JIMMA UNIVERSITY

COLLEGE OF SOCIAL SCIENCES AND HUMANITIES

DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDIES

DROUGHT VULNERABILITY ASSESSMENT USING GEOSPATIAL TECHNOLOGIES: A CASE OF BORANA ZONE, OROMIYA NATIONAL REGIONAL STATE, ETHIOPIA

A Thesis Submitted to School of Graduate Studies of Jimma University in Partial Fulfillment of Requirement for Degree of Masters of Science in GIS and Remote Sensing

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November, 2021

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List of Abbreviation and Acronyms

AVHRR	Advance very high resolution radiometric
AWC	Available water holding capacity
CHRIPS	Climate Hazards Infrared Precipitation with Stations
CSA	Central Statistics Agency
DSI	Drought Severity Index
DI	Drought Indices
ENSO	El-Niño Southern Oscillation
FEWSnet	Famine early warning System network
FAO	Food and Agriculture Organization
GAO	Government Accountability Office
GIS	Geographic Information system
IRC	International Rescue committee
LAI	Leaf Area Index
MODIS	Moderate Resolution Image Spectrometer
NASA	National Aeronautics and Space Administration
NDBI	Normalized Difference Building index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NMA	National Meteorological Agency
OCHA	Office for the Coordination of Humanitarian Affairs
PARIMA	Pan-Asia Risk and Insurance Management Association.
PCI	Precipitation Concentration Index

PDSI	Palmer Drought Severity Index
PET	Potential Evapo-Transpiration
SBPCI	Satellite based Precipitation Concentration index
SNNP	Southern nation nationalities and peoples
SPEI	Standardized precipitation -Evapotranspiration Index
SPI	Standardized precipitation Index
STNPCI	Station based Precipitation Concentration index
UNFCCC	United Nations framework convention on climate change
UNICEF	United Nations International Children's Emergency Fund
USAID	United States Agency for International Development
VCI	Vegetation Condition index
WFP	World food Programme
WMO	World Meteorological Organization

Abstract

Drought is the dryness due to an acute shortage of water, which lasts for several months or years. The present study aims at analyzing drought vulnerability using Geospatial technologies in case of Borena Zone, Oromiya National Regional State, Ethiopia. Time series satellite data of MODIS vegetation and ten years, CHRIPS rainfall data (2010 to 2020) was used to assess drought vulnerability in the study area. Drought vulnerability assessment were analyzed using drought indices like normalized difference vegetation index (NDVI), vegetation condition index (VCI), drought severity index (DSI), and meteorological indices like standardized precipitation-evapotranspiration index (SPEI), standardized precipitation index (SPI), precipitation concentration index (PCI). In the present study, 16 meteorological stations rainfall and temperature data were used for validation purpose. The correlation between observed rainfall and vegetation indices reveals that there is a positive relationship between the rainfall and NDVI (R^2= 0.4996), VCI and rainfall (R^2 = 0.409) and SPI and rainfall (R^2 = 0.917). The final vulnerability map of the study area reveals that the area as mild vulnerable, moderate vulnerable, severe and extremely vulnerable. Accordingly, most part of south eastern and northern, some parts of the western and central areas are extremely vulnerable. At district level, Arero, Miyo, Moyale, Dehas, Yabello, Melka soda, Bulehora, and Gelana are severely vulnerable to drought. Teltele, Dire, and Abaya are moderately vulnerable, with some portions of the Abaya district categorized as extremely vulnerable. Small parts of Dillo and Teltele districts were among the regions that were mildly susceptible. In general, about 450 hectares is extremely vulnerable 31086 hectare is severely vulnerable and 6933 hectares moderately vulnerable and 1100 hectares are mild vulnerable. For further understanding of drought condition of the study area; increasing the availability of data for all meteorological stations with the required temporal coverage and precision is crucial, some type of data like evapotranspiration at national level is highly needed. Federal disaster prevention and preparedness commission have to be prepared for upcoming drought disaster for the area's delineated as extreme and severely vulnerable to drought. The reason why this study conducted in this study area is that; this area was suffering from extreme events.

Key words: CHRIPS, Climate extreme, Drought vulnerability, MODIS, SPEI, VCI

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the study

Drought is an abnormally prolonged dry period that results from deficiency of precipitation and water availability, below expected or normal amounts and have significant environmental and economic problems, particularly, in agricultural production activities, which in turn affect the balance of food supply and demand (Boken, 2009).

Drought is the dryness due to an acute shortage of water, which lasts for several months or years. As a complex natural event, it stems from a lack of precipitation over a prolonged period, and its effect can be only witnessed slowly over a period (Cheng, *et al* 2014).

The onset and impact of droughts over space and time is therefore highly variable and usually occurs in large regions. Every year, over half of the world is vulnerable to drought. Since droughts are a recurrent phenomenon and are widespread in all climate zones, it is difficult to forecast and track droughts in large areas using traditional approaches. (Senay, *et al*, 2015).

These characteristics make the definition of drought complex and, thus, there is no single universally accepted definition. Owing to the lack of comprehensiveness of a single agreed definition, the identification and monitoring of key characteristics of drought is difficult (Hayes, *et al* 2012). Due to the lack of a universally accepted definition of drought, and in consideration of the research's purpose and objectives, the definition suggested by (Hayes *et al*. 2012) was used.

Climate change increases the odds of worsening drought in many parts of the world. Global climate change affects a variety of factors associated with drought. Warmer temperatures can enhance evaporation from soil, there also is high confidence that increased temperatures will lead to more precipitation falling as rain rather than snow. (Mote, 2006).

Drought is a widespread natural disaster also in Ethiopia; that occurred in the years 1996, 1997, 1998, and 1999. During 2000, less rainfall had a significant impact on rural communities across the world, (Amare, 2007).

Traditional drought tracking techniques are limited by timeliness, objectivity, unreliability, and inadequacy; however, satellite sensors offer spatial details on drought-induced vegetation stress. This demonstrates that satellite sensors can be used to perform a systematic drought analysis. The most important indicators available in agricultural drought monitoring are those that are responsive to rainfall data and satellite images (Narendra, 2008).

Different study has been conducted throughout the country by different authors However, there is a gap in including temperature and evapotranspiration data in the analysis of drought in these articles; using GIS and remote sensing technologies.

Remote sensing technologies provide an important source of spatiotemporal data in the study of vegetation dynamics and climate change, (Piao S, et al 2006). Over the years, more than 150 DI's have been developed (Vicente-Serrano, *et al* 2010). Drought indices (DI's) have been extensively used in drought assessment, monitoring, and forecasting, such as SPI, SPEI, and PDSI and vegetation indices are like NDVI, VCI, DSI. (Bayarjargal, et *al* ,2006).

Therefore, integrating such approaches is the best strategy for collecting detailed, accurate, and consistent quantitative climate data that assist in preparing to better minimization of the effects of droughts in the Borana Zone.

1.2 Statement of the Problem

Drought is regarded as the most dynamic, but the least understood, it creates variables that affect more people than any other threat, considering the effects of all-natural hazards. Virtually all climatic regions are affected by drought and more than half the world is vulnerable to drought every year. (Brice *et al*., 2015).

Droughts are the world's costliest natural disasters, causing an average \$6–\$8 billion in global damages annually and collectively affecting more people than any other form of natural disaster (Wilhite, 2000).

Understanding people's vulnerability to drought is complex because this depends on both biophysical and socioeconomic drivers of drought impact that determine the capacity to cope with drought (Naumann et al., 2013).

In the era of climate change, there is a continuous need to thoroughly assess vulnerabilities caused by complex environmental, ecological, and anthropogenic factors. Drought, as a natural phenomenon, creates numerous multidimensional effects on agriculture, human health, and disease prevalence (Singh, *et al.*, 2014).

In addition, unsustainable use of land and other resources increase the vulnerability of people in Sub Saharan Africa. Millions of smallholder farmers and pastoralists earn a living in degraded areas which make them highly vulnerable to droughts and other climate hazards. Land degradation often stems from the nexus between poverty and lack of capacity to invest in more sustainable agricultural practices and change extractive land-use systems (Holden et al., 2011).

Eastern and southern Africa regions are characterized mainly by semi-arid and sub-humid climates with a pronounced dry season in part of the year. Therefore, in contrast to West Africa, the variability of rainfall in these regions is concentrated on relatively short time scales in a year and it has a direct connection with global processes such as El Niño/La Niña-Southern Oscillation (ENSO) (Nicholson, 2001).

Two main categories of drought risk areas are applied in Ethiopia : a) high risk drought areas which include western and eastern Tigray, all parts of Afar and Somali regions, the eastern Amhara region, South Omo of the SNNPR and the Borana zone of Oromia region; and b) medium drought risk areas that are central Tigray, small areas in central Wollo, most of northern Omo, the northern part of north Gondar, the Metema area, Gambella, most of Shewa, parts of east and west Hararghe, parts of Arsi and Bale, Sidama, Gedio and central Borana. (Cordaid/Farm Africa, 2013).

Since the catastrophic famine of 1983-1984, Ethiopia has endured at least six major droughts: from 1988-1989, 1999-2000, 2003, 2005, 2007-2008, and 2011-2012. Many of these droughts have affected the semi-arid and arid regions located in the eastern, southern, and south-eastern lowlands, where pastoralism and agro-pastoralism remain the dominant forms of livelihoods. (World Bank,2011).

Revenue from livestock sales in Borana underlines the sheer significance of this field to the communities of pastoralists. Droughts resulted in the deaths of 37-42 % of all cattle in the 1980s and 1990s, respectively. Losses in the form of cattle mortality in Borana were estimated at some US$300 million over a 17-year period. (Desta and Coppock, 2000).

Although there are many drought risk assessment studies conducted in different part of country Legesse, 2010, Ashenif, 2016, Wondwosan, 2017, Chaltu ,2018. Different drought indices were used including NDVI, VCI, DSI, SPI to quantify and monitor drought. However, there is a gap in including temperature and evapotranspiration data in the analysis of drought in different articles; to fill this gap, this research was trying analyze the effect of temperature and evapotranspiration data to drought vulnerability across Borana zone by applying geospatial technologies.

1.3 Objective of the study

1.3.1 General Objective

The general objective of the study is to assess drought vulnerability using Geospatial technologies in case of Borena Zone, Oromiya National Regional State, Ethiopia.

1.3.2 Specific Objectives

- ✓ To analyze precipitation and temperature-based drought severity indices across Borana Zone.
- ✓ To analyze vegetation-based drought severity indices across Borana Zone.
- ✓ To quantify and analyze Spatio-temporal patterns of drought across Borena Zone.
- ✓ To identify the most drought vulnerable area of Borena Zone.

1.4 Significance of the study

This study provides quantitative and qualitative information regarding drought vulnerability in the study area. The information's are valuable to make pre, and post–drought risk management plans by decision and policy makers. The most drought–vulnerable area was delineated based on the drought vulnerability analysis map of the zone, which is important for regional and the federal government of Ethiopia to identify the most drought–prone areas to save the life of communities in the vulnerable area of zone. It also provides a baseline information on the most vulnerable areas so that systematic surveillance and monitoring of drought and its effect could be undertaken.

1.5 Scope of the study

The scope of the study is geographically focused on the Borana zone, Oromiya national regional state, Ethiopia, which is a drought-prone area of the country. Conceptually, this study is delimited on the drought vulnerable area assessment related issues. Methodologically this study incorporated different satellite-based drought indices like NDVI, VCI, DSI, from remotely sensed MODIS Vegetation data as it also uses SPI, SPEI, and PCI from the meteorological station's rainfall data and CHRIPS monthly rainfall data.

1.6 Limitation of the study

The limitation of this study was lack of fully organized agricultural yield at zonal level to include in the study. Another limitation is the evapotranspiration data is not available at zonal level even at national level in gridded format and it may affect analysis quality and it is important to incorporate in the study.

1.7 Organization of the paper

This paper was organized in five chapters. The first chapter deals with the introduction part of the paper, the second chapter review of related literature, the third chapter covers materials and methods, the fourth chapter covers result and discussion; and the fifth chapter covers conclusion and recommendation.

CHAPTER TWO

REVIEW OF LITERATURE

2.1 Basic Concept of Drought

Development of droughts is a slow and very complex process. Thus, the causes and mechanisms involved are still not fully understood. Among the contributing factors of drought development are precipitation, evapotranspiration, and soil conditions. All those are in turn affected by climate, winds, and long-time atmospheric and oceanic oscillations. There are multiple types of droughts, and even though no official definition is agreed upon the following types are generally accepted (Fleig *et al*., 2006).

Metrological drought is related with deficit in precipitation, agricultural drought is with deficit in soil moisture, affects vegetation and food production. Also increases the risk of forest fires as vegetation is dryer. Hydrological drought with deficit of surface water and/or ground water. Reduces drinking water supply, hydropower possibilities and water for industrial needs. Affects wild life and humans alike. Socio-economical drought is a measurement of impact of droughts, including supply and demand. Usually expressed as economical value (Fleig *et al*., 2006)

According to Fleig *et al*., (2006), the development of droughts may start as a metrological drought initially, and thereafter become an agricultural drought and, if storages are not refilled, develop into a hydrological drought. An analysis of metrological droughts patterns may give information about initial stages of droughts.

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 disastrous natural phenomenon that has significant impact on agricultural, environment and socio-economic conditions of the community. Normally, drought occurrence, as a climate change phenomenon, becomes obvious when there are abnormal dry weather conditions, events of lower rainfalls and insufficient soil moisture in an area. In some cases, it results in decreased water levels of rivers, ponds, and lakes with long lasting impacts on agricultural production, livestock, and overall economic activities (Shaheen and Baig, 2011; Akhtar, 2014).

In some counties, like Ethiopia, drought occurrence is closely associated with the timing of the rainfall. In other words, the period of rainfall occurrence, the late or early arrival of rain and its duration, in relation to the principal crop growth stages are given greater attention (Lagese, 2010).

2.2. Types of droughts

There are four major types of droughts namely: agricultural drought, meteorological drought, hydrological drought, and socio-economic drought.

A. Agricultural drought: Is a deficit of soil moisture (mostly in the root zone), reducing the supply of moisture to vegetation. It is also called soil moisture drought, because it is strongly linked to crop failure. As soil moisture deficits have additional impacts on, (Aghakouchak, *et al*, 2014).

Depletion of soil moisture storage is related to its antecedent condition, evaporation from bare soil, evapotranspiration through plants, drainage to the groundwater, and runoff to streams. During a dry spell, drainage and runoff are usually low, but potential evapotranspiration can increase due to increased radiation, wind speed, or vapor pressure deficit. This can lead to increased actual evapotranspiration, resulting in an extra loss of water from the soil and open water bodies. In extreme drought, a lack of available soil moisture and wilting of plants can limit evapotranspiration, thus limiting a further soil moisture depletion, but possibly also limiting locally generated precipitation, contributing to the maintenance of drought conditions. Vegetation is an important factor in modifying these feedbacks. (Teuling, *et al* 2005).

B. Meteorological drought: Refers to a precipitation deficiency, possibly combined with increased potential evapotranspiration, extending over a large area, and spanning an extensive period. The precipitation anomaly directly measures the shortage of rainfall, and is the difference between the observation and the long-term climatological mean. This anomaly is a primitive index of drought, and is not especially informative, since the importance of the anomaly depends on climate; a monthly deficit of 1 cm is substantially more significant for a desert ecosystem compared to a montane forest. (Keyantash, 2002).

C. Hydrological drought: Hydrological drought refers to a lack of water in the hydrological system, manifesting itself in abnormally low streamflow in rivers and abnormally low levels in lakes, reservoirs, and groundwater. Is associated with a deficiency in the bulk water supply, which may include water levels in streams, lakes, reservoirs, and aquifers. Hydrological drought may be the slowest to develop. It can persist longer than other forms of drought. (Tallaksen, Van, 2004).

In general, hydrological droughts develop differently in relatively constant climates as compared with climates with strong seasonality. In a constant climate, the main factor for drought development is a below-normal precipitation (possibly combined with higher-than-normal potential evapotranspiration), as described in section Drought Propagation (Hisdal, *et al*, 2004).

D. Socio-economic drought: Occurs when the demand for an economic good exceeds supply as a result of a weather-related shortfall in water supply. In most instances, the demand for economic goods is increasing as a result of increasing population and per capita consumption. The supply of many economic goods, such as water, forage, food grains, fish, and hydroelectric power, depends on weather. Because of the natural variability of climate, water supply is ample in some years but unable to meet human and environmental needs in other years. Socioeconomic drought occurs when the demand for an economic good exceeds supply as a result of a weather-related shortfall in water supply. In most instances, the demand for economic goods is increasing as a result of increasing population and per capita consumption. Supply may also increase because of improved production efficiency, technology, or the construction of reservoirs that increase surface water storage capacity. (Wilhite, *et al*, 1985).

2.3. Impact of drought

The primary impact of droughts is on food production, as agriculture is by far the largest water user. Droughts may also have severe environmental, economic, and social impacts. The environmental and socioeconomic impacts of droughts are controlled to a large degree by the duration of droughts, rather than their severity, because recovery from the cumulative damage of consecutive drought years is more difficult (Shahen, 2011).

The impacts of drought also depend upon human and ecosystem demand for water, available water-resources management capabilities and practices, as well as the meteorological and hydrological characteristics of the drought (Loucks, Gladwell, 1999).

2.3.1 Types of drought impact

2.3.1.1. Social and economic impact

Drought can have substantial negative economic impacts on farmers and the local economy. These impacts have been frequently documented (Edwards et al. 2009). However, the broader social effects of drought have received far less attention (Fritze et al. 2008). There are several social impacts of drought – for example, indirect effects of economic factors such as the hardship and stress of lost productivity; population decline; disruption of social connections because of the negative economic effects of drought; and the trauma of witnessing damage to livestock, crops, soil, and native vegetation (Berry *et al,* 2008).

Impacts are commonly referred to as direct and indirect. Direct impacts include reduced crop, rangeland, and forest productivity, increased fire hazard, reduced water levels, increased livestock and wildlife mortality rates, and damage to wildlife and fish habitat. The consequences of these direct impacts illustrate indirect impacts. For example, a reduction in crop, rangeland, and forest productivity may result in reduced income for farmers and agribusiness, increased prices for food and timber, unemployment, reduced tax revenues because of reduced expenditures, foreclosures on bank loans to farmers and businesses, migration, and disaster relief programs (Berry *et al*. 2008)

Many economic impacts occur in agriculture and related sectors, because of the reliance of these sectors on surface and groundwater supplies. In addition to losses in yields in both crop and livestock production, drought is associated with insect infestations, plant disease, and wind erosion. The incidence of forest and range fires increases substantially during extended periods of droughts, which in turn places both human and wildlife populations at higher levels of risk (Diersen *et al*. 2002).

2.3.1.2. Environmental Impacts

Environmental losses are the result of damages to plant and animal species, wildlife habitat, and air and water quality, forest and range fires, degradation of landscape quality, loss of biodiversity, and soil erosion. Some of these effects are short-term, conditions returning to normal following the end of the drought. Other environmental effects last for some time and may even become permanent. Wildlife habitat, for example, may be degraded through the loss of wetlands, lakes, and vegetation. However, many species eventually recover from this temporary aberration. The degradation of landscape quality, including increased soil erosion, may lead to a more permanent loss of biological productivity. Reduced water supply impairs the navigability of rivers and results in increased transportation costs because products must be transported by alternative means. Hydropower production may also be significantly affected (Vose, *et al*, 2016).

Indirect effects of drought on forests can be widespread and devastating. Notable recent examples include insect and pathogen outbreaks and increased wildfire risk, Available evidence suggests a nonlinear relationship between drought intensity and bark beetle outbreaks; moderate drought reduces outbreaks whereas long, intense drought can increase it (Little et al, 2016).

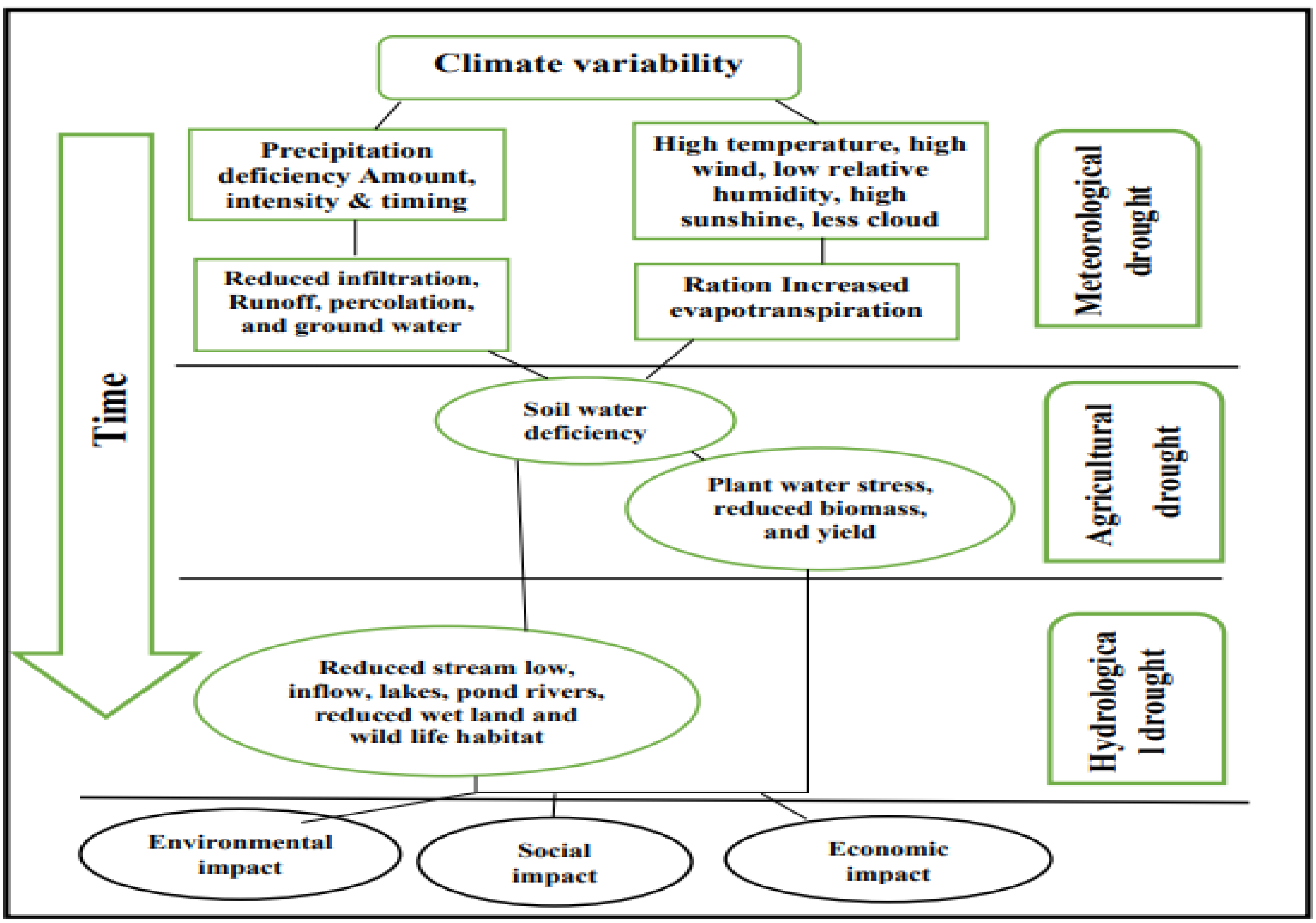


Figure 1 The Impact of Drought on Livelihoods adopted from Defferew (2011).

2.4. Impact of Drought in Ethiopia

Ethiopia is situated within the sub-equatorial zone, and the climate is typically one of the rainy seasons which runs from (June to September) and dry (March to May). The mountainous terrain also has a considerable effect on the country's climate, which is often influenced by the climate in the neighboring Arabian Peninsula. The country covers a considerable area from north to south, but the air temperature in different areas depends largely on the altitude. The topographic variation ranges from 4621m maximum elevation to -116m of the lowest elevation. therefore, it causes considerable fluctuation in the average annual rainfall and temperature. (Girma, 1998).

The cyclical drought has tremendous impact on long term food security. This is because recovery from previous crisis is cut short by the next drought (GAO, 2002). Since the entire agricultural activity of Ethiopia is associated with the behavior of rainfall, drought should be given an important attention and its impact should not be divorced from the societal context (Birhanu Gedif, 2009).

2.4.1 Trend of Drought in Ethiopia

Drought is one of the most probable climate shocks, regularly affecting food production, livestock production and livelihoods of the poor. Since the 1970s, the severity, frequency and impacts of drought have increased and the areas affected by drought and desertification are expanding (World Bank, 2009).

Ethiopia’s economy is based mainly on agriculture, including crop and livestock production, which contributes 45% of the national Gross Domestic Product (GDP), more than 80% of employment opportunities and over 90% of the foreign exchange earnings of the country. However, the Ethiopian economy, particularly agricultural development, is extremely vulnerable to external shocks like climate change, global price fluctuations of exports and imports and other external factors. (Behnke *et al*, 2007).

Between 1974 and 2003, Ethiopia reportedly experienced about 54 natural disasters, with the worst famine the country has experienced in 1983-1985. During this period, the number of affected people increased from nearly 2 million between 1974 and 1978 to about 42 million during 1999-2003 (Ababa, 2007).

2.4.2 Drought in Borana Zone

Pastoralists in Ethiopia are found in seven regions including Afar, Somali, SNNP, Oromia, Diredawa, Benishangul Gumuz and Gambella Regional States. The main livelihood systems include pastoralism, farming and ex-pastoralism – those who have dropped out of pastoralism and now survive on petty income-earning activities (Behnke *et al.*, 2007).

Based on their work in the semi-arid Borana plateau, however, PARIMA researchers argue that it is not only the annual rainfall that controls the livestock population in a given arid or semi-arid pastoralist area, but also the interaction between the livestock population density and forage resources that affects the livestock population each year. Livestock crashes in Borana appeared to be predictable. They seemed to suggest that livestock die off due to drought is likely to happen when the livestock density exceeds a certain threshold (Desta and Coppock, 2002).

Borena was one of the most affected areas in Ethiopia by the 2011 drought. It has been difficult to obtain official estimates of the actual damage e.g., loss of animals resulting from the severe drought. However, according to the Food and Agriculture Organization (FAO), the total death rate could reach 60%, 40%, and 25-30% (an average of 27%) for cattle, sheep, and goats respectively. The FAO estimate did not include the mortality or morbidity rate of other animals such as camels and equines. (OCHA, 2011).

A timely and predictable intervention before a crisis occurs can prevent households from using destructive risk-coping strategies, and would reduce the need for a massive emergency response. (Hess, *et al* 2006) Drought is among the most probable hazards routinely affecting pastoralists in Ethiopia It has been estimated that there is a 40% likelihood that eastern and western Ethiopia will experience a severe drought in any given year. This implies that, with a sound early warning system, it will be possible to predict the effect of imminent drought in pastoralist areas. This suggests that early action will help to avoid or reduce the risk of losing productive assets. (Asana *et al*, 2007)

2.5 Role of GIS and remote sensing in drought Assessment

Several indices for drought quantification have been developed. Conventional drought monitoring methods suffer from timeliness, objectivity, unreliability, and inadequacy constraints, but satellite sensors provide spatial information on vegetation stress caused by drought conditions. This shows that a comprehensive study on drought can be conducted using satellite sensors. Diff erent types of droughts require different drought indicators. The factors that are sensitive to rainf all data and satellite images are the most appropriate indicators required in agricultural drought monitoring, as a result of moisture deficit having a critical relationship it is necessary to assess the impact of drought on crops with the requirements for crop water. The option depends on the region's hydro-climatology, the type of drought, society's vulnerability, the purpose of the study and the data available. (Narendra, 2008).

2.6 Drought Indices

Indices make it easier to communicate climate anomaly data Scientists can quantitatively evaluate climate anomalies in terms of frequency, intensity, duration, and spatial extent in order to earn user audiences. To quantify whether a region is experiencing a drought and to classify the severity of the drought, several drought indices have been developed. It is important to manage water resources on a continuous basis, so water shortages do not have great operational significance or do not exceed a defined numerical threshold. Drought indices are useful, both temporal and spatial, for mapping regional water supply patterns. Drought indices are also used to describe conditions for disasters that qualify for government assistance and where and when restrictions on emergency water can be needed. (Wilhite *et al*., (2000).

2.6.1. Meteorological based drought indices

2.6.1.1. Palmer drought severity index

The Palmer Drought Severity Index (PDSI) is a significant meteorological drought index established by Palmer (1965) based on precipitation, evapotranspiration, and soil moisture conditions to determine drought severity in time and space. PDSI measures four terms in the water balance equation using these inputs: evapotranspiration, runoff, soil recharge, and moisture. The index of the palmer has been commonly used, but it has some boundaries. Among these, the index is highly sensitive to soil-type AWCs, and it is difficult to compare the results obtained in regions with different water balances.

Table 1 PDSI and their classes Manacelli (2005).

PDSI	**Classes**
4+	Extreme wet
3.0 to 3.99	Very wet
2.0 to 2.99	Moderate wet
1.0 to 1.99	Slightly wet
0.5 to 0.99	Insipient wet spell
0.49 to -0.49	Near normal
-0.5 to -0.99	Insipient drought
-1.9 to -1.99	Slightly drought
-2.0 to -2.99	Moderate drought
-3.0 to -3.99	Very drought
<4	Extreme drought

2.6.1.2 Standard precipitation and evapotranspiration index

The Standard precipitation and evapotranspiration index **(**SPEI) fulfils the requirements of a drought index since its multi-scalar character enables it to be used by different scientific disciplines to detect, monitor, and analyze droughts.

Like the sc-PDSI and the SPI, the SPEI can measure drought severity according to its intensity and duration, and can identify the onset and end of drought episodes. The SPEI allows comparison of drought severity through time and space, since it can be calculated over a wide range of climates, as can the SPI. Moreover, Keyantash and Dracup (2002) indicated that drought indices must be statistically robust and easily calculated, and have a clear and comprehensible calculation procedure. All these requirements are met by the SPEI. However, a crucial advantage of the SPEI over other widely used drought indices that consider the effect of PET on drought severity is that its multi-scalar characteristics enable identification of different drought types and impacts in the context of global warming. The SPEI can account for the possible effects of temperature variability and temperature extremes beyond the context of global warming. Therefore, given the minor additional data requirements of the SPEI relative to the SPI, use of the former is preferable for the identification, analysis and monitoring of droughts in any climate region of the world, one of the nice advantages of SPEI is: Statistically based index that requires only climatological information without assumptions about the characteristics of the underlying system. It has few limitations, such as: SPEI needs more data requirements than the precipitation SPI, also SPEI sensitive to the method to calculate potential evapotranspiration (PET) (McKee,1993).

Table 2 Range of SPEI and their classes (Vicente Serrano et al 2010).

Value	**SPEI Class**
>= 2	Extremely wet
1.5 to 1.99	Very wet
1 to 1.49	Moderately wet
-0.99 to 0.99	Normal
-1 to -1.49	Moderately dry
-1.5 to -1.99	Very dry
<= -2	Extremely dry

2.6.1.4 Precipitation concentration index (PCI)

The precipitation concentration index (PCI), proposed by Oliver (1980) and developed by De Luis *et al* (1997). It is an index to analyze the heterogeneity of precipitation and the relationship between variability and monthly precipitation distribution. PCI can be calculated as the following formula:

$$PCI = \frac{\sum_{i=1}^{12} P_i^2}{(\sum_{i=1}^{12} P_i)^2} \times 100$$

Where Pi is the monthly precipitation in the i^{th} month. Usually, the distribution of precipitation is uneven in different month. The large the difference in monthly precipitation, the larger the concentration of precipitation during intra-annual, PCI values that less than 10 indicate a uniform monthly rainfall distribution in the year, whereas values from 11 to 20 denote seasonality of precipitation distribution. Values above 20 correspond to climates with substantial monthly variability in precipitation amounts, therefore, the greater the PCI value, the more variable the monthly precipitation (Oliver,1980)

Table 3 PCI range and their classes (Oliver, 1980)

PCI value	Classes
≤ 10	Less precipitation concentration
11 to 15	Moderate precipitation concentration
16-20	Irregular precipitation distribution
> 20	Strong irregular precipitation distribution

2.6.2. Satellite based drought indices

2.6.2.1 Normalized different vegetation index (NDVI)

Tucker (1979) first introduced the Normalized Difference Vegetation Index (NDVI) as an index of vegetation health and density. NDVI represents the vigor of vegetation (Teillet, *et al.* 1997), percent green cover, Leaf Area Index (LAI) and biomass. (Thenkabail, *et al*., 2004).

NDVI has been used extensively for vegetation control, crop yield evaluation and detection of drought (Tornros and Menzel, 2014). The relationship between NDVI and rainfall differs spatially, mainly because of the effects of variance in characteristics such as vegetation type and soil history, with the sensitivity of NDVI values to rainfall fluctuations, thus showing a major regional variation (Tornros and Menzel, 2014).

NDVI is a vegetation index that is associated with vegetation density. It is often used to distinguish vegetation from non-vegetation features. It normalizes the difference between the green leaf scatterings in the near-infrared to the chlorophyll absorption. The NDVI is computed from MODIS data as follows:

$$\frac{(R_{NIR} - R_{red})}{(R_{NIR} + R_{red})}$$

Where *RNIR* is the reflectance in the near infrared part of the spectrum, and *Rred* is reflectance in the red part of the spectrum. The value of the index ranges from -1 to 1. A common range for green vegetation is 0.2 to 0.8. (Tucker and Sellers, 1986).

2.6.2.2 The Vegetation Condition Index (VCI)

Compares the current NDVI to the range of values observed in the same period in previous years. The VCI is expressed in % and gives an idea where the observed value is situated between the extreme values (minimum and maximum) in the previous years. Lower and higher values indicate bad and good vegetation state conditions, respectively **(**Kogan, 1990).

$$VCIijk = \frac{VIijk - \mathrm{VIi,min}}{VIi,max - \mathrm{VIi,min}} x100$$

where VCI_{ijk} is the VCI value for the pixel *i* during week/month/DOY *j* for year *k*, VI_{ijk} is the weekly/monthly/DOYs VI value for pixel *i* in week/month/DOY *j* for year *k* whereby both the NDVI or EVI can utilized as VI, $VI_{i, min}$ and $VI_{i, max}$ is the multiyear minimum and maximum VI, respectively, for pixel *i*. The resulting percentage of the observed value is situated between the extreme values (minimum and maximum) in the previous years. Lower and higher values therefore indicate bad and good vegetation state conditions, respectively **(**Kogan, 1990).

Table 4 VCI range and their classes **(**Kogan, 1990).

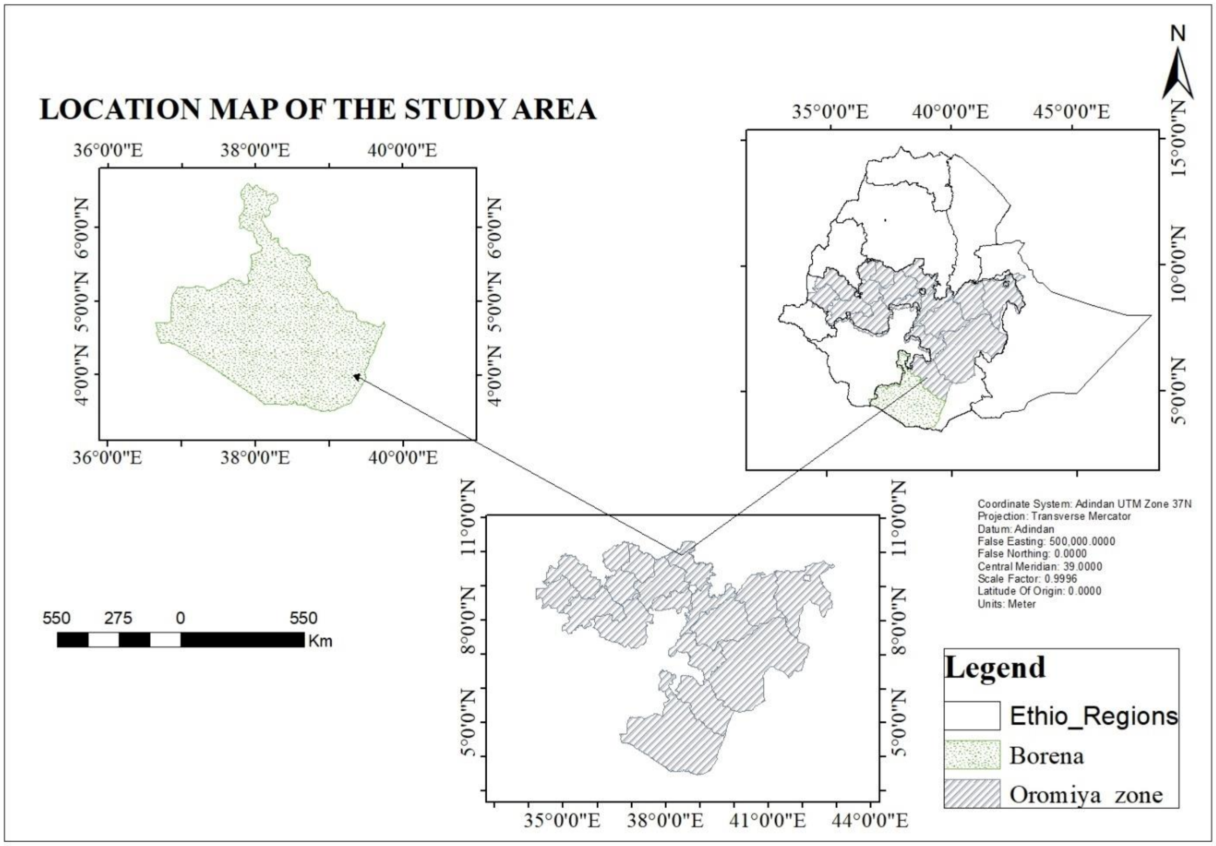
Value	**Classes**
>50-100	No drought
40%-50%	No drought
30%-40%	Light drought
20%-30%	Moderate drought
10%-20%	*Severe drought*
0%-10%	*Extreme drought*

CHAPTER THREE

DESCRIPTION OF THE STUDY AREA AND METHODOLOGY

3.1 Description of study area

3.1.1 Location of the study area



Borana is one of 21 administrative zones in Oromia National Regional State. The zone has 13 districts and situated between 3°36’00’’ – 6°38’00’’N latitude and 3°43’00’’ – 39°30’00’’ E longitude in the southern part of Ethiopia and the state. It borders Kenya in the south, Somali Regional State and Guji Zone in the east, and the Southern Nations, Nationalities, and Peoples Region (SNNPR) in the north and west (CSA, 2019)

Figure 2 location map of the study area

3.1.2 Climate and Topography

The zone covers 48,360 km^2 of which 75% consists of lowland, with an average altitude of ,479m-2482m above sea level. The zone is frequently exposed to drought. Rangelands are dominated by tropical savannah vegetation with varying proportions of open grasslands and perennial woody vegetation. Divided between two agro-ecological zones the semi-arid lowlands to the south and the more humid lands at higher altitudes to the north (CSA, 2011).

Ecologically, 70% of the zone landmass is classified as it is an arid and semi-arid area, with pockets of sub humid zones semi-arid lowland. The semi-arid lowlands are predominantly flat, covered with bushes and shrubs. According to data collected from national meteorological agency the annnual average of rainfall of borana zone ranges from 581 mm to 1073 mm with annual mean temperature range from 21.7 ̊C to 22.7 ̊C during the period.

In general, the warmest period in the year is from March to May, while the lowest annual minimum temperatures occur between the months of November and January (CSA, 2013).

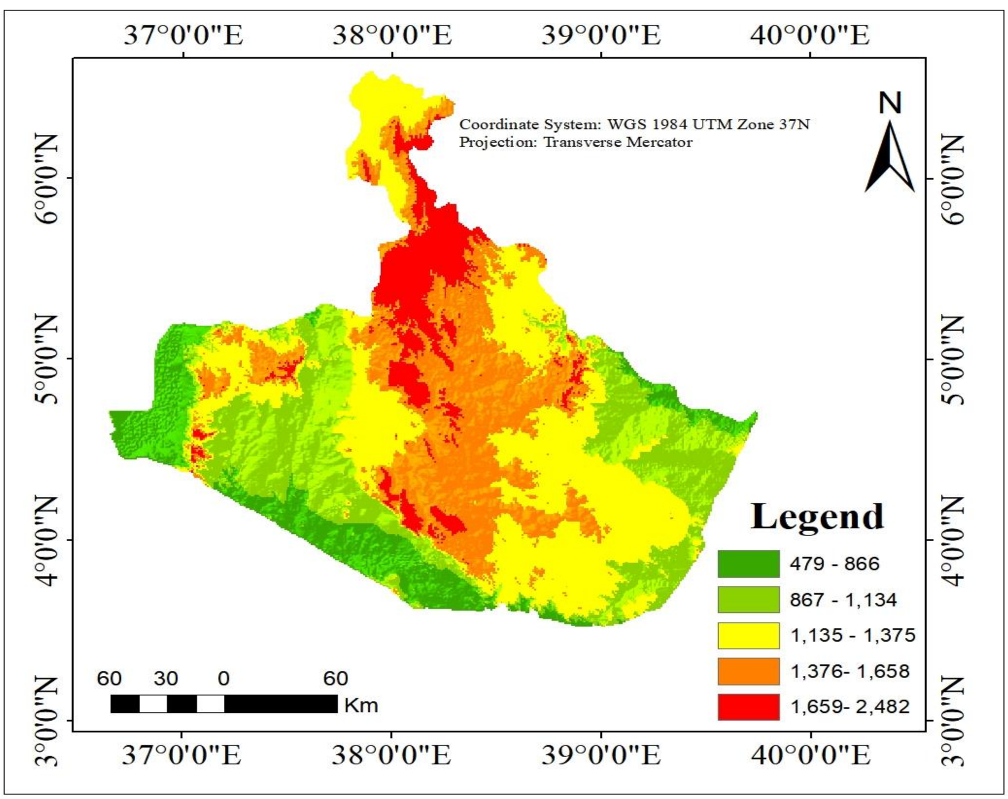


Figure 3 Topographic map of study area

3.1.3 Natural Resources

3.1.3.1 Geology of the zone

Borana zone has its oldest rocks of pre-Cambrian origin syntectonic gramitods upper and lower middle protozid (metamorphic) and lower complex (archalan metamorphic) of Precambrian an or basement complex rocks origin have been found in several parts of the zone particularly in the Yabello and Mega. Similarly, Mesozoic, and Cenozoic deposition have been exposed in Yabello, Dire, Arero and Teltele (Dalle, Maass, *et al*, 2015).

3.1.3.2. Major types of natural vegetation

High forest, broad leafed forests, wood land, bush and shrub land, grass land and plantations trees are found in the zone. The high forest sub-classification of upland dry evergreen (juniperusprocera) forest which is known as forest of Borana is found on the southern escarpment and hills of the zone between 1500 and 2000masl Arero, Mega and Yabello forests are included within this category.

3.1.4 Socio-economic characteristics

3.1.4.1 Population

According to the projected population of Ethiopia 2019, the zone is inhabited by 1,312,944 central statistical agency of Ethiopia (CSA, 2019). Based on the 2019 population projection conducted by (CSA), of whom 661,825 are men and 651,119 women; with an area of 45,434.97 square kilometers, Borena has a population density of 21.18. The three largest ethnic groups reported were the Oromo (88.78%), the Gedeo (4.42%) and the Burji (3.17%); all other ethnic groups made up 3.63% of the population. Afan Oromo was spoken as a first language by 90.94%, Gedeogna was spoken by 4.06% and Konsogna by 2.72%; the remaining 2.28% spoke all other primary languages reported (CSA, 2019).

Table 4 Population description of study area according to CSA Ethiopian population projection 2019

No	District Name	Population		
		Male	Female	Total
1	Abaya	69,609	69,290	138,899
2	Arero	32,708	32,379	65,087
3	Dire	50,184	49,808	99,992
4	Dugda	100,312	97,239	197,551
5	Gelana	48,312	47,766	96,078
6	Yabello	72,038	71,293	143,331
7	Teltele	48,928	46,633	95,561
8	Miyo	33,936	34,868	68,804
9	Moyale	21,262	19,974	41,236
10	B_hora	184,536	181,869	366,405
	Zone	661,825	651,119	1,312,944

3.1.4.2 Economic activities

In addition to the rearing of animals, the Pastoralist community of Borana zone is also involved in small scale crop production. In relation to this, in 2019 during spring season the production obtained was 2,179,521 quintals. In addition, in the same year during 'summer' season 144,083.5 was cultivated and the production obtained was 818,355 quintals. (Fentahun, 2020).

3.2 Methodology

3.2.1. Research design

Since the data was analyzed numerically and the results was descriptive, a quantitative research design was used, and the study's findings is presented in the form of Map, graphs, charts, and tables.

3.2.2 Software's to be used

Table 5 software's used

No	Name of software	Version	Purpose
1	ArcGIS	10.3	Data Analysis and interpretation
2	QGIS	3.16	Data Analysis and interpretation
3	MS Excel	2019	Data preparation
4	R studio	1.4	Meteorological data Analysis
5	GeoCLIM	1.2	Meteorological data acquisition

3.2.3 Data Acquisition Techniques

Table 6 Data acquisition techniques

NO	Dataset	Variable	Description	Resolution		Period	Source
				Spatial	Temporal		
1	MODIS	NDVI, VCI,	Satellite	250 meters	10 days	2010-2020	NASA
3	Metrological Data	Rainfall, Temp & PCI	Ground data	Average mm	Monthly	2010-2020	NMS
4	CHRIPS	Rainfall Raster	Satellite	0.05°×0.05°	Monthly	2010-2020	FEWSnet

3.2.4 Source and Methods of data collection

3.2.4.1. Satellite data Acquisition

1 MODIS

The MODIS is the primary sensor for monitoring terrestrial ecosystems for the NASA Earth Observing System (EOS) program (Justice et al., 2002). The MODIS is more sensitive to changes in vegetation dynamics and was found to be a more accurate and versatile tool to monitor global vegetation conditions. Expedited MODIS 5-day maximum-value composite NDVI images at 250 m spatial resolution were used to monitor vegetation condition. The real-time and historical NDVI products were composited in 10-day intervals (Huete et al., 2002).

MODIS vegetation indices, produced on 10-day intervals and at multiple spatial resolutions, provide consistent spatial and temporal comparisons of vegetation canopy greenness, a composite property of leaf area and canopy structure. Two vegetation indices are derived from atmospherically-corrected reflectance in the red, near-infrared, and blue wavebands; the normalized difference vegetation index (NDVI), which provides continuity with NOAA's AVHRR NDVI time series record for historical and climate applications, and the vegetation condition index. In this study the MODIS data was used due to the large spatial resolution of the product.

3.2.4.2. Rainfall Data Acquisition

The rainfall data was collected from directly using the GeoCLIM software from the FEWS. The rainfall data was downloaded entirely for east Africa and finally masked out for the study area using GeoCLIM software. The rainfall data used is the data from CHIRPS. And, monthly rainfall data recorded for 11 years was collected from Ethiopian national meteorological service agency. Rainfall data is used to analyze relation between NDVI with variability of rainfall and to drive (SPI & SPEI).

3.3. DATA PROCESSING TECHNIQUES

3.3.1. Rainfall Data Processing

3.3.1.1 The Standardized Precipitation- Evapotranspiration Index

The Standardized Precipitation- Evapotranspiration Index (SPEI) fulfils the requirements of a drought index since its multi-scalar character enables it to be used by different scientific disciplines to detect, monitor, and analyze droughts.

Like the PDSI and the SPI, the SPEI can measure drought severity according to its intensity and duration, and can identify the onset and end of drought episodes. The SPEI allows comparison of drought severity through time and space, since it can be calculated over a wide range of climates, as can the SPI. A crucial advantage of the SPEI over other widely used drought indices that consider the effect of PET on drought severity is that its multi-scalar characteristics enable identification of different drought types and impacts in the context of global warming. (Williams, 2018). For the purpose of this study SPEI3, SPEI6 and SPEI12 was computed for study area.

For the SPEI drought classes, there are 5 classes, namely: 1- non-Drought (in this class the value of SPEI greater than -0.5), 2- Mild (the value of SPEI is between -0.5 and -1), 3- Moderate (SPEI is between -1.5 and -1), 4- Severe (SPEI is between -2 and -1.5), and 5- Extreme (Less than -2). (Williams, 2018).

Where; $w = \sqrt{-2\ln(\mathrm{P})}$ P ≤0.5

P is the probability of exceeding a determined D value

$$\mathrm{SPEI} = W - \frac{\mathrm{C0} + C1W + C2W^2}{1 + d1W + d2W^2 + d3W^3}$$

The constants are C_0 5 2.515517, C_1 5 0.802853, C_2 5 0.010328, d_1 5 1.432788, d_2 5 0.189269, and d_3 5 0.001308. (Vicente Serrano *et al*, 2010).

3.3.1.2 Standardized precipitation index

In 2009, WMO recommended SPI as the main meteorological drought index that countries should use to monitor and follow drought conditions (Hayes, 2011). Uses historical precipitation records for any location to develop a probability of precipitation that can be computed at any number of timescales, from 1 month to 48 months or longer. As with other climatic indicators, the time series of data used to calculate SPI does not need to be of a specific length (Guttman,1998, 1999).

The time period from the arrival of water inputs to availability of a given usable resource differs considerably. Thus, the time scale over which water deficits accumulate becomes extremely important, and functionally separates hydrological, environmental, agricultural, and other droughts. For this reason, drought indices must be associated with a specific timescale to be useful for monitoring and management of different usable water resources. This explains the wide acceptance of the SPI, which is comparable in time and space (Hayes *et al*., 1999).

The ability of SPI to be calculated at various timescales allows for multiple applications. Depending on the drought impact in question, SPI-1 to SPI-3 is computed for shorter accumulation periods (1 to 3 months), it can be used as an indicator for immediate impacts such as reduced soil moisture, snowpack, and flow in smaller creeks. SPI-3 to SPI-12 is computed for medium accumulation periods (3 to 12 months), it can be used as an indicator for reduced stream flow and reservoir storage. SPI-12 to SPI-48 is computed for longer accumulation periods, it can be used as an indicator for reduced reservoir and groundwater recharge (McKee 1993).

Precipitation-based drought indices including the SPI rely on two assumptions: I) the variability of precipitation is much higher than that of other variables, such as temperature and potential evapotranspiration (PET), and II) the other variables are stationary (i.e., they have no temporal trend). In this scenario the importance of these other variables is negligible, and droughts are controlled by the temporal variability in precipitation. However, some authors have warned against systematically neglecting the importance of the effect of temperature on drought conditions. Empirical studies have shown that temperature rise markedly affects the severity of droughts, SPI values more negative than -1 indicate a condition of drought, the more negative the value the more severe the situation. SPI values higher than +1 indicate more humid conditions compared to a normal situation. When the SPI has a value between -1 and +1 the situation is identified as normal (McKee 1993).

SPI was computed in different time scale from short to medium of SPI3, SPI6 and SPI12 for the zone in the process of tracking the impacts of ten years of climatic pattern fluctuations on Borana zone meteorological condition. It is computed by fitting a gamma probability density function to the frequency distribution of precipitation and transforming the gamma distribution into a standardized normal distribution (McKee, et al 1993).

Table 5 Range for SPI and classes Source (McKee, 1993)

Value	**SPI Classes**
> 2	Extremely wet
1.5 to 2	Severely wet
1 to 1.5	Moderately wet
0.5 to 1	Wet
0 to -0.5	Normal
-0.5 to -1	Moderately dry
-1 to -1.5	Dry
-1.5 to -1	Severely dry
< -2	Extremely dry

3.3.1.3 precipitation concentration index

The precipitation concentration index (PCI), proposed by Oliver (1980) and developed by De Luis *et al* (1997). It is an index to analyze the heterogeneity of precipitation and the relationship between variability and monthly precipitation distribution. PCI can be calculated as the following formula:

$$PCI = \frac{\sum_{i=1}^{12} P_i^{\,2}}{(\sum_{i=1}^{12} P_i)^2} \times 100$$

(Oliver,1980).

Where Pi is the monthly precipitation in the i^{th} month. Usually, the distribution of precipitation is uneven in different month. The large the difference in monthly precipitation, the larger the concentration of precipitation during intra-annual, PCI values that are less than 10 indicate a uniform monthly rainfall distribution in the year, whereas values from 11 to 20 denote seasonality of precipitation distribution. Values above 20 correspond to climates with substantial monthly variability in precipitation amounts, therefore, the greater the PCI value, the more variable the monthly precipitation (Oliver,1980).

3.3.2 Vegetation data Processing

3.3.2.1 Normalized different vegetation index

Normalized different vegetation index (NDVI) **is** One of the most widely used for identification of environmental condition. The NDVI values range from +1.0 to -1.0. Areas of barren rock, sand, or snow usually show very low NDVI values (for example, 0.1 or less). Sparse vegetation such as shrubs and grasslands or senescing crops may result in moderate NDVI values (approximately 0.2 to 0.5). High NDVI values (approximately 0.6 to 0.9) correspond to dense vegetation such as that found in temperate and tropical forests or crops at their peak growth stage. By transforming raw satellite data into NDVI values, researchers can create images and other products that give a rough measure of vegetation type, amount, and condition on land surfaces around the world.

The NDVI value calculated from MODIS using this formula

$$\frac{(R_{NIR} - R_{red})}{(R_{NIR} + R_{red})}$$

3.3.2.2 Vegetation condition index

The Vegetation Condition Index (VCI) compares the current NDVI to the range of values observed in the same period in previous years. The VCI is expressed in % and gives an idea where the observed value is situated between the extreme values (minimum and maximum) in the previous years. Lower and higher values indicate bad and good vegetation state conditions, respectively.

NDVI is the most used indicator that is sufficiently stable to permit meaningful comparisons of seasonal, inter-annual, and long-term variations of vegetation structure, phenology, and biophysical parameters (Tucker, 1986). The calculation of vegetation condition index was carried out using:

$$\mathrm{VCIi} = \frac{\mathrm{NDVIi} - \mathrm{NDVImin}}{\mathrm{NDVImax} - \mathrm{NDVImin}}$$

Where NDVI*i* is current Value, NDVI *max* is overall maximum value of NDVI and NDVI *min* is overall minimum value (Kogan,1995).

3.4. Regression analysis of station rainfall data with drought indices

The relationship between rainfall data and data derived from drought indices were prepared and computed for simple regression analysis in order to validate the impact of the derived indice on each year's rainfall distribution. For this reason, the average SPI, NDVI and VCI anomaly raster cell values was used.

3.5. Drought vulnerability assessment

Drought vulnerability map of the Borana zone was produced from the output obtained from satellite-based vegetation indices and climatic variable (rainfall and temperature) by using multi criteria evaluation technique. All drought indices mean monthly frequency maps were reclassified into a common scale based on literature. Such, as Lemma (1996), Gizachew and Suryabhavan (2014) demonstrated that the likelihood of drought occurrence in each region can be divided into three categories: extreme (if drought occurrence likelihood is more than 50%), moderate (if drought occurrence likelihood 30 to 50%), and low drought likelihood zones (if drought occurrence likelihood is less than 30%). Based on the above literature the value of drought indices to be weighted overlay is NDVI 10%, VCI 20%, DSI 35%, SPEI 20%, SPI 10%, PCI 5%. The frequency maps of each drought class are reclassified into four; based on the regularity of drought rate during the study times, using the above parameters. Accordingly, the value ranges from 2 to 3 as mild, 4 to 5 as moderately vulnerable, 6 to 8 as severely vulnerable, and 9 to 11 as extremely vulnerable. Lemma (1996),

NO	Variables	Weighted Value
1	Standardized precipitation index (SPI)	10%
2	Standardized precipitation and evapotranspiration index (SPEI)	20%
3	Precipitation concentration index (PCI)	5%
4	Normalized different vegetation index (NDVI)	10%
5	Vegetation condition index (VCI)	20%
6	Drought severity index (DSI)	35%

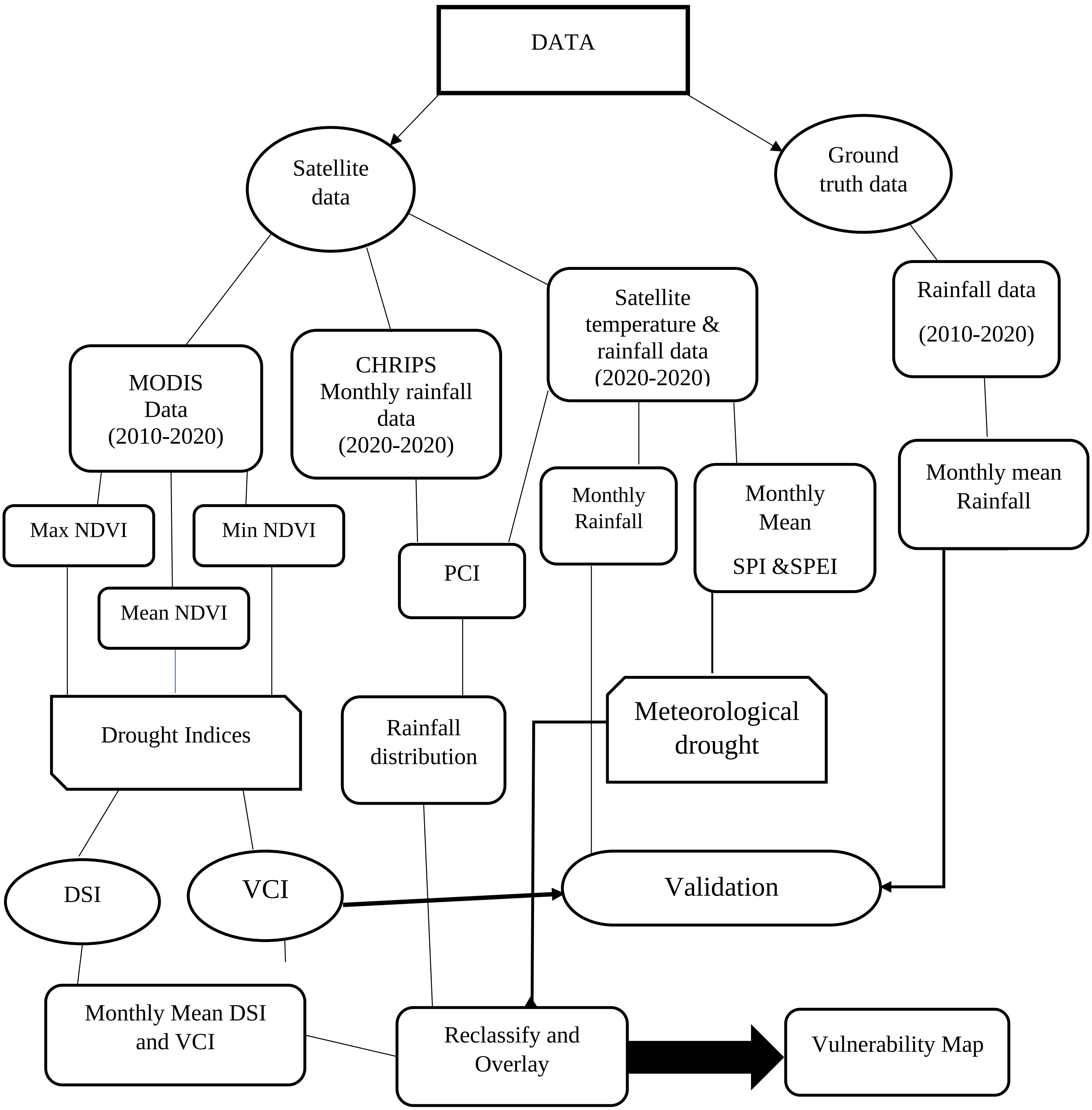


Figure 3 Methodological work flow of the study

CHAPTER FOUR

4.RESULTS AND DISCUSSIONS

4.1 Standardized precipitation index

The interaction of precipitation and vegetation are highly connected. In a rain-fed based cropping system; seasonal rainfall variability is inevitably reflected by vegetation density. To analyze the impact of rainfall deficiency on drought, SPI is important to quantify the precipitation deficit (Eshetie, *et al* 2016).

SPI is used to quantify precipitation deficits as anomaly percentile on multiple timescales. SPI depends on commonly available precipitation data and is relatively easy to implement in the assessment of drought severity at different timescales.

SPI result derived from satellite-based rainfall data shows that there is no extreme drought and extreme wet year between 2010-2020

During the periods 2010-2012 and 2014-2017, moderate dry years were recorded while wet years were observed during the year of 2013, 2018, 2019 and 2020. The value of SPI during wet months ranges from normal to wet (0 to ≥ 0.05) and the value of SPI during moderate dry months ranges from normal to dry (0 to ≤-0.99).

During 2014, 2015,2016 and 2017 almost all of the southern part and during the period of 2012, 2015 and 2016 some part of western region was vulnerable to drought and also 2010,2014, and 2016 Some part of east was affected (Figure 6). While during the year of 2011 and 2019 northern part was affected by drought.

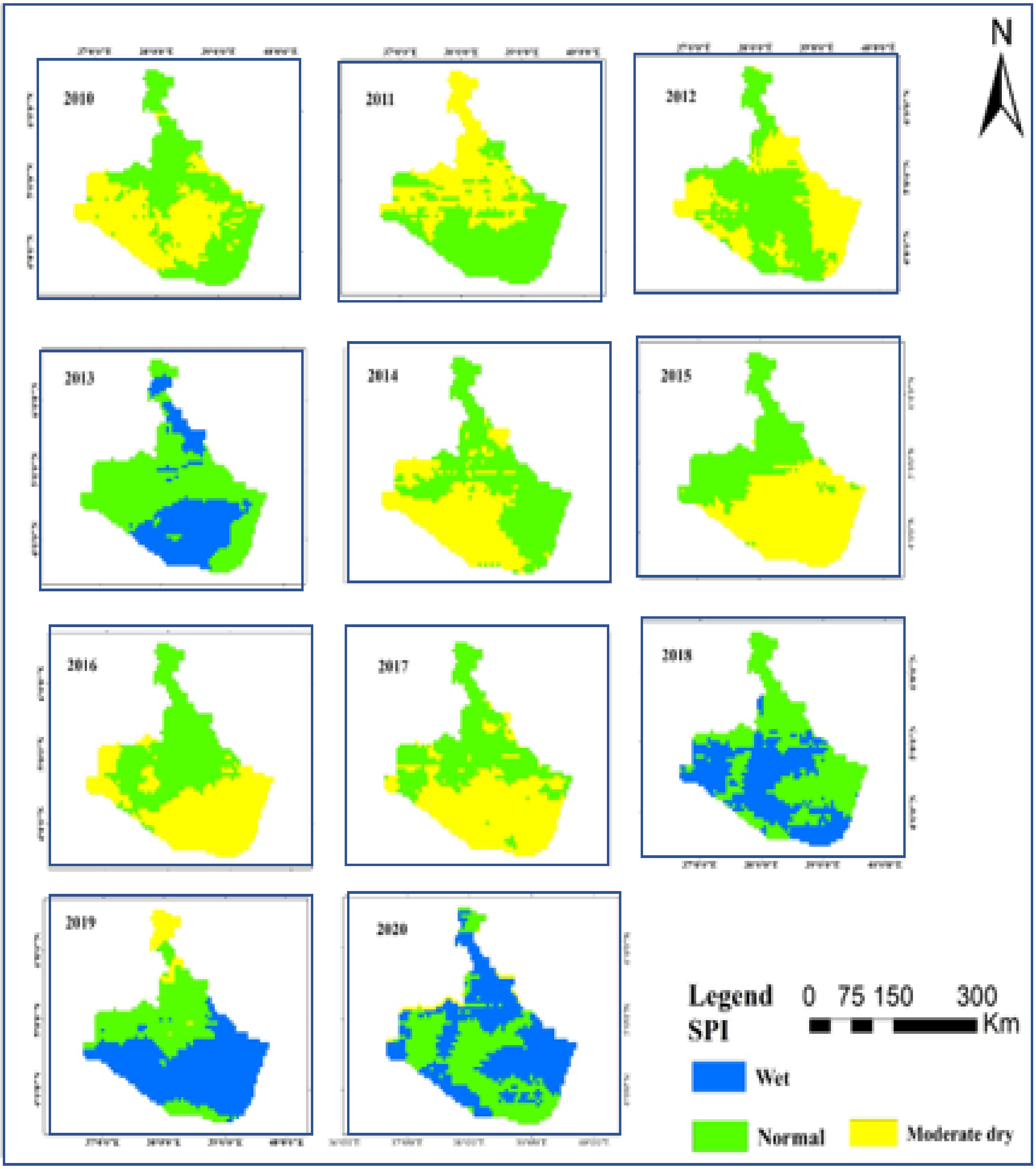


Figure 4 Spatio-temporal pattern of drought in Borana zone using SPI for 2010 to 2020.

4.1.1 Station based Standardized precipitation index

SPI-1 to SPI-3: When SPI is computed for shorter accumulation periods (1 to 3 months), it can be used as an indicator for immediate impacts such as reduced soil moisture, snowpack, and flow in smaller creeks. When SPI is computed for medium accumulation periods (3 to 12 months), it can be used as an indicator for reduced stream flow and reservoir storage. (WMO. 2012).

In SPI calculation, the precipitation distribution function is obtained from the precipitation data of the same month, so it is necessary to check the precipitation distribution of each month. SPI is basically the transformation of the precipitation time series into a standardized normal distribution, and the SPI is calculated by first determining a probability density function that describes a lengthy sequence of precipitation measurements. It is a commonly used index for describing meteorological dryness over a variety of timeframes. The SPI is strongly connected to soil moisture on short timeframes, and also on longer timeframes it is highly related to groundwater and reservoir storage.

The calculated SPI for 3-month, 6-month, and 12-months reveals that there is variability in short- and long-term of drought occurrence. During the year of 2010, 2011, 2012, 2017 and 2019 the SPI value is in negative value that is between 0 and -1.5 that describe there was dry condition during this study period and the year of 2013, 2014, 2015, 2016, 2018 and 2020 are the year of relatively wet year with the SPI value of between 0 and 1. The find of the study is in line with the research conducted by Pramudya and Onishi 2018 in Tegal City, Central Java, Indonesia.

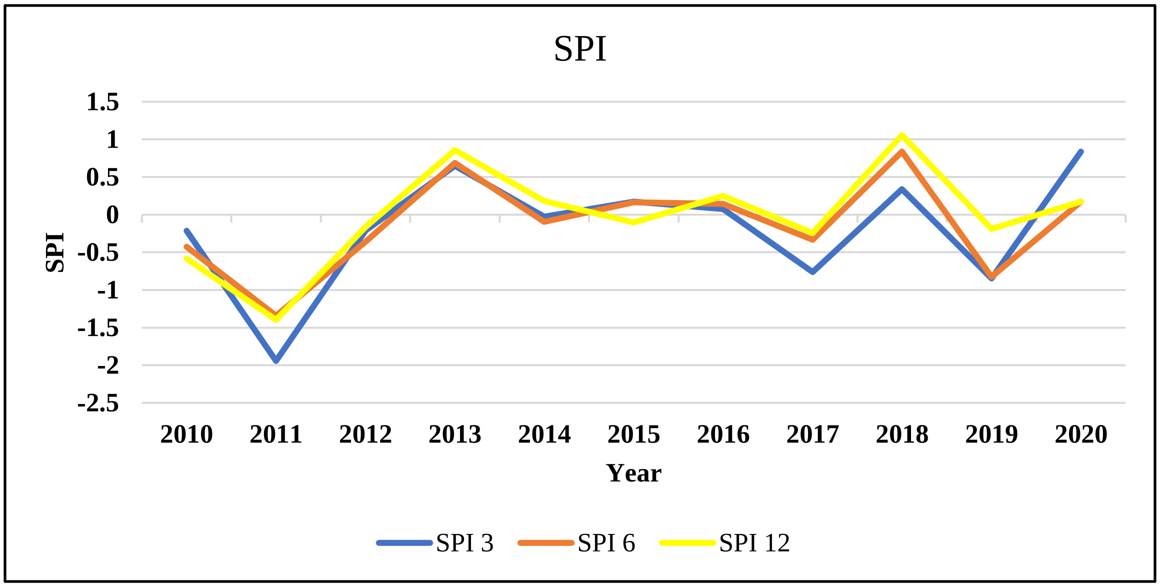


Figure 5 Temporal trend of Standardized precipitation index for short and long term from 2010 to 2020.

4.1.2 Relationship between Station based SPI and Satellite based SPI

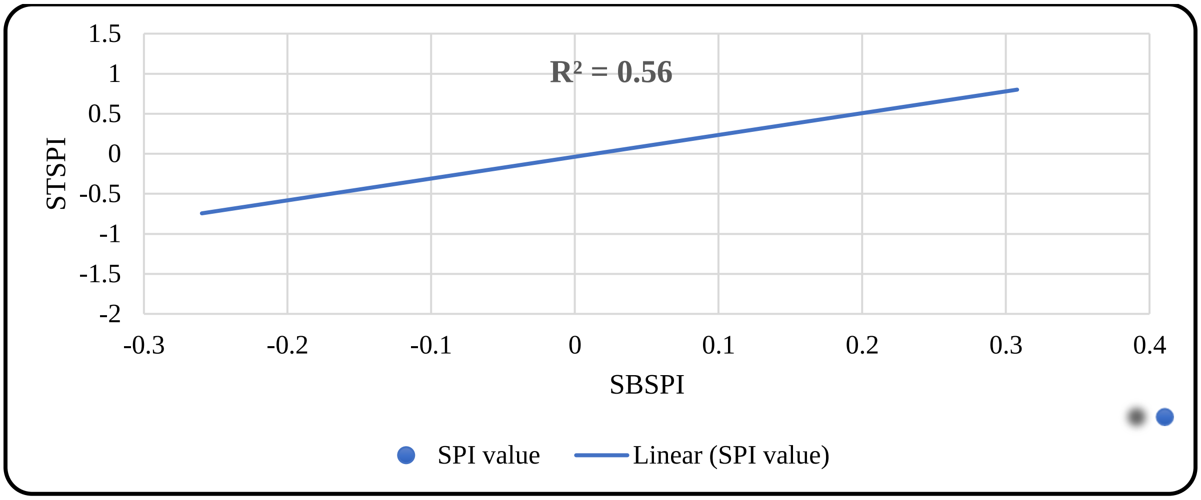


Figure 6 Correlation coefficient for Satellite based PCI and Station based PCI

According to the above correlation coefficient plot, there was a positive and good relationship between satellite-based SPI and station-based SPI (r^2 = 0.56) and it was statistically significant with coefficient variation, signifying a positive relationship between the two drought indices in the study area.

4.2. Standardized precipitation and evapotranspiration index

The SPEI may be computed at various time scales to adapt to the typical durations of reaction to drought of target natural and economic systems, allowing for the determination of drought resistance. The SPEI has a significant advantage over other multiscale drought indicators such as the SPI in that it incorporates the impact of temperature on potential evapotranspiration. Also, it utilizes a more complete measure of water availability, climatic water balance. SPEI is derived from SPI by standardizing the difference between water supply (precipitation) and water demand estimated from potential evapotranspiration (Vicente Serrano, et al 2012).

SPEI has considerable promise as a meteorological drought index. This index enables identification of distinct drought types and impacts in the context of global warming, which is a significant benefit over other frequently used drought indices that incorporate the effect of PET on drought severity. SPEI which is done using a time series of the climatic water balance (precipitation minus potential evapotranspiration) the study area was experienced moderately wet condition to severely dry condition thus, during the period 2011 and 2019 northern part and during the period 2015,2016 south-eastern and during the year of 2010, 2013, 2017, 2018, and 2020 some central part of the study area experienced mild dry condition, Some of northern, southern, eastern part during the year of 2013, 2019 and 2020 respectively had experienced slightly wet to moderately wet condition. And also, during 2017 and 2019 southern and some part of northern part had experienced severely drought.

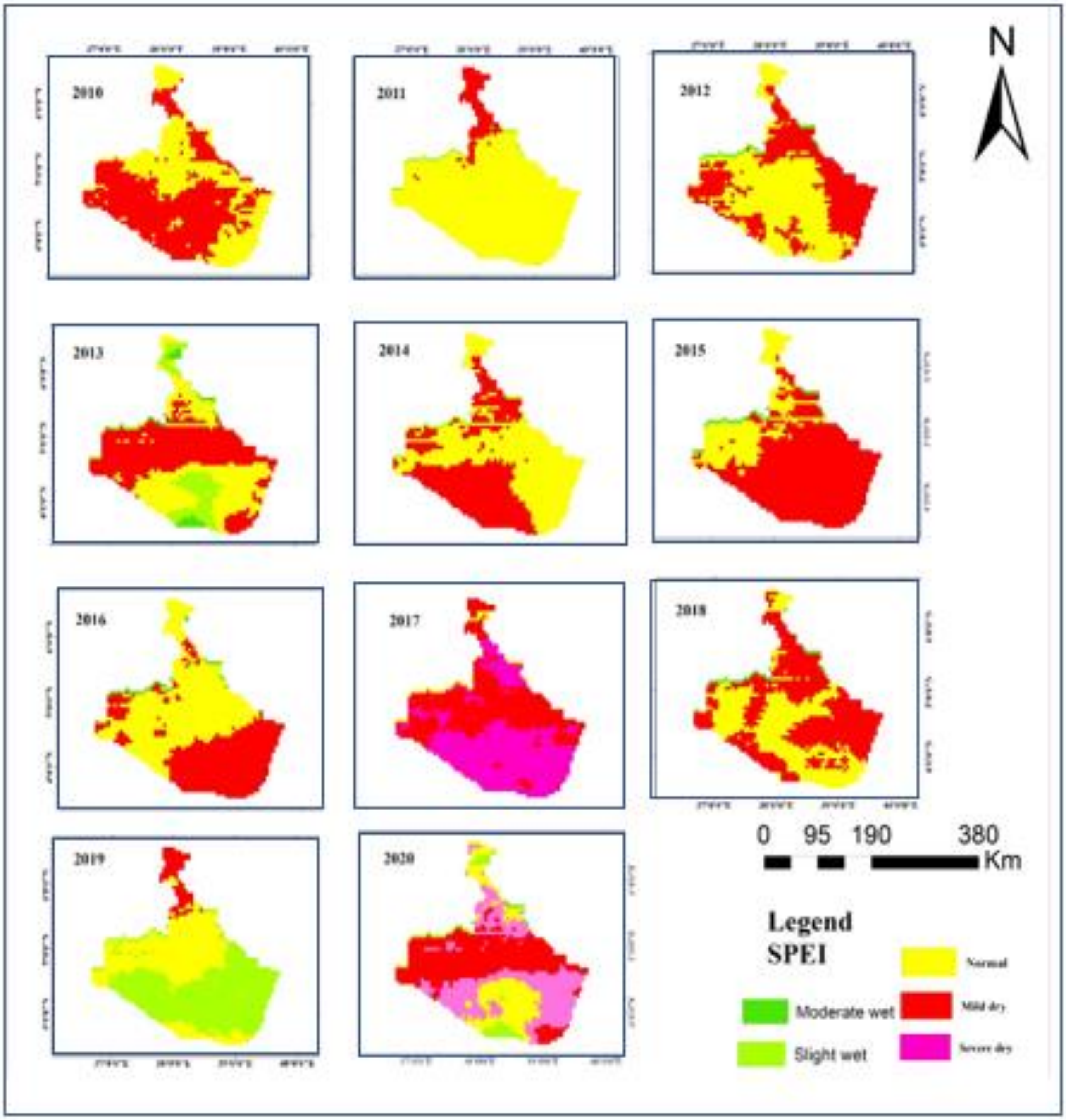


Figure 7 Spatial trend of SPEI from the year 2010 to 2020.

4.2.1 Station Based Standardized precipitation and evapotranspiration index

The SPEI is widely used for climatological and hydrological studies, in which the estimation of potential evapotranspiration is of great importance. The normalization of the cumulative probability value of the difference series between precipitation and evapotranspiration achieved by adding evapotranspiration based on the SPI is referred to as the SPEI. The SPEI estimates evapotranspiration based on precipitation, temperature, and humidity, and other data deviates from its typical state by using the difference between precipitation and evapotranspiration.

The SPEI for 3 month and 12 months timescales of all of the stations in Borana zone were calculated from 2010 to 2020, which reflected the change of the drought and wet occurrence in the zone.

The SPEI 3 values varied a lot, and the short-term precipitation had a big impact on values. As time scales expanded, the importance of precipitation accumulation grew, and the distinctions between dryness and wetness became stronger. Those SPEI 3 values show a decreasing trend with time. It shows that the frequency of droughts is gradually increasing, which may be closely related to climate warming. During the year of 2010,2011 and 2019 the was drought event related with short term precipitation deficit. With the value of -0.637, -1.519 and -0.743 respectively. Also, there was the year of short-term wet condition which are the year of 2012, 2013, 2014,2015,2016,2017 and 2018 with SPEI value of 0.228, 0.669,0.038, 0.034, 0.079, 0.038, and 0.33 respectively.

The SPEI 6 used shows relatively long period of agricultural drought. The calculated SPEI 6 for Borana zone shows the value that is between 0 to -1.17 to 0.92 which reveals dry and wet condition between 2010 to 2020 throughout. Accordingly, during 2010,2011, 2015,2017 and 2019 are the years of dry condition with SPEI 6 value of -0.373, -1.17, -0.091, -0.029, -0.228, and -0.385 respectively. And during the years of 2012,2013,2016, ,2018 and 2020 are the year of relatively wet condition with value of 0.467,0.852,0.519, 0.927 and0.0327

The SPEI 12 values show that there was basically a drought throughout the 2010-2020 years, even if the extent of drought is different. From the value of SPEI12, it can also be seen that the dry and wet distribution characteristics of the study area have a certain periodicity. During the year of 2010,2011,2015,2017 and 2019 was drought event ranges from mild drought to moderate drought.

Accordingly, the SPEI value is -0.332, -1.293, -0.798, -0.764, and -0.691 respectively. And the wet years are 2012, 2013, 2014, 2016, and 2018. With the value of 0.11, 0.991, 0.289, 0.217 and 1.112 respectively.

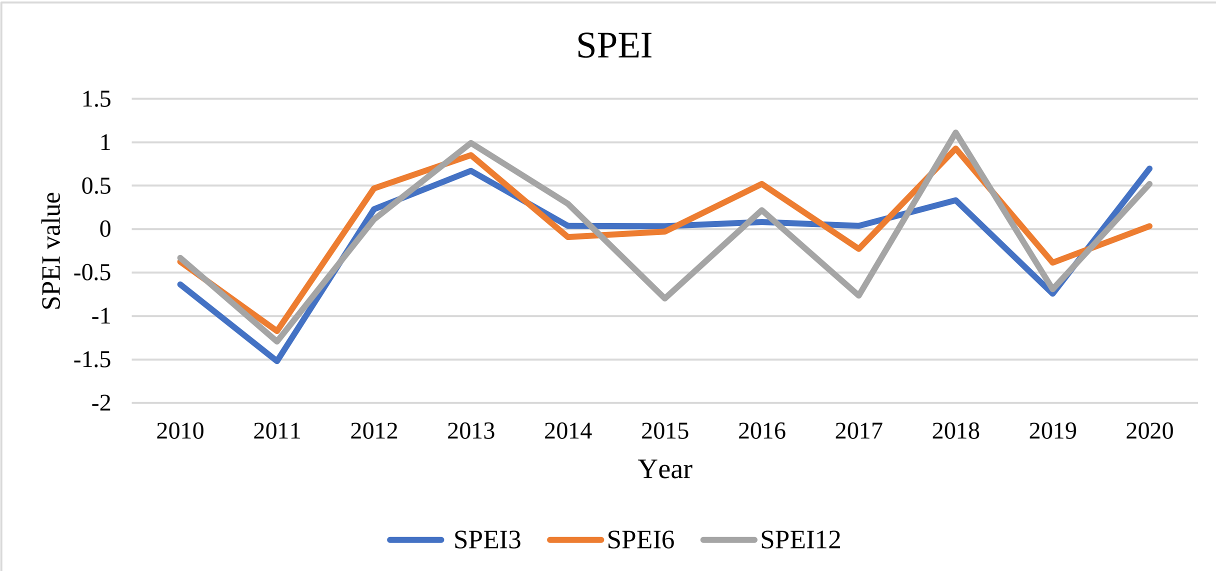


Figure 8 Graphical representation SPEI value of the year from 2010 to 2020

4.2.2 Relationship between Satellite based SPEI and Station based SPEI

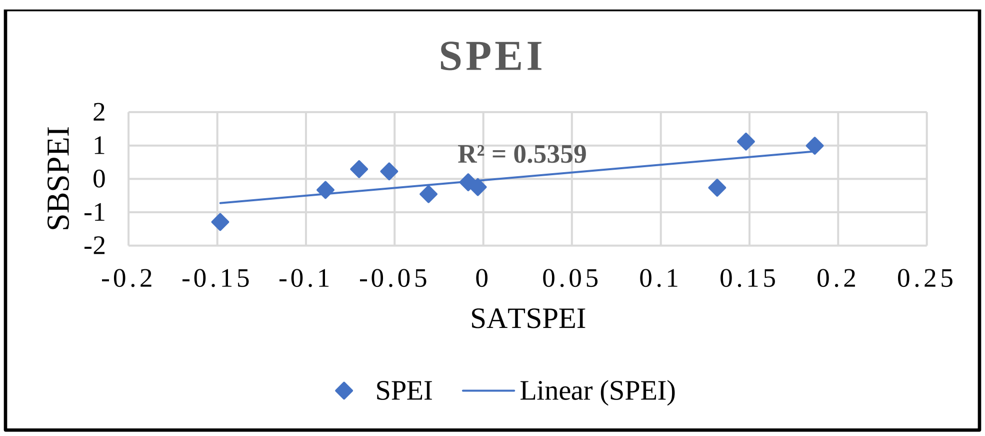


Figure 9 Correlation between Satellite based SPEI and Station based SPEI

The above correlation coefficient plot shows that the satellite-based SPEI and the station-based SPEI had a positive and good connection ($r^2 = 0.53$) with coefficient variation, showing a positive link between the two drought indicators in the study area.

4.3 Precipitation Concentration Index

Precipitation concentration index (PCI) is a powerful indicator for temporal precipitation distribution. According to PCI, explains the degree of precipitation concentration during a given year on an annual scale, ranging from 8.3 to 100. When the PCI value is less than 10, the precipitation is uniformly distributed throughout the year, and when the PCI value is from 11 to 15, precipitation is moderately concentrated, and if the values vary from 16 to 20, the precipitation has an irregular distribution, and the precipitation with PCI over 20 represents a significant or extremely irregular distribution. According to the value obtained from the calculation of PCI from satellite based and station based the concentration of precipitation has variability in terms of space and time. Spatially there was normal distribution of precipitation at North-western part of the study area in different period of time and South-eastern and central part of the study are had experienced an extremely irregular distribution of precipitation in different time period. Specially during the year of 2010, 2014,2015and 2019 north and north-western experienced regular distribution precipitation (ranges from >10) and the year of 2010, 2011,2016,2017, and 2020 South-eastern part of the study had experienced extremely irregular distribution of precipitation (ranges from >20). and during 2012, 2018 and 2020 the central part of the area was under extremely irregular distribution of precipitation (ranges from >20).

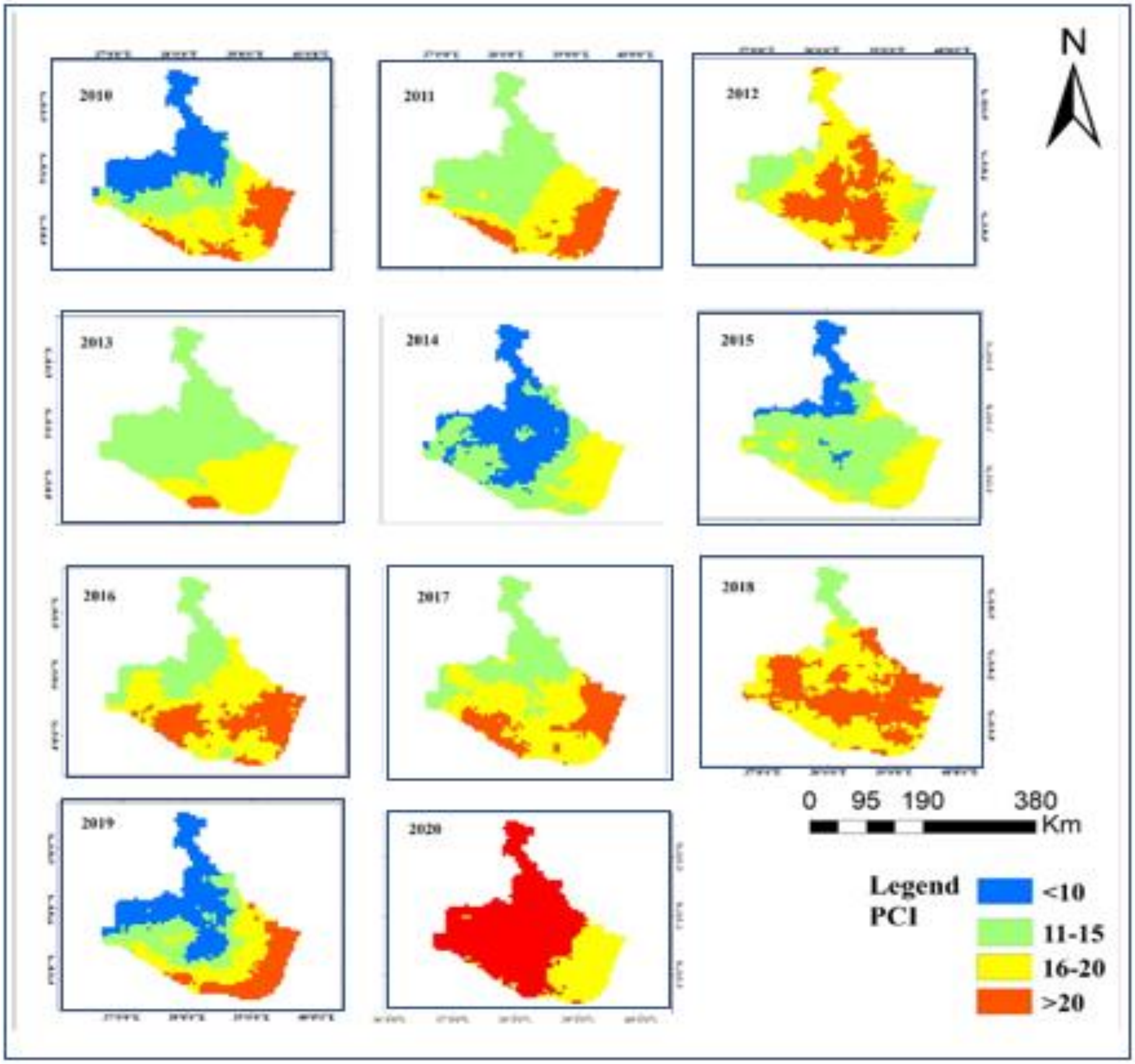


Figure 10 Spatial distribution of precipitation using PCI for the year of 2010 to 2020

4.3.1 Station based Precipitation concentration index

Rainfall distribution causes periods of surplus or drought, making a significant contribution to pl ant and agriculture production. Because a small number of highly wet months account for a large portion of the annul total precipitation. The relative distribution of rainfall patterns is quantified using a statistically determined concentration index. The monthly precipitation concentration index (PCI) was calculated.

A high PCI value implies that precipitation is highly Irregular during a few wet months, and the concentration index is employed as a concentration measure.

Using the PCI for a time span between 2010 and 2020 a rainfall concentration index was generated over Borana zone, and the calculated precipitation concentration index reveals that the study area has Very unstable distribution of rainfall through time. There is time that there is regular distribution and also there is time that experiences extremely irregular rainfall distribution. During the year of 2010 there was normal distribution of rainfall throughout the zone and the during 2011, 2014, 2015, 2016,2017 and 2018 moderate. 2012,2013, 2019 and 2020 extremely irregular distribution and the year of 2013 and extremely irregular distribution.

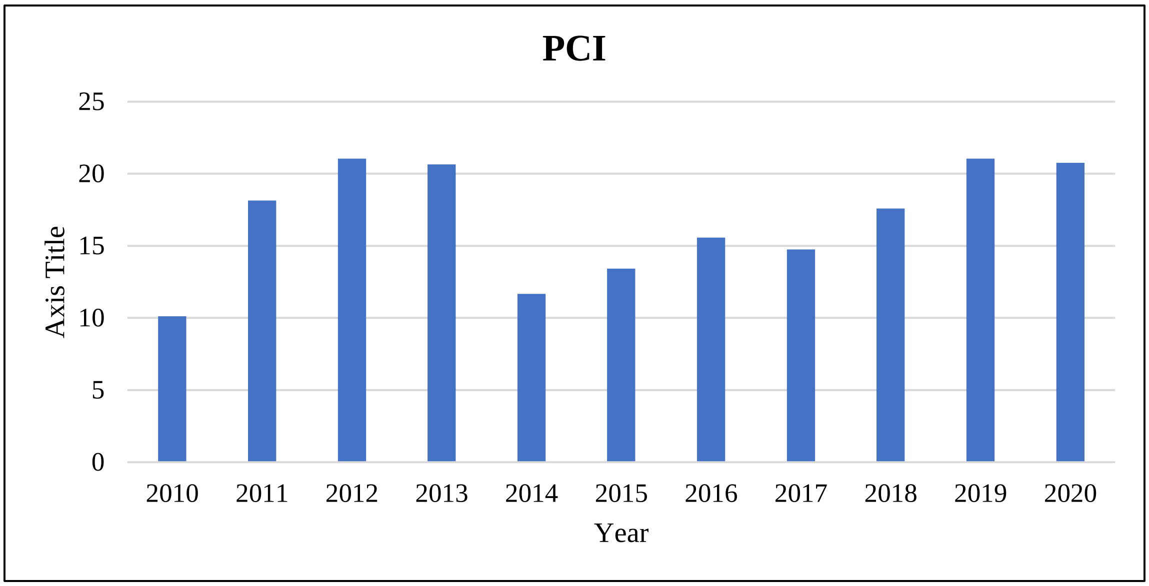


Figure 11 Spatial distribution of Precipitation using PCI for the year of 2010-2020

4.3.2 Correlation between station-based PCI and satellite-based PCI

The following correlation coefficient plot, the satellite-based PCI and station-based PCI had a positive and good connection (r2 = 0.484) that was statistically significant with coefficient variation, indicating a positive link between the two drought indicators in the study area.

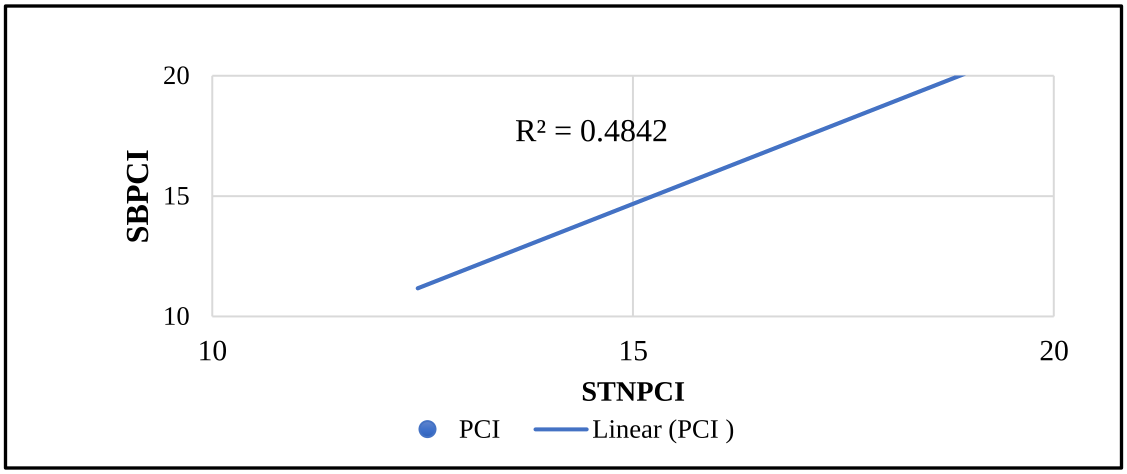


Figure 12 Correlation coefficient between satellite-based PCI and Station based PCI.

4.4 Vegetation condition index

The VCI is the most widely used satellite-based drought index to monitor vegetation conditions. VCI is determined based on the Normalized Difference Vegetation Index (NDVI) which assesses live green vegetation for the observed target (Kogan,1995).

The VCI compares the present NDVI to a range of prior years' values for the same time period. The VCI is stated in percent and indicates where the measured value falls in relation to the prior year's extreme values. Lower and higher numbers, respectively, indicate poor and favorable vegetative state conditions. There are different papers that uses vegetation condition index (VCI) to illustrate the drought level like figure 15 illustrate that severe drought conditions occurred for months in 2011, 2014, 2016, and 2017. During the years 2010 to 2020, the VCI map of the Zone simply demonstrated the onset and spatial extent of drought.

The VCI varied in the range to 100, with 0 indicating no vegetation and 100 signifying extensive vegetation. Droughts occurred in various years from 2011 was the year with the lowest VCI values, followed by 2014, 2016, and 2017. However, the severity of the condition varied according to the years stated above.

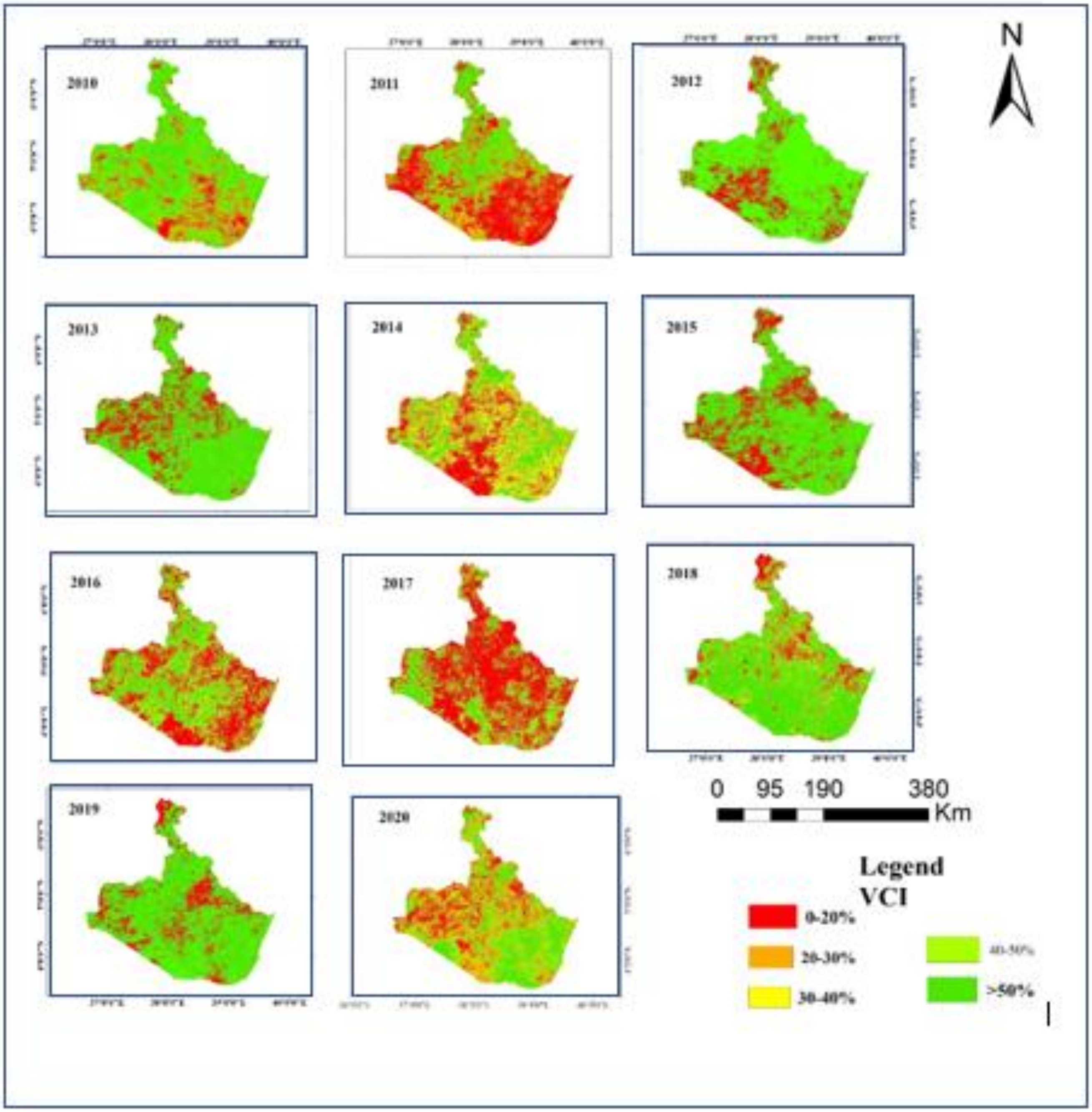


Figure 13 Spatial pattern of VCI of Borana zone from 2010 to 2020

4.5 Normalized Difference Vegetation Index

The NDVI is a remote sensing method used to measure the greenness of plants. This simple index is derived from images taken with visible and near infrared light, which are then combined in a ratio where the red channel multiplies the near infrared channel by 100. The values can range from -1 to 1, with higher NDVI indicating greater vegetative growth. NDVI is especially useful for detecting changes in plant canopy health and density due to natural or human causes like droughts or deforestation. The result is often shown as a map.

The findings of NDVI indicated that there was fluctuation in each month, indicating vegetation stress. As demonstrated in, for each of the mean monthly NDVI values, certain portions of the study regions have the lowest NDVI value compared to other sections of the zone, while others have the highest NDVI value of 0.86. The maximum NDVI value recorded is during the year of 2011 is between -0.08 and 0.86, while the lowest NDVI value recorded is between -0.08 and 0.83 for the years 2018, 2019, and 2020. The study area's south westerly region has the lowest value. The presence of low vegetation in the Borana zone was shown by historical NDVI values. Its quantity and geographic extent, on the other hand, varied.

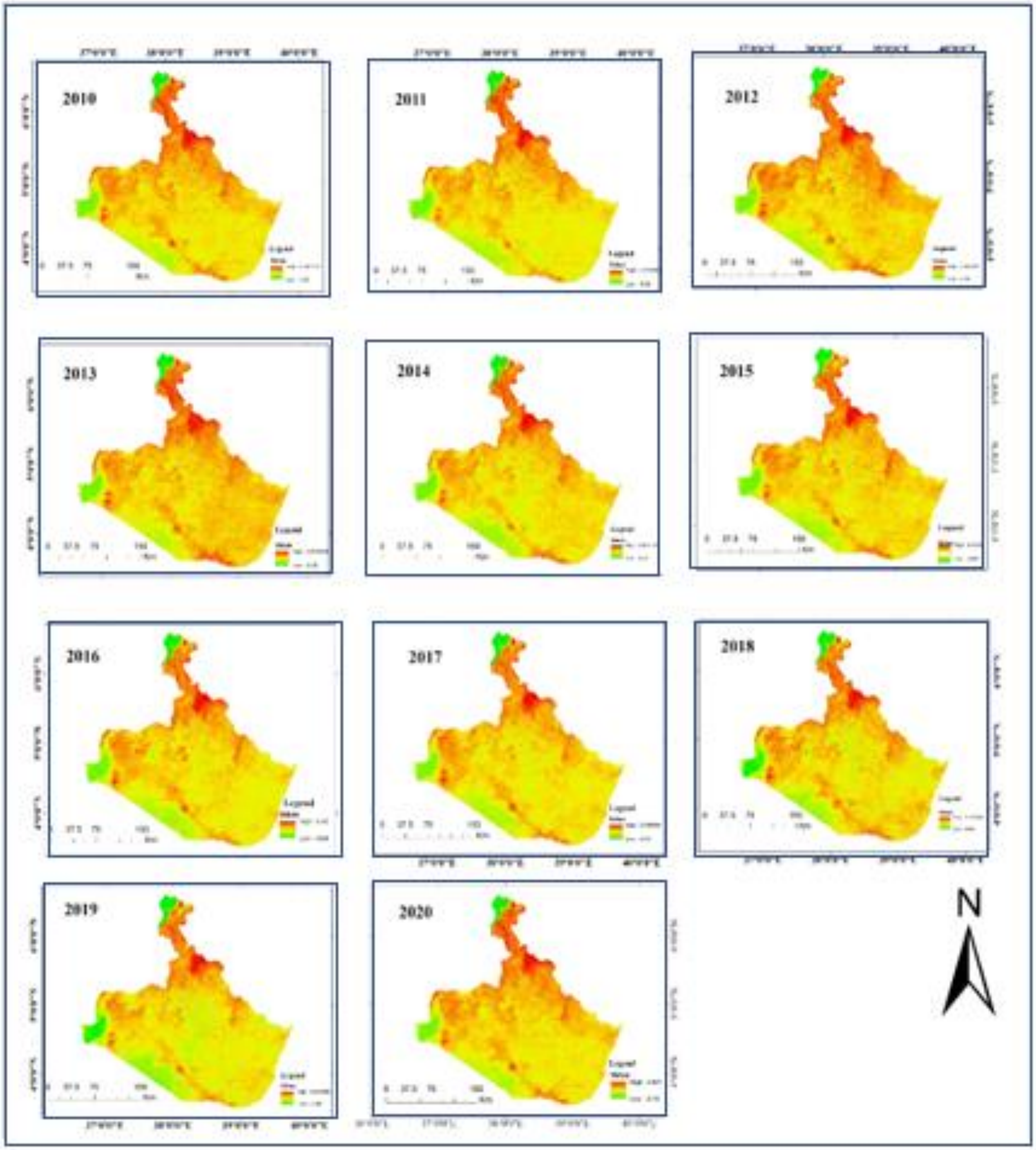


Figure 14 mean monthly NDVI for 2010 to 2020

4.6 Drought Severity Index

The Drought Severity Index (DSI) which was based on MODIS data. Their proposed DSI matched well with the (PDSI) and (SPI) data which designated that the index was useful for assessing drought stimuli on crop production and forest growth (Mu et al, 2013).

Drought was present in the Borana during the study periods, as shown by the DSI values. as illustrated in Figures 17, its severity varied spatially and temporally across the zone during the study period. Drought Severity Index values that show drought is the value with less than 0. According to spatial pattern map of drought severity index of the study area during the year of 2010 and 2011 some part of southern are had experienced abnormal dry condition. During the period of 2016, 2017, most of south-eastern and some central parts had experienced drought condition which ranges from abnormally dry to moderately dry conditions that ranges from -0.5 to -1.2. And during 2018 and 2020 northern part was affected by abnormal dry to moderately dry condition that ranges from -0.5 to -0.79 and the year 2012, 2013,2014, and 2019 are the year of relatively normal condition throughout the year in the study area, which ranges between -0.49 to 0.79.

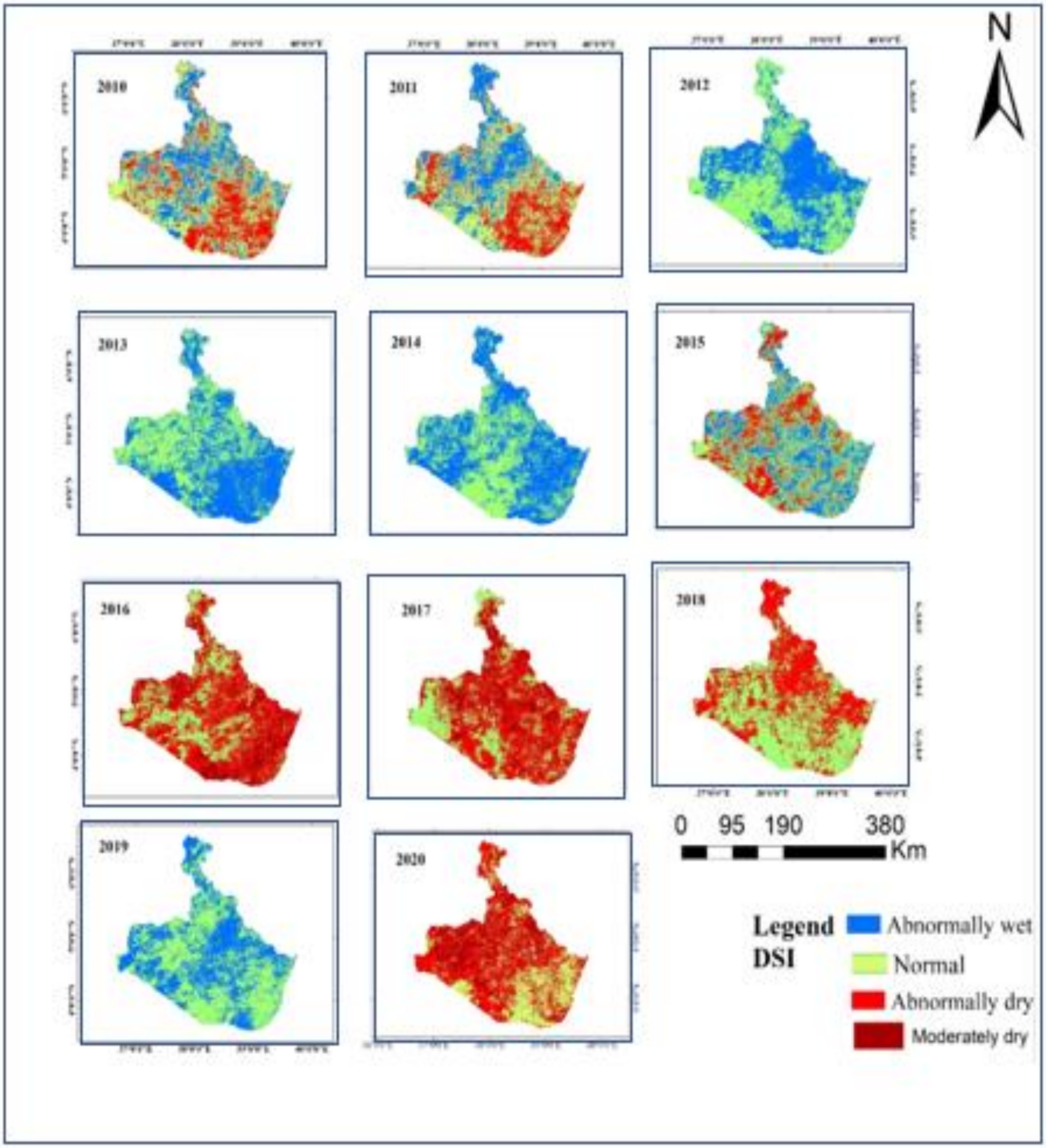


Figure 15 Spatial pattern of drought; using DSI for the year of 2010 to 2020

4.6.1 Relationship between Drought severity index and Vagetation condition index

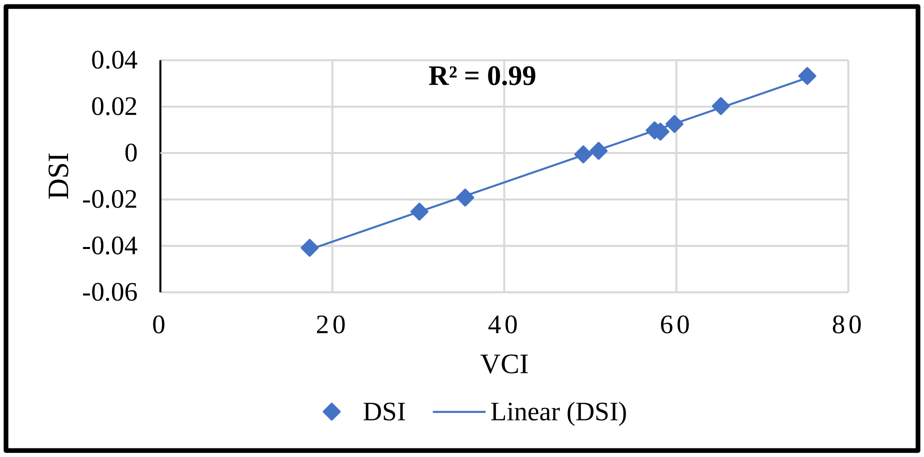


Figure 16 Correlation plot between DSI and vegetation condition index

The above correlation coefficient plot shows that the DSI and VCI had a positive and Excellent relationship (r2 = 0.99) that was statistically significant with coefficient variation, indicating a positive relationship between the two drought indices in the study area.

4.7 Regression analysis of Station Rainfall data with Drought indices

4.7.1 Regression analysis of Station Rainfall data with Standardized precipitation index

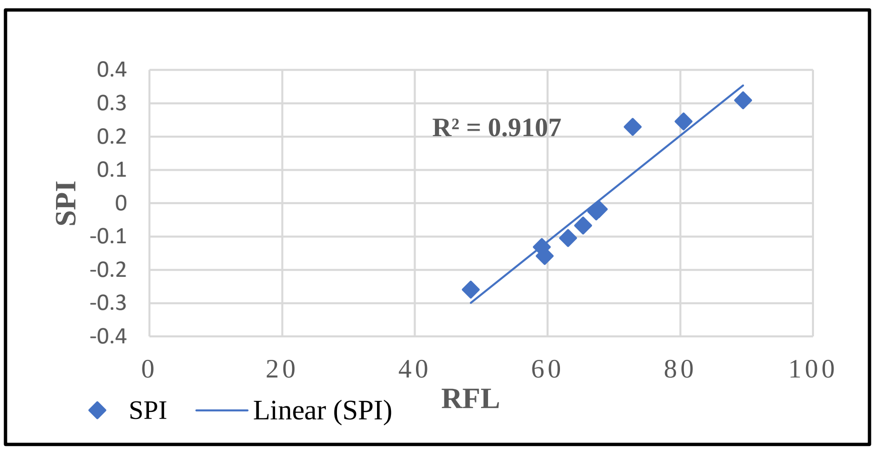


Figure 17 Regression analysis of station rainfall data with SPI

According to the above correlation coefficient plot, there was a positive and Excellent relationship between SPI and rainfall data (r^2 = 0.91) and it was statistically significant with coefficient variation, signifying a positive relationship between the two Variables in the study area.

between. The relationship between rainfall and vegetation indices was also analyzed by Ashenif, 2016 to identify drought-vulnerable areas in Afar region of Ethiopia using 11 years' time series of decadal NDVI, VCI, DSI and SPI using SPOT (2005-2013) and PROVA-V (2014-2015) data. For the validation of drought indices, correlation and regression analyses between NDVI and rainfall (r = 75%), VCI and rainfall (r = 90%) were done.

4.7.2 Regression analysis of Station Rainfall data with NDVI

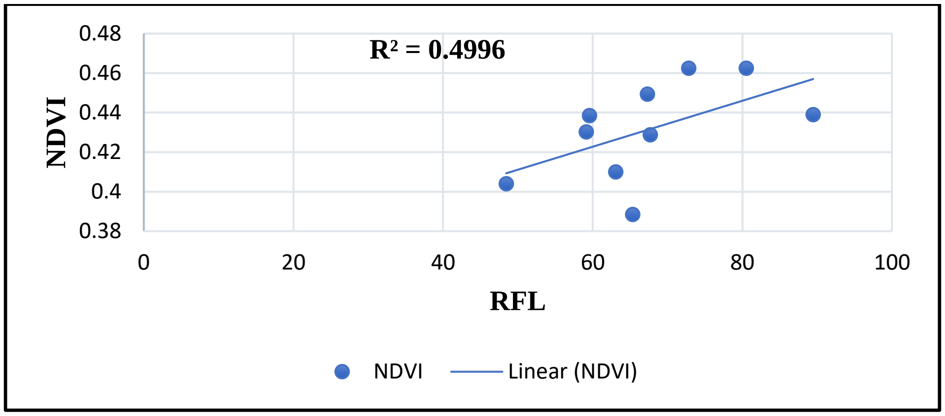


Figure 18 Regression analysis of station rainfall data with NDVI

Different researchers have tried to correlate NDVI and rainfall; in the same way this research was trying to show the relationship between NDVI and Rainfall like, Murthy, C et al 2017, Faridatul, m, 2020, Li et al., 2002; Nicholson & Farrar, 1994. According to the above correlation coefficient plot, there was a positive and good relationship between NDVI and rainfall data of station (r^2 = 0.49) and it was statistically significant with coefficient variation, signifying a positive relationship between the two Variables in the study area

4.7.3 Regression analysis of Station Rainfall data with VCI

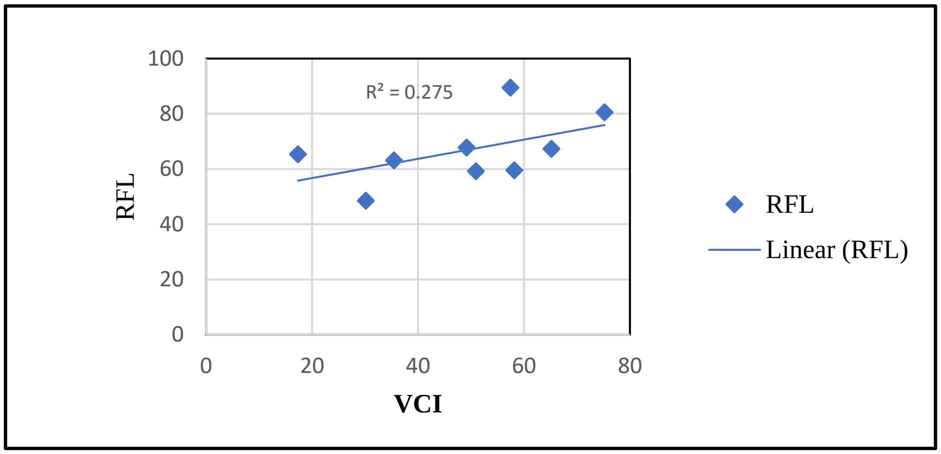


Figure 19 Regression analysis of station rainfall data with VCI

To confirm the existence of drought in study area, the link between VCI and mean monthly rainfall was examined. As a result, VCI and rainfall fluctuated. Spatially and temporally and the result shows positive with value of (r^2=0.275) relationship between both Variables. Chopra, (2006), Ashenif (2016), had made the same procedure and this study also tried to Assess the relationship between Rainfall and VCI.

4.8 Drought Vulnerability Classification

The final result of this paper is to categorize the drought vulnerable area of the Borana zone and also to produce the spatial drought vulnerability map of the zone. Based on this; drought vulnerability classification map was produced. It reveals that the area as mild vulnerable, moderate vulnerable, severe and extremely vulnerable. Based on this most part of south eastern and northern Some parts of the western and central areas are extremely vulnerable, while others are somewhat exposed. Arero, Miyo, Moyale, Dehas, Yabello, Melka soda, Bulehora, and Gelana are among the districts that are severely vulnerable to drought. Teltele, Dire, and Abaya are somewhat vulnerable, with some portions of the Abaya district categorized as extremely vulnerable. Small parts of Dillo and Teltele districts were among the regions that were mildly susceptible. Quantitively, about 752 hectare is extremely vulnerable 31086 hectare is severely vulnerable and 6933 hectares moderately vulnerable and 1100 hectares are mild vulnerable

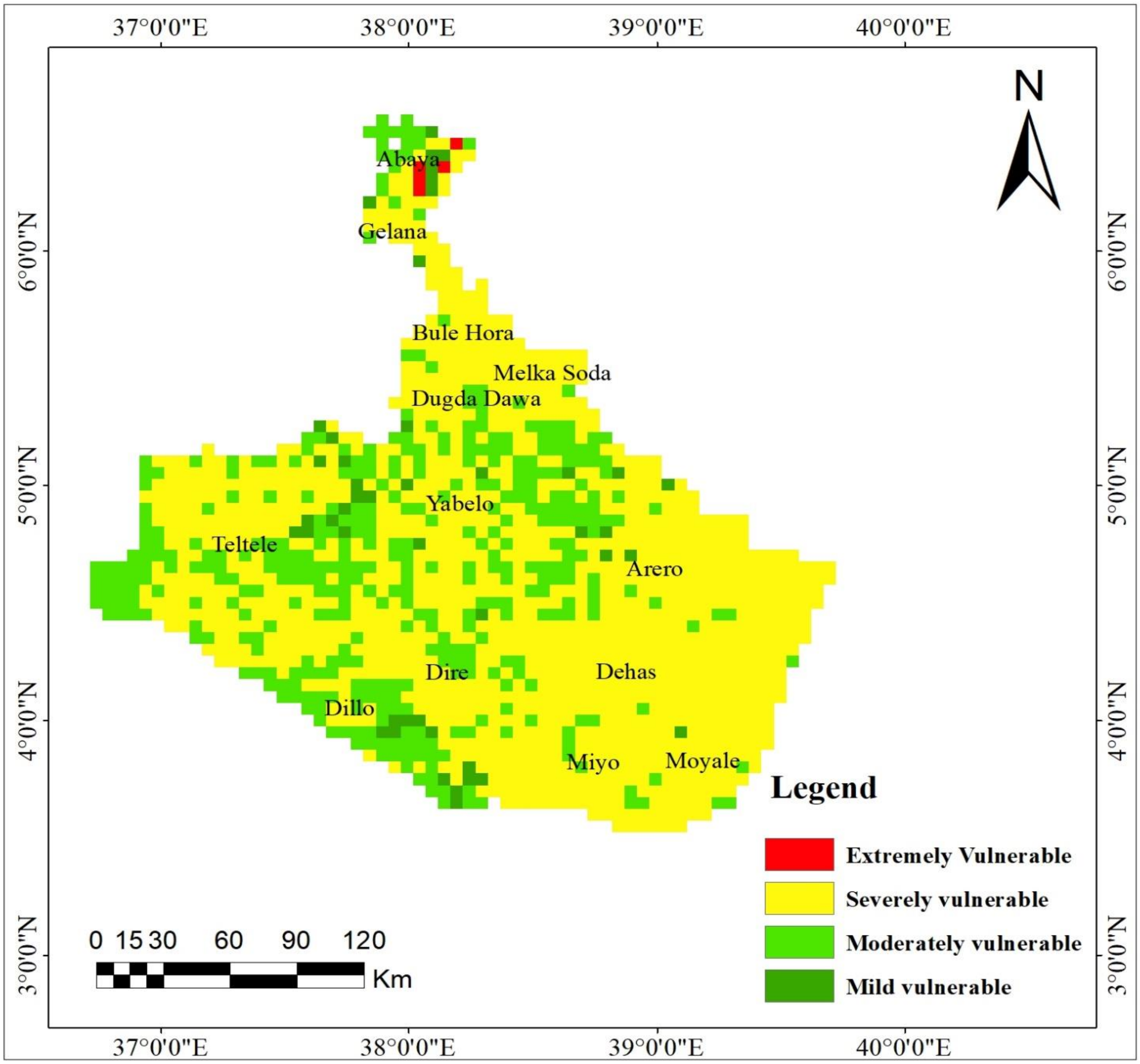


Figure 20 Drought Vulnerability map of Borana zone

Chapter five

5. Conclusion and Recommendation

5.1 Conclusion

Remotely sensed data, such as MODIS vegetation data, can be used to detect, monitor, and map the temporal and geographical extents and features of drought. Drought indices based on remote sensing were efficient in assessing drought in arid and semi-arid areas.

Droughts have occurred in Ethiopia on a semi-regular basis during the past several decades. Drought is caused by either natural or man-made factors, or both. The fundamental reason is a variation in the overall atmospheric circulation. As a consequence of such fluctuations the rain-producing components for Ethiopia have been weakened or dislocated during drought years. Drought recurrences are made more severe and last longer due to human interferences such as deforestation, overgrazing, and overcultivation in different pastoralist areas. The most affected were identified as inhabitants of the country’s southern and south-eastern Oromiya and Somali regions whose traditional livelihoods depend on the fertility of the land and the health of their livestock.

For those agro-pastoral and pastoral communities located near border areas, it is a normal coping mechanism to rely on the cross-border movement of livestock to search for water and land suitable for grazing. This mechanism works well under circumstances in which resources are adequate, however in case, resource- related conflicts and tensions were noted, as the movement of people and livestock in search of water and fertile land increased. According the federal Disaster Prevention and Preparedness Commission, Borana zone is one of the zones found at the border where drought is more frequent.

Accordingly, in this research, drought indices like NDVI, VCI, DSI, derived from MODIS vegetation data and PCI, SPEI and SPI which are from generated from Satellite rainfall and rain gauge rainfall data.

The correlation coefficient of derived drought indices and station rainfall data of the study area shows that there is positive and good relationship. As a result, it's possible to assume that the area is particularly vulnerable to drought. The area's drought sensitivity map reveals that the region is sensitive to drought in the mild to extreme range.

5.2 Recommendation

The researcher would like to make the following recommendations based on the findings of the study:

- ✓ Ethiopian meteorology Agency have to increase the availability of data for all meteorological stations with the required temporal and precision ranges to increase the effectiveness of analysis.
- ✓ According to the study's findings, areas with severe and extreme drought vulnerability require special attention in terms of preparedness in order to mitigate the effect and the Federal Disaster Prevention and Preparedness Commission have to be prepared for upcoming drought disaster.
- ✓ Based on the finding most part of south eastern and northern, some parts of the western and central areas are extremely vulnerable, as a result, catastrophe risk management is required, Preparedness, prevention, and response or mitigation.
- ✓ NGOs like UNICEF, WFP, IRC and USAID and other humanitarian organization have to prepare the way to mitigate the disaster.
- ✓ More study is needed to enhance the findings by factoring in other elements that determine drought risk areas.

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Appendix

Appendix 1 Simple linear Regression between NDVI and mean Annual rainfall

Regression Statistics	
Multiple R	0.747357
R Square	0.4996
Adjusted R Square	0.21205
Standard Error	0.021772
Observations	10

ANOVA

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.001622	0.001622	3.422045	0.101496
Residual	8	0.003792	0.000474		
Total	9	0.005414			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.353001	0.042864	8.235321	3.54E-05	0.254156	0.451846	0.254156	0.451846
RFL	0.001162	0.000628	1.849877	0.101496	-0.00029	0.002611	-0.00029	0.002611

Appendix 2 Simple Linear Regression between SPI Mean Annual Rainfall

Regression Statistics	
Multiple R	0.954305
R Square	0.910698
Adjusted R Square	0.899536
Standard Error	0.061026
Observations	10

ANOVA

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.303835	0.303835	81.584	1.8E-05
Residual	8	0.029794	0.003724		
Total	9	0.333628			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-1.06975	0.120149	-8.90354	2.01E-05	-1.34682	-0.79269	-1.34682	-0.79269
RFL	0.015906	0.001761	9.032386	1.8E-05	0.011845	0.019967	0.011845	0.019967

Appendix 3 Simple linear Regression Analysis between VCI and Mean Annual rainfall

Regression Statistics	
Multiple R	0.639969
R Square	0.409157
Adjusted R Square	0.203012
Standard Error	10.31238
Observations	10

ANOVA

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	350.1436	350.1436	3.292521	0.107145
Residual	8	850.7611	106.3451		
Total	9	1200.905			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	49.56741	10.32402	4.801172	0.001354	25.76017	73.37465	25.76017	73.37465
VCI	0.356275	0.196346	1.81453	0.107145	-0.0965	0.80905	-0.0965	0.80905

Appendix 4 Simple linear Regression Analysis between DSI and VCI

Regression Statistics	
Multiple R	0.999506
R Square	0.999013
Adjusted R Square	0.998889
Standard Error	0.000746
Observations	10

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.004507	0.004507	8096.056	2.6E-13
Residual	8	4.45E-06	5.57E-07		
Total	9	0.004511			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.06377	0.000747	-85.3714	3.95E-13	-0.06549	-0.06205	-0.06549	-0.06205
VCI	0.001278	1.42E-05	89.97809	2.6E-13	0.001245	0.001311	0.001245	0.001311

Appendix 5 Simple linear Regression Analysis between station-based and satellite-based PCI

Regression Statistics	
Multiple R	0.695865
R Square	0.484228
Adjusted R Square	0.419757
Standard Error	3.00349
Observations	10

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	67.75401	67.75401	7.510739	0.025427
Residual	8	72.16761	9.020952		
Total	9	139.9216			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-5.89094	8.18961	-0.71932	0.492419	-24.7762	12.99434	-24.7762	12.99434
STPCI	1.371184	0.500328	2.740573	0.025427	0.217427	2.524942	0.217427	2.524942

Appendix 6 Simple linear Regression Analysis between station based SPEI and satellite based SPEI

Regression Statistics	
Multiple R	0.732079
R Square	0.53594
Adjusted R Square	0.477932
Standard Error	0.510396
Observations	10

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.406831	2.406831	9.239144	0.016073
Residual	8	2.08403	0.260504		
Total	9	4.490861			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.0402	0.161692	-0.2486	0.809936	-0.41306	0.332667	-0.41306	0.332667
SATSPEI	4.62689	1.522205	3.039596	0.016073	1.116678	8.137102	1.116678	8.137102