AGRICULTURAL DROUGHT ASSESSMENT USING VARIOUS DROUGHT INDICES IN EAST SHEWA ZONE, CENTRAL ETHIOPIA

BEKELE ALEMAYEHU SIRAW

A THESIS SUBMITTED TO

THE DEPARTMENT OF GEOMATICS ENGINEERING

SCHOOL OF CIVIL ENGINEERING AND ARCHITECTURE (SOCEA)

PRESENTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE OF MASTER'S IN GEOINFORMATICS ENGINEERING

OFFICE OF GRADUATE STUDIES

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Approval of Board of Examiners

We, the undersigned, members of the Board of Examiners of the final open defense by Bekele Alemayehu have read and evaluated his thesis entitled “Agricultural Drought Assessment using Various Drought Indices in East Shewa Zone, Central Ethiopia” and examined the candidate. This is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirement of the Degree of Master’s in Geoinformatics Engineering.

Supervisor /Advisor	Signature	Date
Chairperson	Signature	Date
Internal Examiner	Signature	Date
External Examiner	Signature	Date

Declaration

I Bekele Alemayehu Siraw hereby declare that this MSc Thesis is my original work and has not been presented for a degree in any other university, and all sources of material used for this thesis have been duly acknowledged.

Name: …………………………………………….

Signature: ………………………………………….

This MSc Thesis has been submitted for examination with our approval as thesis advisor.

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Signature: ……………………………………………………………

Name (Co Advisor): ………………………………………………….

Signature: ……………………………………………………………

Date of submission: …..

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LIST OF ACRONYMS

AMSR-E	Advanced Microwave Scanning Radiometer-Earth observing system
ATJK	Adami Tulu Jido Kombolch
AVHRR	Advanced Very High-Resolution Radiometer
CAFOD	Catholic Agency for Overseas Development
CSA	Central Statistical Agency
ENFS	Ethiopia Network on Food Security
FEWS NET	Famine Early Warning System Network
GPS	Global Positioning System
GRACE	Gravity Recovery and Climate Experiment
GrADS	Grid Analysis and Display System
LST	Land Surface Temperature
MODIS	Moderate-resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NASDA	United States and the National Space Development Agency
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
NSIDC DAAC	National Snow and Ice Data Center Distributed Active Archive Center
OVDI	Optimized Vegetation Drought Index

PCA	Principal Component Analysis
PCI	Precipitation Condition Index
PDSI	Palmer Drought Severity Index
SDCI	Scaled Drought Condition Index
SDI	Synthesized Drought Index
SMCI	Soil Moisture Condition Index
SPI	Standardized Precipitation Index
TCI	Temperature Condition Index
TRMM	Tropical Rainfall Measuring Mission
TVDI	Temperature Vegetation Dryness Index
UNICEF	United Nations Children's Fund
USDM	United Nations Drought Monitoring
USGS	United States Geological Survey
VCI	Vegetation Condition Index
VHI	Vegetation Health Index
WMO	World Meteorological Organization
WWF	World Wildlife Fund

ABSTRACT

Drought is one of the natural hazards that will occur because of the deficiency of water or moisture in the area, which leads to famine and total disaster. Drought collectively reviewed in four perspectives i.e. Metrological, Agricultural, Social, and Hydrological. The primary objective of this research is to assess the spatial extent, and frequency of agricultural drought in East Shewa Zone. This study employed various drought indices in two categories (single and combined). Precipitation condition Index (PCI), Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and Soil Moisture Condition Index (SMCI) were categorized as single drought indicators. Whereas, three drought indices namely Optimized Vegetation Drought Index (OVDI), Vegetation Health Index (VHI) and Scaled Drought Condition Index (SDCI) grouped as combined drought indices. The results of both single and combined drought indicators were validated by employing Standardized Precipitation Index (SPI) using five time scales(one, three, six, nine and twelve months respectively). Bringing all the single drought indices to a common platform using Empirical weight method outperformed constrained optimization method. Interestingly, results showed distinct drought conditions for different indices and varies between Kiremt (rainy) and Bega (non-rainy) seasons. The scaled single condition indices and raw drought indicators showed maximum correlation coefficients of 0.764 and 0.494 respectively. The combined agricultural indices and single condition indices also showed minimum correlation of 0.12 and -0.25 respectively. It is evident that PCI and SDCI has showed maximum correlation of 0.764 and 0.741 respectively. Moreover, PCI provided better results with shorter SPI timescales. The overall result of single and combined agricultural drought indices identified Fentale as severe drought wereda followed by ATJK, Boset, Adama and Gimbichu. Therefore, comprehensive method between in situ and remote sensing drought indices with multiple parameters are effective for agricultural drought assessment.

Keywords: Agricultural Drought, Indices, SPI

CHAPTER ONE

1 INTRODUCTION

1.1. Background of the Study

Drought is a normal, recurrent feature of climate having a consequence of a reduction of precipitation and/or abnormal temperature over an extended period of time, which will result in famine, and starving in the society. In urban drought events, which is a temporary aberration, the drought might turn; pastures brown, threaten shrubs and trees and result in low vegetation cover and high land surface temperature (LST) simultaneously. Given that drought is a normal, recurrent feature of climate, it occurs in virtually all climatic regimes (Gao, et al., 2010). According to Aslam and Mohammed Drought is also defined as a long-term condition imbalance between precipitation and Evapotranspiration, which anyway represent water shortage and that intern, remembers lack of rainfall in that area (Aslam & Mohammed, 2015).

In Ethiopia, drought had been a number one natural disaster that occurs frequently in the last 40 years by living most peoples of the country to starve to death because of food shortage and it resulted in a high shortage of drinking water for peoples and for the animals. Drought in1983 to 1985's is the most devastating in the history of the country that result in famine and health problems. Next, to this, the recent 2015 drought is the biggest drought that happens in history, which lives 10 million women, men, and children to hunger, and starvation. According to CAFOD, the starvation is because of the drought caused by El Niño, no food reserves, climate change, high food price in the market, low price of cattle, and lack of knowledge about adaptive farming techniques. The 2008's drought that affected the southern and southeastern part of the country is the third, which resulted in 3.4 million peoples to acquire aid for the three months according to United Nations Children's Fund (UNICEF, 2008). The drought limited the production of both food and cash crops like coffee, which reduces the income of farmers and their domestic income resources.

East Shewa Zone suffers drought ranging from slight to severe according to a study from 1996 to 2008 (Legesse & Suryabhagavan, 2014) which happened in different frequency and extent in each Administrative wereda. The East Shewa Zone Disaster and Risk Management Offices report (2018) showed Fentalle, Boset, ATJK, and Adama had higher drought affected weredas in terms of population aid. The Ethiopian humanitarian and disaster resilience plan of 2018 indicated that the amount of rainfall in the lowland areas of East Shewa Zone had a poor performance in rainy season starting from 2017 to 2018. The problem behind this effects is poor regular and timely spatiotemporal information on the problem, lack of early warning systems, and unable to understand the recurrence and trend of drought in the regional level.

The field of remote sensing is the new era for drought assessment and forecasting starting from the late 1990s because of available datasets from various climate and metrological satellites. Now a day many countries are developing their own drought indicator maps and information's in the national stage. The United States Drought Monitoring (USDM) is one of them that best designed to monitor and develop severity maps of the area in the required period.

Due to the limited metrological stations, limited soil moisture data, and barriers in data sharing the in situ data sets are unable to meet this global demand for drought assessment monitoring. In the last 30 years, many satellites were launched for this purpose such as Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E), and Tropical Rainfall Measuring Mission (TRMM). Studies using remote sensing methods (Rhee, et al, 2010, Zhang,et al., 2017, and Hao, et al., 2015)) had tested their results in terms of different areas with different climatic conditions not in different seasons. This study intern tested the result of remote sensing drought assessment in the same area but in different seasons to see whether there was a comparative difference in two seasons.

To more effectively monitor drought and provide early warning requires a comprehensive and integrated approach between in situ (SPI) and remote sensing drought assessment methods. Problems such as inadequate meteorological and hydrological data, inadequate data sharing between government agencies and research institutions (universities), untimely information delivery of early warning systems, and drought indices are sometimes inadequate to detect early onset and end of drought makes difficult to study and assess drought severity (Wilhite, 2009). The collection of climatic and hydrologic data is fragmented between many agencies or ministries in most countries because these data are often not reported in a timely manner. Automating the data collection process can substantially improve the timeliness and reliability of drought assessment and early warning systems. A 4-6 month or early detection of drought is now possible at each corner of the world (Kogan, 2001).

1.2. Statement of the Problem

Agriculture remains by far the most vulnerable and sensitive sector that is seriously affected by the impacts of climate variability and climate change, usually manifested through rainfall variability and recurrent droughts (Legesse and Suryabhagavan, 2014). As more than 80% of the total cultivated area in Ethiopia is directly dependent on monsoon rainfall, any potential change in seasonal rainfall critically influences crop production and the well-being of smallholder farmers in the region (Suryabhagavan, 2017). The use of rainfall as a source of water for agricultural production is not to be trusted totally because of the variability and its effect when it is not as expected.

Drought is the main natural and environmental disaster that happens frequently in East Shewa due to the changing ecosystem and global effects. In the study area (East Shewa Zone), there are areas that did not have rain in each rainy season (June-September) which makes difficult to predict productivity. The report from East Shewa Zone Disaster and Risk Management Office shows that over 940,000 people's required urgent food and related supports from 2015 to 2018. According to the report from the total 10 administrative weredas that the office collected the data only two of them (Lomme and Gimbichu) required no aid from 2008 to 2018. In that area, the range of drought reaches 2 to 3 years because of insufficient rainfall that makes peoples plant, their seeds only when they get rain, which means there, is no other way to grow seeds. Because of the insufficient water people loss their animals as they will not be able to feed them. Those areas that are frequently vulnerable to agricultural drought is not noticeable only the society that lives there knows the condition of the rainfall and its length in a single season.

The long year historical drought assessment information is not available in the respective wereda's or zones that shows the spatial as well as the temporal variability. The availability of this information helps to analyze the long-term trend of agricultural drought, which is supportive of decision-makers and policy formulators. The historical drought of an area is also not being assessed in each year.

Assessment of drought severity, spatial extent, and impact is key for drought monitoring to use the information for appropriate response in drought early warning system. In Ethiopia, the National Policy for Disaster Prevention, Preparedness, and Management that is formulated in 1993 give this responsibility to each wereda to be local and determine the problem in a specific area, but the institutions do not go as planned and the impact on the problem is very limited. In East Shewa, there is East Shewa zone disaster and risk management offices organized in a zone level. The well-established Famine Early Warning System Network (FEWS NET) is one of such systems that addresses food security issues for any location in the world.

The lack of frequent drought assessment systems at national as well as regional level makes the drought impact bigger in the study area because of the lack of both spatial and statistical information in that period. How big the extent of the drought matters the assessment process even after it happens. Lack of Spatiotemporal drought information in East Shewa Zone had made difficult for decision-makers to formulate techniques of minimizing the effect. The meteorological method of disaster prediction or assessment is not enough because of the extent and the installation cost of those instruments but remote sensing technology shows a better and low-cost method of drought assessment. There are many remote sensing methods for drought assessment methods, which requires analysis and proper selection of the method for a specific area because those methods depend on the environmental conditions. The lack of drought forecast and early warning system leads the farmers to stick to traditional farming because of the lack of information they are not adopting the farming process with drought.

In this study, the available data from remote sensing and available metrological precipitation information used to solve problems on drought spatial extent and frequency, remote sensing drought assessment and presentation method for East Shewa Zone, and drought recurrence information in the area.

1.3. Objective

1.3.1. General Objective

In this study, the primary objective is to assess drought spatial extent and frequency in the study area by identifying the Sever areas with in situ precipitation indices.

1.3.2. Specific Objectives

This study incorporates the following specific objectives:

- To conduct a theoretical analysis of drought assessment
- To compare the performance of drought indices
- To validate drought Indices

1.4. Research Questions

- What is drought assessment and its methods implemented so far?
- Which remote sensing drought assessment methods is better?
- How to validate the remote sensing drought indices?

1.5. Significance of the Study

The significance of this study is primarily for East Shewa Zone Disaster and Risk Management Offices, which helps the office by providing the spatial and multi-temporal variability of agricultural drought. The categorized severity level of drought in classes allows the office to take measures by prioritizing the most and frequent affected areas. The office can be benefited from this study as a prototype and prepare their own assessments in each season which allows obtaining the historical information of drought in the area. The identification of drought Sever areas will make the food security and disaster prevention work easy for the office, which decreases the cost for preliminary studies. Measures of the Office using the resulting drought severity information they get can help the farming society to adapt themselves to the situation by not risking their animals as well as their own lives. Hence, agricultural drought risk mapping helps to guide decision-making processes in drought assessment and to reduce the risk of drought on agricultural productivity. The formulated drought assessment result can help decision-makers to formulate the strategies and policies that have to be done to minimize the impact of agricultural drought. Finally, the result of this work may benefit Geospatial professionals to adopt the remote sensing drought assessment methods or benefited by developing similar methods for their own environmental conditions.

1.6. Scope of the Study

The geographical scope of this study is East Shewa Zone where drought is prone in the area, which covers 992,253.641 hectares with 11-Administrative wereda including Akaki recently incorporated in Addis Ababa City Administration. The main scope of the study is to assess agricultural drought using remotely sensed and in situ drought assessment methods and includes the validations of remote sensing drought indices. The study incorporates discussions and results based on the spatiotemporal results of various agricultural remote sensing drought indices and in situ drought index. Comparison between various remote sensing drought indices made using the Pearson's correlation with different time scale SPI results.

1.7. Limitation of the Study

The following are the limitation of this study:

- Lack of adequate crop yield data
- Course resolution of TRMM precipitation and AMSR-E soil moisture data

Crop yield data of the study area needed for correlation and validation works but the limited sample points 10 (data in wereda level) and it lacks consistency because of the frequent migration of employees which affect the data collection and recording work. It was not possible to strengthen the validation of agricultural drought indices with crop yield because of barrier on the data, which cause a low correlation coefficient, and insignificance correlation between crop yield and remotely sensed drought indices. The poor spatial resolution of TRMM precipitation data and AMSR-E soil moisture data is one of the barriers that hinders such regional drought assessment studies. Resampling in Arc GIS helped to combine the poor resolution precipitation, and soil moisture data from TRMM and AMSR-E respectively with MODIS images.

1.8. Operational Definition of Terms

Agricultural Drought: Drought type that includes drought conditions for crop and vegetation.

“Bega”: is Amharic word, which describes the dry months including December, January, and February.

“Belg”: is Amharic word, which describes the semi-rainy months, which includes March, April, and May.

“Kiremt”: is Amharic word, which describes rainy months including June, July, and August.

Negative Correlation: correlation result shows an indirect relationship between two variables.

Positive Correlation: correlation result that shows a direct relationship between two variables.

Standardized Precipitation Index (SPI): “*The difference of precipitation from the mean for a specific time divided by the standard deviation*” (McKee, et al., 1993), which is helpful for both validation and drought detection.

“Tsedey”: is Amharic word, which describes seasons next to “Kiremt” which includes September, October, and November.

CHAPTER TWO

2 LITERATURE REVIEW

2.1. Theoretical Review

2.1.1. Drought

One-third of the world population lives in areas of water shortage and 1.1 billion people live in a shortage of access to safe and clean drinking water (WWF, 2019). Worldwide, drought is the second natural hazard next to flood that accounts for 11% of the world geographical extent while drought accounts for 7.5% of the extent. The percentage of area in the world affected by drought increases by a double from the 1970s to early 2000 in which Europe, Asia, Canada, Western and Southern Africa, and Eastern Australia are the areas, which experienced widespread drought in the period (Nagarajan, 2009). Because of the lack of precipitation in the areas the surface temperature and the atmospheric temperature is increased that will lead to desertification. Even a small (up to 0.2 Kelvin) rise in temperature is likely to accompanied by many other changes such as cloud cover, wind pattern, sea surface temperature, and sea level rise (Wilhite, 2009).

There are many definitions for drought in different effects that drought had such as economic and social. The meaning of drought various according to the locations it happened for example in a dry area which rain falls once in a week the lack of rain for two weeks may be drought. In the United Kingdom, drought is the shortage of rainwater for consecutive 15 days whereas in the United States of America drought occurs if the daily precipitation of the area is below 30% of the average annual daily precipitation in the area (Wilhite & Glantz, 1985). Drought is a period of drier than normal precipitation condition that results in many problems. In this period where rainfall amount is less for weeks, months or years, the flow of rivers decreases and the accumulated water level in lakes and ponds decreases. Therefore, the number of groundwater decreases and if the condition continues, the shortage of precipitation in the area will grow to drought, which defines drought as a spatially extended phenomenon (Salvadori & Michele, 2015).

The definition of drought is broad because of it's disciplinary which is also broad and have to identify and determined individually. Each drought disciplinarians incorporates different physical, biological, and socioeconomic factors in its definition of drought. Drought can be grouped as; - meteorological, hydrological, agricultural, and socioeconomic droughts (Wilhite & Glantz, 1985). Dryness or shortage of rain is a Meteorological drought while agricultural drought best expressed with its relation with evapotranspiration.

2.1.1.1. Meteorological Drought

Meteorological drought usually expressed as the degree of dryness compared to the normal or average amount of precipitation that an area obtains in the specific duration of the dry period which is different from area to area even now a day every country defines meteorological drought in different length of dry duration. Taking such meteorological definition of one area to the other area is not correct because meteorological characteristics are different in different areas so, the appropriate numerical definitions (Wilhite & Glantz, 1985) (for example, if the average is less than 2.5 inches) for the area has to be identified if necessary.

The meteorological drought has its own behavioral parameters using those parameters that it has it makes specific value for different areas. Temperature and precipitation are the two main parameters that determine the meteorological condition of the area. Percent of normal precipitation is the commonly used technique and best suited for the needs of the general audience through television in expressing the variation of precipitation amount. The method works by dividing the actual precipitation value of the day by the normal (mean precipitation value for 30 years) and expressed as a percentage of all inputs.

Meteorological drought is a single day, specific period precipitation concern or the temporal variability of the drought is small, or it may be more by collecting and analyzing those meteorological station data that gives the trend and the return period of drought if there is. The analysis and its impact valuation with average crop yield in the area is more efficient and easily performed in another drought types.

2.1.1.2. Hydrological Drought

Hydrological droughts are the period of time when the natural or aquifer source of water system does not provide enough water to meet the required amount of water for humanitarian as well as the needs of the environment in the ecosystem to support the living in the ecological system. Hydrological drought is not the first evidence for drought and it shows lagged response to precipitation deficiency (Li & Rodell, 2015). Water level may or may not reflect the shortage of rainfall for many years after the drought happens. During rainy seasons, water enters the ground and recharge the groundwater which intern enables to sustain vegetation, and feeds streams during periods when it is not raining.

Hydrological drought usually is slow to develop and persists longer than meteorological drought. Hydrological droughts have related the effect of a period of precipitation on the surface or below the surface water supply system of the ground such as stream flow, reservoirs, lakes, levels, and groundwater (Gustard, 2000). Hydrological drought is usually fallen behind the occurrence of agricultural and meteorological drought by supplying the required water from the aquifer. Water in hydrological storage (lakes, rivers, and reservoirs) that are very useful for human activities for power generation, irrigation, recreation, which identified as a factor influence hydrological drought duration (Loon & Laaha, 2015). The persistence of hydrological drought for 20 or more years will lead to several land surface processes. Because of this long period of the unrealized result, hydrological impact assessment and analysis will require a long period of drought assessment parameters. Hydrological drought in the consequence of long agricultural and meteorological drought which is not important for areas which rainfall frequently available in its natural raining season, because effective hydrological drought quantification requires a long period of data and a long period of drought season (Gustard, 2000).

2.1.1.3. Agricultural Drought

Cultivation of crop now affected by economic considerations as well as the decision of the farmer, which requires quantitative information on crop weather related parameters that need to be determined for effective crop production. Water requirement for crops, water availability in the period, and different diseases that occur because of the weather will matter when selecting the type of crop, the farmer wants to produce. In addition, the drought condition and length in that production seasons determine the productivity of the crop.

Agricultural drought exists because of the reduction of soil moisture in the root zone of crops, which affect the crop by reducing the water content that needs to grow (Mishra & Singh, 2010). Days with less than certain threshold precipitation (0.25 inches) down the ground are dry in a rainy season of the year which signifies that the availability of water in the soil describes agricultural drought (Ashok, et al., 2015). Meteorological and hydrological drought leads to agricultural drought because the main characteristics of agricultural drought are precipitation, which mainly related to meteorology and hydrology (Michael, et al., 2012). Not only precipitation agricultural drought is the differences between actual and potential evapotranspiration and soil water deficits. There is a possibility to detect Agricultural drought in a short period if it occurs in a period of cropping (Kiremt in Ethiopia) and that makes the issue very urgent and need to be monitored. Ethiopia is dependent on domestic agricultural products and more than 80% of the peoples are farmers so the assessment of such problems is important. The Ethiopian drought history in the past 30 years, which result in devastating famine and starvation, makes this issue important for the area. There are small-irrigated lands in the country compared to the area that is cultivated by rainwater, which if drought occurs like in the past the country will starve and this problem is noticed in the 2015 drought, which impacts for the death of many animals and many peoples.

2.1.1.4. Socioeconomic Drought

Socioeconomic drought is a shortage of supplies and high demand of the economic good, which is elements or can be the impact of agricultural, meteorological, and hydrological drought (Michael, et al., 2012). Economic goods such as electric power from river dams, factory food products, and water are weather dependent demands which if the weather is not normal because of drought those economic goods will decrease in supply. So socioeconomic drought is the occurrence of drought when demand exceeds the supply because of the weather-related supply shortage.

Socioeconomic drought is the last stage of drought in its impact on society as well as the wildlife that support the system of living. It involves social safety, health problem, the conflict between water users, and a reduction in the quality of life because of the limited resources left (Nagarajan, 2009). Population migration is also the main effect of socioeconomic drought many countries especially those who live in areas which are frequently affected by drought. Either death, which is the result of famine because of the drought directly or war (the second impact of drought). Environmental losses are the damages of plant and animal species and it leads to the extinction of those species. The absence of water in that area causes a fire, degradation of the landscape, loss of biodiversity, and soil erosion.

Socioeconomic drought results from the impact of the other drought categories (agricultural, hydrological, and meteorological) which mainly results in water scarcity, food shortage, and instability of the society. Socioeconomic drought is an outcome, therefore, the scientific method that needs to be implemented has to work on the driving parameters or categories of drought because by controlling agricultural drought the famine, ware driven by interest on goods, and the loss of biodiversity can be avoided.

2.1.2. Drought Assessment Parameters

Drought assessment parameters contain precipitation, soil moisture, evapotranspiration, stream flow, and vegetation health. The selection and utilization of any drought assessment parameters depend on the type of drought to monitor and the relationship between the parameter and the assessment technique (Nagarajan, 2009). Streamflow directly related to groundwater and the concentration of aquifer that supports rivers and lakes. Whereas rainfall, precipitation, vegetation health, and evaporation (evapotranspiration) are agricultural drought assessment parameters. Continuous measurement and recording of drought assessment parameters used for drought frequency detection and preparedness plans.

2.1.2.1. Rainfall and Temperature

Rainfall data from meteorological site with the help of various kinds of rain gauges by intended organizations, which spreads over the whole world and it, is available online except for some countries that enable a user to access. Not only by rain gauge satellites are now another means of measuring and obtaining rainfall (precipitation) information of the whole globe with coarse resolution (for example, TRMM precipitation information) (Nagarajan, 2009). This rainfall data from different sources used for forecasting and preparedness plan of natural hazards and enables to assess the historical comeback of hazards. Temperature and precipitation are inputs to drive another parameter such as evapotranspiration that in turn indicates the amount of precipitation required by crops. Temperature and precipitation use to generate Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), which in turn uses for generation of another drought index.

Normalized Difference Vegetation Index (NDVI) is a ration obtained from the near-infrared (NIR) and red channel of the remotely sensed data since the 1980s. Researchers used NDVI and LST from the advanced very high-resolution radiometer (AVHRR) from the national oceanic and atmospheric administration (NOAA) (Bayarjargal, et al., 2006) and (Julien, 2009). Land Surface Temperature (LST) shows the temperature of the surface and it is different from air temperature but it shows the temperature that reflected from the surface of each natural or artificial feature in raster format. The successor MODIS satellite launched in 1999 provides data that contains both NDVI and LST with a spatial resolution ranging 250, 500, and 1000 meters. MODIS data spectral resolution ranges from 0.405 to 14.385 micrometers with 36 spectral bands and it is wider than AVHRR.

The tropical rainfall measuring mission (TRMM) is a joint mission between the National Aeronautics and Space Administration (NASA) of the United States and the National Space Development Agency (NASDA) of Japan. The objectives of TRMM are to measure tropical and subtropical precipitation and estimate its associated energy exchange. This precipitation information from TRMM is required to calculate Precipitation Condition Index (PCI) and the metrological drought indices. The TRMM monthly precipitation information in the period of drought enables to determine and calculate the metrological drought indices.

2.1.2.2. Evaporation

Evaporation is one process of rain in which happened before cloud and in this case evaporation from plant leaves are the parameters used for drought assessment. The obtained rainfall and the maximum and minimum temperature as an input data and the length of solar heat can detect Evapotranspiration of the area in a day (Nagarajan, 2009). Spatial and temporal differences in evapotranspiration in the world are because of the different soil moisture availability, cloud cover, sun angle, vegetation amount, and local atmospheric conditions such as wind speed, temperature, and humidity of the area (Li &Tang, 2014). The total vegetation covers and obtained sunlight in a day affect the evapotranspiration rate of the specific area. Ethiopia gets sunlight all over the area in the whole year that increases the rate of evaporation and the humidity will be maximum. The plants have to regain the amount of water lost during that process otherwise the soil moisture content will decrease because of the prolonged absence of rainfall.

2.1.2.3. Vegetation Health

The health of vegetation depends on the parameters of the other that indicates the presence of water shortage, diseases, and the thermal condition of the area. Vegetation health index that is a combination of Vegetation Condition Index (VCI) and Temperature Condition Index (TCI), which in turn used to monitor and indicate the spatial distribution of agricultural drought, can indicate the health of vegetation. Stressed and unstressed vegetation characteristics indicate the health of vegetation (Kogan, 1995a).

2.1.2.4. Soil Moisture

The amount of soil moisture available inside the soil under the roots of crops with depth 10 centimeters during the plant growth determines the productivity of crops (Nagarajan, 2009). Soil moisture is directly related to precipitation or rain that remains from the evapotranspiration process. There has to be some remaining amount of moisture that enables the crop to obtain a regularly similar amount of water from the moisture. The amount of soil moisture is very crucial in the early growth of crops because at that, stage crops are unable to sack both water and nutrient from the depth and they are unable to protect their roots from solar exposure by their leaves to avoid their roots to be exposed.

For irrigated areas, the amount and way of watering are essential because the roots of crops are not enough to protect and survive from flooding. The channel lines distribution over the irrigated area determines the amount of water the crop will get. The distribution of water outlets in irrigation farmland needs to quantify for all area to avoid flooding and shortage of water at the same time. Soil moisture depends on the type of soil some soils preserve water for a long period of time and some are preserving for a short period of time so by efficient identification of those the regular watering period and schedule have to be established accordingly.

Remote sensed soil moisture information is from the NASA National Snow and Ice Data Center Distributed Active Archive Center (NSIDC DAAC) archives and distributes daily, weekly, and monthly. Level-1A, Level-2A, Level-2B, and Level-3 data products from the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) sensor on NASA's Aqua satellite are available. The AMSR-E instrument launched on 02 May 2002 and ceased operations 04 December 2011. Temporal coverage for the data products is from 18 June 2002 through 04 October 2011. (http://nsidc.org/data/amsre/)

2.1.2.5. Stream Flow

Streams generate or flow because of rainfall or ice melt in cold areas that decides the possible amount of storage. The concentration of aquifers in the ground determines the flow length in a year and the concentration of streams (Nagarajan, 2009). When rainfall is much more than the normal cases in an area the number of streams that generates unfortunately increase and stored below the ground. The amount of water in the deep soil depends on the soil types and its infiltration rate. River or stream flow is not the causative parameter for the drought but it changes the usage and accessibility of water for drinking as well as agricultural purpose although it has a directly related to groundwater (Gustard, 2000). Modern human life generates hydroelectric power system depending on rivers, agricultural irrigation using rivers, a source of drinking water, and way of recreation.

2.1.3. Methods of Drought Assessment

Two kinds of drought assessment techniques helped for drought assessment, which was remote sensing based and in situ based drought assessment. Remote sensing drought assessment method further classified as single and combined drought indices and in situ method includes Palmer Drought severity Index (PDSI) and Standardized Precipitation Index (SPI) as indicated in the following sections.

Remote sensing is a new era that enables to execute a large area even the whole world and determine the parameters according to their classes such as climate, biophysics, and satellite. The meteorological or in situ method of drought assessment has difficulties to determine and analyze the complexity of drought that is why remote sensing has introduced to the system.

There are many satellites that are operational starting from the late 1990s which allow retrieving drought parameters that show the severity of drought and the way that need to be monitored without resulting a devastating effect in the people as well as the ecosystem. Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E), and Tropical Rainfall Measuring Mission (TRMM) are the satellites that drive parametric information using the different algorithms that they have on the systems. In the past AVHRR VI, data were the primary remote sensing products used to assess drought (primarily the effects of agricultural drought). Now the capability exists to analyze various components of the hydrologic cycle either individually or collectively to define drought conditions and determine the correlation of those methods that enables to see and select a single method that suits the area because it depends on the climate and biophysics (slop, land use land cover, and groundwater concentration) of the area.

These new types of remote sensing data sets, in combination with traditional in situ–based, hydroclimate index and indicator data, should provide a more complete depiction of current drought conditions for decision makers by allowing to see satellite-based, climate based, and biophysical based. Satellite-based drought assessment in cost and time efficient method to represent a large area that enables to collect meteorological information. This especially helps in data-poor areas of meteorological stations in dry areas such as the Kalahari Desert in Africa. Drought assessment and early warning system using remotely sensed data is a key to assess the desert areas and to see the retrieved information from the satellite data such as soil moisture, precipitation, and surface temperature.

2.1.3.1. Single Drought Indicators

Single drought indicators or indices represent only one parameter vegetation for example and the performance depends on the environment. VCI and TCI are indices that depend on vegetation and temperature or LST and NDVI respectively. VCI usually mentioned to strongly correlated with the 6-month SPI, 9-month SPI, and PDSI. The PDSI heavily influenced by antecedent moisture conditions and shown to have a memory of at least 9 months. This indicates that, at least over Texas, the VCI shows the strongest response to prolonged precipitation (moisture) deficiencies and it appears to be less sensitive to short-term precipitation deficiencies (Quiring & Ganesh, 2010).

Researchers in the past 30 years identified that LST and NDVI has a negative strong correlation (Deve, et al., 2017). There are also papers explores the spatial and temporal relationship between LST and NDVI in the context of its utility for drought assessment. In contrast to the common perception that LST and NDVI typically had negatively correlated, there are demonstrations that this relationship, in fact, varies with location, season, and vegetation type. Many attempts have been made to interpret this relationship in terms of throughout the year, making this assumption correct. Subsequently, the application of these indices shows globally with the implicit assumption that NDVI and LST always and everywhere correlated negatively.

On the bases of the current study, there is a need to reconsider this assumption and restrict applications of such an approach to areas and periods where negative correlations are observed (Karnieli, et al., 2010). The NDVI model variability across the spatial scaling have shown the dependence of NDVI on topography, elevation gradient, and the steepness of local slop. Stephen and others in 1997 identified that the degree of details in the variation of NDVI because of elevation gradually increased from the base resolution, which is 30 meter to approximately 300 meters with a second increase extending from 400 meters to 700 meters. At higher resolution (30 meters), the level of details of NDVI increases with the inclusion of slop and solar radiation (Stephen, et al., 1997).

Indices that incorporate NDVI and LST, such as VHI and the Vegetation Temperature Condition Index (VTCI), rely on a strong inverse relationship between NDVI and LST. Increasing LST assumed to negatively influence vegetation vigor and consequently cause plant stress. However, this hypothesis does not hold across all global ecosystems. For example, in northern hemisphere and high-altitude ecosystems (like Mongolia), where the temperature is a limiting factor on vegetation growth, a positive correlation is found between these two variables. Ecosystems such as the grasslands of East Africa, the Sahel, and North America are excellent examples of where NDVI effectively used to monitor vegetation and drought conditions (Tucker & Anyamba, 2012).

Kogan and Sullivan (1993) introduced a vegetation index-based drought metric called the Vegetation Condition Index (VCI) and developed a global drought-watch system using this index derived from AVHRR smoothed weekly NDVI data. Low values of VCI indicate poor (stressed) vegetation due to unfavorable weather conditions, and high values of VCI indicate healthy vegetation conditions and that healthiness is related to soil moisture, precipitation, and temperature which is key information for drought assessment and early warning system (Kogan & Sullivan, 1993). However, VCI is more suitable for those areas of high vegetation coverage such as the area of Amazon forest in South America therefore there need to be another method for desert areas to monitor and determine the condition and degree of drought. Temperature Condition Index (TCI) is one that is developed and applied first in India (dry and hot area). TCI derived from AVHRR's thermal data using the brightness temperature now available there is MODIS Land Surface Temperature (LST) data the TCI considered as such drought indicator.

2.1.3.2. Combined Drought Indicators

Vegetation Health Index (VHI) can provide a solid basis for detecting drought-related yield losses. However, the performance strongly depends on the quality of yield and satellite data, as well as regional and local specifics. The effectiveness of the satellite-based VHI insurance improved by employing satellite data of a higher resolution, using more sophisticated way of time aggregation of VHI, and constructing VHI for single farms (Bokushevaa, et al., 2016). Temperature Vegetation Dryness Index (TVDI) anomalies are shown as in agreement with those of precipitation, it was found to have only significant relationships with precipitation in plain rangeland, whereas, no significant relationships were observed in the other land covers. The relationship between the TVDI and soil moisture was only significant at the 0–5 cm depth (Rahimzadeh-Bajgiran, et al., 2012).

2.1.3.3. Palmer Drought Severity Index (PDSI)

Palmer Drought Severity Index (PSDI) is a soil moisture algorithm for drought assessment that is calibrated by Palmer (1964) for the relatively homogenous area and not for areas of mountainous. The index works based on precipitation, temperature, and locally available water content of the soil, as well as land cover and slop of the area, has to be included in the model. PSDI uses a water balance model, designed for, and mostly applied in North America (Palmer, 1964).

2.1.3.4. Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) first developed in Colorado and specifically designed to quantify the precipitation deficit for multiple timescales with the understanding that a deficit has different impacts on groundwater, reservoir storage, soil moisture, snowpack, and streamflow. SPI is a valuable tool for assessing the spatiotemporal variability of dryness/wetness due to its capacity to represent precipitation anomaly. Meanwhile, it would also be a potential tool for assessment hydrological conditions and drought/flood risks which given the advantage and enables us to calculate at multiple time scales (Juan Du, et al., 2013). SPI originally calculated for 3, 6, 12, 24, and 48-month timescales to address these different impacts, but the index can further calculate values for any weekly or monthly timescale to check the variability and complexity. Because SPI normalizes the data based on the statistical representation of the historical record at every location, wetter and drier climates significantly represent in the same way. An SPI value also places the severity of a current event (either dry or wet) into a historical perspective for further analysis in the same area and that helps to understand the trend. This feature differentiates the SPI from the PDSI.

The SPI is now the accepted standard worldwide and a recommended method at a World Meteorological Organization (WMO) meeting held in December 2009 in Lincoln, Nebraska, as the primary meteorological drought index applied by national meteorological and hydrological agencies to track meteorological drought (Michael, et al., 2012). Ideally, 20-30-year monthly precipitation data is enough but if there, is 50-60-year data is optimal and preferred by the World Metrological Organization (WMO). The Standardized Precipitation Index user guide that is developed in 2012 by the World Metrological Organization indicates that SPI program will run with missing data but the Climatologists would prefer to see serially complete data sets, which means there should be no missing data (Svoboda, et al., 2012). However, it is more than likely that data sets would only have 90% or even 85% complete records. In reality, many users do not have this luxury and may have to settle for less (75-85% complete) unless they look to estimation techniques to fill in the gaps in the record. SPI described well the drought conditions. The indicator established the onset, the ending, and the severity levels of exceptional drought events by extension to other similar parts of the world facing such problems. The spatial SPI visualization provided a stakeholder-oriented tool for immediate drought categorization. However, due to specific climatic conditions and the resulting precipitation patterns, a more populated meteorological network with the inclusion of as many as possible of the existing stations would have contributed to the approach (Karavitis, et al., 2011).

McKee, et al. first introduced the standardized precipitation index (SPI) in 1993 at Colorado state university and it depends only on precipitation alone. The fundamental strength of SPI is to calculate with different time scales (1- month, 3- month, 6- month, 9- month, and 12- month) and more than 12-month timescale SPI value cannot be valid and applied.

SPI is a time scale that is important to the water analyst because of the different time-varying analysis. Moving total time series are data, which constructed from the observed precipitation data and then used for the SPI computation. For example, if the observed data consist of a time series of monthly precipitation amounts, and the analyst is interested in three-month events, then a new time series is constructed by summing the first three monthly amounts, then summing the amounts in months 2, 3 and 4, then summing the amounts in months 3, 4 and 5, etc. Probability density function that describes the long-term series of observations enables to calculate SPI. The probability function depends on applying the inverse normal (Gaussian) function. SPI values are positive (negative) for greater (less) than median precipitation. The departure from zero is a probability indication of the severity of the wetness or aridity that helps for risk assessment (Guttman, 1998).

It is appropriate to examine SPI values derived from a short length of record to monitor current conditions in the light of recent ‘climate’. Under this circumstance, one should be aware that the reduced effective sample size leads to instability of the parameter estimates. If the parameter estimates have little confidence, then the resulting SPI values will also have little confidence. The longer the record data for SPI calculation the reliable the calculated SPI value will be at the end especially when the time scale SPI is longer (Hong WU, et al, 2005).

Conceptually, SPI is equivalent to the *Z*-score used in statistics and is formulated as by Patel, et al., (2007).

$$SPIij \approx \frac{Xij-\mu ij}{\sigma ij}$$

Where,

SPIij is the SPI of the i^{th} month at j^{th} time-scale; *Xij* is precipitation total for an *i*th month at j^{th} time-scale, *μij* and *σij* are long-term mean and standard deviation associated with an i^{th} month at j^{th} time-scale. Since precipitation has a skewed distribution, the precipitation data are first transformed to a more normal or Gaussian distribution, and then calculated in a manner as demonstrated in Equation above.

2.1.4. Drought Adaptive Mechanisms

According to Mark Pelling Adaptation is defined as;

> "*the process through which an actor is able to reflect upon and enact change in those practices and underlying institutions that generate root and proximate causes of risk, frame capacity to cope and further rounds of adaptation to climate change"* (Pelling, 2011).

Whereas coping with climate change such as drought is the process through which established practices and give the responsibility for respective governmental organizations when confronted by the impacts of climate change.

Every adaptation strategy should include elements of learning, cooperation, and communication to address social factors. The strategies associated with these areas may partly overlap and do not represent all essential elements of an adaptation strategy. Social factors are the main factor influencing the adaptation of climate change. Therefore, there is a need to address social factors explicitly in adaptation strategies or risk becoming significant barriers to adaptation (Grothmann, 2011). There are different types of adaptation from those the following are the basic and general climatic adaptation methods discussed by scholars.

- ***Reducing the sensitivity*** of the affected system, which can be achieved, for example, by investing in flood defenses or increased reservoir storage capacity; planting hardier crops that can withstand more climate variability; or ensuring that infrastructure in flood-prone areas is constructed to allow flooding.
- ***Altering the exposure*** of a system to the effects of climate change that achieved, for example, by investing in hazard preparedness and early warnings, such as seasonal forecasts and other anticipatory actions.
- ***Increasing the resilience*** of social and ecological systems, which can be achieved through generic actions that aim to conserve resources, but also include specific measures to enable specific populations to recover from loss as described by Tompkins and Adger, 2004 (cited in Wreford, et al., 2010)

A study in Nigeria listed crop diversification, cultivation of early maturing, high yield crop varieties, and food storage as adaptive mechanisms identified and used by more than half of the surveyed households, an indication of their wide acceptance and effectiveness. Extension services could support coping strategies by increasing awareness of them and their utility for reducing climate-related risks and helping farm households to develop the knowledge and skills needed to adapt and apply them effectively (Daniel, et al., 2008). Longtime period drought forecasting is also one mans of adaptations that help to get time to think about the coming disaster. Skilfull, timely and effective communicated forecasts of climate variables that matter to farmers can be applied in comprehensive adaptation strategies to predict the negative consequence of climate variability and climate change. As well as improving the skills of the forecasts, constraints that prevent the use of forecasts by peasant farmers need to be addressed. These include inadequate or lack of credibility, late publication of forecasts, cognitive deficiencies, and absence of clear choices associated with specific forecasts (Oladipo, et al., 2008).

A study in Mongolia's pastures takes stakeholders and respective available organizations that work drought and disaster prevention work and collect all the mentioned adaptive methods raised by those stakeholders and after thorough analysis, the following four main adaptation mechanisms are chosen.

The first adaptive mechanism is to conserve natural resources which if degraded because of heavy grazing and other drought effects, which affect the land and can make it very vulnerable for another disaster. Such kind of problem requires better management of grazing by limited livestock numbers. Returning to the traditional rotation of herds to different pasture each season would control grazing pressures, prevent degradation of pastures and help degraded pastures to recover. Degraded land can be restored by using reforestation or by planting trees and allow to recover for some time which is important to avoid any kind of contact either from peoples or animals.

Strengthen animal bio-capacity is another adaptive mechanism allows to reduce the effect of animals from devastating droughts. The animal bio-capacity can be strengthened by scheduling the grazing period, use of supplementary foods, and collect foods. Livestock grazes little or no when the temperature is high or midday, which allows feed them in the evening and afternoon intern minimizes the daily consumption.

Supplementary foods and food storing for dry seasons are also important methods that help to feed them even in drought seasons. Increase food security and improve understanding of seasonal climate forecasting in national and regional level are the rest adaptive mechanisms (Punsalmaa, et al., 2008).

2.1.4.1. Rainwater Harvesting

Use of rainwater for the three combination applications in houses as well as for outside the house (toilet and laundry, irrigation, and a combination of the toilet, laundry, and irrigation) shows rainwater thanks are a strong and positive correlation with annual average rainfall. Different size thanks available in the market help for specific applications, which increases the financial benefit of homeowners by increasing the productivity and minimized the cost of water and helps in minimizing the effect of climate impacts like drought (Rahman, et al., 2012).

Rainwater harvesting has the potential to preserve the livelihood of rural and small households in its minimal functionality but legal, institutional, and financial factors prevent the technology from realizing its depth potential and help more households. There are no legal frameworks that allow adopting the technology in a town or rural areas and also institutionally they are limited in number and are not organized. Financially, one household may have his own small tank in their own home side but to increase the number of households that use such technology much more organized project finances are required (Kahinda & Taigbenu, 2011).

2.1.4.2. Planting Drought Resisting Crops

A wider range of adaptation capacity of plants usually has high protection against various stress the change in how the plant development also changes the physiological programs. Drought affects the photosynthetic mechanism at both photochemical and biochemical levels the technological approach has to incorporate the two to adapt the plant in a stress period (Yordanov, et al., 2000). Plants respond to drought stress in a number of ways depending on the time of occurrence. Drought stress may result in reduced germination, reduced seminal root growth, and delay on the establishment and development of a coronal root system. Plant breeding is one of the methods which helps to tackle those kinds of problems to get better drought stress resisting crop (Schmidt, 1983).

Significant improvement and progress can be achieved if breeding and other interdisciplinary experts work together with a common goal of drought resisting plants and maximum yield productions. Technologies such as high throughput phenotyping and genetic engineering should be utilized for wheat to improve the performance and productivity in drought stress period (Mwadzingeni, et al., 2016).

2.1.4.3. Changing the Calendar for Planting

Research by Hai- dong shows the growth stage of plants correlates significantly with planting date. Of course, the productivity of crops also depends on the amount of soil moisture available and by sunshine period, which matters the period of harvesting by shortening the time of flower and development that allows the plant to give yield in a short period (Hai-dong, et al., 2017). Late planting resulted in a significant deterioration of the environmental conditions such as temperature, and water availability during grain filling periods usually not recommended in drought-prone soils, at high elevation, and in a cool and short rain season environment. This will lead the crop to mature late that are generally more susceptible in drought, and declining temperature compared to early-planted grains (Tsimba, et al., 2013).

2.1.4.4. Mixed Cropping

The use of mixed cropping system helps to maximize productivity, which needs preliminary study before mixing to identify the property of the two crops. Monocropping helps to increase the density and biomass but in case of intercropping (mixed cropping) the population and biomass decreases and the weed management. A particular intercropping of wheat and chickpea in 30cm row spacing weeded twice was found to be the most effective (Banik, et al., 2006). A study in Turkey don by mixing Cauliflower with different types of crops in the same cropland with same preliminary conditions shows that intercropping of such crops can increase the productivity of vegetables per unit area, and improve net income. The result of this research indicates intercropping cauliflower with crops such as bean, lettuce, and onion produce higher yields and economic return compared to monocrop of cauliflower (Yildirim & Guvenc, 2004).

2.1.4.5. Adopting Soil Conservation Mechanisms

Many cropping systems leave the surface exposed during the planted year. The impact of flood and wind on the soil in that exposed time cause high erosion and serious damage by avoiding the nutrient from the top surface of the soil. Such kinds of damages controlled by adjusting the cropping system, which allows minimizing the exposure of surface soil to erosive winds or floods. Plant cover, management of mono-cropping, crop rotation, sequential or multiple cropping in a single season are mechanisms allows minimizing the exposure of soil (Troeh, et al., 2004).

A study in Peru applied contour hedgerows for soil conservation mechanism suited for farming in moderate hill slopes. The hedgerows conserved 93% of the soil and 83% of the water that was from the surface of the soil in the annual crop system. The research shows that the hedgerows controlled the soil during cropping as well as non-cropping seasons that is effective by applying the hedgerows for soil conservation by forming the terraces 25-30 cm high at the base of the hedgerows (Alegre & Rao, 1996). Application Contour furrows in the Tigray northern Ethiopia decrease the amount of runoff on the soil surface. The study indicated a promising fill of the bed after such conservation, which actually takes a Capel of years. Such kinds of conservation also can be part of the ongoing processes, which includes physical soil and water conservation, slop reforestation, irrigational development, and agroforestry (Gebreegziabher, et al., 2009).

2.2. Empirical Review

There are several studies performed in drought and the related field of study beginning from the starting point of the problem here below are some of the studies with their objectives, methods, and results. A study by G. Caccamo, L.A. Chisholm, R.A. Bradstock, and M.L. Puotinen entitled as “Assessing the sensitivity of MODIS to monitor drought in high biomass ecosystems’ done in Australia had objectives to assess the performance of MODIS based reflectance spectral indices to monitor drought across the forest and woodland vegetation types in 2011. They implemented the standardized precipitation index (SPI) in the study to check the correlation and significance with the MODIS derived drought-monitoring indices. The researchers took eight-time series spectral MODIS images to create the respective drought indices to see the variability and effect of seasons in the area. The result shows that Normalized Difference Infrared Index-band 6 (NDIIb6) outperforms the other drought monitoring indices. Normalized Difference Vegetation Index (NDVI) and its implementation in the existing drought monitoring system was recommended. The capacity of MODIS based drought assessment is affected by time step over which observations are integrated which means MODIS is weak in terms of detecting short-term droughts such as 1, 3, and 6 months as the study by mentioned authors show there is a weak correlation between short month SPI with MODIS derived drought indices (Caccamo, et al., 2011).

A study in North America entitled as “Use of NDVI and Land Surface Temperature for Drought Assessment: Merit and Limitations” had an objective to see the spatiotemporal relationship between NDVI and LST which is admitted that the two variables have a negative correlation in the previous studies. They found that in areas of typically low latitude and when water in a limiting factor for vegetation growth the two variables show a strong negative correlation. However, when energy (sunshine) is a limiting factor for vegetation growth in higher latitude areas like tropical rainforest the two variables show a positive correlation that indicates the relationship differs in location, season and vegetation type. Finally, the researchers recommended, as there is a need to use empirical LST-NDVI relationship with caution and to restrict their application to drought monitoring to areas and periods where negative correlation are observed (Karnieli, et al., 2010).

A study by Nathaniel B. Guttman with a title “Accepting the standardized precipitation index: a calculation algorithm” in 1999 had an objective of identifying the performance of Standardized Precipitation Index (SPI) whether it can be used as a calculation algorithm. Guttman describes the effect of SPI computation in different probability model. The result was the Pearson distribution is the best universal model the reliability of SPI depends on the sample size. The finding by Guttman also shows because of data limitation SPI results more than 24 months is not appropriate for any kind of dryness and wetness analysis (Guttman, 1999). The same author in another study compares standardized precipitation Index (SPI) with Palmer Drought Index (PDI) by comparing historical time series data available. Finally, Guttman found that spectral characteristics of PDI varies from site to site and they show that PDI has a complex structure with long memory while SPI is an easy interpretation task (Guttman., 1998).

A study in South America by W. T. Liu and Kogan with title “Monitoring regional drought using the Vegetation Condition Index” had an objective to monitor large-scale drought patterns and their climate impact on vegetation and to separate the use of Vegetation Condition Index (VCI) and Normalized Difference Vegetation Index (NDVI) to assess the regional drought variability. Weekly NDVI for the period 1985 to 1992 were used to produce NDVI and VCI images of the South America continent. The result of the study shows that there was a quite wall agreement between VCI and rainfall anomaly data with a minimum correlation coefficient (R^2) of 0.01 in different sampled and tested areas. The researchers admit that VCI is a useful tool to analyze the temporal and spatial evolution of regional drought (Liu & Kogan, 2007).

A study by Virgílio A. Bento, Célia M. Gouveia, Carlos C. DaCamara, and Isabel F. Trigo in a title “A climatological assessment of drought impact on vegetation health index” conducted in Portugal to assess the effect of Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) while calculating Vegetation Health Index (VHI). The researchers mentioned because of the absence of prior knowledge about the two condition indices the weight of the two limiting factors assumed as an average value (0.5). The result shows the effect of drought is evident in VCI in semi-aired areas where the limiting factor is vegetation but the effect of drought is visible when the area is moisture climate in TCI in the case when the limiting factor is solar radiation. Bento and co finally concluded that by analyzing the maximum correlation of VCI and TCI with scaled drought indicators such as Standardized Precipitation Evapotranspiration Index (SPEI) allows identifying the relative weight of the two factors (Bento, et al., 2018).

Cui Hao, Jiahua Zhang and, Fengmei Yao in 2015 studied on “Combination of multi-sensor remote sensing data for drought monitoring over Southwest China” to propose the Optimized Vegetation Drought Index (OVDI) from multi-source satellite data. The researchers started by integrating OVDI with parameters such as vegetation, precipitation, soil moisture, and temperature. Hao and co used Tropical Rainfall Measuring Mission (TRMM), Moderate Resolution Imaging Spectrometer (MODIS), and AMSR-E soil moisture data to retrieve the above-mentioned parameters. For combination and weight determination of each satellite-based indices, they implemented a constrained optimization method. The result shows that OVDI has a high and strong correlation with standardized drought indices suggesting as a potential indicator of agricultural drought (Hao, et al., 2015).

CHAPTER THREE

3 METHODOLOGY

3.1. Description of the Study Area

3.1.1. Location

East Shewa is one of the Zones of the Ethiopian Region of Oromia. East Shewa is located in the middle of Oromia, connecting the western regions to the eastern ones. This zone shares more borders compared to the nearby administrative Zones including the capital Addis Ababa. On the south by the West Arsi Zone, on the southwest by the Southern Nations, Nationalities and Peoples Region, on the west by Southwest Shewa and Oromia Special Zone Surrounding Addis Ababa, on the northwest by North Shewa, on the north by the Amhara Region, on the northeast by the Afar Region, and on the southeast by Arsi. Towns and cities in East Shewa include Bishoftu (Debre Zeit), Metehara, and Ziway. The town of Adama was separated from East Shewa and is a special zone now but in this study, the analysis and data collection work was done by including the specialized zone because it is at the center of the study area it will never be excluded. East Shewa zone geographically located at the center of Ethiopia south of the capital Addis Ababa with latitudes ranging from 7^0 30’0” to 9^0 15’0” and its longitude ranges from 38^0 15’0” to 41^0 12’0”. The elevation of the area ranges from 835 to 3000 meters above mean sea level as it is seen in the following map below the area has higher elevation in the northwest (Gimbichu, Adea, and Akaki) towards Addis Ababa and lower elevation in the northeast (Fentale and Boset) portion. The southern portion of the Zone comprises of medium elevation compared to others in the study area. East Shewa zone contains 11 administrative weredas, which is 992,253.641 hectares including Adama specialized zone and Akaki wereda now it is included to Addis Ababa City Administration. Fentale, Boset and Adami Tulu Jido Kombolcha are the largest weredas ascending.

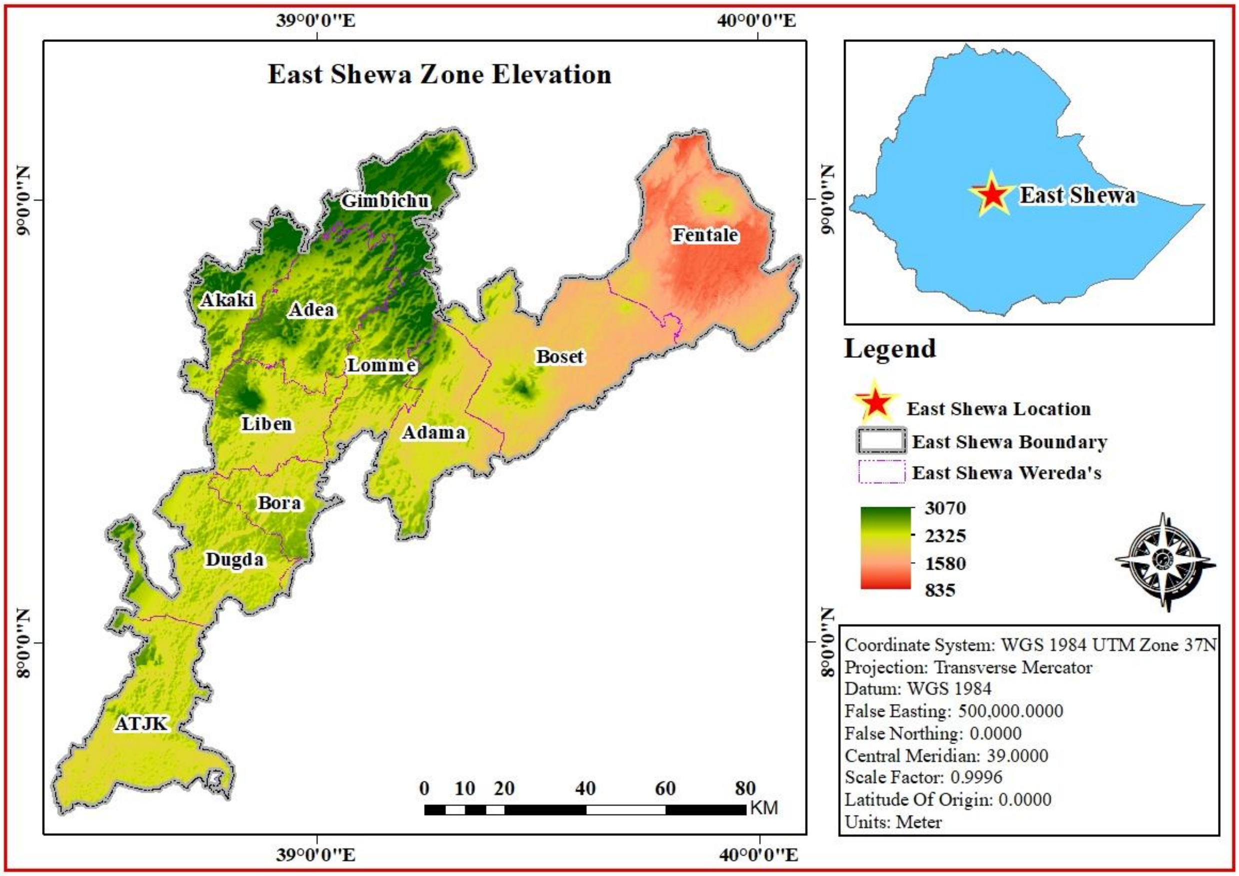

Figure 3.1 Location Map of Study Area

3.1.2. Population

Based on the 2017 Census projected from the 2007 census conducted by the Central Statistical Agency of Ethiopia (CSA), East Shewa Zone has a total population of 1,841,379, of whom 938,800 are males and 902,579 women. The 2007 data shows total household of 307,510 from those households 95,145 are urban and 212,365 are rural households. East Shewa has a population density of 162.03. The projected 2017 data shows 549,166 or 33.5% are urban inhabitants. This zone has 309,726 households were counted in 2007, which results in an average of 4.38 persons to a household, and 296,342 housing units. From the total persons live in East Shewa 549,166 persons dwell in urban whereas, 1,292,215 persons are dwelling in rural residences. According to the agency, the unemployment rate in East Shewa is 16.7 and 1.5 in urban and rural areas respectively and from persons of aged 10 and above in the zone, 127,595 and 508,810 persons are employed in urban and rural areas respectively whereas, 25,632 and 7,859 person's area unemployed in urban and rural areas respectively.

Wereda Name	Person	Households	Household Unit	Household Per Housing Unit
Fentale	79,468	19,426	17,939	1.083
Boset	140,457	32,793	31,455	1.043
Adama Zuriya	154,958	35,644	34,512	1.033
Lome	116,057	27,342	26,567	1.029
Gimbichu	86,735	17,881	17,321	1.038
Adea	130,078	27,206	26,003	1.046
Dugda	143,920	31,722	30,810	1.030
Adami Tulu Jido Kombolcha	141,097	28,979	27,993	1.035
Bishoftu/Town	97,812	27,552	26,806	1.028
Bora	58,314	13,238	12,715	1.041
Liben	76,149	15,895	15,370	1.034
Akaki	76,853	16,545	16,065	1.030
Ziway /Batu/Town	41,920	13,287	12,876	1.032

Table 3.1 Population of East Shewa Zone 2007 census (CSA, 2007)

3.1.3. Climate

The study area contains the rift valley portion in Boset and Fentale weredas, which is dry with sparse vegetation with a minimum of 27^0c of average temperature. The rest portion of the area containing highland areas compared to the other part of the study area such as Akaki and Gimbichu weredas are hot semi aired experiencing lower annual average temperature ranging from 18^0c to 27^0c. Precipitation in this zone starts usually in mid-June and it will be strong in the starting two or three weeks of July. In some drought years, June had almost dry and the precipitation amount is low. The chart below shows the TRMM precipitation of the area starting from 1998 to 2016 of only the June month, which is low precipitation. June 2009 the lowest precipitation 0.065mm/hr. because there was a historic drought in that season as a country level. The rest 1998, 2000, 2002, 2012, and 2014 are also showing minimum precipitation results compared to the rest.

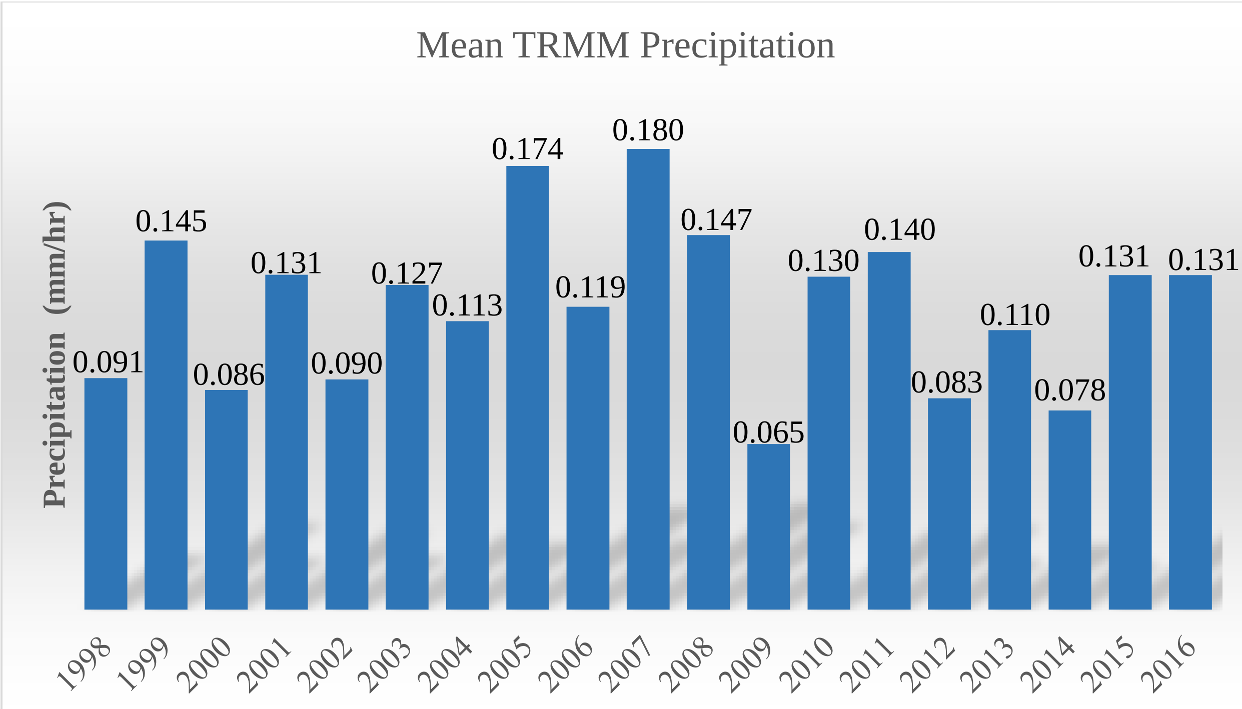

Figure 3.2 Average TRMM Precipitation of East Shewa in June

3.1.4. Agricultural Drought History

A report from East Shewa Zone disaster and risk management office found in East Shewa Zone shows the number of population in each wereda which was supported by the government because of drought. The office recorded the information for all wereda except Akaki, which shows Fentale, Bosete, and ATJK are the highly affected weredas from 2015 to 2018 see Figure 3.3. The report also shows that only about 20% of the woredas in the study area were free from such kinds of aids in the year from 2008 to 2018.

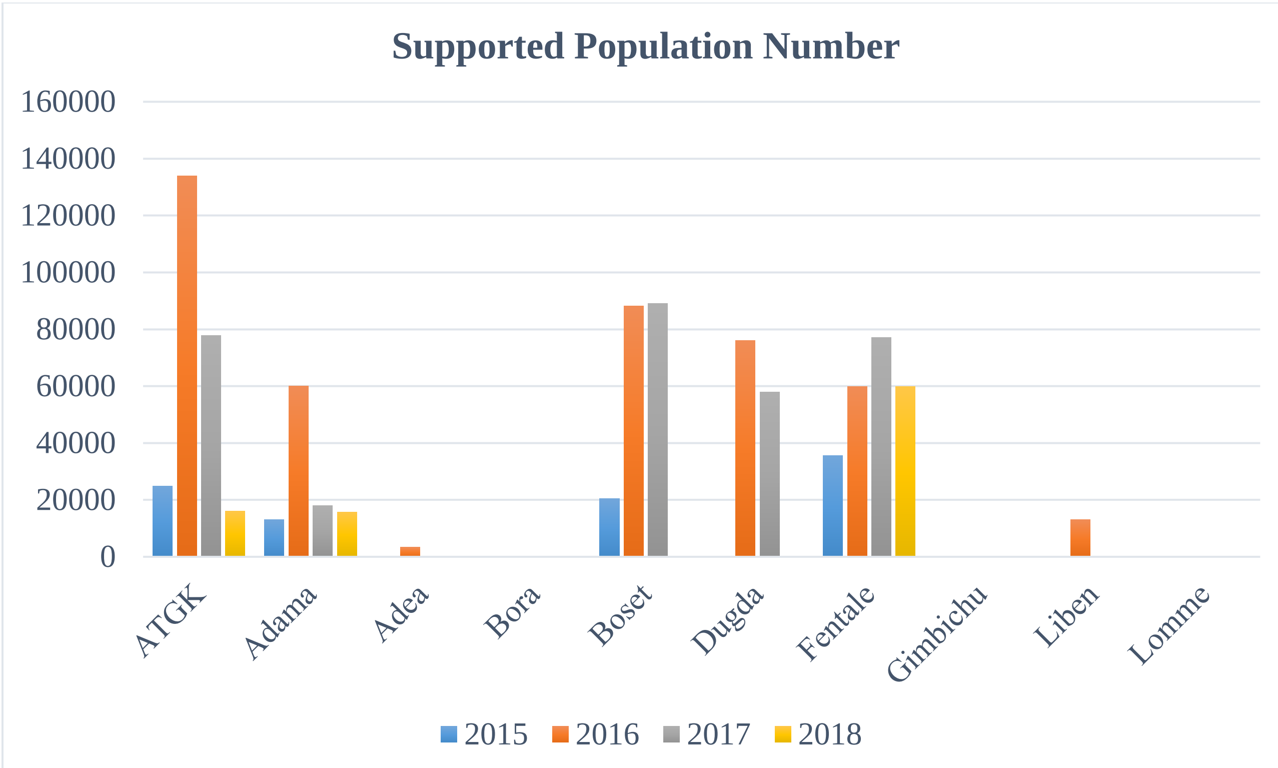

Figure 3.3 Chart Showing number of population aided in East Shewa Zone

3.2. Software Used

Arc GIS, ERDAS imagine, IBM SPSS, and SPI 6 program are widely accepted software and used in recent studies. In this study, Arc GIS components such as Arc Map, Arc Catalog, and Arc Toolbox helped to create and edit geodatabase, data management, interpolation, layout, and resample datasets. Inverse Distance Weighted (IDW) in Arc GIS spatial analysis tool used for interpolation that suitable for dens enough and evenly spaced points and mentioned by along Kriging and Spline by Svoboda et al., (2012). This method is common in Africa for an early warning system for drought and famine and in Northern America, this method was used to display or map drought severity in the national level. ERDAS imagine helped in this study to drive combined drought indices by using the different weights of combination methods, such as constrained optimization, and empirical weight. The latest version of C++ SPI (SPI_SL_6.exe) program helped to calculate the 5-time scale (1 month, 3 months, 6 months, 9 months, and 12 months) SPI information of each weather station obtained in the study area. Table 3.2 shows the implemented software lists with their corresponding version and purposes.

No	Software	Version	Purpose
1	Arc GIS	10.4.1	Interpolation, Index calculation, and Layout preparation
2	ERDAS Imagine	2014	Drought Condition index combination
3	IBM SPSS	21	Correlation, Chart and Graph generation, and to check the statistical property of data
4	SPI Program	6	Time scale SPI calculation

Table 3.2 Software and their purposes

3.3. Data Source and Collection Method

Rainfall data from National Meteorological agency were collected by requesting the collaboration of the office. The Earth data website enables to download Net CDF TRMM precipitation and AMSR-E soil moisture data whereas the Earth Explorer (USGS) website helped to download the MODIS land surface temperature and normalized difference vegetation index.

The metrological data for the SPI validation purpose is from the National Meteorological Agency, which is 30-year monthly precipitation data starting from 1985 to 2015. The other data is MODIS NDVI and LST data taken from the United States Geological Survey website (USGS) for single or conditional drought index calculations.

Table *3.3* shows the source, scale (resolution), data type, and the purpose of the collected data for this study.

No	Data	Source	Scale (m)	Purpose	Data Type
1	Land Surface Temperature (LST)	USGS	1000	TCI calculation	Raster
2	Normalized Difference Vegetation Index (NDVI)	USGS	1000	VCI and VHI calculation	Raster
3	Rainfall	National Meteorological Agency	-	SPI generation and validation	Tabular monthly data in mm/hr.
4	Remote sensing Precipitation (TRMM)	NASDA	127000	PCI calculation	Net CDF
5	Soil Moisture (AMSR-E)	NSIDC DAAC	127000 (0-30cm depth)	SMCI calculation	Net CDF
6	Administrative Boundary	Central Statistical Agency (CSA)	-	Help to extract information using Administrative Zones	Shapefile

Table 3.3 Data and Data Source of the Study

3.4. Method of Data Analysis

Data analysis of agricultural Drought assessment in this study used a compressive method between remote sensing and in situ drought assessment methods. The remote sensing drought assessment methods involve using single and combined drought indices whereas the in situ drought assessment method involves on validation of the remote sensing drought indices. Empirical weight and constrained optimization methods helped to combine single drought indices. Generally, the method and data analysis of this study showed in Figure 3.4 with four stages. The first stage was data collection and preparation work, the second stage shows single drought index calculation, third stage shows combining the single drought indices and the fourth stage involves on validating remote sensing drought indices using SPI data.

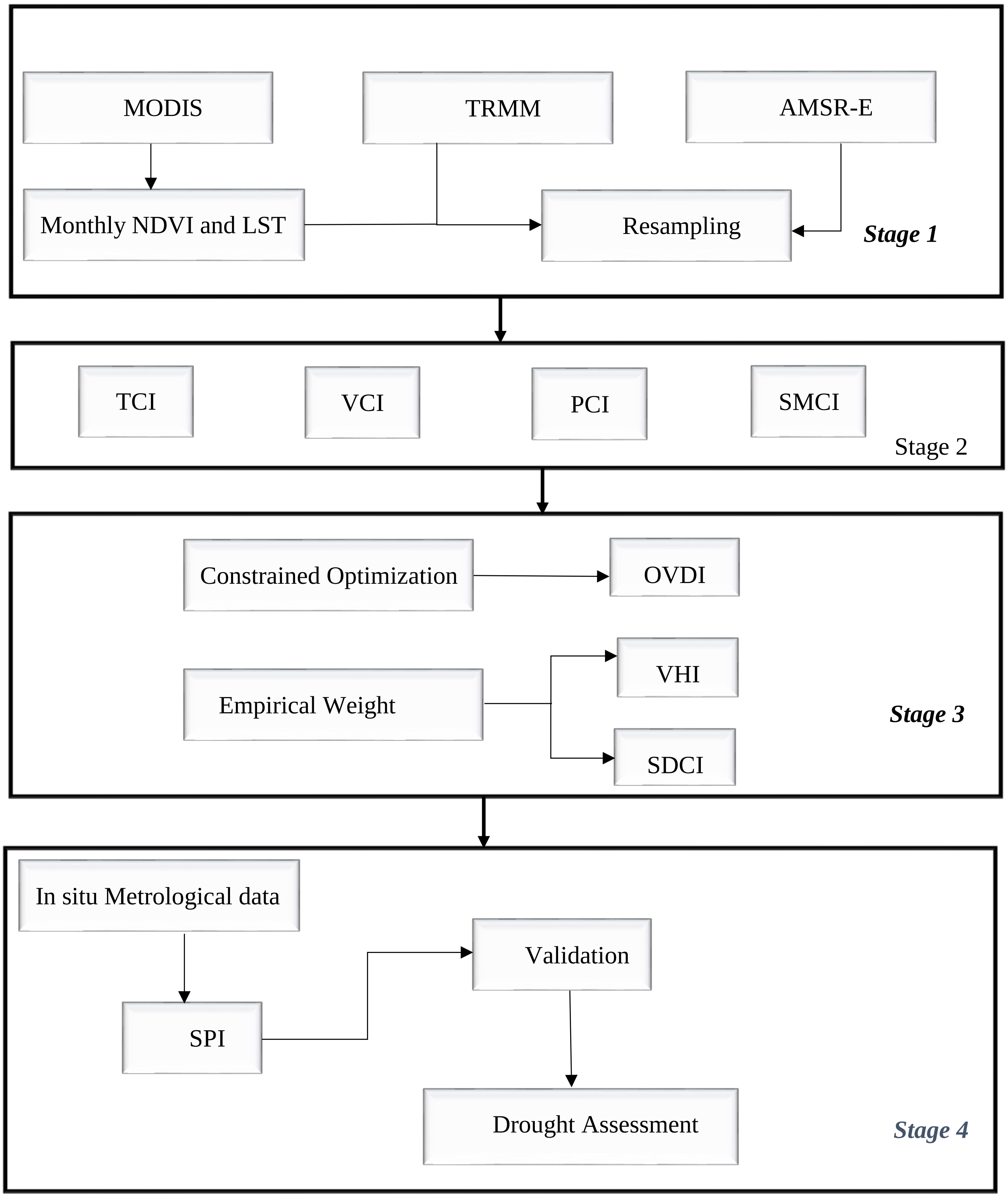

Figure 3.4 Flow Chart Showing the Method and Procedure of Data Analysis

CHAPTER FOUR

4 DATA ANALYSIS, RESULT, AND DISCUSSION

The application of remote sensing drought assessment indices helped to detect the spatial variability and seasonal effect of the problem in previous studies. This study attempted to identify and compare the performance of various remote sensing drought indices in East Shewa Zone. Four factors are considered in the study for single and combined drought index analysis i.e. Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), remotely sensed soil moisture, and remote sensed Precipitation. The scaled remote sensed drought parameters from zero to one helped to combine the single drought indices either using constrained optimization or empirically to get combined drought indices. The following section of this chapter shows the detailed data analysis, result, and discussion part of the study.

4.1. Data Analysis and Result

4.1.1. SPI Calculation Using SPI C++ Program

The SPI program helps to calculate the 5-month time series standardized precipitation. Stations that have no data in the range of year has given a value of -99, which the SPI program understands that the particular month of a year has no data. The obtained meteorological data of each station arranged in a format that enables the program to run correctly. Table 4.1 shows sample input (precipitation) and output five-time period SPI of a single station. “Melkasa” is the station name, the first column is the year, the second column shows the month of the year, and the last column is precipitation in millimeter per month.

Melkasa		
1985	1	6
1985	2	0
1985	3	14
1985	4	43
1985	5	81
1985	6	27
1985	7	280
1985	8	262
1985	9	79
1985	10	3
1985	11	1
1985	12	0
1986	1	0
1986	2	56
1986	3	68
1986	4	56
1986	5	26
1986	6	107
1986	7	149
1986	8	90

Table 4.1 Rainfall data preparation for SPI_6 program

The arrangement is done in notepad text format and after the arrangement, the data is saved as a .cor format. After the arrangement of all station data, the SPI calculation is obtained by inserting the .cor data in the SPI program and insert the number of time scales which is 5 i.e. 1 month, 3 months, 6 months, 9 months, and 12 months. After inserting those time scales the program asks for the name of the data (melkasa.cor) and allows to give output file name (melkasa_12mspi.dat). Figure 4.1 shows the input setup of the program.

```
Standardized Precipitation Index Calculator

Number of time scales: 5

timeScale1 1

timeScale2 3

timeScale3 6

timeScale4 9

timeScale5 12

Input file: melkasa.cor

Output file: melkasa_12mspi.dat_
```

Figure 4.1 SPI calculation data entry and setup

The output of this result is in a .dat format and can be opened in MS Word, Microsoft Excel, or with word pad and notepad. The output contains 8 columns with the input station name at the top. Year, month, 1-month SPI, 3-month SPI, 6-month SPI, 9-month SPI, and 12-month SPI are the 8 columns from left to right the output sample is shown (Table 4.2) in Melkasa station. The -99 is not a valid result it shows the SPI is not calculated because of the number of months available before that month. The 1-month SPI started with a valid result because the required number of monthly data to calculate 1 month SPI was only a single month but for others, the result started after the required number of monthly data is satisfied (for 3 months SPI a 3-month precipitation data requires and same for the other time series SPI results).

Melkasa						
1985	1	0.11	-99.00	-99.00	-99.00	-99.00
1985	2	-0.29	-99.00	-99.00	-99.00	-99.00
1985	3	-0.62	-0.96	-99.00	-99.00	-99.00
1985	4	-0.23	-0.90	-99.00	-99.00	-99.00
1985	5	0.90	-0.06	-99.00	-99.00	-99.00
1985	6	-0.78	-0.27	-0.93	-99.00	-99.00
1985	7	0.96	0.72	-0.02	-99.00	-99.00
1985	8	1.15	1.00	0.73	-99.00	-99.00
1985	9	-0.33	1.04	0.80	0.26	-99.00
1985	10	-0.51	0.32	0.67	0.11	-99.00
1985	11	0.05	-0.73	0.41	0.23	-99.00
1985	12	-0.12	-0.97	0.67	0.47	-0.03
1986	1	-0.04	-1.13	-0.09	0.43	-0.06
1986	2	1.18	0.52	-0.61	0.45	0.31
1986	3	0.55	0.71	-0.00	0.64	0.56
1986	4	0.19	0.78	0.34	0.31	0.51
1986	5	-0.15	0.09	0.20	-0.42	0.33
1986	6	0.96	0.39	0.65	0.09	0.85
1986	7	-0.54	-0.28	0.14	-0.16	-0.04
1986	8	-1.42	-1.04	-1.06	-0.89	-1.06

Table 4.2 Sample of SPI calculation result

McKee and others (1993) classified the result of SPI to define the drought intensity from different SPI time scale. Drought exists when the SPI is negative and which continued up to -0.99 and from -0.99 to 0.99 the condition is normal (neither wet nor dry) and from 0.99 onwards the wet condition comes from less cold season to flooded seasons. The SPI classification or ranking includes extreme wet, very wet, moderately wet, near normal, moderately dry, severely dry, and extremely dry as indicated in Table 4.3.

SPI Value Range	*Ranking*
2.0 and more	Extreme Wet
1.5 to 1.99	Very Wet
1.0 to 1.49	Moderately Wet
-0.99 to 0.99	Near Normal
-1 to -1.49	Moderately Dry
-1.5 to -1.99	Severely Dry
-2.0 and less	Extremely Dry

Table 4.3 Standardized Precipitation Index (SPI) ranking *(*McKee, et al., 1993)

4.1.2. Frequency and Occurrence of Dry and Wet Years

According to the threshold values set by the World Meteorological Organization, dry seasons are seasons, which had SPI value of less or equal to -1 while wet seasons had SPI values more or equal to 1 as indicated in Table 4.3. Figure 4.2 shows the spatial distribution and frequency of the 21 stations with dry seasons (a) and wet seasons (b). Stations belonging to 0.233 to 0.267 category in Figure 4.2 (a) had experienced a dry season in 23.3% to 26.7% of all years in the study period. Stations belonging to 0.333 to 0.400 category in Figure 4.2 (b) had experienced a 33.3% to 40% wet seasons of all the year that used for the study. Generally, the spatial distribution and frequency of wet seasons had mostly distributed around North West and North East of the area while the dry seasonal frequency had a maximum value in the North East and central part of East Shewa Zone. Stations inside the great rift valley of Ethiopia revealed a minimum frequency in both dry and wet seasons. Wet years showed a maximum frequency of 12 years and minimum frequency of 6- years while dry years showed a maximum frequency of 8-years and minimum frequency of no dry years in all meteorological stations (Table 4.4).

Meteorological Station	Wet Frequency in 30 Years	Dry Frequency in 30 Years	Wet Frequency %	Dry Frequency %
Abomsa	7	6	23.3	20
Addis Ababa Bole	9	7	30	23.3
Alem Tena	12	5	40	16.7
Awash 7 Kilo	11	8	36.7	26.7
Sendafa	10	6	33.3	20
Chefedonsa	10	6	33.3	20
Debre Zeit	11	8	36.7	26.7
Mojo	9	6	30	20
Ejere	12	6	40	20
Welenchiti	8	6	26.7	20
Koka Dam	10	8	33.3	26.7
Melkasa	6	7	20	23.3
Metehara	9	5	30	16.7
Sire	10	0	33.3	0.00
Etheya	7	5	23.3	16.7
Kulumsa	6	7	20	23.3
Ogolcho	9	5	30	16.7
Meki	9	6	30	20
Ejersa Lele	7	6	23.3	20
Ziway	10	7	33.3	23.3
Bulbula	6	5	20	16.7

Table 4.4 Wet and dry year frequency in all meteorological stations

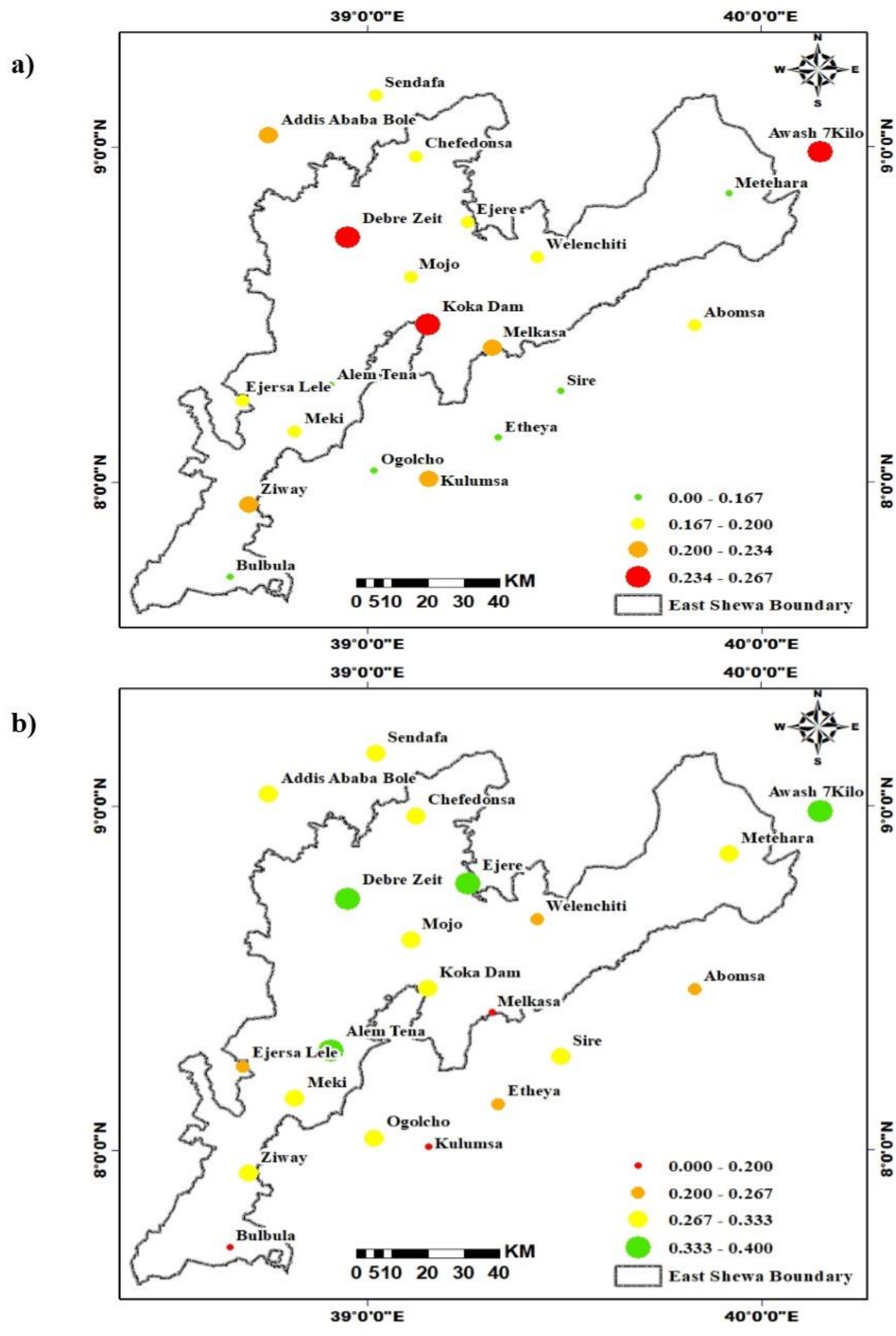

Figure 4.2 Frequency occurrence of the wet and dry year in East Shewa Zone and neighboring stations. The dry year (a) was defined when SPI is below 0 while wet years (b) are defined when SPI is more than 0

From the total 21 stations, studied 11 stations had minimum SPI values less than Negative one and had minimum SPI value in more than one month of the same years. This helps to detect the months that each station is going to have from slight to extreme drought conditions, which differs from one station to another station. For instance, Abomsa Meteorological Station showed severe drought in 1986 and 1987 with 8, 9,10, and 11 (August, September, October, and November) months which indicates those months are drought prone in that specific location. Moreover, Alem Tena Meteorological Station revealed moderate drought in five years from 1985 to 2015 which was 1986, 1987, 1991, 1992, and 2012 in similar month 10 (October). This means if there was a drought in the previous year with a month recorded the probability of drought happening in the next year with same month is possible. Table 4.5 below shows the count of the drought-prone stations, years, and months including all meteorological stations and all studied SPI years starting from 1985 to 2015 using the 12-month SPI result. The minimum SPI value from all stations from 1985 to 2015 was -1.85, which, was recorded in Bulbula station in December 2014, and 2015. The month indicated in number to denote the consecutive calendar months starting from one (January) to 12 (December). The SPI row indicates the minimum 12-month SPI value of the corresponding month and year with similar magnitude.

Abomsa	**Year**	**1986**	**1987**				
	Month	8,9, 10, & 11	8,9, 10, & 11				
	SPI	-1.5					
Alem Tena	**Year**	**1986**	**1987**	**1991**	**1992**	**2012**	
	Month	10	10	10	10	10	
	SPI	-1.11					
Bulbula	Year	**2014**	**2015**				
	Month	12	12				
	SPI	-1.85					
Chefedonsa	Year	**1994**	**1995**	**1996**	**1997**	**2009**	
	Month	9, 10, & 11	9, 10, & 11	9, 10, & 11	9	11	
	SPI	-1.28					
Ejere	Year	**1992**	**1993**	**1998**	**2009**	**2010**	**2014**
	Month	7	2, 5 6, & 7	2	7	2, 5, & 6	2, 5 6, & 7
	SPI	-1.28					
Etheya	Year	**1986**	**1987**	**2009**			
	Month	9, 10, & 11	9	9, 10, & 11			
	SPI	-1.5					
Koka Dam	Year	2009	2015				
	Month	8	8				
	SPI	-1.5					
Meki	Year	**1996**	**1997**	**2009**			
	Month	8	8	8			
	SPI	-1.28					
Melkasa	Year	**2014**	**2015**				
	Month	2, 3, & 4	1,2, 3, & 4				
	SPI	-1.83					
Sendafa	Year	**2010**	**2012**	**2013**			
	Month	1, 2, and 3	1, 2, and 3	1, 2, and 3			
	SPI	-1.5					
Ziway	Year	**2010**	**2012**	**2015**			
	Month	12	12	12			
	SPI	-1.52					

Table 4.5 Minimum value 12-month SPI counts for each station by corresponding year and month

4.1.3. Spatiotemporal Pattern of SPI and Drought Severity

The analysis of SPI indicated that there was a long-range drought in two cases from 1985 to 2015, which includes drought from 2000 to 2004 and drought caused by El Nino from 2014 to 2016. The drought from 2014 to 2016 was very severe compared to other drought periods in term of persisting period and magnitude. The spatial pattern of the drought year 2002 and 2015 and wet year 2006 and 2007 helped to analyze the spatiotemporal pattern of drought in East Shewa Zone.

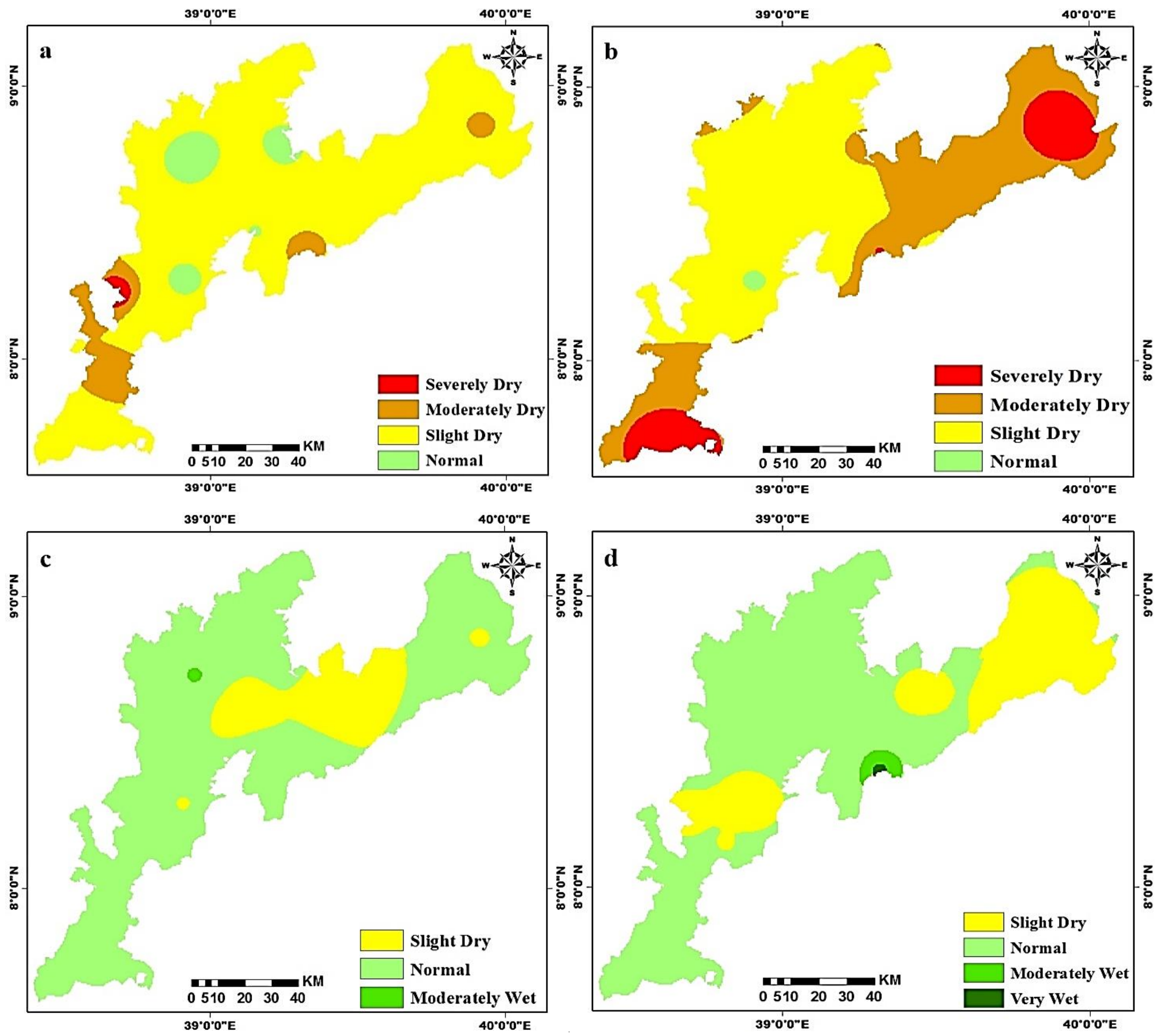

Figure 4.3 Spatiotemporal pattern of drought using 9-month SPI result of dry years October 2002 (a) and October 2015 (b) and no drought years October 2006 (c) and October 2007 (d)

The drought severity classification for the dry year 2002 and 2015 and wet years 2006 and 2007 were same as McKee except for the normal category, which primarily ranges from -0.99 to 0.99. In this study, SPI values above zero (0 to 0.99) had classified as normal (no drought) and values from below zero (-0.99 to 0) had classified as slight drought which helps to minimize the range and identify the peak drought conditions (Legesse & Suryabhagavan, 2014). The analysis of SPI results in 2002, 2006, 2007, and 2015 shows that the year 2002 and 2015 were dry years and 2006 and 2007 were wet years compared to other years in this study area. The drought severity is more in 2015 compared to 2002 in terms of severity and area coverage see Figure 4.3.

Wereda Name	Severely Dry		Moderately Dry		Slightly Dry		Normal		Total
	Area km^2	%	Area km^2	%	Area km^2	%	Area km^2	%	Area km^2
Fentale	592.5	39%	926.5	61%	0	0%	0	0%	1519
Boset	0	0%	1398.3	98%	25.5	2%	0	0%	1424
Adama	4.5	1%	351.25	39%	544.3	60%	0	0%	900
Lomme	0	0%	73.75	11%	598	89%	0	0%	671.8
Gimbichu	0	0%	5.5	1%	685.5	99%	0	0%	691
Adea	0	0%	0	0%	938.3	100%	0	0%	938.3
Dugda	0	0%	43	5%	871.8	95%	0	0%	914.8
ATJK	445.25	41%	647	59%	2.75	0%	0	0%	1095
Bora	0	0%	1.25	0%	380	88%	51.75	12%	433
Liben	0	0%	0	0%	701.3	100%	0	0%	701.3
Akaki	0	0%	56.75	10%	514.5	90%	0	0%	571.3
Total	1042.3	11%	3503.3	36%	5262	53%	51.75	1%	9859

Table 4.6 Drought Patten and distribution of 9-month SPI in October 2015 in wereda level

Wereda Name	Severely Dry		Moderately Dry		Slightly Dry		Normal		Total
	Area km^2	%	Area km^2	%	Area km^2	%	Area km^2	%	Area km^2
Fentale	0	0%	87	6%	1432	94%	0	0%	1519
Boset	0	0%	0	0%	1413.8	99%	10	1%	1423.8
Adama	0	0%	114.25	13%	777.75	86%	8	1%	900
Lomme	0	0%	0	0%	556.75	83%	115	17%	671.75
Gimbichu	0	0%	0	0%	672.25	97%	18.75	3%	691
Adea	0	0%	0	0%	631.5	67%	306.75	33%	938.25
Dugda	55	6%	278.25	30%	579.75	63%	1.75	0%	914.75
ATJK	0	0%	357	33%	738	67%	0	0%	1095
Bora	0	0%	0	0%	315.25	73%	117.75	27%	433
Liben	0	0%	0	0%	701.25	100%	0	0%	701.25
Akaki	0	0%	0	0%	542.25	95%	29	5%	571.25
Total	55	1%	836.5	8%	8360.5	85%	607	6%	9859

Table 4.7 Drought pattern and distribution of 9-month SPI in October 2002 in wereda level of the study area

In 2002, there was only one wereda that had a severely dry class with 55 square kilometers, which covers 6% of the wereda and accounts 1% of East Shewa Zone Table 4.7 whereas, there are three weredas (Fentale, Adama, and ATJK) in 2015 drought season in the severely dry class, which accounts for 11% of the whole study area. In 2015, (1042.3 km^2) 11% of the study area had severe drought, (3503.3 km^2) 36% had a moderate drought, (5262 km^2) 53% of the area had a slight drought, and about (51.75 km^2) 1% had no drought Table 4.6. Whereas in 2002 (55 km^2) 1% of the area had the severe drought-affected area, (8360.5 km^2) 85% had a moderate drought, (607 km^2) 6% of the total study area was normal. In 2015, the severity of drought covers the northeast and southern portion of the study area, which was strike by a severe to moderate drought, the rest of the study area, which is found in the northwest, and the middle part of the study area indicated a slight drought that accounts for 53% of East Shewa Zone.

4.1.4. Severity of Drought Based on SPI

Standardized Precipitation Index (SPI) allows determining the rarity of a current drought and the probability of precipitation needed to end the danger. As McKee and others identified and sited on the World Meteorological Organization SPI user guide the recurrence work allows comparing historical and current droughts whatever the location and climate of the area is (Svoboda, et al., 2012). The manual classified from slight drought to extreme drought and gives the recurrence period of all the classes which helps to identify how rare or frequent a drought is showed in Table 4.8.

Range	Category	Number of times in 100 years	The severity of the event
0 to -0.99	Slight Dryness	33	1 in 3 years
-1 to -1.49	Moderate Dryness	10	1 in 10 years
-1.5 to -1.99	Severe Dryness	5	1 in 20 years
<-2.0	Extreme Dryness	2.5	1 in 50 years

Table 4.8 Recurrence of drought with its severity level. Source: (Svoboda, et al., 2012)

Table 4.9 shows the severity level of drought in a wereda level to see the severity of drought in wereda level in October 2015 based on the maximum SPI value. The October 2015 minimum and maximum SPI values helped to identify the severity of each area with ranges. Fentale, ATJK, and Adama showed severe drought, Liben, and Adea weredas showed slight drought whereas the rest weredas had moderate drought in 2015.

Wereda Name	Area km^2	Minimum SPI	Maximum SPI	Severity
Fentale	1519	-1.85	-1.19	Severe Dryness
ATJK	1095	-1.82	-0.98	Severe Dryness
Adama	900	-1.52	-0.21	Severe Dryness
Boset	1423.75	-1.38	-0.93	Moderate Dryness
Akaki	571.25	-1.23	-0.59	Moderate Dryness
Lomme	671.75	-1.11	-0.01	Moderate Dryness
Dugda	914.75	-1.09	-0.13	Moderate Dryness
Bora	433	-1.04	0.15	Moderate Dryness
Gimbichu	691	-1.02	-0.62	Moderate Dryness
Adea	938.25	-0.90	-0.18	Slight Dryness
Liben	701.25	-0.65	-0.15	Slight Dryness

Table 4.9 Drought recurrence in East Shewa Zone based on October 2015 SPI result

4.1.5. Agricultural Drought Assessment Parameters

Based on literature the parameters used for agricultural drought assessment was selected because of the availability of data without the cost and the range of the data coverage. Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), soil moisture, and precipitation are parameters used for the analysis. Those parameters first resampled to make a similar spatial resolution before any kind of combination and analysis process. NDVI and LST retrieved from the MODIS image, resampled to 500-meter spatial resolution, and masked to the study area. The Net CDF NSIDC DAAC and TRMM soil moisture and precipitation data respectively collected from 2000 to 2016, converted to raster gridded format, and resampled to 500-meter spatial resolution. Satellite data collection started from 2002 up to 2016 except soil moisture, which covers from 2002 to 2010 by selecting one month for each Ethiopian season. Ethiopia has four seasons in the calendar year three months each Tsedey (September, October, and November), Bega (December, January, and February), Belg (March, April, and May), and Kiremt (June, July, and August). The selected months was October from Tsedey, January from the Bega May from Belg, and June from Kiremt that helped to show the drought effect and variability from season to season that enables seasonal comparisons.

A simple linear regression model using SPSS helped to identify the correlation of drought assessment parameters with the in situ SPI time scale. The correlation of drought assessment parameters with SPI result was done by taking January 2008 and June 2013 data from both sides, which enables to see the correlation of drought parameters with SPI in a different year and different season. In January 2008, the correlation of NDVI with time scale SPI result showed no significance, which indicated a positive correlation with 1 month and 3-month SPI and negative correlation with 6-month, 9-month, and 12-month SPI. In general, the four drought assessment parameters showed a negative correlation with significance except for NDVI as indicated in Table 4.10. In June 2013, NDVI and TRMM precipitation show a positive correlation with a significance level of less than 0.01. Whereas, LST shows a significant negative correlation with all SPI, time scales. These may be due to the available precipitation in the season as the precipitation increases the NDVI value becomes higher and enables to correlate positively with the positive SPI see Table 4.11. This result shows the correlation between the two seasons are quite different in terms of the level of significance as well as the correlation direction (positive or negative).

Parameters January 2008	1-month SPI	3-month SPI	6-month SPI	9-month SPI	12-month SPI
LST	-0.187*	-0.297**	-0.142	-0.365**	-0.360**
NDVI	0.103	0.015	-0.020	-0.053	-0.011
Precipitation	-0.517**	-0.515**	-0.365**	0.207**	0.109
Soil Moisture	-0.460**	-0.174*	-0.093	0.118	0.026
**. Correlation is significant at the 0.01 level.					
*. Correlation is significant at the 0.05 level.					

Table 4.10 Correlation coefficient between remote sensing based drought assessment parameters and timescale SPI of January 2008

Parameters June 2013	1-month SPI	3-month SPI	6-month SPI	9-month SPI	12-month SPI
LST	-0.184*	-0.493**	-0.410**	-0.366**	-0.200**
NDVI	0.244**	0.280**	0.199**	0.314**	0.333**
Precipitation	0.415**	0.434**	0.350**	0.494**	0.333**
**. Correlation is significant at the 0.01 level.					
*. Correlation is significant at the 0.05 level.					

Table 4.11 Correlation coefficient between remote sensing based drought assessment parameters and timescale SPI of June 2013

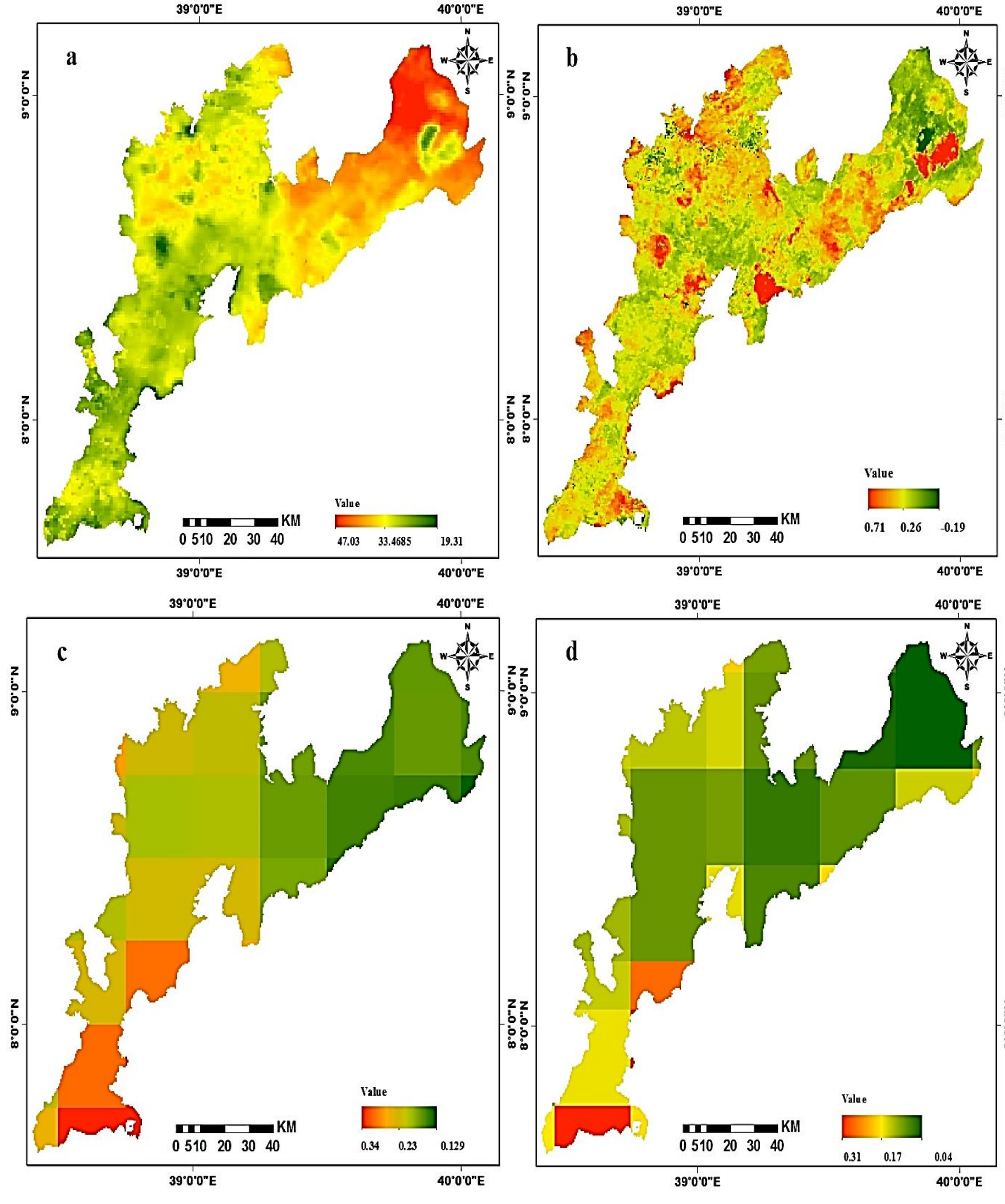

Figure 4.4 Spatial pattern of remote sensing drought assessment parameters of June 2008 LST (a), NDVI (b), soil moisture (c) and precipitation (d).

4.1.6. Single Drought Indicators

In order to detect and make an assessment of drought in such regional level the study used the TRMM precipitation Condition Index (PCI), the AMSR-E Soil Moisture Condition Index (SMCI), and the MODIS Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) based on microwave remote sensing method. Calculation of single condition drought indices was by scaling the drought parameters from zero to one with the indicated formula in Table 4.12. The maximum and minimum LST, NDVI, soil moisture, and precipitation was calculated by taking the maximum and minimum pixel value of each month from 2002, 2005, 2008, 2013, and 2015.

Drought Index	Data Source	Formula	Reference
VCI	USGS	(NDVIijk-NDVIi.min)/(NDVIi.max - NDVIi.min)	(Jiao, et al., 2017)
TCI	USGS	(LSTi.max − LSTijk)/(LSTi.max – LSTi.min)	(Anderson, et al., 2013)
SMCI	AMSR-E	(SMijk − SMi,min)/(SMi,max – SMi.min)	(Anzhi & Jia, 2013)
PCI	NSIDC DAAC	(TRMMijk-TRMMi.min)/(TRMMi.max+ TRMMi.min)	(Zhang, et al., 2017)

Table 4.12 Single agricultural drought indices calculation

Where:

- ✓ NDVIijk, TRMMijk, SMijk, and LSTijk —is the NDVI, Precipitation, Soil moisture, and Land Surface temperature of pixel “i,” month “j”, and year “k” respectively.
- ✓ NDVIi.min, LSTi.min, SMi.min, and TRMMi.min-- is the minimum NDVI, LST, Soil moisture, and Precipitation in pixel “i” of the area respectively.
- ✓ NDVIi.max, LSTi.max, SMi.max, and TRMMi.max—is the maximum NDVI, LST, Soil moisture, and Precipitation of pixel “i” respectively.

The Pearson two-tailed correlation of remote sensing drought assessment parameters with the in situ SPI indicated in the previous section shows poor and negative correlation values. The reason behind this problem is the weather impact on the retrieved parameters, which requires separation from the ecosystem component.

Linearly scaling the parameters by taking the absolute minimum and maximum values of each parameter helped to separate the weather and ecosystem component. The result of the scaled parameters ranges from zero to one that corresponds to the parameters change from extremely unfavorable to optimal conditions as indicated by (Kogan, 1995b). Therefore, these scaled values of the parameters known as condition indices if the parameter in precipitation it will be a Precipitation Condition Index (PCI) and VCI, SMCI, TCI from vegetation, soil moisture, and temperature.

The implementation of Pearson two-tailed correlation analysis between 1 month, 3month, 6 months, 9 months, and 12-month SPI and the remotely sensed drought indices for January 2008 and June 2013 helped to detect the variability of correlation in terms of the season. The correlation was made monthly by taking the in situ metrological stations as a sample point and extracting the SPI value of those meteorological stations from the corresponding remote sensed drought index. Because of the limited number of station in the study area, the in situ SPI data interpolation technique helped to increase the number of sample points that enables to take a similar number of samples from the SPI and remotely sensed drought index. Table 4.13 and Table 4.15 show the correlation coefficient (r - value) between the time series SPI and the remotely sensed drought index of January 2008 and June 2013 respectively. In January 2008, the TCI correlates positively with 1-month, 3-month, and 6-month SPI and correlates significantly 99% ($P < 0.01$) with 1 month, 3 months, 6-month, 9 months, and 12-month SPI. The correlation coefficient of VCI was positive in short timescales (1 month, 3 months, and 6 months) and negative for long SPI timescales. The correlation between 1 month SPI and PCI in January 2008 was 0.466 more than other single condition indices. Moreover, the correlation coefficient decreases when the SPI time scale increases while correlating SPI with PCI. In January 2008 TCI, shows to be a maximum of 0.364 and 0.43 correlation with 1 month and 6 month SPI respectively while PCI showed 0.466 correlation coefficient with only 1 month SPI compared to other remote sensed drought indices.

Correlation coefficient (r) in January 2008 n=181					
Single Indices January 2008	1 Month SPI	3 Month SPI	6 Month SPI	9 Month SPI	12 Month SPI
TCI	0.364**	0.334**	0.430**	-0.241**	-0.164*
VCI	0.06	0.08	0.289**	-0.254**	-0.231**
PCI	0.466**	0.246**	-0.250**	0.05	0.239**
SMCI	0.01	-0.13	0.334**	-0.395**	-0.398**
**. Correlation is significant at the 0.01 level.					
*. Correlation is significant at the 0.05 level.					

Table 4.13 January 2008 Pearson correlation coefficient between different SPI time scale and remotely sensed drought indices

The classification of drought severity indicated by Zhang, et al., (2017) used to categorize the sevierity level of both single and combined indices in this study. All single indices had similar class of sevierity level but in combined drought indices VHI and SDCI had similar classes which was different from OVDI's severity level because of the methods used to generate those indices. Morover, there are no any similar rules to classify drought severity level in related studies. For example (Rhee, et al., 2010), (Hao, et al., 2015) and (Zhang & Jia, 2013) used extrem, severe, moderate, abnormal, and no drought classes to categorize either single or combined drought indices.

Name of class	*PCI*	*TCI*	*VCI*	*SMCI*	*VHI*	*SDCI*	*OVDI*
Extreme drought	0–0.1	0–0.1	0–0.1	0–0.1	0–0.1	0–0.1	0–0.2
Severe drought	0.1–0.2	0.1–0.2	0.1–0.2	0.1–0.2	0.1–0.2	0.1–0.2	0.2–0.3
Moderate drought	0.2–0.3	0.2–0.3	0.2–0.3	0.2–0.3	0.2–0.3	0.2–0.3	0.3–0.5
Mild drought	0.3–0.4	0.3–0.4	0.3–0.4	0.3–0.4	0.3–0.4	0.3–0.4	0.5–0.7
Abnormally dry	0.4–0.5	0.4–0.5	0.4–0.5	0.4–0.5			
No drought	0.5–1	0.5–1	0.5–1	0.5–1	0.4–1	0.4–1	0.7–1

Table 4.14 Drought severity level classes for single and combined indices *(Zhang & Jia, 2013)*

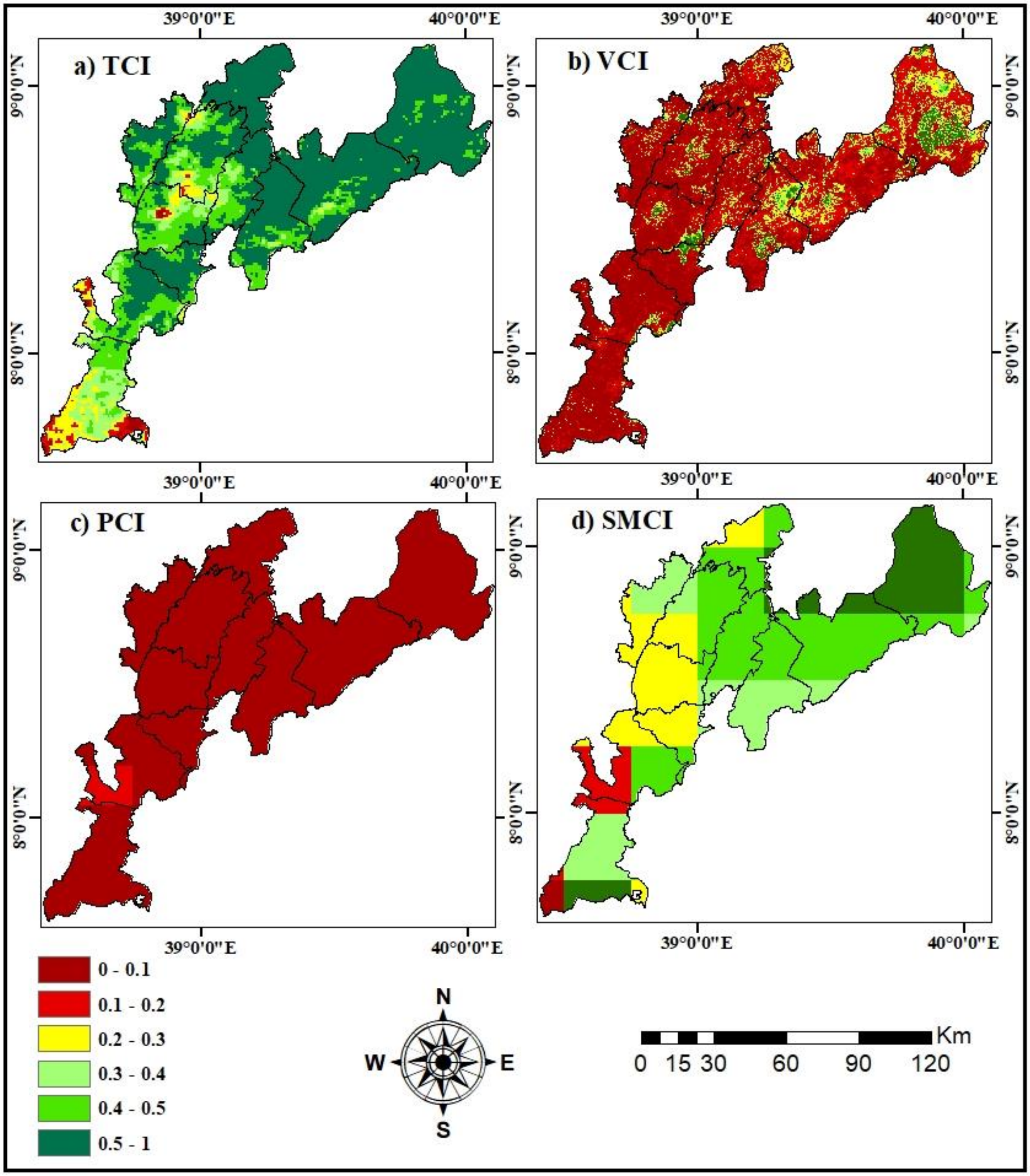

Figure 4.5 January 2008 Single Condition Indices

In June 2013 except the correlation of TCI with 1-month, 9-month, and 12-month SPI and VCI with 6-month SPI which is not bad correlated positively, the rest correlation between single condition index and SPI displayed a positive correlation and significance level at least less than 0.05 (more than 95%). This may be because of the availability of rainfall, which helps to decrease vegetation stress. Similar to the correlation of January 2008 in June 2013 PCI showed maximum correlation coefficient of 0.764 in shorter time scales and gets low when the SPI timescale increases (Table 4.15). The range of SPI varies depending on the amount of precipitation and dryness in a period but let us say value ranges from -3 to 3 and always remote sensed drought indices value ranges from 0 to 1 and when precipitation increase the probability of SPI to be positive will be high. Therefore, the seasonal variability in remote sensing drought assessment showed different correlation result in Kiremt (rainy) and Bega (dry) season. Both the scaled and non-scaled drought assessment parameters indicated positive and significant correlation with tested SPI time scales in the Kiremt season compared to Bega seasons in East Shewa Zone. This maximum correlation is because of the availability of rainfall in the Kiremt (rainy) season in the study area, which makes rainfall a dominant parameter in drought detection in the Kiremt season. Whereas in Bega (non-rainy) the dominant parameter was temperature.

Correlation coefficient (r) in June 2013 n=181					
Single Indices June 2013	1 Month SPI	3 Month SPI	6 Month SPI	9 Month SPI	12 Month SPI
TCI	0.04	0.210**	0.229**	0.08	0.11
VCI	0.201**	0.175*	0.14	0.338**	0.290**
PCI	0.764**	0.558**	0.649**	0.254**	0.038
**. Correlation is significant at the 0.01 level.					
*. Correlation is significant at the 0.05 level.					

Table 4.15 June 2013 Pearson correlation coefficient between the different times scale SPI and remotely sensed drought indices

Figure 4.6 shows the distribution of drought indicated in the northeast portion of the study area compared to other areas. drought distribution in the study area showed a similar extent in TCI, VCI, and PCI. Fentale, Boset, and Adama weredas showed as drought-prone areas by the three condition indices. the lower the scaled values in the description indicates the higher the drought will be. Drought exists in the range from 0 to 0.4 in different scales descendingly but normal or no drought conditions were observed above 0.5.

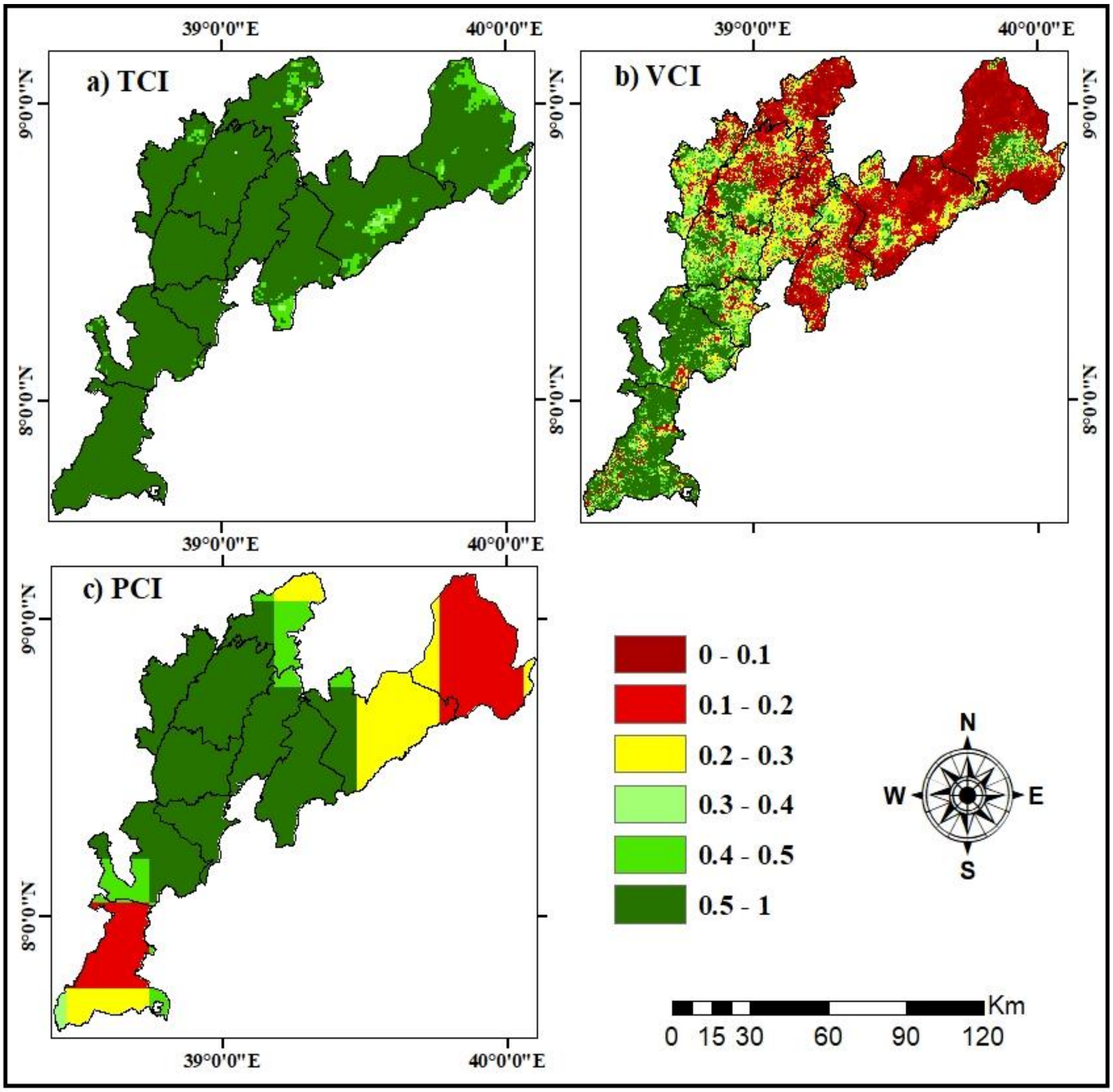

Figure 4.6 June 2013 remote sensed single drought indices

4.1.7. Combined Drought Indicators

The reason behind the use of combined drought indices for monitoring and drought assessment is to get the advantage of both parameters by combining the parameters with respective weights, which enables to determine regional droughts conditions. Vegetation Health Index (VHI), Optimized Vegetation Dryness Index (OVDI), and Scaled Drought Condition Index (SDCI) are the combined drought indices combined with empirically for both VHI and SDCI and constrained optimization for OVDI. Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) combined empirically for vegetation health index, TCI, VCI, and PCI are parameters combined empirically for SDCI, and constrained optimization method used to combine TCI, VCI, PCI, and SMCI for OVDI.

4.1.7.1. Vegetation Health Index (VHI)

The Empirical weight method helped to combine Temperature Condition Index (TCI), and Vegetation Condition Index (VCI) to identify the level of vegetation stress. The weight of the two parameters was analyzed by taking five different empirical weight values for each and correlate the resulting VHI with the different SPI timescale. Maximum correlation coefficient and significance values helped to select the appropriate weight value for the parameters. January 2008 and June 2013-time scale SPI and VHI parameters (TCI and VCI) used for correlations. The January 2008 correlation Table 4.16 showed 0.458 correlation coefficients with weight values of 70% and 30% for TCI and VCI respectively when correlated with 6-month SPI. The rest SPI time scales show a maximum correlation coefficient with weight values 80% and 20% for TCI and VCI respectively. Therefore, 80% for TCI and 20% for VCI showed maximum correlation in four-time scales of SPI except for 6-month SPI with a 99% significance. The double asterisk shows the significance of correlation was more than 99%, the single asterisk shows that the significance level was above 95%, and correlation coefficients without asterisk indicated no significant correlation with the in situ data (SPI) which was more than 0.05 (less than 95%).

Weights		January 2008 SPI				
TCI	VCI	1 Month	3 Month	6 Month	9 Month	12 Month
0.3	0.7	0.208**	0.206**	0.411**	-0.301**	-0.250**
0.2	0.8	0.160*	0.164*	0.375**	-0.290**	-0.249**
0.5	0.5	0.288**	0.274**	0.453**	-0.302**	-0.237**
0.7	0.3	0.336**	0.314**	0.458**	-0.282**	-0.209**
0.8	0.2	0.350**	0.324**	0.451**	-0.268**	-0.194**
*. Correlation is significant at the 0.05 level.						
**. Correlation is significant at the 0.01 level.						

Table 4.16 Correlation coefficients and the significance level of empirically weighted VHI with SPI in January 2008

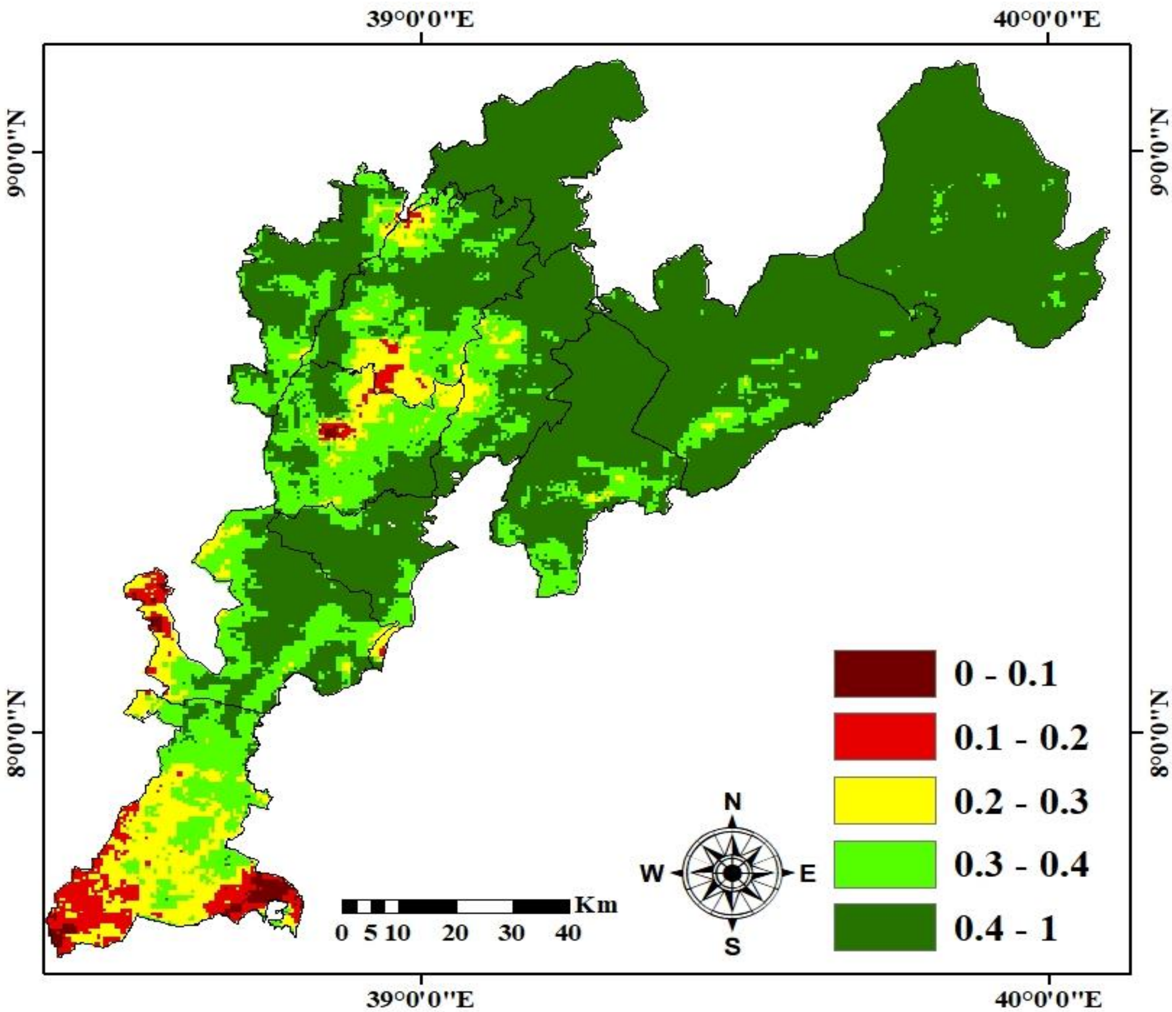

Figure 4.7 Spatial pattern of drought using VHI in January 2008 with 80% TCI and 20% VCI

For June 2013, the correlation coefficient (r) values showed there was 99% significance level with positive correlation coefficient between VHI and all SPI time scales compared to January 2008. The selection of the best weights from the five empirical weights made by highlighting the maximum correlation coefficient for each SPI time scale columns as indicated in Table 4.17. For 1-month and 9-month SPI, the 20% and 80% weight values for TCI and VCI respectively showed maximum correlation coefficients. For 3-month SPI 70% and 30% weighting coefficients for TCI and VCI respectively had 0.249 correlation coefficients. Whereas for 6-month SPI the r - value was 0.246 when using 80% and 20%, weight values for TCI and VCI respectively. For 12-month SPI the r - value was maximum when using 30% weight for TCI and 70% weight for VCI as indicated in Table 4.17. This shows that like SPI the length of drought determines the weights for VHI calculation in a specific area with a defined season.

Weights		June 2013 SPI				
TCI	VCI	1 Month	3 Month	6 Month	9 Month	12 Month
0.3	0.7	0.197**	0.206**	0.174*	0.334**	0.296**
0.2	0.8	0.200**	0.195**	0.159*	0.337**	0.295**
0.5	0.5	0.185*	0.232**	0.208**	0.314**	0.288**
0.7	0.3	0.151*	0.249**	0.239**	0.258**	0.252**
0.8	0.2	0.12	0.247**	0.246**	0.209**	0.215**
*. Correlation is significant at the 0.05 level.						
**. Correlation is significant at the 0.01 level.						

Table 4.17 Correlation coefficient and significance level for VHI and SPI correlation studied for June 2013

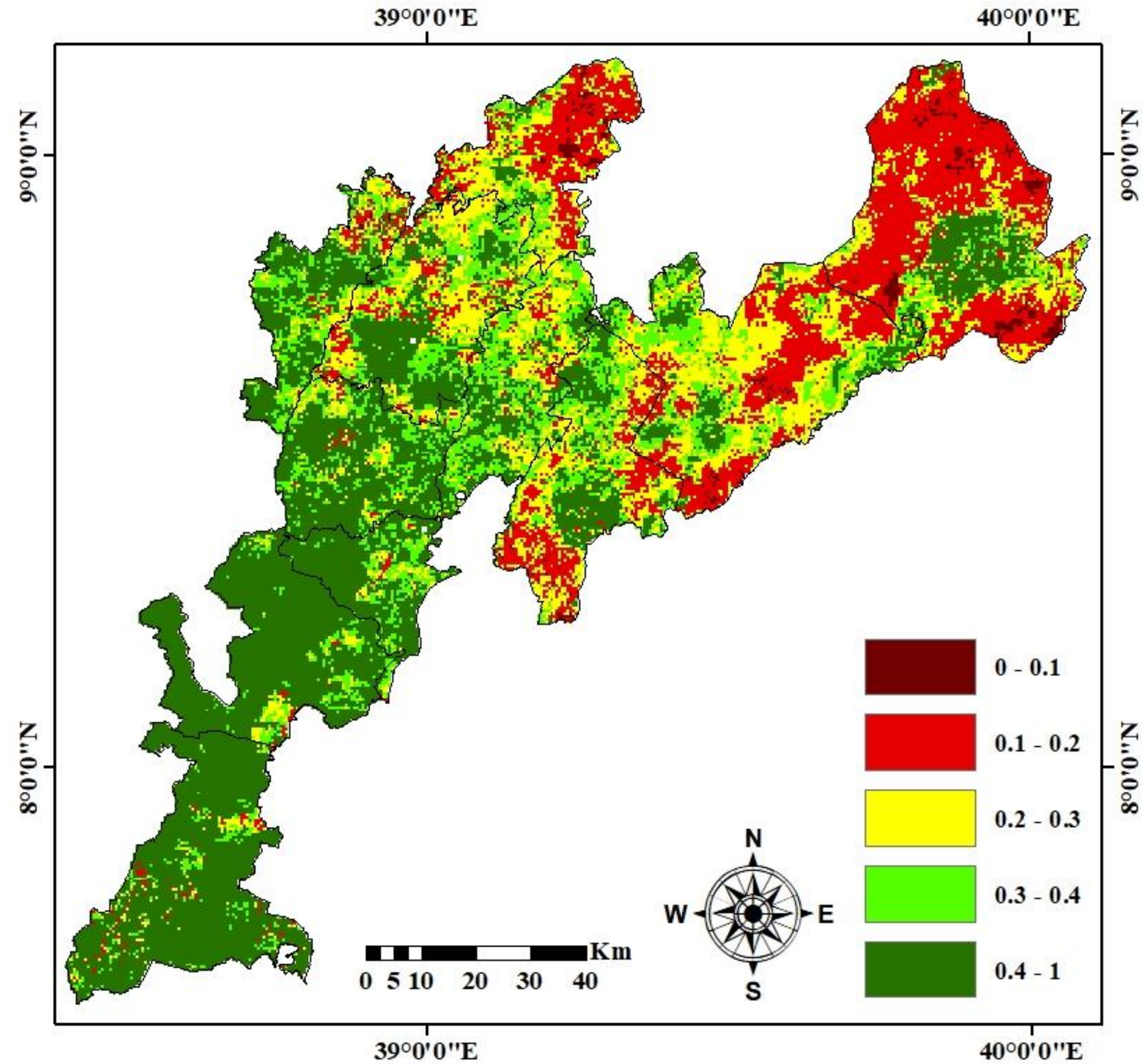

Figure 4.8 Spatial Pattern of drought using VHI in June 2013 with 20% TCI and 80% VCI

4.1.7.2. Scaled Drought Condition Index (SDCI)

Scaled Drought Condition Index (SDCI) first developed by (Rhee, et al., 2010) used three parameters combined empirically which helped to monitor agricultural drought using remotely sensed drought parameters, which is Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Precipitation Condition Index (PCI). Rhee and others performed the study in North America, which is different climatic zones and used 50% weight for precipitation and 25% weight for both Temperature and Vegetation. However, here the weights of the SDCI parameters obtained by testing the weights empirically and correlate with the different SPI time scales to select the weights with the maximum correlation coefficient and significance. The correlation of January 2008 fourteen different weight of parameters with SPI time scales showed maximum correlation coefficients with shorter SPI time scales (1-month, 3-month, and 6-month) with a significance of more than 99% but the correlation showed no significance with the rest of SPI time scales. From all parameters, coefficients tested the maximum correlation coefficient result in each SPI timescale was marked in Table 4.18 signifying that 50%, 10%, and 40% weight values resulted in a maximum correlation coefficient and significant for PCI, VCI, and TCI respectively.

Weight			January 2008 SDCI with SPI Correlation coefficient				
PCI	VCI	TCI	1 Month	3 Month	6 Month	9 Month	12 Month
0.3	0.4	0.3	0.306**	0.277**	0.424**	-.303**	-.225**
0.3	0.5	0.2	0.245**	0.224**	0.387**	-.298**	-.231**
0.4	0.3	0.3	0.353**	0.310**	0.423**	-.298**	-.207**
0.4	0.4	0.2	0.291**	0.256**	0.390**	-.299**	-.218**
0.4	0.5	0.1	0.209**	0.185*	0.331**	-.281**	-.216**
0.5	0.3	0.2	0.350**	0.297**	0.388**	-.296**	-.198**
0.5	0.4	0.1	0.258**	0.216**	0.326**	-.282**	-.201**
0.2	0.3	0.5	0.345**	0.315**	0.450**	-.290**	-.210**
0.1	0.5	0.4	0.280**	0.265**	0.441**	-.304**	-.238**
0.5	0.1	0.4	0.429**	0.367**	0.411**	-.261**	-.154*
0.6	0.2	0.2	0.425**	0.346**	0.376**	-.285**	-.164*
0.7	0.2	0.1	0.429**	0.323**	0.285**	-.265**	-.127
0.1	0.2	0.7	0.356**	0.328**	0.449**	-.271**	-.193**
0.2	0.6	0.2	0.210**	0.199**	0.383**	-.296**	-.239**
**. Correlation is significant at the 0.01 level							
*. Correlation is significant at the 0.05 level							

Table 4.18 Correlation coefficient and significance level between SDCI and multiple time scale SPI for January 2008

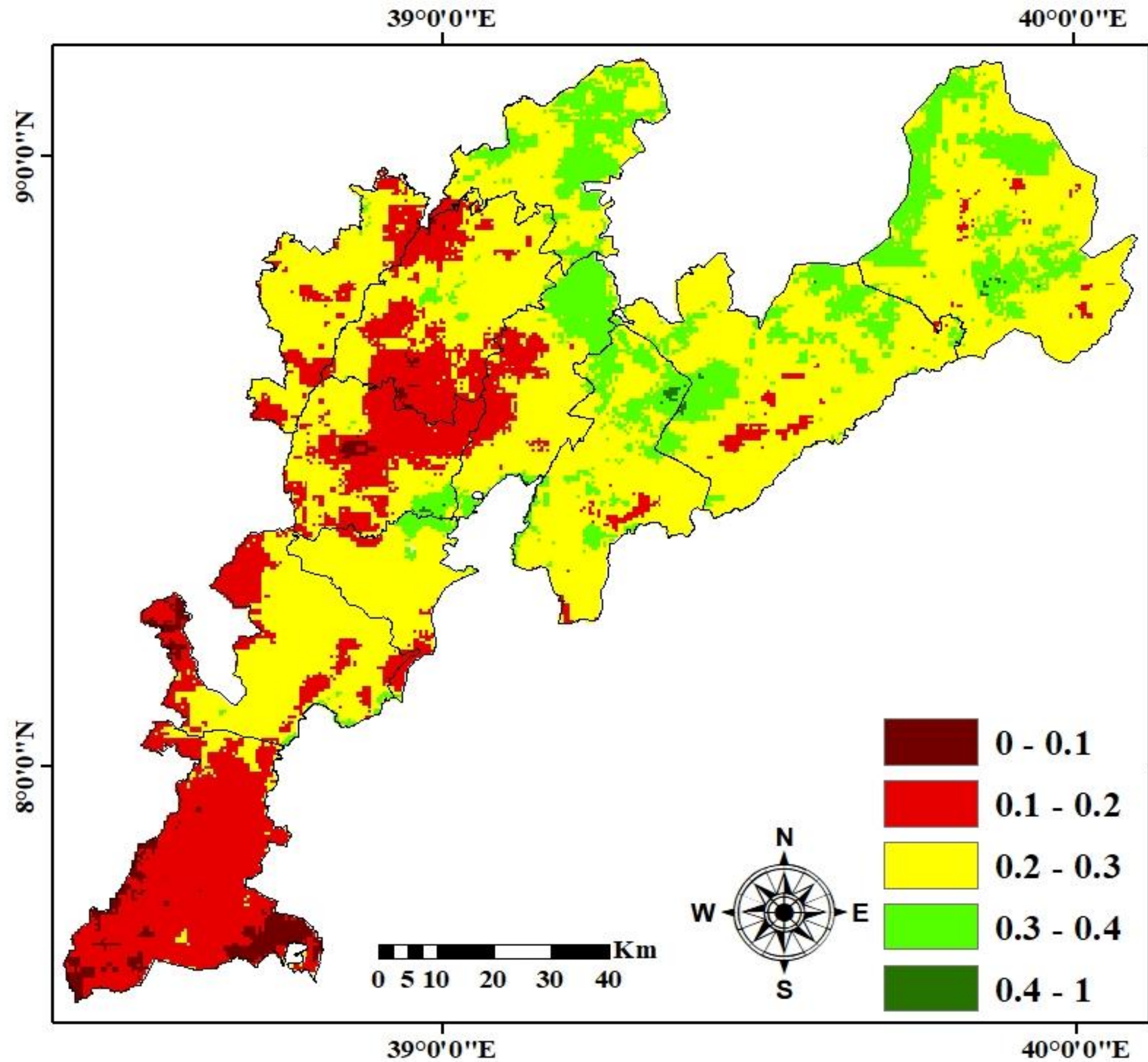

Figure 4.9 January 2008 SDCI for 50%, 10%, and 40% weights for PCI, VCI and TCI respectively

The correlation of different SDCI parameter weights used for June 2013 to identify the correlation and weight values of those parameters in the rainy season. The correlation between the SDCI empirical weight and SPI time scales in June 2013 indicated that all SDCI weights correlate positively with a significance level of more than 0.01 (99%) except with 12- month SPI. The maximum correlation coefficients for each SPI timescale marked in Table 4.19 helped to select the maximum correlated weights of all conditions. SDCI weights showed a maximum of 0.741 correlation when it correlates with a 1-month SPI and when the weights are 70%, 20%, and 10% for PCI, VCI, and TCI respectively. Similar weight values of SDCI achieved a maximum of 0.562 correlation when correlated with 3-month SPI. The 6-month SPI showed a maximum of 0.634

correlation by combining PCI, VCI, and TCI with respective weights of 50%, 10%, and 40%. The 40%, 50%, and 10% empirical weights for PCI, VCI, and TCI respectively showed a maximum of 0.389 correlation when correlated with the 9-month SPI values. 12-month SPI values showed a maximum correlation of 0.286 when correlated using 10%, 50%, and 40% empirically weight for PCI, VCI, and TCI respectively (Table 4.19). The result of the correlation between the different time scale SPI and different weighed SDCI shows that SDCI weight enables to detect different drought length. In June 2013, 10%, 50%, 40%, and 40%, 50%, 10% weights can detect long drought seasons whereas 70%, 20%, 10% weight can detect droughts with short duration period for PCI, VCI, and TCI respectively.

Weight			June 2013 SDCI with SPI Correlation coefficient				
PCI	VCI	TCI	1 Month	3 Month	6 Month	9 Month	12 Month
0.3	0.4	0.3	0.505**	0.435**	0.455**	0.375**	0.250**
0.3	0.5	0.2	0.482**	0.401**	0.412**	0.384**	0.261**
0.4	0.3	0.3	0.604**	0.504**	0.546**	0.365**	0.211**
0.4	0.4	0.2	0.580**	0.471**	0.501**	0.382**	0.231**
0.4	0.5	0.1	0.551**	0.436**	0.457**	0.389**	0.243**
0.5	0.3	0.2	0.662**	0.526**	0.576**	0.366**	0.190*
0.5	0.4	0.1	0.636**	0.495**	0.533**	0.381**	0.210**
0.2	0.3	0.5	0.415**	0.409**	0.428**	0.336**	0.246**
0.1	0.5	0.4	0.295**	0.298**	0.285**	0.346**	0.286**
0.5	0.1	0.4	0.672**	0.561**	0.634**	0.298**	0.125
0.6	0.2	0.2	0.716**	0.560**	0.627**	0.336**	0.143
0.7	0.2	0.1	0.741**	0.562**	0.633**	0.330**	0.125
0.1	0.2	0.7	0.267**	0.341**	0.355**	0.257**	0.219**
0.2	0.6	0.2	0.379**	0.327**	0.319**	0.373**	0.281**
**. Correlation is significant at the 0.01 level							
*. Correlation is significant at the 0.05 level							

Table 4.19 Correlation coefficient and significance level between SDCI and multiple time scale SPI for June 2013

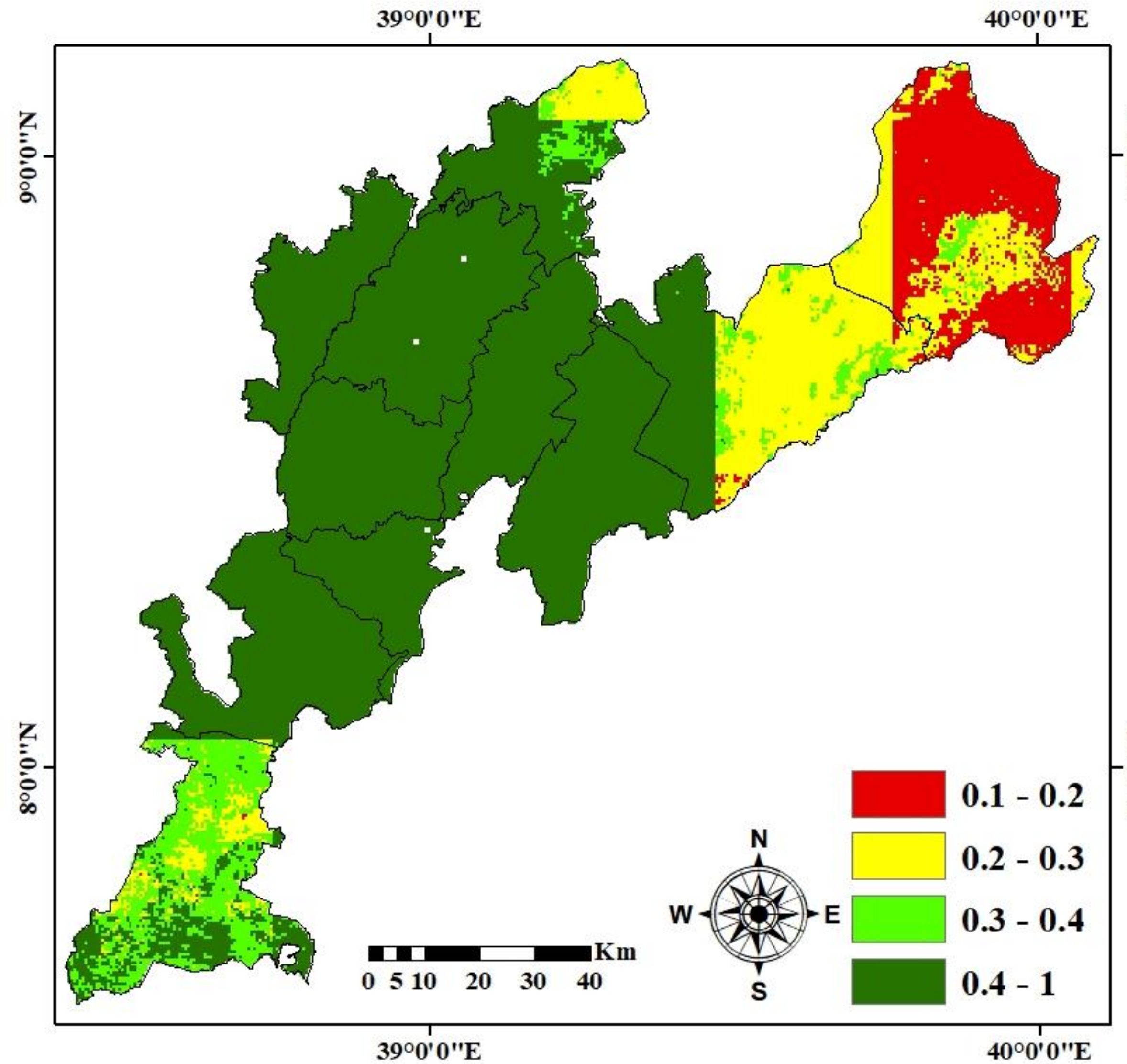

Figure 4.10 SDCI of June 2013 using 70%, 20%, and 10% empirical weights for PCI, VCI, and TCI respectively

4.1.7.3. Optimized Vegetation Dryness Index (OVDI)

Optimized Vegetation Dryness Index (OVDI) used for this study to detect regional drought in East Shewa Zone administrative province by combining Soil Moisture Condition Index (SMCI), Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Precipitation Condition Index using constrained optimization method. Constrained optimization method for combining the agricultural drought parameters first analyzed by Hao and others in China in 2015. The general principle of constrained optimization is to optimize remotely sensed drought parameters when to combine them for another drought index through maximizing the correlation with the in situ data (i.e. SPI).

$$f(x, y) = \max \left(\frac{E[(x-ux)-(y-uy)]}{\delta x * \delta y}\right)$$ (Hao, et al., 2015)

X= SPI

$$Y\ (OVDI) = \alpha * TCI + \beta * PCI + \gamma * SMCI + (1 - \alpha - \beta - \gamma) * VCI$$

$0 < \alpha < 1$

$0 < \beta < 1$

$0 < \gamma < 1$

Where: f(x,y) is the highest correlation between X and Y, X is the in situ index result which includes different time scales, Y is the combined drought index (OVDI) derived from VCI, TCI, SMCI, and TCI, $\delta_{x,}$ and δ_y are the standard deviation of X and Y or SPI and OVDI. ux and u_y are the mean value of X and Y or SPI and OVDI. E means the expectation or mean value of the result computed using the indicated formula, and α, ß, and γ are the optimization variables for TCI, PCI and SMCI respectively.

Similar to other combined remote sensed drought indices OVDI optimization was applied for June 2008 and January 2008. In January 2008, the optimization was checked for 19 optimization variables and the result indicates 20%, 60%, 10%, and 10% (for TCI, PCI, SMCI and VCI respectively) optimization variable values correlated with a maximum of 0.432 coefficient with the 1 month SPI which implies this weight can be used for shorter drought management. Optimization variable weights of 40%, 10%, 20%, and 30% for TCI, PCI, SMCI and VCI respectively showed a maximum of 0.482 correlation coefficient when correlated with 6-month SPI. Whereas in the rest SPI time scales 70%, 2.5%, 2.5%, and 25% for TCI, PCI, SMCI and VCI respectively showed maximum correlations which indicates temperature was a prominent factor for longer drought cases in Bega season.

For June 2008, OVDI values from 70%, 10%, 10%, and 10% for TCI, PCI, SMCI, and VCI respectively showed a maximum of 0.542 correlation with 1-month SPI values. 3-month SPI intern correlated with resulting OVDI when optimization variables had 70%, 10%, 10%, 10% and 60%, 20%, 10%, 10% weights for TCI, PCI, SMCI and VCI respectively. Whereas OVDI values from 30%, 50%, 10%, and 10% optimization variables TCI, PCI, SMCI and VCI respectively showed a maximum of 0.393 correlation with the 6 month SPI value and OVDI values from 60%, 20%, 10%, and 10% optimization variable for TCI, PCI, SMCI and VCI respectively showed a maximum of 0.453 correlation with the 9 month SPI values. The use of maximum weight for TCI compared to PCI helped to identify shorter and longer drought cases while maximum weight for PCI compared to TCI will help to identify mid drought cases. Which implies there was a need to implement different weighting cases in different seasons and in different drought cases (long or short).

The correlation of OVDI from a different optimal variable in the two cases (Kiremt and Bega) shows different consistency because of the seasonal variability in the study area. January 2008 was consistence compared to June 2008 in terms of the optimization variables used for OVDI calculation. Appendix 4 shows the optimization coefficients for the variables and the correlation coefficient. Figure 4.11 shows the OVDI result of January (a) with 70% TCI, 2.5% for PCI and SMCI each, and 25% of VCI and June 2008 (b) with 60% of TCI, 20% of PCI, 10% of each SMCI and VCI. January 2008 OVDI showed drought extent in southern part whereas June 2008 OVDI showed less drought extent compared to January 2008 in Figure 4.11.

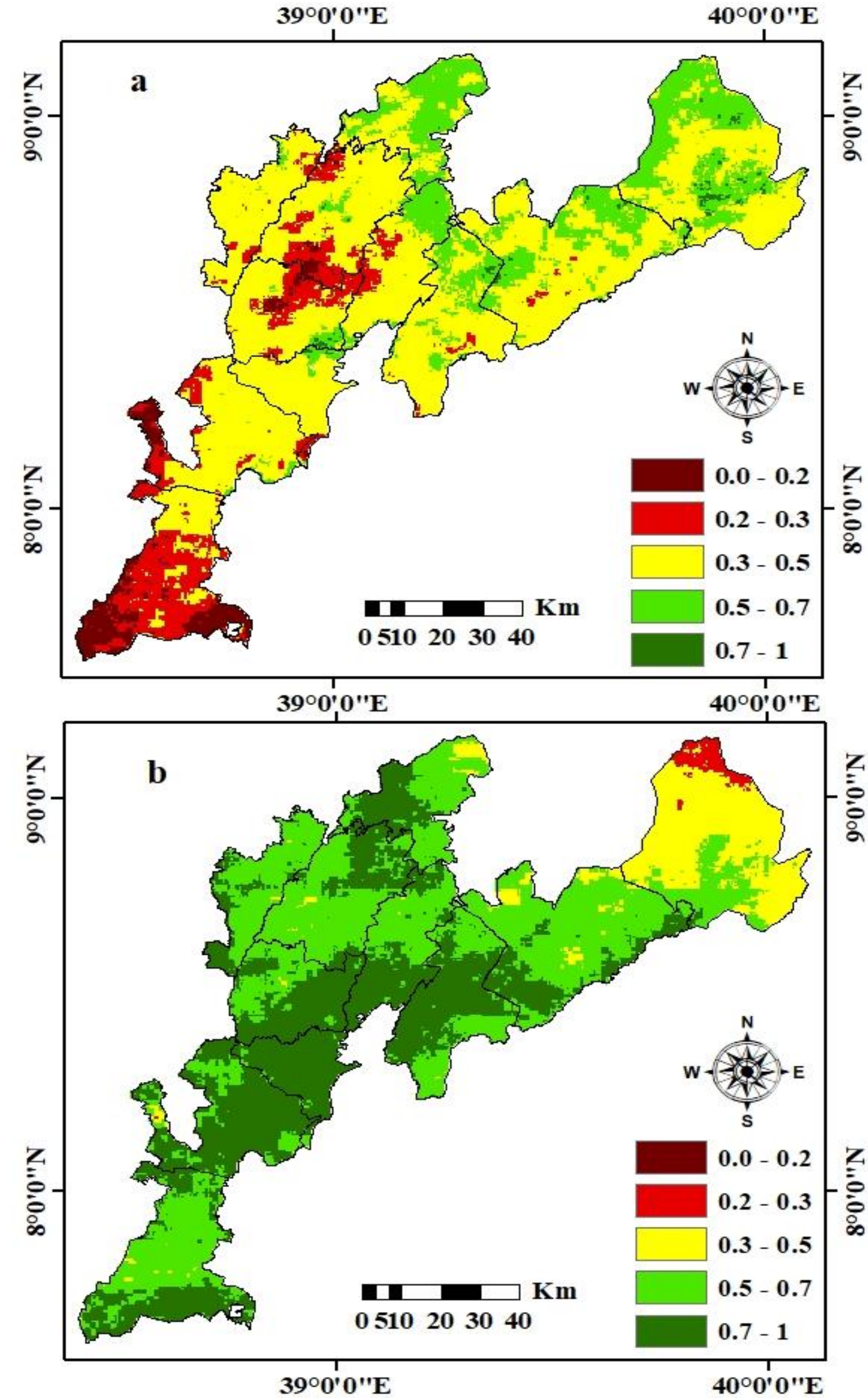

Figure 4.11 Optimized Vegetation Dryness Index (OVDI) for January 2008 (a), and June 2008 (b).

4.2. Validation of Remote Sensing Drought Indices

The Standardized Precipitation Index (SPI) in similar drought assessment year enable to check the validity of the result. The correlation of the remotely sensed drought indices with SPI used to validate the result of agricultural drought indices. Such validation methods helped in similar researches such as (Rhee, et al., 2010) and (Hao, et al., 2015).

Validation of remotely sensed drought indices using Standardized Precipitation Index (SPI) helped to see the performance of combined drought indices. The validation work for January 2008 implemented on all of the combined remote sensed drought indices shows that all the indices correlated with SPI positively with a significance of less than 0.01 (99%) (Figure 4.12) which indicates that the implemented drought indices can assess agricultural drought in the Bega season. The in situ meteorological 3-month SPI value also correlated with remotely sensed drought indices (VHI and SDCI) in June 2013 with a significance of less than 0.01 (99%) for SDCI and less than 0.05 (more than 95%) for VHI (Figure 4.13) indicating that those combined drought indices from remotely sensed data can monitor drought conditions in different seasons. Optimized Vegetation Dryness Index (OVDI) of June 2008 was validated using 6-month SPI of June 2008 and showed positive and significant result as shown in Figure 4.14.

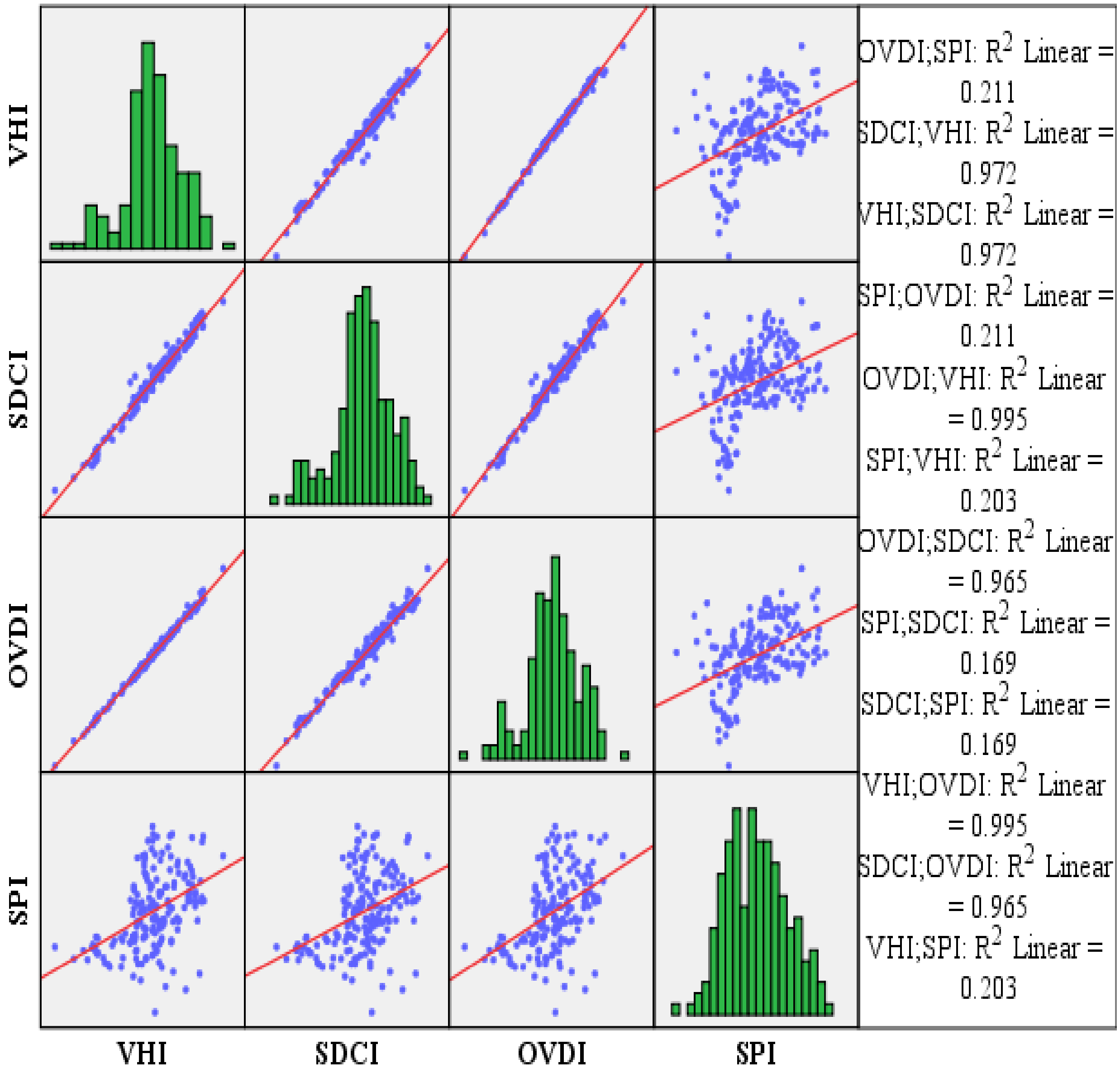

Figure 4.12 Scatter plot correlation showing the validation result of SDCI, OVDI, and VHI with 6-month SPI of January 2008

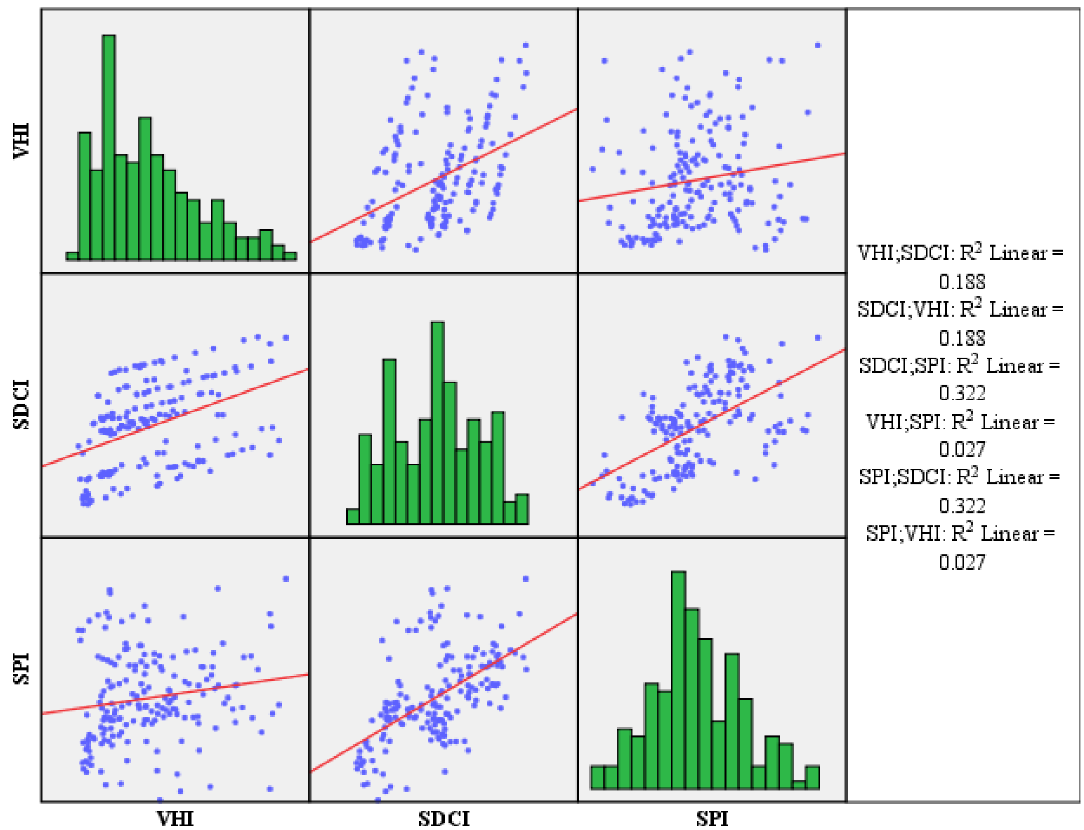

Figure 4.13 Scatter plot correlation showing the validation result of SDCI and VHI with 3 month SPI of June 2013

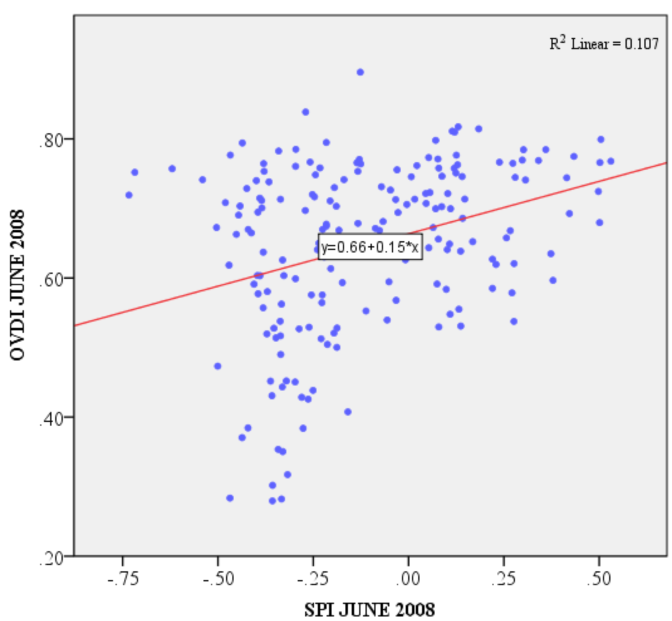

Figure 4.14 Scatter plot correlation showing validation result of OVDI in June 2008 using 6 month SPI

4.3. Discussion

The remotely sensed drought assessment parameters derived from optical and infrared bands helped for the assessment of agricultural drought in the study. The parameters showed a different response to the drought in different seasons either in single or in combined indices. This section discuss the effect of season on drought detection, comparison of drought indices, and drought-prone areas of East Shewa Zone.

4.3.1. Seasonal Effect on Drought Detection

In all the results demonstrated for single and combined drought indices except VHI it was shown that, rainy seasons had showed maximum correlation coefficient (r) and significant compared to Bega or non-rainy seasons. Vegetation Health index (VHI) had no PCI component, which helped to increase the correlation coefficients in SDCI and OVDI in Kiremt season. Kogan, (1990) showed maximum correlation of NDVI with SPI in wet seasons which agrees with this study. Moreover, Hao, et al., (2015) found maximum correlation in wet (rainy) seasons compared to dry seasons while in dry cases VCI showed no significance except with 6-month SPI with minimum correlation coefficent which is similar with the result of this study indicated in Table 4.13 and Table 4.15. Rhee, et al., (2010) found maximum correlation coefficent in humid (rainy) areas compared to aired (dry) areas which agrees with the result of this study even if this study concentrated on the same climate condition with different seasons. This shows that drought indices showed maximum correlation in wet cases compared to dry cases whether the case was in different season or climate.

Standardized Precipitation Index (SPI) works only with one parameter i.e. precipitation therefore the increase in rainfall in rainy season helped to increase the correlation of drought indices with SPI. Table 4.13 and Table 4.15 showed the variation of correlation with in the rainy and non-rainy seasons, which indicates negative correlation in non-rainy (January) and maximum and positive correlation in rainy (June) season. Rainy (Kiremt) season intern helps to minimize vegetation stress because of thermal heat and preserve healthy vegetation. Figure 4.15, and Figure 4.16 show precipitation and soil moisture had positive correlation in both rainy and non-rainy seasons, which means when precipitation increase, soil moisture also increases but precipitation had a negative strong correlation with LST in rainy seasons (Figure 4.15). Table 4.13 shows that

TCI had a maximum of 0.430 correlation coefficents in Bega season when corelated with 6-month SPI compared to VCI and SMCI while Table 4.15 showed maximum correlation coefficent of 0.764 by correlating PCI with 6-month SPI in Kiremt season.

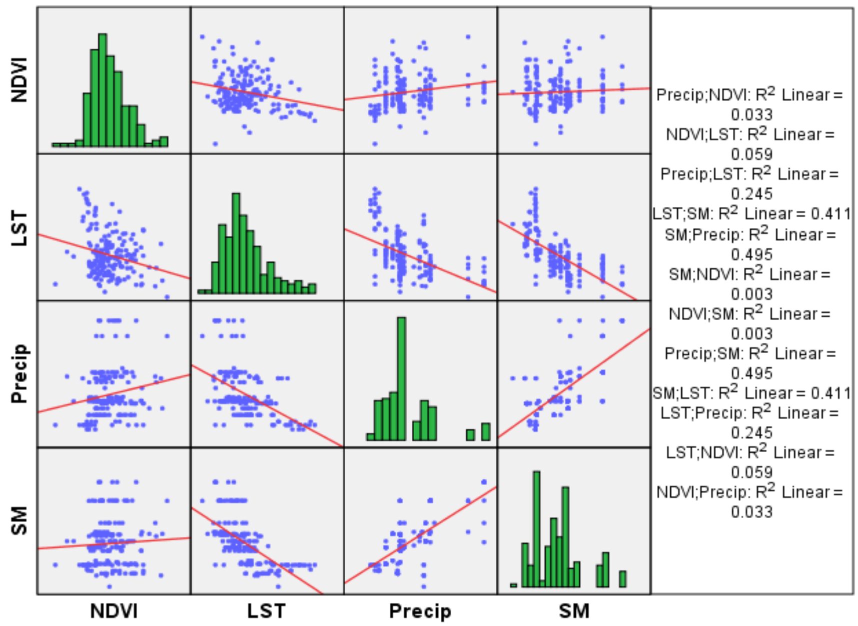

Figure 4.15 Relationship between LST, NDVI, Soil Moisture, and TRMM precipitation of Kiremt (June 2008)

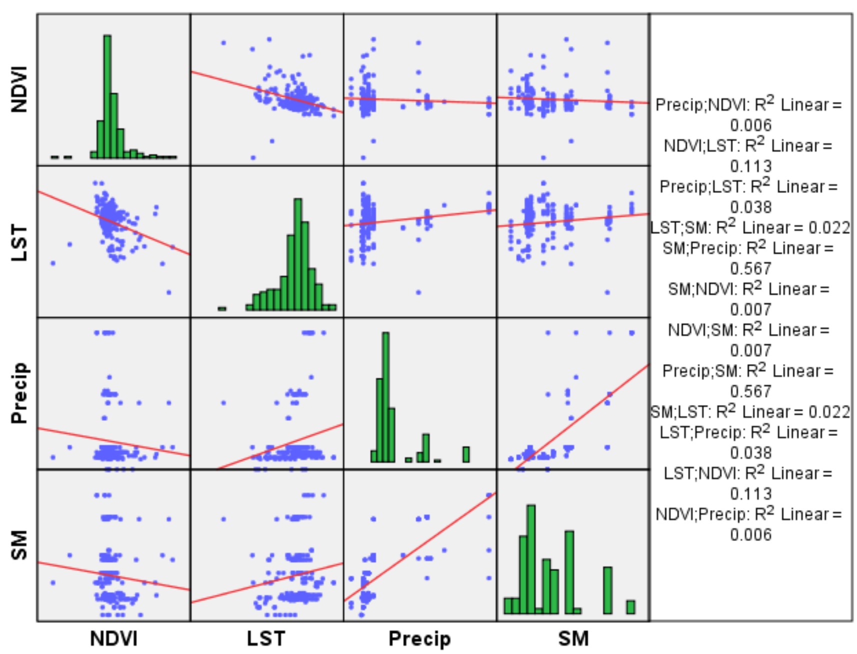

Figure 4.16 Relationship between NDVI, LST, Soil Moisture, and TRMM Precipitation of Bega (January 2008)

4.3.2. Comparison of Agricultural Drought Indices

The correlation result of all scaled single agricultural condition indices with SPI time-scale showed a maximum correlation as compared to raw remote sensed Agricultural drought parameters. Intern combined drought indices outperforms the single agricultural drought indices. This shows that combined agricultural drought indices are preferred drought indices compared to single drought indices in detecting drought frequency and spatial extent. This result was similar in studies such as Hao, et al., (2015), Rhee, et al., (2010), and Zhang, et al., (2017). Table 4.20 below indicates the minimum correlation result of agricultural drought indices with respective indices which shows combined indices exceeds single drought indices in minimum correlation coefficent. The correlation coefficent increases as the number of parameters increases used to calculate combined indices. SDCI which used three drought parameters (TCI, PCI, and VCI) showed a minimum of 0.267 correlation which is superior than other indices in Table 4.20, which was similar with the study of Hao, et al., (2015). Optimized Vegetation Dryness Index (OVDI) used constrained optimization method to combine drought parameters which resulted minimum correlation compared to VHI and SDCI but had maximum correlation with 6-month SPI in January and 1-month SPI in June as indicated in Appendix 4. This shows that emperical weighting of the drought parameters are more effective than constrained optimization method which was also indicated by Zhang, et al., (2017).

Indices	January 2008		June 2013	
	Minimum r-value	Time Scale	Minimum r-value	Time Scale
Raw drought parameters	-0.517 (Precipitation)	1 month	-0.493 (LST)	3 month
Scaled single condition index	-0.250 (PCI)	6 month	0.04 (TCI)	1 month
VHI	0.16	1 month	0.12	1 month
SDCI	0.185	3 month	0.267	1 month

Table 4.20 Comparison of drought indices using correlation coefficient value

4.3.3. Drought Prone Areas

From the 11-adminstrative wereda of East Shewa Zone Fentale, Boset, ATJK, and Adama were indicated as frequent drought prone areas using the number of population supported in a year starting from 2015 to 2018 (Figure 3.3). The remote sensing drought assessment result shows same extent of drought in these wereda's. The January 2008 combined drought indices result showed maximum drought in the south and central part of the area including ATJK. While the June 2013 combined and single drought indices showed, severe drought in northeast part of the area including Fentale, Boset, and Adama. The Ethiopia Network on Food Security report in 2002 confirmed Fentale as a drought prone area (ENFS, 2002). The average minimum pixel value of both single and combined drought indices in January 2008 and June 2013 for each wereda was extracted to see the drought prone weredas in 2008 and 2013. Both the 2008 and 2013 average minimum pixel value of single and combined drought indices showed that Fentale had maximum severity of drought compared to other weredas in East Shewa Zone (Table 4.21).

No	January 2008			June 2013		
	Wereda Name	Area (Km^2)	Minimum Value	Wereda Name	Area (Km^2)	Minimum Value
1	Fentale	1533.41	0.003	Fentale	1533.41	0.070
2	ATJK	1105.32	0.015	Gimbichu	705.23	0.123
3	Akaki	582.58	0.015	Boset	1434.18	0.147
4	Gimbichu	705.23	0.018	Adama	901.04	0.218
5	Bora	435.67	0.019	ATJK	1105.32	0.232
6	Liben	703.51	0.019	Lomme	675.15	0.234
7	Adea	936.96	0.020	Adea	936.96	0.267
8	Dugda	923.68	0.027	Akaki	582.58	0.326
9	Boset	1434.18	0.031	Liben	703.51	0.406
10	Lomme	675.15	0.037	Bora	435.67	0.428
11	Adama	901.04	0.048	Dugda	923.68	0.508

Table 4.21 Average minimum pixel value for single and combined drought indices for each Wereda

CHAPTER FIVE

5 CONCLUSIONS AND RECOMMENDATION

5.1. Conclusion

The main objective of this study was to identify agricultural drought frequency and its spatiotemporal extent in the area by employing remotely sensed and in situ drought monitoring methods. Parameters such as temperature, vegetation, precipitation, and soil moisture were used to detect drought. The correlation of time scale SPI values with those drought parameters was very low and insignificance (Table 4.10 and Table 4.11) but by scaling the variables from zero to one and correlating with the SPI gives a maximum correlation coefficient and significance level (Table 4.13 and Table 4.15). The results of either the raw or the scaled indices with the SPI showed maximum correlation in precipitation, PCI (Kiremt season), LST and TCI (Bega seasons). It is inferred that PCI and LST can detect drought better for Kiremt and Bega seasons, respectively

All of the combined drought indices outperform the single condition drought indices because of the multiple variable consideration and enables to detect long or short drought duration by changing the weighting values for each parameter (Table 4.20). Validation of all combined drought indices using 6-month or 3- month SPI showed a maximum correlation coefficient with a significance level of more than 99% (Figure 4.15 and Figure 4.16). From the obtained result, it concludes that, merging the single drought indices can help to address the issue in a better way. Fentalle, Boset, ATJK, Gimbichu, and Adama are the five weredas identified as maximum drought affected area (Table 4.21). The 2015 SPI indicated Fentale, ATJK, and Adama in severe drought .whereas, Adea and Liben under slight drought and the remaining six wereda falling in moderate drought prone zones (Table 4.9).

5.2. Recommendation

The remotely sensed indices and SPI drought assessment techniques helped in identifying the drought-prone areas in the regional level. The MODIS, TRMM, AMSR-E data are data available free of charge for the whole world which makes remote sensing method less cost. This study points out the following recommendation for specific organizations and for the researchers.

- First, the application of remotely sensed based indices for drought assessment needs caution in implementing the methods because it depends much on the parameters, which varies according to seasonal variations and environmental conditions. The weight values and correlation results between SPI and remotely sensed indices vary from place to place. In humid and dense vegetated areas, temperature and vegetation may have positive correlation but in aired areas, they had a positive correlation. Therefore, preliminary analysis of the data with different environment and seasons helps to address this issue.
- The in situ and remotely sensed drought indices are helpful for such analysis by selecting the methods by studying the seasonal variability and environmental condition of the area.
- Regular drought assessment is required in the East Shewa Zone, which helps to identify the trend of drought in a specific area. East Shewa Zone Disaster and Risk Management Offices can perform such tasks in order to identify the high-risk areas.
- Proper agricultural crop adaptive mechanisms are required for severe drought affected areas such as Fentale, Bosete, ATJK, and Adama to preserve the livelihood of the society and their livestock. This study recommends the use of scientific crop adaptation mechanisms such as intercropping, mixed cropping, soil conservation, and rainwater harvesting enables to maximize the productivity of the farmer when there is a scarcity of rainwater.
- Finally, for the good of the society, the study recommends the need for a regular drought early warning system in the national level, which enables to develop by studying the trend of drought in a historical base.

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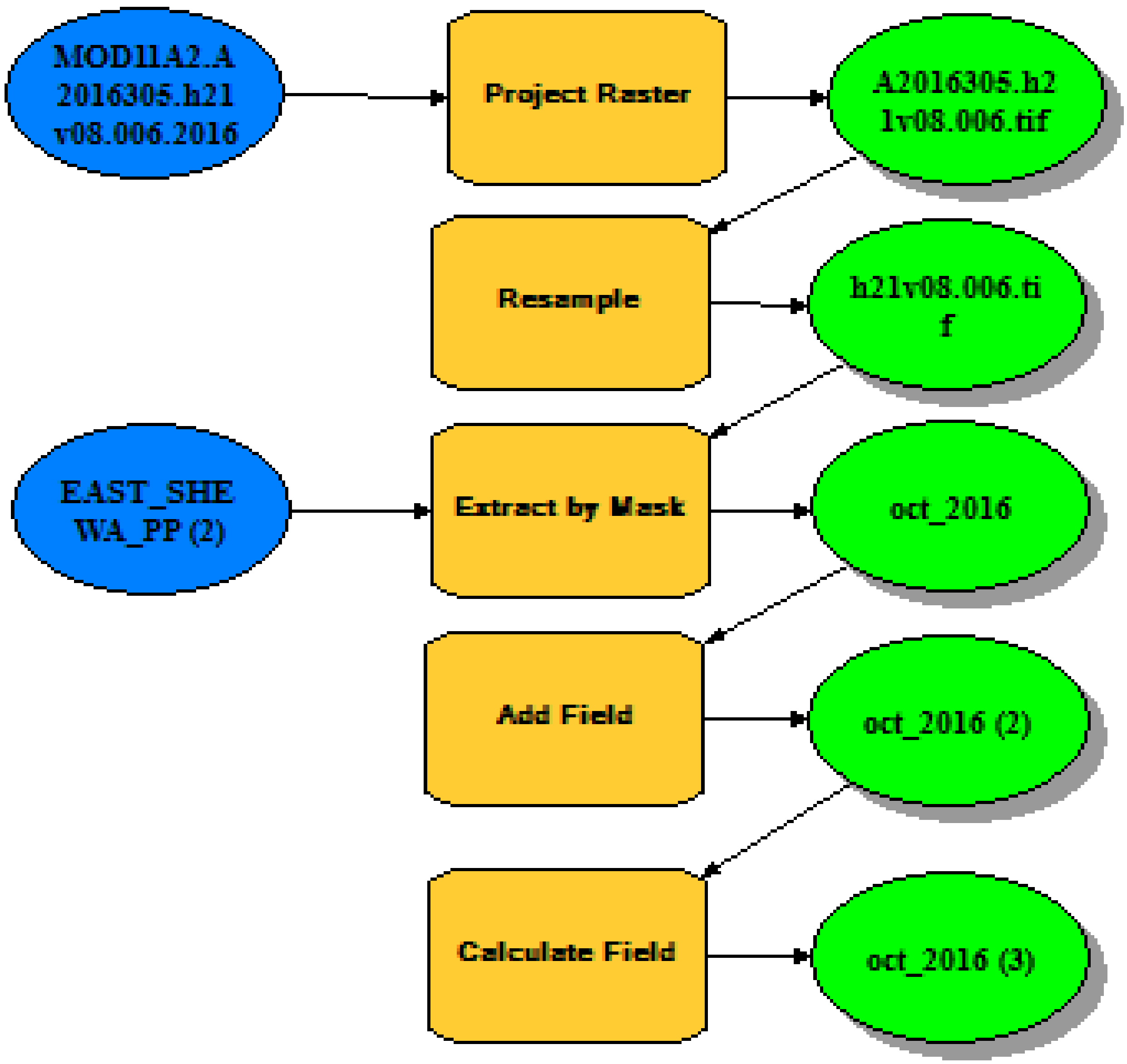
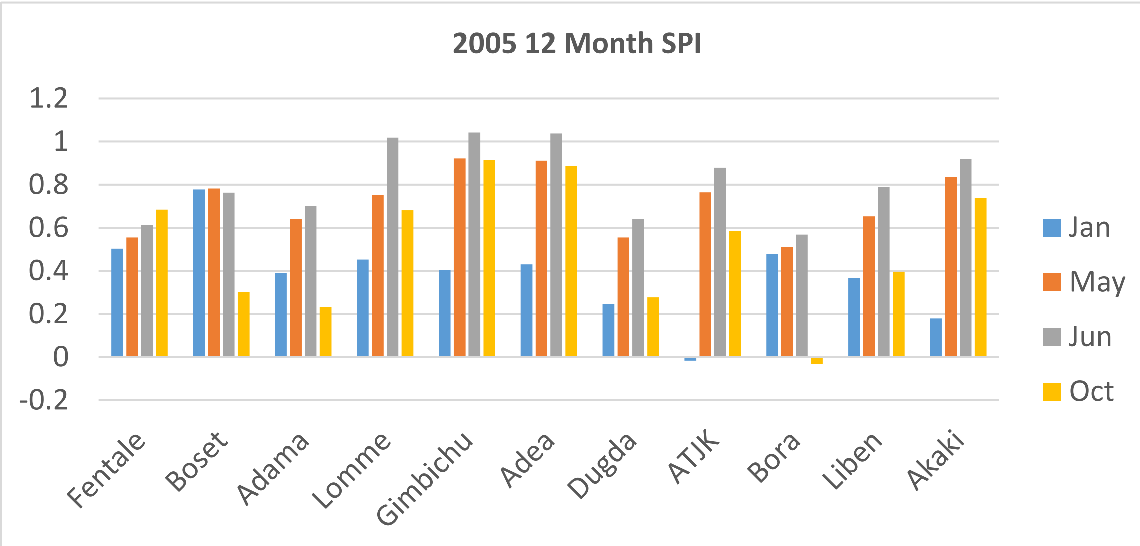
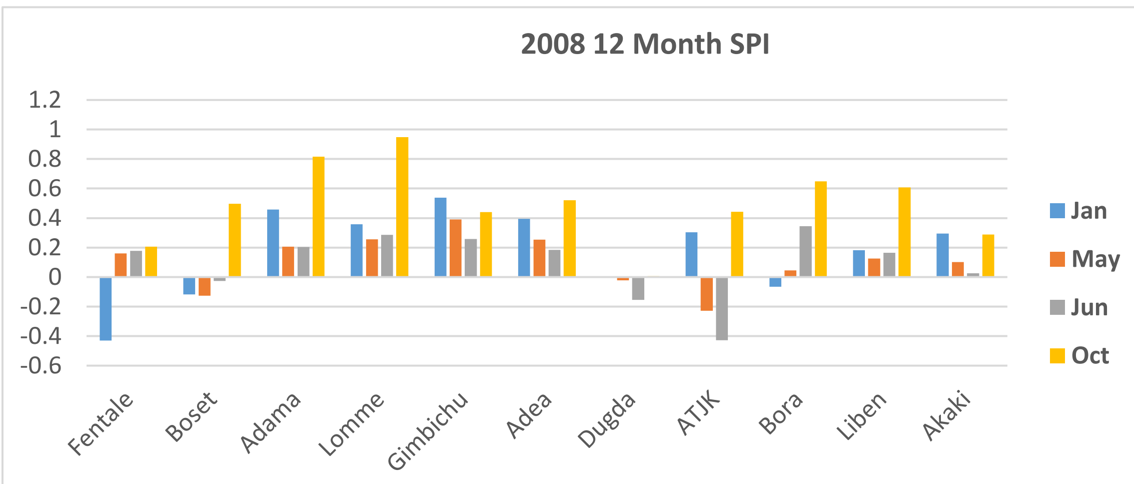
APPENDICES

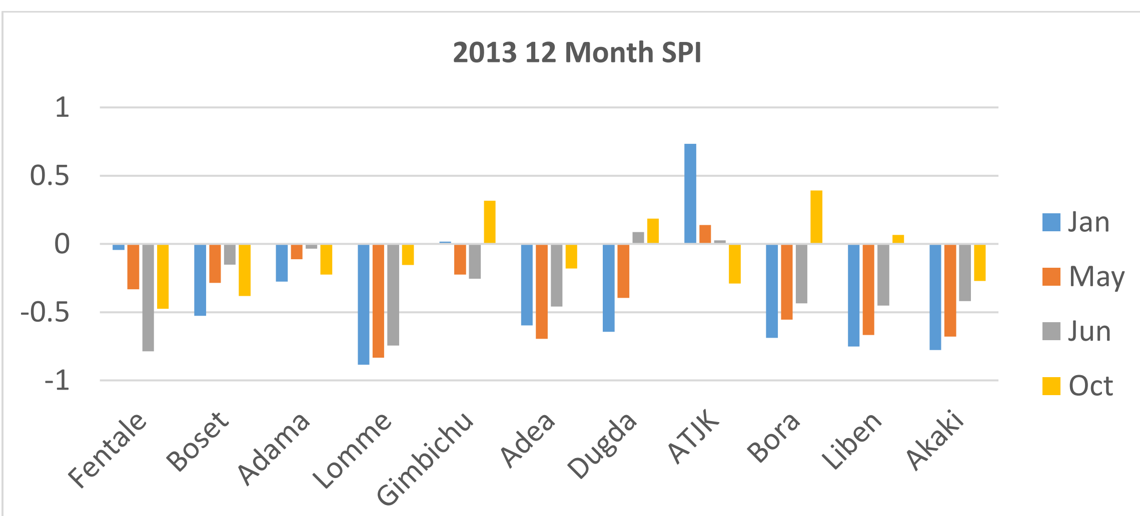
Appendix 1: Condition Index Calculation using Model Builder



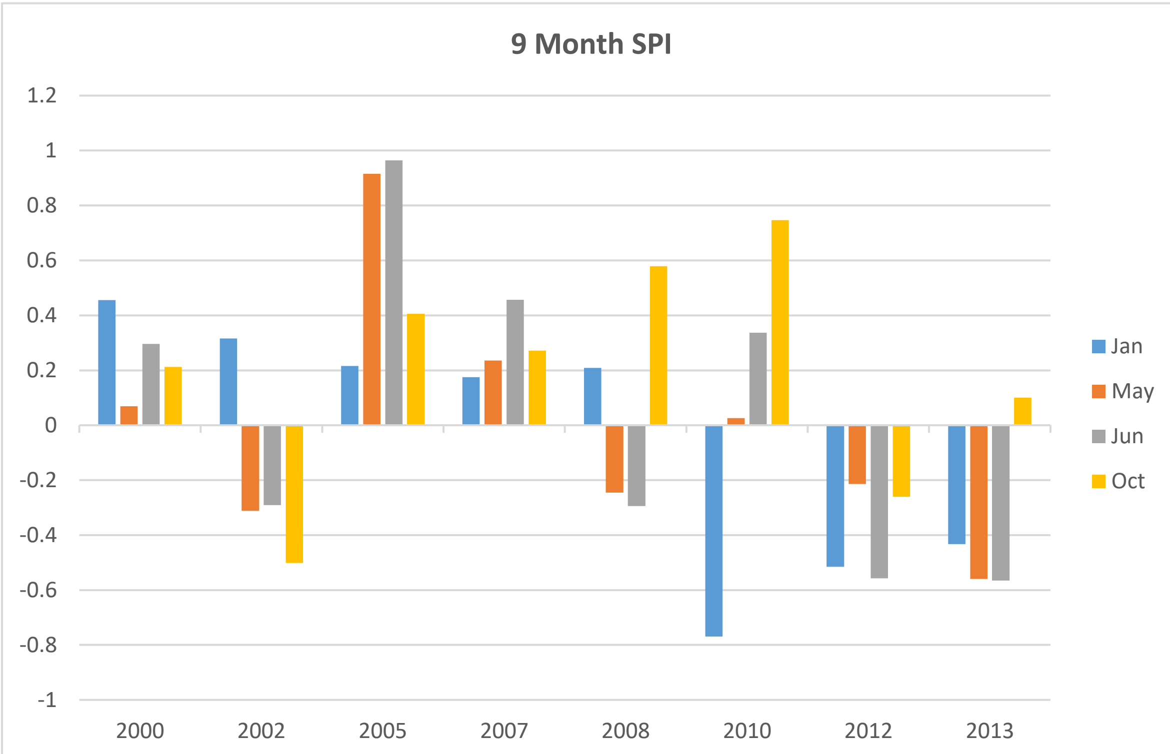
Appendix 2: Spatiotemporal Pattern of drought







Appendix 3: Temporal Variability of Drought using SPI



Appendix 4: Constrained Optimization Results for June and January 2008

Jan 2008 OVDI Optimization								
Weights				Constrained Optimized Value				
α	ß	δ	(1-α-ß-δ)	1 M. SPI	3 M. SPI	6 M. SPI	9 M. SPI	12 M. SPI
0.25	0.25	0.25	0.25	0.26	0.173	0.473	-0.399	-0.337
0.4	0.3	0.2	0.1	0.338	0.254	0.467	-0.349	-0.271
0.3	0.4	0.2	0.1	0.344	0.24	0.461	-0.369	-0.285
0.3	0.2	0.4	0.1	0.241	0.132	0.468	-0.405	-0.352
0.2	0.3	0.4	0.1	0.219	0.09	0.449	-0.422	-0.37
0.1	0.2	0.3	0.4	0.149	0.068	0.429	-0.41	-0.37
0.4	0.1	0.2	0.3	0.281	0.224	0.482	-0.363	-0.3
0.4	0.2	0.1	0.3	0.315	0.268	0.466	-0.334	-0.26
0.5	0.3	0.1	0.1	0.369	0.308	0.451	-0.301	-0.217
0.3	0.5	0.1	0.1	0.404	0.309	0.437	-0.327	-0.224
0.3	0.1	0.5	0.1	0.203	0.093	0.464	-0.411	-0.369
0.1	0.3	0.1	0.5	0.181	0.141	0.377	-0.335	-0.281
0.6	0.2	0.1	0.1	0.358	0.306	0.453	-0.293	-0.214
0.2	0.6	0.1	0.1	0.432	0.304	0.414	-0.346	-0.227
0.2	0.1	0.6	0.1	0.144	0.021	0.436	-0.422	-0.393
0.1	0.2	0.1	0.6	0.152	0.125	0.372	-0.325	-0.281
0.7	0.1	0.1	0.1	0.35	0.305	0.454	-0.287	-0.212
0.6	0.1	0.1	0.2	0.336	0.293	0.465	-0.306	-0.232
0.7	0.025	0.025	0.25	0.339	0.311	0.456	-0.283	-0.21

June 2008 OVDI Optimization								
Weights				Constrained Optimized Value				
α	ß	δ	(1-α-ß-δ)	1 M. SPI	3 M. SPI	6 M. SPI	9 M. SPI	12 M. SPI
0.25	0.25	0.25	0.25	0.221	0.108	0.328	0.272	0.023
0.4	0.3	0.2	0.1	0.377	0.243	0.382	0.401	0.036
0.3	0.4	0.2	0.1	0.299	0.215	0.391	0.362	0.063
0.3	0.2	0.4	0.1	0.231	0.113	0.362	0.298	0.058
0.2	0.3	0.4	0.1	0.157	0.088	0.359	0.256	0.081
0.1	0.2	0.3	0.4	0.036	0.004	0.237	0.109	0.007
0.4	0.1	0.2	0.3	0.341	0.176	0.27	0.308	-0.047
0.4	0.2	0.1	0.3	0.368	0.228	0.277	0.333	-0.043
0.5	0.3	0.1	0.1	0.463	0.305	0.359	0.443	0.008
0.3	0.5	0.1	0.1	0.322	0.257	0.393	0.382	0.064
0.3	0.1	0.5	0.1	0.192	0.061	0.336	0.258	0.054
0.1	0.3	0.1	0.5	0.069	0.067	0.195	0.112	-0.028
0.6	0.2	0.1	0.1	0.511	0.314	0.325	0.453	-0.021
0.2	0.6	0.1	0.1	0.245	0.225	0.391	0.338	0.087
0.2	0.1	0.6	0.1	0.088	-0.004	0.309	0.183	0.071
0.1	0.2	0.1	0.6	0.031	0.023	0.118	0.045	-0.066
0.7	0.1	0.1	0.1	0.542	0.314	0.285	0.449	-0.046
0.6	0.1	0.1	0.2	0.494	0.284	0.268	0.407	-0.059
0.7	0.025	0.025	0.25	0.503	0.285	0.196	0.377	-0.094

Appendix 5: Single and Combined Drought Indices Correlation with SPI in two Seasons

Single condition index correlations with SPI time scale of January 2008						
		SPI_1	SPI_3	SPI_6	SPI_9	SPI_12
TCI	Pearson Correlation	.364**	.334**	.430**	-.241**	-.164*
	Sig. (2-tailed)	.000	.000	.000	.001	.027
	N	181	181	181	181	181
VCI	Pearson Correlation	.064	.078	.289**	-.254**	-.231**
	Sig. (2-tailed)	.393	.296	.000	.001	.002
	N	181	181	181	181	181
PCI	Pearson Correlation	.466**	.246**	-.250**	.052	.239**
	Sig. (2-tailed)	.000	.001	.001	.489	.001
	N	181	181	181	181	181
SMCI	Pearson Correlation	.008	-.130	.334**	-.395**	-.398**
	Sig. (2-tailed)	.917	.081	.000	.000	.000
	N	181	181	181	181	181
**. Correlation is significant at the 0.01 level (2-tailed).						
*. Correlation is significant at the 0.05 level (2-tailed).						

Single condition index correlations with SPI time scale of June 2013						
		SPI_1	SPI_3	SPI_6	SPI_9	SPI_12
TCI	Pearson Correlation	.044	.210**	.229**	.081	.113
	Sig. (2-tailed)	.554	.005	.002	.276	.128
	N	181	181	181	181	181
VCI	Pearson Correlation	.201**	.175*	.136	.338**	.290**
	Sig. (2-tailed)	.007	.019	.067	.000	.000
	N	181	181	181	181	181
PCI	Pearson Correlation	.764**	.558**	.649**	.254**	.038
	Sig. (2-tailed)	.000	.000	.000	.001	.615
	N	181	181	181	181	181
SMCI	Pearson Correlation	.153*	.577**	.467**	.416**	.139
	Sig. (2-tailed)	.040	.000	.000	.000	.061
	N	181	181	181	181	181
**. Correlation is significant at the 0.01 level (2-tailed).						
*. Correlation is significant at the 0.05 level (2-tailed).						

Different VHI weight correlation with SPI of January 2008, F37 indicates 30% of TCI and 70% of VCI						
		SPI_1	SPI_3	SPI_6	SPI_9	SPI_12
F37	Pearson Correlation	.208**	.206**	.411**	-.301**	-.250**
	Sig. (2-tailed)	.005	.005	.000	.000	.001
	N	181	181	181	181	181
F28	Pearson Correlation	.160*	.164*	.375**	-.290**	-.249**
	Sig. (2-tailed)	.031	.027	.000	.000	.001
	N	181	181	181	181	181
F55	Pearson Correlation	.288**	.274**	.453**	-.302**	-.237**
	Sig. (2-tailed)	.000	.000	.000	.000	.001
	N	181	181	181	181	181
F73	Pearson Correlation	.336**	.314**	.458**	-.282**	-.209**
	Sig. (2-tailed)	.000	.000	.000	.000	.005
	N	181	181	181	181	181
F82	Pearson Correlation	.350**	.324**	.451**	-.268**	-.194**
	Sig. (2-tailed)	.000	.000	.000	.000	.009
	N	181	181	181	181	181
**. Correlation is significant at the 0.01 level (2-tailed).						
*. Correlation is significant at the 0.05 level (2-tailed).						

Different VHI weight correlation with SPI of June 2013, F37 indicates 30% of TCI and 70% of VCI						
		SPI_1	SPI_3	SPI_6	SPI_9	SPI_12
F37	Pearson Correlation	.197**	.206**	.174*	.334**	.296**
	Sig. (2-tailed)	.008	.005	.019	.000	.000
	N	181	181	181	181	181
F28	Pearson Correlation	.200**	.195**	.159*	.337**	.295**
	Sig. (2-tailed)	.007	.009	.032	.000	.000
	N	181	181	181	181	181
F55	Pearson Correlation	.185*	.232**	.208**	.314**	.288**
	Sig. (2-tailed)	.013	.002	.005	.000	.000
	N	181	181	181	181	181
F73	Pearson Correlation	.151*	.249**	.239**	.258**	.252**
	Sig. (2-tailed)	.043	.001	.001	.000	.001
	N	181	181	181	181	181
F82	Pearson Correlation	.121	.247**	.246**	.209**	.215**
	Sig. (2-tailed)	.106	.001	.001	.005	.004
	N	181	181	181	181	181
**. Correlation is significant at the 0.01 level (2-tailed).						
*. Correlation is significant at the 0.05 level (2-tailed).						

Different SDCI weight correlation with SPI of January 2008, F343 indicates 30%, 40%, and 30% of PCI, VCI, and TCI respectively						
		SPI_1	SPI_3	SPI_6	SPI_9	SPI_12
F343	Pearson Correlation	.306**	.277**	.424**	-.303**	-.225**
	Sig. (2-tailed)	.000	.000	.000	.000	.002
	N	181	181	181	181	181
F352	Pearson Correlation	.245**	.224**	.387**	-.298**	-.231**
	Sig. (2-tailed)	.001	.002	.000	.000	.002
	N	181	181	181	181	181
F433	Pearson Correlation	.353**	.310**	.423**	-.298**	-.207**
	Sig. (2-tailed)	.000	.000	.000	.000	.005
	N	181	181	181	181	181
F442	Pearson Correlation	.291**	.256**	.390**	-.299**	-.218**
	Sig. (2-tailed)	.000	.001	.000	.000	.003
	N	181	181	181	181	181
F451	Pearson Correlation	.209**	.185*	.331**	-.281**	-.216**
	Sig. (2-tailed)	.005	.013	.000	.000	.003
	N	181	181	181	181	181
F532	Pearson Correlation	.350**	.297**	.388**	-.296**	-.198**
	Sig. (2-tailed)	.000	.000	.000	.000	.007
	N	181	181	181	181	181
F541	Pearson Correlation	.258**	.216**	.326**	-.282**	-.201**
	Sig. (2-tailed)	.000	.003	.000	.000	.007
	N	181	181	181	181	181
F235	Pearson Correlation	.345**	.315**	.450**	-.290**	-.210**
	Sig. (2-tailed)	.000	.000	.000	.000	.005
	N	181	181	181	181	181
F154	Pearson Correlation	.280**	.265**	.441**	-.304**	-.238**
	Sig. (2-tailed)	.000	.000	.000	.000	.001
	N	181	181	181	181	181
F514	Pearson Correlation	.429**	.367**	.411**	-.261**	-.154*
	Sig. (2-tailed)	.000	.000	.000	.000	.038
	N	181	181	181	181	181
F622	Pearson Correlation	.425**	.346**	.376**	-.285**	-.164*
	Sig. (2-tailed)	.000	.000	.000	.000	.027
	N	181	181	181	181	181
F721	Pearson Correlation	.429**	.323**	.285**	-.265**	-.127
	Sig. (2-tailed)	.000	.000	.000	.000	.089
	N	181	181	181	181	181
F127	Pearson Correlation	.356**	.328**	.449**	-.271**	-.193**
	Sig. (2-tailed)	.000	.000	.000	.000	.009
	N	181	181	181	181	181
F262	Pearson Correlation	.210**	.199**	.383**	-.296**	-.239**
	Sig. (2-tailed)	.005	.007	.000	.000	.001
	N	181	181	181	181	181

Different SDCI weight correlation with SPI of June 2013, F343 indicates 30%, 40%, and 30% of PCI, VCI, and TCI respectively						
		SPI_1	SPI_3	SPI_6	SPI_9	SPI_12
F343	Pearson Correlation	.505**	.435**	.455**	.375**	.250**
	Sig. (2-tailed)	.000	.000	.000	.000	.001
	N	181	181	181	181	181
F352	Pearson Correlation	.482**	.401**	.412**	.384**	.261**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	181	181	181	181	181
F433	Pearson Correlation	.604**	.504**	.546**	.365**	.211**
	Sig. (2-tailed)	.000	.000	.000	.000	.004
	N	181	181	181	181	181
F442	Pearson Correlation	.580**	.471**	.501**	.382**	.231**
	Sig. (2-tailed)	.000	.000	.000	.000	.002
	N	181	181	181	181	181
F451	Pearson Correlation	.551**	.436**	.457**	.389**	.243**
	Sig. (2-tailed)	.000	.000	.000	.000	.001
	N	181	181	181	181	181
F532	Pearson Correlation	.662**	.526**	.576**	.366**	.190*
	Sig. (2-tailed)	.000	.000	.000	.000	.011
	N	181	181	181	181	181
F541	Pearson Correlation	.636**	.495**	.533**	.381**	.210**
	Sig. (2-tailed)	.000	.000	.000	.000	.005
	N	181	181	181	181	181
F235	Pearson Correlation	.415**	.409**	.428**	.336**	.246**
	Sig. (2-tailed)	.000	.000	.000	.000	.001
	N	181	181	181	181	181
F154	Pearson Correlation	.295**	.298**	.285**	.346**	.286**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	181	181	181	181	181
F514	Pearson Correlation	.672**	.561**	.634**	.298**	.125
	Sig. (2-tailed)	.000	.000	.000	.000	.093
	N	181	181	181	181	181
F622	Pearson Correlation	.716**	.560**	.627**	.336**	.143
	Sig. (2-tailed)	.000	.000	.000	.000	.056
	N	181	181	181	181	181
F721	Pearson Correlation	.741**	.562**	.633**	.330**	.125
	Sig. (2-tailed)	.000	.000	.000	.000	.093
	N	181	181	181	181	181
F127	Pearson Correlation	.267**	.341**	.355**	.257**	.219**
	Sig. (2-tailed)	.000	.000	.000	.000	.003
	N	181	181	181	181	181
F262	Pearson Correlation	.379**	.327**	.319**	.373**	.281**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	181	181	181	181	181

Appendix 6: Combined Drought Indices Correlation Table used for Validation

Combined Drought Indices Validation for January 2008 Correlations					
		VHI	SDCI	OVDI	**SPI**
VHI	Pearson Correlation	1	.986**	.998**	**.451****
	Sig. (2-tailed)		.000	.000	**.000**
	N	181	181	181	**181**
SDCI	Pearson Correlation	.986**	1	.982**	**.411****
	Sig. (2-tailed)	.000		.000	**.000**
	N	181	181	181	**181**
OVDI	Pearson Correlation	.998**	.982**	1	**.459****
	Sig. (2-tailed)	.000	.000		**.000**
	N	181	181	181	**181**
**. Correlation is significant at the 0.01 level (2-tailed).					

Combined Drought Indices Validation for June 2013 Correlations				
		VHI	SDCI	SPI
VHI	Pearson Correlation	1	.448**	**.165***
	Sig. (2-tailed)		.000	**.027**
	N	181	181	**180**
SDCI	Pearson Correlation	.448**	1	**.567****
	Sig. (2-tailed)	.000		**.000**
	N	181	181	**180**
**. Correlation is significant at the 0.01 level (2-tailed).				
*. Correlation is significant at the 0.05 level (2-tailed).				