ADDIS ABABA UNIVERSITY
COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES
SCHOOL OF EARTH SCIENCES

REMOTE SENSING AND GIS BASED DROUGHT VULNERABILITY ASSESSMENT: A CASE OF AFAR REGIONAL STATE, ETHIOPIA

A Thesis submitted to

The School of Graduate Studies of Addis Ababa University In partial Fulfillment of the requirements for the Degree of Masters of Science in Remote Sensing and Geo-informatics

BY

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A THESIS SUBMITTED TO THE SCHOOL OF GRADUATE STUDIES OF ADDIS ABABA UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTERS OF SCIENCE IN REMOTE SENSING AND GEO-INFORMATICS

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DECLARATION

I hereby declare that the thesis entitled "Remote Sensing and GIS Based Drought Vulnerability Assessment: A Case of Afar Regional Sate, Ethiopia" has been carried out by me under the supervision of Dr. K. V. Suryabhagavan, Associate Professor, School of Earth Sciences and Prof. M. Balakrishnan, Department of Zoological Sciences, Addis Ababa University, Addis Ababa during the year 2015 2016 as a part of Master of Science Program in Remote sensing and Geo-informatics. I further declare that this work has not been submitted to any other University or Institution for the award of any Degree or Diploma.

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C E R T I F I C A T E

This is to certify that the thesis entitled as "Remote Sensing and GIS Based Drought vulnerability Assessment: A case of Afar Regional State, Ethiopia" is authenticated work carried out by Ashenif Melese under our guidance and supervision. This is the actual work done for the partial fulfillment of award of the Degree of Masters of Science in Remote Sensing and Geo-informatics from Addis Ababa University.

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Ashenif Melese

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LIST OF ABBREVIATIONS

AKLDP	Agricultural, Knowledge, Learning, Documentation and Policy
ANRS	Afar National Regional State
AVHRR	Advanced Very High Radiometric Resolution
AWC	Aviation Weather Center
CNES	Centre National d'Études Spatiales
CSA	Central Statistics Agency
CWCB	Colorado Water Conservation Board
CWRM	Commission Water Resource Management
DN	Digital Number
DSI	Drought Severity Index
El Nino	EL Nino-Northern Oscillation
ENSO	El Niño -Southern Oscillation
ERDAS	Earth Resource Data Analysis System
FEWS NET	Famine Early Warning Systems Network
GIS	Geographic Information System
IPCC	International Panel on Climate Change
ISDR/WB	International Strategy for Disaster Reduction/ World Bank
LAI	Leaf Area Index
MODIS	Moderate Resolution Image Spectrometer
NDVI	Normalized Difference Vegetation Index
$NDVI_{max}$	Normalized Difference Vegetation Index Maximum
$NDVI_{min}$	Normalized Difference Vegetation Index minimum
NMA	National Meteorological Agency
PARDB	Pastoral, Agriculture and Rural Development Bureau
PDSI	Palmer Drought Severity Index
PET	Potential Evapo-Transpiration

PROBA-V	Project on-Board Automation Vegetation
Pixel	Picture Element
RFA	Rainfall Anomaly
RF	Rainfall
SST	Sea Surface Temperature
SWSI	Surface Water Supply Index
SPI	Standardized Precipitation Index
SPOT	Satellite Pour l' Observation de la Terra
TCI	Temperature Condition Index
URL	Universal Resource Locator
VCI	Vegetation Condition Index
VGT Extract	Vegetation Extraction
WMO	World Meteorological Organization
WWF	World Wide Fund

Appendix

Abstract

Ethiopia is one of the sub-Saharan countries and highly prone to drought hazards. Drought is water related natural disaster, which affects a wide range of environmental factors. It is mainly a climatic phenomenon that cannot be eradicated. In 2015, there was short, poor and delayed rainfall which caused critical water shortage, livestock death, and decline in milk production mainly in the pastoral regions of Ethiopia. The present study attempted to investigate the effectiveness of Remote Sensing based drought indices as an indicator for drought assessment in arid and semi-arid areas, examined the relation between rainfall and vegetation indices of drought and identified the most drought–vulnerable areas using Remote Sensing (RS) and GIS in the Afar Regional State of Ethiopia, which is a drought-prone area. In this study, 11 years' time series of decadal SPOT (2005 2013) and PROVA-V (2014 2015) Normalized Difference Vegetation Index (NDVI) and rainfall data were used. Vegetation indices; Vegetation Condition Index (VCI) and Drought Severity Index (DSI) derived from SPOT and PROVA-V used for the study. Standardized Precipitation Index (SPI) was calculated. For the validation of drought indices, correlation and regression analysis between NDVI and rainfall (r = 75%), NDVI and crop yield, VCI and rainfall (r = 90%) were done. Results of this study showed that there was extreme drought in the Region in 2005, 2009, 2011 and 2015. The findings indicated that the study area is highly prone to drought even if its severity level varied. The result map obtained by integrating NDVI, VCI, DSI and SPI, showed that about 2% of the region is extremely, 32% is severe, 59% is moderate and 6% is mild vulnerable to drought. For the future, besides delineating drought vulnerable areas importance of vulnerability assessment could be made more meaningful, if detail study of these areas in terms of water availability, temperature conditions and crops grown. As well as remedial actions could be implemented before the occurrence of the drought and timely updated information about the prevalence of drought is important.

Keywords: Drought Vulnerability, SPOT, Remote Sensing, Drought Indices

CHAPTER I

INTRODUCTION

1.1 Background of the Study

Ethiopia is one of the sub-Saharan African countries highly vulnerable to hazards. Different hazards have been recorded in Ethiopia. However, drought has remained the leading cause of disaster and human sufferings in Ethiopia in terms of frequency, area coverage and the number of people affected. The history of drought in Ethiopia goes back to 250 B.C and there had been many national and localized droughts even before that of the 1970s for which international support was sought for the first time, which were managed mainly by communities. However, the magnitude, frequency and the effects of the droughts have increased since mid 1970s. The severity and persistence of the latest droughts has produced a wide range of impacts across the country (Sara Abebe, 2010; Defferew Kebede, 2011).

Drought is a water-related natural disaster, which affects a wide range of environmental factors and economic activities related to agriculture, vegetation, human and wildlife, and the local economy. Drought is a single most important weather-related natural disaster aggravated by human actions, as it affects large areas continuously for months, and years and thus has a serious impact on regional food production, life expectancy of populations and economic performance of large regions or countries (Dutta et al., 2015). During 1967–1991, drought have affected 50 percent of the 2.8 billion people globally, who suffered from all natural disasters and killed 35 percent of the 3.5 million people, who lost their lives. In recent years, large-scale intensive droughts have been observed in all continents leading to huge economic losses, destruction of ecological resources, food shortages and starvations of millions of people (WMO, 2004). Droughts are the world's costliest natural disasters, causing an annual average of $6-8 billion globally, and collectively affecting more people than any other form of natural disaster (Wilhite, 2000; Keyantash and Dracup, 2004; Melaku Estifanos, 2013).

Drought is an insidious hazard of nature. It is related to a deficiency of precipitation over an extended period of time, usually for a season or more. This deficiency results in water shortage for some activity, group, or environmental sector. Drought is also related to the timing of precipitation (Rojas et al, 2011). Other climatic factors such as high temperature, high wind, and low relative humidity are often associated with drought. It is more than physical phenomenon or natural event. Its impact results from the relation between a natural event and demands on the water supply, and it is often exacerbated by human activities. The experience from droughts has underscored the vulnerability of human societies to this natural hazard (Birhanu Gedif et al., 2014).

In Ethiopia, drought is a common natural hazard which occurred in different years of 1996, 1997, 1998, and 1999. Less rainfall had a major impact on rural populations throughout the country during 2000, resulting in drought conditions and less crop harvests. This had a cumulative impact on households in both pastoral and agricultural communities, leading to greater vulnerability to drought. Many households were forced to sell their livestock and other assets and some migrated from their traditional land to other areas in search of income and food for survival (Amare Degefaw, 2007; Viste et al., 2013).

Several users and stakeholders such as top level policy makers of national and international organizations, researchers, middle level policy makers of the state, province and local levels consultants, relief agencies and local producers including farmers, suppliers, traders and water managers are interested in reliable and accurate drought information for effective management. Disaster management activities can be grouped into the following three major phases: Preparedness phase where activities such as prediction and risk zone identification are taken up long before the event occurs; Prevention phase where activities such as early warning/forecasting, monitoring and preparation of contingency plans are taken up just before or during the event; and Response/Mitigation phase when activities are undertaken just after the event, which include damage assessment and relief management (Dutta et al., 2015).

Remote sensing techniques make it possible to obtain and distribute information rapidly over large areas by means of sensors operating in several spectral bands, mounted on aircraft or satellites. A satellite, which orbits the Earth, is able to explore the whole surface in a few days and repeat the survey at regular intervals, whilst an aircraft can give a more detailed analysis of a smaller area, if a specific need occurs (Brice et al., 2015). The spectral bands used by these sensors cover the whole range between visible and microwaves. Rapid developments in computer technology and the Geographical Information Systems (GIS) help to process Remote Sensing (RS) observations from satellites in a spatial format of maps–both individually and along with tabular data and "crunch" them together to provide a new perception–the spatial visualization of information of natural resources. Integration of information derived from RS techniques with other datasets–both in spatial and non-spatial formats, provides tremendous potential for identification, monitoring and assessment of droughts (Dodamani et al., 2015).

According to World Meteorological Organization (WMO), monitoring and assessment of drought through RS and GIS depends on factors that cause drought and of its drought impacts (WMO, 2004). Drought–prone area or risk–zone identification is usually carried out on the basis of historic data analysis of rainfall or rainfall and evaporation and the area of irrigation support. Conventional methods lack identification of spatial variations and do not cover man's influence such as land–use changes like irrigated area developed and the area affected due to water logging and salinity. The RS based method for identification of drought–prone areas uses historical vegetation indices data derived from NOAA, SPOT Vegetation satellite series and provides spatial information on drought–prone area depending on the trend in vegetation development, and their standard deviations (WMO, 2004).

The combination of information derived from remote sensing techniques with the in-situ systems provides tremendous potential for identification, monitoring and assessment of droughts (Berhan et al., 2011). Therefore, the remote sensing and GIS technology can significantly contribute in all the three phases of drought risk management: preparedness, monitoring and relief (Jeyaseelan, 2003).

1.2. Statement of the problem

The massive population explosion, economic development and adverse impacts of land use and climate changes are mounting a tremendously increasing pressure on water resources. Any shortage in water supply will be most critical in drought periods, due to challenging water needs. Drought is considered to be the most intricate but least understood of all natural hazards, considering the impact, it causes factors affecting more people than any other hazard. Drought affects virtually all climatic regions and more than one half of the earth is susceptible to drought each year (Brice et al., 2015).

In dry and semiarid areas covering large part of Eastern and Northeastern regions of Ethiopia, drought and crop failures have been common. Recurrent years of low/no rainfall during the months of March–May and September–November in the region resulted in crop failure and loss of biomass, predominantly in shrub land and grassland areas that support thousands of pastoral households. It has raised paramount food security concern over the region (Elias Fekade, 2012).

According to Famine Early Warning Systems Network (FEWS NET) and OXFAM (2015), the northern pastoral areas of Ethiopia typically have a long dry season from October to February; followed by the March to May, Spring rains and then the July to September Summer rains. In 2015, March to May rainfall was only 50 to 80 percent of the 1981–2010 average. The March to May rains then started late, and has been interrupted by long dry spells. In some lowland areas, there was not any rain until late August. With no moisture, vegetation has dried up at a time of year when it would normally be regenerating. Normalized Difference Vegetation Index (NDVI), a satellite derived measure of vegetation health, has values similar to that of 2009 and 2011, years of severe drought. In 2015 there was short, poor, delayed rain which caused critical water shortages, livestock death, and milk production decline mainly in the pastoral regions of Ethiopia. Usual livestock migration is occurring, with households moving their herds' great distances towards Amhara, Tigray, Oromia, Dire-Dawa, and Djibouti in search of forage and water. With low access to forage and long trekking distances, livestock body conditions have deteriorated (UNICEF, 2015).

A vulnerability assessment is the process of identifying, quantifying, and prioritizing (or scoring) the vulnerabilities in a system. Vulnerability from the perspective of drought planning means "assessing the threat from potential drought hazards to various sectors across social, economic, environmental and political fields" (CWCB, 2013). Vulnerability assessment has many things in common with risk assessment. Risk assessment for natural hazard planning is principally concerned with investigating the risks surrounding infrastructure (or some other object) and people. Such analyses tend to focus on causes and the direct consequences for the studied object. Risk assessment thus involves determination of vulnerabilities and hazards to establish risks and risk probabilities in terms of frequency of occurrence, magnitude and severity, and consequences (CWCB, 2013).

Due to low spatial coverage of weather and hydrological stations and incomplete data, classical weather data collection is replaced by data which is generated by atmospheric circulation models and/or satellite observations for drought assessment. Vegetation abundance and development information, which is strongly related with rainfall, can be used for drought assessment. Since the 1980s, there are many satellite derived vegetation indices at global scale and with a high temporal frequency. These include; Moderate Resolution Image Spectrometer

(MODIS), Satellite Pour l'Observation de la Terre (SPOT) and Advanced Very High Resolution Radiometer (AVHRR) (Rojas et al., 2011).

The Afar regional state is frequently affected by the drought but the area is scarce in in-situ based data for drought monitoring. Therefore, by applying RS and GIS technology, the most drought–vulnerable areas would be identified in the Afar Regional state of Ethiopia.

1.3. Research Objectives

1.3.1 General objective:

The general objective of this research was to assess drought–vulnerable areas using RS and GIS technology in Afar Regional state of Ethiopia.

1.3.2 Specific objectives

The specific objective of this study includes:

- To investigate the effectiveness of remote sensing based drought indices as an indicator for drought assessment in arid and semi-arid areas
- To examine the relation between rainfall and vegetation indices of drought
- To identify the most drought–vulnerable areas of the study area

1.4. Significance of the study

The need for proper quantification of drought impacts and monitoring and reporting of drought development are of critical importance politically in drought sensitive areas. Ability of governments in the region and international relief agencies to deal with droughts is constrained by the absence of reliable data, weak information network as well as lack of technical and institutional capacities.

The current study is expected to provide quantified information regarding drought. This will be valuable information to take pre, and post–drought risk management plans by decision and policy makers. The most drought–vulnerable area will be delineated based on the livelihood class of the region, which will be important for Afar Regional State government and the Federal government of Ethiopia. This will help also the NGOs to identify the most drought–prone areas to save the life of pastoral communities in the region.

1.5. Scope of the study

The scope of the study is geographically focused on the Afar Regional State of Ethiopia, which is a drought-prone area. Conceptually, this study is delimited on the drought vulnerable area assessment related issues. Methodologically this study incorporated different satellite based drought indices like NDVI, DSI, VCI, from remotely sensed SPOT and PROVA-V Vegetation data as it also used SPI from the rainfall data.

1.6. Limitation of the Study

The limitation of this study was lack of adequate data in availability of water resource and poverty index data of the region to include in the study. Lack population and livestock data affected by the drought to incorporate in the study.

1.7. Thesis organization

This thesis was organized in six chapters. The first chapter deals with the introduction part of the paper, the second chapter review of related literature, the third chapter materials and methods, the chapter four result, the chapter five discussion and chapter six conclusion and recommendations.

CHAPTER II

REVIEW OF RELATED LITERATURE

2.1. Concept of Drought

Drought is the most multifaceted but least understood among all natural hazards. There is no single universally accepted definition of drought as it is dependent on many climatologically limitations with noteworthy spatial unpredictability (Loukas et al., 2002; Rossi, 2009; Akhtar, 2014). Drought occurrence is obvious when there are abnormal dry weather conditions and low rainfall more than normal condition of the area with resulting in decrease of water level in rivers, lakes along with long lasting impact on agricultural production, livestock and overall economy (Shaheen et al., 2011; Akhtar 2014). Drought is a recurrent climate process which occurs with uneven temporal and spatial characteristics over a broad area and over an extended period of time (Bayarjargal et al., 2006). It is an insidious hazard of nature and begins from a deficiency of precipitation those consequences in a water deficiency for some activities or some group (WMO, 2006).

According to Glossary of Meteorology (1959) drought is defined as; "a period of abnormally dry weather sufficiently prolonged for the lack of water to cause serious hydrologic imbalance in the affected area." Drought occurs in almost all climatic zones, but its characteristics vary significantly from one region to another and its definition varies from region to region and may depend upon the controlling insight, and the task for which it is defined. It originates from a deficiency of precipitation over an extended period of time, usually a season or more. It should generally be defined relative to some long-term average condition in a particular area, a condition often perceived as "normal" (Verdin, 2007). It is also related to the timing (i.e., principal season of occurrence, delays in the start of the rainy season, occurrence of rains in relation to principal crop growth stages) and the effectiveness (i.e., rainfall intensity, number of rainfall events) of the rains. Other climatic factors such as high temperature, high wind, and low relative humidity are often associated with it in many regions of the world and can significantly aggravate its severity. Drought is a temporary deviation; it differs from aridity, which is restricted to low rainfall regions and is a permanent feature of climate (Sara Abebe, 2009).

2.2. Types of drought

Many disciplinary perspectives of drought exist. Each discipline incorporates different physical, biological, and/or socio-economic factors in its definition of drought (WMO, 2006).

The many definitions lead to drought being grouped by type as follows: meteorological, hydrological, agricultural, and socio-economic. These classifications are done according to a number of criteria involving several variables, used either alone or in combination: rainfall, temperature, humidity, and evaporation from free water, transpiration from plants, soil moisture, wind, river and stream flow, and plant condition.

2.2.1. Meteorological drought

The classification based solely on precipitation is called Meteorological Drought and refers to short-period droughts or dry spells, when precipitation received is far below the expected normal. Meteorological drought is expressed solely on the basis of the degree of dryness (often in comparison to some "normal" or average amount) and the duration of the dry period. Definitions of meteorological drought must be considered as region specific since the atmospheric conditions that result in deficiencies of precipitation are highly variable from region to region. For example, some definitions differentiate meteorological drought on the basis of the number of days with precipitation less than some specified threshold. Extended periods without rainfall are common for many regions; such a definition is unrealistic these instances (CWRM, 2003). Other definitions may include actual precipitation departures to average amounts on monthly, seasonal, year, or annual time-scales. Definitions derived for application to one on precipitation is called Meteorological Drought and refers to short-period droughts or dry spells, when precipitation received is far below the expected normal. Meteorological drought is expressed solely on the basis of the degree of dryness (often in comparison to some "normal" or average amount) and the duration of the dry period. Definitions of meteorological drought must be considered as region specific since the atmospheric conditions that result in deficiencies of precipitation are highly variable from region to region. For example, some definitions differentiate meteorological drought on the basis of the number of days with precipitation less than some specified threshold. Extended periods without rainfall are common for many regions; such a definition is unrealistic these instances. Other definitions may include actual precipitation departures to average amounts on monthly, seasonal, year, or annual time-scales. Definitions derived for application to one region usually are not transferable to another since meteorological characteristics differ. Human perceptions of these conditions are equally variable. Both of these points must be taken into account in order to identify the characteristics of drought and make comparisons between regions (WMO, 2006).

2.2.2. Agricultural drought

According to Palmer (1965), agricultural drought is probably the most important aspects of drought. But that problem is far more specialized and complicated than some investigators seem to realize. This is related to physiological drought, which is determined from conditions of natural vegetation, crops, livestock, pastures and other agricultural systems. It is defined by measure of the availability of soil water to plants or animals. In this case, radiation (heat), drying wind and evaporation become important factors. It is usually measured by the effects of water deficit in terms of economic losses to agriculturists. The economic loss terms can include factors like drop in crop production, livestock deaths, industrial losses; plants not planted or replanted changes in land use, emergency relief expenses, as well as losses incurred after the agricultural drought (e.g. losses through wind and water erosion). Agricultural losses from economic terms may be very difficult to assess or compare with some previous episodes since similar patterns of drought may have a different economic impact at various stages of development to the agriculturist (WMO**,** 2006).

Drought episode may cause a drop in agricultural production similar to some earlier ones, but a sharp rise in the market prices of the products during the drought period may result into higher profits to the agriculturist. Thus agricultural drought links characteristics of meteorological and hydrological droughts to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, and so forth. A plant's demand for water is dependent on prevailing weather conditions, biological characteristics of the specific plant, its stage of growth, and the physical and biological properties of the soil. An operational definition of agricultural drought should account for the variable susceptibility of crops at different stages of crop development (URL[1]).

2.2.3. Hydrological drought

Hydrological drought is the deficit of runoff into rivers and other surface water resources and in groundwater resources. It involves the description of availability of water, in the form of precipitation runoff, evaporation, infiltration, river systems, and other surface/ groundwater inflow/outflow systems, which may be included in the hydrological water balance equation as follows:

$$W = G - L \qquad \text{eq. 1}$$

URL[1] http://ponce.sdsu.edu/three_issues_droughtfacts01.html

Where: W= available water for the system use, G= total incoming water of the system (precipitation, Infiltration, storage, etc.) and L= total water loss (evaporation runoff, etc.)

Thus hydrological droughts are related more with the effects of periods of precipitation shortfall on surface or subsurface water supply (i.e. stream flow, reservoir and lake levels) rather than precipitation shortfalls. Meteorological droughts result from precipitation deficiencies. More time elapses before precipitation deficiencies show up in components of the hydrological system (e.g. reservoirs, groundwater). As a result, impacts are out of phase with those in other economic sectors. Also, water in hydrological storage systems is often used for multiple and competing purposes (e.g. power generation, flood control, irrigation, recreation) further complicating the sequence and quantification of impacts. Competition for water in these storage systems escalates during drought, and conflicts between water users increased significantly (WMO, 2004; URL[2]).

2.2.4. Socio-economic drought

This type of drought associates the supply and demand of some economic good or service with elements of meteorological, hydrological, and agricultural drought. Some scientists suggest that the time and space processes of supply and demand are the two basic processes that should be included in an objective definition of drought (WMO, 2006). Drought may possibly be defined as occurring when the demand exceeds supply as result of a weather-related supply deficit. This thought of drought supports the strong symbiosis that survives between drought and human activities. Thus, the incidence of drought could increase because of a change in the frequency of the physical event, a change in societal vulnerability to water shortages or both (URL[3]). Figure 1, shows the relationship between types of droughts and processes.

URL[2] http://ponce.sdsu.edu/three_issues_droughtfacts01.html
URL[3] http://ponce.sdsu.edu/three_issues_droughtfacts01.html

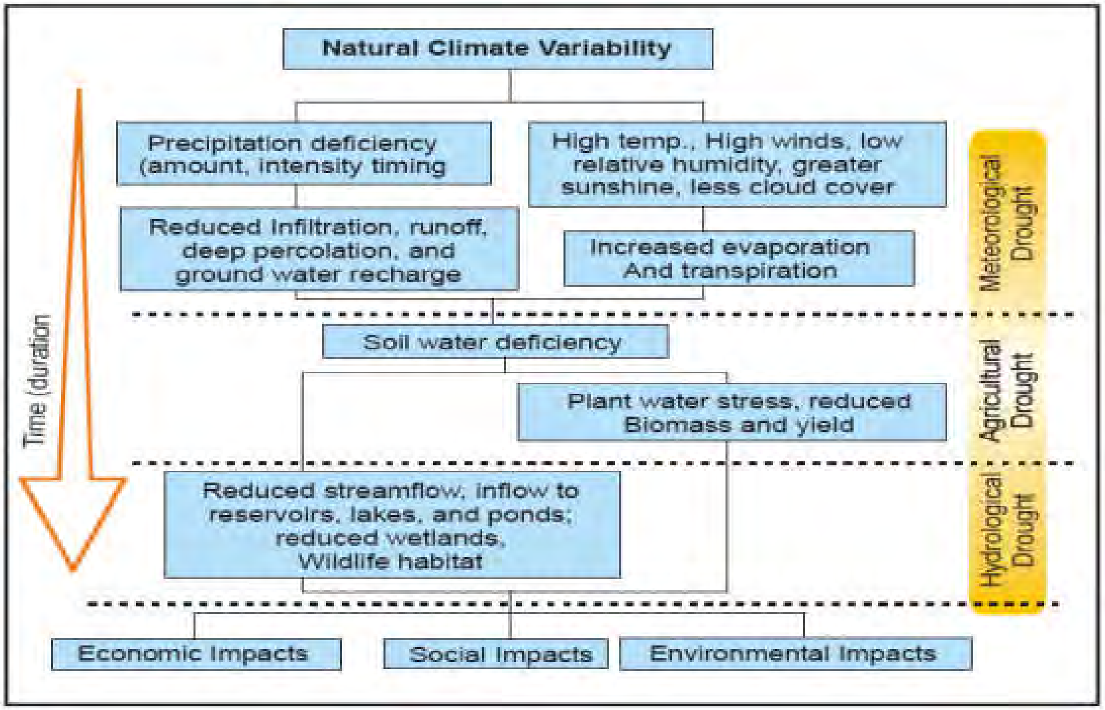


Figure 1.Relationship between drought types and processes.

Source: National Drought Mitigation Center, (2007) cited in Defferew kebede (2011)

2.3. Drought in Ethiopia

Drought is the manifestation of climate change and a common phenomenon in Ethiopia. Ethiopia faces widespread droughts, causing large economic and social damages. Ethiopia has been devastated by severe drought for many of the last 35 years, primarily due to the failure of its main rainy (*kiremt*) months. The agricultural sector on which 85 percent of the population depends is by far the major sector being affected by drought. In dry-land semi-arid areas, the major factors that aggravate the impacts of drought are poor water management and hence agricultural production and livestock population is below the potential.

Ethiopia is the most susceptible to natural drought. Drought induced famine has, for many years, been the worst disaster from which millions of Ethiopians, mostly rural residents, experienced enormous suffering and still remains a national policy agenda and problem. Over the last three decades, Ethiopia has erudite the hardest way to make over its disaster management from a meager apparatus of response and recovery to preparedness, mitigation, and development. Resources and technical (technological) capacities aside, Ethiopia now possesses a means of drought disaster management experiences (Mulugeta Abebe, 2010).

The 1973/74 and 1983/84 famines in Ethiopia that left millions of deaths, suffering and dislocation to the poor farmers in the country were mainly attributed to absence in the systems of government administration that failed to put an early warning system in place. Historically, severe drought has been particularly important causes of loss of lives and livelihood and of political instability. There have been many national and localized droughts in the past and communities managed most of them through their coping mechanisms (DPPC, 2004).

As it has been stated that, between the 9thcentury, the Great Ethiopian famine of 1888-1892 and thirteen drought years were recorded (DPPC, 2004). On the other hand, since the 1970s, impacts of drought have become harsher, in terms of frequency, area covered and the number of people affected (DPPC, 2004).

2.3.1 Relationship between Drought Occurrence and El Nino in Ethiopia

There are different scientific views about the existence and the strength of El Niño relationships to the Ethiopian region. According to Kassahun Bokretsion (1999), giving emphasis about El Niño in Ethiopia began following the shocking 1983-84 drought. ENSO was found to be one of the main factors that lead to drought in Ethiopia. Research at the NMA began to focus on the links between the distribution of rainfall, Sea Surface Temperatures (SST) (including the Pacific, Indian and Atlantic Oceans), and Ethiopian weather (Kassahun Bokretsion, 1999). The National Meteorological Agency (NMA) has generalized that increases or decreases in the Sea Surface Temperature (SST) on the Pacific Ocean impacts on the amount and distribution of rainfall in Ethiopia (Tsegaye Wolde-Georgis et al, 2000). Normal summer rainfall is disrupted because El Niño weakens the atmospheric systems that strengthen rainfall and its distribution during the summer season (Kassahun Bokretsion, 1999).

2.4. Drought in Afar Regional State

Warming temperatures are projected to cause more frequent and more intense extreme weather events, such as heavy rain storms, flooding, fires, hurricanes, tropical storms and El Niño events (IPCC, 2001; WWF, 2006). In 1997, floods and high rainfall, triggered by an El Niño event in eastern Africa, resulted in a disrupted agricultural production and pastoral systems (Lovett et al., 2005). While climate change is projected to cause more frequent and intense ENSO events impacts are not uniform across East Africa (Wara et al., 2005); WWF,2006).

Droughts have been closely associated with food security shocks, and hunger, has been prominent in the history of the pastoral societies of the Horn. These explanations also clarify why the effects of droughts will not be equally distributed in a population, and that there will always be some parts of society that are more exposed to starvation than others (Helland, 2015).

A drought has been reported from Afar every second or third year since the turn of the century (Pantuliano and Wekesa, 2008), which is more frequently than what used to be the case. Furthermore, and in light of the climate change debates, the forecasts for the region indicate that higher temperatures could translate into more frequent and more extreme weather events in the future (Oxfam, 2011). Climate change impacts are still uncertain, however, because the human populations of the Horn are not simply going to be passive bystander to the outcomes of climate change. There may be new or intensified risks produced by climate change, but depending on how they are encountered, climate change could offer a range of new opportunities as well (Ericksen et al., 2011).

The Horn of Africa drought of 2011 was triggered by a deep and prolonged *La Niña* episode and resulted in a severe food security and nutrition crisis that affected the lives and livelihoods of more than 12.5 million people living in the region's dry lands including the Afar Regional State in Ethiopia (AKLDP, 2014).

2.5. Application of Remote Sensing in Drought Monitoring

Remote sensing is the science and art of obtaining information about an object, area or phenomena through the analysis of data acquired by a device that is not in contact with the object, area, or phenomena under investigation(Lillisand et.al., 2004).

The detection, monitoring and mitigation of disasters require gathering of rapid and continuous relevant information that are not effectively collected by conventional methods. Remote sensing tools and techniques make it possible to obtain and distribute continuous information rapidly over large areas by means of sensors operating in several spectral bands, mounted on air craft or satellites. A satellite, which orbits the earth, is able to explore the whole surface in a few days and repeat the survey of the same area at regular intervals while an aircraft can give a more detailed analysis of a smaller area, if a specific need occurs. The spectral bands used by these sensors cover the whole range between visible and microwaves (Birhanu Gedif et al., 2014; Belal et al., 2012).

The remote sensing monitoring of drought can get frequent and sustained information on the surface characteristics of planar with full using information of the surface spectrum of time, space, and direction. It can provide macro, dynamic monitoring of drought. Satellite remote sensing provides an alternative approach to monitoring drought over large areas. Remote sensing methods differ from most existing methods because they are not precipitation driven, but rather monitor vegetation stress or soil moisture status using diagnostic observations of key land-surface states (Zhang et al., 2011 a, b).

As reviewed by Moran (2003), the thermal infrared (TIR) remote sensing approach can provide effective estimates of water stress in many plant ecosystems. The Vegetation Health Index (VHI) uses TIR satellite imagery to monitor the increase in canopy temperature that occurs when plants undergo stress (Kogan, 1997). The Evaporative Stress Index (ESI) described by Anderson et al. (2007a, 2007b & 2011a) also uses TIR observations via the Atmosphere-Land Exchange Inverse (ALEXI) remote sensing model to quantify anomalies, the ratio of the actual evapo-transpiration (AET) to the potential evapo-transpiration (PET). This ratio decreases with decreasing plant available soil water. Microwave remote sensing also provides direct observations of near surface soil water stress (Choi et al., 2008, 2013).

In contrast to the standard precipitation-driven drought indices, remotely sensed drought indices have a shorter period of record, commensurate with the satellite era. While preliminary research shows promising results, there are limited analyses of the relative value of remotely sensed drought products and inter comparisons have typically been conducted only at large (continental) spatial scales (Anderson et al., 2007b, 2011a; Choi et al., 2013).

2.6. Role of GIS in Drought Monitoring

Improvements in information technology have provided unimaginable opportunities to support data analyses and communications in the last two decades. GIS has provided new and exciting ways of acquiring natural resource data and also providing efficient means of processing, managing, integrating, and visualizing this data.

According to Opadeyi (1992) and Konecny (2003), GIS is defined as; GIS is an organized collection of computer hardware, software, geographic data and personnel, designed to efficiently capture, store, update, manipulate, analyze and display all forms of geographically referenced information. The increasing use of GIS in the varying professional fields has produced both tangible and insubstantial benefits that are enough to maintain its use into the future (Opadeyi, 2009). Some of the uses of GIS in disaster preparedness and management operations (DPMO) provides integrated data storage and data retrieval capabilities, encourages a more systematic approach to data collection, leads to reduction in the overall costs of data collection and management by facilitating data sharing, 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 natural disaster (Opadieyi, 1992, 2009).

For the last three decades, advancements in the fields of GIS and remote sensing (RS) have greatly facilitated the operation of drought risk assessment. Most data required for drought risk assessment have a spatial component and also change over time. Therefore, the use of GIS and RS has become essential. It is evident that GIS has a great role to play in drought risk assessment because natural hazards are multi-dimensional. The main advantage of using GIS for drought risk assessment is that it not only generates a visualization of hazard but also creates potential to further analyze this product to estimate probable damage due to drought hazard. Drought risk assessment requires up-to-date and accurate information on the terrain topography and the use of the land. The remotely sensed images from satellites and aircrafts are often the only source that can provide this information for large areas at acceptable costs (Wipulanusat et al., 2009). A meteorological station can connect to GIS and keep receiving meteorological information directly entered into GIS, and then these data will managed and analyzed uniformly by the system database. GIS transformed the model to its language and analyzes the data by powerful analysis function, and then adds drought assessment early warning function into drought assessment system, the technical procedure for early warning and drought risk assessment (Tao et al., 2011).

2.7 Drought Indices

There are several indices that measure how much precipitation for a given period of time has deviated from historically established norms. Although none of the major indices is inherently superior to the rest in all circumstances, some indices are better suited than others for certain uses. A drought index value is typically a single number, far more useful than raw data for decision making. There are different indices that have relation with drought. These are grouped as;

I, Rainfall based temperature based and

II, Remote Sensing based drought indices

Table 1. Rainfall, Temperature and Remote Sensing based drought indices

No	Rainfall and Temperature Based drought indices	Remote Sensing based drought indices
1	Percent of Normal	Normalized Difference Vegetation Index
2	Deciles	Vegetation Condition Index
3	Palmer Drought Severity Index	Drought Severity Index
4	Surface Water Supply Index	Temperature Condition Index
5	Standardized Precipitation Index	
6	Rainfall Anomalies	

2.7.1 Rainfall and Temperature based drought Indices

2.7.1.1. Percent of Normal

This index is computed by dividing the actual precipitation by the normal precipitation (typically considered to be a 30-year mean) and multiplying by 100. This index can be calculated for the variety of time scales. Usually these timescales range from a single month to a group of months. One problem is that the distribution of the precipitation, on time scales less than one year, is not Gaussian. For this reason the mean usually differs from the median. This introduces an error in the evaluation of the deviation from the values of the cumulated precipitation considered "normal" for a specific time-space scale (Monacelli, 2005).

According to Monacelli (2005), the equation for this index is:

$$\mathbf{I}= \left(\frac{P}{p30}\right) \quad \mathbf{100} \qquad \text{Eq. 2}$$

Where, P; is for precipitation, $P_{30;}$ is for 30 years mean of precipitation Values of the index less than 100 means drought conditions exist.

2.7.1.2. Deciles

This drought indices is that drought can be identified by the distribution of the time series of the cumulative precipitation for a given period is divided into intervals each corresponding to 10 % of the total distribution (deciles) (Moncelli, 2005). According to Gibbs e Maher (1967) cited in Moncelli (2005); deciles are proposed to be grouped into classes of events as listed in the following (Table 2.1).

Table 2. Deciles.

Class	Percent	Period
Deciles 1-2	20% lower	Much below normal
Deciles 3-4	20% following	Below normal
Deciles 5-6	20% medium	Near normal
Deciles 7-8	20% following	Above normal
Deciles 9-10	20% more high	Much above normal

Source: Monacelli (2005).

2.7.1.3. Palmer Drought Severity Index (PDSI)

Palmer developed this index based on the supply and demand concept of the water balance equation. The objective of this equation is to measure the departure of moisture supply for normal condition at specific location (Palmer, 1965). The PDSI is based on precipitation and temperature data, on the local Available Water Content (AWC) of the soil and other meteorological parameters. The palmer index has been widely used but it has some limitations. Among this the index is highly sensitive to the AWC of a soil type and that there are some difficulties in comparing the results obtained in regions with a different water balances. The palmer Index varies between -6.0 and +6.0. The index classification is shown in the following (Table 2.2).

Table 3. Palmer Drought Severity Index.

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

Source: Manacelli (2005).

2.7.1.4. Standard Precipitation Index (SPI)

The SPI was developed by McKee et al (1993). It was designed to quantify the precipitation deficit for multiple time scales. These time scales reflect the impact of drought on the availability of different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale (Shaheen and Biag, 2011). Table 2.3 presented Standard Precipitation Index values.

According to McKee et al (1993) SPI is calculated as:

$Z\ score = (\mathrm{X}\quad \mathrm{Pa})/\mathrm{Standard\ deviation}$ Eq. 3

Where; Z score is SPI value, X is precipitation for particular month and Pa is mean rainfall for six months.

Table 4. Classification of Standard Precipitation Index values

SPI value	Drought category
2.00 and above	Extremely wet
1.50 to 1.99	Very wet
1.00 to 1.49	Moderately wet
0.99 to 0.99	Near normal
1.00 to 1.49	Moderately dry
1.50 to 1.99	Severely dry
2.00 and less	Extremely dry

Source: McKee et al., (1993)

2.7.1.5. Rainfall Anomalies

To indicate the meteorological drought for the growing seasons of regions, it is computed as:

$$RFA\ i = \left[\frac{RFi - RF\ a}{RF\ a}\right] \quad 100 \qquad \text{Eq. 4}$$

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

2.7.2. Remote sensing Based Drought Indices

2.7.2.1. Normalized Difference Vegetation Index

Normalized Difference Vegetation Index (NDVI) was first suggested by Tucker (1979) as an index of vegetation health and density. NDVI reflects vegetation vigor (Teillet et al. 1997), percent green cover, Leaf Area Index (LAI (Baret and Guyot, 1991) and biomass (Thenkabail et al., 2004).

NDVI has been extensively used for vegetation monitoring, crop yield assessment and drought detection. The relationship between NDVI and rainfall varies spatially, primarily due to the effects of variation in properties such as vegetation type and soil background, with the sensitivity of NDVI values to fluctuations in rainfall, therefore, showing a notable variation regionally (Tornros and Menzel, 2014).

Vegetation is constantly monitored for conditions of drought using the Normalized Difference Vegetation Index (NDVI) (Li et al., 2014). This index is computed using near-infrared (NIR) and red (R) channels as:

$NDVI = (NIR \quad R)/(NIR + R)$ Eq. 5

Where, NDVI; normalized difference vegetation index, NIR; near infrared reflectance and R; red reflectance.

Deering (1978) normalized this ratio from -1 to +1, with the Normalized Difference Vegetation Index (NDVI), by taking the ratio between the difference between the NIR and red bands and their sum. Since then the NDVI is the almost only operational and global-based vegetation index utilized.

The ‘rationing’ properties of the NDVI enable this index to cancel out a large proportion of signal variations attributed to calibration, noise, and changing irradiance conditions that accompany changing sun angles, topography, clouds/shadow and atmospheric conditions (Brown et al.,2008).

2.7.2.2. Vegetation Condition Index

The vegetation condition index reflects the overall effect of rainfall, soil moisture, weather and agricultural practices. Satellite based monitoring can play an important role in vegetation monitoring.

According to Kogan (1995) this drought monitoring algorithm also considers separation of the short-term weather-related NDVI fluctuations from the long-term ecosystem changes. This is a very important procedure because the weather signal in an NDVI value is weaker than the ecological one. Therefore, weather-related NDVI fluctuations are not easily detectable. The weather-related NDVI, to 100, maximum NDVI for each grid cell and week. The resulting component was named the vegetation condition index (VCI) and was defined by the following expression:

$$VCI = 100 \quad (\mathrm{NDVImax} \quad \mathrm{NDVImin})/(\mathrm{NDVImax} \quad \mathrm{NDVImin}) \qquad \text{Eq. 6}$$

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

The VCI approximates the weather component in NDVI value. It changes from 0 to 100, corresponding to the changes in vegetation conditions from extremely bad to optimal. The range of VCI values appropriate for drought analysis from 0% to 35% was accepted as VCI-derived drought indicators (Kogan, 1995). It shows how close the NDVI of the current month or week (i) is to the minimum NDVI calculated from the long-term record (NDVI max and NDVI min) for that month (week). The condition/health of the ground vegetation presented by VCI is measured in percent. A value around 50% reflect fair vegetation conditions, values between 50 and 100% indicate optimal or above normal conditions. Different degrees of severity are indicated by VCI values below 50% (Kogan, 1995).

2.7.2.3. Drought Severity Index

The Drought Severity Index (DSI) is one of the most consulted for detecting drought conditions in a prompt and reliable manner. The DSI algorithm uses satellite derived evapotranspiration (EP), potential evapotranspiration (PET) and NDVI products to detect and monitor droughts on a global basis (Mu et al., 2013).

DSI is a dimensionless index ranging theoretically from unlimited negative values (drier than normal) to unlimited positive values (wetter than normal). One of the advantages over other global drought indices is the fact that the DSI model uses relatively fine scale (1-km resolution) NDVI inputs from MODIS. Other studies also conducted the study based on the DSI using SPOT- 4 and 5 vegetation data (Berhanu Gedif et al., 2014) in drought risk assessment using remote sensing and GIS in Tigray region, Ethiopia. Other studies also used this indices derived from the NDVI in different parts of countries.

2.7.2.4. Temperature Condition Index (TCI)

The Temperature Condition Index (Kogan, 1995), is based on brightness temperature and represents the deviation of the current month's (week's) value from the recorded maximum. The higher the temperature value, more extreme the drought occurrence. Low TCI values (close to 0%) indicate very hot weather in that month or week. Consistently low TCI values over several consecutive time intervals may point to drought development (Kogan, 1995).

The algorithm was similar to the VCI. The conditions are estimated relative to the minimum/maximum temperature envelope. However, the formula was modified to reflect different response of vegetation to temperature. Opposite to the NDVI, high temperature in the middle of the season indicates while low temperature indicates mostly favorable conditions. The TCI has the following expression.

$$\text{TCI}= \left(\frac{Tmax-T\min}{Tmax-Tmin}\right)*100 \qquad \text{Eq. 7}$$

Where; T, T_{max}, and T_{min} are the smoothed weekly temperature its multi-year maximum, and minimum temperature, respectively (Kogan, 1995).

2.9. Identified Research Gaps

For this study different research papers, published articles, websites and newspapers have been reviewed. The findings indicated that application of remote sensing and GIS technology is crucial and recently emerging in the drought monitoring and risk assessment across the world (Dutta et al., 2015).

Different studies have been conducted in different parts of Ethiopia which are largely agriculture specifically crop production dependent. In Afar Regional State different studies have also conducted. But as findings in the area indicated the region is vulnerable to drought. But none of the studies incorporated the remote sensing and GIS technology to monitor as well as identify drought vulnerable areas. The application of remote sensing indices were not applied the pastoral and agro-pastoral parts of Ethiopia like Afar. The Region is pastoral and agro-pastoral which needs timely information on the drought risk areas as it is drought prone. Therefore the findings of this study are expected to fill this gap in the regional state.

Chapter III

MATERIALS AND METHODS

3. Study Area Description

3.1.1. Location of study the area

Geographically, Afar Regional State is located in the eastern part of Ethiopia (Figure 3.1). The total geographical area of the region is about 94,243.8 km^2. It covers approximately 10 percent of the country. It is located between latitude 8^{o}49' 14^{o}30' N and longitude 39^{o}34' E 42^{o}28' E. The region shares common international boundaries with the State of Eritrea in the north-east and Djibouti in the east, regional boundaries with the Regional States of Tigray in the north-west, Amhara in the South-West and Oromia in the South and Somali in the South-East (CSA, 2008).

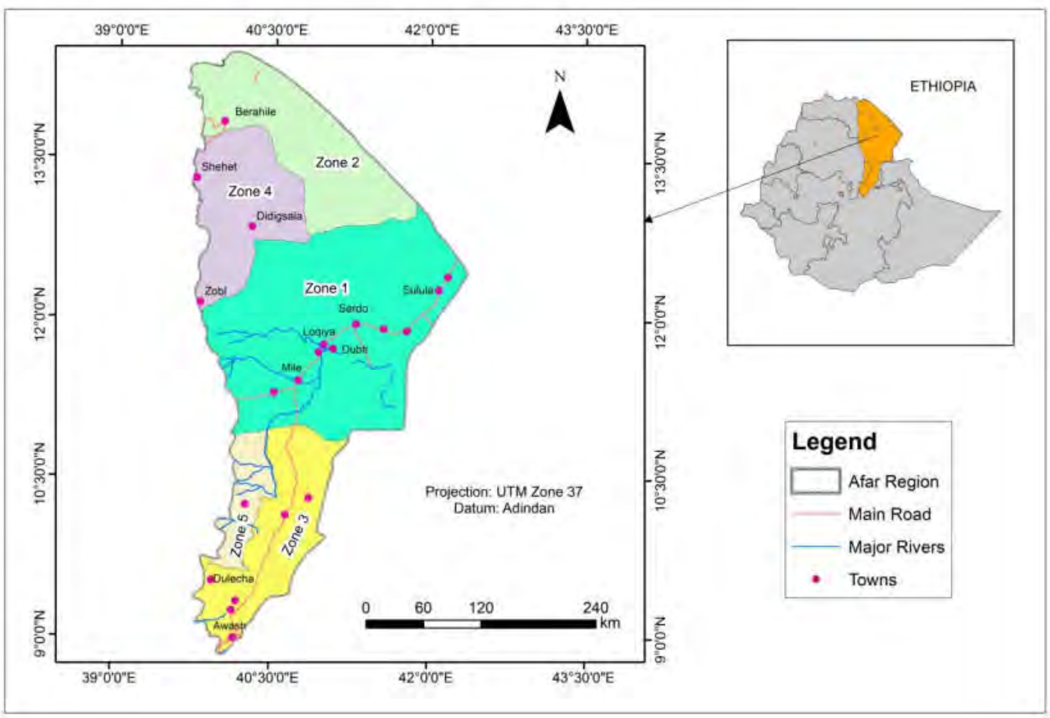


Figure 2. Location Map of the Study Area

The Afar National Regional State consists of 5 administrative zones (sub-regions), 32 administrative districts, 28 towns, and 401 rural and urban Sub-districts (*Kebeles*). The southern part consists of the valley of the Awash River, which empties into a string of lakes along the Ethiopian-Djibouti border. Other notable landmarks to this region include the Awash and Yangudi Rasa National Parks (ANRS, 2004).

3.1.2 Topography and Climate

Most part of Afar Region is flat land with the altitude of the region ranges from 116 meter below sea level to 2063 meters above sea level. The Afar Depression, also known as the Danakil depression is a plate tectonic triple junction in the Afar Regional State. The Afar Depression is a part of the Great East African Rift Valley, and it is the lowest point in Ethiopia. It is also one of the lowest elevations in Africa and is located in the north of the Afar Region. The highest peak in the Afar region is Mt. Mussa-Alle is 2063 meters above sea level (ANRS, 2004).

Afar is characterized by arid and semi-arid climates with low and erratic rainfall. Rainfall is bi-modal throughout the region with a mean annual rainfall below 600 mm in the most favored areas in the south and semi-arid western escarpments decreasing to 200mm in the arid zones to the east. Afar is increasingly drought prone. The region receives three rainy seasons. The main rain, summer (*kiremit*) accounts for 60% of annual rainfall and occurs from mid-June to mid-September. This is followed by little rain in mid-December and a minor rainy season during March–April. Disturbances on the performance of any rainy season will impact on the availability of pasture and water as well as the overall food security situation of the pastoral and agro-pastoral communities (Diress et al, 1998).

The temperature of Afar varies from 25^{o}C during the rainy season (March to September) to 48^{o}C during the dry season (October to February). The satellite based average annual rainfall was 187.9mm (Figure.3). The Afar Depression where one of the highest temperatures (48^{o}C) on earth has been recorded (Yirgalem, 2001).

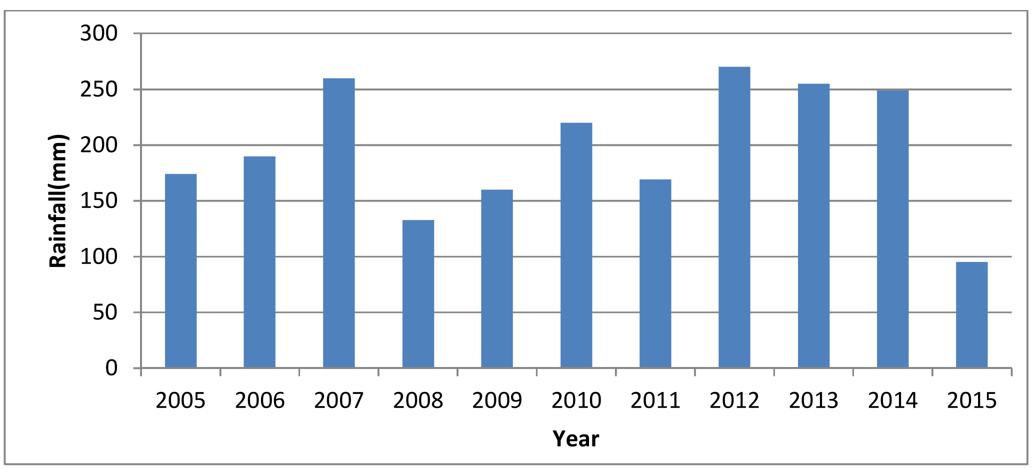


Figure 3. Satellite based Mean Annual Rainfall of Afar Region (2005 to 2015)

3.1.3 Major Rivers and Lakes

Afar region has a number of perennial rivers that include Awash, Mille, Kesem Kebena, Awura, Gulina, Dewie, Borkena, Telalak, and numerous seasonal rivers that flows to different basins. There are also a number of seasonal lakes, such as Lake Asahle, Lake Afdera, Lake Abe and Lake Gemeri in the region (Regional Atlas, 2009). The Awash River, Mille and Logia, which are tributaries of the Awash River, traverse the region. Abbe Bil, Afambo and Adebel lakes, which are connected to the last section of the river Awash, are found in this region. They form an important habitat for river and Lake Fauna (ANRS, 2004).

3.1.4 Natural Resources

The Afar Region covers about 29% of the pastoral lowlands of the country. Though most of the Region is arid and semi-arid, it is able to support the population of the Afar pastoralists mainly due to the presence of Awash River which is the life-belt of the Afar people and their livestock population. Moreover, most of the large-scale farms in the Region and subsistence irrigated crop cultivation have been possible due to the Awash and other rivers in the region (Yirgalem, 2001).

The presence of other natural resources including 18 perennial and 19 seasonal rivers, 26 major forest sites, 17 lakes and a number of mineral sites. Natural resources such as water and forage vegetation play key roles in providing fodder and water points for livestock production in the Region. The wetlands, which are found along the Awash River, are classified as seasonal swamps and marshy areas. The seasonal swamps found in Zones 2, 3 and 4 serve as dry season grazing areas. The Awash River floods the Afar land during the months of July – September due to the heavy rainfall in the head water areas. Pastoralists move away from the flood plains usually to the escarpments on the west or to the Alledeghi plain on the east (ANRS, 2004).

The vegetation types, which are the main stay of the pastoral livestock economy, comprise riverine woodland, bush land, shrub land and grassland. Currently, livestock get their feed from bush land, shrub lands, riverine forests, grassland and seasonal marshes and swamps. However, land-use and vegetation cover survey carried out by Afar rangelands and water development study estimated that 48% of the region is barren land and only slightly less than 52% of the area is considered potentially productive rangeland. This implies the limited feed resources from these areas, given the increase in livestock population and human populations (Yigalem, 2001).

3.1.5 Vegetation and Land-cover

The major land-cover patterns are closely related to patterns of rainfall and temperature, with local variations due to soil and drainage factors. In the southern and central parts of the western piedmont hills and plains, dense shrub land/woodland changes to open shrub land with decreasing altitude and rainfall. To the north with decreasing rainfall in Zones 2 and 4, the vegetation is lower and less dense (ANRS, 2004).

The northern part of Afar around the lower Danakil Plain is predominantly a semi-desert with thorny species of shrubs and *Acacia*; further south in the Awash valley, steppe vegetation is dominant. Both ecological stages are facing bush encroachment with *Prosopis juliflora*, which drive out more nutritive browsing vegetation (Guinand, 2000).

About 15% of the total land area of the Region is covered by grassland; 31.5% shrub land, 1.7% woodland and 0.11% forest land. Whereas water bodies and wetland together account for 1.37% of the total land, the vast area of the region, 48%, has exposed soil, sand or rock 7% of the region’s land is cultivable land. The Afar rangelands and water development study also reported “almost all the land in the Afar region is classified as rangeland which serves as a source of forage for the livestock. The region is one of the least developed regions in the country having 56% of the inhabitants living below the line for absolute poverty. The service and infrastructure condition is far below satisfactory (ANRS, 2004).

3.1.6 Major Soil types and Minerals

The major soil types in the Afar region includes; Cambisols, Fluvisols and Lithosols. This geologic feature is one of earth's great active volcanic areas. Due to the volcanic activity the floor of the depression is composed of lava, mostly basalt. In terms of mineral resources, Salt, Potash, Sulfur, Manganese, Bentonite, Aluminum, Marble, Gypsum and Petroleum are potential major resources of this region. Most of the region's mineral potential is found in Dalol, Brhale and Afdera weredas of Zone two. Elidar, Dubti and Mile in Zone one and Gewane in Zone three also have some mineral potentials. Tendaho geothermal energy is the most promising power source for electricity. The state has also a plausible source for solar energy (ANRS, 2004).

3.1.7 Demographics

Afar is the origin of human race, from where a 4.4 million years old humanoid (Lucy) was discovered with in the region. Afar Regional State is populated with roughly 1.4 million people (Figure. 4 and Table 5) (CSA, 2008). Among them 87 are rural people mainly dependent on pastoral and agro-pastoral livelihood systems. Of the total population in this Region, women constitute about 44%, while men constitute 56%. In terms of age distribution, about 43 percent of the population is young, below the age of 15 years. The region has an estimated density of 14.59 people per square kilometer. For the entire Region, 247,284 households were counted which gives an average one household for 5.7 people, with urban households having on average 3.9 and rural households 6.1 people (CSA, 2008).

The major ethnic composition in the Region are Afar 91.8%, Amhara 4.5%, Argoba 0.92%, Tigray 0.82%, Oromo, 0.7%, Wolaita, 0.45% and Hadiya, 0.013 %, (CSA, 2008). In terms of religious composition, the over-whelming majorities (about 96%) of the regional population are Muslim, 3.86% Orthodox Christians, 0.43% Protestants, 0.09% Catholics. Afarigna language is predominantly (90.8%) spoken in the region (CSA, 2008).

Table 5. Population size of Afar Region Based on Zonal level

Sub-region/ Zone	Total Population	Male Population	Female Population	Urban Population	Rural Population
Afar Region	1,411,092	786,338	624,754	188,973	1,222,119
Zone 1	421,790	230,573	191,217	82,827	338,963
Zone 2	351,431	196,137	155,294	26,190	325,241
Zone 3	198,628	108,903	89,725	58,267	140,361
Zone 4	255,542	145,471	110,071	9,430	246,112
Zone 5	183,701	105, 254	78, 447	12,259	71,442

Source: CSA (2008).

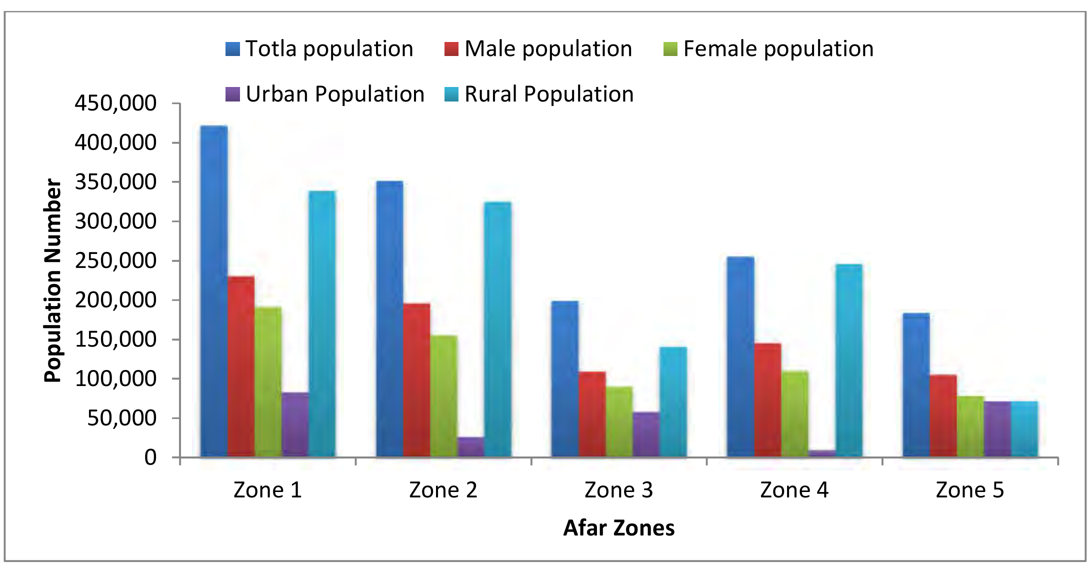


Figure 4. Population size of Afar Region Based on Zonal level.

3.1.8 Major economic activities

About 90% of the population in the State of Afar is leading a pastoral life by rearing camels, cattle, goats, sheep and donkeys. The CSA estimated in 2015 that farmers in the Afar Regional State had a total of 1,580,313 cattle, 1,665,727 sheep, 3,149,351 goats, 377 mules, 124,787 donkeys, 434,291 camels, 132,215 poultry of all species and 2,360 beehives (CSA, 2015).

Afar Regional State in Ethiopia is in arid and semi-arid lands of the rift valley province of Ethiopia, it experiences frequent drought, and drought related losses like any other regions in the horn of Africa. The livelihoods in the Afar Region are primarily pastoral, agro-pastoral, mixed i.e. crop cultivation and animal rearing (Figure 5).

Agriculture of maize, beans, sorghum, papaya, banana and orange is practiced. Cotton production is also typical to the Region. Commerce, especially of salt production is another area of occupation. Based on the economic activities the major livelihood activities of the people in the Regional State have been classified as; Pastoral, which consists the largest livelihood, agro-pastoral, the second largest livelihood on which people have engaged as a means of living and crop cultivation is practiced in some parts (URL[4]).

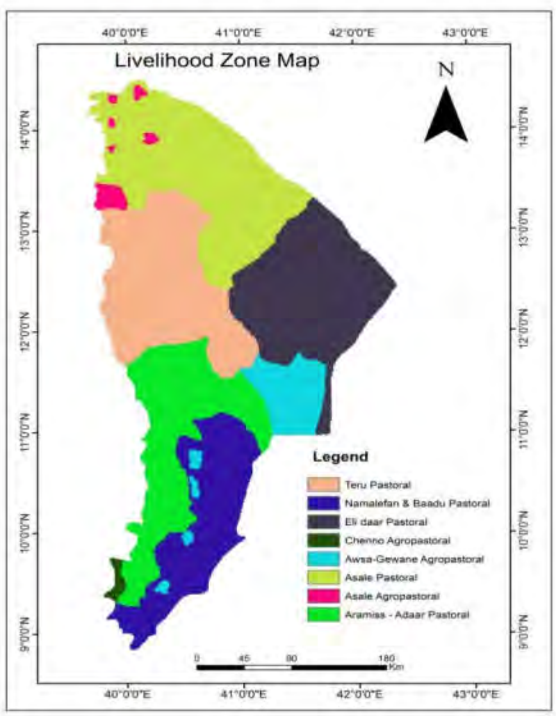


Figure 5. Livelihood Zone Map of Afar Region.

[4] http://www.ethiopia.gov.et/stateafar

3.2. Materials and Methods

3.2.1 Software packages

The following software packages were used for this study for graphical display and statistical analysis: ArcGIS 10.3, ERDAS Imagine 2014, GeoCLIM software, Vegetation Extraction tool (VGTExtract) and Microsoft excels.

3.2.2 Data Acquisition

This section gives a brief overview of the data used and the methodology adopted for the research. Table 6, shows the data used for this study.

Table 6. Data used for the study.

Data sets	Variable	Description	Resolution		Period	Source
			Spatial	Temporal		
SPOT vegetation	NDVI	Satellite	1km by 1km	Daily	2005 to 2013	VITO
PROVA vegetation	NDVI	Satellite	1km by 1km	Two days	2014 to 2015	VITO
CHIRPS_PPT_AFRICA_MONTHLY"	Rainfall	Satellite	0.05km	Monthly	1981 to 2015	FEWS NET
Agricultural data	Yield	Ground data	Quintal/H	Year	2005 to 2015	CSA

3.2.2.1 Agricultural Yield Data

Agricultural yield data of the Afar Regional State for the year 2005–2015 were obtained from the CSA. The data were important for verification of the drought identified. The Figure 6, shows the yield production in the Afar region from 2005 2015 in the regional state.

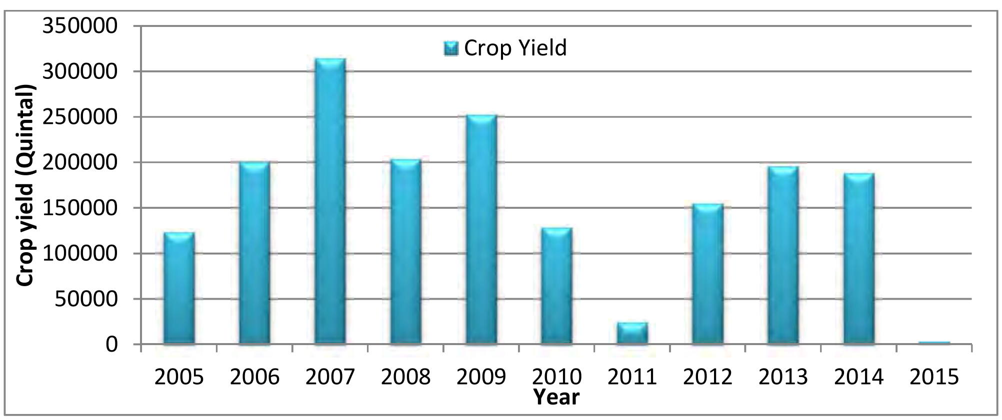


Figure 6. Total Crop Yield in Afar region during the years from 2005 to 2015.

3.2.2.2. Satellite Data Acquisition

3.2.2.2.1. Spot Vegetation Data Acquisition

SPOT-5 vegetation 10-day synthesis archive products were downloaded for years 2005–2013 from Vito. The vegetation data contains all products, including high level products, derived from the vegetation instrument on board of the SPOT satellite **(**Yang et al., 1998; Karabulut et al., 2003; Shilong et al., 2004).

The SPOT VEGETATION S10 product with 1 km spatial resolution and swath width of nearly 2250km, this gives almost daily access to any point on the earth surface. It is composed by merging atmospherically corrected segments acquired over a ten days interval (Kabo-bah, 2013).

3.2.2.2.2. PROBA-V vegetation Data acquisition

PROBA vegetation data were also downloaded for 2014–2015 of the above mentioned months of the study period from the freely accessible website hosted by Vito. PROBA vegetation data were used for this study had 1km spatial resolution similar with that of SPOT vegetation data but of two days temporal resolution. The PROBA-V vegetation is successor of SPOT vegetation since May, 2014. It continuously provides land surface data for researchers, land monitoring services as well as drought monitoring applications (URL[5]).

3.2.2.2.3. Rainfall data acquisition

The rainfall data was downloaded directly using the GeoCLIM software from the Famine Early Warning Network (FEWS). The rainfall data was downloaded entirely for Ethiopia and finally masked out for the study area using GeoCLIM software. Rainfall data was Climate Hazard Group Infrared Precipitation with station data (CHIRPS). A CHIRP is a 30^+ year quasi-global rainfall data set. Spanning 50^oS to 50^oN (and all longitudes), starting in 1981 to near present. CHIRPS incorporate 0.05^o resolution satellite imagery with in-situ station data to create gridded rainfall time series for trend and seasonal drought monitoring.

3.3. Data Processing and Analysis Methods

3.3.2. Vegetation Data Processing and Analysis

For this study, indices for drought monitoring were derived from SPOT NDVI raw data from SPOT-5 VEGETATION System, PROBA-V vegetation and Rainfall Data. These characteristics suit the observation and study of seasonal evolutions in the biosphere and its

ULR[5] http://proba-v.vgt.vito.be/content/mission processes. The indices from SPOT-5 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 (Centre National d'Études Spatiales (CNES) (ULR[6]*)*. The Spot vegetation data are re-projected from Albers Equal Area Conic to UTM projection (UTM, Zone 37).

A SPOT Vegetation NDVI products were collected for Africa level (2005–2013), which was not directly compatible with ERDAS Imagine and ArcGIS software's, and converted to be compatible to GIS environment using Vegetation Extraction tool, which masks out the raw data for Ethiopia boundary and coverts raw HDF format data into GeoTiff and the Ethiopia NDVI data was masked for Afar region. There are three 10-day composites per month in this data set, from the first of the month to the 10th, from the 11th to the 20th, and from the 21st to the end of the month. The last compositing period may vary from 8–11 days, depending upon the number of days in the month.

3.3.2.1. Computing Normalized Difference Vegetation Index

NDVI were calculated from two bands, the near-infrared (NIR) and RED wavelengths, using the following algorithm mentioned in equation 6. NDVI is a nonlinear function that ranges between -1 and +1. The raw data from SPOT vegetation system was rescaled to 1 to +1 to obtain actual NDVI value. The raw data is digital number for a pixel plus certain coefficients and ranges from 0 to 255. The valid range of eight bit raw data value is 3 to 255. A raw value of zero denotes a land pixel with no NDVI calculated due to quality control flagging i.e. cloud/snow/ice. And the raw value of 1 is not used in the binary files; this is reserved for the graphics plane. A raw value of 2 denotes a water pixel (Shilong et al., 2004).

The relationship between the Digital Number (DN) and the real NDVI is expressed as:

Actual NDVI= Coefficient a*DN plus coefficient b eq. 8

NDVI = Coefficient a*DN + b, where; Coefficient a = 0.004, Coefficient b = 0.1

Then actual NDVI was calculated from the raw data as (Raw data pixel value * 0.004) 0.1 using Raster map algebra in ArcGIS. While in the case of PROVA-V vegetation data, rescaling is different from SPOT vegetation data processing. The PROVA-V vegetation data was also rescaled to obtain the actual NDVI value that ranges 1 to +1. Raw digital value

[6] http://sirius-ci.cst.cnes.fr:8080/

ranges from 3 to 255, which was similar of SPOT vegetation data but its offset value is different (URL[7]). Therefore, the rescaling value is expressed as:

Actual NDVI =$(Digital\ Number/Coefficient\ a\ )$ – Coefficient b eq. 9

Where, coefficient a = 250 and Coefficient b = 0.08

Therefore, $Actual\ NDVI = (\text{Raster}/250)\quad 0.08$

The actual NDVI value for PROBA-V data together with SPOT vegetation data was calculated for each decadal images of the year using ArcGIS raster calculator tool. And Monthly averages; Seasonal and Long term mean values of totally 132 images of SPOT and PROBA-V data together were calculated for each of the years using ArcGIS cell statistics. Based on the threshold value each of the drought indices was computed. The following (Table 7) shows the Vegetation indices and respective threshold values.

Table 7. Remote Sensing Data and threshold values for drought vulnerability assessment used in the study (Kogan, 2004).

Drought Index	Range	Normal	Severe drought	Healthy vegetation
Normalized Difference Vegetation Index	1 to +1		1	+1
Vegetation Condition Index	0 to 100	50%	0%	100%
Drought severity Index	1 to +1	0	1	+1

3.3.2.2 Computation of Vegetation Condition Index (VCI)

According to Kogan (1995) the drought monitoring algorithm also considers separation of the short-term weather related NDVI fluctuations from the long-term ecosystem changes. This is a very important procedure because the weather signal in an NDVI value is weaker than the ecological one. Therefore, weather-related NDVI fluctuations are not easily detectable. The weather related NDVI envelop should be rescaled from 0 to 100. The resulting drought index is named as the Vegetation Condition Index (VCI) and was defined by equation 6.

Therefore, for each monthly and seasonal NDVI image, VCI was processed from 2005 to 2015 using the ArcGIS raster calculator. Its value changes from 0 to 100, corresponding to the vegetation conditions from extremely bad to optimal (Table 8). Based on the value obtained drought classes were classified accordingly. The VCI values were computed for each of the seasons for analysis. And also the absolute maximum and minimum of NDVI map of the

[7] http://proba-v.vgt.vito.be/content

study area was derived from the long term images that were used as input. Finally based on the formula given, map raster was used to calculate the DEV_{NDVI}.

Table 8. Vegetation Condition Index threshold classes applied in the study.

Vegetation Condition Index	Severity
50% to 100%	Normal to above normal condition (wet)
<50% to 35%	Moderate drought
<35% to 20%	Severe Drought
<20% to 0%	Extreme drought

Source: Kogan (1997).

3.3.2.3 Computation of Deviation of NDVI (Drought Severity Index (DSI)

Drought Severity Index (DSI) was computed based on the seasonal level using ArcGIS raster calculator. To derive the DEV_{NDVI} (DSI) map of the study area, the decadal long term mean images were stacked together and monthly long term mean was calculated. For this study 11 years long-term seasonal mean NDVI maps were derived from SPOT-5 and PROBA-V vegetation data. The DSI was computed for the seasonal basis to identify the drought years and its severity class (Table 9). It is computed using the following algorithm,

$$DEVNDVI = NDVI_I \quad NDVI_{mean,\, m} \qquad \text{eq. 10}$$

Where, $NDVI_I$ is the NDVI value for season and NDVI mean, m is the long-term mean NDVI for the same season m (e.g. in a data record from 2005 to 2015) there are eleven seasonal NDVI values for the same season (e.g. 11 June – September NDVI values).

Table 9. Drought classes based on Drought Severity Index.

Drought Severity Index	Severity
< 0.25	Extreme drought
0.1 to 0.25	Severe drought
0.1 to 0.1	Moderate drought
0.1 to 0.25	Mild drought
>0.25	No drought

Source: Kogan (2004).

3.3.3 Rainfall Data Processing and Analysis

3.3.3.1 Computation of Standardized Precipitation Index (SPI)

Standardized precipitation Index (SPI) was designed to quantify the precipitation deficit for multiple time scales. These time scales reflect the impact of drought on the availability of different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale (Shaheen and Biag, 2011). It is calculated as:

$$SPI = (X \quad Pa)/Standard\ deviation \qquad \text{eq.11}$$

Where, X is total seasonal precipitation, Pa is long term mean of total seasonal mean

The SPI was calculated using GeoClim software. The GeoCLIM is a spatial analysis tool designed for climatological analysis of historical rainfall and temperature data.

Standardized precipitation Index **(**SPI) was used to calculate the seasonal precipitation deficit in the study area from 34 years of rainfall data and used to analyze the impact of rainfall deficiency on the development of drought. The results computed from seasonal rainfall data were assigned for each grid cell and reclassified based on the drought severity class of SPI. The following (Table 10) shows SPI based drought severity class used in the Region for the study.

Table 10. Standardized precipitation Index based drought severity class.

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

Source: McKee et al., (1993).

3.3.3. Regression Analysis of Crop Yield with Drought Indices

The crop yield data and data obtained from drought indices were prepared for simple regression analysis. The mean raster cell values of NDVI, VCI, DSI and SPI images were extracted using ArcGIS cell statistics and Geoclim software (for the rainfall data). The relationship between NDVI, VCI, DSI and SPI result from each seasonal year with corresponding crop yield was computed to validate the derived drought indices.

3.3.4. Drought Vulnerability Assessment

Drought vulnerability map of the Afar region was produced from the output obtained from satellite based vegetation indices and climatic variable (rainfall) by using multi criteria evaluation (MCE) technique.

The seasonal frequency maps obtained from each drought indices were reclassified into common scale obtained from literatures. For example Lemma Gonfa (1996), Gizachew Legesse and Suryabhavan (2014) showed as the probability of drought occurrence in a given area can be classified in to high, moderate and low drought probability areas when drought is prevalent in more than 50%, 30 to 50% and less than 30% of the years, respectively. Based on the mentioned criteria, the frequency of maps of each drought classes were reclassified into four classes on the regularity of drought rate during the study periods. Accordingly, the occurrences of drought from 2 to 3 mild vulnerable, 4 to 5 moderate vulnerable, 6 to 8 severe vulnerable and 9 to 11 extreme vulnerable. Finally, maps from each drought indices were weighted overlaid based on the percentage of influence using ArcGIS software (Table 11). The detailed study methodological flowchart was presented in Figure 7.

Table 11. Weighted values of drought indices

No	Drought Indices	Weight (%)
1	NDVI	10
2	VCI	20
3	DSI	35
4	SPI	35

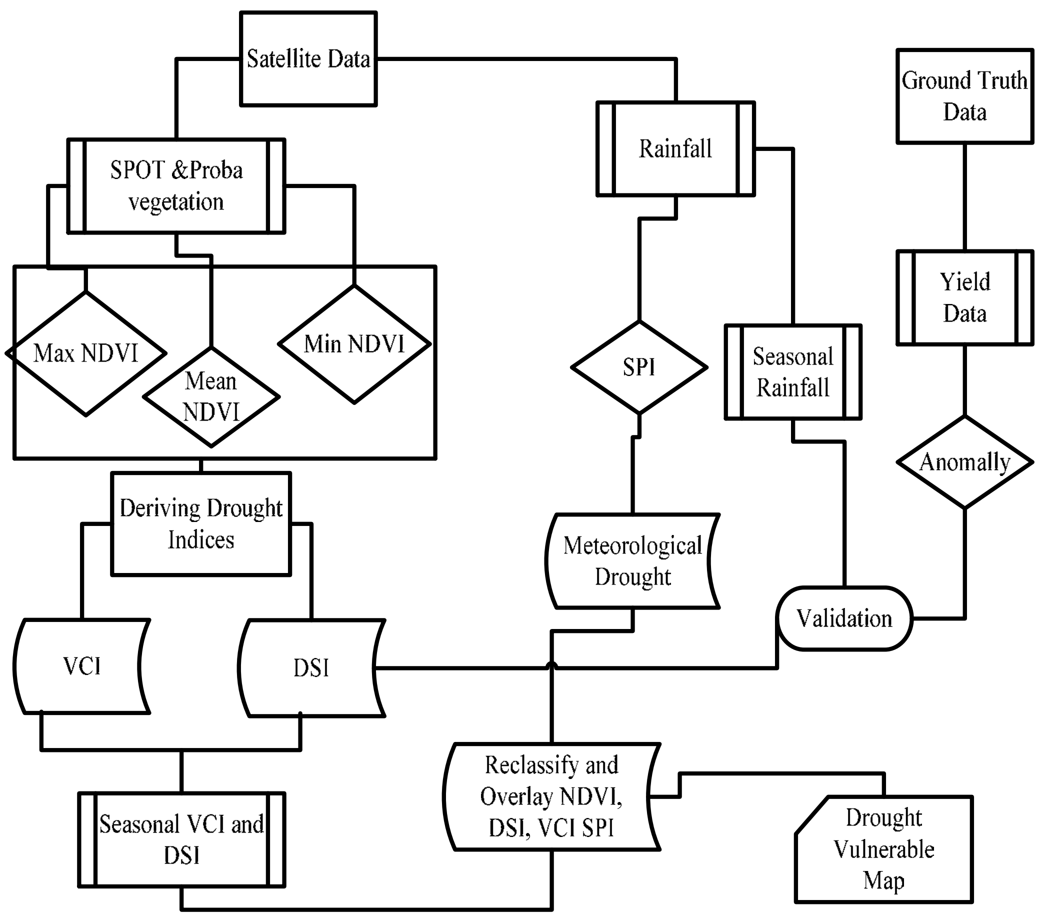


Figure 7. Schematic flow chart of the study.

CHAPTER IV

RESULTS

4.1 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) results showed that there was variability that indicates vegetation stress in different seasons. Accordingly, as it is shown on Figure 8 and 9, each of the eleven maps of mean seasonal NDVI value indicated that the eastern and northeastern parts of the study areas have the lowest NDVI value compared with other parts of the Regional State. Relatively, the south western and western parts have high vegetation with the highest NDVI value of 0.9. These areas were more vegetated than eastern and north eastern parts of the Regional State. Therefore, based on the drought index scale, areas affected by the drought have the lowest NDVI value. During 2005, seasonal NDVI value varied from the 0.08 to 0.74 (Figure 8). Northeastern and eastern parts had the values less than 0, indicating very low vegetation. On the other hand, in 2006, seasonal NDVI value ranged from -0.09 to 0.7, showing the low vegetation cover during the growing season in the northeastern and eastern parts of the study area. The historical NDVI (long term seasonal) values indicated the existence of low vegetation in the Afar Regional State. However, its magnitude and spatial extension varied. Negative values indicated the dry season, while positive values showed wet season. Even though, the seasonal mean values of each year were positive, its values varied spatially and seasonally across the Region in different growing seasons during 2005–2015. The vegetation covers identified in terms of NDVI values were higher in the western and southwestern parts of the Regional State.

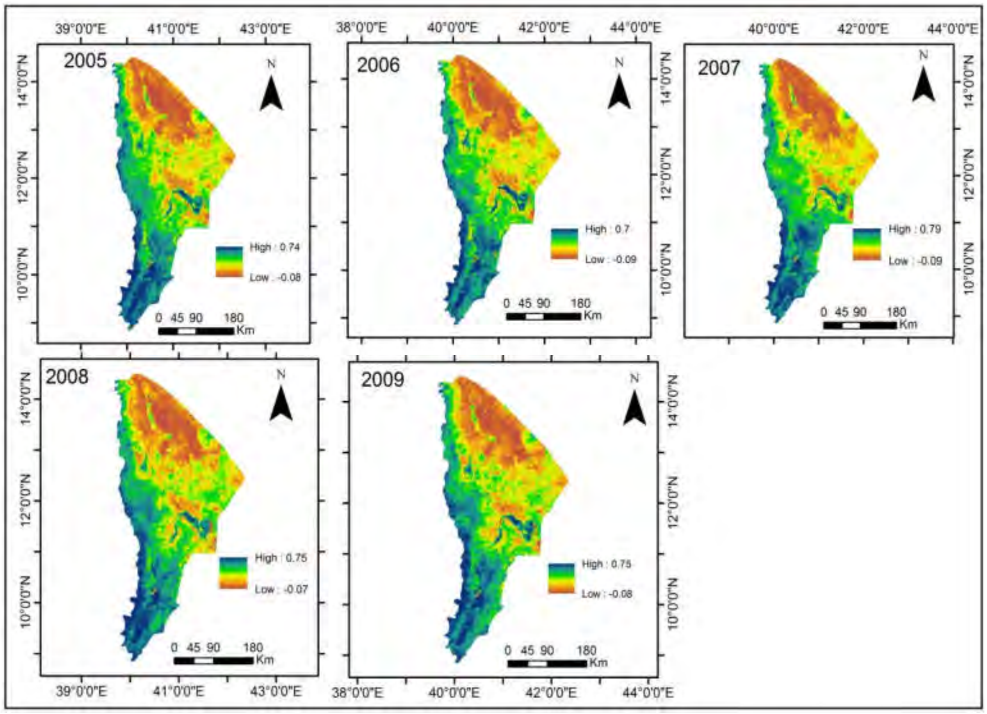
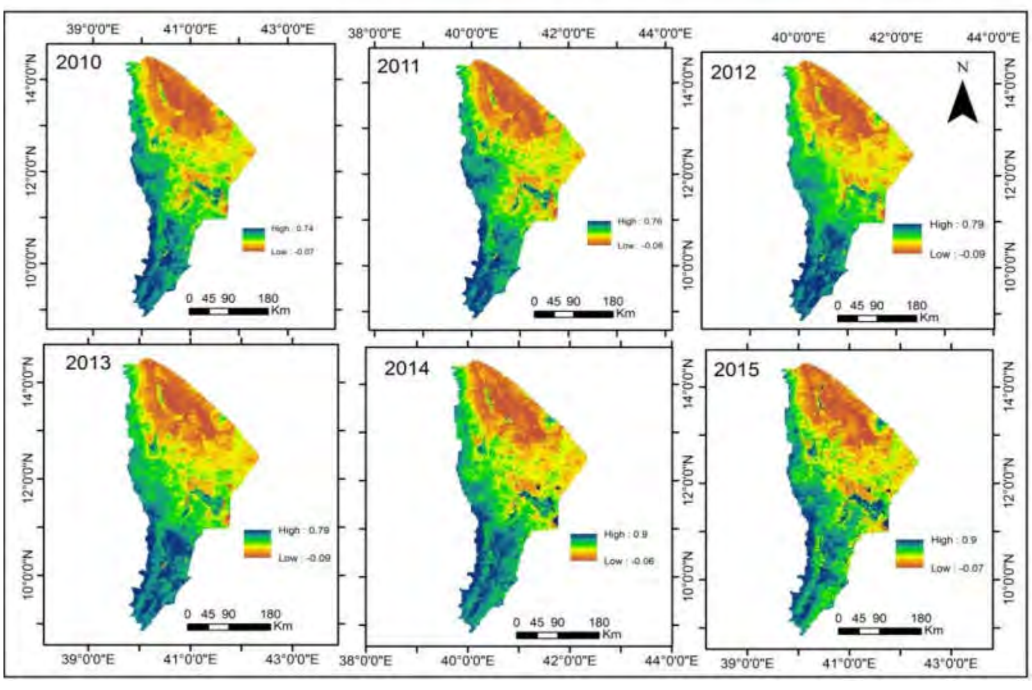


Figure 8. Mean Seasonal Normalized Difference Vegetation Index for the period from 2005 to 2009.



.Figure 9. Seasonal mean Normalized Difference Vegetation Index for the period from 2010 to 2015.

4.2 Relationship between Normalized Difference Vegetation Index (NDVI) and Rainfall

NDVI is very sensitive to the spatial distribution of rainfall. This causes a significant impact in the development of chlorophyll density. Considering the average seasonal NDVI and rainfall patterns of the Afar Region from 2005 to 2015, NDVI values have increased proportionally as the mean seasonal rainfall increased (Figure 11). Spatially, the NDVI and rainfall values increased from the eastern part to the western and southwestern parts of the Region, with its values reached up to 0.9 (maximum) and 575 mm (maximum), respectively. But, in the eastern and northeastern parts of the Region, the NDVI and rainfall values were very low with the minimum 0.07 and 133 mm, respectively. The seasonal NDVI and rainfall varied from 0.14 to 0.2 (with NDVI average value, 0.17), and 95 to 270 mm (rainfall average, 197mm), respectively. The correlation between NDVI and seasonal rainfall was statistically significant with ($r = 0.75$) and ($p < 0.05$). During the 11 years, there was a considerable change in the NDVI and rainfall values. The highest NDVI value was observed when the mean seasonal rainfall was better distributed (Figure. 12). Similarly, the lowest NDVI value was recorded when little rainfall was registered during the year. Rainfall was less during the years 2005, 2008, 2011 and 2015. The minimum NDVI responded as rainfall changed during the dry years, particularly 2005, 2009, 2011 and 2015. During these years, the NDVI values were low as compared with the remaining years in the study period. A rainfall characteristic was not only the amount of rainfall, but also rainfall distribution that plays a significant role for the growth of vegetation.

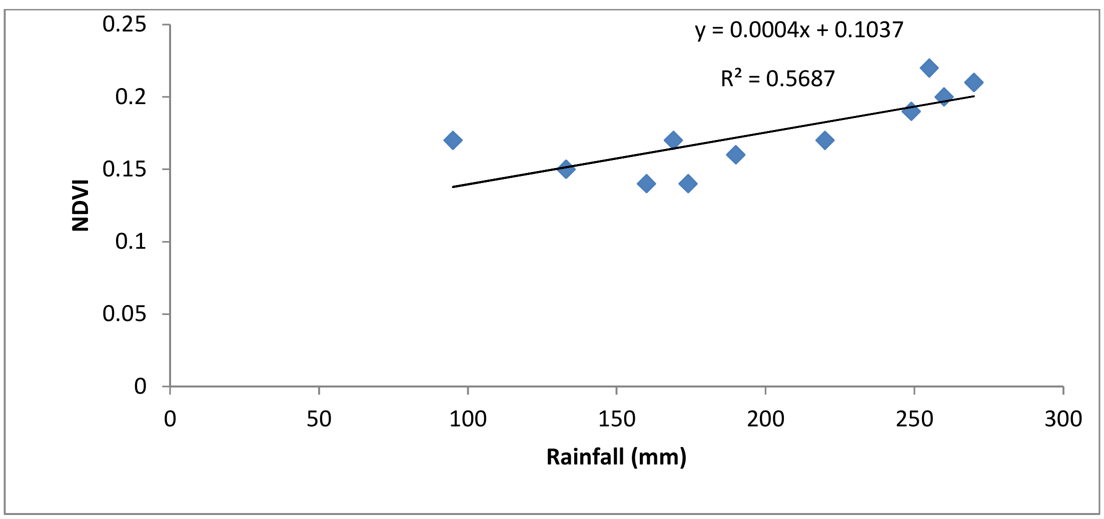


Figure 10. Mean Seasonal Normalized Difference Vegetation Index (NDVI) and Rainfall pattern in Afar Region during the years from 2005 to 2015

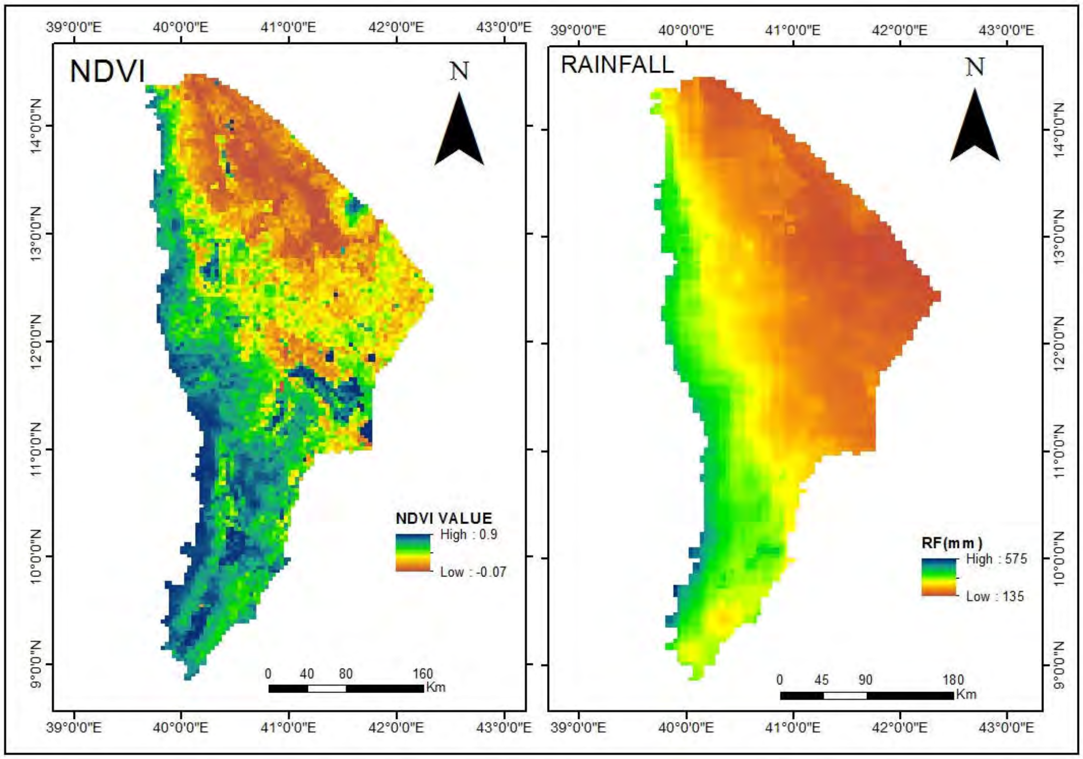


Figure 11. Long term seasonal (June–September) Normalized Difference Vegetation Index and rainfall during the period of 2005 to 2015.

As shown in Figure 12, there was failure of rainfall seasonally in the years 2008, 2009, 2011 and extremely in 2015 as compared with that of the other years in the Region. Contrary to these years, 2007, 2010, 2012, 2013 and 2014 seasonal rainfall was good in the Region. Similarly, the seasonal NDVI values were also low in the years 2005, 2009, 2010, 2011 and 2015. Contrary to this, the NDVI value was high during the years 2007, 2012, 2014 and 2013. Thus, it is clear that, vegetation stress occurred during the years 2005, 2006, 2008, 2009, 2011 and 2015, based on the seasonal NDVI value and seasonal rainfall in the study area during the study period. A detail regression analysis result was shown in Appendix 1.

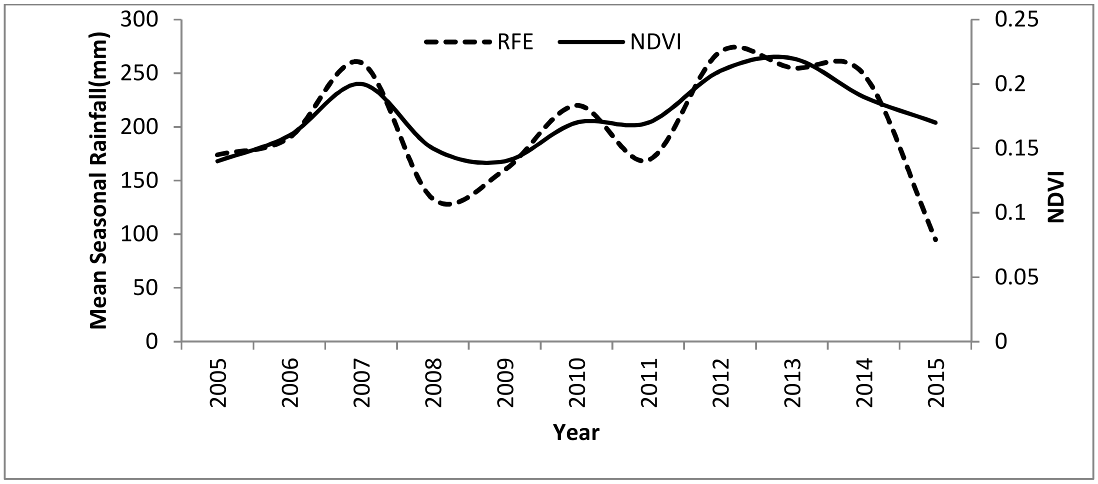


Figure 12. Temporal trends of seasonal (June–September) Normalized Difference Vegetation Index and Rainfall during the period from 2005 to 2015.

4.3 Vegetation Condition Index (VCI)

In order to quantify drought from a long term observation from the space the VCI derived from the NDVI was used in this study. It was found that severe drought condition prevailed during the rainy seasons of the years 2005, 2006, 2009, 2011 and 2015. The onset and spatial extent of drought were clearly observed from the VCI map of the Region during the years 2005 to 2015 (Figure 13 to 15).

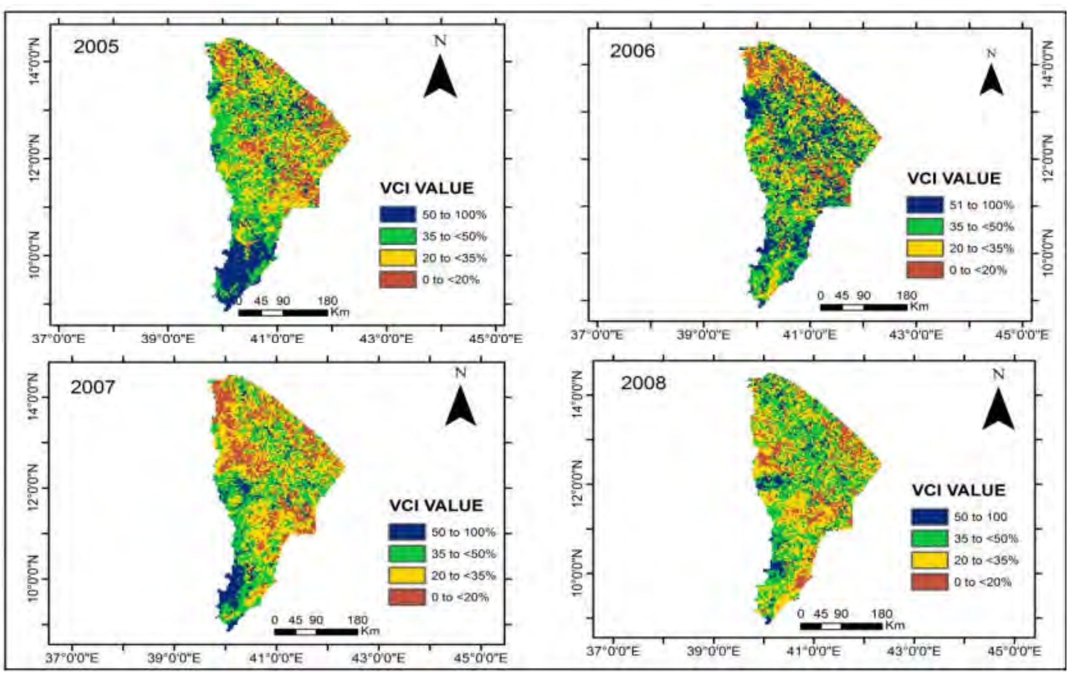


Figure 13. Vegetation Condition Index for the years from 2005 to 2008.

Vegetation Condition Index (VCI) values ranged from 0 to 100, where 0 indicates absence of vegetation and 100 indicates high availability of vegetation. Figure 16, shows the temporal trends of VCI index of the Afar Region from 2005 to 2015. Based on the result obtained from computed mean seasonal VCI, the mean of value VCI ranged from 25% (lowest) in 2015 to 75.9 % (highest) in 2013. Based on the threshold value of 35% for East Africa and less than 50 % of VCI value as drought indicator, drought occurred in different years. From 2005 to 2015, the lower VCI values were observed were in 2005 (32.29), 2006 (46.7), 2008 (36.68), 2009 (36.68), 2010 (39.24), 2011 (42.7), and 2015 (25). Therefore, drought years in this Regional State were identified as 2005, 2006, 2008, 2009, 2010, 2011 and 2015. However, its severity varied as given above for the respective years.

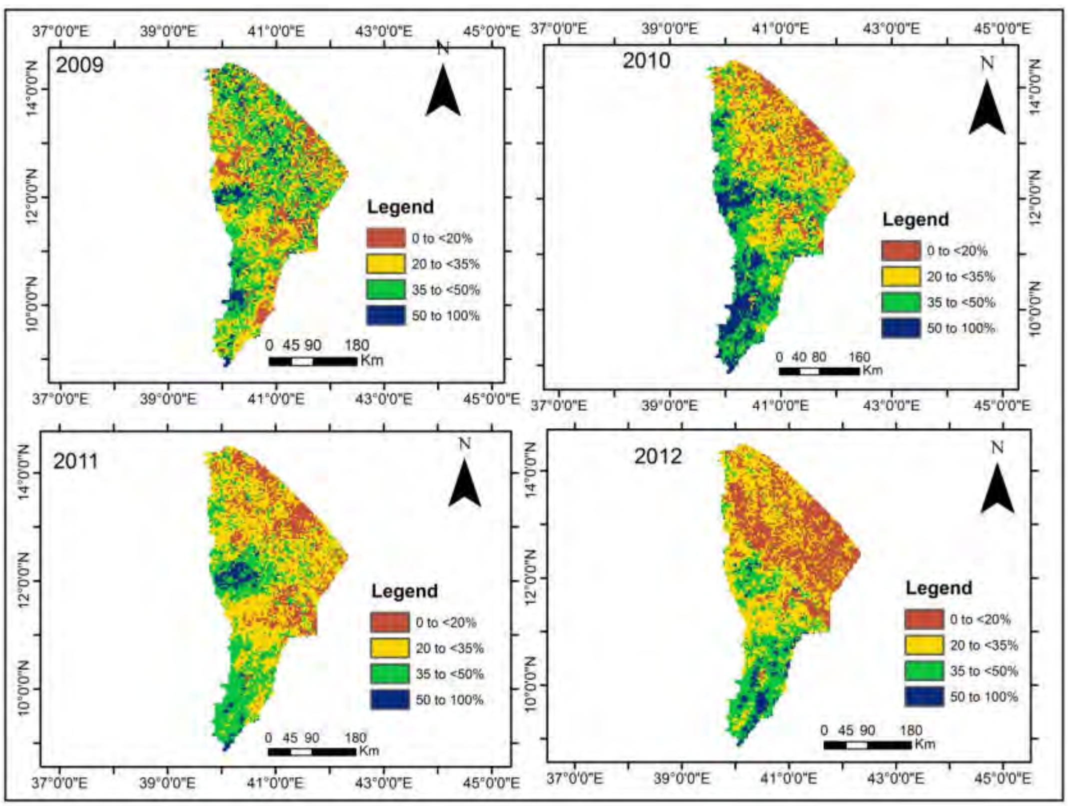


Figure 14. Vegetation Condition Index during the years from 2009 to 2012.

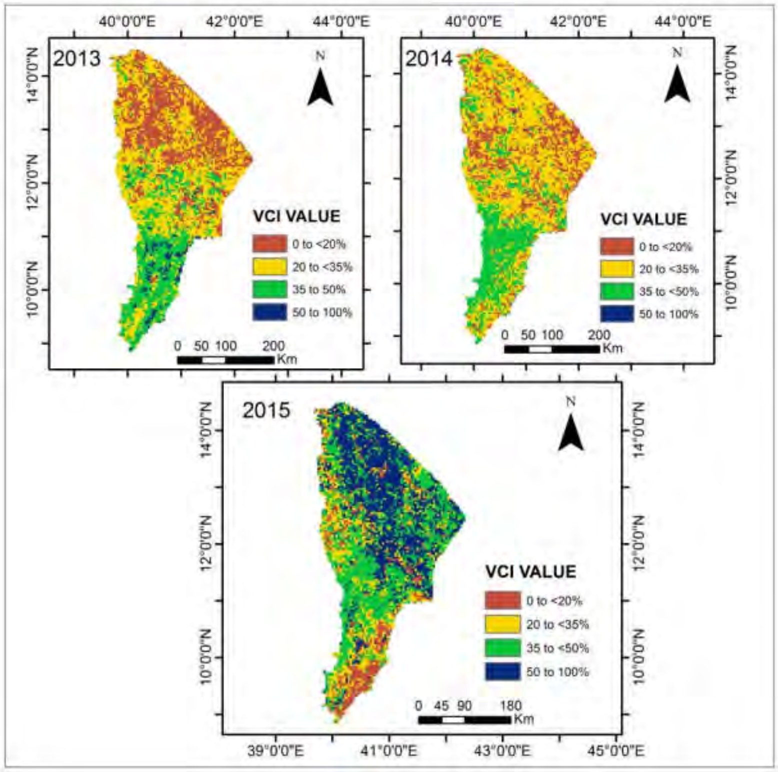


Figure 15. Vegetation Condition Index during the years from 2013 to 2015.

4.4 Relationship between VCI and mean seasonal rainfall

The relation has evaluated with correlation coefficient (R^2= 0.83) that indicated statistically high and significant relationship (Figure 17). The VCI was strongly correlated with mean seasonal rainfall in the Afar Region. The VCI (79.5%) was highest during 2013, when the mean seasonal rainfall was at its peak (270 mm). The mean seasonal rainfall and VCI were increasing and decreasing with nearly the same proportion. A detail regression analysis was depicted in Appendix 2.

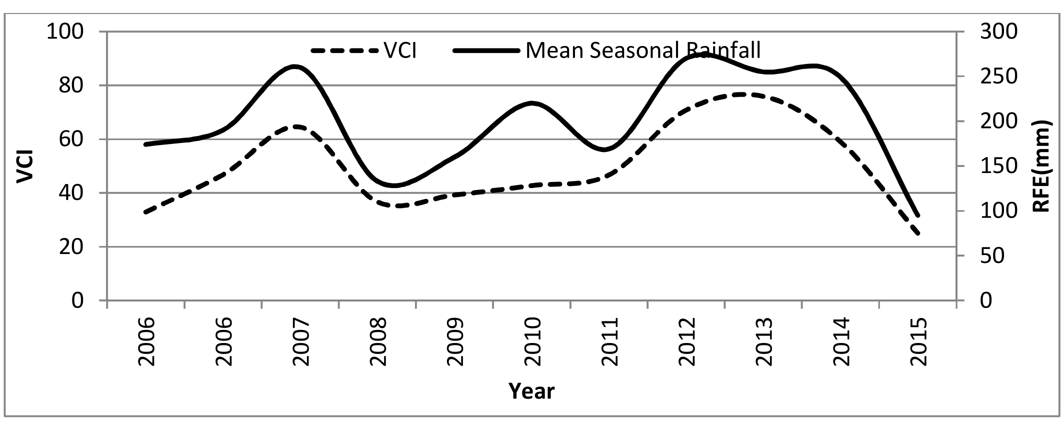


Figure 16. Temporal trends of mean seasonal VCI and rainfall during years 2005 to 2015.

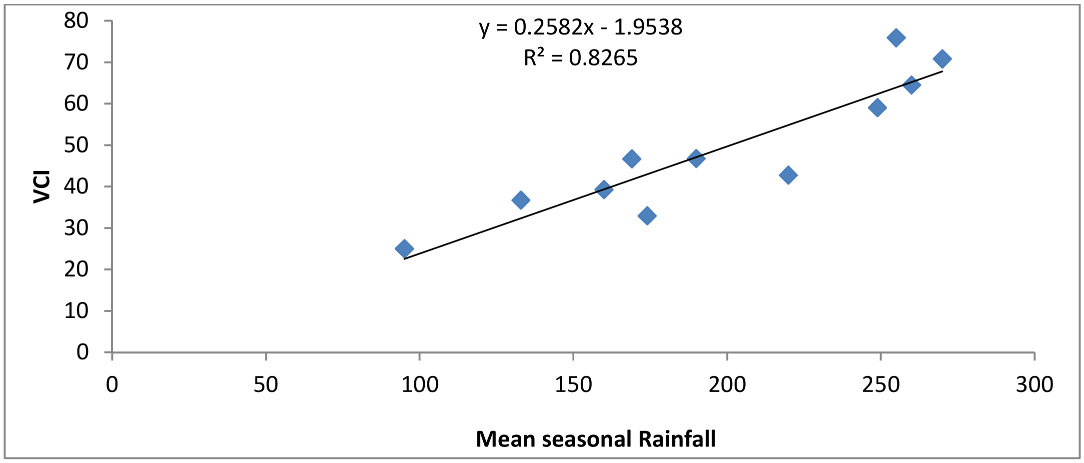


Figure 17. Relationship between VCI and Mean seasonal rainfall.

4.5. Relationship between Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI)

As shown in Figure 18, the relationship between VCI and mean SPI was positive and had good relationship (r = 0.55) and it was statistically significant with coefficient variation, which indicated positive relationship between the two drought indices in the study area (Fig. 4.10). From 11 years of VCI data, 29% of VCI variability could be explained by SPI. Therefore, VCI and SPI have fitted to indicate drought. However, both drought indices have different applications. Standardized Precipitation Index (SPI) was the meteorological drought indicator, while VCI was the agricultural indicator. For this study, it was revealed that both the drought indices and as good indicators in the pastoral areas of Afar Regional State. The temporal trend of VCI and SPI was indicated on the Figure 19.

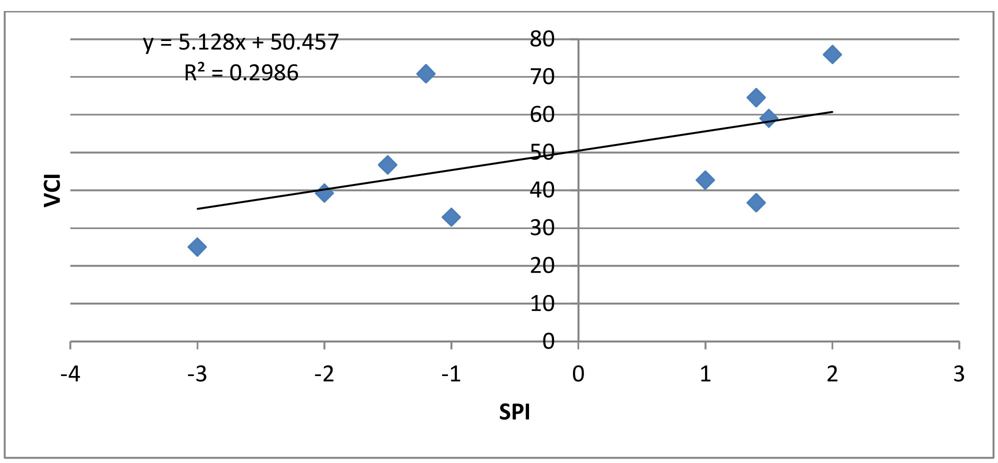


Figure 18. Relationship between Standardized Precipitation Index and Vegetation Condition Index.

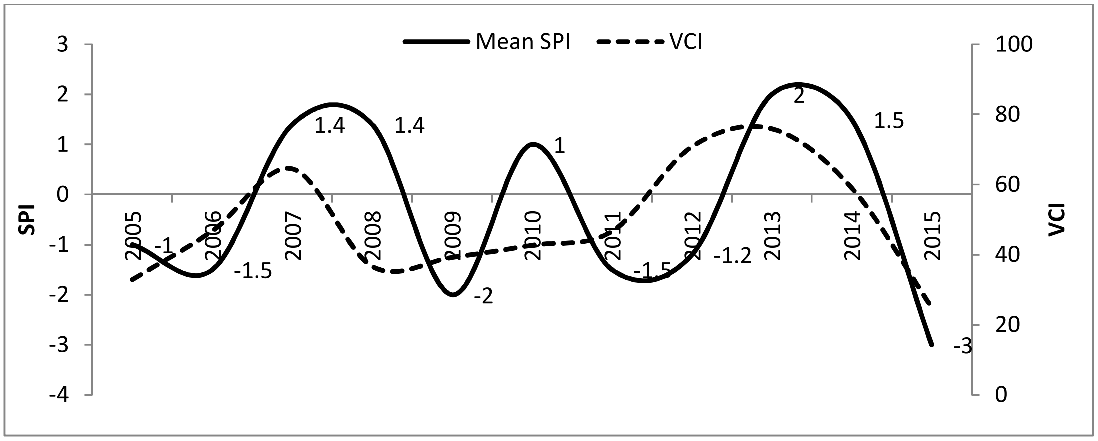


Figure 19. Temporal Trend of Vegetation Condition Index and Standardized Precipitation Index for the years from 2005 to 2015.

4.6 Vegetative Condition Index (VCI) and Yield

To characterize the drought situation in the Afar Regional State, it was necessary to statistically compute VCI with the crop yield production. As revealed in Figure 20, the correlation coefficient was r= 68%. It was statistically significant with $p< 0.05$, with a good relationship. This revealed that the crop value increased by 68% as a result of increase in VCI. As the Figure 21 shows, VCI was low, at the same time; the crop production yield was also low. However, there was no consistent increase or decrease as one of the variable increase or decrease. In some years, VCI was low, but crop yield production was relatively moderate.

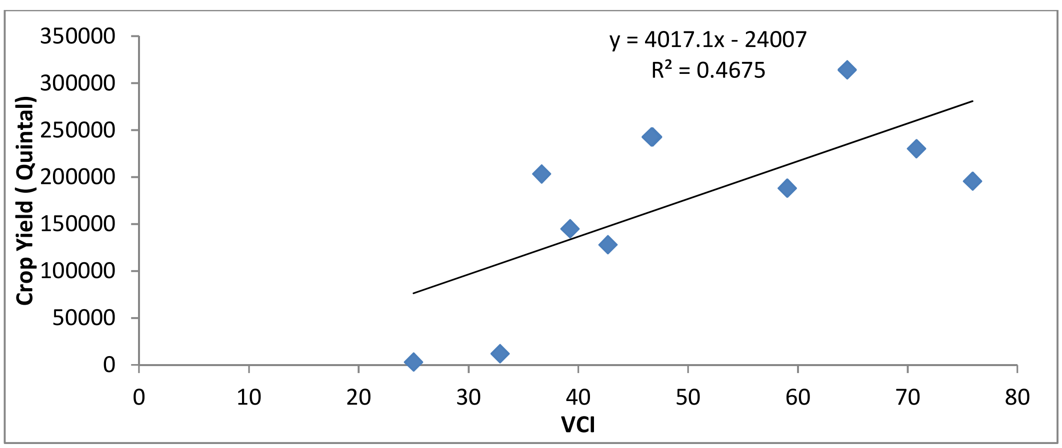


Figure 20. Relationship between VCI and Crop production for the years from 2005 to 2015.

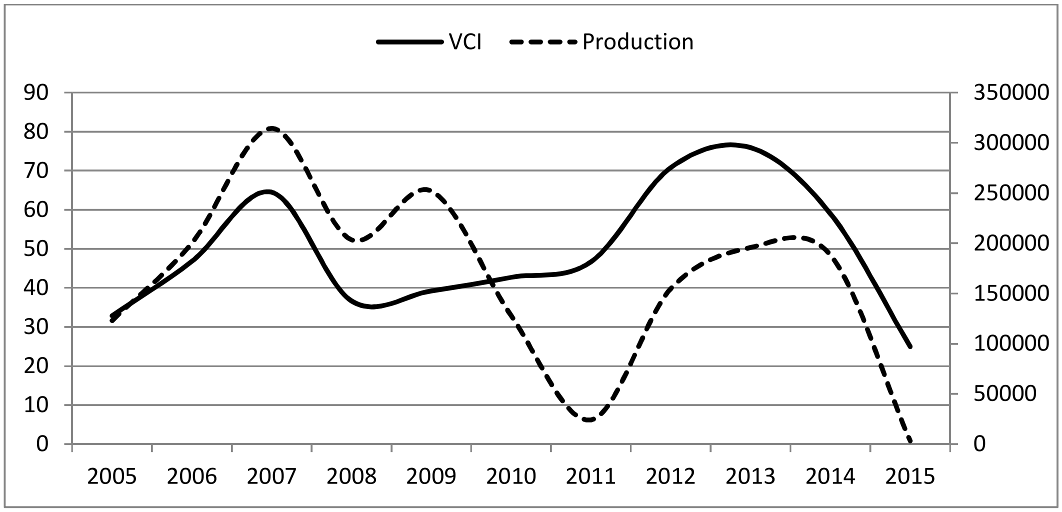


Figure 21. Temporal Trends of VCI and Crop Yield for the years from 2005 to 2015.

4.6 Drought Severity Index (DSI)

The DSI values indicated that the existence of drought during the study periods in the Afar Region. As shown in Figures 22 to 24 DSI values ranged from 1 to +1. Drought Severity Index values less than 0 indicated the existence of drought, while greater than 0 indicated wet season. During the years 2005, 2006, 2008, 2009, 2010, 2011 and 2015, the mean seasonal DSI values were -0.04, -0.02, -0.03, -0.03, -0.01, -0.01, -0.004, respectively. While the wet years were also identified as 2007, 2012, 2013 and 2014 with Mean Seasonal DSI values of 0.11, 0.03, 0.04 and 0.01, respectively. As shown in Figure 25, on the temporal trend of DSI, there was prevalence of drought in different years. However, its severity varied spatially and temporally across the Region during the study period. For instance, in 2015, the DSI value was less than 0 throughout the Region indicating drought.

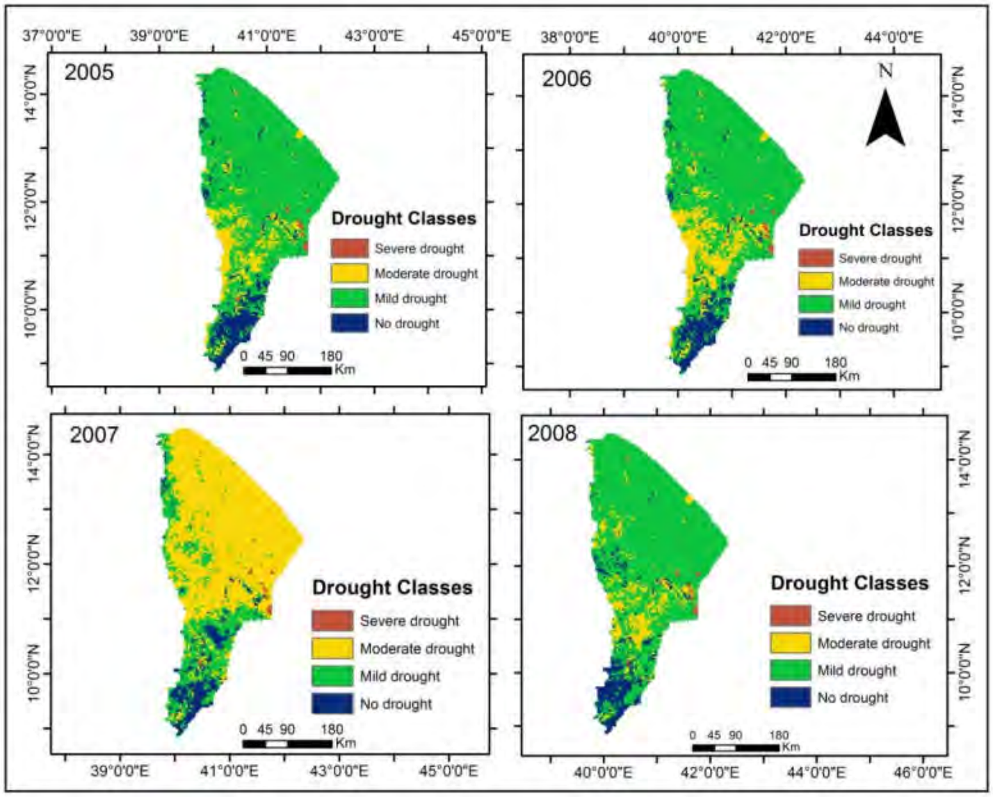


Figure 22. Spatial patterns of drought in Afar Region as revealed by Drought Severity Index during the period from 2005 to 2008.

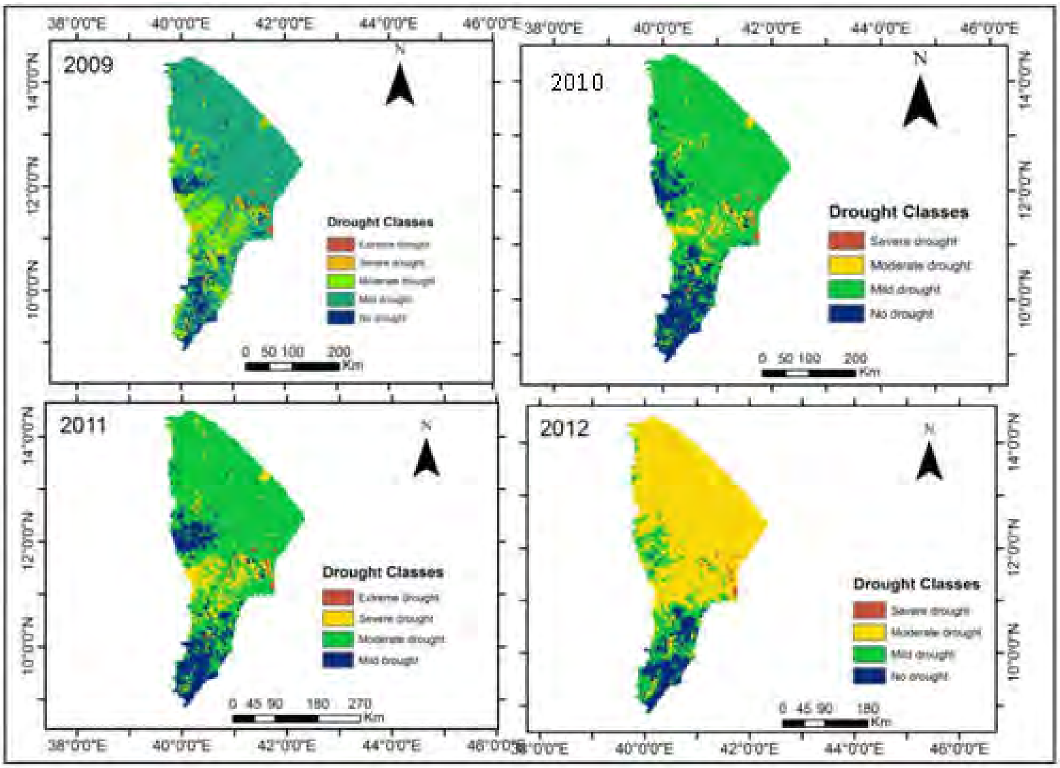


Figure 23. Spatial pattern of Drought in Afar Region during 2009–2012 as revealed by Drought Severity Index.

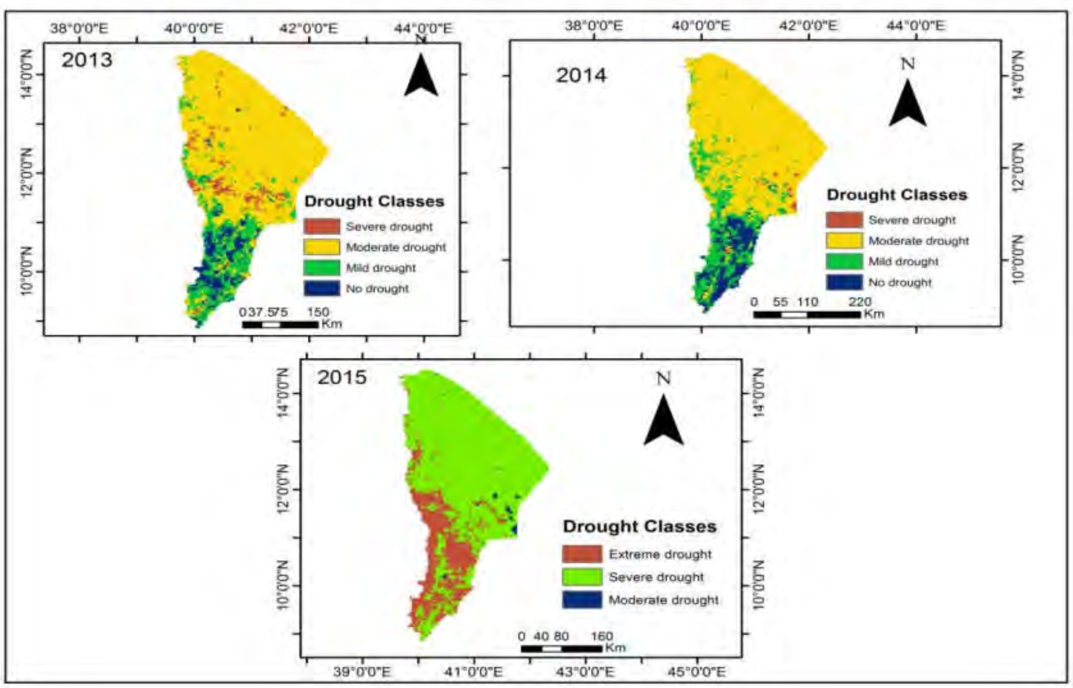


Figure 24. Spatial pattern of drought in Afar Region during 2013–2015 as revealed by Drought Severity Index.

4.7 Relationship between Drought Severity Index and Yield

Drought Severity Index (DSI) and yield production indicated a positive relationship with r= 41%. Figure 25, shows the trends in seasonal DSI and annual yield production in the study area. Based on the result of DSI and yield, there was a considerable change on the agricultural production. Thus, DSI could be effective in drought assessment in the pastoral and agro-pastoral areas. During the 2011 and 2015 very low crop yield was recorded in the Region, as it is shown clearly on the graph. How ever there was relatively high yield production when there was low DSI.

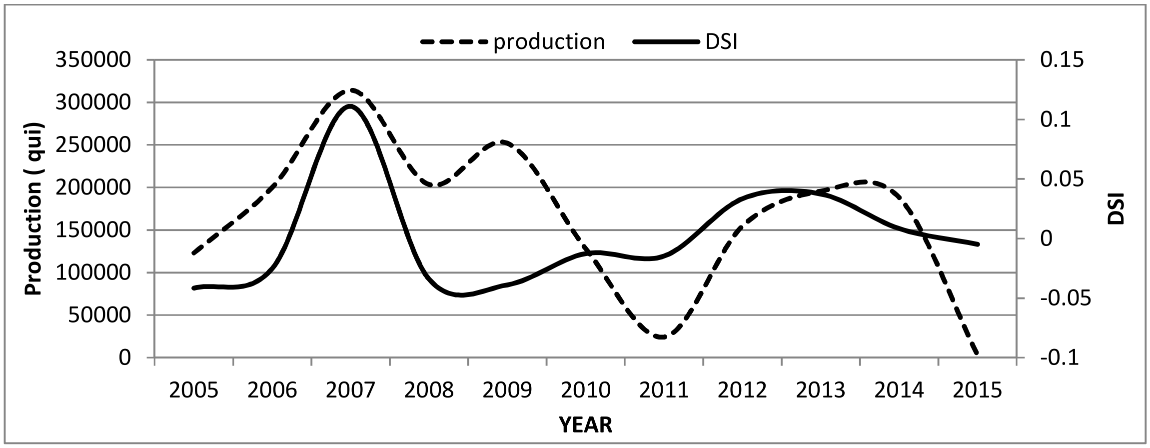


Figure 25. Temporal trends of Drought Severity Index and Production during the period 2005 2015.

Relatively, DSI was also low, but lower DSI was observed during 2005, 2006, 2008, 2009, 2011 and 2015. Hence, these years were drought years in the Region.

4.8 Standardized Precipitation Index (SPI)

Based on the Standardized Precipitation Index (SPI) for 11 years the values ranged from less than 3 to more than 3 in the study years (Figure 28). The threshold value for the drought severity class was 1.5. The values were low in 2005 (-1.5), 2006 (-1), 2009 (-2.0), 2011(1.5) and 2015 (-3) (Figure 29). However in some years the mean seasonal rainfall was low but the SPI value was positive. For instance in 2008, the mean seasonal rainfall was low but its SPI value was greater than 0. Based on the considered threshold value 1.5, severe meteorological drought occurred during 2005, 2009, 2011 and 2015 (Figure 26 and 27).

The results of SPI value indicated that there was dry condition prevailing during the summer (rainy) seasons. The SPI value varied in different years ranged from < 3 to +3.

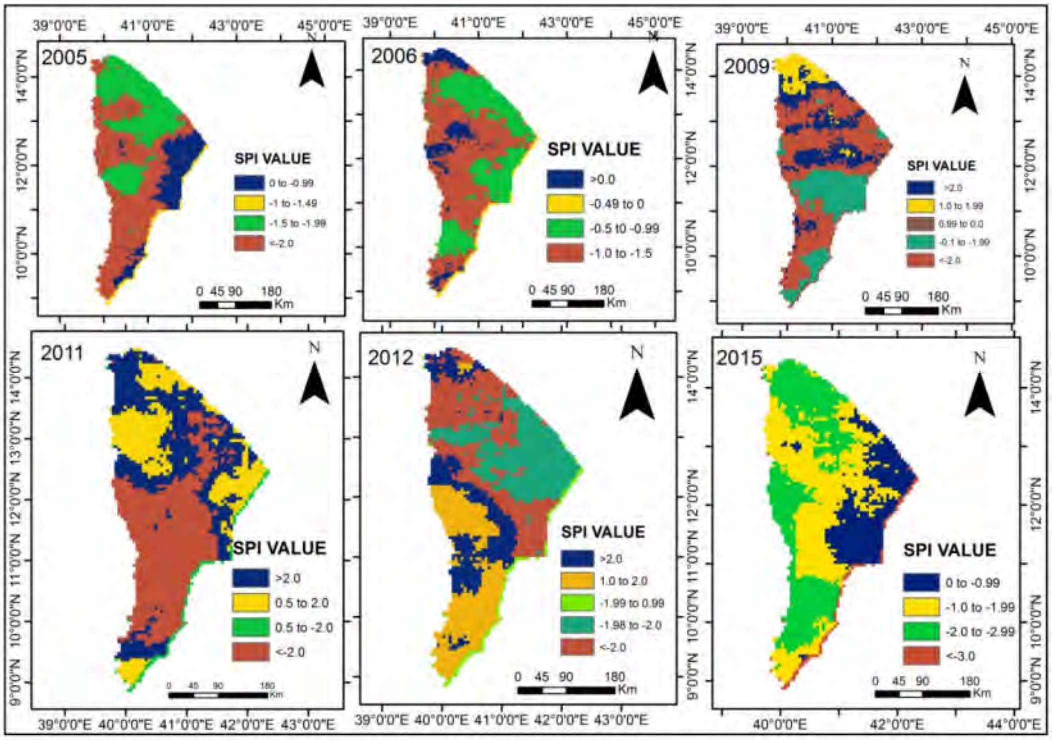


Figure 26. Spatial-temporal pattern of drought in Afar Region for dry years as expressed by Standardized Precipitation Index

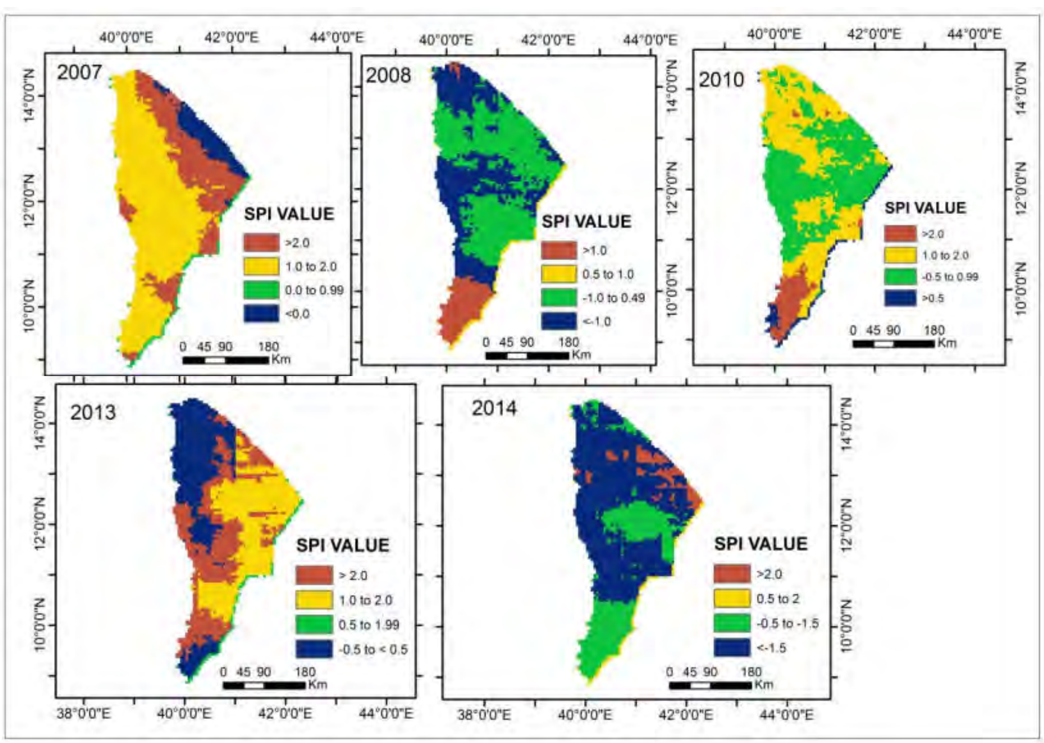


Figure 27. Spatial pattern of drought in Afar Region for relatively wet yeas as expressed by Standardized Precipitation Index

4.9 Standardized Precipitation Index (SPI) and Yield

The correlation and regression analysis between SPI and yield indicated that the relationship between the two variables was positive with r= 0.73. It revealed that 54% of yield variability could be explained by SPI (Figure 28). A detailed summary of regression is presented on Appendix 2.

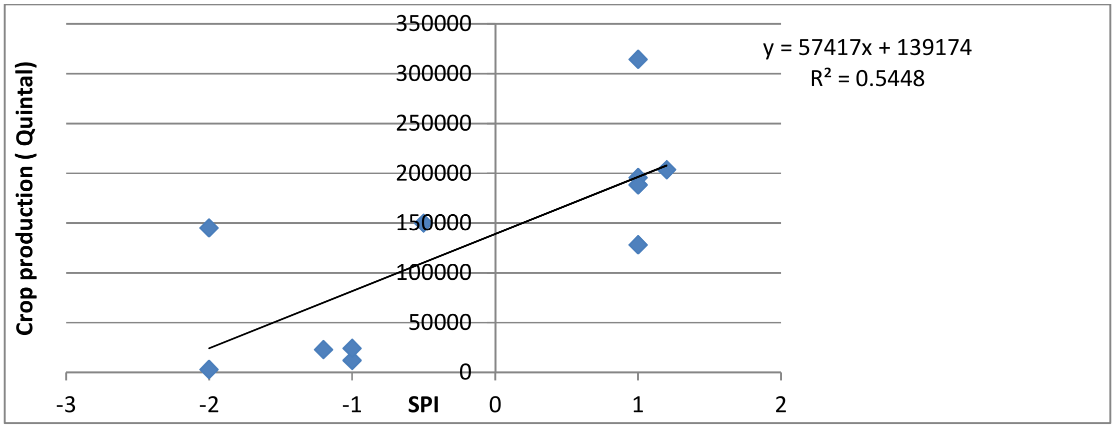
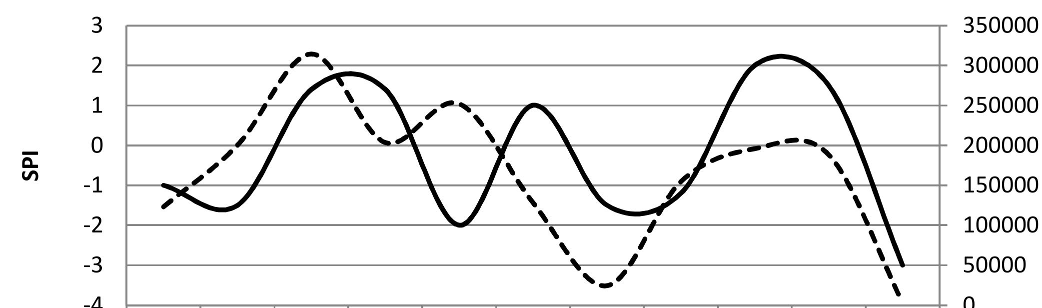


Figure 28. Relationship between Crop production and Standardized Precipitation Index.

During the years from 2005 to 2015, there was low production in agricultural crop in the Region. Similarly, the Standardized Precipitation Index value was also low. For instance in the years 2011 and 2015 there was low crop production and SPI value was less than 0. However, in 2009 the SPI value was low but agricultural crop production was relatively better. This might be different factors which were not included in the present study.

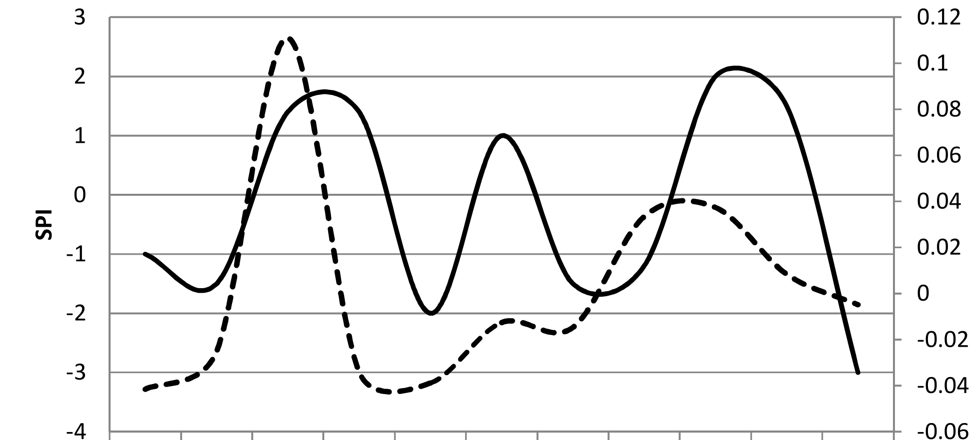


	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Mean SPI	-1	-1.5	1.4	1.4	-2	1	-1.5	-1.2	2	1.5	-3
production	1E+05	2E+05	3E+05	2E+05	3E+05	1E+05	24245	2E+05	2E+05	2E+05	3123

Figure 29. Temporal Trends of Standardized Precipitation Index and crop production during the years 2005–2015

4.10 Drought Severity Index (DSI) and Standardized Precipitation Index (SPI)

When both these indices were compared, the values of drought indices similar either increased or decreased. The DSI values were low in 2005, 2006, 2008, 2009, 2010, 2011 and 2015 with the values less than 0 (Figure 30). The SPI value was also low during 2005, 2006, 2009, 2011, 2012 and 2015 with values less than 0. Therefore, both of these drought indices indicated the prevalence of drought in the Afar Region during the study period.



	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Mean SPI	-1	-1.5	1.4	1.4	-2	1	-1.5	-1.2	2	1.5	-3
DSI	-0.04	-0.03	0.111	-0.03	-0.04	-0.01	-0.01	0.033	0.037	0.008	-0

Figure 30. Temporal trends of Standardized Precipitation Index and Drought Severity Index

4.11 Comparison of Drought Indices

Different remotely sensed and meteorological based drought indices have been effectively assessed. Based on the findings, the drought years and severity classes were also identified and classified. The remote sensing based indices like NDVI, VCI and DSI were assessed based on their threshold values to identify drought years and severity classes. Accordingly, NDVI value was nearly similar with a little fluctuation in different years. However, its mean value is positive throughout the study periods indicating the presence of vegetation. In the case of VCI, the value ranged from 0 to 79.5%. But, in the Regional State, the lowest VCI was observed in 2015 and the highest in 2013, indicating the vegetation condition index. This result better fits with drought years recorded in the study area. The DSI was also used as a drought index, and hence this result is a better index. The other index applied was SPI and its result was relatively better fitted with DSI values and the lowest values coincide with drought years occurred in the region. Relatively, DSI and SPI are good drought indices.

4.12 Drought Vulnerability Classification

The final result map of Afar Regional State (Figure 31) shows the area as mild, moderate, severe and extreme drought vulnerable. Therefore, based on the drought vulnerable classes, about 2% of the region is categorized as extreme vulnerable, 33% severe vulnerable, 59% moderate vulnerable and only 6% is mild vulnerable (Table 12). The region is in the vulnerable class of drought; however, its severity varies.

Table 12. Drought Vulnerability Class of Afar Region.

Vulnerability Class	Area(Km^2)	%
Extreme Vulnerable	1711.76	2
Severe Vulnerable	31061.17	33
Moderate Vulnerable	55774.4	59
Mild Vulnerable	5696.54	6
Total Area (Km^2)	94243.88	100

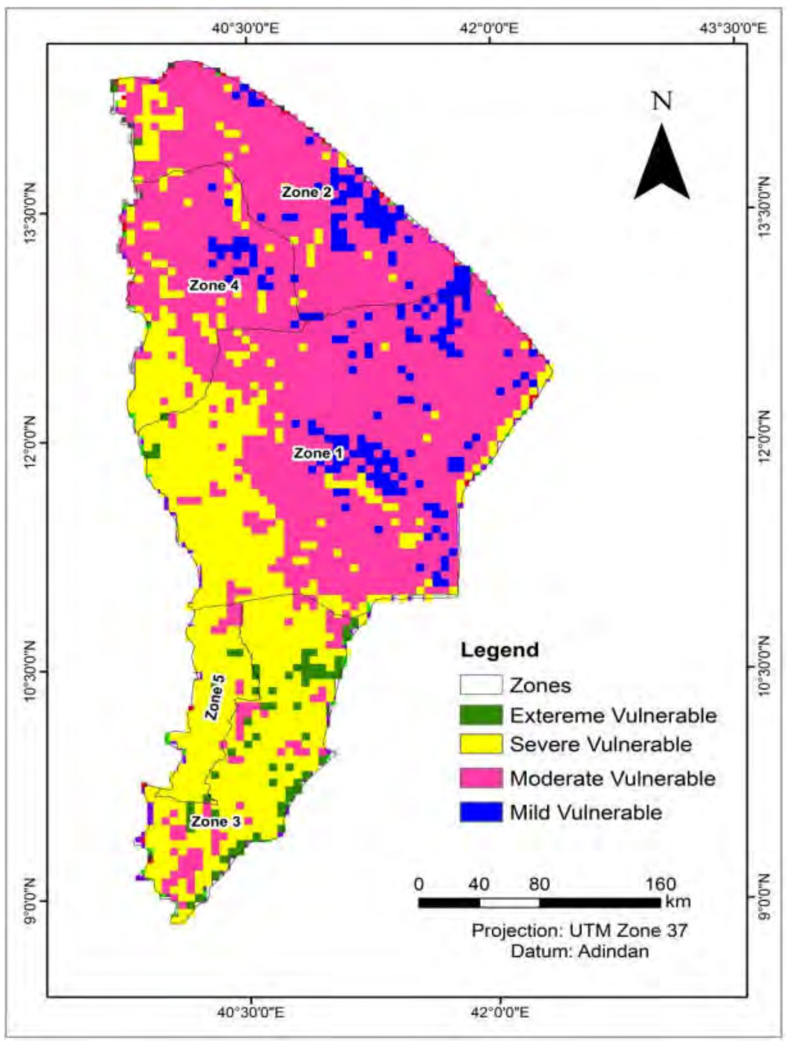


Figure 31. Drought Vulnerability Map of Afar Region.

CHAPTER V

DISCUSSION

5.1 Normalized Difference Vegetation Index (NDVI) and Rainfall

The NDVI is a measure of greenness or vigor of vegetation. Kabo-bah et al. (2013) showed the effectiveness of the SPOT vegetation NDVI for monitoring the vegetation cover in northern Ghana. Belal et al. (2012) have also found that inter-annual variations in the magnitude and evolution of the NDVI for particular location governed by meteorological variables such as precipitation, temperature and relative humidity. It was also noted that interpretation of NDVI values was spatially dependent as more productive ecosystems have different radiometric properties than less productive ones due to difference in climate, soil and topography. The findings of the present study also revealed that NDVI varied from east towards to the west of the arid and semi-arid regions of Afar spatially. As the present study area is largely of pastoral and agro-pastoral land, the vegetation condition or cover also varied accordingly. The NDVI and rainfall relationship was evaluated in this study as $r = 0.75$, which indicated a good relationship. Mahyou et al. (2010) have revealed a good relationship between NDVI and rainfall with the coefficient of variation (r, 76%) in the pastoral areas of Morocco using Landsat NDVI. Davenport and Nicholson (1993) also showed a high correlation between NDVI and rainfall. Similarly Gizachew and Suryabhagavan (2014) showed good relationship between rainfall and NDVI in East Shewa Zone, Ethiopia. Gaikwad et al. (2015) also concluded in their review the findings that the mean seasonal NDVI indicating greenness of the vegetation and seasonal rainfall has strong relationship and also concluded that NDVI can be used as an indicator for drought. The present study also revealed that the NDVI responded as a result of rainfall variation seasonally and spatially. Therefore, NDVI is found to be a relatively good indicator of drought in pastoral and agro-pastoral areas of Afar Region of Ethiopia.

5.2 Vegetation Condition Index (VCI)

Vegetation Condition Indices (VCI) as drought index was developed by Kogan (1998) to separate ecosystem variability of vegetation resulted from components of the ecosystem. The lowest VCI value observed in 2015 coincides with drought occurred in the Afar Region and has been called severe drought in 30 years of history in relation with el-Niño event that occurred in Ethiopia and the Horn of Africa. As per the report of Oxfam (2015), the year 2011 was the worst drought affected year in the horn of Africa that affected around 258,000 lives in

Somalia and devastated livelihoods across Ethiopia and Kenya. In addition to the 2011 drought, 2015 was also a very severe that occurred and affected almost the whole parts of the Regional State. Kogan (1995) showed VCI as a good tool to detect and monitor drought, and used to detect prolong widespread, intense and localized droughts. Kogan (1995) also evaluated the relationship between corn crop and VCI, and found good relation and concluded as better matched. In a study by Dutta et al. (2015) found that remote sensing-based VCI can be successfully used for delineating the spatial-temporal extent of agricultural drought in Rajasthan (India).

5.3 Vegetation Condition Index (VCI) and Rainfall

The relationship between VCI and mean seasonal rainfall was evaluated to verify the occurrence of drought in the Afar Region of Ethiopia. As a result, VCI and the rainfall varied seasonally. Similar approach was made to assess drought-risk in Gujarat (India) and found good relationship between VCI and rainfall (Chopra, 2006). The present study also revealed a strong relationship in the Regional State with r=0.90. Similarly, Mahyou et al. (2010) have also studied VCI and rainfall relationship in drought-risk assessment in pastoral lands of Morocco and showed high correlation. Wang et al. (2004); Vogt et al. (2000) and Thenkabail et al. (2004) have also showed high correlation between VCI and rainfall. Vegetation Condition Index was observed low during 2015 and this might be due to the effect of El-Niño in the Region. However, this study did not incorporate the Sea Surface Temperature (SST), which is the main cause of El-Niño. According to Kogan (2000), vegetation was in severe stress during the El-Niño event. Kogan (1998) also noted that the relation between rainfall and VCI was high with a strong coefficient of variation. Therefore, VCI was effective for drought assessment in the pastoral and agro-pastoral lands of Afar Region.

5.4 Vegetation Condition Index (VCI) and Crop Yield

Unganai and Kogan (1998) have used VCI for drought monitoring and corn yield estimation and corn crop to validate criteria for satellite algorithms for the assessment of drought severity in South Africa. According to them, VCI was highly correlated with corn (r, greater than 0.75). The present study also revealed the relationship with crop yield production in the study area (r, 0.68). In addition, Dutta et al. (2015) have also found good relationship between VCI with major crops in India.

5.5. Drought Severity Index (DSI)

The Drought Severity Index (DSI) is an index which shows the deviation of the current NDVI from its long-term mean. It revealed the drought and non-drought condition of in study area. As it is shown from the eleven years of DSI maps, Similarly Beyene Ergogo (2007) applied the DSI in drought assessment for the Nile Basin using Meteosat Second Generation data. He come up with conclusion DSI was the best index of drought in his study. This study is in line with the study. On the other hand, Berhanu Gedif et al. (2014) used DSI to assess drought risk in southern Tigray using SPOT Vegetation data and concluded as DSI was become the best drought index. The present study has identified drought severity using the DSI in the Afar Region. Therefore, the study was in line with other studies.

5.6. Standardized Precipitation Index (SPI)

The SPI is a very popular meteorological drought index, which has been frequently used by decision maker for measuring and monitoring the intensity of meteorological drought events. Standardized Precipitation Index is useful for identifying spatiotemporal extent of long term historical droughts. Different studies across the world used SPI as a drought indicator, particularly meteorological drought. The present study incorporated SPI to assess meteorological drought in the Afar Region of Ethiopia. Results indicated occurrence of meteorological drought in different years in the Region. The Standardized Precipitation Index (SPI) value felled within the range of -3 (severe drought) to 2 (wet). Shah et al. (2015) and Dutta et al. (2015) have also used SPI for drought risk assessment. Farahmand and Aghakouchak (2015) obtained SPI using 33 years of precipitation data and concluded that the result obtained was realistic and more reliable. Similarly, Dodomani et al. (2015) carried out SPI in their research on Agricultural drought modeling using Remote Sensing.

5.5 Standardized Precipitation Index and Crop Yield

The present study correlated SPI with crop yield ($r = 0.73$), that revealed statistically significant positive relationship. Similarly, Li et al. (2014) conducted Index based assessment of agricultural drought in semi-arid region of Inner Mongolia, and found significant correlation between SPI and crop yield. In other parts of the world, particularly in the Sub-Saharan Sudan, Elagib (2013) had come up with an impressive correlation between SPI and crop yields. Therefore, the result of the present study agrees with the available information and as effective for drought assessment in the dry and semi-arid areas.

CHAPTER VI

CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

The pastoral and agro-pastoral areas of Ethiopia particularly the Afar Region is frequently affected by drought. Temporal and spatial extents and characteristics of drought can be noticed, monitored and mapped from remotely sensed data such as, SPOT and PROVA-V vegetation data. The Remote Sensing based drought indices were effective in drought assessment in the arid and semi-arid areas. The present study has revealed that drought-vulnerable areas can be delineated using Normalized Difference Vegetation Index, Vegetation Condition Index and Drought Severity Index derived from vegetation data. Vegetation Condition Index and DSI are harmonizing and are found to be sensitive indicators of drought conditions. In addition, Standardized Precipitation Index from the satellite rainfall data was effective in drought assessment in the Afar Region.

The temporal variation of NDVI values were closely related with rainfall to validate how vegetation stress condition was changing with the variability of rainfall. The existence of a reasonably good relationship between NDVI and rainfall variability during the growing season was established. In addition, a strong correlation also existed between Vegetation Condition Index and rainfall. Vegetation Condition Index and crop yield also had good relationship. Standardized Precipitation Index and DSI were also highly correlated.

The present study shows the occurrence of drought at least in every two or three years. Within the eleven years of the study period, the drought was observed in different years. Therefore it could be concluded as the Region is highly prone to the drought. The drought vulnerability map of the region shows, the region is within the drought vulnerability range from mild to extreme vulnerable.

The findings of this study can be used for improvement of regional drought monitoring. Taking into account the spatial extension and frequency of drought and lack of timely ground data observations, the application of remotely sensed data could play a key role for drought monitoring and drought prediction.

5.2 RECOMMENDATIONS

Based on the findings of the present study, the following recommendations are suggested for future studies:

- Further investigations are needed to improve the findings from this by incorporating other factors for determining drought vulnerable areas. These include; population density, poverty index and water resources.
- Besides delineating drought vulnerable areas, importance of vulnerability assessment could be made more meaningfully if detail study of the these areas in terms of soil, water availability, temperature conditions, crops grown and economic importance of the area included.
- It is found that the eastern, northern and northeastern parts of the study areas are moisture stressed as indicated by the vegetation greenness indices. It is evident that the drought in different years affected the region largely dependent on the agro-pastoralist and pastoralist. Therefore, disaster-risk management activities are needed. These are preparedness, prevention and response or mitigation phases.
- Remedial actions could be implemented before the occurrence of drought. Timely updated information about the prevalence of drought is important.

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Appendix

1. Simple Linear Regression between NDVI and Mean seasonal Rainfall

Regression Statistics	
Multiple R	0.754105146
R Square	0.568674571
Adjusted R Square	0.520749523
Standard Error	39.84076171
Number of years	11

ANOVA

	df	SS	MS	F	Significance F
Regression	1	18834.6052	18834.60518	11.86591559	0.00733592
Residual	9	14285.5766	1587.286294		
Total	10	33120.1818			

	Coefficients	Standard Error	t Stat	P-value
Intercept	-79.37956204	81.3364856	-0.9759404	0.354594821
NDVI	1587.591241	460.880217	3.444693831	0.007335921

2. Simple Linear Regression Analysis between VCI and Rainfall

Multiple R	0.909137
R Square	0.82653
Adjusted R Square	0.807255
Standard Error	7.176567
Number of years	11

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2208.5607	2208.561	42.882	0.000105
Residual	9	463.528	51.50311		
Total	10	2672.0887			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	
Intercept	-1.95385	8.0918445	-0.241459	0.8146	-20.2589
X Variable 1	0.258231	0.039434	6.548441	0.0001	0.169025

3. Simple Regression Analysis between DSI and Crop yield production

Multiple R	0.41602422
R Square	0.17307615
Adjusted R Square	0.08119573
Standard Error	87460.8555
Number of years	11

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.441E+10	1.44E+10	1.883711	0.203143
Residual	9	6.884E+10	7.65E+09		
Total	10	8.325E+10			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-1412.1454	26390.505	-0.05351	0.958495
X Variable 1	842568.85	613900.92	1.372483	0.203143

4. Simple Regression Statistics between VCI and SPI

Multiple R	0.546478539
R Square	0.298638794
Adjusted R Square	0.220709771
Standard Error	1.537787899
Number of years	11

ANOVA

	df	*SS*	*MS*	*Significance F*
Regression	1	9.0623299	9.06232994	0.08196
Residual	9	21.283125	2.364791623	
Total	10	30.345455		

	Coefficients	*Standard Error*	*t Stat*
Intercept	-3.123361135	1.5326499	-2.037882943
X Variable 1	0.058236398	0.0297489	1.957597924