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DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDIES

SPATIO-TEMPORAL DYNAMICS OF AGRICULTURAL DROUGHT AND SOIL ORGANIC CARBON IN THE HIGHLANDS OF ETHIOPIA

BY

ZERIHUN CHERE

NOVEMBER, 2019

ADDIS ABABA, ETHIOPIA

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A THESIS SUBMITTED TO THE DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDIES OF ADDIS ABABA UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTERS OF ARTS IN GEOGRAPHY AND ENVIRONMENTAL STUDIES (specialization in Geographic Information System, Remote Sensing and Digital Cartography)

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APPROVAL SHEET

This is to certify that the thesis prepared by Zerihun Chere entitled as Spatio-temporal Dynamics of Agricultural Drought and Soil Organic Carbon in the Highlands of Ethiopia is Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Arts in Geography and Environmental Studies (specialization in Geographic Information System, Remote Sensing and Digital Cartography) compiles with the regulations of the university and meets the accepted standards with respect to originality and quality.

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DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDIES

DECLARATION

I declare that, this thesis prepared for the partial fulfillment of the requirements for the Degree of Master of Arts in Geography and Environmental Studies (specialization in Geographic Information System, Remote Sensing and Digital Cartography) entitled "Spatio-temporal Dynamics of Agricultural Drought and Soil Organic Carbon in the Highlands of Ethiopia" is my original research work prepared independently by my own effort with the close advice and guidance of my adviser. I also declare that this thesis has not been presented in any university and all sources that I have used or quoted have been indicated and acknowledged by means of complete references.

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LIST OF ACRONOMYS

AVHRR	Advanced Very High Resolution Radiometer
EROS	United States Geological Survey's Earth Resources Observation and Science
NMA	National Meteorological Agency of Ethiopia
AFDM	African Flood and Drought Monitor
ASAP	Anomaly hot Spots of Agricultural Production
CCI LC	Climate Change Initiative Land Cover
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CMI	Crop Moisture Index
CSA	Central Statistics Agency of Ethiopia
DPPC	Disaster Prevention and Preparedness Commission
DRMFSS	Disaster Risk Management Unit of the Ministry of Agriculture
eMODIS	Enhanced Moderate Resolution Imaging Spectrometer
ENSO	El Niño-Southern Oscillation
ESA	European Space Agency
ETDI	Evapotranspiration Deficit Index
FAO	Food and Agriculture Organization of United Nations
FEWSNET	Famine Early Warning System Network
GADM	Global Administrative Areas
GDIS	Global Drought Information System
GIS	Geographical Information System
IDA	International Development Association
ITCZ	Inter Tropical Convergence Zone
LST	Land Surface Temperature
MODIS	Moderate Resolution Imaging Spectroradiometer

NADM	North American Drought Monitor
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
PDSI	Palmer Drought Severity Index
PHDI	Palmer Hydrological Drought Index
SMDI	Soil Moisture Drought Index
SPEI	Standardized Precipitation Evaporation Index
SPI	Standardized Precipitation Index
SPIRITS	Software for the Processing and Interpretation of Remotely Sensed Image Time Series
SST	Sea Surface Temperature
SWAT	Soil and Water Assessment Tool
TCI	Temperature Condition Index
TIR	Thermal Infrared
TRMM	Tropical Rainfall Measuring Mission
TVDI	Temperature Vegetation Dryness Index
UNCSD	United Nations Commission on Sustainable Development
UNOCHA	United Nations Office for the Coordination of Humanitarian Affairs
UN-WFP	United Nation World Food Program
USAID	U.S. Agency for International Development
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
VCI	Vegetation Condition Index
VHI	Vegetation Health Index
WRSI	Water Requirement Satisfaction Indices

ABSTRACT

Ranked amongst the most destructive natural disasters of the world, droughts may have severe impacts on ecosystems and society, and usually occurs from a deficiency of precipitation and water availability from normal amounts. Particularly in Ethiopia, where the economy is strongly relying on rain-fed agriculture, droughts have constantly led to widespread crop failure, food shortages and even humanitarian crises. In this favor, remote sensing data and Geographic Information System (GIS) techniques provide new opportunities for producing large information on the evolution of droughts at large spatio-temporal scales. This thesis aims to map and examine the spatio-temporal patterns of agricultural droughts and soil organic carbon stock (SOC) during 2004-2018 based on Vegetation Health Index (VHI) and Standardized Precipitation Index (SPI) at monthly time-scale in the highlands of Ethiopia. In particular, MOD11A2 Terra Land Surface Temperature and Enhanced Moderate Resolution Imaging Spectrometer Normalized Difference Vegetation Index and Climate Hazard Group Infrared Precipitation with station data (CHIRPS) monthly rainfall data were used. A simple linear regression and Pearson correlation model was applied to examine the relationship between VHI and SPI as well as to validate satellite based VHI estimation based on crop yield data. Based on the results of VHI and SPI the years 2009 and 2015 were considered as the drought years while 2006 and 2018 were taken as slight and non-drought years. The spatial analysis revealed that the central and northern highlands (Eastern, central and southern Tigray Zones, Easter Amhara Zones, East Shewa4), West and East Hararge in Oromiya and Silti and Alaba zones in Sothern Nations, Nationalities and Peoples' region were frequently struck by agricultural drought over the last 15 years. The highest agricultural drought incidence was observed in Central Tigray (18), Eastern Tigray (17), East Shewa (16), Alaba (15), Southern Tigray (14) and Wag Himra (14). The study showed strong positive correlation between VHI and SPI. There is also strong positive correlation between VHI and detrending crop yield. In this study strong positive correlation was captured between VHI and SOC stock ($R^2/P = 0.41/0.000$). VHI and SPI based analysis accurately indicates the onset, spatial, and temporal dynamics of agricultural drought in Ethiopia. This study can help to improve the existing agricultural drought monitoring systems carried out over Ethiopia in general and the study area in particular. Thus, decision makers can potentially use VHI and SPI in drought monitoring and early warning system.

Keywords: Soil Organic Carbon, Vegetation Health Index, Standardized Precipitation Index

CHAPTER 1

INTRODUCTION

1.1. Background and justification of the study

Drought is considered as a naturally occurring, slow onset and most complex disaster which is mostly related to the reduction in the amount of precipitation from the normal or expected over an extended period of time (Mutsotso et al., 2018; Mishra & Singh, 2010). Its occurrence, extent and severity is influenced by local topographic, temperatures, high winds, relative humidity, timing and characteristics of rains, including distribution of rainy days during crop growing seasons, intensity and duration of rain, and onset and termination (Mishra & Singh, 2010).

There is no universally accepted and precise definition of drought. But most drought types originate from insufficient amount of precipitation (Wilhite & Glantz, 1985). Generally, the definition of drought varies based on its functional description like hydro meteorological drought, socioeconomic factors, and the supply and demand of water are the major characteristics that create an obstacle for the lack of a precise and universal definition of drought (Mishra & Singh, 2010). A generally accepted definition of drought is that it is a naturally occurring phenomenon that exists when low precipitation is prevailing for an extended period of time, which causes serious hydrological effect that adversely affects land resource production systems (Wilhite, 2000; Mishra & Singh, 2010).

Drought can occur in any climate regime around the world. However, over the past few decades major drought events have been reported in the USA, the Horn of Africa, Australia, and Southern Europe (Damberg & AghaKouchak, 2014). In recent years, due to climate variability, population pressure, land use change and ENSO (El Nino Southern Oscillation, the frequency and severity of drought increased in space and time (Dai, 2011;Vicent, 2010). This brought a huge damage in the economic, social and environmental sectors. Drought results a complex web of impacts that touch many sectors of the economy and reach well beyond the area experiencing physical drought. It takes a high human toll in terms of hunger, poverty and the perpetuation of under-development. They are associated with widespread agricultural failures, loss of livestock, water shortages, outbreaks of epidemic diseases and land degradation (Masih et al., 2014). Several studies have showed that drought results a substantial decline in agricultural production and productivity all over the world. For example, during the periods of 2001–2012, moderate to exceptional, severe to exceptional and extreme to exceptional droughts covered about 17–35%, 7–15% and 2–6% of the total land mass of the world, respectively (Kogan et al. 2013). However, the impact of drought is different between developed and developing nations due to their response capacity and economic as well as social status (Mishra & Singh, 2010).

For instance, over Africa, drought is one of the most frequent natural disasters. Combined with high consumption and low water quality, droughts exacerbate already challenging water scarcity related issues (Mishra & Singh, 2010). As sited in many literatures, sub-Sahara African countries are the most drought affected area, since the region is experienced poor land resource management with rained agriculture based economy, ever increasing population induced degraded land, declining soil moisture and amount of rainfall. Amongst the sub-Sahara African regions, East Africa is frequently portrayed as a drought-stricken region. For instance, during the period 1995–2015, there were 334 drought events conveyed across the world resulting in more than one billion people affected and 22,000 numbers of people died. Among these 136 events (41% of the global total) were detected in Africa of which 77 droughts recorded in East Africa (UNISDR, 2015).

In Ethiopia, drought is a frequently recurring phenomenon that has remained the leading cause of disaster and human sufferings in terms of frequency, area coverage and the number of people affected. It affects many sectors, including agriculture. More than 85% of the population depends on income generated from agricultural products (Gates, 2016). However, agricultural practices in the majority of the country are traditional and dependent on annual rainfall (Gebrehiwot et al., 2011). The shortfall and mistimed periods of rainfall significantly affect the agricultural sector, resulting in crop yield reductions, food security concerns and other economic losses (Bayissa et al., 2017). Recently, this sector is highly suffered from climate variability and drought.

Although the recorded history of drought dates back to 250 BC, its frequency has increased over the past few decades and brought long-lasting impacts on natural and human lives. It is also causing in decreasing soil moisture, reducing ground water discharge and impact on the economic condition of the farming community. Since the mid of 1970s the spatial extent, magnitude, frequency and the effects of drought has been increased and it has been occurring once in less than 10 years. For instance, in 1884/5, around a million people were died, crops and livestock population were damaged (Gebrehiwot et al., 2011).

Soil is a major carbon reservoir containing more carbon than the atmosphere and terrestrial vegetation (FAO, 2017). However, because of land degradation and unsustainable land use changes, soil organic carbon (SOC) stock has become most vulnerable world-wide. The losses of SOC stocks strongly affect climate change. Climate change is also exacerbated by droughts. Climate change and droughts negatively affect crop and livestock production, and poses a major threat to food security in the highlands of Ethiopia.

However, the spatial extent and severity of drought and SOC stock are varying in the country. Particularly, in recent years, drought occurred more frequently and causing for crop failure, death of livestock and millions of people are looking for food aid in the northern and central highlands (Gebrehiwot et al., 2016). Thus, agricultural drought SOC stock assessment and monitoring are crucial to minimize the adverse impact of drought as well as for drought preparedness and mitigation plans.

Agricultural drought preparedness and mitigation can be achieved by using different drought indicators that are continuous functions of hydro- meteorological variables such as rainfall, evapotranspiration, vegetation activity, soil moisture availability (Senay et al., 2015). Agricultural drought monitoring is depending on in-situ data and remote sensing-based data. The in-situ based agricultural drought monitoring indices are the most accurate ones which obtained by ground measurements. However, their sparsely distribution may impose uncertainty in delineating spatial context of agricultural drought. In order to address the limitations of in-situ based indices remote sensing-based drought indices and GIS techniques have a paramount role.

Remote sensing and GIS-based agricultural drought monitoring has attracted interest of various scientists such as agriculturalists, hydrologists, meteorologists, and environmentalists since it provides more accurate, flexible and reliable results in drought studies. Earth observation satellites provide the unique opportunity to obtain continuous, consistent and timely information over large areas where ground observations are unreliable (Berhan et al., 2011; Hazaymeh & Hassan, 2016). Therefore, satellite observations overcome the limitations of station based meteorological observations. Similarly, satellite observation products such as eMODIS NDVI and MOD11A2 LST supported with advanced remote sensing drought indices such as Vegetation Health Index (VHI) can help to assess the incidence of agricultural droughts.

Thus, this work was undertaken to assess the frequency, magnitude and spatio-temporal patterns of agricultural drought and soil organic carbon stock in the highlands of Ethiopia using GIS and Remote sensing techniques for the period of 2004-2018.

1.2. Statement of the problem

Droughts, as climate change factors, are characterized, predominantly, by hot dry weather conditions with very low or no life supporting moisture. Today, as many parts of the world are experiencing the devastation of natural balance and obstruction of human economic activities, it is apparent that drought is posing serious challenges to the World (Turral et al., 2011). Drought-related fatalities may occur both in poor & wealthy countries. Economic and social consequences of drought can range far beyond the directly impacted areas. For instance, persistent unemployment, migration and social instability related to failures in public water supply and food insecurity (GWP and WMO, 2016).

In the 21th century, because of strong economic dependence on climate related activities and low adaptive capacity, Africa has been identified as one of the parts of the world most vulnerable to the impacts of climate change (Welborn, 2018). Due to climate change, severe and frequent drought is become one of the most important natural disasters in Sub Saharan Africa, where the majority of the poor are dependent on rainfed agriculture, with 85% deriving at least a part of their livelihood from the sector (Gautam, 2006). This sector is now among the most vulnerable of all sectors to drought. Persistent soil moisture deficits due to drought cause damage to crops and pastures (Ding et al., 2011). Crop and pastures failure results food insecurity. For instance, households’ incomes are affected, as returns to assets such as land, livestock, and human capital tend to collapse, which may lead to poverty.

Drought may also have impact on the structure, composition, and functioning of terrestrial ecosystems and can thereby severely affect the regional carbon cycle, with the potential of causing a shift from a carbon sink towards a carbon source (Molen et al., 2011). Drought affects the carbon cycle through direct concurrent impacts on plant physiology and soil microbial activity, and direct lagged impacts on the phenology of plants, reduced growth in the following year due to lower carbohydrate storage in the year of the drought, altered composition of plant species, soil microbial community structure and activity (Karmakar et al., 2016; Molen et al., 2011; Frank et al., 2015).

Ethiopia is one of the sub Saharan Africa countries that has been affected by periodic drought which causes severe damage in social, economic and environmental sectors (Gadisso, 2007). Recently, the frequency of drought has increased during the second half of the twentieth century (Viste et al., 2013). According to Block (2008), in the 1970s and 1980s, droughts occurred on average once per decade; presently, droughts are anticipated to occur about once in every three years. Moreover, from the 1980s to 2004 16 drought events have been occurred. This makes Ethiopia the most drought affected country out of 39 drought-affected countries of Africa (IDA, 2006). Major droughts occurred in 1964–1966, 1972–1974, 1982–1984, 1987–1988, 1990, 1999, 2000, 2002–2003, 2006, 2009 and 2011, 2015/16 (Degefu & Bewket, 2015; Edossa et al., 2010; OCHA, 2016). The greatest loss of life associated with drought in Ethiopia occurred in 1973, 1974 and 1984, while the greatest number of affected people was in 2002 (14.2 million affected, over 20% of the total population of the country) (Block, 2008; Viste et al., 2013; Kumar, 1987). During 1974- 1986, nationwide production of the major food crops during 1974-1975 was 38% less than during the good years of 1979-1983; and similarly during 1984-1985 it was 37% (Kiros, 1991)**.**

In the highlands of Ethiopia, particularly in the northern and central highlands, agricultural drought is currently more pronounced (Gebrehiwot et al., 2016). The area is highly sensitive for rainfall fluctuation and characterized by late beginning and early endings of the rainy seasons that results moisture deficit to support crops (Engdaw, 2014). Many farms have shifted to more drought-resistant crops in northern Ethiopia, as a consequence of the decline in rainfall during the last decades (Meze-Hausken, 2004).Therefore, agricultural drought assessment and monitoring is vital to mitigate the potential impacts of drought. One way to mitigate drought impacts relies on the provision of timely information by early warning and monitoring systems that can be used to ensure an appropriate response.

Moreover, due to its contribution to agricultural and land productivity, the maintenance of SOC is critically important both in potential climate change mitigation and in adaptation strategies. The

17 Sustainable Development Goals (SDGs) of the 2030 Agenda underlined the need to restore degraded soils, in order to increase SOC stock and achieve the five SDGs ("Zero Hunger"⊳ SDG 2; "Good Health and Well Being" ⊳ SDG 3; "Clean Water and Sanitation" ⊳ SDG 6, maintain biodiversity "Life on Land" ⊳ SDG 15; and increase ecosystem resilience in a changing climate "Climate Action" ⊳ SDG 13) (FAO, 2017). Thus, estimates of soil organic carbon (SOC) stocks in the highlands of Ethiopia is critical to develop strategies to help mitigate impacts of climate change.

Drought assessment and monitoring with conventional methods that rely on the accessibility of ground weather stations may provide a fairly good source of information. However, in sub-Saharan Africa in general, in Ethiopia in particular, the sparsity of weather stations makes drought monitoring a tedious and time consuming task (Gadisso, 2007). In addition, telecommunication problems, economic disturbances, and political and military conflicts also limit the availability of weather information (Kogan, 1997). In contrast, a growing number of Earth observation satellites provide useful data sources to monitor the changing dynamics of soil, water, and vegetation in terrestrial surface which could not be possible by conventional methods (Hazaymeh & Hassan, 2016). Today, remote sensing and GIS in agricultural drought detection, assessment and management has become crucial, mainly due to the increasing number of relevant satellite systems and their gradually improving abilities and provide up to date information in different range of spatial and temporal scales (Dalezios, 2017).

Several studies have been conducted on the assessment of agricultural drought using GIS and remote sensing techniques in Ethiopia in local, regional and country level. These studies undertaken in Ethiopia as well as in the study area were limited in their area of interest. Fore example, some of those are conducted based on SPI which is only using precipitation as an input (Degefu & Bewket, 2015; Edossa et al., 2010; Viste et al., 2013; Mohammed et al., 2018; Kenawy et al., 2016). Edossa et al. (2010) and Viste et al. (2013) assessed drought conditions for the last four decades for the Awash River Basin and the whole of Ethiopia, respectively. Results from these studies indicated that frequency and severity of drought events are common in Awash Basin and Ethiopia at both seasonal and annual time scales, and concluded that Ethiopia as a whole is particularly prone to droughts.

Moreover, Gebrehiwot et al. (2011) employed precipitation and remotely sensed data to assess spatial and temporal variability of drought in semi-arid and arid regions of Northern Ethiopia. They demonstrated that the eastern and southern areas of the Tigray region suffered from a recurrent cycle of drought over the last decade. Also, Birhanu et al. (2014) investigated drought through $DEV_{NDV,}$ VCI and rainfall in southern Tigray and reported that the northern, western and eastern parts of the study area are prone to drought. Other study in Raya and its environs during 2001 to 2015 revealed that agricultural drought occurred in a different frequency, duration and recurrence interval for the study period (Gidey et al., 2018). As a country scale, Gebrehiwot et al. (2016) examined the spatial and temporal aspect of seasonal agricultural drought from 1998 to 2013 based on Vegetation Condition Index (VCI) derived from SPOT-VGT S10 NDVI and found that 2002 and 2009 were drought years. Besides, a number of studies have been done to estimate SOC stocks based on information derived from different global soil maps and soil organic carbon (SOC) concentration and other attributes (Post et al., 1982; Eswaran et al., 1993; Sombroek et al., 1993; Batjes, 1996).

However, these studies mainly produced from SPOT VGT S10 NDVI data with 1km spatial resolution and precipitation data that derived from weather stations which mainly sparse in distribution and incomplete data record. Furthermore, recently, due to global warming the role of temperature in drought monitoring become crucial and only using the above explained indices is not quite enough to fully characterization of agricultural drought. And in Ethiopia use of intensive drought assessment tool for regional and country scale study is infrequent. Due to this reason, it is very difficult to fully characterize agricultural drought conditions. And also, no studies conducted on the relationship between soil organic carbon stock and VHI in the study area. Mapping spatial distribution of the SOC stock using remote sensing and GIS is considered very essential for regional planning and management (Mondal et al., 2016; Piccini et al., 2014). Mapped spatial distribution of SOC stock can serve as communication tools to initiate discussions with stakeholders; supports decision makers for relevant policy measures to spatially identify priority areas for planning and management of SOC stocks (World Bank, 2012).

In order to fill this gap, this thesis applied CHIRPS rainfall data with 5.5 km spatial resolution and Vegetation Health Index (VHI) which is based on relative changes in the NDVI and land surface temperature with 250m and 1km spatial resolution respectively and the relationship between VHI and SOC stock with the objectives of mapping and analyzing the spatio-temporal patterns of agricultural drought and soil organic carbon in the highlands of Ethiopia.

1.3. Objective of the study

1.3.1. General objective

The main objective of this study was to map and analyze the spatio-temporal patterns of agricultural drought and soil organic carbon stock in the highlands of Ethiopia using remote sensing and GIS techniques.

1.3.2. Specific objectives

Based on the above stated general objective, the following specific objectives are formulated.

- ✓ To evaluate the relationship between LST and NDVI across the study area
- ✓ To explore spatio-temporal patterns of agricultural drought
- ✓ To examine magnitude and frequency of agricultural drought
- ✓ To examine the relationship between crop yield and VHI in the study area
- ✓ To evaluate the status of spatial pattern/land use of soil organic carbon stock and its relationship with VHI

1.4. Research questions

Therefore, in order to achieve the above objectives, the study attempted to answer the following research questions:

- What is the relationship between LST and NDVI across the study area
- How is the spatial and temporal patterns of agricultural drought condition during the growing seasons from 2004 to 2018?
- How is the magnitude and frequency of agricultural drought in the highlands of Ethiopia?
- what is the relationship VHI with crop yield?
- Whatis the status of the spatial distributio/land use of soil organic carbon stock and its relationship with VHI

1.5. Significance of the study

Agricultural drought assessment and identification of drought affected areas have been used to design strategies and decisions for reducing the adverse impacts of agricultural drought. To do so, the use of Remote Sensing data and Geographical Information System can effectively facilitate and quantify the detection, identification and mapping of agricultural drought prone areas to enhance decision making process for drought monitoring and mitigation actions. This study has focused on assessment of agricultural drought in terms of intensity, duration and spatial extents in the highlands of Ethiopia. This research offers the opportunity to use different agricultural drought monitoring indices (VHI and SPI), with improved efficiency in spatial and temporal resolutions, to determine the intensity, magnitude and spatial extent of agricultural drought and its effects on crop production.

Basically, this study provides relevant information to policy makers on drought affected areas, which is vibrant for decision making and implementation of localized programs that aim to reduce food insecurity in the affected areas. In addition, it can be helpful for development agents and Non-Governmental Organizations (NGO) to facilitate scaling up of the best techniques with success stories to similar drought prone area to another place. The study also helpful for local farming communities with basic knowledge and awareness that can empower and enable them to make competitive and constructive efforts towards adapt and mitigate drought threats through effective management of their cultivated land and water resources. It also serves as a starting point for further study on agricultural drought.

1.6. The scope of the study

This study has spatial, temporal, methodological and conceptual scopes. Geographically, the scope of the study is focused on the crop growing areas of Ethiopian highlands from 1500-2800m above sea level, which has high potential for crop growing and has become more vulnerable for recurrent drought. This region also hosts over 60% of the human and livestock population of Ethiopia. Methodologically, the study has incorporated satellite-based drought indices such Normalized Vegetation Index (NDVI), Land Surface Temperature (LST), Vegetation Condition Index (VCI), Temperature Condition Index (TCI) and Vegetation Health Index (VHI) from remotely sensed eMODIS NDVI and MOD11A2 and SPI from CHIRPS precipitation data and stock of soil organic carbon. Temporally, the study is also limited to 15 years (2004 – 2018) for Kiremt season (June to September) which is considered as the main rainy season in which about 85% to 95% of the food crops of the country are produced. Due to data management issue the temporal coverage of the study is limited to 15 years.

1.7. Limitations of the study

One of the limitations of the study was lack of historical record of drought, population and livestock data affected by the existed drought from the zones. The other limitation of this study was unavailability of crop yield data for some zones and also the crop yield data were for fifteen years only, and three years out of fifteen years were missing for all zones. The missing data have profound impact on detrending crop yield data. Furthermore, using zone level crop yield may affect the result of this study due to its coarse spatial resolution. Though CHIRPS have a consistently good agreement with ground rainfall at different spatio-temporal scales in Ethiopia, it includes uncertainties that lead to errors in rainfall estimates. For Ethiopia, uncertainties are Potential and limitations mainly related to areas with complex topography (Dinku et al., 2007). Further, calculations of VHI are based on NDVI as an index for vegetation vigor. However, NDVI holds certain limitation. Nevertheless, this study provides valuable information and insight that can be of great importance for the relevant information regarding drought assessment.

1.8. Organization of the study

This thesis is organized into five chapters. The second chapter deals with review of literature which contains a brief description of theoretical basis and some previous works relevant to the present research. The third chapter is devoted to brief description of the study area and a thorough explanation of the methodologies employed for data collection and analysis. Chapter four deals with the results and discussion and finally chapter five present conclusion and recommendations of the study.

CHAPTER 2

LITERATURE REVIEW

2.1. Concept and types of drought

2.1.1. Definition of drought

Professed as a natural occurring phenomenon, droughts are characterized as an extreme climate feature aggravated by below-normal precipitation during a period of several months to years (Mishra & Singh, 2010). Specifically, no single universally accepted definition of drought exist that works everywhere. This is due to the concept and definition of drought is spatially variant and context dependent. Because drought affects so many environmental, economic and social sectors, and occurs with varying frequency, duration and severity in all regions of the globe; in all types of economic systems, and in developed and less developed countries, many definitions have been developed by a variety of disciplines (Dai, 2011b; Mishra & Singh, 2010; Wilhite &Glantz, 1985).

Generally, the definitions of drought might be categorized as either conceptual or operational. Conceptual definitions are stated in general term to identify the boundaries and help the public to understand the concept of drought, whereas operational definitions try to identify the onset, severity, and termination of drought episodes (Mishra & Singh, 2010; Wilhite & Glantz, 1987). An operational definition, for example, would be one that compares daily precipitation values to evapotranspiration (ET) rates to determine the rate of soil moisture depletion, and expresses these relationships in standings of drought effects on plant behavior at numerous stages of crop development. In addition, operational definitions can also be used to analyze drought frequency, severity, spatial characteristics, and duration for a given historical period (Wilhite & Glantz, 1987).

As an example of conceptual definition, drought is an insidious natural hazard that results from a deficiency of precipitation lower levels of precipitations than what is considered normal and those consequences in a water deficiency for some activities or some group (WMO, 2012). The National Meteorological Service Agency of Ethiopia (2017) defines drought as a general deficit of moisture below the norm and is explained in its three variants: meteorological (deviation of precipitation below the normal), hydrological (deviation of surface and underground water volumes below the normal) and agricultural (variation of soil moisture for crop and pasture development below the normal). Farmers of Ethiopia define drought as the failure of rain for crop growing and any rain coming at the wrong time (Mekuriaw, 2006).

Although drought has many definitions, it can be best characterized as a period of abnormally dry weather for a sufficiently long period due to lack of precipitation that causes a serious hydrological imbalance and has implications of a moisture deficiency for environmental functions and human activities.

2.1.2. Types of drought

Regarding the operational definition, drought generally classified in to meteorological, hydrological, agricultural, and socio-economic (Wilhite &Glantz, 1985; WMO, 2002). The first three focuses on measuring drought as a physical phenomena while socioeconomic drought deals with drought in terms of supply and demand as a result of deficiency of rainfall.

2.1.2.1. Meteorological drought

Meteorological drought is a region specific natural event that defined on the basis of the degree of dryness in comparison to some normal or average amount and the duration of the dry period (WMO, 2006b). According to Wilhite &Glantz (1985) meteorological drought is context dependent, and varies across different climatic region. As example, drought for United States is when rainfall value less than 2.5mm in 48hours while for Libya, annual rainfall less than 180mm is the threshold.

2.1.2.2. Agricultural drought

Agriculture is usually the primary economic sector to be affected by drought. Agricultural drought links various characteristics of meteorological drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, and soil water deficits. Therefore, prevailing weather conditions, biological characteristics of the specific plant, its stage of growth, and the physical and biological properties of the soil determine plant’s demand for water. Consequently, definition of agricultural drought should account for the variable susceptibility of crops at different stages of crop development (Oliver, 2008). Agricultural drought mainly measured by the effects of water deficit in terms of economic losses to such as drop in crop production, livestock deaths, industrial losses, plants not planted or replanted, changes in land use, emergency relief expenses (WMO, 2006b). Agricultural drought therefore, occur when soil moisture is not enough or support plant growth due to meteorological and hydrological drought.

2.1.2.3. Hydrological drought

Hydrological drought is normally defined by deficiencies in surface and subsurface water supplies relative to average conditions at various points in time through the seasons. Such like agricultural drought, there is no direct relationship between precipitation amounts and the status of surface and subsurface water supplies because these hydrological system components are used for different purposes. It is inevitable that there is time lag between departures of precipitation and the point at which these deficiencies become evident in surface and subsurface components of the hydrologic system (WMO, 2006a).

2.1.2.4. Socio- economic drought

Socioeconomic drought significantly differs from the other types of drought because it associates the supply and demand of some economic good or services such as water, livestock forage, or hydroelectric power with elements of meteorological, agricultural, and hydrological drought. Supply fluctuates annually as a function of precipitation or water availability. Demand also fluctuates and is often associated with a positive trend as a result of increasing population, development and other factors (ISDR, 2007; Wilhite & Pulwarty, 2014).

To see the relationships among four types of drought, a conceptual model suggested by Wilhte (2000) is taken as a conceptual framework. In this model, weather and climatic variations of the atmosphere cause meteorological drought. This influences the amount of water available in the soil and leads to the depletion of surface water and runoff from lakes, rivers, and reservoirs for generation of power and other uses. An overview of those drought types and their order of occurrence is displayed in Figure 1.

As portrayed Figure 1, meteorological drought occurs more frequently than agricultural, hydrological and socio-economic drought because impacts in these sectors (the later three) are associated to the accessibility of surface and subsurface water supplies. It generally takes more than a few weeks before precipitation shortages begin to produce soil moisture deficiencies leading to stress on crops, pastures, and rangeland.

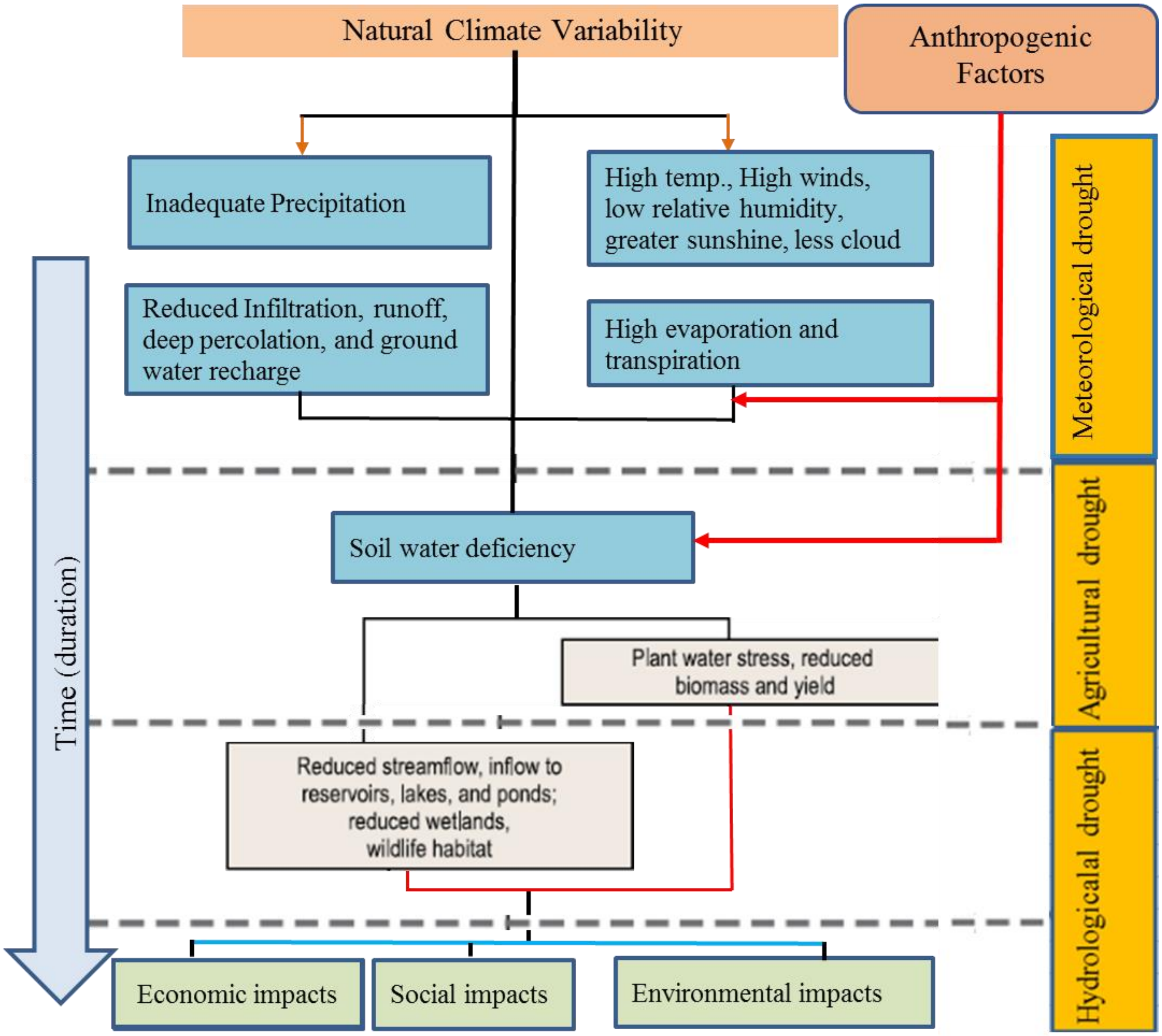


Figure 1. Relationship between meteorological, agricultural, hydrological and socio-economic drought Source: Wilhite, (2000)

Continued dry conditions for several months at a time bring about a decline in streamflow and reduced reservoir and lake levels and, potentially, a lowering of the groundwater table. When drought conditions continue for a period of time, agricultural, hydrological and socio economic drought occur, producing associated impacts (ISDR, 2007).

2.2. Cause of drought

The causes of drought in Eastern Africa are diverse in nature, as this region is characterized by different geographical factors, regional oceanic circulations and coastal influences (Lyon, 2014). In eastern Africa, El Nino Southern Oscillation (ENSO), abnormal sea surface temperature patterns in areas other than the equatorial eastern Pacific, soil moisture desiccation, as well as nonlinear behavior of the climate system are identified as potential causes of drought (Masih et al., 2014). It is also suggested that climate is changing and that droughts are becoming more frequent and/or more severe (Dai, 2011). Moreover, Zeng (2003) identified atmospheric circulation changes triggered by multidecadal variations in global sea surface temperature and anthropogenic factors as the major causes drought in Sahel region.

2.2.1. Climate variability

Drought is a part of natural climatic variability on the African continent, which is quite high at intra-annual, inter-annual, decadal and century timescales (Masih et al., 2014). One of the main driving forces of drought in eastern Africa is the high seasonal and interannual variability of the climate system (Haile, 2005). The complexity and variability of the El Niño–Southern Oscillation (ENSO), SSTs and land-atmosphere feedbacks are closely related to the occurrence of drought in East Africa (Masih et al., 2014). The climate of East Africa is associated with climate dynamics in the Indian Ocean and the Inter-tropical Convergence Zone (ITCZ) exacerbated by local complex topographies (Tierney et al., 2013).

El Nino is an abnormal warming of surface ocean waters in the eastern tropical Pacific and is one part of what is called the Southern Oscillation. The Southern Oscillation is the oscillate pattern of withdrawing surface air pressure between the eastern and western tropical Pacific (Karamouz & Nazif, 2012). Cold and warm ENSO events affect both seasonal weather of adjacent regions in the equatorial Pacific and precipitation and temperature variability across the globe. Therefore, in Africa, ENSO and SSTs are regarded major influencing factors for drought (Masih et al., 2014). For instance, from 1986 to 2013, nine El Nino events had occurred (FAO, 2014).

2.2.2. Anthropogenic factors

Beyond the influence of climate variability, anthropogenic effects on the environment have also change drought patterns under conditions of growing population (Masih et al., 2014). These effects include land use change, land degradation, deforestation, firing and mining. Moreover, human activities such as the expansion of cultivation and grazing lands, overexploitation of water resources, new settlements and urbanization have an impact on droughts (Masih et al., 2014). In addition, studies have reported that global warming is mainly attributed to human activities (Loon, 2015; Masih et al., 2014; Zeng, 2003).

2.3. Drought in Ethiopia

Drought is a normal part of climate phenomenon in almost every parts of the world, but it has serious economic, environmental, and social impacts which affect more people than any other natural hazard, especially in Africa where majority of the population depend on rainfed agriculture (Edossa et al., 2014). Ethiopia is among the African countries which frequently exposed to extreme drought and famine. For instance, in the past nine centuries there were about 30 major drought episodes. Of these drought episodes 13 of them are known to have covered the entire nation and they were reported as severe (Gebrehiwot et al., 2011). An overview of droughts and related famine in Ethiopia is provided in Table 1.

Table 1. Major drought years and region affected in Ethiopia for the period 1970–2018

Year	Region	Impacts
1971-73	Tigray and Wollo	Death of about 200,000 people and 30% of livestock population in the area
1975-76	Wello & Tigray	2-3 million people were affected
1978-79	Southern Ethiopia	1.4 4-5 million people were affected
1982	Northern Ethiopia	Morethan 2 million people were affected
1983-84	All regions	8 million people affected, 1 million people died
1987-88	All regions	7 million people were affected
1991-92	Most part of Ethiopia	4 million people were affected
1993-94	Tigray and Wollo	7.6 million people were affected

1999-00	Most part of Ethiopia	10.5 million people were affected
2002-03	Most part of Ethiopia	More than 15 million people were affected; 1.4 million livestock died
2004-05	Most part of Ethiopia	More than 13 million people were affected
2006	Borena	About 7.4 million people affected; 247,000 livestock died
2008	Borena	About 26,000 livestock died
2008-09	All regions	About 5 million people were affected
2011	South, southeastern, & eastern Ethiopia	About 4.5 million were affected
2015-16	Northern, Southern and Eastern Ethiopia	About 10.2 million people were affected

Sources: Compiled from Degefu (1987), Webb et al. (1992, Meze-Hausken (2000), FAO (2003), Segele and Lamb (2005), Amsalu and Adem (2009), Deressa et al. (2010), Mekuriaw (2006), Viste et al. (2013), Gebrehiwot et al. (2011, 2016), Degefu and Bewket, (2015) and OCHA (2016)

Even though, the history of drought in Ethiopia goes back to 250 BC and there had been many national and localized droughts even before that of the 1970s for which were managed mainly by communities' own coping mechanisms. However, the magnitude, frequency and the effects of the droughts have increased since mid-1970s (DPPC, 2004).

2.4. Impacts of drought

Through human existence drought has been a threat to the survival of societies. It has often been a trigger for massive human famines, migrations, and resettlements altering the course of history itself. Its impact is diverse on the environment and plagues all societies at different levels of development (Wilhite & Vanyarkho, 2000). Impacts of drought can be classified as direct such as reduced crop, range land, and forest productivity and indirect (Dalezios, 2017). The same author stated that the consequences of direct impacts are considered as indirect impacts. For instance, a reduction in crop, range land, and forest productivity may result in reduced income for farmers, increased prices for food and timber and unemployment (Dalezios, 2017).

Based on the affected sector, the impacts of drought are commonly classified as economic, environmental, and social (Belal & El-ramady, 2012). Many economic impacts occur in broad agricultural and agriculturally related sectors, including forestry and fisheries (Belal & El-ramady, 2012). The impact of drought to environment is seen as damages to flora and fauna including different species, wildlife habitat, forests; degradation of landscape quality, loss of biodiversity, and soil erosion (UNCSD, 2008). Social impacts mostly encompass public safety, health, conflicts between water users, reduced quality of life, and injustices in the distribution of impacts and disaster relief. Several economic and environmental impacts have also social dimensions (Belal & El-ramady, 2012).

Large parts of Ethiopia are prone to drought, making it one of the most chronically vulnerable countries in the world to food insecurity and famine. Particularly, the central and northern highlands are mainly prone to drought and food crisis events (Gebrehiwot, Veen, & Maathuis, 2016; Gebrehiwot et al., 2011). More recently, a severe drought in Ethiopia in 2015/16 resulted in more than 10.2 million people are food insecure in December 2015 (OCHA, 2016).

2.5. Role of Remote sensing and GIS in drought studies

Monitoring drought based on conventional methods is difficult due to large area coverage of drought. On the other hand, timely information about the onset, extent, duration, and impacts can limit drought-related losses of life and reduce damage to the economy and environment (Wilhite, 1993). Though, weather data is a fairly good source of information that can be used for drought assessment, the sparsity of weather stations in some areas (e.g., sub-Saharan Africa) with incomplete data for the few available weather stations could not enable timely drought detection and impact assessment (Gadisso, 2007). However, recently, most of these problems are removed by using satellite that provide permanent data archive, cost effectiveness, and a regular, repetitive view of nearly all of the earth’s surfaces (Kogan, 1997).

According to Gadisso (2007) the detection, monitoring and mitigation of drought require consistent gathering of rapid and relevant information that cannot be effectively done by conventional methods. As has been evidenced across many parts of the world, remote sensing and Geographical Information System techniques are increasingly being regarded as the most useful drought detection techniques (Chopra, 2006). In the late 1980s, drought detection, monitoring and impact assessment were applied by using satellite data in order to minimize the effects of drought in agriculture (Kogan, 1997). As indicated by Kogan (2001), use of environmental satellite can help to detected drought for 4–6 weeks earlier than before and outlined more accurately.

On the other hand, Geographic Information Systems (GIS) in drought preparedness and management operations provides integrated data storage and data retrieval capabilities, encourages a more systematic approach to data collection, increases comparability and compatibility of diverse data sets and makes data accessible to a wider range of decision makers and encourages the spatial analysis of the impacts of drought (Eshetie et al., 2016).

2.6. Operational drought information platforms

For the sake of provide broad-scale information on droughts for the public, various drought-related data and information platforms emerged both at regional and global level. Today, there are four major regional/continental models, which are developed, are the North American Drought Monitor (NADM), which consists of USDM, Canada and Mexico, the European Drought Observatory (EDO) model, the African Drought Monitor (ADM) and the Australian Drought Monitor model (Dalezios, 2018).

For example, Famine Early Warning Systems Network (FEWS NET) is drought detection and early warning platform that combines rainfall, vegetation index-based indicators such as the SPI and NDVI (Senay et al., 2015). In recent years, Global Integrated Drought Monitoring and Prediction System (GIDMaPS) was developed to provide meteorological and agricultural drought information based on multiple satellite and model-based precipitation and soil moisture data sets (Hao et al, 2014). Global Agricultural Drought Monitoring and Forecasting System (GADMFS) is a more recent platform which was presented by Deng et al. (2011) based on the NDVI-based agricultural drought indicators, soil moisture, land cover type, weather data for agricultural drought. In the case of Africa, African Flood and Drought Monitor (AFDM) web-based platform that developed by Princeton University, provide most consistent and comprehensive drought information. AFDM monitors and forecasts meteorological, agricultural and hydrological drought at various temporal and spatial scales (Sheffield, 2014).

In Ethiopia, the LEAP model was developed by combined efforts of the Ethiopian Government Disaster Risk Management Unit of the Ministry of Agriculture (DRMFSS), the National Meteorological Agency (NMA) with the support of United Nation World Food Program (UN-WFP) (Hoefsloot, 2012). The model source is the water balance model developed by the Food and Agricultural Organization (FAO) with 0.1 x 0.1 degree spatial resolution and 10 day temporal resolution.

2.7. GIS & Remote sensing-based drought monitoring studies over Ethiopia

Regarding regional and local drought monitoring, several remote sensing and GIS based studies have been conducted in Ethiopia. For instance, Birhanu et al. (2014) investigated drought through $DEV_{NDV,}$ VCI and Rainfall southern Tigray and reported that the northern, western and eastern parts of the study areas have low rainfall distribution and NDVI during farming season. Other study in Raya and its environs examined agricultural drought by means of VHI and rainfall during 2001 to 2015. The study revealed that agricultural drought occurred in a different frequency, duration and recurrence interval for the study period (Gidey et al., 2018). Furthermore, Gebrehiwot et al., (2011) evaluated drought through SPI and VCI in Tigray regional state. The study indicate that the eastern and southern zones of Tigray are most likely to suffer from drought. Degefu & Bewket (2015) explore trends and spatial patterns of drought incidence in the Omo-Ghibe river basin by means of SPI. The study revealed that the frequency and magnitude become critical and there is a need for local-scale planning for drought management and response. The same technique or SPI was applied to study trends and spatial patterns of eastern Amhara highlands (Mohammed et al, 2018).

As a country scale, Gebrehiwot et al. (2016) examined the spatial and temporal aspect of seasonal agricultural drought in Ethiopia during the cropping season from 1998 to 2013 based on Vegetation Condition Index (VCI) derived from SPOT-VGT S10 NDVI. Based on the study central and northern highlands of Ethiopia were identified as the most drought prone areas. Furthermore, A study conducted out by Viste et al. (2013) showed 2009 as a year of extraordinary large-scale drought in Ethiopia based on a SPI time series (1972-2011). This thesis particularly focused on spatio-temporal patterns of agricultural drought and soil organic carbon based on GIS and remote sensing techniques.

2.8. Drought indices

Drought indices can be used to quantify the moisture condition of a region and thereby detect the onset, strength, duration, and spatial extent of drought events based on meteorological, pedological, hydrological and vegetation-related parameters(GWP &WMO, 2016). With the aim of drought identification and the given constraints of slow onset, gradual recovery as well as the existence of different drought categories and several influenced sectors, multiple indices have been developed (GWP &WMO, 2016). Selected meteorological, soil moisture (agricultural), hydrological drought and remote sensing based drought indices area presented in the following sections.

2.8.1. Meteorological drought indices

Meteorological drought indicators use precipitation (rain and snow) data to determine meteorological droughts. A challenge for all indicators based on precipitation is the high variety in temporal and spatial distribution of precipitation (Wanders et al., 2010). Though, there are several meteorological drought indices, the most widely used drought indices are Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI) and Standardized Precipitation Evaporation Index.

The Palmer Drought Severity Index (PDSI) one of the most widely used index, was developed by Palmer (1965) based on the supply and demand concept of the water balance equation. The PDSI takes into account precipitation, evapotranspiration, and soil moisture. The objective of this equation is to measure the departure of moisture supply for normal condition at specific location. Another recently developed index is the Standardized Precipitation Evapotranspiration Index (SPEI) wich was developed by Vicente-Serrano et al. (2009) with the intention of defining a drought index that would be sensitive to climate change. The SPEI incorporate the sensitivity of PDSI to changes in evaporation demand and with the simplicity of calculation and the multi-temporal nature of the SPI (Sergio et al., 2010).

Standardized Precipitation Index (SPI) is the most widely applied meteorological index, which is utilized in this thesis. It was developed by (Mckee et all., 1993). It was designed to quantify the precipitation deficit for multiple time scales. The time scales imply the impact of drought on the availability of different water resources (WMO, 2012). The SPI can be computed on seasonal scales and, thus, used in order to quantify agricultural drought. The negative and positive value of the index indicate drought and wet conditions respectively. The relative simplicity of the SPI is one strong advantage of the index (Guttman, 1998).

Computation of the SPI involves fitting a gamma probability density function to a given frequency distribution of precipitation totals of a station. The alpha and beta parameters of the gamma probability density function are estimated for each station and for each time scale of interest (3-, 6-, 12-, 24-, 48-months, etc.). The resulting parameters are then used to find the cumulative probability of an observed precipitation event for the given month and time scale for the station in question. The cumulative probability is transformed to the standard normal random variable Z with a mean of zero and variance of one, which is the value of the SPI. Gamma distribution functions are most often found to fit the precipitation data well because the distribution of rainfall totals is not normally distributed. The computation of SPI is presented in chapter three (methodology part, see section 3.5.6).

2.8.2. Soil moisture (agricultural) drought indices

Approaches to characterize agricultural drought mainly involve monitoring of soil water balance and the subsequent deficit when drought occurs. This applies to several non-remote-sensing agricultural drought indices, Palmer Drought Severity Index (PSDI) uses precipitation and temperature (Palmer, 1965), Crop Moisture Index (CMI) incorporates soil moisture, precipitation and temperature (Palmer, 1968), Crop Specific Drought Index (CSDI) employs temperature, precipitation, evapotranspiration information, originally designed for corn and its variant for soybean (Meyer et al., 1993), and Soil Moisture Drought Index (SMDI) and Evapotranspiration Deficit Index (ETDI) which incorporate soil moisture and evapotranspiration values simulated by the Soil and Water Assessment Tool (SWAT) (Narasimhan & Srinivasan, 2005). In addition, remotely sensed vegetation indices, such as NDVI (Sruthi & Aslam, 2015), Temperature Vegetation Dryness Index (TVDI) (Chen et al., 2011), Vegetation Drought Response Index (VegDRI) (Brown et al., 2008) and Temperature Condition Index (TCI) Vegetation Condition Index and Vegetation Health Index (Kogan, 1995) are also used to monitor general vegetation state and health.

2.8.3. Hydrological drought indices

Indices for hydrological drought are based on parameters describing the bulk water supply such as water levels in streams and lakes, reservoir storage, groundwater levels and snowpack. They aim to provide a comprehensive picture of delayed hydrological drought impacts. Generally, discharge or stream flow is the most prominent variable for indicating hydrological drought (Zargar et al., 2011). Some of the commonly used hydrological drought indices are Palmer Hydrological Drought Index (PHDI) which incorporate precipitation, temperature and available water content (Palmer, 1965), Surface Water Supply Index (SWSI) which employed precipitation, reservoir, snowpack and streamflow (Shafer & Dezman, 1982).

2.8.4. Remote sensing-based drought indices

Drought assessment based on remote sensing data and methods is growing rapidly, mainly due to the increasing number of relevant satellite systems and their gradually improving capabilities (Kogan, 2001). It is stated that remote sensing data and methods can delineate the spatial and temporal variability of several drought features in quantitative terms. (Dalezios, 2017). Most of remote sensing based drought indices rely on the difference between the absorption of radiation in the visible red (RED) spectral domain, indicating chlorophyll density, and the reflectance in the near infrared (NIR) electromagnetic spectrum (Anyamba & Tucker, 2012). NDVI was suggested by Tucker (1979) as an index of vegetation health. It is described as the most prominent remote sensing-based vegetation index, which subsequently has given rise to numerous NDVI-based and refined indices for drought monitoring. NDVI is the difference between reflected R and NIR radiation divided by their sum. The NDVI is computed as:

$$NDVI = (NIR-RED) / (NIR+RED) \tag{2.6}$$

where RED and NIR are the spectral reflectance measurements in the red and near-infrared regions of the electromagnetic spectrum respectively. The NDVI values range from -1 to +1.

Consequently, NDVI has been widely used to monitor ecosystem dynamics, crop yield assessment and to detect the spatial extent of drought episodes and their impact (Ahmed, 2016; Yengoh et al., 2014). However, the spatial and temporal variability of NDVI values is closely related to the contribution of geographical resources to the amount of vegetation. This contribution fluctuates considerably depending mainly on climate, soils, vegetation type and topography of an area (Sing et al., 2003). NDVI cannot detect weather-related fluctuations (Kogan, 1990). However, Kogan (1990) proposed VCI to separate short-term weather dynamics from the long-term ecological signal for drought monitoring.

Furthermore, remotely sensed surface temperature, which is derived from thermal channels of various satellite instruments, can successfully contribute to the quantification of drought conditions. For this purpose, Land Surface Temperature (LST) is computed from bands representing the thermal infrared (TIR) spectrum. Prominent indicators based on TIR data are the Temperature Condition Index (TCI) and the Vegetation Health Index (VHI) (AghaKouchak et al., 2015; Karnieli et al., 2010). Land surface temperature is a good indicator of the energy balance at the earth's surface because it is one of the key parameters in the physics of land surface process on regional and global scales (Parviz, 2016).Kogan (1995) proposed another index, the Vegetation Health Index (VHI), which is an additive combination of VCI and TCI. VHI is a widely used remote sensing-based drought index designed as the weighted sum of two components, the Vegetation Condition Index (VCI) and the Thermal Condition Index (TCI). The computation of VCI, TCI and VHI are presented in chapter three (methodology part, see section 3.4).

2.9. Overview of soil organic carbon

Soil organic carbon is the content of carbon in soils as a result of decaying remains of living organisms such as plants, animals and microorganism in various stages (Mengesha et al., 2017). Soil organic carbon (SOC) is the essential nutrient for plant growth (Batjes, 1996) and it helps particle aggregation and porosity promoting soil structure, increases water storage capacity and availability for plants, protects soil from erosion and provides a habitat for soil biota (Rossel et al., 2016). Moreover, soil organic carbon is the part of the much larger global carbon cycle (FAO, 2017). As stated by FAO and ITPS (2015) the SOC pool stores an estimated 1 500 PgC in the first meter of soil, which is more carbon than is contained in the atmosphere (roughly 800 PgC) and terrestrial vegetation (500 PgC) combined.

According to Govers et al. (2013), the global distribution of soil organic carbon is spatially uneven and for instance, it is high in forest areas and relatively low in cropland areas. The reservoir of soil organic carbon is dynamic, and is constantly cycling between different carbon pools of soil, vegetation, ocean and the atmosphere (FAO, 2017). Soils can store large amounts of soil organic carbon when decomposition rates are very low (as in peatlands) or when primary productivity is high (as in tropical rainforests). Low soil organic carbon densities such as those in shrublands and croplands are explained by a low C input rate due to low primary productivity or the removal of plant organic matter at harvest and a high soil organic matter decomposition rate due to a warm climate or soil disturbance or a combination of both (Govers et al., 2013).

Therefore, the magnitude of the soil organic carbon stock is spatially and temporally variable and determined by soil characteristics (for example texture, pH and drainage conditions), environmental factors (for example parent material, climate, vegetation, topo-graphic position and time), and human activities (for example land management and land-use change) (FAO, 2017).

One of the main monitoring factors for soil organic carbon stock changes is land use. In a global meta-analysis (Guo and Gifford, 2002) land use change from cropland to grassland or forest resulted in increased soil organic carbon stock. It is well documented that historical agricultural activity, compared to natural land, has depleted soil organic carbon stock levels (Assefa et al., 2017). According to Toru and Kibret (2019) the highest carbon stock content in forest area might be due to the frequent addition of litter, the presence of network of roots, and modified microclimate, which retard decomposition rate of organic matter and the lowest organic carbon stock in cultivated land might be because of repeated cultivation before sowing, burning of crop residues during land preparation or removal of crop residues and loss of soil structure by continues mono cropping.

2.10. Conceptual framework

Conceptual framework depicts that diagrammatic representation of agricultural drought. The conceptual framework indicates that the cause of agricultural drought, its effect and monitoring mechanisms. As shown in the framework, agricultural drought is originated from short-term precipitation shortage that reduces soil moisture levels and temperature increasing that causes increase in evapotranspiration levels above water supply that adversely affect the economy and reducing food supplies. Hence agricultural drought adversely affects the agricultural production, monitoring agricultural drought helps to avoid drought related crises as well as food insecurity issues.

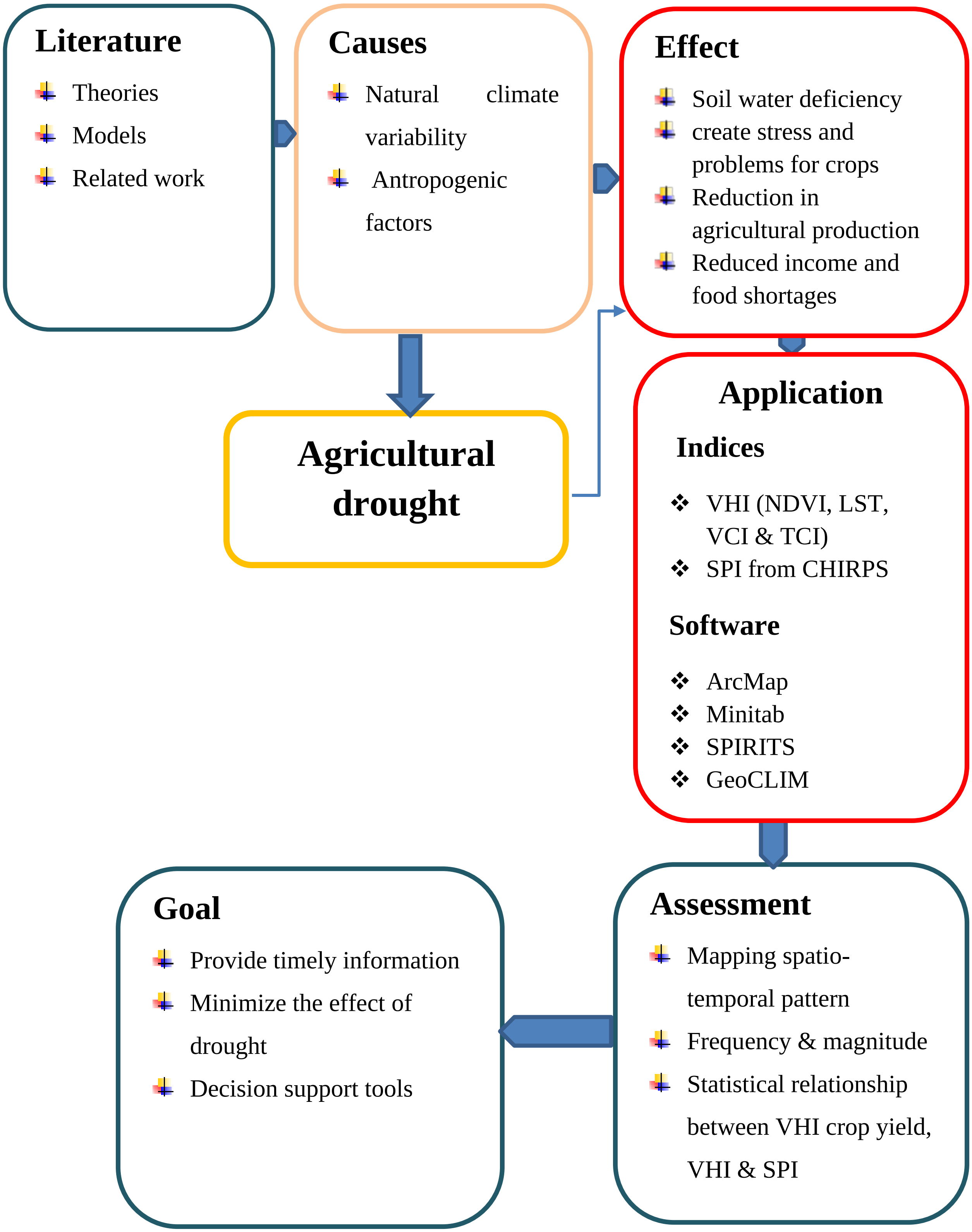


Figure 2. Conceptual framework (Source: own Survey)

CHAPTER 3

MATERIALS AND METHODS

3.1. Description of study area

3.1.1. Location and topography

Ethiopia is a land-locked country in the Horn of Africa. It shares borders to the east and southeast with Djibouti and Somalia, to the north with Eritrea, to the south with Kenya, and to the west with the Sudan and Southern Sudan. Geographically, it lies between 3°24' N and 14° 53' N, and 33° E and 48° E. The extension of the country is approximately 1270 kilometer in the direction north-south, and approximately 1650 kilometer in the direction west-east with area of 1,104,300 km^2 (Friis, 2010).

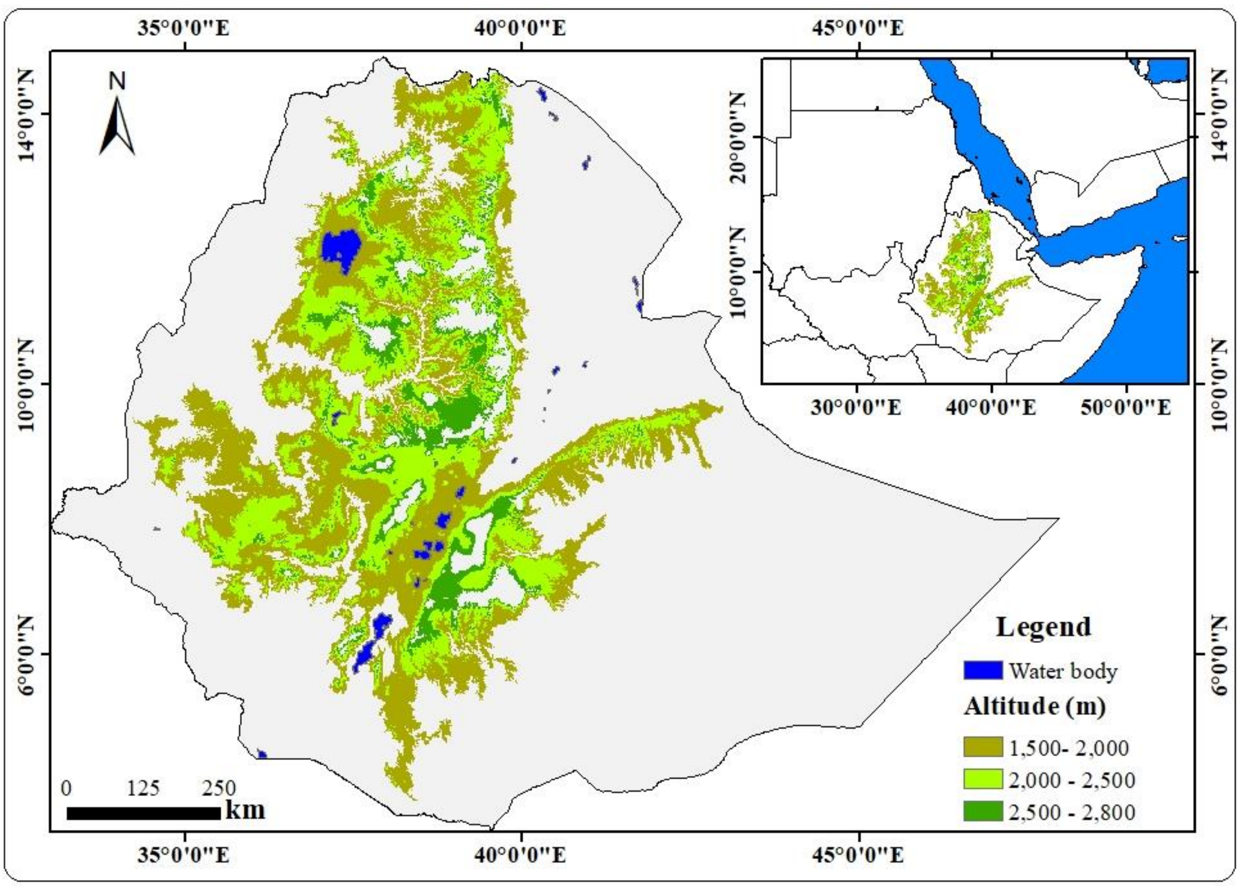


Figure 3. Location map of the study area (Source: CSA, 2007; GADM, 2018 data)

The country has a complex topography with an altitude ranging from 125 meter below sea level to 4533 meter above sea level (Engida & Esteves, 2011; Friis, 2010). According to Gebeyehu (2002) the highlands > 1500 m above sea level (a.s.l.) constitute around 45% of the total area of the country. The highlands were formed by lava effused during the uplifting of the basement rocks and they are dominated by hills, mountains, cliffs and flat tablelands separated by canyons. The highlands cover the central lava highlands and massifs consisting of the Gondar, Wello and Gojam highlands; and the southwestern plateau of Gamo Gofa, Illubabor and Wellega. In the South-Eastern parts are found highlands of Arsi, Bale, Hararge and Sidamo. These highlands have high mountains on their western rim with continuous slopes running from the highest peak of mountain Batu towards the southeastern lowlands (Friis, 2010). Because this thesis was focused on assessment of agricultural drought on selected cereal crops (Maize, Teff and Wheat), the study area covers the highlands of Ethiopia which lies between 1500 to 2800 meter above sea level. Geographically, it lies approximately between 3°48'5″N and 14°37'28″N and about 34°12'6″E and 42°58′48″E, with a total geographical area of 320, 442 square kilometers (Figure. 3).

3.1.2. Climate

Though Ethiopia belongs to the tropics, its climatic conditions are highly influenced by altitude and the seasonal migration of the Inter Tropical Convergence Zone (ITCZ) following the position of the sun relative to the earth and the associated atmospheric circulation. Thus, the country has a diversified climate ranging from semi-arid desert type in the lowlands to humid and warm (temperate) type in the southwest (Beyene & Meissner, 2010). Mean annual temperature distribution over the country varies from about 10^0C over the highlands of northwest, central and southeast to about 35^0C over north-eastern lowlands (NMA, 2007).

Ethiopia’s rainfall has complex patterns of spatial and temporal variability associated with the diverse topography and the seasonal north-south oscillation of the Inter-Tropical Convergence Zone (ITCZ) (Segele & Lamb, 2005). The ITCZ movement causes variation in the wind flow patterns and the onset and withdrawal of winds from north and south. The mean annual rainfall ranges from 100 mm to 2800 mm depending on the site. The highest annual rainfall records in the South-western region which riches up to 2800 mm. The central and northern regions receive moderate rainfall that gradually declines towards the low-lying arid and semiarid lands that receive an annual rainfall ranging between 100 - 700 mm. The Danakil Depression, the lower Awash River Basin and Eastern Ogden are the driest areas of Ethiopia (FDRE, 2012).

Overall, three seasons exist in Ethiopia. These seasons are Kiremt (long rain season) which extends from June-September, Bega (dry season) which extends from October-January and Belg (short rain season) which extends from (February-May) (NMA, 2017). Kiremt rains (June–September (JJAS) account for 65–95% of annual rainfall totals (Segele & Lamb, 2005). It also is considered as the main rainy season in which about 90% to 95% of the food crops of the country are produced (FDRE, 2012; FEWS NET,2003).

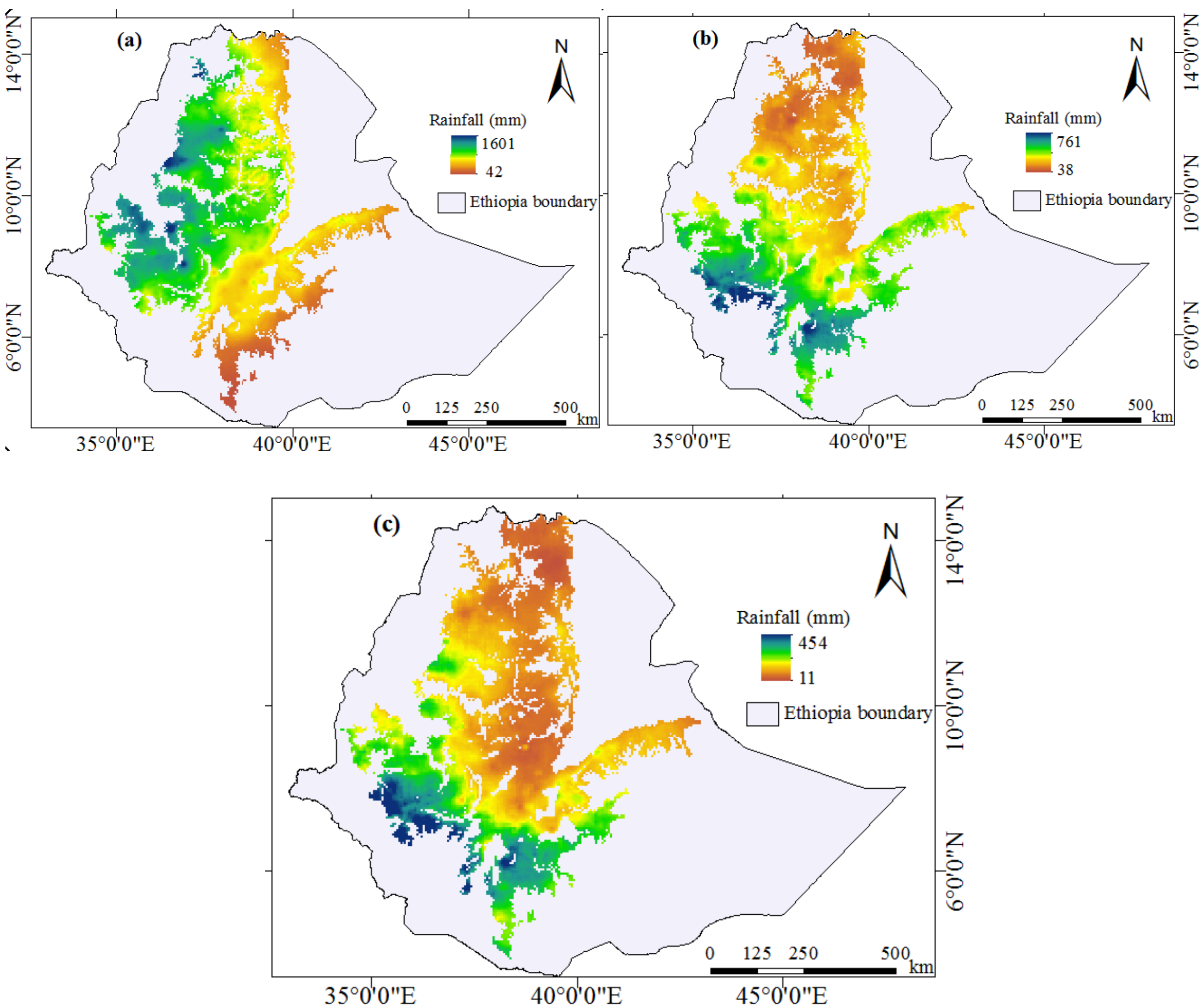


Figure 4. Long term seasonal rainfall (mm) distribution of Kiremt (a), Belg (b) and Bega (c) (Source: Long-term CHIRPS rainfall data from 1989 to 2018).

Thus, the most severe droughts are usually related to a failure of the JJAS rainfall to meet Ethiopia's agricultural and water resources need. The spatial distribution of Ethiopian drought indicates that most of the drought and food crises events are concentrated in the central and northern highlands, extending from North Shewa through Wollo to Tigray. Therefore, this study is devoted to analyze and characterize the agricultural drought condition in the highlands during this season.

3.1.3. Soil types

The diversified topographic, climatic factors, parent material and land use have resulted in extreme variability of soils in Ethiopia (FAO, 1984). In different parts of the country, different soil forming factors have taken place (Haileslassiea et al., 2005). The big proportion of the country's landmass is covered by lithosols, nitosols, cambisols, regosols and Vertisols in order of their importance (FAO, 1984, 1986).

The FAO soil classification is based on generalizations about soils paedogenesis. Red or brown Ferralsols derived from volcanic parent material are dominant in the Ethiopian highlands. Umbrisols are found chiefly in the humid parts of the highlands. Andosols are associated with recent volcanic activity in tectonically active areas, mainly in the highlands (Friis, 2010).

3.1.4. Land use/cover

LULC is one of the most easily detectable indicators of human intervention on land. Because it can change quickly over time, it is also a good proxy for dynamics of the earth surface resulting from a variety of drivers and factors (FAO, 2016). Understanding LULC status of a given geographical area is highly essential for managing its natural resources and monitoring environmental changes such as deforestation, drought and land degradation.

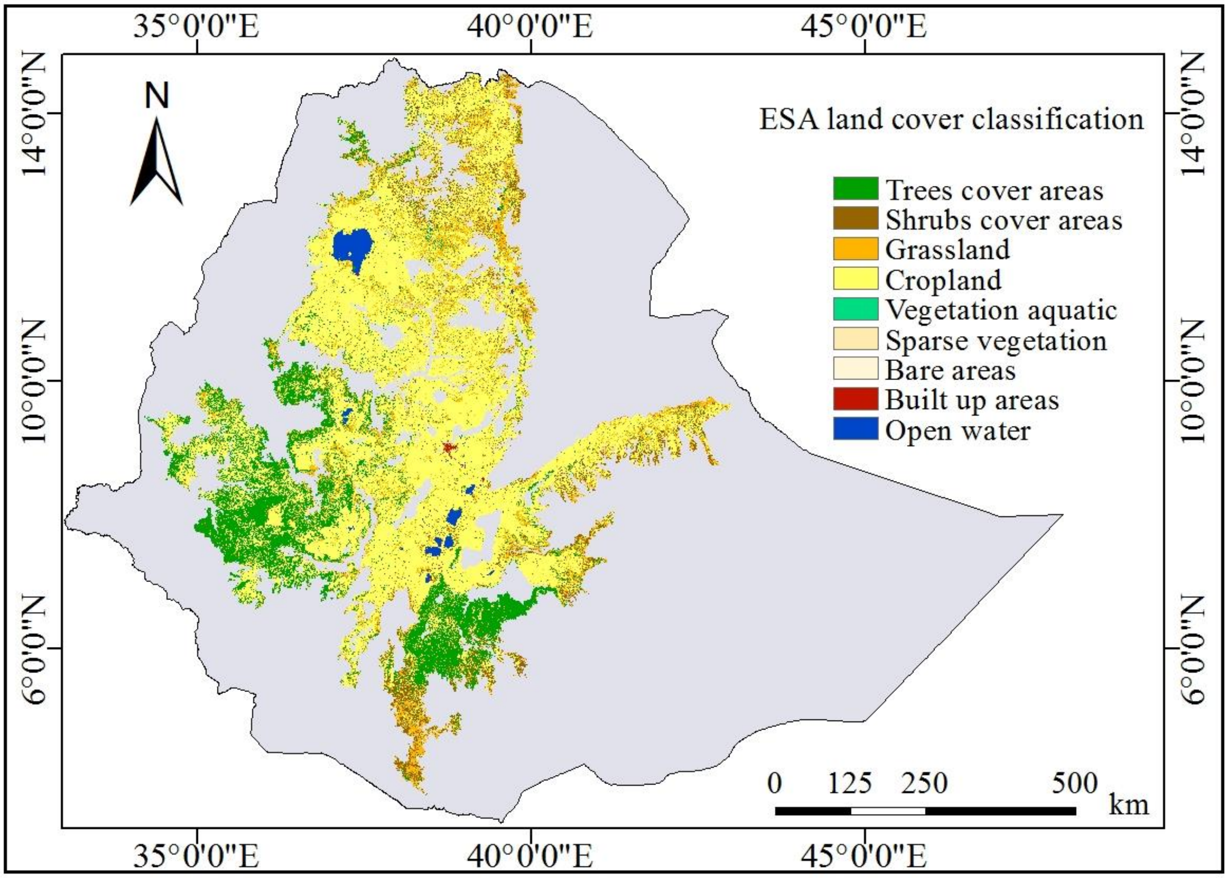


Figure 5. Land cover map of Ethiopia at 20 m spatial resolution (Source: ESA S2 prototype LC map of Africa, 2016)

In the highlands of Ethiopia, the major land-cover patterns are closely related to patterns of rainfall and temperature, with local variations due to soil and drainage factors. The wide ranging altitudes and associated agro-ecological zones have produced varied landscape and vegetation types, that varies from tropical moist forests (high forest) in the southwest and the Bale Mountains, to desert shrubs in the east and northeast and parkland agroforestry on the southern highlands. Pressures on forestlands from agriculture expansion and wood fuel consumption are likely to increase in the future as the population in Ethiopia is increasing (Beyene, 2010). In Ethiopia highlands, deforestation is one of the major processes of LULC change. Fuel wood collection, timber extraction, commercial agriculture and charcoal production are the primary direct drivers of deforestation in the highlands of Ethiopia (Hailu et al., 2018). According to Hurni et al. (2010) more than 90% of the Highlands of Ethiopia were forested but recently only 20% of this area is covered by trees, and the percentage of forest cover is less than 4%.

The land cover map of the Ethiopian highlands was extracted from the European Space Agency Climate Change Initiative Land Cover 2016 (ESA CCI LC 2016). The 20m high resolution LC map was produced based on Sentinel-2A observation from December 2015 to December 2016. The product has a legend of 10 classes that reviewed from LCCS, GLC-share, Globland30 with Geographic coordinate system based on WGS84 reference ellipsoid (Lesiv et al., 2017). Based on this LC map, cultivation occupies 60% of the study area, trees 18 %, shrubland 7%, and grassland 13%. The remaining land cover types occupy about 2% of the highland. However, for our purpose, we re-classified the highland land use cover classes into five classes (Forest, shrubland, grassland, cropland and others). Generally, due to the persistent agricultural activities and higher population density the LC in the highlands continually changes.

3.1.5. Socio-economic setting

Agriculture is the main source of livelihood and is a key driver of Ethiopia's economic growth and food security. It contributes more than 40% to Gross Domestic Product (GDP) and about 80% of employment is still concentrated in agriculture and 70% of the raw material requirements of local industries are supplied by the agriculture sector. Thus, the national economy is highly correlated with the performance of the agricultural sector, which suffers from frequent drought, poor cultivation practices and soil degradation (Demessie, 2015). It is dominated by small scale crop-livestock mixed farming systems and cereals are the most important food crops occupying about 81% of the total cultivated area (CSA,2017).

More than 90% of Ethiopia's population which is currently estimated at 100 million live in the highlands including about 90% of the cultivated land, around 60% of the country's livestock (Hurni et al., 2010). Farmers in the highlands of Ethiopia are engaged in small scale and subsistence mixed agriculture. Thus, land and livestock are the basic sources of livelihood. Cereals (e.g., teff, wheat, barley, sorghum, maize) are the main staples over most of the highlands, except in parts of the southwest, where enset is the main sources of food. The livestock component within this system is essential where animals are used as draft power for ploughing, threshing and transport, and their products serve as a major source of fuel, food and manure for soil fertility. Livestock is kept throughout the year, mostly grazing on natural pastures and crop residues.

3.2. Research approach and design

Research design is considered as the foundation of any study since it facilitates various research operations. In this regard, Kothari (2006) argues that research design helps the researcher plan in advance of the methods to be adopted for collecting the relevant data and techniques to be used during analysis. Regarding the selection of the research design, Kothari (2006) noted that, if the major emphasis of the study is on discovery of ideas and insights the appropriate research design is found to be exploratory while if the purpose of the study is on the accurate description of a situation the appropriate research design is descriptive. For this study, descriptive and correlational research design types were appropriately applied. Descriptive research designs help provide answers to the questions of who, what, when, where, and how associated with a particular research problem (Kothari, 2006). Agricultural drought conditions of different administrative zones in the highlands of Ethiopia were described based drought indices that derived from vegetation, temperature and rainfall data. Besides descriptive research design, correlational research design which is a non-experimental research design technique was applied to determine the association between drought indices and drought indices with crop yield.

This study also employed both qualitative and quantitative approaches. In fact, this study made use of more of quantitative and some of qualitative approach in integrated system. The approaches helped the researcher to connect diverse ideas about agricultural drought assessment and assisted in cross-checking the results which increase the validity and reliability of the findings.

3.3. Data type, sources and acquisition

Effective assessment and monitoring of agricultural drought rely on the availability, acquisition and sources of data. In precise, the accuracy of the findings of empirical research undertakings, like this one, has to be supported by reliable, relevant and quantitatively adequate data to be considered genuine. In order to ensure the validity of the present study, therefore, especial efforts were made to carefully secure the necessary data. To this effect, both primary and secondary sources were employed. Primary information was secured through an interview with key informants and field observations. Secondary data were collected from different existing sources that are, intensive desk review of published and unpublished literatures like published and unpublished institutional reports, peer reviewed journals, books, online data and digital published media. An overview of used remote sensing-based data sets and the respective specifications is given in Table 2.

Table 2. Data type and sources

Data set	Variable	Source	Coverage		Resolution		Format
			Temporal	Spatial	Spatial	Temporal	
eMODIS	NDVI	FEWS NET	2004-2018	East Africa	250m	dekadal	GeoTIFF
MOD11A2	LST & Emissivity	LPDAAC	2004-2018	Global	1km	8 days	GeoTIFF
CHIRPS	Precipitation	FEWS NET	1989-2018	Global	0.05	1 Month	BIL
LULC	LC	ESA CCI	2016	Africa	20m	No	GeoTIFF
Crop Mask	Crop	ASAP/EU	2018	Global	1km	Annual	GeoTIFF
SOC	Stock	ISRIC	2019	Ethiopia	250m		GeoTIFF

3.3.1. Remotely sensed data

Climate Hazard Group Infrared Precipitation with Station data (CHIRPS)

In the present thesis, Climate Hazard Group Infrared Precipitation with Station data (CHIRPS) is used in order to assess meteorological drought. This product was chosen due to its successful implementation in different studies in Ethiopia which has complex topography (Dinku et al., 2018; Bayissa et al., 2017). These studies indicated that CHIRPS performed very well during the monthly and seasonal time scales than other RFE. Additionally, CHIRPS data have relatively higher spatial resolution (~5 km) and longer periods of records (1981-present) than other products.

The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset is developed by the United States Geological Survey (USGS) and the Climate Hazards Group at the University of California, Santa Barbara, providing data from 1981 to present. It is a blended product combining, quasi-global geostationary Thermal Infrared (TIR) satellite observations from two National Oceanic and Atmospheric Administration (NOAA) sources, the Tropical Rainfall Measuring Mission (TRMM) 3B42 product from NASA, atmospheric model rainfall fields from NOAA Climate Forecast System and in situ precipitation observations obtained from a variety of sources including national and regional meteorological services (Funk et al., 2014). The data have a spatial resolution of approximately 5.3 km (0.05° × 0.05°), with coverage between 50°N to 50°S, 180°W to 180°E. CHIRPS time series have been used for trend analysis and seasonal drought monitoring. It is available at daily, pentad, dekadal, and monthly temporal intervals (Funk et al., 2015). For this thesis, the monthly time series data of CHIRPS Version 2.0 rainfall were acquired for the period 1989 to 2018. To maintain the seasonal (longer time) effect of rainfall on vegetation, a 1-month SPI was calculated using the long-term monthly time series data (1989–2018) **(WWW://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/).**

Surface reflectance data (NDVI)

Several studies have been conducting on drought monitoring using earth observation data and they proved earth observation data has a capability for drought monitoring. For instance, Berhan et al. (2011) reported that the earth observation data could effectively be used to monitor drought onset, cessation and the vegetation's response to drought. In this thesis, the agricultural drought condition of the study area was investigated using the real-time and historical EROS Moderate Resolution Imaging Spectroradiometer Earth observation products (eMODIS) that the United States Geological Survey (USGS) produces from MODIS data acquired by the Terra satellite (Jenkerson et al., 2010) currently generate these vegetation products from MODIS L1B Aqua surface reflectance.

The ultimate reason to use eMODIS NDVI data in this study was that the eMODIS data are corrected from molecular scattering, ozone absorption, and aerosols. The smoothening process using the weighted least-squares approach developed by Swets et al. (1999) was opted to be used to minimize such problems and enable to more effectively map land cover, identify phonological trends, and monitor vegetation. Likewise, its spatial resolution is better than other satellite images such as SPOT-Vegetation products SPOT the Advanced Very High Resolution Spectroradiometer (AVHRR). For this thesis, a multi-temporal smoothed dekadal eMODIS-NDVI data for the East

Africa window from Famine Early Warning System Network (FEWS-NET) from the year 2004 to 2018 (June – September) at 250 m spatial resolution was downloaded in GeoTIFF format with Geographical coordinate system (180 images). The eMODIS NDVI data was used as an input to compute the VCI and VHI.

Land Surface Temperature (LST) data

Land surface temperature (LST) is vital parameter in the climate system, impacting vegetation development, snow cover, runoff, and human livelihoods. Knowledge of LST dynamics can furthermore be used as an indicator for climate variability and change (Frey & Kuenzer, 2015). Therefore, for better characterization of agricultural drought, incorporating temperature data from LST is essential. As stated by Cai et al. (2018) and Gidey (2018) MOD11A2 LST and Emissivity Terra is better for assessing and monitoring agricultural drought. In this thesis, MODIS LST dataset from the Terra satellite (MOD11A2, version 006– https://lpdaacsvc.cr.usgs.gov/appeears/) is the main data source for this analysis. The main reason that for chosen this data is the better spatial, temporal variation and up-to-date algorithm such as time of acquisition, satellite view zenith and azimuth angle, quality flags for easy interpretation of the products than AVHRR sensor (Frey et al., 2012). Moreover, Terra LST data enables to get in depth information than Aqua (night) because significant change in LST can be recorded during daytime (Frey et al., 2012).

The MOD11A2 Version 6 product affords an average 8-day per-pixel Land Surface Temperature and Emissivity (LST&E) with a 1 kilometer (km) spatial resolution in a 1,200 by 1,200 km grid. Each pixel value in the MOD11A2 is a simple average of all the corresponding MOD11A1 LST pixels collected within that 8-day period . The 8-day compositing period was chosen because twice that period is the exact ground track repeat period of the Terra and Aqua platforms (Wan, 2013). In the present thesis, a total of 240 MOD11A2 Terra LST were downloaded from the period 2004-2018 (June to September) in GeoTIFF format and Geographical coordinate system. The data is used as an input to calculate TCI and VHI.

3.3.2. Ground data

Field work

Field work is used as a supportive technique to collect data that may complement or set in perspective data obtained by other means.The field work was conducted from August 28 to September 17, 2019. The field work involved office secondary data collection in relevant institution and a field campaign. Regional offices visited are South Wollo Zone agricultural office because it has a record of frequent drought occurrence. A field campaign comprised of interviewing local farmers and agriculture experts and observations of land cover. During the field work, fifteen farmers and experts (Zonal and Woreda Rural and Agricultural Development Offices, Zonal and Wereda Disaster Prevention and Preparedness Office) (key informants) that selected purposively were interviewed. These helped in understanding the zone historical crop production, the crop condition, pattern, drought years. The information obtained from key informants interview also used for the evaluation of the drought indices result that obtained from satellite data. The interviews were conducted in Amhara region South Wello Zone, in Jamma and Wereilu Wereda, North Shewa3 (Mida Wereda) and Southwest Shewa zone, Dawo wereda. Guiding questions for key informant interviews is attached in the appendix part (Appendix 1).

Agricultural production yield data

The characteristics of satellite derived meteorological parameters and the derived drought indexes must be validated by ground truth data. In this study the data used for validation purpose is mainly agricultural production yield. Even though, there are two main rainy seasons in Ethiopia, Kiremt is the main rainy season across most parts of Ethiopia, except the extreme south and southeast part of the country. The onset and withdrawal as well as the amount and distribution of precipitation during Kiremt have a substantial impact on crop production than Belg. Moreover, Kiremt season yield accounts for 90–95% of the annual crop production of Ethiopia (FEWSNET, 2003). Therefore, this thesis focused on a crop yield anomaly for the Kiremt growing season in order to find out the relationship between crop yield and the existing drought condition as well as validate satellite-based drought events.

According to CSA (2016) cereals are the major food crops in terms of area planted and volume of production in the highlands of Ethiopia. Thus, crop yield data of wheat, maize and teff for 41 administrative zones were collected from the Central Statistics Agency (CSA) of Ethiopia for the period 2004 to 2018. However, three years of data (2009, 2017, and 2018) were missing and therefore discarded. Since all zones are not fulfilled the existing criteria, only 41 zones that are crop producing and located between 1500-2800 meter above sea level were selected for comparison with crop yield. Agricultural production yield data that obtained from CSA for 12 years are given in Appendix 3.

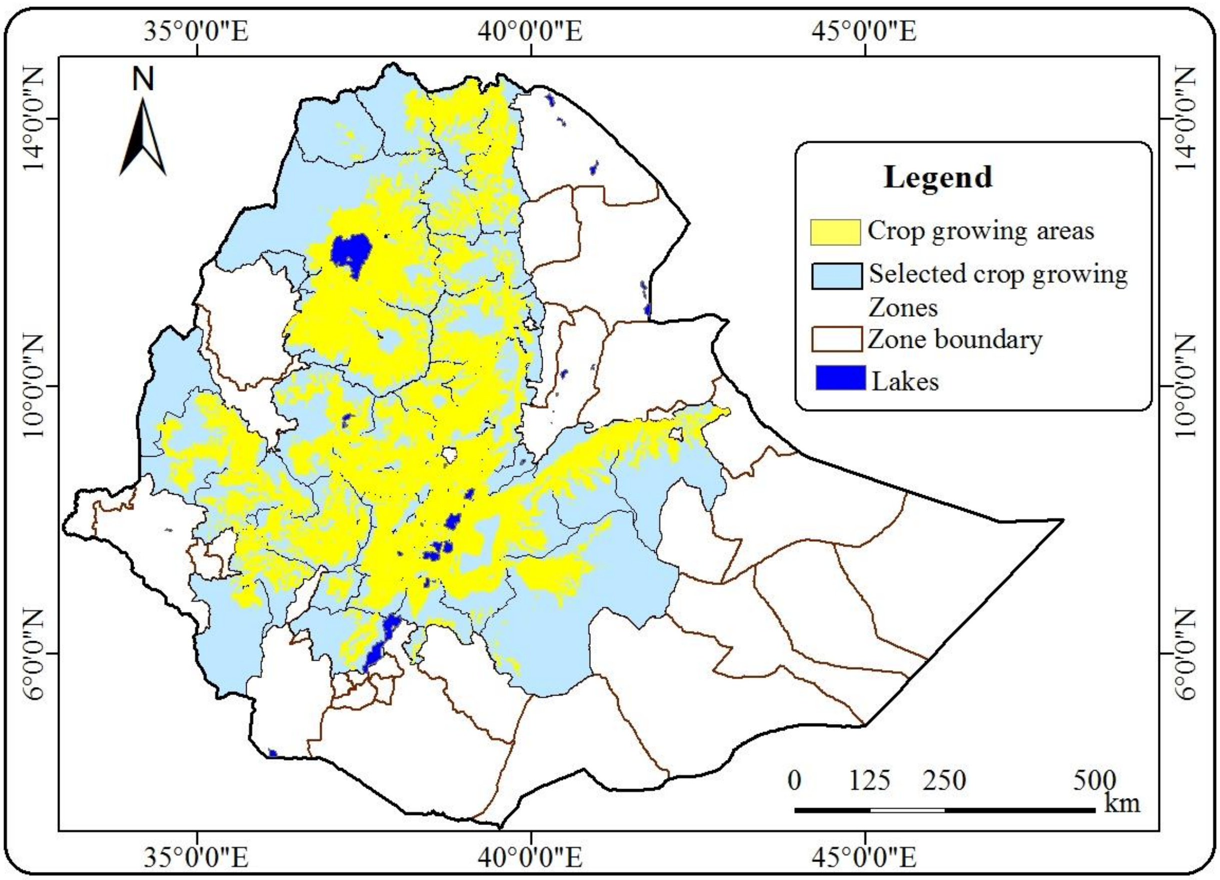


Figure 6. The spatial locations of selected crop growing zones and crop growing area (GADM, 2018; ASAP/EU, 2019 crop mask)

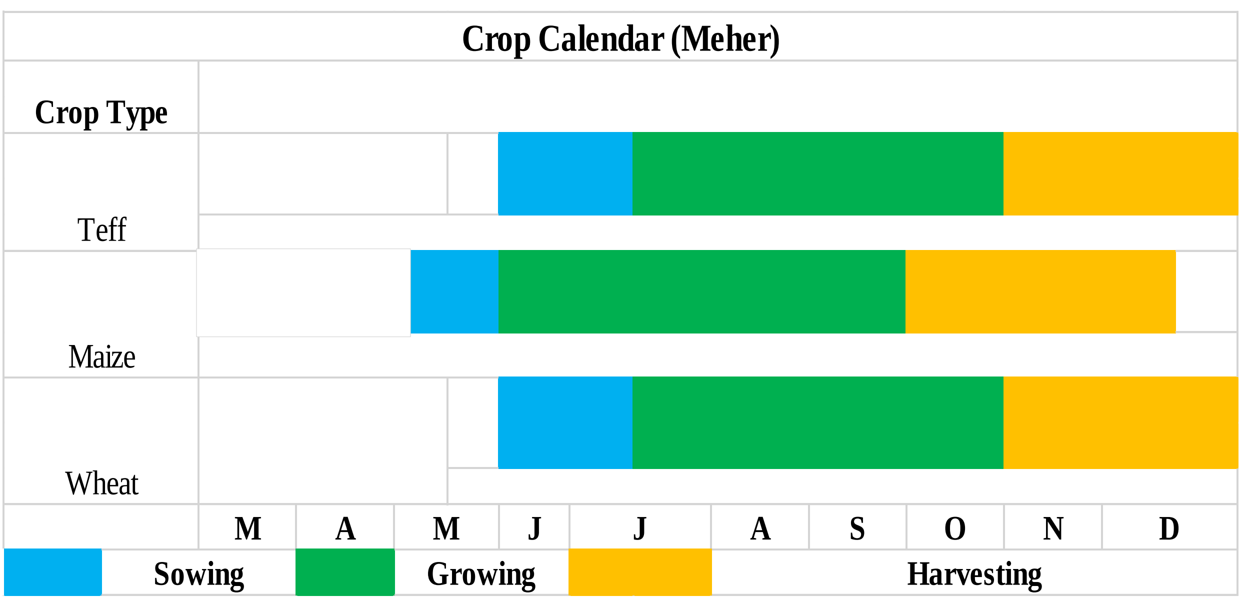
Crop Calendar

For agricultural drought monitoring, understanding the crop calendar is essential to assess crop status during growth seasons. The crop calendar used for this study was obtained from the Global

Information and Early Warning System (GIEWS). Table 3 shows the main crop calendar for the whole of Ethiopia which is considered similar to the highlands. This was further enhanced by field work to obtain the main crop calendar of the study area. For this study, the main crops of Ethiopian highlands namely teff (Eragrostis tef), maize (Zea mays) and wheat (Durum wheat) were taking in to account. Because of these cereal crops are the major food crops both in terms of the area they are planted and volume of production obtained (CSA, 2017).

Based on the results of the year 2016/17 (2009 E.C.) survey, out of the total grain crop area, 81.27% (10,219,443.46) hectares) was under cereals. Teff, maize and wheat took up 24.00% (about 3,017,914.36 hectares), 16.98% (about 2,135,571.85 hectares), and 13.49% (1,696,082.59 hectares) of the grain crop area, respectively. As to production, cereals contributed 87.42% (about 253,847,239.63 quintals) of the grain production. Maize, teff and wheat made up 27.02% (78,471,746.57 quintals), 17.29% (50,204,400.47 quintals) and 15.63% (45,378,523.39 quintals) of the grain production, in the same order (CSA, 2017).

Table 3. Crop calendar of Ethiopia (GIEWS, 2011)



According to GIEWS (2011) and FEWS NET (2003) the Meher crop production in Ethiopia combines high yield long cycle crops (planted in the Belg season in March and harvested in September-December, after the end of the Meher season in September like maize and lower-yield ‘short cycle’ (June-September) varieties which mainly planted during June/July such as teff and wheat.

Maize is one of the main long cycle crops which is the second most widely cultivated crop in Ethiopia and is grown under diverse agro-ecologies and socioeconomic conditions typically under rain-fed production. It is mainly cultivated in the SW and W Oromia, W and NW Amhara and parts of the Southern Nations Nationalities and Peoples Region (SNNPR). Now-a-days maize is grown chiefly between elevations of l500 and 2200 meters and requires large amounts of rainfall to ensure good harvests.

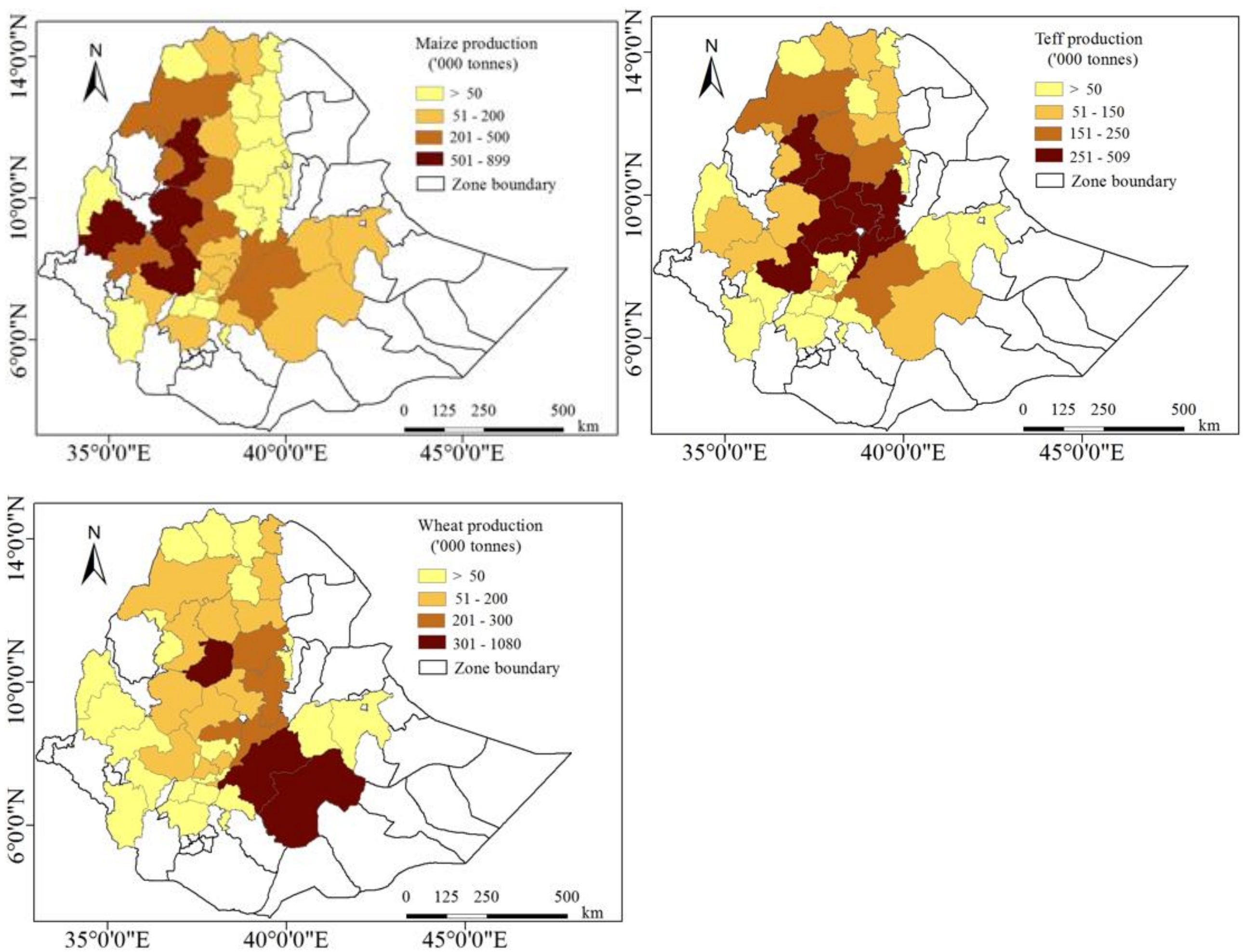


Figure 7. Distribution of maize, teff and wheat production in Ethiopia. Source: based on CSA data for 2016/17 (www.CSA.gov.et)

The top five maize producing zones of Ethiopia, according to the 2016/17 CSA data, are West Gojjam, Jimma, East Welega, West Welega and Illubabor. As depicted in Table 3, maize appears to require a more even distribution of rainfall throughout the belg and kiremt seasons particularly April-May rainfall are decisive for maize production (FEWS NET, 2003; MoANR, 2016).

Teff (Eragrostis teff) is the short cycle cool weather crop grown predominantly in the Ethiopian highlands at optimum altitude range of 1800 to 2200 meters. This crop occupies the largest area and has relatively large amount of grain production (MoANR 2016). According to the 2016/17 CSA data, the top five teff producing zones of Ethiopia, were East Gojjam, West Shewa, East Shewa, South West Shewa and North Shewa3. Overall, Teff is sown between mid-June and July, and hence the influence of the kiremt rains is as expected. Fluctuations in teff production generally follow the patterns of inter-annual variability of the kiremt rainfall (Bewket, 2009).

Wheat is another important cool weather crop grown predominantly in the Ethiopian highlands at optimum altitude ranging from 1500 to 2800 meters above sea level. It sown in June, usually earlier than teff. According to Bewket (2009) wheat production show higher correlations with the kiremt rainfall like teff. Wheat cropping dominates the Arsi, Bale, East Gojjam, South Wollo and North Shewa3 zones based on 2016/17 CSA data.

3.3.3. Ancillary data

In addition to the above-mentioned datasets, the following datasets were used in this study. With regard to agricultural areas, ASAP dataset on cropland and rangeland masks is used. This data product is relied on a multi criteria analysis (MCA) that evaluated eight global datasets (i.e. CGLS-LC100 v1.0, GLC2000, GLCNMO v2, Glob Cover 2009, Globeland30, LC-CCI 2015, MODISLC 2010, S2 Prototype Land Cover) and 16 regional land cover datasets (Pérez-Hoyos et al., 2017a). Gridded cropland and pasture area fraction data are available at spatial resolutions of 0.0089286 deg resolution (about 1 square kilometer). Individual pixel represents the area fraction of the specific cover (i.e. percentage of the pixel with crops/rangeland). In this thesis, only cropland information is used in order to locate agricultural land cover type, which was used to extract the NDVI, LST, TCI and VCI statistics for the detection of agricultural droughts. In this dataset cropland is defined as the land used for cultivation of crops, encompassing both total areas under arable land and permanent crops. Soil orgamic carbon stock for the top 0-30 cm soil depth of the highlands of Ethiopia extracted from ISRIC world soil information system (https://data.isric.org/geonetwork/srv/eng/catalog.search#/metadata/9a66a37e8a4e463bb83afd49049c323a).

All required data downloaded in GeoTIFF format and cut to the extent of the study area. Image pixels where the fraction of cropland area exceeds zero are included into the applied drought analysis, whereas pixels without cropland are masked. In addition, the land cover map for Ethiopia was extracted from the ESA CCI S2 prototype land cover map of 2016 at 20m spatial resolution. Administrative boundary was acquired from the database of Global Administrative Areas version 3.6 (GADM, 2018) in shape file format. Only those GADM lying within the study area were Extracted.

3.4. Software package

In this study the following software packages were used at different level of the study

Table 4. Software used for the Study

No	Software	Major application Area
1	SPIRITS	Image processing (NDVI, LST), calculate SPI
2	ArcMap 10.5	Image processing and statistical analysis for SPI, VHI and crop yield mapping
3	Microsoft Excel 2016	For statistical computations such as mean, CV, crop yield and regression analysis
4	GeoCLIM software 1.2.0	For downloading CHIRPS precipitation data and to calculate long term average
5	Minitab	Statistical analysis

3.5. Data processing and analysis

3.5.1. Normalized difference vegetation index (NDVI)

For this study, the indices from eMODIS NDVI image were measures of vegetation condition by exploiting the unique spectral signatures of canopy elements in the RED and NIR portions of the spectrum (Kogan, 1995). NDVI is a widely used index to monitor vegetation condition by measuring the density of chlorophyll contents of the vegetation cover (Rhee et al., 2010). It has a wide application in developing drought monitoring systems because it reflects the collective effects of water stress during the growing period of plants.

In this thesis, a10-day composite eMODIS NDVI raw data for each month of the indicated period were masked out for the study area, re-projected from Geographical to UTM projection (UTM, Zone 37) and rescaled in ArcGIS 10.5.1 package to find out the real NDVI value of the study area as follows (Eq.3.1).

$$\text{eMODIS NDVI} = \text{Float}(\text{Smoothed eMODIS NDVI} - 100) / 100 \qquad (3.1)$$

According to Thenkabail et al. (2004) the value of NDVI ranges from − 1.0 to + 1.0. The negative NDVI value shows unhealthy vegetation cover mainly occurred in a barren rock (rock outcrop), and sand, while the positive NDVI value depicts the healthy vegetation cover. In healthy and dense vegetation NDVI values became higher than rocks, water, and bare soil (Kogan 1995). In this thesis, the eMODIS NDVI data were used as input to compute the VCI only. The NDVI values below 0.1 have been reclassified in all dataset as they represent areas other than vegetation ((Vaani, 2017; Eshetie et al., 2016). Therefore, the scaled NDVI data contain only positive values, which are required for VCI computation.

3.5.2. Vegetation Condition Index (VCI)

NDVI is an important index for studying vegetation greenness or health status, and mapping vegetation cover dynamics. However, according to Wang et al. (2001) NDVI is not effective to characterize drought or non-drought periods because the temporal lag between the rainfall event (or deficit) and its manifestation in the vegetation health and the consequent change in the NDVI values NDVI cannot take into account differences due to the productivity of the local ecosystem in order to determine vegetation health. For example, in arid and semi-arid regions low NDVI values are expected, whereas in rainforests high NDVI values are expected though precipitation is relatively low in a particular season. These NDVI differences represent the difference in local ecosystem resources rather than weather conditions. But VCI can fill this gap and this was the reason that VCI was selected for this thesis. The VCI is an indicator of the relative healthiness (vigor) of the vegetation in response to weather with respect to the ecologically defined minimum and maximum limits (Kogan, 1995).

The VCI captures rainfall dynamics better than the NDVI particularly in geographically non homogeneous areas and also it permits to quantify the impact of weather on vegetation as well as the description of land cover and spatial and temporal vegetation change (Kogan, 1995). Moreover, the VCI makes it possible for one to compare the weather impact in areas with different ecological and economical resources (Kogan, 1995). VCI values indicate how much the vegetation has advanced or deteriorated in response to weather and how far vegetation development is from the potential maximum and minimum defined by ecological limits. Thereupon, the VCI is derived according to equation 3.2. First, the processed eMODIS NDVI images, (15for each month a totally of 60 images) was composited (e.g. June 2004-2018). After this, absolute minimum and maximum maps were produced for every month (June-September) based on the following formula (Eq.3.2).

$$VCI = 100 \times (NDVI\ i - NDVI\ min) / (NDVI\ max - NDVI\ min) \qquad (3.2)$$

where NDVI i = the current smoothed NDVI value of ith month, NDVI min, and NDVI max, is a multi-year (2004– 2018) absolute minimum and maximum NDVI value for every pixel at a particular period. The value of VCI is measured in percentile ranged from 0 to 100. A high value of VCI signifies healthy and/or unstressed vegetation condition (50-100%) whereas values a low value indicates unhealthy vegetation which indicates drought condition (Kogan, 1997). In the present thesis, VCI used as input for VHI computation.

3.5.3. Land Surface Temperature (LST)

The second data is Land Surface Temperature (LST) that was obtained from MOD11A2. It described as the radiative skin temperature of the land derived from solar radiation. This data used as an indicator of the energy balance at the Earth’s surface and the so-called greenhouse effect in climate change studies (Frey et al., 2012b). The MOD11A2 Terra v.005 LST and emissivity has play indispensable role to measure the ground temperature of the earth's surface that enables to assess the overall vegetation health, soil moisture status and impact of thermal.

In this study, the MOD11A2 Terra 8 days LST data obtained from APPEARS in Geo TIFF format from 2004 to 2018 in 8 days' temporal resolution. To remove noise from the given images caused by clouds or weather, the maximum value composite (MVC) method is used for data processing in ArcGIS 10.5.1 package, cell statistics tool.

Finally, the 8 days aggregated 1 km MOD11A2 LST data were re-projected into Universal Transverse Mercator (UTM) projection zone 37 and resampled to 250 m to correspond to the entire images. The values of the MOD11A2 Terra LST data were calculated by averaging all the valid pixels under clear-sky. The valid LST value ranges from 7500 to 65,535 and it was rescaled by 0.02 to get the correct LST value in Kelvin unit. In the current study, the LST data was rescaled and converted into °C (degree Celsius) unit as follows by using ArcGIS 10.5.1 package (Eq. 3.3):

$$LST = (\varpi \times 0.02) - 273.15 \qquad \text{(Eq. 3.3)}$$

where LST = Land Surface Temperature in Degree Celsius (oC), ϖ = Row Scientific data (SDS)

LST provide information about vegetation condition. The assumption is an increase in evaporation along with a decrease in soil moisture, caused by higher temperatures, resulting in a decline in the vegetation cover (Kogan, 1997). Thermal conditions are particularly vital when moisture shortage is convoyed by high temperature, increasing the severity of agricultural drought and having a straight influence to vegetation health. Therefore, low LST value indicates favorable vegetation conditions and vice versa. In the current study, the MOD11A2 LST were used as input to compute the TCI only.

3.5.4. Temperature Condition Index (TCI)

Recently, due to global warming the role of temperature in drought monitoring become crucial and only using NDVI based VCI index is not quite enough to fully characterization of agricultural drought. Therefore, TCI is a thermal stress indicator used to incorporate temperature related drought situations. The assumption of this index is that during the drought event soil moisture diminished significantly and cause high vegetation stress, whereas low temperatures are mainly favorable to vegetation during its development. The computation of this index is more likely similar to the VCI but the model has considerably improved to assess the response of vegetation to temperature. Hence, low TCI values correspond with vegetation stress due to dryness or harsh weather by high-temperature condition (Kogan, 1995a).

In this study the TCI was computed using smoothed monthly MOD11A2 data for the period 2004 to 2018 based on the following mathematical expression (Eq. 3.4):

$$TCI = 100 \times (LST\ max - LST\ i) / (LST\ max - LST\ min) \qquad \text{(Eq. 3.4)}$$

Where LST i = LST value of ith month (June-September), LST max and LST min are the smoothed multi-year maximum and minimum LST (2004– 2018, 15 years records).

Similar to VCI, value of TCI is measured in percentile ranged from 0 to 100. At the TCI of around 50%, the fair or normal temperature conditions exist. When TCI values are close to 100%, the brightness temperature for this month, LSTi, is equal to the long-term minimum LST for the pixel. On the other hand, low TCI values (near to 0%) show very hot weather in that month. When TCI is equal to zero percent brightness temperature for this month, LSTi, is equal to maximum long-term LST for the pixel. Constantly low TCI values over several consecutive time intervals may point to drought occurrence. In the present thesis, TCI used as input for VHI computation.

3.5.5. Vegetation Health Index (VHI)

Several researches have been conducted using VHI for assessment and monitoring of drought across the world (Amalo et al., 2017; Bhuiyan et al., 2017; Bhuiyan et al., 2006; Cai et al., 2018; Chen et al., 2017; Karnieli et al., 2017; Rahman et al., 2009; Singh & Kogan, 2003; Sun et al., 2013; Yagci et al., 2011; Frey et al., 2012; Gidey et al., 2018). These studies proved that VHI model has been found to be a robust agricultural drought-monitoring index and it has good efficiency to explore the spatial extent of agricultural severity drought. According to Kogan (1997) VHI is the combination of TCI and VCI and is very important to characterize the spatial extent, magnitude, and severity of agricultural droughts in a good agreement with precipitation patterns. Similarly, they are chiefly significant to examine the effect of weather on vegetation and to demonstrate the condition of crop development. Gidey et al. (2018) reported that the combination of both VCI and TCI the so-called VHI has shown satisfactory results in Ethiopia when it is used for drought detection, assessment of weather impact and/or evaluation of vegetation condition.

The computation of VHI is based on satellite data of temperature and the NDVI. The VHI is a combination of the VCI and the TCI, both derived from NOAA/AVHRR satellite data (Kogan, 1997). Because VCI and TCI are characterized by varying moisture and thermal conditions of vegetation, Vegetation Health Index (VHI) represents overall vegetation health. In this study, VHI is computed based on TCI and VCI indices from 2004 to 2018 in monthly and seasonal basis using the following formula (Karnieli et al., 2017; Kogan, 1995) (Eq. 3.5):

$$VHI = a \times VCI + (1 - a) \times TCI \qquad \text{(Eq. 3.5)}$$

Where VHI = Vegetation Health Index, a = 0.5 (contribution of VCI and TCI), VCI = Vegetation Condition Index, TCI = Temperature Condition Index.

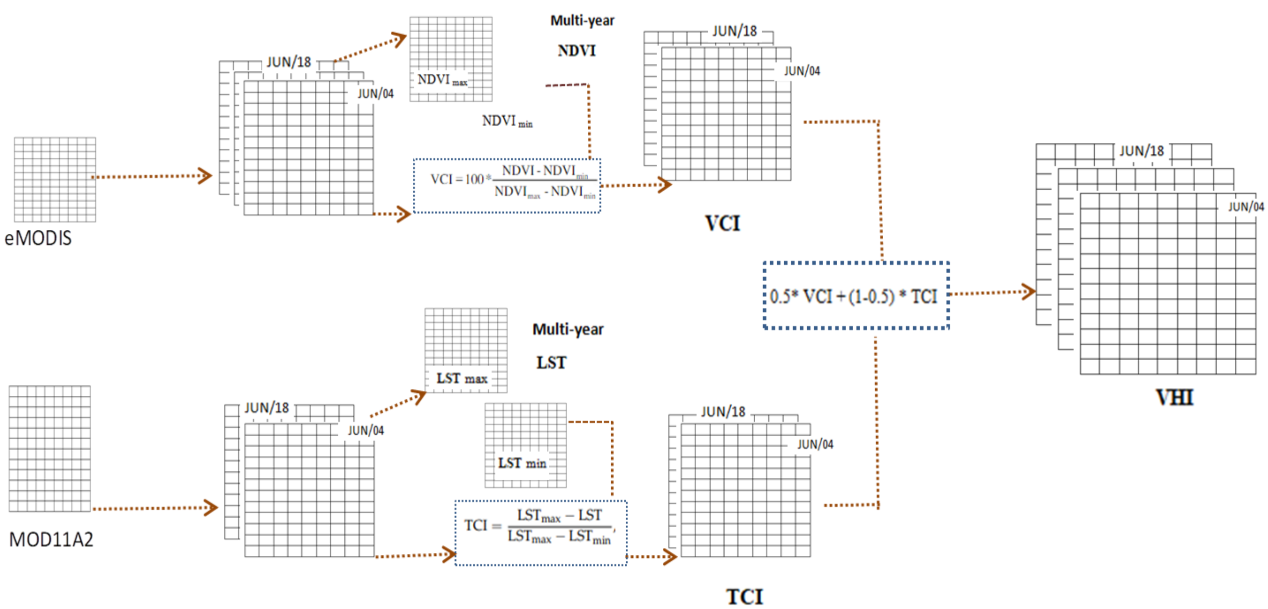


Figure 8. Workflow of the performed derivation of vegetation health index

In VHI calculation, an equal weight has been assumed for both VCI and TCI, since temperature and moisture contribution during the vegetation cycle is currently not known. VHI vary from 0 for extremely unfavorable conditions to 100 for optimal conditions. Studies showed that agricultural drought is striking when the VHI value is ≤ 40, which ranges from extreme to moderate drough, and no-drought or no effect on agriculture if the value exceeds 40 (Table 5) (Bhuiyan et al., 2017; Kogan, 2019).

Table 5. Vegetation Health Index classification schemes (Kogan, 2019)

Level of severity	**VHI values**
Extreme drought	≤ 15
Severe drought	16-25
Moderate drought	26-40
No drought (no effect on agriculture)	> 40

3.5.6. Standardized Precipitation Index (SPI)

In this thesis, Standardized Precipitation Index (SPI) is used as a meteorological drought indicator since it has been selected as a key indicator for global drought monitoring by the World Meteorological Organization (WMO, 2012) and successfully implemented into multiple drought monitoring approaches (e.g. (Gebrehiwot et al., 2011; Gidey et al., 2018).

The SPI is a probability index that expresses the observed cumulative precipitation for a given timescale (i.e., the period during which precipitation is accumulated) as the standardized departure from the rainfall probability distribution function. The frequency distribution of historical rainfall data for a given grid cell and timescale is fitted to a gamma distribution and then transformed into a standard normal distribution (McKee et al. 1993). The same author, recommended that a minimum of 30 years of precipitation data should be used to fit the parametric distribution. Therefore, to maintain the long-time effects of rainfall on vegetation, we used monthly long-term time series CHIRPS rainfall data (1989–2018) for SPI calculation.

Computation of the SPI involves fitting a gamma probability density function to a given frequency distribution of precipitation totals of a station. The alpha and beta parameters of the gamma probability density function are estimated for each station and for each time scale of interest (3-, 6-, 12-, 24-, 48-months, etc.). The resulting parameters are then used to find the cumulative probability of an observed precipitation event for the given month and time scale for the station in question. The cumulative probability is transformed to the standard normal random variable Z with a mean of zero and variance of one, which is the value of the SPI.

The gamma distribution is defined by its probability density function:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad \text{for } x > 0 \tag{3.6}$$

Where: α >0 is the shape parameter, β>0 is a scale parameter and x> is the amount of precipitation. (α) defines the gamma function. α and β are parameters to be estimated for each station for each time step of interest. The maximum likelihood solutions are used to estimate the gamma distribution parameters α and β;

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \quad \text{and} \quad \hat{\beta} = \frac{\bar{\chi}}{\hat{\alpha}} \tag{3.7}$$

Where,

$$A = \ln(\bar{\chi}) - \frac{\sum \ln(\overline{\overline{\chi}})}{n} \tag{3.8}$$

and *n* = number of precipitation observations. This allows the rainfall distribution a be effectively represented by a mathematical cumulative probability function given by:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \int_0^x x^{\alpha-1} e^{-\frac{x}{\beta}} dx \tag{3.9}$$

Meanwhile the gamma function is undefined for x = 0 and a precipitation distribution may contain zeros, the cumulative probability becomes:

$$H(x) = q + (1 - q)G(x) \tag{3.10}$$

where q is the probability of a zero. The cumulative probability H(x) is then transformed to the standard normal distribution to yield SPI (Mckee, Doesken, & Kleist, 1993).

In this thesis, monthly (SPI-1) for Kiremt season (June-September) was calculated by using the SPIRITS software. According to Rembold et al. (2015) SPIRITS software has the capability to calculate Standardized Precipitation Index recommended by World Meteorological Organization (WMO, 2012). SPIRITS software can compute SPI with rainfall cumulative values for different time periods from 1 to 48 months depending on the application. In the current study monthly (SPI-1) was selected to examine the spatial and temporal patterns of agricultural drought. According to WMO (2012) the 1-month SPI reflects short-term conditions that can be related closely to meteorological types of drought along with short-term soil moisture and crop stress, especially during the growing season. Therefore, this time interval is selected to detect moisture stress in the highlands of Ethiopia during crop growing season.

the monthly SPI was calculated using the long-term monthly time series data (1989–2018). However, monthly calculated SPI for June to September months from 2004-2018 were selected for analysis. The final SPI value was categorized based on the classification of Mckee et al. (1993) and WMO (2012), which is outlined in Table 6. Accordingly, a threshold of -1 was used for SPI, with values below this threshold representing moderate to extreme drought conditions.

Table 6. Classification of drought based on Standardized Precipitation Index (WMO, 2012)

Drought category	**SPI values**
Extreme drought	≤ -2
Severe drought	-1.99 to -1.5
Moderate drought	-1.49 to -1
No drought	> -1

3.5.7. Detrending crop yield

Identifying the spatiotemporal impacts of drought on agriculture sector and create a quantitative relationship between drought and agriculture losses could provide stakeholders with scientific information regarding the agricultural area that are most vulnerable and sensitive to drought. Therefore, using crop yield data has played a predominant role to evaluate the reliability of satellite-based drought monitoring. However, according to Lu et al. (2017) crop yields and productions are mainly controlled by many factors, such as technological and management trends (e.g., improvements in plant genetics, fertilizer, pesticides, irrigation facilities, and the farmers' know-how), weather and climate factors which makes difficult to quantifying and comparing drought losses across space and time. Therefore, modeling drought impacts on agriculture need proper distinctions between the high frequency fluctuations caused by the climate variability and the long-term trend caused by technological factors.

In this thesis, the evaluation of VHI using crop yield data is focused mainly on the effect of climate on crop yield. According to Wu et al. (2007) one of the most important method to use crop yield for such kind of condition is removing trend (called detrending). Detrending involves removing trends from regularly sampled time-domain input-output data (FAO, 1999). This data processing operation helps to estimate more accurate linear models because linear models cannot capture arbitrary differences between the input and output signal levels (Tadesse et al., 2015). Therefore, the crop yield data of teff, wheat and maize were detrended before simple linear regression were conducted between VHI and crop yield data.

There are different methods to detrending long-term crop yield, such as simple linear regression model, a second order polynomial regression model, a moving average model, a locally weighted regression model (LOWESS), a smoothing spline model, and an empirical mode decomposition model (EMD) (Lu et al., 2017). Out of these methods, simple linear regression model was used to eliminate the upward linear trend of crop yields in this thesis. Simple linear regression model is the most commonly used statistical method to identify a linear trend. Twelve years of crop yield data (2004–2016) from CSA were used to detrend the zonal yield statistics using Eq. 3.11.

$$Ydt = Yat - (Y(t) = \alpha + \beta X(t)) \quad \text{(Eq. 3.11)}$$

where Ydt is detraind yield at time t; Yat is actual yield at time t; Y(t) is predicted yield at time t, α is the y-intercept (the estimated value of the crop yield at time t = 0 or first-year record), β is the slope of the trend line (or the average change in crop yield per year), and X(t) is the year that the yield is estimated.

3.5.8. Mapping soil organic carbon

In this thesis, the spatial distribution of soil organic carbon stock for the top 0 -30 cm depth in the highlands of Ethiopia is mapped based on the ISRIC soil organic carbon stock data. Moreover, the mean value of soil organic carbon stock was extracted for four land use cover classes (Forest, shrubland, grassland, cropland) that obtained from ESA CCI S2 prototype land cover map of 2016 at 20m spatial resolution to determine the stock of soil organic carbon in each land use classes.

3.5.9. Coefficient of variation (CV) analysis

In this thesis, the coefficient of variation (CV) analyses was incorporated to evaluate the monthly (June-September) VHI variability relative to the mean percent from the periods of 2004–2018 in selected zones. The coefficient of variation particularly determined by the absolute dispersion of data relative to the mean and mainly expressed as a percentage. According to Gidey et al. (2018) coefficient of variation is an important parameter to determine statistical precision of estimation.

$$CV(\%) = 100 \times \frac{\sigma}{\bar{x}} \quad \text{(Eq. 3.12)}$$

where CV (%) = Coefficient of variation of VHI in percentage, σ = Standard deviation of VHI = long-term mean of VHI (e.g., June 2004 - 2018).

According to Ayanlade et al. (2018) CV is used to classify the degree of variability of events as less variable where CV < 20%, moderately variable where CV is between 20% and 30% and high variable CV > 30%. Therefore, in this study, CV of VHI > 30% is considered as highly variable, VHI between 20% and 30% moderately variable and CV of VHI < 30 represents less variability.

3.5.10. Validation of prediction Vegetation Health Index (VHI)

In order to validate the accuracy and predictive potential of VHI for agricultural drought monitoring, validation of the remotely sensed VHI with ground observation is necessary. To do so, the crop yield data and data obtained from drought indices were prepared for simple regression and pearson correlation analysis. The mean raster cell values of VHI images were extracted using ArcGIS zonal statistics for each zone. Finally, a simple linear regression model was applied to examine how VHI-crop yield relate to each other. Besides, the Pearson correlation matrix was applied to evaluate the relationships of each index. The regression analysis was conducted as follows (Eq. 3.13):

$$Yi = \beta 0 + \beta 1Xi + \varepsilon i \qquad \text{(Eq. 3.13)}$$

where Yi = VHI for the ith period, Xi = crop yield, $\beta 0 + \beta 1\chi i$ = linear relationships between the independent and dependent variables, $\beta 0$ = Mean of Yi when Xi= 0 (intercept), $\beta 1$ = cofficent of change in Yi, with a unit value of Xi changes , εi = Random error term.

Besides, it is necessary to examine the relationship between drought indices such as LST-NDVI and VHI-SPI. Particularly, the relationship between LST and NDVI determine the potential of VHI to predict and identify agricultural drought. In this study, thus, the correlation between LST and NDVI was done based on simple linear regression and pearson correlation.

Further more, in this study, a simple linear regression model was applied to examine how the drought index (VHI) and soil organic carbon stock relate to each other. Besides, the Pearson correlation matrix was applied to evaluate the relationships of soil organic carbon stock and VHI.This helps to evaluate the relationship between drought or the influence of drought on soil organic carbon stock and vice versa. Several studies have been conducted on the correlation between NDVI and soil organic carbon (Kumar et. al, 2018; Wang et al., 2013) reported that NDVI is the main factor to control SOC stock. Further more, Kumar et. al (2018) reported that Vegetation Temperature Condition Index (VTCI) is strongly correlated with soil organic carbon stock.

Therefore, in the present study, the correlation between VHI and SOC was determined based on the long term mean value of Vegetation Health Index and the drought frequency for the last 15 years. The Evans standard (1996) was adopted to determine the level of Pearson correlation matrix and coefficient of determination (R^2) strengths (Table 7).

Table 7. Strengths of Pearson correlation matrix and linear regression model (R^2) (Evans, 1996)

Level of statistical strength	**Pearson correlation matrix (r)**	**Coefficient of determination (R^2)**
Strong	≥ 0.60	≥ 0.36
Moderate	0.40 – 0.59	0.16 - 0.35
Weak	< 0.40	< 0.16

The overall schematic representation of methodology has been illustrated in figure 9.

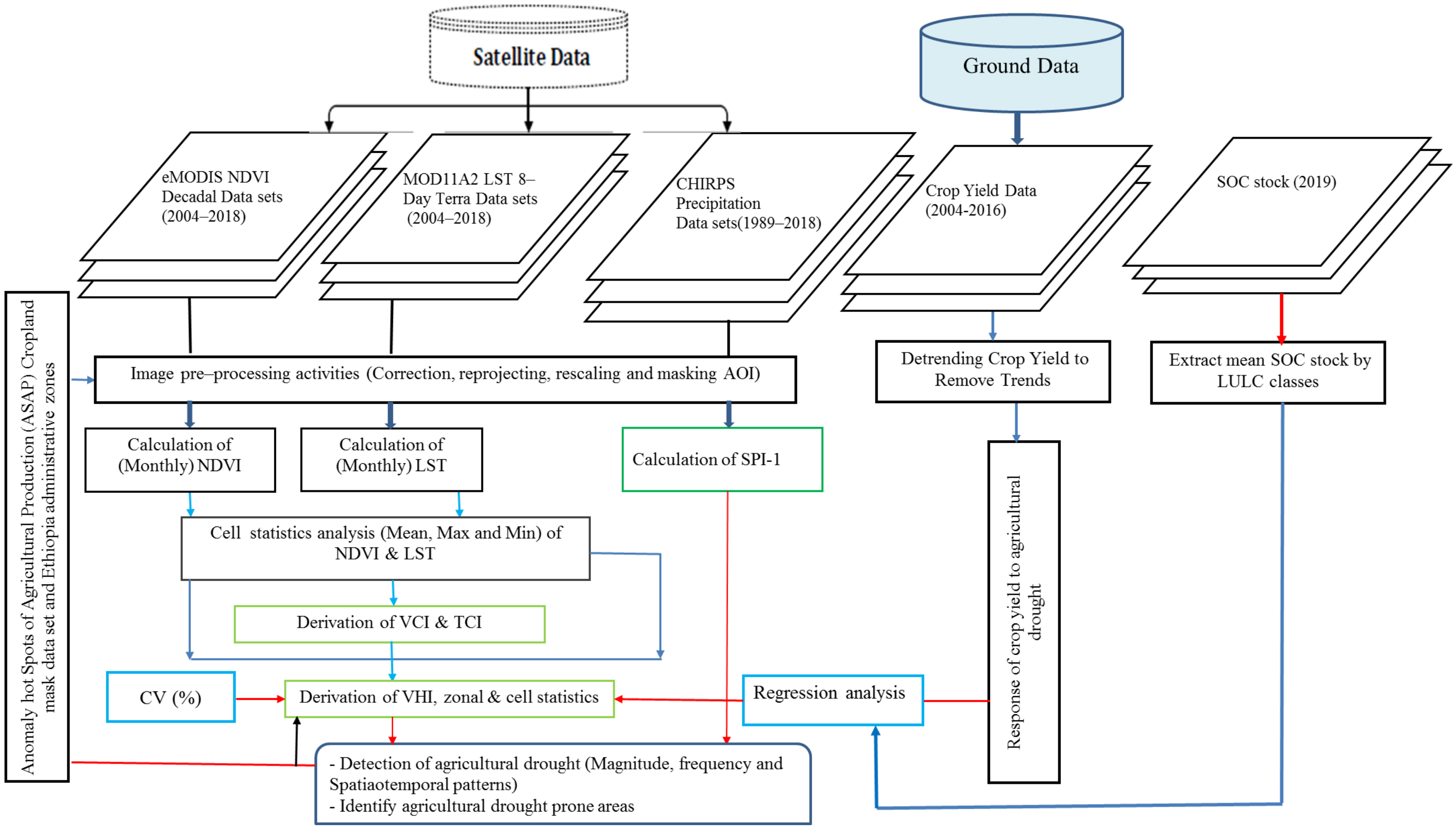


Figure 9. Schematic flow chart of the study

CHAPTER 4

RESULTS AND DISCUSSIONS

This chapter deals with results and discussions of drought indices (VHI and SPI) for analyzing and mapping the frequency, magnitude and spatiotemporal patterns of agricultural drought, coefficient of variation analysis of VHI. Moreover, the analysis of results includes evaluation and validation of the remotely sensed VHI series with crop yield in order to assess its accuracy and predictive potential for agricultural drought monitoring.

4.1. Agricultural drought monitoring through Vegetation Health Index (VHI)

In order to quantify agricultural drought from a long term observation from space, the NDVI and LST derived drought index, VHI was used in the current study. The magnitude, frequency, spatial and temporal pattern of agricultural drought events over highlands of Ethiopia is displayed through the means of VHI where the relative duration of drought conditions based on Kogan's VHI threshold of 40% or less as drought condition.

4.1.1. Relationship between Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI)

The results of the study showed that LST is negatively related to NDVI. The regression result indicated that the relation between LST and NDVI was negative in 32 zones where as it was positive in 9 administrative zones. Those with positive associations are located in the southern and southwestern part of the study area (i.e. Asosa, Kaffa, Illubabor, Benchi Maji, Dawro, Gamo Gofa, Gedeo, Hadiya Kembata). Strong positive relationship was observed in Gamo Gofa (r = 0.74), Dawro and Asosa (r = 0.44).

In this study, strong positive correlations were observed in the zone of West Hararge and Alaba (Figure 10) and were lower in East Welega and Gurage (r = 0.01). According to Zhang and Jia (2013) the relationship between NDVI and LST show that when the LST increases at certain value, NDVI tends to decrease and this causes a higher level of vegetation stress which can lead to the incidence of drought.

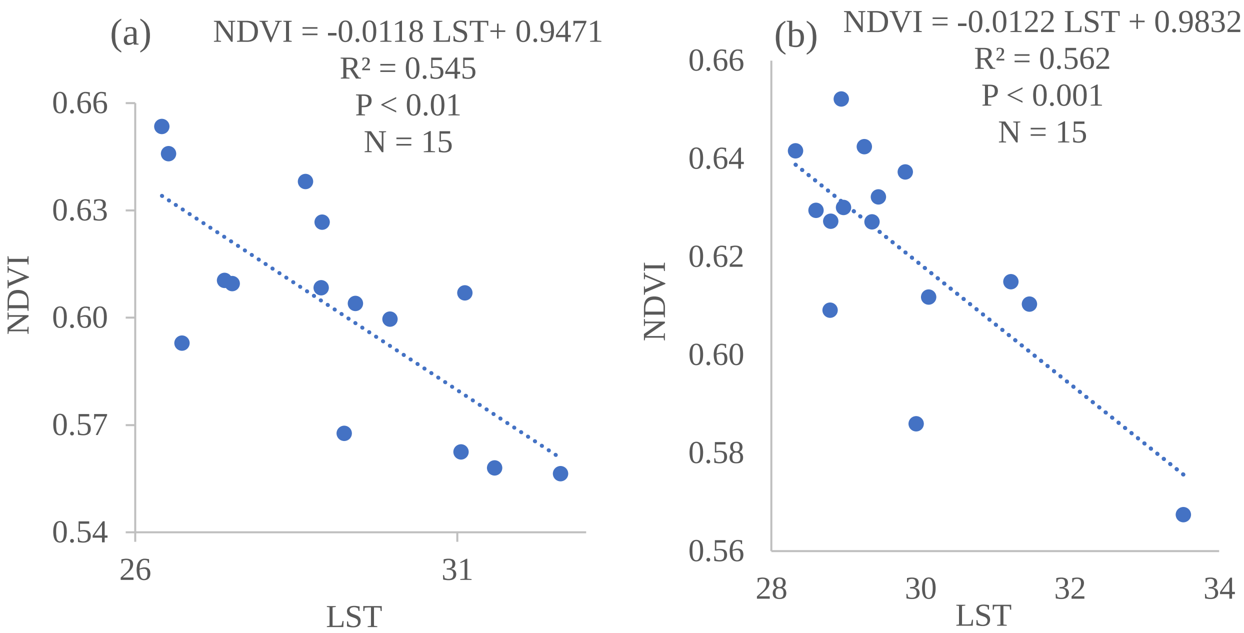


Figure 10. Sample Normalized Difference Vegetation Index and Land Surface Temperature relationships over the highlands of Ethiopia for the period 2004-2018 (a = Alaba, and b= West

The increase in LST and the decrease in NDVI contribute considerable moisture stress that can prompt the frequencies of agricultural drought. According to Kogan (2000) the NDVI and LST interpret extreme weather vegetation and land surface condition oppositely. Accordingly, during drought periods, the NDVI is low, while LST is expected to be high since both vegetation deterioration and higher contribution of a soil signal, on the contrary, the NDVI is expected to be high while LST is low. The findings of Bhuiyan et. al (2017) in Gujarat indicated that the influences of thermal stress determine the extent of damage and intensity of agricultural drought in a given area. The study concludes that a good moisture condition was accompanied by a favorable thermal condition and vice versa in most of the monsoons.

Beside the regression analysis, the time series of NDVI and LST was further analyzed at the beginning of the Kiremt season (June), because the inverse relationship between NDVI and LST was clearly detected in this month. Existing literature indicated that June is the beginning of main rainy season and the late start of rainfall in June remain a threat to agricultural production in Ethiopia, Whereas cessation of rainy season is the date when the available soil water content drops in mid-September and the vegetation condition reaches its maximum during September (Tesfaye and Walker, 2004; Segele and Lamb, 2005).

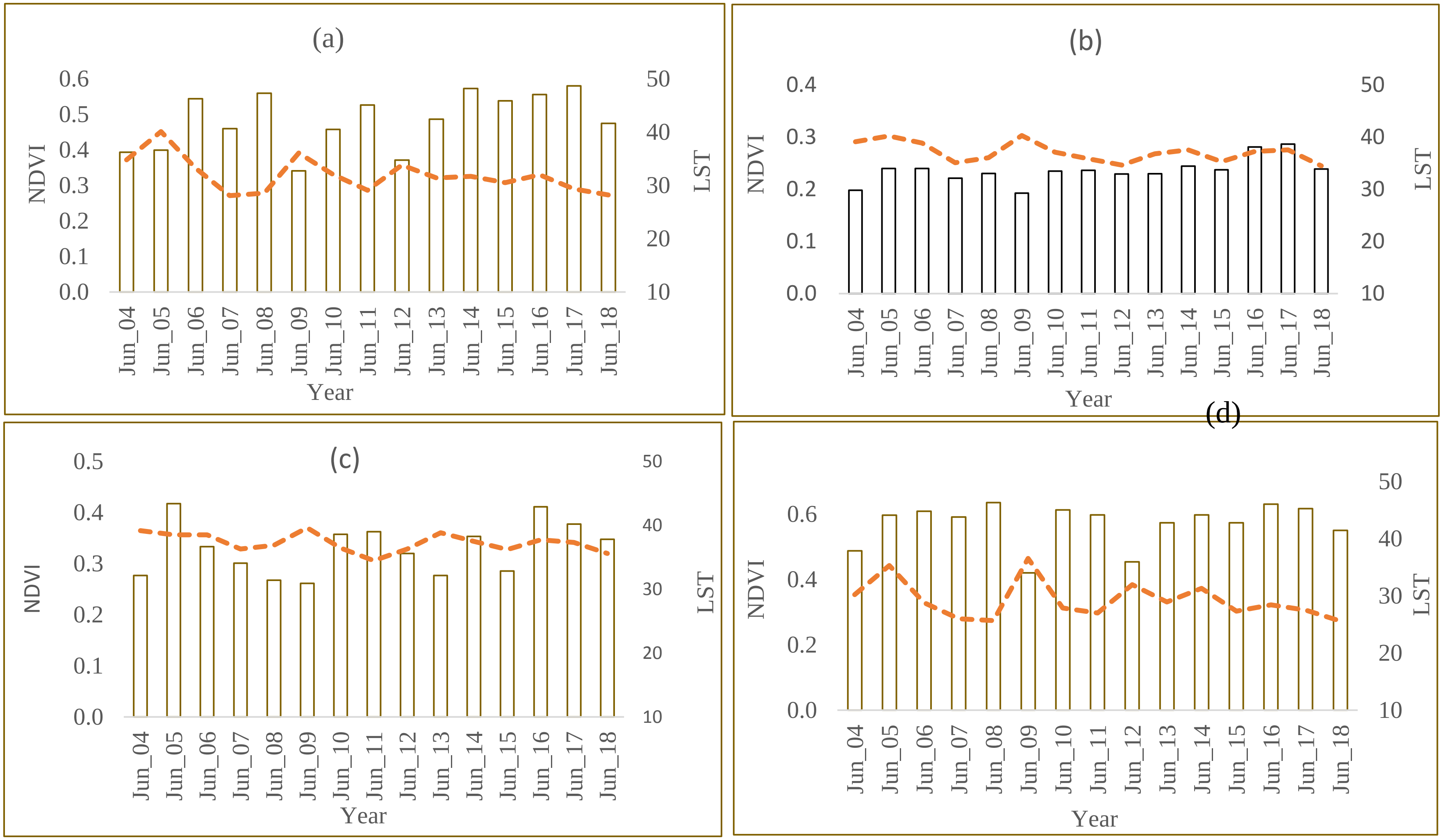


Figure 11. Sample temporal patterns of June Normalized Difference Vegetation Index-Land Surface Temperature: a. West Gojjam, b. Eastern Tigray c. South Wollo, d. West Shewa

Figure 11 shows the multi-temporal patterns of NDVI -LST at the start of crop growing season from 2004 to 2018 for four agricultural production zones in the highlands of Ethiopia as a representative example.

The temporal analysis of this study indicated that the monthly mean NDVI values for June in the study area varied between 0.19 and 0.82 in Central Tigray and Asosa, respectively, while the mean LST of the study area varied between 19°C in Gedeo and 41°C in Wag Himra. As indicated at Figure 11, low NDVI values were occurred with when the values of LST increases and vice versa. For instance, Figure 11a (West Gojjam) showed low NDVI values in 2004-2005, 2009 and 2012, while the value of LST in these years during starts of crop growing season were higher. Moreover, Figure 11b (Eastern Tigray) indicated that the NDVI value for the last 15 years at the start of crop growing period was between 0.19 (2009) to 0.29 (2017) which was very low, while the LST was maximum. Overall, the results of this study revealed that NDVI coverage at the beginning of cropping period was decreased between -0.08 to -0.24 (8-24%) in all zones of the study area. But average decrease in 2009 was very high almost in all zones. On other side, the LST increased by 0.01to 0.4 °C in 2009 across all Zones. The temporal analysis based on NDVI and LST showed that minimum NDVI and maximum LST was observed at the beginning of the cropping period during the year 2004, 2005, 2006, 2009, 2012 and 2015 with high spatial and temporal variability across the study area.

The results of this study are consistent with previous studies with an inverse relationship between NDVI and LST in the Raya and Mongolia (Karnieli et al., 2006; Sruthi and Aslam,2015; Gidey et al., 2018). According to Sruthi and Aslam (2015) and Gidey et al. (2018) LST increased, whereas NDVI significantly decreased during drought period because of poor moisture availability and rising surface temperature. The main reason for this situation is low precipitation. Kumar and Shekhar (2015) also confirmed that the statistical relationship between NDVI and LST during drought is negative.

4.1.2. Temporal agricultural drought assessment using Vegetation Health Index

The time series data of the VHI were used to analyses the trends of drought occurrence. The temporal patterns of agricultural drought (VHI) were calculated for the same period and time scale. An example of the assessment of combined weather-related (moisture and thermal) conditions from the VHI is shown in Figure 12 for selected Zones (South Gonder, Southern Tigray and East Shewa).

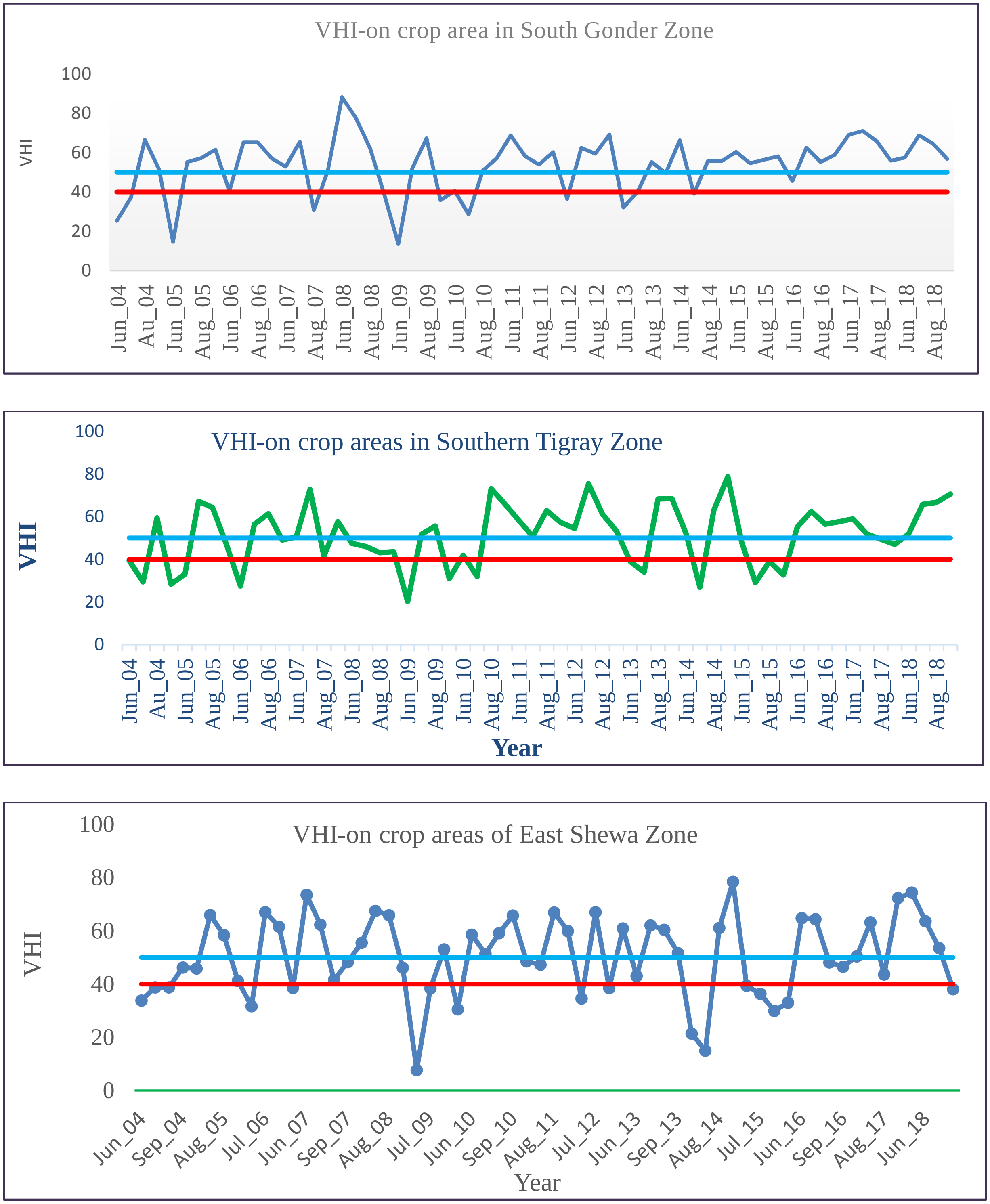


Figure 12. Temporal patterns of VHI for South Gonder, Southern Tigray and East Shewa Zones

The red line indicates the threshold of moderate to extreme drought (VHI ≤ 40) and the blue line indicates the threshold of fair vegetation (40 ≤ VHI ≤ 50%). For the last 15 years, drought episodes were occurred in June 2004, 2005, 2007, 2009 and 2013 in South Gonder Zone. Similarly, severe drought events were observed at the same period in Southern Tigray Zone. The obtained result is also in concurrence with the finding of Birhanu et.al., (2014) that stated 2004 was a drought period for Southern Tigray which was related to the reduction in rainfall amount in both belg and meher seasons of the years. The calculated SPI value for Southern Tigray for May and June that indicated the presence of dry spell during the year 2004. In East Shewa Zone, several drought events were occurred in 2004 June-August, during 2009, 2014 and 2015 almost in all months.

Overall, the information obtained from the processing result of the 15 years' VHI for each month from June to September, several drought events were identified in the highlands of Ethiopia. Major drought events were occurred during 2004, 2009, 2014 and 2015 (Table 9). For instance, in 2004, Southeren, Eastern and Central Tigray zonesm, Eastern Amhara (South Wollo, North Wollo and Wag Himra), East Shewa, North Shewa4, East and West Hararge in Oromia region were affected by agricultural drought. Furthermore, in 2009, three zones (Northwest, Eastern Tigray and Central Tigray zones) in Tigray region, six zones (West Hararge, East Shewa, West Shewa and North Shewa4, Southwest Shewa and Arsi zones) Oromia region, in three zones (Wag Himra, East Gojjam and South Gonder zones) in Amhara regon and Alaba zone in SNNP were struck by extreme drought, while six zones (South wollo, West Gojjam, North Shewa3, Ormia, North Gonder and North Wollo zones) in Amhara region, East Hararge in Oromia and Gurage, Sidama, Silti and Wolayita zones in SNNP were struck by severe drought.

All in all, major droughts mentioned in scientific studies could be observed in this thesis. For instance, Gebrehiwot et. al., (2011) pointed out that the worst drought situation was encountered in Tigray region during the year 2004 and 2009 monsoon, which 20.1%, and 17.4% of the region suffered drought condition respectively which had VCI values less than 35%. The results of this study also in line with the findings of Kogan (2019) who has reported that Ethiopia was affected by drought in 2009 and 2015. He added, one of the regions with large grain crops area, called Amhara, droughts severe-to-exceptional and extreme-to-exceptional (extremely severe) intensity covered 50–75% and up to 25% of panted grain crop area, respectively, every year since 2011 except for 2014 when the area was below 30% and 4%, respectively.

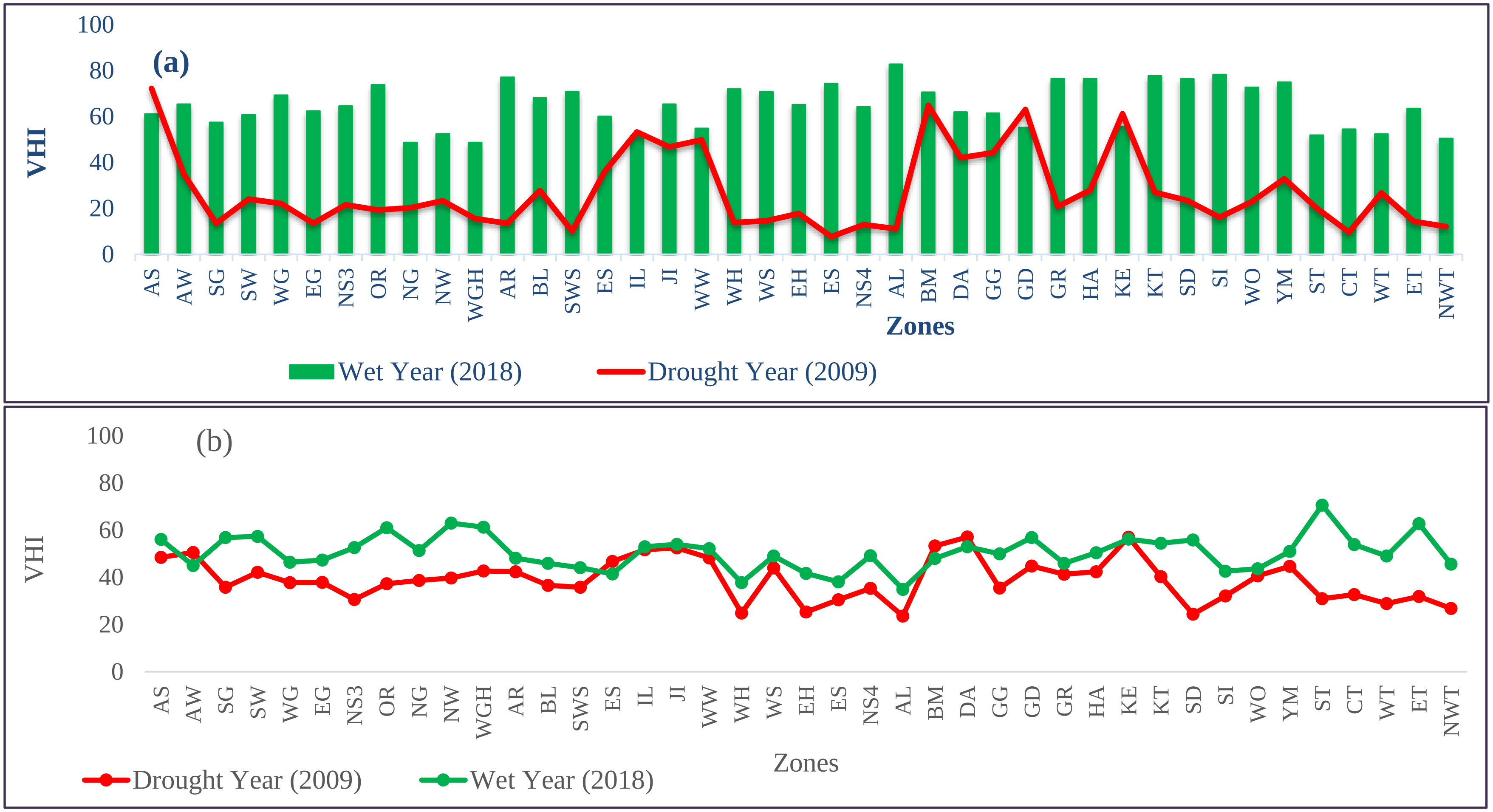


Figure 13. Comparison of drought and normal year Vegetation Health Index during June (a) and September (b) for different Zones

Looking at the Zonal level, low VHI value (VHI < 40) were observed in the northern highlands of Ethiopia (Southern Tigray Zone, eastern Tigray, most parts of Amhara region, West and East Harargie) in 2004, in 2009 almost all parts of the study area, central and northern highlands in 2015 and 2012 at the beginning of the cropping period. For instance, in 2009 all zones had a mean VHI values less than 30 which represents moderate and severe droughts. However, the remaining years show above average VHI. In the year 2018, the mean VHI value were more than 65 which is the indicator of healthy vegetation (Figure 13).

Generally, a high intensity of agricultural drought episodes was occurred in June 2004, 2005, 2006, 2009, 2013, 2014 and 2015 at the start of crop growing season which is the most critical period for crop sowing in the highlands of Ethiopia. On the other side, in June 2007, 2008 and 2018 vegetation health was in good status. In July 2004, severe droughts were recorded in Eastern Tigray and Alaba zone. In August, extreme drought was occurred in Ormia zone Amhara region (VHI=13) and moderate drought observed in 16 zones in 2015 and 14 zones were hit by moderate drought in 2007. Likewise, severe drought events were recorded in 2004 (Wag Himra VHI=22 and Eastern Tigray VHI=17), 2009 (East Hararge VHI=25 and Sidama VHI=24) and 2015 (Arsi VHI=23). Most moderate drought events were recorded in September for the years 2007, 2008, 2009 and 2015 in the highlands of Ethiopia. However, the intensity of these drought events was less significant than the onset of the main growing season in June. In contrast, most of the zones showed normal vegetation conditions during September 2005, 2016, 2017and 2018.

In order to study the temporal variation of VHI, a drought year VHI sequence was compared with that of a wet year (Figure 13). The average VHI value was found below 40 for more than 75% of the Zones during the drought year, which indicates existence of a severe drought condition over the region, whereas, the vegetation condition was maximum during 2018 both June and September. The difference between VHI of drought year and normal year was highest in the month of June indicating the effect of varying in starting of rainfall in June, while the difference between VHI of drought and normal year was relatively low in the month of September even though rainfall was offset early September in 2009.

4.1.3. Frequency of agricultural drought incidence

In this thesis, VHI was considered as a basic parameter to declare the regularity of agricultural drought based on the threshold for each month from 2004-2015. The frequency of agricultural drought was determined by calculating the mean value of VHI for administrative Zones for June to September. Kogan (2019) and Kogan and Guo (2016) reported that during the first 17 years of the twenty-first century, the Horn of Africa experienced seven major droughts as projected by the VHI for a few countries. They added the Horn of Africa (including the study area) was affected by droughts yearly. They also confirmed that early drought detection and prediction using VHI is crucial. The findings of this thesis indicated that there are no Zones that were free from the incidence of agricultural drought during the study period except Dawro.

Table 8 shows the number of drought months with different intensity classes at monthly timescales as calculated by the VHI. It is clear from the table that the highest agricultural drought incidence was observed in Central Tigray (18), Eastern Tigray (17), East Shewa (16), Alaba (15), Southern Tigray (14) and Wag Himra (14). In contrary, the incidence of agricultural drought in some Zones such as Kaffa, West Welega, East Welega, Awi, Asosa, Illubabor and Jimma was relatively lower and the area has been under the spell of drought for about 1–4 times.

The highest extreme and severe drought events were occurred in Tigray and Eastern Amhara, for instance, severe drought occurred 4 times in South Wollo, 5 times in North Wollo and Wag Himra Zones. Oromia zone was struck by two extreme drought events in the last 15 years. Spatial patterns of the above drought frequencies and magnitudes are presented in appendix 5. The frequencies of drought for different intensity classes show complex and local scale spatial patterns. However, the drought frequency map for all intensity classes (Appendix 5) shows that the northern, eastern, south eastern and central part of the highlands experienced recurrent droughts during the study period.

The spatial pattern of drought frequency showed high local-scale variability when we considered intensity classes. For example, more frequent moderate intensity (VHI between 26 & 40) drought events were observed in the northern and southeastern parts of the study area. Likewise, the occurrence of severe droughts (VHI between 16 & 25) were relatively high for the northern part of the study area (Appendix 5). However, southern, southwestern and western part of the study area showed less frequent drought events except some pockets that affected by frequent agricultural drought such as Alaba and Silti.

Table 8. Frequency of agricultural drought incidence per administrative zones at monthly time scale from 2004 to 2018

Zones	**E**	**S**	**M**	**T**	**Zones**	**E**	**S**	**M**	**T**
AS			2	2	EH		3	8	11
AW		1	3	4	ES	2		14	16
SG	1	2	10	13	NS	1		8	9
SW		4	8	12	Al	1	4	10	15
WG		2	8	10	BM			2	2
EG	1	1	6	8	GG			6	6
NS3		3	7	10	GD			4	4
OR	2	3	8	13	GR		1	3	4
NG		2	10	12	HA			4	4
NW		5	7	12	KF			1	1
WGH		5	9	14	KT			4	4
AR	1		6	7	SD		2	6	8
BL			12	12	SI		1	12	13
SWS	1		9	10	WO		1	6	7
EW			4	4	YM			6	6
IL			3	3	ST		1	13	14
JI			4	4	CT	1	1	16	18
WW			3	3	WT		2	10	12
WH	1	2	9	12	ET	1	2	14	17
WS	1		5	6	NWT	1	3	8	12
					Total	15	51	288	354

E- Extreme, S- Severe, M- Moderate, T-Total

Zone codes: AS=Asosa, AW=Awi, SG = South Gonder, SW = South Wollo, WG = West Gojjam, EG = East Gojjam, NS3 = North Shewa3, OR =Oromia, NG = North Gonder, NW = North Wollo, WGH = Wag Himra, AR = Arsi, BL = Bale, SWS = South West Shewa, EW = East Welega, IL = Illubabor, JM = Jimma, WW = West Welega, WH = West Harargie, WS = West Shewa, EH = East Harargie, ES = East Shewa, NS4= North Shewa4, AL= Alaba, BM = Bench Maji, GG = Gamo Gofa, GD = Gedeo, GR = Gurage, HA = Hadiya, KF = Keffa, KT = Kembata Tembaro, SD = Sidama, SI = Silti, WO = Wolayita, YM = Yem, ST = Southern Tigray, CT = Central Tigray, WT = Western Tigray, ET = Eastern Tigray, NWT = North Western Tigray

Based on the VHI, the Central, Eastern and Southern parts of Tigray, North and South Wello, North Shewa, Wag Himra, Oromia and South Gondar of the Amhara region, East and West Hararge, East Shewa and Bale Zones of Oromia region and Alaba, Sidama and Silti in SNNP can be delineated as a drought prone zones. This result supported earlier study conducted by Gebrehiwot et. al. (2016) in their evaluation of the spatial and temporal aspects of seasonal agricultural drought conditions in Ethiopia's during the crop growing season from 1998 to 2013 in major crop producing regions. They concluded that central and northern highlands of Ethiopia, particularly the Amhara and Tigray regions, as the most vulnerable agricultural production regions. They also added that historically, the two regions have been known as the most severely affected regions during the well-known Ethiopian famine period and a slight drought that result a failure in crop harvest can undermine household food security. And Gebrehiwot et al. (2011) in their evaluation of the spatial and temporal characteristics delineated Southern and Eastern Tigray as drought prone area based on SPI which also identified as drought prone zone in this thesis.

Furthermore, the frequency of agricultural drought during June-September is shown in Figure 14. The result indicated that the major extreme drought events were observed during June, out of 15 extreme drought events recorded during the study period, 13 (87%) were occurred during this month. Additionally, 59% of severe drought also observed in June. This implies that Kiremt rainfall starts late June in the study area in the study period.

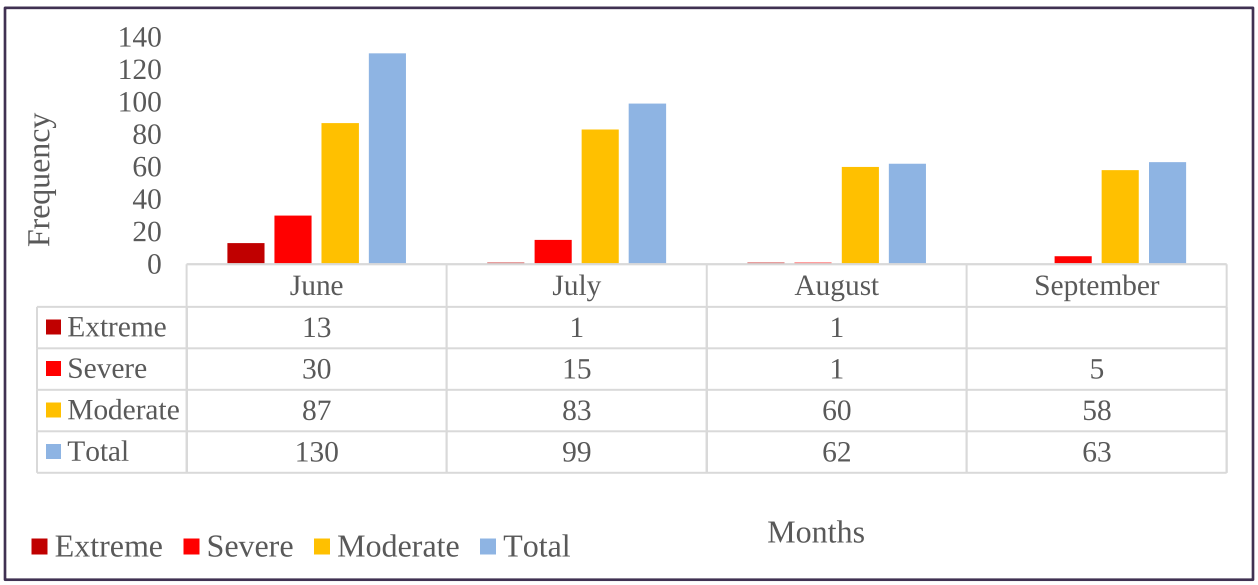


Figure 14. Frequency and magnitude of agricultural drought for each month from 2004-2018

In this figure, it is clearly depicting that the magnitude of agricultural drought incidence decreased in August and September. The frequency of Severe drought condition was highest in July than August and September. Severe drought also observed in September that affect the grain filling and maturing period of crops. Most of extreme and severe drought events were occurred in the years 2004, 2009 and 2015.

4.1.4. Spatial extent of agricultural drought using Vegetation Health Index

The spatial pattern of agricultural drought over the Ethiopian highlands is displayed through the means of VHI based on Kogan's VHI threshold of 40 % or less as moderate to extreme drought condition. A consistently low VHI value over several successive period intervals indicates drought development. Accordingly, the series of VHI maps show the spatial and temporal persistence of agricultural drought conditions in Ethiopia highlands over the past fifteen years. The spatial VHI patterns during the crop growing season for selected representative years are shown in Figure 15.

Investigation of the temporal VHI-based agricultural drought maps clearly indicate that a wide range of moderate to extreme drought conditions were observed during the crop growing periods of 2004, 2005, 2009, 2010, 2014, and 2015 in the central, northern, and southwest parts of the study area. For instance, in 2009, most part of the Ethiopian highlands particularly in the major crop producing areas of Amhara, Tigray, Oromia and Southern Nations, Nationalities, and Peoples' region (SNNPR) show the prevalence of moderate to extreme drought conditions. Moreover, multitemporal drought maps showed a poor vegetation health and incidence of drought event in Eastern Amhara, Tigray, and Eastern and South Eastern Oromia zones, in the years 2004, 2010 and 2015. On the other hand, the cropping seasons (years), 2007, 2008, 2011, 2017, and 2018 reflect the near-normal vegetation conditions that may leading or implying a good crop harvest.

The spatial aspect of agricultural drought was further analyzed by taking in to account the start and end of kiremt season (June and September respectively). The study shows that moderate to extreme vegetation stress at the start of the crop growing season for the years 2004 (20 Zones), 2005 (21 Zones), 2006 (13 Zones), 2009 (31 Zones), 2013 (11 Zones) and 2015 (10 Zones) (Table 9) which was mainly due to delay of rainfall at the beginning of the crop growing season.

Likewise, the spatial patterns of agricultural drought at the end of the crop growing season, September, revealed that the years 2004, 2009 and 2015 were drought years. The experience of drought condition at the end of crop season was mainly resulted from failure of rainfall to the end of the crop growing period that caused crop failure. Moreover, this study revealed that moderate to extreme drought events were occurred in July 2004,2009, 2010, 2014 and 2015 due to failure of rainfall which is the most important month for sowing some important crops.

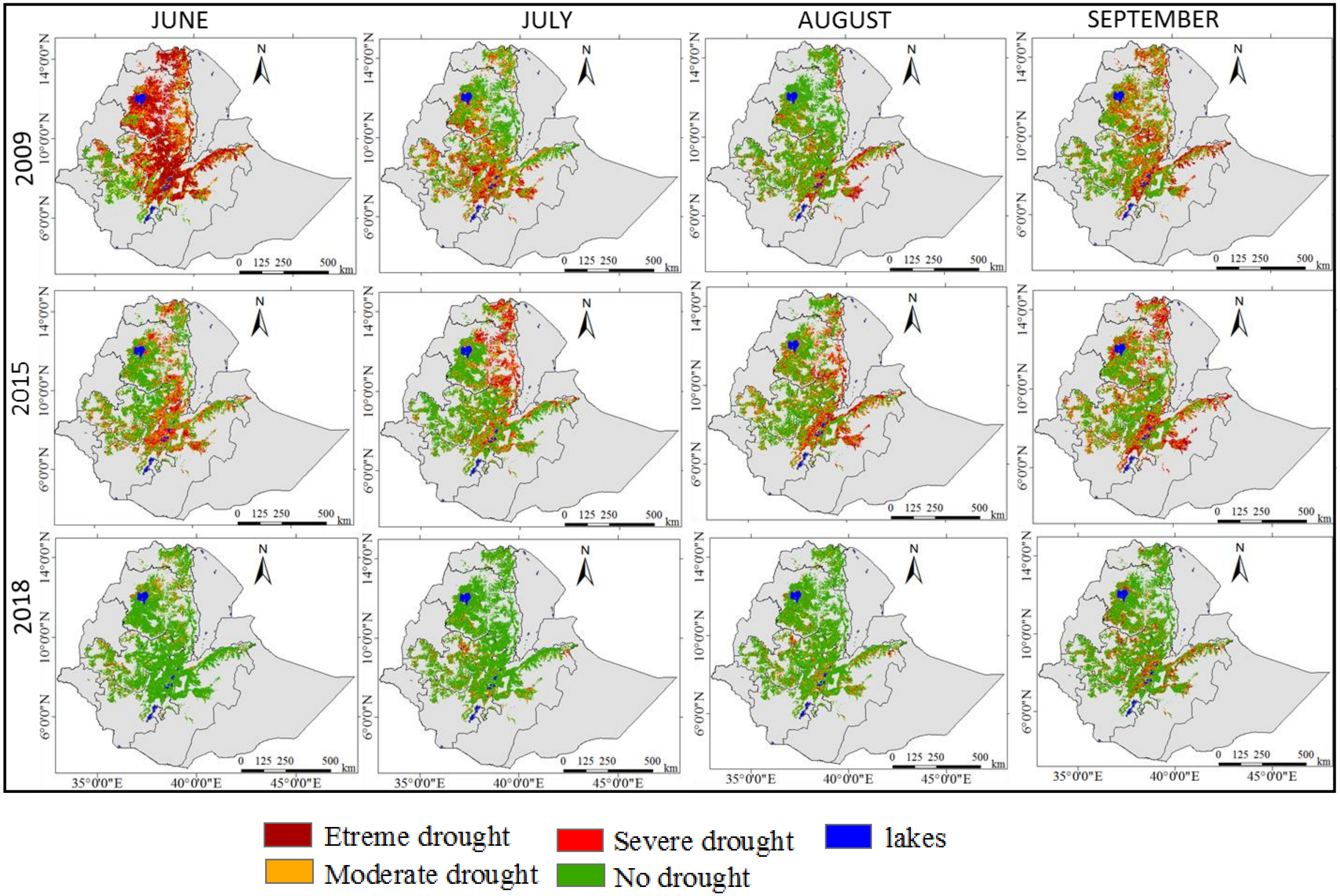


Figure 15. Vegetation Health Index (VHI) for drought year (2009 and 2015) and normal year (2018)

The result of this study lines with the findings of Gebrehiwot et al. (2016) who has reported that severe drought events were observed during 2004, 2009 and 2010 in Ethiopia. They added the main causes responsible for these drought events like for example, the 2009 drought event occurred by failure of timely rainfall at the commencement of crop growing, while the 2010 drought episode occurred due to rainfall failure at the end of crop growing season. Additionally, Winkler et al. (2017) reported that drought was detected in 2009 and 2015 over central Ethiopia. In 2009, major precipitation deficit was concentrated in northern Ethiopia.

The results obtained for drought years 2009 and 2015 are further discussed in this section. Because both drought years were well noted for severe drought that wide spread across the study area. And also, the normal year 2018 was selected for comparison. Figure 16 shows the percent area of Kiremt rainfall-receiving regions experiencing moderate to extreme drought conditions during June, July, August, and September for the selected drought and normal years. In 2018, normal vegetation conditions were observed in many areas, except for some small localized pockets in the southeastern, northwestern and southern eastern parts that revealed severe drought conditions. In this year, moderate to extreme drought conditions affected relatively large portion of the study area in September (22%) due to failure of rain fall. However, more than 85 % of the study area in June, July and August showed normal conditions (Figure 15 and Table 9)

On the other hand, drought in 2009 and 2015 affected very large areas. In 2009, for instance, 30–78% of the total area was affected by moderate to extreme drought conditions. Particularly, in June, large portion of (78%) the area was affected by moderate to extreme drought conditions, while in August it dropped in to 30%. According to Bayissa et al. (2018) the main reason for the reduction of the drought area during this month was the incidence of heavy precipitation over the western and northern highlands. However, in September 2009, the drought affected area was increased in to 51% due to deficiency of precipitation at the end of crop growing period.

Table 9. Seasonal years, months and administrative zones of Ethiopian affected by agricultural droughts based on monthly Vegetation Health Index

Year	June	July	August	September
2004	AS,SG,SW,WG,EG,NG,WGH,BL,ES,NS4,AL,GG,SD,SI,WO,ST,CT,WT,ET,NWT	Awi,SG,SW,WG,EG,OR,NG,NW,WGH,BL,WH,WS,EH,ES,AL,KT,SD,SI,ST,CT,WT,ET	WH,EH,ES,SI,ET	NW,WGH,YM,ST,CT,ET
2005	Awi,SG,WG,EG,NG,NW,EW,IL,JI,WW,WS,AL,GD,SIL,YM,ST,CT,WT,ET,NWT	YM		SIL,CT,ET,
2006	SG,SW,NS3,OR,NW,WGH,WH,EH,ES,NS4,ST,ET,NWT			SWS,EW,CT,ET
2007			SG,SW,NS3,NG,NW,WGH,SWS,WS,YM,CT,WT,ET,NWT	JI
2008	SW,OR	OR	ET	SG,CT,ET,NWT
2009	AWI,SG,SW,EG,NS3,OR,NG,NW,WGH,AR,BL,SWS,EW,WW,WH,WS,EH,ES,NS4,GU,HA,KT,SD,SI,WO,YM,ST,CT,WT,ET,NWT	AR,BL,SWS,EW,WS,ES,AL,GG,GU,HA,KT,SD,SI,WO,YM	AW,AR,BL,WH,BM,GG,GD,SD,WO	SG,WG,EG,NS3,OR,NG,NW,BL,SWS,WH,EH,ES,NS4,KT,SD,SI,ST,CT,WT,ET,NWT
2010	NG,CT,WT,NWT	SG,SW,WG,NS3,OR,NG,NW,WGH,NS4,GD,ST,CT,ET	EG,KE	
2011		OR,NS3,ES,SW		NS,SW,NS3,OR
2012	SG,WG,EG,EH,ES,NS4		ES	
2013	SG,SW,NS3,NG,NW,AR,NSR,ST,CT,WT,NWT	Awi,SG,WG,OR,WGH,WH,ST,CT,WT,NWT	WG	
2014	AR,SWS,EH,ES,AL,SI,CT	SG,SW,EG,NS3,OR,NG,NW,WGH,AR,BL,SWS,WH,WS,EH,ES,NS4,AL,ET	WT	
2015	SW,NS3,BL,SWS,ES,NS4,AL,GU,SI,CT	SW,NS3,OR,NG,NW,WGH,EH,ES,AL,HA,SI,WO,ST,CT,ET	SW,NS3,OR,NW,WGH,AR,WH,EH,ES,AL,GG,SD,SI,WO,ET	AS,NG,WGH,BL,WH,ES,AL,BM,GG,GD,SD,SI,WO,ST,ST,CT,ET,NWT
2016	WGH,NWT	IL,JI	AL,WT	BL,GG
2017	AL		BL,WH,AL	
2018	OR			WH,ES

Zone codes: AS=Asosa, AW=Awi, SG = South Gonder, SW = South Wollo, WG = West Gojjam, EG = East Gojjam, NS3 = North Shewa3, OR =Oromia, NG = North Gonder, NW = North Wollo, WGH = Wag Himra, AR = Arsi, BL = Bale, SWS = South West Shewa, EW = East Welega, IL = Illubabor, JM = Jimma, WW = West Welega, WH = West Harargie, WS = West Shewa, EH = East Harargie, ES = East Shewa, NS4= North Shewa4, AL= Alaba, BM = Bench Maji, GG = Gamo Gofa, GD = Gedeo, GR = Gurage, HA = Hadiya, KF = Keffa, KT = Kembata Tembaro, SD = Sidama, SI = Silti, WO = Wolayita, YM = Yem, ST = Southern Tigray, CT = Central Tigray, WT = Western Tigray, ET = Eastern Tigray, NWT = North Western Tigray

Similarly, during 2015 cropping season, the percentage area hit by agricultural drought was between 40- 48%. In general, large parts of the study area were struck by agricultural drought in June and the central, southeastern and northern parts of the study area were affected by extreme drought in 2015 while severe drought condition was observed in central, northern and northwestern parts of the study area in 2009.

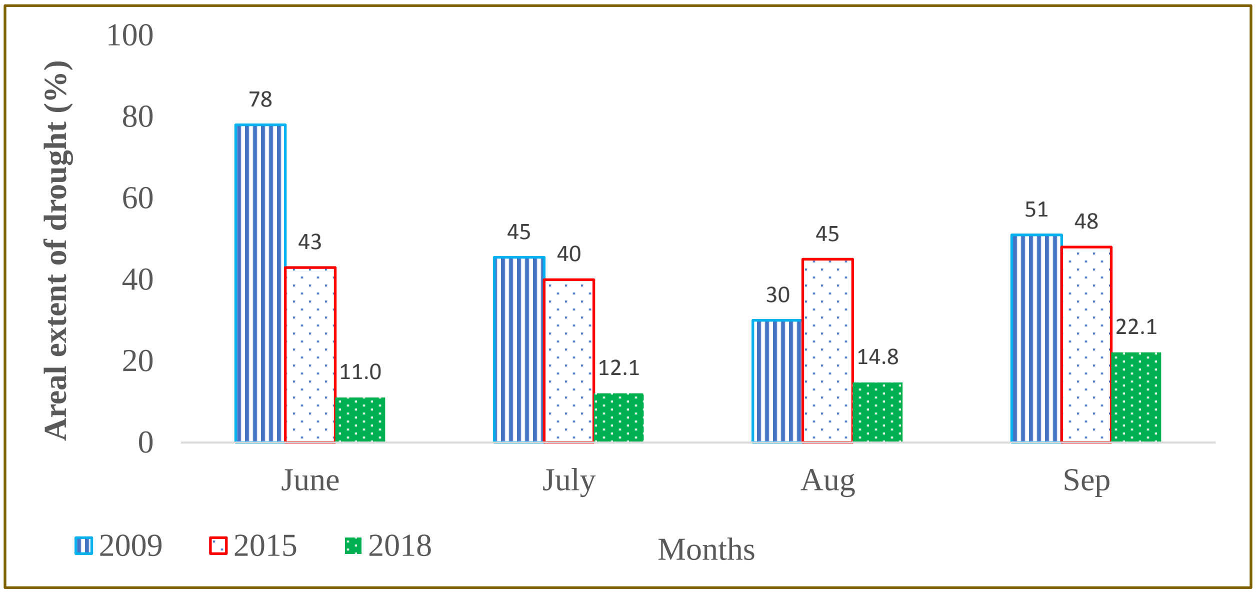


Figure 16. The area affected (%) by moderate to extreme drought conditions for drought year (2009 & 2015) and normal year (2018)

According Viste et al. (2013) 2009 was the only year during 1972–2011 that most zones were struck by moderate to severe drought condition. The researchers also indicated that the year 2010 was drought year in most parts of the country. On the other side, Sohnesen (2019) reported that 2015 was a drought year with low rainfall in the growing season and even worse than previous historical drought years (2009 and 2002/2003) based on meteorological evidence (rainfall anomalies) and household self-reported data from ESS. The study further indicated that Worse vegetation condition mainly concentrated in a smaller area in the northeast of the country which has low contribution for agricultural production.

Moreover, the 2015 drought was informed as one of the most severe recent droughts in the country, and it prolonged into 2016 in some parts of the country (Qu et al., 2019). According to Mera (2018) and OCHA (2016) more than one third of Ethiopia's woredas were officially classified as facing a dire food security and nutrition crisis over the year. At the end of 2015, more than 10.2 million people were targeted with life-saving food assistance, and additional 7.9 million people were targeted through the Productive Safety Net Programme. The report identified Afar, Amhara, Dire Dawa, Harari, Oromia, SNNPR, Somali and Tigray as most affected regions. However, regions such as Tigray, Afar and Somali were hard hit and 24%, 25% and 21% population were affected.

Another study by Liou and Mulualem (2019) showed that the direct influence of ENSO on the vegetation of Ethiopia, especially, during the El Niño years 2009–2010 and 2014–2015 were visible and the NDVI values gradually declined and remained marginally below average during these El Niño years and the hardest hit areas are located in the northeast and southeast part of the country.

Key informants' interview in South Wollo zone (Jamma, Kalu, Wereilu woredas) confirmed that the 2015 years drought was very severe and the crops have not produced grain. The interviewee further stated that the rainfall was failed in September before the crop matured. The South Wollo zone agricultural expert described this year very critical for woredas in the eastern part of the zone.

The findings of this study lines with the findings of Berehan et al. (2017) who have reported that crops have failed and hunger and malnutrition has risen sharply, affecting millions in North Wollo zone. Moreover, almost 41% area where considerable crop loss was reported in the South Tigray zone based on sample of 31 sub-kebeles (Warner & Mann, 2018). Figure 17 shows food-secure and insecure regions in the highlands of Ethiopia during 2015. The data was obtained from FEWS NET web based early warning system for the period 2015 (July-September). Based on the map the eastern, northern, northeastern, and southern regions were highly food-insecure in 2015 and the main reason for food-insecurity in Ethiopia were the shortfall and late starting date of the main rainfall season due to El Niño (FEWSNET 2015).

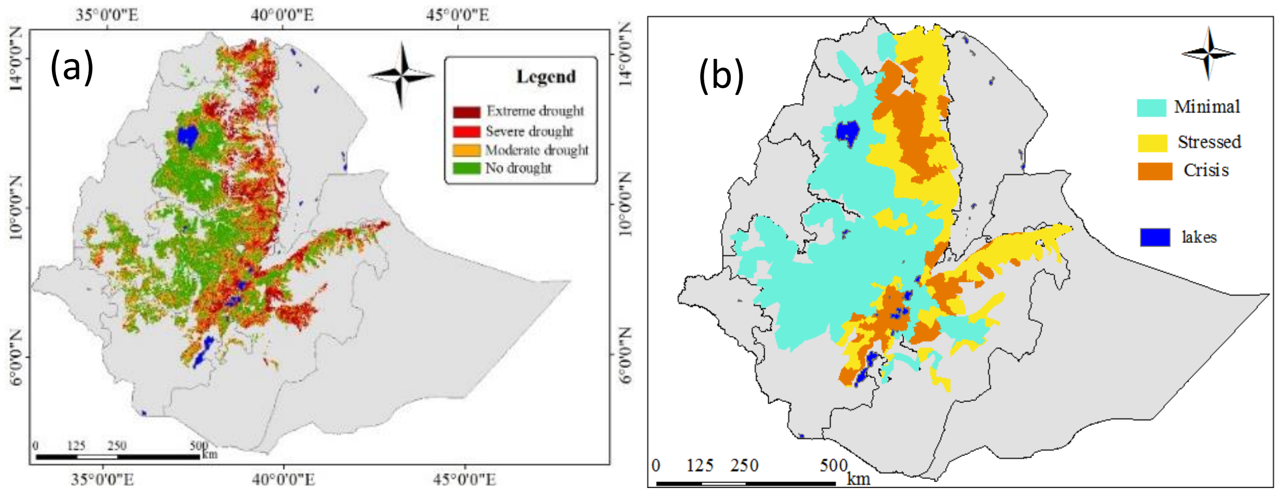


Figure 17. Average Vegetation Health Index for June to September 2015 (a) and food-security situation for July to September 2015 (b) based on USAID and the Famine Early Warning Systems Network (FEWSNET 2015.

As portrayed above (Figure 17), the maps of VHI and food security shows good spatial agreement between drought affected areas and food insecure areas based on visual comparison. Moderate to extreme drought conditions were clearly identified in Tigray, eastern Amhara, Eastern Oromia and SNNP as the same time the food security situation map displayed that there was food crisis issue in these areas.

Furthermore, the average values of the VHI for the referenced food-secure status zones of FEWSNET were extracted to assess the drought severity ranges in these zones. Then, Pearson correlation and simple linear regression were held to determine the relationship between VHI and food security. The results show that extreme to moderate droughts were observed during stress and crisis food-security status zones. The statistical analysis of this study indicated that VHI and food security status zones of FEWSNET has positive correlation ($r = 0.77$, $R2 = 0.6$, $P < 0.01$) (Figure 18). This indicates a strong linkage between drought and food-security in Ethiopia. According to Kogan (2019) drought poses a more substantial threat to main crops and food security than any other factors.

Therefore, the result of this study is consistent with FEWS NET food security map and thus, VHI can possibly be used to monitor and provide early warning in identifying food insecure regions, as well as helping decision makers to start action in terms of planning for future drought and mitigating its adverse impact on crop yields. Kogan (2019) stated applying VHI enables users to monitor effectively agricultural production as first step, secondly climate and weather changes and finally, food security.

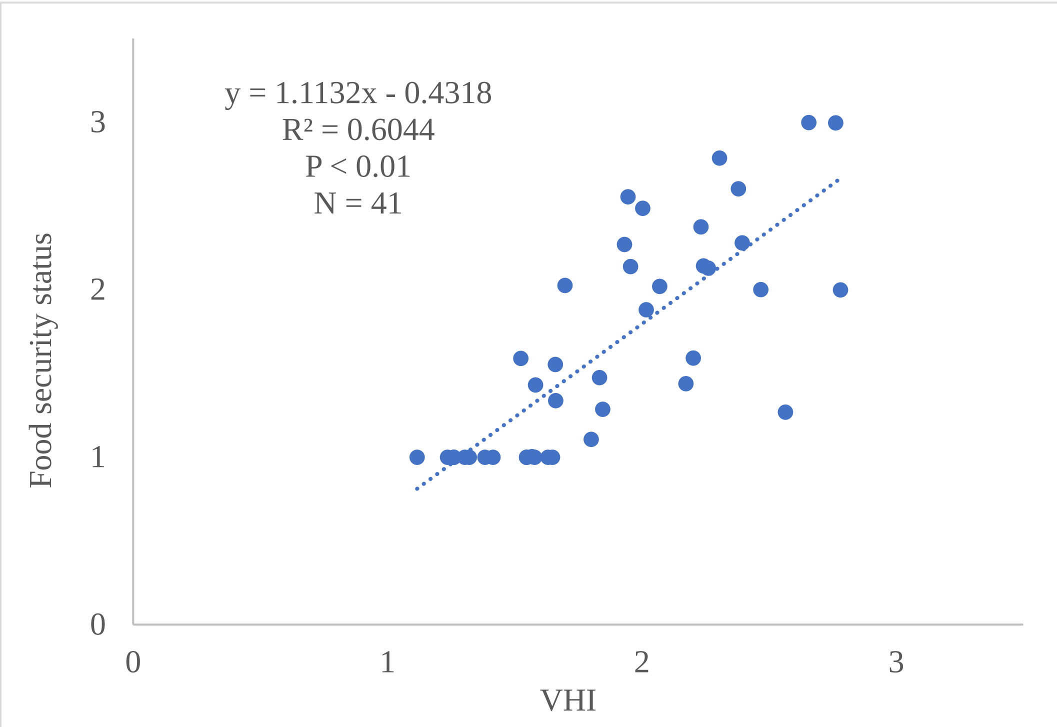


Figure 18. Vegetation Health Index and Food security status over the highlands of Ethiopia for the drought year 2015

4.1.5. Vegetation Health Index and its variability

Studies (e.g., Gidey et al. 2018; Ayanlade et al., 2018) revealed that the coefficient of variation determined by the absolute dispersion of data relative to the mean and mainly expressed as a percentage. Examining the coefficient of variation is, thus, valuable to determine the statistical precision of estimation of VHI in the current study. Based on the calculation of CV, the lowest value of the coefficient of variation corresponds to good precision, whereas, the highest coefficient of variation representing the greater level of dispersion of the estimation. In this study, the coefficient of variation was examined for four months (June-September) from 2004 to 2018 (fifteen years). The general results of this study show that high precision estimation in August, July and September (Figure 19).

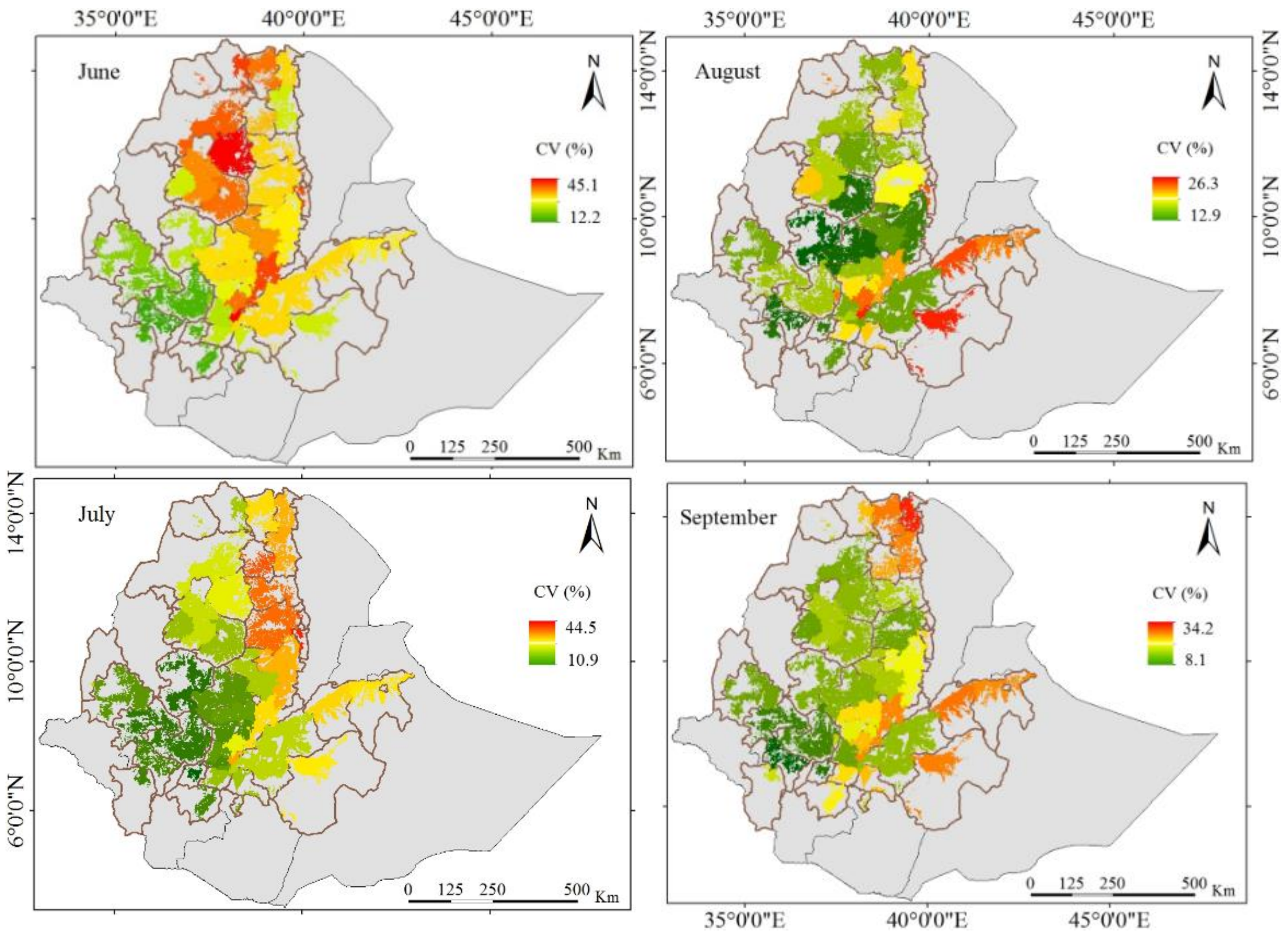


Figure 19. Percentage cofficient of variation (CV%) of Vegetation Health Index June-September for the period of 2004-2018

The overall coefficient of variation in June ranges from 12 to 45%. Hence, a higher (45%) coefficient variation has reported in the zones of South Gondar and Alaba and lower in Kaffa (12%). Generally, the coefficient of variation of twenty zones in June was greater than 30% which is above the maximum acceptable thresholds of 29%, while the coefficient of variation in the remaining zones were highly reliable as the maximum acceptable thresholds are below 29.9%. One of the main reasons for high coefficient of variation for these zones could be failure of rainfall towards the start of crop growing period (June). These values further imply that rainfall in the onset month (June), in most of the central and northern highlands are not reliable. The coefficient variation of rainfall in this month is also very high (rainfall is highly variable).

On the other hand, very low coefficient of variation was observed in August (Figure 19). During this month, the overall coefficient of variation was found between 13 and 26% that indicated highly reliable estimation and were below the maximum acceptable thresholds of 29.9% in all zones. Except eight zones in July and one zone in September, the coefficient of variation was below the maximum acceptable value. The findings of this study support the findings of previous study (Gidey et al. 2018) that reported seasonal variability in vegetation condition was determined by erratic rainfall distribution in Raya and its environment. Other study by Bewket (2009) indicated that rainfall shows moderate interannual variability in most of the highlands of Amhara region that determined the interannual variability of vegetation condition (cereal crops).

4.2. Spatio-temporal assessment of agricultural drought with Standardized Precipitation Index (SPI)

The spatio-temporal pattern of agricultural drought events over highlands of Ethiopia was identified from SPI time series of multiple-time steps. In our study, SPI-1 (monthly) time step was computed to examine the characteristics of agricultural drought because it has been adequate to monitor agricultural drought in short term. 1-month SPI reflects short-term conditions, its application can be related closely to meteorological types of drought along with short-term soil moisture and crop stress, especially during the growing season (WMO, 2012). The monthly SPI was calculated from April-September to characterize droughts that occur due to rainfall deficit in monsoon months. In particular, April and May were incorporated to determine moisture availability for long cycle crops such as maize.

4.2.1. Temporal agricultural drought assessment using Standardized Precipitation Index (SPI)

As stated in the methodology part agricultural drought would be happening when SPI is negative and its intensity comes -1 or lower. The extent of negative SPI values are powerful indicators of drought magnitude and determination. Figure 20 illustrates the time series plots of the 1-month CHIRPS SPI for the entire study area for the period 2004 to 2018 during Kiremt season.

The result of this study revealed that drought has occurred at different levels of severity from 2004 to 2018 during kiremt season. For example, 2014–2015 and 2009–2010 were some of the historic drought years in the study area. The drought that happened in year 2009 and 2015 were very severe than others that the SPI value was below 0 in all months. The result indicates that during those years, there was rainfall deficit in the growing season and it, therefore, was the worst dry seasons. These drought years typically caused by ENSO events.

Moreover, Severe to extreme drought episodes were observed at the begging of cropping period (June) during 2004, 2005, 2009, 2014, 2015 and 2017. Additionally, at the end of cropping period (September) severe to extreme drought events were occurred in the years 2004,2009, 2015, 2016 and 2018. In July 2009, 2014 and 2018 almost, all administrative zones were struck by severe to extreme drought. In June the peak drought intensity was -3.6, whereas -3.41, -2.27 and -2.77 were drought Peak intensity for July-2015, August-2016 and September-2015 respectively.

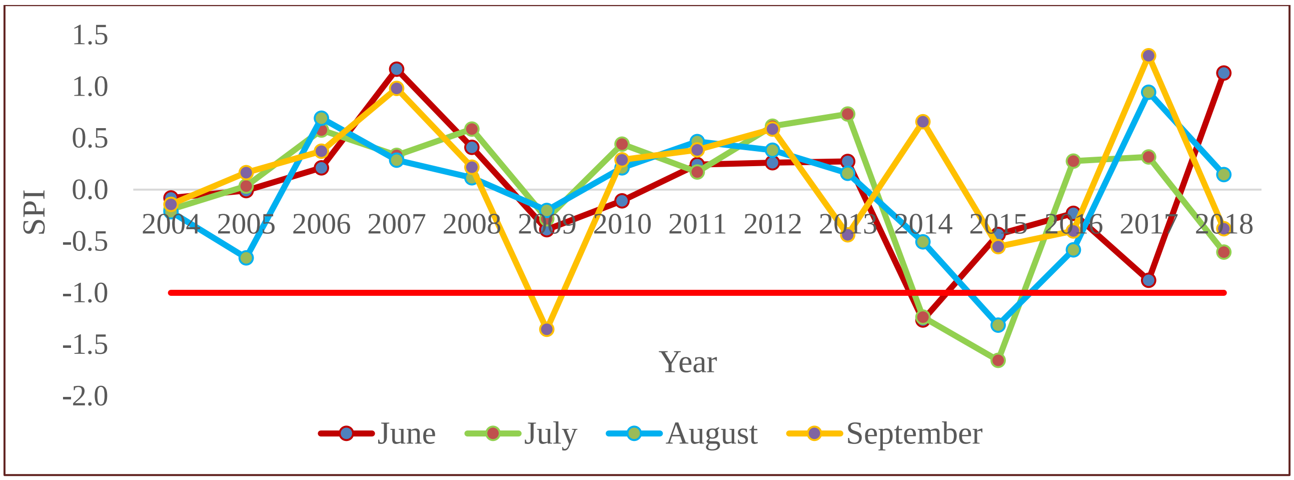


Figure 20. Time series plots of Standardized Precipitation Index for the entire study area for the period 2004 to 2018

In zonal level, during July 2015 and September 2009, almost all Zones in Amhara and Tigray regional state experienced low SPI values which indicated that the areas were affected by severe drought conditions. Furthermore, in August 2015, except Zones in Tigray region and the two Hararge, central, western and southern highlands of Ethiopia were hit by severe drought.

Plots of time series of SPI at monthly time scale for the major maize, teff and wheat producers (East Welega, East Gojjam and Arsi respectively) is shown in Figure 21 for Kiremt season as representative example.

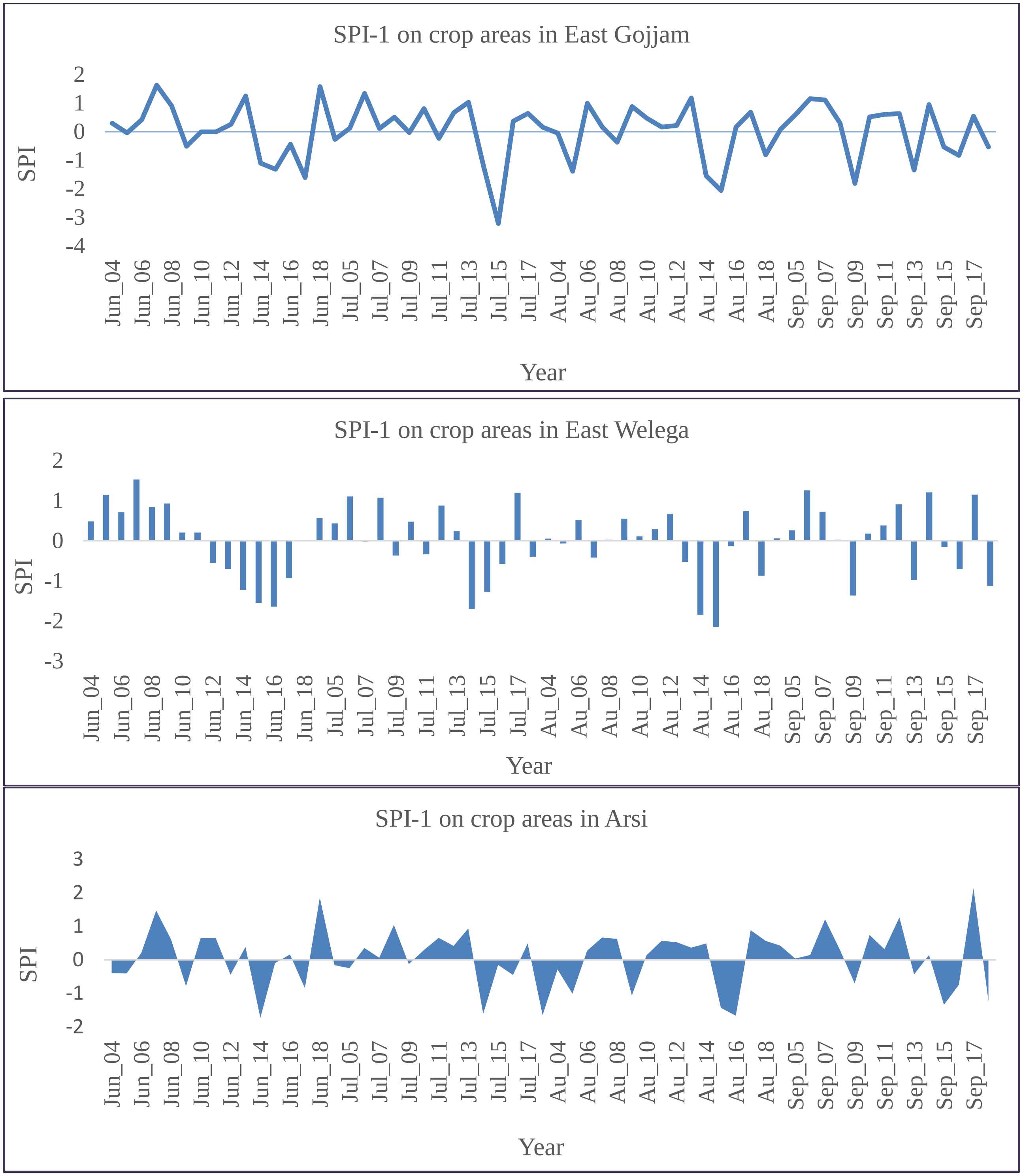


Figure 21. Time series plots of monthly Standardized Precipitation Index on selected Zones (East Gojjam, Arsi and East Welega for the period 2004-2018

For instance, in East Gojjam, extreme drought events were observed in July and August 2015, while many moderate and severe drought events were recorded in 2009, 2014 and 2015 in all months. Similarly, in East Welega moderate to severe drought conditions were occurred during 2014 and 2015 for three months (June-August), June 2016 and September 2009. On the other hand, moderate to extreme drought events were struck Arsi zone at the beginning of Kiremt (June) 2014, July 2014, 2016 and 2018, August 2005, 2009, 2014 and 2015 and September 2015 and 2018 (Figure 21).

The 1-month SPI temporal analysis further showed that extremely low SPI were observed at the beginning of the cropping period (sowing) for long-maturing Meher crops like maize (April-May) which are not displayed here during the years 2004, 2008-2009, 2011-12, and 2017. On the other hand, moderate to extreme drought episodes were observed at the begging of monsoon (sowing period for major crops such as Teff, Wheat and Barley), during 2009 in Tigray, central and northern parts of Amhara, central and south east Oromia and Southern SNNP, 2014 in most parts of Oromia and north east Amhara, 2015 in western Amhara and Oromia and in 2017 most parts of Amhara, Oromia and SNNP. In contrast, most of the study area showed normal rainfall conditions during the beginning of crop growing season in 2006, 2007, 2008 and 2018.

4.2.2. Spatial characteristics of agricultural drought using Standardized Precipitation Index (SPI)

With the aim of labeling the spatial patterns and severity levels of drought in the study area, the month with higher magnitude of drought and normal months for the last fifteen years was analyzed. Examination of the temporal SPI-based agricultural drought maps clearly indicate that there were a wide range of drought conditions during the cropping periods of June (2004, 2009, 2010, 2014, 2015 and 2016), July (2009, 2014, 2015 and 2015), August (2005, 2009, 2014, 2015 and 2016) and September (2004, 2009, 2015, 2016 and 2018) in the study area with different magnitude. In these years, over 25% of the study area was struck by moderate to extreme drought conditions. In contrast, the cropping seasons of 2006, 2007, 2008, 2011, 2012 and 2013 show normal conditions implying a good precipitation condition. According to the recorded rainfall data of CHIRPS, the years of 2009 and 2015 were the driest and 2006 was wet years.

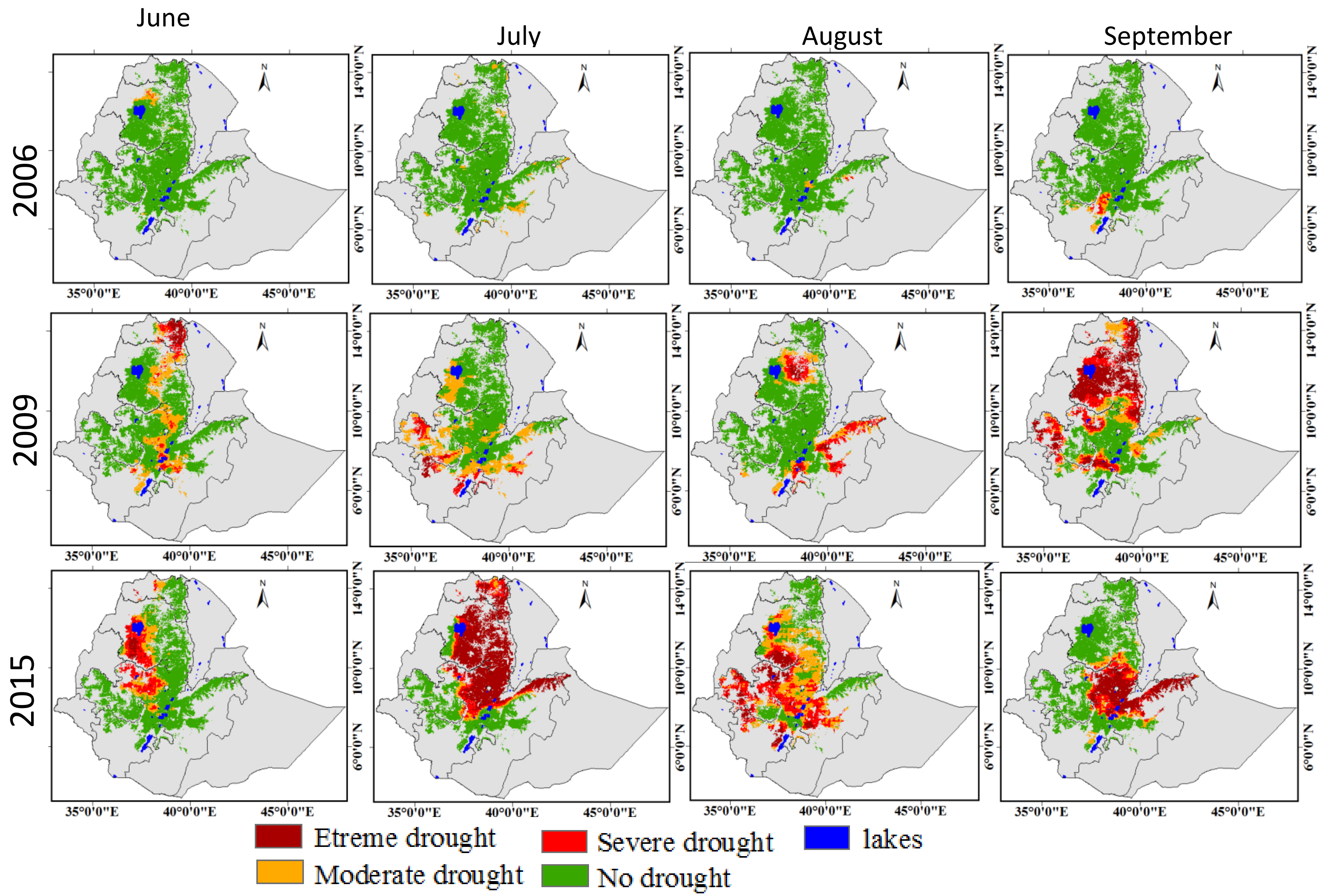


Figure 22. Standardized Precipitation Index (SPI) for drought year (2009 and 2015) and normal year (2006).

Figure 22 shows the spatial extents of selected drought (2009 and 2015) and normal (2006) years during the main rainy season (June, July, August and September). As it has been shown in the figure, in 2009, severe to extreme drought conditions have shown from June-September. During these months, the northern, central and southern parts of the study area were affected by moderate to extreme drought. But the area affected by moderate to extreme drought in September was largest than the remaining months. Table 10 shows the percent area of moderate to extreme drought conditions during June to September for the selected drought and wet years. In September 2009, major precipitation deficit was concentrated in northern highlands of Ethiopia. In this year, 29%, 36%, 26% and 64% of the study area was affected by drought in June, July, August and September respectively. The largest portion (64%) of the study area was affected by drought in September. This situation (failure of rainfall) at the time of maturity for major crops may cause crop failure.

Table 10. The area affected (%) by moderate to extreme drought conditions for drought years (2009 and 2015) and wet year (2006)

	Area affected by drought (%)			
Year	June	July	August	September
2006	2.2	4.1	1.1	4.7
2009	28.8	35.8	25.6	63.9
2015	27	66.5	68.3	37.7

As indicated in Figure 22 and Table 10, in 2015 (June-September), except the south western part of the study area, all parts particularly northern, northeastern and southern part of the study area were affected by extreme drought. About 27-68 % of the total area was affected by moderate to extreme drought conditions. Particularly in July and August most of the study area was struck by extreme drought condition. Central and northern highlands of Ethiopia were highly affected by extreme drought conditions during August 2015, whereas the southern and western part of the study area was experience normal conditions (Figure 22). Furthermore, drought condition during July 2015 were occurred in the southern, central and western parts of the study area, while the northern part of the study area was found under normal conditions. The report by United Nation indicated that the 2015 drought was grew primarily in the eastern and north-eastern areas of the country. The report also clearly explained that total average rainfall across this area averaged 480 mm between March and September 2015, and leading water availability per capita to drop to below 35% of the average (OCHA, 2016). According to the information obtained from Agricultural and Rural Development of South Wollo Zone, during the year 2015 there was severe agricultural drought in south Wollo zone. According to the key informants, the Zone had faced crop failures due to failures of rainfall in August and September.

Since SPI can be used to identify both dry and wet years, SPI analysis was applied to the identification of the wet year conditions too. As clearly shown on Figure 22 and Table 10, the year 2006 was indicated as a non-drought year because of all parts except some pockets in southern, eastern and northern parts that revealed moderate drought conditions. In September 2006, moderate drought conditions affected 4.7 % of the total area. However, more than 95 % of the total area showed normal conditions in all months in 2006. This may be due to the influences of the mal-distribution of rainfall or occurrence of considerable dry spells during the preceding long dry seasons.

This finding is again in agreement with Bayissa et al. (2017) that on meteorological drought for the Upper Blue Nile Basin, showed that the known historic drought years in the study area were 2014–2015, 2009–2010 which were identified as drought year in this thesis. The author confirmed that 2015 was a drought year almost for all parts of the study area. Suryabhagavan (2017) and Viste et al. (2013) found high spatial variation in drought frequency and magnitudes across Ethiopia that reflects the variation in the seasonal precipitation cycle between regions in the country. The year 2009 were identified as dry in most of Ethiopia by these authors.

4.3. Relationships between Vegetation Health Index (VHI) and Standardized Precipitation Index (SPI)

In countries like Ethiopia, where agricultural operations are predominantly rainfall oriented, there is a high probability for fluctuations in the seasonal rainfalls to negatively affect agricultural production and /or yields. Both satellite images and ground based practical observations; for instance, have affirmed that in highlands of Ethiopia, where the farming activities are, totally, based on seasonal rainfalls, agricultural yields have shown significant reductions, mainly, due to the effects of the seasonal rainfall irregularities. Thus, the statistical relationship between SPI and VHI depicted how the agricultural drought monitored by VHI associate with the meteorological drought measured by SPI. In order to understand the relationship between VH and precipitation, the entire study area and zone-wise average SPI values were correlated with the zone-wise average VHI values

Accordingly, the result of this study discovered that SPI and VHI were positively correlated for the entire study area. The correlation was ($r = 0.4$ or $R^2 = 0.16$ /$P = 0.14$) in June, ($r = 0.51$ or $R^2 = 0.26$ /$P > 0.05$) in July, ($r = 0.52$ or $R^2 = 0.27$ /$P > 0.05$) in August and ($r = 0.62$ or $R^2 = 0.38$ /$P > 0.01$) in September. The highest positive correlation was observed in September while low correlation was observed in June and statistically significant at all months except June for the entire study area. Figure 23 provides a detailed summary of SPI and VHI for each months for the entire study area. Wang et al. (2014) stated that statistical relationship between SPI and VHI has strong spatiotemporal correlation during a drought period in Southwest China. Therefore, this study has also observed similar findings in the highlands of Ethiopia for the entire study area.

However, in case of zonal-wise evaluation, the correlation between VHI and the same month SPI1 is both negative and positive in the study area. For instance, in June, out of 41 zones, standardized precipitation index and vegetation health index has positive relationships in 30 zones. The remaining 11 zones has negative correlation. These zones are located in southern and southwestern parts of the country which mainly get surplus rainfall. In 15 zones (out of 30 which has positive correlation between SPI and VHI), the relationship between these two indices was statistically significant (< 0.05). In July, SPI and VHI were positively correlated in all administrative zones with different level of strength. It ranges between ($r = 0.03$ to $r = 0.72$). The highest positive correlation was observed in the northern and central highlands such as East Shewa, North wollo, Wag Himra, North Shewa3.

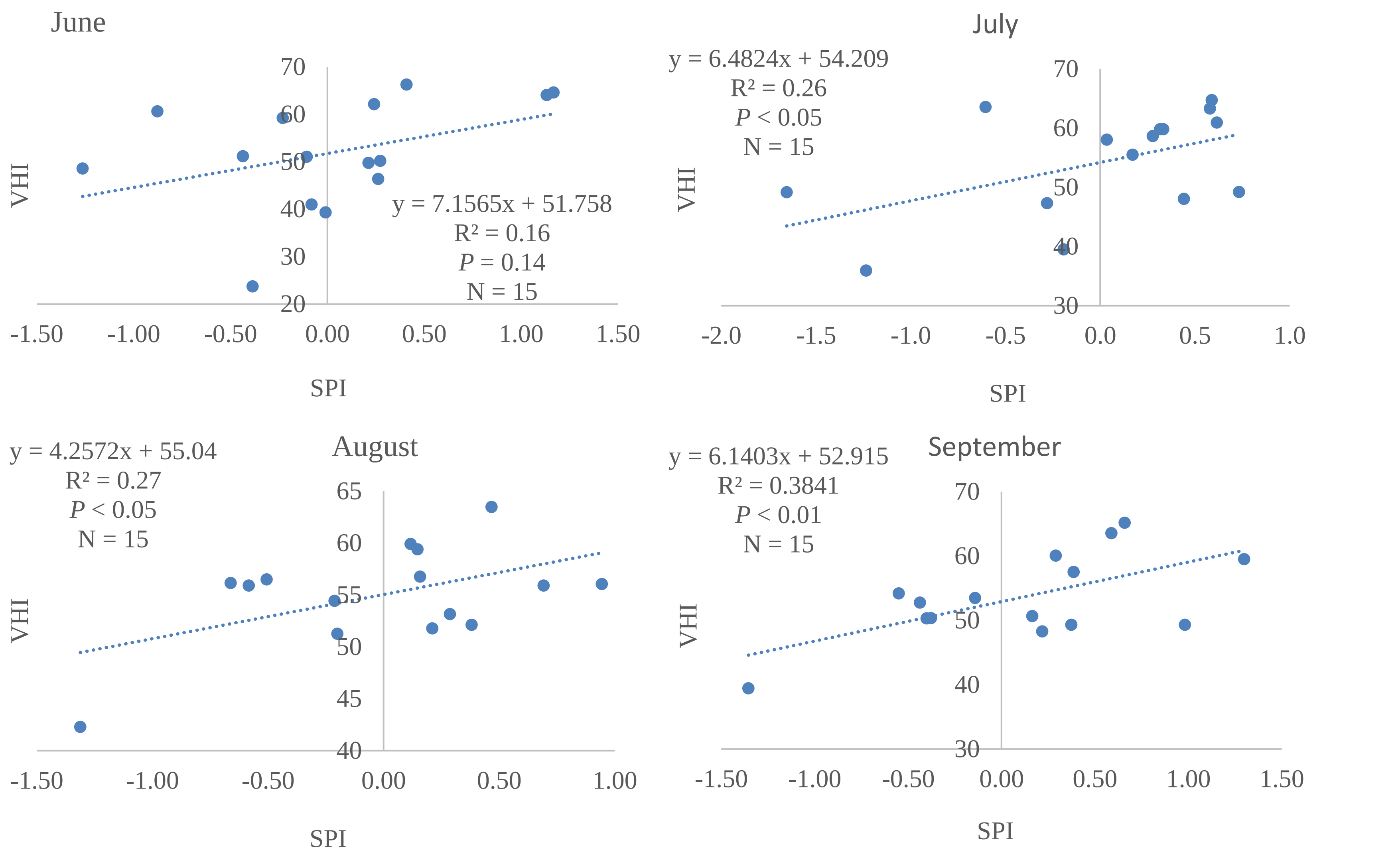


Figure 23. Standardized Precipitation Index (SPI) and Vegetation Health Index (VHI) relationships over Ethiopia highlands for the period 2004–2018

In August, SPI and VHI was negatively correlated in seven zones (South Gonder, North Shewa3, Illubabor, North Shewa4, North Gonder, Wag Himra, and Central Tigray). In the remaining zones SPI and VHI was positively correlated between ranges (r = 0.01 to r = 0.77). Furthermore, in September, negative correlation was observed in two zones (Illubabor and Kaffa). However, positive correlation was observed in the remaining zones. Here the highest correlation was found in West Hararge zone (r = 0.78).

Even though drought patterns indicated by SPI and VHI agree to a large extent, major deviations can be found for each months and seasonal years. These differences can be explained by the particular characteristics of the drought indices itself. For example, SPI measures the rainfall deficit from a primarily meteorological point of view, whereas VHI assesses the condition of the vegetation cover. The latter is not only influenced by water availability from precipitation but is also affected by human activities in form of agricultural practices (e.g. irrigation, tillage, fertilization), land use changes (e.g. exploitation of natural resources) and by natural influences like extreme temperatures, fires, pests or plant diseases. These inducing factors can be equally responsible for variations in NDVI, which provides the basis of VHI. In this case, the role of temperature on evapotranspiration is incorporated, which in turn considerably controls vegetation condition while, is neglected in the application of the SPI (Bhuiyan et al., 2017; Yan et al., 2016). Bhuiyan et al. (2017) reported that the major reason for low correlation between SPI and VHI could be memory effect of past surplus precipitation that helps vegetation to maintain health and vigor during low rainfall events, while recovery effect is responsible for delayed recovery of VH after a severe drought in spite of adequate precipitation. Thus, the storage of water in the soil reservoir is an important buffer between rainfall events and soil moisture availability for plants, which controls vegetation condition.

4.4. Validation the prediction of Vegetation Health Index (VHI)

The relationships between the detrended crop yield and VHI was examined for 41 selected crop growing zones for the main rainfall season. In this study, the three main cereals (maize, teff and wheat) were treated separately. According to Tadesse et al. (2015) pesticide applications, and improved farming systems through agricultural extension, cereals yield data in Ethiopia showed a gradual increase in annual production i.e. an upward trend in time.

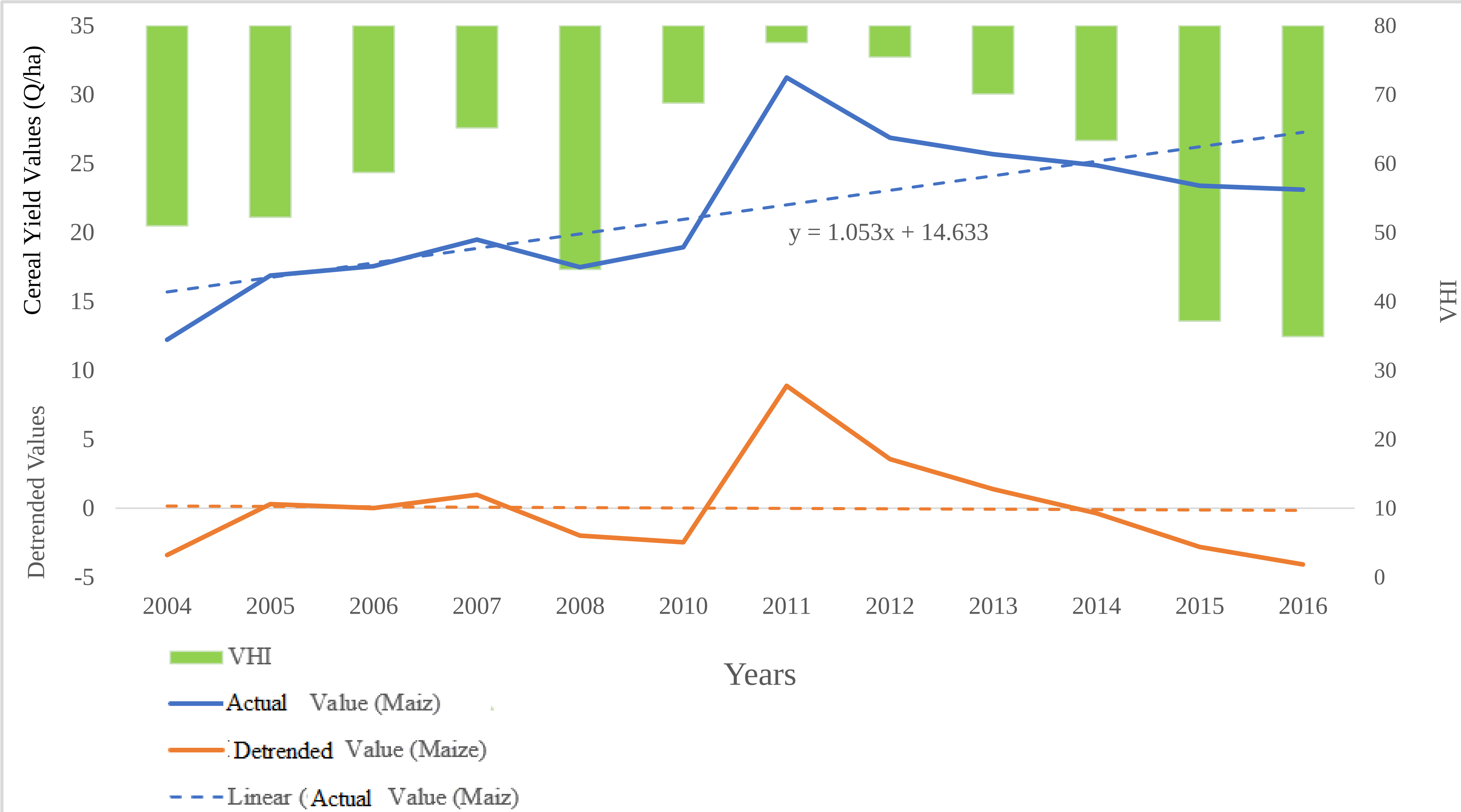


Figure 24. An example of crop yield detrending and Vegetation Health Index (VHI) using West Harerge zone. The data in the year 2009, 2017, and 2018 are missing.

Therefore, the trend that observed in annual production was removed to identify meaningful relationship between VHI and crop yield. Figure 24 shows an example of detrended maize yields for West Harerge zone. The detrending activity or removing of trends were applied for all selected cropping zones. After detrending, the VHI at the end month of the Kiremt rainfall season (September) was used to correlate with the selected cereal crop yield. As stated by Bayissa et al. (2018) and (Gebrehiwot et al., 2011) the vegetation cover (NDVI) reaches its maximum value in September in the majority of the highlands of Ethiopia. The results of the study showed there was a significant correlation between VHI and selected cereal crops yield in some zones.

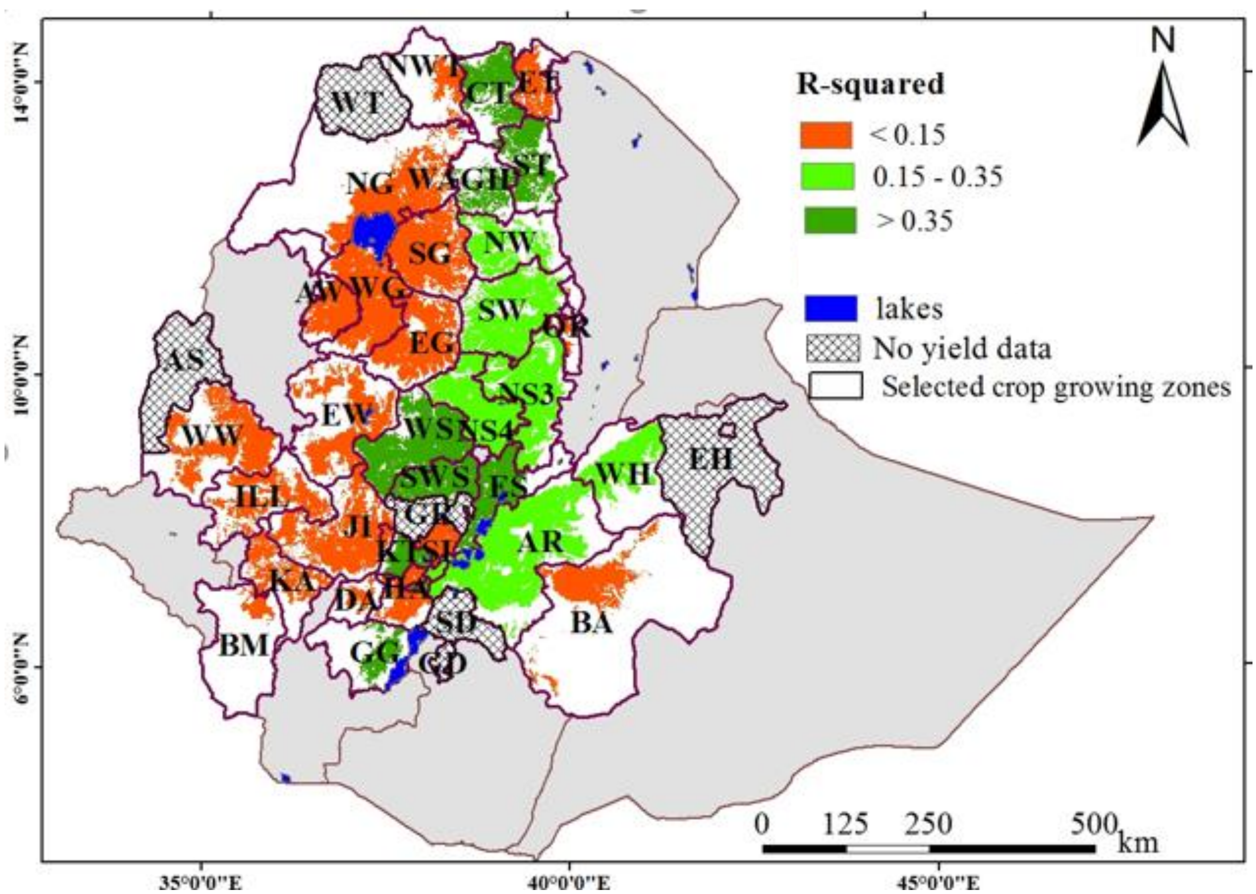


Figure 25. Spatial distribution of correlations between Vegetation Health Index (VHI) and detrended teff crop yield in the crop growing areas

On the other hand, there was weak correlation between crops yield and VHI in some zones. Overall, the correlation between selected crops and VHI were varied in each zone. Figures 25, 26 and 27 show correlation coefficient values between the VHI and the selected detrended cereal crops yield (teff, maize and wheat respectively) for the selected crop growing zones for the main rainfall season (June-September).

Regarding teff, it has been observed that there was a good correlation between teff yield and VHI in 15 out of 35 crop zones in the study area. In the present study, higher correlation coefficient values ($r > 0.5$ or $R^2 = 0.25$) were observed in10 zones, and 8 of these were statistically significant ($P < 0.05$; see Appendix 4). The highest correlation between teff and VHI ($r = 0.75$ or $R^2 = 0.56$; $P < 0.01$) was observed for Southern Tigray zone in the northern highlands of Ethiopia, whereas the lowest r or R^2 was -0.06 /0.0032 respectively for North Gonder zone. Generally, the northern and central highlands of Ethiopia showed better correlation than the rest of the study area (Figure 25).

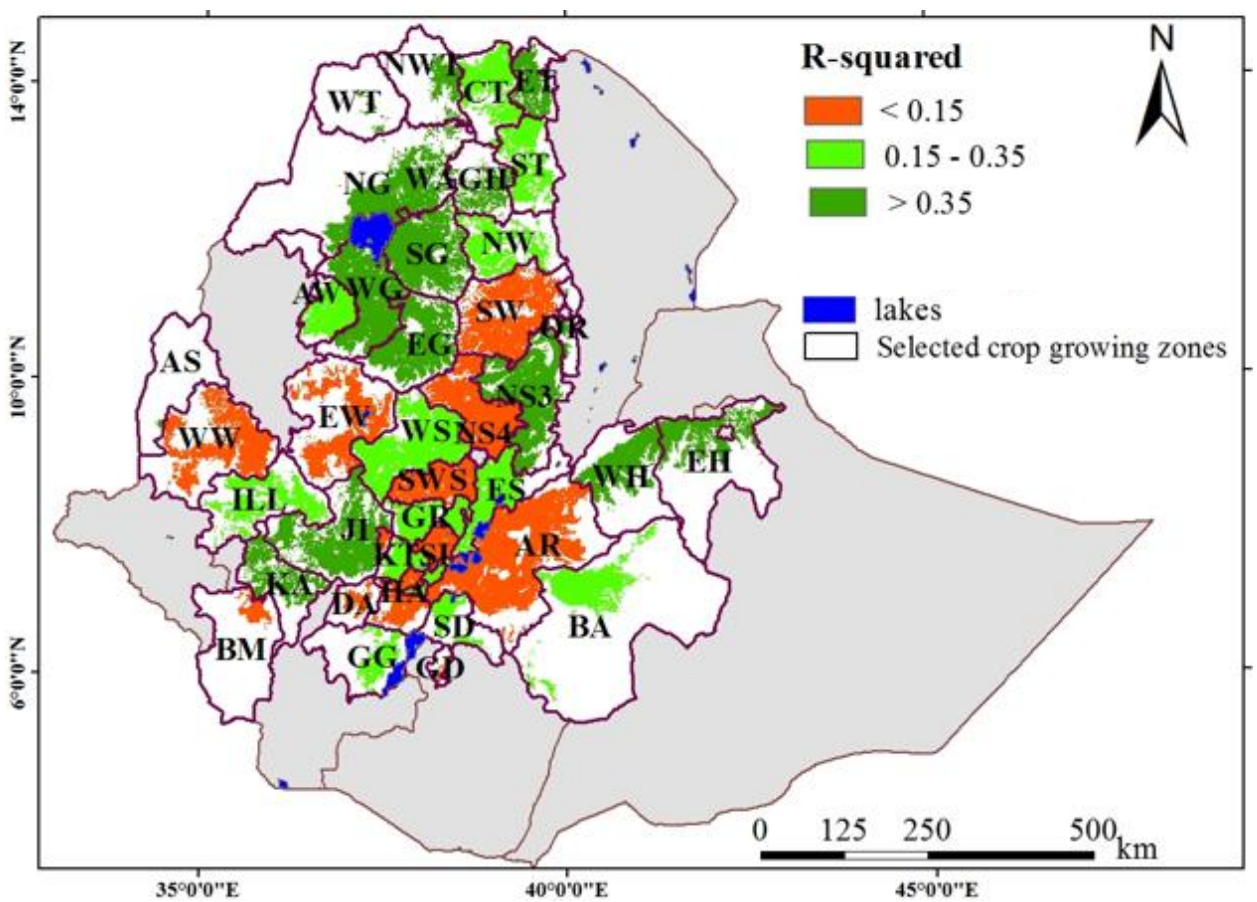


Figure 26. Spatial distribution of correlations between Vegetation Health Index (VHI) and detrended maize crop yield in the crop growing areas

As shown in Figure 26, the correlation between maize yield and VHI was produced promising or higher correlation coefficient or R^2 value. The results of this analysis indicate that 21 and 28 out of 41 crop zones in the study area had greater than 0.5/0.26 and 40/0.17 r and R^2, respectively. Furthermore, the correlation between maize and VHI in 18 zones were statistically significant at $\leq$ 0.05 level of significant (Appendix 4). Strong correlation ($r \geq 60$ or $R^2 \geq 36/P < 0.05$) between maize yield and VHI was observed in West Harerge, Wag Himra, Oromia, Eastern Tigray, East Harerge, North Gondar, EastGojjam, North Shewa3, Asosa, Keffa and Jimma, while low correlation were observed in all most all zones of SNNP.

Furthermore, the analysis of this study revealed that the correlation between wheat yield and VHI was higher for 13 zones out of 26 zones. In 9 zones the relationship between these two variables were statistically significant at $\leq$ 0.05 level of significance (Appendix 4).

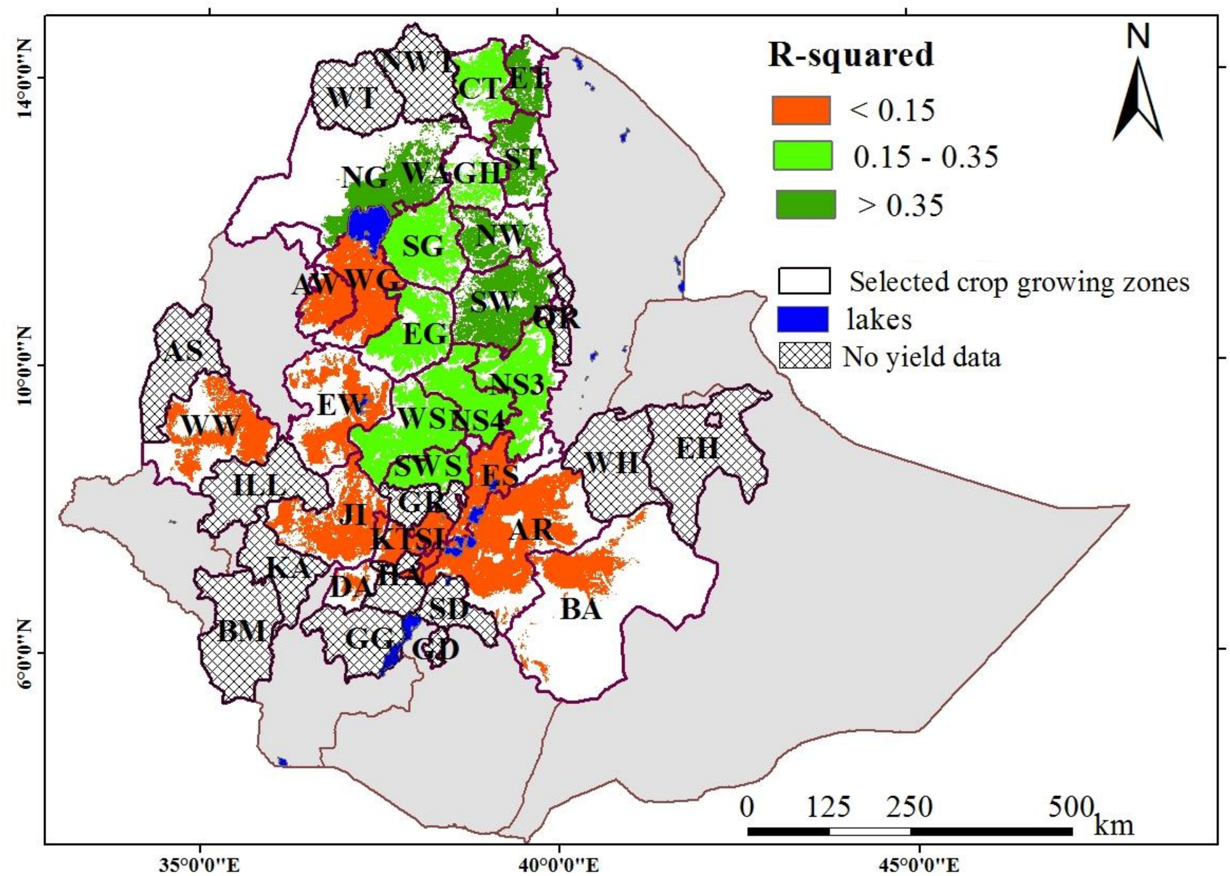


Figure 27. Spatial distribution of correlations between Vegetation Health Index (VHI) and detrended wheat crop yield in the crop growing areas

The highest r/R^2 (0.67/0.45) respectively was observed for Southern Tigray zone in the northern highlands. The lowest R^2 was 0.001 for Yem zone in the Southern Nations, Nationalities, and Peoples' region (SNNP) of Ethiopia. Out of 9 zones 8 zones are located in the northern highlands of Ethiopia (Figure 27).

The correlation analysis obtained in this study is consistent with Bayissa et al. (2018) and Tadesse et al. (2015), that tried to evaluate combined drought indicator to monitor agricultural drought (CDI) and evapotranspiration products with cereal crop yield respectively. In these studies, the northern and central regions had a higher correlation ($r > 0.5$), while southern and eastern parts of the country had lower correlations ($r < 0.5$). However, there is a disagreement in some parts of the Ethiopian highlands. For instance, in Asosa, Jimma, Illubabor and Kaffa the relationship between VHI and maize yield were positive and statistically significant at 0.05 level. Even in north western part of the study area such like East Gojjam and North Gonder the correlation was strong enough for maize. Generally, this study agreed on the previous two studies which reported lower correlation between drought indices and crops yield in the SNNP. According to Bayissa et al. (2018) the quality of crop yield data, data length used in correlation analysis and spatial representation of the data could be the possible reasons for lower correlation between detrended crop yield anomalies and drought indices.

Moreover, in the study area, since agriculture is mostly dependent on rain-fed practices, it is the most impacted system by drought. It can be observed that crop yield of major cereal crop like maize, teff and wheat were less during the year 2015 and higher during the previous year 2014 and the later year 2016. During the drought year 2015, there was low production in agricultural crop in the selected zones. Similarly, the Standardized Precipitation Index and Vegetation Health Index value was also low. In addition to this, the informal interview with zonal agriculture expert's and farmers result showed that there was drought in the past 15 years for selected zones like North shewa3, South Wollo zone and South West Shewa. They explained that the fluctuation of rainfall and temperature are no unusual for them that it affects considerably human life, animals, crops as well as other natural resources. Furthermore, information obtained from different published and unpublished sources confirms that there was severe agricultural drought in different zones of the study area, and consequently complete crop failure occurred in most of the study area. For instance, Gidey et al. (2018), reported that the year 2015 observed extreme drought period across Raya and its environment where the mean VHI value was less than 10.

4.5. Mapping the dynamics of soil organic carbon stock and its relation with land use and Vegetation Health Index (VHI)

4.5.1. Mapping soil organic carbon stock along different land uses

In this study, the mean soil organic carbon sock (t/ha) under four land-use types were evaluated and presented in Table 11. The result indicated that the forest land use is having higher average measured soil organic carbon stock (70.3 t/ha) followed by cropland (85.3 t/ha), grassland (76.1 t/ha) and least was found in shrubland (70.3 t/ha). Comparing of the mean measured soil organic carbon stock value was worked out for all land use land cover as compared to each other.

The result showed that the mean soil organic carbon stock for forest land is 1.25, 1.5 and 1.4 times greater than cropland, shrubland and grassland respectively. Mean soil organic carbon stock for cropland is 1.2 times greater than shrubland and 1.1 times greater than grassland. However, there was no significant difference in soil organic carbon stock between shrubland, cropland and grassland use. Higher soil organic carbon stock in forest land might be credited to deposition of litter under trees that decomposes more slowly than plant residues from grass, shrub and croplands.

Table 11. Statistical summary of Soil organic carbon stock in different landuse types derived for 0-30 cm depth

Major landuse types	**Mean (tonne/hectar)**
Forest land	107.0
Shrubland	70.3
Grassland	76.1
Cropland	85.3

Assefa et al. (2016) reported that higher soil organic carbon stocks were observed in soils of shrublands and forestlands than in soils of cultivated and grazing lands in the site of the Upper Blue Nile Basin of the Ethiopian highlands. Furthermore, they reported that the positive relation between SOC and shrubland or forest distribution might be attributed to deposition of litter under trees and shrubs that decomposes more slowly than plant residues from grass and croplands.

On the other hand, Tilahun and Assefa (2009) observed higher organic carbon stocks in natural forest followed by natural grasslands while the lowest SOC was recorded in cultivated fields in Bale highlands of Ethiopia. Teshome et al. (2013) also reported that soil organic matter content of cultivated land was significantly lower than that of forest and grazing lands of Western Ethiopia. This study, however, found out soil organic carbon stock in cropland is greater than grassland that might be poor grassland management and the problem that might be raised from land use/cover that used to extract stock of SOC. According to Lesiv et al (2017) one of the limitations of ESA CCI prototype land cover map of Africa at 20m is a high confusion between crops, shrubs and grasslands.

The positive impacts of forest land on soil organic carbon stock suggests the need to focus on introduction of proper restoration methods like agroforestry systems in shrub, crop and grasslands and control grazing management practice for grassland. Agro-forestry systems, where trees are deliberately combined with crops and/or livestock, are widely recognized to have a high potential to sequester C as trees are more able to capture and utilize resources than cropping or grassland systems and also controlled grazing management where livestock is kept in a stand and feed with cut and carried fodder might be contribute for carbon sequester (Assefa et. al., 2016).

Moreover, the spatial distribution of the stock of soil organic carbon (t/ha) are shown in Figure 28. The map of soil organic carbon revealed that there was considerable variability in the stock of soil organic carbon in the highlands of Ethiopia (ranges between 23 to 348 t/ha). Stock of soil organic carbon tend to be higher in the southern, southwestern and northwestern parts of the study area, while the lowest contents were located in the central, northern and southeastern parts of the study area (Figure 28). This was particularly evident in the south, northwestern and southwestern parts of the study area, where the highest soil organic carbon stock value was found for forest lands.

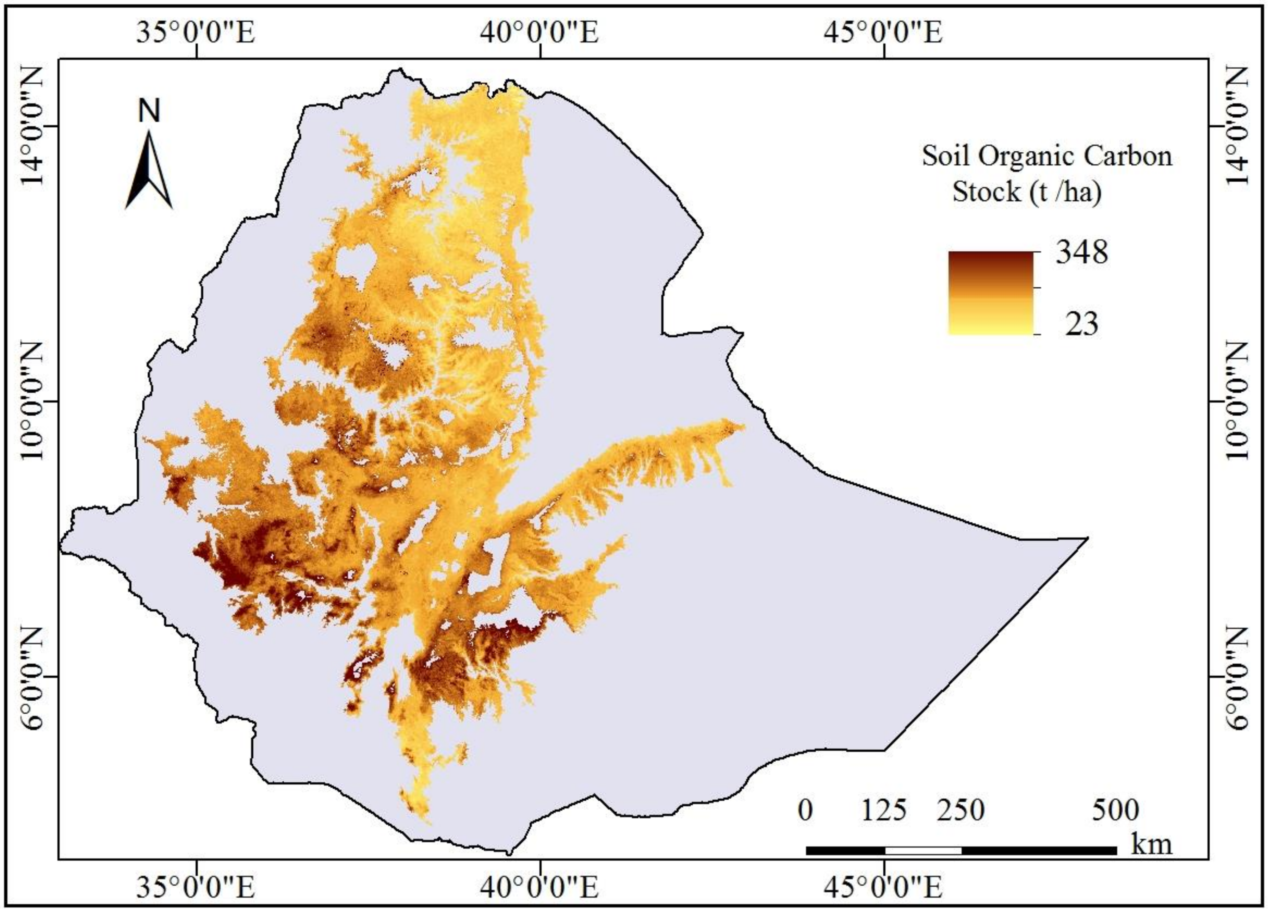


Figure 28. Spatial distribution of soil organic carbon stock (SOC) at 0–30 cm depth

4.5.2. Mapping the dynamics of soil organic carbon stock and Vegetation Health Index (VHI)

Soil organic carbon (SOC) is one part in the much larger global carbon cycle that involves the cycling of carbon through the soil, vegetation, ocean and the atmosphere (FAO, 2017). Now days more emphasis is given to understand the dynamics of SOC because the significance of SOC in food, water and energy security, as well as in climate change mitigation, ecosystem services and biodiversity protection has been recognized (Szatmari et al., 2019). The existed literature indicated that the magnitude of the SOC storage is spatially and temporally variable and determined by different abiotic and biotic factors (Weissert et al., 2016). Among these, temperature and precipitation are the most significant factors that control SOC dynamics (Deb et al., 2015). According to FAO and ITPS (2015) with climate change, more frequent extreme precipitation and drought events are projected which may have greater impacts on ecosystem dynamics. The increasing of extreme events may affect soil organic carbon dynamics by altering its decomposition rate and plant litter production, thus negatively affecting the rate of SOC accumulation.

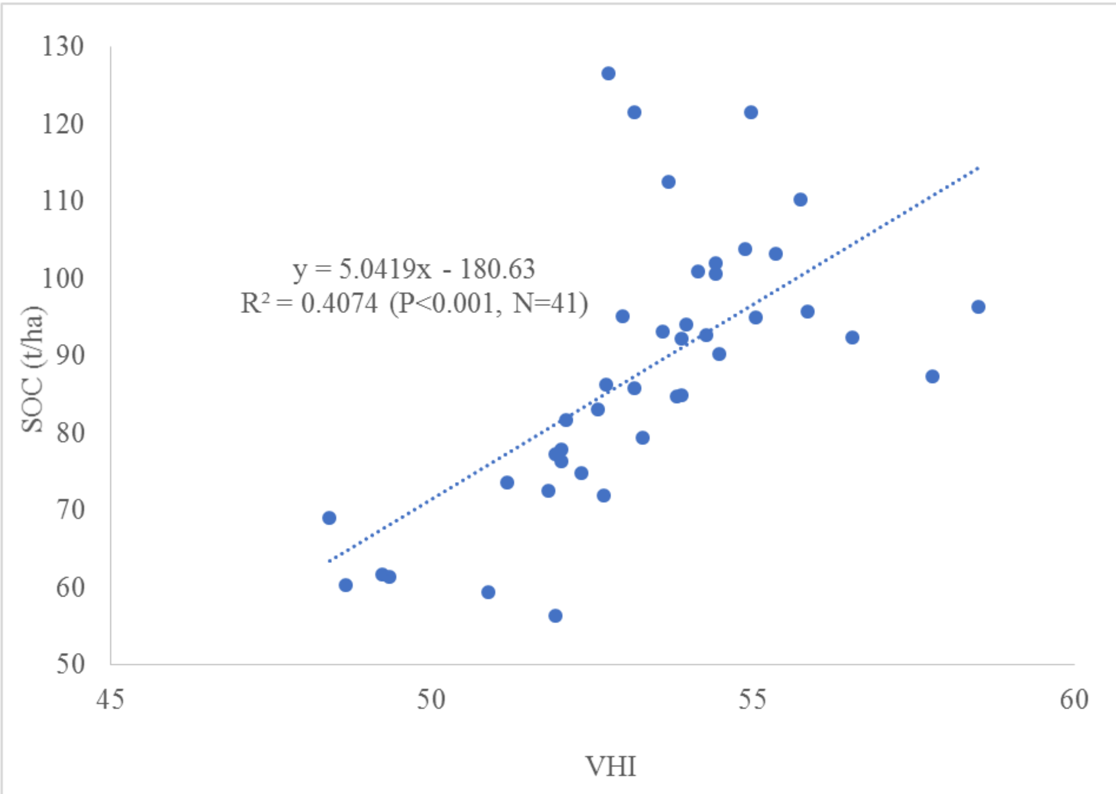


Figure 29. Relationships between long term mean Vegetation Health Index (VHI) and Soil Organic Carbon (SOC) over Ethiopia highlands

In this study, the relationships between soil organic carbon stock and VHI was examined using simple linear regression analysis and Pearson correlation for selected crop growing zones based on long term mean VHI and drought frequency.

Figure 29 shows the statistical relationships between long term mean VHI and SOC. The regression analysis result shows that a strong positive relation exists between long term mean VHI and soil organic carbon. VHI positively related to SOC (r = 0.64, R2 = 0.41/P = 0.41/P = 0.000) and statistically significant. Kumar et al. (2018) reported the statistical relationship between SOC and VTCI has strong correlation in Khala sub-watershed, India. This study has also observed similar findings in the highlands of Ethiopia. The high correlation of VHI with SOC is related to biomass which in turn correlated with the addition of organic materials by way of litter fall and decay of roots thereby improves the SOC. It is to be noted that VHI was influenced by the amount and density of green vegetation and temperature. Therefore, as VHI has not been much explored for its relationship with soil organic carbon the findings of this research are significant and put emphasis to explore and use the new potential predictor variables in the regression analysis for spatial mapping of soil organic carbon.

Furthermore, Figure 30 shows the statistical relationships between drought frequency based on 15 years VHI and soil organic carbon.

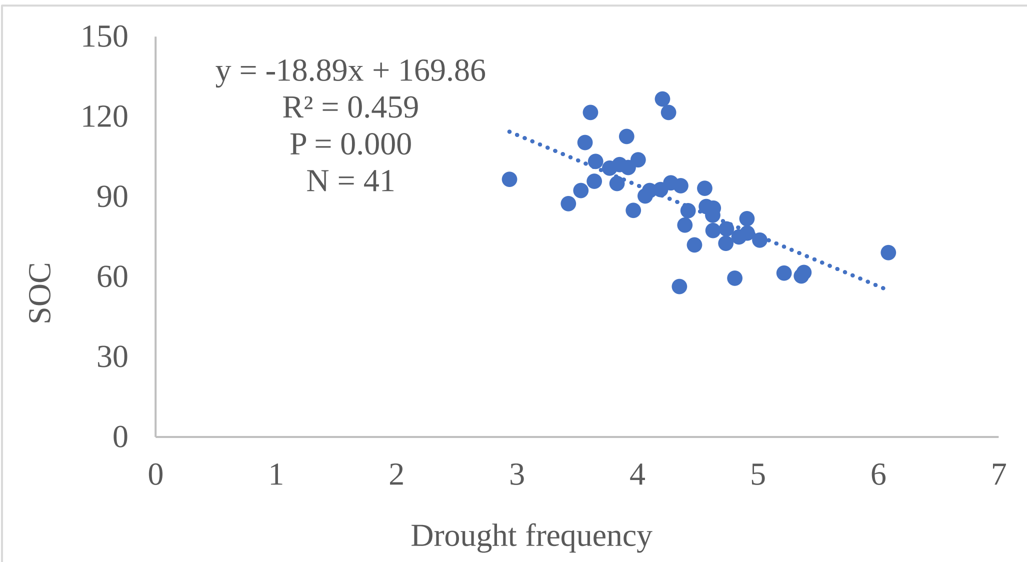


Figure 30. Relationships between drought frequency and SOC over Ethiopia highland

The result revealed that soil organic carbon is negatively related to drought frequency (R^2/P = 0.46/0.000) and statistically significant. The analysis revealed that areas with high drought frequency had low soil organic carbon stock (northern highlands) while high SOC stock observed in less drought frequent areas (Southern and southwester highlands). Sippel et al. (2018) suggested that drought adversely affect plant productivity. Hence, the immediate effect of drought on the overall carbon balance is rather negative as confirmed by this study. Other studies focused on the impact of drought on terrestrial ecosystem confirmed that droughts may impact the structure, composition, and functioning of terrestrial ecosystems, and thus carbon cycling and its feedbacks to the climate system (Velde et al., 2015)

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

The study examined the spatio-temporal patterns of agricultural drought and soil organic carbon using VHI and SPI at monthly time-scale during the main rainy season (June – September) in the highlands of Ethiopia. The result of this study revealed that GIS and remote sensing based agricultural drought can be better monitored by VHI composed of VCI and TCI drought indices and SPI. The results of the study showed that LST is negatively related to NDVI. The regression result indicated that the relation between LST and NDVI was negative in 32 zones where as it was positive in 9 administrative zones. The increase in LST and the decrease in NDVI may contribute considerable moisture stress that can trigger the incidences of agricultural drought. Furthermore, the VHI and SPI value reduced significantly during the main rainy season (Kiremt). This revealed that the incidence of agricultural drought became more frequent in the study area.

The study was able to identify the spatio-temporal patterns of agricultural drought as droughts are recurrent phenomena over Ethiopian highlands. Although the study area has experienced various levels of droughts during the study period, the years 2009 and 2015 were considered as the drought years both in VHI and SPI. In these two years, 2009 and 2015, agricultural drought conditions prevailed in all of highlands of Ethiopia in the main rainy season. On the other hand, 2006 and 2018 were taken as slight and non-drought years. The study also was able to specially identify the regions exposed to recurrent cycle of agricultural drought. Accordingly, the analysis indicated that the central and northern highlands of Ethiopia, particularly the Amhara and Tigray regions (Eastern, central and southern Tigray Zones, Easter Amhara Zones, East Shewa4), West and East Hararge in Oromiya and Silti and Alaba zones in Sothern Nations, Nationalities and Peoples'region as the most vulnerable agricultural production regions. Historically, the Amhara and Tigray regions have been known as the most severely affected regions during the well-known Ethiopian famine periods. Thus, a slight drought that result a failure in crop harvest can undermine household food security in the areas.

It is also observed that there exists a positive correlation between VHI and SPl in the major crop growth season for the entire study area in (r = 0.4 or R^2 = 0.16 to r = 0.62 or R^2 = 0.38) and statistically significant at ($p < 0.05$) across all months (July, August and September) except June. The study found that there is a strong correlation between VHI and detrending crop yield. Strong positive correlation was found between maize crop yield and VHI than teff and wheat. Generally higher correlation between VHI and crop yields of Teff and Wheat in the central and northern highlands, whereas low correlation was observed in the western and southwestern parts of the study area. Therefore, effective drought mitigation measures could be executed prior to the onset of drought as part of preparedness and strategic planning within this time period. The relationship results are vital for successful near real time drought assessment and detection of vegetation stress resulting in yield reductions. The revealed that long term mean VHI has a positive relationship with soil organic carbon stock (R^2/P = 0.41/0.000) and also correlation of drought frequency from VHI and soil organic carbon stock turned out negative (R^2/P = 0.46/P = 0.000).

Modern remote sensing satellite data and Geographical Information System are effective in providing information regarding drought monitoring. All in all, a complete insight into spatio-temporal drought dynamics was gained through this thesis. The usage of remotely sensed input data for drought indices SPI and VHI provided a complementary perspective on agricultural droughts based on both rainfall and vegetation condition. At this time, the opportunities of drought monitoring provided by advanced remote sensing techniques and the increased availability of earth observation data will likely continue contributing to establish a solid knowledge base related to droughts particularly countries where drought monitoring system is mainly depending on sparsely distributed weather stations. Altogether, this lays the foundation for decision making and capacity building to mitigate the effects of severe droughts and adapt to existent drought hazards.

5.2. Recommendations

Based on the findings indicated in this research, the following recommendations are formulated.

- This study has used satellite data monthly CHIRPS at 5 kilometer spatial resolution, dekadal eMODIS NDVI at 250m spatial resolution and 8 days MOD11A2 LST at 1km spatial resolution. Therefore, it is important for future researches to conduct a study with better temporal resolution.

- The spatial averaging of the VHI, SPI and crop yield over zonal level may not show the local variability of drought and crop yield. Thus, it is vital for future researchers to use high spatial resolution or micro level crop yield averaging for better characterization of the nature and effects of drought on crop yield.

- Drought from socio-economic part could not be studied in this thesis. Thus, it is recommended for future researches to include the socio-economic data to better understand the effect of drought.

- GIS and remote sensing-based drought analysis and mapping is useful for drought monitoring and early warning system. Therefore, VHI could use for drought early warning system by government and other stakeholders who work on drought to enhance the accessibility of farmers to drought forecasts which could lead them to timely adoption of effective drought coping strategies.

- Training farmers regarding how to make use of weather forecast information on radio and television is vital for timely responding to drought periods.

- Hence, the severity levels of agricultural drought vary spatially, prioritization and implementation of adaptation and mitigation schemes should be focused on site specific. Selection of adaptation and mitigation strategies such as agricultural technologies and information (drought tolerance crops, the type of crop variety and soil moisture conservation practices) should be made to fit in to the agricultural drought severity levels as well as the nature of the site.

- In order to increase soil organic carbon sequestration and minimize the effect of climate change appropriate farming and management practice, agroforestry and grassland management which increase inputs and reduces losses of the soil organic carbon should be designed and implemented by the stakeholders of both governmental and non-governmental organizations.

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APPENDICES

Appendix 1: Guiding questions for key informant interviews

This guiding question is prepared to collect data related to Agricultural Drought in the highlands of Ethiopia. The study will be conducted to full fill the requirements of a MA degree in Remote Sensing and GIS at Addis Ababa University. As this research is entirely for academic purposes, all the information you provide is confidential and the researcher will guaranty your full secrecy. I would like to thank you in advance for your voluntary participation in this study.

1. What are the major crops growing in the Meher season? How do you explain the agricultural potential and cropping calendar?
2. When did agricultural drought occurs between 2004-2018 G.C in the area? Which one was the most devastating event?
3. How the frequency of agricultural drought was looks like in the past growing seasons (low, Medium, high)?
4. How do you describe the characteristic of the local rainfall during the past 15 years, in terms of amount, spatial distribution as well as time of occurrence in relation to crop water requirement?
5. Was there any attempt to change the cropping system due to the consequence of climate change in general and agricultural drought in particular?

Appendix 2: Field Photographs

Wheat field in Mida Woremo Wereda (North Shewa zone)   Teff field in Dawo Wereda (SW Shewa zone)

Maize and Wheat field in Wereilu Wereda (South Wollo zone)

Appendix-3 Agricultural Statistics of all zones in the study area 2004 – 2016 (qt/ha)

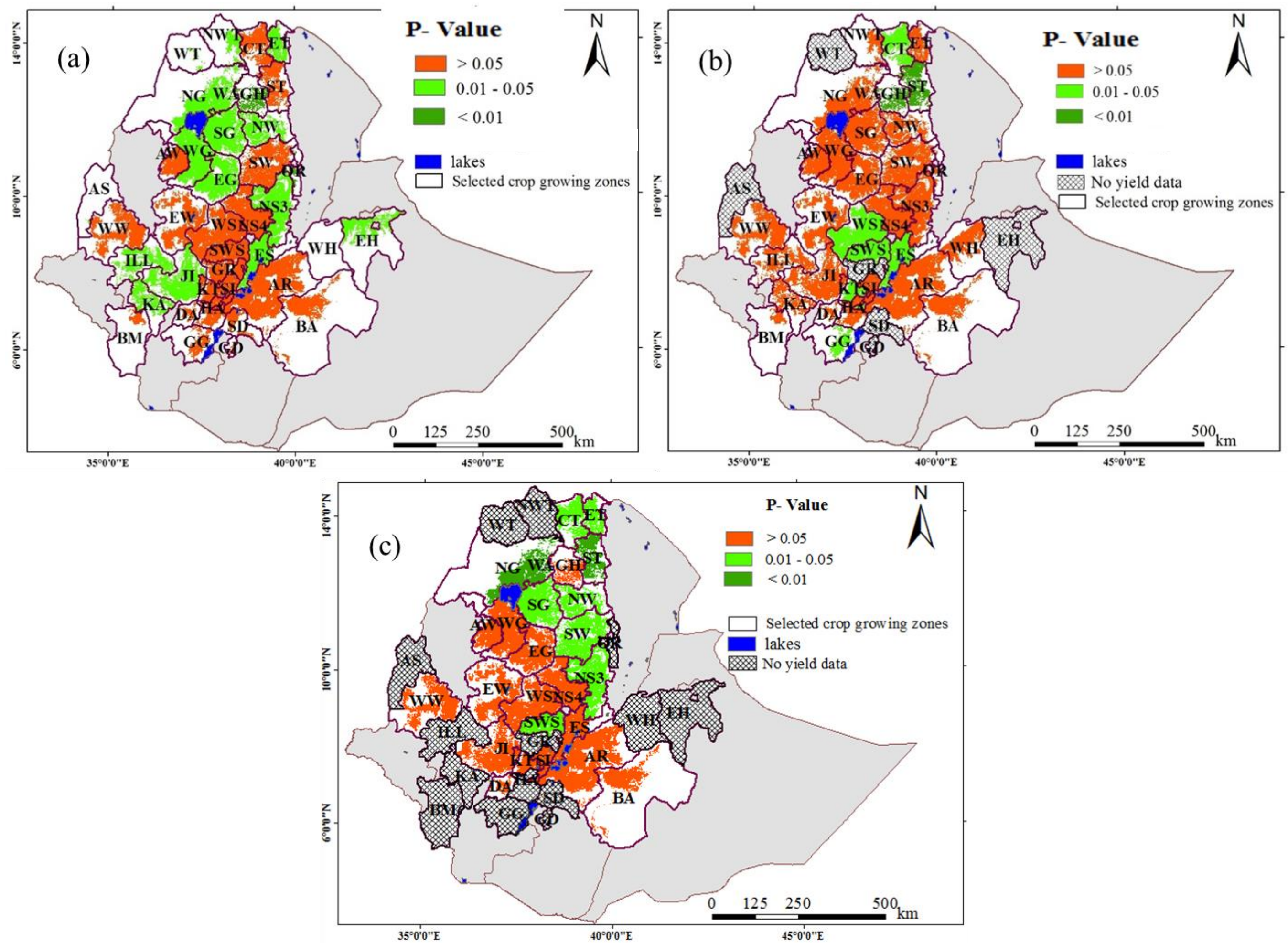
Zone	Crop	2004/05	2005/06	2006/07	2007/08	2008/09	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17
Central Tigary	Teff	6.8	8.7	8.7	10.0	11.7	13.7	12.3	13.7	13.4	13.9	12.1	14.0
	Maize	9.2	16.9	14.0	14.6	15.0	22.8	19.2	18.9	19.5	20.7	19.0	22.8
	Wheat	11.8	12.0	12.2	13.9	16.4	20.1	18.7	17.5	18.8	18.7	18.2	18.9
Eastern Tigray	Teff	7.6	7.9	9.4	NA	16.1	13.0	12.9	12.5	15.9	14.8	11.6	14.8
	Maize	8.3	16.1	15.0	14.1	14.7	20.6	19.8	19.1	16.8	20.1	17.7	20.8
	Wheat	9.4	12.0	14.3	14.4	10.5	19.6	17.8	17.6	14.5	16.5	16.1	18.8
Southern Tigray	Teff	4.7	9.0	11.5	11.3	10.9	12.5	12.6	12.5	13.0	13.8	8.0	14.0
	Maize	7.1	17.3	17.9	14.7	15.7	21.6	15.4	12.3	12.3	14.5	12.9	16.6
	Wheat	9.3	13.6	15.8	14.3	14.6	18.5	19.9	19.3	20.2	19.9	17.0	20.7
North W Tigray	Teff	7.3	9.2	9.1	12.8	16.7	10.5	12.8	12.8	12.9	15.0	14.2	15.1
	Maize	14.1	18.8	20.9	15.3	20.3	25.9	28.9	28.0	28.0	29.4	27.0	30.1
Western Tigray	Teff	14.5	10.5	12.9	12.3	11.6	14.1	NA	14.2	14.2	16.1	14.4	15.8
	Maize	14.5	14.6	16.7	14.5	18.4	24.8	31.3	34.5	30.2	33.4	31.0	32.6
North Gonder	Teff	10.0	8.6	8.7	10.9	12.2	13.4	13.7	15.7	15.8	16.2	16.8	16.8
	Maize	19.3	20.0	22.2	17.8	22.6	23.7	27.2	27.5	28.0	29.2	28.2	32.0
	wheat	12.9	13.2	15.5	13.1	14.9	19.5	19.3	19.6	24.0	25.1	24.2	24.9
South Gonder	Teff	6.8	8.8	8.1	9.2	10.5	12.6	13.6	14.3	14.8	15.3	16.0	16.1
	Maize	10.7	15.1	16.0	16.1	16.9	22.1	23.9	23.6	24.2	26.7	26.8	30.4
	wheat	7.5	9.8	10.4	11.7	12.5	17.1	17.0	18.5	17.5	19.2	20.0	20.7
North Wollo	Teff	9.2	8.5	9.8	13.1	13.9	11.8	12.7	12.9	13.4	13.9	10.4	13.3
	Maize	6.7	13.2	13.4	18.9	17.6	12.9	13.4	15.9	18.1	20.1	16.0	20.0
	wheat	11.9	12.3	12.3	12.7	15.0	13.4	13.2	13.7	18.1	18.9	14.8	18.1
South Wollo	Teff	11.6	10.2	11.2	11.2	11.4	12.5	12.1	13.4	13.7	14.7	15.1	15.5
	Maize	9.8	16.1	16.3	20.0	15.1	22.4	24.4	24.1	22.3	24.5	22.0	24.6
	wheat	15.4	12.4	13.6	14.4	15.9	14.1	15.4	15.9	19.4	20.2	20.3	23.0
North Shewa3	Teff	10.5	14.0	16.0	12.1	12.3	11.0	12.5	13.5	15.1	16.1	16.5	17.8
	Maize	12.3	18.7	20.6	16.2	18.6	21.2	NA	23.8	30.1	29.5	25.7	29.8
	wheat	16.7	20.9	26.6	12.4	12.1	17.6	15.2	18.5	23.4	25.6	24.6	26.0

	Teff	11.7	10.0	10.9	13.6	12.5	14.0	14.3	15.1	17.1	17.4	18.5	19.2
	Maize	18.1	17.9	22.9	21.9	28.0	25.9	27.3	27.7	30.5	35.8	35.0	41.1
East Gojjam	wheat	16.4	13.7	13.7	19.8	19.0	17.0	17.9	18.6	22.7	23.7	24.7	25.1
	Teff	8.2	8.4	8.3	15.3	14.7	12.4	12.2	13.0	13.6	15.8	16.1	17.2
West Gojjam	Maize	19.4	24.2	26.6	27.6	26.0	27.6	29.7	32.2	39.4	40.9	40.9	42.3
	wheat	21.4	17.3	16.1	20.0	17.1	17.1	15.3	17.7	23.2	26.1	26.4	28.4
	Teff	3.8	9.8	10.3	9.3	11.2	10.9	11.4	11.7	12.5	13.5	8.3	13.6
	Maize	4.3	11.3	12.6	12.7	13.0	14.7	14.1	14.6	14.5	15.8	13.4	15.5
Wag Himra	wheat	8.6	11.5	14.1	10.9	10.3	12.1	12.0	13.8	13.9	13.7	11.1	14.8
	Teff	8.7	7.3	7.8	9.9	11.1	11.7	12.4	12.8	13.3	15.0	15.7	16.2
	Maize	20.5	25.1	24.9	25.6	20.8	28.7	30.2	31.1	37.5	39.0	38.0	39.5
Awi	wheat	9.2	9.7	11.6	17.0	13.2	13.7	18.3	18.4	21.3	22.6	23.1	23.7
	Teff	9.6	12.0	13.1	11.5	10.0	13.3	12.4	12.9	13.7	14.0	13.7	14.4
Oromia	Maize	11.6	16.9	14.9	17.0	17.0	18.0	17.3	17.8	21.7	25.3	22.4	23.3
	Teff	8.3	8.9	7.0	9.7	11.0	11.0	10.8	11.3	12.2	13.6	13.5	15.1
West Wellega	Maize	21.1	25.0	24.6	21.9	23.9	26.7	34.0	35.6	39.3	40.3	41.0	43.2
	wheat	13.8	12.6	10.2	14.1	16.9	13.9	13.0	13.5	19.3	19.1	20.2	20.9
	Teff	10.6	9.6	8.3	12.5	14.6	12.1	12.2	14.4	16.4	17.1	17.6	18.2
East Wellega	Maize	23.0	26.6	27.7	26.3	27.2	28.8	36.3	37.2	38.9	41.5	43.0	44.7
	wheat	10.9	16.6	13.3	16.2	15.4	16.3	17.2	18.2	18.8	20.3	21.0	22.7
	Teff	11.2	9.4	9.6	14.7	12.1	10.8	10.0	10.7	12.5	12.6	13.0	15.1
Illubabor	Maize	15.8	20.8	21.2	19.1	22.7	26.8	31.5	31.6	33.8	36.1	36.5	42.3
	Teff	12.4	13.4	13.5	11.3	12.0	13.7	15.0	15.6	16.7	18.7	18.5	18.8
	Maize	19.4	27.6	23.6	21.5	24.0	29.9	30.5	32.5	31.7	34.5	34.8	41.1
West Shewa	wheat	18.8	19.3	21.7	15.0	17.8	18.3	21.7	22.6	24.2	25.5	25.7	27.2
	Teff	10.9	13.7	14.8	12.8	11.6	14.0	14.0	15.3	16.5	16.8	16.3	17.6
	Maize	16.0	27.9	28.5	27.3	27.1	23.9	34.4	34.0	31.7	34.0	31.9	35.0
East Shewa	wheat	15.8	19.8	23.4	16.6	19.3	17.8	24.1	22.8	30.7	29.6	29.1	29.4
East Hara	Maize	13.3	18.9	21.3	24.6	21.8	22.2	28.9	27.9	24.1	26.8	26.7	25.7
West Hararge	Teff	9.0	9.8	9.2	12.6	9.6	9.3	10.8	12.0	12.9	13.0	8.6	12.4
	Maize	12.2	16.9	17.6	19.5	17.5	18.9	31.2	26.9	25.7	24.9	23.4	23.1

	Teff	9.5	7.8	8.0	10.5	10.5	12.2	12.3	12.8	13.1	13.6	14.5	15.1
	Maize	22.9	23.5	23.4	20.9	24.8	26.1	28.2	31.5	32.8	35.1	35.8	40.2
Jimma	wheat	15.1	10.9	12.1	16.3	14.5	14.2	13.6	16.3	17.0	18.0	18.2	20.6
	Teff	10.1	9.4	9.4	9.7	11.6	13.9	13.2	13.9	14.2	17.8	16.6	17.8
North	Maize	11.9	10.6	11.1	15.8	17.6	23.1	15.8	15.0		25.0	11.2	25.2
Shewa4	wheat	11.6	13.1	14.2	12.5	15.2	13.3	16.1	18.0	23.5	23.7	23.3	25.0
	Teff	9.0	7.8	8.1	9.9	10.5	13.6	13.4	13.9	14.8	15.4	15.1	15.9
	Maize	20.0	23.1	22.7	20.7	22.4	26.6	30.5	30.5	32.5	33.0	33.0	35.5
Arsi	wheat	20.6	17.5	17.0	18.2	20.7	21.7	26.6	26.4	31.7	32.8	32.3	33.2
	Teff	6.3	6.4	9.3	9.7	10.9	11.5	11.3	11.9	12.5	15.5	14.5	16.4
	Maize	15.7	19.0	19.9	19.5	27.0	18.2	20.3	21.5	27.0	28.5	28.1	31.9
Bale	wheat	17.3	16.1	18.1	21.8	23.9	23.2	22.1	25.5	29.2	28.6	29.0	33.3
	Teff	11.7	11.9	11.8	12.2	11.7	14.5	13.9	14.9	16.6	18.0	18.0	18.9
South West	Maize	14.9	21.9	22.6	14.9	17.6	27.7	32.8	32.4	27.4	28.2	28.8	34.1
Shewa	wheat	17.1	16.9	17.6	15.4	15.0	19.6	21.2	20.9	26.4	26.5	27.1	28.1
Asosa	Maize	15.9	16.1	15.4	18.4	19.9	26.0	26.2	29.4	28.0	26.7	28.3	34.0
Gurage	Teff	21.7	22.3	25.2	22.7	20.5	28.8	38.4	36.6	35.6	36.5	36.8	39.4
	Teff	9.7	8.3	7.9	9.7	10.7	11.3	11.5	12.3	12.6	14.8	14.1	14.7
	Maize	17.4	18.1	20.7	15.7	18.9	18.3	26.2	26.6	31.5	34.4	32.9	36.2
Hadiya	wheat	16.3	18.4	18.7	19.1	22.1	18.7	22.6	26.1	24.9	26.4	27.5	28.8
Kembata	Teff	7.9	7.1	6.4	8.7	11.7	9.6	13.6	13.0	13.2	14.1	14.1	14.3
Tembaro	wheat	16.4	17.9	17.6	16.5	17.5	17.4	20.9	18.7	26.1	26.4	26.5	27.0
Sidama	Maize	19.5	21.1	21.0	22.1	21.4	27.5	34.2	33.0	32.9	33.1	32.3	36.1
	Teff	5.6	8.4	8.8	7.8	10.3	9.1	10.6	11.6	12.1	13.1	13.0	14.4
Wolayita	Maize	13.1	18.9	19.2		18.2	17.1	24.1	25.7	25.2	26.4	27.0	30.6
	Teff	8.2	8.3	8.5	9.7	10.3	11.1	11.6	12.9	12.9	14.4	14.3	14.5
Kaffa	Maize	23.6	23.6	24.3	17.5	20.2	25.3	21.8	25.7	28.5	29.9	29.5	35.6
	Teff	7.1	7.1	7.8	10.4	10.5	11.0	10.9	12.9	12.5	14.4	14.0	15.2
	Maize	11.9	18.5	22.3	19.4	18.3	27.3	33.6	31.6	39.4	39.4	35.6	39.9
Silti	wheat	13.2	14.0	17.0	18.3	20.4	18.4	27.6	24.9	32.8	28.5	28.3	28.5
Alaba	Teff	11.1	6.0	6.7	10.8	12.1	12.2	10.1	12.0	12.0	13.6	11.0	12.5

	Maize	16.0	17.8	21.8	20.0	19.9	25.4	26.8	27.3	30.6	34.9	31.6	36.7
	wheat	20.1	13.5	17.5	20.0	19.9	23.2	17.3	21.3	27.2	26.7	27.1	28.6
	Teff	6.7	7.1	7.0	11.6	11.3	11.8	11.7	14.3	12.7	14.1	12.8	13.3
Gamo Gofa	Maize	3.6	12.7	12.3	13.3	16.4	20.1	25.5	29.2	33.1	34.2	33.5	31.5
	Teff	6.7	8.1	7.9	12.1	9.6	14.7	12.5	12.3	13.5	14.1	14.0	14.4
Bench Maji	Maize	8.5	19.3	24.2	16.5	18.3	27.0	22.2	23.1	18.9	24.5	24.3	32.5
	Teff	7.0	8.3	8.9	8.0	10.7	9.9	9.9	11.3	11.7	11.8	12.0	13.0
	Maize	13.9	19.5	18.4	14.3	14.2	18.7	16.8	16.5	21.9	22.5	23.1	27.9
Yem	wheat	11.3	11.8	12.6	13.7	13.5	13.8	15.1	16.1	17.6	17.7	19.0	19.0
	Teff	5.2	6.0	6.6	8.0	11.4	10.0	8.7	9.8	10.3	10.0	8.9	10.1
	Maize	11.3	14.5	14.4		14.9	26.4	28.5	16.7	25.2	31.9	24.9	
Dawro	wheat	7.5	8.7	9.3		10.8	13.5	16.1	30.8	19.3	19.8	18.5	19.0

Appendix 4: The spatial distribution of the significant result map of the correlation coefficient values between VHI and crop yield; a, Maize b, Wheat c, Teff



Appendix 5. Spatial distribution of drought frequency in the highlands of ethiopia, Ethiopia: (a) Extreme drought; (b) Severe drought (c) Moderate drought