DROUGHT RISK ANALYSIS AND MAPPING PART OF GOMBI LOCAL GOVERNMENT AREA, ADAMAWA STATE, NIGERIA USING REMOTE SENSING TECHNIQUES

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JANUARY, 2020

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BY

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A THESIS SUBMITTED TO THE DEPARTMENT OF SURVEYING AND GEO - INFORMATICS, SCHOOL OF ENVIRONMENTAL SCIENCES, MODIBBO ADAMA UNIVERSITY TECHNOLOGY, YOLA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTER OF TECHNOLOGY (M.TECH) DEGREE IN SURVEYING AND GEO-INFORMATICS

JANUARY, 2020

DECLARATION

I hereby declare that this project was written by me and it is a record of my own research work. It has not been presented before in any previous application for a higher degree. All references cited have been duly acknowledged.

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TUMBA, Luka Date

DEDICATION

This project work is dedicated to my Lord and Savior Jesus Christ for His infinite mercy.

APPROVAL PAGE

This project report entitled "**Drought Risk Analysis and Mapping part of Gombi L. G. A., Adamawa state, Nigeria using remote sensing techniques**" meets the regulations governing the award of Master of Technology of the Modibbo Adama University of Technology, Yola and is approved for its contribution to knowledge and literary presentation.

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Abstract

Drought is a natural hazard which has caused several impacts, such as decreasing of air and water quality, land degradation, forest fire, decreasing of agricultural crops production. This research aim is to monitor drought risk using remote sensing techniques this was achieved through analysis of changes in vegetation cover as a proxy to drought indices. To compute the Land Surface Temperature and map the areas facing drought based on risk categories. Landsat OLI 8 April for 2015, 2016, 2017, 2018 and 2019 were used which derived the following parameters NDVI, LST, VCI, TCI and VHI which ware used for drought risk analysis and mapping, the maps of those indices ware generated in QGIS environment, The results obtained from indices derived from the satellite-based indicators showed that, the year 2018 was the most drought-affected year in comparison to the other years. The results also indicate that in the year 2018 most of the areas that were affected by severe and extreme drought conditions has poor vegetation Health, 2017 and 2019 some of the areas that were affected by moderate to mild drought conditions. While in 2015 most of the area was affected by slight drought, from the research, findings shown that some of the villages that are under the threat and has to be prepared for mitigation to reduce the impacts of agricultural drought. It recommends that satellite data can be well utilized for regional level agricultural vulnerability detection for early warning of agricultural drought. Therefore recommends that the Society should seriously look into the drought issue through improving resource management practices and development of drought assessment and implementation unit to help minimize the adverse effects of drought. In doing this, concerned authorities should work closely with stakeholders who might be directly or indirectly affected by drought. Socio-economic data should also be taken into consideration when assessing drought risk to better understand the vulnerable groups.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AVHRR	Advanced Very -High-Resolution Radiometer
AVI	Anomaly Vegetation Index
BT	Brightness Temperature
DIS	Drought Information System
EDI	Effective Drought Index
et al.	and others
etc.	Etcetera
GIS	Geographical Information System
GVI	Global Vegetation Index
LAI	Leaf Area Index
LST	Land Surface Temperature
MID	Multi-index Drought
MIS	Moisture Stress Index
MODIS	Moderate Resolution Imaging Spectro- radiometer
NADA MAS	National Agricultural Drought Assessment and Monitoring System
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
% :	Per cent
OLI	Operational Land Imager
PDSI	Palmer Drought Severity Index
RAI	Rainfall Anomaly Index
SPI	Standardized Precipitation Index
SWI	Standardized Water –level Index
TCI	Temperature Condition Index
TIR	Thermal Infrared
TOA	Top of Atmosphere
TVDI	Temperature Vegetation Dryness Index
TVI	Temperature Vegetation Index
USGS	United State Geological Survey
VCADI	Vegetation Condition Albedo Drought Index

VCI	Vegetation Condition Index
VDI	Vegetation Drought Index
VDRI	Vegetation Drought Response Index
VHI	Vegetation Health Index
VTCI	Vegetation Temperature Condition Index
WiFS	Wide -image Field Sensor
YVI	Yellow Vegetation Index

CHAPTER ONE: INTRODUCTION

1.1 Background to the Study

Drought is natural hazards that frequently occur in some regions and is caused by the deficiency of precipitation. It has negative impacts such as decreasing air and water quality, land degradation, forest fire, decreasing agricultural crop production. It has led to water conflict at the same time, forcing people to migrate. The Drought mapping is essential to prevent and minimize the impact of drought occurrence. The Drought indices are a combination of drought indicators (temperature, Precipitation, vegetation condition, evapotranspiration, etc.) to provide more comprehensive information for drought analysis than using raw data of each indicator. Niemeyer (2005) categorized drought indices into three types, namely; comprehensive, combined and remote-sensing-based drought indices.

The Comprehensive drought indices using meteorology, hydrology and vegetation indicators for describing the drought more widely, Palmer Drought Severity Index (PDSI) is one of the comprehensive drought index calculated by using evapotranspiration, runoff, soil recharge, and precipitation indicators. Combination drought indices are an index combination of two or several drought indices used for drought mapping and monitoring. Examples of such are the combination of several drought indexes, namely the Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), vegetation, and hydrology variable. Remote sensed indices defined as an index that using remote sensing data for mapping the drought condition in a particular area or region. Zargar *et al.* (2011) Remote-sensing-based drought indices are widely used because the processing of satellite data is a faster, inexpensive, and efficient tools for drought monitoring than using observational data Dalezios *et al.* (2014)There are many remote-sensing-based drought indices used for drought assessment, the vegetation condition index is commonly used to identify the changes of vegetation from bad to optimum condition while Vegetation Health Index (VHI) describes vegetation health from the combination of (TCI) Temperature Condition Index and vegetation condition Index. TCI, VCI, and VHI are remote-sensing-based indices used for drought monitoring in a particular area.

Wilhite *et al.* (1985), American Meteorological Society Intensity refers to the degree of precipitation shortfall and is closely linked to the duration in the determination of its impacts. To some extent, drought occurs with uncertainty at a micro-scale, and drought occurrence sites vary from time to time when studying spatial distributions of drought (Wang 1998). Meteorologically based drought monitoring refers to point-based analyses, which might include simple presentations of specific events relative to their long-term historical averages (often denoted as ‘normal’). The point-based drought indices have been used extensively for monitoring drought and for making operational water indices such as the Normalized Difference Vegetation Index (NDVI) and to retrieve Land Surface Temperature (LST). NDVI not only maps the presence of vegetation on a pixel basis but also provides the density of vegetation within a pixel. LST is a good indicator of the energy balance at the Earth’s surface because it is one of the key parameters in the physics of land-surface processes on regional and global scales. AVHRR NDVI was applied successfully to classify land vegetation types Menenti *et al.* (1993) and monitor vegetation growth conditions from excellent to stress.

1.2 Statement of the Problem

Drought is one of the major environmental disasters which have been occurring in almost all climatic zones and damage to the environment and economics of Adamawa State has been extensive and the death toll of livestock unprecedented. Drought damages are more pronounced or prominent in areas where there is a direct threat to livelihoods. Gombi Local Government Area with a population of 101,100 people according to (NPC 2006),and is an agriculture Area which is 85 percent out of the population is engaged in agriculture and earn livelihood directly from this occupation. Moreover, agriculture provides indirect employment to a large portion of the population in agro-based occupations. Thus, the prosperity and wellbeing of people in Gombi are closely linked with agriculture and allied activities. Agriculture Development in the Local Government is to a large extent dependent, on availability of water. The arid climatic condition in Gombi, characterized by erratic rainfall and successive drought years together with a high rate of industrial development and excessive water mining has adversely affected production levels thereby increasing drought risk, As the drought and desertification are increasing to affect Northern Nigeria at large Oladipo, EO (1993).The evaluation of probable risk arising out of the drought in the region would help in developing better management plans for mitigating drought impacts.

1.3 Aim and Objectives

The aim of this research is to monitor drought risk using remote sensing techniques The aim are be achieved through the following objectives

i. To analyze changes in vegetation cover as a proxy to drought indices.
ii. To compute the Land Surface Temperature.
iii. To mapped the areas facing drought based on risk categories.

1.4 Justification

From the foregoing literature, Drought impacts in various ways. The effect of drought may be direct or indirect, singular or cumulative, immediate or delayed. Droughts lead directly to poor crop yield, famine, deterioration of pasture, dead of livestock, etc. The direct losses caused by drought are more complex and many. Some of them lead to changes in land-use practices, abandonment of fertile lands, migration of rural population, heavy pressure on urban areas and so on. These put a severe strain on the economic development of a nation, either immediately or with a time lag Appa, (1987). Documentation on the extent and consequences of some drought events has well been well made, but with most limited in scope (Oladipo *et al,* 1995). For example, Apeldoorn (1981) considered only the spatial coverage and socio-economic impacts of some drought events. Little or no efforts have so far been made by scholars to assess drought incidences in Yola, Adamawa State Nigeria. The present study hence assesses the characteristics of meteorological drought in the town. The area is characterized by marked rainfall variability both seasonally and annually, this makes the area highly susceptible to drought.

1.5 Significance of the Study

The research shows motivating results that can be used in taking corrective measures timely to minimize the reduction in agricultural production in drought-prone areas. The results obtained provide objective information on prevalence, severity level and persistence of drought conditions, which will be helpful to the resource managers in optimally allocating scarce resources. Barring a few reports on drought, a systematic study in relation to drought in Gombi has not been done earlier. Similarly, a comprehensive scientific analysis of drought and usage of advanced technologies like Remote Sensing and GIS has not been effectively exploited. Such a study will help in making drought mitigation plans for the Local Government which further can be useful in the proper management of water resources to avert any drought kind of situation in the Local

Government. Hence, there is a need for a systematic scientific study on the assessment of drought based on various drought indices for the Gombi Local Government area.

1.6 Scope of the Study

The study area is limited to part of Gombi Local Government Area, Adamawa state. The study was to carry out drought risk analysis and mapping in the areas, using remote sensing techniques. The approach involved analyze change in vegetation cover as a proxy to drought, computing Land Surface Temperature and mapping or indentify areas facing drought based on risk categories. The data used Landsat 8 OLI which derived the following indices Vegetation Condition Index (VCI) derived from the Normalized Difference Vegetation Index (NDVI) and Temperature Condition Index (TCI) derived from Land Surface Temperature (LST) and Vegetation Health Index (VHI) is the combination of Vegetation Condition Index and Temperature Condition Index, QGIS software ware used to produce the results.

1.7 The Study Area

1.7.1 Location and Extent

The study area compasses the following villages; Dongo Gure, Dongo, Wuro Sanyobe, Ga'anda, Ujabeda , Sabon gari, Sabon gida, Guyaku, Dadwari, Wano, Muchalla, Usenyi, Gombi Fulani, Nyadanya, Zavatiniyan, Sabon gari, Wungala,Kaudi, Boga, Waro, Shidrinda, Kaninkafa and Wandekwuna as shown in(Figure 1.2) The study area lies between latitude 08^{o} 54' 40" to 11^{o} 50'30" N and longitude 12^{o} 20' 40" to 18°14'30" E. Gombi local government area as shown in (figure 1.1) and statistical summary of the observed weather conditions of the study area from 1979 to 2014 are shown in (Table1.1), the study area shares common boundaries with Hong Local Government to the east, Song Local Government Area to the South, Shani and Hawul Local Government area of Borno State.

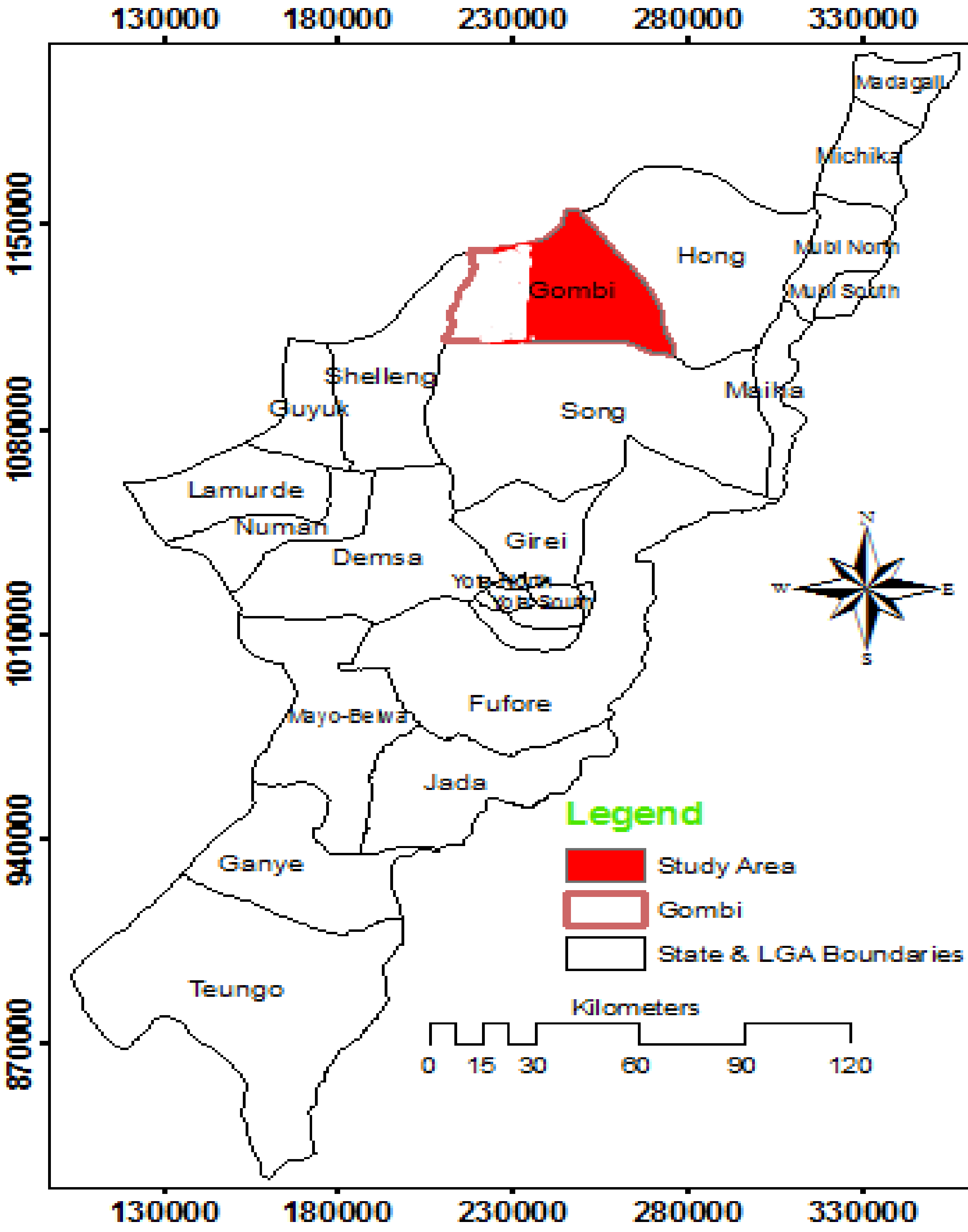


Figure 1.1 map of Adamawa shows the study area

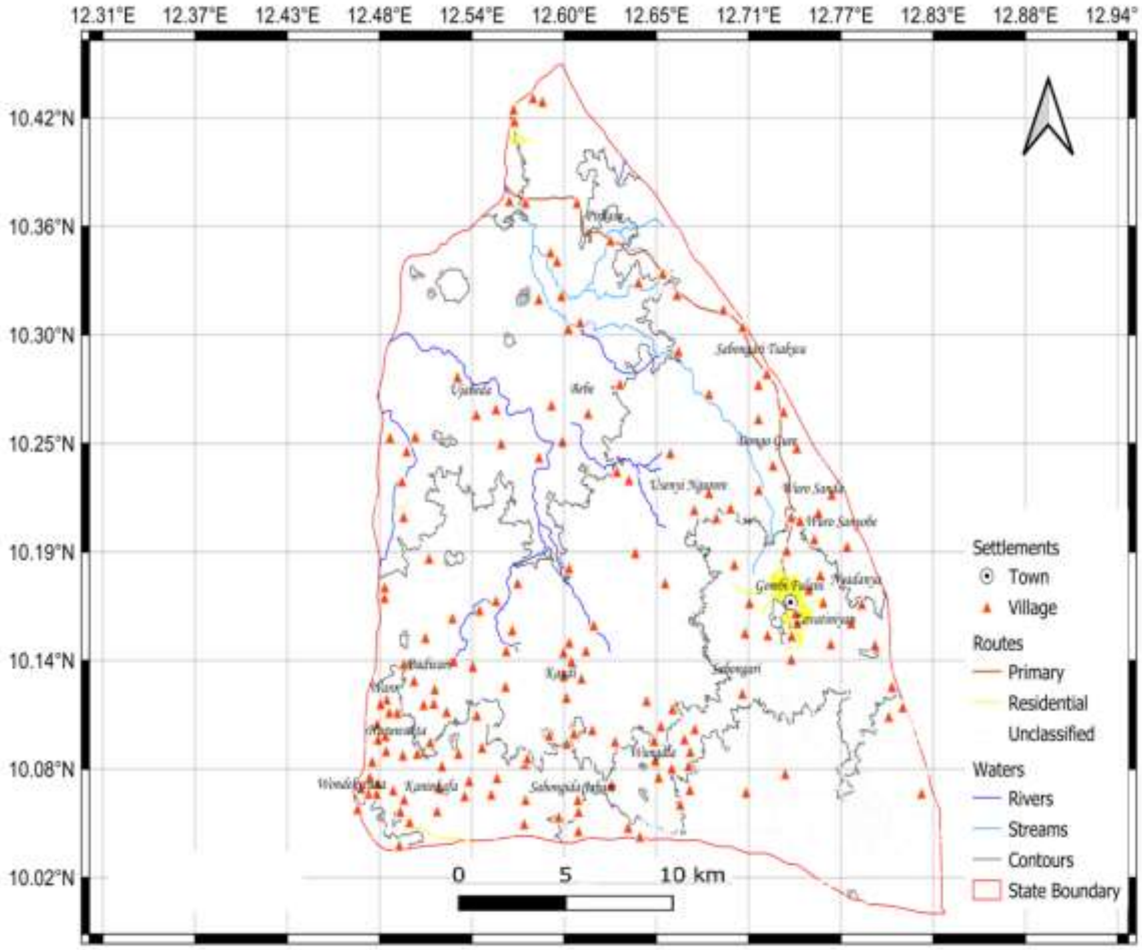


Figure 1.2: A map of the study area with settlements and 30m contours intervals.

Table 2.1: A statistical summary of the observed weather conditions of the study area from 1979 to 2014

	Max. Temperature (°C)	Min. Temperature (°C)	Precipitation (mm)	Wind Speed (m/s)	Relative Humidity (fractions)	Solar Flux (MJ/m^2)
Minimum	18.770	7.564	0.000	0.690	0.039	0.807
Average	35.340	19.296	3.891	2.448	0.459	20.230
Maximum	49.970	29.241	177.398	5.805	0.976	30.226

1.7.2 Climate

The climatic conditions of the region are fairly constant; temperature in this region is high during most parts of the year because of the radiation flux which is relatively high and distributed throughout the year. The highest Maximum temperature of 49.97°C and Minimum temperature of 7.56°C (Table 1.1) was recorded during the period of 1979 to 2014. The average temperature recorded for the period of the observation was 35.34° maximum and 19.29°C minimum. The yearly average revealed that the lowest ambient temperature (about 35.15°C) year 2010 while the highest (about 37.64°C) was recorded in 2006 (Figure 1.3). The rainfall is the most variable element with the highest precipitation of 177.39mm but, the average observed was 3.89mm. The monthly average revealed that the rainfall starts in April and ends in October from the following years 1979 to 2014 while the year 1995 was observed to have the highest precipitation (Figure 1.4). The maximum relative humidity observed was 0.9 fractions with an average of 0.46 fractions. The yearly average revealed that the highest relative humidity (about 0.97 fractions) was observed in 1982 which coincides with peak precipitation (Figure 1.6). The maximum wind speed observed was 5.80m/s with an average of 2.44m/s. however, the yearly average revealed that the wind speeds are high in the year 2000 (Figure 1.5). The maximum observed of solar radiation flux 2011 and minimum observed is 1992 as shows in (figure 1.7)

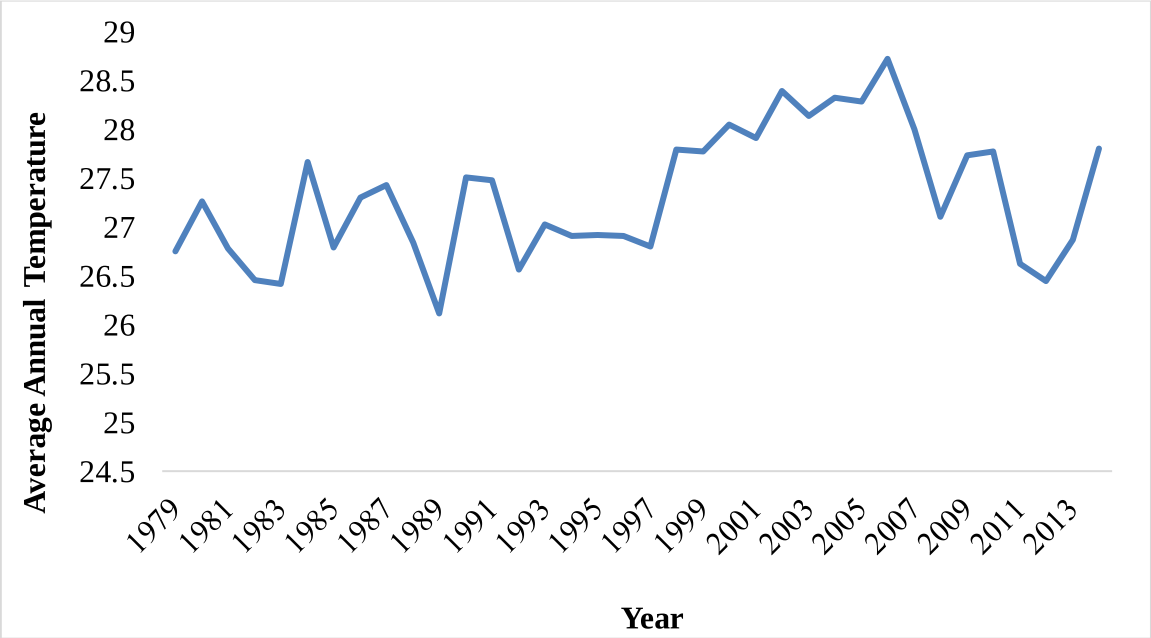


Figure1.3: Yearly Average Maximum and Minimum Temperature for the Study area.

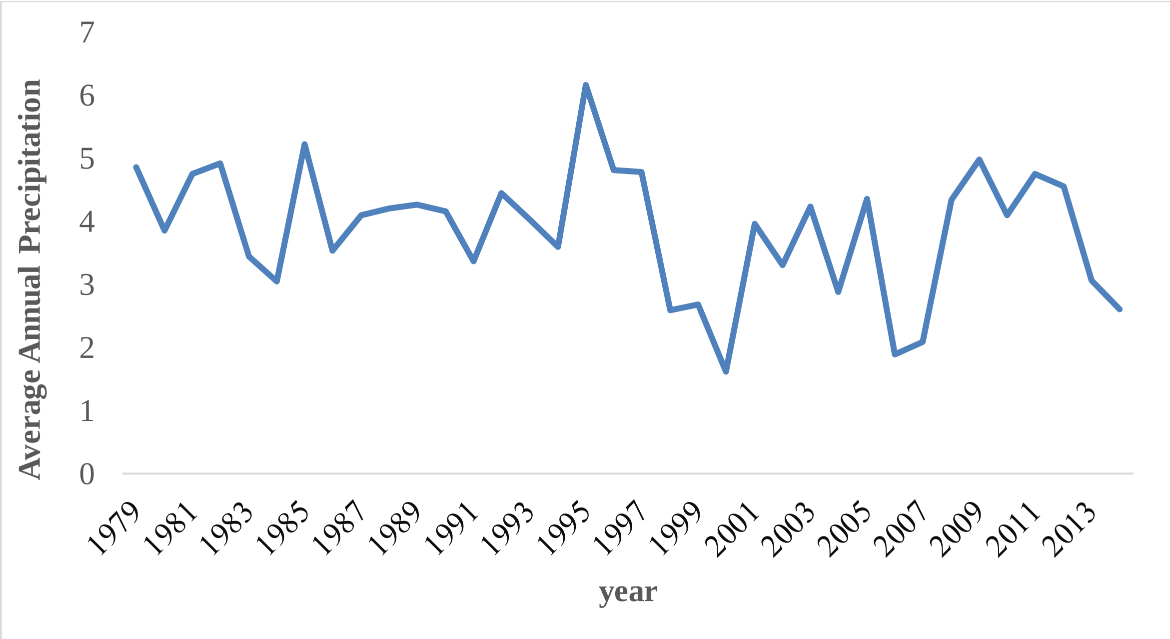


Figure 1.4: Yearly Average Precipitation for the Study Area.

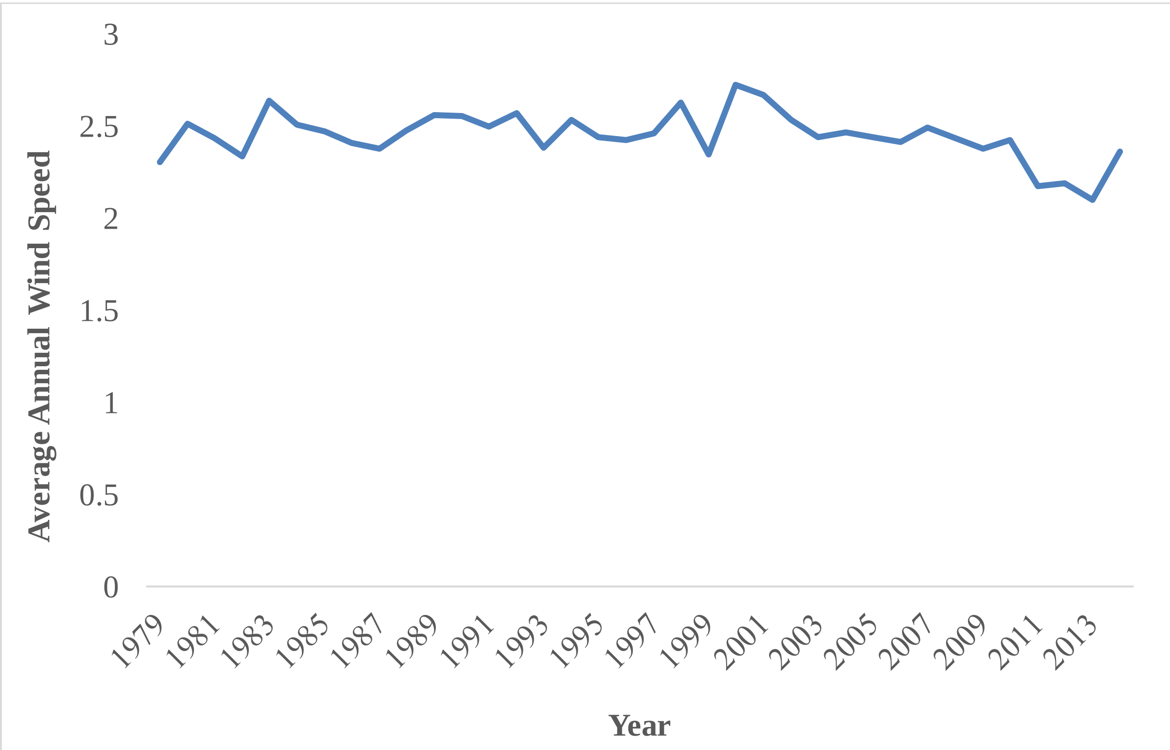


Figure 1.5: Yearly average wind speed for the study area

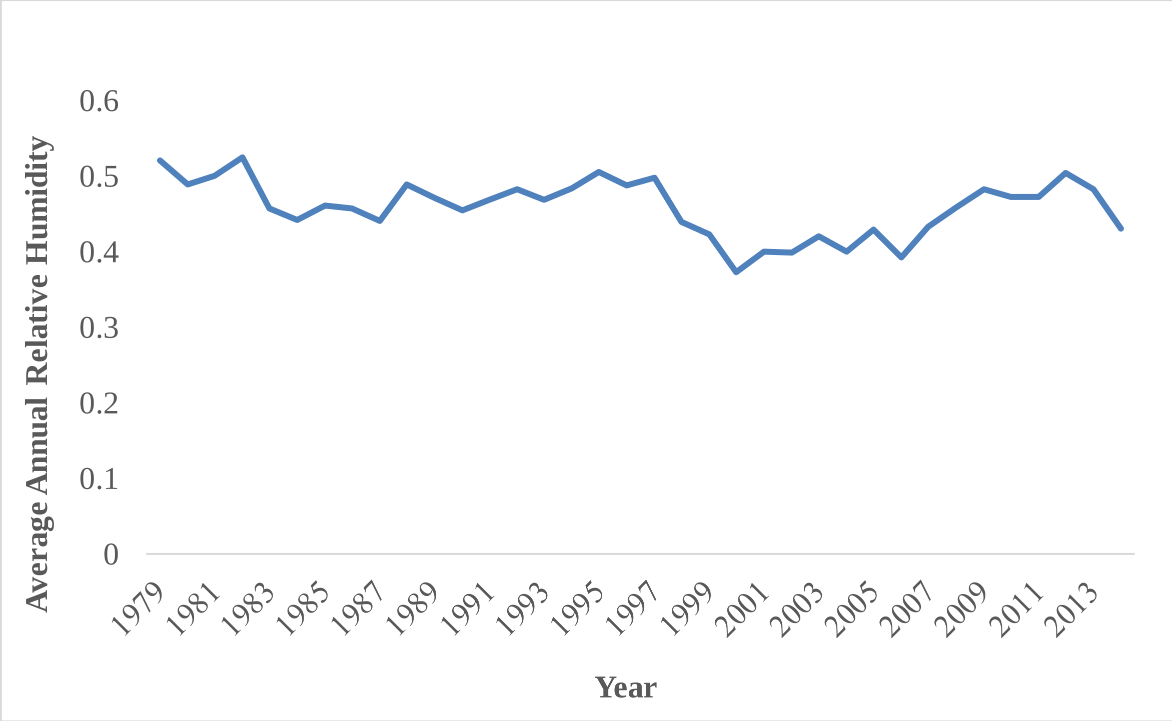


Figure 1.6: Yearly average Relative Humidity for the study area

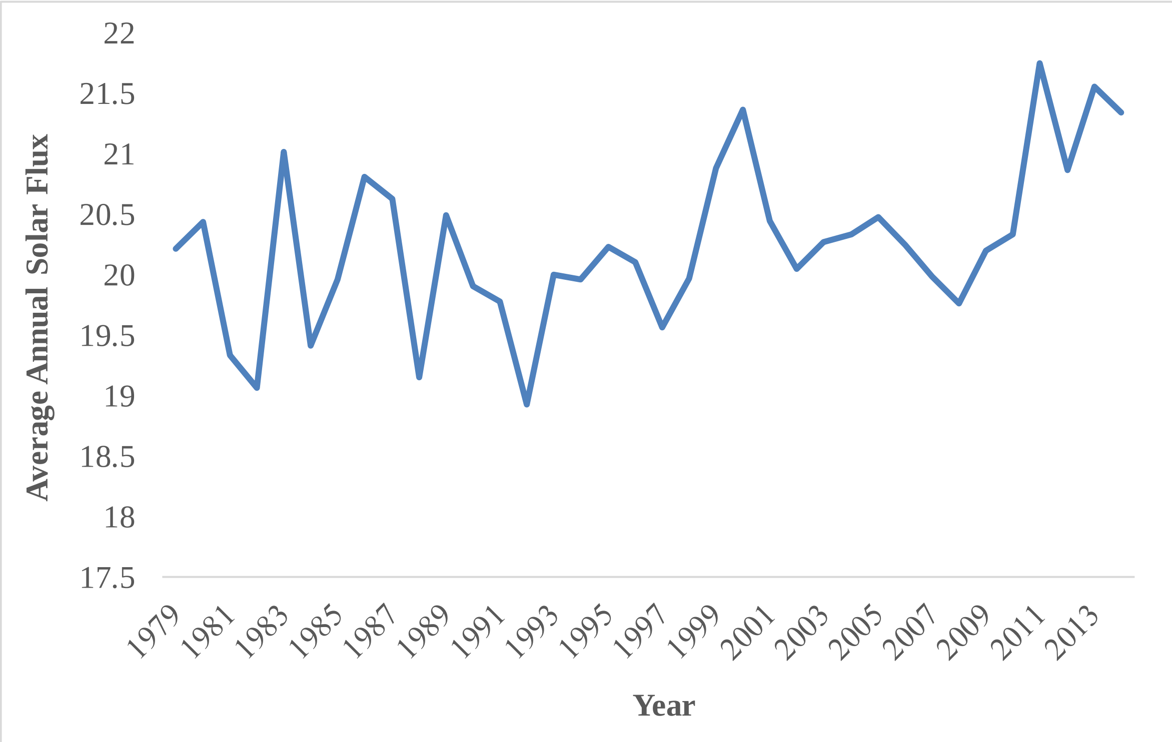


Figure 1.7; Yearly average solar radiation flux for the Study Area,

1.7.3 Soil and Vegetation

The study area (Figure 1.2) the vegetation is Guinea Savannah, this zone is characterized by tall grasses and short scattered grasses and trees. It has a hilly and mountainous terrain. The hill has a general height of about 750-800 meters above sea level. Some of the physical features found around the area include Garkida Fwuhar escarpment, Virgwi escarpment, Ga'anda escarpment and Girgithlang hills which form part of the undulating landscape.

1.7.4 Topography

Gombi Local Government is the fourth largest in Adamawa State. The total land area is approximately 2,093.3 square kilometers; the population constitutes an essentials segment of the resources based and development potential of any society

1.7.5 Population and land use

According to the 2006 population census in Nigeria, the population of Gombi Local Government area was 101,100 people, this population is made up of several ethnic groups, among which are Bura, Ngwaba, Hwona, Fulani, Ga'ada, Lala, Kilba, Chibok, Margi, and Yungur. These heterogeneous ethnic groups have been coexisting peacefully and they pay greater attention to agriculture and trade. Farming is the major occupation of the people of the area with cowpea, groundnut, and maize as the most cultivated crops. Other crops cultivated include soybeans, rice, and sorghum. However, the people also engage in some activities like rearing of animals, fishing, hunting, and trading.

CHAPTER TWO: LITERATURE REVIEW

2.1 Concept of Remote Sensing Technique in Drought risk Mapping

The mitigation of the effects of disasters requires relevant information regarding the disaster in real-time. Also, the possible prediction and monitoring of the disaster requires rapid and continuous data and information generation or gathering. Since disasters that cause huge social and economic disruptions normally affect large areas or territories and are linked to global change, it is not possible to effectively collect continuous data on them using conventional methods. The space technology or remote sensing tools offer excellent possibilities of collecting this vital data. This is because the technology has the capability of collecting data at global and regional scales rapidly and repetitively and the data is collected in digital form. The technology further provides an excellent communication medium. The satellite or remote sensing techniques can be used to monitor the current situation- before, during or after a disaster. They can be used to provide baseline data against which future changes can be compared while the GIS techniques provide a suitable framework for integrating and analyzing the many types of data sources required for disaster monitoring. In recent years, the ever-increasing population and overstress on natural resources, soil degradation, decrease in water resources, and future projected climate change scenarios have become important areas of concern. The main goal of global agriculture is to feed 6 billion people, a number likely to double by Kogan (2000).

The first requirement of a living creature is food, and a setback in agricultural and fodder production leads to socio-economic unrest especially in developing countries. Therefore, the management of natural resources in developing as well as developed countries requires information on the state and changes in a range of biophysical variables. Droughts have been viewed as such a disaster wherein a shortfall in precipitation has led to a substantial reduction in production levels thereby leading to conditions that cause large scale migration and death of people and animals. The impact of drought on society and agriculture is a real issue but it is not easily quantified. Reliable indices to detect the spatial and temporal dimensions of drought occurrences and its intensity are necessary to assess the impact and also for decision-making and crop research priorities for alleviation (Kogan *et al,* 1998). The development and advancements in space technology, to address issues like drought detection, monitoring and assessment have been dealt with very successfully and helped in the formulation of plans to deal with this slow-onset disaster. With the help of environmental satellite, drought can be detected 4-6weeks earlier than before and delineated more accurately, and its impact on agriculture can be diagnosed far in advance of harvest, which is the most vital for global food security and trade (Kogan 1990).

Several indices have been developed for the quantification of drought based on the type of drought. Palmer Drought Severity Index (PDSI) developed by Palmer (1965), is the most widely used drought index based on the demand and supply concept of the water balance equation. Palmer (1968) derived another index, the Crop Moisture Index (CMI) by modifying PDSI to find out the severity of the agricultural drought. Hydrological droughts characterized by low precipitation, lowering of groundwater tables, fall in the level of lakes and Surface Water Supply Index (SWSI) assessed reservoirs. A brief review of these indices is given in the next section. With the advancements in remote sensing technology, the historical drought indices were overpowered by the newly developed indices from remote sensing data that are considered to be real-time. Also, remote sensing has provided complete coverage of extended regions with a spatial resolution of a few hundred meters to a few kilometers. Thus, for an accurate assessment of the occurrence extent and severity drought, it is necessary to get a correct picture of the spatial and temporal distribution of a number of meteorological, hydrological and surface variables. Space observation having this potential has made a significant contribution to this field. The satellite sensors that have the capability to retrieve surface parameters with high spatial and temporal resolutions over large areas have provided a comprehensive view of the situation. Many drought studies have made extensive use of the AVHRR derived data, as it monitors earth's surface changes continuously, freely accessible and moreover it’s widely recognized around the world.

2.2 Drought Definitions

According to McMahan *et al.* (1982), “Drought is a period of abnormally dry weather sufficiently for the lack of precipitation to cause a serious hydrological imbalance and carries the connotation of a moisture deficiency with respect to man’s usage of water. Another definition given by the flag is worth mentioning. “Drought is a period of rainfall deficiency extending over months or year of such a nature that crops and pasture for stock are seriously affected, if not completely burnt up and destroyed, water supplies are seriously depleted or dried up and sheep and cattle perish.

Studying the above definitions, it can be understood that drought is mainly concerned with the shortage of water which in turn affects the availability of food and fodder, thereby, leading to displacement and loss to economics as a whole.

2.2.1 Types of Drought

Drought can be classified into four major categories;

a) **Meteorological Drought**; It simply implies rainfall deficiency where the precipitation is reduced by more than 25% from normal in any given area, these are region-specific, since deficiency of precipitation is highly variable from region to region.

b) **Hydrological Drought;** These are associated with the deficiency of water on the surface or sub-surface due to shortfall in precipitation, hydrological drought is mainly concerned about how this deficiency affects components of the hydrological system such as soil moisture, stream flow, groundwater and reservoir level, etc.

c) **Agricultural Drought;** this links various characteristics of meteorological drought to agricultural impacts, focusing on precipitation shortages, Difference between actual potential evapotranspiration, soil water deficit, and reduced groundwater or reservoir levels. Plant water demands UN prevailing weather conditions, biological characteristics of the specific pant, and its stage of growth and the physical and biological properties of the soil.

d) **Socio-Economic drought;** it is associated with the demand and supply aspect of economic goods together with the elements of Meteorological, Hydrological and Agricultural drought. This type of drought mainly occurs when the demand for an economic good exceeds its supply due to the weather-related shortfall in the water supply.

2.2.2 Effects of Drought

The impacts of drought, in general, include mass starvation, famine, and cessation of economic activity especially in areas where rain-fed agriculture is the mainstay of the rural economy. It is common knowledge that drought is the major cause of forced human migration and environmental refugees, deadly conflicts over the use of dwindling natural resources, food insecurity, and starvation, destruction of critical habitats and loss of biological diversity, socio-economic instability, poverty and climatic variability through reduced carbon sequestration potential. The impacts of drought and desertification are among the most costly events and processes in Africa.

The widespread poverty, the fact that Nigeria’s economy depends on climate-sensitive sectors mainly rain-fed agriculture, poor infrastructure, heavy disease burdens, high dependence and unsustainable exploitation of natural resources, and conflicts render the country especially vulnerable to impacts of drought.

2 .3 Impacts of Drought

The impact of a drought can be economic, environmental or social drought produces a complex Wels of the impact that spans many sectors of the economy and reaches well beyond the area experiencing physical drought. The complexity exists because water is integral to society's ability to produce goods and services. Impacts are commonly referred to as direct and indirect. Direct impacts include reduced crop rangeland, and forest productivity increased fire hazard, reduced water levels, and increased livestock and wildlife mortality rates and damage to wildlife and fish habitats. The consequences of this direct impact illustrate indirect impacts, for example, a reduction in crop, rangeland and forest productivity may result in reduced income for farmers and agricultural businesses. Increased prices for food and timber unemployment and reduced tax revenue because of reduced expenditures on bank loans to farmers and business.

2.3.1 Economic Impacts

Many economic impacts occur in agriculture and related sectors, including forestry and fisheries, because of the reliance of these sectors on surface and subsurface water supplies, in addition to obvious losses in yields in crop and livestock production, drought is associated with increases in insect infestation, plant disease, and wind erosion drought also bring increased problems with insects and disease to forests and reduce growth. The incidence of forest and range fires increases substantially during extended droughts, which in turn places both human and wildlife populations at higher levels of risk.

2.3.2 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 the effects are short. Term and condition quickly return to normal following the end of the drought. Other environmental effects linger for some time or may even become permanent. Wildlife habitat, for example, maybe degraded through the loss of wetlands, lakes, and vegetation. However, many from this temporary aberration the degradation of landscape quality, including increased soil erosion, may lead to a more permanent loss of biological awareness and concern for erosion

.productivity of the landscape, Although environmental quality has forced public officials to focus greater attention and resources on the effects.

2.3.3 Social Impacts

Social impacts involve public safety, health, conflicts between water users, reduced quality of life, and inequities in the distribution of impacts and disaster relief. Many of the impacts identified as economic environmental have social components as well; population migration is a significant problem in many countries, often stimulated by a greater supply of food and water elsewhere. Migration is usually to urban areas within the stressed area, or to regions outside the drought area. Migration may even be to adjacent countries.

2.4 Drought risk evaluation

Risk assessment involves evaluation of the significance of a risk, either quantitatively or qualitatively. Risk assessment/evaluation according to Kates and Kas person (1983) comprises of three steps:

- Identification of hazards, which may cause disasters.
- Estimation of risks arising out of such events and
- Estimation of losses

Even though there has been a tremendous increase in food production since the green revolution, frequent droughts offset this gain and result in food shortages to feed the ever-growing population, thereby leading to famines, deaths and human suffering on the whole. It has been said, “Drought follows the plow” (Glantz1994), a statement that has proved true. Since drought is basically related to the shortage of water, it has far-reaching economic, social and environmental impacts. These impacts affect a much greater area than is the case with the other natural hazards, which are limited in terms of spatial coverage. For example, floods are confined to areas along flood plains; tornadoes are local in coverage; hurricanes may affect relatively large areas but mainly along coastlines, even the area affected by the recent tsunami doesn't compare in the area affected by droughts. Droughts may affect hundreds of thousands of square kilometers. Impacts, therefore, occur every year and have cumulative effects because they are often multi-year events. Drought impacts have not been well quantified economically; officials tend to underestimate the importance of drought and often fail to be proactive in preparing for droughts. Also, society’s vulnerability to drought is affected by population growth and shifts, urbanization, technology, demographic characteristics, water use trends, government policy, social behavior, and environmental awareness. These factors are continually changing and society's vulnerability to drought may rise or fall in response to these changes. Therefore assessment of probable risk arising out of this slow disaster would certainly help people adopt corrective measures in time to rule out the social and economic disruption caused.

2.4 .1 Need for drought risk evaluation and management

In drought management, making the transition from crisis to risk management is difficult because little has been done to understand and address the risks associated with drought. Droughts cause misery to both the human and livestock population, accelerate the degradation of natural resources and put heavy pressure on the government's resources through relief measures.

2.4.2 Drought in Nigeria

Drought occurrences and reoccurrences have been reported in Nigeria for decades Abaje *et al*, (2011), however, of recent, the occurrences have increased, while gradually the occurrences have spread southward especially to the Sudan zone of Nigeria. At the same time, it seems the severity of drought in the Sahel zone has increased Olatunde (2011) this means drought occurrence is a constant hazard and reality for people in this area. Therefore, there is a need to constantly look into its characteristics over time. Drought or dry spells at the beginning or end of the season had a constant reoccurrence decimal since the beginning of the 20th century. Large areas of Northern Nigeria falling within the Sahel and Sudan ecological zones between latitude 9°-14°N are prone to recurrent droughts in one form or the other. The area is estimated to be about 38% of the total land area of Nigeria and it is the grain belt of the country populated by small scale subsistence farmers and nomadic livestock herders. The underlying cause of most droughts can be related to changing weather patterns such as low rainfall, reduced cloud cover and greater evaporation rates which are exacerbated by human activities such as deforestation, bush burning, overgrazing, and poor cropping methods, which reduce water retention of the soil. The impacts of drought are mass starvation, famine, and cessation of economic activity especially in areas where agriculture is the mainstay of the economy. Drought is the major cause of forced human migration and environmental refugees, deadly conflicts over the use of dwindling natural resources, food insecurity and starvation, destruction of critical habitats and loss of biological diversity, socio-economic instability, poverty, and climatic variability through reduced carbon sequestration potential. The impact of the drought could be reduced through irrigation, use of drought-tolerant and early and extraearly maturing varieties, reduction of post-harvest crop losses, increased fisheries and micro livestock production and strategic grain storage.

Usman *et al.* (2014) investigated the temporal variation of drought in Nigeria from 1922 to 2013 using SPI. Their assessment showed that drought severity and frequency of occurrence vary in the study area. The results revealed that there was only one occurrence of extreme drought from 1922 to 1970 whereas from 1971 to 1983 severe and three extreme droughts were recorded. They concluded that severe and extreme droughts have severities of 1 in 30 and 1 in 23 years, respectively.

2.5 Indices use for this Research

Several indices, which could be used for drought monitoring, have been developed over the past few decades using remote sensing data. They are calculated from reflectance and brightness temperature in different bands and may be obtained for each pixel (the size of the pixel depends upon the resolution of a sensor). These indices have a few advantages over conventional climate data related indices, as they cover large areas and may show drought is progressing over the area. They have to be calibrated against ground climate data most commonly applied are discussed below

2.5.1 Normalized Difference Vegetation Index (NDVI)

The normalized Vegetation Index (NDVI) is related to the proportion of photo synthetically absorbed radiation many natural surfaces are about equally as bright in the visible red and near-infrared part of the spectrum with the notable exception of green vegetation. Red light is strongly absorbed by photosynthetic pigments (such as chlorophyll) found in green leaves, while near-infrared light either passes through or is reflected by life leaf tissues, regardless of their color. This means that areas of bare soil having little or no green plant vegetation will be very bright in the red infrared regions of the spectrum. The Normalized Difference Vegetation Index (NDVI) provides measures of the amount and vigor of Vegetation at the land surface. The magnitude of NDVI is related to the level of photosynthetic activity in the observed vegetation. In general higher values of NDVI indicates greater vigor and amount of vegetation so, the Normalized Difference Vegetation Index (NDVI) provides us with an indication of how much green vegetation exists at a particular place on the ground. The NDVI values range from -1 to 1 with most values ranging from 0 to 0.6. Healthy green vegetation has a high NDVI value because more near-infrared light is reflected so the NDVI would be near zero water and ice reflect a light redder the near-infrared light so those values tend to be slightly negative, two characteristic of the NDVI that make it ideal for vegetation monitoring is that no other surface exhibits higher NDVI values than Vegetated surfaces and that, when vegetation vigor changes due to the nature of vegetation growth and development or environmental induced stress such as drought.

2.5.2 Land surface temperature (LST)

To estimate the LST from thermal infrared (TIR) band data of Landsat-8 OLI, DN of sensors were transformed to spectral radiance using equation(2.1) Barsi *et al.* (2014).

$$Ll=ML\times Qcal+AL-Q \qquad (2.1)$$

Where:

ML = the band-specific multiplicative rescaling factor

•Qcal = the Band 10/11 image

•AL = the band-specific additive rescaling factor

•Qi = the correction for Band 10/11

Spectral radiance is converted to brightness temperature by assuming the earth of surface is a black body (Chander *et al.*, 2009; Coll *et al.*, 2010): NDVI and LST can be compared to analyses drought conditions in the region since these products are sensitive to drought-related stress. Similar studies are reported in the USA (Swain *et al.*., 2011) and Iran (Zarei *et al.*., 2013).

When changes in vegetation cover and soil moisture occur the surface temperature can rise rapidly with water stress. There is a strong correlation between surface temperature and NDVI and LST is a good indicator of the energy balance at the Earth’s surface which can provide important information about the surface physical properties and climate (Sruthi *et al.*., 2015).

However, Sruthi *et al.* (2015) also reported that although NDVI data of the region indicate the changes in vegetation cover present in the area and also the trend in occurrence of agricultural drought but this index is not free from defects such as data error during rainy season, saturation effect on dense vegetation, etc. Hence it is always better to merge it with other parameters to ensure more accuracy.

2.5.3 Vegetation Condition Index (VCI)

Although the NDVI has been extensively used in the past for vegetation monitoring, is often very difficult to interpret in relation to vegetation condition, especially when comparing different ecosystem, vegetation condition index was first suggested by Kogan (1995). It shows effectively. How close the current months NDVI is to the minimum NDVI calculated from the long-term record or remote sensing images VCI enables to separate the short-term signal from the ecological signal, equation (2.2).

$$\text{VCIi} = \frac{\text{NDVIj} - \text{NDVImin}}{\text{NDVImax} - \text{NDVImin}} \times 100 \tag{2.2}$$

Where $NDVI_{max}$ and $NDVI_{min}$ is calculated from the long-term record for the month and j is the index of the current month.

NDVI values are calculated using the formula above the condition of the ground vegetation presented by the VCI is measured in percent the VCI values around 50 % reflect fair vegetation condition. The VCI values between 50 to 100% indicates optimal or above normal condition. At the VCI value of 100, the NDVI for selected month (week) is equal to NDVImax, which indicates optimal condition vegetation. Different degrees of drought severity are indicates by VCI values below 50% Kogan (1995) illustrated that a VCI threshold of 35% may be used to identify extreme drought conditions, and suggested that further research is necessary to categorize the VCI its by severity in the range between 0 and 35% (thenkabail 2004), the VCI value close zero percent reflects an extremely dry month when the NDVI values are close to its long term minimum. Low VCI values indicate drought development. Intervals captures rainfall dynamics better than the NDVI particularly in geographically non homogeneous areas the VCI not only permits the description of land cover and spatial and temporal vegetation change but also allows quantifying the impact of weather on vegetation also the VCI makes it possible for one to compare the weather impact in areas with different ecological and economic resources. VCI values indicate easily how much the vegetation has advanced or deteriorated in response to weather and the potential maximum and minimum defined by ecological limits.

Das *et al.* (2013) also assessed agricultural drought risk in West Bengal by using different NDVI based drought indices including VCI and suggested that NDVI coupled with VCI could be a better tool for assessment of drought in the study region. Similarly, Dhakar *et al.* (2013) analyzed the Spatio-temporal drought in Rajasthan using NDVI and

VCI and reported that relationships between drought indices could be used to study the response of crops to water availability for early detection and better prognosis of agricultural drought. Some researchers reported that the two remote sensing-based indices NDVI and VCI were found to be complementary for agricultural drought assessment and also suggested to use NDVI based maps for land use planning in West Bengal Mandal, (2013).

Mala *et al.* (2014) studied different drought indices in Rajasthan and also suggested to use the VCI index in addition to the NDVI since VCI gives the complete picture of Vegetation health in response to drought condition in the study area. Kogan (1990) also noted that the relation between rainfall and VCI was high and VCI was effective for drought assessment in the region.

2.5.4 Temperature Condition Index (TCI)

During the rainy season, it is common for overcast condition to prevail for long periods of time if this period lasts more than 3weeks, the weekly NDVI values tend to be depressed given the false impression of water stress or drought condition to remove the effects of cloud contamination in satellite assessment of vegetation condition, Kogan (1995,1997) suggested Temperature Condition Index (TCI) and is calculated similarly to VCI but its formulation was modified to reflect vegetation response to temperature (the higher the temperature more extreme the drought) TCI is based on brightness temperature and represents the deviation of the current months values from the recorded maximum. In combination with meteorological observation, the relationship between surface temperature and the moisture regime on the ground will detect drought-affected areas before biomass degradation occurs hence, TCI can play an important role in drought monitoring equation (2.3).

$$\text{TCIi} = \frac{\text{BTmax} - \text{BTj}}{\text{BTmax} - \text{BTmin}} \times 100 \qquad (2.3)$$

Where BT is the brightness temperature, the maximum and minimum values of BT are calculated from the long-term records of remote sensing images (www.lwmi.cgiar.org).

Das *et al.* (2013) also assessed agricultural drought in West Bengal using NDVI based drought indices and TCI and developed drought vulnerability map for the study area. They also reported that agricultural drought risk mapping was useful to guide the decision-making process in drought monitoring and to reduce the risk of drought on agricultural production and productivity.

Similarly, Zarei *et al.* (2013) also assessed agricultural drought in Iran by using different drought indices and reported that the spatial extent of the satellite-derived drought-indices and SPI generally confirmed with each other. Tabassum *et al.* (2015) also used remote sensing data to assess the patio-temporal condition of agricultural drought in Pakistan and reported that the vegetation indices provide continuous spatial surface data for monitoring the drought condition over a region which was impossible to get from the meteorological stations. Senthil Kumar *et al.* (2016) also monitored vegetation health in Tamilnadu using remote sensing data and also suggested that agricultural drought severity maps would be useful for regional level agricultural vulnerability detection and early warning of agricultural drought.

2.5.5 Vegetation Health Index (VHI)

VHI is a widely used remote sensing-based drought index designed as the weighted sum of two components: the Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI). The first component characterizes moisture conditions and is typically based on information from the visible and near infra-red windows of the electromagnetic spectrum, whereas the latter characterizes the thermal condition and is based on information from the thermal infra-red window.

McVicar and Bier (2001) use the ratio of LST and NDVI (LST/NDVI) to provide a rapid means of assessing drought conditions. Following the above-mentioned hypothesis, Kogan (1995) proposed another index, the Vegetation Health Index (VHI), which is an additive combination of VCI and TCI, equation (2.4).

$$VHI = \alpha \, VCI + (1 - \alpha) \, TCI \qquad (2.4)$$

Where α is the relative contribution of VCI and TCI in the VHI. In most published Analyses, α has been assigned a value of 0.5, assuming an even contribution from both elements in the combined index, due to the lack of more accurate information Kogan (2000).

The VHI has been applied for different applications, such as drought detection, drought severity, and duration, early drought warning Seiler *et al.* (1998). It can be helpful for the development of a regional drought monitoring system Thenkabail *et al.* (2004) identifying agricultural drought-affected areas (Owrangi *et al.* 2011) and seems to be a potentially promising method for early drought awareness which can be used for drought risk management in semi-arid climates.

Similar studies conducted by other researchers showed that agricultural drought can well be assessed by using VHI and VHI maps were useful for the detection of agricultural drought in the study area.

2.6 Review of Related Literature

A review of a similar study carried out by other prominent authors on the subject matter attempted to justify the importance of the study.

Mongkolsawat *et al.* (2000) modeled the drought risk area with a set of themes using remotely sensed data and GIS. They reported that the severity of drought can be considered as a function of rainfall, hydrology and physical aspect of the landscape. In their study, each theme of the drought consisted of a set of logically related geographic features and attributes were used as data input for analysis. The matrix overlay operation of the drought risk layers was performed. The risk layers were classified into 4 drought classes of drought risk: very mild, mild, moderate and severe.

Choudhary *et al.* (2012) demonstrated the use of remote sensing and GIS in the mapping of drought in Rajasthan. They assessed the drought condition using temporal images from Landsat TM, ETM+ in Jodhpur District, particularly where the occurrence of drought is high. The yield and production analysis of crops were carried out for a period of 21 years (1991–2011). On the basis of the satellite-based indices, the study area was divided into several drought categories; moderate, mild and no drought using GIS software. It was found that in the years 2000, 2002 and 2010, the entire study area was affected by moderate drought with greater intensity.

Mandal (2013) assessed agricultural drought in the Kangshabati river basin in West Bengal, India using NDVI for 2007-2009. The result showed that a large part of the study area suffers from moderate to severe drought conditions. They suggested that NDVI maps would be helpful in the study region for land use planning purposes.

Sashikkumar *et al.* (2013) analyzed rainfall status and assessed the drought severity of the Chittar sub-asinine meteorological aspect using GIS which provides tools to incorporate spatial and temporal variations of water resources data. The assessment of drought severity in the meteorological context was carried out by the India Meteorological Department (IMD) method. The meteorological drought risk index for each rainfall station in the sub-basin was calculated by frequency analysis. Spatial interpolation of meteorological drought risk index was mapped in Arc view GIS 3.2a software. They concluded that the meteorological drought risk map scan helps the administrators and planners to plan various alternative measures to overcome the drought and its impacts.

Tabassum *et al.* (2015)used satellite remote sensing and digital image processing techniques to monitor the drought conditions in the Shaheed Benazir Abad district, Pakistan using LANDSAT data from 1992-2011. They derived NDVI, VCI, LST and TVX drought indices using this data set. Their study revealed that the vegetation indices; NDVI, VCI, and TVX provide continuous spatial surface data for monitoring the drought condition over a region, which is impossible to get from the discrete and distant meteorological stations. They concluded from the VCI and TVX map analysis that most parts of the Shaheed Benazir Abad were affected by a moderate drought condition.

Kogan *et al.* (2006) a spatial distribution of precipitation or soil moisture is required. These data are in coarse spatial resolutions, which limit their utility to regional or continental scales. Drought metrics based on remote sensing methods improve spatial detail without requiring an extensive meteorological precipitation network and have become the most promising tool for drought monitoring of larger regions Brown JF, Ward low BD, Normalized Difference Vegetation Index (NDVI)-based drought metrics have been extensively used for vegetation drought monitoring during the last several decades because of their sensitivity to surface vegetation cover change from climatic effects on dryness conditions. Gibbs (1960) designed the vegetation condition index (VCI) to monitor crop water stress by using the statistical data of NDVI. Developed the anomaly vegetation index (AVI) to study land surface dryness by analyzing annual NDVI dynamics. However, the accuracy of drought monitoring based on NDVI may be affected by the variability of vegetation cover in different ecosystems and time lags between drought occurrences at some consecutive time periods and NDVI change.

Wilhelmi (2004), to overcome the deficiency of traditional NDVI-based drought metrics, other hybrid NDVI-based drought measures, such as the vegetation drought response index VDRI, integrate traditional climate-based drought indicators, and satellite-derived vegetation indices, and provide new potential for land surface drought assessment. Mooney (1997) Because land surface temperature (LST) is highly related to canopy water content or soil moisture availability, the methods that combine NDVI and LST provide a better characterization of surface drought status by providing a two-dimensional spectral feature space. Based on these features, the temperature–vegetation index TVI; calculated by the ratio of LST to NDVI better correlates with canopy water or soil moisture in different land cover conditions. Subsequently, the vegetation health index) and the temperature–vegetation dryness index (TVDI; Moreira (2008) were designed to estimate surface dryness. Used leaf area index LAI instead of NDVI to analyze the surface drought status under saturated NDVI and replaced LST with albedo to further interpret the mechanism of the vegetation condition albedo drought index VCADI. Evapotranspiration, a key component of the land surface water budget and an indicator linked to land drought status, is a significant process that drives energy and water exchange between the atmospheres and land surface. Mishra *et al.* (2010) when drought occurs, stomata of stressed plants close to minimize water loss by transpiration, which leads to decreased latent heat flux; in order to keep an energy balance, sensible heat flux may increase. As a result of this process, leaf temperature will ultimately increase.

Tripathy *et al.* (1996) attempted to by making use of temporal satellite information (Landsat 4 MSS 1984 and 1985 and IRS-1A LISS-II 1988 and 1991) along with the surface and statistical data with the aid of GIS to evaluate the indicators of desertification process in semi-arid lands of Shahapura and Shorapura taluks of Kalburgi district of Karnataka. A desertification severity map was produced by integrating meteorological, hydrological and biological indicators. The study concluded that the average severity of desertification was moderate and was aggravated by human activity.

Nagler *et al.* (2000) worked on remote sensing-based drought information systems for the Palar and Thamiravaruni basins of Tamilnadu, using GIS in the study of meteorological, hydrological and agricultural droughts. They integrated the IRS WiFS data and satellite-based vegetation index. They further looked at creating a QGIS based drought information system. The Drought Information System (DIS) was developed with modules on water-related databases, meteorological drought, hydrological drought, agricultural drought, and drought risk area analysis.

Saunders *et al.* (2002) in their study on coherent rainfall zones in Karnataka illustrated the methodology developed for the identification of coherent rainfall zones by delineating the variations of rainfall in different zones. The extent to which the zones thus derived were coherent with respect to the occurrence of large anomalies in seasonal and annual rainfall estimated. They also discussed threadbare the implications of the different definitions of meteorological droughts. The extent to which the objective of this study was achieved could be assessed in defining precisely what constituted a drought or a situation with above/below normal rainfall.

Venter *et al.* (1998) in his agricultural drought assessment in different agro-climatic zones of the Bund elk hand region, under irrigated and rain-fed conditions, used Effective

Drought Index (EDI) derived from the precipitation observations of the IMD. The remote sensing-derived NDVI and soil moisture were the popular elements in the study for drought identification and monitoring. The soil moisture probably had relationships with the meteorological drought indicator and the NDVI and could serve as an estimator plus a prediction element for agricultural drought. The study made an attempt also to identify the sensitiveness of downscaled soil moisture to meteorological drought in the assessment of agricultural drought. Anomalies in the NDVI and soil moisture (16-day composites) for Rabi seasons (October – December) of 2000-01 to 2009-10 were also computed. Correlation between the EDI and soil moisture anomaly and soil moisture anomaly and the NDVI were found to have larger values in rain-fed areas than in the irrigated areas.

Sumanta *et al.* (2011) in a study of the agricultural drought risk and impacts on yield reduction in India using remote sensing and GIS techniques, The Normalized Difference Vegetation Index (NDVI) and anomaly from the long term mean values of maximum NDVI to assess the severity of the drought. Many indices of Vegetation Conditions Index (VCI), Temperature Conditions Index (TCI), Standardized Precipitation Index (SPI), Moisture Stress Index (MSI) and Yellowness Vegetation Index (YVI) were used in the study. The impact of agricultural drought on crop production was measured through an estimation of the yield reduction by Simple regression analyses performed between land surface temperature with the NDVI, the TCI with the VCI and the SPI, MSI, NDVI anomaly. From the study, it was concluded VCI with yield reduction showed the resultant drought vulnerability obtained by integrating the NDVI anomaly, MSI, SPI, VCI, TCI and YVI which indicated the area facing a combined drought.

Drought risk is a product of a region's exposure to the natural hazard and its vulnerability to extended periods of water shortage Willhit (2000). If nations and regions are to make progress in reducing the serious consequences of drought, they must improve their understanding of the hazard and the factors that influence vulnerability. It is critical for drought-prone regions to better understand their drought climatology (i.e., the probability of drought at different levels of intensity and duration) and establish comprehensive and integrated drought information system that incorporate climate, soil and water supply factors such as precipitation, temperature, soil, moisture, snowpack, reservoir and lake levels, groundwater levels, and stream flow. Liu and Kogan (1996) A study on monitoring the regional drought of the South American continent, using AVHRR data, was carried out. Drought areas were delineated with certain threshold values of NDVI and Vegetation Condition Index (VCI) in the study. The study reported that drought patterns delineated by NDVI and VCI agreed quite well with rainfall anomalies observed from the rainfall map. The results also showed that the NDVI images provided a useful tool to study large scale climatic variability, while the VCI images provided to analyze the temporal and spatial evolution of regional drought as well as to estimate the crop production, qualitatively. Seiler *et al.* (1998) made a study using AVHRR based Vegetation and Temperature Conditions indices for drought detection and impact assessment on agricultural yields. And found that the VCI and TCI were useful to assess the spatial aspects, the duration and severity of drought, these were in good agreement with precipitation patterns.

Bayarjargal *et al.* (2000) made a study on drought and vegetation monitoring in the arid and semi-arid regions of Mongolia using NOAA/AVHRR satellite data. Drought affected regions were detected by calculating the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) values of the drought and wet years. Due to moisture stress on the vegetation, the NDVI (LST) value recorded in the dry years was lower (higher) than those values recorded in a normal year. Through this study concluded that the AVHRR based NDVI and LST could provide valuable information for operational drought detection and monitoring.

Hostert *et al.* (2001), on the other, made a study on monitoring and assessment of desertification using remote sensing and GIS. The study provided additional values that could be added by integrating remote sensing derived information with auxiliary data through GIS analysis. The study outlined also the importance of integrating socio-economic boundary conditions and anthropogenic influences. The study further highlighted the perspectives of future developments and their likely implications on remote sensing and GIS-based desertification research.

Jayaseelan (2002) discussed the recent trends in remote sensing applications towards drought assessment and monitoring with a case study on the National Agricultural Drought Assessment and Monitoring System (NADA MAS). After the country-wide drought in 1987, the emphasis on using space technology for drought monitoring grew in 1989, The NADA MAS uses NOAA AVHRR data to monitor the country level vegetation dynamics. Bi-weekly NDVI time series is used to monitor the vegetation phonology throughout the season. For regional drought monitoring (at the State level), the NADA MAS uses Wide image Field Sensor (WiFS) data of the IRS-1C/1D and IRS-P3. The project covered 14 agriculturally important and drought vulnerable states of the country, which included Karnataka state.

Singh (2003) investigated the monitoring of drought over India by examining the VCI and TCI of NOAA AVHRR data. Time series of satellite data for 1985-1996 over various Indian regions were used for mapping the vegetation cover and the classification employing the NDVI. The VCI quantified the weather component which varied from 0 to 100, corresponding to changes in the vegetation conditions from extremely unfavorable to optimal. The study reiterated that VCI and TCI could be used for drought detection and mapping. The TCI alone could not be used for predicting drought due to stressed vegetation and wetting of lands. The VCI together with the TCI could be employed as a tool to monitor both drought and excessive wetness.

Lei and Peter (2003) presented a study for assessing the vegetation response to drought in the Northern Great Plains using AVHRR data from 1989 to 2000. The derived vegetation condition and moisture availability for the grassland cropland in the Northern Great Plains fitted very well with the predicted and observed, NDVI values in most cases. From the study, it was concluded that the NDVI was a good indicator of moisture conditions and could be an important data source when used for detecting and monitoring the drought. Wan *et al.* (2004) Terra Moderate Resolution Imaging Spectro-radiometer (MODIS) derived NDVI of 2001 and Land Surface Temperature (LST) were used and carried out studies for drought monitoring in the Southern Great Plains, USA. The Vegetation Temperature Conditions Index (VTCI) ranged from 0 to 1. The lower the value, the higher is the occurrence of drought. The study concluded that the VTCI was physically interpreted as the ratio of LST differences among the specific NDVI values in an area large enough to provide wide ranges of the NDVI and soil moisture at the surface layers. Drought monitoring approach by the VTCI integrated the remotely sensed land surface reflectance and thermal properties and gave emphasis on the changes in both the LST and the NDVI over a region. The VTCI was time-dependant and usually region-specific and was useful during the plant growing seasons.

Bhuiyan (2004) used multi-sensors data to deduce surface and meteorological parameters (vegetation index, temperature, evapotranspiration) of the Aravalli region for 1984-2000, together with the actual ground data (rainfall, temperature, groundwater level) for detailed drought analysis. The Standardized Precipitation Index (SPI) was used to quantify the precipitation deficit. A Standardized Water-level Index (SWI) was also developed to assess the groundwater recharge deficit. Vegetation Drought Index (VDI) was calculated using the NDVI values obtained from the Global Vegetation Index (GVI) of NOAA AVHRR data. Spatial and temporal variations in meteorological, hydrological and vegetative droughts in the Aravalli terrain were also analyzed and correlated for monsoon and non-monsoon seasons during 1984-2000. Based on the results, it was concluded that none of the drought indices followed any particular spatial and temporal patterns in the region. The analysis revealed that the meteorological, hydrological and vegetative droughts were not linearly inter-related and suggested that a combination of various indices offered better understanding and monitoring of drought conditions for the hilly and the semi-arid terrains such as the Aravalli of Western India.

Nageswara *et al.* (2005) used METEOSAT5 thermal infrared (TIR) data for assessing the spatial and temporal distribution of rainfall and the impact of successive agricultural droughts in the state of Karnataka. The study was emphasized that there was the need for an independent system that could enhance the severity, duration and aerial extent of drought and its impact on the actual conditions of the crops/vegetation so that the authorities concerned could take appropriate relief measures. A comparison of the NDVI was also made for drought and non-drought year, permanent vegetation like forests, agricultural lands under irrigation, did not show much variation between a normal year and a severe drought year. The study concluded that the NDVI was a good indicator of agricultural drought but the reduction in green cover due to drought might be inferred and interpreted carefully by comparing the NDVI values of the years under study with a normal year.

Liu *et al.* (2011) used a multi-index drought (MID) model to combine the strengths of various drought indices derived and to provide a more reliable and comprehensive assessment of drought conditions and the presented an operational model framework that combined the strengths of various drought indices are provide a more comprehensive assessment of agricultural drought conditions in the Canadian Prairies. The results show the prediction accuracy of the MID model was better than using any single drought index, early drought risk detection, and prediction and accuracy drought assessment.

Jainet *et al.* (2009) carried out the analysis for a period of 4 years (2002– 2005) by using the Advanced Very High-Resolution Radiometer (AVHRR) satellite data for calculating Brightness Temperature (BT), Normalized Difference Vegetative Index (NDVI) and the Water Supplying Vegetation Index (WSVI).

Sholihah *et al.* (2016) tested satellite-borne remote sensing Landsat data for monitoring drought extent in Indonesia for a period of 2000 to 2015 in the dry season; VHI was used as drought indicator for monitoring agricultural drought. Their result showed that VHI decreased more than 50 percent, from 30.86%in 2000 to 14.66%in 2015 indicating drought extent in research area from mild drought to severe drought. When VHI was compared with individual LST and NDVI values, the severity was mainly found due to the rising of LST from 27°C in 2000 to 40°C in 2015. In addition, there was a decreasing trend of NDVI values in recent years, from 0.43 in 2000 to 0.176 in 2015 which indicated the absence of planting activities during recent dry seasons. They concluded that VHI can be successfully used to identify the patio-temporal extent of agricultural drought and it can also be employed to explain drought severity classes in the research areas through composite analysis of both vegetation heaths by vegetation condition and temperature condition of vegetation.

Nezar *et al.* (2007) assessed drought for Amman-Zarqa basin, north Jordan using two different drought indices SPI and the NDVI to evaluate drought using rainfall data and satellite images.GIS software was used in this study to create spatial digital database to hold meteorological information for the study area, to generate thematic layers representing spatial distribution of drought for both SPI and NDVI, to delineate areas with high drought risk using SPI and NDVI and compare the results of both models. Their results showed that Amman-Zarqa basin was currently facing drought conditions and concluded that the combination of various indices offers better understanding and monitoring of drought conditions for semi-arid basins like Amman-Zarqa Basin.

Abdol *et al.* (2011) evaluated area under hazard of meteorological drought using GIS technique in Ghareh Aghaj watershed in Iran where meteorological drought had the most profound effect on the way of living and regional economy. Meteorological hazard indicator was estimated using average annual rainfall data and average annual temperature of 16 years record for 20 stations. The final hazard map was classified into 4 hazard classes of drought: mild, moderate, severe and very severe. The final hazard classes were defined on the basis of hazard scores arrived at by assigning the appropriate attributes to the indicators and the final hazard map was prepared by overlaying different hazard indicator maps in the GIS, deploying the new model. The final Hazard Map showed that moderate hazard areas (67% of the basin) were much widespread than areas under severe hazard (37% of the basin) observed in the Southeast of the region.

Hasan *et al.* (2011) applied RS and GIS techniques for drought detection in the north-west region which was the most drought prone area of Bangladesh. Meteorological drought was determined based on SPI. SPI values were interpolated to determine the spatial pattern of meteorological drought and its threshold value for different types of drought. Agricultural drought risk areas were identified based on NDVI by using surface reflectance with 250m resolution from MODIS satellite during 2000-2008. Anomaly of the NDVI from the mean values was classified to determine the agricultural drought risk. Meteorological and agricultural drought risk maps were prepared by integrating the various classes of drought. Finally, a resultant risk map was obtained by integrating agricultural and meteorological drought risk maps which indicated the areas facing a combined drought. The combined risk map showed that approximately 17% area has no risk, 23 % area face slight risk, 30 % area face moderate risk and 31 % area face severe to very severe risk within the study area. It was evident from the study that central, northern and southwestern districts of the north-west region of Bangladesh were more prone to agricultural and meteorological drought.

Owrangi *et al.* (2011) compared AVHRR data and SPOT data for identification of agricultural drought affected area in Iran using Vegetation Health Index (VHI) from 1998 to 2007.The results revealed that highest correlation values were obtained when VHI values were correlated with the current month surface water data. The resulted VHI maps also showed strong vegetation conditions existing for the majority of the study period. They concluded that method was a potentially promising for early drought awareness which can be used for drought risk management in semi-arid climates such as in Iran.

Shaheen *et al.* (2011) analyzed meteorological and agricultural parameters for the variety of data for the years 1989, 1995, 2001 and 2007. Initially anomalies were calculated for NDVI, rainfall and crop yield to evaluate percent change in different years. Crop yield and NDVI possessed negative anomalies during drought years while in case of non-drought years, static and positive anomalies were found. Then SPI was computed on six monthly bases for the time series of nineteen years (1989-2007). The correlation regression analysis was performed to identify the dependency level among different parameters. Positive correlation was found among SPI, NDVI, crop yield, rainfall anomalies, NDVI anomalies and total seasonal rainfall. The meteorological and agricultural drought were assessed by overlaying SPI, rainfall anomalies, crop yield, NDVI anomalies and water table depth data. The well-known 2001 drought year was confined by using above method applied in this research. Finally, drought severity maps were generated by integrating the meteorological and agricultural drought severity maps, indicating the areas facing combine hazard condition. They reported that these maps can be extremely helpful to the planners to reveal the situation in the area.

Swain *et al.* (2011) analyzed the response of different land cover types to drought by comparing their Terra-MODIS–derived cumulative LST and NDVI signals during the summer growing season (2002-2007) of a drought and a non-drought year in Nebraska, USA. They concluded that Terra-MODIS eight-day composite LST and NDVI products are sensitive to drought-related stress in vegetation. Similarly, they also observed that, AVHRR-based vegetation condition monitoring indices such as VCI, TCI, Vegetation Health (VH), Relative Greenness (RG), and Standardized Vegetation Index (SVI) require a longer period of LST and/or NDVI data.

Choudhary *et al.* (2012) demonstrated the use of remote sensing and GIS in the mapping of drought in Rajasthan. They assessed the drought condition using temporal images from Landsat TM, ETM+ in Jodhpur District, particularly where the occurrence of drought is high. The yield and production analysis of crops was carried out for a period of 21 years (1991–2011). On the basis of the satellite-based indices, the study area was divided into several drought categories; moderate, mild and no drought using GIS software. It was found that in years 2000, 2002 and 2010, the entire study area was affected by moderate drought with greater intensity.

Dubey *et al.* (2012) studied rainfall data (from IMD) and MODIS-NDVI data (GLAM project) for 28 states of India. NDVI data from MODIS (with a resolution of 250 km) images was correlated with state wise annual precipitation for the period 2004-2008. The critical changes of NDVI and the correlation coefficients between NDVI and rainfall were examined for each pixel. The average correlation value for NDVI and rainfall was observed to be 0.64 and R2 value was 0.40. Spatially very strong relationship was observed in north east and southern part of country. They concluded that the NDVI is majorly dependent on the rainfall. Other factors like temperature, humidity, radiation also influenced the vegetation growth and productivity but in lesser proportion compared to precipitation.

Choudhary *et al.* (2013) interpolated meteorological based drought indices such as Normalized Deviation (ND), De Martonne’s Index (IA), Pluvothermic Quotient (PQ), Negative Moisture Index (NMI) and SPI for a period of 21 years (1991–2011).Monthly rainfall data from six stations were used to derive the indices. These indices values were interpolated to get the spatial pattern of meteorological based drought. Crop yield and production trend was plotted and an equivalent NDVI threshold was identified to get the agricultural drought risk in Jodhpur district, where the occurrence was high in Jodhpur district. They concluded from the SPI analysis that in the year 2002 all of the area under study was affected by drought with greater intensity which can be classified as extreme and severe drought conditions.

Das *et al.* (2013) assessed agricultural drought risk and its impacts on yield reduction in Bankura, West Bengal using remote sensing and GIS techniques. The digital indices using satellite data namely, NDVI and NDVI anomaly was prepared from the long term mean values of maximum NDVI to assess the severity of drought. Compared to other cropping seasons of the analysis period, yield reduction for the year 2005 was lesser than the highly drought years 2000 and 2010. Simple regression analyses were performed between Land surface temperature with NDVI, TCI with VCI and SPI, MSI, NDVI Anomaly, VCI with Yield reduction (%). A resultant drought vulnerability map was obtained by integrating NDVI Anomaly, MSI, SPI, VCI, TCI and YVI which indicated that the area was facing a combined drought. The combined vulnerability map showed that 6% area has no risk, 53 % area faced moderate risk and 41 % area faced high risk within the entire geographical area. They concluded that agricultural drought risk mapping was useful to guide decision making process in drought monitoring and to reduce the risk of drought on agricultural production and productivity.

Dhakar *et al.* (2013) analyzed patio-temporal intra-seasonal and inter-seasonal relationships for 24 years between rainfall and NDVI and between SPI and VCI to understand crop response to water availability in the Rajasthan State, India. To separate the effect of weather and technology on crop growth over time, a modification in VCI was proposed and called "Trend Adjusted VCI" (VCI Tadj). Significant linear relationships were found between NDVI and rainfall but phase of crop season affected the strength of this relationship. The SPI and VCI Tadj were linearly related in all the four seasons, the strength of relationship improved with the progress of crop season and these relationships were stronger than those between rainfall and NDVI. These relationships broke down in irrigated crop lands. This suggested that the anomaly indices of SPI and VCI Tadj and their intra-seasonal relationships can be used to study the response of crops to water availability for early detection and better prognosis of agricultural drought.

Dutta *et al.* (2013) studied agricultural drought prediction based on agricultural yield using a model based on NDVI-SPI. The meteorological drought index SPI with different timescale was correlated with NDVI at different lag. The NDVI of current fortnight was found to be highly correlated with SPI of previous fortnight in semi-arid and transitional zones. The correlation between NDVI and crop yield was highest in first fortnight of August. The RMSE of predicted yield in drought year was found to be about 17.07 kg/ha which was about 6.02 per cent of average yield. In normal year, it was 24 kg/ha which was about 2.1 per cent of average yield. Hassan *et al*. (2013) studied MODIS data for assessment of agricultural drought in Bangladesh from 2000 to 2014 with an objective to develop VHI maps of the study area. The results of the study revealed that 29%, 34% and 37% area was affected by extreme, high and moderate drought risk, respectively. They concluded that Naogoan and Chapainabanganj districts were found as the extreme to high drought vulnerable areas in terms of agriculture, (Mandal2013) assessed agricultural drought in Kangshabati river basin in West Bengal, India using NDVI for 2007-2009.The result showed that large part of the study area suffers from moderate to severe drought condition. They suggested that NDVI maps would be helpful in the study region for land use planning purpose.

Sashikkumar *et al.* (2013) analyzed rainfall status and assessed the drought severity of Chittar sub-asinine meteorological aspect using GIS which provides tools to incorporate spatial and temporal variations of water resources data. The assessment of drought severity in the meteorological context was carried out by India Meteorological Department (IMD) method. Meteorological drought risk index for each rainfall station in the sub-basin was calculated by frequency analysis. Spatial interpolation of meteorological drought risk index was mapped in Arc view GIS 3.2a software. They concluded that the meteorological drought risk map scan help the administrators and planners to plan various alternative measures to overcome the drought and its impacts.

Zarei *et al.* (2013) used AVHRR images to evaluate the efficacy of NOAA-AVHRR data for monitoring drought in Iran for the 1997-2005 (March-July) time period and derived NDVI, VCI, LST, TCI and VHI drought indices using this data. The SPI analysis was also carried out using rainfall data in study area. Their results revealed that the spatial extent of the satellite-derived drought-indices and SPI generally confirm each other. The statistical analysis indicated that higher correlations among the satellite-derived indices while lesser or no relationships between the satellite-derived indices and SPI. They concluded that Iran suffered from severe drought during 1999-2001 and the results of remotely sensed indices and the SPI index for 2002-2005in most of the region experienced normal conditions.

Aswathy *et al.* (2014) computed NDVI of the Karur district during the year 2000 and 2009. The NDVI, SPI and Standard Water Level Index (SWI) were used as indicators to evaluate drought. Mean annual rainfall data map and land use/land cover map was also generated for the study area. The results showed that there is a decrease in NDVI values during the year 2009, which correlates to the reduced rainfall quantity of the year. The analysis showed that drought was more frequent in the year 2009 and also it lasted longer than the year 2000.

Gedif *et al.* (2014) studied spatiotemporal drought characteristics in Ethiopia using rainfall data and SPOT NDVI data during the period of 1998-2005.The NDVI, NDVIDEV and VCI were used as drought indicators for assessment of drought. The results revealed that large proportion of the area (31.45%) is at moderate drought risk level, whereas 17%of the area accounted for high drought risk. It was observed that the two remote-sensing indices used, NDVI DEV and VCI are complementary and were found to be sensitive indicators of drought conditions. The results also confirmed that SPOT NDVI, which incorporates the long-term NDVI, was found to be one of the best data for drought risk assessment.

Mala *et al.* (2014) studied different drought indices namely SPI, NDVI and VCI for Jodhpur, Rajasthan for 1957-2012periods. They reported that in last 20 years both SPI and NDVI displayed the same results showing drought in particular periods in year 1991, 2004, 2010 and 2012. They concluded that SPI and NDVI indices are complementary to each other for estimating drought condition in study area. They also suggested using VCI index in addition to the NDVI as, VCI gives the complete picture of vegetation health in response to drought condition.

Mohammad *et al.* (2014) studied the efficiency of agricultural drought indicators for estimating vegetation conditions using MODIS data for estimation of NDVI and VCI and precipitation data of 9 stations for period of 2000-2011.The results of VCI showed that year 2001, 2008, 2000 and 2009 had the most vulnerable effect of drought and years 2010 and 2003 had the minimal effect. By SPI method it was observed that year 2008 and 2001 had a maximum drought and 2010 and 2003 years had the lowest. The results for agricultural drought assessment through remote sensing showed that VCI would be an excellent method when there was lack of ground observation data.

Padhee *et al.* (2014) developed agricultural drought assessment and prediction technique by spatially and temporally assimilating effective drought index (EDI) with remote sensing derived parameters. The proposed technique uses difference in response of rain-fed and irrigated agricultural system towards agricultural drought in the Bundelk hand region. Based on the statistical analysis, good correlations were found among the parameters EDI and soil moisture anomaly, NDVI anomaly and soil moisture anomaly lagged to 16 days and these results were exploited for the development of a linear prediction model. The predictive capability of the developed model was validated on the basis of spatial distribution of predicted NDVI and compared with MODIS NDVI product in the beginning of preceding rabi season (Oct –Dec of 2010). The predictions of the model were based on future meteorological data (year 2010) and were found to be yielding good results. The developed model had good predictive capability based on future meteorological data (rainfall data) availability, which enhances its utility in analyzing future agricultural conditions if meteorological data is available.

Rajpoot *et al.* (2014) analyzed the drought intensity and frequency during 1957 to 2012 to find out environmental stress as meteorological drought. Drought intensity was determined by suggested criteria of Indian Meteorological Department (IMD) and found out the drought frequency. Annual rainfall was good and cyclic for crop saving and 70% years had a normal rainfall (±25% from normal rainfall) and rest 30% years experienced moderate to severe drought. NDVI was showing the effect of no, mild and severe drought on vegetation. Rainfall data showed that Jaipur witnessed almost one drought decade and adjacent high rainfall decade. The recent decade was a heavy rainfall decade and suggested to implement rain water harvesting to utilize as pre-sowing and crop saving irrigation for succeeding rabi crops.

Vashishta *et al.* (2014) reported the use of the range of indices on drought monitoring and different software such as Arc-GIS 9.3, ENVI 4.4, Map Info and Erdas Imagine 9.1. It was concluded that in Adampur, Agroha and Hisar there was no severe drought condition in the district during the study period Dodamani *et al.* (2015) studied SPI and NDVI obtained from MODIS data from 2000 to 2012 for drought modeling in Krishna Basin in Maharashtra and developed correlation between NDVI and SPI. In the assured rainfall zone, the correlation between SPI and NDVI was found to be highly significant than that of scarcity zone. They concluded that agricultural drought was addressed by successfully developing a crop yield prediction model in the assured rainfall zone and the scarcity zone.

Gaikwad *et al.* (2015) used LANDSAT-8 data for drought assessment in post monsoon season for Vaijapur Taluka in Aurangabad district, Maharashtra for 2013 and 2014.They used NDVI, VCI and SAVI indices for determination of agricultural drought in study area. They revealed that the study area was affected by severe drought in year 2013 and normal drought in 2014 and the temporal variations of NDVI were closely linked with VCI, and SAVI indices. Himanshu *et al.* (2015) analyzed rainfall and NDVI data to recognize their relationship in Jamnagar, Gujarat from period of 1977 to 1999.They concluded that drought risk area can be identified by integrating satellite and meteorological data. They also reported that temporal variation in NDVI strongly depends upon rainfall in study area.

Nandeesha *et al.* (2015) studied agricultural drought in central dry agro climatic zone of Karnataka using MODIS data from 2000 to 2012 on the basis of NDVI during kharif season. They concluded that more than 1-2 Taluks suffered by severe drought, 5-10 Taluks low drought and 5-7 Taluks by moderate drought condition. The study concluded that in the year 2000-2003 there were more droughts affected Taluks whereas in 2006, 2011-2012 more than 5 Taluks were affected by sever-low drought condition.

Sruthi *et al.* (2015) analyzed the vegetation stress in the Raichur district with NDVI and LST from MODIS data during period of 2002-2012. It was noticed that both NDVI and LST parameters were inversely proportional to each other. When the temperature is greater, the NDVI value is lesser which points out the decrease in the vegetation density. The decrease in soil moisture due to lack or untimely onset of rainfall along with the increased temperature caused the severe agricultural drought; they suggested that the NDVI value should combined with other drought parameters to obtain better results.

Chen *et al.* (2016) assessed the cultivated areas affected by droughts using MODIS data during 2001–2014 which was processed using VHI in Central America. Comparisons between VHI, AMSR-2 precipitation data and TVDI data indicated significant relationships between these data sets.

The occurrence of probability of a drought event at the department level during the sensitive stage of crop development indicated that large clusters of departments having high probabilities of drought occurrence were observed in Nicaragua and Guatemala during the primer a season and El Salvador and Guatemala in the season .Results obtained in their study could be used by policy makers to successfully conceive strategies to mitigate possible impacts of droughts on crop production.

Sehgal *et al.* (2016) demonstrated a methodology to assess and to map agricultural drought vulnerability of Rajasthan State for main kharif crop season. The study revealed that use of remote sensing-derived indicators of crop sensitivity to drought helped in producing vulnerability ratings at local scales which had better relevance to agencies involved at ground level in drought adaptation and mitigation matters. The results indicated that high to extreme vulnerability occurs in more than 50 % of net sown area in the state and such areas mostly occur in western, central, and southern parts of the state.

2.6.1 Drought severity mapping

The GIS based drought severity maps using meteorological drought indices is useful to evaluate the drought situation of area and to plan the cropping pattern for maximizing value of the agriculture returns. Hence work related to spatial mapping of drought indices is reviewed and presented in this section.

Mishra et al. (2011) investigated the spatial and temporal characteristics of droughts to provide a framework for agriculture practices, engineering facilities and sustainable water resources management in the Tel river basin in Orissa for a period of 1965-2008 using SPI in GIS environment. The study showed that a dramatic and widespread drought event was recorded in the year 2002 at most of the stations and drought categories. They concluded that the study area experienced severe and extreme droughts from time to time leading to unfavorable results on agricultural practices and water resources in the area.

Rezaei et al. (2011) investigated meteorological drought for period of 1986 to 2005 in Iran using SPI, Deciles and PN index and the drought severity was assessed using IDW technique in GIS. The result revealed that most extensive drought occurred in 1989, 1990, 1995, 1996, 2000, and 2001 years. The longest duration of drought based on SPI was in 1994 and 1997 whereas the extreme drought occurred in 1990 and 2001 in all stations. They concluded that central part of Iran was more exposed to extreme drought during study period than other parts of this region.

Alam et al. (2012) analyzed rainfall data from 1971 to 2010 in Bangladesh for estimating SPI to evaluate drought vulnerability based on frequency and severity of drought events at multiple time steps (3, 5 and 12 months). They developed drought severity maps in GIS environment using IDW method. They found that drought vulnerability showed a very diverse but consistent picture with varying time steps. Analysis and interpretation of the map showed a similar spatial distribution of drought in pre-monsoon season but in monsoon season rainfall deficits shifted its position time to time and occurred in certain discrete pockets. In SPI-12 the spatial distribution of drought was almost similar with monsoon season. In pre-monsoon season drought severity was higher in north eastern part of the study area compared to other parts. The study also envisaged that critical threshold values of rainfall to avoid drought condition were higher in the northern part of high Barind than southern part.

Asefjah et al. (2014) compared and evaluated four meteorological drought indices including the SPI, China-Z index (CZI), modified CZI (MCZI) and Z-Score (Z) for monitoring droughts in Salt Lake Basin in Iran. The comparison of indices was carried out based on drought classes that were monitored in the study area using 40 years of data and severity maps were prepared in GIS environment. They concluded that the SPI, CZI and Z-Score drought indices showed high performance in detecting and monitoring drought intensity compared to other drought indices.

Abari et al. (2015) evaluated and compared the impact of meteorological drought on different time scales of the selected stations for 1994 to 2012on wetlands Gandoman, Iran by using SPI and GIS tool. The SPI maps of different scales were plotted using IDW technique in GIS. The SPI at different time scales showed that the occurrence of drought zand wet condition periodically repeated in the region. The zoning maps of the SPI showed that events of extreme droughts of SPI-3 are reached to the maximum limit in the West to the South-West. In the North-West to South-West and North-East the largest expansion of extreme and severe drought related to SPI-9 was reported by them.

Aslam, (2015). Remote sensing and GIS plays an important role in detecting, assessing and managing droughts as they offer up to date information on spatial and temporal scales (Brian et al., 2012). To assess drought conditions in an area, different drought indices are used. Major drought indices use parameters like rainfall, vegetation and land surface temperature, soil moisture etc.

Kundu et al. (2015) attempted to assess the meteorological drought response to extreme climate condition using rainfall data (2002-2013) for estimating SPI in Bundelkhand region in India. A detailed spatio-temporal analysis of drought dynamics was carried out in GIS environment. The results showed the occurrence of a severe drought in Bundelkhand region during several years. They concluded that SPI with geospatial techniques proved to be a robust technique for identifying the spatio-temporal drought stress over the region.

Mokarram et al. (2015) investigated drought for a period of 2008-2014 using SPI and PN drought index in GIS for Iran. For determination of drought severity in study area they used IDW method in GIS. The results using SPI and PN showed that the amount of drought is variable in the different years. They concluded that SPI method was better than the PN method in study area.

Salehvand et al. (2015) investigated meteorological drought in Iran by using SPI, PN, Deciles, CZI and Z-score index during 1951-2010 in 15 stations. The drought severity maps were prepared by using IDW technique in GIS. The result showed that correlation coefficient was very high between drought indicators. Drought amount and duration was increased in recent years and the most severe and widespread drought was occurred in Lorestan area. The study showed that the extensive droughts were occurred in 1960s, 1990s, 1995 and 1996 years.

Wambua et al. (2015) used SPI to assess the spatio-temporal drought characteristics within the upper Tana River basin in Kenya based on precipitation data of eight gauging stations for 41 years within the basin. The Kriging interpolation technique was applied to estimate spatially drought occurrence within the basin. Their results showed that the south-eastern parts of the basin exhibited the highest drought severities while the north-western parts had the lowest drought values with averages of 2.140 and 4.065, and 2.542 and 4.812 in 1970 and 2010 respectively. They reported that their study was useful in formulating a drought early warning system that can be used to assist water resources managers in developing timely mitigation measures in planning and managing water resources within the basin.

2.8 Research gap

Various literatures has review on drought risk analysis and mapping carry out on difference areas Most recently, with the aid of digital technology, research has been addressed to map the area to predict the risk of drought and its environmental, social and economic effects, by applying different approaches, Those approaches include; mapping existing drought area and present unknown drought area, characterization of drought degree on the basis of indices, mapping of drought hazard To the best knowledge of the researcher, there is no scientific study on drought in Gombi, as well as the lack of numbers that accurately describe how the drought affects the Gombi Local Government Area, In this research to carry out on the drought risk analysis and mapping of area with a using remote sense data, the current study tried to bridge such a gap and as a first step to highlight the drought conditions in Gombi, as an attempt to ring the alarm bell to alert the dangers left behind by this serious phenomenon on the environment, economy and society.

CHAPTER THREE: METHODOLOGY

3.1 Research over View

This chapter discusses the general procedure and approach to the research project. It describes the materials/equipment and the methodologies followed to achieve the aim of the research project through its set objectives, and it discusses the data types and sources, instruments used and the method of data acquisition, data processing, the process are shown in(figure 3.1) below

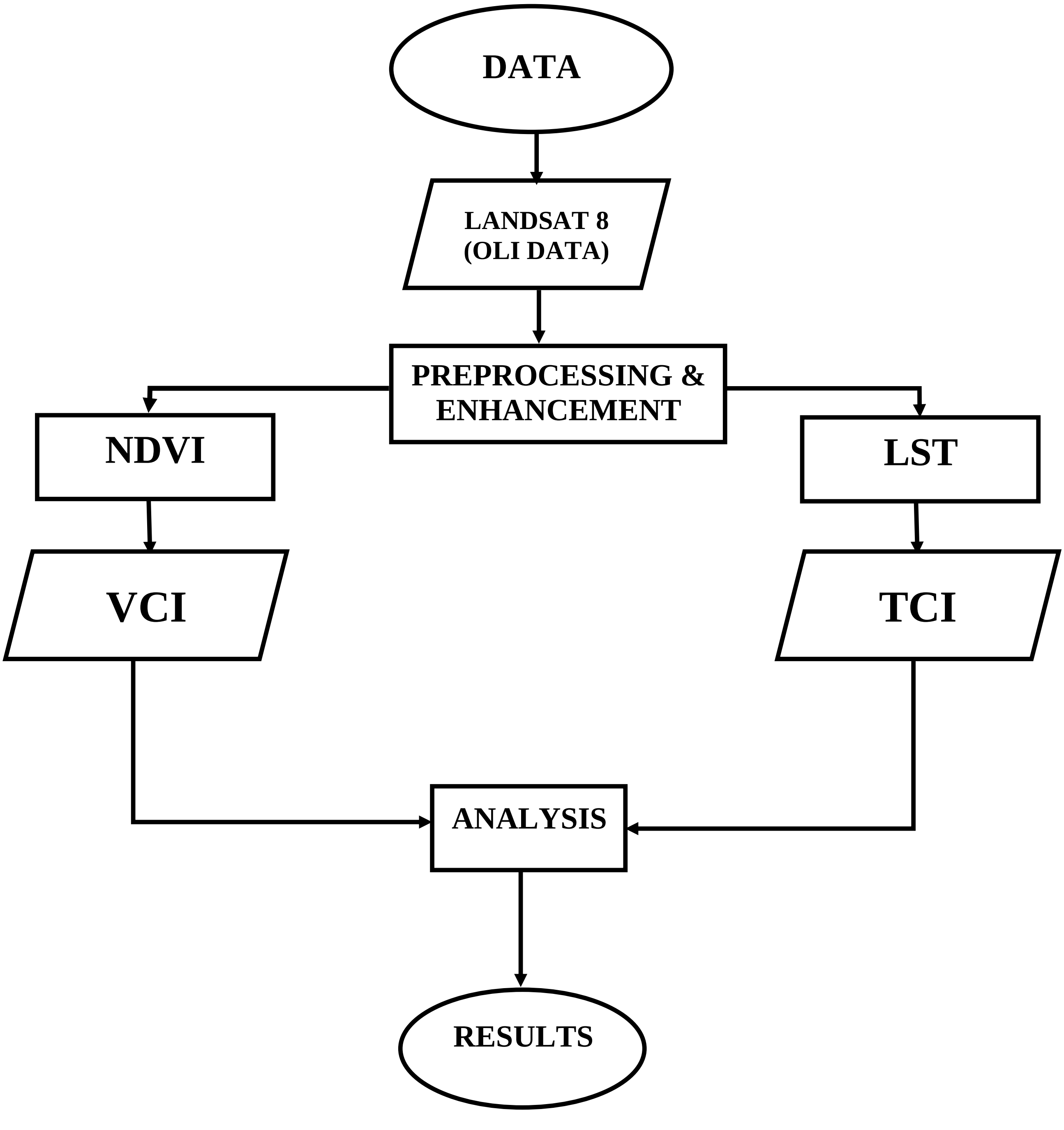


Figure 3.1: Conceptual Flowchart

3.2 Data Collection

The data collected for this research include:

Landsat 8 OLI (Operational Land Imager**)** for April 2015 to 2019, satellite images were obtained from the US Geological Survey (USGS).

3.3 Instruments to be used

The instruments used for this research can be classified into two groups; Software and Hardware.

3.3.1 Software The software used are;

i. QGIS

ii. Micro-soft Excel

3.3.2 Hardware

The hardware used includes;

i. Personal Computer System

ii. Color Printer

3.4 Data Processing

The data was digitally processed in a GIS environment to produce for the drought risk. The remote sensing data From April 2015 to 2019 for Landsat 8 ***(***OLI)

3.4.1 Data preparation

The major data preparation process for this research is clipping. Clipping in the context of computer graphics is a method to selectively enable or disable rendering operations within a defined region of interest. This operation is used to create a spatial subset of a raster, including a raster dataset, image service layer. This was allowing extracting a portion of a raster-based on a template extent. This operation was used in this research to extract the bands required for the exact study area.

3.5.1 Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is a satellite data-driven index measures chlorophyll absorption in the red portion of the spectrum relative to reflectance or radiance in the near-infrared. The NDVI is a measure of greenness or vigor of vegetation.

When sunlight strikes a plant, most of the red wavelengths in the visible portion of the spectrum (400 -700 nm) are absorbed by chlorophyll in the leaves, while the cell structure of leaves reflects the majority of NIR radiation (700-1100 nm). NDVI was compute by using equation (3.1), Kogan1995

$$\mathrm{NDVI} = \frac{\mathrm{NIR-RED}}{NIR+RED} \tag{3.1}$$

In QGIS software, the coordinate system of all images was defined in WGS 1984 and projected into UTM 33N, a coordinate system used for the area. NDVI was computed for each image use bands 4 and 5 for NDVI as extract from (Table 3.1)

Table 3:1 Landsat 8

Bands	**Limit (μm)**	**Resolution**
Band 1 Coastal	0.43-0.45	30
Band 2 Blue	0.45-0.51	30
Band 3 Green	0.53-0.59	30
Band 4 Red	0.64-0.67	30
Band 5 NIR (near-infrared)	0.85-0.88	30
Band 6 SWIR1 (shortwave infrared band 1)	1.57-1.65	30
Band 7 SWIR (shortwave infrared band)	2.11-2.29	30
Band 8 pan (panchromatic)	0.50-0.68	15
Band 9 Cirrus	1.36-1.38	30
Band 10 TIRS1 (thermal infrared band1)	10.6-11.19	30, 100
Band 11 TIRS2 (thermal infrared band2)	11.5-12.51	30, 100

Raster calculator was used for the calculation as tool provide in spatial analyst extension in ‘QGIS by using the following equation (3.2), (Kogan, 1995, 2003).

$$NDVI = \frac{Band5 - Band4}{Band5 + Band\,4} \qquad (3.2)$$

NDVI for Landsat 8 this NIR with band 5 and Red with band 4. The NDVI images generate are reclassify for monitoring drought, the study areas of interest were extracting by overlaying the shape file over NDVI image generated. The NDVI images were generated.

3.5.2 Computation of vegetation condition Index (VCI)

The VCI was computed by using equation (3.3), Kogan, 1995.

$$VCI = \frac{\mathrm{NDVIj - NDVImin}}{\mathrm{NDVImax - NDVImin}} \times 100 \qquad (3.3)$$

Where, NDVImax and NDVImin are calculated from the short term record for that month, and j is the index of the current month here, NDVImax and NDVImin are derived from Landsat 8 data records of 5 years (2015 to 2019) there are 5 decadal NDVI values of the same decade.

From these NDVI values set the maximum and minimum values obtain to function as the vegetation condition index describes the moisture condition the high values of VCI (the red area) corresponded to unstressed vegetation or in drought condition and the VCI close to zero percent reflects an extremely dry month. The duration of the successive months below normal condition and magnitude of the deviation are two powerful indicators, of drought severity, in this case, the VCI and NDVI have a strong correlation that could be used to monitor the drought.

3.5. 3 **Land Surface Temperature**

The land surface temperature was derived from Landsat 8 using various methods which the LST were calculated. The method from the official USGS Webpage using Bands 10 and 11 from the Thermal Infrared Sensor (TIRS) of the Landsat 8 satellites.

3. 5.3.1 Conversion to TOA Radiance

The Landsat Level-1 data can be converted to TOA spectral radiance using the radiance rescaling factors in the MTL file, equation (3.4). Bayarjargal *et al.* (2000)

$$L_{\lambda} = M_L\, Q_{cal} + A_L \qquad (3.4)$$

Where:

L_λ = TOA spectral radiance (Watts/ (m^2 * srad *μm))

M_L = Band-specific multiplicative rescaling factor from the metadata (RADIANCE _MULT_BAND_x, where x is the band number)

A_L = (RADIANCE_ADD _BAND_x, where x is the band number)

Q_{cal} = Quantized and calibrated standard product pixel values (DN)

3.5.3.2 Conversion to TOA Reflectance

Reflective band DN's can be converted to TOA reflectance using the rescaling coefficients in the MTL file, equation (3.5) Sholihah *et al.* (2016).

$$\rho\lambda' = M_\rho Q_{cal} + A_\rho \tag{3.5 }$$

Where:

$\rho\lambda'$ = TOA planetary reflectance, without correction for solar angle.

Note that $\rho\lambda'$ does not contain a correction for the sun angle.

M_ρ = Band-specific multiplicative rescaling factor from the metadata (REFLECTANCE_MULT_BAND_x, where x is the band number)

A_ρ = Band-specific additive rescaling factor from the metadata (REFLECTANCE_ADD_BAND_x, where x is the band number)

Q_{cal} = Quantized and calibrated standard product pixel values (DN)

TOA reflectance with a correction for the sun angle,Sholihah *et al.(*2016). equation (3.6).

$$\rho\lambda = \frac{\rho\lambda}{\cos(\theta_{SZ})} = \frac{\rho\lambda}{\sin(\theta_{SE})} \tag{3.6}$$

Where:

$\boldsymbol{\rho\lambda}$ = TOA planetary reflectance

$\boldsymbol{\theta_{SE}}$ = Local sun elevation angle. The scene center sun elevation angle in degrees is provided

$\boldsymbol{\theta_{SZ}}$ = Local solar zenith angle; $\theta_{SZ} = 90° - \theta_{SE}$

3.5.4 Temperature Condition Index (TCI)

Temperature Condition index was calculated using the following formula below. Temperature condition index is based on brightness and represents the deviation of the current months (decades) value from the recorded maximum, equation (3.7), (thenkabail 2004).

$$\mathrm{TCI} = \frac{\mathrm{BTmax} - \mathrm{BTj}}{\mathrm{BTmax} - \mathrm{BTmin}} \times 100 \tag{3.7}$$

Where BTj, BTmax, and BTmin are the averages decadal Temperature; it is absolute maximum and absolute minimum respectively of each month.

The TCI is similar to the VCI, except that the formula was modified to reflect the response of vegetation to temperature. Persistently, high temperature (low TCI) during the rainy season is usually associated with drought conditions. Here the absolute maximum and minimum brightness was obtained from the daily brightness temperatures were a record for 5 years from 2015 to 2019, the TCI of around 50% are the fair or normal temperature condition exists. When TCI values are close to 100%, the brightness temperatures for these decades are equal to the short-term minimum for the pixel. How TCI values (close to 0 %) indicate when TCI is equal to a zero percent brightness temperature for pixels. consistently low TCI values over several consecutive time intervals may point to the drought development.

The Temperature Condition Index (TCI) is based on the thermal band converted to top of atmosphere Brightness Temperature (BT). TCI is used to determine temperature-related vegetation stress and also stress caused by excessive wetness in combination with meteorological observations, the relationship between surface temperature and the moisture regime on the ground will detect drought monitoring (thenkabail 2004). The temperature condition index (TCI) reflects the different responses of vegetation to temperature. The high temperature in the middle of the ground season indicate the unfavorable condition for drought, while low temperature indicates favorable condition the temperature condition index (TCI) was computed for the following years 2015 to 2019 as summarize in minimum and maximum values

3.5.5 Computation of Vegetation Health Index (VHI)

The Vegetation Health Index (VHI) describes the vegetation health i.e. the difference between TCI, VCI, and VHI Beside drought indices, TCI, VCI, and VHI were classified into vegetation index which describes the condition of vegetation. Vegetation Health Index was calculated using the equation (3.8), Tucker 1979.

$$VHI = 0.5\ (VCI) + 0.5\ (TCI) \qquad (3.8)$$

The minimum and maximum values ware obtained.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Preambles

Generally, this chapter comprises the presentation and discussions of the results achieved in the course of this work. The results are presented in various categories of maps produced in the following Figures and Tables. The Land Surface Temperature and Normalized Difference Vegetation Index as show in (Table 4.1 and Table 4.2)

Table 4.1 NDVI Minimum and Maximum for the duration of the study

Year	Minimum	Maximum
2015	0.12	0.48
2016	0.08	0.63
2017	-0.01	0.55
2018	-0.22	0.42
2019	0.05	0.67

Table 4.2: LST Minimum and Maximum values for the duration of the study

Year	Minimum [°C]	Maximum [°C]
2015	27.77	32.62
2016	29.31	42.17
2017	22.81	37.66
2018	19.27	29.32
2019	21.88	35.09

The remote sensing-based NDVI index was used for drought risk monitoring situations in the Eastern part of Gombi. It is observed that in the year 2015 the minimum NDVI value was 0.12 and the maximum value was 0.48. In 2016 the minimum NDVI value was 0.78 and the maximum was 0.63. In 2017, the minimum NDVI value was -0.01 and the maximum value was 0.55. Similarly, in 2018 the minimum NDVI value was -0.22 and the maximum was 0.42. In 2019 the minimum NDVI value was 0.05 and the maximum was 0.67. From the values of NDVI, we can assess the vegetation healthiness in the study area. Based on the NDVI values it is very clear that in the year 2018 maximum unhealthy condition of vegetation occurred as compared to other years which shows the maximum healthy condition. The severity of drought risk in the area can be accessed on the basis of vegetation conditions and healthiness shown in NDVI maps.

It was noted that in the Eastern part of Gombi, some area is liable to drought risk 2017 and 2019 while 2018 experience higher drought risk with fewer vegetation conditions were dominant as indicated from the vegetation condition during those years in the study area. The results of the NDVI analysis showed the sensitivity of NDVI to detect drought risk yearly vegetation dynamics across all years. Therefore Satellite-based NDVI obtained from Landsat 8 was used to monitoring the drought risk for the eastern part of Gombi for the following years (2015-2019).

Hence, remote sensing and GIS can be the best tool for monitoring drought risk analysis of the eastern part of Gombi. Although NDVI values indicate the overall Vegetation condition in the study area, it does not show the occurrence of drought or no drought condition. Hence NDVI coupled with other indices may be used for Drought risk conditions in the study area.min and max values of VCI,TCI and VHI are shown in (Table 4.3) below

Table 4.3: VCI, TCI and VHI, Min and Max values for the duration of the study.

VCI	Min[%]	Max [%]	TCI	Min [%]	Max [%]	VHI	Min [%]	Max [%]
2015	38.83	78.86	2015	13.67	58.82	2015	27.64	59.72
2016	33.85	95.78	2016	42.69	100.0	2016	40.34	77.25
2017	23.93	87.04	2017	22.93	80.21	2017	28.84	62.22
2018	0.00	72.53	2018	0.00	48.79	2018	10.15	48.49
2019	30.46	100	2019	10.98	60.23	2019	22.91	58.32

From the analysis of table above the vegetation condition index shows that 2015, 2016 & 2019 shows that vegetation minimum and maximum values are high which that 40% of the area falls under moderate drought risk and 60% of the area is mild drought risk while they remain areas are free from drought risk.

The temperature condition index showed from table 4.3 that minimum and maximum values from 2015 to 2019, temperature condition index 2016 & 2017 recorded the highest maximum value while 2018 & 2015 the temperature condition index is low and vegetation health index (VHI) This proves the effect of climate change in Gombi. In 2018, the VHI show a moderate to extreme drought from table 4.3 recorded the lowest maximum vegetation condition index.

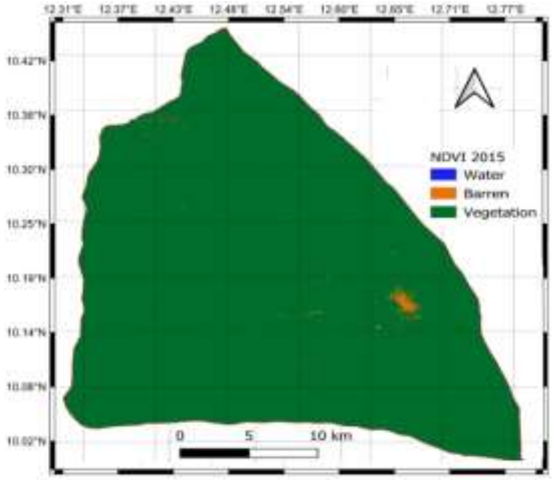
4.2 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) a measure of the" greenness "or vigor of vegetation derived based on the known radiometric properties of plants using visible (red) and near-infrared (NIR) radiation, NDVI maps Eastern part of Gombi Local Government Area for following years 2015 to 2019, figure 4.1 (a,b,c,d, and e) show the NDVI maps for April 2015 to April 2019, as discussed as follows figure 4.1 a NDVI map 2015 Eastern part of Gombi shows a condition of good vegetation while figure 4.1b NDVI 2016 is still of good vegetation but little increase of barren surface compare to 2015 map.

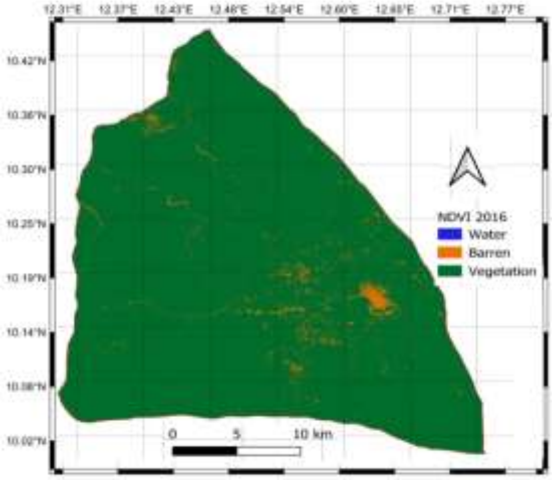
Figure 4.1c NDVI 2017 map shows that some villages in the Eastern part of Gombi are experienced poor vegetation, for example, Gombi Fulani, Zavatiniyan, Sabon gari, and wuro sanda are of poor vegetation. Figure 4.1d NDVI map 2018 for the Eastern part of Gombi shows that very high poor vegetation only few parts of some villages that have good vegetation such as Pirkasa, Sabon gida, Jabare and kaninkafa are of good vegetation.

Figure 4.1e NDVI map 2019 shows that vegetation is of partial good of the Eastern part of Gombi while few of some parts of the village that experience poor vegetation.

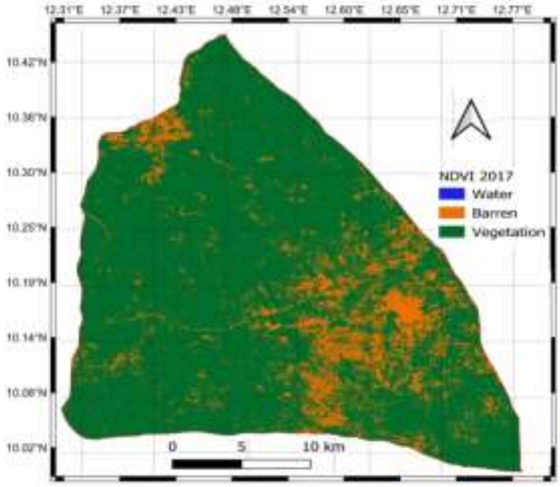
Therefore from the analysis of NDVI maps for Eastern part of Gombi Local Government Area the years 2015 and 2016 experience good vegetation while 2017 and 2019 the vegetation is of partial good because some part of villages experiences poor vegetation. Then 2018 Eastern part of Gombi experience very high poor vegetation as of results of this the minimum NDVI shows negative in table 4.1



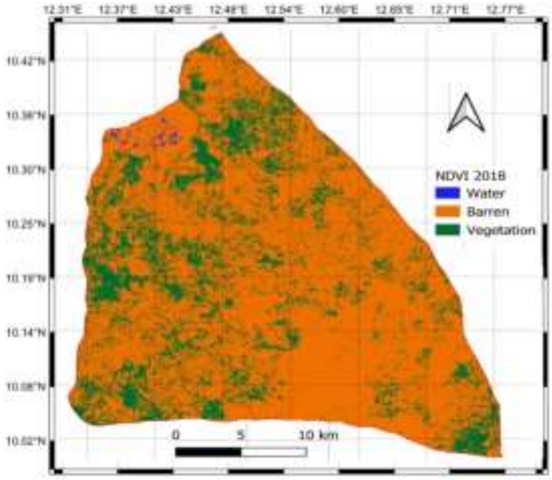
(a)NDVI 2015



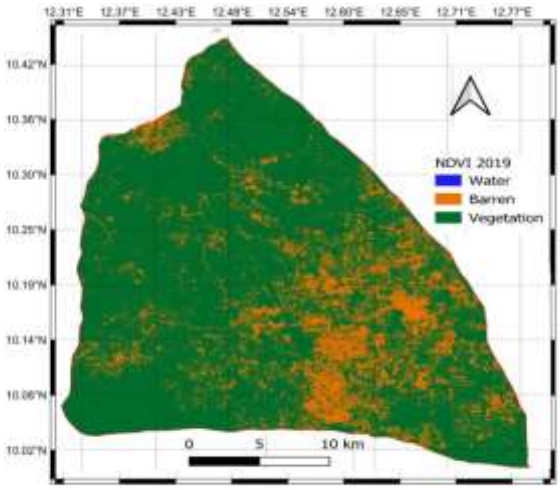
(b) NDVI 2016



(C) NDVI 2017



(d) NDVI 2018



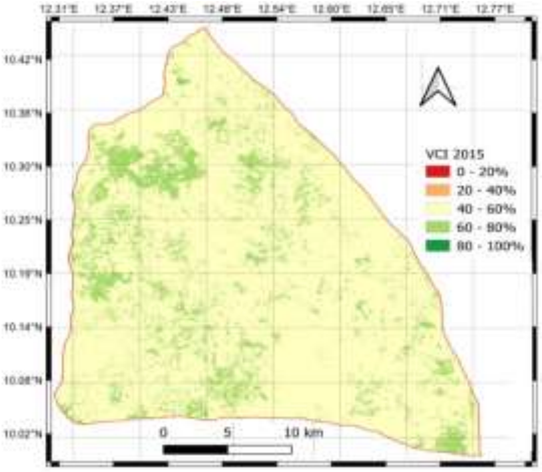
(e) NDVI 2019

Figure 4.1 Normalized Difference Vegetation Index maps for (a 2015), (b) 2016, (c) 2017(d) 2018 and (e) 2019

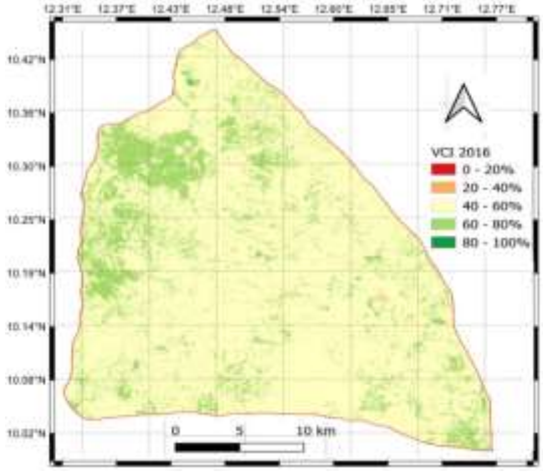
4.2.1 Vegetation Condition Index

Vegetation Condition Index (VCI) was estimated using the range of NDVI which is a good indicator for assessing the severity of agricultural drought (Kogan, 1990). Vegetation condition index was calculated using NDVI which is one of the most important parameters of agricultural drought. As per the criteria, VCI values between 50 to 100 % indicate optimal or above-normal conditions. Different degrees of drought severity can be indicated by classifying the VCI values as (i) 0 to 20% (Extreme Drought) (ii) 20 to 40% (Serve Drought), (iii) 40 to 60% (Moderate Drought), (iv)60 to 80 %(Mild drought) (v) and above 80% (No Drought), Accordingly, VCI images for the study period (2015 to 2019) The month of April VCI values were used to develop VCI map for the period of 2015 to 2019 and is presented in(Fig.4.2 a.b.c.d & e).

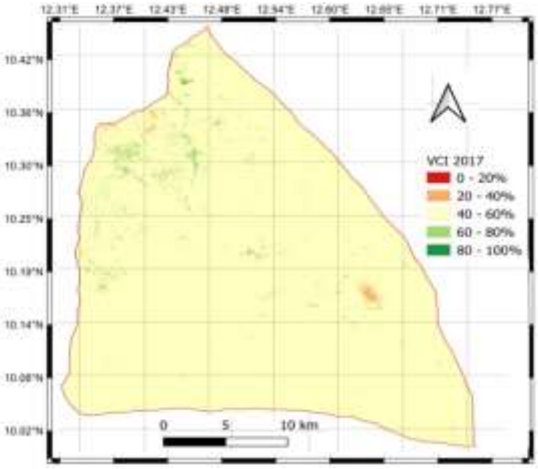
Therefore, from the analysis of vegetation condition index (VCI) for the Eastern part of Gombi, for the following years, 2015 to 2019 are seen in the various figures. For instant figure 4.2, a VCI 2015 shows that 40% to 60% of the Eastern part is moderate drought while 60% to 80% are mild drought. The Eastern part is free from extreme drought and severe risk. The minimum and maximum vegetation condition index as shown in table 4.2 are 38.83% and 78.86% while figure 4.2 b vegetation condition index for 2016 is similar to 2015 just about 5% difference between them. In figure 4.2 c VCI map 2017 part of the Gombi area experience full moderate drought risk, an only little part of Gombi town that experiences severe to drought risk. The minimum vegetation condition index is decreased down 23. 9% while the minimum vegetation condition index 2018 is reduced to 0.00% as shown in table 4.3 the Eastern part of the Gombi Area is 20% to 40% severe drought risk and 60% are moderate drought. Therefore, from the analysis of the vegetation condition index for the Eastern part of Gombi for the following years 2015 to 2019. The condition of vegetation for 2015, 2016 and 2019 are about 40% to 60% are moderate while about 80% of the areas are mild as shown in table 4.3 that minimum and maximum vegetation is of the same range while 2017 the vegetation condition index of Eastern part of Gombi pure moderate. The figure 4.2 e VCI map 2018 shows that the Eastern part of Gombi about 40% to 60% are moderate and 20% above are severe drought risk and some little part is extreme drought risk.



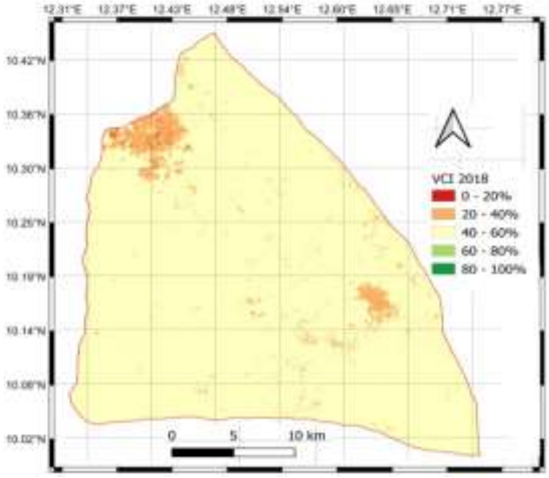
(a) VCI 2015



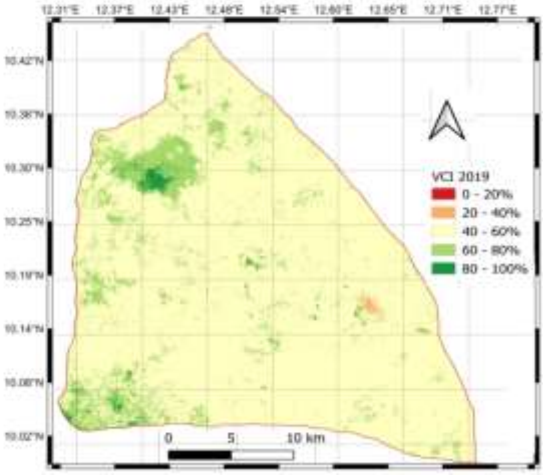
(b) VCI 2016



(c) VCI 2017



(d) VCI 2018



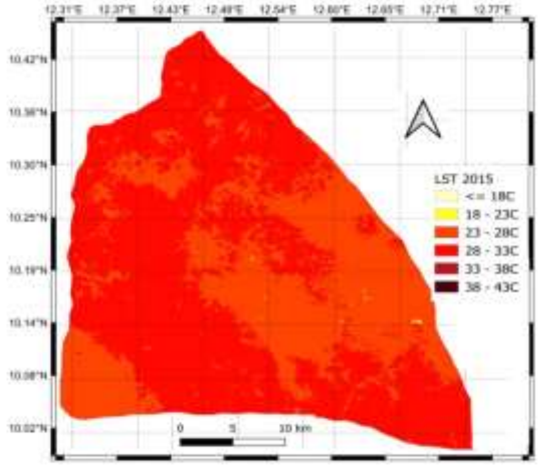
(e) VCI 2019

Figure 4.2 Vegetation Condition Index maps for (a) 2015,(b) 2016,(c) 2017,(d) 2018 and (e) 2019

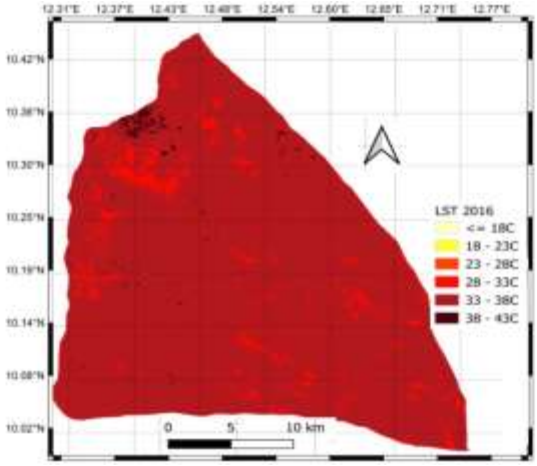
4.2.2 Land Surface Temperature (LST)

The land surface temperature was classified in six classes viz. 0 to 18°C, 18 to 23°C and 23 to 28°C, 28 to 33°C, 33 to 38°C and 38 to 43°C It can be seen from the (Fig 4.3. a, b, c, d, and e), The Land Surface Temperature for Eastern part of Gombi for the following years 2015 to 2019 describe the temperature of the area.

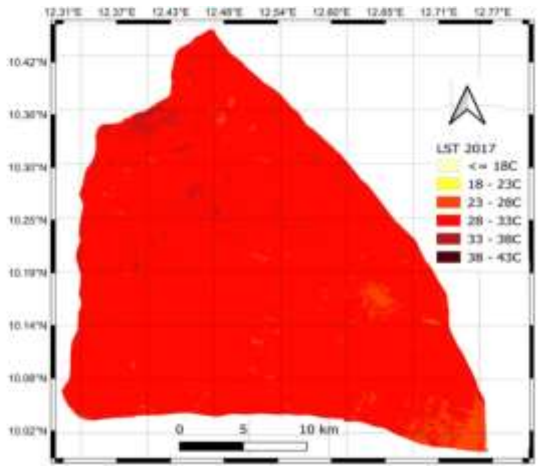
Therefore figure 4.3 a Land Surface Temperature map 2015 shows that Eastern part of Gombi some of the villages experience high temperature such as Sabon gida Jabare,kaudi, Guyaku, Ujabeda, pirkasa, and Gombi fulani some areas are little part Those areas about 32˚c while other villages are about 27˚c, those of high temperature is liable to drought risk for that year. figure 4.3 b shows the land surface temperature map 2016 for Eastern part of Gombi about 90% of total areas there experience 41˚c temperature compare to 2015 the has higher temperature while some little part is about 32˚c, also in 2017 the temperature is little difference with 2015 because most of the villages experience about 28˚c to 33˚c while some little part is 25˚c as shown in figure 4.3c. From the analysis of land surface temperature for the five years, the land surface temperature for the Eastern part of Gombi for 2018 is quite different from others as shown in figure 4.3 d that some of the areas their temperature is 23˚c to 28˚c while another part is about 20˚c. The land surface temperature for 2019 is little bet high then 2018 year as shown in table 4.2 from overall results the land surface temperature for five years, the Eastern part of Gombi experience temperature highest 2016 compares to other years.



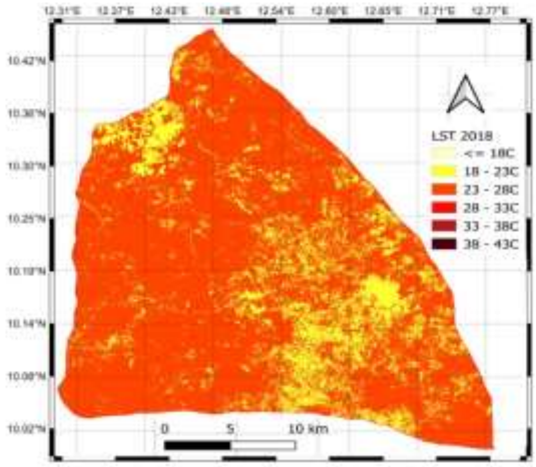
(a) LST 2015



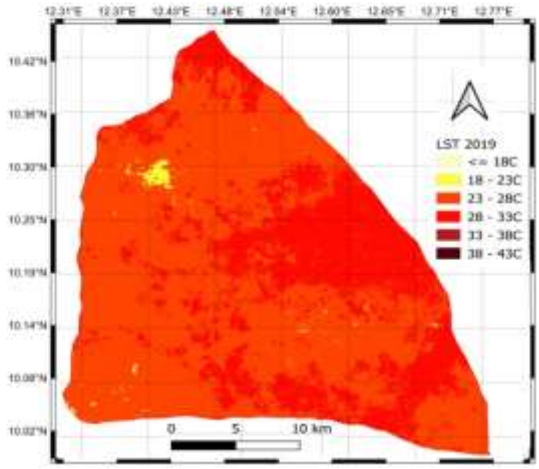
(b) LST 2016



(c) LST 2017



(d) LST 2018



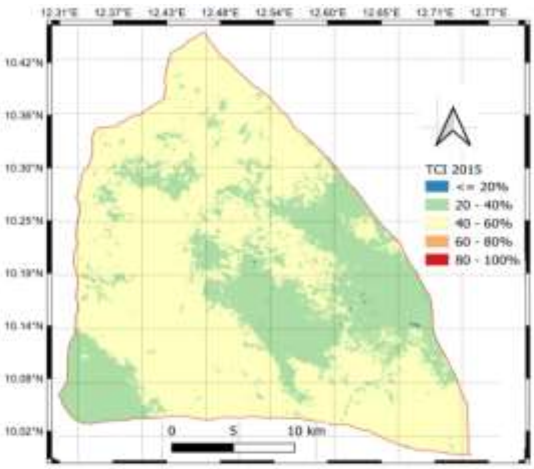
(e) LST 2019

Figure 4.3 Land Surface Temperature maps for (a) 2015, (b) 2016, (c) 2017, (d) 2018 and (e) 2019

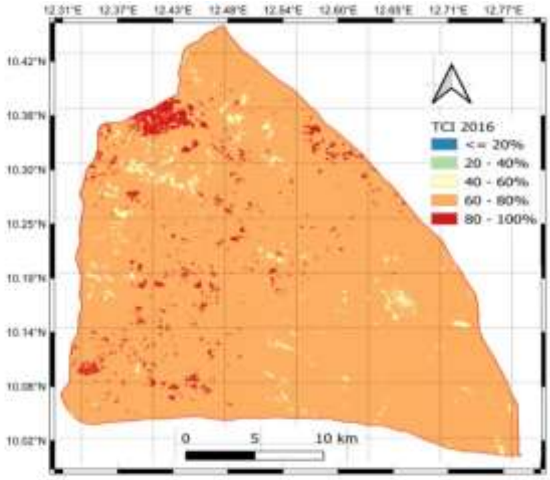
4.2.3 Temperature Condition Index

Therefore figure 4.4 (a.b,c,d,and e) explain the various temperature condition maps for Eastern part of Gombi Local Government Area, Figure 4.4a TCI map for 2015 shows that about 20-40% of area Eastern parts of Gombi are of no drought risk will about 40-60% are mild drought risk some of the villages that fall within the range are Sabon gida Jabare, wungala,kaudi, Guyaku, Ujabeda, and Pirkasa this happen due to the low temperature as shown in table 4.3 that the minimum temperature in the year 2015 is 13.68% and maximum temperature is 58.68%. In figure 4.4b the TCI map 2016 for the Eastern part of Gombi shows that 60% to 80% of the Eastern part severe drought risk while 80% to 100% are extreme drought risk as the temperature maximum increase up 100% this clearly shown that 2016 differ from other years. Figure 4.18 TCI maps 2017. The temperature condition index map for 2017 shows that about 40 % to 60% of Easter part of Gombi area is mild drought risk while 20% to 40% is no drought risk the maximum temperature is reduced down to 80.21 % compare 2016 year as shown in minimum and maximum temperature table. Figure 4.19 TCI maps 2018. The temperature condition index map 2018 for the Eastern part of Gombi shows that less 20% of the area is water and also 20% to 40% of areas are no drought risk. The minimum and maximum temperature condition index is 0.00% and 48.79% as computed as shown in table 4.3.

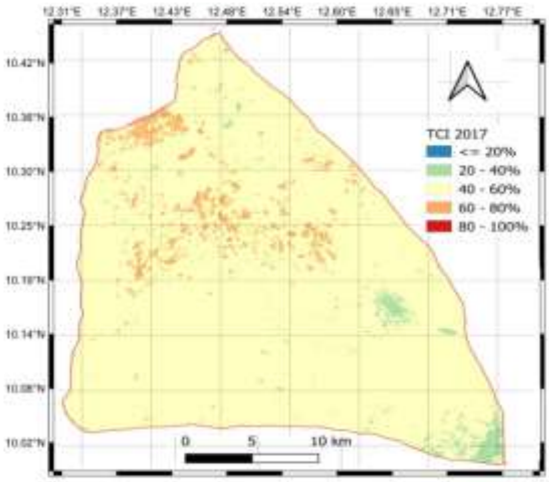
Therefore figure 4.4 e TCI map 2019, the temperature condition index for Eastern part of Gombi 2019 shows that about 20% to 40% area is a non-drought example of villages such as Huruwukta, Ujabeda, Bebe, sabon gari, kaninkafa, and Pirkasa while 40% to 60% of the area is mild drought risk. Therefore, from the analysis of temperature condition index for the following years 2015,2016,2017,2018 and 2019, the TCI 2015 and 2019 are shown that 20% to 40% of the Eastern part of Gombi is free from drought risk and 40% to 60% are experiencing mild drought risk. Than 2016-year Eastern part of Gombi area about 60% to 80% are severe drought risk, it shows that the maximum temperature condition index is up to 100% as indicated in table 4.3 while the 2018 year the temperature condition index is opposite of the 2016 year because less than 20% is water and 20% to 40% non-drought risk, the map clearly shown that Eastern part of Gombi 2018 is free from drought risk. Then 2017 the Eastern part of Gombi about 40% to 60% experience mild drought risk while 20% are a non-drought risk.



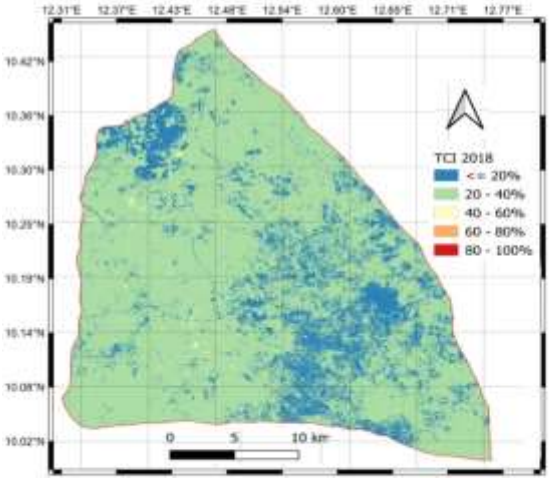
(a) TCI 2015



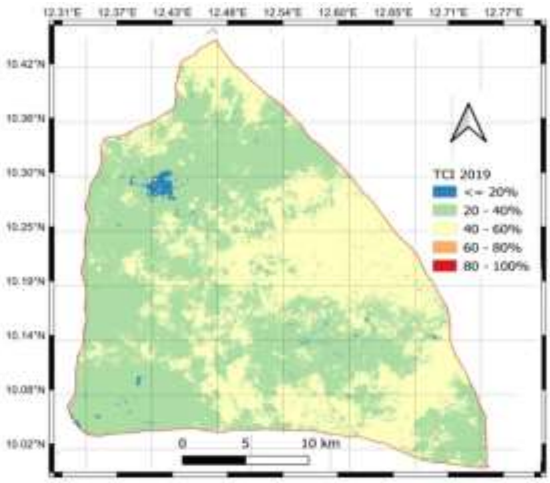
(b) TCI 2016



(c) TCI 2017



(d) TCI 2018



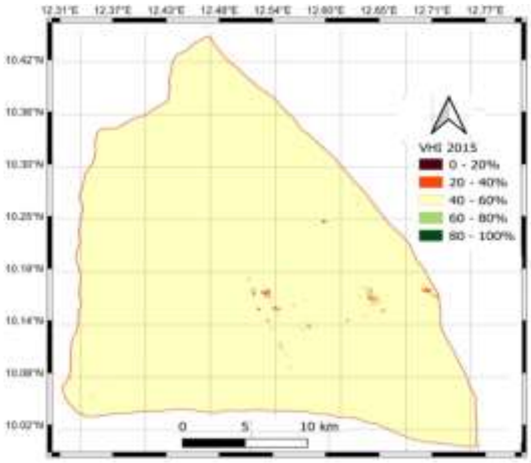
(e) TCI 2019

Figure 4.4 Temperature Condition Index Maps for (a) 2015, (b) 2016, (c) 2017, (d) 2018 and (e) 2019

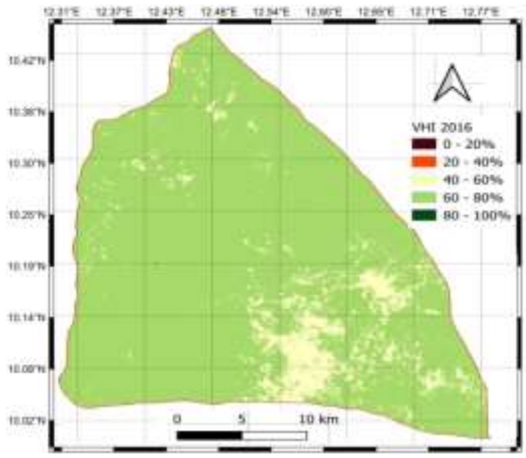
Temperature condition index (TCI) is another most important parameter of agricultural drought assessment. TCI was derived using the data of land surface temperature and by using the range of LST values for the study period. TCI was classified into five classes as 0-20%, 20-40%, 40-60%, 60-80% and 80-100% (Thenkabail *et al.*2004). Chen *et al.* (2016) also stated that TCI is considered as a thermal stress indicator to determine temperature-related drought phenomenon, assuming that a drought event will decrease soil moisture, causing temperature stress, in present research as shown in figure above The maximum temperature condition index was very high in the year 2016, The TCI was rise up to 80 % which is serve drought risk.

4.2.4 Vegetation Health Index (VHI)

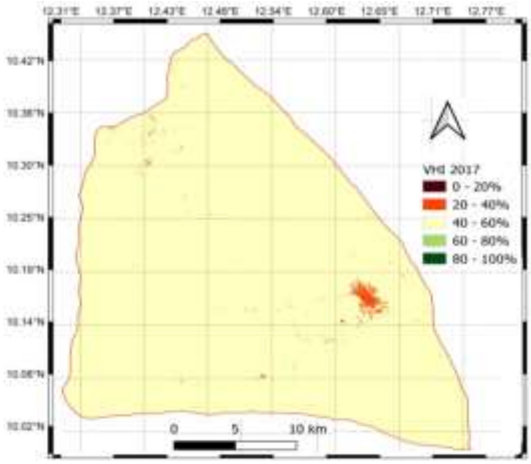
The VCI and TCI characterize variations of moisture and thermal conditions of vegetation, respectively in the Eastern part of Gombi. The combination of these two indices represents overall vegetation health. In the present study, vegetation health index (VHI) is used to investigate the spatiotemporal variation of agricultural drought in the Gombi during 2015–2019. Vegetation health index was derived from VCI and TCI by using mathematical equations (Thenkabail *et al.*2004). The VHI values range from 0 to 100, indicating changes in vegetation conditions from extremely unfavorable (vegetation stress) to optimal (favorable). However, in the present study for better understanding of vegetation condition, the VHI values were classified into five classes to characterize drought levels as extreme drought (0–20%), severe drought (20–40%), moderate drought (40 - 60%), mild drought (60–80%), and no drought (80-100%) conditions. The distribution of VHI for the years 2015, 2016, 2017, 2018 and 2019 is shown in Fig.4.5.(a),(b), (c),(d) and(e) respectively which represents overall vegetation health in the Eastern part of Gombi during a particular time scale. It is seen that in figure 4.5(d) 2018 the most of the area severe drought risk only a little part that is moderate drought risk. The vegetation health index 2015, 2017 and 2019 the conditions are similar because there are moderate to drought risk almost all the part of Eastern part of Gombi during this period only small areas around Gombi town that experience severe to drought risk, this is because the areas around Gombi town is built-up area and has very low vegetation. The vegetation health in the Eastern part of Gombi 2016 as shown in figure 4.5c almost 90% of total areas are mild drought risk the remaining 10% are moderate to drought risk, However, these conditions were found that period of 2016 indicating that there are free from drought risk.



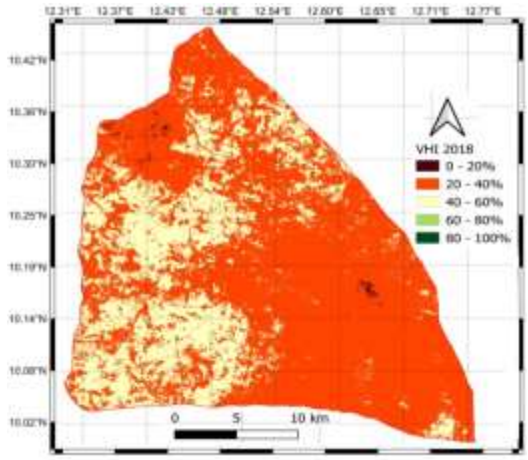
(a) VHI 2015



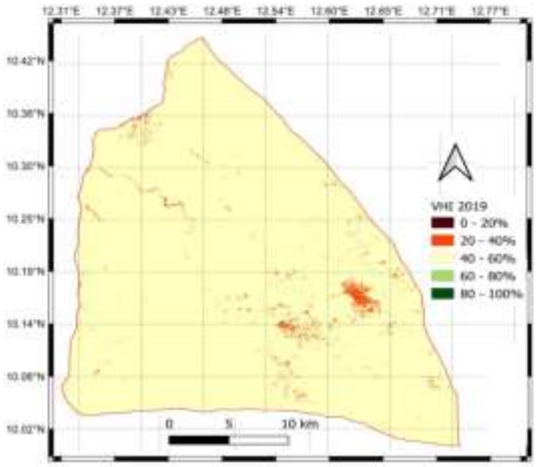
(b) VHI 2016



(c) VHI 2017



(d) VHI 2018



(e)VHI 2019

Figure 4.5 Vegetation Health Index Maps for (a) 2015, (b) 2016 (c) 2017 (d) 2018 and (e) 2019

Fig.4.1, fig 4.2 and fig 4.5 indicated that a large area was under moderate to severe drought during 2017 and 2018 as compared to other years within the study period. These results also coincide with drought severity maps developed based on various indices.

A similar procedure was also explained by Dutta *et al.* (2015) in which remote sensing-based drought indices and SPI were used for the development of drought severity map. They also found the increased area under moderate to severe drought during the study period. Nandeesha *et al.* (2015) in their study on NDVI based drought indices found that area under drought was more from 2000 to 2003 where severe drought-affected areas of the region were identified.

Gedif *et al.* (2014) in Ethiopia using NDVI found that a large proportion of the area (31.45%) was at moderate drought risk level, whereas 17% of the area accounted for high drought risk during the study period. Hassan *et al.* (2013) using MODIS data for assessment of agricultural drought in Bangladesh from 2000 to 2014 reported that 29%, 34%, and 37% area was affected by extreme, high and moderate drought risk, respectively whereas Das *et al.*. (2013) using NDVI in West Bengal reported that 6% area has no risk, 53 % area faced moderate risk and 41 % area faced high risk within the study region.

Most of the researchers concluded that agricultural drought risk mapping is useful to guide the decision-making process in drought monitoring and to reduce the risk of drought on agricultural production and productivity in the study region.

CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

The main objective of the study was to analyze changes in vegetation cover as a proxy to drought indices and to identify areas facing high drought risk by using remote sensing techniques. The first research objective as already stated above it was conducted from the study that NDVI is within a certain range. In this threshold moisture is no longer a limiting factor and NDVI increases very slowly. These areas are more prone to drought, the different factors to define risk areas were still to be attempted for better describing an area at risk.

The first chapter gives an overview of the problem under study, the different definitions, describing drought types and impact and the need for risk evaluation. The chapter also contains aim and the objectives of the study to archives.

The second chapter deals with the previous drought-related studies, different method used to study, monitor drought It was seen that most of the studies have studied about relating either of the satellite defined parameter as NDVI, VCI, TCI, VHI and LST with each other and other meteorological parameters to monitor drought risk condition but inclusion of agricultural drought from the point of agricultural production and its linkage with the satellite parameter could not be found in the literature referred thus this part was undertaken as that drought risk can be marked out taking into consideration .

The third chapter discusses the general procedure and approach to the research project. It describes the materials/equipment and the methodologies followed to achieve the aim of the research project through its set objectives, and it discusses the data types and sources, instruments used and the method of data acquisition, data processing.

The fourth chapter deals with the results obtained after the entire processing of the data and preparation of drought risk maps for Five years from 2015 to 2019 for the Eastern part of Gombi area, However, the accuracy of the results depends much more on the spatial resolution and quality of the input data than on the methodology itself.

Thus an overall outcome presents that risk area can be assessed appropriately by the integration of various data sources and thereby management plans can be prepared to deal with the hazard.

5.2 Conclusions

The remote-sensing-based vegetation health indices, namely, NDVI, LST, TCI, VCI, and VHI are important for drought detection and mapping. These are also a useful tool for monitoring drought risk of the eastern part of Gombi area. These indices ware used to monitor vegetation drought over the Eastern part of Gombi from April month 2015, 2016, 2017, 2018 and 2019. It is found that the TCI values April month 2016 and 2017 are much higher as compared to the drought risk 2018 and 2019. In other words, the year 2017 and 2018 shows higher thermal stress compared to 2019 and 2016. The VCI-based drought monitoring suggests that the vegetation condition was poor along the mountains and residential areas in Gombi with high moisture stress during 2018. The other areas were relatively free from moisture-related stress during the drought year 2018 possibly due to regular availability of moisture, even though the entire Eastern part of Gombi however, shows low VCI values in 2018 as compared to 2016. This may be due to the fact that when there is excessive soil moisture due to heavy rainfall or persistent cloudiness in some regions, the NDVI is depressed and as a result, the VCI values become low, which can be interpreted erroneously as drought in those areas. In such cases, rather than using VCI and TCI alone for drought monitoring, it is desirable to use the VHI that does their combined estimation for distinguishing drought events. The analysis carried out over the Eastern part of Gombi for the following years 2015 to 2019 the results show that 2018 confirms poor overall vegetation health.

The results obtained from indices derived from the satellite-based indicators are similar, that is, the year 2018 was the most drought-affected year in comparison to the other years. The results also indicate that in the year 2018 most of the area was affected by severe and extreme drought conditions and has poor vegetation Health, 2017 and 2019 some of area was affected by moderate to mild drought conditions. While in 2015 most of the area was affected by slight drought. From the research it is found that some of the villages are under threat and has to be prepared for mitigation to reduce the impacts of agricultural drought. This study concludes that real time satellite data can be well utilized for regional level agricultural vulnerability detection for early warning of agricultural drought.

5.3 Recommendations

i. It is recommended that higher spite scales may not be useful for a drought on quantification in the present study area hence shorter time scales of 1month and 2 months should be considered to identify meteorological drought risk.

ii. Monthly and yearly drought severity maps of Eastern part of Gombi developed by integrating corresponding drought indices can be used in decision making for drought monitoring which will help to reduce the impact of drought on agricultural production and productivity and to identify appropriate sites for specific drought adaptation and mitigation actions.

iii. Finally, it is recommended that the Society should seriously look into the drought issue through improving resource management practices and development of drought assessment and implementation unit to help minimize the adverse effects of drought. In doing this, concerned authorities should work closely with stakeholders who might be directly or indirectly affected by drought. Socio-economic data should also be taken into consideration when assessing drought risk to better understand the vulnerable groups.

iv. Furthermore, as the fund risk map give the area facing of high drought risk, a detailed study of this area in term of soil, water availability, rainfall, and the social conditions was not attempted in this study. It is recommended for further research to prevalent can further holy in preferring better management plans.

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APPENDICES

Appendix I: Climatic Parameters of the Study Area

Years	Max. Temperature	Min. Temperature	Precipitation	Wind Speed	Relative Humidity	Solar Flux
1979	34.278	19.221	4.853	2.305	0.521	20.212
1980	35.049	19.474	3.857	2.514	0.489	20.438
1981	34.610	18.957	4.748	2.432	0.500	19.333
1982	33.488	19.429	4.914	2.333	0.525	19.062
1983	34.241	18.590	3.436	2.638	0.458	21.018
1984	36.180	19.149	3.042	2.508	0.442	19.415
1985	34.819	18.766	5.222	2.471	0.461	19.963
1986	35.911	18.695	3.537	2.406	0.457	20.807
1987	35.691	19.158	4.100	2.376	0.441	20.626
1988	34.321	19.356	4.200	2.478	0.489	19.148
1989	33.780	18.450	4.259	2.559	0.471	20.495
1990	35.588	19.432	4.155	2.556	0.455	19.906
1991	35.417	19.537	3.362	2.495	0.469	19.774
1992	34.161	18.975	4.453	2.571	0.483	18.926
1993	35.215	18.838	4.034	2.382	0.469	20.001
1994	34.504	19.303	3.600	2.532	0.484	19.956
1995	34.362	19.473	6.163	2.439	0.506	20.226
1996	34.641	19.170	4.820	2.424	0.488	20.099
1997	34.212	19.395	4.778	2.461	0.498	19.560
1998	35.852	19.742	2.586	2.628	0.439	19.970
1999	36.520	19.021	2.686	2.346	0.423	20.877
2000	37.308	18.780	1.617	2.724	0.373	21.364
2001	36.511	19.320	3.955	2.671	0.400	20.442
2002	37.240	19.539	3.310	2.532	0.399	20.047
2003	36.750	19.522	4.236	2.439	0.420	20.271
2004	37.258	19.397	2.877	2.464	0.400	20.334
2005	36.534	20.029	4.361	2.440	0.429	20.479
2006	37.639	19.804	1.895	2.416	0.392	20.246
2007	36.213	19.781	2.089	2.491	0.433	19.981

2008	34.971	19.242	4.335	2.435	0.459	19.764
2009	35.023	20.443	4.985	2.376	0.483	20.196
2010	35.158	20.380	4.091	2.425	0.473	20.330
2011	34.461	18.792	4.758	2.172	0.473	21.748
2012	34.017	18.866	4.554	2.190	0.504	20.867
2013	34.679	19.053	3.061	2.099	0.483	21.558
2014	35.822	19.777	2.602	2.361	0.431	21.337