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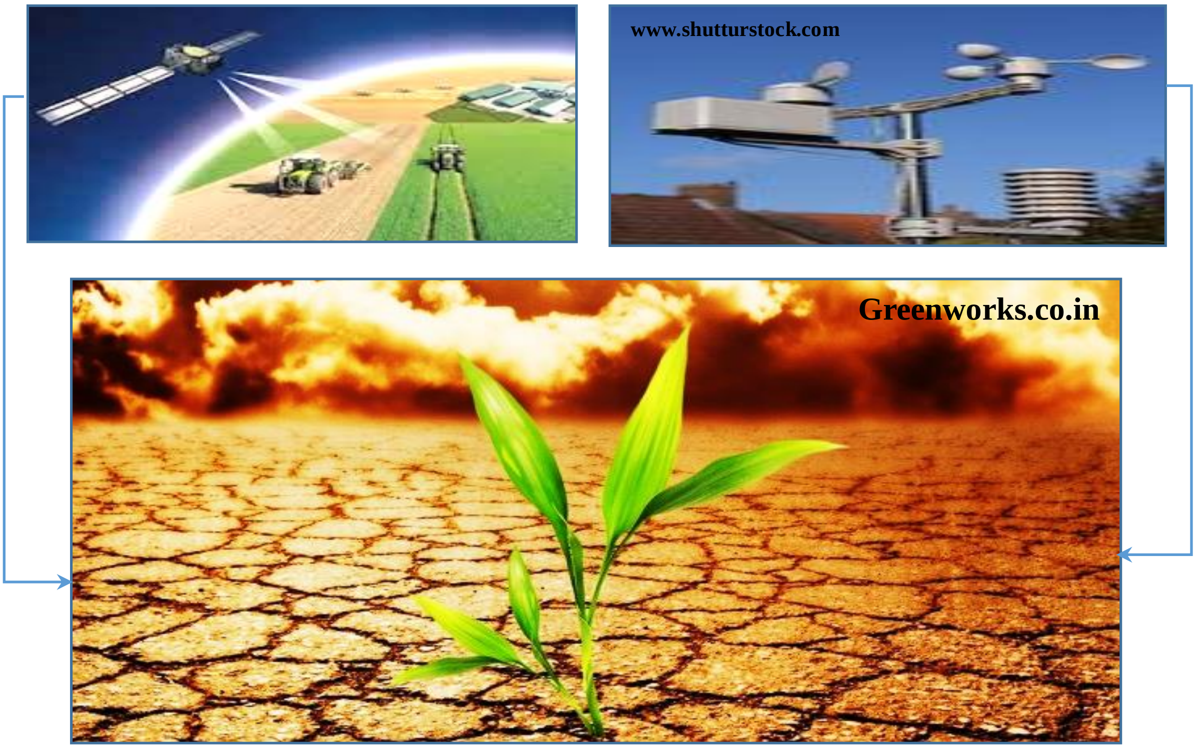
AGRICULTURAL DROUGHT RISK AREA ASSESSMENT AND MAPPING USING REMOTE SENSING AND GIS: A CASE STUDY OF WEST HARARGE ZONE, ETHIOPIA

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
WONDWOSAN NEGASSA
(GSR/3205/08)
Advisor
Dr. BINYAM TESFAW

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Addis Ababa

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BY

WONDWOSAN NEGASSA EJETA

(GSR/3205/08)

Advisor

Dr. BINYAM TESFAW

JUNE, 2017

Addis Ababa

Addis Ababa University

School of Graduate Studies

This is to certify that the thesis prepared by Wondwosan Negassa entitled as "Agricultural Drought Risk Area Assessment and Mapping using Remote Sensing and GIS: A case study of West Hararge Zone, Ethiopia" is submitted in partial fulfillment of the requirements for the Degree of Master of Science in Remote Sensing and GIS compiles with the regulations of the university and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

Dr. Binyam Tesfaw ___________ ______________

Advisor Signature Date

__________________ ____________ _____________

Graduate Committee Signature Date

Dr. K.V. Suryabhagavan _____________ _____________

Examiner Signature Date

Dr. Worash G. _____________ _____________

Examiner Signature Date

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List of Acronyms

AET	Actual Evapotranspiration
ANOVA	Analysis of Variance
CHIRPS	Climate Hazard Group Infrared Precipitation with Station
CSA	Central Statistics Agency
CSWB	Crop Soil Water Balance
DEM	Digital Elevation Model
DPPC	Disaster Prevention and Preparedness Commission
EIAR	Ethiopian Institute of Agricultural Research
EMA	Ethiopian Mapping Agency
ERTS	Earth Resource Technology Satellite
ENSO	El Niño-Southern Oscillation
EWS	Early Warning System
FAO	Food and Agricultural Organization
FCC	False Color Composite
FEWS- NET	Family Early Warning System
GIS	Geographical Information System
GPS	Global Positioning System
ICRAF	International Council for Research in Agro-forestry
IDW	Inverse Distance Weight
LEAP	Lively hood Early Assessment Protection
MASL	Mean Annual Sea Level
MCE	Multi Criteria Evaluation
MOFED	Ministry of Finance and Economic Development
MVC	Maximum Value Composites
MOA	Ministry of Agriculture
NDVI	Normalized Difference Vegetation Index
NGO	Non-Governmental Organization
NMSA	National Meteorological Service Agency
NOAA	National Oceanic and Atmospheric Administration
OWWDSE	Oromiya Water Work Design and Supervision Enterprise
PDSI	Palmer Drought Severity Index

PET	Potential evapotranspiration
PPT	Potential precipitation
PROBA-V	Project on-Board Automation Vegetation
RAI	Rainfall Anomaly Index
RFE	Rainfall Estimate
RS	Remote Sensing
SPI	Standard precipitation Index
SPIRITS	Software for Processing and Interpreting Remote Sensing Images Time Series
SPOT	Satellite Pour l'Observation de la Terre
TCI	Temperature Condition Index
USGS	United States Geological Survey
VITO	Vlaamse Instelling voor Technologish Onderzoek
VCI	Vegetation Condition Index
WFP	World Food Program
WHC	Water Holding Capacity
WMO	World Meteorological Organization
WR	Water Requirement
WRSI	Water Requirement Satisfaction Index

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Abstract

Remote Sensing and GIS Technologies are currently important and timely for draught risk area assessment and mapping. In countries like Ethiopia, experiencing considerable annual regular period of dry seasons, drought is not a new phenomenon. The real drought problem, however, arises when the rainfalls fail to fit with the normal cropping seasons. As this gap brings about eminent crop failure and high yield reduction, drought can be perceived as the quantitative, spatial and temporal mismatch between rainfall and the cropping season. This study aims to identify, analyzing, determining and signifying the impacts of the virtual drought on the local environment and mapping agricultural drought risk prone areas of West Hararge Zone, Oromia region, Ethiopia. In order to effectively realize this goal, efforts were made to collect the ten years (2005-2014) drought behavior data, regarding its onset time, frequency of occurrence, spatial extent, duration and levels of severity on the local environment. In addition, this study utilizes remote sensing data, GIS technology and field observations data. Accordingly, reliable Geo-spatial and temporal data have been obtained through the use of modern Remote Sensing and Geographical Information System. The practical field observations, consultations and discussions played great roles in enhancing the acquisitions of commendable knowledge and experiences on the objective reality of the situation. These data were examined and analyzed to scale up the intensity level of the prevailing drought impacts on the agricultural activities of the local farmers. The general responses to drought and the particular existing correlations between rainfall and crop performances were confirmed using Normalized Difference Vegetation Index, Standard Precipitation Index and Water Requirement Satisfaction Index. Based on the confirmed drought pattern and frequency maps of the three indices, a comprehensive map was produced that indicates agricultural drought risk prone areas of West Hararge Zone. This map shows that 12.34%, 33.89% and 48.48% of the total geographical area of the Zone were slight, moderate and severe agricultural drought risk areas, respectively. The result map was validated based on ground based field data obtained from organizational documents and local field professional practitioners. The validation result show significant relation with a correlation coefficient of r = 94 or R^2 =88. This result map was based on the robust and timely methods and could be used as a guide for concerned government and non-government organizations for drought impacts mitigation activities in the Zone.

Key words: Agricultural drought, GIS, NDVI, Remote Sensing, SPI, SPOT WRSI

Chapter 1

Introduction

1.1. Background

Drought is an abnormally prolonged dry period that results from deficiency of precipitation and water availability, below expected or normal amounts. Therefore, it causes significant environmental and economic problems, particularly, in agricultural production activities, which in turn affect the balance of food supply and demand (Boken, 2009). Although it occurs in various parts of the world, drought, as a climate change factor, highly affects developing countries. Ethiopia, for instance, is one of the most drought prone countries in Africa. (Conway and Schipper, 2011), Climate change is influenced by the general global atmospheric and oceanic changes that affect the weather system (Bekele Feleke, 1993). This climate change and its behavioral variability, particularly, rainfall irregularity and associated droughts, have been causes for food insecurity in the country (Tsegaye Woldegeorgis, 1998; Rosell, 2011).

The Ethiopian traditional, rain fed, agricultural sector supports approximately 80-85% of the population and hence is central to the livelihoods of the rural poor in the country (Temesgen et al., 2009). The existing reality also shows that agriculture, as the main source of input, both as raw material and the required capital for the industry, is subject to irregular rainfall and the resultant drought. In other words, the county's agricultural productivity and the overall national economic wellbeing depend on the spatio-temporally variable and quantitatively inadequate rains. This total dependence on rain fed agriculture has rendered the country's economic development opportunity extremely vulnerable to the effects of climate change.

Ethiopia has been affected by recurrent droughts during the years 1958, 1966, 1972-75, 1977-78 etc. that seriously affected many parts of the country, claiming massive plant, animal and human lives. (Cutler, 1988).Therefore, in order to plan effective programs that can ensure the sustainable development of the sector and its sound contribution to the national economy, it is highly imperative that scientific researches be conducted and effective techniques that would enable the country to take reliable and sustainable measures against drought effects are sought.

In temperate- semiarid areas, like West Hararge Zone, irregular rainfall distributions, for the last many years, have been incurring highly profound negative effects on crop yields, as a result of which the rain fed agriculture failed to provide the minimum food requirements for the rapidly growing population. As the risks associated with agricultural drought, in this area, are spatially variable, they require different adaptation strategies and options. In order to adapt a reliable means in responding to the adverse impacts of agricultural drought, in the area, agricultural drought assessment and identification of risk prone zones have to be given high considerations as primary tasks.

In this regard, it has been learned that, so far, identification of agricultural drought risk areas, in the country, with the exception of some recent efforts, were being conducted on the basis of mechanical analysis of rainfall and evapotranspiration data on limited scopes for longtime (Lemma Gonfa, 1996).Basically, this conventional approach lacks in the capacity to precisely identify spatial weather variations (Jeyaseelan, 2004). Moreover, collecting sufficient spatial and temporal data using the conventional method is very difficult, especially, in areas of rugged topography and less accessibility. Apparently, it is hoped that integration of information derived from RS and GIS techniques with other data sets, both in spatial and non-spatial formats can provide tremendous potential support for identification, monitoring and assessment of droughts (Berhan et al., 2011; Dodamani et al., 2015).

Therefore, the use of such combined techniques becomes the best approach for the acquisition of comprehensive, reliable and consistent quantitative climate information that would help in planning to adequately mitigate the impact of natural environmental hazards, like the droughts in West Hararge Zone

1.2. Statement of the Problem

Regular weather reports and actual life experiences witness the fact that the whole world has been experiencing rapid climate changes for the last many years. Although the spatial and temporal parameters of its occurrences have not yet been predictable, it is unanimously agreed that there are several known factors that can effectuate climate changes. Presumably, the rise in oceanic and atmospheric temperature can be considered as the largest universal factor perpetuating climate changes. Climate changes impact various negative effects on the global set of circumstances of which the prevalence of recurrent rainfall irregularities and the consequential agricultural drought are the major ones.

Droughts, as climate change factors, are characterized, predominantly, by hot dry weather conditions with very low or no life supporting moisture. The scarcity of water and its inability to support life, obviously, results in the devastation and destabilization of the entire ecosystem of the affected locality .Today, as many parts of the world are experiencing the devastation of natural balance and obstruction of human economic activities, it is apparent that drought is posing serious challenges to the World.

In Ethiopia, agricultural activities that engage over 80% of the country's population, is totally dependent on the scanty water that is mostly rain fed. Due to so much dependence on the irregular and scanty rainfall, the country's agriculture has been easily victimized by drought. In fact, some 56 large-scale disasters are reported with an estimated 66 million people affected by droughts that have been recurrently haunting the country, from 1970 to 1998 (Tinebeb Yohannes, 2011). In particular, agricultural drought, generated by climate change and exasperated by human distractive activities, has been rapidly increasing since 1985. In 2002, for example, severe conditions of drought in some part of the country are reported, with an estimated 10 to 14 million exposed for food aid (Tinebeb Yohannes, 2011). Apparently, drought has been obstructing the country's aim of optimizing agricultural production, in particular, and the effective accomplishment of national growth and transformation plan, in general.

West Hararge Zone is, one of the Eastern regions of Ethiopia, persistently affected by the recurrent drought, for the last many years (Cutler, 1988). In this region of the country, drought is manifested by the irregularity of rainfall. The regional risks associated with rainfall variability and the consequential drought are, generally, Characterized by late beginning and early endings of the rainy seasons. Obviously, this results in temporally and spatially inadequate amount of moisture to support crops. The amount and distribution of rainfall obtained, during the short period, is so unsatisfactory that it renders crops vulnerable to moisture deficit, leading to reduced yields. These prominent realities clearly emphasize the degree of vulnerability of agricultural sector products of the zone to sever drought hazards. Apparently, there is a pressing need to conduct more advanced scientific researches to thoroughly understand the intensity of the problem and develop appropriate tools that would enable development planners and practical field workers to mitigate the impact of the drought effectively.

In fact, the need for proper identification of the intensity of environmental climate change effects and devising appropriate mechanisms to alleviate the risks has already been, emphatically, stated in the background sub-section. To this end, there appears to be fundamental technical problems with the existing approaches in Ethiopia. From the existing practices, it has been learned that, in Ethiopia, although some attempts to use satellite data have been made, very recently, identification of agricultural drought risk zones were being conducted, mainly, on the basis of conventional long range rainfall data analysis. Yet, the efforts made through the conventional approaches could not bear fruits as their parameters are spatially and temporally limited. Evidently, it is apparent that the existing conventional approaches lack in the accuracy and precision of the acquisition, identification and recording of temporal and spatial climate variation data.

On top of this, the collection of sufficient temporal and spatial data, through the conventional methods, is hardly possible, mainly, because of ruggedness of the topography and less accessibility of the sites. Apparently, therefore, there is an earnest need to use more advanced technological, modern RS and GIS systems to ensure accurate acquisition of comprehensive, reliable and consistent quantitative climate information that can enable the concerned bodies to devise appropriate mechanisms to alleviate the prevailing regional environmental hazards, in general, and agricultural drought risks of the study area, in particular.

1.3. Objectives of the Research

1.3.1. General objective

The general aim of the study is to, locate and map proper drought risk prone areas for combating agricultural drought in West Hararge Zone.

1.3.2. Specific objectives

In order to effectively realize the intended general objective, attempts have been made to:

- Select appropriate mechanisms for indicating drought risk prone agricultural areas.
- Assess, identify and examine the level of agricultural drought risks in the zone using remotely sensed image based vegetation, climate and crop performance indices of ten years.
- Prepare agricultural drought risk map of the Zone.

1.4. Significance of the Study

There is a firm conviction that the use of Satellite Remote Sensing data and Geographical Information System (GIS) can effectively facilitate the detection, identification and mapping of agricultural drought risk prone areas. Reliable agricultural drought risk area mapping is expected to enhance decision making process for drought monitoring and mitigation actions. Thus, it is hoped that agricultural drought risk zone map produced from this study, can be useful for policy makers to prioritize their action plans based on the indicated risk level. Researchers also can use it to generate agricultural technologies and information including the techniques for the selection of drought tolerant and adaptive crops, as well as for the generation of crop and soil moisture management strategies. Moreover, it may be helpful for development agents and Non-Governmental Organizations (NGO) to facilitate scaling up of the best techniques with success stories to similar risk zones elsewhere.

Apparently, this research has significance in providing a better foundation for using Remote Sensing and GIS-based approaches to assess, monitor and manage drought effects. It also offers the opportunity to use different drought monitoring indices, with increased efficiency in spatial and temporal resolutions, to determine the levels of drought and its effects on crop production. Evidently, therefore, it is hoped that the result of the study will provide agricultural experts, water managers and policy makers with better tools for assessing, forecasting and managing agricultural drought risk areas on much more précised scales. Fundamentally, it is firmly believed that the result of the study will also provide the local farming communities with basic knowledge and awareness that can empower and enable them to make competitive and constructive efforts towards resiliently surviving drought hazards through efficient management of the meager water resources available to them.

1.5. Scope of the study

Geographically, the scope of the study is focused on the agricultural areas of West Hararge Zone of Oromia Regional State, in Ethiopia, presumed to be affected by recurrent drought. Conceptually, this study is determined to concentrate on the Agricultural drought risk area assessment related issues. Methodologically, the study has opted to incorporate different satellite based drought indices like Normalized Vegetation Index (NDVI), Standard Precipitation Index (SPI) and Water Requirement Satisfaction Index (WRSI) from remotely sensed SPOT, PROVA-V Vegetation and

FEWS Net data. In short, all efforts have been made to limit the scope of the study within the domain of its objectives.

1.6. Limitation of the Study

Lack of quantitatively and temporally appropriate meteorological information and drought affected population data were the major limitations of the study.

1.7. Thesis organization

This thesis is organized in five chapters. The first chapter deals with the introduction describing the background of the problem and objectives the study, the second chapter reviews related literature. The third chapter deals with materials and methods while chapter four presents and discusses the results of the study. Finally, chapter five draws conclusions and makes pertinent recommendations.

Chapter 2

Literature Review

It is commonly believed that reading variable books and articles is opening multiple windows of knowledge. Likewise, research authors (Koul, 1996) commend that review of related literatures enriches and enhances the adequacy of the researchers' works by exposing them to the rich store of knowledge and experiences, available in the field. Apart from enabling them to extract supportive ideas, principles, methods and techniques from the works of experts, review of literature benefits researchers to avoid unnecessary duplications and efficiently plan the structural organization of their works.

In order to lay reliable foundations for the strength of this work, therefore, considerable efforts have been made to thoroughly survey the works of several notable experts in the field. The major aim of the effort is to acquire the following pertinent conceptual and methodological knowledge from the works of these professionals.

2.1. Concept and Types of Drought

Drought, is the deficit that results when soil moisture is insufficient to meet the demands of potential evapotranspiration (Critchfield, 2003). Normally, drought occurrence, as a climate change phenomena, 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). Other climatic factors, like high temperature, high wind and relatively lower humidity may also indicate the appearance of drought. 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). Generally, therefore, manifested, dominantly, by erratic distribution of rainfall and deficiency of precipitation over an extended period of time (Bayarjargal et al., 2006), drought can occur in almost all climatic zones of the world. Characteristically, however, as its time of onset, spatio-temporal distribution, severity and durations vary from region to region; its definitions may also vary.

As has been cited above, drought is one of the most commonly experienced causes of environmental disasters in the world. Yet, on the contrary, it is also considered as one of the least precisely and properly understood global climate change phenomena. Conventionally, drought was defined, in its broader sense, as an abnormally prolonged absence of rainfall resulting in the destabilization of natural ecological balance. Critical investigators of this view, however, strongly oppose the conventional approach to drought definition. To them, drought mean much more than that. In order to, rationally, support their arguments, they produced tangible evidences by stating the fact that the broad definition of drought and its impacts on the natural environment is highly vague and needs some sort of logical categorization.

In fact, some researchers began suggesting series of criteria to substantiate these arguments. Thus, in order to widen the scope of the existing conventional approach to drought definition, attempts were made, initially, to divide drought definition into two; based on its conceptual meaning and operational functions. Apparently, the conceptual definition was associated with the clarification of the literal meanings of drought based on its immediate effects on the objective situation, while the operational definition attempted to identify the onset, distribution, duration and levels of severity of drought (Mishra and Singh, 2010; Bartels, 2014). 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).

The dissatisfaction with the conventional drought definition, persistently, continued as more people began to come up with new ideas for not only categorizing, but also for localizing drought meaning. One of the new arguments, for instance, holds that, since the actual impacts of drought, characteristically, vary from region to region, its definition should also be regionalized, accordingly. In fact, some of the researchers Rossi (2009) and Akhtar (2014) moved further and evidently came up with stronger inferences, stating that, as the actual spatio-temporal occurrences, causes and effects of drought are so varied and inconsistent, there is no single comprehensive description that can satisfactorily expose its global attributes. Evidently, therefore, the need to characteristically delineate and localize drought definition grew ever stronger.

Other proponents of the need for limiting drought definition to its specific regional behaviors, Legase Hadish (2010); Al-Timimi et al. (2012) came forward with more concrete and particular reasons for the need to localize drought definitions. According to this group, since the characteristics of regional climate is very closely related to the specific physical, biological and socio-economic conditions of the affected area, it is not possible to transfer a particular drought definition derived from one region to another region of the world. Accordingly, with the persistent in-depth observation of drought behaviors, based on its particular area of prevalence, researchers WMO (2006) were able to come up with stronger evidences that can enable them to, precisely, categorize drought definition based on its impacts on the physical, biological and socio-economic conditions of the particular locality. Evidently, it is apparent that the rational for the new proposals and their influential success, emanated from the consistent observations made on the pragmatic effects of climate changes on particular area rainfall, combination of rainfall with temperature, humidity, evaporation from free water, transpiration from plants, soil moisture, wind, rivers or stream flow and vegetation conditions.

Eventually, the apparent success in the conviction to characterize drought in terms of its detailed local events, and the use of modern Remote Sensing as well as Geographical Information System enhanced the works of these researchers like Mishra and Singh (2010); Getachew Berhan (2013) and Senay et al. (2015) to effectively monitor, assess and analyze specific area drought behaviors like its onset, frequency, duration and severity levels. Accordingly, scientists have now been able to, successfully, further break down drought definition, based on its impacts on a particular geographical area. The new categorization criteria is very closely associated with the principles of the four disciplinary areas of meteorological, hydrological, agricultural and socio-economic studies of climate change effects on a given environment (Figure1). Currently, therefore, there are four types of operational definitions that can efficiently characterize the pragmatic effects of drought on a given particular geographical area.

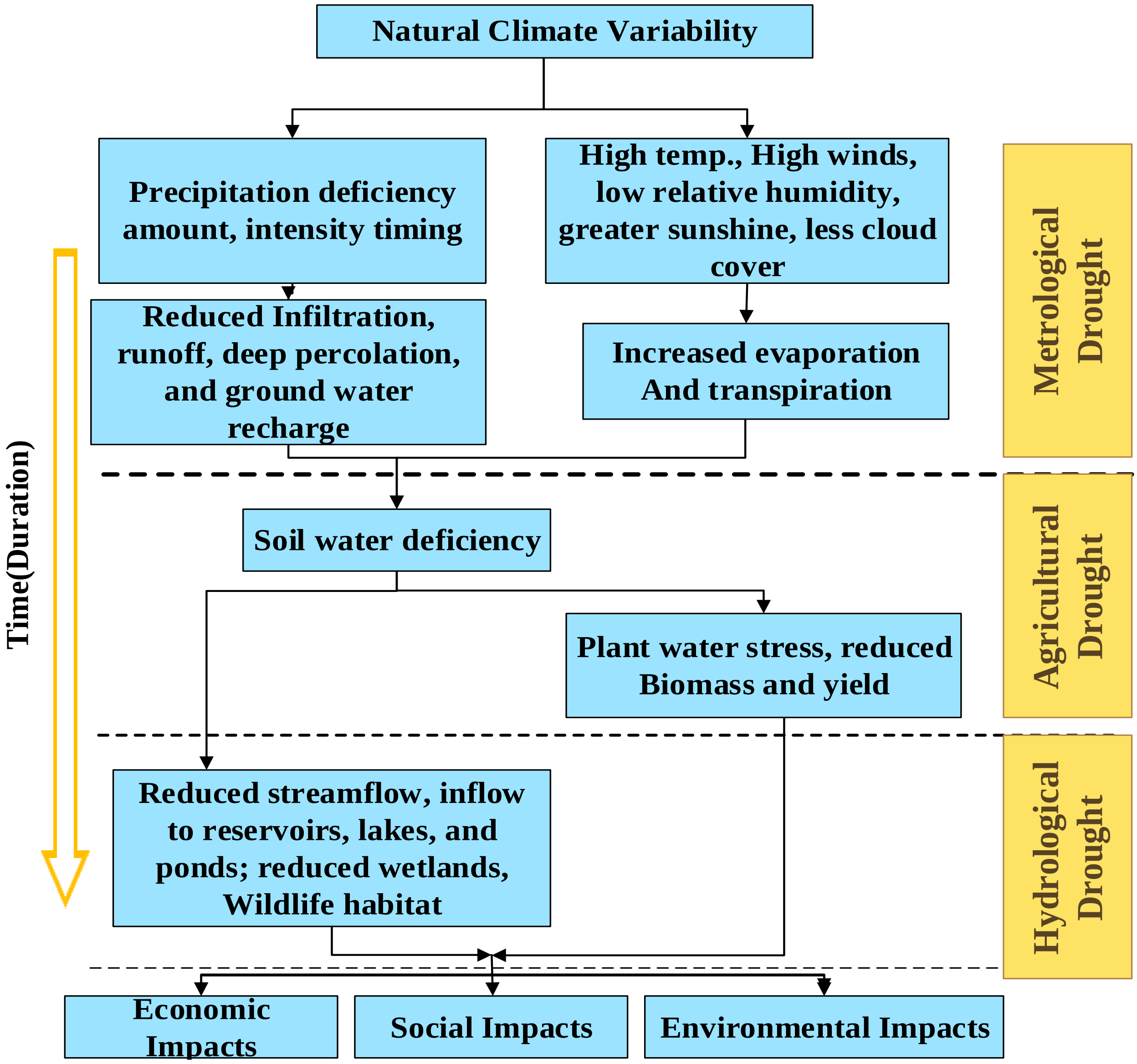

Figure 1: Categories of drought impacts

Source: Adapted from Droughts &Floods Assessment and Monitoring using Remote Sensing and GIS (Jeyaseelan, 2004).

2.1.1. Meteorological Drought

Precipitation has been commonly used for meteorological drought analysis. As a matter of fact, several studies have dwelled on analyzing droughts using monthly precipitation data. These approaches focused on analyzing drought duration and intensity in relation to precipitation shortages. Daily rainfall information, temperature, humidity, wind velocity and pressure, and evaporation are the major data sets required to assess meteorological drought in general.

Definitions of meteorological drought are region specific, since the atmospheric conditions that result in deficiencies of precipitation are highly region specific. Many authors explain meteorological drought by comparing the degree of specific area dryness with that of normal or average amount, and the duration of the dry period. Bayarjargal et al. (2006) for instance, described drought as a recurring extreme climate event over a given land, characterized by below-normal precipitation over a period of months to years. 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 (2011a) 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.

2.1.2. Agricultural Drought

As stated earlier, the world has been experiencing disastrous effects of drought for a long period of time. In particular, agricultural drought, 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. Apparently, therefore, today, greater attention is given to the study of agricultural droughts, more than ever before.

On the other hand, it appears that some researchers found it difficult to associate particular drought characteristics to agricultural problems. In other words, despite the recent efforts made to delineate drought definition based on the principles of the four different disciplinary area categories, some of the basic characteristics of drought still appear to be so intrinsically interwoven with each other that it is difficult to single out and assign them to a particular area discipline. Evidently, therefore, agricultural drought impacts have to be realized as the combination effects of different drought elements on vegetation and crops. Therefore, many of the area researchers, had to define agricultural drought, more or less, by linking various characteristics of meteorological and hydrological drought impacts on agricultural situations by focusing on precipitation shortage, differences between actual potential evapotranspiration, soil type, soil water deficit, and reduced ground water or reservoir levels resulting in reduced crop yield.

Accordingly, Dai (2011b) defines agricultural drought as the decline in the productivity of crops due to irregularities in the rainfall as well as decrease in the amount of soil moisture. In fact, the very concept of agricultural drought is, broadly, defined as a prolonged abnormally dry period when there is not enough water for agricultural consumers' normal needs, resulting in extensive damage to crops and diminishing amount and quality of yields (Getachew Berhan, 2013). According to the information available so fare, therefore, data sets required to assess agricultural drought are soil texture, fertility and soil moisture, crop type and area, crop water requirements, pest infestation and the general climate conditions.

Therefore, it can, clearly, be seen that most of the drought indices, based on the combination of precipitation, temperature and soil moisture, have been key focal centers for the study of agricultural droughts. In some cases, vegetation water demand may also depend on the prevailing weather conditions, biological characteristics of the specific plant and stage of growth as well as the physical and biological properties of the soil. In terms of duration, agricultural drought occurs and disappears so quickly that it tends to cover the shortest period of time among all other droughts (Keyantash and Dracup, 2004). The start and end may lag behind that of a meteorological drought, depending on the preceding soil moisture status.

2.1.3. Hydrological Drought

Hydrological drought refers to a persistently low discharge and/or volume of water in streams and reservoirs, lasting months or years. It is the slowest type of drought to form, but lasts the longest. Hydrological drought is, normally, a natural phenomenon, but it may be exacerbated by aggressive human activities. Hydrological droughts are usually related to meteorological droughts, but their recurrence interval may vary accordingly. Changes in land use and the consequential land degradation can affect the magnitude and frequency of hydrological droughts.

Stream flow data have been widely applied for hydrological drought analysis. In general, however, data sets required to assess hydrological drought are surface-water area and volume, surface runoff, stream flow measurements, infiltration, water-table fluctuations, and aquifer parameters.

2.1.4. Socio- economic Drought

Socio-economic definitions of drought are closely associated with the demand and supply of some economic goods, with elements of meteorological, hydrological, and agricultural droughts. It differs from the other types of droughts in the sense that its occurrence depends on the processes of supply and demand. The supply of many economic goods such as water, forage, food grains, fish, and hydroelectric power, depends on the weather. Due to the natural variability of climate, water supply is ample in some years, but insufficient to meet human and environmental needs in other years. Socio-economic drought produces a complex web of impacts that spans many sectors of the economy. According to Goddard et al. (2003) economic drought is a severe dilemma which influences different aspects of mankind's life. It can cause many economic and environmental problems, especially, in the agriculture sector. Data sets required to assess socioeconomic drought are human and animal population and growth rate, water and fodder requirements, severity of crop failure, and industry type and water requirements.

2.2. Drought in Ethiopia

2.2.1. Prevalence of Drought in Ethiopia

According to Segele and Lumb (2005) Ethiopia has been ravaged by series of severe drought attacks for most of the last 35 years, primarily, due to the failure of its main (kiremt) rainy season. 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.

Hence, the subsistence agriculture is characterized by significant fluctuations in yield and production due to risks associated with rainfall variability. Practically, more than 95% of the climate dependent crop production is usually conducted by small holders and subsistent farmers, who have the least capacity to cope up with the variability of climate change by resiliently resisting its severe negative impacts (Woldeamlak, 2009).

Apparently, persistent drought risks, associated with the year-to-year variability of rainfall and scarcity of water, have become determining challenges to the sustainable increments of the national agricultural productivity and the household food security. According to Dercon (2002) climate change extremes have had direct and often persistent severe impacts on farmers' assets and livelihoods in Ethiopia, for the last many years. For instance, the 1998-2000 droughts have claimed over 75%of the average annual income of the households in the northern parts of the country. Fraisse et al. (2006) also witness that the seasonal variability of weather has been a major source of production risks all over the country. Others also have noted that whenever rainfall is highly variable in amount and spatio-temporal distribution, its impacts become highly unpredictable across regions and seasons (Kinde Tesfaye and walker, 2004; Ayalew et al., 2012). This type of variability of rainfall, in Ethiopia, has severely affected the lives of many people; as livelihood in the country depends on the scanty rainfall (Viste et al., 2012).

In order to adapt the livelihood systems to the changing climate conditions, therefore, acquisition of climate information can play important role in creation of alternative strategies for risk reduction, early warning and early actions for preparedness measures, such as prepositioning, resource planning, and to inform agricultural management decisions makers (IFRC, 2009).

2.2.2. Drought Risk Prone Zones Assessment in Ethiopia

Risk assessment involves speculation and evaluation of the magnitude and severity of the unexpected negative outcomes, either quantitatively or qualitatively. Risk assessment and evaluation, according to Kasperson and Kates (1983) comprises of identification of hazards, estimation of its eminence and speculation of the magnitude of the resulting losses. The drought prone area or risk zone identification is usually carried out on the basis of historic data analysis of rainfall or rainfall and evaporation and the area of irrigation support activities.

In Ethiopia, drought monitoring mechanisms were based on meteorological information obtained from ground stations such as rainfall, weather conditions, crop performance and water availability. In other words, until recent times, ground stations used to be the major sources of national information for agricultural drought risk assessment. However, this reliance on ground data could not lead to successful results, as a poor density of weather stations, for instance, could make it difficult to acquire sufficient spatial and temporal climate data (Brown et al., 2002).

Besides, the conventional approach does not cover man's influences on the wellbeing of the eco-system, such as land use changes, irrigated area developed and the area affected due to water logging and salinity. The Remote-Sensing based method for identification of drought prone areas Jeyaseelan et al. (2002) on the other hand, uses historical vegetation index data derived from NOAA satellite series and provides spatial information on drought prone area. This approach depends, mainly, on the trends in vegetation development, frequency of low development and their standard deviations.

One of the most well understood and clearly detected climate change phenomena, through the use of Remote Sensing technology, is the natural phenomenon of climate variability known as the El Niño-Southern Oscillation (ENSO). Accordingly, it has been possible to realize that the phenomenon results from an interaction between the oceanic and the atmospheric pressures over the tropical Pacific Ocean. This phenomenon has had vital consequences on the weather conditions around the globe, particularly, in the tropics over the last many years (NOAA, 2011). Evidently, studies have confirmed that ENSO driven climate variability is one of the major cause of food insecurity in most parts of Africa (Serigne, et al., 2006). Anyways, it has been understood that ENSO phenomena has become one of the major driving force behind climate variability.

In some parts of sub-Saharan Africa, including Ethiopia, the Sahel, equatorial eastern Africa and southern Africa, strong ENSO events have been creating unique and persistent anomaly patterns in rainfall (Ogutu, 2007). The impacts of El Niño on the Eastern and Southern African rainfall, for example, exhibit specific spatio-temporal distribution patterns depending on the space-time evolution of each individual ENSO event. Generally, therefore, ENSO driven climatic variability at all of its time-scales has become an acute challenge to economic development of the affected regions.

Apparently, the need to develop flexible and proactive strategies for managing year-to-year climate variations impacts becomes highly commendably. In this regard, concerned professionals and institutions interfacing with the local farming communities can take concrete steps to build well founded capacity to resiliently resist the long-term impacts of climate system changes, based on information obtained from modern satellite data (Hansen, 2002).

In this regard, the Ethiopian use of ENSO information, especially its seasonal forecasts, is based on the existing technical knowledge and experiences of the staff members of NMSA, as well as on the results of continuous studies and investigations. In addition to the available results of preliminary studies and research findings, current ENSO information is very important for the preparation of seasonal outlooks in Ethiopia. In other words, ENSO-based early warning should be more specific in time and space to be relevant to concerned consumers (Bekele, 1997).

In Ethiopia, crop yields are to a large extent predicted by the amount of available water compared to water requirement. However, the total rainfall during the seasons has proven to be too crude indicator of crop yields. The Livelihoods Early Assessment and Protection (LEAP) system is an innovative food security early warning–early action tool. It was developed in 2008 by the Ethiopian national food security early warning system, established with the support of WFP and the World Bank. It uses fixed built-in background images and automatically connects to the internet to download images (Hoefsloot, 2010). Moreover, it provides weather based indices that interpret early warning information into early responses via established social protection frameworks like the multiple donor-sponsored agencies such as the World Bank.

LEAP is a GIS based risk monitoring tool that translates agro-meteorological data into crop or rangeland production estimates. The model, mainly, based on weather parameters, uses real time, historical background and satellite rainfall and other meteorological data. It also uses the FAO Water Requirement Satisfaction Index as the most widely used model, a platform for the calculation of weather based indices. It starts out with the calculation of a water balance indicator (WRSI), that gives yield reduction and helps to predict the number of people affected by the drought (Hoefsloot, 2010).

2.3. The Role of Remote Sensing Technology in Drought Monitoring

The detection, monitoring and mitigation of drought disasters require consistent gathering of rapid and relevant information that cannot be effectively done by conventional methods. As has been evidenced across many parts of the world, Remote Sensing and Geographical Information System techniques are increasingly being regarded as the most useful drought detection techniques (Chopra, 2006; Partheepan and Dayawansa, 2008). Remote Sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation (Lillesand and Keifer, 1994).They make it possible to obtain and distribute information rapidly over large areas by means of sensors operating in several spectral bands, mounted on aircraft or satellites (Kogan, 2001).

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 (Legase Hadish, 2010). Because of advancements in the technology, the use of non-visual parts of the electromagnetic spectrum has enhanced the sustenance of detailed information that can be collected about the environment.

Remote sensing has been considered to be one of the cost-effective approaches to document changes over large areas and even geographic regions, and it has been of immense help in monitoring the changing pattern of vegetation (Kogan, 2001; Lunetta et al., 2004). It has also great advantages, because of its characteristics, in the application to monitoring, evaluating and forecasting of any change in vegetation. Users can grasp the present situation, evaluate processes such as land degradation trends in macroscopic range, and also provide a scientific basis for the prevention and administration of vegetative changes (Hoefsloot, 2010). In addition, vegetation indexes obtained from satellite data allow to identify drought affected areas (McVicar and Jupp, 1998). Identification of drought prone areas uses historical vegetation index data derived from satellite and time series data, and provides spatial information on drought prone areas, depending on the trend in vegetation development or frequency of low development and their standard deviations.

2.4. Drought Indices

Several indices and methods have been developed using meteorological, hydrological, vegetation and soil parameters to identify and monitor droughts at various temporal and spatial scales. These indices are categorized based on meteorological Standardized Precipitation Index (SPI), Rainfall anomaly index (RAI), Palmer drought severity index (PDSI), soil moisture, Crop Water Stress index, hydrological Water stress index, satellite Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Temperature Condition Index (TCI) and other extensively used vegetation indices (Legase Hadish, 2010; Hassan, and Saiful Islam, 2011; Getachew Berhan, 2013). It has been confirmed that no single indicator or index is adequate enough by itself for monitoring drought on regional scale. Instead, a combination of monitoring tools integrated together have been found preferable for producing regional or national maps (Martini et al., 2004). Thus, Spatio-temporal patterns of seasonal drought can be best detected using meteorological, vegetative as well as crop performance indices among others (Gizachew Legesse and Suryabhagavan, 2014).

2.4.1. Meteorological (Rainfall and Temperature) based drought indices

There are a lot of indices developed based on the need to measure rain fall and temperature. The following are some of the most widely used indices.

2.4.1.1. Palmer drought severity index (PDSI)

The Palmer Drought Severity Index was originally developed by a man called Palmer, in1965, with the intention to measure the degree of cumulative departure in surface water balance. In other words, the objectives of PDSI are to provide standardized measurement used to calibrate moisture conditions so that comparison could be made between locations and months (Quiring and Papakryiakou, 2003). It is designed to treat the drought problems in semi-arid and sub humid climates. It incorporates antecedent and current moisture supply (precipitation, P) and demand (potential evapotranspiration, PE) into a hydrological accounting system, which includes a two layer-buckt-type model for soil moisture calculations. The PDSI is a standardized measure, ranging from about −10 (dry) to +10 (wet) with values below −3 representing severe to extreme drought (Dai, 2011a). 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.

Table 1: Palmer drought severity index

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

2.4.1.2. Standard precipitation index (SPI)

Standard Precipitation Index, developed by Mckee et al. (1993) is the most widely used index for calibrating the magnitude and duration of drought events. According to Guttman (1998) and Thavorntam and Mongkolsawat (2006) SPI is used to examine the severity and spatial patterns of drought distribution in a given region. It is designed to quantify the impacts of precipitation deficit on groundwater, reservoir storage, soil moisture, and stream flow for multiple time scales. 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 (Vicente -Serrano, 2006a; Legese Hadish, 2010). According to the results of the study conducted by Ntale and Gan (2003) on each time scale of three different drought indices (PDSI, Bhalme-Mooley index, and SPI), SPI could use any time scale which would aid in measuring any type of drought in Eastern Africa.

2.4.1.3. Rainfall anomaly index (RAI)

Rainfall Anomaly Index is meteorology based index used to indicate the deficiency of rainfall compared to the normal seasonal rainfall in a given region. It is used to indicate the meteorological drought for the growing seasons of regions. It is computed as:

$$RFI = \left[\frac{RFY - RF\ a}{RFa}\right]\ x\ 100 \qquad \text{Eq. 1}$$

Where, RFI is rainfall anomaly for given year, RFY is seasonal rainfall for given year and RF a mean seasonal rainfall. The negative rainfall anomalies signified that precipitation was less than the average seasonal rainfall for a particular place (Shaheen and Biag, 2011).

2.4.1.4. Crop soil water balance model (CSWB)

The Crop Soil Water Balance (CSWB), developed by FAO (1979), is a ground-based calibration model, commonly, used in Africa for drought monitoring purposes .The CSWB model utilizes ground-based agro- meteorological data to estimate crop condition. When combined with crop production functions, the model can estimate yields. These models are based on the physical principles of energy and/or mass (water) conservation equations (Senay et al., 2013a; 2013b). Mukhala and Hoefsloot, (2004) also explain CSWB as the difference between the effective amounts of rainfall received by the crop and the amounts of water lost by the crop and soil due to evaporation, transpiration and deep infiltration , by considering the amounts of moisture held by the soil and water available to the crop. More precisely speaking, the CSWB model is a book-keeping method that accounts for water gained or lost by recording the cumulative water stress of a specific crop for each time increment over the entire growing season.

The ultimate aim of the water balance model is to account for the plant's water consumption during the growing season, as it is used to determine whether the rainfall was adequate for maximum growth of crops (Reynolds et al., 2000).

2.4.1.5. 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. Crop water requirement is the amount of water required to compensate the evapotranspiration loss from the cropped field (FAO, 1977; 1998; 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, 1977; 1986). In the recent past, Senay and Verdin (2001); Verdin and Klaver (2002) demonstrated a regional implementation of WRSI in a grid cell based modeling environment. Seasonal WRSI is currently operational as monitoring and forecasting tool for region wide food security analyses in drought prone countries in Sub-Saharan Africa. According to the results of evaluations made by Verdin and Klaver (2002) on the performance of the model using district level crop yield data of1996-1999 from Ethiopia, WRSI values and reported district yield data were significantly correlated (r = 0.77). Thus, the model was particularly found successful in capturing the response of the crop during relatively dry years. According Gizachew Legesse and Suryabhagavan (2014) WRSI based agricultural drought assessment can better capture agricultural drought events.

2.4.2. Remote sensing Based Drought Indices

Since the recent past, satellite derived drought indicators, calculated from satellite-derived surface parameters, have been widely used to study droughts. Accordingly, several drought indices have been proposed for use, based on normalized difference vegetation index (NDVI) for monitoring drought severity level such as Anomaly Vegetation Index (AVI). Vegetation Condition Index

(VCI) and Temperature Condition Index (TCI) are two of the extensively used vegetation indices (Hassan and Saiful Islam, 2011).

2.4.2.1. The normalized difference vegetation index (NDVI)

The Normalized Difference Vegetation Index (NDVI) was first suggested by Tucker in 1979 as an index of vegetation health and density. Since then, it has been considered as the most important index for mapping agricultural drought areas (Sumanta et al., 2013; Nithya and Suja Rose, 2014). NDVI is a nonlinear function that varies between -1 and +1, and the values of NDVI for vegetated land generally range from about 0.1 to 0.7, with values greater than 0.5 indicating dense vegetation (Sruthi and Mohammed Aslam, 2015). NDVI is based on Computational result from the satellite image using spectral radiance in red and near infrared reflectance using the formula:

$$NDVI= (NIR-R) / (NIR+R) \qquad \text{EQ. (2)}$$

Where NIR= near infrared band, R= Red band

Currently, NDVI is the most commonly used indicator that is sufficiently stable to permit meaningful comparisons of seasonal, inter-annual, and long-term variations of vegetation structure, phenology, and biophysical parameters (Tucker and Sellers, 1986). In addition, it is also a powerful indicator to monitor the vegetation cover of wide areas, and to detect the frequent occurrence and persistence of droughts. It provides a measure of the amount and vigor of vegetation at the land surface. These indices are functions of rate of growth of the plants and are sensitive to the changes of moisture stress in vegetation. In other words, it has been documented that there is a direct correlation between NDVI and the amount of stress vegetation is experiencing (Wang, et al., 2003). The use of NDVI-based indices for monitoring and detecting drought is justified on the basis that vegetation vigor is closely related to moisture condition (Di, et al., 1994; Rundquist, et al., 2000; Legase Hadish, 2010; Getachew Berhan, 2013; Gizachew Legesse and Suryabhagavan, 2014).

The comparison between NDVI values and rainfall data shows dependence of the NDVI values on the sum of the amount of rainfall with a time lag (Rahimzadeh et al., 2008). There are a lot of papers written on the use of NDVI data products for agricultural vulnerability to climate change Kaushaly (2011) for instance, had assessed the agricultural vulnerability to climate change, using NDVI data products and the results were discussed spatio-temporally at district level for India.

Likewise, Sumanta et al. (2013) assessed the severity of drought using long term mean values of maximum NDVI in Bankura District, West Bengal. Thus, the study results show that NDVI has been confirmed to be the best measure of correlation between rainfall and vegetation growth.

2.4.2.2. Vegetation Condition Index (VCI)

Vegetative drought is closely associated with weather impacts. However, in NDVI, the weather components get subdued by strong ecological components. VCI separates the short-term weather-related NDVI fluctuations from the long-term ecosystem changes. Kogan (1990; 1997; 2000) designed the Vegetation Condition Index (VCI) to monitor drought with a very high radiometric resolution (AVHRR) data and obtained good results. The VCI is the difference between the current NDVI and the minimum NDVI for the entire record, normalized by the ranges of maximum minus minimum value. Recently, it was Peters et al. (2002) that clearly described the Standardized Vegetation Index (SVI), which is calculated by using a z score and converted to a probability value to evaluate vegetation and drought status. Therefore, while NDVI shows seasonal vegetation dynamics, VCI rescales vegetation dynamics in between 0 and 100 to reflect relative changes in the vegetation condition from extremely bad to optimal. Several drought monitoring studies using VCI over India, Singh et al. (2003) for instance, suggest that Vegetation Condition Index (VCI) captures rainfall dynamics better than the NDVI (Bhuiyan et al., 2006).

$$VCI = 100 * (NDVI - NDVI\ min) / (NDVI\ max - NDVI\ min) \qquad \text{EQ. 3}$$

Where NDVI, NDVI min, and NDVI max are the seasonal average of smoothed weekly, NDVI, its multi-year absolute minimum and its maximum values respectively.

Source: Monitoring Drought Dynamics in the Aravalli Region (India) (Bhuiyan et al., 2006).

2.4.2.3. Normalized difference vegetation index anomaly

NDVI anomaly is a deviation of vegetation condition from the average and the previous period. The use of anomaly isolates the variability in the vegetation signal and establishes meaningful historical context for the current NDVI to determine relative drought severity (Anyamba and Tucker, 2012). One of the assumptions in using NDVI and NDVI anomaly is that there is no major land cover change that would result in change in NDVI. Generally, the land cover change in the agricultural (heterogeneous) landscapes is small and limited to a small region that would correspond to a sub pixel to pixel change in satellite data. On the other hand, the objective of using

NDVI anomaly is to identify negative anomaly over expanse of large areas covering several tens of square kilometers. Hence, small-scale changes in land cover will not affect the use of NDVI anomaly for drought monitoring.

2.5. Identified Research Gaps

In Ethiopia, various research findings and practical life experiences witness that series of ravaging droughts have been haunting the country, for the last many years, with their life threatening effects. With the aim of effectively alleviating the problem, many researchers, both local and international, have been exerting relentless efforts to understand the nature of the recurrent drought and devise possible means to manage the severity of its impacts on the local ecosystem. Unfortunately, however, most of the efforts made, so far, could not produce viable results leading to effective achievement of the intended goals. This was, mainly, because, except the few recent attempts to use modern satellite resource data and Remote Sensing techniques, the county's conventional research practices used to rely, solely, on ground based data acquisition and processing methods.

In line with the contemporary research approaches, however, it is apparent that there are certain drawbacks with the conventional approaches. Apart from its inefficiency for the acquisitions of the required data for the intended purposes, for example, the conventional method was not time effective, mostly because of lack of efficiency in accesses. Besides, both national and regional level researches have not given adequate considerations for agriculture specific concerns like crop water requirement issues. On top of all, despite the prevalence of severe drought problems, bitterly experienced by the local farming communities, it has not been possible to come across evidences of noticeable drought related researches on West Hararge Zone.

Being aware of the existing research gaps and realizing the pressing need to clearly expose the comprehensive features of the appalling drought problems in the zone, therefore, the present study is intended to make a difference, by using modern satellite data resources and applying Remote Sensing and Geographical Information System to assess, identify, analyze, determine and map proper drought risk prone agricultural areas of West Hararge Zone, so as to enhance the zonal drought risk management efforts.

Chapter 3

Materials and Methods

3.1. Study Area Description

With the aim of casting some bright lights on the existing situation of West Hararge Zone, the description of the study area focuses, mainly, on its major features, like the designation of its geographical locations, exposition of its topographic and climatic conditions, explorations of its major potential resources, delineation of its population characteristics and giving a brief account of the major activities in which the local people are engaged for earning their livelihoods.

3.1.1. Location

West Hararge Zone, as one of the administrative zones of the Oromia Regional State, is located in the Eastern part of Ethiopia, about 325 km away from Addis Ababa.

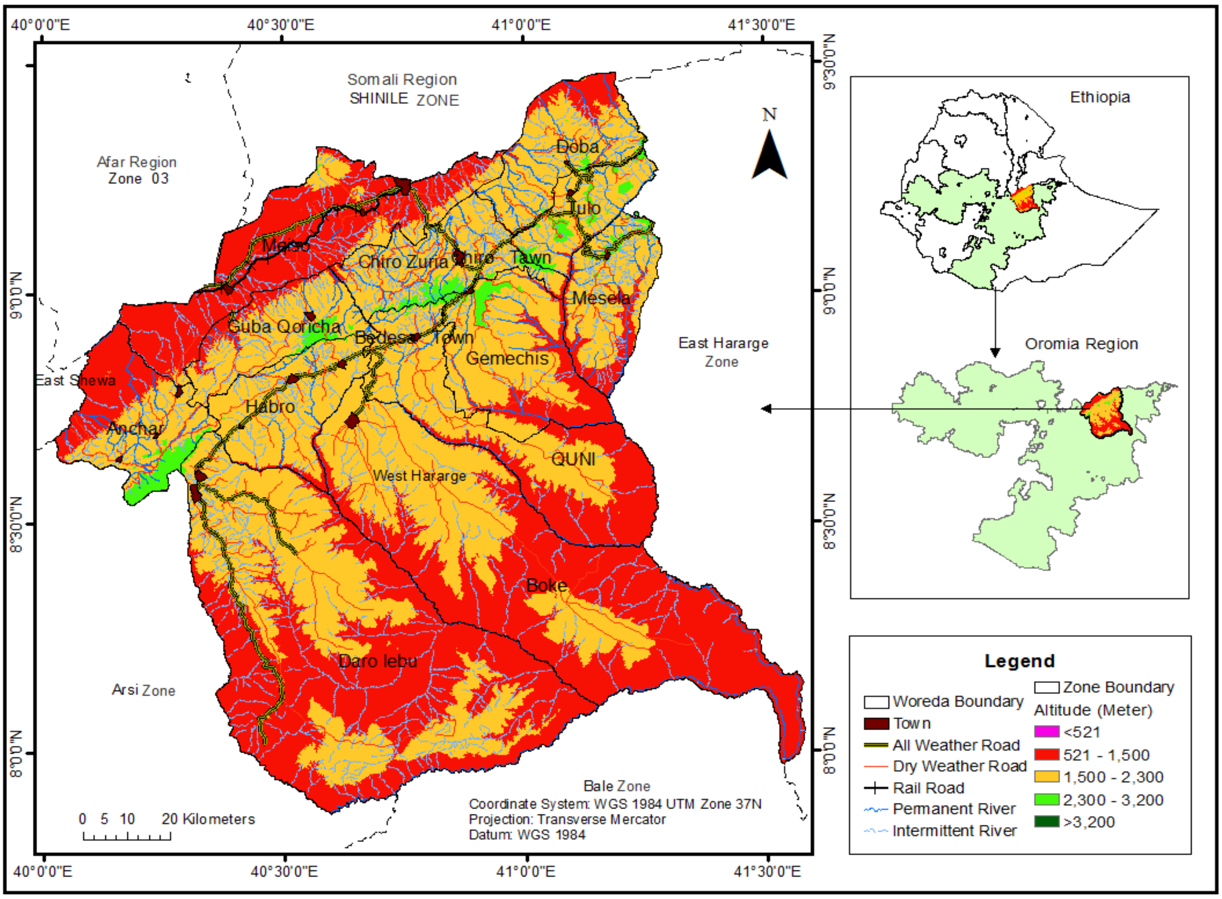

Figure 2: Location map of the study area

It stretches between 7° 51' and 9° 28' N latitude and 40° 01' – 41° 34' E longitude, covering a total area of 1,689,497.6 ha of land. The Zone has 12 rural and 2 urban administrative districts (Woreda) (CSA, 2007). The Zone is bordered on the south by the Shebelle river, that separates it from Bale; on the southwest by Arsi Zone; on the west by East Shewa Zone; on the northwest by the Afar Regional State; on the north by the Somali Regional State and on the east by East Hararge Zonal administration (Figure 2).

3.1.2. Topography and Climate

According to OWWDSE (2010) West Hararge is traditionally categorized into three broad topographical zones. Usually, they are locally referred to as 'kola' or the lowlands (500 – 1500 m) covering about 15 – 20 percent, 'Weyna Dega' or the midlands (1500 – 2300 m), about 35 – 45 percent and 'Dega' or the highlands (2300 – 3200 m) constituting about 30 – 40 percent (Figure.2). On the other hand, according to the data obtained from (FAO) Alemayehu Mengistu (2006) the Zone is scientifically categorized into Tropics – Warm/semi – arid and Tropics – Cool/semi-arid (Figure 3 and Table 2).

Table 2: Thermal Zones in West Hararge (MOA, 2000)

Thermal Name	Temperature (°C)	Elevation (masl)	Common Name	Area (ha)	Area %
T2	21-27.5	500 – 1600	Warm	177,255.1	10.49
T3	17.5-20	1600 – 2400	Tepid	1,512,242.5	89.51
Total				1,689,497.6	100%

The warm tropics or low lands are stretched along river basins and the boarders of the Afar Regional State. On the other hand, the cool tropics, accounting for over 85 percent of the area incorporate the rest of 'weyna dega' and 'dega' zones (Figure 3).

As indicated on the location map, West Hararge Zone lies within the equatorial region or wet tropical climate zone. By this definition, the area must have been experiencing higher temperature and regular tropical rainfall. But, because of the higher altitudes and the intervention of the high subtropical temperature, the zone manifests typical wet and dry tropical climate characteristics.

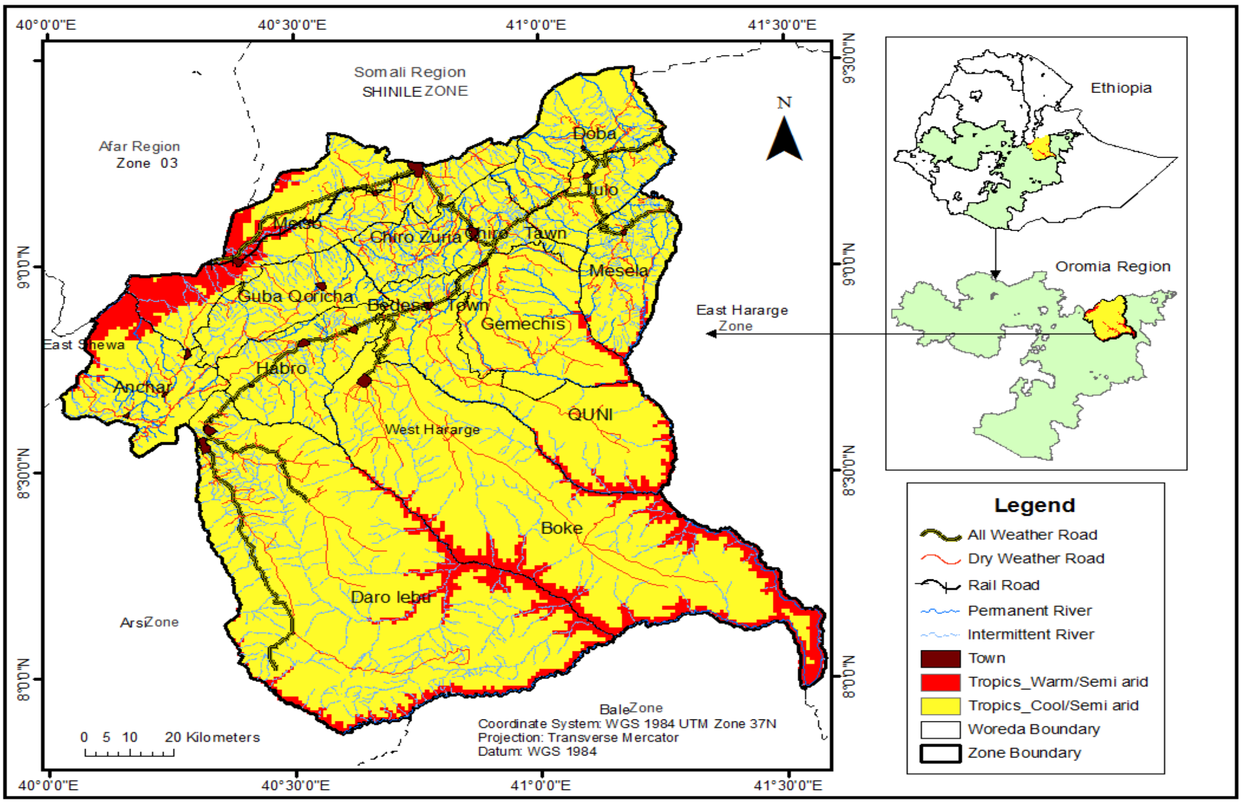

Figure 3: Ecological zone map of the study area based on FAO digital data

Wet and dry tropical climate is, characteristically, taken as a transitional climate region within the latitudinal zone of pole-ward of the wet tropics and equator-ward of the tropical desert, where the rain forests give way to the savanna with scattered drought-tolerant trees (Tarbuck and Lutgens, 1988; Critchfield, 2003).

Thus, although its normal mean monthly temperature range of 17.5^{o} C – 27.5^{o} C is similar to that of the humid tropics, the precipitation of the region is markedly different from the rest of the humid zones. In other words, as this climate is, fundamentally, distinguished by alternating wet and dry seasons, dominantly characterized by two to four months of dry periods, its annual rainfall total is less than that of the wet tropical rains. Evidently, most parts of the region remain vulnerable to occasional drought risks.

Apparently, therefore, situated within the heart of the wet and dry tropical climate zone, West 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. According to the ground stations data of the National

Meteorology Service Agency, for instance, the mean annual rain fall of West Hararge Zone for the study period was found to be 68.7 mm.

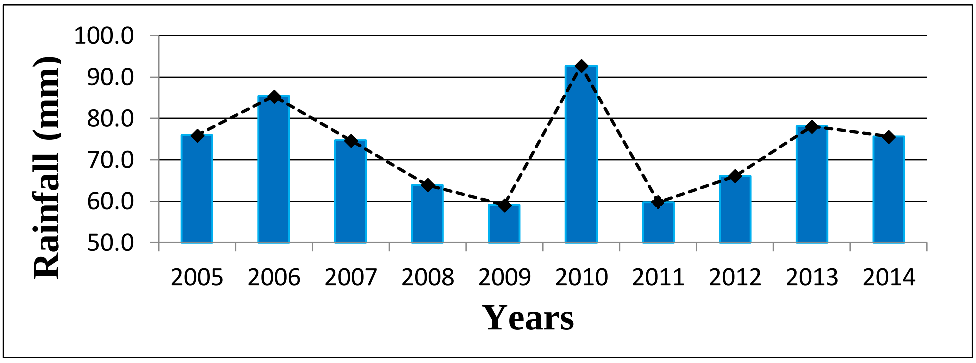

Figure 4: Mean annual rainfall of the study area based on NMSA data (2005 to2014)

On the other hands, the local traditional classifications assert that, normally, West Hararge Zone enjoys two rainy seasons in a year. Locally, these seasons are described as 'belg' the short period (March to May) and 'meher' the long period (June to September) (Figure 5) rainy seasons. 'Belg' rains are mainly used for land preparation and planning 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). Accordingly, the mean monthly rainfall of the Zone can be represented as in figure 5.

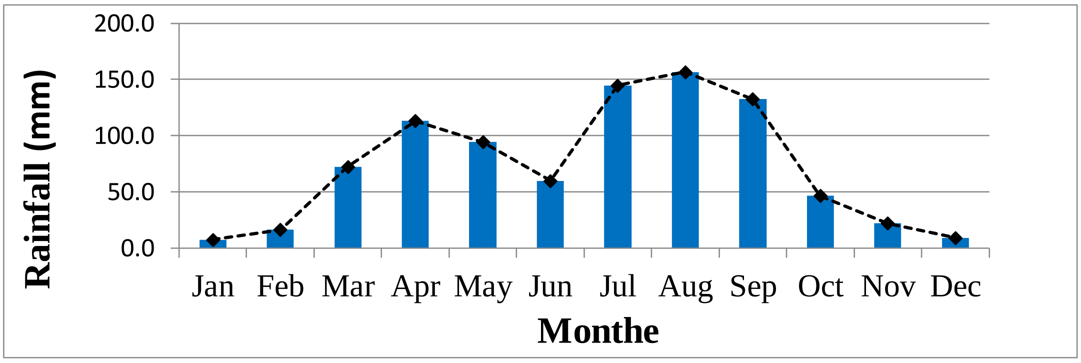

Figure 5: Mean monthly rain fall of the study area based on NMSA (2005 to 2014)

An official document, the 'Agro-ecological Zoning Guidelines', prepared by the Ministry of Agriculture (2000) affirms that Ethiopia experiences six thermal zones referred to as 'bereha' below 500 m, ’kolla ’ 500-1500 m, ’weynadega’ 1500-2300 m,’dega’ 2300-3200 m, ’wurch’ 3200-3700 m and ’kurr’ above 3700 m (T1, T2, T3, T4, T5 and T6 respectively). Out of these, only two of them (T2 and T3) or the warm and tepid zones are experienced in the study area (Table 2).

As shown in the table, T3 or the cooler or tepid zone (17. 5 – 20.50 C), with an area of 1, 512, 242.5 ha (89.51%) of land, covers most of the highlands in the study area. T2, the warmer zone, (21 –27.50 C covering the lower parts of the study area constitutes about 177, 255.1 ha (10. 49 %). Economically, West Hararge lowlands are characterized by unfavorable climatic conditions for economically sound agricultural activities. Most of the crops in the area are drought prone due to moisture stress and dry spell during the months of June and July. Even sorghum, despite its predictable ability to withstand moisture stress, can‘t promise reliable yields. Therefore, as they are suitable only for grazing, the lowlands are used, mostly, for pastures. On the other hands, the highlands and mid highlands are so intensively cultivated that the action impacts high pressure on the land by exposing it to severe erosions.

3.1.3. Natural Resource

Natural resources refer to all the elements of the natural environment like: land, water, soil, forest and wildlife etc. that human beings utilize for the insurance of their livelihood and fulfillment of socio-economic and cultural development needs. This subsection is, therefore, intended to give a brief description of some of these elements.

3.1.3.1. Land use and land cover

Understanding land-use and land-cover status of a given geographical area is highly essential for managing its natural resources and monitoring environmental changes. This is, mainly, because the land use land cover pattern of any natural region is an outcome of various physico-cultural factors and their utilization by man in time and space. Hence, land use land cover is an important component in understanding the interaction of human activities with the natural environment (Prakasam, 2010). Land-use and land-cover are two separate terminologies that are often used interchangeably (Dimyati et al., 1996). In reality, however, the concept land use refers to how societies utilize land for their economic need satisfaction whilst land cover describes the surface area of a given parcel of land, predominantly, covered by bio-physical materials (Tripathi and Manish, 2012).

Based on these fundamental principles and using satellite data, the situation in West Hararge land use land cover patterns were surveyed and classified. From the survey results, it was possible to identify and classify the land-use and land-cover patterns of the Zone into broad classes of bare land (7.51%), bush land (41.57%), built-up areas (0.18%), farm land (46.64%), grassland (1.47%), water body (0.02%) and woodland (2.60%). As can be seen from the digital figures, only 46.64% of the land area is utilized while 53.36% of the area is covered by different physical materials (Figure 6 and Table 3).

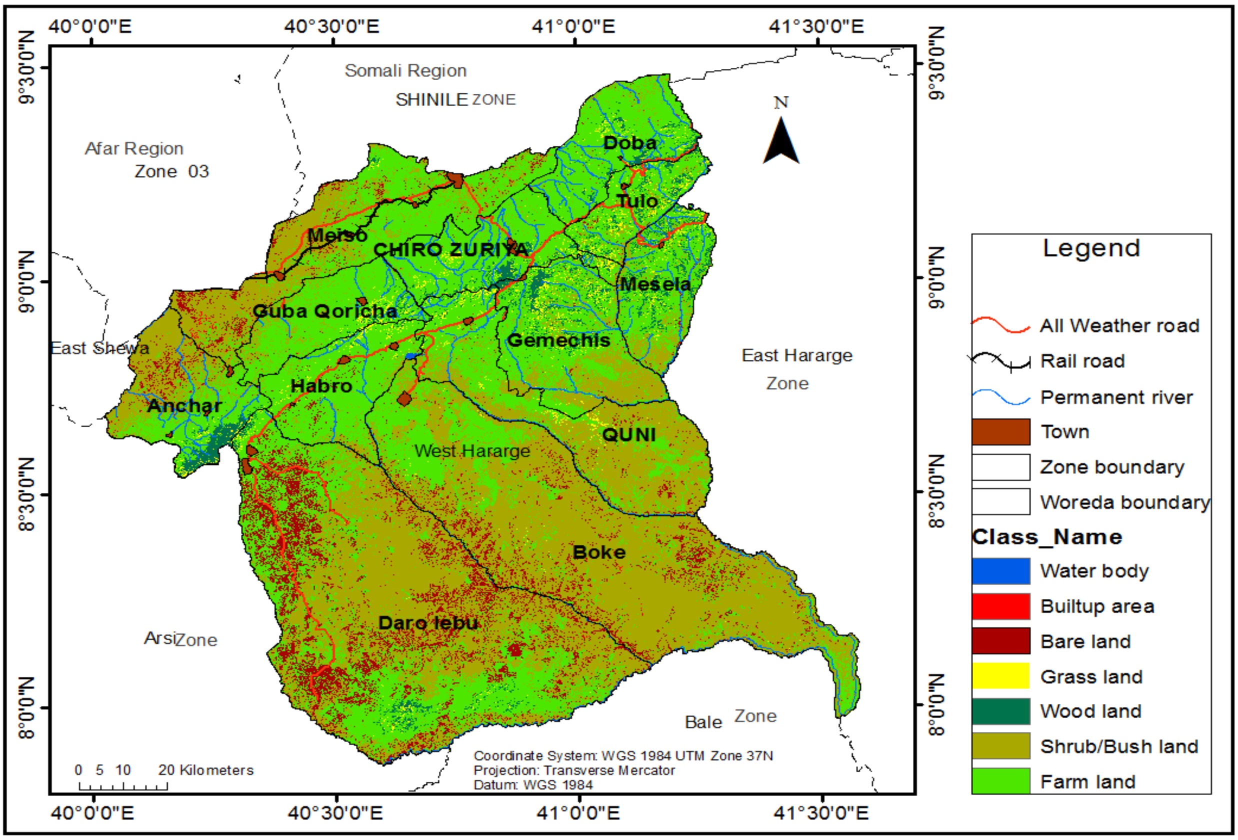

Figure 6: Land-use and land-cover map of the study area

Table 3: Areal coverage of different land covers type of the study area

Land-Cover Type	Area (kM^2)	Area Covered %
Water body	3.38	0.02
Built-up area	30.41	0.18
Bare land	1268.81	7.51
Grass land	248.36	1.47
Wood land	439.27	2.6
Shrubs/Bush land	7023.24	41.57
Farm land	7879.82	46.64
Total	16894.98	100

3.1.3.2. Soil

According to the information obtained from the Oromia Water Works Design and Supervision Enterprise (2010) the dominant soils of the study area are traditionally categorized into black, brown and red types constituting 55, 25 and 20%, respectively. On the other hand, the information obtained from FAO-Ethiopian soil digital data confirms that the major soils of the Zone are scientifically characterized as Eutric Cambisols, Chromic Cambisol and Chromic Vertisols. According to this source, the three dominant soil types constitute 35.37, 32.32 and 26.93% respectively. Although, there are minor activities in extracting some construction materials, observed, here and there, mining plays very insignificant roles in the socio-economic life of the people in West Hararge Zone.

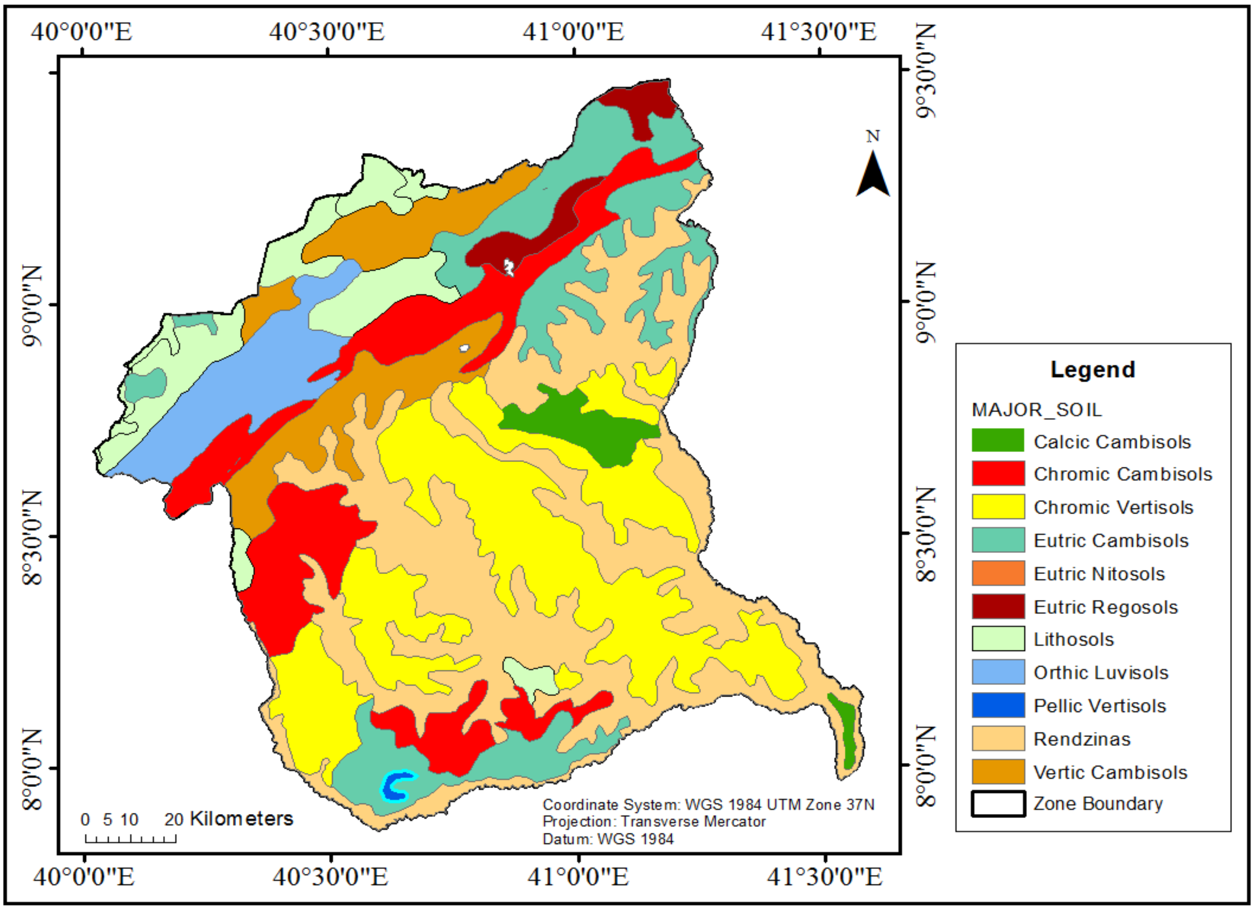

Figure 7: Soil types map of the study area based on FAO digital data

3.1.4. Basic Population Characteristics

According to the results of the 2007 population and housing census of the Ethiopian Central Statistical Agency (CSA, 2007), West Hararge Zone has a total population of 1,871,706 with density of 124.23 people per square kilometer (Table 4 and Figure 9). The sex composition indicates that 958,861 (51.23 %) and 912,845 (48.77 %) are male and female respectively. The habitat type distribution category of the population shows that 160,895 people (8.59 %) are urban dwellers. (Figure 8) The rural agrarian and pastoral populations account for 1,710,811 people (91.40 %) and 10, 567 (0.56 %) respectively. Regarding the age distribution of the Zone, about half of the total populations, (49.87 %) are young people under the age of 15 years. The counting results of the Zone house hold size shows that there were 42,280 and 351,505 urban and rural households respectively. The Census also shows that the average fertility rate is 3.68 persons per household for urban and 4.84 persons for rural. The major ethnic composition of the Zone is 90.12%, Oromo, 7.24%, Amhara, 1.26%, Somali and 0.71%, Argoba. The religious composition shows that the vast majorities (about 88.05 %) of the Zonal population are 88.04% Muslim, 11.11% Orthodox Christians, 0.38% Protestants, 0.37% Catholics and 0.1% traditional. The three major languages predominantly spoken in the Zone are Afan Oromo (89.47 %), Amarigna (8.82 %) and Somaligna (1.19 %) (CSA, 2007).

Table 4: Areal coverage of different land covers type of the Study area

	Urban + Rural			Urban			Rural		
Geographic area	Both Sexes	Male	Female	Both Sexes	Male	Female	Both Sexes	Male	Female
West Hararge Zone	1,871,706	958,861	912,845	160,895	84,851	76,044	1,710,811	874,010	836,801
Mieso wereda	130,709	66,891	63,818	25,388	12,878	12,510	105,321	54,013	51,308
Doba wereda	133,939	68,512	65,427	3,272	1,783	1,489	130,667	66,729	63,938
Tulo wereda	147,384	75,254	72,130	13,768	7,131	6,637	133,616	68,123	65,493
Mesela ereda	151,698	76,864	74,834	4,590	2,452	2,138	147,108	74,412	72,696
Anchar ereda	81,646	42,030	39,616	6,491	3,404	3,087	75,155	38,626	36,529
Guba koricha wereda	122,335	62,633	59,702	2,875	1,477	1,398	119,460	61,156	58,304
Habro wereda	190,455	98,593	91,862	25,233	13,538	11,695	165,222	85,055	80,167
Daro lebu wereda	198,095	101,596	96,499	16,862	9,009	7,853	181,233	92,587	88,646
Boke wereda	151,156	76,980	74,176	6,696	3,543	3,153	144,460	73,437	71,023
Gemches wereda	184,238	93,766	90,472	3,863	1,926	1,937	180,375	91,840	88,535
Kuni wereda-urban	158,282	81,029	77,253	-	-	-	158,282	81,029	77,253
Chiro zuriya wereda	169,912	87,003	82,909	-	-	-	169,912	87,003	82,909
Chiro/town/-wereda	33,670	18,118	15,552	33,670	18,118	15,552	-	-	-
Bedesa/town/-wereda	18,187	9,592	8,595	18,187	9,592	8,595	-	-	-

Source: Population and housing census of Ethiopia (CSA, 2007)

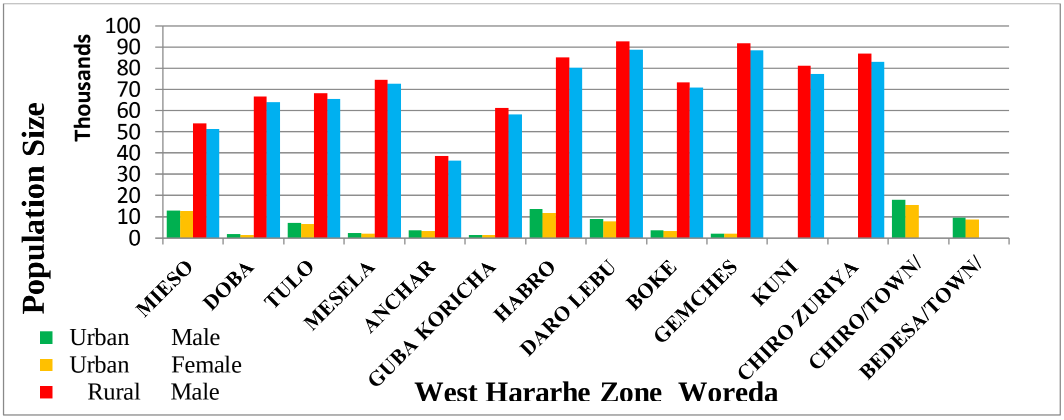

Figure 8: Population size by place of residence and sex of the study area

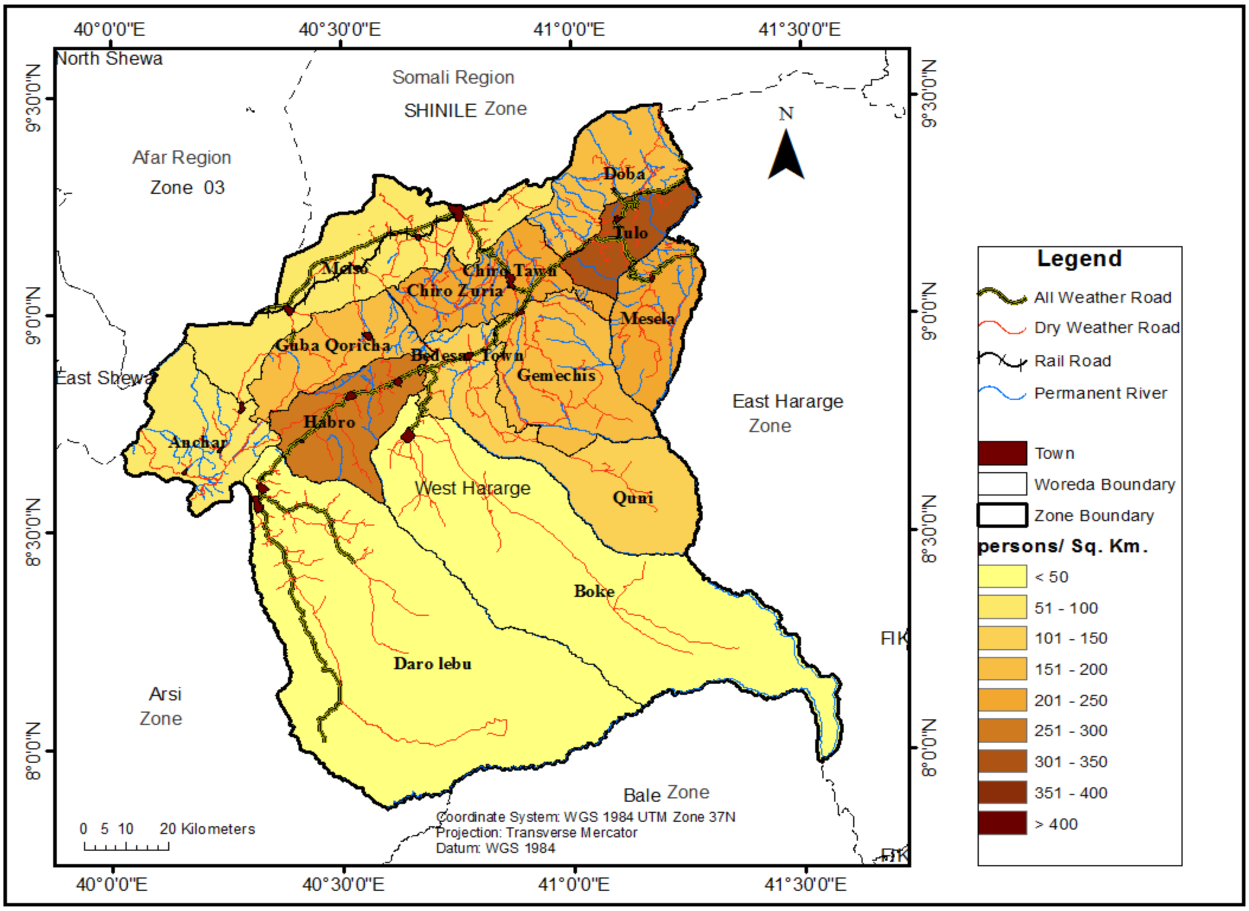

Figure 9: Population density of the stud area by district level.

3.1.5. Economic activities.

As the vast majority of West Hararge Zone population is engaged in agricultural activities, livelihood in the area, mainly, depends on agricultural products. In other words, although coffee and chat are grown as means of earning money, modern businesses like commerce, mining and industry are not prominent activities in the Zone. Because the life styles of the majority of the people are agrarian and semi-pastoral, animal breeding and crop cultivation are the major activities.

According to the 2014 Central Statistical Agency reports, the Zone has over three million (3,036,185) animals. The Agency's detailed reports confirm that the types of locally reared animals are: 1,017,806 cattle, 182,149 sheep, 890,226 goats, 1,102 mules, 2,116,819 donkeys, 40,337 camels, 1,512,784 poultry. The report also shows that there are 65,846 beehives kept in the Zone.

Grain crops, cereals, pulses, oilseeds, vegetables, root crops, fruit crops, Chat, Coffee and Sugar cane are the well-known agricultural products of the zone. According to CSA (2005 to 2014) among the major crop types harvested during the main rainy season (Meher) of the zone, cereal crops take the highest average amount of yield (3,881,285.93 quintals). Out of this amount, crops like sorghum 2,328,624.28, maize 1,253,195.60, teff 105,335.04, barley 67,864.29 and wheat 56,808.38 quintals account for the biggest average yield covering the areas of 116,492.73, 59,019.96, 9,566.27 , 7,031.54,and3,488.73 hectares of land respectively (Fig 10, Tables 5and6).

Table 5: Average productions of crop types by average area in the study area (2005 to2014)

Crop Type	Area in hectare	Production in Quintals
Grain	226,724.54	4,277,812.88
Cereals	198,151.31	3,881,285.93
Pulses	21,336.13	313,124.52
Oilseeds	7,237.10	75,901.15
Vegetables	3,904.77	139,514.91
Root crops	7,336.26	705,199.63
Fruit crops	1,262.39	81,721.68
Chat	30,268.58	214,882.33
Coffee	15,221.57	109,045.74
Hops	35.81	188.21
Sugar cane	685.33	335,684.48

Source: CSA annual yield data (2005 to 2014)

Table 6: Average productions of the major cereal crops in the study area (2005 to 2014)

Cereal Crop Type	Total Cultivated Area in Hectare (2005- 2014)	Production in Quintals
Teff	9,566.27	105,335.04
Barley	7,031.54	67,864.29
Wheat	3,488.73	56,808.38
Maize	59,019.96	1,253,195.60
Sorghum	116,492.73	2,328,624.28
Finger millet	1,121.86	10,034.27
Oats / 'Aja'	179.62	1,946.16

Source: CSA annual yield data (2005 to 2014)

As can be seen from the following chart, sorghum, accounting for over 60% of the total cereal crops, is the biggest single crop in terms of both land coverage and amount of cultivation in the Zone.

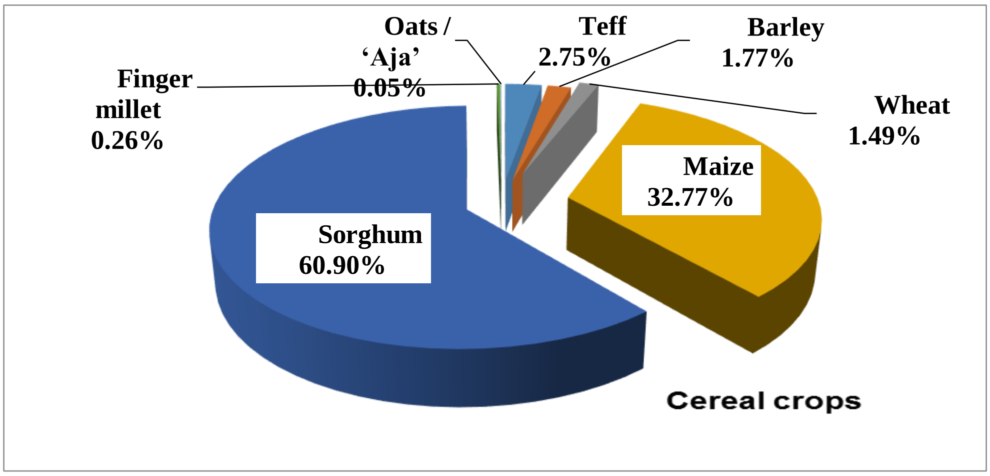

Figure 10: Percentage of land coverage by cereal crop during the main seasons (2005 to 2014)

Source: CSA annual yield data (2005 to 2014).

3.2. Materials and their Acquisition Methods.

In order to arrive at the intended goal, both satellite and ground based data have been obtained. Therefore, attempts are made to describe the selected data sets and the methods employed for their acquisition.

3.2.1. Software package

The following software packages were used at different stages of the study.

Table 7: Types of software packages used

Type	Version	Data Type	Purpose
ArcGIS	10	NDVI, SPI WRSI,	image processing, statistical analysis and graphical display
ERDAS IMAGINE	14	LU/LC	image processing, land use land cover classification and graphical display
SPIRITS	1.4.1.	NDVI, SPI	data extraction, geometric and radiometric correction data conversion
LEAP		WRS	image processing, statistical analysis graphical display
Microsoft Excel	10	Rainfall, crop yield and GPS point data	data processing
IDRISI SILVA	17	Frequency Map of NDVI,SPI,WRSI	Drive Percentage of Influence
STATA	12.1	NDVI, SPI WRSI Rainfall, Crop yield and GPS point data	statistical analysis

Normally, any rationally, sound argument has to be backed by pertinent information and substantial evidences to prove its authenticity. In particular, the accuracy of the findings of empirical research undertakings, like this one, has to be supported by reliable, relevant and quantitatively adequate data, to be considered genuine. In order to ensure the validity of the present study, therefore, especial efforts were made to carefully secure the necessary data. To this effect, the secondary data, required as the basic information input for the study, was collected from different academically recognized official sources like published and unpublished institutional reports, documents, online data and digital published media.

The primary information, on the other hand, was secured through practical ground based personal field observations and collection of relevant evidences from the real situation. Some of them are described in the following table.

Table 8: Data source for present study

Data sets	Variable	Description	Resolution		Period	Source
			Spatial	Temporal		
SPOT vegetation	NDVI	Satellite	1km by 1km	Daily	2005 to 2013	VITO
PROVA vegetation	NDVI	Satellite	1km by 1km	Two days	2014	VITO
CHIRP PPT AFRICA" Dekadal"	Rainfall	Satellite	10km by 10km	Dekadal	2005 to 2014	FEWS NET
Agricultural data	Yield	Ground data	Quintal/H	Year	2005 to 2015	CSA
Metrological Data	Rainfall	Ground data	Average mm	Monthly	2005 to 2015	NMSA
Land use/ Land cover	point	Ground data	UTM	-	2016-2017	Field Visit

3.2.2. Satellite data.

Modern satellite technologies are fundamentally necessary for the acquisition of synoptic, wide-area coverage and frequent temporal information required for effective monitoring, assessment and management of drought risk conditions. Research reports attest that, specially, the use of modern Geo-spatial technology of Remote Sensing (RS) combined with Geographic Information System (GIS), for instance, afford powerful mechanisms, not only to monitor local natural events but also to obtain essential quantitative information at large spatial coverage and frequent temporal intervals (Prenzel, 2004), to be used for developing eco- friendly packages and thereby to optimize production. For this particular research undertaking, therefore, these and other similar mechanisms were used to secure vegetation and rainfall data from satellite sources.

In order to obtain appropriate vegetation data, mapping at regional scales had been carried out, using National Oceanic and Atmospheric Administration (NOAA) – Advanced Very High Resolution Radiometer (AVHRR), for many years. NOAA, as a meteorological satellite, however, suffers certain limitations on calibration, geometry, orbital drift and scope of spectral coverage. Especially, variations in spectral coverage have restricted its utility by introducing substantial errors into various stages of processing and analyzing data (Agrawal et al., 2003).

According to Stibig et al. (2000) Vegetation instrument on-board SPOT 5 overcomes the above mentioned restrictions. This Vegetation instrument is one of the first sensors designed specifically for global vegetation monitoring. It offers a valuable tool for vegetation mapping at regional scale. 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. Reflectance measurements are performed within four spectral windows: Blue, Red, Near Infra-red and Medium Infra-red (http://www.vitoeodata.be/PDF/image/faq_help/Manual_PROBA-V1km/data/ Pdf).

Currently, there are different sources of satellite data, with different formats, resolutions and composition dates (daily, dekadal, monthly and yearly) used to monitor vegetation conditions. Dekad, for instance, is one third of a month having 8 to 11 days. This means a month has three dekads (Dekad 1, 2, 3,) with starting date 1, 11and 21 respectively.

For this particular study SPOT-5 vegetation, dekadal (10-days) synthesis archive products with a spatial resolution of about 1km were downloaded for the years 2005 to 2013 from Vito website (http://www.vitoeodata.be/content/mission). 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, synthesized and distributed by Vlaamse Instelling voor Technologish Onderzoek (VITO) using maximum value composites (MVC) algorithm, were downloaded from Copernicus Global Land Service Website (http://land.copernicus.eu/global).

The PROBA-V satellite was launched at 6 May 2013 and was designed to bridge the gap in space and borne vegetation measurement between SPOT-VGT (March 1998 – May 2014). Its products are similar to that of SPOT-VEGETATION. 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 estimate (REF) from the Famine Early Warning System (FEWS-NET) archive website for the study period (2005 to 2014). (http:// earlywarning.cr.usgs.gov/adds/data/theme/Php). The data set, thus obtained, was Climate Hazard Group Infrared Precipitation with station data (CHIRPS). CHIRP is a 30+ year quasi-global rainfall data set, spanning from 50^{o} S to 50^{o} N (and all longitudes), starting in 1981 to near present. It is10 km by10 km spatial resolution. The main reason for the selection of the data set is based on its qualification of high spatial resolution and availability of near-real time with reasonable accuracy.

3.2.3. Ancillary data

According to kogan (1997); Gezachew legesse and Suryabhagavan (2014) grain crops are sensitive to agricultural drought, and can be used for validation of satellite derived drought events, by using their average yield data. Therefore, in order to find the relationship between crop yield and the existing drought condition, and thus validate the effects of satellite based drought events on the study period, zonal grain yield data of the study area was collected from Central Statistical Agency.

Apart from the agricultural production yield data, 11unevenly distributed ground based stations' Meteorological rainfall data, were used for validation of satellite derived drought information. In order to distribute the influence of the station data over the Zone, Inverse Distance Weight (IDW) were distributed to each station, using ArcGIS version 10.2 Software.

To prepare a generalized land-cover map of the study area, Landsat 8 satellite images of two adjacent path and row of the study area were downloaded from United States Geological Survey (USGS) website. (http://www.earthexplorer.usgs.gov). The images pass through a number of subsequent pre-processing and enhancement techniques, such as, layer stacking, image sub setting, mosaicking, generating false color composite (FCC); radiometric, spectral and spatial enhancement and correction, images, identification and mapping of Land use/Land cover, classification of different land cover classes. Finally, by using maximum likelihood algorithm ArcGIS 10.2 and ERDAS IMAGINE 14 software, and GPS ground truth data, the images were reclassified (Figure 6).

3.3. Data Processing and Analysis Methods

3.3.1. Vegetation Data Processing and Analysis

In order to systematically process and analyze 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 concern. This is, mainly, because it better meets the requirement for assessing and mapping agricultural drought severity 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 10 years' 360 dekadal images together with the information related to image 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. Thus, below normal vegetation indicators may appear in regions where insufficient registrations are available for the Maximum Value Compositing (MVC).

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), rescaled to generate monthly maximum NDVI, using the same 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.

3.3.1.1. Computation of normalized difference vegetation index (NDVI)

The normalized difference vegetation index (NDVI) gives a measure of the vegetative cover as it is sensitive to the chlorophyll content of plants. In other words, dense vegetation shows high value in the NDVI imagery while the areas with little or no vegetation show negative value. NDVI were calculated from two bands, the near-infrared (NIR) and RED wave lengths, as presented in equation (2). In order to transform the imported row data into -1 to 1 range of NDVI, (eq.4) and (eq.5) were used in ArcGIS, Raster map algebra for SPOT Veg. and PROVA-V vegetation respectively.

$$\text{Actual NDVI} = (\text{Raw data pixel value} * \text{Coefficient a}) + \text{Coefficient b} \qquad \text{(eq. 4)}$$

Where Coefficient a = 0.004

Coefficient b= (0.1)

$$\text{Actual NDVI} = (\text{Raw data pixel value} / \text{Coefficient a}) - \text{Coefficient b} \qquad \text{(eq.5)}$$

Where Coefficient a = 250 and Coefficient b= 0.08

3.3.1.2. Computation of normalized difference vegetation index anomaly

According to Murali et al. (2008) and Gizachew Legesse and Suryabhagavan, (2014) an index derived from NDVI can be used to assess seasonal crop conditions. In order to drive the vegetation drought conditions for the study period seasons (June to September) of each year, therefore, calculations were done (eq. 6) using the generated value of seasonal maximum NDVI, and long-term mean maximum NDVI. The results were then reclassified into five drought severity class (Table9).

$$\text{NDVI Anomaly I} = [(\text{NDVI max i} - \text{Mean NDVI max}) / (\text{Mean NDVI max})]*100 \qquad \text{(eq.6)}$$

Where NDVI max i = Maximum NDVI in the growing season in ith year

Mean NDVI max = long term mean maximum NDVI in the growing season.

Table 9: NDVI anomaly based drought severity class

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

3.3.2. Computation of Standardized Precipitation index (SPI).

Since any drought condition is the manifestation of reduced precipitations or depleted moisture content in the soil, rainfall based drought indicators offer direct and simple techniques for monitoring the onset, expansion, and intensity of drought situations. Therefore, 10 years, 360 dekad 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. Thereafter, 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 (equation. 7).

$$\text{SPI} = (X_{ij} - X_{im}) / Ợ \qquad \text{(eq.7)}$$

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 of SPI.

Table 10 : NDVI anomaly 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

3.3.3. Computation of water requirement satisfaction index (WSRI)

The Water Requirement Satisfaction Index (WRSI) is a model-driven drought indicator developed by the Food and Agriculture Organization of the United Nations in the 1980s (FAO, 1986), to monitor seasonal crop performance. The basic idea was to provide an index that can accurately show the percentage of the idealized crop water requirement that is met by rainfall during a crop growing season. WRSI for a season is based on the water supply and demand a crop experiences during a growing season. 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):

$$WRSI = \frac{\text{AET}}{\text{WR}}\ 100 \qquad \text{(eq.8)}$$

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

$$WR = \text{PET x } Kc100 \qquad \text{(eq.9)}$$

WRSI was also computed using LEAP software and imported into GIS environment. The WRSI result was then reclassified based on drought severity classes indicated in Table11 for each grid cell of the study area.

Table 11: 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

3.3.4. Regression analysis of crop yield with drought indices

In order to validate the effects of the derived indices of each year's seasonal grain yield, the relationship between grain yield data and data derived from the drought indices were prepared and computed for simple regression analysis. To this effect, the average raster cell values of SPI, NDVI anomaly and WRSI images were extracted using ERDAS IMAGIN statistical information and LEAP software. In order to verify the response of NDVI to rainfall events at different time intervals, simple regression analysis between zero, one, two, three and four dekad lag time or preceding rainfall, and NDVI was computed using STATA software as well. In addition to this, different supportive information, related to agricultural drought hazards and their impacts on agricultural activities as well as cropping practices, were collected from the Zonal and Woreda Agricultural and Rural Development, and Early Warning and Food Security Bureau through questionnaire (Appendix 2).The outcome was, then, used for the evaluation of the results obtained from satellite images.

3.3.5. Computation of yield reduction due to moisture deficit

The negative impacts of agricultural drought on crop production can be expressed, mainly, by yield reduction. In view of this, yield reduction due to water deficiency was computed using LEAP software. The computation was accomplished by calculating water balance output combined with an empirical formula developed by Doorenbosch and Kassam (Hoefsloot, 2008).

The formula is: 100-((1-(1-A/B) Ky) 100) (eq.10)

Where A is the actual evapotranspiration; B is the total water requirement without water stress and Ky is a crop dependent stress indicator determined by the authors.

In this respect, agricultural drought risk can be viewed as a product of both exposure to the climate hazards and the vulnerability of farming or cropping practices to drought conditions. In view of this, agricultural risk zone map produced by integrating all drought frequency maps derived from all drought indices indicates that West Hararge Zone is classified into slight, moderate and severe agricultural drought risk areas.

Thus, it was found that mapping agricultural drought risk can be useful to guide decision making process in drought monitoring and reducing the impact of drought on agricultural production and productivity level by identifying definite sites for specific adaptation and mitigation actions. In this regard, some of the major crops grown in the study area: sorghum, maize, teff, wheat, finger millet, haricot bean, chick pea, field pea, and lentil, were considered for the computation of aggregated yield reduction.

Based on the level of agricultural drought severity, therefore, two drought and two wet years were identified and mapped for each drought indices.

3.3.6. Agricultural drought risk map

The final Agricultural drought risk map of the study area was prepared by using Multi Criteria Evaluation (MCE) techniques. In order to compute the frequency of drought occurrence, the threshold value of SPI, NDVI anomaly and WRSI indices were reclassified into Boolean image from which10 binary images were generated for each drought index. These binary images were then calculated in Arc GIS Spatial Analysis tools to obtain the desired seasonal maps showing the frequency of drought occurrence at each pixel level. The seasonal frequency maps derived from each drought index were, then, reclassified into common scale based on the frequency of drought occurrence. According to Lemma Gonfa (1996) the probability of drought occurrence in a given area can be classified into high, moderate and low drought probability zones when drought occurs in more than 50 percent, 30 to 50 percent and less than 30 percent of the years, respectively. Applying these criteria, the frequency maps of each drought classes were reclassified into five classes based on the frequency of drought occurrence recorded during the study period. Thus, they are categorized as: 0-2 no drought; 3-4 slight drought; 5-6 moderate drought; 7-8 severe drought and 9-10 very severe drought. 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. The schematic representation of the methodology has been illustrated in Figure 11.

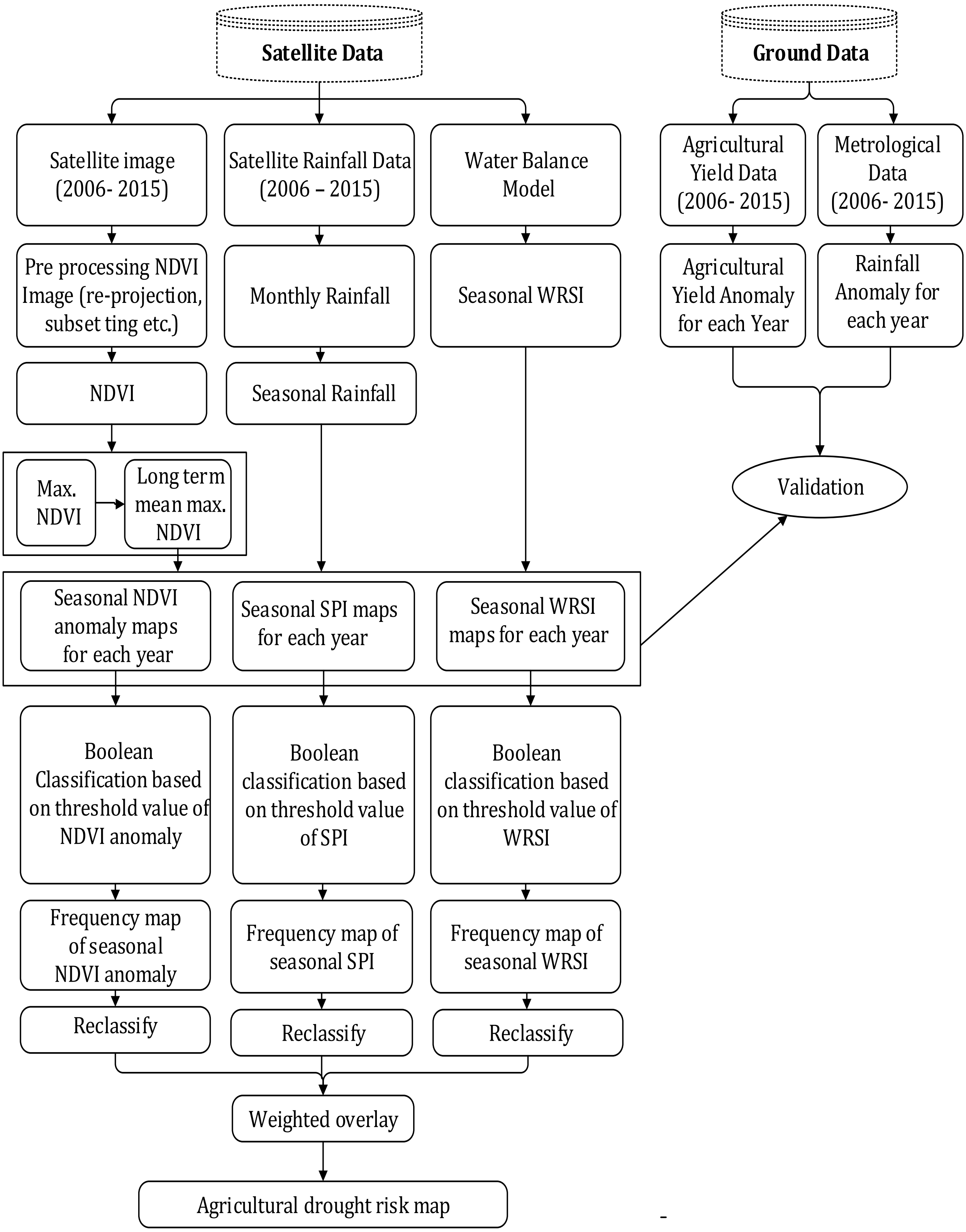

Figure 11: Schematic flow chart of the study

Chapter 4

Results and Discussion

Through the efforts made in the course of the study, it has been possible to obtain results in identifying, quantifying, determining and mapping proper agricultural drought risk prone areas of West Hararge Zone. Thus, the results are presented and discussed in terms of words, maps, graphs and tables.

4.1. Relationship between seasonal Normalized Difference Vegetation Index and Rainfall

In countries like Ethiopia, where agricultural operations are predominantly rainfall oriented, there is a high probability for fluctuations in the seasonal rainfalls to negatively affect agricultural production and /or yields. Both satellite images and ground based practical observations; for instance, have affirmed that in West Hararge Zone, where the farming activities are, totally, based on seasonal rainfalls, agricultural yields have shown significant reductions, mainly, due to the effects of the seasonal rainfall irregularities. Apparently, any struggle to mitigate the impacts of drought in the area, must focus on thorough analysis of long term seasonal rainfall characteristics and determining the nature of the responses of crops and natural vegetation to the eminent drought.

Accordingly, therefore, special consideration was given to the analysis of the reaction of crops and vegetation to the irregularities of the seasonal rainfalls. Apparently, the results of the studies, conducted on the pattern of seasonal rainfall distribution and the NDVI of the entire study area, over a period of ten years (2005- 2014), showed that there was a good correlation (r=0.7) between rainfall and NDVI (Figure 13 and Appendix 3A). In other words, the long term climate variation study revealed that the correlation between rainfall and NDVI appeared to be good; as NDVI, significantly, depends on the time and amount of precipitation.

From the collected 10 years (2005-2014) statistical data, for example, it was found that in about 46 percent of the cases, (Figure 13) the NDVI variability can be explained in terms of seasonal rainfall. In addition to this, the study also revealed that the spatial patterns of long term seasonal rainfall distribution and NDVI reflected similar responses to vegetation conditions in the study area (Figure 12a and 12b). For practical reasons, however, certain disparities have also been observed. Due to lag time, for example, vegetation response to the existing rainfall and the relationship between the two showed disparity in temporal and spatial spectrum.

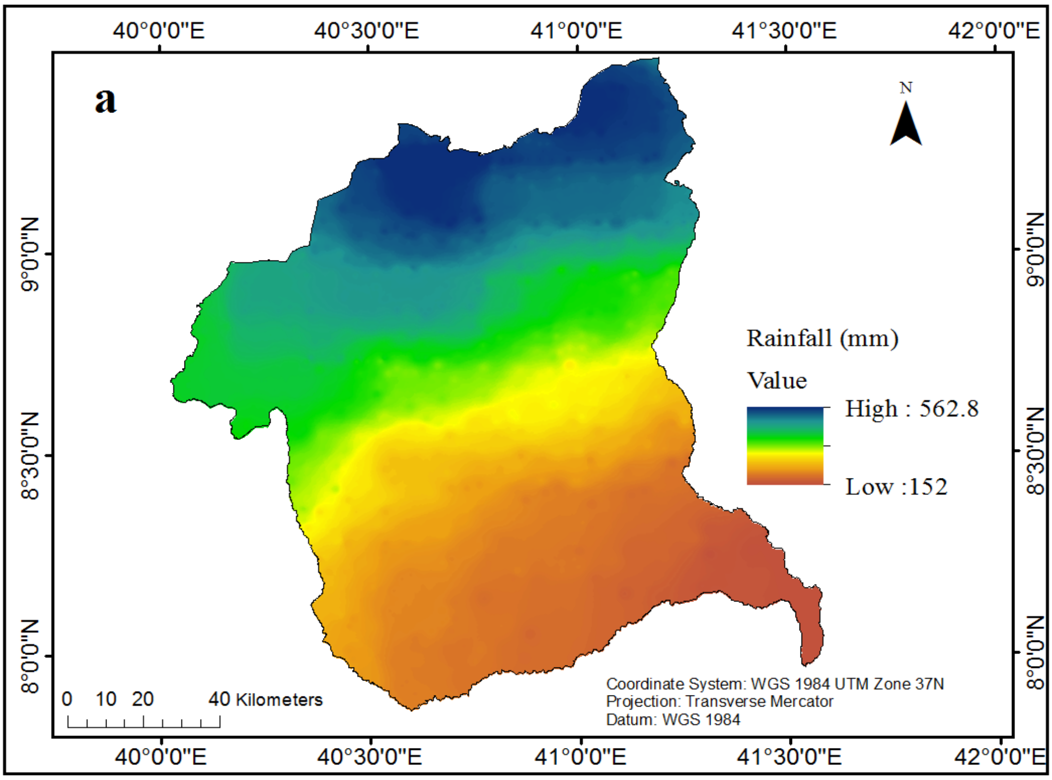

Figure 12a: Spatial pattern of long term seasonal (June-September) (a) Average Rainfall

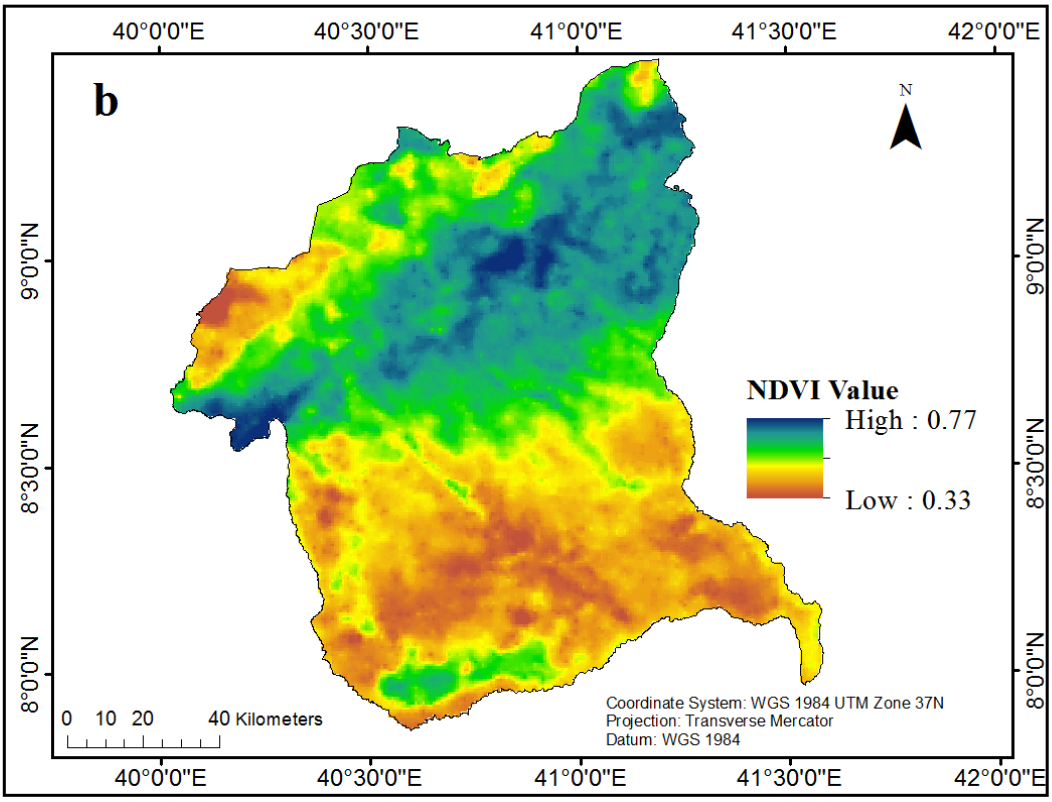

Figure 12b: Spatial pattern of long term seasonal (June-September) (b) Average NDVI

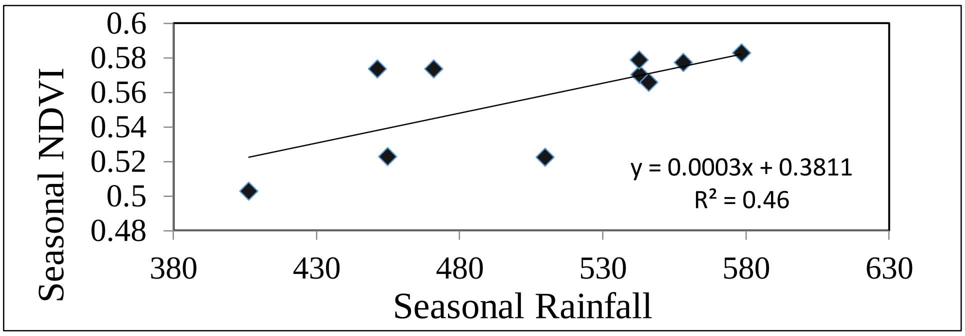

Figure 13: Seasonal (June-September) patterns of rainfall and NDVI (2005 - 2014)

In this particular case, 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 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, therefore, despite the fact that the relationship between temporal trends of seasonal NDVI and seasonal rainfall appeared to be good (Figure 13), it was found that, in the 2005 cropping season, in particular, there was 451mm rainfall which is less than the long term average of 506.225 mm. On the other hand, the corresponding NDVI value was 0.57, which is relatively higher than the long term average value of 0.56 (Figure14). Precisely speaking, despite the low precipitation reported, uncharacteristically very high NDVI value was registered in 2005. Thus, due to the long intra-seasonal dry spell or bad temporal distribution of rainfall, the normal growth and development of the regional vegetation was found to be negatively affected. In other words, the temporal mismatch between seasonal rainfall distribution and crop water requirements, as the main factor of the disparity, has led to occurrence of various levels of drought.

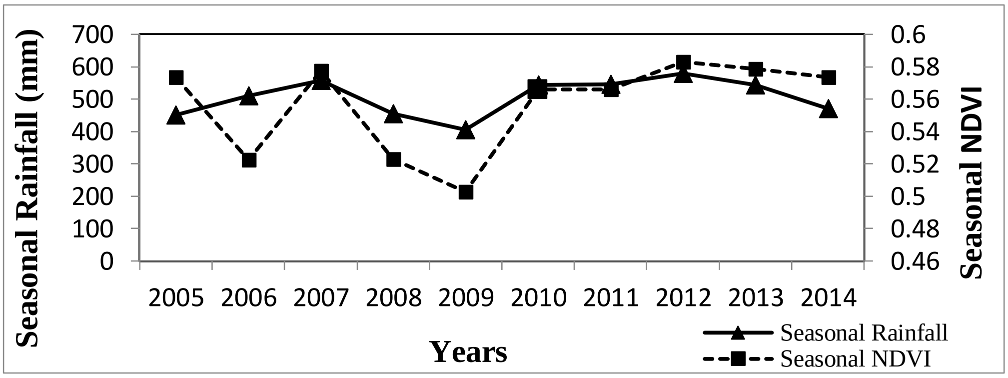

Figure 14: Temporal trends of seasonal (June-September) rainfall and NDVI (2005 to 2014)

Based on this apparent truth, therefore, it was possible to deduce the fact that not only the amount of rainfall, but, also its timing can be a decisive factor determining the nature of the responses of vegetation in general and the cultivated crops in particular. According to Kinde and Walker (2004) for instance, it has been confirmed that for the reliable performance of the predominantly rainfall dependent Ethiopian agriculture, the amount and distribution of rainfall during the crop growing seasons are highly essential and detrimental. In short, the concurrence of rainfall with the growing seasons is highly crucial for satisfactory crop production.

Regarding the degree of inter seasonal rainfall variability, the reckoned coefficient of variation ranged from 23 to 38 percent. This means that there was a high inter seasonal rainfall variability enough to cause long term dry spell. In fact, Kinde and Walker (2004); Kang et al. (2009) have strongly affirmed, the fact that the reduction of crop performance and its yield, mostly, resulted from the mismatches between water supply amount and water demand period. Thus, it is apparent that variable rainfall amount and its erratic temporal distribution can cause long term dry spell, which in turn leads to severe agricultural drought resulting in considerable crop failure and eminent famine.

4.2. Influence of rainfall on the vegetation growth and development

As reflected by the NDVI, precipitation or specifically speaking, rainfall is one of the most important climatic change factors that can influence the growth and development of vegetation. In the study conducted by Henericksen (1986) and cited in Beyene Ergogo (2007), for instance, it has been confirmed that NDVI was highly sensitive to an extended rainfall anomaly.

Thus, in order to understand the influence of rainfall on vegetation growth and development simple linear regression analysis between dekadal rainfall and NDVI were carried out for different lag time periods (Appendix 3B-F).

Accordingly, the result of the process indicated that, compared to lag time of zero, one, two and four dekad rainfall, three dekad or the one month preceding rainfall, had highest influence on the growth and development of vegetation with the correlation coefficient of 0.65 or $R^2 = 0.43$. The ANOVA (Analysis of variance) table, also shows that the calculated F- value (6.038) exceeds the critical F-value or Prob>F (0.039) at 5 percent probability level (Table 12). It confirms that the relationship between the two variables are highly significant at dekad three compared to other dekad.

Table 12: Simple linear regression analysis between decadal rainfall and NDVI

Lag time periods in dekad	R-Square	F_Calculated	F_critical at 5% probability level	Level of significance LSD (0.05)
0	0.012	0.099	0.761	NS
1	0.101	0.903	0.370	NS
2	0.249	2.659	0.142	NS
3	0.430	6.038	0.039	S
4	0.147	1.381	0.274	NS

Thus, the study verifies that the variability of NDVI is more clearly explained by the effect of the three dekad or one month preceding rainfall. The obtained result is also in concurrence with the finding of Chopra (2006). According to Chopra, the time interval between the rainfall events and the time at which rainfall water reaches a plant root and subsequently induces the growth of the plant, can occur in one month's time period in semi-arid areas. Therefore, the study confirms that the influence of rainfall on vegetation growth and development appears to be effective at one month or three dekad lag time. That means the vegetation growth in each month was influenced by the amount of rainfall in the preceding month and, thus, significant changes in soil moisture and vegetation development were clearly observed during that period.

4.3. Normalized Difference Vegetation Index (NDVI) anomaly and agricultural drought

As has been observed in the preceding processes, the NDVI can be considered as a useful measure of agricultural drought when compared to normal plant health. This reality can be reflected through a thorough analysis of NDVI anomaly. NDVI anomaly is one of the best agricultural drought indices that demonstrate the severity levels of the impact on crops and vegetation. Based on the information obtained from the processing result of the ten years' NDVI indices as illustrated in (Figure 15, and 16), the spatial patterns of agricultural drought for the years 2006 and 2009, and wet for the years 2007 and 2012 were computed for crop production areas to determine the severity of agricultural drought (Figure 17a; b and 18a; b).

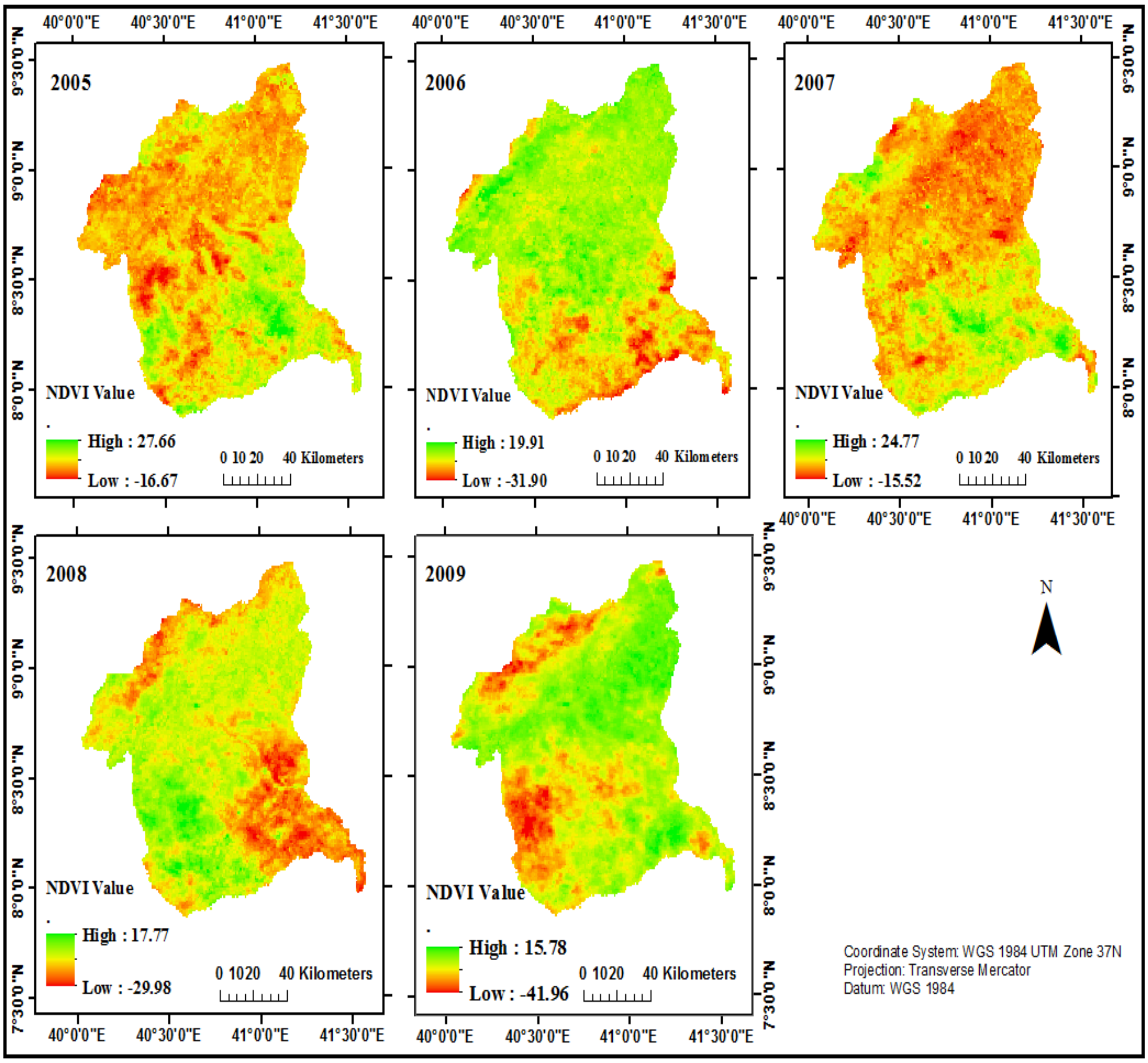

Figure 15: Seasonal Maximum Normalized Difference Vegetation Index (2005 to 2009)

The results of the NDVI computation confirmed that the spatial patterns of agricultural drought events and the levels of its severity ranged from slight in most of the years to severe in 2006 and 2009. It is important to note here that in the NDVI analysis, the regular 2005 drought shifts to 2006. Apparently, therefore, in all the discussions, under this section, references to drought of the early period will be made to 2006. Generally, however, the extent of severe drought coverage, registered in this case, stretched over small pocket areas of south eastern parts which accounted for less than one percent in 2006 and less than seven percent in the north western and southwestern parts of the Study area in 2009. This means that the majority of the study area was stricken by moderate and slight agricultural droughts only.

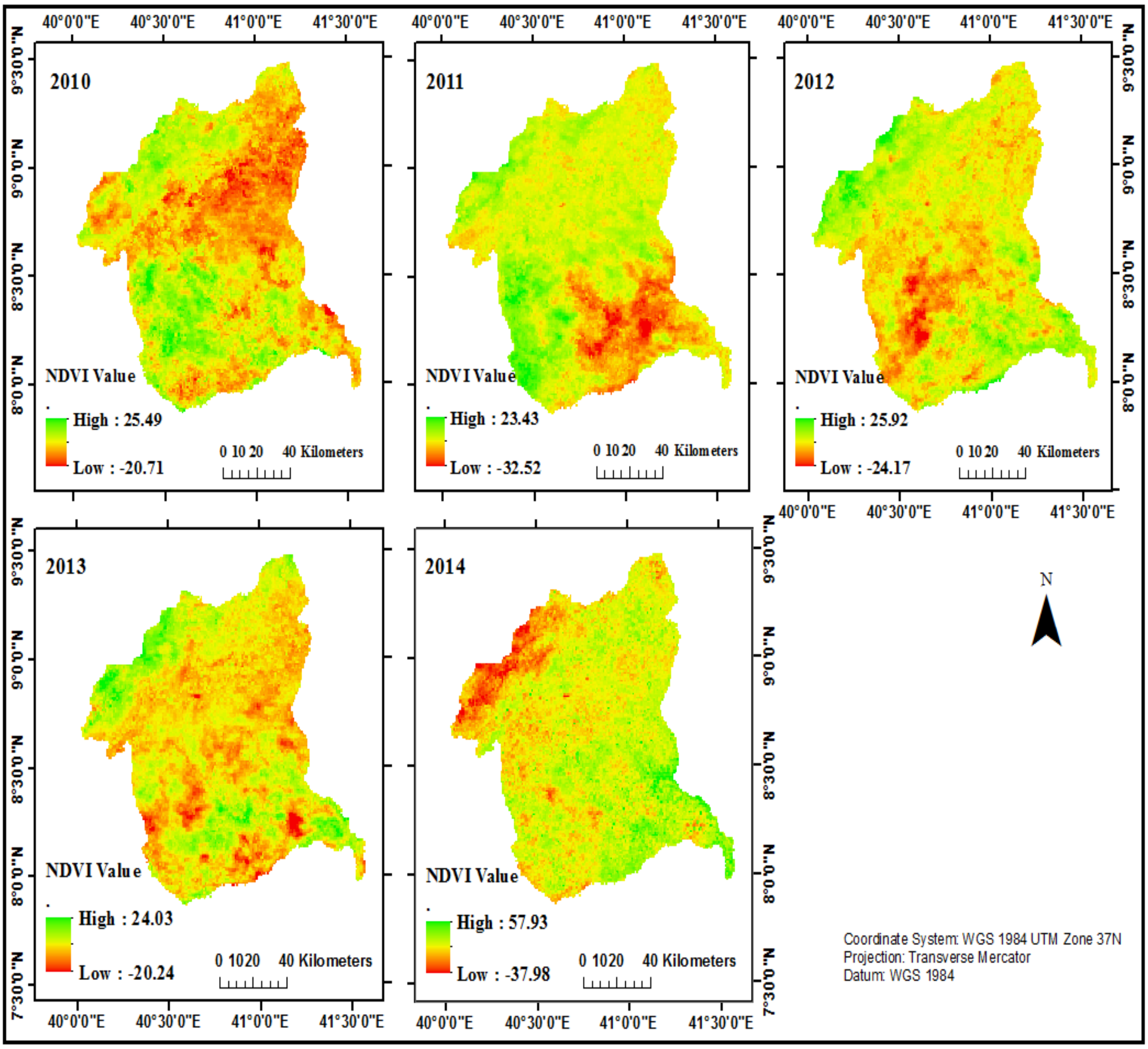

Figure 16: Seasonal Maximum Normalized Difference Vegetation Index (2010 to 2014)

Accordingly, the registered percentage area, hit by agricultural drought (Figure 17 a; b and Table 13) during the 2006 cropping season was found to be 57.09, 19.78 and 0.50 % of the total areas for slight, moderate and severe severity levels respectively, whereas the corresponding agricultural drought severity for 2009 cropping season was 42.36, 36.74 and 6.07 % of the total area respectively.

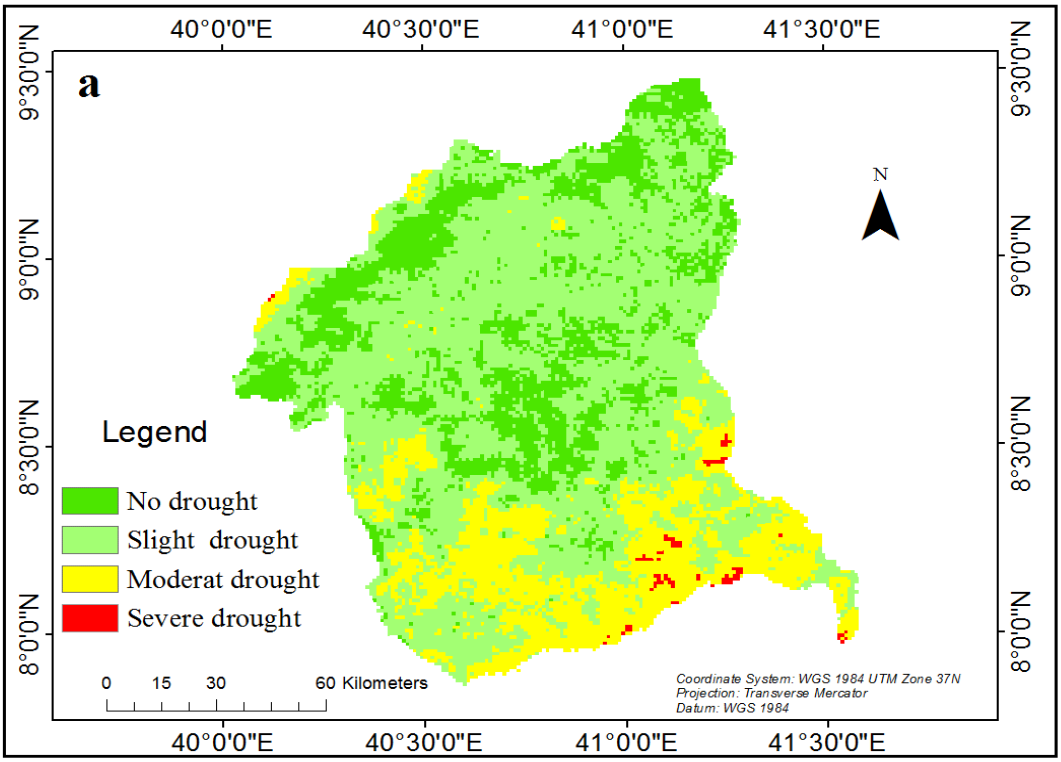

Figure 17a: Spatial pattern of agricultural drought severity for drought years 2006 in NDVI anomaly index

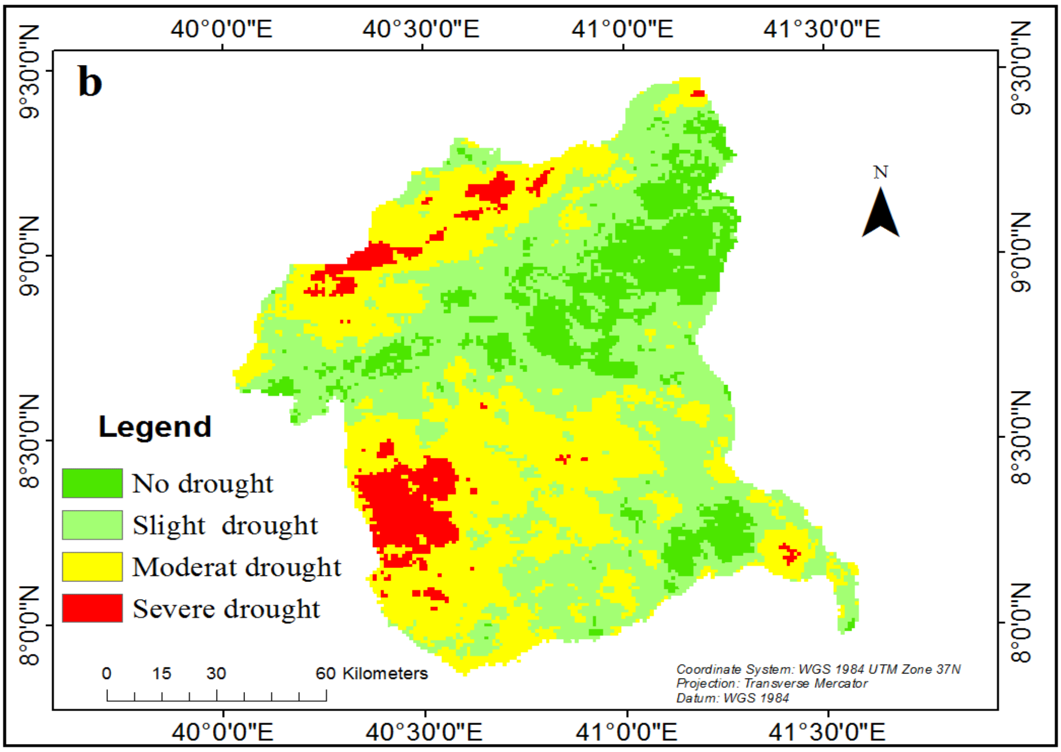

Figure 17b: Spatial pattern of agricultural drought severity for drought years 2009 expressed in NDVI anomaly index

Table 13: Percent of area covered by agricultural drought severity for drought years 2006 and 2009 expressed by NDVI anomaly index

		Drought Year			
		2006 GC.		**2009 GC.**	
No.	**Class**	**Area km²**	**Area %**	**Area km²**	**Area %**
1	No Drought	3823.44	22.63	2505.97	14.83
2	Slight Drought	9644.92	57.09	7156.80	42.36
3	Moderate Drought	3341.30	19.78	6207.39	36.74
4	Severe drought	85.32	0.50	1024.81	6.07
	Total	16894.98	100	16894.98	100

Regarding the wet years, it can be realized from the map, as shown in (Figure 18 a, b and Table 14) that only very small pocket areas (0.02%) of the northern parts were hit by severe level of agricultural drought while the majority of the areas (77 %.) were under the influence of slight and moderate agricultural drought. The percentage range of agricultural drought severity indicates that during the 2007 cropping season, especially, in the north and north eastern parts from 44.27, 0.50 and 0.02 % of the total area were hit by slight, moderate and severe levels of severity respectively. On the other hand, the corresponding agricultural drought severity of 2012 cropping season was found to be 20.12, 1.24, and 0, respectively in most of the southern parts of the Zone.

Table 14: Percentage area affected by drought severity for wet years 2007 and 2012 expressed by NDVI anomaly index

		Wet Year			
		2007 GC.		**2012 GC.**	
No.	**Class**	**Area km²**	**Area %**	**Area km²**	**Area %**
1	No Drought	9327.46	55.21	13285.82	78.64
2	Slight Drought	7480.22	44.27	3399.83	20.12
3	Moderate Drought	84.33	0.50	209.33	1.24
4	Severe drought	2.98	0.02	-	-
	Total	16894.98	100	16894.98	100

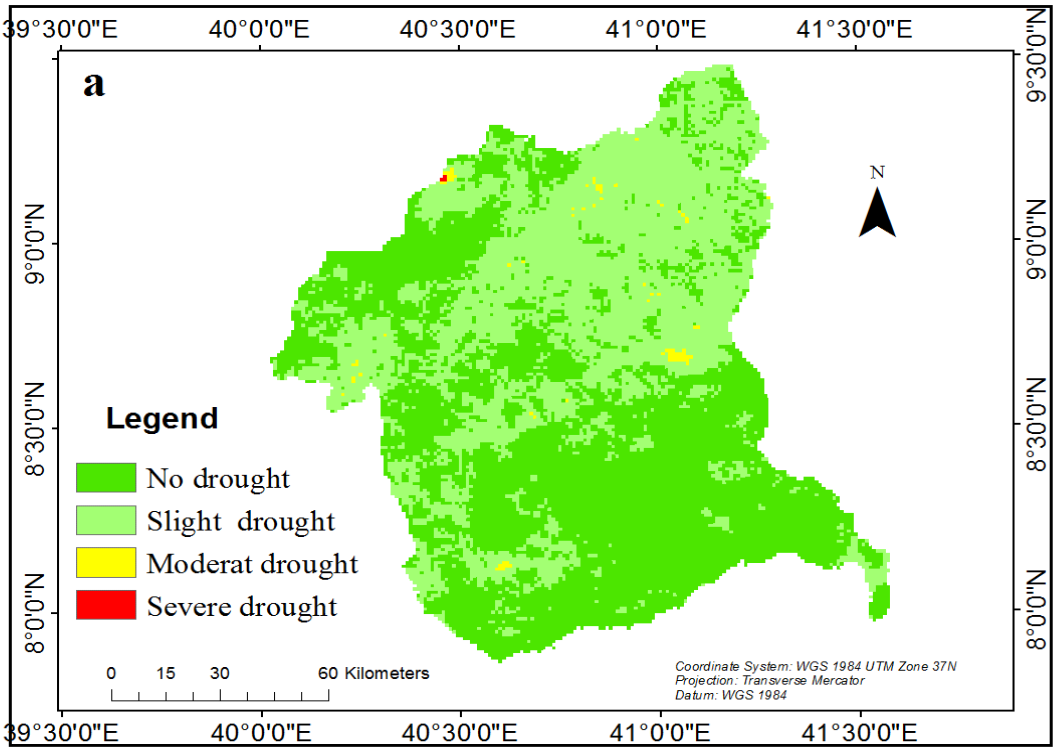

Figure 18a: Spatial pattern of agricultural drought severity for wet years 2007 expressed in NDVI anomaly index

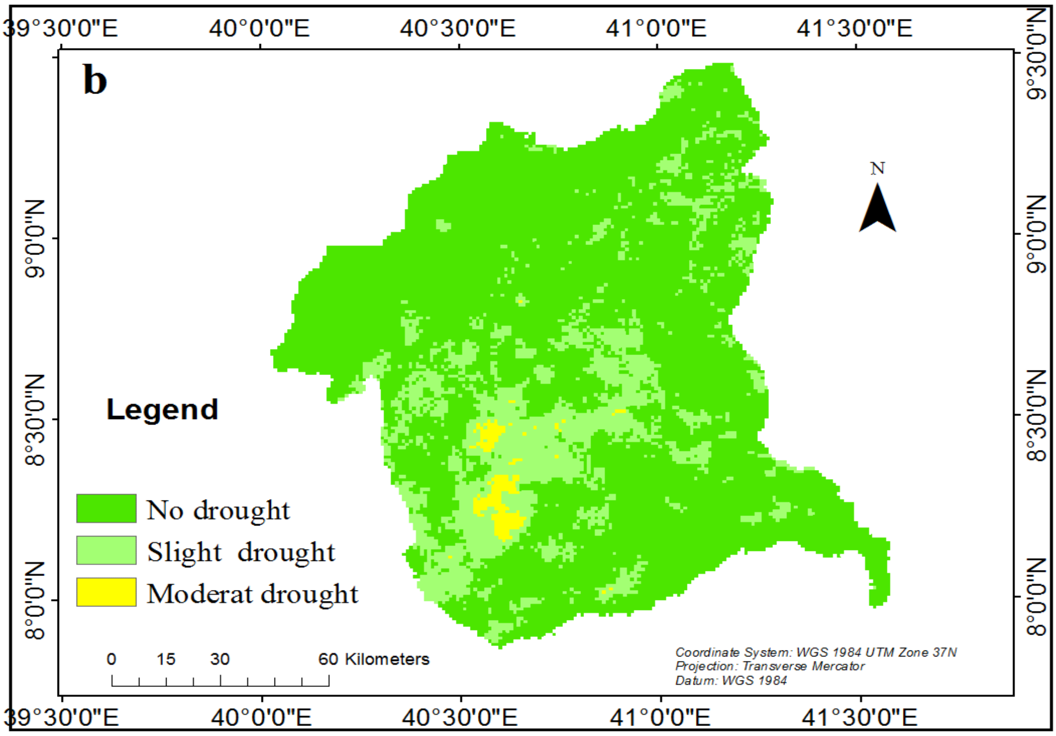

Figure 18b: Spatial pattern of agricultural drought severity for wet years 2012 expressed in NDVI anomaly index

In the quantification of drought severity levels, grain yield of agricultural production in the given geographical area is, usually, taken as one of the most important sources of ground truth data, used to check and validate the accuracy of the satellite image derived results. Therefore, it was found highly crucial, for the study, to consider the relationship between NDVI anomaly and grain yield situation, to effectively quantify the impacts of the eminent drought on the agricultural production of the local farming communities.

To be more pragmatic, the relationships between NDVI anomaly, extracted from the land use or cultivated area map of West Hararge Zone, (Figure 6) and its grain yield anomaly were analyzed to check the severity of agricultural drought on the locality (Appendix 4). As can be seen from the scatter plot (Figure 19), the two variables were found to have good correlation (r = 0.77). This means that 59 percent of the yield variability can be explained by NDVI anomaly. In other words, the result of the study confirmed that the relationship established between the two variables was positive; when NDVI anomaly increases so does agricultural yield and vice-versa. Thus the strength of the NDVI index in explaining the existence of agricultural drought through agricultural yield has been found to be good and reliable.

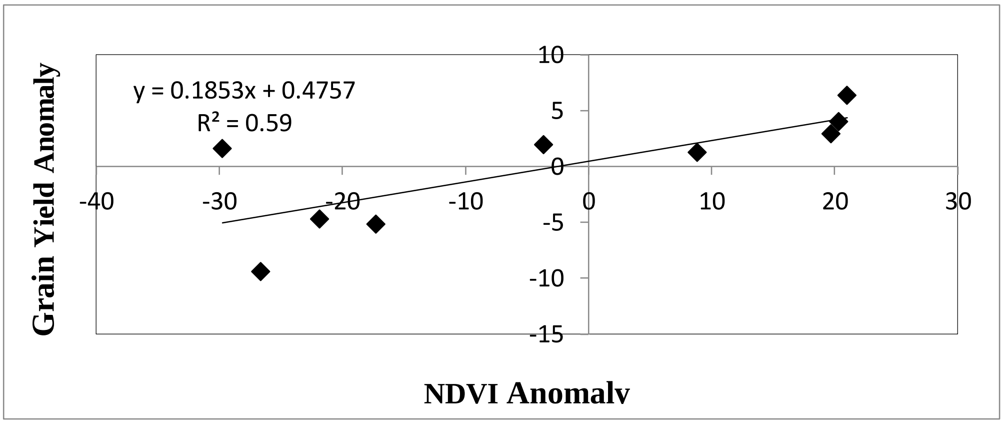

Figure 19: Relationship between NDVI anomaly and grain yield anomaly

Generally, therefore, the long range (2005-2014) investigations of the situation revealed that NDVI, usually, being dependent on the time and amount of precipitation, 2006 and 2009 were marked by low values much below average NDVI and characterized by significantly large scale drought. On the other hand, 2007 and 2012 were marked by very wet trends with regional high values (80 percent) much above average NDVI.

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

In the process of monitoring the effects of the ten years' climate pattern variations on West Hararge Zone agricultural activities, the standard precipitation indices (SPI) were computed for the growing seasons of the area. The results of the analysis (Figure 20 and 21) revealed that droughts have occurred at different levels of severity from 2005 to 2014 cropping seasons.

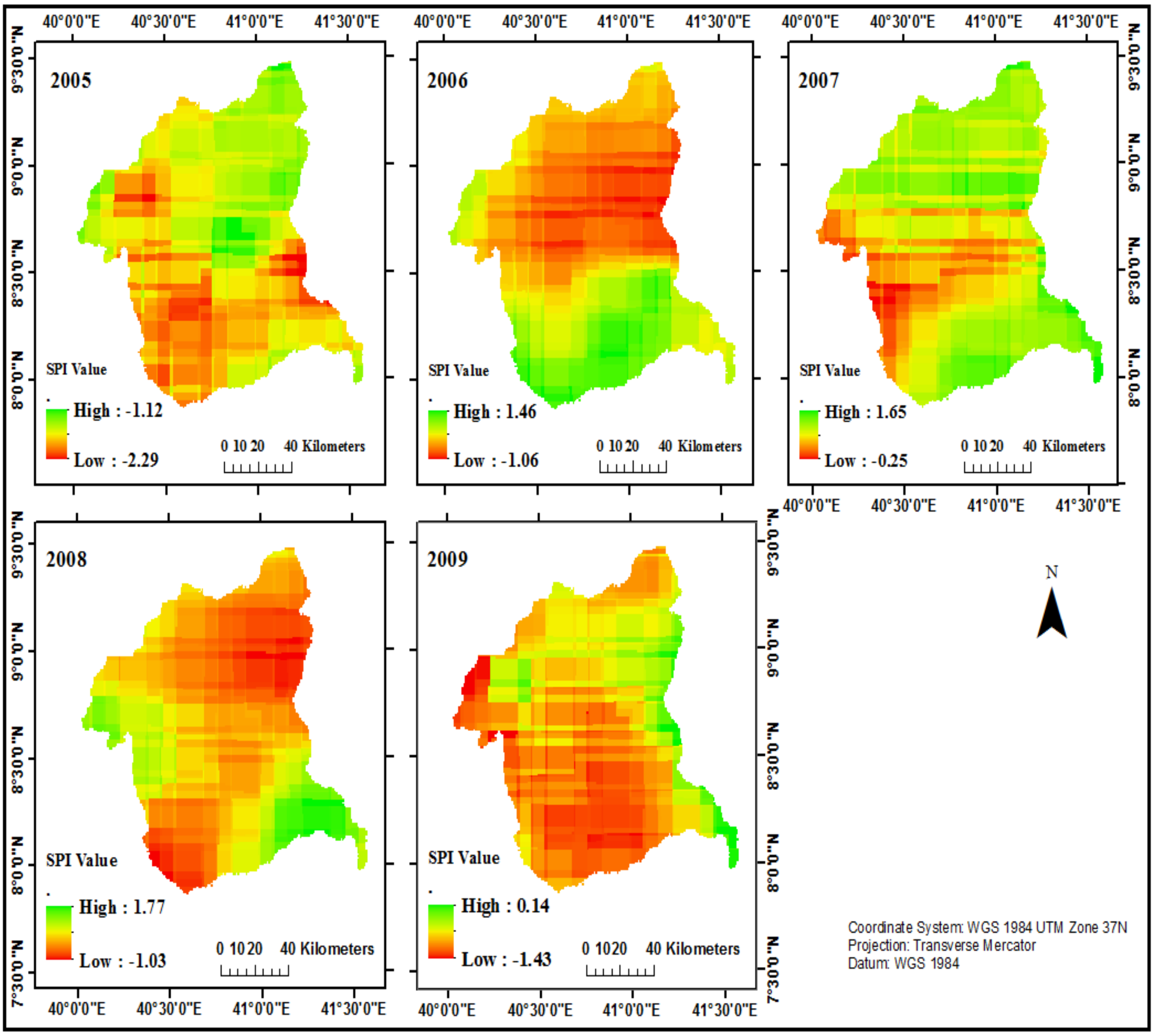

Figure 20: Seasonal Standardized Precipitation Index for the period from 2005 to 2009

Precisely speaking, however, as explained by the SPI values that ranged from -2.3 to -1.12 and -0.21 to 0 respectively, the droughts that happened in the years 2005 and 2009 were much more severe compared to other years. On the average, therefore, as illustrated by the results of the said case analysis, the rainfall deficits, recorded in the growing seasons of the two years were found to be so high that they were considered the worst dry years of the study period.

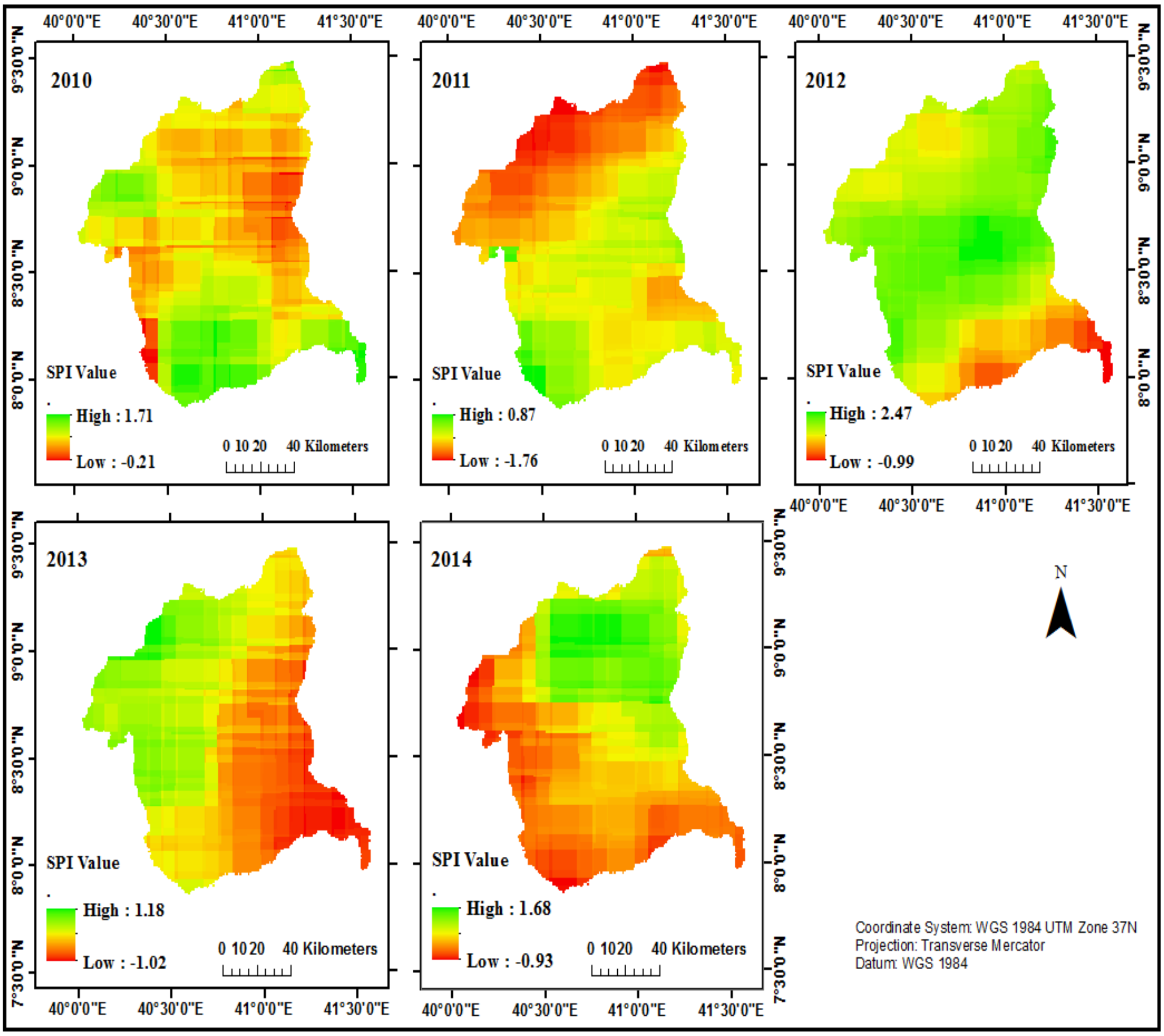

Figure 21: Seasonal Standardized Precipitation Index for the period from 2010 to 2014

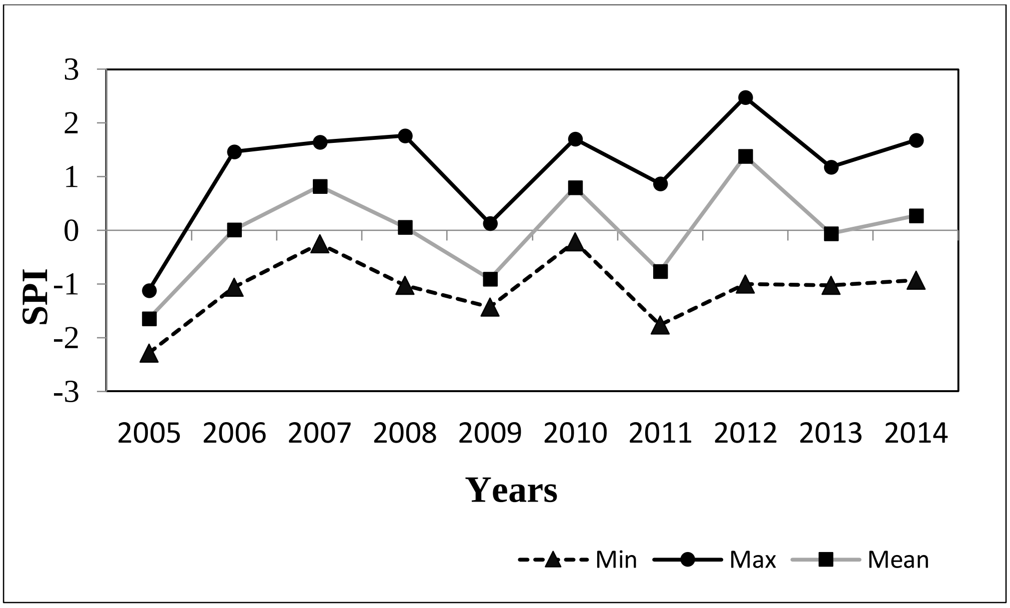

Figure 22: Temporal pattern of seasonal (June-September) SPI (2005-2014)

With the aim of labeling the spatial distribution patterns and severity levels of drought in the study area, the SPI for the two drought years (2005 and 2009) and wet years (2007 and 2012) were analyzed and reclassified. Considering the two most severe drought years (2005 and 2009), the analysis process has proved to be an ideal illustration of the drought extent and intensity in the Zone. As can be seen in (Figure 23a and 23b) in contrast to the NDVI anomaly index output, the SPI spatial pattern analysis result showed that the whole area was hit by drought, ranging from moderate to very severe level of severity, during the year 2005, while in the year 2009, the range of the severity was limited to slight and moderate drought levels only.

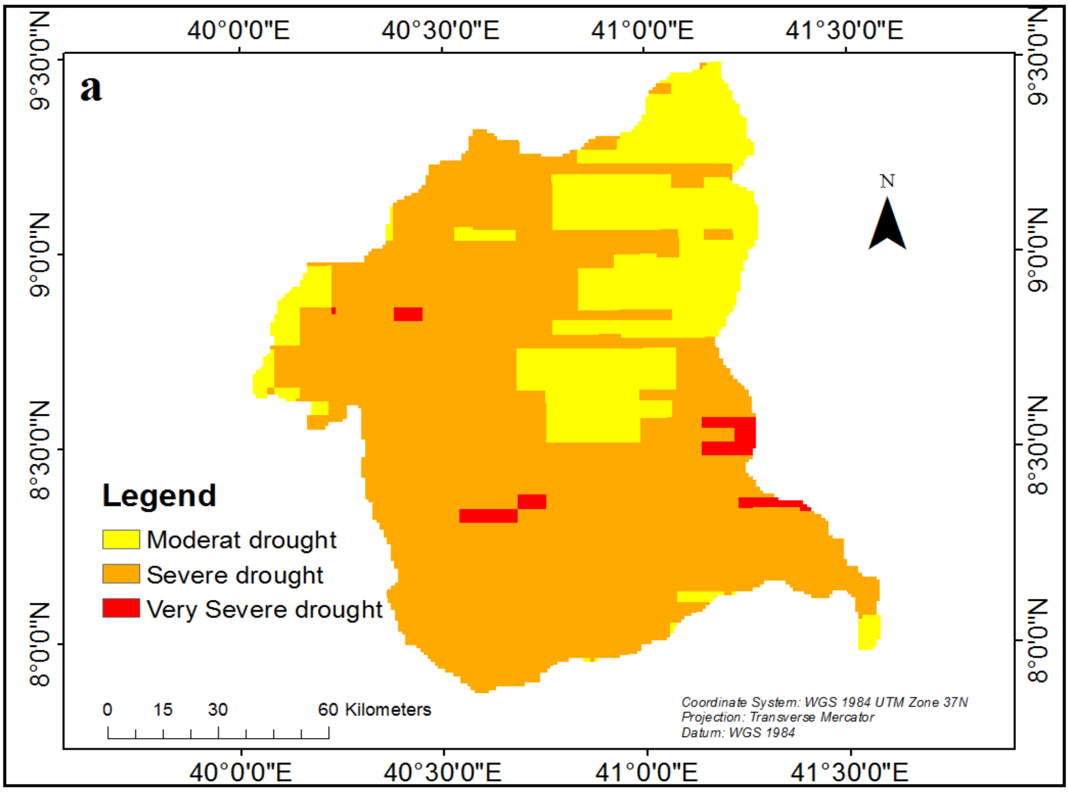

Figure 23a: Spatial pattern of drought severity for the drought years 2005 as expressed in SPI

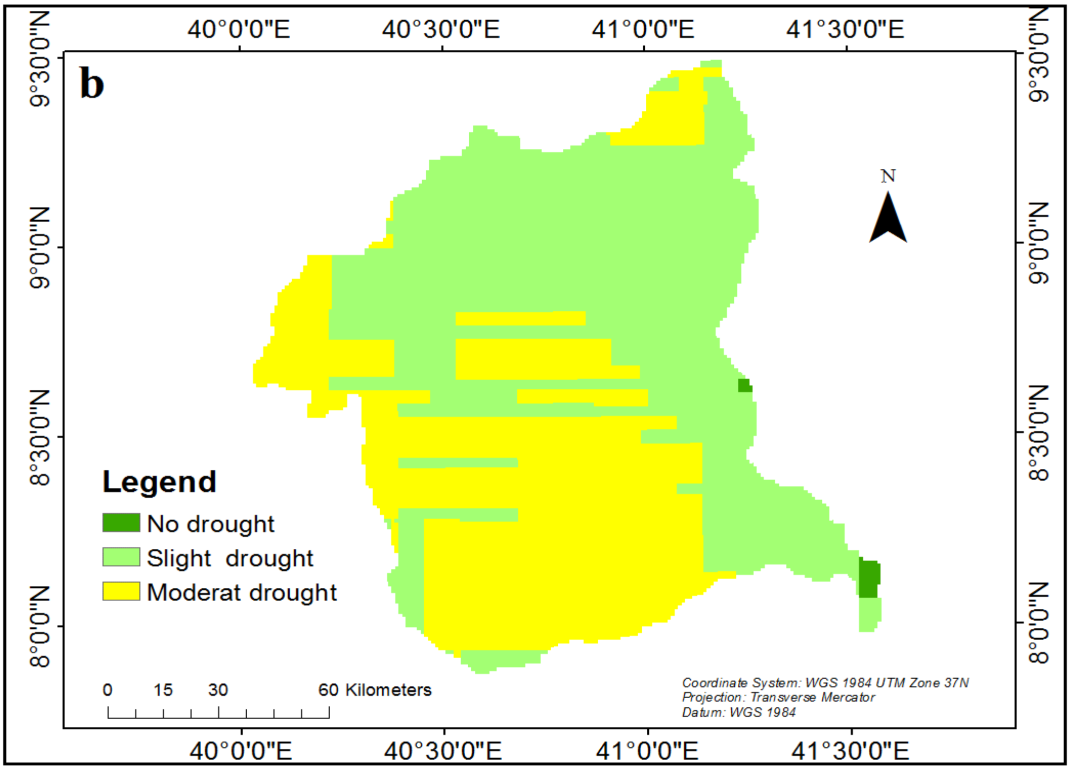

Figure 23b: Spatial pattern of drought severity for the drought years 2009 as expressed in SPI

Table 15: Percentage of area covered by agricultural drought severity for drought years 2005 and 2009 expressed by SPI

		Drought Years			
		2005 GC.		**2009 GC.**	
No.	**Class**	**Area km²**	**Area %**	**Area km²**	**Area %**
1	No Drought	0.00	0.00	73.41	0.43
2	Slight Drought	0.00	0.00	9324.48	55.19
3	Moderate Drought	4158.76	24.62	7497.08	44.37
4	Severe drought	12423.71	73.53	0.00	0.00
5	Very Severe drought	312.50	1.85	0.00	0.00
	Total	16894.98	100.00	16894.98	100.00

The result indicates that in the year 2005, there was a very large area of drought, covering the widest scope accounting for 24.62, 73.53 and 1.85 percent of the total area (Figure 23a) hit by moderate, severe and very severe drought, respectively. During the 2009 drought year, the level of drought severity reduced to slight (55.19) and moderate (44.37) covering larger areas (99.56) of north, western and the southern half of West Hararge Zone(Figure 23b).

Since SPI can be used to identify both dry and wet years, SPI analysis was applied to the identification of the wet years conditions too. As clearly shown on Figure 24 a, b and Table 16, the two years 2007 (98.56%) and 2012 (94.77 %) were the wettest years, for the study period, in the entire West Hararge Zone. In those two years, the degree of drought severity was limited to slight drought only. This, in effect, means that the good seasonal rainfalls had helped the whole Zone to be free of drought during the two years. Yet, some small pockets (6.87 percent) of the total area, covering 1.44 in the south western and 5.43 in the south eastern parts, experienced slight drought in the years 2007 and 2012 respectively. This may be due to the influences of the mal-distribution of rainfall or occurrence of considerable dry spells during the preceding long dry seasons.

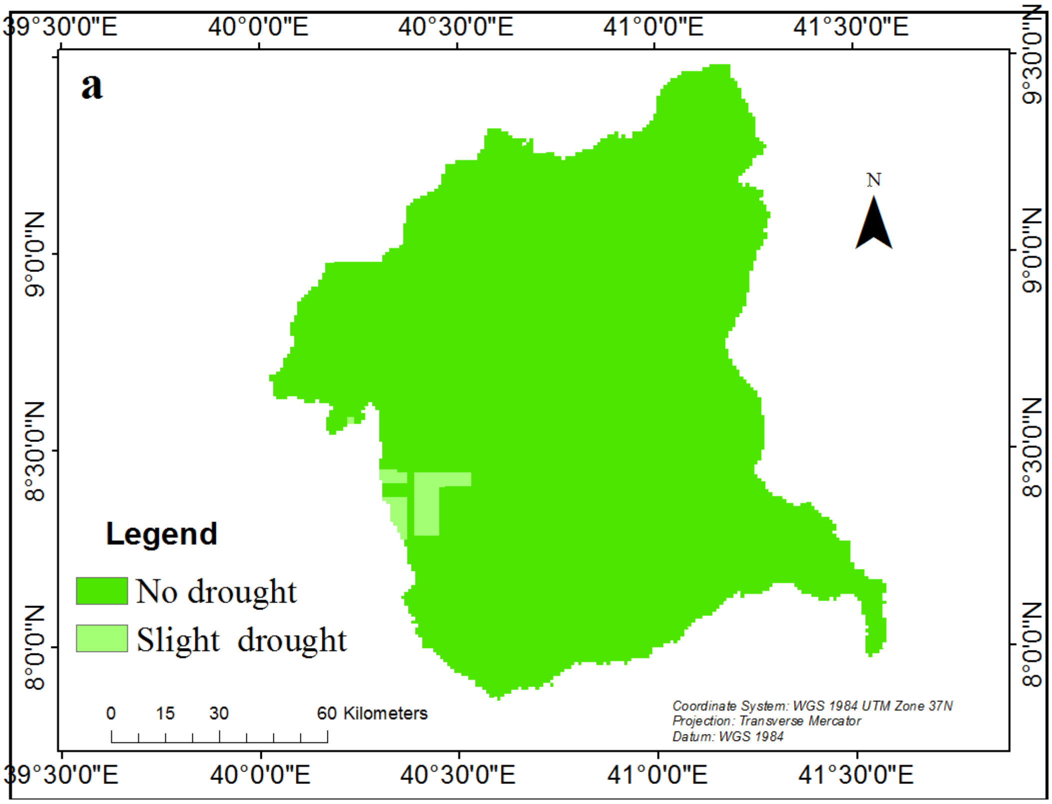

Figure 24a: Spatial pattern of drought severity for wet years 2007 expressed in SPI Index

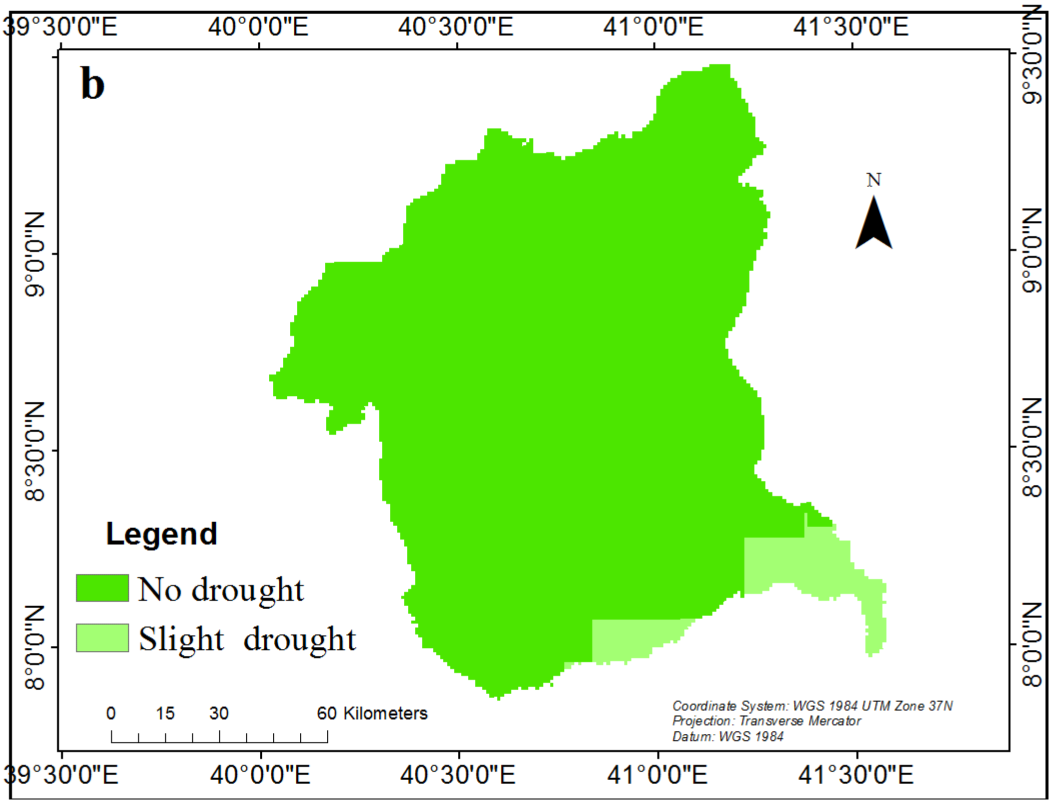

Figure 24b: Spatial pattern of drought severity for wet years 2012 expressed in SPI Index

Table 16: Percentage of area covered by agricultural drought severity for Wet years 2007 and 2012 expressed by Standardized Precipitation Index

		Wet Years			
		2007 GC.		2012 GC.	
No.	Class	Area (km^2)	Area (%)	Area (km^2)	Area (%)
1	No Drought	16650.93	98.56	15978.30	94.57
2	Slight Drought	244.05	1.44	916.67	5.43
	Total	16894.98	100.00	16894.98	100.00

As crop production in areas like West Hararge Zone is, predominantly, a function of seasonal rainfall, crop failures in these areas are, usually, associated with moisture deficits or agricultural drought. Thus, the need to validate the correlation between SPI and the grain yield anomaly becomes highly imperative.

Based on this basic premises, SPI and grain yield anomaly were regressed for the whole of the study period (Appendix 5 and Figure 25) and the result showed that when SPI is positive, grain yield anomaly also turns positive revealing a good positive correlation of r = 0.71. In other words 50 percent of grain yield variability can be explained by SPI. Thus the result reviled that the strength of the index to indicate the prevalence of agricultural drought was good.

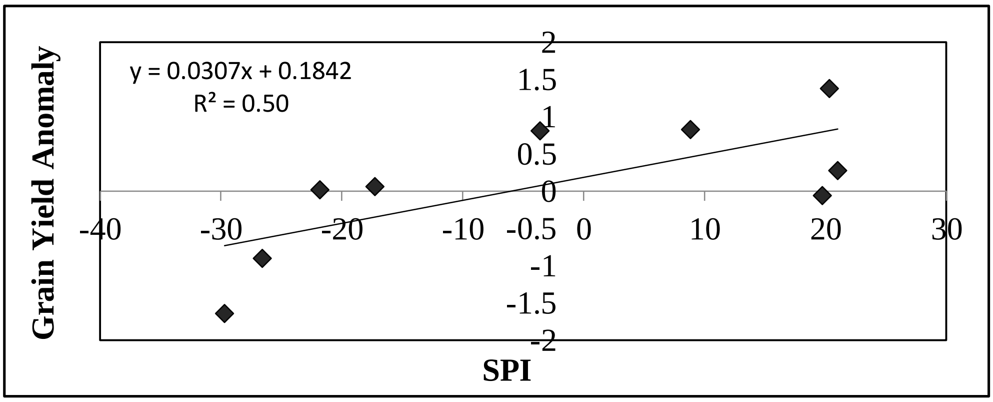

Figure 25: Relationship between SPI and grain yield anomaly

4.5. Water Requirement Satisfaction Index (WRSI) based agricultural drought Characterization

During the study period (2005-2014), the performance of grain crops growing in the study area was investigated using WRSI index. By then the concurrent WRSI anomaly values were found to be ranging, during the dry years, from 37 to 100 % in 2005, 21to 92% in 2009 and from 35 to 100% in 2007 and 36 to 100 during the wet years. Accordingly, the agricultural droughts that occurred during those years ranged from slight to very severe levels (Figure 26 and 27).

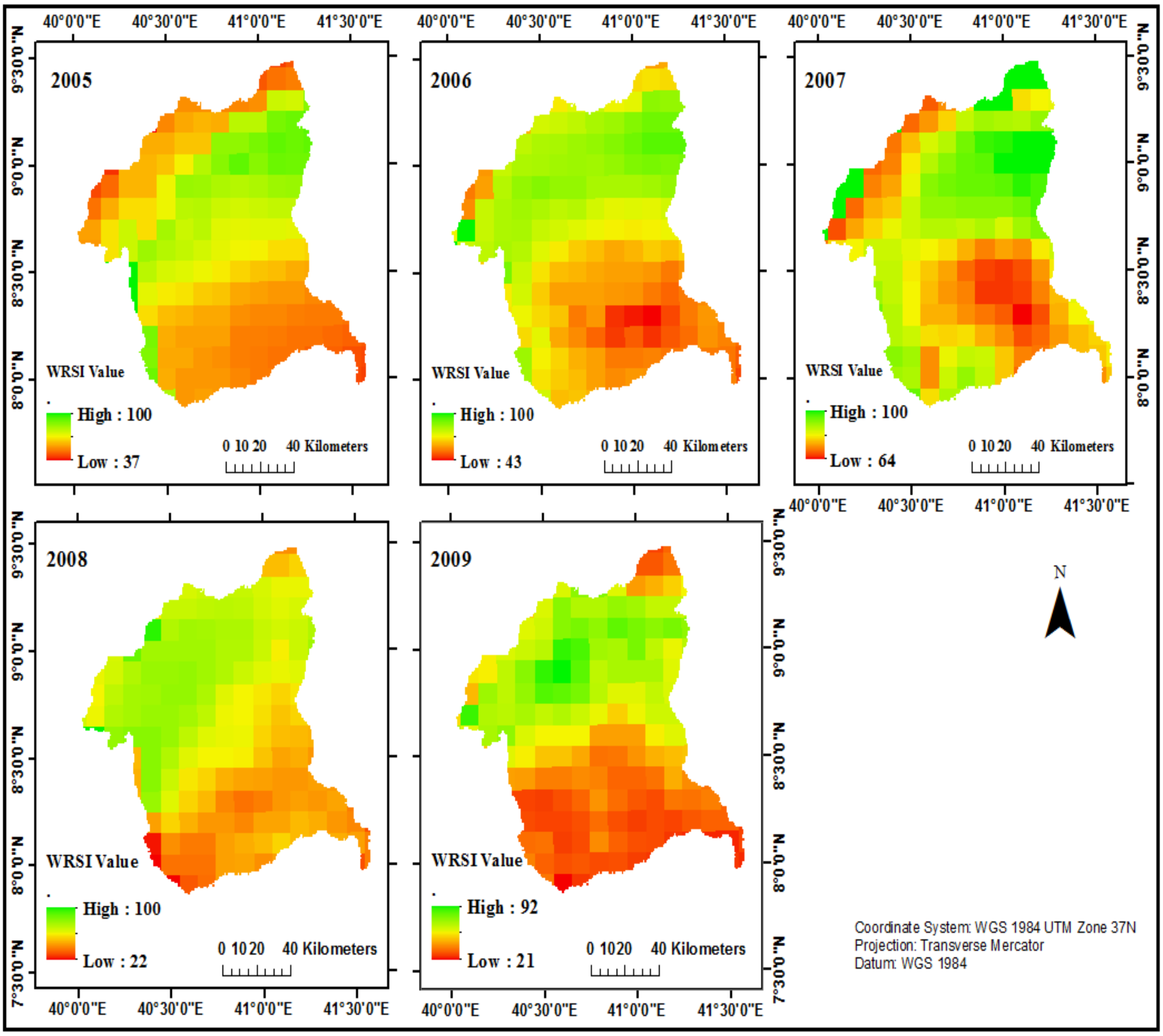

Figure 26: Seasonal WRSI for the period from 2005 to 2009

The result revealed that there were less WRSI percentage values, as low as 21% in large parts of the study area, inflicting moisture deficit, during the drought years of 2005 and 2009. Only 30 % in 2005 and 23 % in 2009 of crop water requirements of the study area were satisfied. According to the result, especially depicted in Figure 28 a, b and Table 17, during the 2009 cropping season, severe agricultural drought was found to be prevalent in most part of the southern half and some areas in the north and north east of West Hararge Zone.

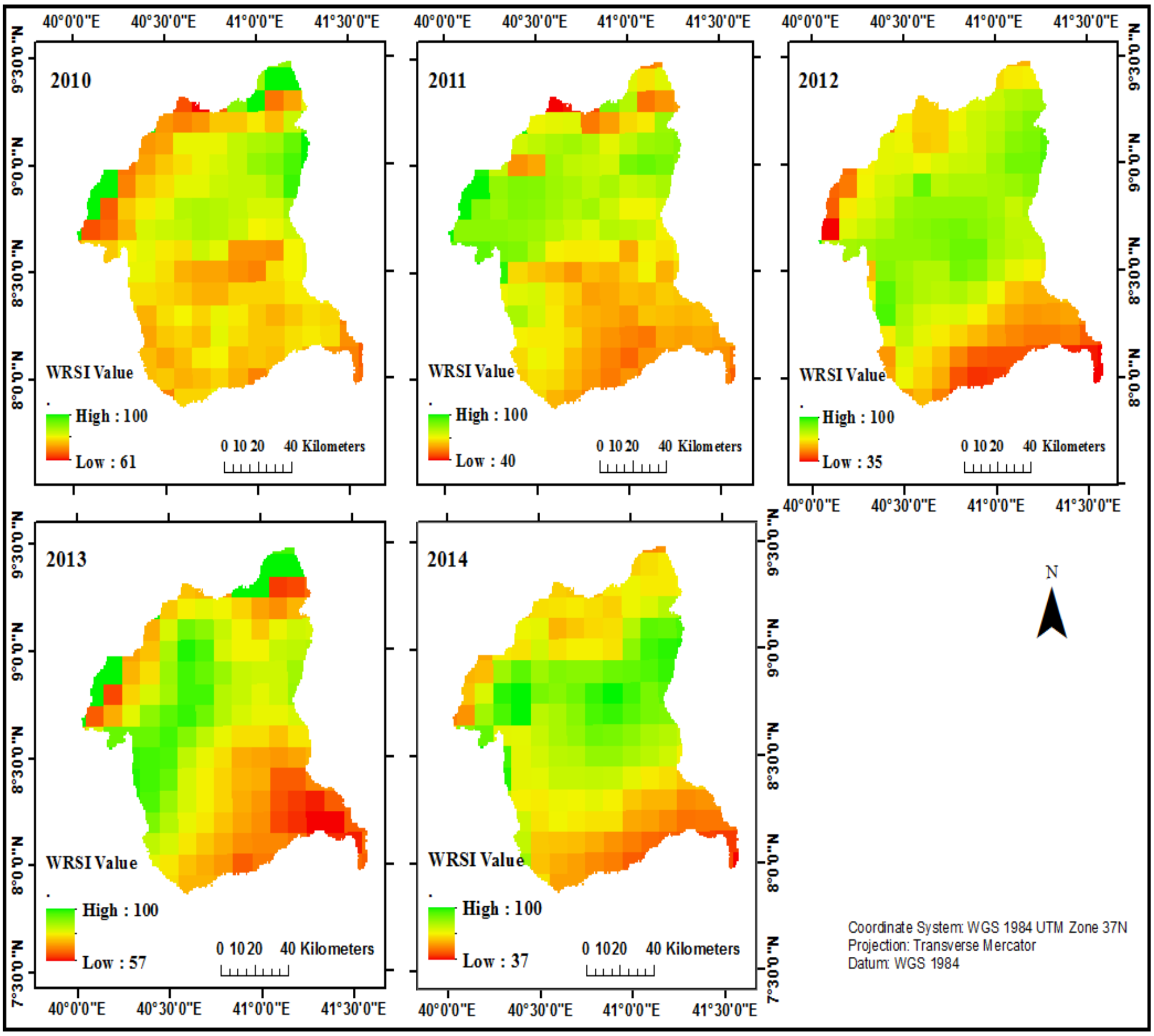

Figure 27: Seasonal WRSI for the period from 2010 to 2014

The percentage of area hit by agricultural droughts ranged from slight (21.64%) to moderate (20.84%) severe (31.88%) and very severe (17.67%) in 2005. In 2009, almost all parts of the area were, similarly, stricken by slight, moderate, severe and very severe agricultural droughts in the percent of 16.38%, 18.17%, 9.72% and 49.10% respectively. Obviously, the low percentages imply that, in the two years, the Zone experienced high yield deficits .This has been confirmed by Senay and Verdin (2002); Gizachew Legesse and Suryabhagavan (2014) whereby they firmly 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 grain yield loss was caused by the prevalence of very severe agricultural drought in the study area, during those two years.

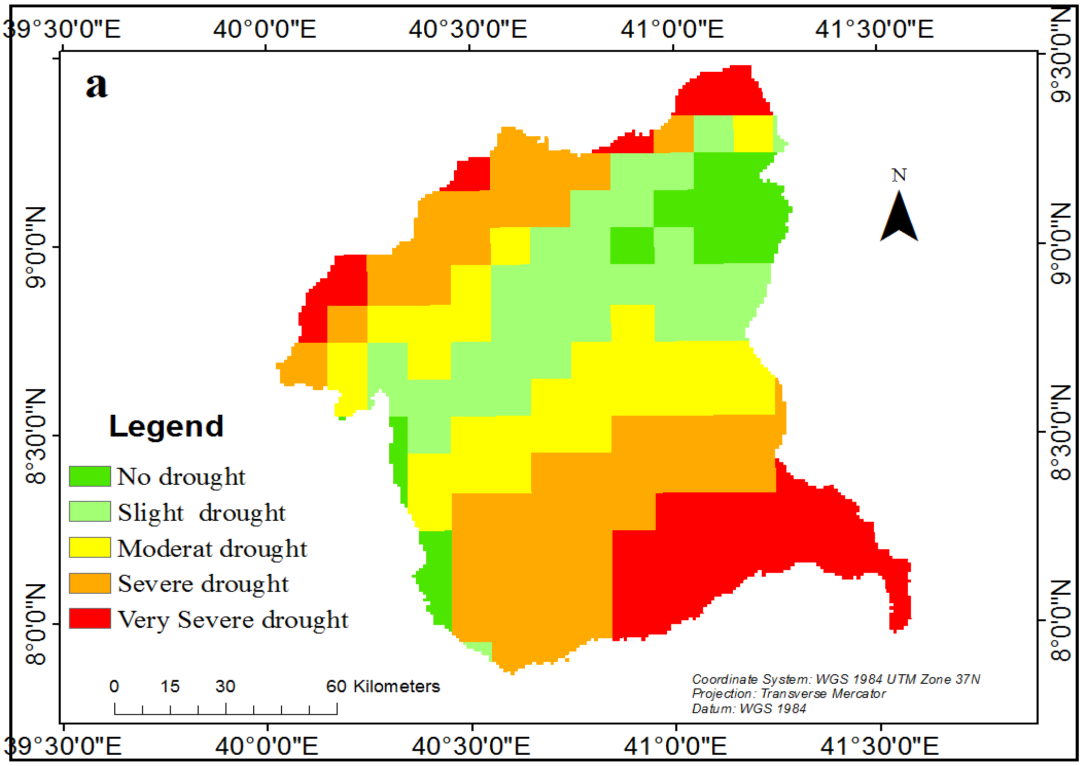

Figure 28a: Spatial pattern of agricultural drought severity for drought years 2005expressed in WRSI

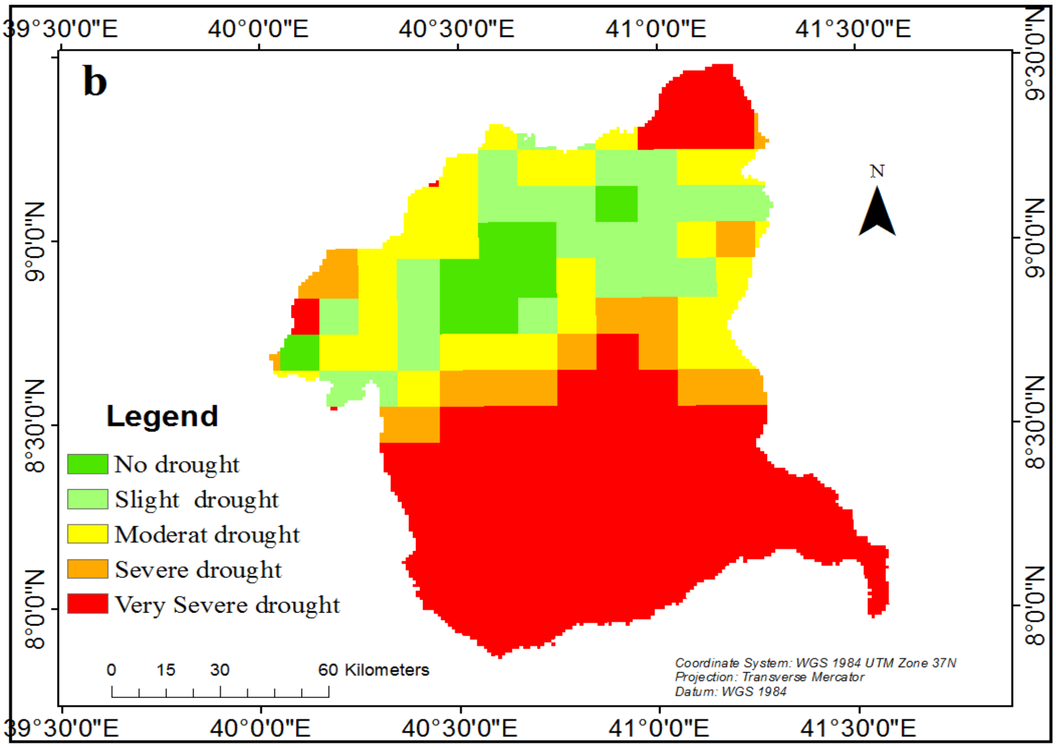

Figure 28b: Spatial pattern of agricultural drought severity for drought years 2009 expressed in WRSI

Table 17: Percentage of area covered by agricultural drought severity for drought years 2005 and 2009 expressed by WRSI

No.	Class	Drought Year			
		2005 GC.		2009 GC.	
		Area km^2	Area %	Area km^2	Area %
1	No Drought	1346.2409	7.96829	1119.06	6.62
2	Slight Drought	3655.7832	21.6383	2767.88	16.38
3	Moderate Drought	3520.8615	20.8397	3070.46	18.17
4	Severe drought	5386.9478	31.8849	1642.87	9.72
5	Very Severe drought	2985.1429	17.6688	8294.71	49.10
	Total	16894.976	100.00	16894.98	100.00

WRSI is effective also in capturing the responses of crops during wet seasons. The result depicted in Figure 29 a, b and Table 18, reveals that even though 2007 and 2012 cropping seasons were wet years, some small pocket areas appeared to have been stricken by slight agricultural drought, especially the southern parts of the study area. During the 2007 cropping season, for instance, some 11.51 % of the total area was hit by moderate agricultural drought while the rest 88.49 % were free or slightly affected by agricultural drought. In 2012, again, 34.10 % of the area was affected by agricultural drought ranging from moderate to very severe while 65.9 % of the area was free or slightly affected by agricultural drought. Generally, however, because 88.49 % (2007) and 65.90 % (2012) of the water requirement of the local growing crops was satisfied, it has been apprehended that most of the area was free from agricultural drought during the two wet years.

Table 18: Percentage of area covered by agricultural drought severity for wet years 2007 and 2012 expressed by WRSI

No.	Class	Wet Year			
		2007 GC.		2012 GC.	
		Area (km^2)	Area (%)	Area (km^2)	Area (%)
1	No Drought	9548.69	56.52	6267.91	37.10
2	Slight Drought	5400.84	31.97	4865.12	28.80
3	Moderate Drought	1945.45	11.51	2860.14	16.93
4	Severe drought	0	0	1715.29	10.15
5	Very Severe drought	0	0	1186.52	7.02
	Total	16894.976	100.00	16894.98	100.00

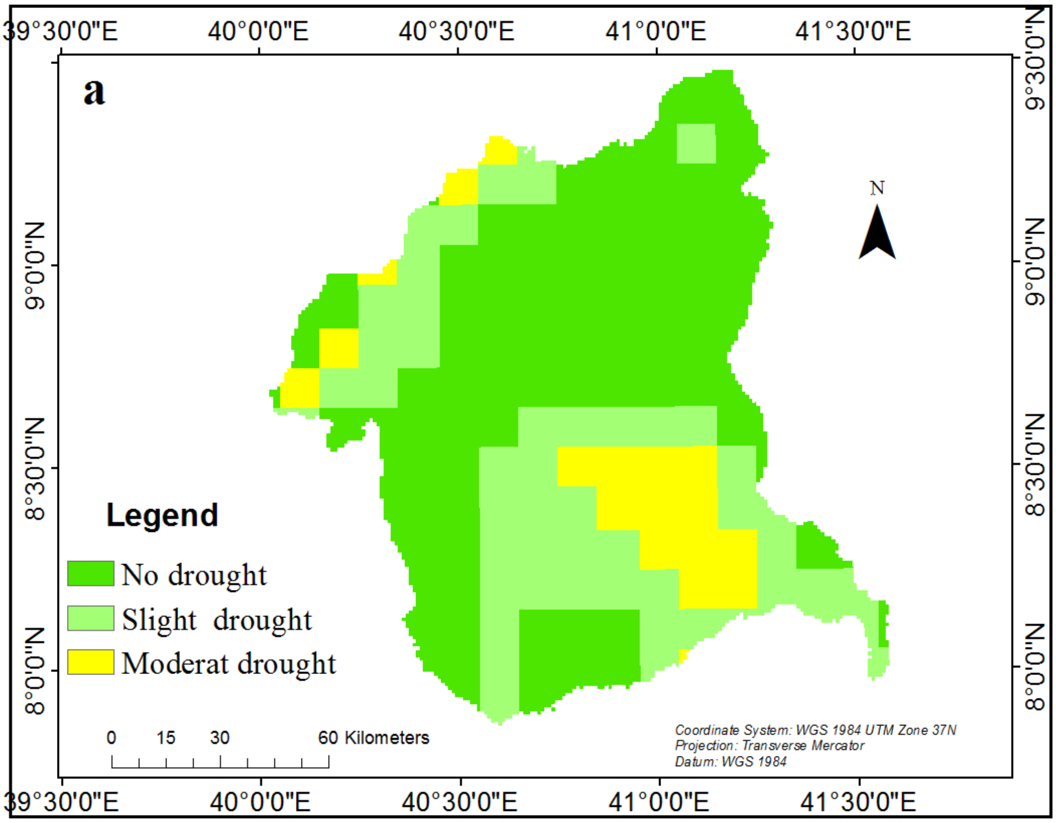

Figure 29a: Spatial pattern of agricultural drought severity for wet years 2007 expressed in WRSI value

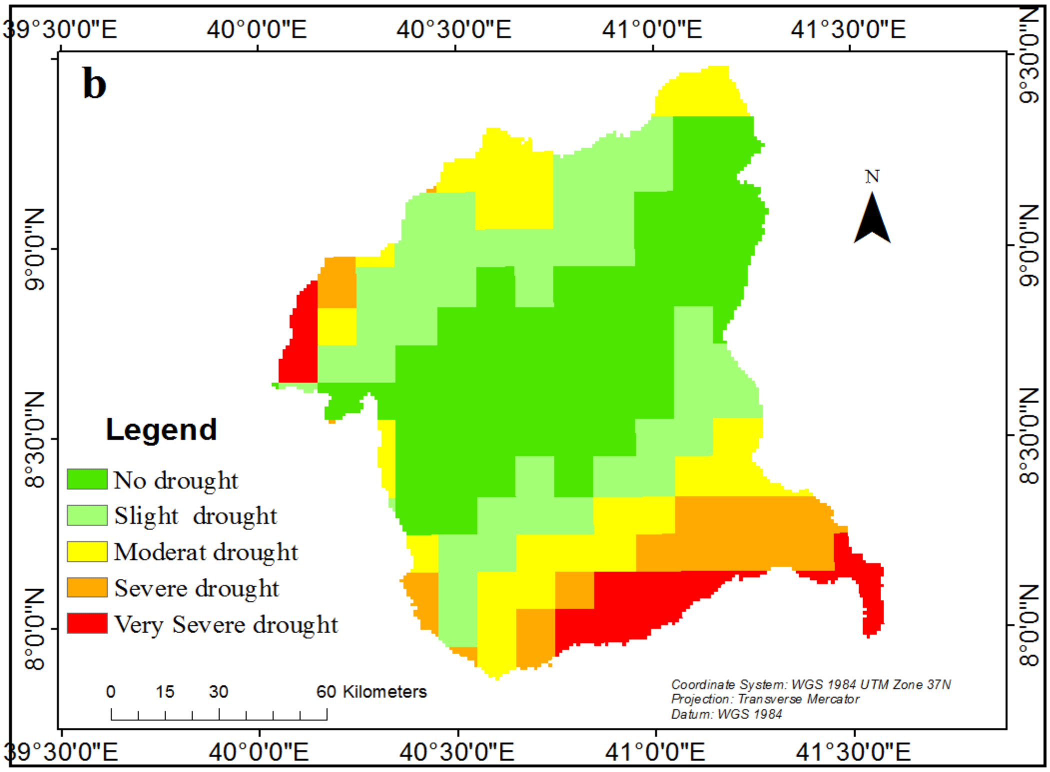

Figure 29b: Spatial pattern of agricultural drought severity for wet years 2012 expressed in WRSI value

In order to verify the correlation between water requirement satisfaction index and agricultural productivity, the relationship between satellites based WRSI and ground based grain yield was analyzed using simple regression analysis (Appendix 6). Accordingly, the resulting temporal patterns of rainfall and relationship of the average WRSI and grain yield are depicted in Figure 30. In the process, it has been observed that there was a good correlation between grain yield and WRSI ($r = 0.81$). In other words, as shown in the appendix and figure, the linear regression test result reveals significant positive relationship between WRSI and grain yield anomaly with a p-value of 0.008 at $\alpha = 0.05$ level of significance. The overall goodness of fit test for the fitted Model using R^2, the so called coefficient of determination or percentage of variance, explained that R^2 is $= 0.66$ suggests that in 66 percent of the case, grain yield variability can be explained by WRSI.

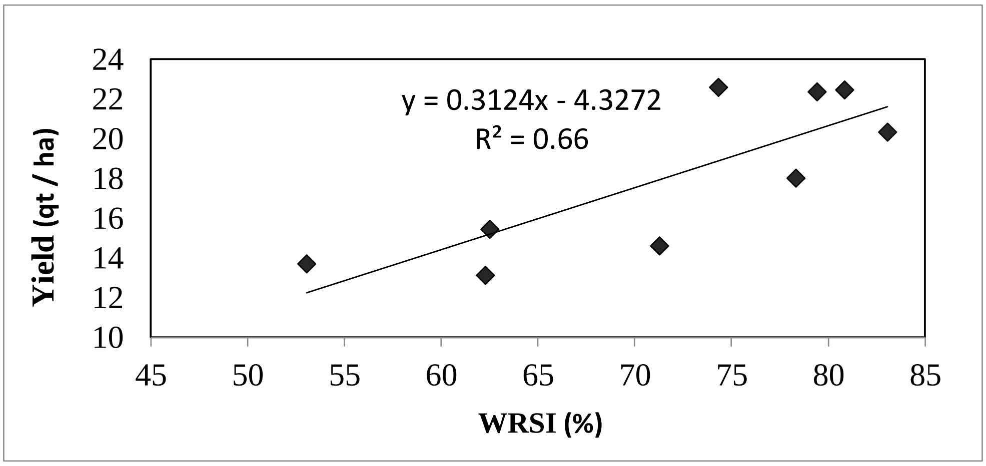

Figure 30: Temporal pattern and relationship of WRSI and grain yield

4.6. Description of yield reduction due to agricultural drought

As can be seen from the analysis results, agricultural drought decreases grain yield by affecting the crop at different stages of growth. Concerning the spatial pattern of yield reduction, analysis was carried out in the study area throughout the study period (2005-2014) cropping seasons Accordingly, the highest yield reductions were observed in the entire central and southern half of the Zone, during the cropping seasons of the years 2005 and 2009. (Figure 31a and b).

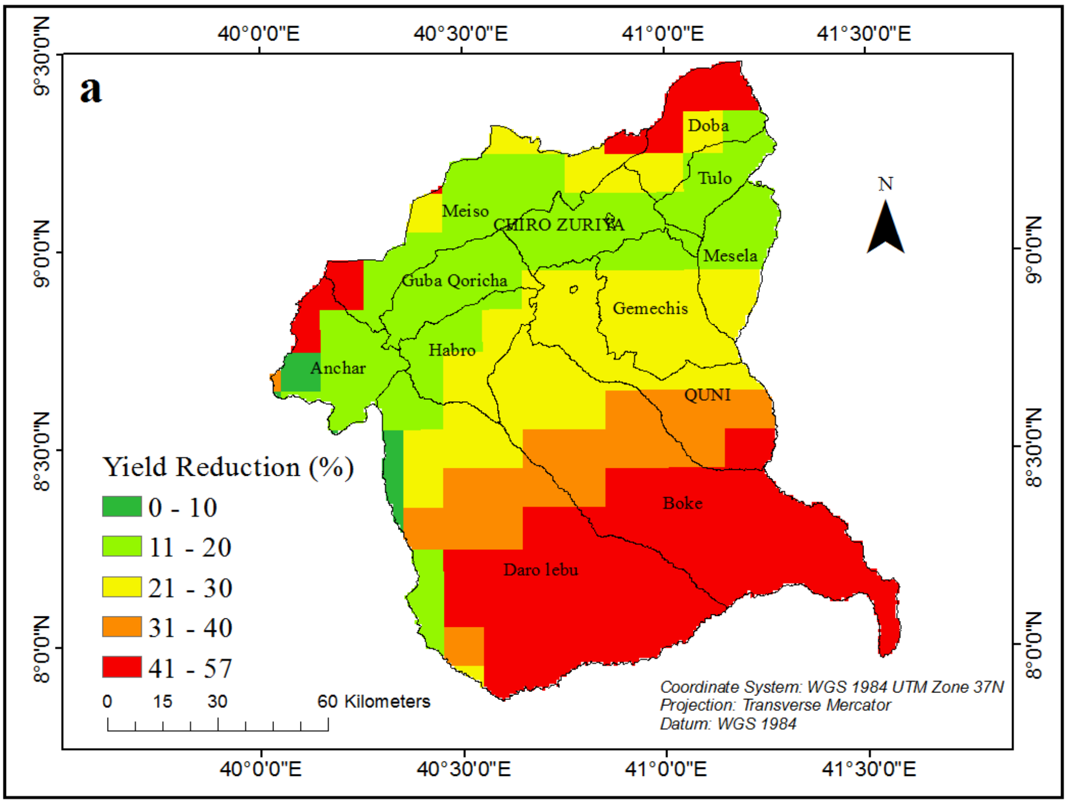

Figure 31a: Spatial pattern of yield reduction in 2005 cropping seasons

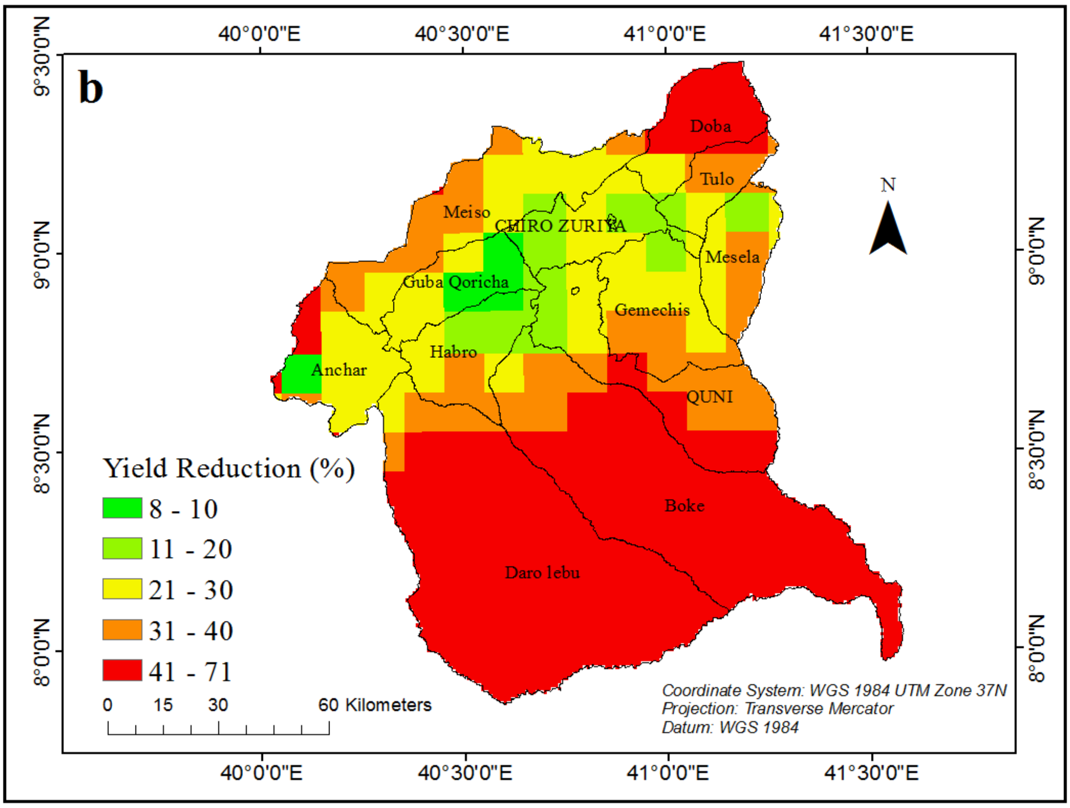

Figure 31b: Spatial pattern of yield reduction in 2009 cropping seasons

According to this result, during the 2009 cropping season, nearly the whole of West Hararge Zone was hit by agricultural drought and the agricultural yield reduction was raised to 71 %. During this season, northwestern, northern and most parts of the southern half encountered 40 to 71% yield reduction covering 50.04 % of the total area. Similarly, small areas in the north western and central parts encountered 30 to 40 % yield reduction covering 18.20 % of the total area. The rest 31.76 % of the area, especially in most parts of the northern highlands encountered 8 to 30 % yield reduction (Appendix 8). In the 2005 cropping season, the level of yield reduction was reduced to 57 % showing similar spatial patterns with that of the year 2009. The area encountered 40 to 57 % yield reduction accounted for 32.56 percent, while the area encountered 30 to 40 and 40 to 57 percent yield reduction accounted for 12.58 and 54.85 % respectively.

In the process of crop yield status analysis, critical investigations of the spatial patterns of yield reduction in the two wet years (2007 and 2012) showed that drought impacts, in most part of the Zone, were very insignificant during those years (Appendix 9). As can be realized from the result, in most parts (89.08 %) of the Zone, the level of yield reduction was very low (<30%). In fact, in some small pocket areas, around the north, western and south eastern parts, yield reduction reached 30 to 40 % covering 10.23 % of the total area in the 2007 cropping season. On the contrary in the 2012 cropping season, the level of agricultural yield reduction was raised to 58 %. In most parts of the area (73.39 %), the level of agricultural yield reduction was <30 %, while in most part of south eastern and some parts of west and the northern parts of the Zone the level of yield reduction raised from 30 to 58 % with an area of 26.61% of the total area of the zone. Most probably, the major reasons, why larger areas of the southern regions fall under low level of yield reduction can be attributed to the quantitative and temporal mismatches between seasonal rainfalls and the crops water requirement period, especially, during the later maturity stages.

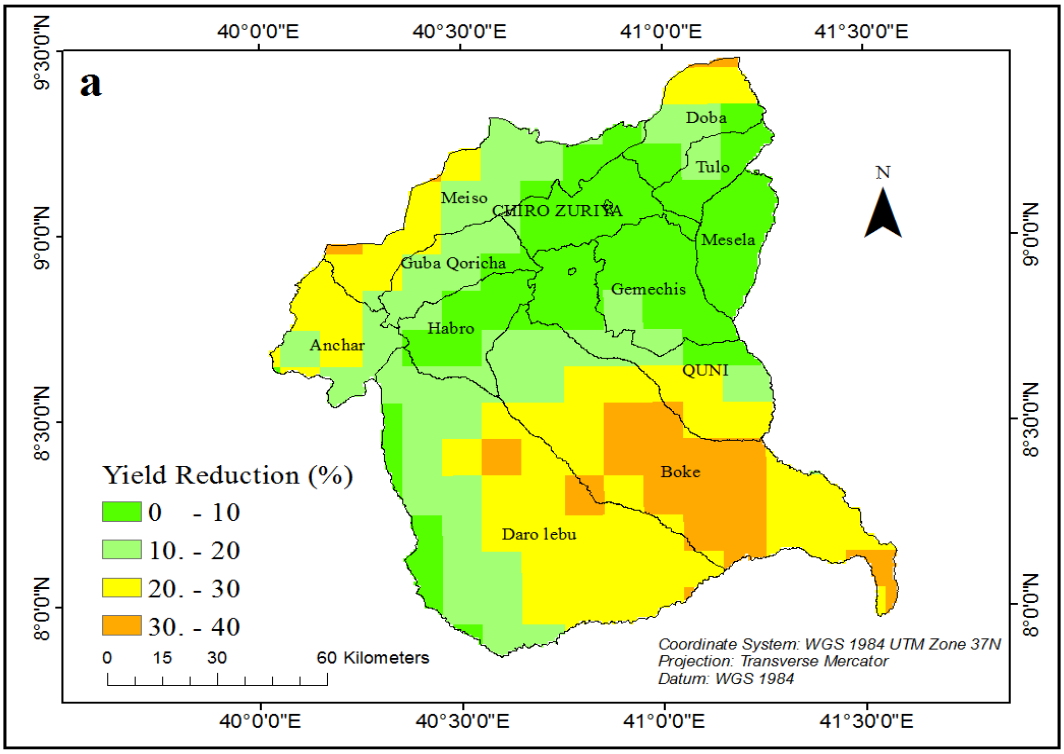

Figure 32a: Spatial pattern of yield reduction in 2007 cropping seasons

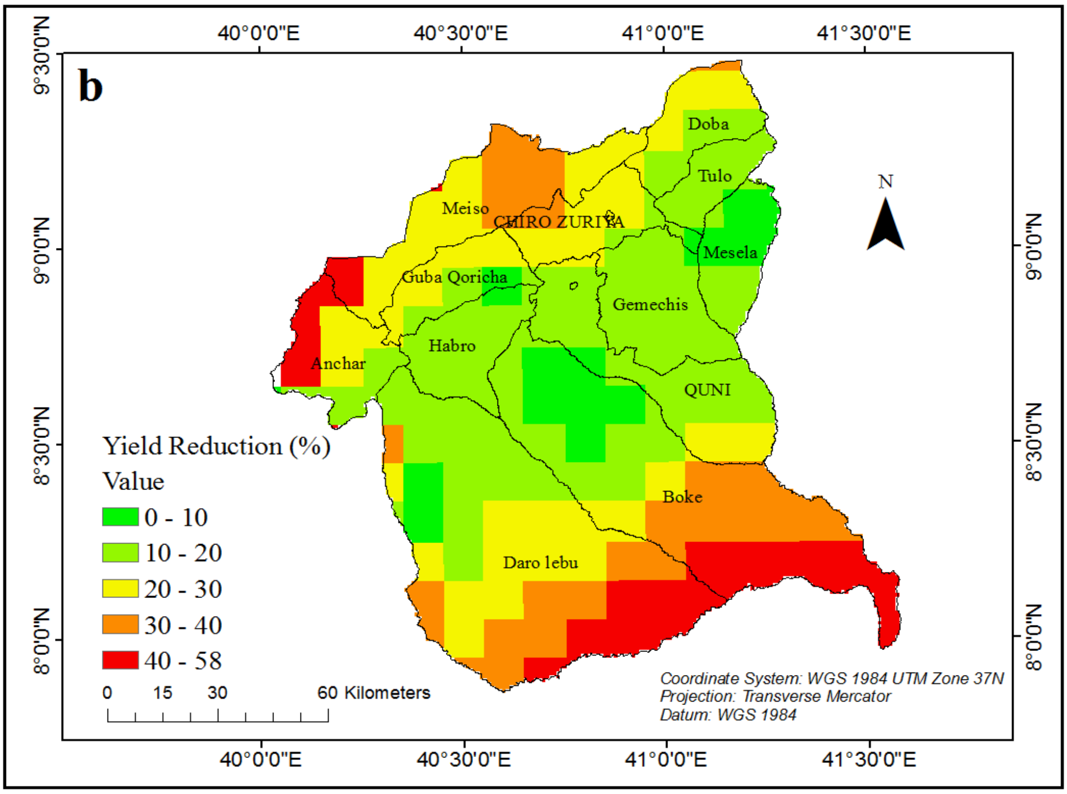

Figure 32b: Spatial pattern of yield reduction in 2012 cropping seasons

Therefore, it is clear to realize, from the above data, that the amount of moisture that prevails during the growing seasons can, significantly, influence crops' growth and development performances and their ultimate yields.

In order to determine the extent of the existing correlation between water requirement satisfaction index and crop yield reduction during the years (2005 and 2014), efforts were made to examine the situation of WRSI values in details. Accordingly, it was possible to learn, from the examination results, that there were some, year to year, variations of WRSI and the corresponding yield reductions in the Zone (Figure 33). In the process, it has also been realized that WRSI values and the corresponding yield reduction of crops growing in the study area displayed an inverse relation. In particular, compared to other cropping seasons of the analysis period, yield reductions for the years 2005and 2009 were relatively higher in the study area. Eventually, it was found that the lowest WRSI (53.03 %) value and highest yield reduction (40%) occurred during the year 2009, whereas the highest WRSI (83.05) and lowest yield reduction (17.8) values were observed during the 2007 cropping season.

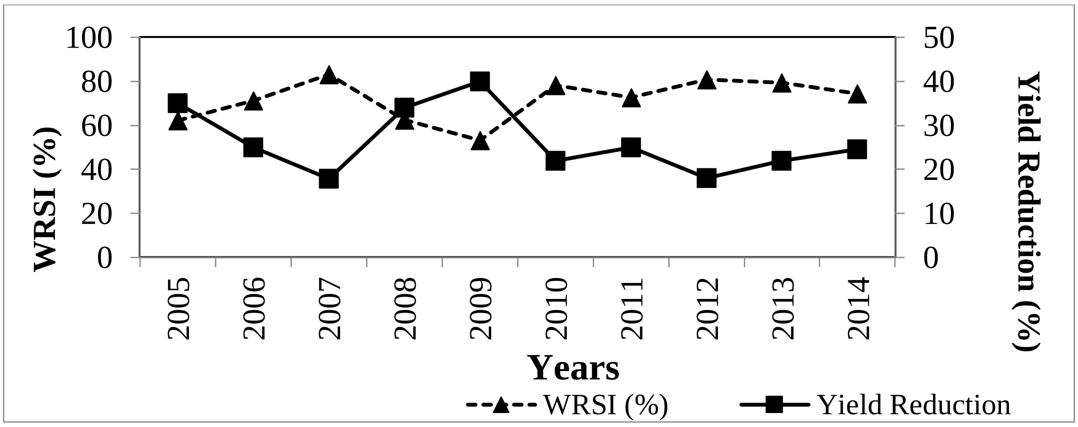

Figure 33: Aggregate crops WRSI and yield reduction trend in West Hararge Zone

According to the data obtained from CSA (2007), maize and sorghum have been found to be the most dominant crops growing in the study area. Both crops showed slightly different trends for WRSI and yield reduction tendencies (Figure 34) from that of the aggregate crops grown in the study area. Normally, it has been presumed that WSRI is the most reliably effective index in estimating crop yield reduction levels in any drought affected area. Accordingly, the highest yield reduction, due to agricultural drought, for maize and sorghum crops, for instance, was found to be 58.8 and 40.2 % respectively, while the lowest WRSI values were 53.1 and 51.1, respectively in the year 2009.

Yet, due to changes in the natural conditions and human interventions, WSRI values tend to show a certain degree of deviations from yield value particularly in the wet years or optimum area. According to Senay (2002) for example, when WRSI value rises closer to 100, in another word in good rainfall years or optimum regions, there is a tendency of occurrence of high yield variability due to factors such as the use of fertilizers and different management practices. Thus, in the years 2007 and 2010, there were 17.7 and 11.8 % yield reduction and 86.1and 86.7 % WRSI for maize and sorghum crops, respectively. Accordingly, therefore, although in most cases, only the years 2007 and 2012 were considered the wet years, because of the above factors, 2010 appeared to be the year of the lowest yield reduction concerning maize and sorghum crops.

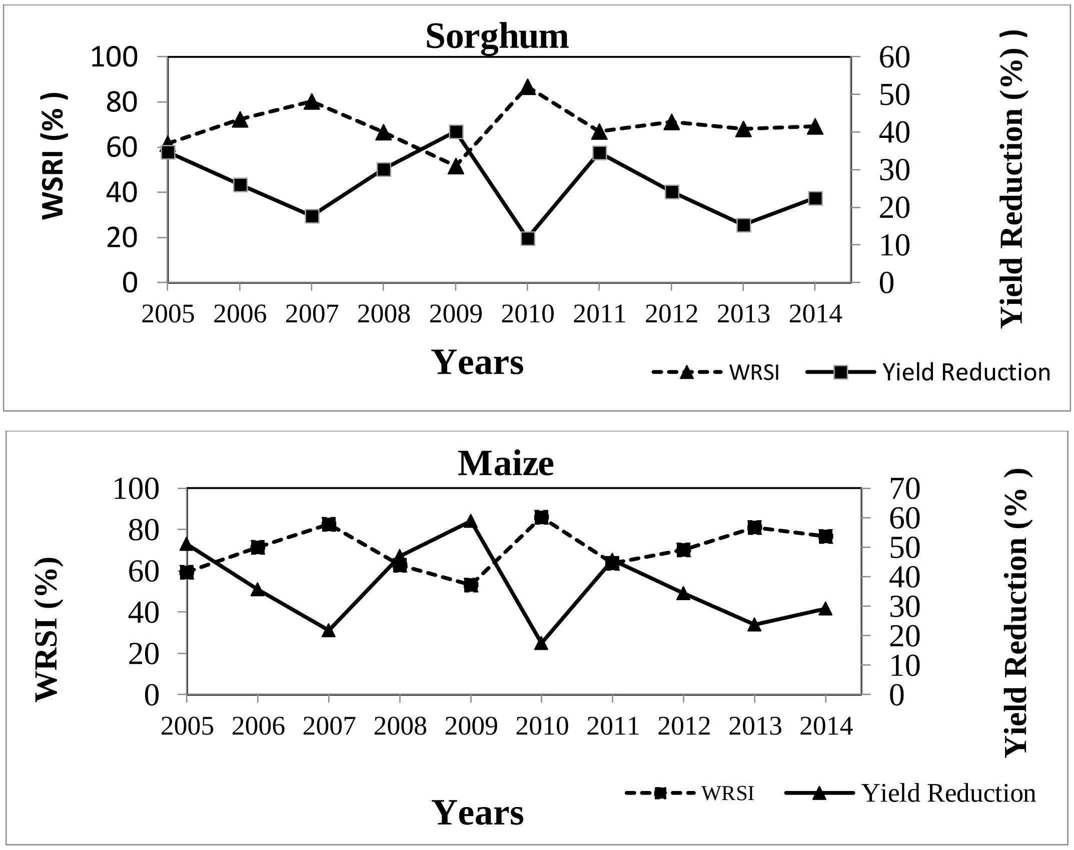

Figure 34: WRSI and yield reduction trend of Sorghum and Maize crops

4.7. Classification of agricultural drought risk prone areas

With the aim of isolating and determining the typical drought risk prone agricultural zones of the study area, a model map was prepared by integrating all drought frequency maps, generated from the three drought indices, NDVI anomaly SPI, and WRSI (Figure 35). The three layers, representing drought indices, were prioritized according to their degree of influence, using pair-wise comparison.

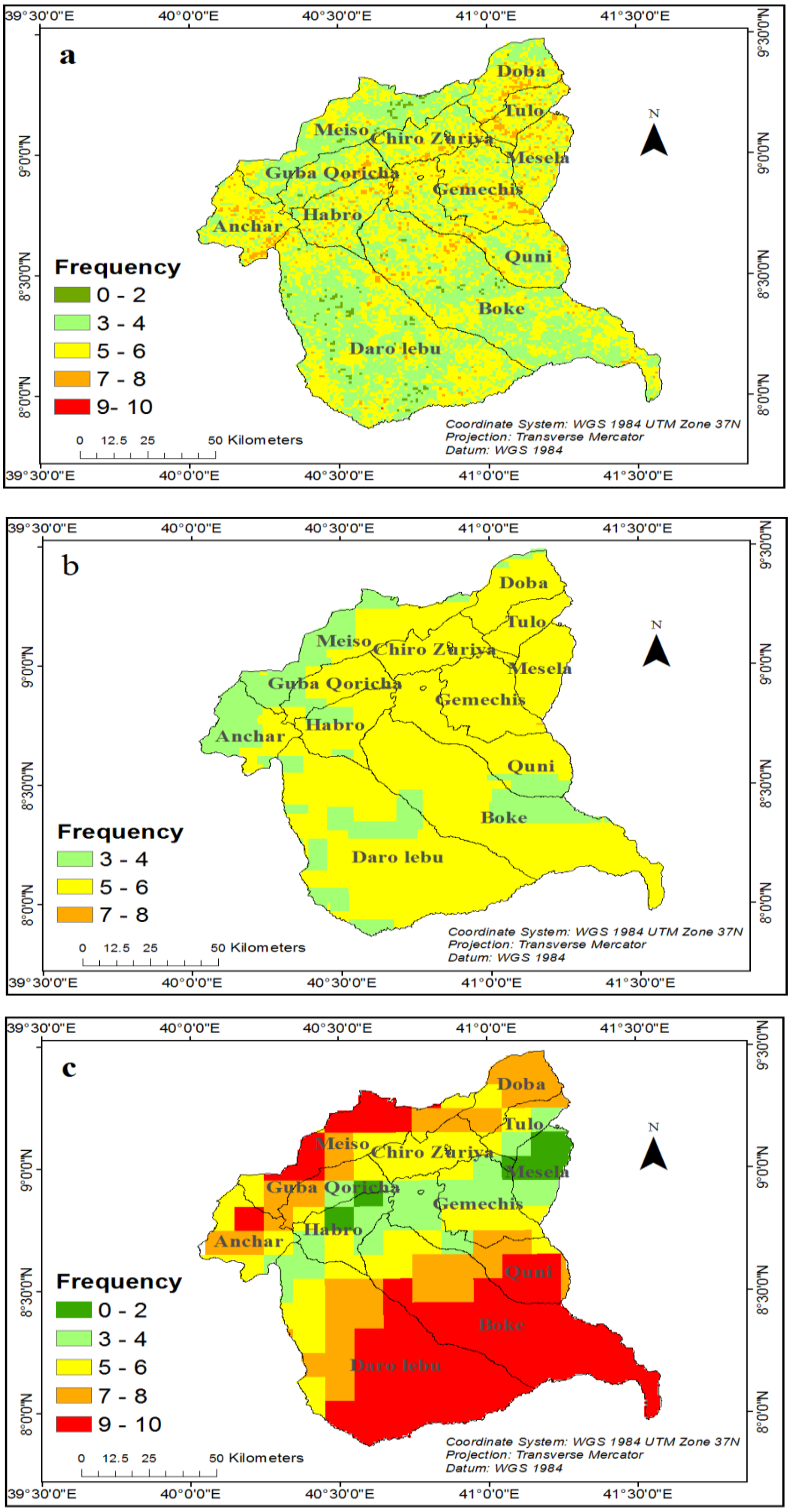

Figure 35: Agricultural drought frequency maps of the three drought indices (a) Normalized Difference Vegetation Index anomaly (b) Standard Precipitation Index and (c) Water Requirement Satisfaction Index

According to the result derived from the integration of all drought frequency maps, West Hararge Zone is classified into three (slight, moderate and severe) levels of agricultural risk categories. Accordingly, the integrated agricultural drought risk map, depicted in Figure 36, shows that the percentage of the area affected by the three categories of agricultural drought risk encompasses 12.34, 33.89 and 48.48% of the total geographical area of the Zone, respectively (Table 19). The probability of occurrence of agricultural drought ranges from 20 to 30 % for slight, 30 to 50 % for moderate and 50 to 80 % for severe drought level. Thus, the western and most of the central parts of West Hararge Zone is categorized into slight and moderate drought probability zone while the north eastern and most of the southern parts are in the severe drought probability zone.

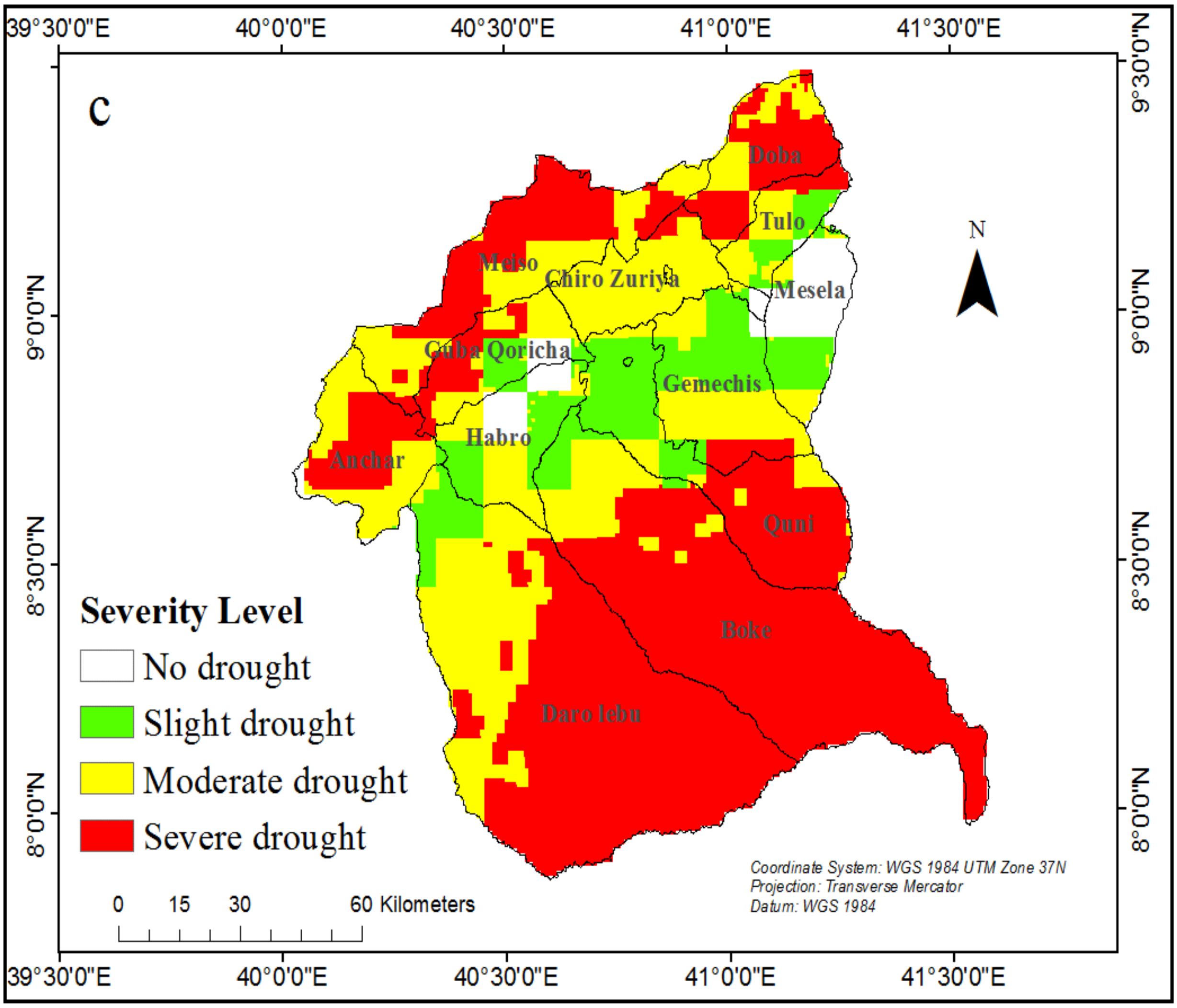

Figure 36: Agricultural drought risk area map, produced by using the three drought indices

Table 19: Percentage area affected by different agricultural drought risk levels

Severity levels	Probability of occurrence (%)	Area (km^2)	Area (%)
No drought	0 -20	894.86	5.30
Slight	20-30	2084.34	12.34
Moderate	30-50	5725.24	33.88
Severe	50-80	8190.54	48.48

Ultimately, in a way of summing up the discussion, a brief summary of the main operational procedures applied are given in the following descriptions. In the entire regression model diagnostic test processes, the fitted models were checked for the presence of outliers and influential observations using studentized residual and the popular Cook's distance test, respectively. Accordingly, the iterative test results showed that 2011 data point was both an outlier and influential observation that tends to affect the regression fit. In the influential observations, that have a studentized residual outliers, the ±2 range were considered statistically significant at 95% level. For the purpose of the influential observations, the recommended Cook (1977) $D_i > 1$ Cutoff values, used for spotting highly influential points, were applied.

4.8. Evaluation of index based results of agricultural drought using ground based Information

Throughout the persistent efforts of the study, occurrences of medium frequency agricultural droughts have been observed as a common phenomenon in West Hararge Zone. According to Early Warning System (EWS, 2005; 2010) reports from national Disaster Prevention and Preparedness Commission (DPPC), late arrival and early departure of the main rainy season or erratic spatial and temporal distribution of the rainfalls, and extended dry spells, especially during the two dry years (2005 and 2009), were the main weather related agricultural production problems in the Zone. Furthermore, the official reports confirm that, even though there were agricultural droughts ranging from slight to very severe all over the years 2005 to 2014 cropping seasons, especially, the 2005 and 2009 cropping seasons was the worst droughts that resulted in substantial yield reductions. As a result, the number of people affected by the recurrent droughts has increased, significantly, aggravating the extents of food shortages and famine related problems in West Hararge (Figure37). The number of affected population and the estimated yield reduction are highly correlated (r^2=0.88).

Similarly, information obtained from the West Hararge Zone agricultural and rural development and DPPC Offices also confirms that during the year 2005 and 2009 cropping seasons, there were severe agricultural drought in West Hararge Zone. According to the information obtained, the impact was so severe that large scale crop failure occurred in most parts of the Zone. In particular, the northern Weredas of Doba and Mi'eso, the western Weredas of Anchar and Guba- Qoricha as well as most parts of Quni, Boke and Daro-Labu in the southern half of the Zone were reported to have been severely affected.

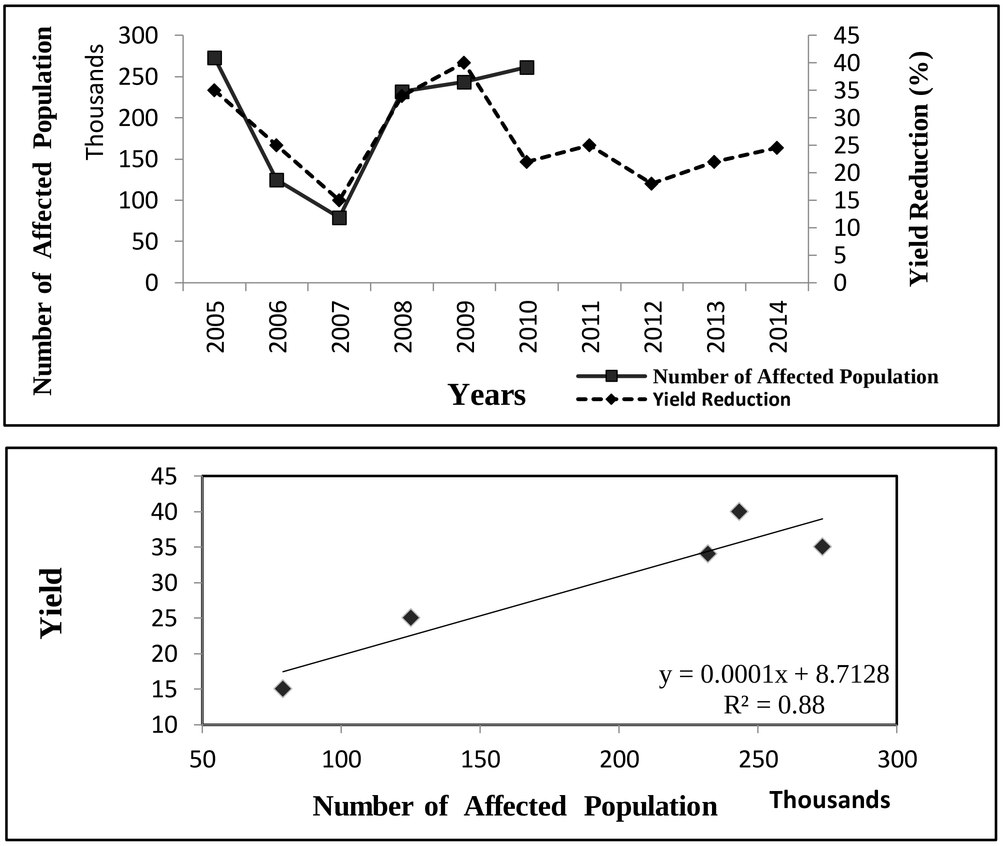

Figure 37: Relationship between yield reduction and number of affected population

According to the information obtained from West Hararge Zone agricultural and rural development offices, agricultural drought occur, mostly, as a result of quantitative and temporal mismatch of rainfall with the seasonal crop water requirement. Moreover, agricultural experts perceive that, now a days, due to the impact of the climate changes, the length of growing period is gradually declining as the production options of farmers, in the area, is gradually shifting to focus on short duration crop varieties. In addition, some farmers have begun adapting irrigation practices, as a means to increase production and reduce the pressures of drought impacts.

Besides creating adverse weather conditions on the general ecosystem, agricultural drought, manifested by the quantitative, spatial and temporal distributions mismatch with the cropping seasons, increases the potential probability for pest infestations and crop diseases occurrence. As has been captured by the crop reduction functions, during the drought years, increased pest infestations and emergence of various diseases, have impacted drastic yield reduction in West Hararge Zone. In particular, infestations by pests like stem borers have inflicted severe crop quality and yield reductions.

Chapter 5

Conclusion and Recommendations

5.1. Conclusions

Based on the objectives of the study, modern Remote Sensing and Geographical Information System technology as well as ground based observations mechanisms have been used to collect ten years' data on the behaviors of agricultural drought in West Hararge Zone. Applying NDVI, SPI and WRSI indices, the actual impacts (onset, distribution, frequency and severity levels) of the drought on the agricultural activities of the Zone's farming communities have been thoroughly investigated and analyzed. Using the results of the investigations and the analyses, a comprehensive map, clearly showing the proper agricultural drought risk prone areas of the Zone, has been produced. Accordingly, it has been possible to draw the following major themes from the long processes of the study.

- Modern Remote Sensing satellite data and Geographical Information System are effective in providing information regarding climate change pattern and its impact on the natural environment.
- NDVI, SPI 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.
- Drought can be taken as a major manifestation of crucial mismatch between the rainfall time and the normal cropping seasons of a given geographical area.
- Mismatch between the quantitative, temporal and spatial distribution of rainfall and the cropping seasons have been found to be inflicting negative effects on the quality and quantity of crop yields.
- The study revealed that West Hararge Zone, normally experiences droughts ranging from slight to severe levels occurring within two to three years gaps.
- Although the Zone has experienced various levels of droughts during the study period, the years 2005 and 2009 have been found to be the years of the worst drought while 2007 and 2012 were the wettest years, showing good yields.
- The ground based experiences and responses of the local informants and discussants have been found to be fairly congruent with the satellite derived data analysis results.

- Based on the drought frequency maps of the three indices of NDVI, SPI and WRSI a comprehensive map, clearly demonstrating the major agricultural drought risk prone Weredas of West Hararge Zone, has been produced.
- In semi-arid climate areas, like West Hararge Zone, slight deviation of rainfall from the normal cropping period can possibly mean drastic crop failure and yield reduction.

5.2. Recommendations

As has been shown in the conclusion section, the study has revealed considerable valid truths about the prevalence of various levels of agricultural drought in the different parts of West Hararge Zone. It is anticipated, therefore, that some of these findings can be beneficial for different individuals and groups with varied interests.

- The comprehensive master map, composed from the drought frequency maps of the three indices-NDVI, SPI and WRSI and clearly delineating the major agricultural drought risk prone Weredas of West Hararge Zone, can be used as a reliable guide for concerned development planners and professional field activists, on where and when to embark on for the campaign to combat the severe agricultural drought problems of the Zone.
- The recurrence pattern and frequency of the local agricultural drought problems, underlined in the discussion of the results, can remind the concerned local development authorities and field actors on the need to prepare pertinent strategic plan and build appropriate capacity to effectively mitigate the impacts of agricultural drought and ensure the sustainability of reliable food supply in the area.
- Some of the results of the study and the analyses methods and principles applied, can be used as stepping stones for interested academicians and action researchers to undertake other similar works.

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Appendices

Appendix 1: Partial view of the study area

Appendix 2: Guiding questions for key informant interviews

This guiding question is prepared to collect data related to Agricultural Drought in West Hararge Zone, of Ethiopia. The study will be conducted to full fill the requirements of a MSc degree in Remote Sensing and GIS at Addis Ababa University. As this research is entirely for academic purposes, you will not be asked for your names or any identifying information. All the information you provide is confidential and the researcher will guaranty your full anonymity. Most importantly open and honest answers are the most valuable as there are no wrong or right answers. If you have any queries about this research, please feel free to ask in any ways. I would like to thank you in advance for your voluntary participation in this study.

1. In which year/years did agricultural drought occur in your area between 2005- 2014 GC?
2. Which was/were the most devastating drought?
3. Which year /years was/were the wettest?
4. What was the severity level of the agricultural droughts that occurred during the 10 years?
   A, low
   B, Medium,
   C, high
5. Which parts of the Zone are more frequently affected by severe drought?
6. What was the level of yield reduction and its impact during the severe drought year/years?
7. How do you describe the characteristic of the local rainfall during the past 10 years, in terms of amount, spatial distribution as well as time of occurrence in relation to crop water requirement?
   A, Amount
   B, Distribution
   C, Time of occurrence
8. Was there any attempt to change the cropping system due to the consequence of climate change in general and agricultural drought in particular?
9. What types of mitigation options have been used so far?

The referents responsibility ________________ Date of reference ____________________

Appendix 3: Simple linear regression analysis between NDVI and Rainfall

A- Simple linear regression between Seasonal (June-September) rainfall and NDVI

Source	SS	df	MS
Model	.003518117	1	.003518117
Residual	.004149599	8	.0005187
Total	.007667716	9	.000851968

Number of obs =	10
F(1, 8) =	6.78
Prob > F =	0.0314
R-squared =	0.4588
Adj R-squared =	0.3912
Root MSE =	.02277

SeasonalNDVI	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SeasonalRainfall	.0003476	.0001335	2.60	0.031	.0000398	.0006555
_cons	.3810648	.0679557	5.61	0.001	.2243585	.537771

B- Simple linear regression between Zero dekad lag time rainfall and NDVI starts from May second dekad.

Equation of the model:

NDVI = 129.469187178916-0.186577635175184*RF

R-squared : 0.012

Analysis of variance:

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	20.024	20.024	0.099	0.761
Error	8	1621.476	202.684		
Corrected Total	9	1641.500			

Computed against model Y=Mean(Y)

C- Simple Linear regression between one dekad lag time rainfall and NDVI.

Equation of the model:

NDVI = 116.605635766566+0.58713426198464*RF

R-squared : 0.101

Analysis of variance:

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	166.482	166.482	0.903	0.370
Error	8	1475.019	184.377		
Corrected Total	9	1641.500			

Computed against model Y=Mean(Y)

D- Simple linear regression between two dekad lag time rainfall and NDVI.

Equation of the model:

NDVI = 13.419844079829+0.370632919338167*RF

R-squared : 0.249

Analysis of variance:

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	409.544	409.544	2.659	0.142
Error	8	1231.957	153.995		
Corrected Total	9	1641.500			

Computed against model Y=Mean(Y)

E- Simple linear regression between three dekad (one month) lag time rainfall and NDVI.

Equation of the model:

NDVI = 11.203981531064+0.495880602768435*RF

R-squared : 0.430

Analysis of variance:

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	636.889	636.889	6.038	0.039
Error	8	843.841	105.480		
Corrected Total	9	1480.730			

Computed against model Y=Mean(Y)

F- Simple linear regression between three four dekad lag time rainfall and NDVI.

Equation of the model:

NDVI = 20.323006297022+0.140028140470869*RF

R-squared : 0.147

Analysis of variance:

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	241.702	241.702	1.381	0.274
Error	8	1399.798	174.975		
Corrected Total	9	1641.500			

Computed against model Y=Mean(Y)

Appendix 4: Simple linear regression analysis between Grain yield anomaly and NDVI Anomaly

Source	SS	df	MS
Model	2119.25643	1	2119.25643
Residual	1486.37072	7	212.338674
Total	3605.62715	8	450.703393

Number of obs =	9
F(1, 7) =	9.98
Prob > F =	0.0159
R-squared =	0.5878
Adj R-squared =	0.5289
Root MSE =	14.572

Grain_Yiel~y	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
NDVI_Ano	3.171129	1.003776	3.16	0.016	.7975766	5.544682
_cons	-2.841579	4.858865	-0.58	0.577	-14.33097	8.647811

Appendix 5: Simple linear regression analysis between Grain yield Anomaly and SPI

Source	SS	df	MS
Model	1819.78744	1	1819.78744
Residual	1785.8397	7	255.119958
Total	3605.62715	8	450.703393

Number of obs =	9
F(1, 7) =	7.13
Prob > F =	0.0320
R-squared =	0.5047
Adj R-squared =	0.4340
Root MSE =	15.972

Grain_Yiel~y	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SPI	16.41984	6.147957	2.67	0.032	1.882232	30.95745
_cons	-4.625427	5.34961	-0.86	0.416	-17.27524	8.024389

Appendix 6: Simple linear regression analysis between Grain yield and WRSI

Source	SS	df	MS
Model	82.4312472	1	82.4312472
Residual	43.1757206	7	6.16796009
Total	125.606968	8	15.700871

Number of obs =	9
F(1, 7) =	13.36
Prob > F =	0.0081
R-squared =	0.6563
Adj R-squared =	0.6072
Root MSE =	2.4835

Yieldqtha	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
WRSI	.3123753	.0854479	3.66	0.008	.1103231	.5144276
_cons	-4.327175	6.17982	-0.70	0.506	-18.94013	10.28578

Appendix 7: Simple linear regression analysis between affected population and yield reduction

Source	SS	df	MS
Model	2.4720e+10	1	2.4720e+10
Residual	3.3583e+09	3	1.1194e+09
Total	2.8078e+10	4	7.0196e+09

Number of obs =	5
F(1, 3) =	22.08
Prob > F =	0.0182
R-squared =	0.8804
Adj R-squared =	0.8405
Root MSE =	33458

AffectecdPop	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
YieldReduction	7953.288	1692.462	4.70	0.018	2567.118	13339.46
_cons	-46510.99	52608.09	-0.88	0.442	-213933.4	120911.4

Appendix 8: Percentage area of yield reduction for the selected drought years

	Yield Reduction (%)	Wet Year 2007 GC.		Yield Reduction (%)	Wet Year 2012 GC.	
		Area Km²	Area %		Area Km²	Area %
Wet Year	0- 10	4708.371	27.8685	0- 10	1546.64	9.15
	11_ 20	4876.0311	28.8608	11_ 20	6542.71	38.73
	20-30	5465.3215	32.3488	21-30	4310.55	25.51
	30_40	1845.2529	10.9219	31_40	2618.08	15.5
	>50	0	0	41_58	1877	11.11

Appendix 9: Percentage area of yield reduction for the selected wet years

	Yield Reduction (%)	Drought Year 2005 GC.		Yield Reduction (%)	Drought Year 2009 GC.	
		Area Km²	Area %		Area Km²	Area %
Drought Year	0- 10	250.99407	1.48561	8_10	475.2	2.81
	11_ 20	4835.3561	28.6201	11_ 20	1288.7	7.63
	21-30	4182.5731	24.7563	21-30	3601.22	21.32
	31_40	2125.017	12.5778	31_40	3075.42	18.2
	41_71	5501.0361	32.5602	41_71	8454.43	50.04
	Total	16894.976	100		16894.98	100

DECLARATION

I hereby declare that the thesis entitled "Agricultural Drought Risk Area Assessment and Mapping using Remote Sensing and GIS: A case study of West Hararge Zone, Ethiopia" has been carried out by me under the supervision of Dr. Binyam Tesfaw, School of Earth Sciences, Addis Ababa University, Addis Ababa; during the year 2016/ 2017, as a part of Master of Science Program in Remote sensing and Geo-informatics. I further declare that this work has not been submitted to any other University or Institution for the award of any Degree or Diploma.

Wondwosan Negassa

(GSR/3205/08)

Place: Addis Ababa

Date: JUNE, 2017

C E R T I F I C A T E

This is to certify that the thesis entitled "Agricultural Drought Risk Area Assessment and Mapping using Remote Sensing and GIS: A case study of West Hararge Zone, Ethiopia" is an authenticated work, carried out by Wondwosan Negassa, under my guidance and supervision. This is the actual work done for the partial fulfillment of award for the Degree of Masters of Science in Remote Sensing and Geo-informatics from Addis Ababa University.

Dr. Binyam Tesfaw
Assistant Professor
School of Earth Sciences
Addis Ababa University

Signature ____________________

Date: ____________________