ADDIS ABABA UNIVERSITY

COLLEGE OF NATURAL SCIENCES

SCHOOL OF EARTH SCIENCE

REMOTE SENSING BASED AGRICULTURAL DROUGHT ASSESSMENT: A CASE STUDY IN SIRE WOREDA, ARSI, ETHIOPIA

Thesis submitted for Partial Fulfillment of the Requirements for the Award of the Degree of Master of Science

In

Remote Sensing and Geographical Information Systems (GIS)

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This is to certify that the thesis prepared by Muhammedsultan Ahmed, entitled*: Remote Sensing Based Agricultural Drought Assessment: A case study in Sire woreda*, *Arsi*, *Ethiopia* and submitted in partial fulfillment of the requirements for the degree of Master of Sciences (Remote Sensing and Geographic Information System) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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ABSTRACT

Drought is one of the major limiting environmental factors for agricultural crop production. Climate change and climate variability will result in agricultural droughts and associated soil water deficiency in turn, can lead to crop failure and ultimately threaten food security. Sire woreda is an Agricultural area where the agricultural sector is highly dependent on climate conditions. Erratic rains and erosion are problematic and wind erosion became a major problem in the area. It is affected by the drought and also suffers from high soil degradation, which has increased risks of desertification in year 2009. Consequently, this study was conducted in this woreda with the objective of assessing agricultural drought using remote sensing based indices. Drought Severity Index (DSI), Vegetation Condition Index (VCI) and Standard precipitation index (SPI) were used in this study to assess and examine spatio-temporal variation of seasonal agricultural drought patterns and severity. The results clearly indicate that the temporal and spatial characteristics of Sire woreda can be detected and mapped by the indices. Agricultural yield data was used to validate the strength of indices in explaining the impact of agricultural drought. The validation result shows that, NDVI based indices could be the best indices for assessing and monitoring the drought occurrences, preparing drought maps on a local level and for studying the spatial pattern of drought occurrences in the study area. The result revealed that DSI, VCI and SPI indices expresses 96, 85 and 51 percent of variability of the agricultural yield respectively. Thus, DSI is more sensitive towards the assessment of agricultural drought which affects the agricultural production. Resultant drought map obtained by integrating DSI, VCI and SPI indicates the area under study faces agricultural drought in different magnitude and areal coverage. It was evident from the study that, the lowland areas in north western parts of Sire woreda are more prone to severe agricultural drought while highland areas of southern parts faces slight agricultural drought. The research shows motivating results that can be used in early assessing agricultural drought in order to prepare for corrective measures taken timely to minimize the reduction in agricultural production in drought prone areas.

Key words : Agricultural drought, DSI, NDVI, Remote Sensing, SPI, VCI

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ACRONYMS

AVHRR	Advanced Very High Resolution Radiometer
DPPD	Disaster Preparedness and Prevention Desk
DSI	Drought Severity Index
ETM	Enhanced Thematic Mapper
FAO	Food and Agricultural Organization
GIS	Geographic Information System
LEAP	Livestock Environmental Assessment and Performance
NDVI	Normalized Difference Vegetation Index
SPI	Standard Precipitation Index
SPIRITS	Software for the Processing and Interpretation of Remotely Sensed Image Time Series
TCI	Temperature Condition Index
VCI	Vegetation Condition Index
VGT	Vegetation
VHI	Vegetation Health

CHAPTER ONE

1. INTRODUCTION

1.1 General Background

Drought is one of the major limiting environmental factors for agricultural crop production. It is a complex phenomenon that is difficult to accurately describe because its definition is both spatially variant and context dependent. Different definitions of drought have been proposed from time to time depending on the moisture needs for specific human activities and subject of interest (Choudhary et al., 2013). According to Hoyt (1936), there is a drought when annual rainfall is less than 85% of normal.

Drought occurs in almost all climatic regimes. It occurs in high as well as low rainfall areas. It is a temporary anomaly and as such it differs from aridity, which is a permanent feature of climate in low rainfall areas (Wilhite, 2000). Climate change and climate variability will result in agricultural droughts and associated soil water deficiency in turn, can lead to crop failure and ultimately threaten food security in the area. Agricultural drought occurs when the moisture supply of a region consistently falls below the climatically appropriate moisture supply such that crop production is adversely affected (Palmer, 1965 cited in Quiring and Papakryiakou, 2003).

When the actual rainfall in an area is significantly less than 25% or more than the climatological mean of that area we call it a meteorological drought. It leads to the hydrological drought with marked depletion of surface water causing very low stream flow and drying of lakes, rivers and reservoirs. This ultimately ends up with agricultural drought with inadequate soil moisture resulting in acute crop stress and fall in agricultural productivity (Chakraborty and Sehgal, 2010).

Even though drought occurs in many parts of the world, developing countries are highly susceptible to drought (Tinebeb Yohannes, 2012). The Greater Horn of Africa, like many parts of the tropics is prone to extreme climatic events such as droughts and floods (WMO, 2006). So far, Ethiopia is one of the most drought prone countries in Africa (Conway and Schipper, 2011). Previous droughts and the frequency of rainfall deviation from the average suggested that drought occur every 8-10 years for the whole country (Haile, 1988 cited in Elias Fekade, 2012).

According to the World Bank (2004) report, Ethiopia's agriculture is dependent on a highly erratic rainfall regime and vulnerable to frequent weather fluctuations and drought episodes that often lead to crop failure. Therefore, as agricultural drought occurs the condition of moisture fails to meet the needs of a particular crop at a particular time, such that the crop production or range productivity is significantly affected.

Agriculture production is closely linked to actual crop evapotranspiration, which is usually monitored by the water balance of the whole crop growing cycle. Therefore, a drought index, which closely describes temporal and spatial variations of crop water use status is suitable for monitoring drought. Satellite remotely sensed data offer considerable advantages and should be an integral part of drought monitoring, especially for the temporal and spatial evolution of drought (Khalil et al., 2013). One of the significant impacts of agricultural droughts is the dramatic fall in yield of almost every kind of crops. Weather-related abiotic factors play a major role in the amount of foods available to humanity each year all over the world, causing regular and sometimes sharp fluctuation of crop yields and prices (Yagci et al., 2011)

Sire woreda is an agricultural area where this sector is highly dependent on climate conditions. Erratic rains and erosion are problematic and wind erosion became a major problem according to the Disaster Preparedness and Prevention Desk (DPPD) at zonal level (Piguet, 2003). Sire woreda is affected by the drought and also suffers from high soil degradation, which has increased risks of desertification in year 2009.

Drought indices derived from satellite imagery are helpful for detecting, monitoring and assessing drought and its spatial information at a regional scale. Agricultural drought indices derived from satellite remote sensing have drawn many scientists' attention lately because of high spatial resolution, large spatial and frequent temporal coverage's and their ability to detect droughts timely and objectively (Kogan, 1995 cited in Yagci et al., 2011).

Different types of drought require different indicators. To monitor agricultural drought, the most suitable indicators are those that are responsive to soil moisture status. Due to this, among many indices Vegetation Condition Index (VCI), Drought Severity Index (DSI) and Standard Precipitation Index (SPI) are used for this study based on SPOT-VEGETATION data and TAMSAT rainfall data acquired in the past 10 years from 2004 to 2013 during the period between June to September.

The NDVI can be used to provide information for agriculture and vegetation health situation. This information is useful in determining water stress levels in vegetation and estimation of crop yield and is useful in drought assessment. It provides information of vegetation health that can be used as a means of monitoring changes in vegetation over time. The healthy vegetation absorbs most of the visible light that it receives and reflects a large proportion of the near infra-red light. Unhealthy or sparse vegetation reflects more visible light and less near infra-red (Abbasova, 2010). The NDVI is related to the photosynthetic activity of green vegetation and a high NDVI indicates a strong level of photosynthetic activity. Vegetation Condition Index (VCI) and Drought Severity Index (DSI) have been proposed using this index. In addition, standard precipitation index (SPI) is meteorological drought index used to quantify the impact of rainfall deficit on soil moisture on which it responds to precipitation anomalies on a relatively short scale (Gizachew Legesse and Suryabhagavan, 2014).

These four remote sensing based indices have been chosen since each has been reported to quantify agricultural drought. The performance of the four drought indices are evaluated using agricultural yield. These indices as proxies of drought and crop and/or vegetation health condition are vital in drought assessment and hence, they are applied in this study.

This research is designed to assess the spatial and temporal agricultural drought levels in Sire woreda using remotely sensed data to determine the agricultural drought severity levels based on precipitation and vegetation health.

1.2 Statement of the Problem

Due to climate change, agriculture is a vulnerable and sensitive sector that is seriously affected by the impact of drought. As one of the main constraints of the world's agricultural development, drought has raised great concerns. The most immediate consequence of agricultural drought is a fall in crop production, due to inadequate and poorly distributed rainfall. The overall effect of a fall in crop production is to reduce the capacity of the farming sector, leading to lower crop output in the subsequent farming season. Agriculture is highly dependent on climate conditions in the study area.

Due to a long-term crop production decrease and the failure of summer rain 2002 (Piguet, 2003), all the woreda kebeles faced seed problems in this year. According to the Disaster Preparedness and Prevention Desk (DPPD) at zonal level, the relief situation for Sire woreda in the year 2003 among 85,724 total affected populations 59,665 were beneficiaries due to 2002 agricultural drought prevails in the area. In those times, the number of farmers had been decreasing due to bad weather and soil conditions. Sire woreda is affected by the drought and also suffers from high soil degradation, which has increased risks of desertification. Erratic rains and erosion are problematic and wind erosion became a major problem.

In order to adapt and/or mitigate the impact of agricultural drought, the near real time assessment through effective monitoring using satellite data plays a significant role in mitigating its adverse impacts.

In Ethiopia, drought assessment and monitoring efforts have been based on conventional methods that rely on the availability of meteorological data, which is very tedious and time consuming to collect. Consequently, millions of lives may be lost before the actual information is submitted to the appropriate decisions makers (Kandji and Verchot, 2006 cited in Getachew Berhan et al., 2011).

In the woreda, the conventional agricultural drought monitoring and early warning system is based on ground data collection and analysis so as to identify drought-prone areas. This assessment is intensive to cover all agricultural drought suspected areas and to identify the actual drought affected areas. The post-harvest assessment compiled mostly by the woreda agricultural experts. The regional and zonal level experts try to crosscheck the report collected by the woreda experts at field. But there is no statistical method of the area selection for the cross checking. Having seen the post-harvest assessment and other early warning reports, the relevant body decides the areas with food deficit and the number of beneficiaries at woreda level which causes misuse of resources. In addition to this, conventional methods of agricultural drought assessment and monitoring rely on ground based meteorological rainfall data, which are limited in the regional level, often inaccessible and most importantly tedious to obtain.

In general, drought assessment and monitoring using conventional methods which rely on the availability of weather data are tedious and time consuming). Satellite sensor data are consistently available, cost effective and can be used to detect the onset of drought, its duration and magnitude (Beyene Ergogo, 2007). The summer season (June-September) is selected to evaluate the performance and distribution (spatial and temporal) of agricultural drought and its impact on crop production.

The initiation of this study is to provide a more comprehensive assessment of agricultural drought conditions by combining various drought indices which can be useful for the decision making process on drought monitoring and to avert its consequences on agricultural production and productivity.

1.3 Objectives

1.3.1 General Objective

The main objective of the study was to develop remote sensing based local level agricultural drought assessment approach.

1.3.1 Specific Objectives

- ❖ To identify major attributes for characterizing agricultural drought using remote sensing approach
- ❖ To assess agricultural drought based on identified attributes with remote sensing approach

- To evaluate the developed remote sensing agricultural drought assessing approach using yield data

1.4 Significance of the Study

Drought cause misery to both human and livestock population by accelerating degradation of natural resources. There are strong link between poverty and proneness of an area to drought. Widespread crop failures lead to acute shortage of food which results in starvation and death. This study, therefore, evaluates the ability of the remote sensing based indices to assess and quantify agricultural drought.

Remote sensing and GIS have been applied to identify agricultural drought spatially and temporally, which can be useful in the decision making process for drought monitoring and mitigation actions. This study is expected to assess agricultural drought based on remote sensing indices which can be useful for Governmental and Non- Governmental organizations in the decision making process for drought monitoring and identifying appropriate site for specific adaptation and mitigation actions.

Further, the outcome of the study is essential for decision making process on agricultural drought monitoring and to avert its consequences on agricultural production and productivity.

1.5 Limitation of the Study

The limitation of the study was lack of data on crop yield at the kebele level that helps to see inter-kebele yield variability and unavailability of data prior 2007 year since the woreda was established independently in 2007. Price of high resolution satellite data is the major constraint of this study. Due to cost of high resolution image this study was based on low resolution images.

1.6 Scope of the study

This study is limited to Sire Woreda in Arsi Zone, Oromia Regional State of Federal Democratic Republic of Ethiopia. It covers a total area of about 474.2 Km^2 and divided into 14 kebeles. The study is concentrated on the assessment of agricultural drought by using remote sensing. The SPOT Vegetation data with a spatial resolution of 1 km and TAMSAT rainfall data with a spatial resolution of 4 km has been used for the analysis of satellite based remote sensing indices. Moreover, this research also employed the Drought Severity Index (DSI), Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI) to assess and evaluate the agricultural drought level of the study area. The analysis is performed during rainy season (June - September) to evaluate the performance and distribution (spatial and temporal) of agricultural drought and its impact on crop production.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 The Concept of Drought

Drought is a recurring phenomenon and it is the most complex of all natural hazards. It occurs almost everywhere, although its features vary from region to region. Defining drought is difficult as it depends on differences in regions, needs and disciplinary perspectives. In the most general sense, drought originates from a deficiency of precipitation over an extended period of time, resulting in a water shortage for some activity, group or environmental sector (Wilhite and Knutson, 1998). Drought can also be thought of as an extended imbalance between precipitation and evaporation (EPA, 2013). Whatever the definition, it is clear that drought cannot be viewed solely as a physical phenomenon.

In general, there are two main definitions of drought: conceptual and operational. Conceptual definitions help people to understand the concept of drought. Also it is important in establishing drought policy.an operational definitions of drought helps people to identify the beginning, end and degree of severity of a drought. It is usually made by comparing the current situation to the historical average, often based on a 30 year period of record. Operational definitions can also be used to analyze drought frequency, severity and duration for a given historical period. Operational definitions are formulated in terms of drought indices (Beyene Ergogo, 2007).

Drought can be generally defined as a temporary meteorological event, which stems from a deficiency of precipitation over an extended period of time compared to some long-term average conditions. Drought always starts with a shortage of precipitation compared to normal or average amounts and affect streams, soil moisture, groundwater, etc. It is a recurring natural event occurs all over the world regardless of how arid or humid they are. Droughts develop slowly and difficult to detect in any single region. It is one of the most complex natural phenomena, that is hard to quantify, manage and has multiple and severe social and economic impacts (IWMI, 2009).

2.2 Types of Drought

Drought is a normal feature of climate which happens in all climate zones from time to time. It is generally defined as a persistent and abnormal moisture deficiency that impacts vegetation, animals and people. WMO (2006), categorized their collection of definitions into four basic approaches to measuring drought: meteorological (climatic), hydrological, agricultural and socioeconomic. The first three approaches deal with ways to measure drought as a physical phenomenon. The last deals with drought in terms of supply and demand of an economic good.

2.2.1 Meteorological Drought

Meteorological drought is defined as the degree of dryness, which is often compared with the normal or average dry period for very long time (Elias Fekade, 2012). It indicates lower precipitation than normal over a period of time. A lack of precipitation is the most common definition of drought. Most locations around the world have their own meteorological definition of drought based on the climate normal in the area. A normally rainy area that gets less rain than usual can be considered as a drought. It should be defined according to specific atmospheric condition over a region. The atmospheric conditions that result in deficient must be expressed solely on the basis of the degree of dryness and the duration of the dry period (Agnew and Chappell, 2000).

2.2.2 Agricultural Drought

Agricultural drought is type of drought generally refers to a period with declining soil moisture that could affect crop production or other utilization of the water resource (Wu and Wilhite, 2004). Agriculture is usually the first sector to be affected by drought because soil moisture supplies are often quickly depleted for plant growth. It is linked to various characteristics of meteorological drought to agricultural impacts focusing on precipitation shortages, differences between actual and potential evapotranspiration and soil water deficits (Agnew and Chappell, 2000).

Agricultural drought which reflects root-zone soil moisture deficits and impacts on crop yields happens after meteorological drought but before hydrological drought. It is usually expressed in terms of the soil moisture needed by a particular crop at a particular time.

When soil moisture becomes a problem, the agricultural industry is in trouble with drought. Shortages in precipitation, changes in evapo-transpiration and reduced ground water levels can create stress and problems for crops.

2.2.3 Hydrological Drought

Hydrological drought refers to deficiencies in surface and subsurface water supplies. It is measured as stream flow, lake, reservoir and ground water levels. There is a time lag between lack of rain and less water in streams, rivers, lakes and reservoirs, so hydrological measurements are not the earliest indicators of drought. When precipitation is reduced or deficient over an extended period of time, this shortage will be reflected in declining surface and subsurface water levels. It is related to a period of inadequate water availability for the use of a given resource management system (Mishra and Singh, 2011).

During Hydrological Droughts many watersheds experience depleted amounts of available water. Lack of water in river systems and reservoirs can impact hydroelectric power companies, farmers, wildlife and communities in general (Elias Fekade, 2012).

2.2.4 Socio-economic Drought

Socioeconomic drought happens when physical water shortage starts to affect people, individually and collectively. Most socioeconomic definitions of drought associate it with the supply and demand of an economic good. It occurs when the demand for economic goods exceeds supply as a result of meteorological, agricultural or hydrological drought.

Socioeconomic definitions of drought associate the supply and demand of some economic good with elements of meteorological, hydrological and agricultural drought (Gizachew Legesse & Suryabhagavan, 2014). It differs from the other types of drought in that its occurrence depends on the processes of supply and demand. The supply of many economic goods such as water, 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.

Meteorological drought is the first phase of drought. It usually leads to agricultural drought due to lack of soil water. If precipitation deficiencies continue, hydrological drought develops. The groundwater is usually the last to be affected and the last to return to normal levels.

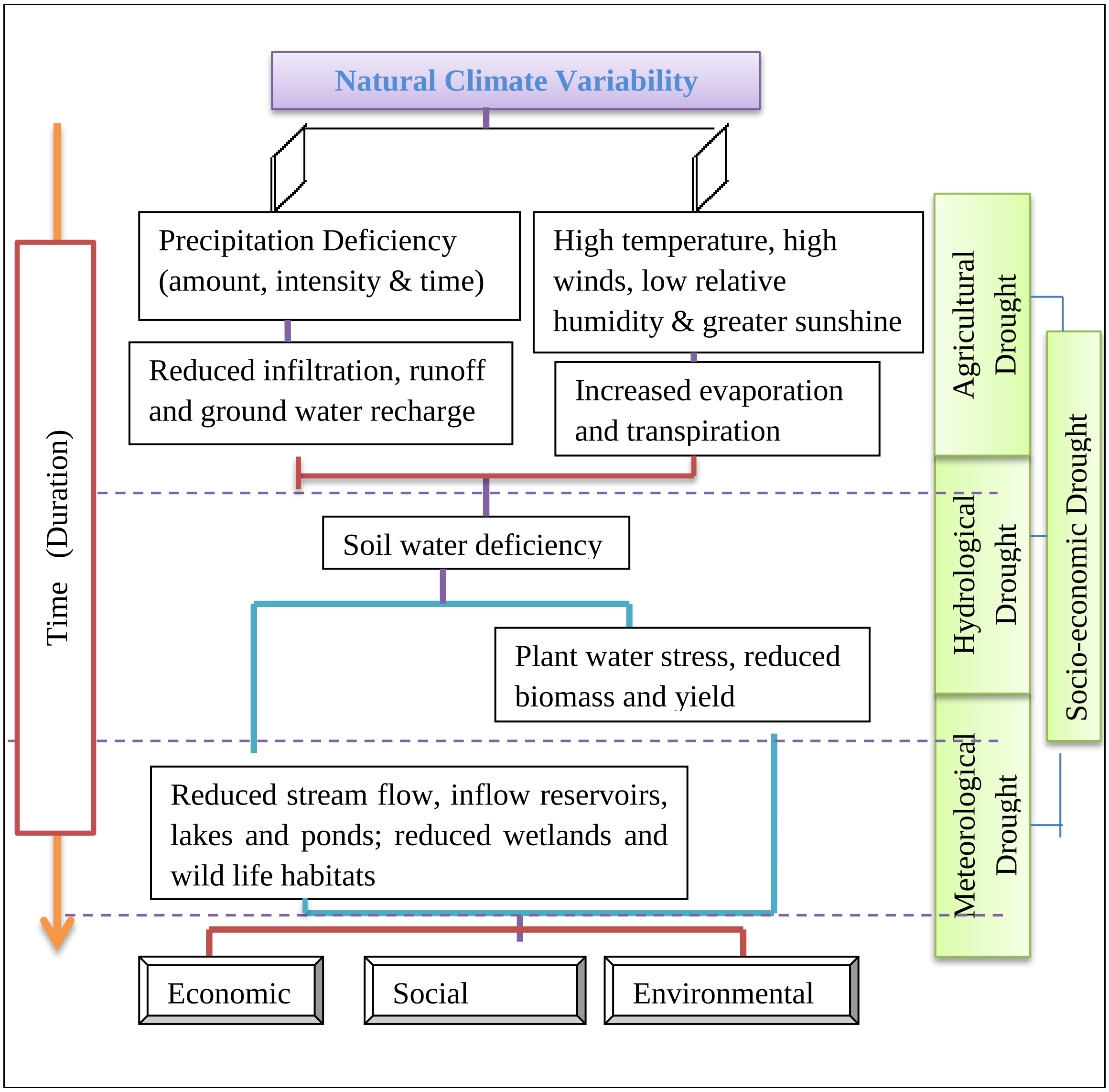


Figure 1. Relationship between different types of drought

(Source: National Drought Mitigation Center)

2.3 Drought in Ethiopia

Agriculture is an important sector of the Ethiopian economy. In addition to providing us with much of our food, the crops and livestock that are grown, raised and caught it contributes billion dollars to the economy each year.

Ethiopia has seen at least five major droughts since 1980 accompanied by an abundance of local droughts. Global warming is a significant reason as to why these droughts are becoming more frequent and prolonged. The effects of drought on the country of Ethiopia are becoming increasingly worse with time, especially due to the fact of how dependent the country is on rainfall. The lack of expected rainfall has also lead to water and pasture shortage within the country, which is absolutely one of the biggest problems (Hendrix, 2012).

In the 1970's and 80's most of the northern and eastern regions of the Ethiopia experienced drought, which affected up to 15 % of the total population. The impact of drought increased from the 1990's, affecting a wider geographical area and up to 20 percent of the population. In 2003, for example over 13 million people were affected by drought. In terms of geographic coverage, drought induced disasters expanded to southern and central parts of the country over recent years (ECB, 2011).

According to World Bank (2004) report, Ethiopia's agriculture is dependent on a highly erratic rainfall regime and vulnerable to frequent weather fluctuations and drought episodes that often lead to failure. Therefore, as agricultural drought occurs the condition of moisture fails to meet the needs of a particular crop at a particular time, such that the crop production or range productivity is significantly affected.

According to OXFAM (2011/12) reports, in 2011 two consecutive seasonal rains failed in Ethiopia. The result was severe drought affecting the southern, eastern and north-eastern parts of the country (Somali, Afar, East and Southern Tigray, Southern Oromia and SNNPR). By July 2011, the Ethiopian government estimated that an acute livelihood due to food security crisis was affecting 4.5 million people (an increase of 40% since its estimate in April that year). The most severely affected regions were Oromia (1.8 million people affected) and Somali region (1.4 million).

Due to greater reliance on climate sensitive sectors such as agriculture, Ethiopia is vulnerable to the risk of climate variability and change such as drought. The agriculture sector plays a central role in the life and livelihood of most Ethiopians, where about 12 million smallholder farming households account for an estimated 95% of agricultural production and 85 percent of all employment (FAO, 2011). According to their report, in the last 20 years, Ethiopia has experienced recurring droughts followed by food shortages and famines .

2.4 Aspects of Remote Sensing in Agricultural Drought Assessment and Monitoring

The growing number and effectiveness of Earth observation satellite systems, along with the increasing reliability of remote sensing methodologies and techniques present a wide range of new capabilities in monitoring and assessing droughts (Dalezios et al., 2012). Many remote sensing applications are devoted to the agricultural sector. The use of remote sensing is necessary, as the monitoring of agricultural activities faces special problems not common to other economic sectors.

In recent days the remote sensing techniques are established well enough for agricultural drought assessment. There are a variety of remotely sensed data acquired from the space by the sensors like MODIS, SPOT, ASTER, ETM+ ,etc. which serves as input for the various methods throughout the electromagnetic spectrum which are capable for the identification and monitoring of the Agricultural drought (Padhee, 2013).

Remote sensing can significantly contribute to providing a timely and accurate picture of the agricultural sector, as it is very suitable for gathering information over large areas with high revisit frequency. In more recent development incorporation of climate, aridity, crop, soil, precipitation and other ground-based information with remotely sensed analysis into hybrid indices have provided a more comprehensive and meaningful way to achieve accurate monitoring (United Nations, 2010).

Moreover, in order to assess and monitor the drought phenomenon and to alleviate the impacts of droughts, it is necessary to detect several drought features such as severity, duration, periodicity, areal extent, on set and end time and to link drought variability to climate (Piechota and Dracup, 1996 cited in Dalezios et al., 2012).

Conventional methods of drought assessment and monitoring rely on rainfall data, which are limited in the regional level, often inaccurate and most importantly difficult to obtain in near-real time (Thenkabail et al., 2004). In contrast, the satellite-sensor data are consistently available and can be used to detect the onset of drought, its duration and magnitude. Compared to the traditional data collection methods the capability of remote sensing techniques of providing timely information over a large spatial extent at a wide range of spatial, temporal and spectral resolutions is appreciated by numerous users in different application fields (Ren et al., 2012)

According to the available literature during last decades several indices has been used to assess agricultural drought using different parameters . The Drought Severity Index (DSI), Vegetation Condition Index (VCI), Standardized Precipitation Index (SPI), Normalized Difference Vegetation Index (NDVI) has been extensively used for agricultural drought monitoring.

Over the years, to our knowledge the majority of drought indices studies have focused on evaluating them for specific regions or the use of a single well-developed drought index to characterize and predict droughts over specific regions (Quiring and Papakyriakou, 2003).

However, because each index provides a somewhat different measure of drought use of a particular specific index has often been demonstrated to be inadequate for completely representing this complex phenomenon (Heim, 2002). A combination of various drought indices may provide a more comprehensive assessment of drought conditions than a single-index approach, but this has been challenging because there has been a lack of systematic methods for their combination, use and evaluation (Steinemann and Cavalcanti, 2006).

2.5 Major Attributes Characterizing Agricultural Drought

The correct agricultural drought characterization provides decision makers with a measurement of abnormal weather variability, so that protection from possible impacts may be implemented. Drought is a three-dimensional phenomenon that can be characterized by its severity or intensity, duration and geographic extent. Drought characterization is complex and there are a wide range of satellite based indices or indicators that can be used. It requires an accurate selection of drought identification methods and/or of drought indices, able to describe in a synthetic and clear manner the evolution of drought conditions in space and time. Each one has its own merit and they are often supportive of each other. A combination of indices and indicators is usually the preferred option. Drought indices can be used to describe all types of droughts (that is meteorological, hydrological, agricultural and socioeconomic drought).

Drought indices are normally continuous functions of rain fall and/or temperature, river discharge or other measurable variable (IWMI, 2004). There are a number of climate based drought indices and vegetation indices used to assess, forecast and to monitor agricultural drought. A drought index provides a comprehensive picture for drought analysis and decision making that is more readily useable compared with raw data from indicators.

Nevertheless, no single indicator or index alone may precisely describe the onset and severity of the event. In this regard, effective early-warning systems for agricultural drought should be based on multiple indicators to fully describe events magnitude and severity.

In general, meteorological and satellite based indices are among the major attributes that are used to signalize agricultural drought using remote sensing data.

2.5.1 Meteorological Drought Indices

Some widely used and advanced meteorological drought indices are Rainfall Anomaly Index, Palmer Drought Severity Index, Bhalme and Mooley Drought Index, Standardized Precipitation Index, Effective Drought Index and Reconnaissance Drought Index (Padhee, 2013).

2.5.1.1 Standardized Precipitation Index

Along the various indices for meteorological drought monitoring, SPI were widely accepted and used for its simplicity. SPI was developed in colorado by Mckee et al.

(1993), to assign a single numeric value to the precipitation that can be compared across regions with markedly different climates.

The SPI was designed to quantify the precipitation deficit for multiple time scales. These time scales reflect the impact of drought on the availability of the different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale. Groundwater, stream flow and reservoir storage reflect the longer-term precipitation anomalies. McKee et al. (1993) originally calculated the SPI for 3, 6, 12, 24 and 48 month time scales to assess anomalous and extreme precipitation.

The SPI calculation for any location is based on the long-term precipitation record for a desired period. This long-term record is fitted to a probability distribution, which is then transformed into a normal distribution so that the mean SPI for the location and desired period is zero (Edwards and McKee, 1997).

The SPI is computed by dividing the difference between the normalized seasonal precipitation and its long-term seasonal mean by the standard deviation.

The SPI is calculated using the following formula, written as;

$$\mathbf{SPI} = \left(\frac{\mathbf{X_{ij} - X_{im}}}{\boldsymbol{\sigma}}\right) \text{--Equation 1}$$

where X_{ij} is the seasonal precipitation at the i^{th} rain-gauge station and j^{th} observation, X_{im} is its long-term seasonal mean and σ is its standard deviation (Alam et al., 2013).

Mathematically, the SPI is based on the cumulative probability of a given rainfall event occurring at a station. Positive SPI values indicate greater than mean precipitation and negative values indicate less than mean precipitation (IWMI, 2004). A drought event starts when SPI value reaches -1 and ends when SPI becomes positive. The positive sum of the SPI for all the months within a drought event is referred to as drought magnitude.

2.5.2 Drought Indices Derived from Satellite data

Satellite based indices offer significant advantages over traditional station-based indices because satellite based indices provide a consistent spatial coverage and higher spatial resolution. Satellites provide regional coverage over wide scales and are thus able to capture the spatial variability of the phenomenon under observation providing information on a real time basis.

The various remotely sensed data serves as input for the various methods, which are used for the identification, monitoring and assessment of agricultural drought. It is facilitated by several satellite based indices like NDVI, VCI, DSI, TCI, VHI, etc. in Visible, Near Infrared, Thermal Infrared and Microwave regions to target and analyze the concerned areas. Among the most widely used satellite based vegetation indices NDVI, DSI and VCI are described in the following sections.

2.5.2.1 Normalized Difference Vegetation Index (NDVI)

Among satellite based drought indices, the NDVI is one of the most popular and globally accepted remote sensing indices for Agricultural drought assessment. In the early 1980s, scientists at NASA's Goddard Space Flight Center, Greenbelt and Md developed the Normalized Difference Vegetation Index (NDVI) an innovative combination of two satellite measurements that allowed them to analyze changes in the greenness of Earth as viewed from space.

Thus, NDVI was one of the most successful of many attempts to simply and quickly identify vegetated areas and their condition and it remains the most well-known and used index to detect live green plant canopies in multispectral remote sensing data. Tucker first suggested NDVI in 1979 as an index of vegetation health and density (Thenkabail et al., 2004).

Generally, healthy vegetation will absorb most of the visible light that falls on it and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. Bare soils on the other hand reflect moderately in both the red and infrared portion of the electromagnetic spectrum.

The NDVI is calculated from reflectance measurements in the red and near infrared (NIR) portion of the spectrum:

$$\mathbf{NDVI} = \left(\frac{\mathbf{R_{NIR}} - \mathbf{R_{Red}}}{\mathbf{R_{NIR}} + \mathbf{R_{Red}}}\right) \quad \text{-- Equation 2}$$

where R_{NIR} is the reflectance of NIR radiation and R_{Red} is the reflectance of visible red radiation (Chopra, 2006).

Calculations of NDVI for a given pixel always result in a number that ranges from minus one (-1) to plus one (+1) with values 0.5 indicating dense vegetation and values < 0 indicating no vegetation. However, no green leaves give a value close to zero. A zero means no vegetation and close to +1 indicates the highest possible density of green leaves. Water typically has an NDVI value less than 0, bare soils between 0 and 0.1.

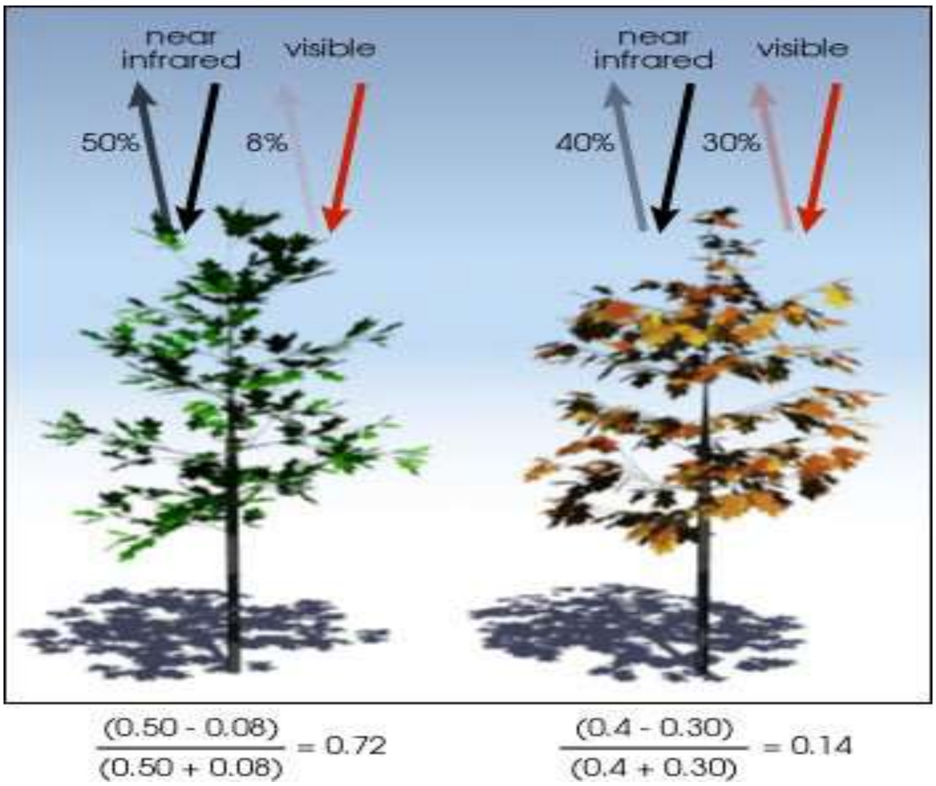


Figure 2. NDVI physical meaning

(Source: http://earthobservatory.nasa.gov)

Vegetation emits and absorbs radiation at different wavelengths. The pigment in plant leaves known as chlorophyll strongly absorbs visible light (0.4 - 0.7 μm) for use in photosynthesis and reflects near-infrared light (0.7 – 1.1 μm). Depending on the amount of the leaves of the plant, the ratio of visible light absorbed or reflected is different.

2.5.2.2 Drought Severity Index (DSI)

NDVI by itself does not reflect drought or non-drought conditions (Beyene Ergogo, 2007). Thus, the severity of a drought or the extent of wetness can be expressed by Drought Severity Index (DEV_{NDVI}). This index is defined as a measure of the deviation of the current NDVI values from their long term mean.

The formula of DSI (DEV_{NDVI}) is :

$DSI = NDVI_{i} - NDVI_{mean,n}$ -- Equation 3

where $NDVI_{i}$ is the NDVI value for month i in i^{th} year and $NDVI_{mean,n}$ is the long term mean NDVI for the month n. (IWMI, 2004)

When DEVNDVI is negative, it indicates the below-normal vegetation condition/health and, therefore, suggests a prevailing drought situation. The greater the negative departure the greater the magnitude of a drought. In general, the departure from the long-term mean NDVI is effectively more than just a drought indicator, as it would reflect the conditions of healthy vegetation in normal and wet months/years (Thenkabail et al, 2004).

2.5.2.3 Vegetation Condition Index (VCI)

The Vegetation Condition Index (VCI), a pixel-wise normalization of NDVI was developed over some time periods to make a relative assessment of changes in the NDVI signal by filtering out the contribution of local geographic resources to the spatial variability of NDVI.

It was first developed from AVHRR NDVI from Goddard Earth Sciences Distributed Active Archive Center (GES-DAAC), for the control of local differences in ecosystem productivity. The Vegetation Condition Index (Kogan, 1990) is a remote sensing index which is derived from the NDVI.

The Equation for the VCI is:

$$\left(\frac{\mathbf{NDVI_i - NDVI_{min}}}{\mathbf{NDVI_{max} - NDVI_{min}}}\right)$$ -- Equation 4

where $NDVI_i$ is the smoothed 10-day NDVI, $NDVI_{max}$ is the absolute maximum NDVI and $NDVI_{min}$ is the minimum NDVI.

Even though NDVI has been shown as an effective indicator of vegetation response, it cannot take into account differences due to the productivity of the local ecosystem in order to determine vegetation health. For example, low NDVI values are expected in arid regions, while tropical rainforests show high NDVI values, even in relatively dry seasons. These NDVI differences represent the difference in local ecosystem resources and not the weather. This defect is addressed by the VCI. The VCI is an indicator of the relative healthiness of the vegetation in response to weather with respect to the ecologically defined minimum and maximum limits. The VCI was demonstrated to be an accurate assessor of unfavorable vegetation conditions particularly related to drought (Ganesh, 2007).

Situation of vegetation cover by VCI, is measured as the percentage. When VCI is below 50 % represents a very dry month and when it closes to its maximum value, drought situation improved. The VCI values low for successive time intervals are pointing to increasing droughts (Thenkabail et al., 2004).

CHAPTER THREE

3. DESCRIPTION OF THE STUDY AREA

3.1 Location

Sire woreda is one of the administrative units of Arsi Zone, Oromia Regional State of Federal Democratic Republic of Ethiopia. From the relative location point of view, it is found in the central part of Ethiopia. Geographically, the woreda is located between 7° 49'35" N – 8° 12'14" N latitude and 39° 20'14" E – 39° 33'14" E longitude covering a total area of 474.2 Km^2 (Figure 3). It shares boundary with East Shewa zone to the north, Jaju woreda to the east and south east, Diksis woreda to the south, Lode Hetosa woreda to the south west and Dodota woreda to the West.

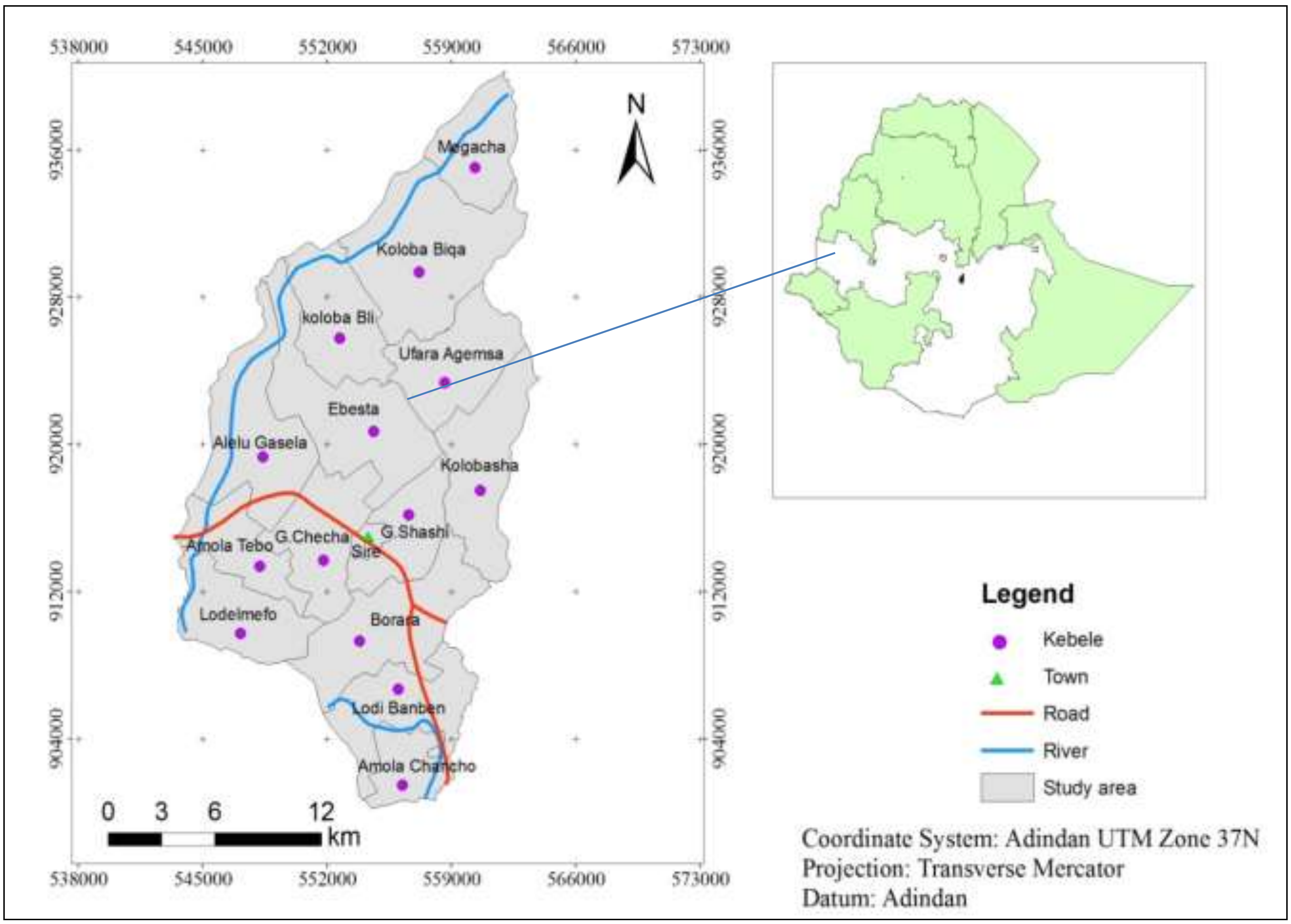


Figure 3. Location map of the Study area

3.2 Climate

Due to its altitudinal location the climatic condition of the woreda is dominantly characterized by moderately cool temperature condition which ranges between $15^{o}C$ - $20^{o}C$. The remaining type are cool and moderately warm having temperature ranges $10\,^{o}C$ - $15\,^{o}C$ and $20\,^{o}C$ - $25\,^{o}C$ respectively. The annual rainfall of the area ranges from 800mm-1200mm and the average rainy days are 115 days in the year (OBoFED, 2007)). The rainfall pattern is bimodal, which are short rainy season (Belg season) from February to May and summer long rainy season (Meher season) from June to September.

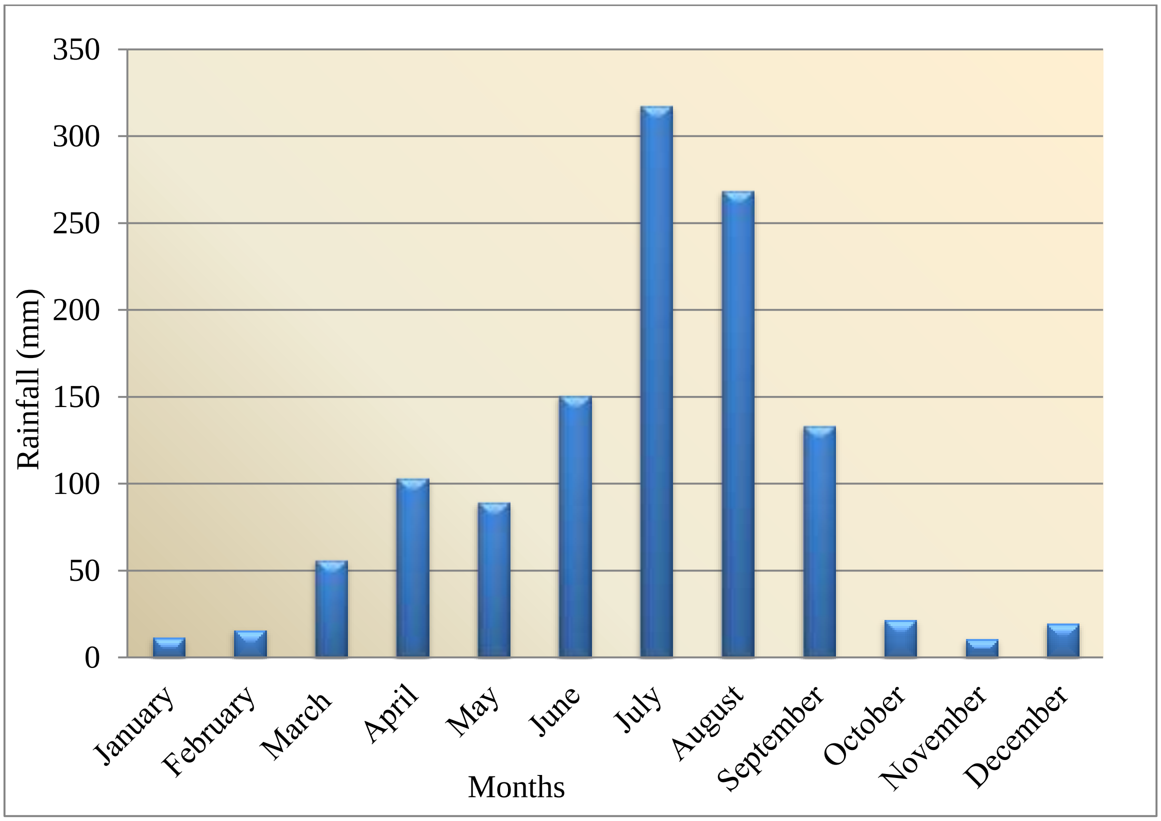


Figure 4. Satellite based long term monthly rainfall of Sire Woreda (2004 - 2013)

Source : (http://www.met.reading.ac.tamsat)

3.3 Topography and Drainage

The relief of Sire woreda is characterized by undulating plain of low land, hill and high plateau with an altitude ranges from less than 1300 to 2600 Meters. Its elevation decreases from south east to west and northwest (to the Rift Valley). All parts of the district are found within Awash basin. Hawas, Keleta and Agemsa river are the major perennial rivers of the woreda. These rivers are being utilized for modern and traditional irrigation (OBoFED, 2007).

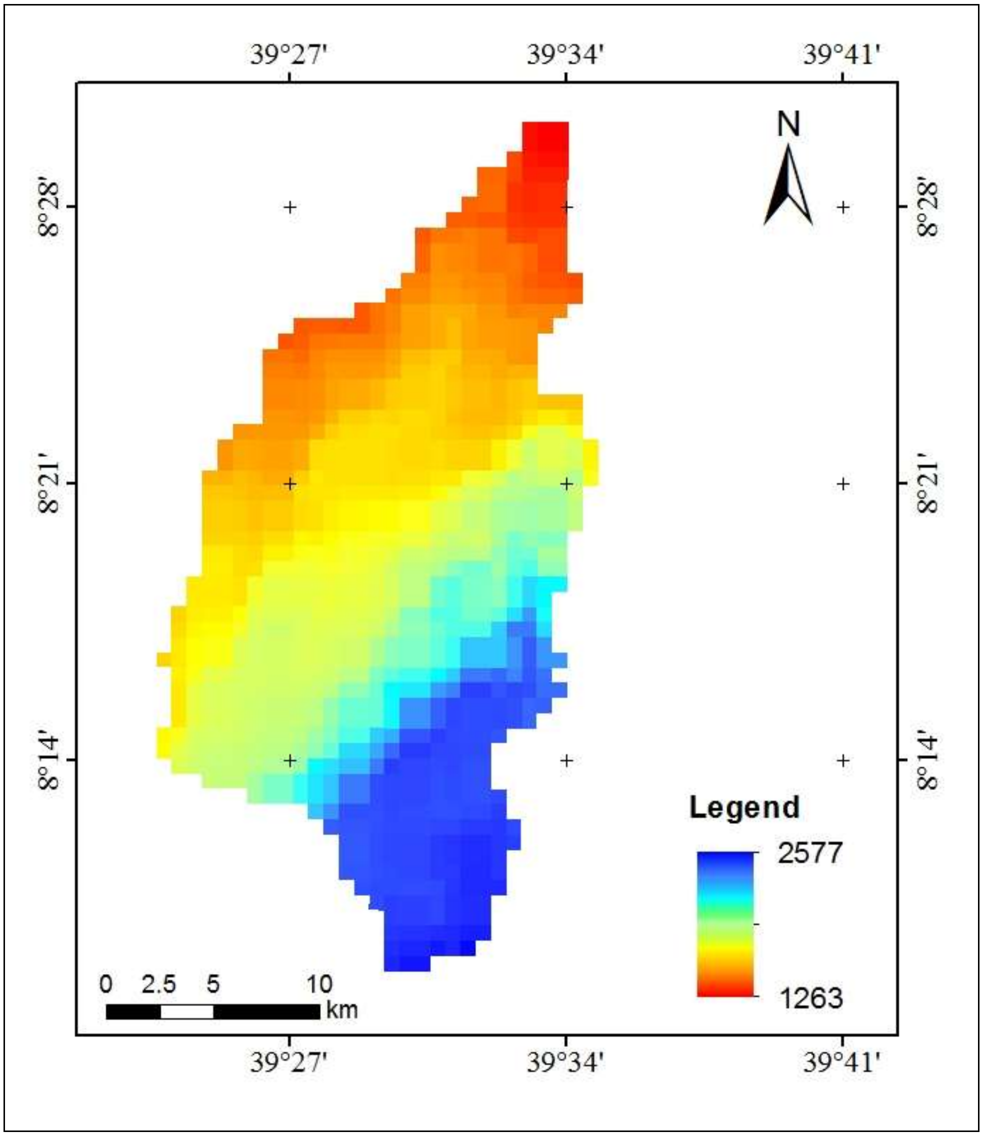


Figure 5. Elevation map of Sire woreda

Source : adopted from DEM

3.4 Soil and Vegetation

Eutric cambisols, pellic vertisols, Dystric Nitosols, Lithosols, Eutric Fluvisols etc are among the soil types present in the Sire woreda (OBoFED, 2007) Their fertility status is very good. However, rapid erosion due to high rate of deforestation is one of the major problems of the district. Regarding vegetation types found in the area different species of Acacia tree are the dominant. In addition to community forest different broad leaf and gallery forests are found in some pocket areas of the woreda.

3.5 Land-use / Land-cover

As far as agricultural activity is concerned, land use pattern is an important factor that influences agricultural production and productivity. The land-use and/or land-cover pattern of the study area includes water body, shrub land, bare land, forest, settlement and farmland, among which the rain fed farm has large area coverage.

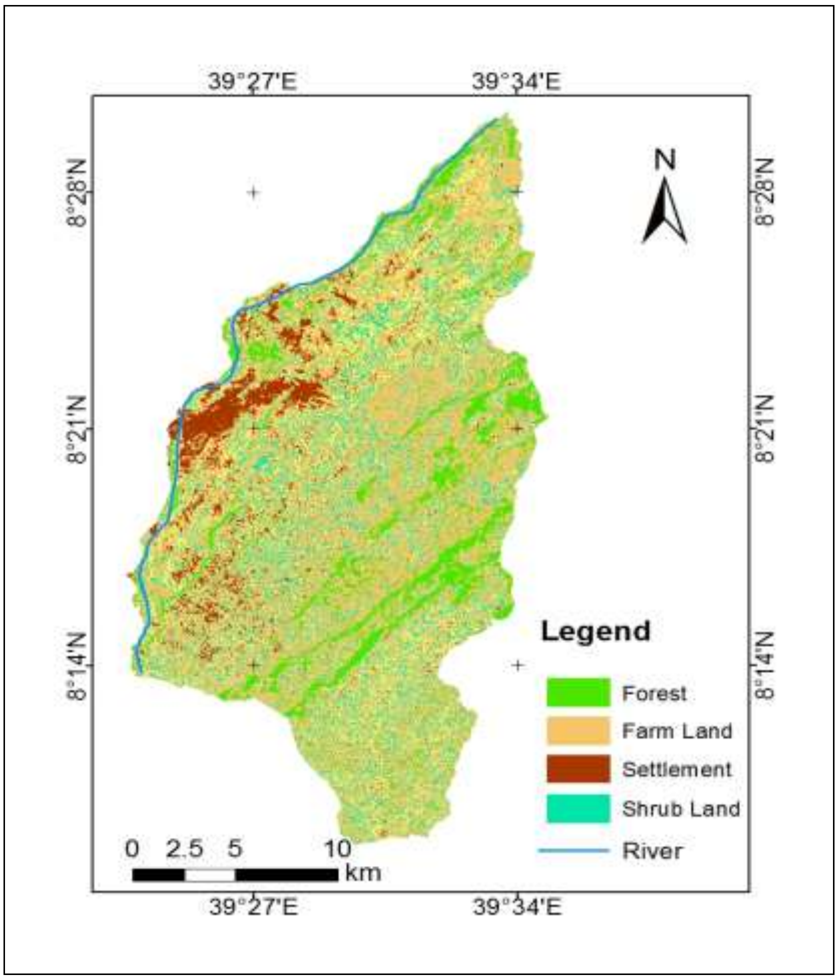


Figure 6. Land use/land cover map of the study area

Source : Land sat downloaded from (http://earthexplorer.usgs.gov/)

CHAPTER FOUR

4. MATERIALS AND METHODS

4.1 Data and acquisition methods

In this research different datasets were used. The overall descriptions of datasets summarized in Table 1 as below.

Table 1. Datasets used for this research

Data sets	Variable	Description	Resolution	
			Spatial	Temporal
Agricultural	Yield	Ground data	Quintal/hectare	Year
TAMSAT	Rainfall	Satellite	4 km	Decadal
Landsat	Land cover	Satellite	30 m	Daily
Meteorological data	Rainfall	Ground station	Point	Point
SPOT vegetation	NDVI	Satellite	1 Km	Decadal

4.1.1 Agricultural yield data

The Characteristics of satellite derived indices must be validated by ground truth data. The ground data intended to be used mainly in this study is agricultural production yield. As agricultural yields are sensitive to weather fluctuations, they reduce abruptly during severe drought periods. Therefore, average yield of grain crops for country's administrative regions can be used for validation of satellite derived drought indices.

The agricultural yield production statistics has been taken for period of 2007-2012 from Oromia Regional State, Finance and Economic Development Bureau. Linear regression has been used to check the relationship between yield data and the existing drought condition assessed through satellite based indices. The total production yield and cultivated land over the main cropping season are depicted in Table 2.

Table 2. Agricultural yield data of Sire woreda

Yield	Cultivated land (ha.)	Production(Quintal)
2007	30222.25	573037.5
2008	28623.00	714977.6
2009	26631.50	256051.3
2010	25921.45	535228.5
2011	92317.00	472098.0
2012	32290.00	883476.3

Source : Oromia Finance and Economic Development Bureau (2007)

4.1.2 Meteorological data acquisition

Meteorological data pertaining to monthly rainfall has been collected for a period of 31 years ranging from 1983 - 2013. The data has been collected from National Meteorology Agency and downloaded from University of Reading Page (http://www.met.reading.ac.tamsat).

4.1.3 Remotely Sensed Data

4.1.3.1 SPOT Vegetation data

The SPOT vegetation synthesis 10 day archive is freely accessible through the website of vegetation programme directly via the free S10 distribution server: http://free.vgt.vito.be/. This data set is comprised of VEGETATION data from the SPOT 4 platform. The VGT-S10 (ten day synthesis) products are composited (maximum-value) products. These products provide data from all spectral bands, the NDVI and auxiliary image acquisition parameter data . SPOT 4 launched in March 1998 while the SPOT 5 platform launched in May 2002. Daily (S1) and ten-day (S10) syntheses are mosaics of acquired image segments, respectively for 24h periods and for the last 10 days. Vegetation indices (NDVI) calculated from daily or ten-day syntheses.

For this study decadal NDVI product were downloaded for Ethiopia from 01/05/2004 to 21/09/2013 and Sire woreda NDVI values are extracted out. The ten day composite per month in this data set is computed from the first of the month to the 10^{th}, from the 11^{th} to the 20^{th} and from 21^{st} to the end of the month. The image projection is Albers Equal Area Conic.

Maximum-value composite (MVC) synthesis is delivered with spatial resolution of 1 x 1 km was selected. The valid range of the eight bit (raw) data values is 3 to 255. A RAW value of zero denotes a land pixel with no NDVI calculated due to quality control flagging (i.e. cloud/snow/ice). A RAW value of 1 is not used in the binary files (this is reserved for the graphics plane). A RAW value of 2 denotes a water pixel.

The equation used to convert the RAW values to NDVI is:

NDVI = (RAW*0.004) - 0.1 -- Equation 5

The relation between the digital numbers and the real NDVI is expressed as:

Real NDVI = Coefficient a * Digital Number plus coefficient b -------- Equation 6

= a * DN + b

Coefficient a = 0.004 Coefficient b = -0.1

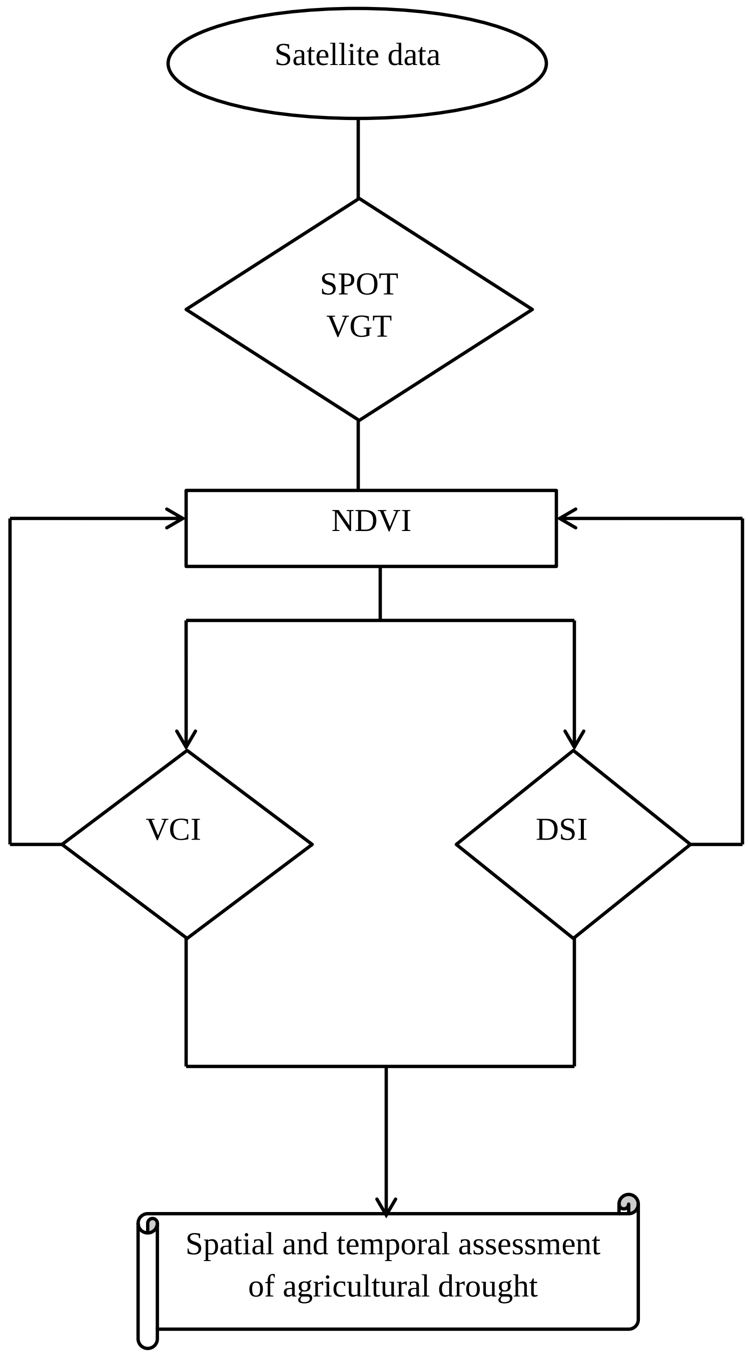


Figure 7. Flow chart of SPOT VGT

4.1.3.2 TAMSAT Rainfall data

Rainfall data collected from weather stations has a limited areal coverage. To alleviate this problem the Tropical Applications of Meteorology using Satellite (TAMSAT) rainfall data was applied. TAMSAT is the product of seasonal rainfall estimates RFE for Africa derived from Meteosat Thermal Infrared (TIR) based on the recognition of storm clouds and calibration against ground based rain gauge data. The product is delivered to user in decadal ten days and monthly temporal resolution and spatial resolution of 4 km. Rainfall estimates for period of a week or more can be mainly used to identify periods of low rainfall which can lead to crop failure, while those estimated at daily or shorter are used for flood forecasting and river management (Melaku Estifanos, 2013). The TAMSAT archive has decadal rainfall for whole Africa since 1983. For this study, the data used for computations of time series was extracted from 1983 to 2013.

Monthly rainfall for 14 kebeles has been extracted out to derive Standardized Precipitation Index(SPI) and also to analyze relations between NDVI and rainfall .

4.2 Software Used

The following software packages have been used to perform the data processing and analysis.

Table 3. List of software used for this study and their function

Soft ware	Function
ERDAS IMAGINE 9.2	Geospatial data processing and analysis
Arc GIS 10.1	Processing, analyzing and presenting data
SPIRITS and VGT Extract	NDVI data extraction
LEAP	Rainfall processing
JMP,SPSS 18 and Micro soft Excel	Analysis, graphics and table creation

4.3 Data Processing and Analysis

4.3.1 Preprocessing of satellite data

Preprocessing such as geometric and radiometric correction was necessary before the analysis and was performed in order to reduce the radiometric distortion in the case of multi date image. Radiometric and geometric corrections were done for the selected images in order to make the input image accessible for time series analysis.

SPOT Vegetation NDVI as explained in section 4.1.3.1 are a ten day composite data as processed by selecting pixels with the mean, minimum and maximum NDVI during a ten day with full 1km x 1km spatial resolution. Time series analysis of long time average NDVI statistics was performed using SPIRIT software. Extractions of NDVI for Sire woreda for growing season (June-September) were performed. The computation starts from 1^{st} of June 2004 to September 21^{th} 2013 on decadal basis using maximum, minimum and mean NDVI.

4.3.2 Analysis of agricultural drought using various drought indices

Agricultural drought for the study area was assessed using Drought Severity Index (DSI), Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI) derived from SPOT VGT and TAMSAT data.

4.3.2.1 Computation of Drought Severity Index (DSI)

NDVI by itself does not reflect drought or non-drought conditions. Thus, the severity of the drought or the extent of wetness can be expressed by Drought Severity Index. This index is defined as a measure of the deviation of the current NDVI values from their long term mean. In this study, the current NDVI values are computed from 2004 to 2013 on decadal basis. To derive DSI, mean NDVI has been computed using the following formula:

NDVI mean,m = (NDVI1 + NDVI 2 + …….+ NDVI n) -------------------------Equation 7

where NDVI mean,m is mean NDVI in m^{th} month in i^{th} year and NDVI 1**…..** NDVI n is NDVI in 1 to NDVI in n year in m^{th} month.

After computing NDVI mean from 2004-2013 NDVI mean images are computed to get DSI during past 10 years. The formula to compute DSI is:

$$DSI = NDVI_{i} - NDVI_{mean,n}$$

where $NDVI_{i}$ is the NDVI value for month i in i^{th} year and $NDVI_{mean,n}$ is the long term mean NDVI for the month n. Where DSI is negative it indicates the below normal vegetation condition and therefore suggests a prevailing drought situation.

The greater the negative deviance from normal leads to the greater magnitude of a drought. The departure from the long-term mean can be used effectively as one of the drought indicators as it would reflect the conditions of healthy vegetation in normal and wet years (Thenkabail et al., 2004). Negative DSI values represent drier than normal conditions and positive values represent relatively wet conditions.

4.3.2.2 Computation of Vegetation Condition Index (VCI)

VCI effectively shows how close the NDVI of the current month was to the minimum NDVI calculated from the long term record. It indicates how much the vegetation has advanced or deteriorated in response to weather. VCI measured in percent has provided an assessment of spatial characteristic of drought, as well as its duration and severity and were in good agreement with precipitation patterns (Chopra, 2006). It is an indicator of the status of the vegetation cover as a function of the NDVI minima and maxima encountered for a given ecosystem over many years. It normalizes the NDVI (or any other vegetation index) and allows for a comparison of different ecosystems. Therefore, it is a better indicator of water stress conditions than the NDVI (Kogan, 1995). VCI is dependent up on the number and quality of images available for the calculation of the absolute minimum and maximum.

VCI was developed by kogan (1990), to separate the ecosystem component from the weather component of NDVI. It is based on the relation between the current NDVI value with the best (NDVI max) and the worst (NDVI min) conditions of the vegetation during the time series.

To derive VCI, Maximum and minimum NDVI has been computed using the following formula:

NDVI max = (NDVI1 + NDVI 2 + …….+ NDVI n) ----------------------------- Equation 8

where NDVI max is maximum NDVI in i^{th} month in i^{th} year and NDVI 1**…..** NDVI n is NDVI in 1 to NDVI in n year in i^{th} month

NDVI min = (NDVI1 + NDVI 2 + …….+ NDVI n) ------------------------------ Equation 9

where NDVI min is minimum NDVI in i^{th} month in i^{th} year and NDVI 1**…..** NDVI n is NDVI in 1 to NDVI in n year in i^{th} month

After computing maximum and minimum NDVI from 2004-2013 NDVI max and NDVI min images are computed to get VCI during past 10 years using the following formula:

$$VCI = \frac{(NDVI\ i - NDVI\ min)}{(NDVI\ max - NDVI\ min)} * 100$$

where NDVI max and NDVI min are calculated from long-term record for a particular month and i is the index of the current month. The condition of the ground vegetation presented by VCI is measured in percent. The VCI values around 50% reflect fair vegetation conditions while the VCI values between 50 and 100% indicate optimal or above normal conditions. The resulting NDVI anomaly percentage assigned to respective grid cell was reclassified into five drought severity classes based on Table 4.

Table 4. Classification of VCI values

VCI Values	Magnitude
0-5	Exceptional
5-15	Very Severe drought
15-25	Severe drought
25-35	Moderate drought
35-50	Slight drought
$\geq$ 50	No drought

Source: (Kogan,1990)

VCI varies from 0 to 100 , corresponding to changes in vegetation condition from extremely unfavourable to optimal. VCI less than 35% (Singh et al, 2003 cited in Covele, 2005) have been used as thresholds to identify areas affected by drought.

4.3.2.3 Computation of Standardized Precipitation Index (SPI)

SPI could be used to compute monthly rainfall or analysis total rainfall in each delight intervals (1 to 12 month). McKee et al. (1993) proposed Standardized Precipitation Index to assess anomalous and extreme precipitation. The SPI is computed by dividing the difference between the normalized seasonal precipitation and its long-term seasonal mean by the standard deviation.

Drought intensity classification into various categories with different values of SPI is given in the following Table 5. Positive SPI values indicate greater than median precipitation and negative values indicate less than median precipitation.

The 3-month SPI provides a comparison of the precipitation over a specific 3-month period with the precipitation totals from the same 3-month period for all the years included in the record. In other words, a 3-month SPI at the end of August compares the June–July–August precipitation total in that particular year with the June–July–August precipitation totals of all the years on record for that location. A 3-month SPI reflects short- and medium-term moisture conditions and provides a seasonal estimation of precipitation. In primary agricultural regions, a 3-month SPI might be more effective in highlighting available moisture conditions than other currently available hydrological indices. Standing from this description the analysis of this study was performed using a 3-month SPI.

Input data to this study consists of SPI Annually values for the period June 2004 to September 2013 from TAMSAT data for statistical period of 30 years (1983 – 2013). SPI results computed from seasonal rainfall data were assigned to each grid cell of the study area, and reclassified based on drought severity classless as shown the Table 5.

Table 5. SPI based drought severity class

SPI value	Drought Magnitude
2.0+	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-.99 to .99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

Source : (http://drought.unl.edu/monitor/spi)

Due to this reason the decadal resolution was selected for this study and it was downloaded from January 1983 to December 2013.

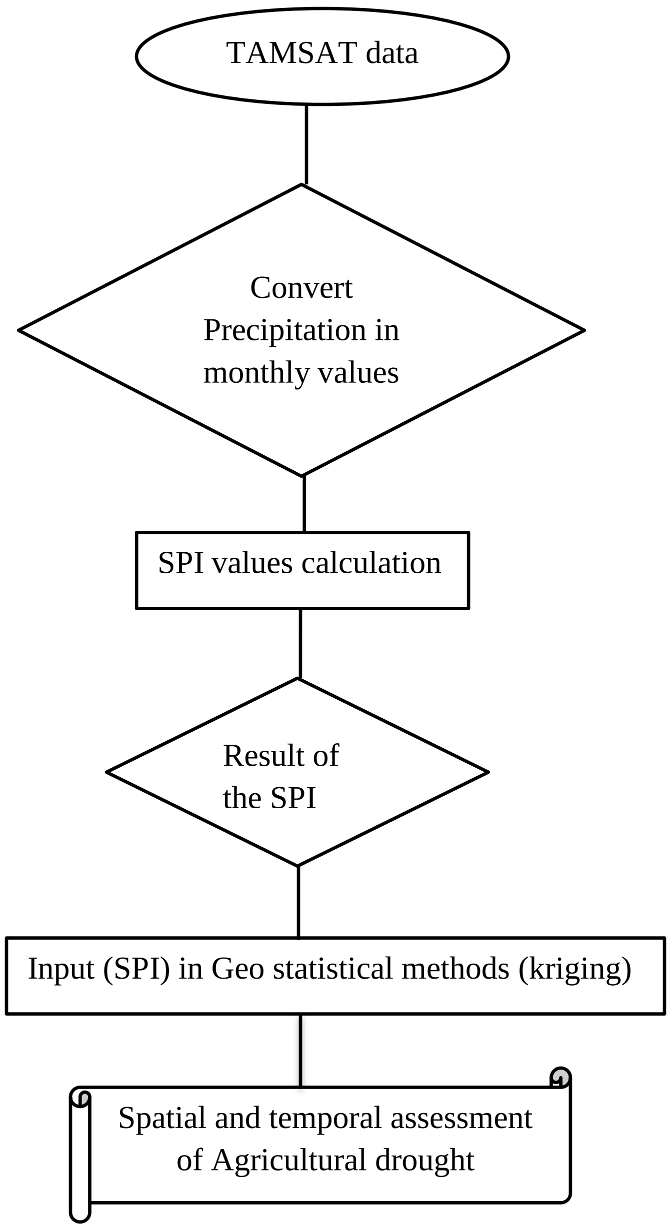


Figure 8. Methodology of SPI estimation and spatial representation.

4.4 Regression analysis of agricultural yield with derived drought indices

To assess the possibility of predicting yield, data derived from the drought indices and agricultural yield data were prepared for simple regression analysis. The relationship between DSI,VCI and SPI result from each seasonal year with corresponding yield data was computed to validate the derived indices. The regression equation would subsequently be used to predict agricultural production using available remotely sensed data in order to take necessary action from losses happen due to agricultural drought.

4.5 Methodology

In this study, to assess agricultural drought four satellite derived indices were used and linear regression analysis is developed to validate the correlation between agricultural yield and derived indices as well as rainfall. The following framework illustrates the general workflow of the methodology which is briefly discussed on the next section (Figure 9).

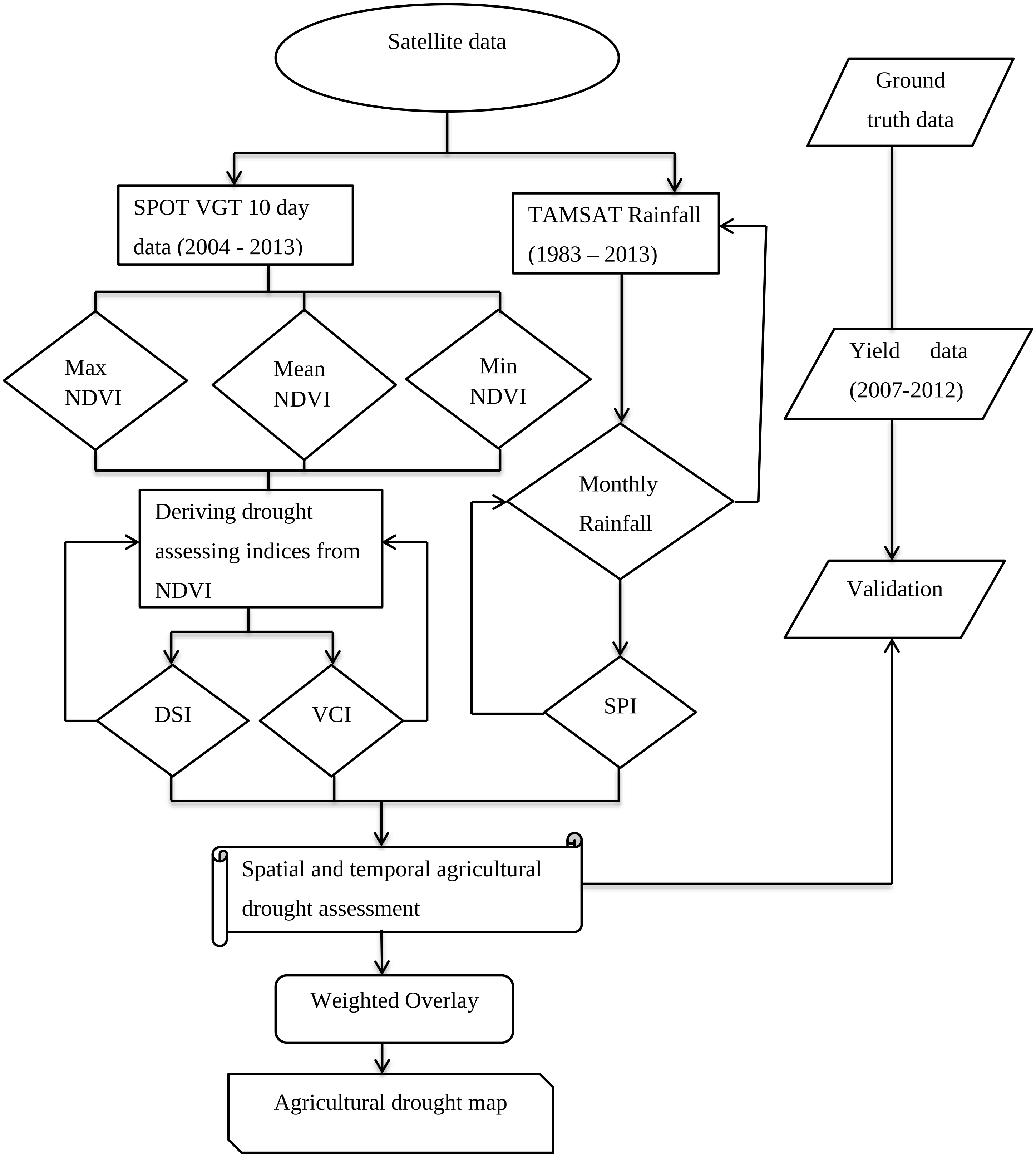


Figure 9. Schematic representation of the methodology

CHAPTER FIVE

5. RESULT AND DISCUSSION

5.1 Relationship between seasonal Rainfall and NDVI

A growing archive of satellite observations has indeed shown a close coupling between vegetation greenness and rainfall variability (Herrmanna et al., 2005). Rainfall emerges as the dominant causative factor in the dynamics of vegetation greenness.

In a rain fed based cropping system, seasonal rainfall variability is inevitably reflected in variable agricultural yield. This implies that seasonal analysis of historical rainfall and the response of vegetation has great importance. Accordingly, seasonal rainfall and NDVI patterns of the entire study area for a period from 2007- 2012 have been studied and the result has shown that there is good correlation (r = 0.77) between rainfall and NDVI (Figure 10).

During the past six years (2007-2012), there was slight year to year variation in rain fall and NDVI. Normalized Difference Vegetation Index (NDVI) responded more rapidly to precipitation during moderate year particularly in 2007.

The role of prevailing climatic conditions on vegetation activity, especially the relationship of Normalized Difference Vegetation Index (NDVI) to climatic variables has been widely validated across different regions of the world. At the regional scale, various studies have focused on different areas where NDVI is highly sensitive to climatic fluctuations. For instance, Nicholson et al. (1998) compared the vegetation response to precipitation in Sahel and East Africa during 1982 to 1985 and found out that the spatial patterns of annually integrated NDVI closely reflected mean annual precipitation. The result of this study also go in line with the above Nicholson et al. (1998) statement as it shows there is strong relationship between NDVI and rainfall.

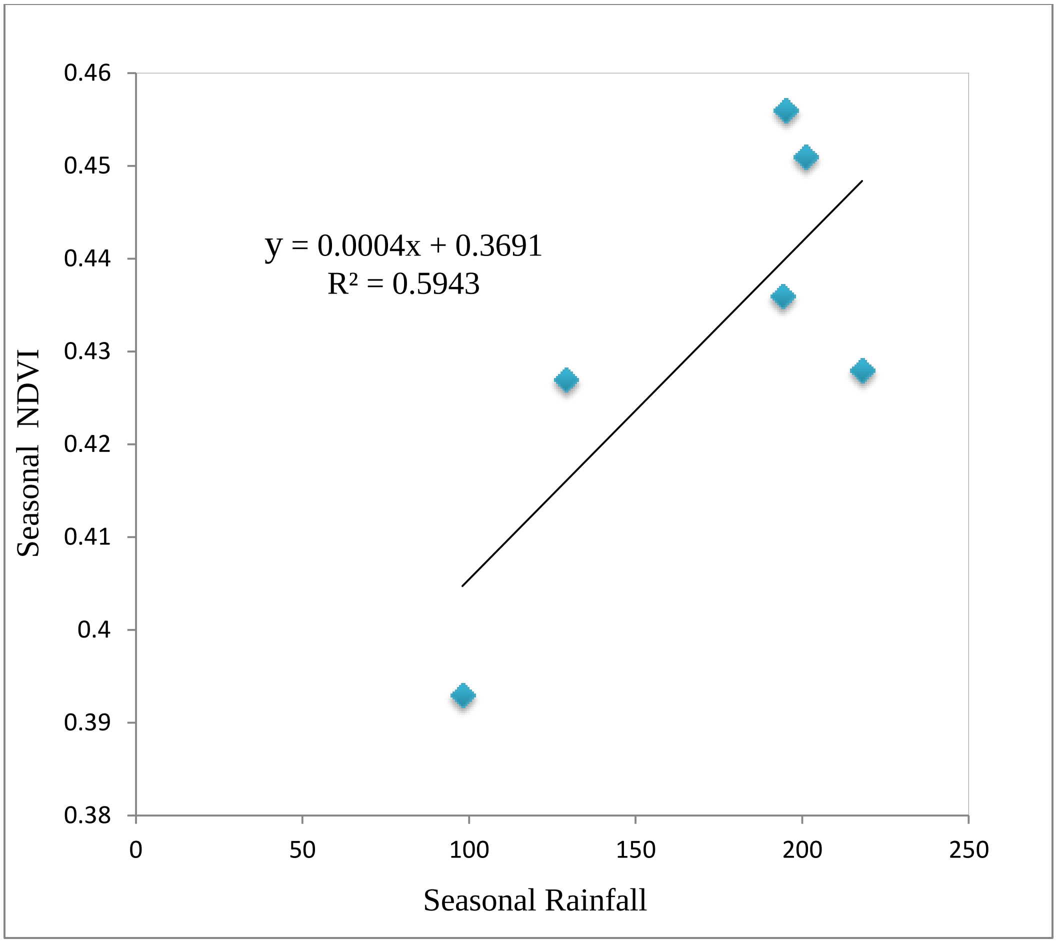


Figure 10. Seasonal pattern of NDVI and rainfall (2007-2012) of Sire woreda

Figure 10 shows, the effect of inter-annual seasonal rainfall variability on NDVI in the study area for growing season. The result shows that the driest years had the lowest NDVI values while the wettest years had maximum NDVI values. For instance, during the dry season 2009 the lowest amounts of rainfall and NDVI value is recorded.

NDVI responded more rapidly to precipitation during moderate years. In contrast, NDVI responded more slowly to precipitation during highly wet and highly driest years . As the result of the analysis shows, rainfall is an important factor for plant growth, but its variation is a contributing factor only at specific times of the growing season.

NDVI and rainfall correlates positively, in which NDVI values increases as rain fall increases and vice versa. It can be analyzed that at around 200 mm rainfall, NDVI almost saturates. The correlation between NDVI and rainfall was 0.77 which shows there is strong relation between these two variables.

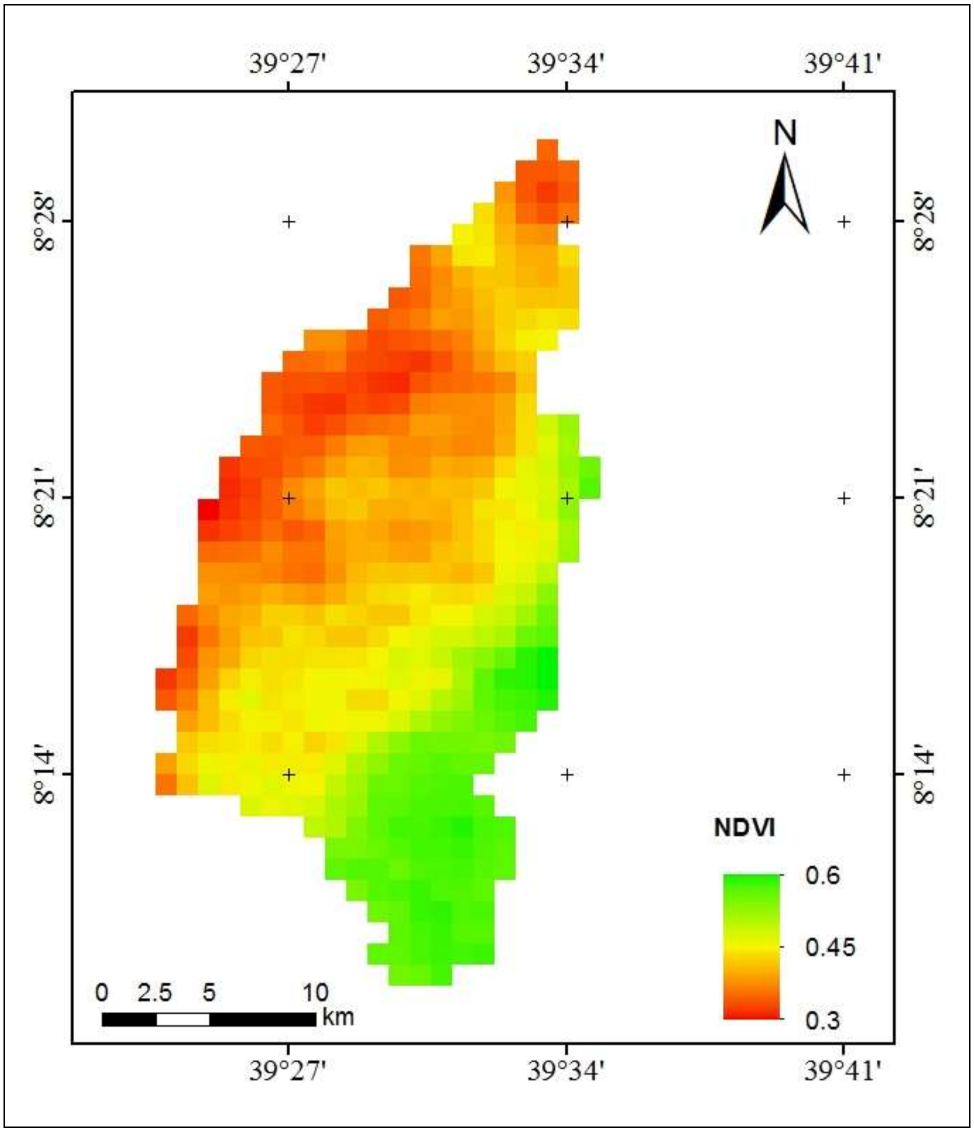


Figure 11. Long term mean NDVI computed from June to September of 2004-2013

As inferred from the above Figure 11, the long term NDVI value ranges from 0.3 to 0.6. Relatively in lowland areas where there is low rainfall in the northern and north west part of the study area NDVI values were nearly 0.3, where as in relatively highland areas where there is better rainfall in southern part of the area under study NDVI of 0.6 were observed.

Investigating the long-term variations in both vegetation condition and climate change is a good method to monitor the changes of the agricultural production of the area.

5.2 Relationship between seasonal NDVI and yield

In order to validate satellite derived output, grain yield of agricultural production is the main ground truth data. Therefore, it is crucial to analyze the relationship between NDVI and grain yield to quantify the impact of agricultural drought on agricultural production.

As the result of this study shows, there exists a strong correlation between NDVI over the growing season and the total agricultural yields of season 2007 to 2012 for Sire woreda. As observed from Figure 12, there is intense relation between two variables in 2010, in which the NDVI almost perfectly correlates with yields for this year.

NDVI curves typically mirrored the yield curves, which shows good correlation between them. NDVI responded more rapidly to agricultural production during 2009 and 2010 which were both dry years. By contrast, NDVI responded more slowly to agricultural production during 2012 which was a wet year.

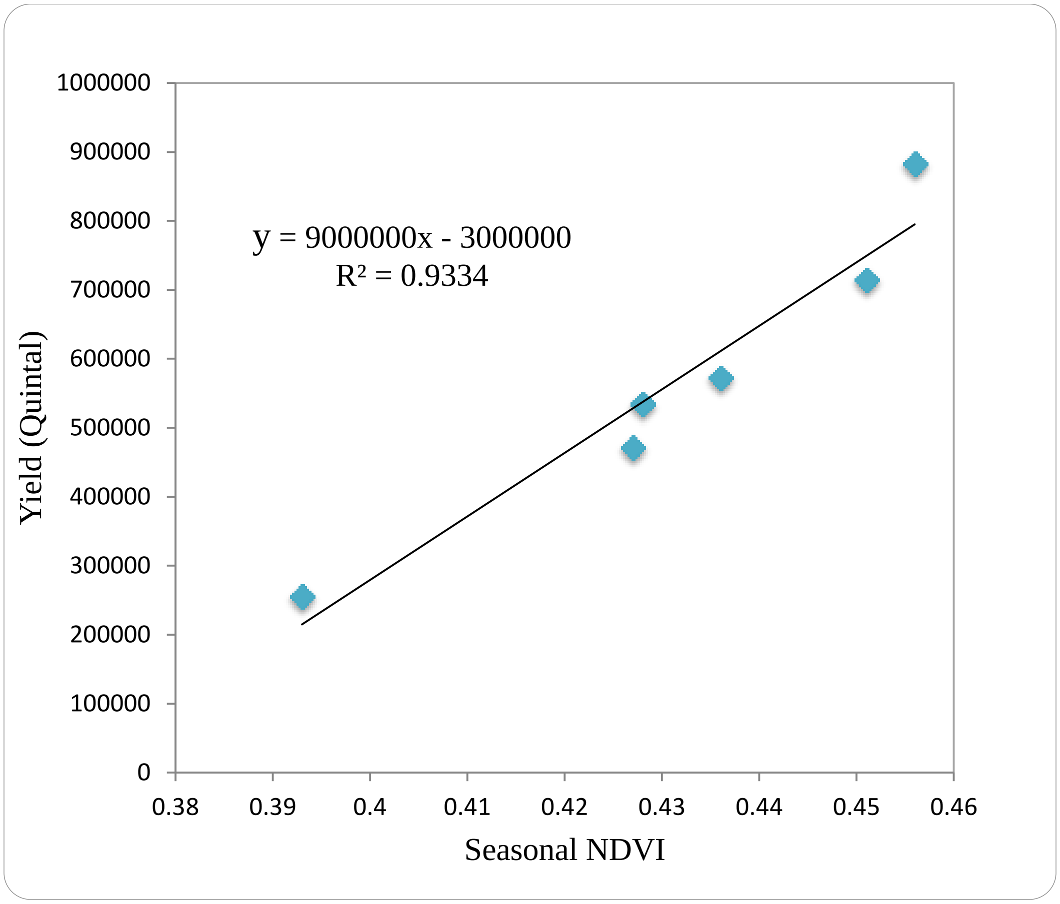


Figure 12. Relationship between Seasonal NDVI and yield (2007-2012)

NDVI explains the yield variability caused by date of transplanting and soil. It does not reflect other production factors like availability of water. As shown in Figure 12, NDVI explains 93% of yield variability.

Agricultural production in Sire woreda was well correlated to NDVI from June to September for 2007 to 2012 years (Figure 12). This study confirmed that there is significant positive relationship between remotely sensed NDVI and agricultural yield ($r = 0.95$, $p < 0.005$) with NDVI variability lower than yield variability. Thus, NDVI can serve as a reliable estimator of crop yield.

It is concluded that seasonal NDVI most strongly influenced agricultural production. In general the results showed that, NDVI is strongly fit to analyze agricultural drought.

5.3 Remote Sensing indices for agricultural drought assessment

5.3.1 Vegetation Condition Index (VCI)

According to the literatures, drought is apparent when the value of VCI threshold is below the value of 50 and severity of drought will decline when the values is more than 50. The time series data of the VCI were used to analyze the trends of drought occurrence. A study in Africa involving the use of VCI to model crop yield and detect the early onset of drought demonstrated that the spatial and temporal characteristics of drought can be monitored by use of the VCI (Kogan, 1997).

The VCI were extracted and compared during the months representing a period of maximum vegetation growth, that is from June to September. This was done because the VCI, as being an indicator of vegetation vigor is only useful for monitoring drought conditions during the growing season (Vicente-Serrano, 2007 cited in Ganesh, 2007). For this study, the Vegetation Condition Index (VCI) as a drought index has been calculated from June to September months for the seasons from 2004 up to 2013. The analysis illustrated the drought variability and spatial distribution in time and space.

Based on the result of the study, the worst situation was encountered during 2006 and 2009 years of main rainy season (June to September) when more than 87 % and 95 % of the area suffered agricultural drought condition respectively. A high value of VCI were found in 2013 with more than 98 % of the area classified as non-drought.

The effect of Agricultural drought on July month among all studied growing seasons was very high, while the effect of drought on September month was low. Even though, the effect of drought was very high in 2009, however it has low effect in 2013. The extreme drought was most effect in the year 2006 during the months of July.

The seasonal Vegetation Condition Index (VCI) over Sire woreda during the seasons from 2004 to 2013 has been shown in Figure 13 for illustration.

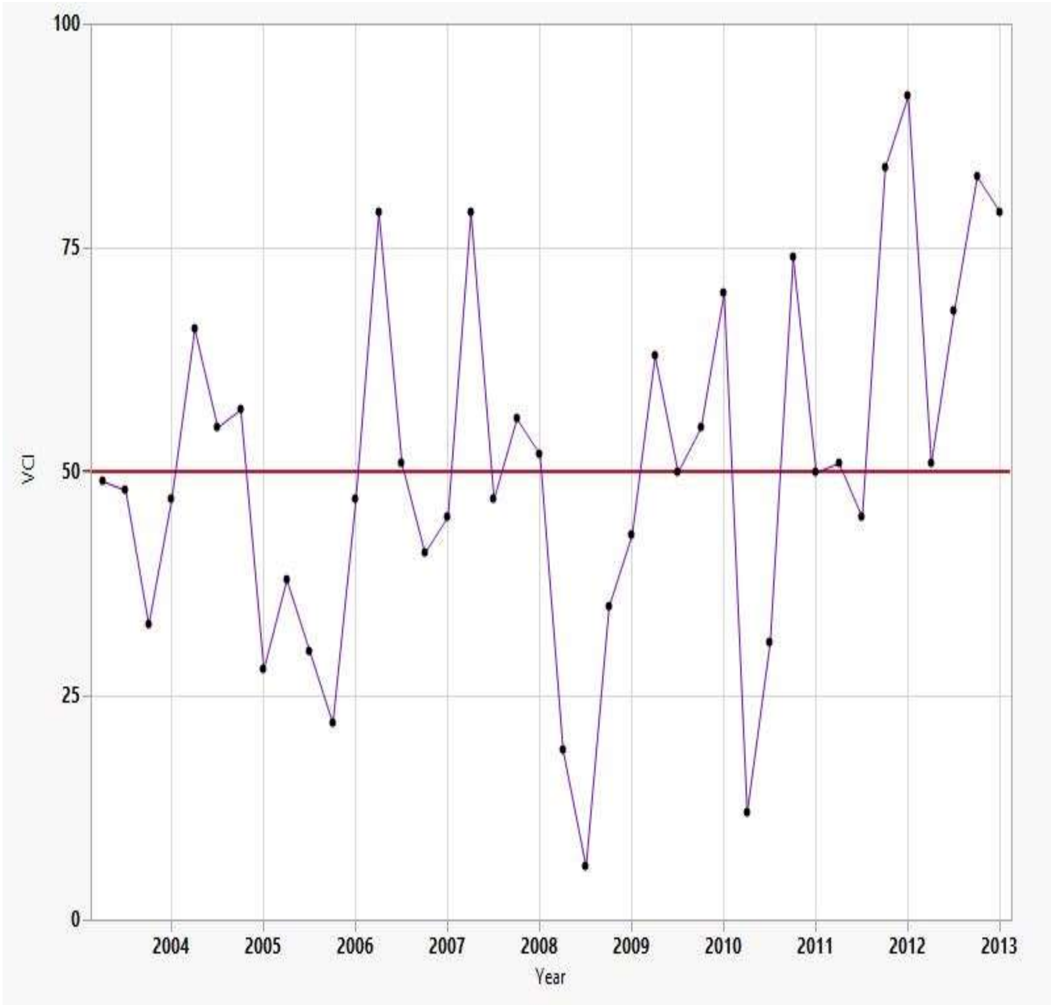


Figure 13. Temporal profile of VCI for Sire woreda from 2004-2013

Figure 13 depicts that, there is agricultural drought variability in time series. As already discussed year 2009 is the worst agricultural season in which all months of growing season (June to September) has values below average especially months in starting of growing season (June and July) were in severe condition. Similarly in 2006 also all months of growing season (June to September) like 2009 has threshold below average. Even though the condition in 2006 is worst when compared to the other seasons but it's better than year 2009.

The other agricultural drought year as VCI implication was 2011 where the two first months of starting growing season (June and July) were below average while the remaining August and September months has values above average. Since favourable weather provides optimal moisture condition, high values of VCI correspond to healthy and unstressed vegetation. As VCI in above Figure 13 shows, year 2013 was the best agricultural season in which all months of growing seasons (June to September) have values above average. Similarly year 2005 was also best agricultural season where all values of growing seasons have values above average except June. The remaining seasons were in medium condition in which they have slight drought in some months and no drought in the remaining months.

It can be seen from Table 6 that, the VCI threshold also fits with drought extent. When there is low VCI as year 2009 then there is high drought condition while there is low drought condition in years scoring high VCI as seen in year 2013.

It has been found that, the season 2013 has the highest agricultural area not affected by the drought while season 2009 has the lowest agricultural area not affected by the drought (Table 6). The agricultural season 2011 has the highest agricultural area affected by slight drought while season 2013 has the lowest agricultural area affected by slight drought. The agricultural season 2006 has the highest agricultural area affected by moderate drought while season 2008 has the lowest agricultural area affected by moderate drought (Table 6).

The agricultural season 2006 and 2009 has the highest agricultural area affected by severe drought while season 2008 has the lowest agricultural area affected by severe drought and the agricultural seasons 2009 have the highest agricultural area affected by extreme drought while season 2004 has the lowest agricultural area affected by high drought (Table 6). The results could summarized that, the agricultural years 2008,2012 and 2013 were the best agricultural seasons compared by other seasons while agricultural years 2006,2009 and 2011 were the worst agricultural seasons.

Table 6. Floors area of drought with VCI

Year	VCI	Drought magnitude				
		No drought(%)	Mild drought (%)	Moderate drought (%)	Severe drought (%)	Extreme drought (%)
2004	44.25	37	33.9	20.4	8.3	0.4
2005	51.5	54.3	32.4	10.6	2.1	0.6
2006	34.25	12.1	36.2	27.2	22.9	1.6
2007	49.25	55.7	25.6	12.5	5.4	0.8
2008	58.5	78.1	20.2	1.5	0.2	-
2009	25.7	4.8	23.4	20.4	23.7	27.7
2010	51.5	65.8	20.2	10.3	3.7	-
2011	41.75	20.8	53	19.5	6.7	-
2012	68	76.5	21.6	1.9	-	-
2013	70.25	98.3	1.7	-	-	-

According to Table 6, in 2009 about 27.7 percent of the area has been facing extreme drought while about 23.7 percent faces severe drought in the same year. 0.4 percent is the lowest rates with very severe drought class which registered in 2004. In contrary to year 2009, 98.3 % of the area under study was wet in year 2013 followed by 2008 (78.1 %) and 2012 (76.5 %) respectively. In 2008, 2010, 2011, 2012 and 2013 there was no extreme drought during the growing season. In general what observed from Table 6, is that year 2006 and 2009 were the worst seasons while 2012 and 2013 were the best seasons. The rest years 2004 and 2011 were moderately drought years while 2005,2007,2008 and 2010 were seasons in which moderately wet condition prevails.

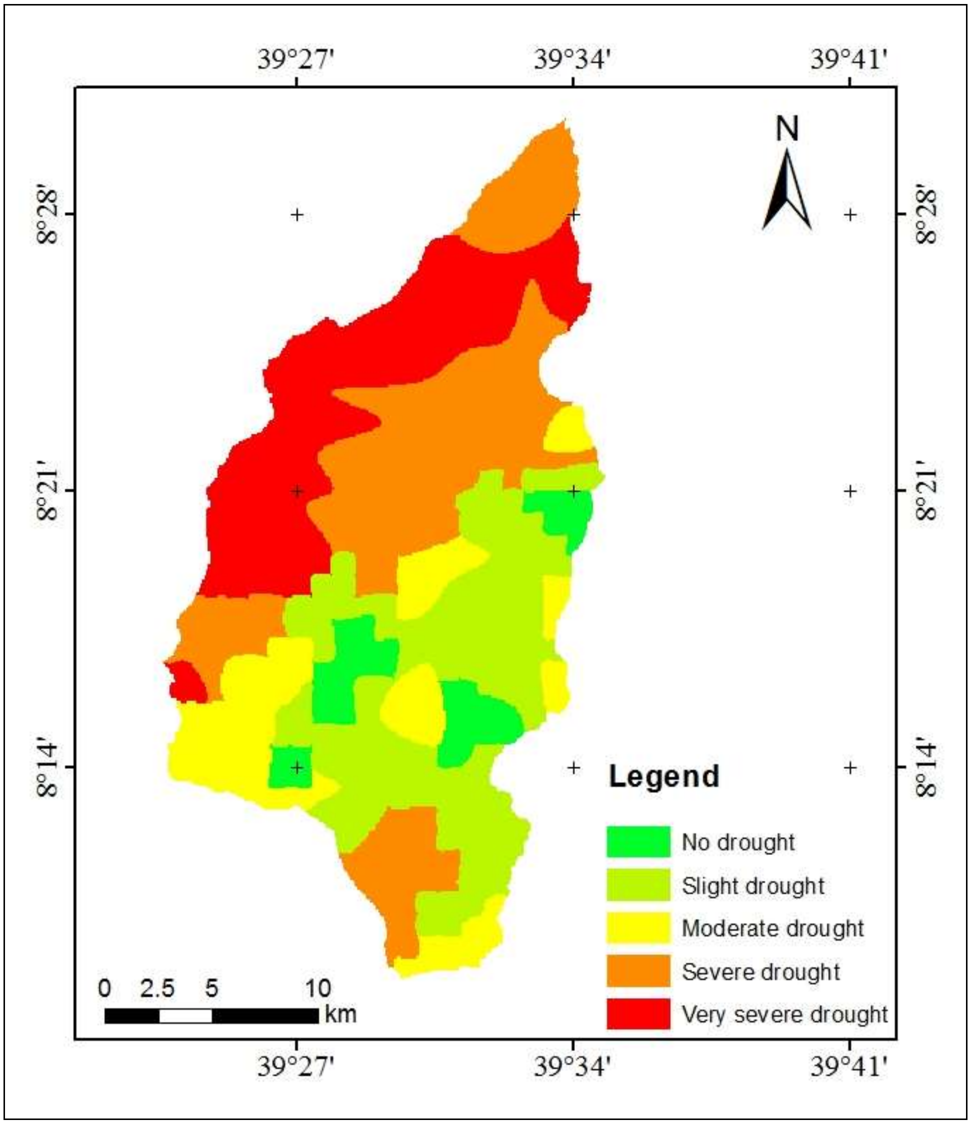


Figure 14. Spatial pattern of agricultural drought severity for drought year 2009 as expressed by Vegetation Condition Index (VCI)

The above Figure 14 shows, the level of drought condition ranges from non-drought to extreme in 2009 drought year. During 2009 growing season, the percentage area hit by agricultural drought was 4.8,23.4,20.4,23.7 and 27.7 percent of the total area for non-drought, slight, moderate, severe and extreme severity level respectively.

As inferred from Figure 14, large areas of the northern part of woreda face very severe and severe drought while there is very severe drought in north west parts of Sire woreda. In contrary better situation observed in southern parts where slight drought prevails largely especially in south eastern part of the area.

Similar to year 2009, there is also severe agricultural drought condition in year 2011. As observed from Figure 15, there is severe and moderate agricultural drought in the western part of the study area while wet condition were seen in southern and northern tip.

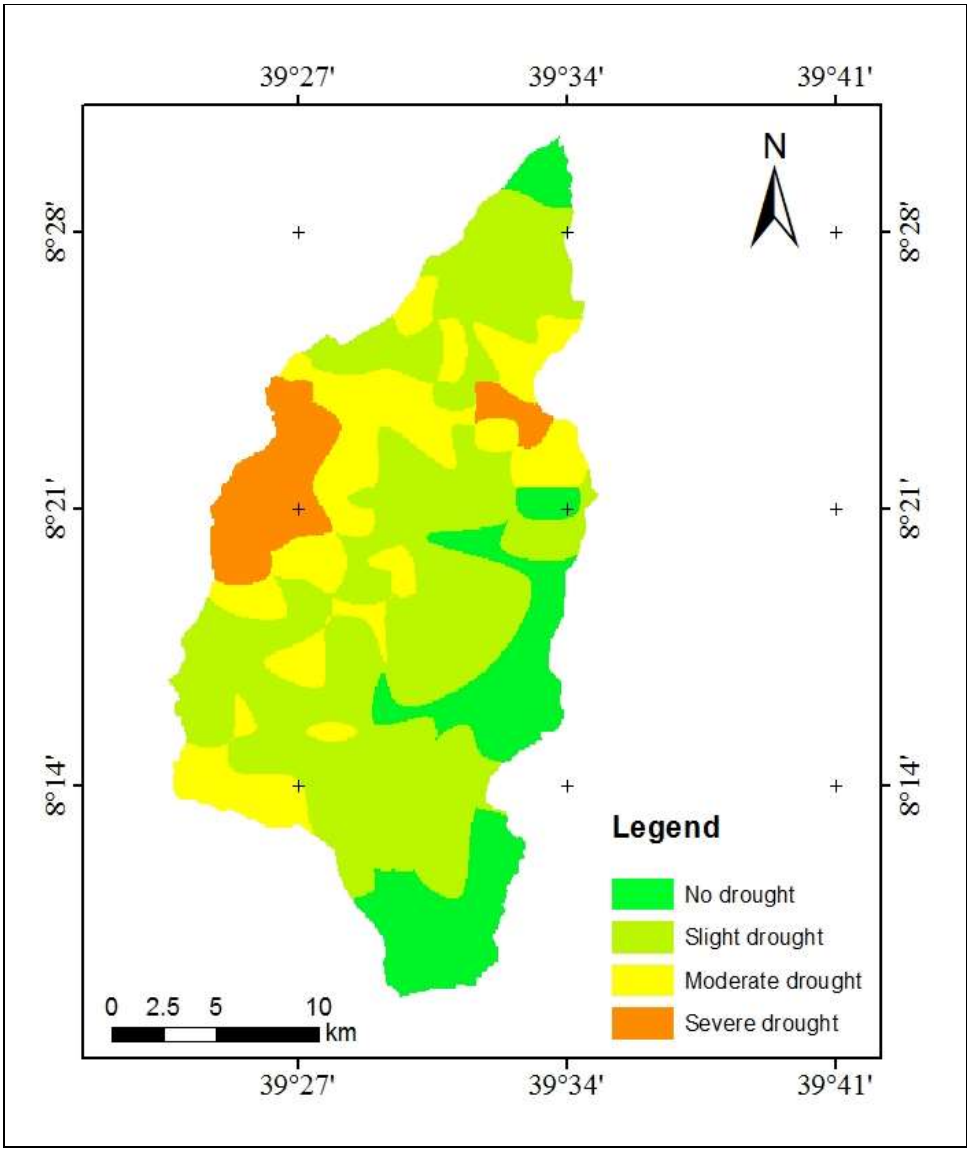


Figure 15. Spatial pattern of agricultural drought severity for drought year 2011 as expressed by Vegetation Condition Index (VCI)

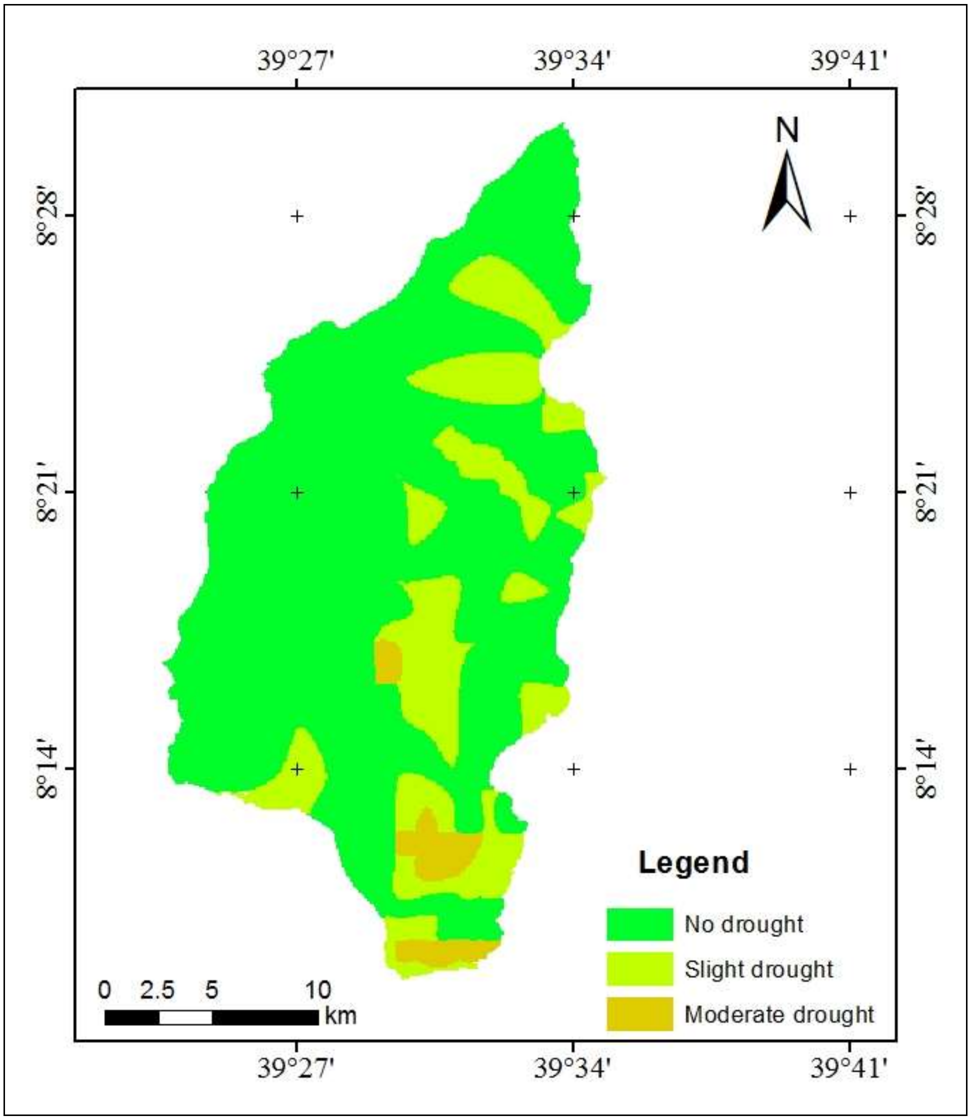


Figure 16. Spatial pattern of agricultural drought severity for wet year 2012 as expressed by Vegetation condition index (VCI)

Figure 16 depicts agricultural drought conditions for wet season 2012 based on Vegetation Condition Index results. As clearly indicated on map for this year there is no severe and extreme drought situations, so that this season was best agricultural year.

The percentage area of agricultural drought condition indicates that 21.6 and 1.9 percent of the total area was hit by slight and moderate level of severity while considerable number (76.5 %) shows no drought occur during year 2012.

As seen from Figure 16, moderate and slight agricultural drought prevails in southern part of the study area while, in northern and north western part of woreda slightly better situation seen with slight agricultural drought prevails in some manner.

The VCI map for another non drought year 2013 is depicted below. In this wet year insignificant amount of agricultural drought were occur (Figure 17).

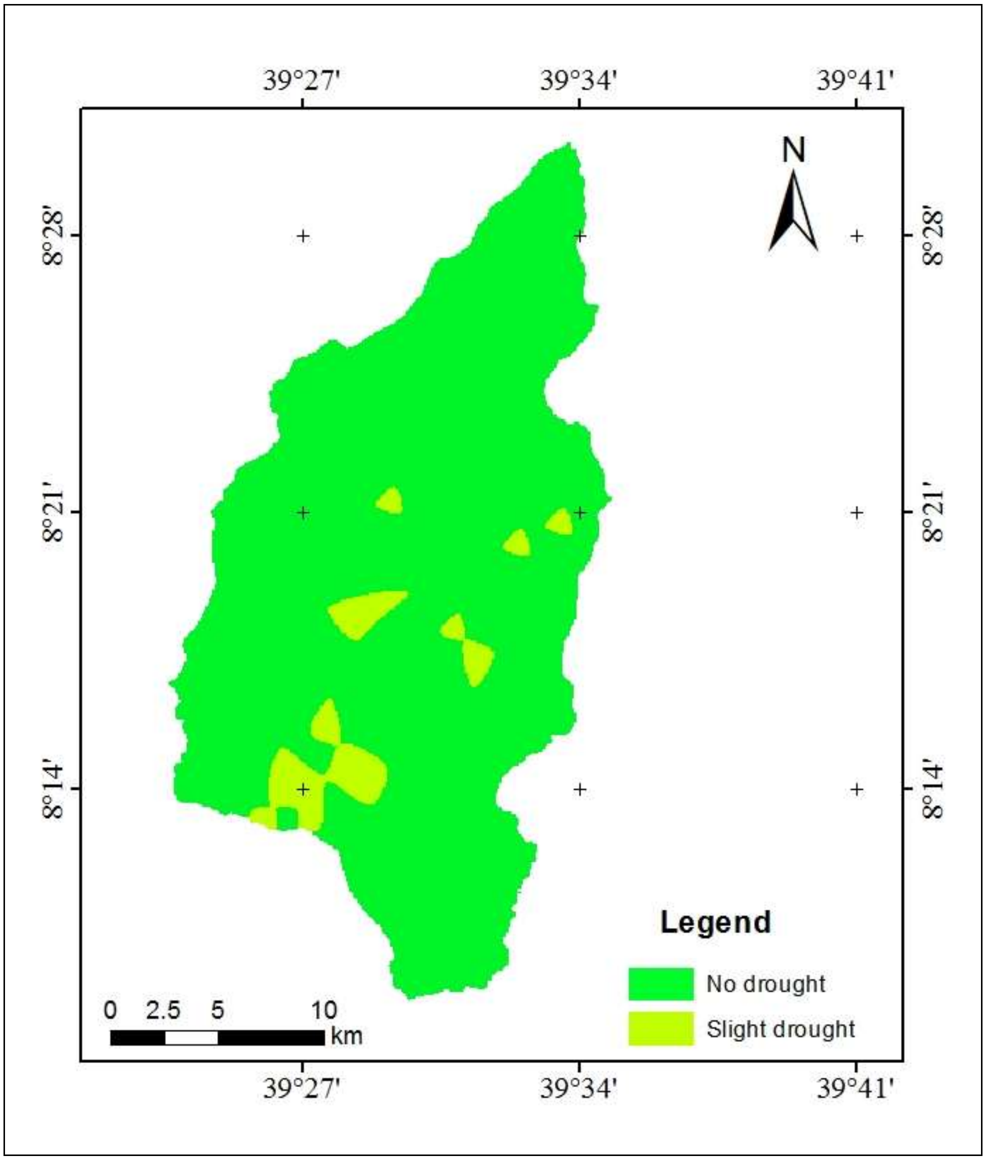


Figure 17 Spatial pattern of agricultural drought severity for wet year 2013 as expressed by Vegetation condition index (VCI)

5.3.2 Drought Severity Index (DSI)

This index is defined as a measure of the deviation of the current NDVI values from their long term mean. In this study the current NDVI values are computed for year 2004 - 2013 on monthly basis. Thus, in the periods where the difference of the current NDVI from its long term is negative, it means that there is a prevailing of the drought situation even though its severity varies on the magnitude of the deviation. So, the results obtained in this study indicate an existence of drought for all months of the year 2006 and 2009 in accordance with the criteria of the drought severity index (DSI).

The result of Drought Severity Index implies that agricultural seasons of years 2006 and 2009 have values below zero in all rainy months. On the contrary, 2013 year was wettest season having values below zero in all rainy months. In the remaining years the value falls below zero in some months while it rise in another months. The peak of Drought Severity Index were seen in August 2010 followed by July 2009. August and September 2012 were months having high values above zero.

As seen from the temporal profile of the area for rainy season in 2004 to 2013 the deviation of current NDVI from values of their respective long term mean is below zero in 2006,2009,2010 and 2011 whereas, above zero in 2005,2008 and 2013. In general, the overall average Drought Severity Index value for growing season of dry season 2009 was -0.042 while the value of index during the wet years 2013 were 0.044. Here below, temporal profiles of the Drought Severity Index for growing season (June-September) in 2004 to 2013 is shown.

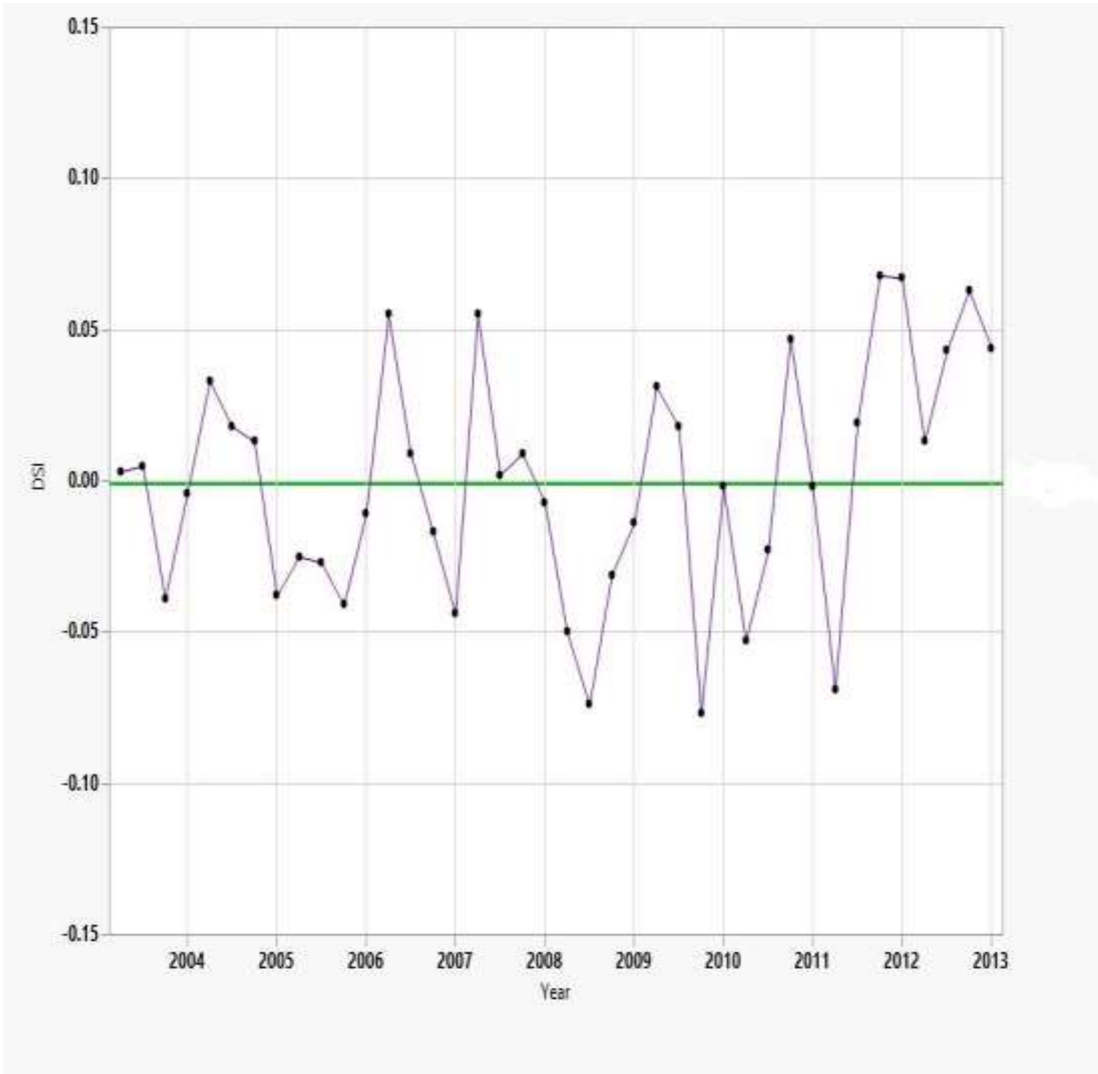


Figure 18.Temporal profile of Drought Severity Index for growing season in 2004 to 2013

In seasons having high deviation values there is existence of drought condition during the main growing seasons. This implies unfavourable vegetation condition of the area and hence implies reduction of the production yield from the long term yield trend.

Since the deviation is less than 0 for the 2004, 2006, 2009, 2010 and 2011 years the Drought Severity Index categorized them as drought years which can possibly lead to yield reduction below average in the area.

As observed from Figure 18, agricultural season of 2009 is more affected with drought in which all months values were below average.

Among the rainy seasons (June to September) July was the worst month while September slightly better than the rest months. Even though there is drought in 2004, the starting months of rainy season (June and July) have values below zero but the value of the rest two months August and September falls below average which shows that there is slight drought in these two rainy seasons. In contrast to season 2004, the first two rainy months score values below average for season 2011,where there is better normal condition in August and September. As discussed above, 2006 and 2009 drought years scores negative deviation for all months of rainy season.

Among the indicated years, 2013 is the best season in which values of all main rainy seasons were above average followed by 2008. However the drought severity condition situation in 2005,2007 and 2012 years was somewhat similar. In these years deviation values fluctuate from one month to another. Some months score values below average whereas others have values above average. There is low drought severity condition and prevailing is restricted in only some months of growing season. So that a better yield production is expected than the former years categorized as dry seasons.

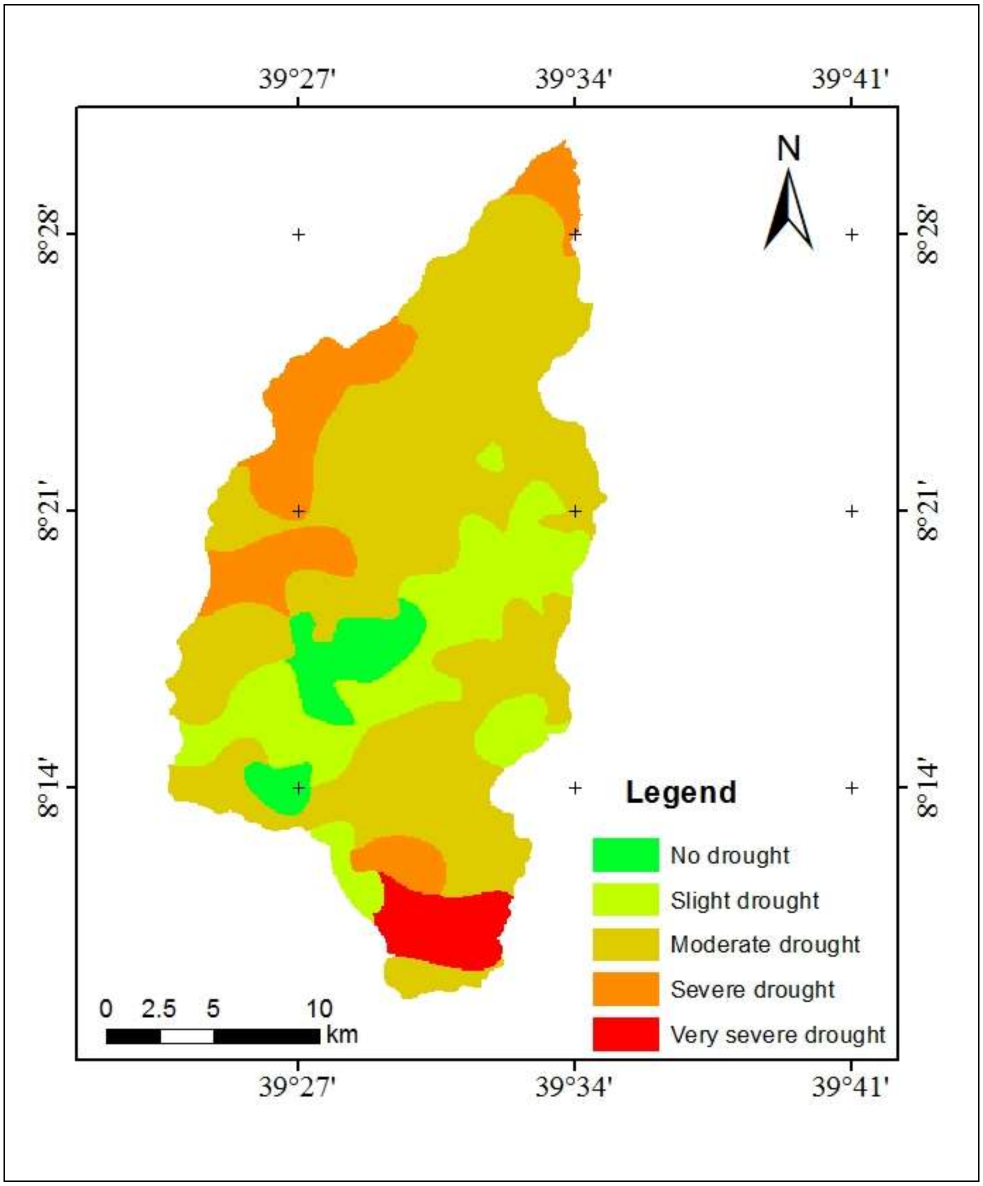


Figure 19. Spatial pattern of agricultural drought severity for drought year 2009 as expressed by Drought Severity Index (DSI)

There is considerable moderate agricultural drought in 2009 as the result of the Drought Severity Index shows on the above map. Of the total area under study 56.3 % is classified as moderate drought in which severe and very severe drought covers 19 % and 3.5 % respectively while the rest 19 % among the drought areas faces slight drought. Only 7.6 % of the area were not touched by drought.

In the drought year 2011, similarly considerable amount of agricultural drought were happen. As seen from Figure 20, there is moderate and slight agricultural drought in western part of Sire woreda whereas southern and northern tips were under wet condition.

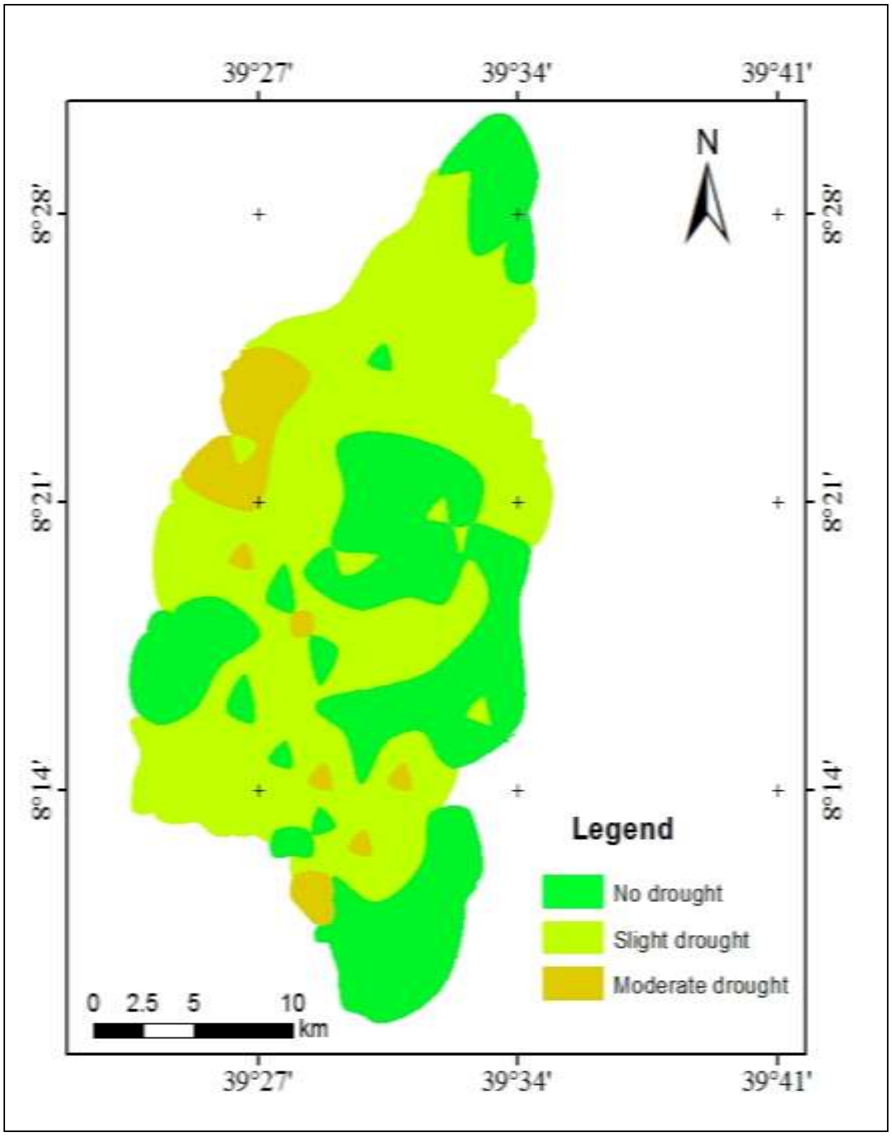


Figure 20. Spatial pattern of agricultural drought severity for drought year 2011 as expressed by Drought Severity Index (DSI)

As we observe from the map, year 2009 was the dry season where drought is more pronounced with great number of value covering the study area. As observed from Figure 20, southern tip of the woreda were hit by very severe ,severe and moderate drought while central part of the woreda faces relatively less drought and no severe drought prevails in the area. There is severe drought in the northern tip and north western part of Sire woreda.

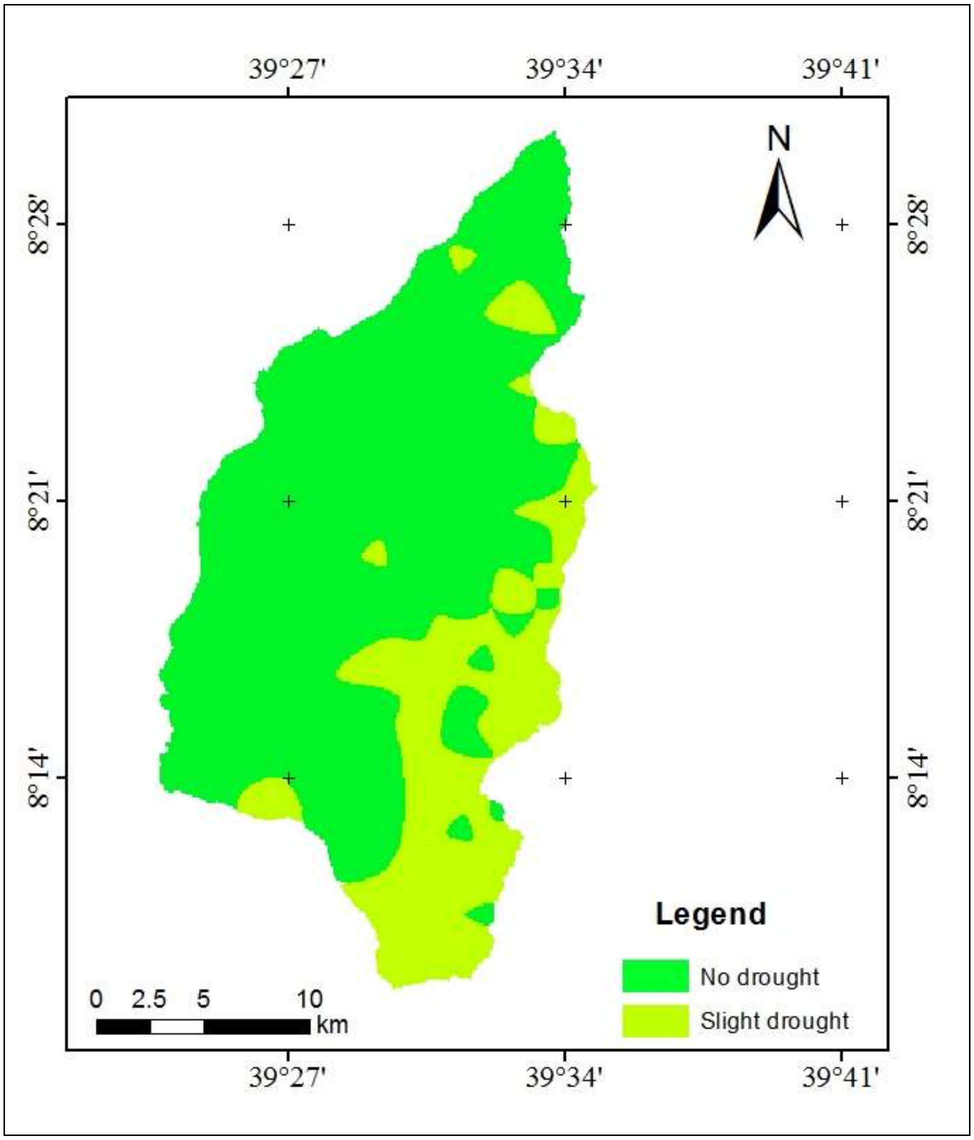


Figure 21. Spatial pattern of agricultural drought severity for wet year 2012 as expressed by Drought Severity Index (DSI)

In seasons having less drought better agricultural yield was expected. Among that seasons, 2012 named first since it has small area hit by agricultural drought. As clearly shown in Figure 21, the area under study faces less drought in respective year. In this year, large part of the study area classified as non-drought where there is favourable situation for agricultural production. About 74.6 % of the area were non drought areas in which no drought severity prevails. The remaining areas covering 25.4 % were seen as places where slight drought was registered. As seen from Figure 21, there is slight drought in the southern and south eastern part of the woreda whereas the rest areas of the woreda were free from drought.

Similarly, year 2013 is also a wet year in which only slight drought seen in some parts of woreda while large area were free from any agricultural drought condition (Figure 22).

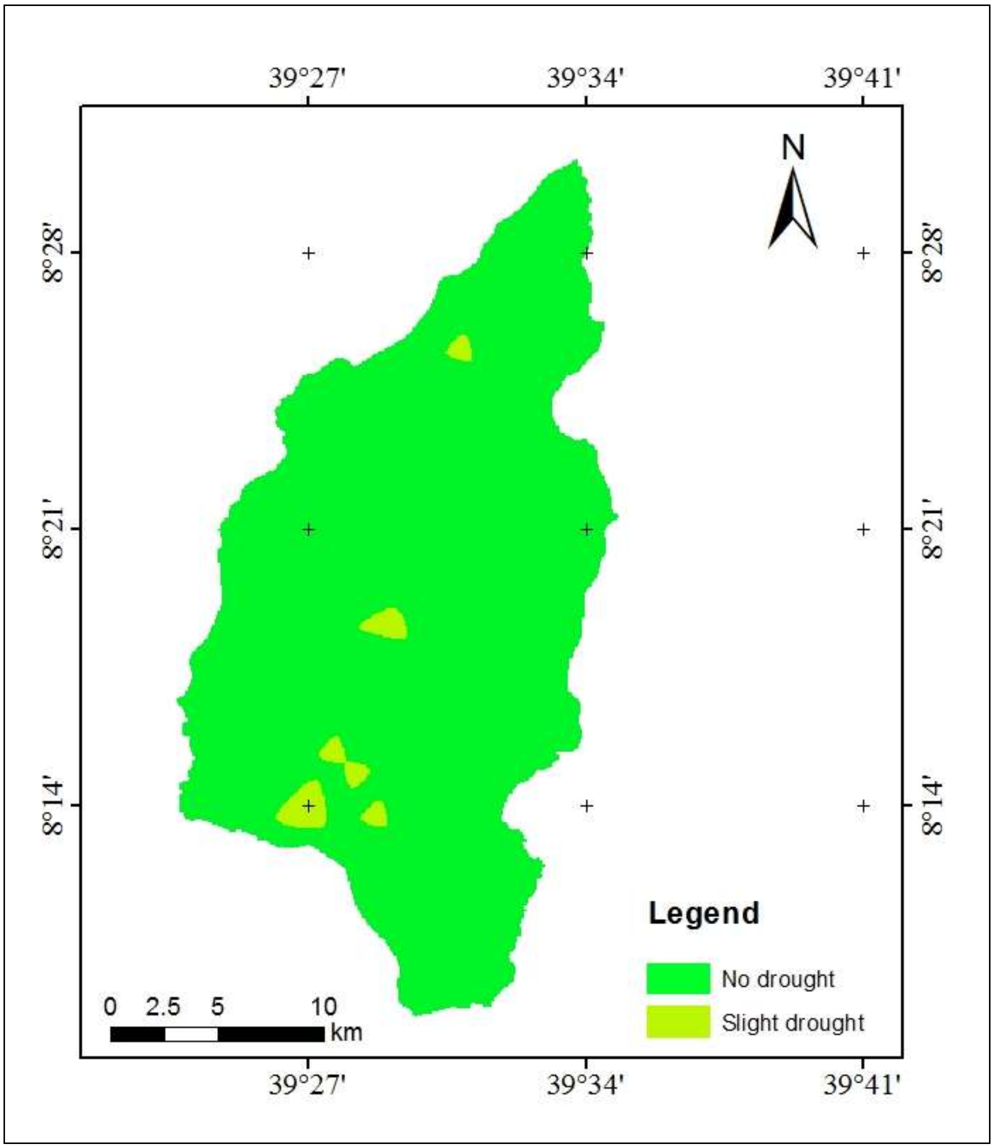


Figure 22 Spatial pattern of agricultural drought severity for wet year 2013 as expressed by Drought Severity Index (DSI)

5.3.3 Standardized Precipitation Index (SPI)

SPI as has been mentioned earlier is an index that was designed to quantify the precipitation deficit for multiple timescales. Soil moisture conditions (agriculture) respond to precipitation anomalies on relatively short timescales anywhere from 1-month to 6-month SPI for agricultural drought.

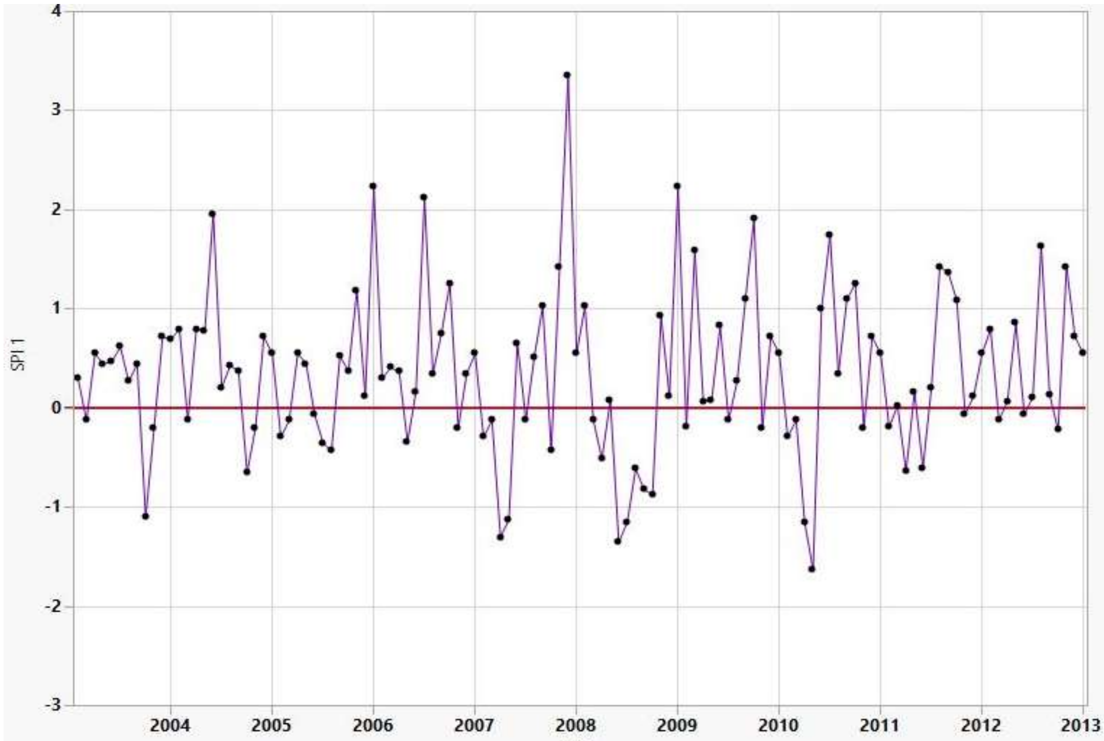
Positive SPI values indicate, the rainfall is greater than median rainfall and negative values indicate less than median rainfall. According to the standard classification of SPI values, an area can suffer extreme drought situation, if the SPI value is below -1 and ends when SPI becomes positive.

The annual SPI values from 2004 to 2013 for 1,3, 6 and 12 months are shown in Figure 23. Agricultural drought has been assessed using SPI in the study area by interpolating SPI values for 10 years. According to the results of the index, agricultural drought years were 2006 and 2009 whereas 2005, 2012 and 2013 years were wettest years.

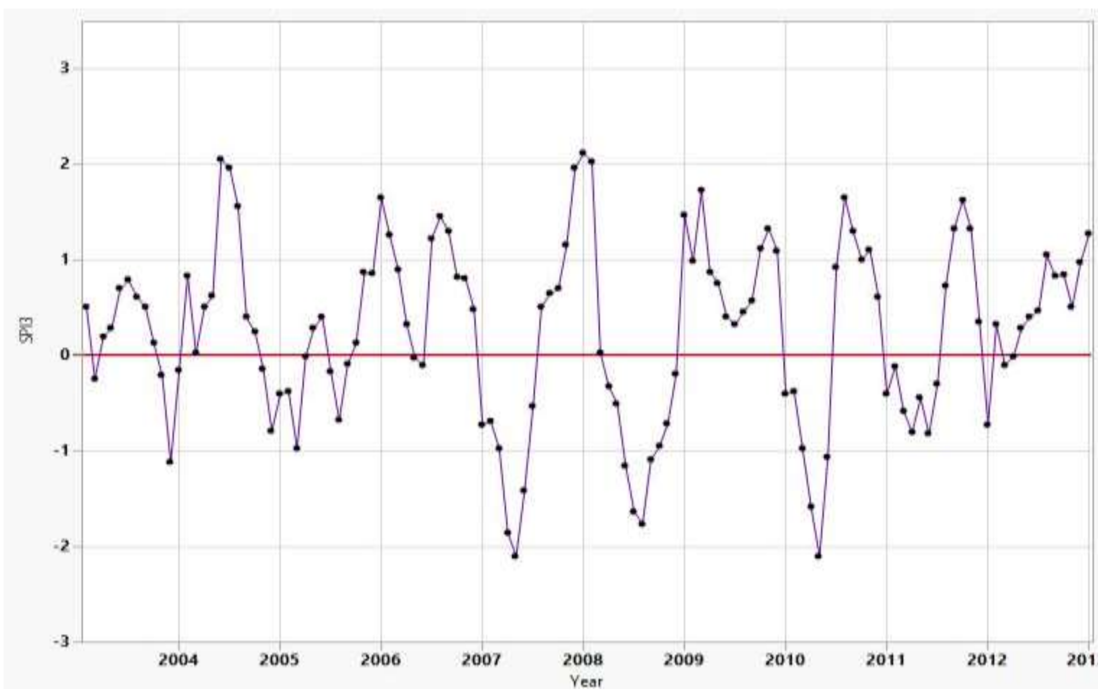
According to the results of the SPI calculation as shown in Figure 23, the lowest SPI 1-month time scale is -1.63 happen in April 2011 , while -2.1 for 3 month time scale registered in April 2008. For 6 month, SPI value of -2.73 recorded in March 2008.

Figure 23 describes the differences of drought frequencies and their duration as the result of different SPI time scales. In a shorter SPI time scale (1 month) the dry season were 2009. The drought and wet months are showed in a high temporal frequency (Figure 23). As observed from the graph the frequencies are decreases as time scale increases.

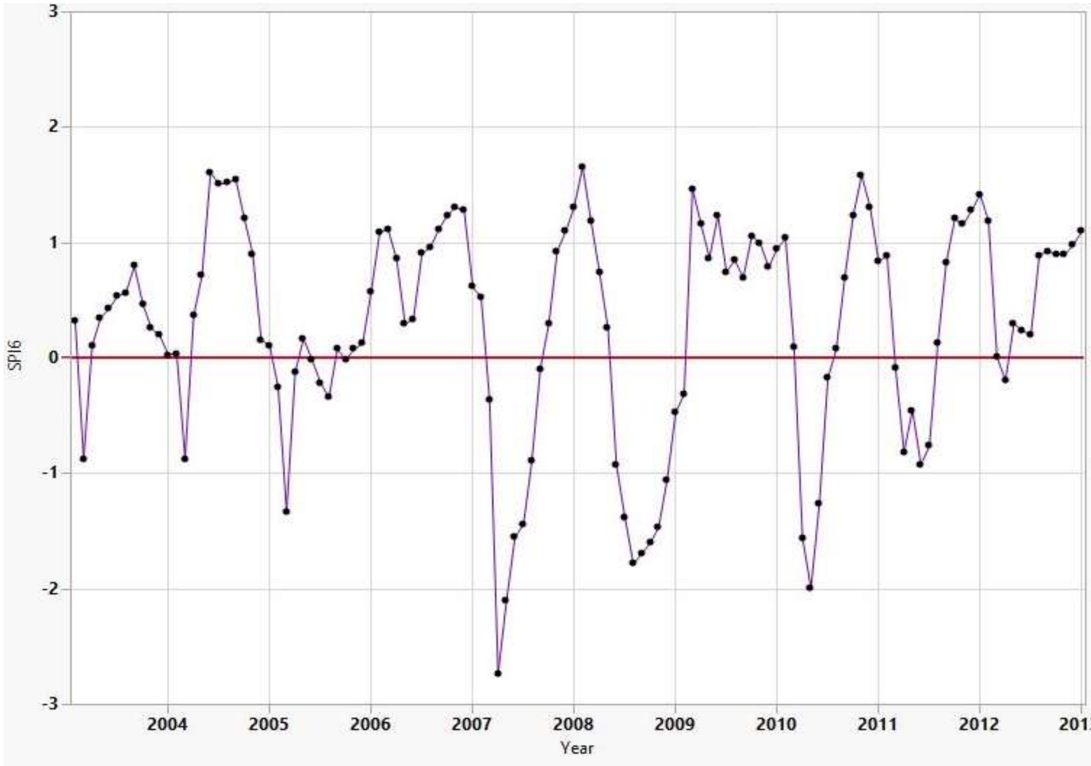
Figure 23 is evident that, the area is affected by different magnitude of drought in different years . The Figure also suggests that, the frequency of drought has increased in SPI 1 and SPI 3 as compare to SPI 6 and SPI 12 and it is clear that the study area is affected by drought almost in one month per year. SPI for 3 month indicated that, 2009 was agricultural drought year where the SPI for growing season (June to September) was found to be -1.76 which is considered to be a situation of severe drought. However, during the years of 2005,2007,2012 and 2013, SPI 3 reached up to value of 1, which states that these years were wet years.



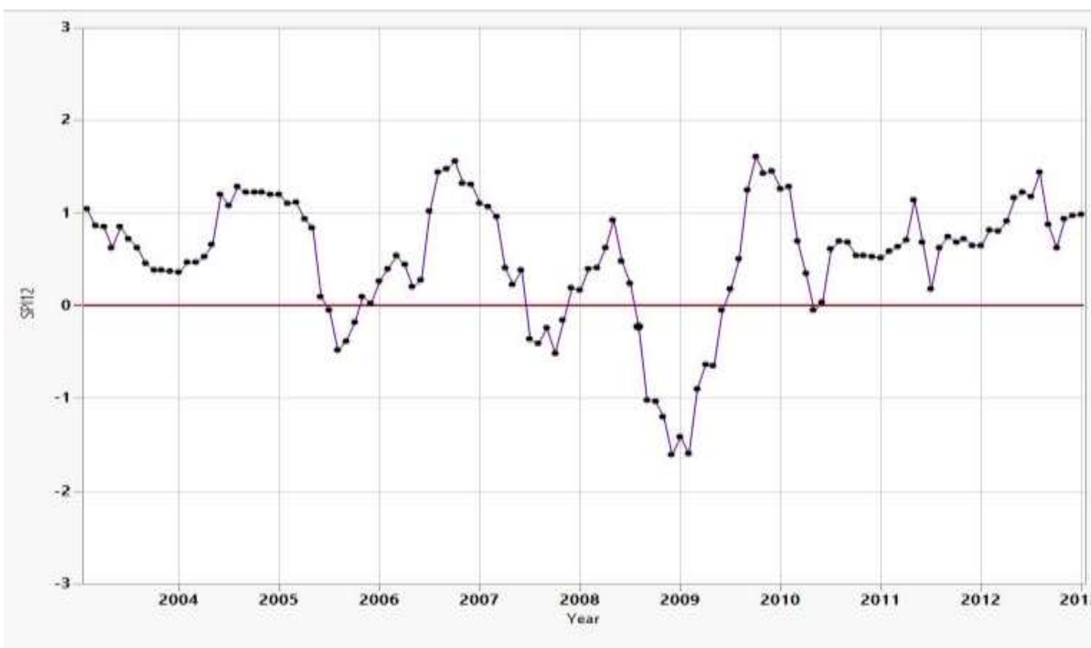
A. Time series of SPI for 1 month



B. Time series of SPI for 3 month



C. Time series of SPI for 6 month



D. Time series of SPI for 12 month

Figure 23. Temporal profile of SPI for growing season in 2004 to 2013

Figure 23 depicts both negative and positive SPI values for the years that were selected, as dry periods are known to have experienced drought. The negative SPI's in some of the months may be the result of late rainfall. This resulted in agricultural drought for rain-fed agricultural farmers since these rains may have late too come.

From the Figure 23, it is evident that during 2004-2013 there were at least 2 years (2006 and 2009) when the entire study area has been affected by the severe drought. .

As the results of the all SPI values analyzed for month 1,3,6 and 12 indicates year 2009 was the drought year. In 2009, a 3-month SPI showed that there was a drought problem (Table 7). It began in March , with its peak in July and by December of the same year the values returned to normal for the area. The annual SPI for 3 months ,which assesses the overall wetness and dryness of the year shows that January is the extremely wet months with value of 2.03 while July is the severely drought months with value of -1.76. Among the all twelve months, the rainy seasons (June to September) have negative values which shows there is high negative deviation of rainfall from normal. In general year 2009, was drought season where all values for growing seasons falls below normal depicting agricultural drought.

Table 7. A 3 month SPI values for all months of drought year 2009

Period		SPI 3	
		Value	Category
2009	January	2.03	Extremely wet
	February	0.03	Normal
	March	-0.32	Near normal
	April	-0.50	Near normal
	May	-1.15	Moderately dry
	June	-1.63	Severely dry
	July	-1.76	Severely dry
	August	-1.09	Moderately dry
	September	-0.95	Near normal
	October	-0.71	Near normal
	November	-0.19	Near normal
	December	1.47	Moderately wet

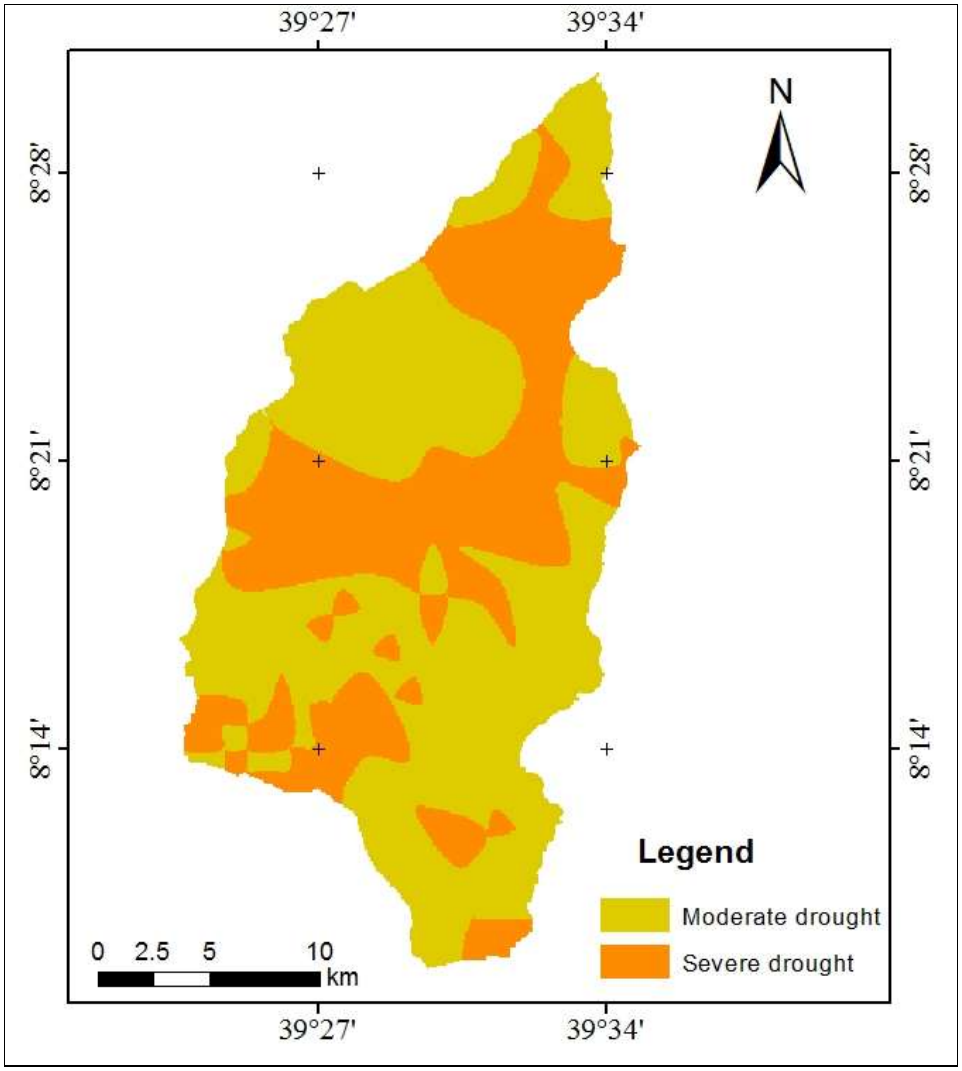


Figure 24. Spatial pattern of agricultural drought severity for drought year 2009 as expressed by Standardized Precipitation Index (SPI)

As the above Figure 24 depicts, in the year 2009 there was a moderate drought in wider extent. About 60.7 % of the area faces moderate drought while the remaining 39.3 % of the area categorized as severe drought. In this year all the area under study were hit by drought. This may be occurred due to the influence of the low distribution of rainfall as well as long dry spells occurrence. This leads the area to chronic agricultural production losses. Figure 24 shows that, there is severe drought in central and south western part of the woreda . Even though it is under drought, the south eastern part faces slight drought.

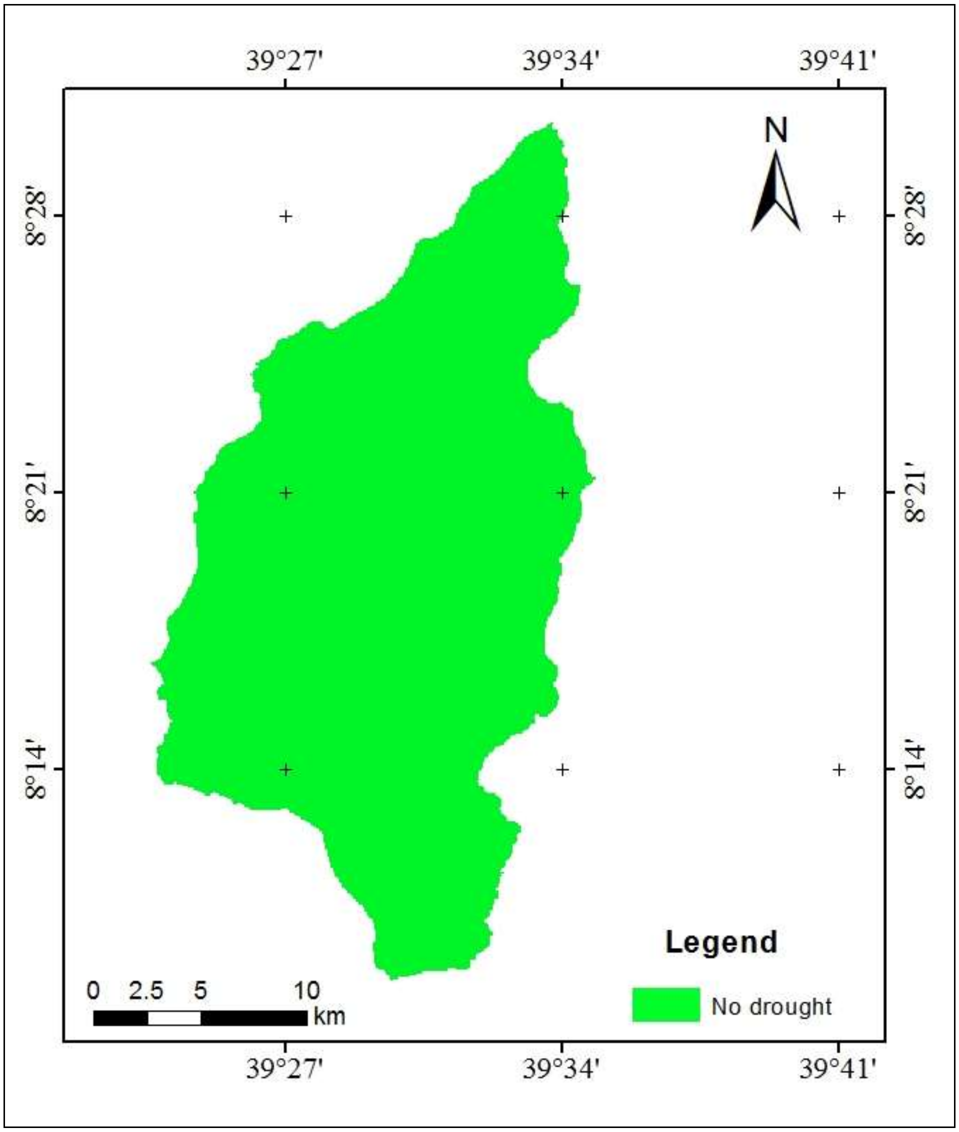


Figure 25. Spatial pattern of agricultural drought severity for wet year 2012 as expressed by Standardized Precipitation Index (SPI)

SPI can be used to identify not only drought years but also wet years. Based on this, analysis was made for wet year 2012. As seen from the above SPI map due to good seasonal rainfall the whole part of Sire woreda did not experience any drought condition in this year.

5.4 Validation

All the results obtained from the space time analysis of satellite derived drought indices were compared with the agricultural yield. The validation was done by quantitative information.

5.4.1 Relationship between Drought Severity Index (DSI) and Yield

The DSI and similar global products derived from operational satellite remote sensing should be useful for regional drought assessment and mitigation efforts, especially for areas of the globe where sparse measurement networks and poor infrastructure development limit other information sources.

Effects of severity of drought on vegetation can be defined as the deviation of current NDVI values from their corresponding long term NDVI values. Negative DSI values represent drier than normal conditions and positive values represent relatively wet conditions. The extent of agricultural droughts in Sire woreda is captured by the annual DSI. Based on the DSI results, 2009, 2010 and 2011 are drought years.

The annual DSI results over growing season were evaluated using agricultural yield dataset. Correlation between DSI for six years (2007 to 2012) and annual agricultural yield for the study area is examined. There exists strong correlation between DSI over the growing season and total yield for the study area.

Table 8. Result of regression analysis between DSI and yield

Year	*Correlation coefficient*	*T stat*	*P-value*	*R^2*	*Equation*
2007 - 2012	0.96	7.7	0.001	0.93	y = 9000000x + 604494

The Statistical data set in Table 8 indicates that, there exists stronger association between the DSI and yield. As the table portrays, positive correlation coefficient (r = 0.96) indicates that an increase in the DSI correspond to an increase in the yield, thus implying a direct relationship between them.

In other words, the relationship existing between these variables is statistically significant ($P < 0.001$), which may indicate that 99.9 % of all DSI values describes yield values within the six years. Coefficient of determination (R^2) is 0.93. This means that about 93% of the total variation in yield can be explained or accounted for by variation in DSI.

Finally, the pattern of the linear relationships between yield compared with DSI for six years (2007- 2012) of growing season is defined by the regression equation $y = 9000000x + 604494$. Where x = Drought Severity Index and y = agricultural yield. For example, in 2010 one of the drought years the value of DSI is -0.0075, then the yield (y) predicted to be 536,994 quintal [9000,000 (-0.0075) + 604494] showing about only 1,765.5 quintal deviation from actual yield which is 535,228.5 quintal (Appendix 2). This regression equation is used to predict the agricultural production in their early growing stage using Drought Severity Index and helps to know whether agricultural drought prevails or not in order to take necessary repressive measures if there is worse condition.

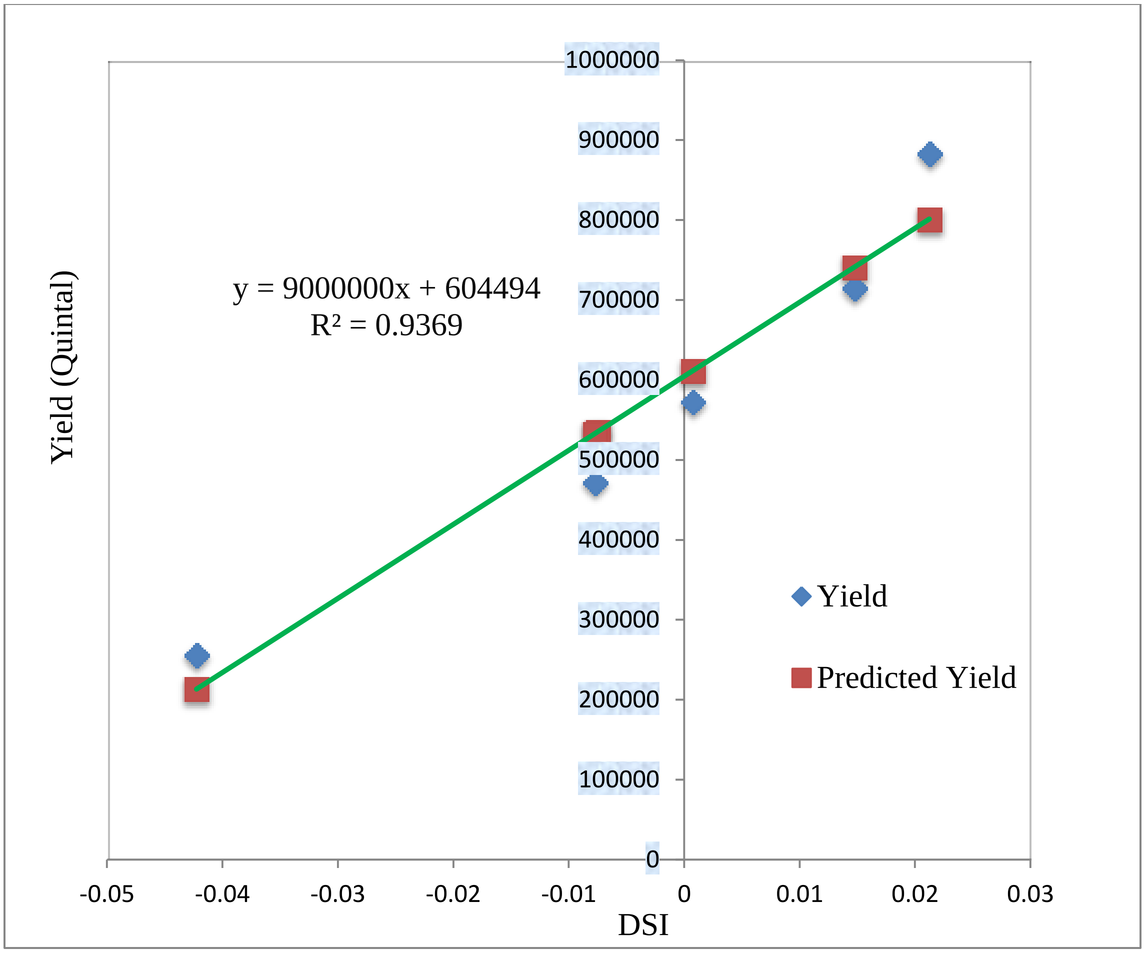


Figure 26. Relationship between DSI and yield

As inferred from the above Figure 26, the yield obtained by regression of Drought Severity Index (DSI) and agricultural yield almost best fits with the actual yield obtained within the time series.

Notably, the correlation between DSI over growing season and yield (Figure 26) is slightly better when the areas were hit by moderate drought. DSI perfectly describes agricultural condition in 2010, whereas slightly more deviation occur in 2012 . In general, DSI describes agricultural condition in drought and non-drought years in almost similar manner with best fit.

5.4.2 Relationship between Vegetation Condition Index (VCI) and Yield

In this investigation agricultural yield was expressed in quintal from 2007 to 2012 for growing season. As seen in Table 3, production yield deviation from multiyear mean fluctuates significantly in 2009 and 2011. The highest and the lowest yield years were 2012,2008,2007,2010,2011 and 2009 respectively.

Since the value of crop yield depends on weather conditions in the growth season and because VCI characterize these conditions, production yield were correlated with the indices for whole study area. The result of correlation for Sire woreda is shown in Table 9, where correlation coefficient between yield and VCI are plotted during the main growing of seasonal cycle. The periods where the correlation is significant are clearly identified in Figure 27. As discussed in section 4.3.1 the drought years indicated by VCI were 2009 and 2011. In these drought years correlation is the highest while it is perfectly fit in 2009.

The VCI index also showed some correlations during wet seasons, although the correlations were not as strong as in the case of drought seasons. The best correlation appeared in 2009 and 2011 of the dry years. It seems that in the drought years, VCI plays a major role in diagnosis of crop yield. Therefore, application of an index based on vegetation gives the possibility of forecasting yield almost earlier. The responsible body can take the value to decide the possible measures that should be taken if there is loss of agricultural production . Hence, a higher VCI value indicates favourable crop growth conditions, which agrees with a higher greenness inferred by vegetation.

Table 9. Result of regression analysis between VCI and yield

Year	*Correlation coefficient*	*T stat*	*P-value*	*R^2*	*Equation*
2007-2012	0.92	4.8	0.008	0.85	y = 13083x - 87561

From the result indicated in the Table 9 observed that, yield is highly correlated with VCI (r = 0.92) during growing season of the year 2007 to 2012.

Correlation coefficient with magnitudes of 0.94 is significant at the 0.008 level. The detailed result of regression analysis is presented in Appendix 1. The coefficient of determination (R^2) was 0.85 which infers eighty five percent of the variation in the yield can be explained by the VCI. This shows there is good relation between yield and VCI.

The regression equation obtained using VCI is used to predict agricultural yield which is a necessary step for concerned body to take possible measures before problem exhibits due to loss of agricultural production. In general, the result obtained shows that the VCI was demonstrated to be an important assessor of unfavourable vegetation conditions particularly related to agricultural drought.

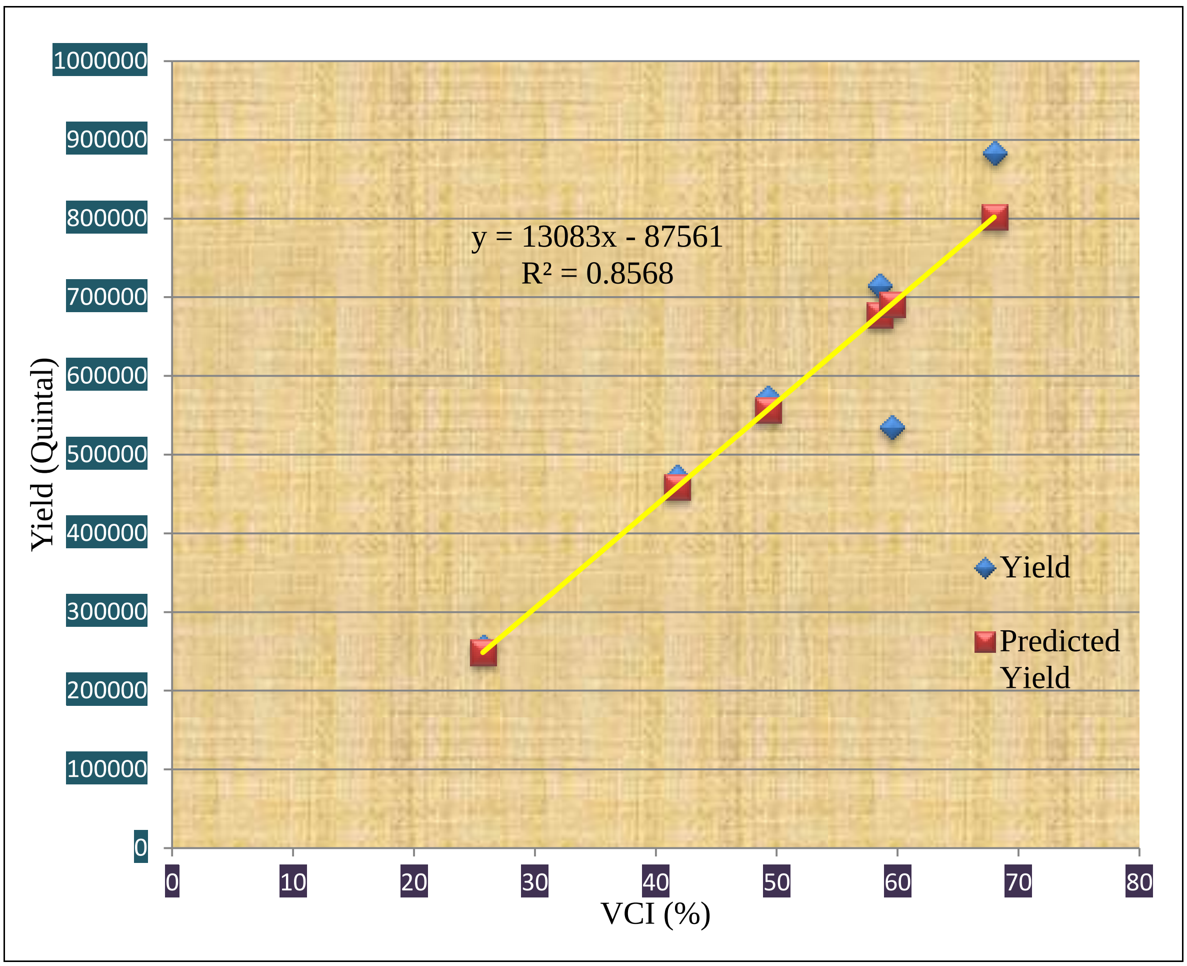


Figure 27. Relationship between VCI and yield

The VCI's calculated over June to September during drought years give significant correlation with yield. As the above Figure 27 shows, the plot of fit line for VCI is strongly correlate over production yield of study area in drought years (2009 and 2011) for growing seasons having a trend almost near to fit. Comparing to wet years which were away from regression line, in drought years especially in 2009 VCI value highly explain the situation in area (i.e. agricultural drought) by almost perfectly fit with regression line. In drought years, VCI series shows the most possibility for assessment. In contrary to the drought years what observed from the result shown in Figure 27 is that, fit line for VCI over production yield for wet years was less fit. In non-drought year 2012, there is less correlation between VCI and agricultural yield.

5.4.3 Relationship between Standardized Precipitation Index (SPI) and Yield

Since SPI is an index that represents water deficit or excess, positive SPI represents that water has been available to plants so that grain yield become above normal condition. Whereas, negative SPI or rainfall deficiency is reflected on crop production through yield reduction.

Due to the fact that crop production is a function of rainfall, crop failure is most often associated with moisture deficit or agricultural drought. The Standardized Precipitation Index (SPI) measures moisture supply. To assess the vulnerability of agricultural yield to the regional drought the relationship between the yields of crops grown in the woreda and the SPI values have been investigated.

The most important consequence of agricultural drought is a reduction in crop yield. While water stress is not the only factor that can affect crop yield, recorded drought events during the growing period are generally accompanied by important reductions in crop production, especially in the case of cereals.

In view of this, SPI and grain yield anomaly were regressed for the whole of the study area and the result has shown that when SPI is positive, grain yield also turns increasing above average revealing a good positive correlation (r = 0.57).

Table 10. Result of regression analysis between SPI and yield

Year	*Correlation coefficient*	*T stat*	*P-value*	R^2	*Equation*
2007-2012	0.57	1.4	0.228	0.51	y = 128657x + 510937

The indices have been quantified at decadal scale within the crop growing season. As shown in the (Table 10) lines that identify the extremes values of significance (α=0.22) has a strong positive linear correlation of r = 0.57 with the regression equation of y = 128657x + 510937. As observed from the equation, the yield decreases with the water deficit (i.e. the SPI decreases).

The above equations demonstrate that, just a mild drought of the order of $-1.0 < SPI < 0$ is capable of causing a drastic loss of yield. In other words, the correlation is statistically significant for the drought years whereas in contrary it is less significant for non-drought years. Coefficient of the determination (R^2) is 0.51, which means that only 51 % of the total variation in yield can be explained by the linear relationship between Standardized Precipitation Index (SPI) and agricultural yield as described by the regression equation. The other 49 % of the total variation in yield remains unexplained by SPI. The detailed result of regression analysis is presented on Appendix 3.

The SPI's calculated over June to September during 2007-2012 years give good correlation with yield. Comparing to wet years which were away from regression line in 2012, in drought years in 2009 SPI values highly explain the situation in area (i.e. drought) by better fit with regression line. The results indicate chances for yield prediction using seasonal values of SPI calculated over June through September, with best results obtained using June to September data. From the impact point of view on agriculture, these results shows that climate change is one factor that reduces agricultural production. It can be seen also that the overall rainfall condition plays an appreciable role in the determination of the yield.

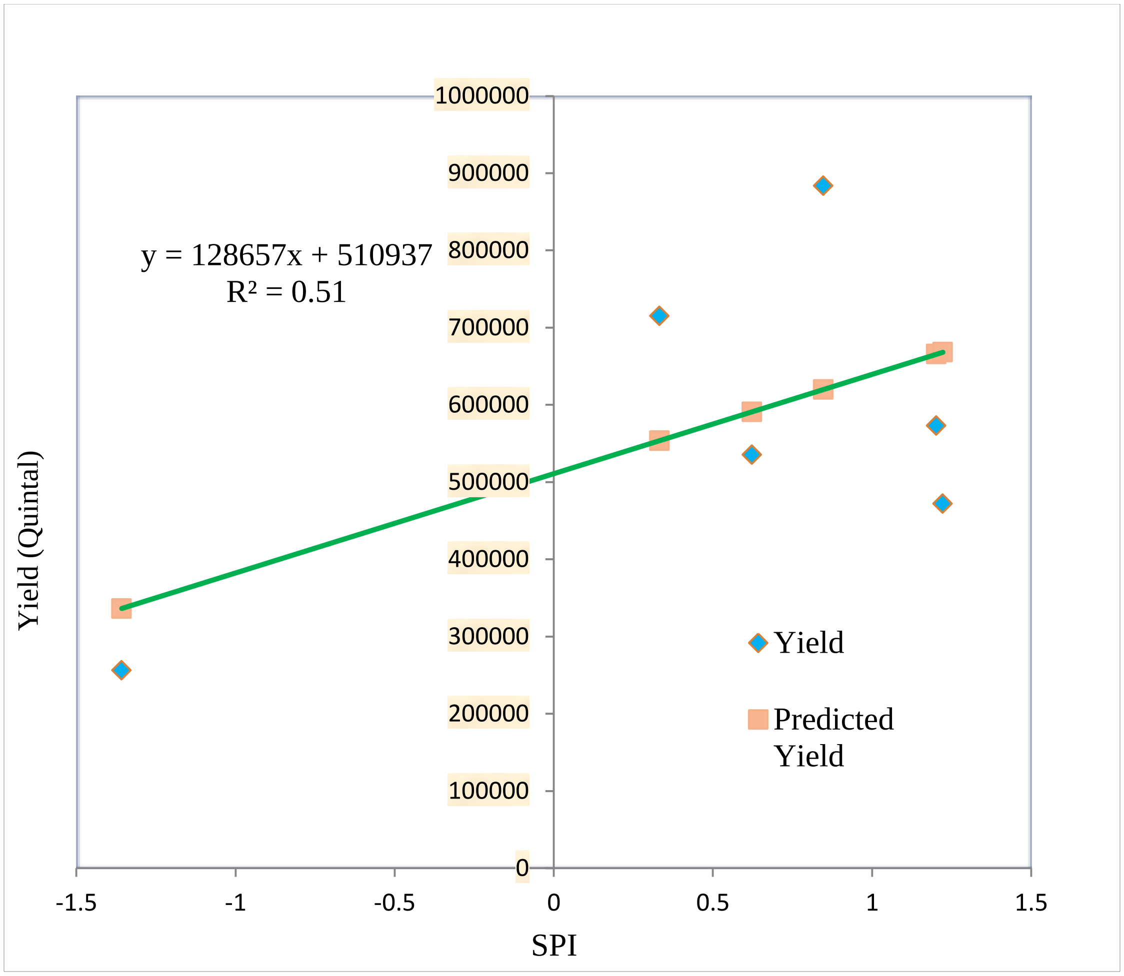


Figure 28. Relationship between SPI and yield

In general, as the Figure 28 shows the plot of fit line for Standardized Precipitation Index (SPI) is good correlate over production yield of study area in years (2007 to 20012) for growing season having a trend less fit. The coefficient of determination (R^2) was too low. This shows that there is low relation between SPI and agricultural production.

In final analysis, positive economical threshold of SPI 3 June to September signifies a territory of wettest season, while negative threshold is associated with resilient to drought areas. In general as observed from the relation, SPI was found to be less reliable indicator for agricultural drought assessment and is not recommended for agricultural drought monitoring as the NDVI based indices were available.

5.5 Classification of Agricultural drough severity

Finally, the agricultural drought severity map has been obtained by integrating all the derived drought assessing and monitoring indices: Vegetation Condition Index (VCI), Drought Severity Index (DSI) and Standardized Precipitation Index (SPI).

The agricultural drought maps from each derived drought indices were weighted according to their degree of influence as obtained by regression analysis and then combined using weighted overly analysis. According to the result derived from the integration of the derived drought assessing and monitoring indices the final map of Sire woreda is classified into severe, moderate, slight and non-drought classes based on the argument that a pixel has a drought and non-drought condition for the three drought assessing and monitoring indices used in this study.

Based on the results, the percentage of the areas not vulnerable to drought is only 3 % where as 97 % of the areas were hit by different magnitude of agricultural drought. Among these, 49.8 % of the woreda areas face slight drought while 46.9 % classified as moderate drought. The remaining 0.3 % of the area hit by severe agricultural drought (Table 11).

Table 11. Total percentage of area facing combined drought risk

No	Agricultural Drought level	Number of Kebeles	% Area
1	Severe	3	0.3
2	Moderate	13	46.9
3	Slight	14	49.8
4	No drought	4	3

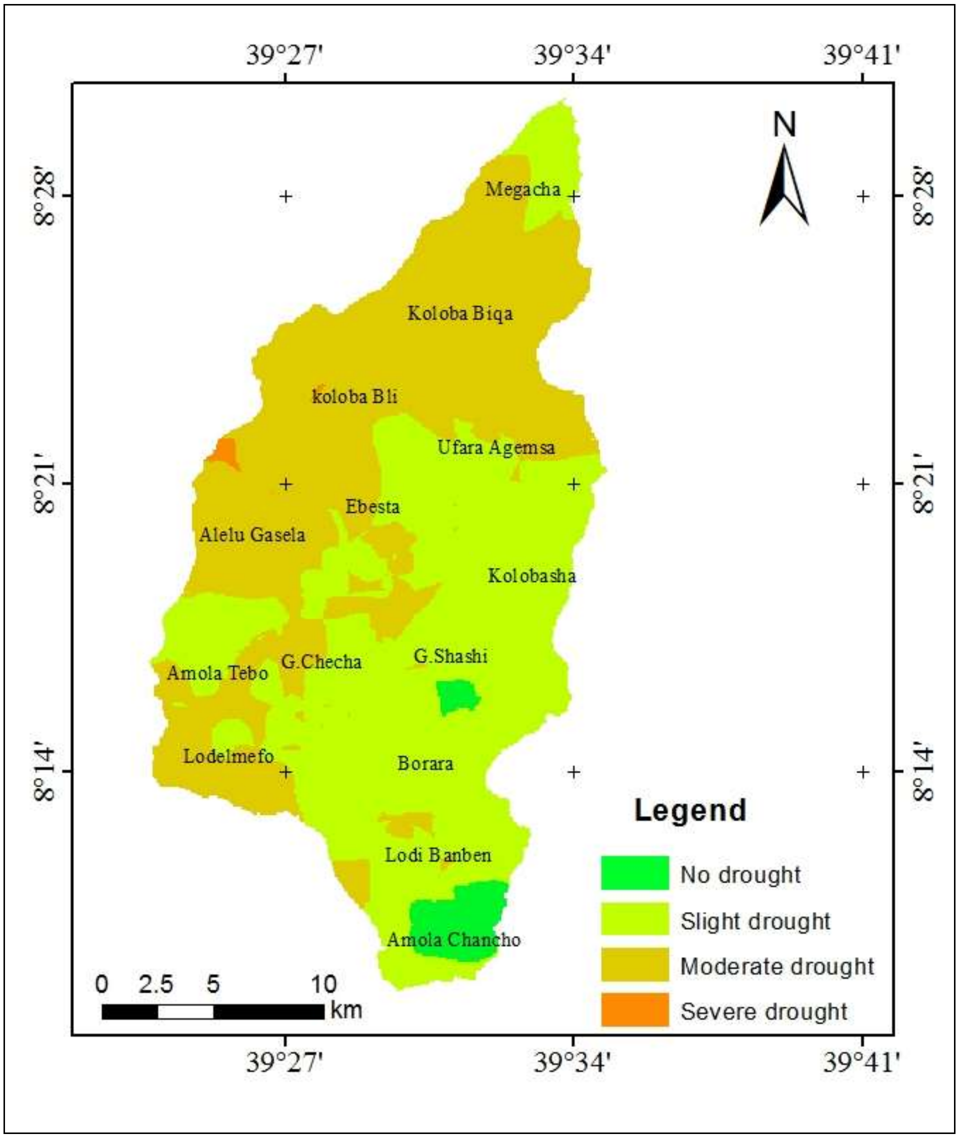


Figure 29. Agricultural drought map of Sire woreda

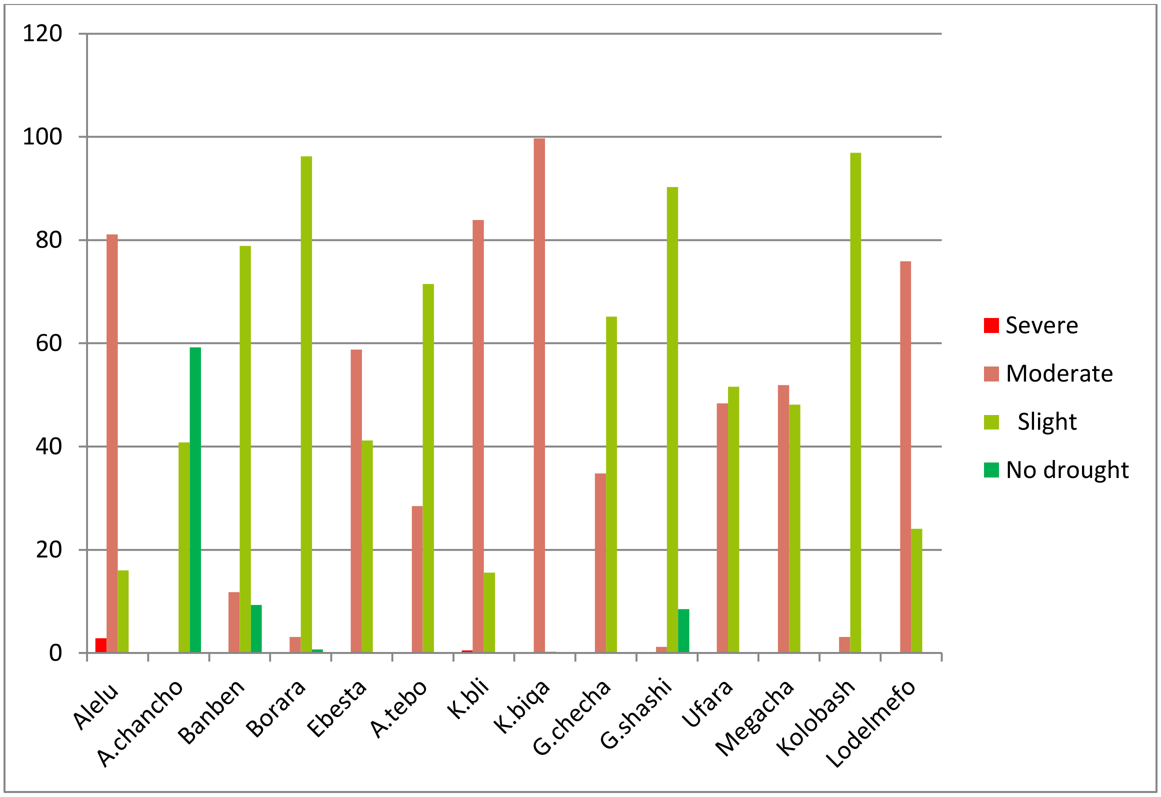


Figure 30. Areal percentage of Agricultural drought per Kebele's

Amola chancho, Banben, Borara and Gesala shashi were kebeles that have areas not touched by agricultural drought during drought years. In Amola chancho 59.2 percent of the area were free from drought severity. In contrary, Alelu, Ebesta and Koloba bli were hit by severe agricultural drought. Kolobash, Gesala shashi and Borara are kebeles where more than 90 % of their areas were hit by slight agricultural drought. In Koloba biqa about 99.7 % of the area faces moderate drought.

In general, the lowland areas in north western part of Sire woreda faces severe drought during assessed drought years while in highland areas of southern part slight drought and wet (non-drought) condition prevails. Northern tip and south eastern part of the area faces slight agricultural drought.

CHAPTER SIX

6. CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

In this study, the agricultural drought prone areas in the Sire woreda were identified by using Remote Sensing and GIS technology and drought risk areas were delineated by integration of satellite images and meteorological information. The role of satellite derived index for drought detection has been exemplified by integrating meteorological derived index called Standardized Precipitation Index in addition to NDVI derived indices as Vegetation Condition Index and Drought Severity Index. It is found that, a strong linear relationship exists between NDVI derived indices and yield. Highest correlation was found between Drought Severity Index and yield with R^2 value of 0.96. Satellite derived drought monitoring indices have also been correlated with precipitation index to see how vegetation stress condition and consequently how agricultural yield is changing with the variability of rainfall. The correlation result between NDVI and rainfall was 0.77 which shows there is strong relation between these two variables, in which NDVI values increase as rain fall increases and vice versa.

However, the result shows that with coefficient of the determination, 51 % of the total variation in yield can be explained by the linear relationship between Standardized Precipitation Index (SPI) and agricultural yield as described by the regression equation.

The Combination of Normalized Difference Vegetation Index (NDVI) derived indices and meteorological derived index, provides very useful information for a drought assessment and early warning system. This is indicated by the graphical analysis that indicated by temporal variation in vegetation index and precipitation over its long term mean average. The magnitude and frequency of agricultural drought vary from years to years. Identification, classification and analysis of agricultural drought dynamics are influenced by monitoring parameter and monitoring methods. The study also identified that there is a statistically good correlation between Standardized Precipitation Index (SPI) and agricultural yield but they are poorly spatially correlated with (R^2) of 0.51. SPI monitor precipitation deficit as it is the primary cause of drought development but a very little impact of agricultural drought have been observed through precipitation deficit in the Sire woreda. Among the drought years, SPI accurately explained agricultural drought in 2009 year only.

The results show that NDVI based indices could be the best indices for assessing and monitoring the drought occurrences, preparing drought maps on a local level and for studying the spatial pattern of drought occurrences in the study area. The study has found that remote sensing satellite based indices are promising to assess agricultural drought based on low resolution. However, the result may show better if assessment is based on high resolution satellite data. SPI was found to be less reliable indicator for agricultural drought assessment and is not recommended for drought monitoring as the NDVI based indices were available. DSI is more sensitive towards the assessment of agricultural drought which affects the agricultural production. This is due to the fact that the DSI is more sensitive towards the dryness than to a higher moisture content in the soil. The crop yields have been used to validate the results obtained from remotely sensed measurements. We have found that, the crop yields decreased in times identified as drought years by satellite based drought indices.

The overall relationship between NDVI derived indices and yield were broadly consistent with the highest correlation occur between yield and NDVI and lowest associations occur between yield and SPI. The result revealed that DSI, VCI and SPI indices express 96, 85 and 51 percent of variability of the grain yield in that order. Thus, the study has found that DSI is more useful for accurate timely agricultural drought mapping and assessing in the woreda.

The investigation showed that agricultural drought has become more probable during 2009 and 2011 years as it recurs at shorter time intervals. These years are considered as the driest years that affect the area largely. Crop yield declines exponentially with increasing agricultural drought in this vulnerable years. The agricultural drought maps on different time frames suggested that northern part of the woreda is becoming prone to drought while southern part has been less vulnerable. Based on above analysis, we can decide that satellite remote sensing can be used to assess and monitor the agricultural drought. Among all indices discussed in this paper, NDVI derived indices match with agricultural production report very well.

When drawing conclusion from the results, it should be noted that the satellite based indices were promising to assess and monitor agricultural drought.

6.2 Recommendations

From the findings of the study, the following recommendations are suggested:

- The satellite data used in this research has low spatial resolution, however the study area have smaller size. Integrating satellite data with the exact location of the area can provide better understanding on the occurrence of agricultural drought. Therefore, high spatial resolution image is recommended in small area.
- The combined use of remote sensing and meteorological indices seems to be a very useful approach for early agricultural drought prediction, having good potential to reduce crop uncertainty for government, farmers and stake holders.
- Government officials, stake holders and farmers should provide strategies for mitigating agro meteorological hazards, reducing the losses from them and adjusting the medium and long-term distribution of agricultural activities so as to adapt to environmental changes.
- An effective system for agricultural drought risk management organization should be established. Specifically, drought risk advisory body should be established for the provision of advisory services to avoid the risk of drought. Based on historic drought data it is important to evaluate past agricultural drought for estimating its trend and to predict future risks based on the observed trend in order to minimize the losses happen due to this hazard.

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APPENDICES

Appendix 1. Simple linear regression analysis between VCI and yield

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.925645
R Square	0.856818
Adjusted R Square	0.821023
Standard Error	90462.22
Observations	6

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.96E+11	1.96E+11	23.9365	0.008088
Residual	4	3.27E+10	8.18E+09		
Total	5	2.29E+11			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-87561.1	139872.2	-0.62601	0.56525	-475908	300786
VCI	13083.04	2674.104	4.892494	0.00808	5658.536	20507

RESIDUAL OUTPUT

Observation	*Predicted Yield*	*Residuals*	*Standard Residuals*
1	556778.5	16258.96	0.200947
2	677796.6	37180.95	0.459524
3	248673	7378.28	0.091189
4	690879.7	-155651	-1.92371
5	458655.7	13442.26	0.166135
6	802085.5	81390.73	1.005918

PROBABILITY OUTPUT

Percentile	*Yield*
8.333333	256051.3
25	472098
41.66667	535228.5
58.33333	573037.5
75	714977.6
91.66667	883476.3

Appendix 2. Simple linear regression analysis between DSI and yield

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.967946
R Square	0.936919
Adjusted R Square	0.921149
Standard Error	60044.37
Observations	6

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.14E+11	2.14E+11	59.4106	0.001525
Residual	4	1.44E+10	3.61E+09		
Total	5	2.29E+11			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	604493.8	24862.43	24.31354	1.7E-05	535464.6	673523
DSI	9257525	1201055	7.707828	0.001525	5922862	12592188

RESIDUAL OUTPUT

Observation	*Predicted Yield*	*Residuals*	*Standard Residuals*
1	611436.9	-38399.4	-0.715
2	741042.3	-26064.7	-0.48533
3	213363.4	42687.89	0.794854
4	535062.4	166.1473	0.003094
5	532748	-60650	-1.12931
6	801216.2	82260.05	1.531693

PROBABILITY OUTPUT

Percentile	*Yield*
8.333333	256051.3
25	472098
41.66667	535228.5
58.33333	573037.5
75	714977.6
91.66667	883476.3

Appendix 3. Simple linear regression analysis between SPI and yield

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.578789
R Square	0.514997
Adjusted R Square	0.168746
Standard Error	194955.3
Observations	6

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	7.66E+10	7.66E+10	2.01501	0.228763
Residual	4	1.52E+11	3.8E+10		
Total	5	2.29E+11			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	510937.4	90631.8	5.637507	0.0048	259303.2	762571
SPI	128656.7	90634.54	1.41951	0.2287	-122985	380298

RESIDUAL OUTPUT

Observation	*Predicted Yield*	*Residuals*	*Standard Residuals*
1	665647.1	-92609.6	-0.5311
2	553715.8	161261.8	0.924808
3	336286	-80234.7	-0.46013
4	591026.2	-55797.7	-0.31999
5	668220.2	-196122	-1.12473
6	619973.9	263502.3	1.511139

PROBABILITY OUTPUT

Percentile	*Yield*
8.333333	256051.3
25	472098
41.66667	535228.5
58.33333	573037.5
75	714977.6
91.66667	883476.3

D E C L A R A T I O N

I hereby declare that the thesis entitled Remote Sensing Based Agricultural Drought Assessment: A case study in Sire woreda, Arsi, Ethiopia has been carried out by me under the supervision of Dr. Getachew Berhan, Department of Earth Sciences, Addis Ababa University, Addis Ababa during the year 2014 as a part of Master of Science program in Remote Sensing and GIS. I further declare that this work has not been submitted to any other University or Institution for the award of any degree or diploma.

MUHAMMEDSULTAN AHMED

Signature: ________________________

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Date: May, 2014

C E R T I F I C A T E

This is certified that the thesis entitled Remote Sensing Based Agricultural Drought Assessment: A case study in Sire woreda, Arsi, Ethiopia is a bonafied work carried out by Muhammedsultan Ahmed under my guidance and supervision. This is the actual work done by Muhammedsultan Ahmed for the partial fulfillment of the award of the Degree of Master of Science in Remote Sensing and GIS from Addis Ababa University, Addis Ababa, Ethiopia.

Dr. GETACHEW BERHAN

Signature: ________________________

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