ADDIS ABABA UNIVERSITY

School of Graduate Studies

Department of Earth Science

AGRICUTLTURAL DROUGHT ASSESSMENT USING REMOTE SENSING AND GIS TECHINQUES

A Thesis Submitted to

The School of Graduate Studies of Addis Ababa University
In Partial Fulfillment of the Requirements for the Degree of Masters of Science in Remote Sensing and Geographic Information System (GIS)

By

GIZACHEW LEGESSE

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BY: GIZACHEW LEGESSE

ADVISOR: Dr. K.V.SURYABHAGAVAN
(Assistant Professor)

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Approved By Board of Examiners:

Dr. Balemual Atnafu ________________________________
Chairman, Department
Graduate Committee

Dr. K.V. Suryabhagavan ________________________________
Advisor

Prof. M. Balakrishnan ________________________________
Examiner

Dr. Mekuria Argaw ________________________________
Examiner

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List of Abbreviations

AET	Actual Evapotranspiration
ANOVA	Analysis of Variance
AVHRR	Advanced Very High Resolution Radiometer
CSA	Central Statistic Agency
DEM	Digital Elevation Model
DPPC	Disaster Prevention and Preparedness Commission
ETo	Reference Crop Evapotranspiration
EWS	Early Warning System
FAO	Food and Agricultural Organization
FEWS-NET	Famine Early Warning System
GIS	Geographic Information System
Kc	Crop coefficient
LEAP	Livelihood Early Assessment and Protection
MCE	Multi Criteria Evaluation
NDVI	Normalized Difference Vegetation Index
NGO	Non Governmental Organization
NOAA	National Oceanic and Atmospheric Administration
PDSI	Palmer Drought Severity Index
PET	Potential Evapotranspiration
SPI	Standard Precipitation Index
TCI	Temperature Condition Index
VCI	Vegetation Condition Index
WFP	World Food Program
WHC	Water Holding Capacity
WR	Water Requirement
WRSI	Water Requirement Satisfaction Index

Abstract

Climate has always been a dynamic entity affecting natural systems through the consequence of its variability and change. Agriculture is the most vulnerable and sensitive sector that is seriously affected by the impact of climate variability and change, which is usually manifested through rainfall variability and recurrent drought. In dryland semiarid areas of Ethiopia, including large part of East Shewa zone, agricultural drought and crop failure have been common, and farmers inhabiting the area experience extreme temporal and spatial variability of rainfall in cropping season with frequent and longer dry spells. This makes them vulnerable to the risk of agricultural drought. Thus, in order to adapt and/or mitigate the impact of agricultural drought, agricultural drought assessment has to form one dimension of research to be done whereas the use of remote sensing and GIS techniques provides wide scope in drought risk detection and mapping. Consequently, this study was conducted in East Shewa zone with the objective of assessing agricultural drought risk and preparing agricultural drought risk zone map using satellite data. To assess and examine spatiotemporal variation of seasonal agricultural drought patterns and severity, three drought indices namely, Water requirement satisfaction index (WRSI), Standard precipitation index (SPI) and NDVI anomaly are applied. A time series advanced very high resolution radiometer (AVHRR) NDVI and rainfall estimate (REF) satellite data for the years 1996-2008 were utilized as input data for the indices while grain yield data was used to validate the strength of indices in explaining the impact of agricultural drought. The result derived from indices for the study period has shown that the 2000 to 2005 cropping seasons experienced enhanced agricultural drought with observed spatial difference in severity level within East Shewa zone. However, the severity level was higher in 2000 and 2002 cropping seasons whereas 2002 being the most severe of all. The impact of agricultural drought on crop production was measured through estimation of yield reduction. Compared to other cropping seasons of the analysis period, yield reduction for the years 2000 to 2005 was also higher in the East Shewa zone. Similarly, the year 2002 had highest reduction followed by that of the year 2000. Generally it is revealed that index results are in agreement with results of yield reduction depicting that yield reduction is largely attributed to agricultural drought. In order to evaluate the strength of the indices for expressing the existence of agricultural drought, simple regression analysis of indices results with total grain yield was computed. The result revealed that WRSI, SPI and NDVI anomaly express 76, 64 and 54 percent of variability of the grain yield in that order. Thus, WRSI can be a good indicator for occurrence of agricultural drought. Agricultural risk map of East Shewa zone was produced by integrating the drought frequency maps derived from the three drought indices in order to guide future prioritization of adaptation and mitigation options for agricultural drought prone areas. The result indicates that East Shewa zone is classified into slight, moderate and severe agricultural drought risk zone covering 17.18, 41.32 and 42.50 percent of the total geographical area respectively. Thus, this agricultural drought risk mapping can be useful to guide decision making process in drought monitoring and to reduce the risk of drought on agricultural production and productivity.

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

1. Introduction

1.1 Background

Climate has always been a dynamic entity, and it can affect natural systems through the consequence of climate variability and climate change. Ethiopia's climate is influenced by general atmospheric and oceanic factors that affect the weather system (Bekele Feleke, 1997) and climatic factors such as droughts has significant impact on agricultural output (Tsegaye Woldegeorgis, 1998).This makes Ethiopia vulnerable to climate variability. Climate variability over the last three decades resulted in drought and famines in Ethiopia and several other countries in Africa (Comenetez and Caviedes, 2002). 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. Drought is a period of abnormally dry weather sufficiently for the lack of precipitation to cause a serious hydrological imbalance and carries connotations of a moisture deficiency (Mohan and Arena, 1982 cited in Chopra, 2006).Drought is also water related natural disaster which affect a wide range of environmental factors and activities related to agriculture.

Agriculture remains by far the most important sector in Ethiopian economy. However, the existences of climate variability influence agricultural sector on which majority of the population depend. According to Sadoff (2006), 80 percent of Ethiopia's population subsists on rainfed agriculture, thus welfare and economic productivity are linked to the variable rains. This dependency on rainfed agriculture has thus made the country's economy extremely vulnerable to the effect of climate variability and climate change. Frequent drought is an important aspect of climate variability and change that human being has been experiencing in current time. Consequently, area affected by drought is increasing in Ethiopia due to climate change, climate variability and other human induced factors (WMO, 1986; NMSA, 1996).

In dryland semiarid areas covering large part of East Shewa zone, agricultural drought and crop failures have been common, and rainfed agriculture has yet to provide minimum food requirement for rapidly growing population. According to Reddy and Kidane Georgis (1993), dryland which covers about 46 percent of the total arable land in Ethiopia, contributes less than

10 percent of the total crop production in the country. It implies that rainfall is highly risky in terms of amount and distribution, and the rate of evapotranspiration is very high as well.

Based on the causative factors, drought can be classified into meteorological, agricultural, hydrological and socioeconomic types. Among these, the occurrence of agricultural drought has increased in East Shewa zone. Farmers inhabiting the area experiences extreme temporal and spatial variability of rainfall in cropping season with frequent and longer dry spell affecting their agricultural production and productivity. This makes them vulnerable to the risk of agricultural drought. The risks associated with agricultural drought are spatially variable; hence they require different adaptation strategies and options.

In order to adapt in response to the adverse impacts of agricultural drought, agricultural drought assessment and identification of risk zone have to be the primary tasks among others. Identification of agricultural drought risk zone is usually carried out on the basis of analysis of rainfall and evapotranspiration data on longtime basis (Lemma Gonfa, 1996). This conventional method lacks identification of spatial variations (Jeyaseelan, 2004). Besides, collecting sufficient spatial and temporal data are of a major difficulty, especially in areas with rugged topography and less accessibility. The use of satellite data is therefore paramount importance.

Fortunately, amongst all the greatest scientific advances of the 20th Century, exploration of outer space has been the most spectacular and significant one. The advent of satellite era, heralded by the launch of satellite in the fifties, has introduced an entirely new technology of satellite remote sensing and a whole range of its application for the benefit of mankind.

As the vegetation condition reflects the overall effect of rainfall and soil moisture, the satellite based monitoring of vegetation plays an important role in drought monitoring and early warning by virtue of its reliable data acquisition capabilities. Thus, the use of satellite data enables to detect drought, and its impacts on crops can be detected prior to harvesting using vegetation indices such as Normalized Difference Vegetation Index (NDVI) and Vegetation Condition Index (VCI) (Kogan, 1997). Consequently, the use of remotely sensed data from satellite platforms for drought assessment has recently become wide spread (Kogan, 1997; Alemayehu

Kassa, 1999; Chopra, 2006; Amare Degefaw, 2007; Beyene Ergogo, 2007). According to Jeyaseelan (2004), the remote sensing based method for identification of agricultural drought prone areas uses historical vegetation index data (NDVI) derived from National Oceanic and Atmospheric Administration (NOAA) satellite series and provides spatial information on drought prone area depending on the trend in vegetation development and frequency on low development. The relationships of red and near-infrared reflected energy through vegetation index (NDVI) indicate the amount of vegetation present on the ground. Information on vegetation cover can in turn be used as a first cut indicator of the possible occurrence of drought. However, additional indicators are also required to carry out a full drought assessment, as the causes and consequences of drought are multi-faced (De Waal, 1989 cited in Alemayew Kassa, 1999). Analyses of time series NDVI data and NDVI derived products help to identify vegetation condition anomalies as a function of rainfall.

Water requirement satisfaction index (WRSI) is also one of crop performance index based on a water balance model that simulates the reduction of crop yield due to water deficit. This model is currently operational as yield monitoring and forecasting tools for region wide food security analyses in drought prone countries in Sub-Saharan Africa (Senay and Verdin, 2002). 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. In general, applications of satellite based vegetation, crop performance and climate derived drought indices become the feasible means and acceptable decision tools for timely action against the negative consequences of agricultural drought. Thus, Assessment of agricultural drought by remote sensing data is believed to be very helpful for providing countermeasures as early as possible.

GIS and Remote sensing techniques are being widely used for analysis of drought monitoring and assessment using various drought indices (Alemayehu Kassa, 1999; Jeyaseelan, 2004; Chopra, 2006, Amare Degefaw, 2007; Beyene Ergogo, 2007). Remote sensing techniques can be used to monitor the past and current condition so that it can be used to provide baseline data against which changes can be compared while the GIS techniques provide suitable framework for integrating and analyzing remote sensing data required for agricultural drought assessment.

Since agricultural activities in the dryland semi arid areas in general and study area, East Shewa zone in particular, are influenced and controlled by seasonal rain, the study of agricultural drought analysis is carried out season-wise using vegetation based drought index (NDVI) and climate based drought index (SPI) as well as crop performance index (WRSI).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.

1.2 Problem statement

Currently world climate in general and that of Ethiopia in particular, has been changing due to mainly anthropogenic (human) factors. In Ethiopia, the major impact of climate change is manifested through rainfall variability and recurrent drought. The risks associated with them are generally late onset and early cessations of rainy season that cause reduction in the growing season. The amount and distribution of rainfall in the growing season is also very erratic, indeed making crops vulnerable to moisture deficit.

Among others, agriculture is the most vulnerable and sensitive sector that is seriously affected by the impact of drought. Agricultural drought is currently more pronounced in the study area. Farmers inhabiting in the study area are exposed to the impact of agricultural drought that resulted from the current climate change. This is due to the fact that most of farmer’s cultivars (long duration crop variety) can no longer resist the exiting agricultural drought and intra-seasonal dry spell. As a result, most of the cultivars have gone obsolete, and yield reduction and crop failure becomes common. Thus, in order to adapt and/or mitigate the impact of agricultural drought through generating different improved drought resistant agricultural technologies, agricultural drought assessment through remote sensing is mandatory.

Agricultural drought risks are not evenly distributed spatially due to variation of locations in exposure to the climate hazards and the vulnerability of farming to drought conditions. Besides, prioritization of adaptation and mitigation options for agricultural prone areas has been a major difficulty due to lack of well defined risk map in the study area. Hence, agricultural drought risk mapping can be useful in this regard 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 evaluate the spatiotemporal occurrence of agricultural drought and their impacts on agricultural production using application of satellite data.

1.3.2 Specific objectives

- To assess agricultural drought risk using remotely sensed image based vegetation, climate and crop performance indices.
- To estimate agricultural yield reduction due to moisture deficit
- To prepare agricultural drought risk zone map showing the severity of drought condition at various levels.

1.4 Significance of the Study

The use of satellite data using advanced techniques such as remote sensing and Geographic information system (GIS) can assist for detection and mapping of agricultural drought prone areas. Agricultural drought risk mapping in turn aims to be useful in the decision making process for drought monitoring and identifying appropriate site for specific adaptation and mitigation actions. Thus, agricultural drought risk zone map produced from this study can be useful on one hand for policy makers to prioritize their actions based on the risk level, on the other hand for researchers to generate agricultural technologies and information including selection of drought tolerant and adaptive crops, as well as generation of crop management and soil moisture conservation practices. Moreover, it may be helpful for development agents and Non-Governmental Organization (NGO) to facilitate scaling up of best technologies with success stories from similar risk zones elsewhere.

1.5 Limitation of the Study

The limitation of the study was lack of data on crop yield at the Woreda level that helps to see inter-woreda yield variability, and unavailability of data related to pest infestation and crop disease as the result of agricultural drought were also the major limitation encountered during implementation of the research study.

2. Literature review

Agriculture is the most important sector in the Ethiopian economy. This sector is always under the full blown impacts of climate change and climate variability. The impact of agricultural drought as the result of climate variability and change is largely pronounced in dry land semi arid areas in general and East Shewa zone in particular where rainfall deficiency is experienced. Besides, the lack or inappropriate distribution of precipitation causes shortage of water during the important phonological stages of plants.

2.1 Drought

Drought is a disastrous natural phenomenon that has significant impact on agricultural, environment and socio-economic conditions of the community. The concept of drought varies among regions of differing climates (Dracup *et al.*, 1980) and resource base. In general, drought gives an impression of water scarcity resulted from insufficient precipitation, high evapotranspiration, and over-exploitation of water resources or combination of these parameters.

Drought is the manifestation of climate change and a common phenomenon in Ethiopia. Ethiopia faces widespread droughts, causing large economical and social damages. According to Segele and Lumb (2005), Ethiopia has been ravaged by severe drought for many of the last 35 years, primarily due to the failure of its main (kiremt) rainy season. The agricultural sector on which 85 percent of the population depends is by far the largest sector being affected by drought. In dryland semi arid areas, the major factors that aggravate the impact of drought are poor water management and hence agricultural production is below the potential. Generally, significant deficiency of precipitation from normal over an extended period of time results in plant water stress or agricultural drought in dry land semi arid areas where most part of East Shewa zone is situated.

2.2 Types of Drought

Drought is a normal and recurrent feature of climate. It occurs virtually in all climatic zones, but its characteristics vary significantly from one region to another. According to Wilhite and Glantz (1985), drought can be classified on sectoral basis as follows:

2.2.1 Meteorological drought

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

2.2.2 Agricultural drought

Agricultural drought is defined by a reduction in soil moisture availability below the optimal level required by a crop during the different growth stages, resulting in impaired growth and reduced yields. It is typically occurred after meteorological drought but before hydrological drought (Flood and Climate Basics, 2004). This drought does not depend only on the amount of rainfall but also the correct use of that water.

2.2.3 Hydrological drought

Hydrological drought results when precipitation deficiencies begin to reduce the availability of natural and artificial surface and subsurface water resources. It occurs when there is substantial deficit in surface runoff below normal conditions or when there is a depletion of ground water recharge.

2.2.4 Socio-economic drought

Socio-economic drought occurs when human activities are affected by reduced precipitation and related water availability. This form of drought associates human activities with elements of meteorological, agricultural, and hydrological drought.

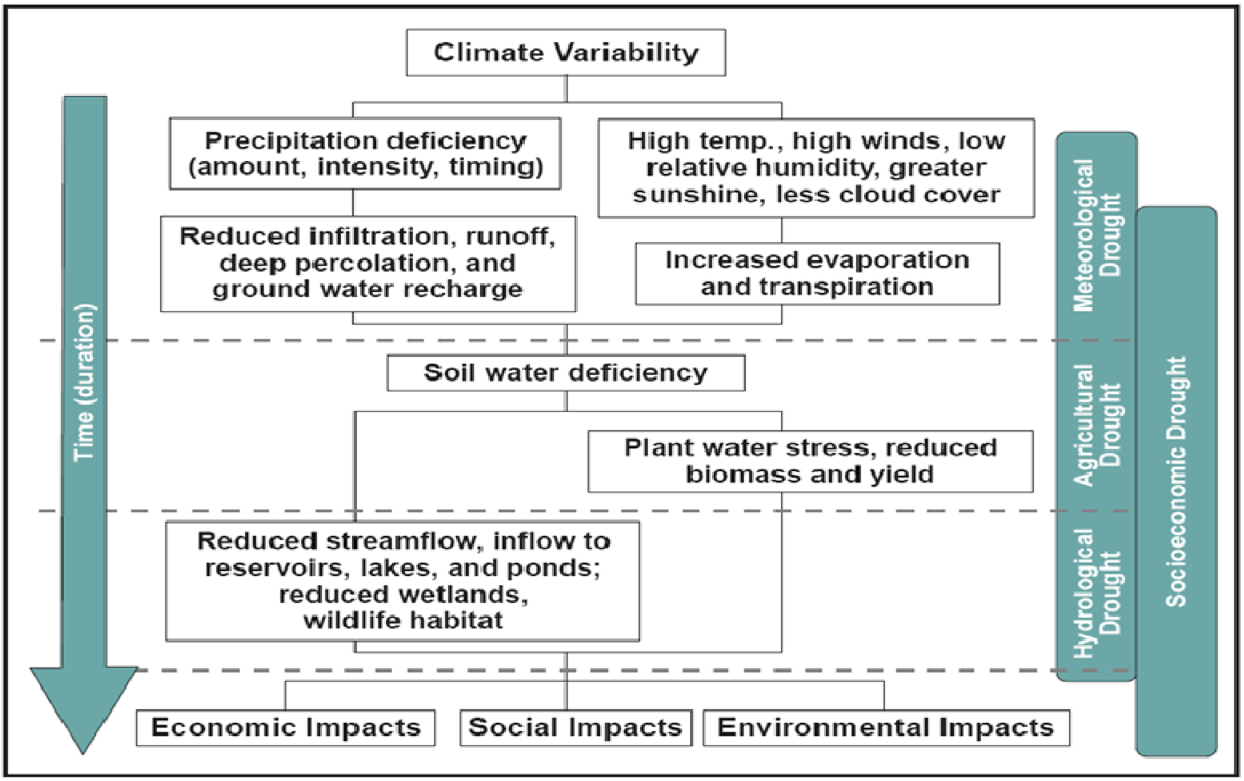


Figure 1. Relationship between different types of drought

(Source: National Drought Mitigation Center, University of Nebraska-Lincoln, USA).

2.3 Agricultural drought impact on agricultural sector

Agricultural drought produce a complex web of impacts that span many economic sectors. Among, agriculture is the primary economic sector affected by agricultural drought and particularly, short term agricultural drought at the critical growth stages has severe impacts on agriculture (Wu and Wilhite, 2004 cited in Mokhtari, 2005). Agriculture is the largest consumer of water and, therefore, the most sensitive to agricultural drought. Moisture deficit is often the most limiting factor for crop production. In Ethiopia, rainfall in main rainy season (Kiremt) is the most important for agricultural activities as nearly 95 percent of crop production is in this season (Workneh Degefu, 1987). Thus the occurrence of agricultural drought during the main rainy season has greater impact on country's food production. This impact is largely prominent in dryland semiarid areas.

Agricultural drought has either direct or indirect impact on agricultural activities. Direct impact includes reduced crop yield, rangeland and forest productivities. The consequence of these impacts result in reduction of income of farmers and agro based industries, increased price for food and other agricultural products such as forest products. Besides, losses in crop production, agricultural drought is associated with increases in insect infestation, plant disease and wind erosion (Mokhtari, 2005). Agricultural drought induced physiological stress increases a plant's susceptibility to disease and insects, and reduces crop survival. Furthermore, the loss of soil organic matter can lessen cropland productivity and facilitate for wind erosion. On the other extreme, agricultural drought has also social impact particularly on farmers that drive the agricultural sectors. It involves food shortage and migration to urban areas. This makes drought migrants increase pressure on social infrastructure of the urban areas and leads to increased poverty.

2.4 The needs of Remote Sensing data for drought assessment

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

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

Even though weather satellites such as NOAA were first designed to help weather forecasts, they are found useful for addressing vegetation status in the earth surface (FEWS-NET). According to Kogan (1997), since the late 1980's, they have also been used for drought detection, monitoring and impact assessment in agriculture.

2.5 Drought indices and their application in drought assessment

Different types of drought require different indices that can be used to quantify the moisture condition of a region and thereby detect the onset and measure the severity of drought events, and to quantify the spatial extent of a drought event thereby allowing a comparison of moisture supply condition between regions (Quiring and Papakryiakou, 2003; Beyene Ergogo, 2007). It has become clear that no single indicator or index is adequate for monitoring drought on regional scale. Instead, a combination of monitoring tools integrated together is preferable for producing regional or national maps (Martini et al., 2004). Thus, spatiotemporal patterns of seasonal drought can be detected using meteorological, vegetative as well as crop performance indices among others.

2.5.1 Meteorological drought index

2.5.1.1 Standard Precipitation Index (SPI)

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

Guttman (1998) has made comparison of Palmers Drought Severity Index (PDSI) and SPI, and recommend SPI as drought index, as it is easy to determine and has greater spatial consistence. Moreover, it can be used in risk assessment analysis and making decisions with special ability for adjustments to time periods for which the users are interested, for example, short time periods in life cycle of crops or longer periods regarding water resources. According to McKee et al. (1993), conditions of soil moisture are reacting to precipitation anomalies in relatively short time period and appearance of drought is happening every time when SPI is negative and its intensity comes to -1.0 or lower, while drought stops when SPI is positive.

2.5.2 Vegetative based drought index

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

2.5.2.1 Normalized Difference Vegetation Index (NDVI)

In satellite image, vegetation appears very different at different light spectrum particularly in the visible and near infrared wavelengths. Healthy or dense vegetation absorbs most of the visible light that reached on it and reflects a large portion of the near infrared light. Unhealthy or sparse vegetation reflects more visible light and less near infrared light. By comparing visible and near infrared light, scientists measure the relative amount of vegetation and its vigor using vegetation Index, NDVI.

NDVI is an index of vegetation health and density and computed from the satellite Image using spectral radiance in red and near infrared reflectance using the formula:

$$NDVI = (NIR - R) / (NIR + R);$$ Where NIR= near infrared band, R= Red band

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

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

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

2.5.3 Crop performance index

2.5.3.1 Water Requirement Satisfaction Index (WRSI)

WRSI is a geospatial model that was developed by Food and Agricultural Organization (FAO) for use with satellite data to monitor water supply and demand for rainfed crop throughout the growing season (Free and Popov, 1986). It is also a crop performance index based on the availability of water in the soil.

In Ethiopia, crop yields are too large extent predicted by the amount of available water compared to water requirement. Taking this into account, new software environment for drought indexing, namely Livelihood Early Assessment and Protection (LEAP) was designed specifically for Ethiopian context commissioned by World Food Program (WFP) in 2006 (Hoefsloot, 2008). One of the goals of LEAP is as a platform for calculation of weather based indices starting out with the calculation of a crop water balance indicator, WRSI. In addition, it uses relevant soil information from FAO digital soil map and topographical parameters derived from the GTOPO30 digital elevation model (DEM) (Gesch et al., 1999).

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

2.6 Satellite indices based drought assessment studies

The Earth observation satellites which include both geostationary and polar orbiting provide comprehensive and multi temporal coverage of large areas in real time and at frequent intervals and thus have become valuable for continuous monitoring of atmospheric as well as surface parameters related to droughts and floods (Jeyaseelan, 2004). Due to lack of spatial detail from station based drought indicators, satellite based derived indices widely used for drought assessment. Many satellite based drought assessment studies are conducted worldwide and most of them uses vegetation indices calculated from long term records of remote sensing data (Nageswara et al., 2005; Murali et al., 2008). According to Seiler et al. (1998), the AVHRR-based Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) have been developed and successfully used for monitoring drought in the USA, the Former Soviet Union, Zimbabwe, and China. This research was designed to apply and validate those indices for drought detection and impact assessment on agricultural yields in Cordoba province of Argentina. They concluded that those indices were useful to assess the spatial characteristics, the duration and severity of drought, and were in good agreement with precipitation patterns.

Drought risk assessment and monitoring can also be conducted using the relationship of NDVI and rainfall. Alemayehu Kassa (1999) used regression techniques in order to monitor drought and verify whether there is a correlation between NDVI and rainfall in Sudan. The result showed that there is strong positive relationship of NDVI to rainfall in Sudan with regression coefficient between 0.74 and 0.8. In another study in East Africa by Eklundh (1997), the possibility of using NDVI data for crop and natural vegetation monitoring has been analyzed by measuring the cross-correlation between time series of NDVI and vegetation indicators such as rainfall for the area where rainfall is a limiting factor. The result has shown that there is good correlation between NDVI and rainfall with coefficients of correlation 0.7 and 0.9.

Rainfall is one of the climatic variables that largely determine the occurrence of drought. The severity of drought is considered to be a function of rainfall. In many research studies, the relationship between rainfall and satellite based vegetation indices have been analyzed in order to see the pattern between them (Pavel et al., 2006; Alemayehu Kassa, 2007). As vegetation indices derived from AVHRR are directly related to plant vigor, density and growth conditions, they may also be used to detect natural hazards such as drought. According to Li et al. (2002) cited in Chopra (2006), Vegetation amount and condition are a functions of environmental variables such as rainfall. Consequently, a strong relationship, involving a brief time lag (1 to12 weeks) in the vegetation response to rainfall, would be expected between vegetation indices such as NDVI and rainfall.

Herrmann and Anyamba (2004) have investigated temporal and spatial patterns of vegetation greenness and explored relationships between rainfall and vegetation dynamics in the Sahel, based on the analyses of NDVI time series and gridded precipitation estimates at different spatial resolutions. They assumed that rainfall is the most important constraint to vegetation growth in this semi-arid zone, which justify the attempt to predict vegetation greenness from rainfall estimates through linear regression. Moreover, Anyamba and Tucker (2005) analyzed seasonal and inter-annual vegetation dynamics in Sahel using NOAA-AVHRR NDVI. The study focused only on NDVI patterns in growing season, which was defined by examining the long term patterns of both rainfall and NDVI. Year to year variability in NDVI patterns was examined by calculating yearly growing season anomalies. The correlation between NDVI and rainfall anomaly time series was found to be positive and significant, indicating the close coupling between rainfall and land surface response patterns over the region.

The correlation between NDVI anomaly and grain yield anomaly were also used to conduct agricultural drought risk assessment (Chopra, 2006; Beyene Ergogo, 2007). Moreover, the correlation between grain yield and NDVI is important to quantify the impact of drought on the crop production. Alemayehu Kassa (1999) also addressed that NDVI can be used for the assessment of weather impact on vegetation, and evaluation of vegetation health and productivity. Besides, as satellite based radiative indices are good indicators of leaf area index, which are good indicators of yield potential.

Rainfed agriculture is always characterized by significant fluctuation in yield due to variation in moisture availability. Agricultural drought in general and extended intra-seasonal dry spell in particular, as moisture deficit can lead to crop failure. Agricultural drought is a permanent constraint to agricultural production in many developing countries, and an occasional cause of losses of agricultural production in developed ones (Ceccarelli and Grando, 1996). Application of satellite derived indices for assessment of crop growth conditions using geospatial rainfall estimate is well known in semiarid countries. Tracking the spatial and temporal patterns of rainfall data from satellite with respect to crop and soil characteristics can reveal situation of yield reduction due to water deficits (Senay and Verdin, 2002). Agricultural drought decreases grain yield through the reduction of various yield components of a crop. Water deficit is one of the most common environmental stresses that affects growth and development of plants (Aslam et al., 2006). Agricultural drought, or more generally, limited water availability is the main factor limiting crop production.

Generally, the use of drought indices using satellite data has been more prominent over that of conventional one. According to Beyene Ergogo (2007), drought assessment and monitoring using conventional method which rely on the availability of weather data are tiresome and time consuming. In contrast, the satellite sensor data (NOAA-AVHRR) are consistently available, cost effective and can be used to detect the onset of drought, its duration and magnitude. Hence, it is important to define drought frequency and its intensity for the past and find appropriate criterion for future agricultural drought appearance using remote sensing.

3. Materials and Methods

3.1 Description of the study area

The study was conducted in East Shewa zone, Oromia Regional State of Ethiopia. Geographically it is situated from 38°03' to 40°05' E longitude and from 7°04' to 9°10' N latitude covering a total area of about 13766 km^2.The altitude of the study area ranges from 538 to 3101m above sea level (Figure 2). The partial view of the study area is depicted in Appendix 1.

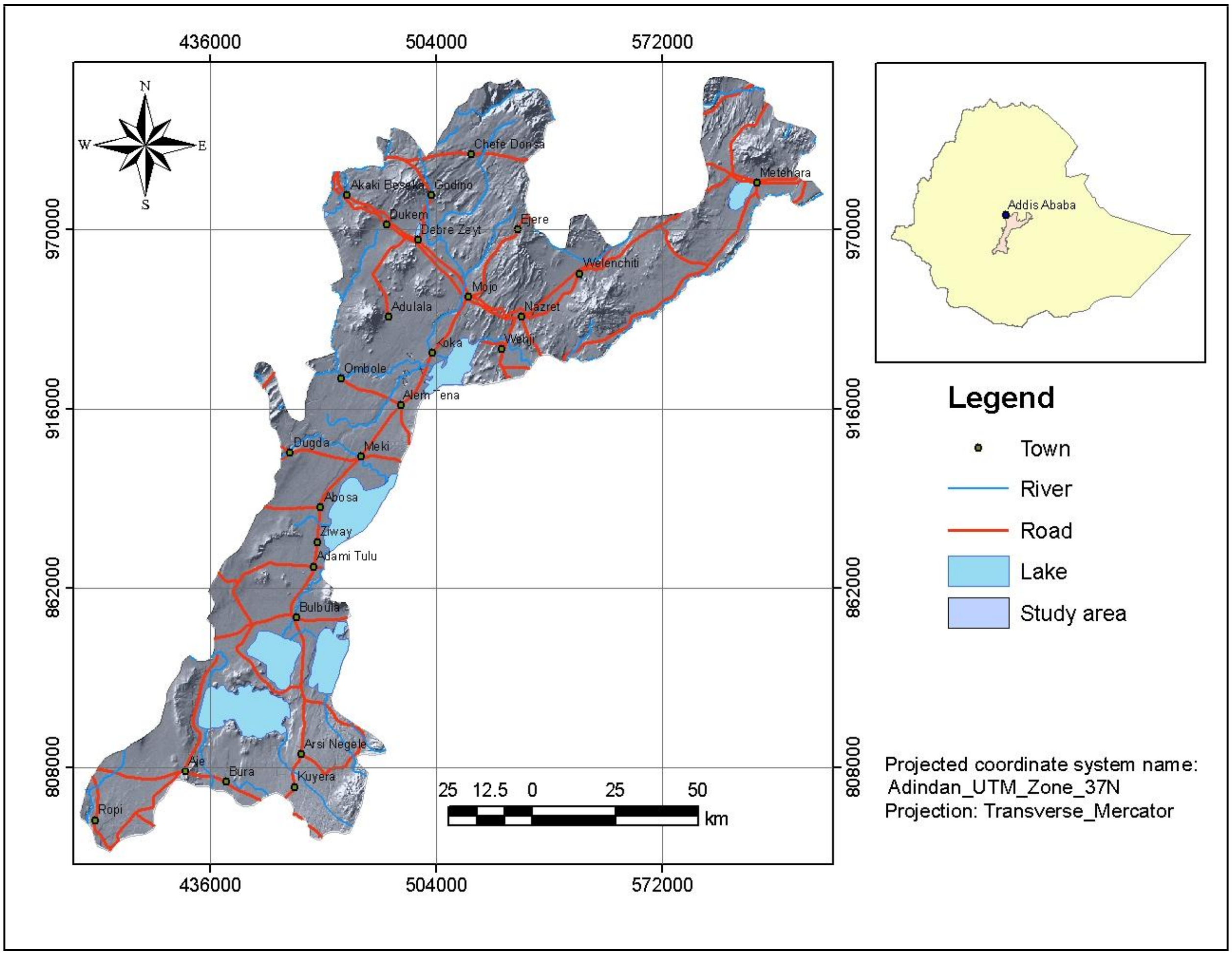


Figure 2. Location map of study area

3.1.1 Climate

East Shewa zone is characterized by semi arid and sub-humid climate based on the moisture index classification of climate (Lemma Gonfa, 1996). The long term average seasonal (June – September) rainfall the area receives ranges from 458 to 518 mm. The long term monthly rainfall distribution has been depicted in Figure 3. According to the information obtained from Finance and Economic development Bureau of Oromia (2007), the major climatic classes found in the zone based on mean annual rainfall and temperature are dry climate and tropical rainy climate. Dry climate includes the arid and semiarid subdivision, while tropical rainy climate is characterized by tropical humid and sub humid climate.

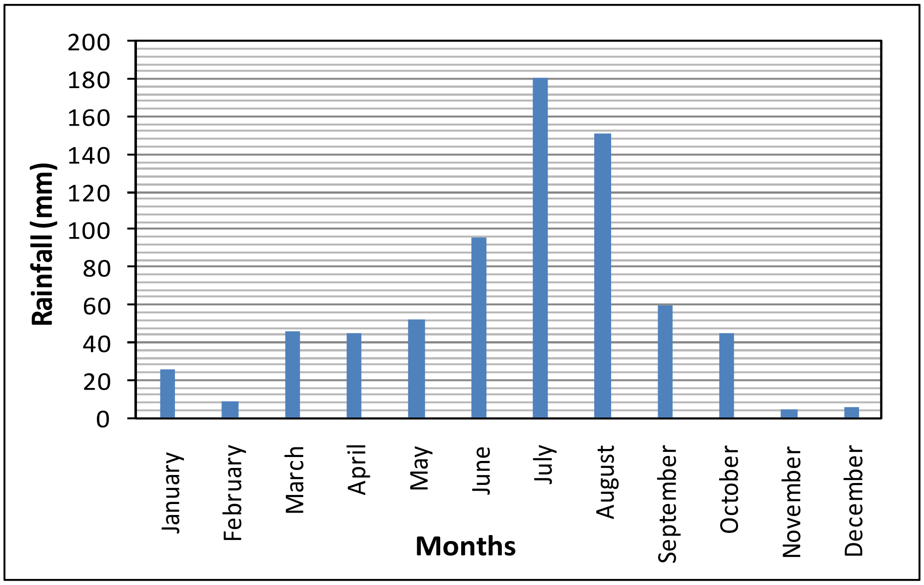


Figure 3. Satelliet based long term monthly rainfall of East Shewa Zone (1996-2008)

3.1.2 Soil

Soil is an important medium for plant growth and development owing to the storage place for water, a medium and an anchorage for root growth and reservoir for mineral nutrients. Soil distribution and characteristics vary by their parent materials, climate vegetation and cultural impacts, and interaction among these factors. In view of this, different types of soils are found in the study area. According to Food and Agricultural Organization (FAO) cited in Finance and Economic Development Bureau of Oromia (2007), Andosols, Vertisols, Rendzinas and Phaeozems, and Fluvisols are the dominant soil type found in East Shewa zone.

3.1.3 Geology

The major geological event in the study area is associated with the formation of Great Rift Valley. Rocks of the rift valley including those of East Shewa zone belongs to the Cenozoic Era. In East Shewa zone, tertiary volcanic covers southern, north eastern and north western part of the zone forming about 59 percent of the zonal area. The later part of Cenozoic era, the quaternary period is characterized by the formation quaternary sediments and Volcanic. Quaternary sediments account for 19 percent of east Shewa zone covers the central and the lake region of the zone (Finance and Economic development Bureau of Oromia, 2007).

3.1.4 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/ land cover pattern of the study area includes water body, shrub land, bare land, forest, sand dune, settlement, rainfed and irrigated farms (Figure 4), among which, the rainfed farm has large area coverage.

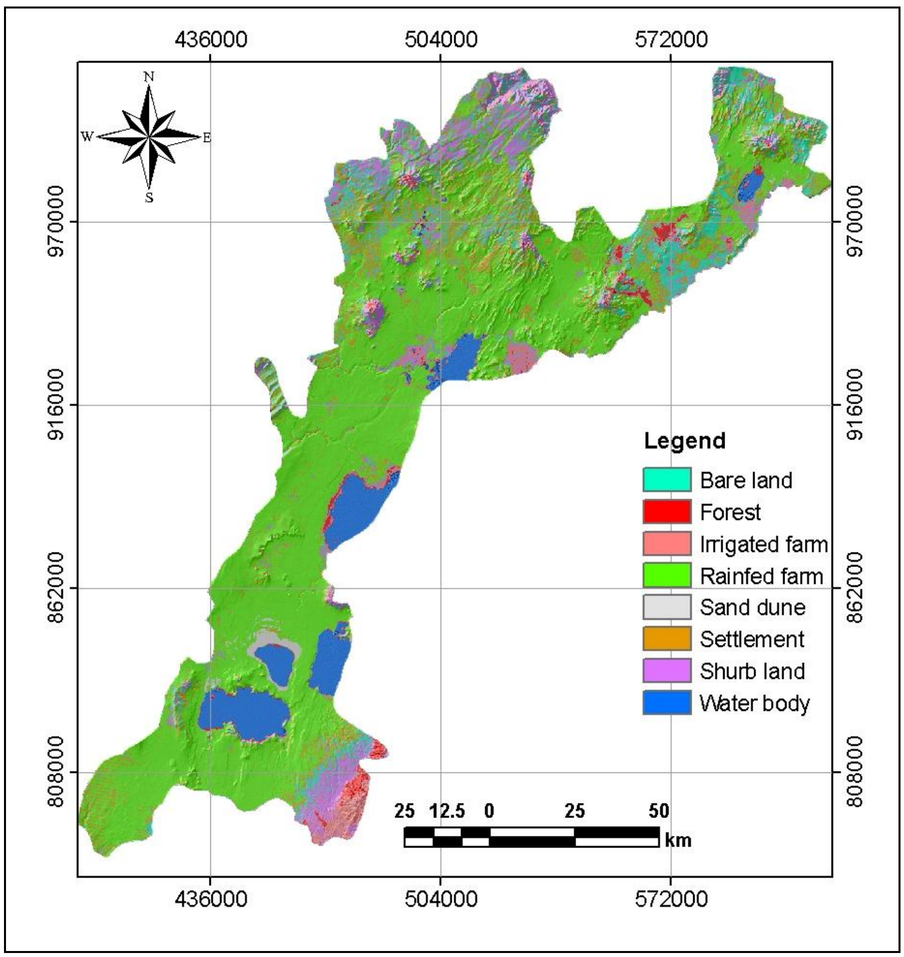


Figure 4. Land use/land cover map of the study area

3.2 Data acquisition and Software package

3.2.1 Satellite images

A time series advanced very high resolution radiometer (AVHRR) NDVI and rainfall estimate (REF) satellite data were used in this study. Both have 8km by 8km spatial resolution and were obtained in dekadal (10 days) time step basis for the period of the main rainy season (June – September) from 1996 to 2008. These data were downloaded from the Famine Early Warning System (FEWS-NET) archive website: http://earlywarning.cr.usgs.gov/adds/datatheme.php

3.2.2 Grain Yield data

Crop production is very sensitive to agricultural drought. According to Kogan (1997), the average yield of grain crops can be used for validation of satellite derived drought events. In order to find out the relationship between crop yield and the existing drought condition and thus validate satellite based drought events, average zonal grain yield data of the study area was collected from Central Statistic Agency (CSA). The total grain yield data of crops grown in the study area is depicted in Table 1.

Table 1. Area and production of zonal crops for Meher season in East Shewa Zone

Year	Cultivated land (ha)	Production (Quintal)
2004	395,577	5,943,733
2005	442,900	5,776,625
2006	495,951.36	9,062,147.21
2007	421,622.48	7,918,711.48
2008	421468.18	7183114.62

Source: Central Statistical Agency

3.2.3 Software package

ArcGIS 9.2, ERDAS IMAGIN 9.1, IDRISI, LEAP, INSTAT and Google Earth softwares were used for data analyses.

3.3 Data processing and analyses methods

3.3.1 Preprocessing satellite images

As the NOAA-AVHRR NDVI satellite images are radiometerically corrected, geometric corrections were done. All images were imported in generic binary format and information related to image dimension (number of rows, columns and bands), projection parameters (Spheroid name, datum name, latitudes of standard parallels, longitudes of central meridian, latitudes of origin of projection, false easting at central meridian and false northing at origin) were incorporated in the row images. In order to transform the imported row data into -1 to 1 range of NDVI, the formula (NDVI= raw data /250) which is provided with row data by FEWS-NET was applied to each NDVI images. Thereafter, the study area was extracted and became ready for further analysis (Figure 5). For this study, 156 dekadal seasonal NDVI images were analysed and used as an input data for NDVI anomaly drought index.

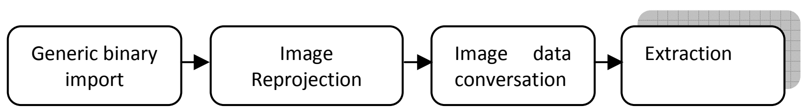


Figure 5. Image preprocessing process

Similar procedure except data conversion was applied to satellite REF images so as to make the input REF image for further analysis.

3.3.2 Land use / Land cover map

Land use / Land cover map of the study area was prepared from Landsat image. The area was classified into different land use types. During land use/ land cover classification, Google earth software was used as reference.

3.3.3 Analysis of agricultural drought using various drought indices

Spatiotemporal variation of seasonal agricultural drought patterns and agricultural drought severity were analysed seasonally using the following drought indices.

3.3.3.1 Normalized Difference Vegetation Index (NDVI)

NOAA-AVHRR NDVI images that were computed from the NOAA Image using spectral radiance in red and near infrared reflectance were used for time series analysis of vegetation dynamics.

3.3.3.2 NDVI anomaly

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

$$\text{NDVI Anomaly } i = [(\text{NDVI}_{\max i} - \text{Mean NDVI}_{\max}) / (\text{Mean NDVI}_{\max})] * 100$$

Where $\text{NDVI}_{\max i}$=Maximum NDVI in the growing season in i^{th} year and Mean $\text{NDVI}_{\max}$=long term mean maximum NDVI in the growing season.

The resulting NDVI anomaly percentage assigned to respective grid cell was reclassified into five drought severity classes based on Table 2.

Table 2. NDVI anomaly based drought severity class.

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

3.3.3.3 Standardized Precipitation Index (SPI)

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

$$SPI = (Xij - Xim) / \sigma$$

Where, *Xij=* is the seasonal precipitation and, *Xim* is its long-term seasonal mean and σ is its standard deviation.

SPI was used to quantify the precipitation deficit in the growing season and analyze the impact of rainfall deficiency on drought development. SPI results computed from seasonal rainfall data were assigned to each grid cell of the study area, and reclassified based on drought severity classless as shown the Table 3.

Table 3. SPI based drought severity class.

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

3.3.3.4 Crop performance index

Water requirement satisfaction index (WRSI) is an indicator of crop performance based on the availability of water to the crop during a growing season. The WRSI was generated by a crop water balance model in LEAP software. The most important input parameters of the model are satellite based rainfall estimate images and spatially distributed potential evapotranspiration images. Besides, the model uses relevant soil information from FAO digital soil map and topographical parameter derived from digital elevation model (DEM). WRSI was calculated as the ratio of seasonal actual evapotranspiration (AET) to the seasonal crop water requirement (WR)

$$WRSI = (AET / WR)\ 100$$

Where, WR is calculated from the Penman-Monteith reference crop evapotranspiration (ETo) using the crop coefficient (Kc) to adjust for the growth stage of the crop: WR = ETo * KC. AET represents the actual amount of water withdrawn from the soil water reservoir where shortfall relative to potential evapotranspiration (PET) was calculated by function that takes into account the amount of soil water in the reservoir. Soil water content was estimated through simple mass balance equation where the total volume was defined by the water holding capacity (WHC) of the soil.

WRSI was computed using LEAP software and imported into GIS environment. The WRSI result was then reclassified based on drought severity classes mentioned in Table 4 for each grid cell of the study area.

Table 4. WRSI based drought severity class

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

3.3.4 Computation of yield reduction due to moisture deficit

The impact of agricultural drought on crop production can be largely expressed by yield reduction. In view of this, yield reduction due to water deficiency was computed using LEAP software. Yield reduction was calculated from water balance output combined with an empirical formula developed by Doorenbosch and Kassam (Hoefsloot, 2008). The formula is:

$$100-((1-(1-A/B)\ Ky)\ 100)$$

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

The major crops grown in the study area, maize, teff , wheat, sorghum, finger millet, haricot bean, chick pea, field pea, and lentil, were considered in computation of aggregated yield reduction.

Regarding the maps, since the coarse resolution of the image being utilized for various drought indices, cell size of all images after analysis of final result are resampled to 90m in order to have better visualization. Based on the level of agricultural drought severity levels, two drought and two wet years were identified and mapped for each drought indices.

3.3.5 Regression analysis of grain yield with drought indices output

Grain yield data and data derived from the drought indices were prepared for simple regression analysis. The average raster cell values of NDVI, SPI, NDVI anomaly and WRSI images were extracted using ERDAS IMAGIN statistic information and LEAP software. The relationship between NDVI anomaly, SPI and WRSI result from each seasonal year with corresponding grain yield anomaly was computed to validate the derived indices.

In order to understand the response of NDVI for rainfall event at different time interval , simple regression analysis between zero, one, two, three and four dekad lag time or preceding rainfall, and NDVI was computed using INSTAT software as well. Besides, different information related to agricultural drought hazard and their impacts on agricultural activities as well as cropping practices were collected from zonal and woreda agricultural and rural development, and early warning and food security bureaus through questionnaire (Appendix 2).It was also used for the evaluation of the result obtained from satellite images.

3.3.6 Agricultural drought risk map

Agricultural drought risk map of the study area was produced from the output derived from satellite based vegetation, climate and crop performance drought indices by using multi criteria evaluation (MCE) techniques. In order to compute the frequency of drought occurrence, drought class image from each index was reclassed into Boolean image based on their threshold value and 13 binary images were generated for each drought index. These binary images were added to obtain the frequency map showing the frequency of drought occurrence at each pixel level.

The seasonal frequency maps derived from each drought indices were reclassified into common scale based on the frequency of drought occurrence. According to Lemma Gonfa (1996), the probability of drought occurrence in a given area can be classified into high, moderate and low drought probability zones when drought occurs in more than 50 percent, 30 to 50 percent and less than 30 percent of the years, respectively. Based on this criteria, the frequency maps of each drought classes are reclassified into five classes based on the frequency of drought occurrence in study periods: 0-2 classified as no drought; 3-4 classified as slight drought; 5-6 classified as moderate drought; 7-10 classified as severe drought; 11-13 classified as very severe drought. Finally, maps from each drought indices were weighted according to the percentage of influence using IDRSI software, and then combined using weighted overly analysis. The schematic representation of the methodology has been depicted in Figure 6.

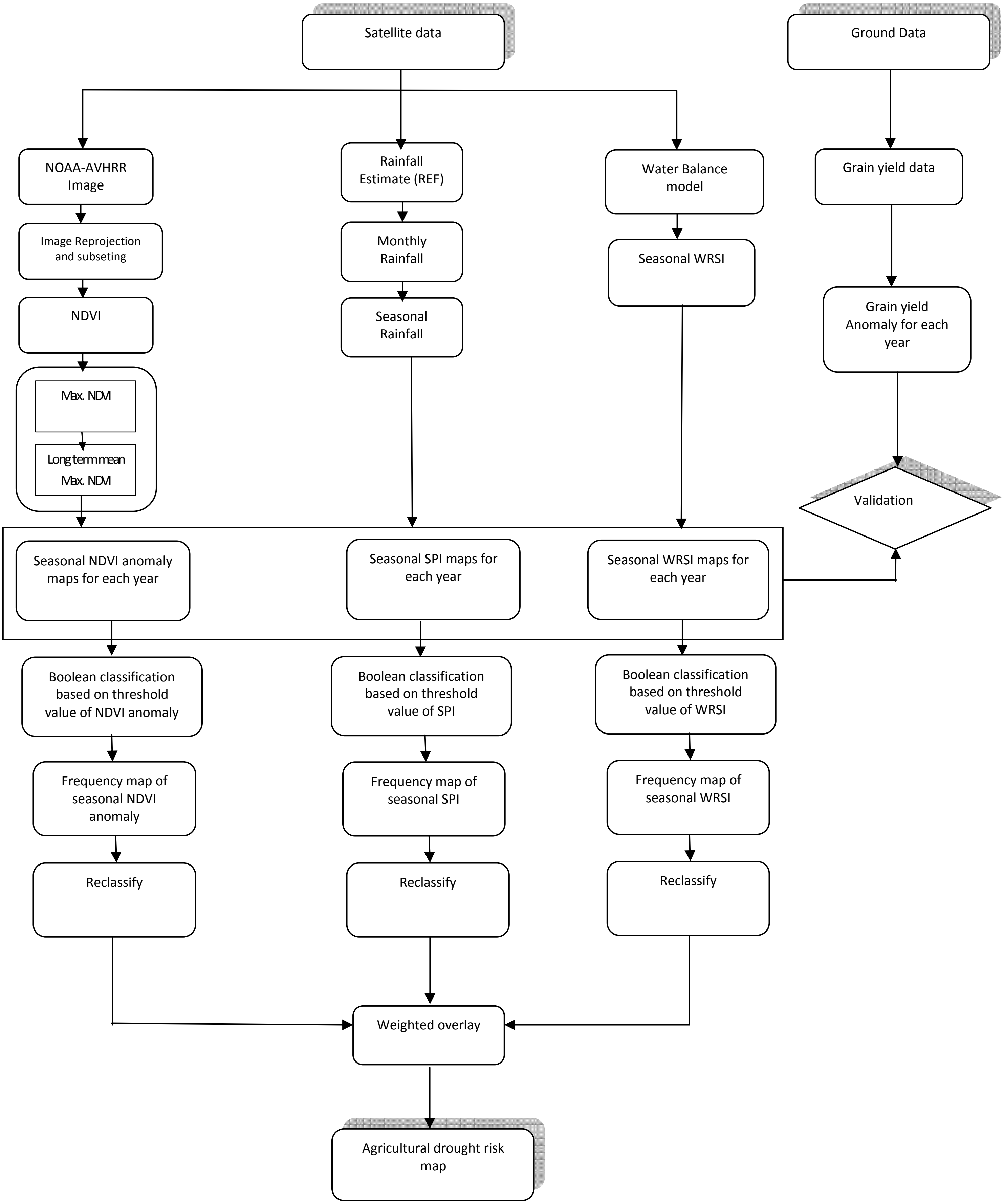


Figure 6. Methodological flow chart of methodology

4. Results and Discussion

4.1 Relationship between seasonal rainfall and NDVI

In a rainfed based cropping system, seasonal rainfall variability is inevitably reflected in variable agricultural production and /or yield. This implies that seasonal analysis of historical rainfall and the response of vegetation are of paramount importance. Accordingly, seasonal rainfall and NDVI patterns of the entire study area for a period from 1996- 2008 have been studied and the result has shown that there is good correlation (r=0.7) between rainfall and NDVI (Figure 7). It revealed that there is an increasing trend both in rainfall and NDVI. From all 13 years data, 42 percent of NDVI variability can be explained by seasonal rainfall. In addition, spatial patterns of long term seasonal rainfall and NDVI also reflected similar response (Figure 8). However, due to lag time response of vegetation to the existing rainfall, the relationship between the two variables may vary some places.

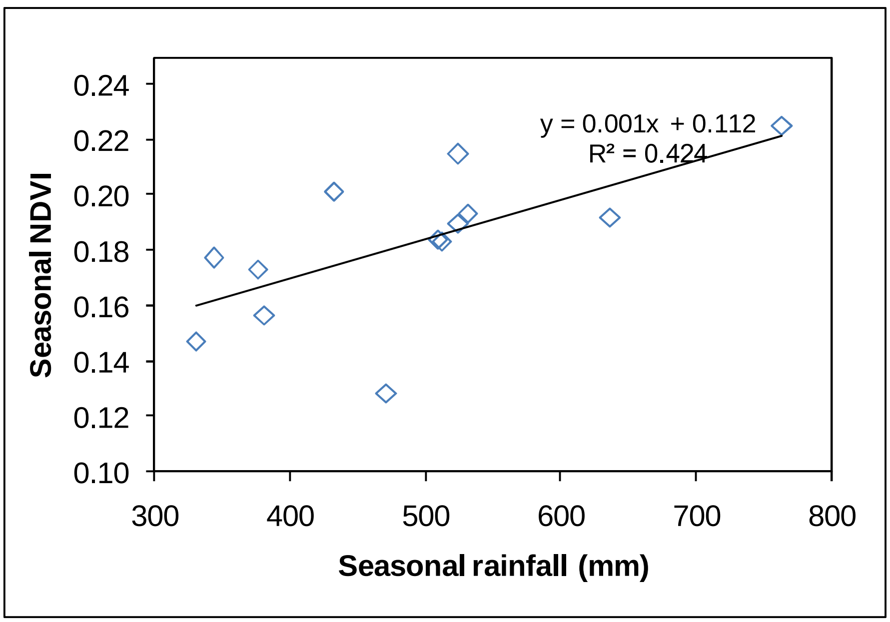


Figure 7. Seasonal (June-September) patterns of rainfall and NDVI (1996 – 2008)

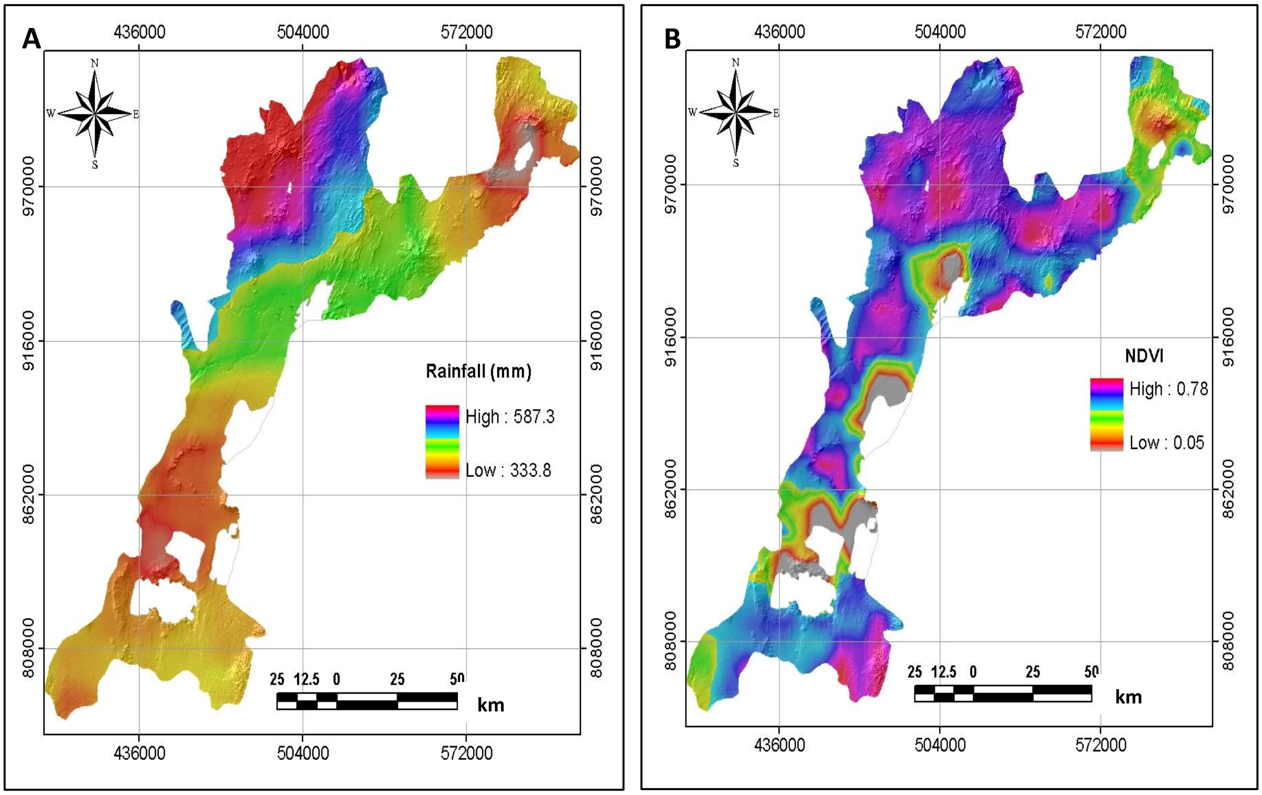


Figure 8. Spatial pattern of long term seasonal (June- September) average rainfall (A) and NDVI (B)

In this case, the amount and timing of rainfall relative to crop or vegetation requirement must be considered. Besides, the distribution of rainfall might be another factor that affects the response of vegetation to the existing rainfall. The temporal trends of seasonal NDVI and seasonal rainfall depict a good relationship (Figure 9). However, in 2000 cropping season, there was near to average rainfall while the corresponding NDVI was relatively low. This may be due to long intra-seasonal dry spell or bad distribution of rainfall that affect the growth and development of vegetation. This resulted from mismatch between seasonal rainfall distribution and crop water requirement at critical developmental stages.

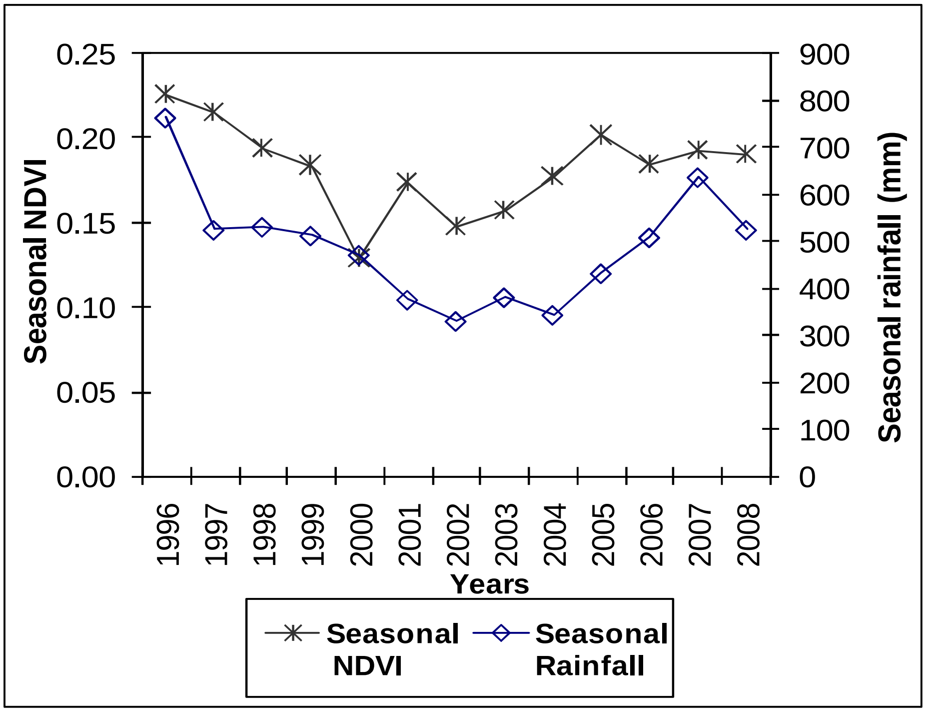


Figure 9. Temporal trends of seasonal (June-September) rainfall and NDVI (1996-2008).

In view of this, from rainfall characteristics, not only rainfall amount but also rainfall distribution is a critical factor for response of vegetation in general and crop production in particular. According to Kinde Tesfaye (2004), for highly rainfall dependant Ethiopian agriculture, the amount and the distribution of rainfall during the crop growing seasons are more critical and detrimental. Regarding inter seasonal rainfall variability, the coefficient of variation ranges from 23 to 37 percent. This shows that there is high inter seasonal rainfall variability that causes long term dry spell within a season. Kinde Tesfaye and Walker (2004) explained that the reduction of crop performance and yield result from mismatches between water supply and demand. Thus, variable rainfall amount and its erratic distribution can cause long term dry spell, which in turn result in agricultural drought that cause complete crop failure.

4.2 Influence of rainfall on the vegetation growth and development

Rainfall is an important climatic variable that influence the growth and development of vegetations, which is reflected by NDVI. According to the study Henericksen (1986) cited in Beyene Ergogo (2007), it has been shown that NDVI was highly sensitive to an extended rainfall anomaly. In this regard, simple linear regression analysis between dekadal rainfall and NDVI were carried out for different lag time periods so as to better understand the influence of rainfall on vegetation growth and development (Appendix 3B-E). The result indicated that compared to lag time of zero, one, two and four dekad rainfall, three dekad or one month preceding rainfall had highest influence on the growth and development of vegetation with the correlation coefficient of 0.8. Besides, comparing the calculated and critical F- value in the ANOVA (Analysis of variance) table, the calculated F- value (16.89) exceeds the critical F-value or Prob>F (0.0021) at 5 percent probability level (Table 5). It confirms that the relationship between the two variables are highly significant compared to other dekad.

Table 5: Simple linear regression analysis between dekadal NDVI and different lag time dekadal rainfall

Lag time periods in dekad	R-Square	F_calculated	F_critical at 5% probability level	Level of significance LSD(0.05)
0	0.02	0.32	0.58	NS
1	0.04	0.51	0.48	NS
2	0.22	3.26	0.98	S
3	0.63	16.89	0.002	S
4	0.54	10.64	0.009	S

Note: NS-Non significant S- significant

It explains that the variability of NDVI is highly explained by three dekad or one month preceding rainfall. The obtained result is also in concurrence with the finding of Chopra (2007) that states the time interval between rainfall event and the time when rainfall water might reach a plant root and induce subsequent plant growth can occur in one month time period in semi arid areas. Therefore, the influence of rainfall on vegetation growth and development occurs at one month or three dekad lag time. That means the vegetation growth in each month is influenced by rainfall in the preceding month, and change in soil moisture and vegetation development are significantly observed during this period.

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

The NDVI is useful indicator as a measure of agricultural drought when compared to normal plant health. It is reflected through NDVI anomaly. NDVI anomaly is one of agricultural drought index that shows the severity level. Based on this index, spatial pattern of agricultural drought for drought years (2000 and 2002) and wet years (2007 and 2008) was computed for agricultural production area to determine the severity of agricultural drought (Figure 10 and 11).The result provided the spatial patterns of agricultural drought events, and the level of drought severity ranges from slight to very severe in both 2000 and 2002 drought years. However, the extent of very severe drought covers small pocket areas which account for less than four percent of the total area. The majority of the study area was stricken by moderate and severe agricultural drought. During 2000 cropping season, the percentage area hit by agricultural drought (Appendix 4) was 10.15, 71.28, 16.53 and 2.04 percent of the total area for slight, moderate, severe and very severe severity level, respectively, whereas the corresponding agricultural drought severity for 2002 cropping season was 40.38, 34.43, 22.63 and 2.56 percent of the total area, respectively.

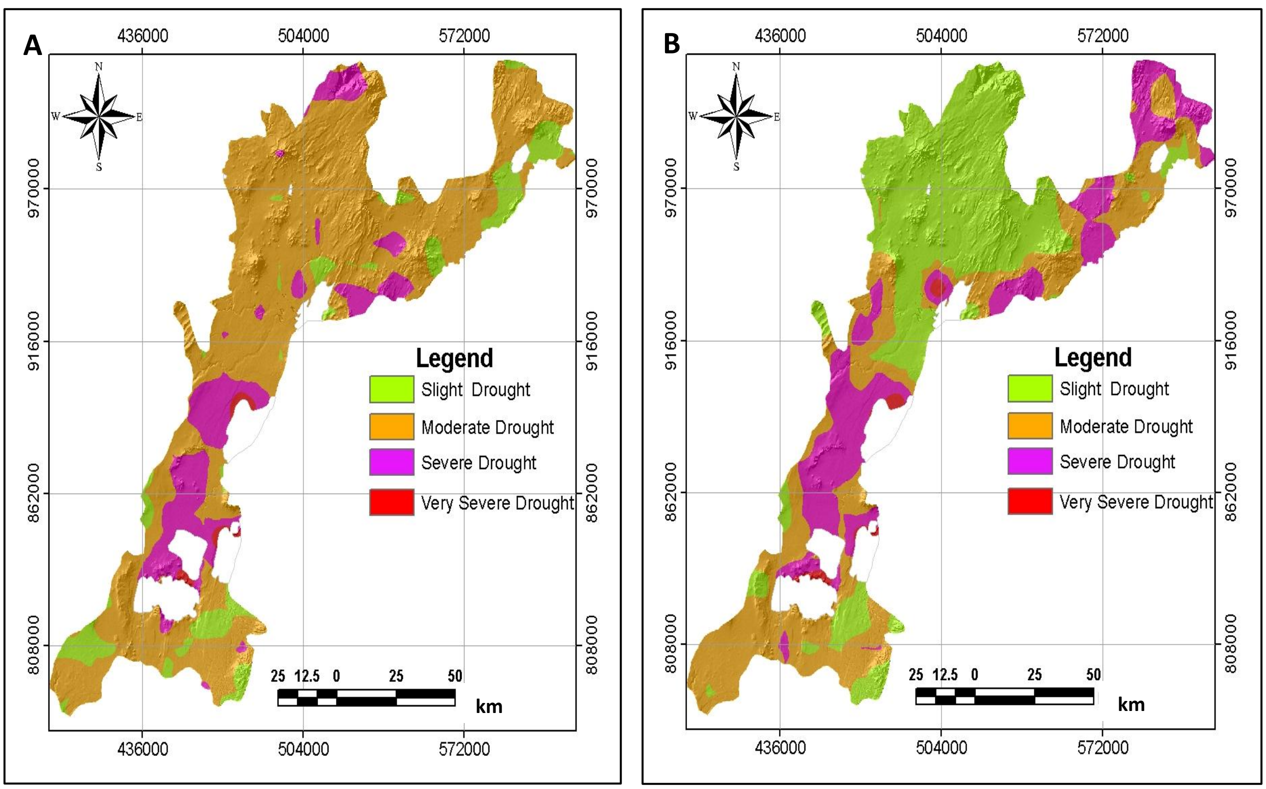


Figure 10. Spatial pattern of agricultural drought severity for drought years 2000 (A) and 2002 (B) expressed in NDVI anomaly index

Regarding the wet years, it can be observed from the map depicted in the Figure 11 that some very small pocket areas were hit by severe and very severe level of agricultural drought while the majority of the areas under the influence of slight and moderate agricultural drought. The percentage area of agricultural drought severity indicates that 64.32, 30.90, 4.18 and 0.60 percent of the total area was hit by slight, moderate, severe and very severe level of severity respectively during 2007 cropping season, whereas the corresponding agricultural drought severity in 2008 cropping season was 22.41, 64.69, 11.07 and 1.83, respectively.

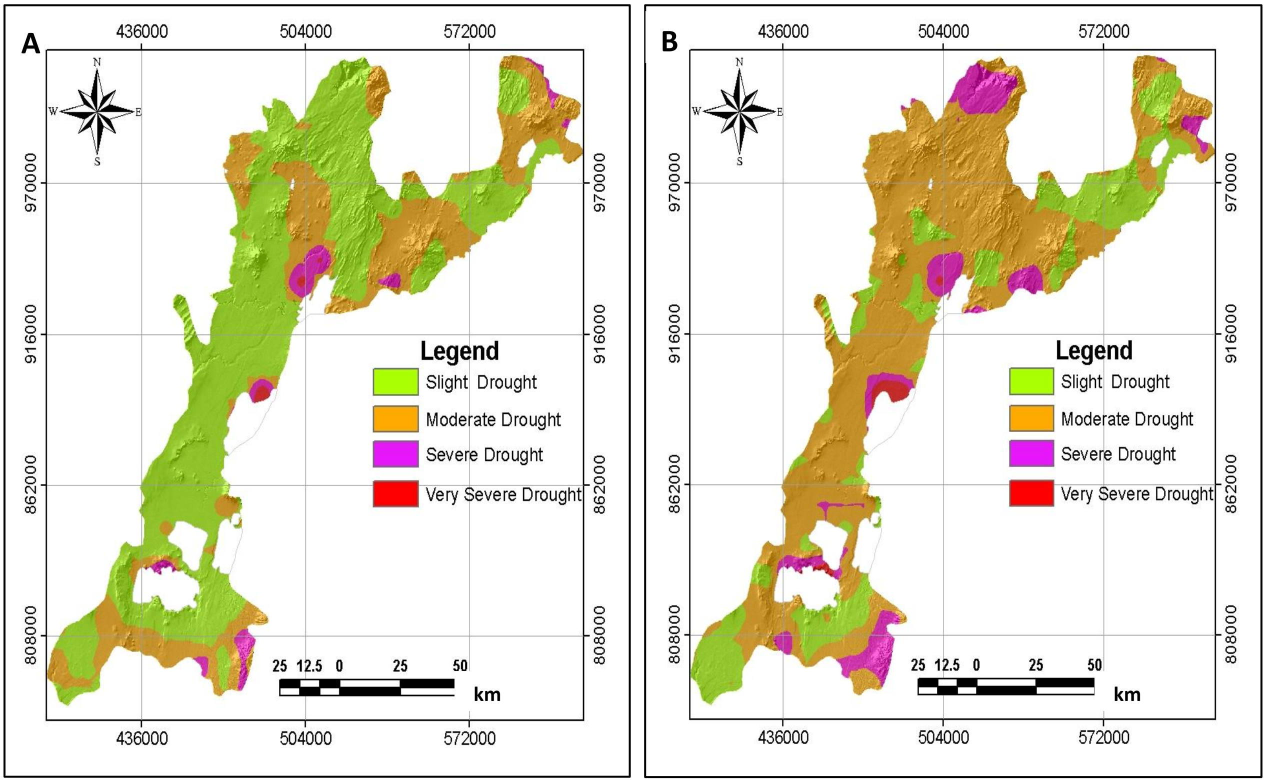


Figure 11. Spatial pattern of agricultural drought severity for wet years 2007 (A) and 2008 (B) expressed in NDVI anomaly index

4.3.1 Relationship between NDVI anomaly and grain yield anomaly

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 anomaly and grain yield to quantify the impact of agricultural drought on agricultural production. The relationship between NDVI anomaly extracted only for cultivated area from land use/ land cover map of East Shewa zone (Figure 4) and grain yield anomaly were analyzed and from scatter plot (Figure 12), it can be observed that the two variables have established good correlation (r=0.74). This means that 54 percent of yield variability can be explained by NDVI anomaly. The result revealed that the relationship established between the two variables is positive; NDVI anomaly increases so do agricultural yield and vice-versa. Thus the strength of the index to explain the existence of agricultural drought through agricultural yield is relatively good (Appendix 5).

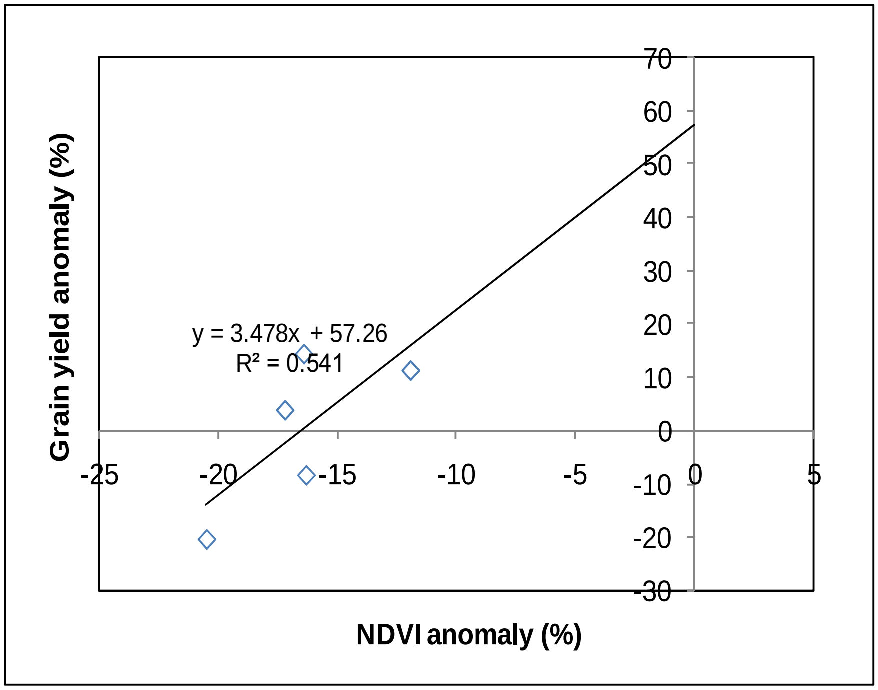


Figure 12. Relationship between NDVI anomaly and grain yield anomaly

4.4 Spatial and temporal patterns of SPI and drought severity

SPI is computed for growing season of East Shewa zone. The analysis of SPI (Figure 13) revealed that drought has occurred at different level of severity from 2000 to 2005 cropping season. The drought that happened in year 2000 and 2002 was a very severe one compare to other years as explained by the SPI values that range from -1.6 to 0 and -2.25 to 0, respectively. The result indicates that during those years, there was rainfall deficit in the growing season and it, therefore, was the worst dry seasons.

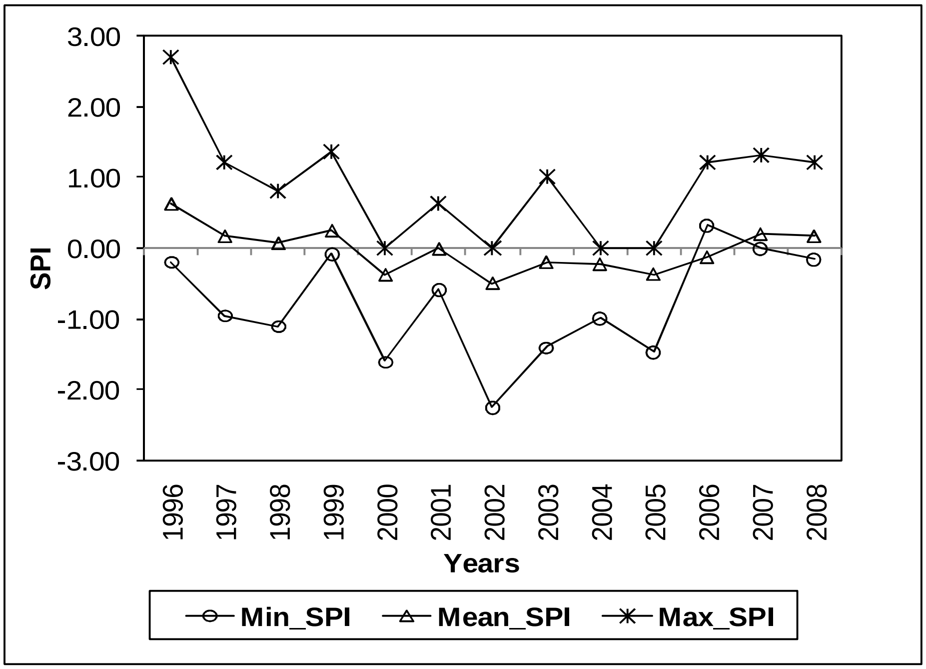


Figure 13. Temporal pattern of seasonal (June-September) SPI (1996-2008)

Regarding spatial patterns of SPI for drought years (2000 and 2002) and wet years (2007and 2008) analysed and reclassified to show spatial trends of drought severity. Considering two of the most severe droughts years (2000 and 2002) during analysed period is a better illustration of the drought extent and intensity in East Shewa Zone. In Figure 14, it can be seen that unlike NDVI anomaly index output, whole area were hit by drought from slight to very severe level of severity during year 2002, while in year 2000, the range of severity was limited from slight to severe drought levels.

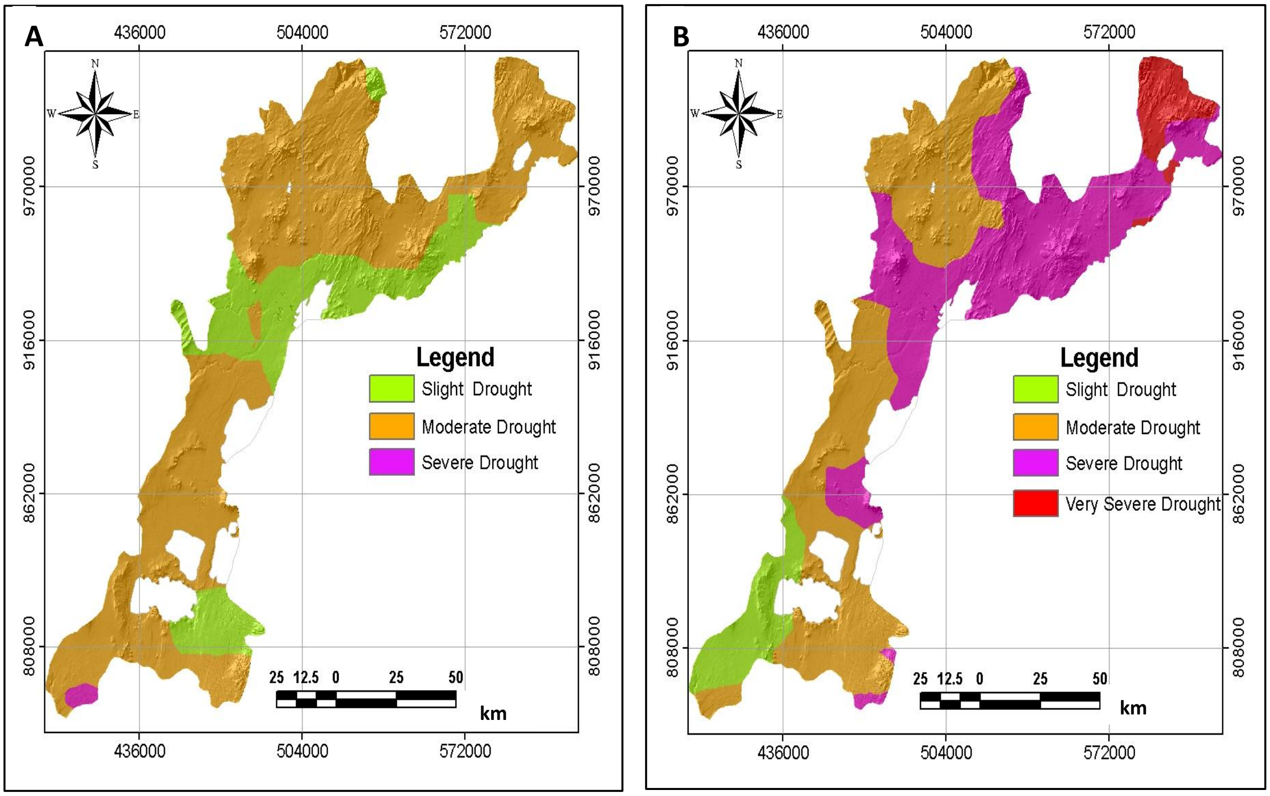


Figure 14. Spatial pattern of drought severity for drought year 2000 (A) and 2002 (B) expressed in SPI index

It indicates that in the year 2002, there was a very severe drought in wider extent that accounts for 8.84, 46.04, 39.95 and 5.17 percent of the total area (Appendix 6) hit by slight, moderate, severe and very severe drought, respectively. In 2000, the level of severity reduced to severe one only in some pocket area of southern part covering 0.65 percent of the total area while strike of moderate drought was expanding over majority of the East Shewa zone covering 75.69 percent. During the 2002 drought year, North eastern, eastern and central parts of the East Shewa zone were more stricken by severe and very severe drought.

SPI can be used to identify not only drought years but also wet years. In this regard, using SPI analysis, wet years were also identified. As the maps shown in the Figure 15, the year 2007 and 2008 were very wet years in East Shewa zone. The range of severity was from slight drought to no drought. Although good seasonal rainfall helped almost the whole zone to avoid drought during 2008, some small pocket area covering 2 percent of the total area in the western part experienced slight drought. This may be occurred due to the influence of the bad distribution of rainfall as well as long dry spells occurrence.

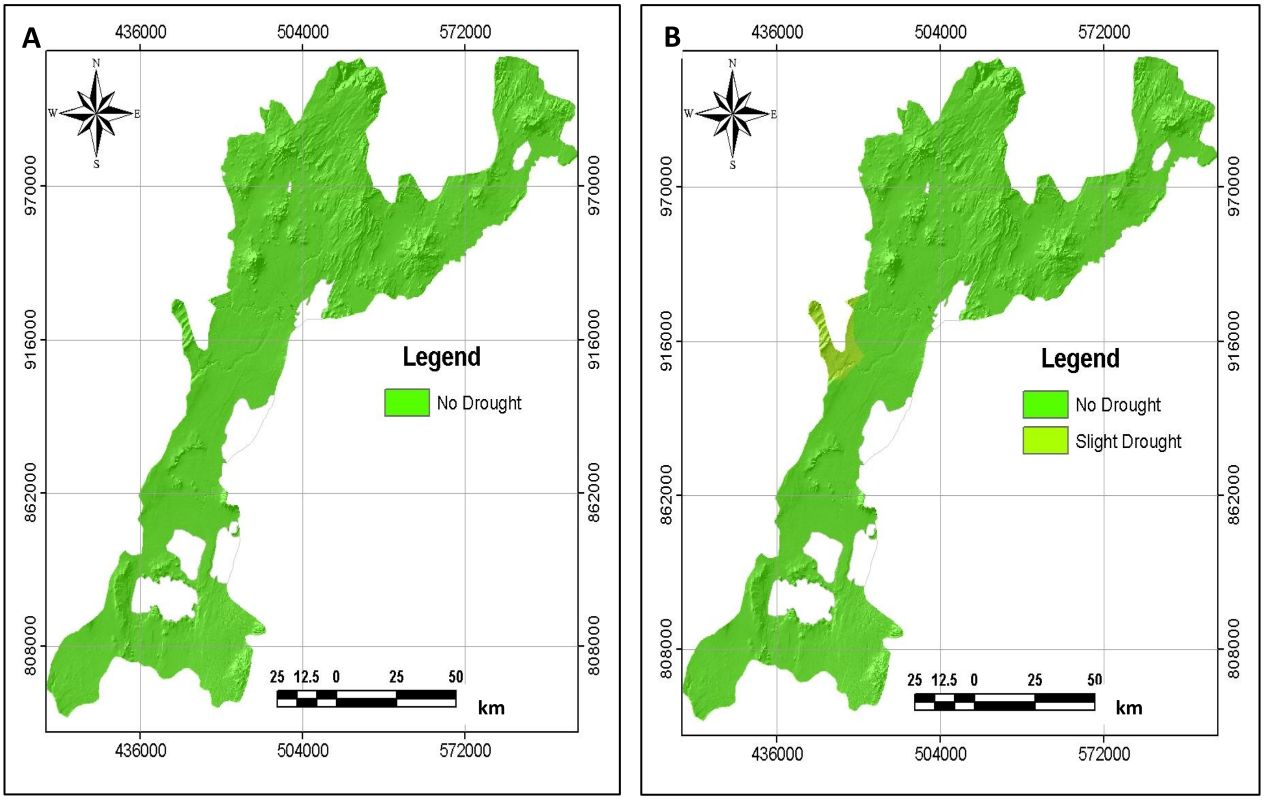


Figure 15. Spatial pattern of drought severity for wet Year 2007 (A) and 2008 (B) expressed in SPI index

4.4.1 Standard Precipitation Index (SPI) and grain yield anomaly

Due to the fact that crop production is a function of rainfall, crop failure is most often associated with moisture deficit or agricultural drought. Thus, the regression analysis between drought index and grain yield anomaly is indispensable for validation. 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 anomaly also turns positive revealing a good positive correlation (r=0.8). The detailed result of regression analysis is presented on Appendix 7. 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 (Figure 13), Whereas, negative SPI or rainfall deficiency is reflected on crop production through yield reduction. Yield reduction due to moisture deficiency is clearly explained in section 4.6

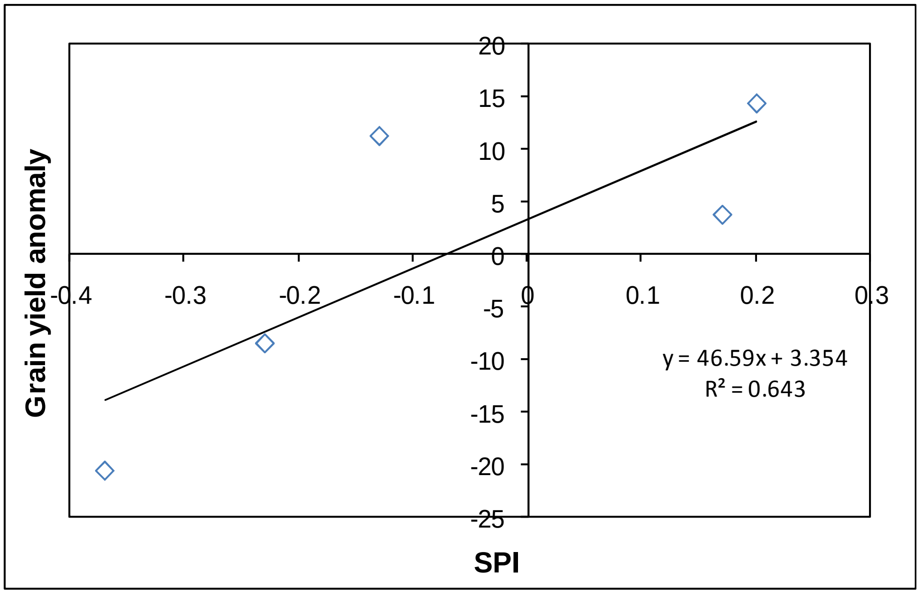


Figure 16. Relationship between SPI and grain yield anomaly

4.5 Water Requirement Satisfaction Index (WRSI) based agricultural drought characterization

The performance of grain crops growing in the study area has been estimated using WRSI index, for the analysis period. The result revealed that less WRSI values in large part of the study area showing moisture deficit during the drought years (2000 and 2002). According to the result, spatially depicted in the Figure 17, during 2002 cropping season, severe agricultural drought was prevalent in the central, eastern and north eastern part of East Shewa. In line with this, most of the areas especially in central, eastern and north eastern part remain under very severe agricultural drought class revealing that less than 50 percent of crop requirement was satisfied. According to smith (1992) cited in Senay and Verdin (2002), seasonal WRSI value less than 50 is regarded as a complete crop failure condition due to moisture deficit. As a result, the index has revealed that high grain yield loss encountered in the area due to agricultural drought.

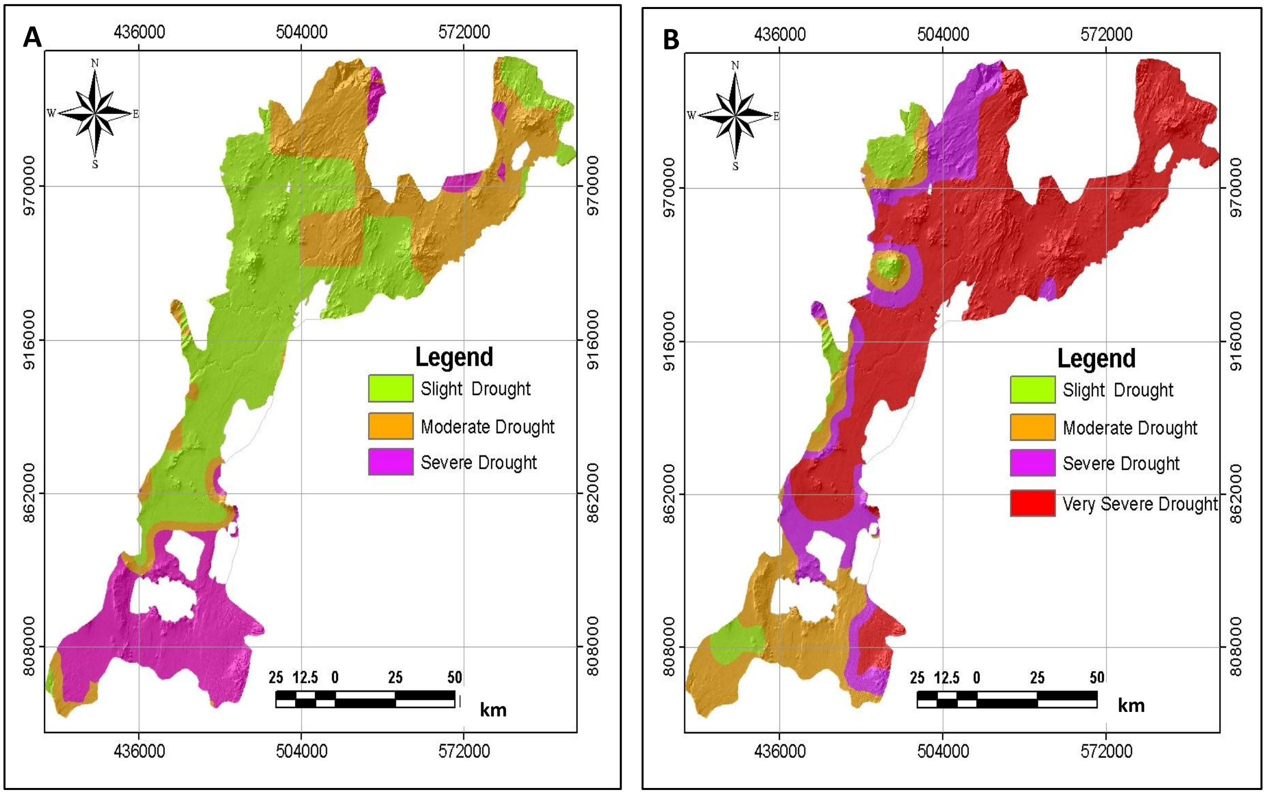


Figure 17. Spatial pattern of agricultural drought severity for drought years 2000 (A) and 2002 (B) expressed in WRSI index

Agricultural drought occurred spatially in the range from slight to very severe severity level in East Shewa during 2002 cropping season (Figure 17). Large area coverage in north eastern, eastern and central part that accounts for 56.22 percent of the total area was hit by very severe agricultural drought, whereas other parts of the area were stricken by severe, moderate and slight agricultural drought in percent of 18.30, 20.00 and 5.48, respectively (Appendix 8). As crop growing on most of the area getting above 50 percent of their crop requirement, the level of agricultural drought was reduced during 2000 cropping season as compared to 2002 cropping season. The percentage of the area was 45.52, 29.71 and 24.77 for slight, moderate and severe agricultural drought severity level.

WRSI is also successful in capturing the response of the crop during wet years. The result depicted in Figure 18 reveled that even though 2007 and 2008 cropping seasons were wet years, some small pocket areas were stricken by agricultural drought, especially the southern

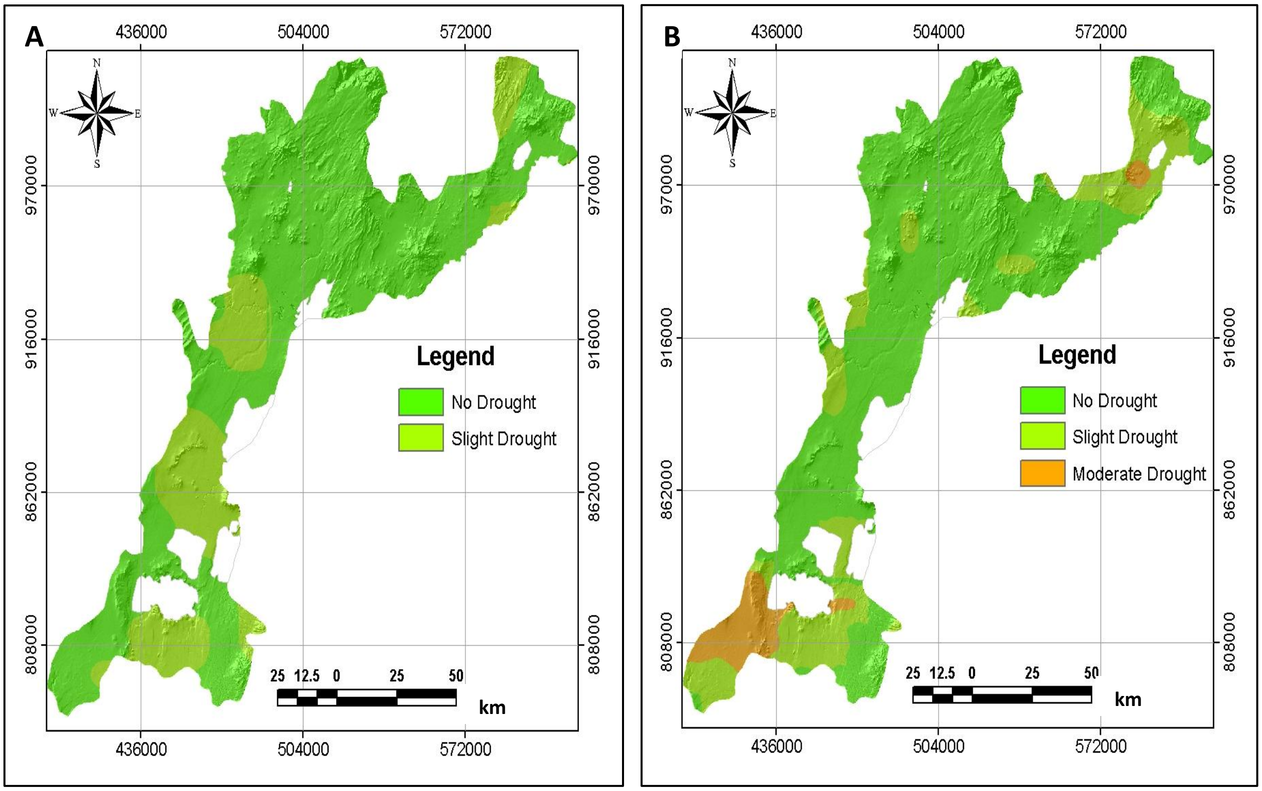


Figure 18. Spatial pattern of agricultural drought severity for wet years 2007 (A) and 2008 (B) expressed in WRSI value

part of the study area. During 2007 cropping season, only 23.76 percent of the total area was hit by slight agricultural drought while 76.24 were free from agricultural drought whereas in 2008, besides slight agricultural drought covering 23.07 percent of the total area, moderate agricultural drought was also experienced in some small pocket area accounting for 6.36 percent. Generally, those growing seasons, the water requirements of growing crops were satisfied above 80 percent nearly all over the study areas indicating that most of the area was free from agricultural drought.

4.5.1 Water Requirement Satisfaction Index (WRSI) and grain yield

The relationship between satellite based WRSI and grain yield was analyzed using simple regression analysis (Appendix 9). The temporal patterns and relationship of average WRSI and grain yield is depicted in Figure 19. It can be observed that there is a good correlation between grain yield and WRSI (r=0.87). Moreover, a linear best fit curve was plotted to see the strength of relationship between the dependant and independent variables. The result has shown that, 76 percent of grain yield variability can be explained by WRSI.

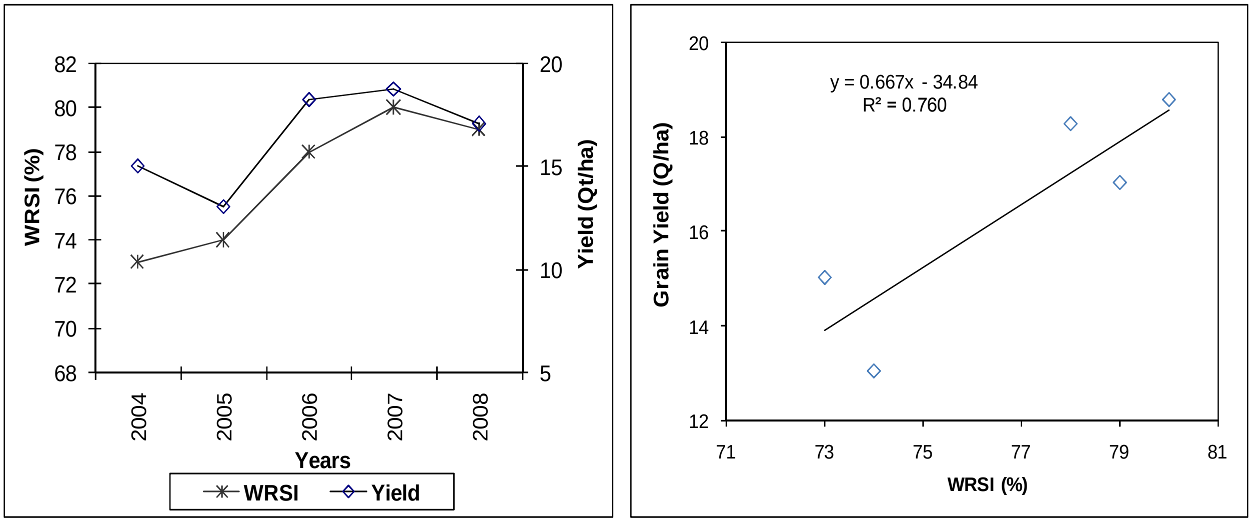


Figure 19. Temporal pattern and relationship of WRSI and grain yield

Furthermore, comparing the calculated and critical F- value in the ANOVA (Analysis of variance) Table (Appendix 9), the calculated F- value (9.47) exceeds the critical F-value or Prob>F (0.0542) at 5 percent probability level. Thus, WRSI can be a good indicator for occurrence of agricultural drought.

4.6 Characterization of yield reduction due to agricultural drought

Agricultural drought decreases grain yield through the reduction of various yield components of a crop. Considering spatial pattern of yield reduction, analysis has been carried out in the study area from 1996 to 2008 cropping season. Among them, the highest yield reduction occurred in 2000 and 2002 cropping season and the spatial pattern of yield reduction has been illustrated on the Figure 20.

According to the result, 2002 cropping season, nearly all area was hit by agricultural drought and the agricultural yield reduction was reached to 80 percent. During this season, eastern, north eastern and central parts of the East Shewa zone encountered 60 to 80 percent yield reduction covering 26.51 percent of the total area while small areas in western and southern part encountered 0 to 20 percent yield reduction covering 12.64 percent of the total area. Whereas 20 to 60 percent yield reduction was encountered 60.84 percent of the total area

(Appendix 10). In 2000 cropping season, the level of yield reduction has been reduced to 40 percent. 0 to 20 and 20 to 40 percent yield reduction cover 42.78 and 57.22 percent of the total area of East Shewa. According to Wilhelmi et al. (2002), agricultural drought is the leading cause of crop failure throughout the world. Thus, moisture deficit significantly influence the growth and development of crops and the ultimate yields.

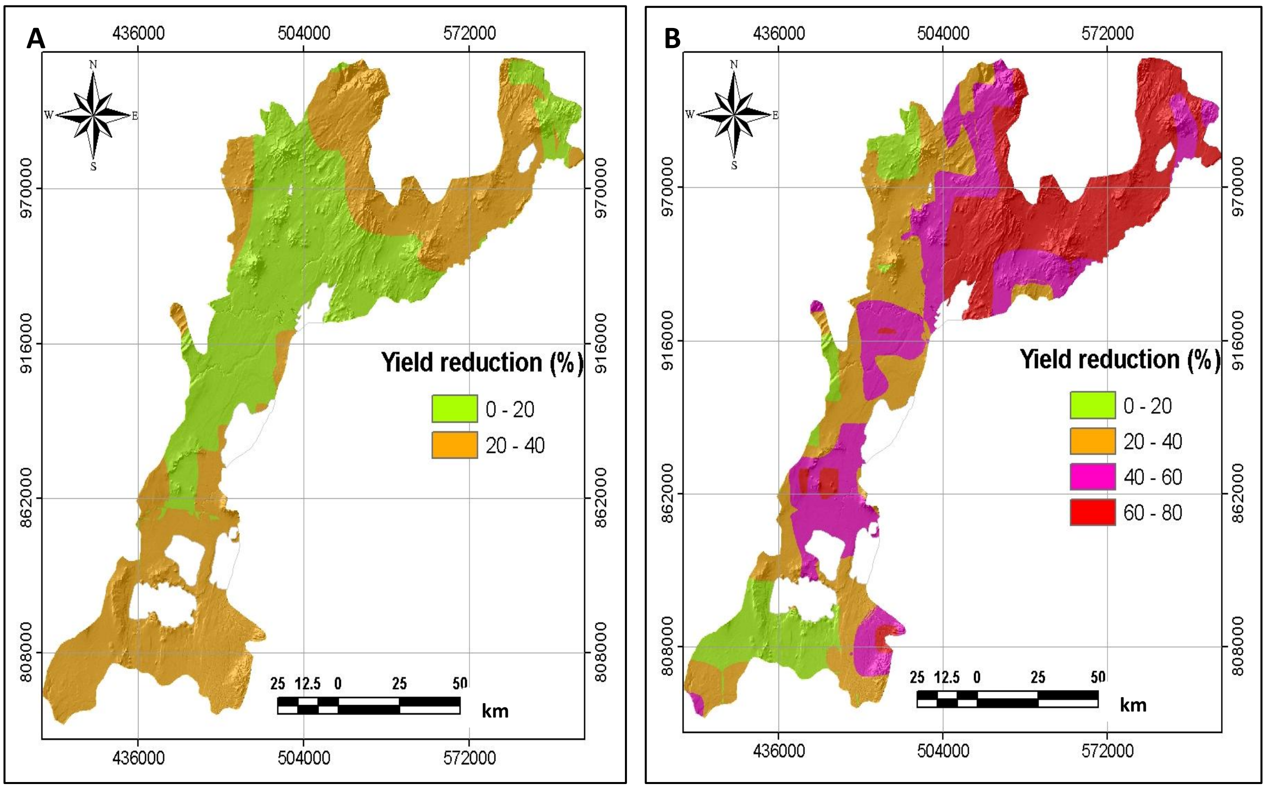


Figure 20. Spatial pattern of yield reduction in 2000 (A) and 2002 (B) cropping seasons

Regarding the wet years (2007 and 2008), spatial pattern of yield reduction is depicted in Figure 21. The result indicted that the level of yield reduction was very low (<30%) in most part while small pocket areas around north eastern reached to 3 to 6 percent covering 0.23 percent of the total area in 2007 cropping season. In 2008 cropping season, 20 to 25 percent yield reduction was observed in small pocket area covering 2.06 percent of the total area in southern part of the zone, although the dominant part remains under low level of yield reduction. This may be attributed to mismatch of seasonal rainfall and crop requirement during the critical growth stage.

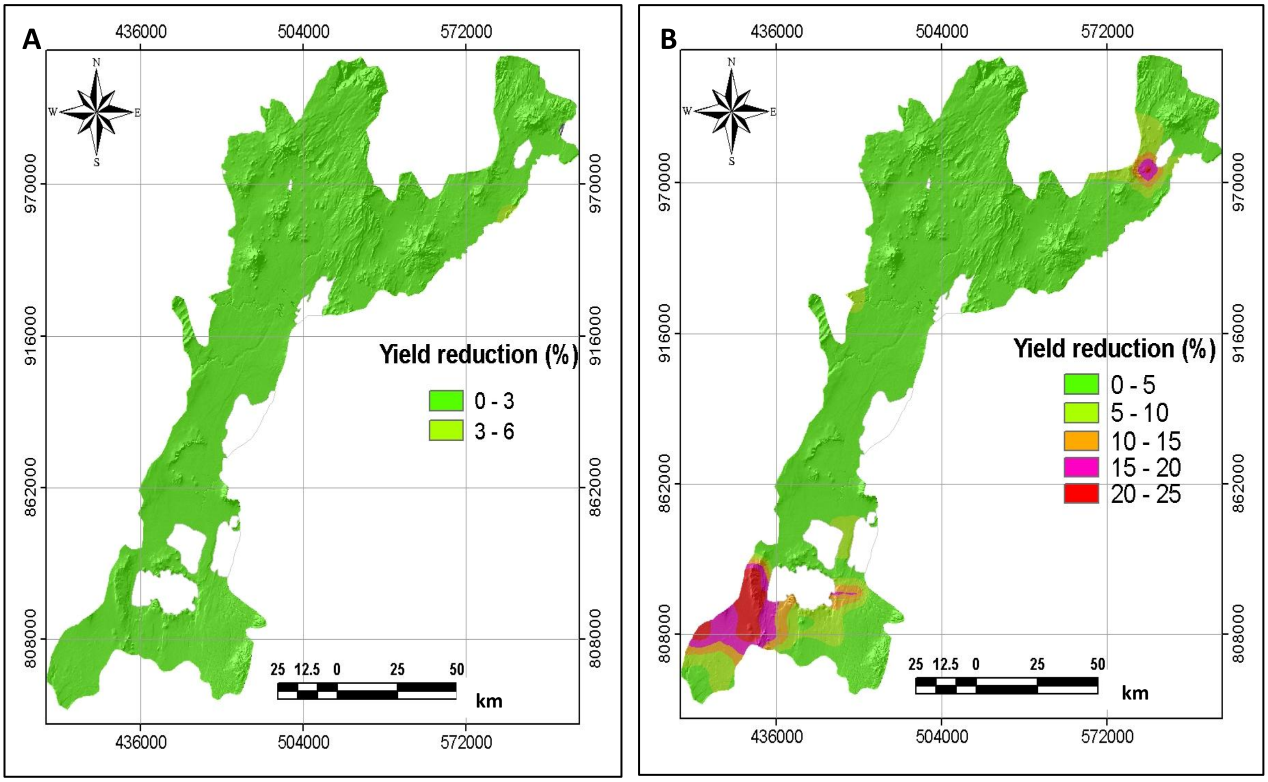


Figure 21. Spatial pattern of yield reduction in 2007 (A) and 2008 (B) cropping seasons

4.6.1 Relationship between yield reduction and Water Requirement Satisfaction Index

The year to year variation of WRSI and the corresponding yield reduction are illustrated in Figure 22. The figure shows that the WRSI values and the corresponding yield reduction of crops growing in the study area have followed an inverse relation. Compared to other cropping seasons of the analysis period, yield reduction for the years 2000 to 2005 was relatively higher in the study area. However, the year 2002 had highest reduction followed by that of the year 2000 showing that there was severe agricultural drought in East Shewa zone. It is found that the lowest WRSI (44 %) value and highest yield reduction (33.4%) have occurred during the year 2002, whereas in 2000 the values were 73 and 13.5 percent, respectively. Although only limited number of years was involved in statistical correlation, an encouraging R- squared value (0.93) was obtained from the 13 years of data.

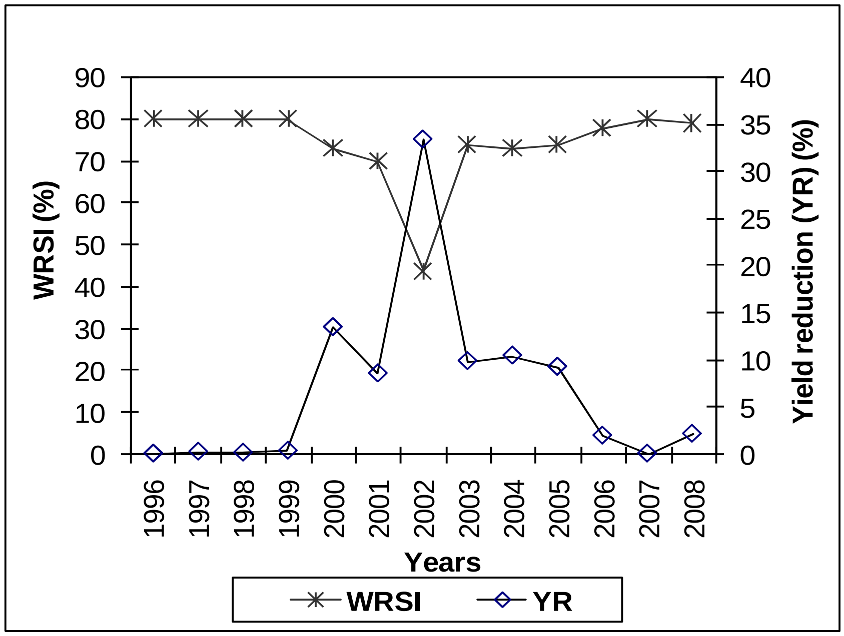
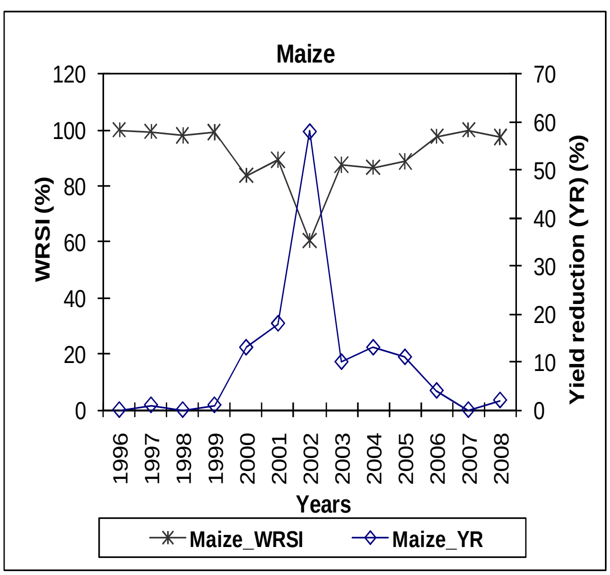


Figure 22. Aggregate crops WRSI and Yield reduction trend in East Shewa zone

Maize and Teff are the dominant crops growing in the study area. Both crops show similar trends for WRSI and yield reduction (Figure 23) to that of the aggregate crops growing in the study area. The highest yield reduction due to agricultural drought for maize and teff crops account for 58 and 50 percent while the lowest WRSI are 60.3 and 63.3, respectively in the year 2002. Whereas in the year 2000, there was 13 and 9 percent yield reduction and 83.6 and 85 percent WRSI for maize and Teff crops, respectively.



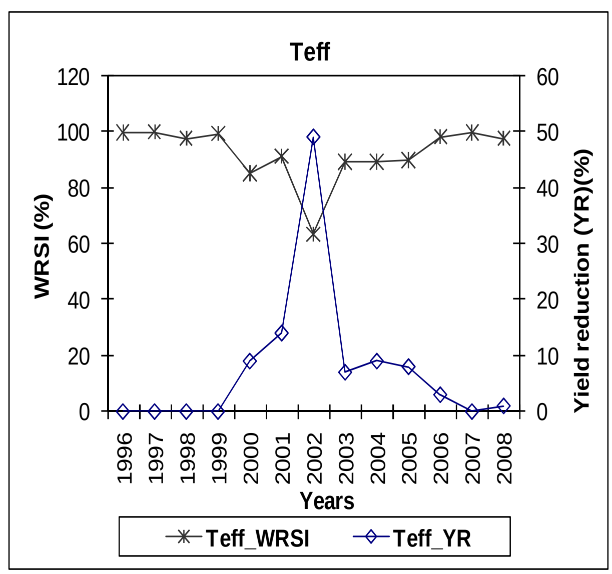


Figure 23. WRSI and yield reduction trend of Maize and Teff crops

4.7 Classification of agricultural drought risk zone.

The agricultural drought risk map has been prepared by integrating all drought frequency maps generated from the three drought indices, SPI, WRSI and NDVI anomaly (Figure 24). The three layers representing drought indices were prioritized according to their degree of influence using pair-wise comparison. According to the result derived from the integration of all drought

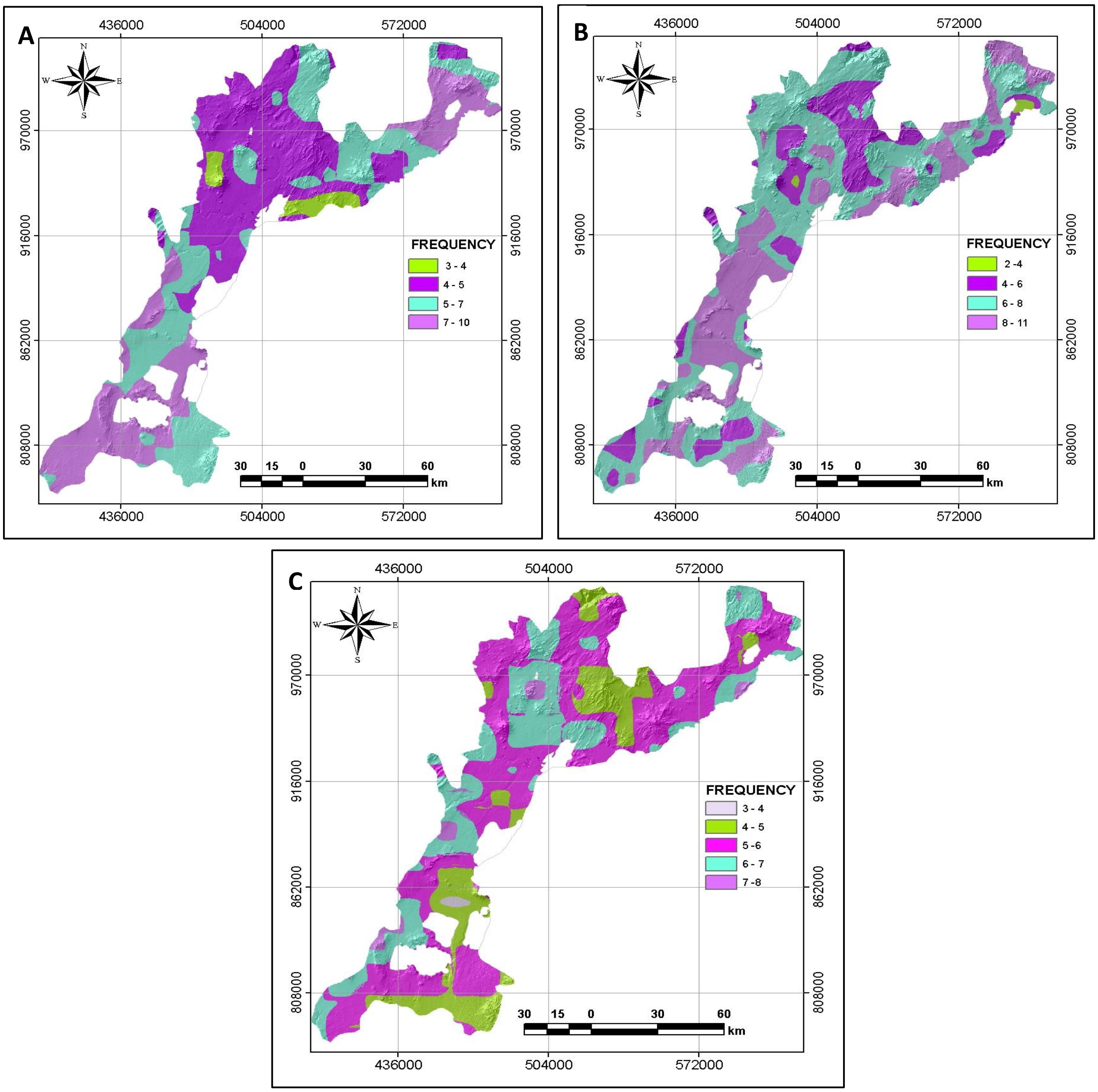


Figure 24. Frequency of agricultural drought risk map using drought indices (A)WRSI, (B)NDVI anomaly and (C)SPI.

frequency maps, East Shewa zone is classified into slight, moderate and severe agricultural risk zones (Figure 25). Agricultural drought risk map depicted in Figure 25 showing that the percentage area affected by slight, moderate and severe agricultural drought risk encompasses 17.18, 41.32 and 41.50 percent of the total geographical area of East Shewa zone, respectively (Table 6). The probability of occurrence of agricultural drought ranges from 15 to 30 percent for slight severity level, 30 to 46 percent for moderate severity level and 46 to 76 percent for severe severity level. Thus, the western and most of central part of East Shewa zone is categorized into slight and moderate drought probability zone while most of north eastern and southern part is into severe drought probability zone.

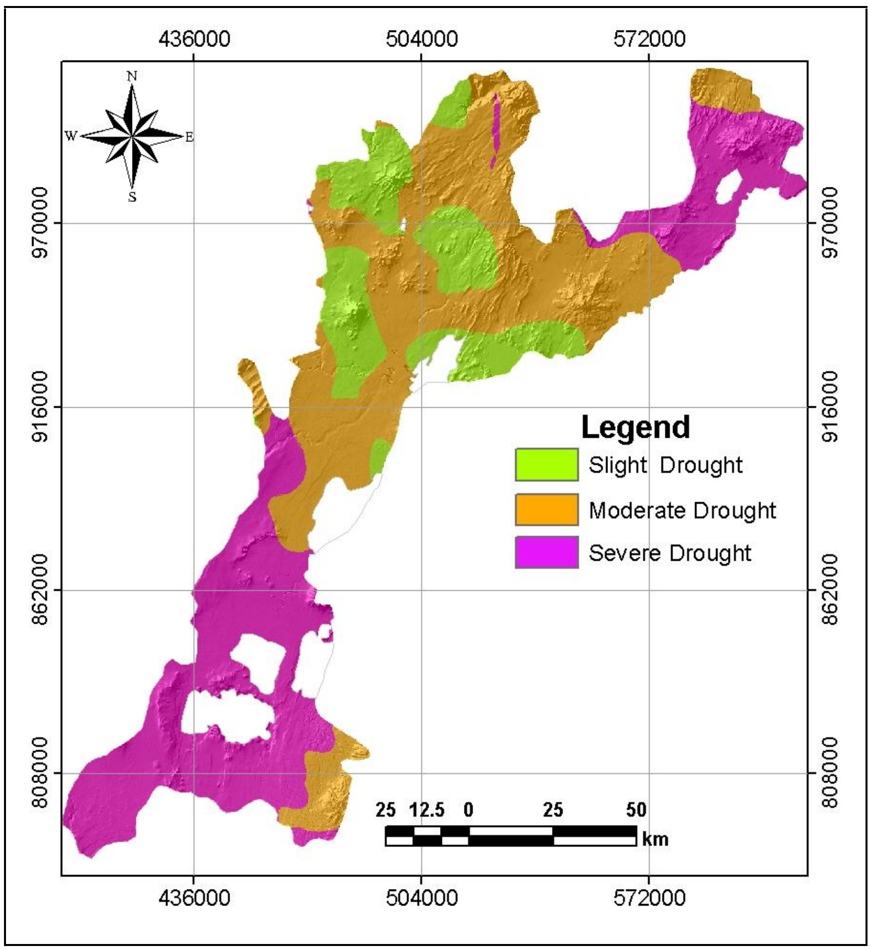


Figure 25. Agricultural drought risk map

Table 6. Percentage area affected by different agricultural drought risk levels

Agricultural drought severity levels	Probability of occurrence (%)	Area (km^2)	Area (%)
Slight	15 - 30	2365.3	17.18
Moderate	30 - 46	5688.3	41.32
Severe	46 - 76	5712.9	41.50

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

Agricultural drought having medium frequency of occurrence is a common phenomenon in East Shewa zone. According to Early warning system (EWS) reports from national Disaster Prevention and Preparedness Commission (DPPC), late onset and early cessation of the main rainy season, erratic distribution of rainfall and extended dry spells are the main weather related problems that cause agricultural drought. Furthermore, reports show that even though there was agricultural drought from the year 2000 through 2005 cropping season, the 2002 cropping season was the worst season that result in substantial yield reduction (EWS, 2003). As a result, the number of people affected by recurrent drought have increased significantly and the extents of food shortages and related problems have grown in East Shewa zone (Figure 26). The number of affected population and the estimated yield reduction are highly correlated (r^2=0.8). Furthermore, information obtained from East Shewa zone agricultural and rural development, and DPPC offices confirms that during the year 2000 and 2002 cropping seasons, there was severe agricultural drought in East Shewa zone, and consequently complete crop failure occurred in most of the area particularly, north eastern part of the area including Fentale, Bosset and part of Adama and southern part particularly Adamitulu. On the other hand, 1996, 1997, 2007 and 2008 cropping seasons were relatively good in most of the areas. This information is in agreement with the result obtained from the analysis of satellite data.

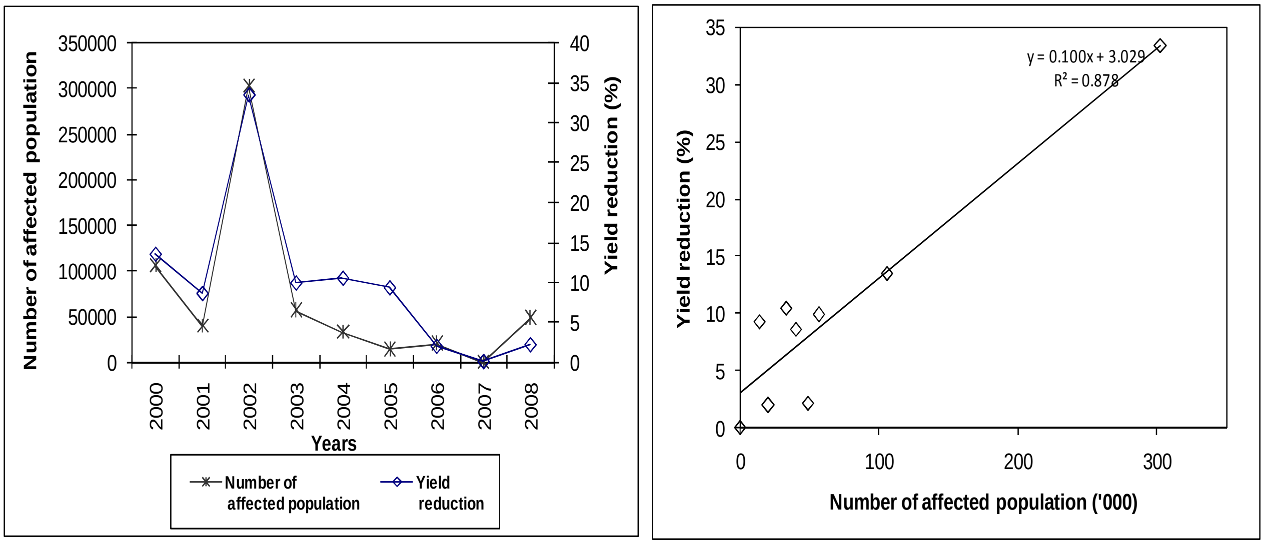


Figure 26. Relationship between yield reduction and number of affected population

According to the information obtained from East Shewa zone agricultural and rural development offices, agricultural drought mostly occurred as a result of mismatch of rainfall with crop requirement. Moreover, agricultural experts perceive that the length of growing period was decline due to climate change and thus the production options of farmers in central rift valley are becoming limited to short duration crop varieties. Irrigation practice has also been introduced as adaptation options in the area to strengthen the agricultural activities while reducing the impact of agricultural drought on the area.

Besides, adverse weather condition as a result of rainfall variability in terms of amount and distribution, agricultural drought increases the potential for pest infestations and crop diseases occurrence like stem borer reducing the crop quality and yield. Increased pest infestation and occurrence of disease during the drought years also contributes significant yield reduction in East Shewa zone, which could be captured by the yield reduction function.

5. Conclusion and Recommendations

5.1. Conclusion

Agriculture remains by far the most vulnerable and sensitive sector that is seriously affected by the impacts of climate variability and climate change, which is usually manifested through rainfall variability and recurrent drought. Rainfall is one of the climatic variables that largely determine the occurrence of drought and also influences the growth and development of vegetations which is reflected by NDVI. East Shewa zone experiences high rainfall variability with coefficient of variation 23 to 37 percent. This seasonal rainfall variability is inevitably reflected in variable agricultural production. The study confirmed that seasonal rainfall and NDVI patterns of the entire study area have good correlation (r=0.7), and 42 percent of NDVI variability can be explained by seasonal rainfall. Since NDVI has lagged response to existing rainfall, the amount and timing of rainfall relative to crop or vegetation requirement must be matched. In this regard, a three dekad or one month preceding rainfall is found to have highest influence on the growth and development of vegetation in East Shewa zone. That means the vegetation growth in each month is influenced by rainfall in the preceding month, and significant change in soil moisture and vegetation development are observed in this period. Therefore, three to four weeks lag time could be used in future activities that require rainfall and NDVI relationships.

Using satellite data as input parameters for drought indices, spatiotemporal variation of seasonal agricultural drought patterns and severity are detected and mapped with the help of advanced techniques of GIS and remote sensing. The obtained result is in agreement with the ground based surveyed information. Hence, agricultural drought assessment using satellite data are paramount importance in order to assess the past and the current agricultural drought conditions , and generate baseline information that helps to monitor real time situation in the future for different adaptation options within relatively large geographical area and repetitive time scale coverage.

In order to evaluate the strength of the indices in explaining the existence of agricultural drought, simple regression analysis was conducted between indices result and total grain yield. The result revealed that WRSI, SPI and NDVI anomaly express 76, 64 and 54 percent of variability of the grain yield, respectively. Thus, WRSI can be a good indicator for occurrence of agricultural drought. Generally, in this study WRSI express the real picture of agricultural drought followed by SPI and NDVI anomaly. Therefore, WRSI based agricultural drought assessment can better capture agricultural drought events.

Agricultural drought risk can be viewed as a product of both exposure to the climate hazards and the vulnerability of farming or cropping practices to drought conditions. In view of this, agricultural risk zone map produced by integrating all drought frequency maps derived from all drought indices indicates that East Shewa zone is classified into slight, moderate and severe agricultural drought risk zone, respectively. Thus, Agricultural drought risk mapping can be useful to guide decision making process in drought monitoring and to reduce the impact of drought on agricultural production and productivity, while identifying appropriate sites for specific adaptation and mitigation actions.

5.2 Recommendations

Based on the findings of the study, the following recommendations are suggested:

- Prioritization and implementation of site specific adaptation and/or mitigation projects should be made based on such identification of risk levels of specific locations.
- Since agricultural drought severity levels vary spatially, selection of agricultural technologies and information (drought tolerance crops, the type of crop variety and soil moisture conservation practices) should be made to fit in to the agricultural drought severity levels.
- The methods as well as results of agricultural drought assessment and risk mapping are believed to be highly important for decision makers and stakeholders, who have a stake in the study area. However, it is recommended that future studies can build up on this work by including real time seasonal rainfall forecasts as model parameter so that stakeholders can get early warning information that helps to take necessary adaptation measures and reduce the impact of agricultural drought.

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Appendices

Appendix 1. Partial view of the study area

Appendix 2. Questionnaire

1. When agricultural drought occurs between 1996 – 2008G.C in the area? Which one the most devastating one?
2. How the frequency of agricultural drought was looks like in the past growing seasons (low, Medium, high)?
3. How is a rainfall characteristic in terms of amount and distribution as well as time of occurrence related to crop requirement?
4. Is there any disease and pest infestation occurred in the area during drought year?
5. How was rainfall pattern in terms of amount and distribution the last 13years?
6. Is there yield reduction due to mismatch of rainfall and crop water needs at different growth stage?
7. Is there any change in cropping system due to the consequence of climate change in general and agricultural drought in particular?
8. What types of mitigation options used during drought years?
9. Can you tell two good and bad cropping seasons in terms of seasonal rainfall and grain yield harvest?
10. What types of crops are growing in the area? Amongst those which one is the major one in terms of large area coverage?

Appendix 3. Simple linear regression analysis between NDVI and Rainfall

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

---------------- DETAILS OF THE FITTED LINE -----------------

Fitted equation : NDVI = 0.112 + 0.0001 * RF

R-squared : 0.424

ANOVA for regression of NDVI on rainfall

Source	df	SS	MS	F value	Prob>F
Regression	1	0.003499	0.0035	8.61	0.0136
Residual	11	0.00447	0.00041		
Total	12	0.007969			

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

---------------- DETAILS OF THE FITTED LINE -----------------

Fitted equation : NDVI = 0.1956 - 0.0006 * RF

R-squared : 0.0241

ANOVA for regression of NDVI on Rainfall

Source	df	SS	MS	F value	Prob>F
Regression	1	0.000695	0.0007	0.32	0.5808
Residual	13	0.028177	0.00217		
Total	14	0.028872			

R-squared =0.0241
Residual variance is larger than total variance

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

----------------- DETAILS OF THE FITTED LINE ------------------

Fitted equation : NDVI = 0.1526 + 0.0008 * RF

R-squared : 0.0408

ANOVA for regression of NDVI on rainfall

Source	df	SS	MS	F value	Prob>F
Regression	1	0.001143	0.00114	0.51	0.4888
Residual	12	0.026901	0.00224		
Total	13	0.028044			

R-squared = 0.0408
Residual variance is larger than total variance

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

----------------- DETAILS OF THE FITTED LINE ------------------

Fitted equation : NDVI = 0.1146 + 0.0019 * RF

R-squared : 0.2288

ANOVA for regression of NDVI on Rainfall

Source	df	SS	MS	F value	Prob>F
Regression	1	0.006251	0.00625	3.26	0.0982
Residual	11	0.021069	0.00192		
Total	12	0.02732			

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

----------------- DETAILS OF THE FITTED LINE ------------------

Fitted equation : NDVI = 0.0692 + 0.0032 * RF

R-squared : 0.6281

ANOVA for regression of NDVI on Rainfall

Source	df	SS	MS	F value	Prob>F
Regression	1	0.016333	0.01633	16.89	0.0021
Residual	10	0.009672	0.00097		
Total	11	0.026004			

Appendix 4. Agricultural drought severity coverage based on NDVI anomaly index for the selected drought and wet years

Drought index	Drought severity levels	Drought Year: 2000		Drought Year: 2002		Wet year: 2007		Wet year: 2008	
		Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)
NDVI anomaly	No drought								
	Slight drought	1398.2	10.15	5559.1	40.38	8854.1	64.32	3084.6	22.41
	Moderate drought	9812.3	71.28	4739.1	34.43	4254.9	30.90	8905.3	64.69
	Severe drought	2275.2	16.53	3115.3	22.63	575.3	4.18	1524.0	11.07
	Very severe drought	280.8	2.04	352.9	2.56	82.1	0.60	252.6	1.83

Appendix 5. Simple linear regression analysis between NDVI anomaly and grain yield anomaly

----------------- DETAILS OF THE FITTED LINE ----------------------

Fitted equation : Grain yield anomaly = 57.26 + 3.479 * NDVI anomaly
R-squared : 0.5416

ANOVA for regression of Grain yield anomaly on NDVI anomaly

Source	df	SS	MS	F value	Prob >F
Regression	1	456.171	456.17	3.54	0.1563
Residual	3	386.124	128.71		
Total	4	842.294			

Appendix 6. Agricultural drought severity coverage based on SPI index for the selected drought and wet years

Drought index	Drought severity levels	Drought Year: 2000		Drought Year: 2002		Wet year: 2007		Wet year: 2008	
		Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)
SPI	No drought					13766.5	100	13492.2	98
	Slight drought	3257.2	23.00	711.5	8.84			274.3	2
	Moderate drought	10420.1	75.69	5500.0	46.04				
	Severe drought	89.2	0.65	6338.5	39.95				
	Very severe drought			1216.6	5.17				

Appendix 7. Simple linear regression analysis between SPI and grain yield anomaly

---------------- DETAILS OF THE FITTED LINE -------------------------

Fitted equation : Grain yield anomaly = 3.355 + 46.59 * SPI

R-squared : 0.6438

ANOVA for regression of Grain yield anomaly on SPI

Source	df	SS	MS	F value	Prob>F
Regression	1	541.992	541.99	5.42	0.1023
Residual	3	299.911	99.97		
Total	4	841.903			

Appendix 8. Agricultural drought severity coverage based on WRSI index for the selected drought and wet years

Drought index	Drought severity levels	Drought Year: 2000		Drought Year: 2002		Wet year: 2007		Wet year: 2008	
		Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)
WRSI	No drought					10496.2	76.24	9715.0	70.57
	Slight drought	6265.6	45.00	756.1	5.48	3270.3	23.76	3175.3	23.07
	Moderate drought	4090.6	29.71	2751.6	20.00			876.2	6.36
	Severe drought	3410.3	24.77	2519.2	18.30				
	Very severe drought			7739.6	56.22				

Appendix 9. Simple linear regression analysis between WRSI and grain yield anomaly

---------------- DETAILS OF THE FITTED LINE ------------------

Fitted equation : Grain yield anomaly = -34.8 + 0.6671 * WRSI

R-squared : 0.760

ANOVA for regression of Grain yield anomaly on WRSI

Source	df	SS	MS	F value	Prob>F
Regression	1	17.2649	17.265	9.47	0.0542
Residual	3	5.46739	1.8225		
Total	4	22.7323			

Appendix 10. Percentage area of yield reduction for the selected drought and wet years

<table>
<tr><th rowspan="6">Drought Year</th><th rowspan="2">Yield reduction (%)</th><th colspan="2">Drought Year: 2000</th><th colspan="3">Drought Year: 2002</th></tr>
<tr><th>Area (Km^2)</th><th>Area (%)</th><th>Area (Km^2)</th><th colspan="2">Area (%)</th></tr>
<tr><td>0 - 20</td><td>5889.3</td><td>42.78</td><td>1740.1</td><td colspan="2">12.64</td></tr>
<tr><td>20 - 40</td><td>7877.2</td><td>57.22</td><td>4152.0</td><td colspan="2">30.16</td></tr>
<tr><td>40 - 60</td><td></td><td></td><td>4223.6</td><td colspan="2">30.68</td></tr>
<tr><td>60 - 80</td><td></td><td></td><td>3650.9</td><td colspan="2">26.52</td></tr>
<tr><th rowspan="7">Wet Year</th><th rowspan="2">Yield reduction (%)</th><th colspan="2">Wet Year: 2007</th><th rowspan="2">Yield reduction (%)</th><th colspan="2">Wet Year: 2008</th></tr>
<tr><th>Area (Km^2)</th><th>Area (%)</th><th>Area (Km^2)</th><th>Area (%)</th></tr>
<tr><td>0 - 3</td><td>13734.8</td><td>99.77</td><td>0 - 5</td><td>11438.6</td><td>83.09</td></tr>
<tr><td>3 - 6</td><td>31.7</td><td>0.23</td><td>5 - 10</td><td>1203.2</td><td>8.74</td></tr>
<tr><td></td><td></td><td></td><td>10 - 15</td><td>457.1</td><td>3.32</td></tr>
<tr><td></td><td></td><td></td><td>15 - 20</td><td>384.1</td><td>2.79</td></tr>
<tr><td></td><td></td><td></td><td>20 - 25</td><td>283.6</td><td>2.06</td></tr>
</table>

D E C L A R A T I O N

I hereby declare that the thesis entitled "Agricultural Drought Assessment using Remote sensing and GIS techniques" has been carried out by me under the supervision of Dr. K. V. Suryabhagavan, Department of Earth Sciences, Addis Ababa University, Addis Ababa during the year 2010 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.

Gizachew Legesse

Signature: ________________________

Addis Ababa University

Addis Ababa

Date: June, 2010

C E R T I F I C A T E

This is certified that the thesis entitled "Agricultural Drought Assessment using Remote sensing and GIS techniques" is a bonafied work carried out by Gizachew Legesse under my guidance and supervision. This is the actual work done by Gizachew Legesse 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. K. V. Suryabhagavan

Assistant Professor

Signature: ________________________

Department of Earth Science

Addis Ababa University

Addis Ababa

Date: June, 2010