) is NDVI-derived product that compares the current observed (actual) NDVI to the NDVI value of previous year. VCI is an indicator of environmental stress that characterizes the moisture condition of vegetation (Kogan, 2001). VCI uses AVHRR thermal bands to identify drought situations such as onset, duration and severity, especially in areas where drought episodes are localized and ill defined by noting vegetation changes and comparing them with historical values (Kogan,1995; Liu et al., 1996). The VCI 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 (i) 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).

2.6.3 Standardized precipitation index (SPI)

Tom Mckee, Nolan Doesken and John Kleist of the Colorado Climate Centre formulated the SPI in 1993. The purpose is to assign a single numeric value to the precipitation that can be compared across regions with markedly different climates. Technically, the SPI is the number of standard deviations that the observed value would deviate from the long-term mean, for a normally distributed random variable. Since precipitation is not normally distributed, a transformation is first applied so that the transformed precipitation values follow a normal distribution. The SPI was designed to quantify the precipitation deficit for multiple time scales. These time scales reflect the impact of drought on the availability of the different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale while groundwater, stream flow, and reservoir storage reflect the longer-term precipitation anomalies. The SPI calculation for any location is based on the long-term precipitation record that is fitted to a probability distribution, which is then transformed into a normal distribution so that the mean SPI for the location and desired period is zero (McKee, 1993). A drought event occurs any time the SPI is continuously negative and reaches intensity of -1.0 or less. The event ends when the SPI becomes positive. Each drought event, therefore, has a duration defined by its beginning and end, and intensity for each month that the event continues. The positive sum of the SPI for all the months within a drought event can be termed the drought's magnitude.

2.6.4 Temperature Condition Index (TCI)

TCI is used to determine stress on vegetation caused by temperature and excessive wetness's characterizes the thermal condition of vegetation (Kogan, 2001). It is used in conjunction with NDVI and VCI for drought assessment of vegetation in situations where agricultural impacts are the primary concern. TCI provides opportunity to capture drought due to thermal effect and identify subtle changes in vegetation health due to high temperature accompanied by moisture shortage (Kogan, 2002). The higher the temperature value, more extreme the drought occurrence. Low TCI values (close to 0%) indicate very hot weather in that month or week. Consistently low TCI values over several consecutive time intervals may point to drought development (Kogan, 1995).

2.6.5 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) quantifies vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs). NDVI has been extensively used for vegetation monitoring, crop yield assessment and drought detection. NDVI provides a measure of the amount and vigor of vegetation at the land surface. The magnitude of NDVI is related to the level of photosynthetic activity in the observed vegetation. In general, higher values of NDVI indicate greater vigor and amounts of vegetation. So, the normalized difference vegetation index (NDVI) provides us with an indication of how much green vegetation exists at a particular place on the ground. The NDVI values range from -1 to +1 with most values ranging from 0 to 0.6. Healthy green vegetation has a high NDVI value because more near-infrared light is reflected than red light. For bare soil on the other hand, both near-infrared and red light are strongly reflected so the NDVI would be near zero. Water and ice reflect a little redder than near-infrared light so those values tend to be slightly negative. 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 (Anyamba and Tucker, 2005). Therefore, the NDVI does have potential in drought detection and climate impact assessment. NDVI is calculated from two channels sensor, the near-infrared (NIR) and Red wavelengths, using the following algorithm:

$$NDVI = (NIR - RED) / (NIR + RED)$$

2.6.6 Aridity index

Aridity indices were reviewed by Walton (1969) and (Vicente -Serrano, 2006a). Aridity indices have greater value for the tracking the effects of climate change on local water resources, if sufficiently accurate data are available for mapping local changes in the values of the indices over time. The simplest aridity index is based solely on precipitation. A commonly used rainfall-based definition is that an arid region receives less than 10-in or 250 mm of precipitation per year. This criterion for aridity was used by the Intergovernmental Panel on Climate Change (IPCC, 2007). Semiarid regions are commonly defined by annual rainfalls between 10 and 20-in (250 and 500 mm). The UNESCO (1979) aridity index (AI) is based on the ratio of annual precipitation (P) and potential evapotranspiration rates.

$$AI = P/ETp$$ where, ETp is calculated using the Penman (1948) formula.

Table 1: AI based drought severity class.

Classification	Aridity index
Hyper arid	$AI<0.03$
Arid	$0.03<AI<0.20$
Semiarid	$0.20<AI<0.50$
Dry sub humid	$0.50<AI<0.65$

2.6.7 Water Requirement Satisfaction Index(WRSI)

WRSI is an indicator of crop performance based on the availability of water to the crop during the growing season. Based on the water supply and demand of a crop. Water Requirement Satisfaction Index is a useful indicator of crop performance based on the availability of water during the crop growing season. Crop water requirement is the amount of water required to compensate the evapotranspiration loss from the cropped field (Gizachew Legesse and Suryabhagavan, 2014). WRSI was developed, mainly, for monitoring seasonal crop performance through its growth and development, and for final yield prediction well in advance. It depends mainly on the nature and stage of growth of the crop together with the environmental conditions. FAO studies have shown that, WRSI can be related to crop production, using a linear yield-reduction function specific to a crop (FAO, 1986).

CHAPTER THREE

3 DATA AND METHODOLOGY

3.1 Description of the study area

3.1.1 Location:

The study area is located geographically between 7° 31' 27" to 9˚45′ 40″ N Latitude and 41° 10' 15" to 42˚58′ 30″ E Longitude covering the total area of 25161.5 $km^{2.}$ (Fig 3.1). The East Hararge zone is located eastern part of Oromia regional state in Ethiopia at the distance of around 526 km from Addis Ababa, and it is found within the altitude range of 500 to 3400m above mean sea level. East Hararge zone is bordered on the Southwest by the Shebelle river which separates it from Bale, on the West by West Hararge, on the North by Dire Dawa and on the northeast by Ethiopian Somali region. Harari regional state is located within East Hararge zone.

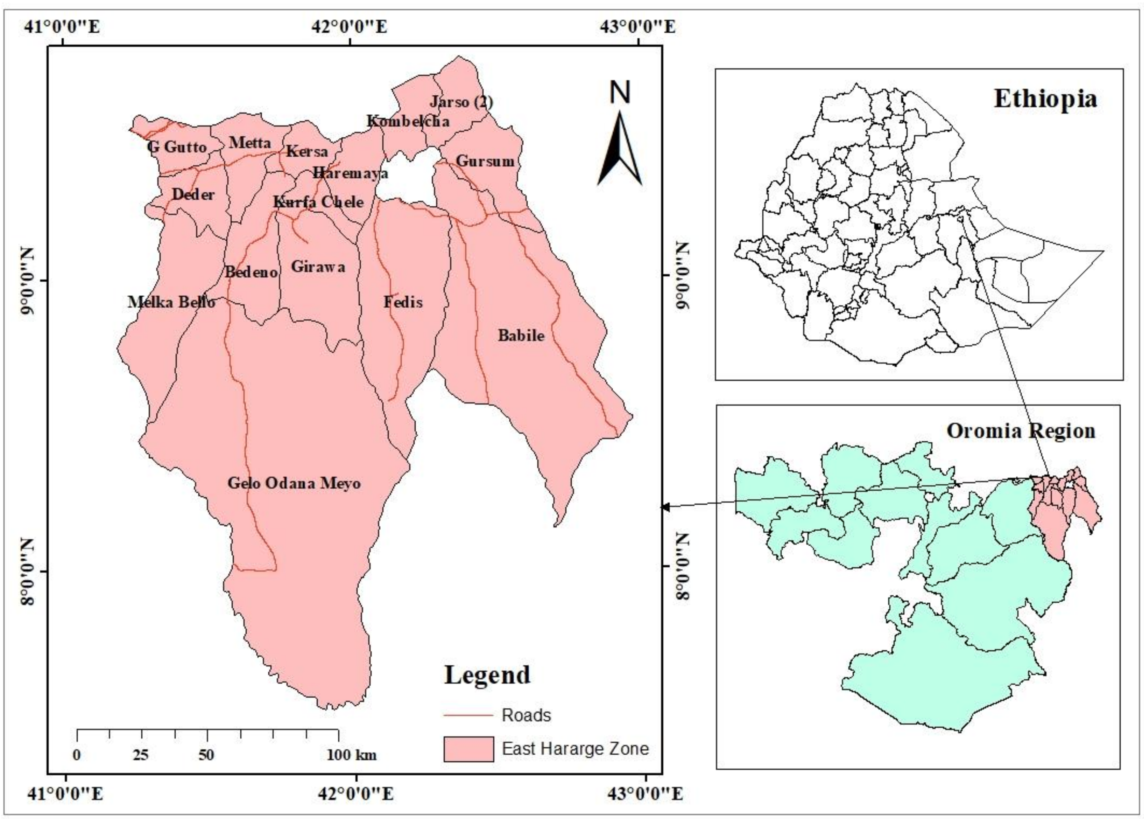

Figure 3.1: Location map of the study area

3.1.2 Topography and Climate:

The topography of East Hararge is characterized by steep slopes in the highlands and mid-highlands, and large plains in the lowland areas. The highlands and mid-highlands are normally extensively cultivated but only partially protected by soil conservation structures and practices such as grass strips, alley cropping and bench terraces. In these areas, land scarcity leads farmers to destroy the few remaining forests in order to cultivate on steep slopes, resulting in additional erosion. The lowlands are partly cultivated and partly used for pasture. These areas are also subject to erosion, which is exacerbated by extensive charcoal production in certain parts. East Hararge is traditionally categorized into three broad topographical zones. Usually, they are referred to as Dega or highlands(2300-3400m) covering about 10-15%, Weyna Dega or midlands(1500-2300m), about 30-35% and Kola or Lowlands(500-1500m) covering about 40-45% (Fig 3.2).

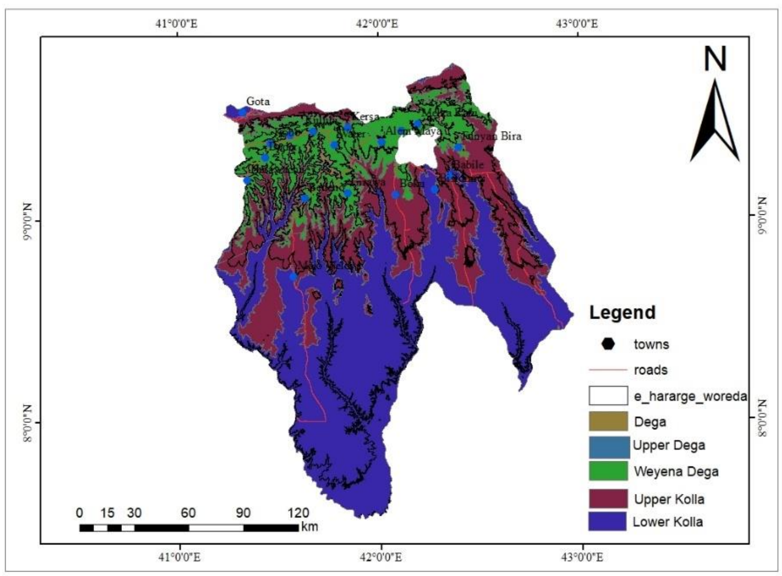

Figure 3.2 Ecological zone map of the study area.

East Hararge Zone is recurrently affected by scarcity and irregularity of seasonal rainfalls, that results in intensive drought conditions; mainly, due to the impacts of the advancing high subtropical desert climates during the winter seasons. The local traditional classifications assert that, normally, East Hararge Zone enjoys two rainy seasons in a year. These seasons are locally described as 'Belg' the short period (March to May) and Meher' the long period (June to

September) rainy seasons. ‘Belg’ rains are mainly used for land preparation and planting of long cycle crops such as Maize and Sorghum, and seed bed preparation for ‘Meher’ crops. The ‘Meher’ rains are used for planting cereal crops like barley, ‘teff’, wheat and vegetable crops like onion, shallots and potatoes in the mid highlands and the highlands; and peanut in the lowlands. Besides, ‘meher’ rains are also responsible for the growth and development of perennial crops such as coffee and ‘chat’ (OWWDSE, 2010). According to the ground data of National Metrological Agency, the mean annual rainfall of East Hararge Zone for the period of (2005-2015) is 349.8mm

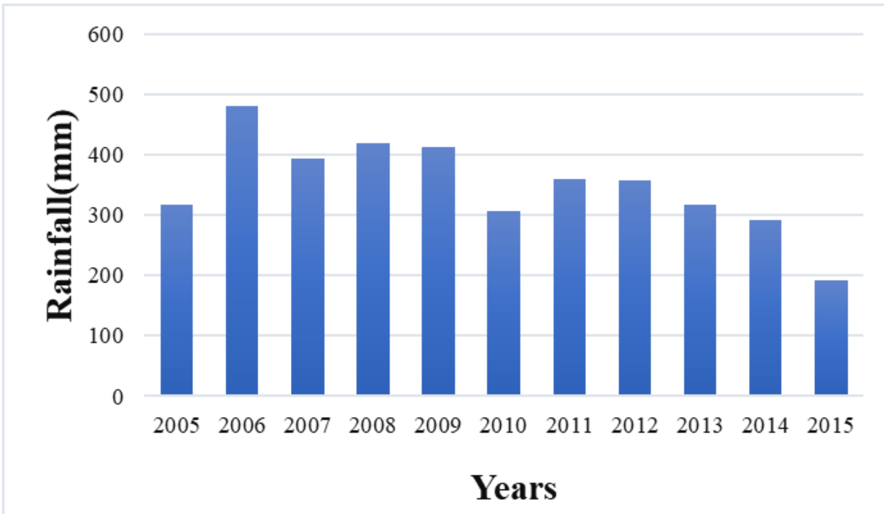

Figure 3.3: Annual rainfall of the study area based on NMSA data (2005 to 2015).

3.1.3 Natural Resources:

3.1.3.1 Land use and land cover:

Land use land cover is an important component in understanding the interaction of human activities with the natural environment (Prakasam, 2010). The land use types within the study area were classified into five major classes. These are built up area, bare land, wood land, shrub and farm land. Among them farm land and shrub land cover large area (Fig 3.4 & Table 3.1).

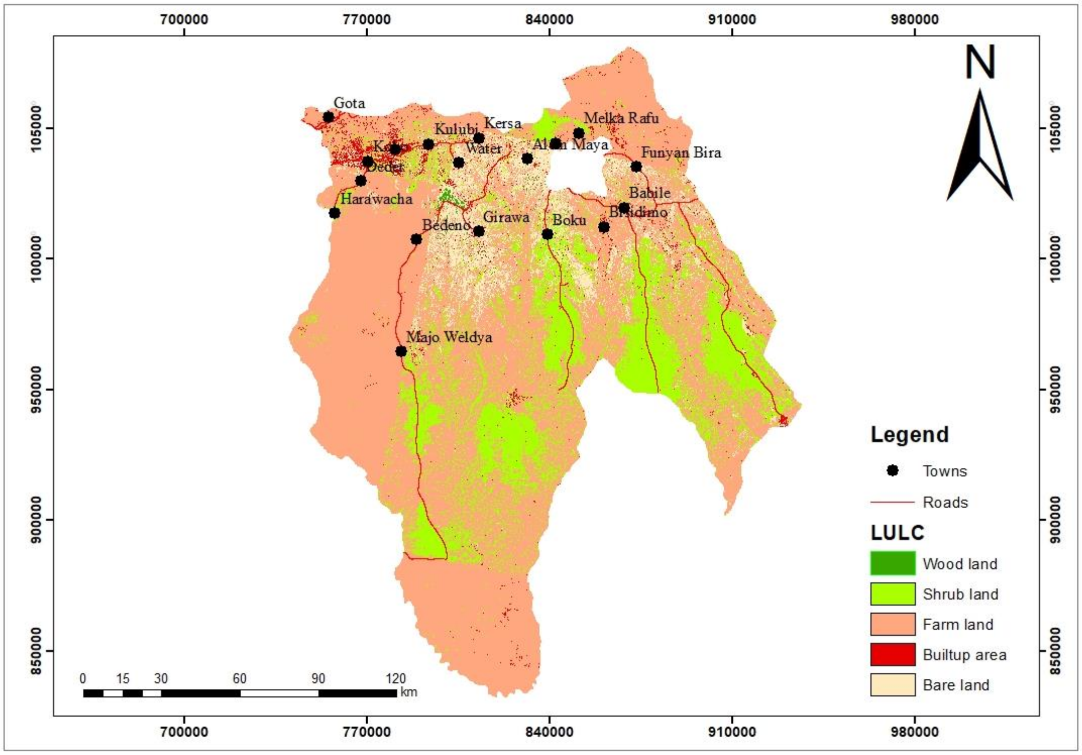

Figure 3.4: Land use land cover map of the study area

Table 2: Areal coverage of different land covers type of the study area

LULC Classes	Area(km^2)	Area (%)
Built up area	462	1.8
Farm land	17131	67
Shrub land	5272	20
Wood land	59	0.2
Bare land	2236	8.7
Total	25,160	100

3.1.3.2 Soil:

Soil plays a vital role in the survival of living things on the earth. Healthy soil is the foundation of the food system. It produces healthy crops that in turn nourish people. Soils provide readily available nutrients to plants and animals by converting dead organic matter into various nutrient forms. According to Food and Agricultural Organization (FAO) cited in Finance and Economic

Development Bureau of Oromia (2007), Andosols, Vertisols, Rendzinas and Phaeozems, and Fluvisols are the dominant soil type found in East Hararge zone (Fig 3.5).

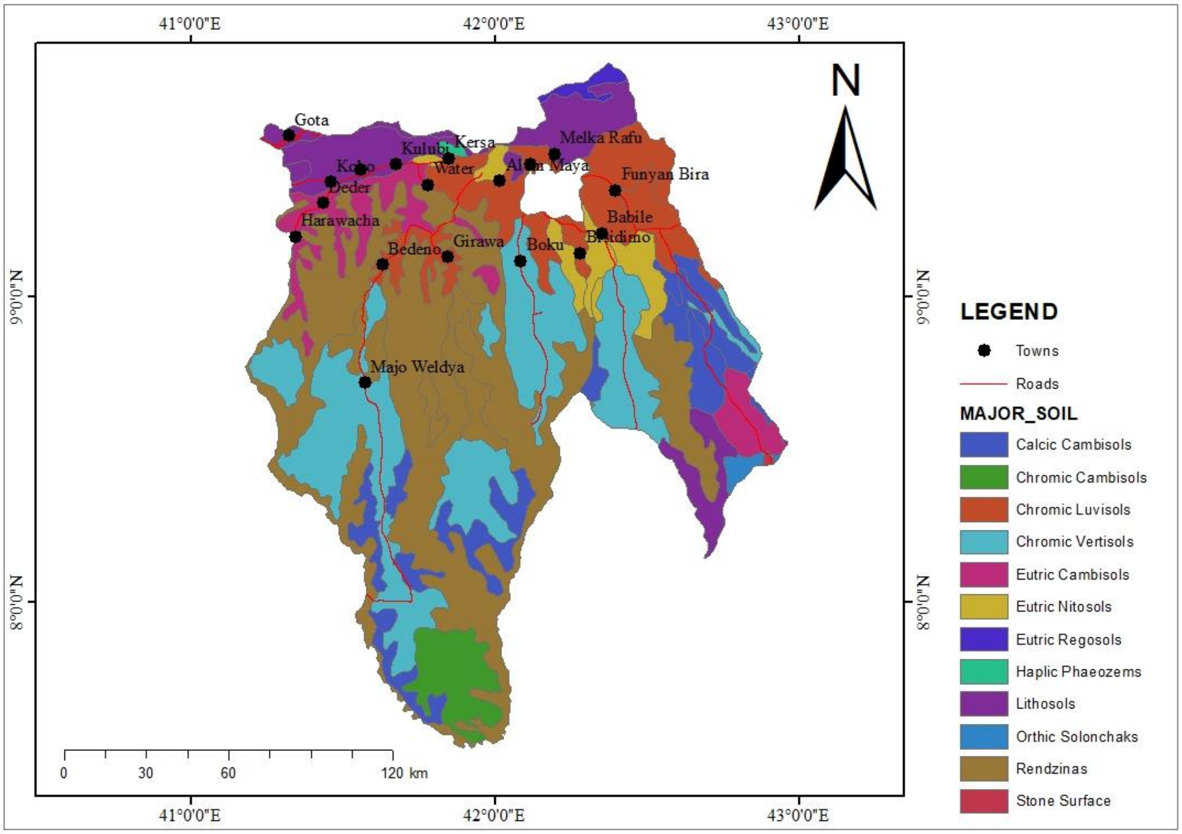

Figure 3.5: Soil types map of the study area

3.1.4 Basic Population Characteristics:

According to results of the 2007 population and housing census of Ethiopian Central Statistical Agency (CSA,2007), East Hararge zone has total population of 2,723,850 an increase of 48.79% over the 1994 census, of whom 1,383,198 are men and 1,340,652 are women. The habitat type distribution category of the population shows that 216,943 or 8.27% are urban dwellers, 30,215 or 1.11% are pastoralists and 2,476,692or 90.62% are rural. The major ethnic group of the zone is 96.43% Oromo, 2.26% Amhara and 1.31% are other ethnic groups. The religious composition shows that the vast majorities 96.51% are Muslim and 3.12% of the population professed Ethiopian Orthodox Christianity. The three major language predominantly spoken in the zone are Oromic (94.6%), Somali (2.92%) and Amharic (2.06%) (CSA, 2007).

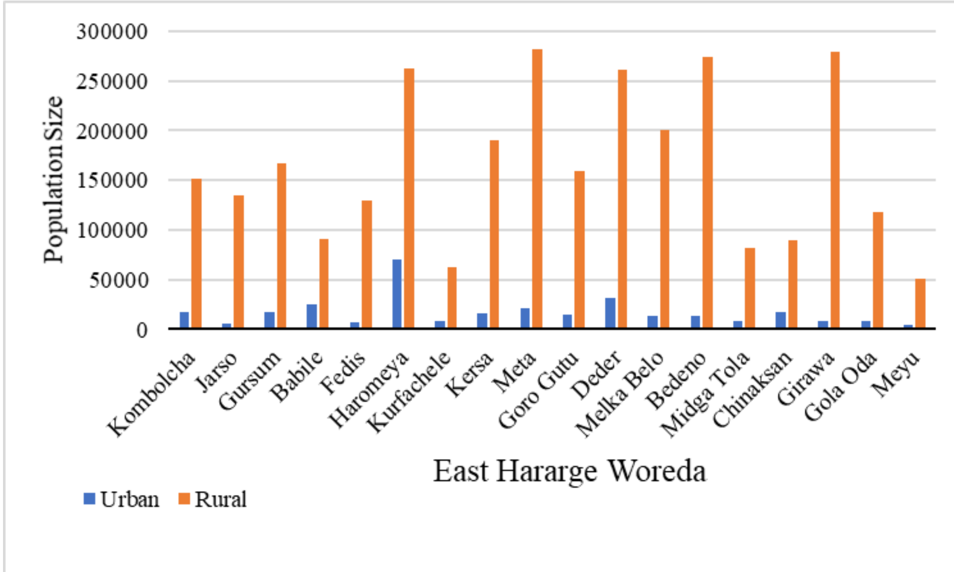

Figure 3.6: Population size by place of residence

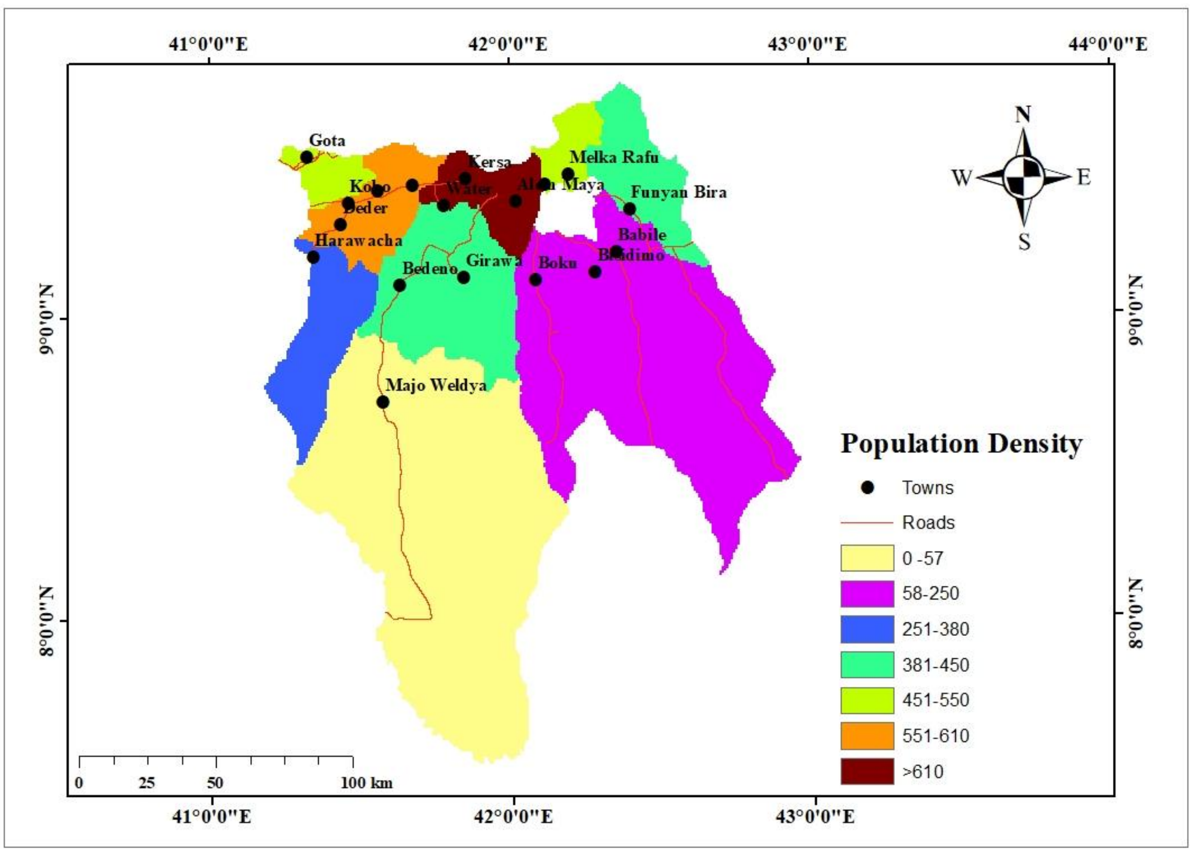

Figure 3.7: Population density of the study area

3.2 Economic activities.

Grain crops, cereals, pulses, oilseeds, vegetables, root crops, fruit crops, Chat and Coffee are the well-known agricultural products of the zone. According to CSA (2005 to 2015) among the major crop types harvested during the main rainy season of the zone, cereal crops take the highest average amount of yield (4,850,228 quintals). Out of this amount, crops like teff 1,635,006, maize 1,324,080, sorghum 2,340,948 and wheat 143,873 quintals account for the biggest average yield covering the areas of 132,171, 47,516, 1,129,153 and 19,629 hectares of land respectively (Tables 3 and 4).

Table:3 Average productions of the major cereal crops in the study area (2005 to 2015).

Crop Type	Production in Quintals	Area in hectare
Teff	1635006	132171
sorghum	2340948	1129153
maize	1324080	47516
wheat	143873	19629

Table:4 Average productions of crop types by average area in the study area (2005 to2015).

Crop Type	Production in quintals	Area in hectare
Cereals	4850228	250835
Pulses	222771	12913
Oilseeds	369219	30238
Vegetables	12128	287
Root crops	615801	7261
Fruit crops	33363	741
Chat	647529	56523
Coffee	17624	56797

Source: CSA annual yield data (2005 to 2015)

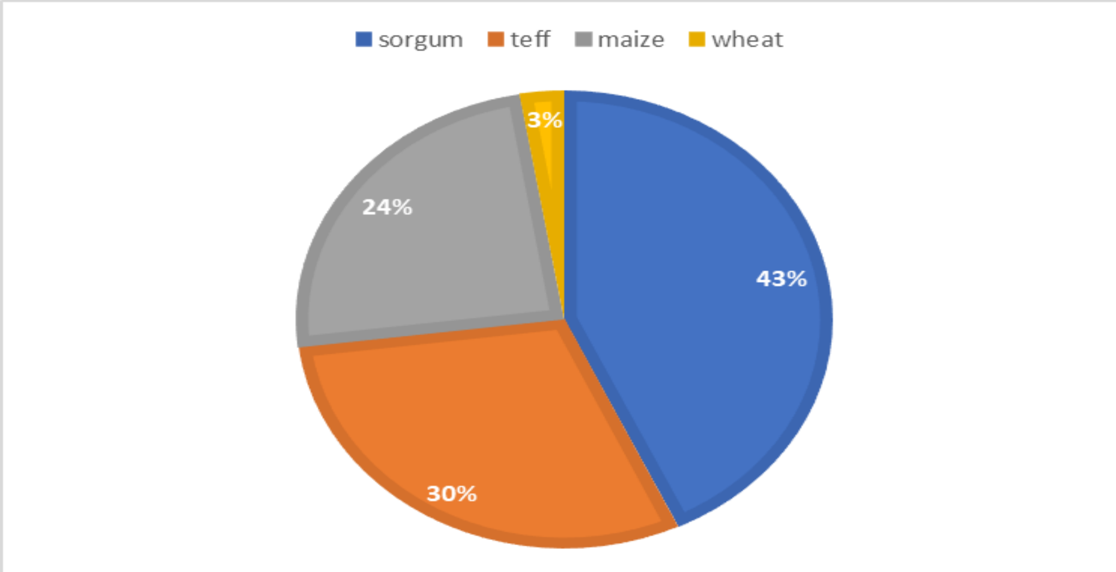

Figure:3.8 Percentage of land coverage by cereal crop during the main seasons (2005 to 2015).

3.3 Data Description and Software:

3.3.1 Data Description:

The primary and secondary data that were identified as criteria and constraint factors for analysis were collected from different sources. Primary data and information were generated from analysis of satellite images, field observation, and the secondary data were obtained from different sources such as terrain model of the area, surveys and mappings that have already been conducted in the area.

Table 3:Data source.

			Resolution			
Data set	Variable	Description	Spatial	Temporal	Period	Source
SPOT V	NDVI	Satellite	1km by 1km	Daily	2005-2013	VITO
PROBA V	NDVI	Satellite	1km by 1km	Two days	2014-2015	VITO
MODIS	PET	Satellite	500m	8 days	2005-2015	USGS
CHIRPS Africa Decadal	Rainfall	Satellite	10km by 10km		2005-2015	FEWS NET
Agricultural data	Yield	Ground data	Quintal/H	Year	2005-2015	CSA
Metrological Data	Rainfall	Ground data	Average mm	Monthly	2005-2015	NMA
Land use/ Land cover		Ground data			2017	field visit

3.3.2 Software packages

Table 4:Types of software packages used

Type	Version	Data Type	Purpose
ArcGIS	10	NDVI, SPI, AI & WRSI	image processing, statistical analysis, graphical display and map preparation
ERDAS IMAGINE	15	LULC	image processing, land use land cover classification
SPIRITS	1.5.1	NDVI & SPI	data extraction, geometric and radiometric correction
IDRISI SILVA	17.01	Frequency map of NDVI, SPI, AI & WRSI	Drive percentage of influence
CROPWAT	8.0	AI	Data processing

3.4 Methodology

3.4.1 Satellite Data processing

For this study, indices for drought monitoring were derived from SPOT VEGETATION, PROBA-V, MODIS and Rainfall Data. SPOT VEGETATION instrument is one of the first sensors designed specifically for global vegetation monitoring. It offers a valuable tool for vegetation mapping and monitoring at regional scale. Reflectance measurements are performed within four spectral windows: Blue, Red, Near Infra-red and Medium Infra-Red. The high temporal resolution of one day allows the capability for image selection according to best quality, least cloud cover and the optimal phonological stage of vegetation cover, which plays a significant role in vegetation condition monitoring and mapping. For this study SPOT-5 vegetation, decadal (10-days) synthesis archive products with a spatial resolution of 1km were downloaded for the years 2005 to 2013 from the Flemish institute for technological research (Dutch: Vlaamse Instelling voor Technologisch Onderzoek or VITO) website. The Spectral Bands and range of the data are Blue (0.43 to 0.47 µm), Red (0.61 to 0.68 µm), Near-infrared (0.78 to 0.89 µm) and Mid-infrared (1.58 to 1.75 µm). For the year 2014, on the other hand, the ten-day composites which were generated and distributed by VITO using maximum value composites (MVC) algorithm, were downloaded from Copernicus Global Land Service Website (http://land.copernicus.eu/global). It has 1km spatial and 2-day temporal resolution. Although several satellite-based precipitation data sets were available, it was found necessary to download a time series decadal (10 days) rainfall from the Famine Early Warning System (FEWS-NET) archive website for the study period (2005 to 2015). The data set, was Climate Hazard Group Infrared Precipitation with station data (CHIRPS). It has a 10km by10 km spatial resolution. Satellite based monthly potential evapotranspiration data were available to download from (https://earthexplorer.usgs.gov/) archive website for the study period of (2005-2015). The main reason for the selection of the data set is due to its relative high spatial resolution and availability at near-real time with reasonable accuracy.

3.4.1.1 Normalized Difference Vegetation Index (NDVI)

This index is widely used for determining water stress levels in vegetation and assessment of agricultural drought (Singh et al., 2003) thereby enabling to monitor changes in vegetation over time. NDVI is one of the indices of vegetation that are used to study vegetation water stress, health and density. It can be calculated from two bands, the near-infrared (NIR) and RED wavelengths. NDVI= (NIR-R) / (NIR+R); Where NIR= near infrared band, R= Red band. NDVI is a nonlinear function that ranges between -1 and +1. Processing and analyzing of the projected vegetation data, a time series SPOT VEGETATION Africa level data at a spatial resolution of 1 km and temporal resolution of 1 day was given a prime importance because, it better meets the requirement for assessing and mapping drought vulnerability at regional level. The raw data which were received from VITO and Copernicus were a 10 day (S10), Maximum Value Composite (MVCs) already geometrically and radio metrically corrected. All the 11 years' 396 decadal images together with the information related to image (metadata) were imported in generic binary format. But these Decadal composite series images (S10), are still perturbed, mainly, by noise due to missing values, data errors and especially clouds. Therefore, the smoothening process using the weighted least-squares approach developed by Swets et al., (1999) was opted to be used to minimize such problems and enable to more effectively map land cover, identify phonological trends, and monitor vegetation. The process is found to be effective, particularly, in monitoring the development of seasonal metrics such as onset and duration of the growing season. Therefore, the weighted least-squares approach of Swets was used to smoothen the imported S10 NDVI images using SPIRIT software. The smoothed image was, then, masked out for Ethiopian boundary. It was re-projected from Albers Equal Area Conic to UTM projection

(UTM, Zone 37 N), rescaled to generate monthly maximum NDVI, using the SPIRITS software. Then the monthly maximum NDVI was exported in to ArcGIS, in order to generate seasonal maximum NDVI and long-term mean maximum NDVI in the cell statistics tool box.

3.4.1.2 Standard Precipitation Index(SPI)

The SPI was developed by McKee et al (1993). It was designed to quantify the precipitation deficit for multiple time scales. These time scales reflect the impact of drought on the availability of different water resources (Shaheen and Biag, 2011). 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 (Legese Hadish, 2010). It is designed to quantify the impacts of precipitation deficit on groundwater, reservoir storage, soil moisture, and stream flow for multiple time scales. 11 years, 396 dekadal images were imported, re-projected, and masked using the study area shape file, to prepare monthly and seasonal rainfall value, using ArcGIS cell statistic tool. Then, Standardized precipitation Index (SPI) was calculated using map algebra raster calculator tool of the same software in order to prepare the yearly seasonal precipitation deficit in the study area.

$$SPI = (Xij - Xim) / Ợ$$

Where, Xij = is the seasonal precipitation and, Xim is its long-term seasonal mean and Ợ is its standard deviation. Finally, the results computed from seasonal rainfall data were assigned for each grid cell and reclassified based on the drought severity class.

Table 5: SPI based drought severity class

SPI value	Drought severity class
Above 0	No drought
0.0 to -0.99	Slight drought
-1.0 to -1.49	Moderate drought
-1.5 to -1.99	Severe drought
-2 and less	Very Severe drought

3.4.1.3 Water Requirement Satisfaction Index (WRSI)

WRSI was developed, mainly, for monitoring seasonal crop performance through its growth and development, and for final yield reduction well in advance. It depends mainly on the nature and stage of growth of the crop together with the environmental conditions. Water Requirement Satisfaction Index is a useful indicator of crop performance based on the availability of water during the crop growing season. According to Gizachew Legesse and Suryabhagavan (2014) WRSI based drought assessment can better capture drought events. The most important inputs to this model are Potential Precipitation (PPT), Potential Evapotranspiration (PET) relevant soil information from the FAO 1986 digital soils map, and topographical parameters derived from HYDRO-1K digital elevation data and water holding capacity WRSI is taken as the ratio of seasonal actual AET (ET) to the seasonal crop water requirement (WR):

$$WRSI = \text{AETWR } 100$$

Where WR is calculated from the Penman Monteith potential ET (PET) using the crop coefficient (Kc) to adjust for the growth stage of the crop as

$$WR = \text{PET x } Kc100$$

WRSI was also computed using LEAP software. The WRSI result was then reclassified based on drought severity classes.

Table 6: WRSI based drought severity class

WRSI value (%)	Drought severity class
80-100	No drought
70- 79	Slight drought
60-69	Moderate drought
50-59	Severe drought
< 50	Very Severe drought

3.4.1.4 Aridity index(AI)

An aridity index (AI) is a numerical indicator of the degree of dryness of the climate at a given location. Aridity Index can be used to quantify precipitation availability over atmospheric water demand.

$$\text{Aridity Index (AI)} = \text{MAP} / \text{MAE}$$

Where: MAP = Mean Annual Precipitation

MAE = Mean Annual Potential Evapotranspiration

Potential Evapo-Transpiration (PET) is a measure of the ability of the atmosphere to remove water through Evapo-Transpiration (ET) processes. 11 years, 132 monthly images were imported, re-projected, and masked using the study area shape file, to prepare seasonal and mean annual potential evapotranspiration value, using ArcGIS cell statistic tool. Then aridity index was calculated using map algebra raster calculator tool of the ArcGIS software. Finally, aridity index results reclassified into drought severity classes using the same software.

Table 7: AI based drought severity class.

Aridity index	Drought severity class
AI<0.03	Hyper arid
0.03<AI<0.20	Arid
0.20<AI<0.50	Semiarid
0.50<AI<0.65	Dry sub humid

3.5 Regression Analysis of Crop Yield with Drought Indices

The crop yield data and data obtained from drought indices were prepared for simple regression analysis. The mean raster cell values of NDVI, SPI, WRSI and AI images were extracted using ArcGIS cell statistics. The relationship between NDVI, SPI, WRSI and AI result from each seasonal year with corresponding crop yield was computed to validate the derived drought indices.

3.6 Drought Vulnerability Assessment

Drought vulnerability map of the study area was produced from the output obtained from satellite-based drought indices by using Multi Criteria Evaluation (MCE) technique. According to Lemma Gonfa (1996), Gizachew Legesse and Suryabhavan (2014) showed as the probability of drought occurrence in a given area can be classified in to high, moderate and low drought probability areas when drought is prevalent in more than 50%, 30 to 50% and less than 30% of the years, respectively. Based on this the seasonal frequency maps obtained from each drought indices were reclassified into common scale and the frequency of maps of each drought classes were reclassified into four classes on the regularity of drought rate during the study periods. They categorized as from 2 to 3 mild vulnerable, 4 to 5 moderate vulnerable, 6 to 8 severe vulnerable and 9 to 11 extreme vulnerable. Finally, maps from each drought indices were weighted according to the percentage of their influences, using ArcGIS software; and then combined using weighted overly analysis.

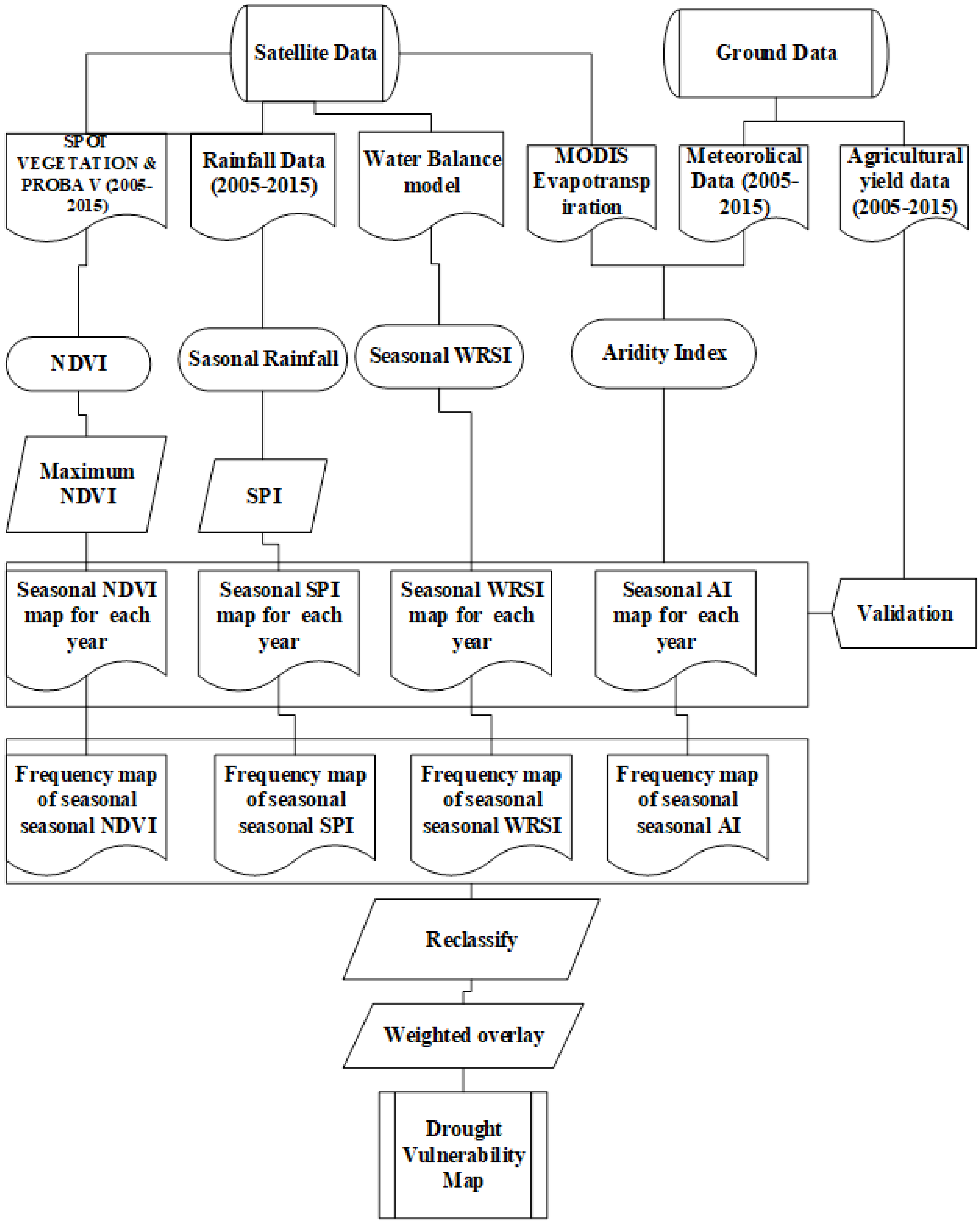

Figure 3.8: Schematic flow chart of the study.

CHAPTER FOUR

4 RESULTS

4.1 Relationship between Seasonal Rainfall and NDVI

Seasonal analysis of historical rainfall and the response of vegetation in terms of NDVI are very important. Considering the average seasonal NDVI and rainfall patterns of the East Hararge zone from 2005 to 2015, NDVI values have increased proportionally as the mean seasonal rainfall increased (Fig 4.1 and Appendix 2). It has been shown that there is good correlation (r=0.7) between the two. Spatially, the NDVI and rainfall values increased from the eastern to the western part of the Zone and North Western part of the Zone with its values reaching up to 0.79 (maximum) and 502 mm (maximum), respectively. But in the Southern and North Eastern part of the Zone, NDVI and Rainfall were decreased. During the 11 years, there was a considerable change in the NDVI and rainfall values. The highest NDVI value was observed when the mean seasonal rainfall was better distributed. Similarly, the lowest NDVI value was recorded when little rainfall was registered during the year. Rainfall was less during the years 2005, 2007, 2014 and 2015. The minimum NDVI values were recorded as rainfall changed during the dry years, particularly 2005, 2007, 2014and 2015.

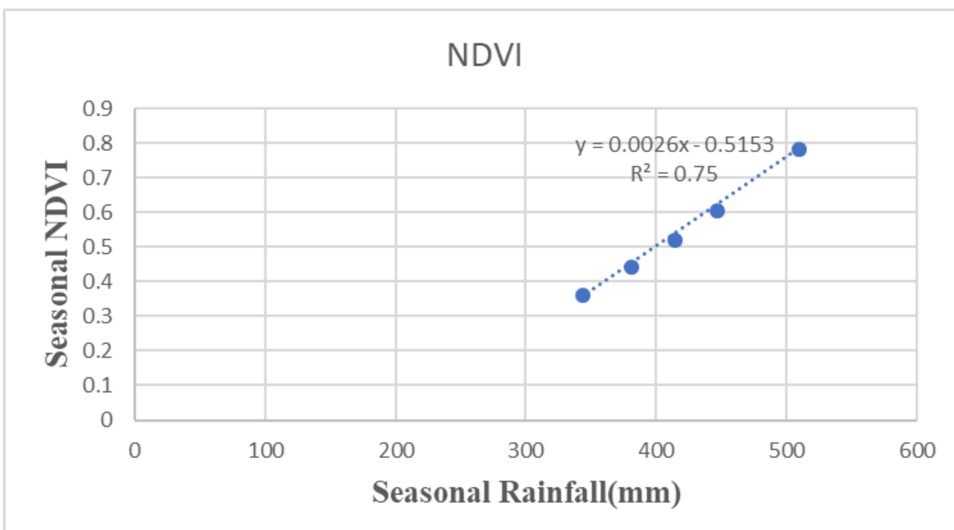

Figure 4.1: Relationship between long term NDVI and seasonal rainfall (2005 – 2015)

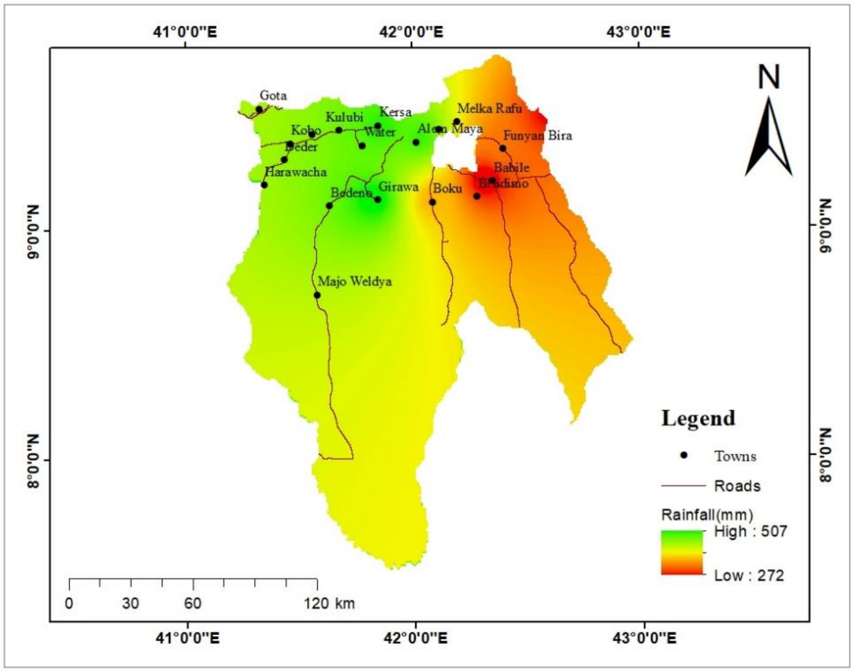

Figure 4.2: Spatial patterns of long term seasonal (June-September)

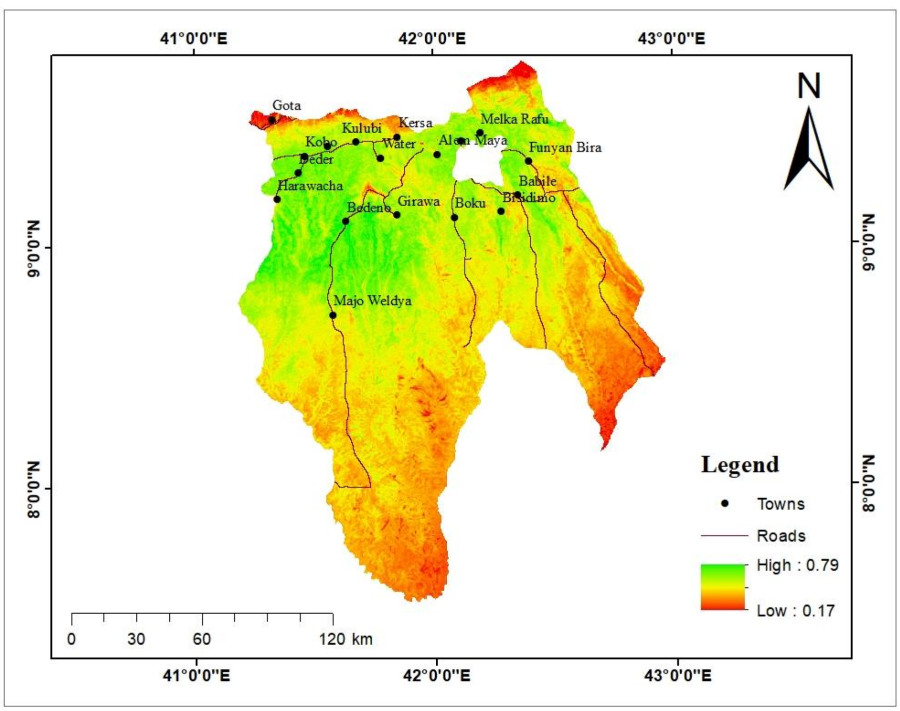

Figure 4.3: Long term seasonal (June–September) Normalized Difference Vegetation Index

It is evident from the seasonal NDVI values and rainfall distribution (Fig 4.2 & 4.3) and that, vegetation stress occurred during the years 2005, 2007, 2014 and 2015. Therefore, special emphasis was given to the need to thoroughly investigate the amount and spatio-temporal distribution patterns of rainfall in relation to the normal volume of water required for effective crop growth or vegetation needs satisfaction. Accordingly, it was possible to detect the fact that the probability for the temporal variation of rainfall distribution to be one of the major factors affecting the responses of vegetation to the existing rainfall was considerably high. Evidently, despite the fact that the relationship between temporal trends of seasonal NDVI and seasonal rainfall appeared to be good (Fig 4.4). The temporal mismatch between seasonal rainfall distribution and NDVI, as the main factor of the disparity, has led to occurrence of various levels of drought.

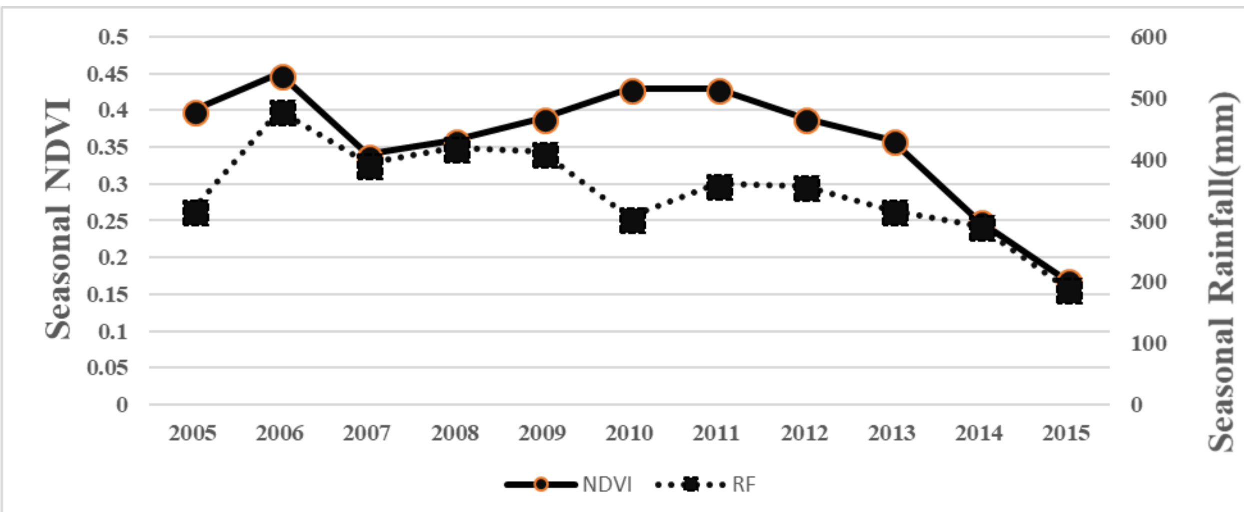

Figure 4.4: Temporal trends of seasonal (June-September) rainfall and NDVI (2005 to 2015).

4.2 Normalized Difference Vegetation Index (NDVI) and Drought

NDVI is useful indicator as a measure of drought when compared to normal plant health. Based on this index, spatial pattern of drought for dry years (2005 to 2015) was computed to determine the severity of drought. This result shows that there was variability that indicates vegetation stress in different seasons. Accordingly, as it is shown on (Fig 4.5, 4.6 and 4.7), each of the maps of seasonal NDVI value indicated that the Southern and some parts of North eastern of the study areas have the lowest NDVI value compared with other parts within the Zone. Relatively, North western and some parts of North eastern have high NDVI value. The long term seasonal NDVI values indicated the existence of poor vegetation performance in the Zone. However, its magnitude and spatial extent varied. Negative NDVI values indicated the dry season, while the positive values showed wet season. Based on the information obtained from the processing result of the eleven years' NDVI values, the spatial patterns of drought for the years2005, 2007 and 2014 and wet for the years 2006 and 2011 were computed to determine the severity of drought. The results of the NDVI computation confirmed that the spatial patterns of drought events and the levels of its severity ranged from slight in most of the years to severe in 2005, 2007 and 2014.

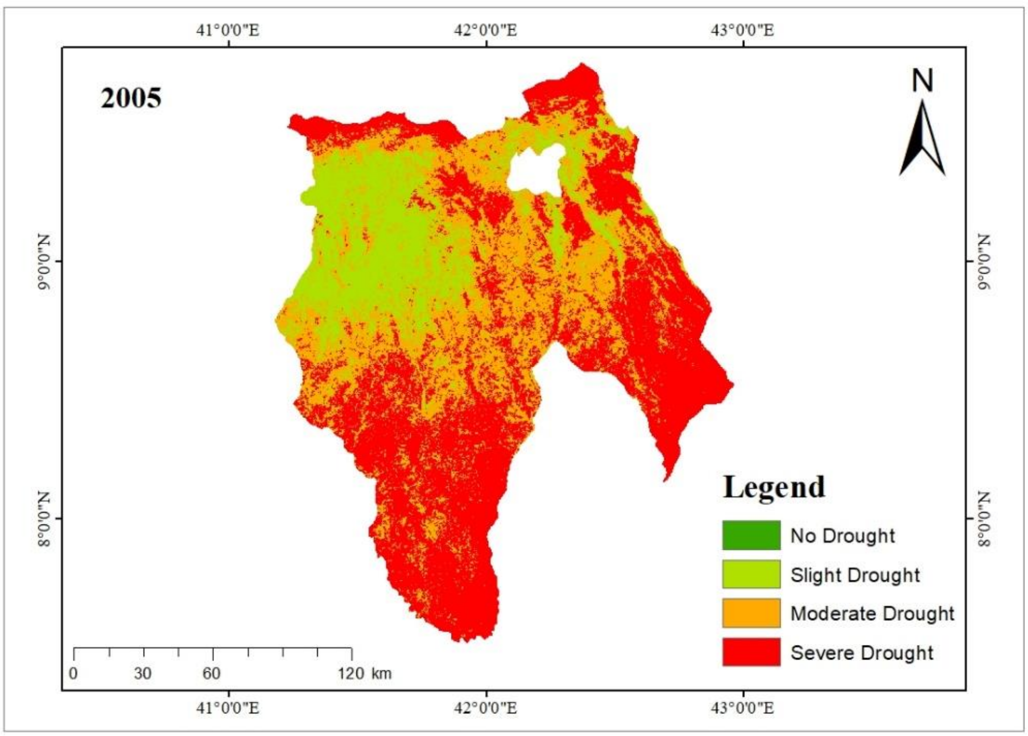

Figure 4.5: Spatial pattern of drought severity for drought years 2005 in NDVI

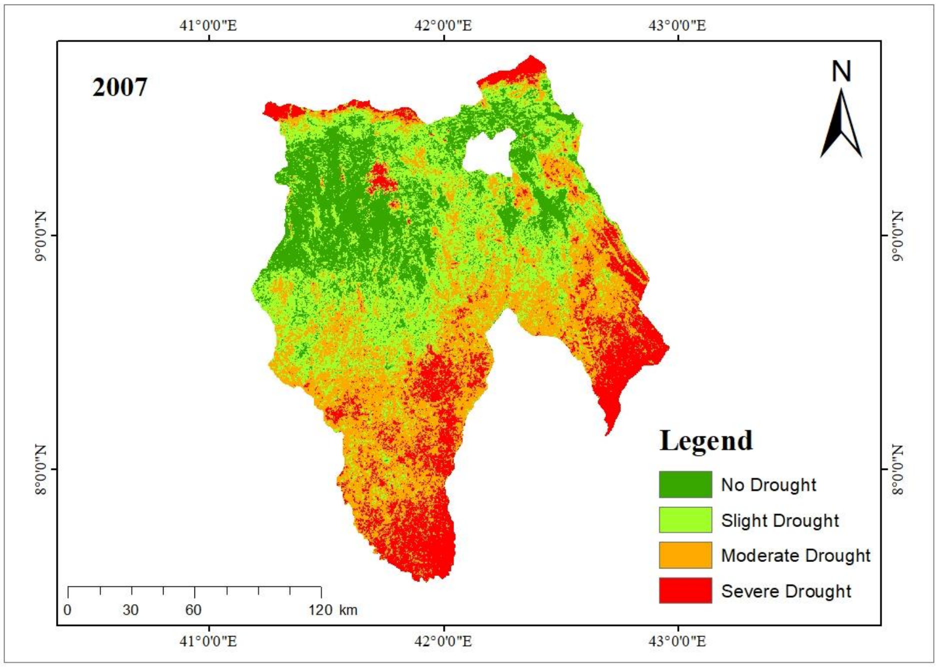

Figure 4.6: Spatial pattern of drought severity for drought years 2007 in NDVI

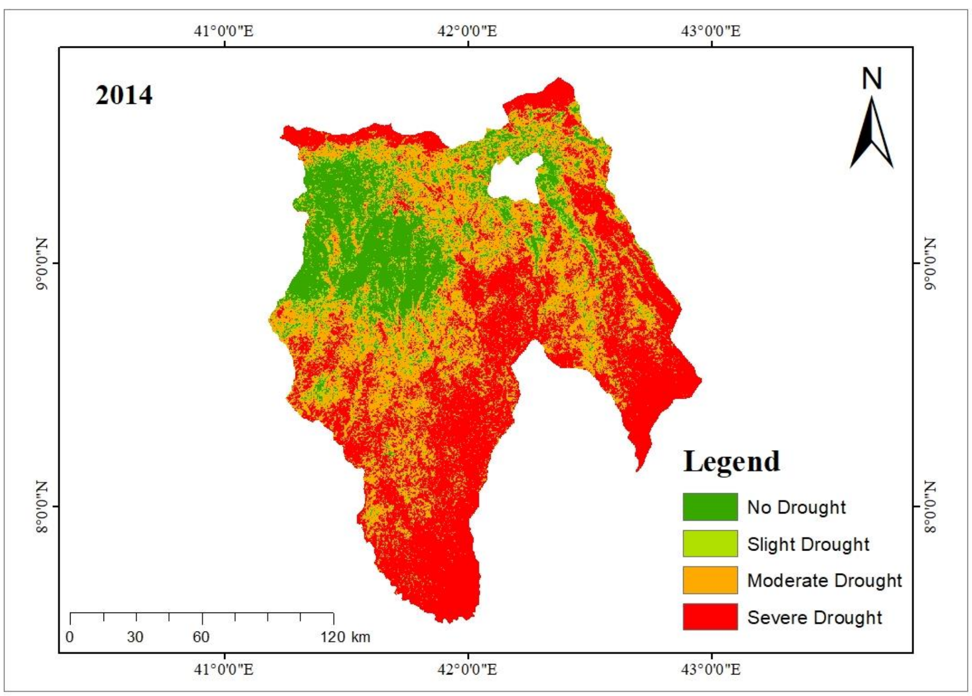

Figure 4.7: Spatial pattern of drought severity for drought years 2014 in NDVI

The percentage area hit by drought (Fig 4.5, 4.6, 4.7 and Table 8) during the 2005 cropping season was found to be 18%, 35% and 46% of the total areas for slight, moderate and severe severity levels respectively. The next dry season for the study area in NDVI were 2007. Drought severity for 2007 cropping season were 49%, 30% and 21% of the total areas for slight, moderate and severe severity levels respectively, whereas the corresponding drought severity for 2014 cropping season was 24%, 35% and 41 % of the total area respectively.

Table 8: Percent of area covered by drought severity for dry years 2005, 2007 and 2014 expressed by NDVI

	Drought Years					
	2005		2007		2014	
Class	Area km²	Area (%)	Area km²	Area (%)	Area km²	Area (%)
No Drought	0	0	4741	20	4027	16
Slight Drought	4429	18	6750	29	2322	8
Moderate Drought	7343	35	6998	30	9140.8	35
Severe Drought	10,382	46	3665	21	9675.6	41
Total	23,850	100	23850	100	23,850	100

Regarding the wet years, it can be observed from the map (Fig 4.8 & 4.9) that some very small pocket areas were hit by severe level of drought while the majority of the areas under the influence of slight and moderate drought. The percentage range of drought severity indicates that during the 2006 cropping season from 55%, 9% and 0 % of the total area were hit by slight, moderate and severe levels of severity respectively (Table 9). On the other hand, the corresponding drought severity of 2011 cropping season was found to be 58%, 8%, and,0.2% for slight, moderate and severe respectively.

Table 9: Percent of area covered by drought severity for wet years 2006 and 2011 expressed by NDVI

	Wet years			
	2006		2011	
Class	Area km²	Area (%)	Area km²	Area (%)
No Drought	7870	36	6494	31.8
Slight Drought	12,189	55	13,731	58
Moderate Drought	2095	9	1881	10
Severe Drought	0	0	47	0.2
Total	23,850	100	23850	100

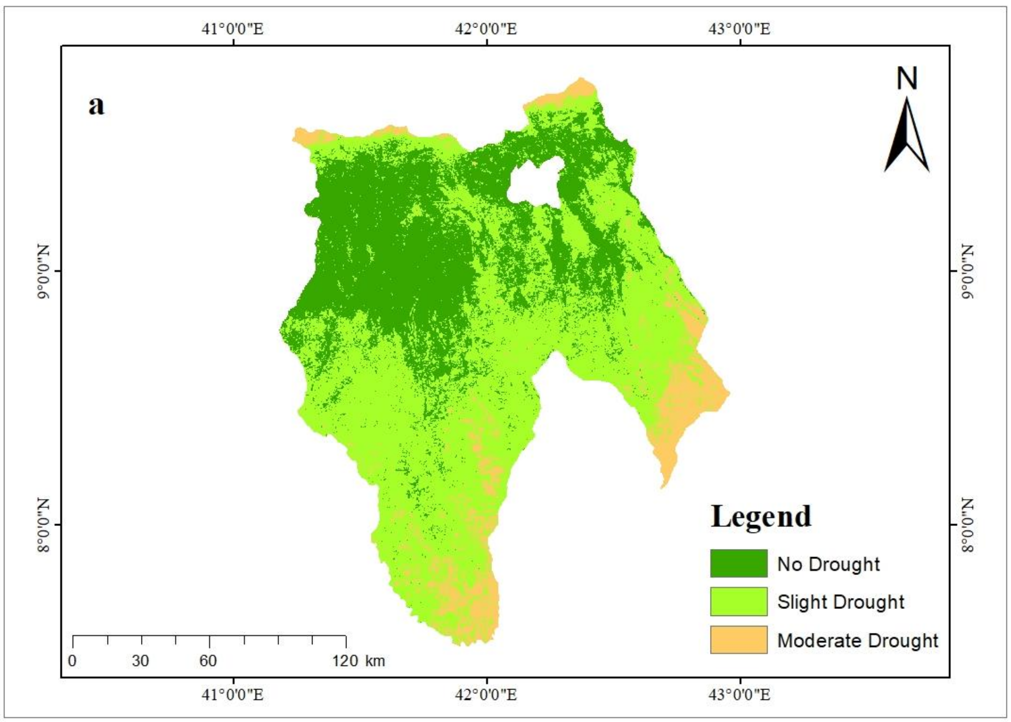

Figure 4.8: Spatial pattern of drought severity for wet years 2006 expressed in NDVI

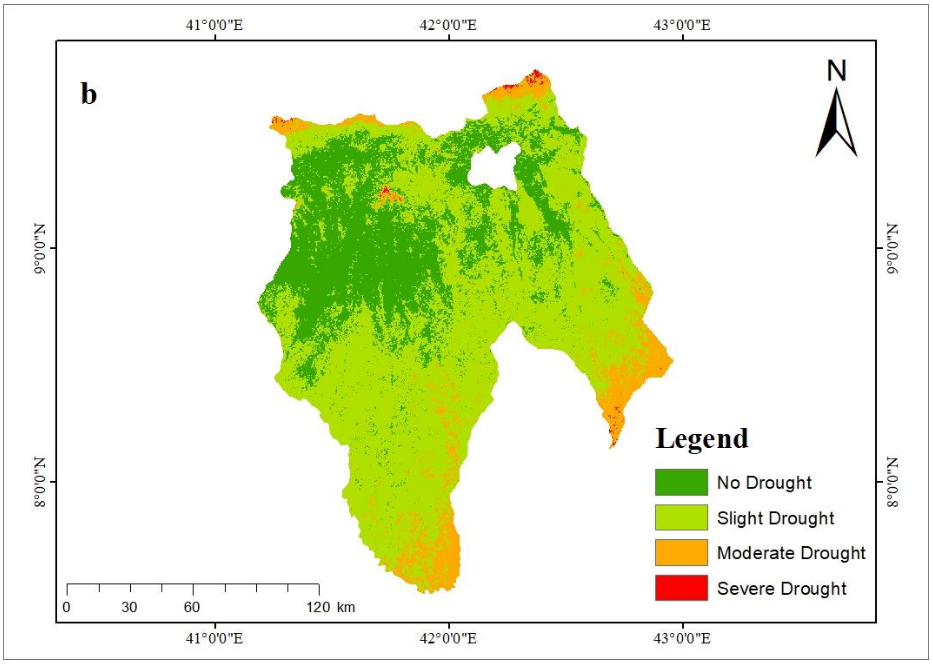

Figure 4.9: Spatial pattern of drought severity for wet years 2011 expressed in NDVI.

4.2.1 Relationship between NDVI and crop yield anomaly

In order to validate satellite derived output, crop yield of agricultural production is the main ground truth data. Therefore, it is crucial to analyze the relationship between NDVI and crop yield to quantify the impact of drought on agricultural production. (Fig 4.10 and Appendix 3) shows that, that the two variables have established good correlation (r=0.92). The result revealed that the relationship established between the two variables is positive; NDVI anomaly increases so do agricultural yield and vice-versa. Thus, the strength of the index to explain the existence of agricultural drought through agricultural yield is relatively good.

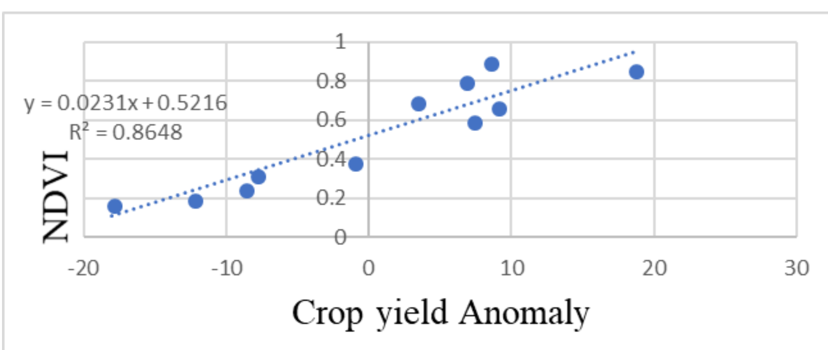

Figure 4.10: Relationship between NDVI and Crop yield anomaly

4.3 Spatial and temporal patterns of Aridity Index and drought severity

The Aridity Index (AI) values indicated that droughts have occurred at different levels of severity from 2005 to 2015 cropping seasons in the study area. The drought that occurred in year 2005, 2007 and 2014 were much more severe compared to other years as explained by the AI values that range from 0.017 to 2.6, 0.02 to 1.75 and 0.029 to 2.3 respectively (Fig 4.11, 4.12 and 4.13).

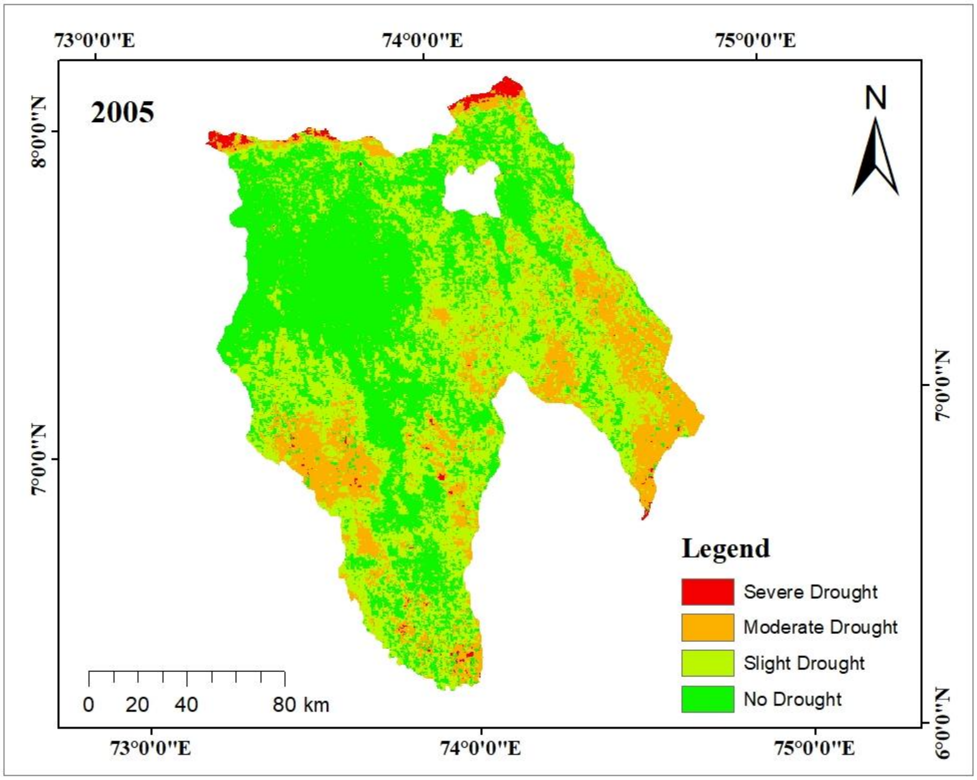

Figure 4.11: Spatial pattern of drought severity for drought years 2005 expressed in AI.

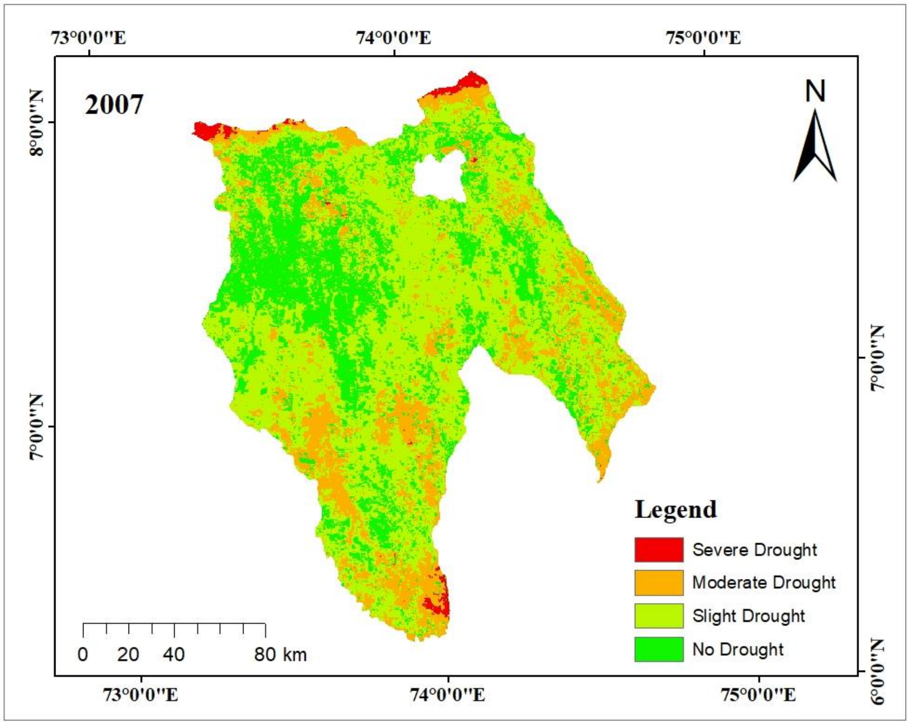

Figure 4.12: Spatial pattern of drought severity for drought years 2007 expressed in AI.

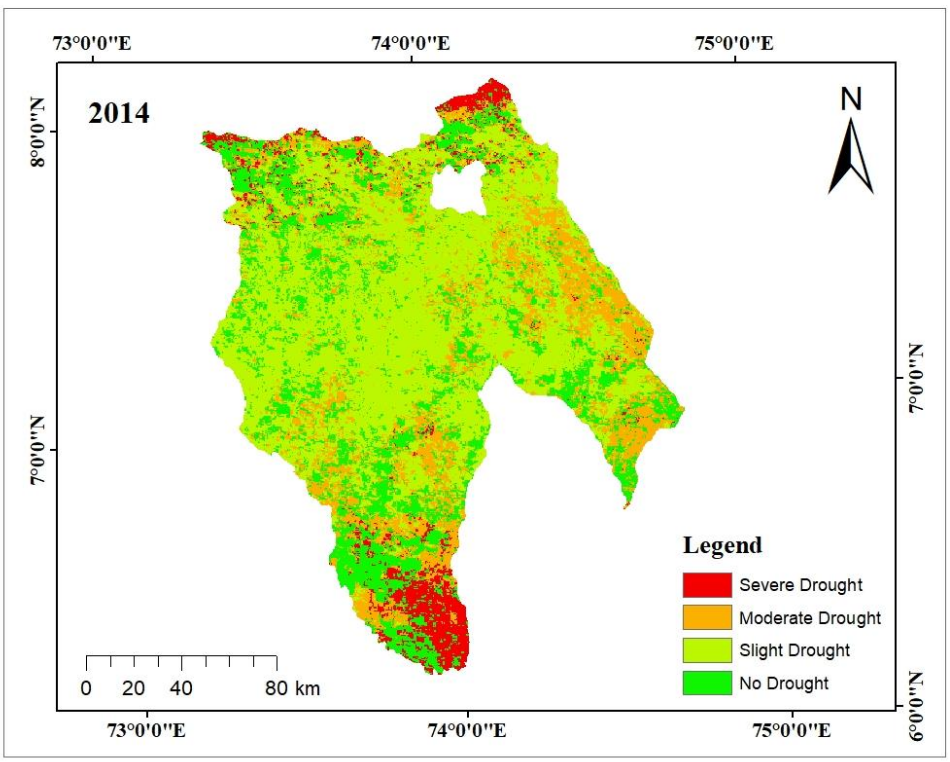

Figure 4.13: Spatial pattern of drought severity for drought years 2014 in AI.

The result indicates that in the year 2005, there was a very large area covered affected by drought was found to be 46%, 42% and 10% of the total area were hit by severe, moderate and severe levels of severity respectively. The percentage range of drought severity during 2007 cropping season from 20.5%, 44% and 34% of the total area were hit by Severe, Moderate and Slight drought, respectively. During the 2014 drought year, the level of drought severity shows that severe 18%, moderate 43% and slight covering areas 31% of the Zone (Table 10).

Table 10: Percentage of area covered by drought severity for dry years 2005, 2007 and 2014 expressed by AI.

	Drought Years					
	2005		2007		2014	
Class	Area km²	Area (%)	Area km²	Area (%)	Area km²	Area (%)
No Drought	304	2	333.5	1.5	1776.5	8
Slight Drought	2874	10	8495	34	7290	31
Moderate Drought	9552	42	15927	44	14559	43
Severe Drought	10,640	46	5619	20.5	5245	18
Total	23,850	100	23,850	100	23850	100

Since AI can be used to identify both dry and wet years, AI analysis was applied to the identification of the wet years conditions too. As clearly shown on (Fig 4.14, 4.15 and Table 11), the two years 2006 (98.56%) and 2012 (94.77 %) were the wettest years, for the study period, in the East Hararge Zone.

Table 11: Percentage of area covered by drought severity for wet years 2006 and 2012 expressed by AI.

	Wet years			
	2006		2012	
Class	Area km²	Area (%)	Area km²	Area (%)
No Drought	59.25	2	65.5	1
Slight Drought	1805	8	328.5	1.5
Moderate Drought	9563.5	48	5260	21
Severe Drought	12,943	42	16,714	76.5
Total	23,850	100	23850	100

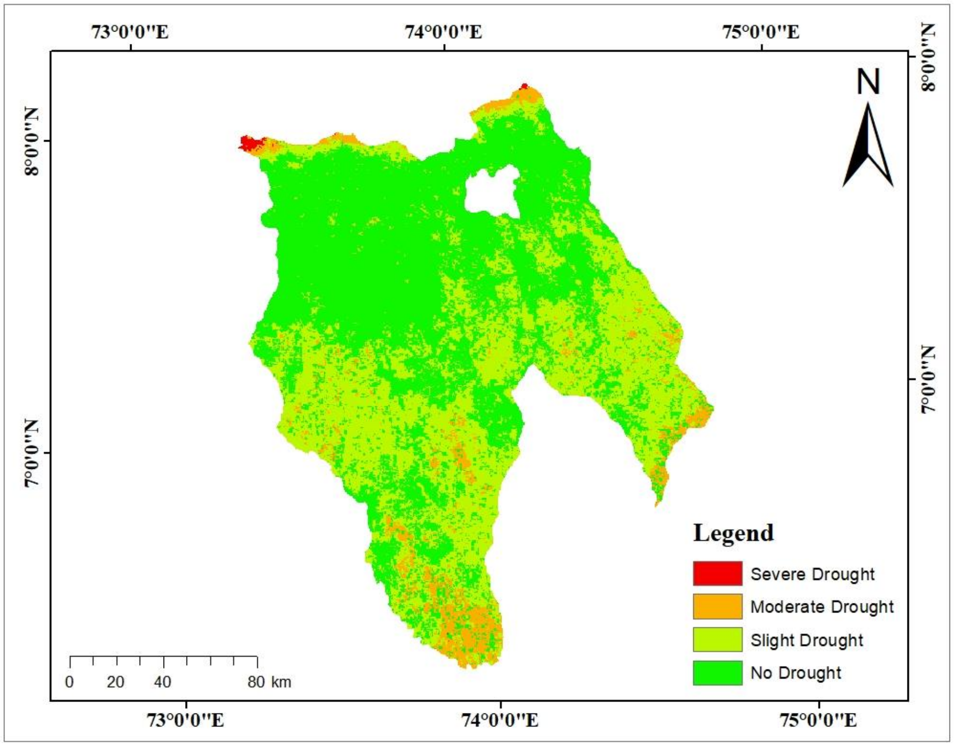

Figure 4.14: Spatial pattern of drought severity for the wet years 2006 as expressed in AI.

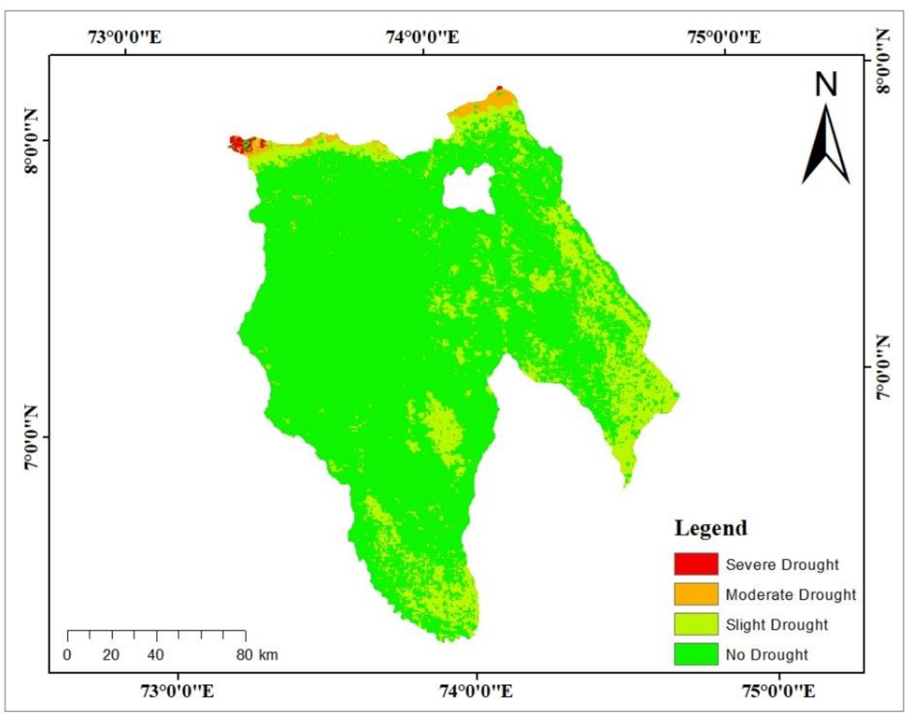

Figure 4.15: Spatial pattern of drought severity for the wet years 2012 as expressed in AI.

4.3.1 Aridity Index (AI) and Crop yield anomaly

The correlation and regression analysis between AI and crop yield indicated that the relationship between the two variables was positive with r= 0.91. It revealed that 82% of yield variability could be explained by AI. (Fig 4.16 & Appendix 4), shows the trends in seasonal AI and Crop yield production in the study area. Based on the result of AI and crop yield, there was a considerable change on the agricultural production. During the 2005, 2007 and 2014 very low crop yield was recorded in the Zone. However, there was relatively high yield production when there was low AI.

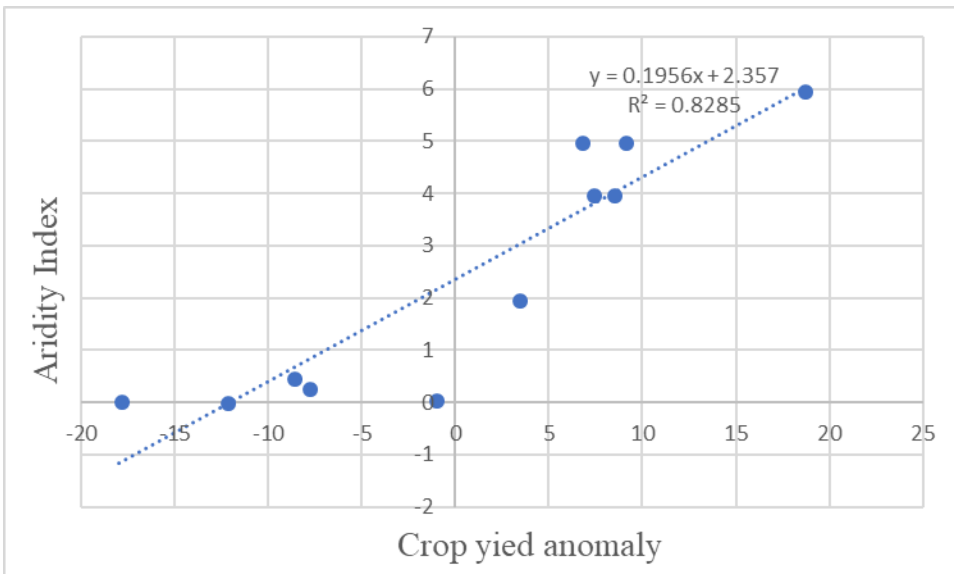

Figure 4.16: Relationship between AI and Crop yield anomaly.

4.4 Spatial and temporal patterns of Standard Precipitation Index (SPI) and drought severity

SPI was computed for growing season of East Hararge zone. The results of the analysis revealed that droughts have occurred at different levels of severity from 2005 to 2015 cropping seasons. The drought that occurred in year 2005, 2007 and 2014 was the severe compared to other years as explained by the SPI values (Fig 4.17). The result indicates that during these three years, there was rainfall deficit in the growing season and that they were considered the worst dry years of the study period.

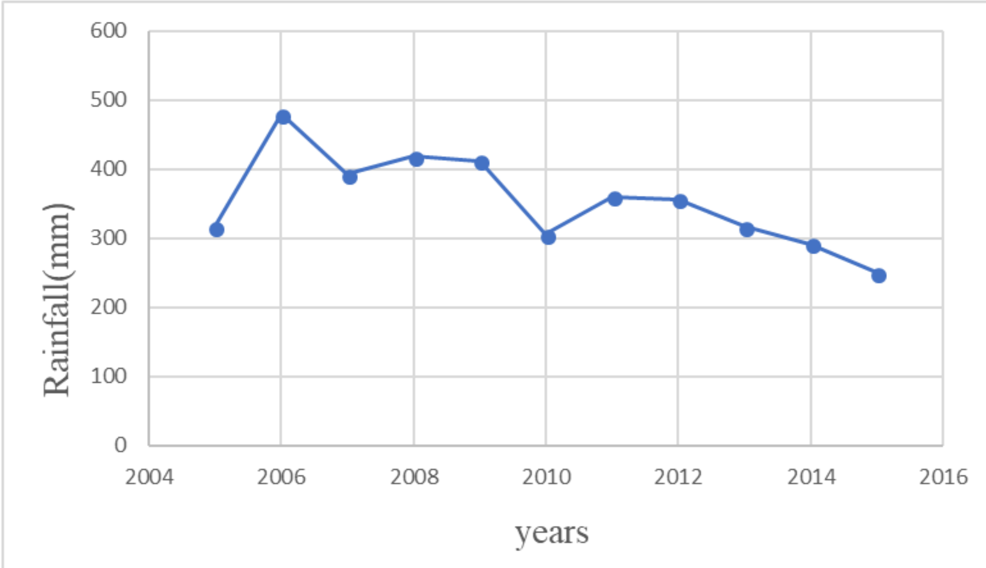

Figure 4.17: Temporal pattern of seasonal (June-September) SPI (2005-2015).

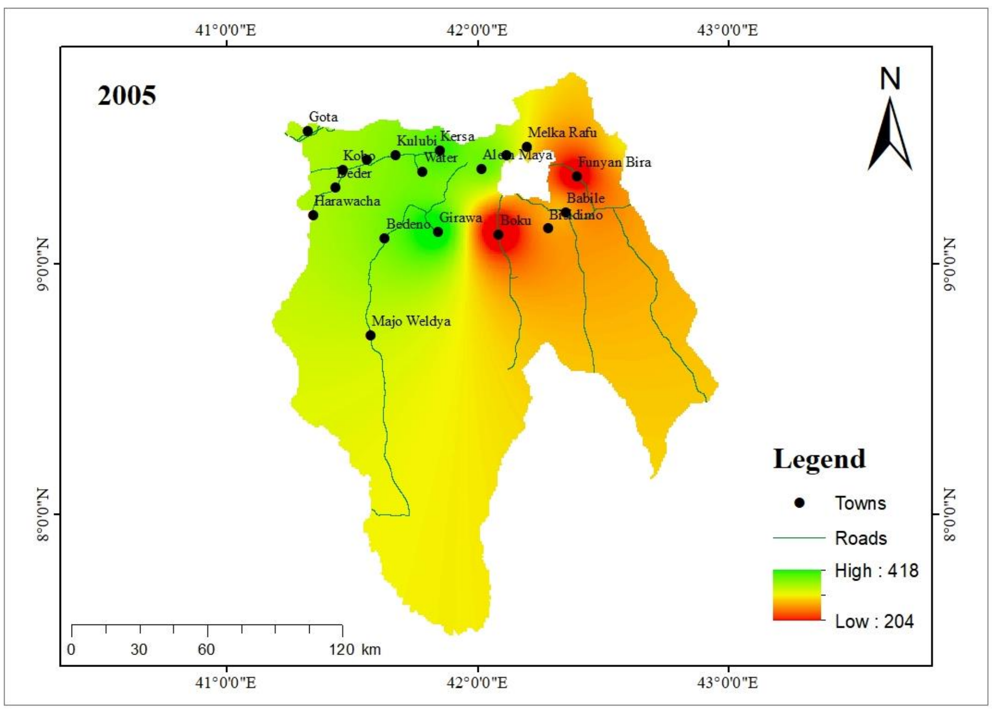

Figure 4.18: Spatial pattern of drought severity for dry years 2005 as expressed in SPI.

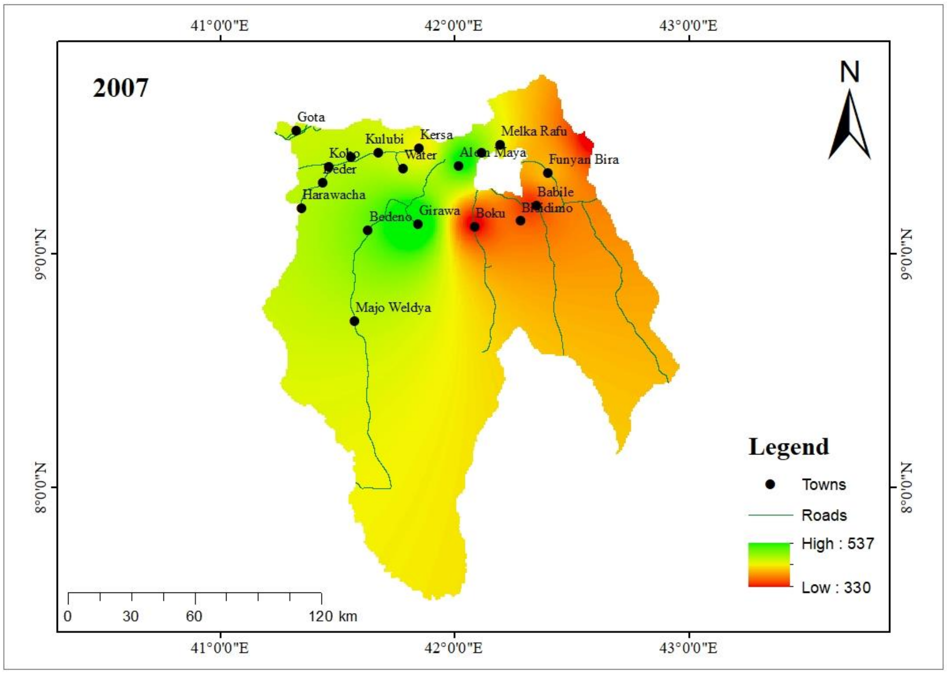

Figure 4.19: Spatial pattern of drought severity for dry years 2007 as expressed in SPI.

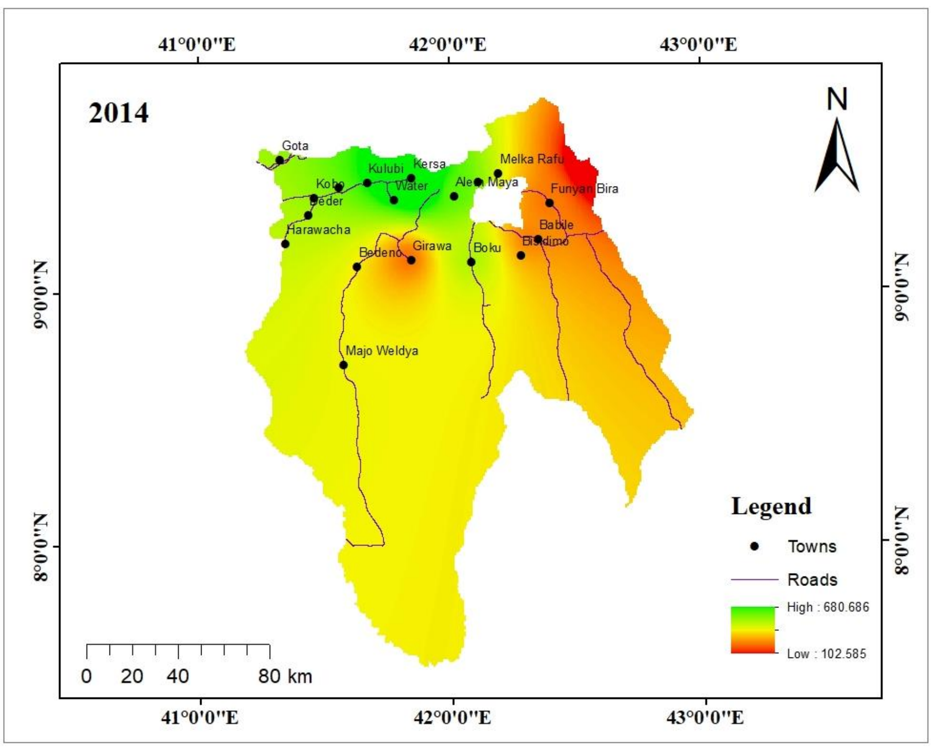

Figure 4.20: Spatial pattern of drought severity for dry years 2014 as expressed in SPI.

Spatial patterns of SPI for drought years (2005, 2007 and 2014) and wet years (2011 and 2012) analyzed and reclassified to show spatial trends of drought severity. Considering three of the most severe droughts years (2005, 2007 and 2014), drought intensity and extent is illustrated for the Zone. SPI spatial pattern analysis result showed that the whole area was hit by drought, ranging from slight to severe level of severity, during these three seasons. The result indicates that in the year 2005 and 2007, there was a very widely distributed drought, covering the widest area (Fig 4.18, 4.19 and 4.20) accounting for 11%, 23%, and 59% for 2005 and 17.2%, 32% and 49% for 2007 of the total area hit by slight, moderate, and severe drought, respectively. During the 2014 drought year, the level of drought severity was shown that slight (17%), moderate (59%) and severe (21%).

Table 12: Percentage of area covered by drought severity for dry years 2005, 2007 and 2014 expressed by SPI.

	Drought Years					
	2005		2007		2014	
Class	Area km²	Area (%)	Area km²	Area (%)	Area km²	Area (%)
No Drought	76	6	320	1.8	776.5	3
Slight Drought	3200	11	8495	17.2	8290	17
Moderate Drought	5800	23	15927	32	14559	59
Severe Drought	14,975	59	5619	49	5245	21
Total	23,850	100	23,850	100	23850	100

Standard Precipitation Index can also be used to identify not only drought years but also wet years. Thus, using SPI analysis, wet years were also identified. As the maps shown in the (Fig 4.21, 4.22 and Table 13) the year 2011 and 2012 were wettest years in East Hararge zone. The range of severity was from moderate drought to no drought.

Table 13: Percentage of area covered by drought severity for wet years 2011 and 2012 expressed by SPI.

	Wet years			
	2011		2012	
Class	Area km²	Area (%)	Area km²	Area (%)
No Drought	8150	26	7800	31
Slight Drought	10,225	49	12,050	48
Moderate drought	5502	25	4029	21

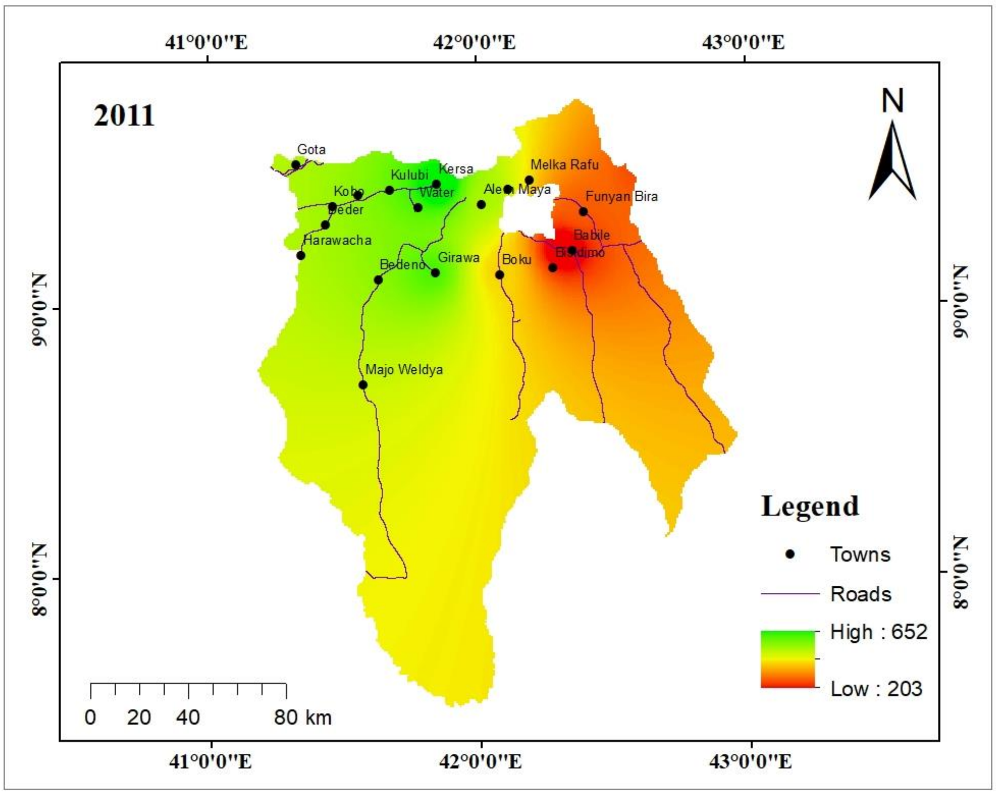

Figure 4.21: Spatial pattern of drought severity for the wet years 2011 as expressed in SPI.

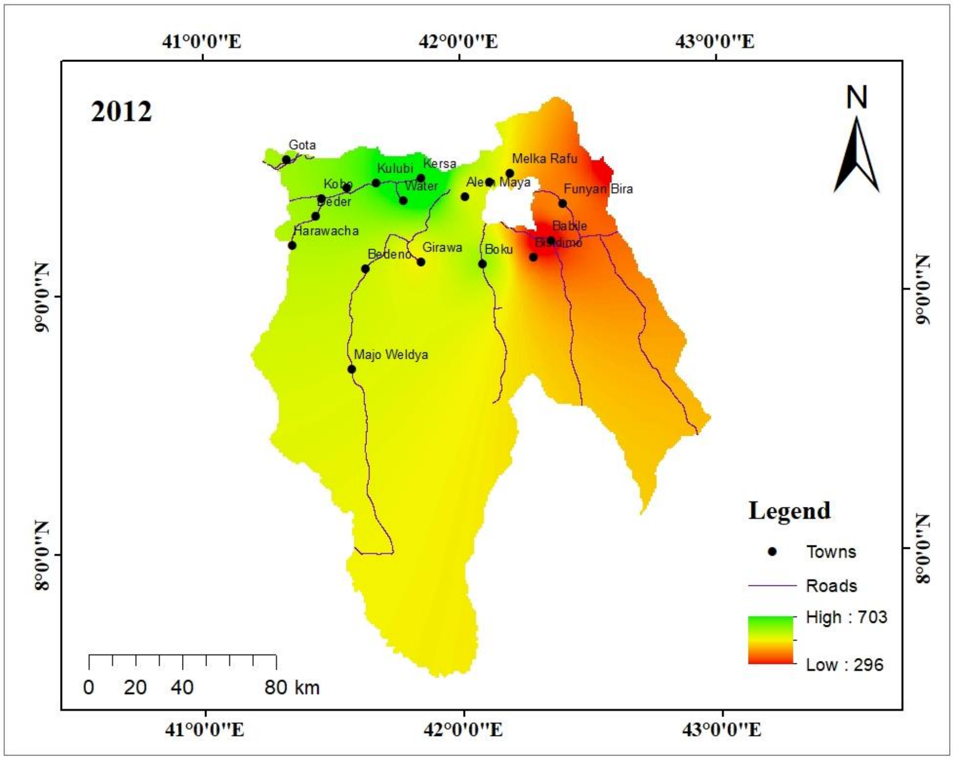

Figure 4.22: Spatial pattern of drought severity for the wet years 2012 as expressed in SPI.

4.4.1 Standard Precipitation Index (SPI) and Crop yield anomaly

Due to the fact that crop production is a function of rainfall, crop failure is most often associated with moisture deficit or drought. Thus, the regression analysis between Standardized precipitation Index and crop yield anomaly is important for validation. In view of this, SPI and crop yield anomaly were regressed for the whole of the study area and the result has shown that when SPI is positive, crop yield anomaly also turns positive revealing a good positive correlation (r=0.84) (Fig 4.23 and Appendix 6). Since SPI is an index that represents water deficit or excess, positive SPI represents that water has been available to plants so that crop yield become above normal condition, Whereas, negative SPI or rainfall deficiency is reflected on crop production through yield reduction.

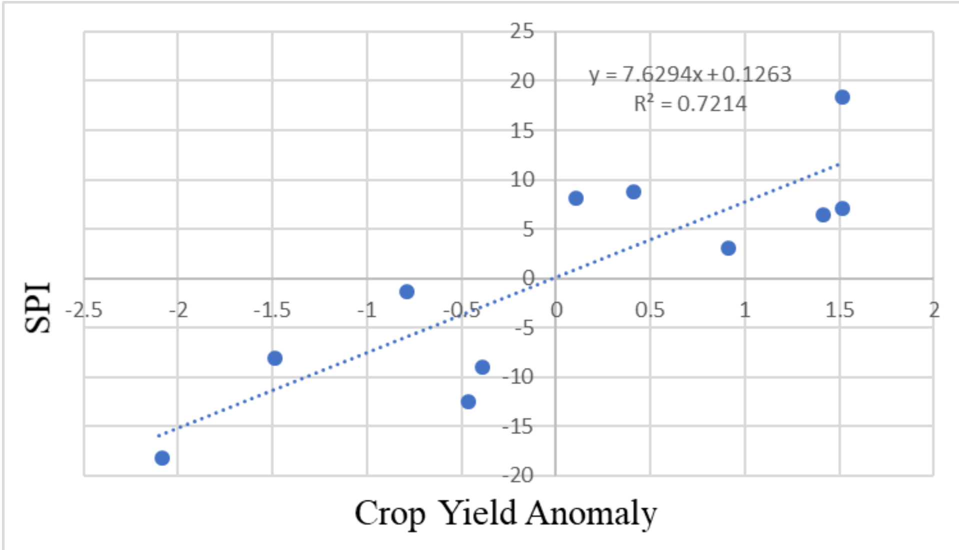

Figure 4.23: Relationship between SPI and Crop yield anomaly.

4.5 Water Requirement Satisfaction Index (WRSI) based drought Characterization

The performance of crops growing in the study area has been investigated using WRSI index, for the study period. The result revealed that less WRSI values in large part of the study area showing moisture deficit during the drought years (2005, 2007 and 2014). According to the results indicated in (Fig 4.24, 4.25, 4.26 and Table 14), during the 2005, 2007 and 2014 cropping season, severe drought was observed to be prevalent in most part of the southern and some areas in the north of the Zone.

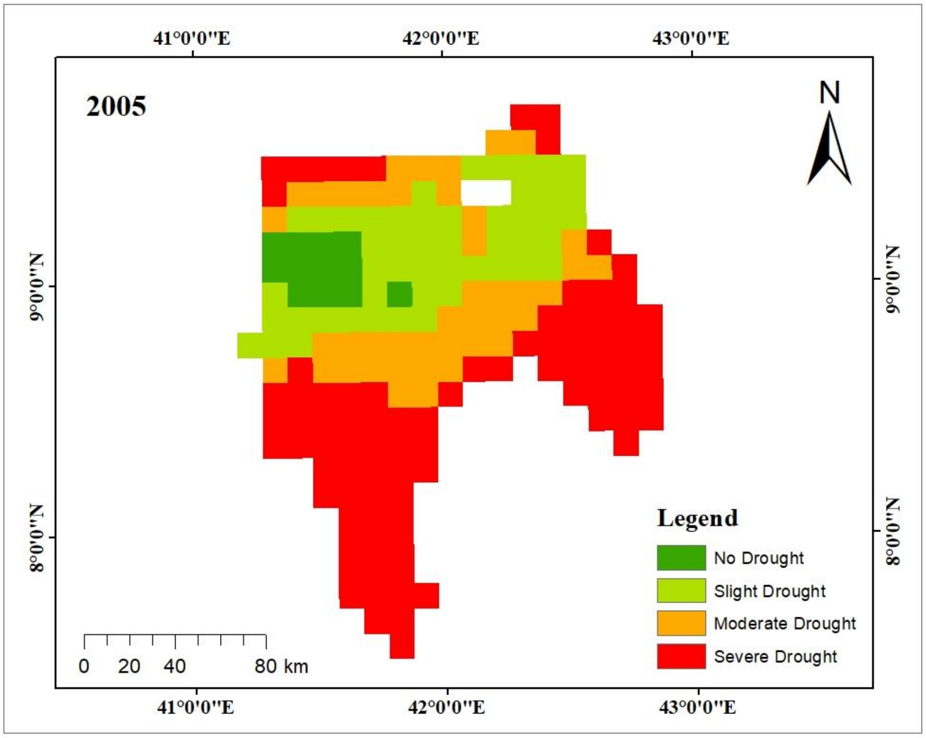

Figure 4.24: Spatial pattern of drought severity for the dry years 2005 as expressed in WRSI.

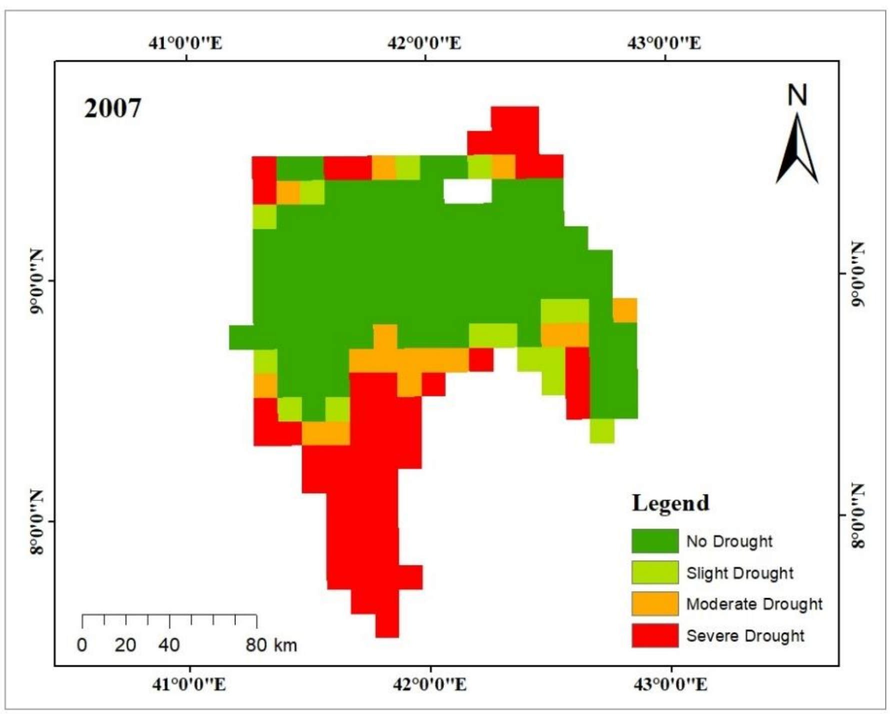

Figure 4.25: Spatial pattern of drought severity for the dry years 2007 as expressed in WRSI.

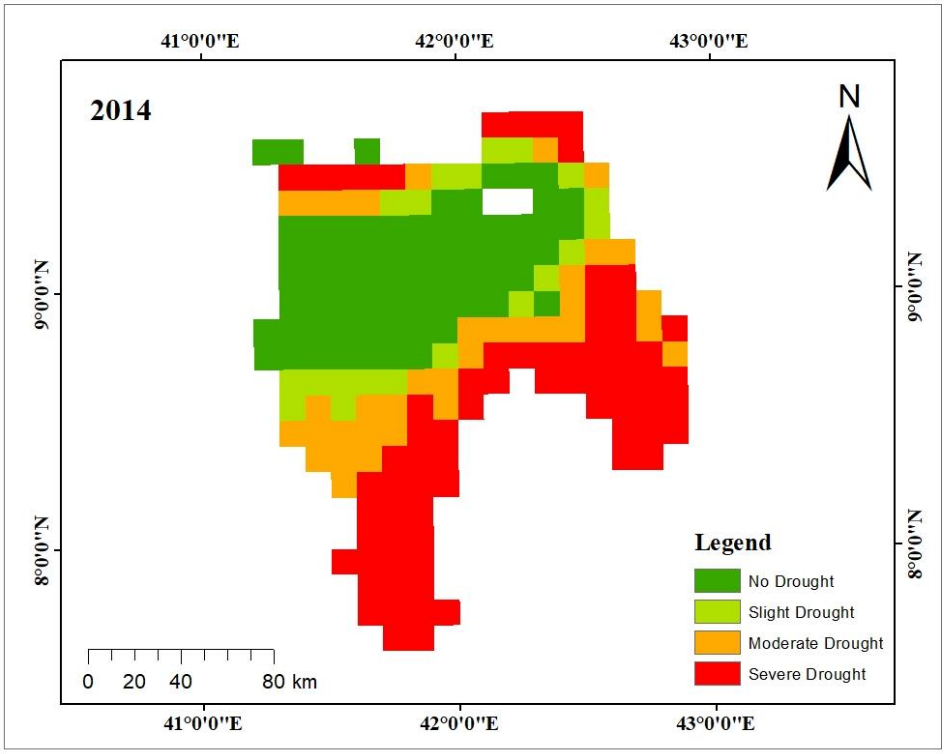

Figure 4.26: Spatial pattern of drought severity for the dry years 2014 as expressed in WRSI.

Spatial pattern of WRSI for the drought year range from no drought (4%), slight (20%), moderate (31%) and severe (45%) in 2005. In 2007 and 2014, almost all parts of the area were, similarly, stricken by slight, moderate, and severe droughts in the percent of, 16%, 18% and 26% and 19%, 23% and 34% respectively. Gizachew Legesse and Suryabhagavan (2014) stated that seasonal WRSI value of less than 50 percent is regarded as a complete crop failure condition. Evidently, therefore, the index revealed that the encountered high crop yield loss was caused by the prevalence of severe drought in the study area, during those three years.

Table 14: Percentage of area covered by drought severity for drought years 2006 and 2014 expressed by WRSI.

	Drought Years					
	2005		2007		2014	
Class	Area km²	Area (%)	Area km²	Area (%)	Area km²	Area (%)
No Drought	278	4	9540	40	5724	24
Slight Drought	3200	20	3816	16	4531	19
Moderate Drought	8560	31	4293	18	5485	23
Severe Drought	11,975	45	6201	26	8109	34
Total	23,850	100	23,850	100	23850	100

WRSI is also successful in capturing the response of the crop during wet years. The result reveals that even though 2006 and 2012 cropping seasons were wet years, some small pocket areas appeared to have been stricken by slight drought, especially the southern parts of the study area (Fig 4.27, 4.28 and Table 15). During the 2006 cropping season the percentage range of drought severity is from no drought to moderate drought. In 2012, again, 36 % of the area was affected by drought while, 64% of the area was free or slightly affected by drought.

Table 15: Percentage of area covered by drought severity for wet years 2006 and 2012 expressed by WRSI.

	Wet years			
	2006		2012	
Class	Area km²	Area (%)	Area km²	Area (%)
No Drought	14500	52	20100	64
Slight Drought	8400	26	5000	20
Moderate Drought	0.00	22	0.00	16
Severe Drought	0.00	0	0.00	0
Total	23,850	100	23850	100

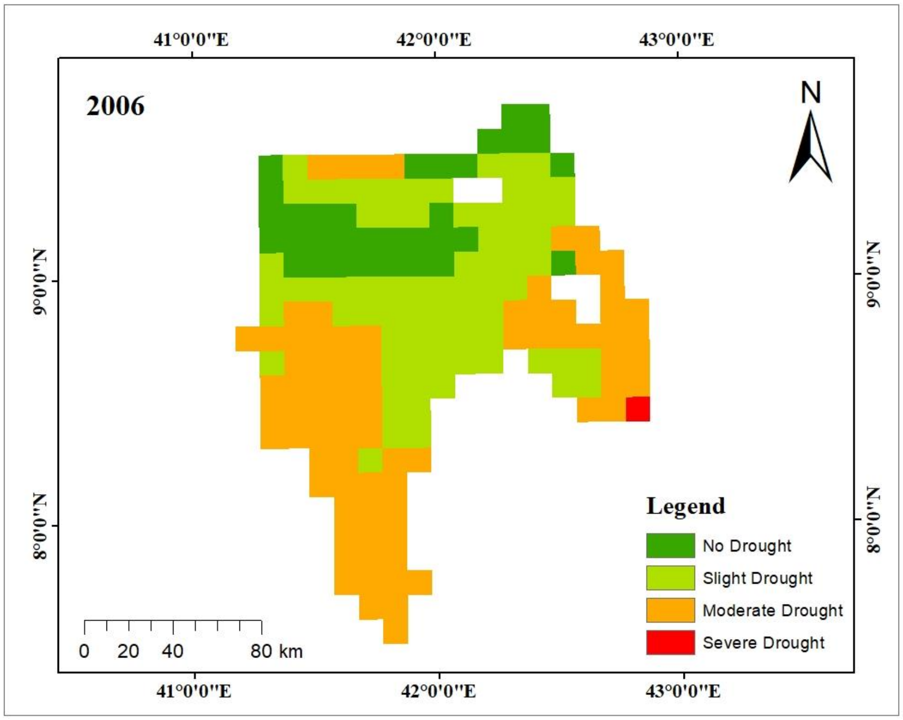

Figure 4.27: Spatial pattern of drought severity for the wet years 2006 as expressed in WRSI

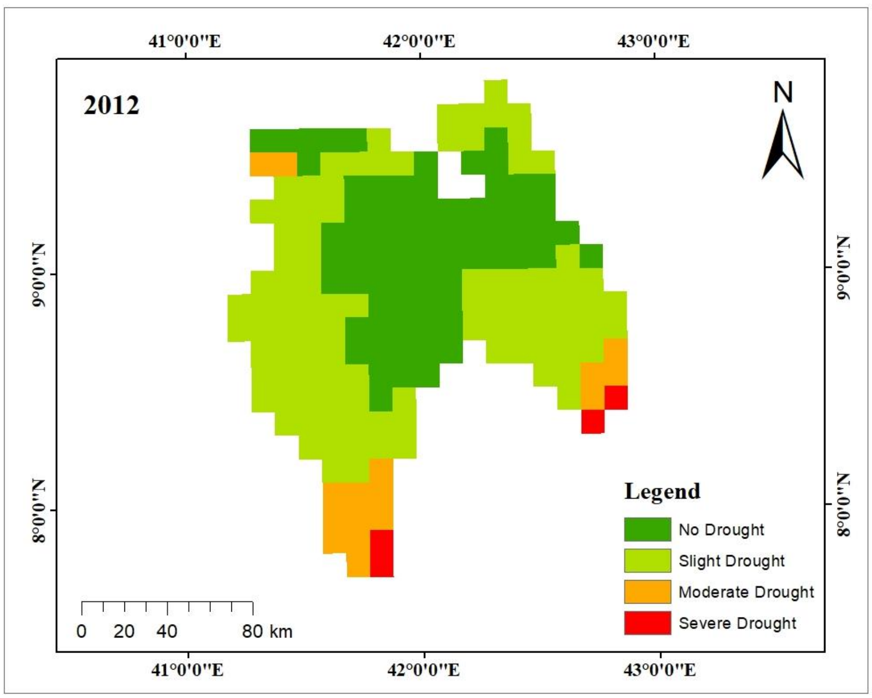

Figure 4.28: Spatial pattern of drought severity for the wet years 2012 as expressed in WRSI.

4.5.1 Water Requirement Satisfaction Index (WRSI) and Crop yield

The relationship between satellite based WRSI and crop yield was analyzed using simple regression analysis (Fig 4.29 and Appendix 5). It can be observed that there is a good correlation between crop yield and WRSI (r=0.84).

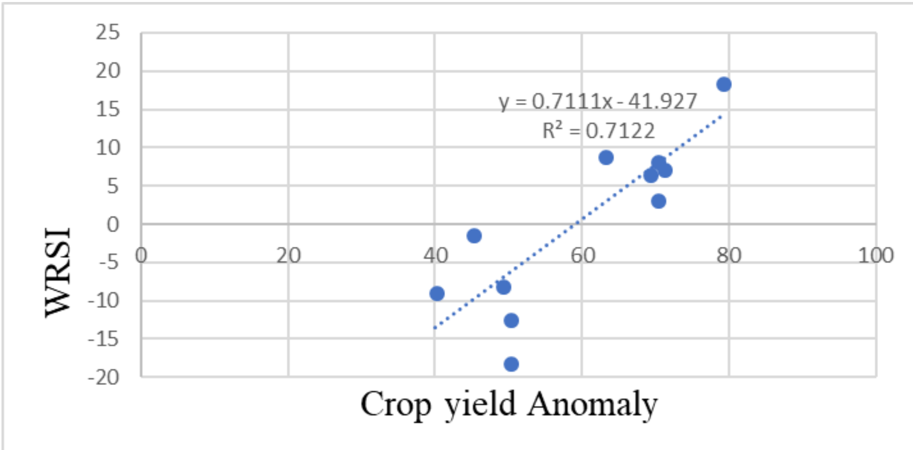

Figure 4.29: Relationship between WRSI and crop yield anomaly.

4.6 Comparison of Drought Indices

Different remotely sensed and meteorological based drought indices have been effectively assessed. Based on the findings, the drought years and severity classes were also identified and classified. Indices like NDVI, AI, SPI and WRSI were assessed to identify drought years and severity classes. NDVI is useful indicator as a measure of drought when compared to normal plant health in the study area. NDVI values have increased proportionally as the mean seasonal rainfall increased. In the Zone, the lowest AI was observed in 2014 and the highest in 2012, indicating the Aridity index. This result better fits with drought years recorded in the study area. The WRSI was also used as a drought index. Used to monitor crop performance during the growing season and based upon how much water is available for the crop. This index is the most reliable indicator of drought events. The other index applied was SPI and its result were relatively better fitted with WRSI values and the lowest values coincide with drought years occurred in the Zone. Of all the indices, WRSI has been identified as the most reliable indicator of drought events.

4.7 Evaluation of index-based results of drought using ground-based Information

According to Early warning system (EWS, 2007; 2010) reports from national Disaster Prevention and Preparedness Commission (DPPC), 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. The information obtained from East Hararge zone agricultural and rural development and DPPC offices during the year 2005, 2007 and 2014 cropping seasons, there was severe drought in East Hararge zone. The official reports confirm that, even though there were droughts ranging from slight to severe all over the years 2005 to 2015 cropping seasons, especially, the 2005, 2007 and 2014 cropping seasons was the worst droughts that resulted in substantial yield reductions. The number of people affected by recurrent drought have increased significantly and the extents of food shortages and related problems have grown in East Hararge zone (Fig 4.30). The number of affected population and the estimated yield reduction are highly correlated (r=0.84). According to the information obtained from East Hararge Zone agricultural and rural development offices, severe drought occurred in most of the area particularly, north eastern part of the area including, Gursum, Fedis, Babile, Boku and southern part particularly Gelo oda and meyo.

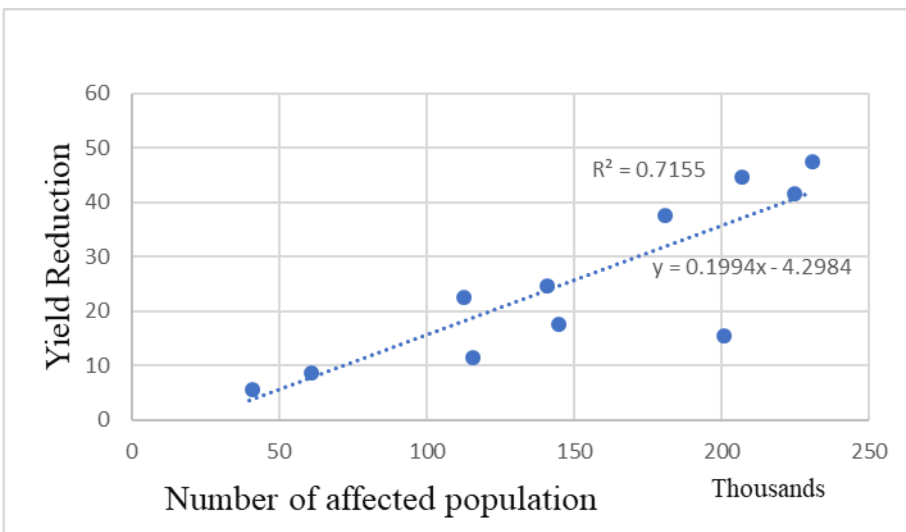

Figure 4.30: Relationship between Yield reduction and Number of affected population.

4.8 Drought Vulnerability Classification

With the aim of determining the typical drought vulnerable areas of the Zone, A model map was prepared by integrating all drought frequency maps, generated from the four drought indices, NDVI, SPI, AI and WRSI (Fig 4.31 - 4.34). The four layers representing drought indices were prioritized according to their degree of influence using pair-wise comparison.

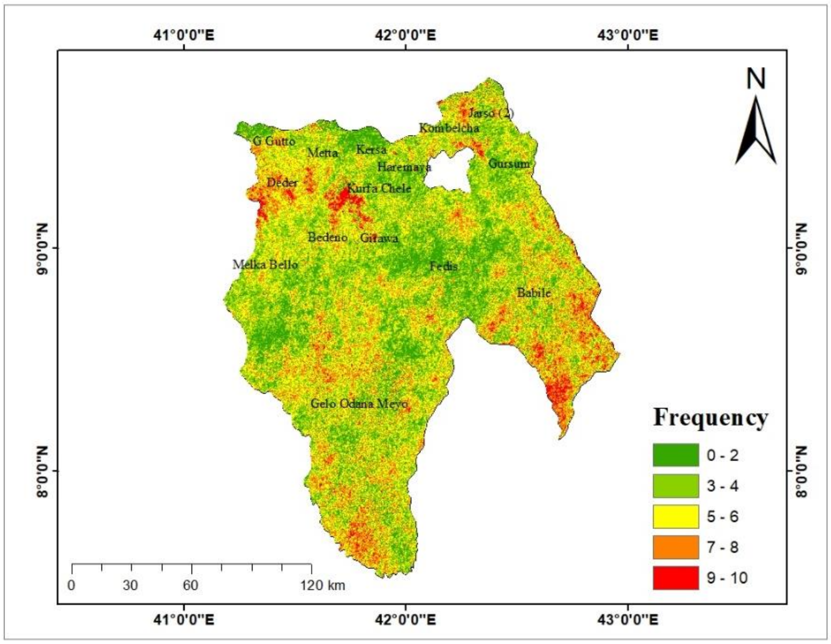

Figure 4.31: Drought frequency of Normalized difference vegetation index map.

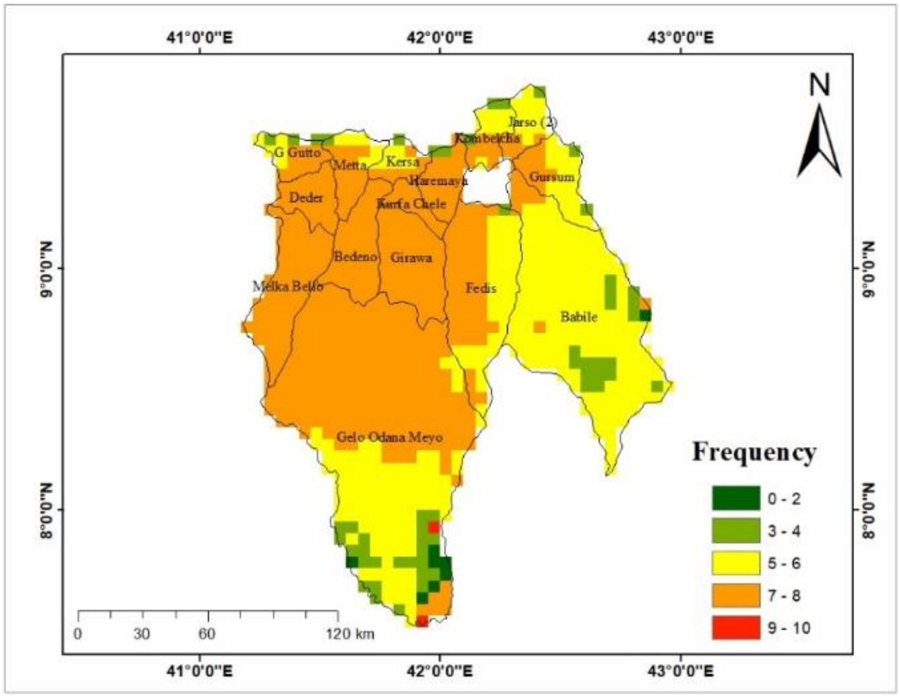

Figure 4.32: Drought frequency of standard precipitation index map .

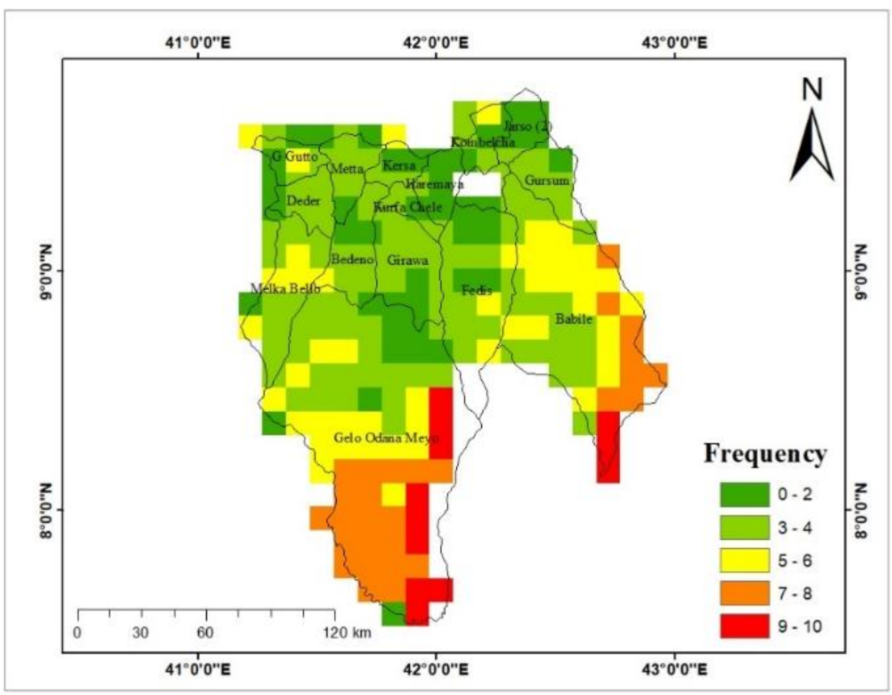

Figure 4.33: Drought frequency map of water requirement satisfaction index map.

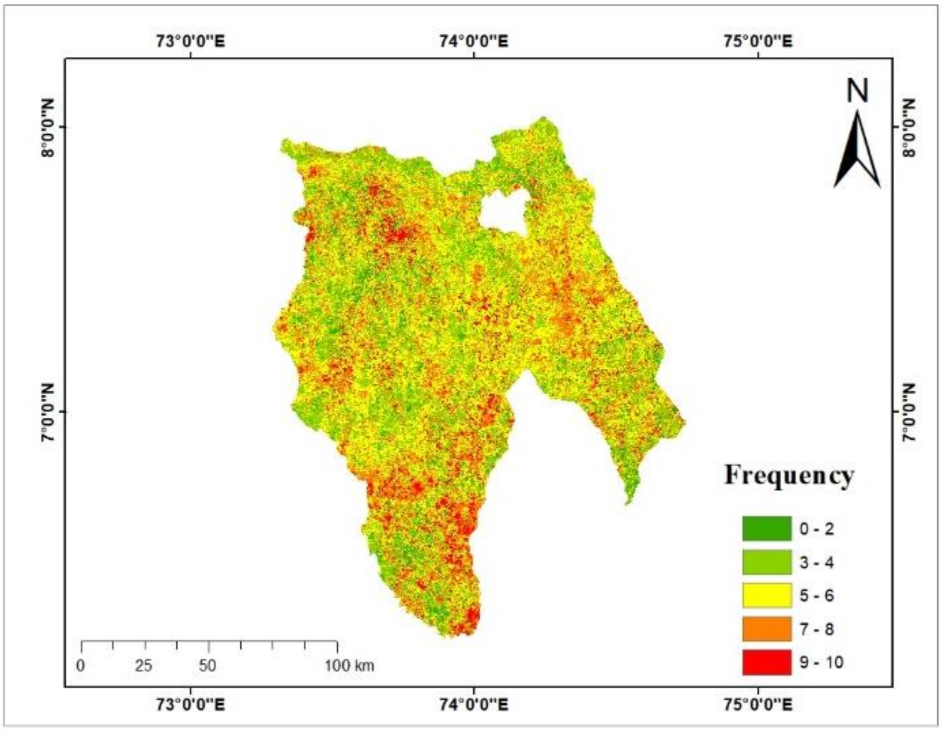

Figure 4.34: Drought frequency of Aridity index map.

The final result map of East Hararge Zone shows the area as mild, moderate and severe drought vulnerable. Therefore, based on the drought vulnerable classes, about 40% is categorized as severe vulnerable, 54% moderate vulnerable and only 6% is mild vulnerable (Fig 35). The probability of occurrence of drought ranges from 20 to 30 % for mild, 30 to 50 % for moderate, 50 to 70 % for severe and >70 extreme vulnerable level. Thus, the North Western and most of the North Eastern parts of East Hararge Zone is categorized into slight and moderate drought probability zone while some parts of north eastern and the southern parts are in the severe drought probability zone. Accuracy assessment was done for the final drought vulnerability map so that the overall accuracy is 89.5%. This means it was indicated a strong agreement between the classified drought map and the layers.

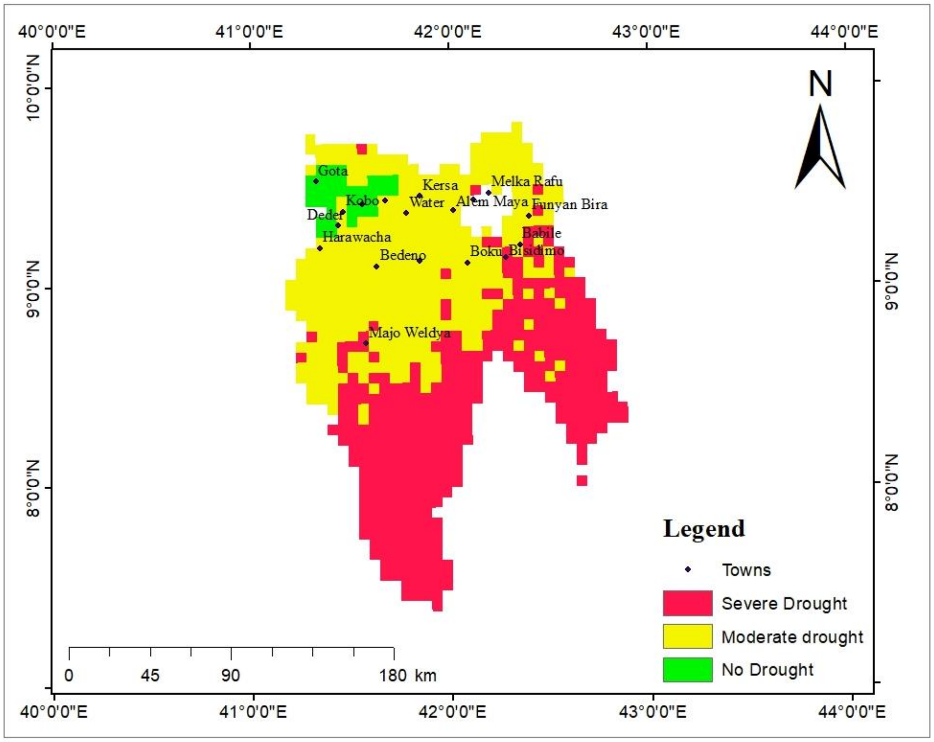

Figure 4.35: Drought vulnerable area map produced by using the four drought indices.

CHAPTER FIVE

5 DISCUSSION

5.1 Normalized Difference Vegetation Index (NDVI) and Rainfall

NDVI is a measure of greenness of vegetation. Kabo-bah et al., (2013) showed the effectiveness of the SPOT vegetation NDVI for monitoring the vegetation cover in northern Ghana. Belal et al., (2012) have also found that inter-annual variations in the magnitude and evolution of the NDVI for particular location governed by meteorological variables such as precipitation, temperature and relative humidity. It was also noted that interpretation of NDVI values was spatially dependent as more productive ecosystems have different radiometric properties than less productive ones due to difference in climate, soil and topography. The findings of this study also revealed that NDVI increased from the eastern part to the western part of the Zone and towards the North Western part of the area as well. The NDVI and rainfall relationship was evaluated in this study as r = 0.7, which indicated a good correlation. Gizachew and Suryabhagavan (2014) showed good relationship between rainfall and NDVI in East Shewa Zone, Ethiopia. Gaikwad et al., (2015) also concluded in their review that the mean seasonal NDVI indicating greenness of the vegetation and seasonal rainfall has strong relationship and also concluded that NDVI can be used as an indicator for drought. This study also revealed that the NDVI responded to the rainfall variation seasonally and spatially. Therefore, NDVI is found to be a relatively good indicator of drought in East Hararge Zone, Ethiopia.

5.2 Standardized Precipitation Index (SPI)

Standardized Precipitation Index is useful for identifying spatiotemporal extent of long term historical droughts. Different studies across the world used SPI as a drought indicator, particularly meteorological drought. This study incorporated SPI to assess meteorological drought in East Hararge Zone, Ethiopia. Results indicated occurrence of meteorological drought in different years in the Zone. Shah et al., (2015) and Dutta et al., (2015) have also used SPI for drought risk assessment. Farahmand and Aghakouchak (2015) derived SPI using 33 years of precipitation data and concluded that the result obtained was realistic and more reliable. Similarly, Dodomani et al., (2015) carried out SPI in their research on Agricultural drought modeling using Remote Sensing.

This study correlated SPI with crop yield (r = 0.72), that revealed statistically significant positive relationship. Similarly, Li et al., (2014) conducted Index based assessment of agricultural drought in semi-arid region of Inner Mongolia and found significant correlation between SPI and crop yield. In other parts of the world, particularly in the Sub- Saharan Sudan, Elagib, (2013) had come up with an impressive correlation between SPI and crop yields. Therefore, the result of this study agrees with the available information and as effective for drought assessment in the dry and semi-arid areas.

5.3 Water requirement satisfaction index (WRSI)

Water Requirement Satisfaction Index is a useful indicator of crop performance based on the availability of water during the crop growing season. According to Gizachew Legesse and Suryabhagavan, (2014) WRSI based agricultural drought assessment can better capture agricultural drought events. According to the results of evaluations made by Verdin and Klaver, (2002) on the performance of the model using district level crop yield data of 1996-1999 from Ethiopia, WRSI values and reported district yield data were significantly correlated (r = 0.77). Thus, the model was particularly found to be successful in capturing the response of the crop during relatively dry years. This study revealed that the WSRI is the most reliably effective index in capturing the responses of crops during drought and also wet seasons.

5.4 Aridity Index(AI)

An aridity index (AI) is a numerical indicator of the degree of dryness of the climate at a given location. According to FAO 1986, aridity index (AI) is a key parameter in drought characterization. It has also been widely used for evaluating the trends of aridity or humidity (Zhang, 2013). The result of this study agrees with Aridity index (AI) is effective for drought assessment.

CHAPTER SIX

6 CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

Modern Remote Sensing satellite data and Geographical Information System techniques have been used to collect and process eleven years data on drought in East Hararge Zone. The actual impacts of drought on the Zone have been thoroughly investigated and analyzed using Normalized difference vegetation index (NDVI), Aridity Index (AI), standard precipitation Index (SPI) and Water Requirement Satisfaction Index (WRSI). Using the results of the investigations and the analyses, a comprehensive map that clearly shows the proper drought vulnerable areas of the Zone, has been produced.

The temporal variation of NDVI values were closely related with rainfall to validate how vegetation stress condition was changing with the variability of rainfall. The existence of a reasonably good relationship between NDVI and rainfall variability during the growing season was established. NDVI, SPI, AI and WRSI are found to be good indicators of the occurrence of drought and its impacts on the crop performance. Of all the indices, WRSI has been identified as the most reliable indicator of drought events.

This study shows the occurrence of recurrent drought in the area. Within the eleven years of the study period, the drought was observed in different years. Therefore, it could be concluded as the zone is highly prone to the drought. The drought vulnerability map of the Zone shows; the Zone is within the drought vulnerability range from mild to severe vulnerability. Accuracy assessment of the final result map indicates that there is strong agreement between the layers and the final result map.

The findings of this study can be used for improvement of drought monitoring in the Zone. The ground-based experiences have been found to be fairly congruent with the satellite derived data analysis results. Based on the drought frequency maps of the four indices of NDVI, SPI, AI and WRSI a comprehensive map, clearly demonstrating the major drought vulnerable Woredas of East Hararge Zone, has been produced. This map shows that 40%, 54% and 6% of the total geographical area of the Zone were severe, moderate and mild vulnerable, respectively.

6.2 Recommendations

- Satellite dataset employed in this study is SPOT VEGETATION having 1km and for water requirement satisfaction index having 10km spatial resolution. In order to monitor and forecast effectively the occurrences of drought in study area, satellite data products characterized by higher resolution is essential.
- Drought has been observed as a recurrent phenomenon in the area. It is recommended that an operational service for drought forecast be put in place. So that the measure of mitigation strategy be put in place.
- Further investigations are required to improve this study by incorporating socio-economic data, which help in preparing better management plans.
- Timely updated information about the prevalence of drought is important.

REFERENCES

Abbasi, S. (2014). Adaptation to Drought in Saskatchewan Rural Communities A Case Study of Kindersley and Maidstone, Saskatchewan. Unpublished Msc thesis University of Saskatchewan, Saskatoon, 156pp.

ACAPS, 2016. Ethiopia Drought and Food Insecurity. Assessments Capability Project. Geneva, Switzerland.

Agrawal, S. Joshi, P. K. and Yogita, S. (2003). SPOT VEGETATION multi temporal data for classifying vegetation in south central Asia. *Current Science*. **84:**1440-1448.

Akhtar, I. H. (2014). Identification of Drought Events from Multi years Temporal SPOT NDVI Data for Potohar Region in Pakistan. *International Journal of Remote Sensing and GIS*. **3:** 39-52.

Anyamba, A. and Tucker, C.J. (2005). Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981-2003. *Journal of Arid Environment*. **63:**596-614.

Belal, A., Hassan, R. E., Mohamed, E., Ahmed, S. and Saleh, M. (2012). Drought Risk Assessment Using Remote Sensing and GIS techniques. *Arabian Journal of Geosciences*. **7:**35-53.

Beyene Ergogo (2007). Drought assessment for Nile Basin using Meteosat Second Generation data with special emphasis on the upper Blue Nile Region. Unpublished MSc Thesis, ITC, Enschede, 90pp.

Birhanu Gediff, Legesse Hadish, Solomon Addisu and Suryabhagavan, K.V. (2014). Drought Risk Assessment using Remote Sensing and GIS: The case of Southern Zone, Tigray Region, Ethiopia. *Journal of Natural Sciences Research*. **4:** 87-94.

(CSA) 2007 Central Statistical Agency. Population and Housing Census of Ethiopia, Addis Ababa.

Chopra, P. (2006). Drought Risk Assessment Using Remote Sensing and GIS: A case study of Gujarat. Unpublished MSc Thesis of Indian Institute of Remote Sensing (IIRS), Dehradun, India and International Institute for Geo-Information Science and Earth Observation, Enscheda, Netherlands, 81pp.

(CWCB) (2013). Colorado Water Conservation Board. Drought Vulnerability Assessment Technical Information; Annex B to the Colorado Drought Mitigation and Response Plan.

Cutler, P. V. (1988). The development of the 1983-85 famine in northern Ethiopia. Unpublished PhD thesis, London School of Hygiene & Tropical Medicine. Accessed on: http://researchonlime1shtm.ac.uk/682234/pdf.On 26. 08. 2017, 490pp.

Dai, A. (2011b). Drought under global warming: a review, Advanced Review, *National Center for Atmospheric Research*. **2:** 45-65.

Defferew Kebebe (2011). The Impact of Drought on Livelihoods, Vulnerability and Coping Mechanisms: The Case of North Shoa Zone, Oromiya. Unpublished MSc Thesis Addis Ababa University, Addis Ababa Ethiopia, 96pp.

Dodamani, B.M., Anoop, R. and Mahajan, D.R. (2015). Agricultural Drought Modeling Using Remote Sensing. *International Journal of Environmental Sciences and Development*. **6:**326-331.

Domenikiotis, C., Spiliotopoulos, M., Tsiros, E. and Dalezios, N. (2004). Early Cotton Yield Assessment by the Use of the NOAA/AVHRR Derived Drought Vegetation Condition Index in Greece. *International Journal of Remote Sensing*. **25:** 2807–2819.

Dutta D., Kundu, A., Patel, N.R., Saha, S.K. and Siddiqui, A.R. (2015). Assessment of agricultural drought in Rajasthan (India) using remote sensing derived vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI). *The Egyptian Journal of Remote Sensing and Space Sciences*. **18:** 53-63.

Early Warning System (2007). Food supply prospect. URL: www.dppc.gov.et.

Early Warning System (2015). Special report on: Update on Emergency Food Requirement from August to December 2015. URL: www.dppc.gov.et.

Elagib, N.A. (2013). Meteorological Drought and Crop Yield in Sub-Saharan Sudan. *International Journal of Water Resources and Arid Environments*. **2(3):** 164-171.

Farahmand, A. and Aghakouchak, A. (2015). A Generalized framework for deriving nonparametric Standardized drought indicators. *Advanced Water Resources*.**76:** 140-145.

(FAO) (2011). Food and Agricultural Organization, *Fao-Adapt Framework Programme on Climate Change Adaptation:* Viale Delle Terme Di Caracalla: Rome, Italy.

(FAO) (1986). Food and Agricultural Organization, *Early Agro-meteorological crop yield forecasting*. FAO Plant Production and Protection paper No. 73, (Frere, M. and Popov, G.F, ed.) FAO, Rome, Italy.

Gaikwad, S. V., Kale, K. V., Kulkami S. B., Varpe A. B. and Pathare G. N. (2015). Agricultural Drought Risk Assessment using Remotely Sensed data: A Review. *International Journal of Advanced Remote Sensing and GIS*. **4(1):** 1159-1203.

Getachew Berhan, Hill, S., Tsegaye Tadesse and Solomon Atnafu (2011). Using Satellite Images for Drought Monitoring: A Knowledge Discovery Approach, *Journal of Strategic Innovation and Sustainability, vol*. **7(1):** 135 -153.

Gizachew Legesse (2010). Agricultural drought assessment using remote sensing and GIS techniques. Unpublished Msc thesis Addis Ababa University, Addis Ababa, 76pp.

Gizachew Legesse and Suryabhagavan, K.V. (2014). Remote sensing and GIS based agricultural drought assessment in East Shewa Zone, Ethiopia, *Tropical Ecology*. **55:** 349-363.

Himanshu, S.K., Singh, G. and Kharola, N. (2015). Monitoring of Drought using Satellite Data. *International Research Journal of Earth Sciences*. **3(1):** 66-72.

Huailiang, C., Hongwei, Z., Ronghua, L. and Weidong, Y. (2009). Agricultural Drought Monitoring, Forecasting and Loss Assessment in China. *International journal of Remote sensing*. **34:**8987-9001.

Huang, Y., Tian, Q., Du, L. and Sun, S. (2013). Analysis of Spatial-Temporal Variation of Agricultural Drought and Its Response to ENSO over the Past 30 Years in the Huang-Huai-Hai Region, China. *Terr. Atmos. Ocean. Sci.* **24:**745-759.

(IPCC) (2007). Intergovernmental Panel on Climate Change Climate Change 2007, Synthesis report, Cambridge University Press, Cambridge.

Jeyaseelan, A. T. 2004. Drought and Flood Assessment and Monitoring Using Remote Sensing and GIS. Accessed on: www.wamis.org/agm/pubs/agm8/Paper-14.pdf on 8.05.2017.

Kabo-bah A.T, Nkurmah P.N., Murava R.T. and Amin D.O. (2013). Evaluation of NDVI Using SPOT-5 Satellite Data for Northern Ghana. *Environmental Management and Sustainable Development*. **2(1):**167-182.

Kapoi, K. J. and Alabi, O. (2013). Agricultural Drought Severity Assessment Using Land Surface Temperature and NDVI in Nakuru region, Kenya. In: *Proceedings of Global Geospatial Conference*. Addis Ababa, Ethiopia, 4-8 November2013.

Keyantash, J. A and Dracup, J. A. (2002). The quantification of drought: an evaluation of drought indices. The drought monitors. *Bull. Am. Meteorol. Soc*. **83:** 1167–1180.

Kogan, F. N. (1990). Remote sensing of weather impacts on vegetation on non- homogeneous areas. *International Journal of Remote sensing*. **11:**1405-1421.

Kogan, F. N. (1997). Global Drought Watch from space. *Bulletin of American Meteorological Society*. **78:**621- 636.

Kogan, F. N. (2001). Operational space technology for global vegetation assessment, *Remote Sensing Environ*. **82:**1949–1964.

Legesse Hadish (2010). Drought risk assessment using remote sensing and GIS: a case study in southern zones, Tigray Region, Ethiopia, Unpublished MSc Thesis, Addis Ababa University, Addis Ababa, Ethiopia, 79pp.

Lemma Gonfa (1996). Climate classification of Ethiopia. In: *Metrological Research Report Series* No.3: Addis Ababa, pp.1-8.

Li, R., Tsunekawa, A. and Tsubo, M. (2014). Index-based assessment of Agricultural Drought in a Semi-arid Region of Inner Mongolia China. *Journal of Arid Land*, **6(1):** 3-15.

Lovett, J.C., Midgely, G.F. and Barnard, P.B. (2005). Climate change and ecology in Africa. *African Journal of Ecology* **43:**279 281.

Loucks, A. and Gladwell, F (1999). Potential climate change impacts on flood producing mechanisms in southern British Columbia, Canada using the simulation results, *Journal of Hydrology*, **259:** 163–188.

McKee, T. B., Doesken, N. J. And John, K. (1993). The relationship of drought frequency and duration to time scales. **In:** *Proceedings of the 8thConference on Applied Climatology*, 17:179-183 Boston, MA: American Meteorological Society.

Mishra, A. K. and Singh, V. P. (2010). A review of drought concepts. *Journal of hydrology,* **391:**202–216.

Mokhtari, M. H. (2005). Agricultural drought Impact assessment using Remote Sensing: A case study Borkhar district Iran. Unpublished MSc thesis International Institute for Geo-Information Science and Earth Observation, Enschede, 137pp.

National Meteorological Services (NMS) (2007). Climate Change National Adaptation Program of Action (NAPA) of Ethiopia. NMS, Addis Ababa, Ethiopia.

National Meterological Service Agency (NMSA). (1996). Assessment of drought in Ethiopia. In: *Meterological research report series No.2*.Addis Ababa.

(OWWDSE) (2010). Oromia Water Works Design & Supervision East Hararge & West Hararge Zone Land Use Plan Study Project: Arba Kurkura Sub Basin Integrated Land Use. OWWDSE, Addis Ababa, Ethiopia, 30 pp.

Palmer, W. C. (1965). Meteorological Drought U.S. Weather Bureau, Research Paper No 45, Washington, D.C, 55pp.

Penman, H. (1948). Natural evaporation from open water, bare soil and grass. Proceedings of the Royal Society, **193:** 120-146.

Prakasam, C. (2010). Land use land cover change detection through remote sensing approach: A case study of Kadaikanal Taluk, Tamil Nadu. *International Journal of Geomatics and Geosciences*. **2:**46-55.

ReliefWeb. (2017). UNICEF Ethiopia Humanitarian Situation Report #7 – Reporting Period: November-December 2015. [online] Available from: http://reliefweb.int/report/ethiopia/unicef-ethiopia-humanitarian-situation-report-7-reporting-period-november-december [Accessed 25 March. 2017].

Sara Abebe (2010). Mitigating Drought: Policy Impact Evaluation: A Case of Tigray Region, Ethiopia. Unpublished MSc Thesis University of Twente, Enschede, The Netherlands, 99pp.

Segele, Z. T. and Lamb, P. J. (2005). Characterization and variability of Kiremt rainy season over Ethiopia. *Meteorology and Atmospheric Physics*. **89:**153-180.

Shah, R., Bharadiya, N. and Manekar, V. (2015). Drought Index Computation Using Standardized Precipitation Index (SPI) Aquatic *Procedia*, **4:**1243 1249.

Shaheen, A. and Baig, M. A. (2011). Drought severity assessment in arid area of Thal-Doab: using Remote Sensing and GIS. *International Journal of Water Resources and Arid Environments*. **2:**92-101.

Shilong, P., Jingyun, F., Wei, J., Qinghua, G., Jinhu, K. and Shu, T. (2004). Variation in a Satellite-based Vegetation index in relation to climate in China. *Journal of Vegetation Science*. **15:**219-226.

Singh, R. P., Roy, S., and Kogan, F. N., (2003). Vegetation and temperature condition indices from NOAA-AVHRRA data for drought monitoring over India. *International Journal of Remote Sensing*. **24:**4393-4402.

Son, N.T., Chen, C.F., Chen, C.R., Chang, L.Y. and Minh, V.Q., 2012. Monitoring agricultural drought in the Lower Mekong Basin using MODIS NDVI and land surface temperature data. *International Journal of Applied Earth Observation and Geoinformation*, 1**8:**417-427.

Stibig, H-J. Malingreau, J. P. and Beuchle, R (2001). New Possibilities of regional assessment of tropical forest cover in insular Southeast Asia using SPOT-VEGETATION satellite image mosaics. *International Journal of Remote Sensing*. **22:** 503-505.

Stern, N., 2006. Stern Review**:** The economics of climate change I. Executive Summary.Accessed onhttp://unionsforenergydemocracy.org/wpcontent/uploads/2015/08/sternreview_report_complete.pdf.

Swets, D., Reed, B., Rowland, J. and Marko, S. (1999). A weighted least-squares approach to temporal NDVI smoothing. On: *ASPRS Annual Conference*, pp.526-536.ASPRS, Portland, Oregon.

Tadesse Temesgen, Wilhite, D., Harms, S., Hayes, M. and Goddard, S. (2004). Drought Monitoring Using Data Mining Techniques: A Case Study for Nebraska, USA. *Natural Hazards*. **33(1):** 137-159.

Tao, J., Zhongfa, Z. and Shui, C. (2011). Drought monitoring and analyzing on typical karst Ecological fragile area based on GIS. *Procedia Environmental Sciences*. **10:** 2091–2096.

(UNESCO), (1979). United Nations Educational, Scientific and Cultural Organization, Map of the world distribution of arid regions: Map at scale 1:25,000,000 with explanatory note. Technical Notes 7, UNESCO, Paris.

Verdin, J. and Klaver, R. (2002). Grid cell-based crop water accounting for the famine early warning system. *Hydrological Processes*. **16:**1617-1630.

Vicente-Serrano, S. M., Cuadrat, J. M. and Romo, A. (2006b), Aridity influence on vegetation patterns in the middle Ebro valley (Spain): evaluation by means of AVHRR images and climate interpolation techniques. *Journal of Arid Environ*. **10:** 121-132.

Viste, E., Korecha, D. and Sorteberg, A., 2012. Recent drought and precipitation tendencies in Ethiopia. *Theoretical and Applied Climatology*, *112*(3-4), pp.535-551.

Walton, K. (1969). The arid zone. Chicago, IL: *International Journal of Water Resources and Arid Environments*. **5:** 204-221.

Wang, P., Wan, Z., and Li, X. (2004). Using MODIS Land Surface Temperature and Normalized Difference Vegetation Index products for Monitoring Drought in the Southern Great Plains, USA. *International Journal of Remote Sensing*. **25:** 61-72.

Webb, P., Von Braun, J. and Yohannes, Y., (1992). *Famine in Ethiopia: policy implications of coping failure at national and household levels* (Vol. 92).

Wilhite, D.A., Hayes, M.J. and Svoboda, M.D., 2000. Monitoring drought using the standardized precipitation index. *Drought: A Global Assessment. Edited by DA Wilhite. Routledge, London, UK*, 168-180.

Wondewosen Negesse (2016). Agricultural Drought Risk assessment in West Hararge, Ethiopia. unpublished MSc thesis Addis Ababa University, Addis Ababa Ethiopia.112pp.

(WMO), (2006). World Meteorological Organization. Commission for Agricultural Meteorology (CAgM) report on: impacts of desertification and drought and other extreme meteorological events. Unpublished technical report, Geneva, Switzerland WMO/TD No. 1343.

Zhang, D., Wang, G. and Zhou, H. (2011a). Assessment on agricultural drought risk based on variable fuzzy sets model. *Chinese Geographical Science*. **21(2):**167-175.

Zargar, A., Sadiq, R., Naser, B. and Khan, F.I., 2011. A review of drought indices. *Environmental Reviews*, *19*(NA), pp.333-349.

Appendices

Appendix 1: Partial view of the study area





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

Regression Statistics	
Multiple R	0.705824737
R Square	0.49818856
Adjusted R Square	0.442431733
Standard Error	0.062425118
Observations	11

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.034818851	0.034818851	8.935023547	0.01522187
Residual	9	0.035072058	0.003896895		
Total	10	0.069890909			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.095272477	0.090838269	1.048814311	0.321610679
NDVI	0.000760146	0.000254302	2.989150974	0.01522187

Appendix 3: Simple linear regression analysis between Crop yield anomaly and NDVI

Regression Statistics	
Multiple R	0.929928001
R Square	0.864766087
Adjusted R Square	0.849740097
Standard Error	0.106342999
Observations	11

	df	*SS*	*MS*	*F*	*Sign*
Regression	1	0.65083868	0.65083868	57.55135394	0.0335
Residual	9	0.101779502	0.011308834		
Total	10	0.752618182			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.521634771	0.032096943	16.25185209	5.43E-02

NDVI	0.023109379	0.003046215	7.586260867	0.0337

Appendix 4: Simple linear regression analysis between Crop yield anomaly and Aridity Index

Regression Statistics	
Multiple R	0.910233751
R Square	0.828525481
Adjusted R Square	0.809472757
Standard Error	1.03544399
Observations	11

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	46.62319259	46.62319259	43.4859323	0.0999
Residual	9	9.649298316	1.072144257		
Total	10	56.27249091			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	2.357024604	0.312522564	7.541934177	0.0362
AI	0.195592681	0.029660482	6.594386424	0.0994

Appendix 5: Simple linear regression analysis between Crop yield anomaly and WRSI

Regression Statistics	
Multiple R	0.843926107
R Square	0.712211274
Adjusted R Square	0.680234749
Standard Error	7.40872181
Observations	11

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1222.543025	1222.543025	22.27294151	0.001089975
Residual	9	494.0024297	54.88915885		

Total	10	1716.545455

	Coefficients	*Standard Error*	*t Stat*
Intercept	59.15560742	2.23613518	26.45439683
WRSI	1.001575449	0.212224189	4.719421735

Appendix 6: Simple linear regression analysis between Crop yield anomaly and SPI

Regression Statistics	
Multiple R	0.849378165
R Square	0.721443268
Adjusted R Square	0.69049252
Standard Error	0.683744504
Observations	11

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	10.89729562	10.89729562	23.30939684	0.000936528
Residual	9	4.207558921	0.467506547		
Total	10	15.10485455			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.000974471	0.206370974	0.004721938	0.996335462
SPI	0.094560761	0.019585986	4.827980617	0.000936528

Addis Ababa University

School of Earth Sciences

Name of student	CHALTU TADESSE AMANTE
ID No	GSR/8405/09
Stream	Remote sensing and Geo-informatics
Thesis title	Drought vulnerability assessment using Geospatial data and Modelling techniques: A case study of East Hararge Zone, Ethiopia.
Online site used for originally test	http://www.paperrater.com/plagiarisim_checker

FORMAT FOR THESIS ORIGINALITY TEST REPORT

No	particulars	Test I		Test II		Test II		Test IV		Test V		Average	Remark
		Originality (%)	Plagiarism (%)	Originality (%)	Plagiarism (%)	Originality (%)	Plagiarism (%)	Originality (%)	Plagiarism (%)	Originality (%)	Plagiarism (%)		
1	Abstract	100	-	-	-	-	-	-	-	-	-	100	
2	Introduction	100	-	-	-	-	-	-	-	-	-	100	
3	Literature review	98	2	99	1	100	-	-	-	-	-	99	
4	Methodology	100	-	100	-	100	-	-	-	-	-	100	
5	Results	100	-	100	-	100	-	-	-	-	-	100	
6	Discussion	100	-	-	-	-	-	-	-	-	-	100	
7	Conclusion	100	-	-	-	-	-	-	-	-	-	100	
	Overall Thesis											99.8	

	Name	Signature
Student	CHALTU TADESSE AMANTE	
Advisor (1)	Dr. TESFAYE KORME	

DECLARATION

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

Chaltu Tadesse Amante

Signature ________________________ Date_______________________

School of Earth Science

May, 2018

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

Advisor:

Dr. Tesfaye Korme

Signature ________________________ Date ___________________