DROUGHT VULNERABILITY ASSESSMENT OF MINNA USING STANDARDIZED PRECIPITATION INDEX METHOD

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ABSTRACT

Drought is one of the most naturally occurring menace and threat to human existence and the environment through the ages and the Standardized Precipitation Index (SPI) has become a popular measure of drought across the globe. In this study, Standardized Precipitation Index (SPI) was used for observing and describing drought based on seventy (70) year precipitation data of Minna sub-station. This is evident from the obtained results as the driest and the wettest years were observed with the SPI at a 3-month, 6-month and 12-months scale. 1987 was observed as the driest year with the worst drought using SPI at a 12-month scale while 2019 was observed to be the wettest year. The data was also used to determine the rainfall anomaly of Minna with aid of rainfall anomaly index (RAI). SPI 12 was found to correlate with RAI which confirmed the accuracy and sensitivity of SPI 12. Therefore, the present study concludes that the 12-month SPI of June to November represents a good indicator of any drought vulnerability assessment for any drought-prone areas.

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ABBREVIATIONS, GLOSSARIES AND SYMBOLS

GDP	Gross Domestic Product
IPCC	Intergovernmental Panel on Climate Change
NIMET	Nigerian Meteorological Agency
NDMC	National Drought Mitigation Centre
RAI	Rainfall Anomaly Index
SPI	Standardized Precipitation Index
UNISDDR	United Nations International Strategy for Disaster Reduction
WMO	World Meteorological Organization

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

Drought is one of the most naturally occurring menace and threat to human existence and the environment through the ages; as it cut across all geographic regions (Hao *et al.*, 2018; Eze, 2018). This climatic hazard is as old as the existence of man. It is a temporary, recurring natural disaster which originates from lack of precipitation, bringing significant economic loss (Smakhtin and Hughes, 2004). It is a multifaceted and multidimensional phenomenon and is considered by many to be the most complex but least understood natural hazards due to its multiple causing mechanisms or contributing factors operating at different temporal and spatial scales (Kiem *et al*., 2016; Mishra and Desai, 2005).

It is very difficult to determine when a drought begins or ends but its origin usually starts with the lack of precipitation (Mishra and Desai, 2005). Depending on its severity, it may affect agriculture and water supplies with respect to soil moisture, streams, and groundwater. In certain cases, unusual deviation of environmental variables such as evapotranspiration, high wind, low relative humidity, temperature, characteristics and duration of rain, intensity and onset may result to drought (Livneh and Hoerling, 2016; Luo *et al*., 2017; Cook *et al.*, 2020).

However, the role of deficient long-term precipitation records greatly contributes in all these (Vardharajula *et al.*, 2011). Specifically, high temperature may lead to increased evaporation and reduced soil moisture, causing drought in agricultural sectors. However, drought may not be a purely natural hazard as human activities such as land use changes, overexploitation of surface water resources and reservoir operation may alter hydrologic processes and could deteriorate to drought development (Van Loon *et al.,* 2016).

Minna, the capital city of Niger State in Northern Nigeria constitutes one of the „grain baskets‟ of Nigeria in terms of food production, producing a large proportion of the grains such as; maize, millet, sorghum, and wheat (Oladipo, 1993) that provide the main staple diet of Nigerians. Despite the heavy investment in agriculture by both Federal and State governments in the area of massive irrigation schemes in this region, for instance, agriculture is still largely rain fed, depending majorly on rainfall which is between the months of April and October in average.

However, with rainfall in northern part of Nigeria largely seasonal and highly variable from year to year, agriculture in the region has suffered serious setbacks and this has thus led to insecurity in food supply in the region and by extension food scarcity in the entire country. Because of the large inter-annual variability of rainfall, this region has also been subjected to frequent dry spells of which has affected the farming activities in the entire region. These can sometimes result in severe and widespread droughts that are capable of imposing serious socio-economic constraints as reiterated by Lange *et al.,* (2017) and Dar *et al.,* (2020).

1.2 Statement of the Research Problem

Drought has not been well documented in recent years and the impacts are increasing in magnitude and complexity. Rain-fed farming is the dominant source of food production and means of livelihood for many poor rural farmers in Sub-Saharan Africa, including Nigeria (Cooper *et al.,* 2008). Drought episodes persisted for about five-six years in the region, where it affected millions of people in northern Nigeria.

The number of people affected in northern Nigeria is more than those affected in the other Sahelian countries combined (Mortimore, 2001). Lack of international media attention can be attributed to Nigeria‟s economic stability, which is related to national oil wealth. The northern Nigerian States severely affected by the 1970s droughts are those adjacent to the Niger Republic.

In Nigeria, agriculture contributes 18.4% of national GDP, but after the droughts of the 1970s, crop production declined to contribute only 7.3% of GDP, leaving many Nigerians from the north in acute poverty and starvation (Abubakar and Yamusa, 2013). Hence, study of drought vulnerability in northern Nigeria is necessary. This study however, involves emphasizing the need for proper attention to drought and its mitigation.

1.3 Aim and Objectives of the study

1.3.1 Aim

The aim of this research is to assess drought vulnerability of Minna using Standardized Precipitation Index (SPI) Method.

1.3.2 Objectives

To achieve these aims, the following objectives were set out.

i To determine the rainfall anomaly index (RAI) for Minna Meteorological Station.

ii To determine the drought vulnerability of Minna at 3-month, 6-month and 12 month time scales using Standardized Precipitation Index (SPI)

1.4 Justification for the Study

Droughts occur throughout the length and breadth of Nigeria. However, they are more frequent and much more severe in the Sudano-Sahelian States of Kebbi, Sokoto, Zamfara, Katsina, Kano, Jigawa, Yobe, Gombe and Borno. It is in these dry belt areas that drought of disaster scale occurs from time to time, hence the need for a close monitoring over this region in order to identify its onset, intensity, cessation, duration and spatial extent as well as its frequency in a timely manner for its proper management.

Furthermore, there is a need for appropriate techniques to be used to determine drought occurrence so as to reduce its impact on the environment. It also appears that future climate changes may lead to more frequent and severe droughts. Therefore, it is imperative that increased emphasis be placed on mitigation, preparedness, and prediction and early warning if society is to reduce the economic and environmental damages associated with drought and its personal hardships.

The early warning systems will Improve land use practices, which can help decrease soil and land degradation, strengthens overall drought management, including preparedness, response and recovery. Effective systems can give a lead-time of up to a few weeks, mitigates human fatalities, health risks and poor water and food security, reduces high costs related to post-drought rehabilitation and relief efforts, and improves network connectivity within and between local communities.

1.5 Scope of the Study

The study investigates the occurrences of drought, its general effect on Nigeria"s socioeconomic activities. However, the research was limited to Minna, Niger state.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Drought

The menace of Drought and Desertification is one of the ecological disasters currently plaguing the country. About eleven (11) out of the thirty-six (36) states of the country falls within the desert prone zones. These frontline states are: Adamawa, Borno, Bauchi, Gombe, Jigawa, Kano, Katsina, Kebbi, Sokoto, Yobe and Zamfara (Abubakar & Yamusa, 2013). These states have an estimated population of about 43 million people (2004 projection) and occupy about 397,222 Square Kilometer of Nigeria"s total land in Figure 2.1.

Figure 2.1: Map of Nigeria showing the northern states affected by desertification

Nigeria is experiencing unfriendly climate conditions with negative impacts on the welfare of millions of people. Persistent drought, delay in onset of rains, early cessation of the rains and short rainy season including pronounced dry spells have caused low agricultural productivity for a country that is mostly dependent on rain fed agriculture. Inadequate water resources resulting from reduction in quantity of river flow and Lakes have fewer water supplies for use in agriculture, hydropower generation and other uses. The main cause of all these havocs is the changing climate (Abubakar & Yamusa, 2013).

Arid and semi-arid areas in Northern Nigeria are becoming drier and Sahara Desert characteristics are encroaching fast into the country. We already have an increasing incidence of diseases, declining agricultural productivity and rising number of heat waves.

Declining rainfall in already desert-prone areas in Northern Nigeria is causing increasing desertification. The Northern part of Nigeria is endowed with a large expanse of arable land that has over the years provided a vital resource for agriculture and other economic activities, but the Sahara Desert is advancing Southward at the rate of 0.6 km every year 1. Consequently, Nigeria loses about 350,000 hectares of land every year to desert encroachment5. This has led to demographic displacements in villages across 11 states in the North. It is estimated that Nigeria loses about $5 billion every year due to rapid desert encroachment and drought (Azare *et al.*, 2020). About 5 million livestock are being threatened by desertification according to estimate from states Ministry of Environment. The Fulani population is known to be mostly affected as their herdsmen are constantly seeking new grazing lands and water as a result of the desert encroachment.

2.2 Types of Drought

Sequence of drought occurrence and impacts for commonly accepted drought types. All droughts originate from a deficiency of precipitation or meteorological drought but other types of drought and impacts cascade from this deficiency (Farahmand *et al*., 2021)

Droughts are complex climatic events that can be characterized by different properties, such as frequency, duration and intensity. They can come in different forms, which also depend on their impacts. For example, when soil moisture or water flow is affected, they have different impacts (Leng *et al*., 2015). All types of drought have different causal factors and characteristics. However, all types of drought are detrimental to both anthropogenic and natural systems (Leng *et al*., 2015). Ecosystems need sufficient water for their functioning (for plants to grow and aquatic organisms to survive (Yaduvanshi *et al*., 2015). Growing demand for water due to increased population and economic growth makes it insufficient for both systems (Yaduvanshi *et al*., 2015). Intensity is the level of precipitation shortage in an area, and it is related to the severity of the drought, which is measured by the reduction in precipitation and water level in the hydrological cycle (Van Loon and Laaha, 2014). The duration of drought usually takes at least 2-3 months to manifest, after which it can exist for months, years and even decades. Distribution areas usually affected by intense drought gradually evolve over time (Van Loon and Laaha, 2014). There are four types of drought, namely: meteorological; agricultural; hydrological and socio-economic, which are further discussed below

2.2.1 Meteorological drought

Meteorological drought is defined usually based on the degree of dryness (in comparison to some “normal” or average amount) and the duration of the dry period.

It is related to water shortage, characterized by abnormal weather conditions, such as low precipitation amounts and high 4 temperatures (Qin *et al*., 2014). This type of drought is difficult to prevent, but it can be projected and monitored. Deficient precipitation causes drought and it is linked to other types of drought, depending on impacts (Qin *et al*., 2014).

Definitions of meteorological drought must be considered as region specific since the atmospheric conditions that result in deficiencies of precipitation are highly variable from region to region.

For example, some definitions of meteorological drought identify periods of drought on the basis of the number of days with precipitation less than some specified threshold. This measure is only appropriate for regions characterized by a year-round precipitation regime such as a tropical rainforest, humid subtropical climate, or humid mid-latitude climate. Other definitions may relate actual precipitation departures to average amounts on monthly, seasonal, or annual time scales.

2.2.2 Agricultural drought

Agricultural drought is defined by the availability of soil moisture content to sustain plants or crop growth and maintain pastures for grazing. Soil moisture content below annual average level decreases crop yield and is described as agricultural drought (Qin *et al*., 2014).

Agricultural drought links various characteristics of meteorological (or hydrological) drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced groundwater or reservoir levels, and so forth. Plant water demand depends on prevailing weather conditions, biological characteristics of the specific plant, its stage of growth, and the physical and biological properties of the soil. A good definition of agricultural drought should be able to account for the variable susceptibility of crops during different stages of crop development, from emergence to maturity (National Drought mitigation Centre 2021).

This drought depends on soil moisture that supports plants after the cessation of precipitation. Normally, after rainy seasons, plants sustain themselves using soil moisture. However, the water holding capacities of soils vary. Soil water relationships are one of the vital characteristics that support plant growth, which simultaneously influence carbon allocation, nutrient cycling, microbial activity and photosynthesis. Soil with low water holding capacity is more liable to drought (Piedallu *et al*., 2011).

Deficient topsoil moisture at planting may hinder germination, leading to low plant populations per hectare and a reduction of final yield. However, if topsoil moisture is sufficient for early growth requirements, deficiencies in subsoil moisture at this early stage may not affect final yield if subsoil moisture is replenished as the growing season progresses or if rainfall meets plant water needs.

2.2.3 Hydrological drought

Hydrological drought is associated with the effects of periods of precipitation (including snowfall) shortfalls on surface or subsurface water supply (that is, stream flow, reservoir and lake levels, groundwater). It is defined as insufficient terrestrial availability of precipitation (Van Loon and Laaha, 2014). The frequency and severity of hydrological drought is often defined on a watershed or river basin scale. Although all droughts originate with a deficiency of precipitation, hydrologists are more concerned with how this deficiency plays out through the hydrologic system. It usually affects the levels of water bodies from average to low, which makes it insufficient to meet human and ecosystem demands. Hydrological droughts are usually out of phase with or lag the occurrence of meteorological and agricultural droughts. It takes longer for precipitation deficiencies to show up in components of the hydrological system such as soil moisture, stream flow, and groundwater and reservoir levels. As a result, these impacts are out of phase with impacts in other economic sectors (National Drought Mitigation Centre, 2021).

2.2.4 Socioeconomic drought

Socio-economic drought is insufficient precipitation to meet human and environmental demands, it is triggered by human activities and elements of other types of drought such as hydrological, meteorological and agricultural (Wilhite, 2005). Socioeconomic definitions of drought associate the supply and demand of some economic good with elements of meteorological, hydrological, and agricultural drought. It differs from the aforementioned types of drought because its occurrence depends on the time and space processes of supply and demand to identify or classify droughts. The supply of many economic goods, such as water, forage, food grains, fish, and hydroelectric power, depends on weather. Because of the natural variability of climate, water supply is ample in some years but unable to meet human and environmental needs in other years. Socioeconomic drought occurs when the demand for an economic good exceeds supply as a result of a weather-related shortfall in water supply (National Drought Mitigation Centre 2021).

2.3 Factors Responsible for Drought

2.3.1 Lack or insufficient rainfall (or precipitation)

This is the major cause of droughts in most regions. A long-drawn-out period without rainfall can cause an area to dry out. The quantity of water vapor in the atmosphere pretty much impacts the precipitation of an area. When a region has moist and low-pressure systems, there is huge probability that rain, hail, and snow will occur. The exact opposite would happen when the region has high-pressure systems, and less water vapor. Farmers‟ plant crops in anticipation of rains, and so when the rains fail, and irrigation systems are not in place, agricultural drought happens.

2.3.2 Changes in climate

Changes in climate, for instance, global warming can contribute to droughts. Global warming is likely to impact the whole world, especially third world economies. This increase in greenhouse gasses has resulted in warmer temperatures. Warmer temperatures are recipes for dryness and bushfires. These set of conditions mightily contribute to prolonged droughts (Abubakar and Yamusa, 2013).

2.3.3 Human activities

Forests are critical components of the water cycle. They help store water, minimize evaporation, and contribute a great deal of atmospheric moisture in the form of transpiration. This, in essence, implies that deforestation, aimed at uplifting the economic status of a region, will expose vast quantities of water to evaporation. Cutting down trees will also take away the capability of the ground to retain water and allow desertification to occur easily (Abubakar and Yamusa, 2013).

Deforestation also greatly minimizes watershed potential. Over-farming is another human activity contributing to droughts. Over-farming loosens the soil allowing erosion to take place. Soil erosion compromises the capacity of soil to hold water.

2.3.4 Overexploitation of surface water resources

Specific areas are endowed with surface water resources like rivers and streams whose sources are watersheds and mountains. These surface water resources could dry out if their main sources are interfered with. Irrigation systems and hydroelectric dams are just some of the aspects that contribute to over-exploitation of surface water resources. They also cut off supply of water to downstream communities.

2.4 Drought Vulnerability

IPCC (2001; 2007) defined vulnerability as the level to which a system (natural or social system) will resist damage from climate change. Vicente-Serrano *et al*. (2012) defined vulnerability to drought as the ability of a region to withstand drought. Adaptive ability to vulnerability is how quickly systems adjust to climate change.

Antwi-Agyei *et al*. (2012) identified factors such as poor soil, poor water management, poverty, rural vulnerability, population growth, changing consumption patterns, climate variability and land use change as factors that can exacerbate the impacts of drought. Population growth and over-exploitation of natural resources compromise adaptation to drought in Africa, due to social and economic stresses on communities (Antwi-Agyei *et al*., 2012). Vulnerability level has increased amongst African communities over last few decades (Wilhite, 2007; Vicente-Serrano *et al*., 2012). Furthermore, responses vary as drought impacts also differ spatially and temporally in every region (Wilhite, 2007)

The Sudano-Sahelian regions of Nigeria are the most vulnerable areas to drought and desertification processes. These regions already have low level of biological productivity, organic matter and aggregate stability. Their vegetation and plant covers are relatively sparse, and soils are relatively more susceptible to accelerated erosion by water and wind. People at risk and at loss in the Sudano-Sahelian region are more than 19 million and 17 million respectively (Chevrier *et al*., 2020).

The most vulnerable sector to drought in Nigeria is the water resources. Water resources represent a major prerequisite and driver of social-economic development and cater for other economic sectors such as; domestic, agriculture and fisheries, industry, bio-diversity, power and energy generation.

Agriculture is one of the main economic activities in Nigeria and accounts for around 40 percent of the country"s GDP and employs about 60 percent of the active labor force thus drought would lead to a catastrophe with unprecedented repercussions (Oluwatayo & Ojo 2018).

Agricultural production is reduced in periods of drought, majority of the populations in the drought prone areas are peasant farmers, living on marginal lands in rural areas and practicing rain fed agriculture. Drought threatens agricultural production on these marginal lands, exacerbating poverty and undermining economic development. The poor crop yields due to drought result in mass poverty and starvation as agriculture is the mainstream of Nigeria"s rural economy.

One of the most important effects of drought is the depletion of biodiversity. Existing fauna and flora that are not resistant to drought are likely to go extinct. Studies have shown that several animal and plant species are disappearing in the drought prone region of Nigeria. The combined effects of drought and bush burning (during dry season) have made the flora to go extinct and the animals migrate to safer havens. Drought, land degradation and desertification have had serious impact on the richness and diversity of plants and animals in the dry land region. Plant biodiversity will change over time. Emerging and invasive species will dominate and total biomass production will be reduced (Chevrier *et al*., 2020).

The impacts of drought and desertification on the energy sector are felt primarily through losses in hydropower potential for electricity generation. In Nigeria, electricity is largely generated through hydropower, thus drought is likely to reduce the volume of water in dams and rivers and consequently lead to reduction in hydro-electricity generation and hence load shedding of electricity in the country. Energy impacts can also be experienced through reduction in the growth rate of trees due to drought. Majority of peasant people in Nigeria rely on fuel wood as source of energy (Oluwatayo & Ojo 2018).

2.5 Characteristics of Drought and Its Severity

Drought severity is dependent not only on the duration, intensity, and geographical extent of a specific drought episode but also on the demands made by human activities and vegetation on a region‟s water supplies. The characteristics of drought, along with its far-reaching impacts, make its effects on society, economy, and environment difficult, though not impossible, to identify and quantify (Van Loon and Laaha 2014).

Droughts differ from one another in three essential characteristics: intensity, duration, and spatial coverage. Intensity refers to the degree of the precipitation shortfall and/or the severity of impacts associated with the shortfall (Wilhite 2007). It is generally measured by the departure of some climatic index from normal and is closely linked to duration in the determination of impact. Impacts of a drought are generally dependent on the severity of the hydrological drought event, which can be expressed by streamflow drought duration or deficit volume. For prediction and the selection of drought sensitive regions, it is crucial to know how streamflow drought severity relates to climate and catchment characteristics (Van Loon and Laaha 2014). A relatively new index that is gaining increasing popularity in the United States and worldwide is the Standardized Precipitation Index (SPI), developed by McKee *et al.* (1995).

Another distinguishing feature of drought is its duration. Droughts usually require a minimum of two to three months to become established but then can continue for months or years (Van loon and Laaha 2014). The magnitude of drought impacts is closely related to the timing of the onset of the precipitation shortage, its intensity, and the duration of the event. Droughts also differ in terms of their spatial characteristics. The areas affected by severe drought evolve gradually, and regions of maximum intensity shift from season to season.

Droughts also differ in terms of their spatial characteristics. The areas affected by severe drought evolve gradually, and regions of maximum intensity shift from season to season. In larger countries, such as Brazil, China, India, the United States, or Australia, drought would rarely, if ever, affect the entire country. During the severe drought of the 1930s in the United States, for example, the area affected by severe drought never exceeded 65 percent of the country (Vicente-Serrano *et al* 2020). By contrast, drought affected more than 95 percent of the Great Plains region in 1934. In India, the droughts of this century have rarely affected more than 50 percent of the country. An exception occurred in 1918–19, when 73 percent of the country was affected. On the other hand, it is indeed rare for drought not to exist in a portion of these countries in every year (Wilhite 2007).

2.6 Impact of Climate Change in Nigeria

Recently, Nigeria is experiencing the negative impacts of climate change, which affected the welfare of millions of people, especially farmers (Olaniyi 2021). In the arid zones, droughts are getting worse and climate uncertainty is growing, climate change is an unprecedented and threat to food security. Arid and semi-arid areas in northern Nigeria are becoming drier, while the southern part of the country is getting wetter, global warming means that many dry areas are going to get drier and wet areas are going to get wetter (Olaniyi *et al*., 2013).

Droughts and floods are some of the major impacts of climate change in the country. This problem needs proper attention and mitigation considering that most people depend on agriculture in Nigeria (Olaniyi *et al.,* 2013). Rivers, lakes, hydro-electric power stations are drying up and have witnessed low level capacities over the last few years (Olaniyi *et al.,* 2013). The impacts are evident in northern Nigeria, as drought severity and aridity are increasing which threatens food security (Olaniyi *et al*., 2013).

Agriculture contributes substantially to Nigeria‟s GDP, where most of the rural population (70%) relies on agriculture for livelihoods (Olaniyi *et al.,* 2013). Changes in climate and weather patterns have had devastating impacts on these peoples‟ lives. These are further aggravated by over-grazing, over-exploitation, deforestation, poor irrigation practices, resources conflict, lack of food security and losses in fauna and flora (Medugu *et al*., 2011).

2.7 Impact of Drought

Drought has been a problem in West Africa for many decades, but did not receive adequate attention until during the Great Sahelian droughts of the 1970s (Hassan *et al*., 2019). Drought has not been well documented in recent years and the impacts are increasing in magnitude and complexity. Drought and desertification are particularly pronounced in north-eastern Nigeria (Hassan *et al*., 2019).

Dry spells at the beginning of the season usually result in multiple plantings and low or no yields leading to low food security index. In the same vein, end of season drought could bring about water stress at critical periods of need during the reproductive stages of most crops thus resulting in crop failures and shrinking of yields.

Drought can have a wide range of impacts on the environment, the economy and on society. Drought becomes most obvious to us when we feel its impacts and consequences, such as municipal watering restrictions or higher food prices. However, drought can have many impacts that are not as noticeable – for example, it may result in changes in water quality, such as increased water temperature and reduced dissolved oxygen, which can affect aquatic organisms (Saber *et al*., 2020).

The impacts of drought can be direct or indirect. Direct impacts are usually environmental changes that can be directly attributed to drought (e.g. poor soil quality as a result of insufficient soil moisture). Indirect impacts are the consequences of direct impacts (e.g. poor soil quality resulting from lack of moisture may lead to increased food prices, because the soil cannot produce as much crop as usual) (Alberta Water Portal 2014).

The impacts of drought are related to how severe the drought is, and how long it lasts. If a drought is fairly mild, it may go unnoticed by the majority of people, even though the drought may have negative environmental impacts

The impacts of drought and desertification on the energy sector are felt primarily through losses in hydropower potential for electricity generation. In Nigeria, electricity is largely generated through hydropower, thus drought is likely to reduce the volume of water in dams and rivers and consequently lead to reduction in hydro-electricity generation and hence load shedding of electricity in the country. Energy impacts can also be experienced through reduction in the growth rate of trees due to drought.

Majority of peasant people in Nigeria rely on fuel wood as source of energy (Hassan *et al*., 2019).

Drought impacts are classified into three major categories: economic impacts, environmental impacts, and social impacts (Crystal 2009).

2.7.1 Economic Impacts

Many economic impacts occur in agriculture and related sectors, because of the reliance of these sectors on surface and groundwater supplies. In addition to losses in yields in both crop and livestock production, drought is associated with insect infestations, plant disease, and wind erosion. Income loss is another indicator used in assessing the impacts of drought. Reduced income for farmers has a ripple effect. Retailers and others who provide goods and services to farmers face reduced business (Crystal 2009). This leads to unemployment, increased credit risk for financial institutions, capital shortfalls, and eventual loss of tax revenue for local, state, and federal governments. Prices for food, energy, and other products increase as supplies are reduced (Nasra 2020). In some cases, local shortages of certain goods result in importing these goods from outside the drought-stricken region. Reduced water supply impairs the navigability of rivers and results in increased transportation costs because products must be transported by alternative means. Hydropower production may also be significantly affected.

2.7.2 Environmental Impacts

Environmental losses are the result of damages to plant and animal species, wildlife habitat, and air and water quality, forest and range fires, degradation of landscape quality, loss of biodiversity, and soil erosion. Some of these effects are short-term, conditions returning to normal following the end of the drought. Other environmental effects last for some time and may even become permanent (NDMC 2021). Wildlife habitat, for example, may be degraded through the loss of wetlands, lakes, and vegetation. However, many species eventually recover from this temporary aberration. The degradation of landscape quality, including increased soil erosion, may lead to a more permanent loss of biological productivity.

2.7.3 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 and 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 (NDMC 2021). Migration is usually to urban 17 areas within the stressed area, or to regions outside the drought area. Migration may even be to adjacent countries. When the drought has abated, the migrants seldom return home, depriving rural areas of valuable human resources. The drought migrants place increasing pressure on the social infrastructure of the urban areas, leading to increased poverty and social unrest.

2.8 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 main stay 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 (Abubakar and

Yamusa 2013). The impacts of drought and desertification are among the costliest 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 on and unsustainable exploitation of natural resources, and conflicts render the country especially vulnerable to impacts of drought**.** Ahmed (2020) highlighted the effects of Drought as follows: low or no crop yields resulting in low food security index; mass famine; death of livestock; low groundwater levels resulting in dry wells (which needed to be dug deeper and deeper to obtain water for drinking); drying of lakes and dams; loss of biodiversity and impoverishment of ecosystem; acute shortage of water for domestic use and for livestock; decline in GDP; migration into urban areas; separation of families; and increased indebtedness.

2.8.1 Effects of drought on agriculture and food security

The majority of the populations in the drought prone states live on marginal lands in rural areas practicing rain-fed agriculture. Drought threatens agricultural production on these marginal lands, exacerbating poverty and undermining economic development (Mbuli *et al*., 2021). The impact of drought and climatic variability in both economic and mortality terms is generally larger for relatively simple and predominantly agricultural economies. The drought of 1971-72 for example reduced Agricultural contribution to GDP in Nigeria from 18.4% in 1971-72 to 7.3% in 1972-1973. The poor crop yields or total crop failure due to drought result in mass poverty and starvation as agriculture is the mainstay of Nigeria‟s rural economy.

Although agriculture will remain for many years as major contributor to the economies of most developing countries (Kogo *et al*., 2021). In some countries, according to

(Kogo *et al*., 2021), however, its share of GDP will progressively decline as drought and desertification take their toll with food shortages increasing at the same time. The poor households that are affected by drought and desertification do not have adequate resources to deal with food shortages leading to food insecurity and hunger that affects millions of people. Agriculture is one of the main economic activities in Nigeria which accounts for around 40 percent of the country‟s GDP and employs about 60 percent of the active labour force (Odusola 2021). Thus drought would lead to a catastrophe with unprecedented repercussions. The most severe consequence of drought is famine.

2.9 Impact of drought on water availability

According to Swann (2018), drought influences water availability, which is projected to be one of the greatest constraints to economic growth in future (Zargar *et al*., 2017). Reduced annual average rainfall and its run-off would increase desertification in Nigeria. According to Mahmood & Jia (2019), most of the rivers and streams in the drought prone areas in Northeastern Nigeria flow into Lake Chad. Drought, therefore exacerbates the shrinking of the lake. The rivers in addition to contributing in recharging Lake Chad are catchments to several dams built for irrigation and domestic water supply (Mahmood & Jia 2019). This means that the regions will not have sufficient water resources to maintain their current level of per capita food production from irrigated agriculture – even at high levels of irrigation efficiency – and also to meet reasonable water needs for domestic, industrial, and environmental purposes.

2.9.1 Impact of drought on biodiversity

One of the most important effects of drought is the depletion of biodiversity (Aguirre *et al*., 2021). Aguirre *et al*. (2021) further posited that existing fauna and flora that are not resistant to drought are likely to go extinct. Several animal and plant species are disappearing in the drought prone region of Nigeria. The combined effects of drought and bush burning (during dry season) have made the flora to go extinct and the animals to migrate to safer havens (Reside *et al*., 2019). Drought, land degradation and desertification have had serious impact on the richness and diversity of plants and animals in the region. Plant biodiversity will change over time, unpalatable species will dominate, and total biomass production will be reduced.

2.9.2 Impact of drought on energy availability

The impacts of drought and desertification on the energy sector are felt primarily through losses in hydropower potential for electricity generation and the effects of increased runoff (and consequent siltation) on hydropower generation (Weng *et al*., 2020). In Nigeria, electricity is largely generated through hydropower thus drought is likely to reduce the volume of water in the dams and rivers and consequently lead to reduction in hydroelectricity generation and hence load shedding of electricity in the country (Obahoundje *et al*., 2021). Mohammed *et al*., (2017) opined that load shedding as a result of low water volume in Kainji and Jebba electricity projects has become more pronounced during the dry season thus compounding the energy crisis in Nigeria. Energy impacts can also be experienced through reduction in the growth rates of trees due to drought (Mohammed *et al*. 2017). Majority of peasant people in Nigeria rely on fuel wood as source of energy.

2.10 Vulnerability Assessment/Vulnerability to Drought

Intergovernmental Panel on Climate Change IPCC (2001; 2014) defined vulnerability as the level to which a system (natural or social system) will resist damage from climate change. Vicente-Serrano *et al.* (2012) defined vulnerability to drought as the ability of a region to withstand drought. Adaptive ability to vulnerability is how quickly systems adjust to climate change. Vulnerability of individuals is based on their capability to withstand exposure, stress and their coping strategy.

Resistance means the ability to slow and reduce the impacts of drought, whereas resilience refers to capacity of a system to recover from drought. Antwi-Agyei *et al.* (2012) identified factors such as poor soil, poor water management, poverty, rural vulnerability, population growth, changing consumption patterns, climate variability and land use change as factors that can exacerbate the impacts of drought. Population growth and over-exploitation of natural resources compromise adaptation to drought in Africa, due to social and economic stresses on communities (Antwi-Agyei *et al.*, 2012). Vulnerability level has increased amongst African communities over last few decades (Wilhite, 2007; Vicente-Serrano *et al.,* 2012). Furthermore, responses vary as drought impacts also differ spatially and temporally in every region (Wilhite, 2007). The United Nations International Strategy for Disaster Reduction Report UNISDR (2004) categorized vulnerability factors into three:

i Environmental factors are those that describe the condition of the environment in an area.

ii Social factors describe the state of well-being of individuals, groups, the population and communities, which is also known as the non-economic factor.

iii Economic factors describe the state of the economy in the region (UNISDR, 2004).

Assessment of drought vulnerability is complex (Kim *et al.,* 2015). Guiqin *et al.,* (2012) investigated vulnerability of agriculture to drought in 31 provinces and cities in China. The study employed the Grey Relation Analysis (GRA) method to identify factors influencing agricultural drought and translated them into quantitative indicators. The studies found that the South-east coast of China had least vulnerability to agricultural drought than central areas, due to high precipitation and irrigation. The western area had high vulnerability to agricultural drought, due to low precipitation and excessive irrigation.

The results further show that farmers" vulnerability is influenced by social, economic, infrastructural and psychological factors. Understanding vulnerability to drought is complex, because it depends on socio-economic and biophysical indicators (Kim *et al.,* 2015). Factors considered while studying vulnerability to drought, include population, policy, technology, social behavior, land use patterns, water use and economic development (Wilhelmi & Wilhite 2002).

2.11 Drought Monitoring and Forecasting

Monitoring different aspects of the hydrologic cycle may require a variety of indicators and indices. It is desirable to align these and their depiction with the impacts of emerging conditions on the ground and management decisions being taken by different individuals, groups and organizations. Although drought early warning system (DEWS) is ultimately concerned with impacts, drought impact assessment is a large gap in many DEWSs used around the globe at this time. Assessment of impacts is complicated, as socioeconomic factors other than the physical nature of droughts influence the levels and types of impacts related to drought exposure and vulnerability. Understanding how droughts affect people, communities, businesses or economic sectors is key to taking steps towards mitigating the impacts of future drought (Wilhite *et al*., 2007).

Given that the occurrence of drought can lead to crop failures, interrupted food chains and reduced water supply, forecasting of drought events is indeed a vital component of water resources planning and management. While compounded by the fact that the starts and ends of droughts are very difficult to determine precisely, however, many drought forecasting models have been developed to improve the drought forecasting capability (Dikshit *et al*., 2020). These models are founded on sound methodologies such as: regression analysis, autoregressive integrated moving average (ARIMA), Markov chain, artificial neural network (ANN), fuzzy logic (FL), support vector regression (SVR) and different hybrid models (Dikshit *et al*., 2020; Khan *et al*., 2020). With the large variety of forecasting models available, it can be very difficult for researchers to decide which model is best suited to their research work, not to mention that there is a slight chance that researchers may overlook the best models for their problem if they are not aware of the potential types of model available. Therefore, below are some of the models available.

2.12 Drought Forecasting Models

2.12.1 Regression analysis

Regression analysis is considered one of the early candidates and widely adopted forecasting approach used for time series predictions. Regression analysis is a statistical method to examine the relationships between variables (Sykes, 1993; Heikkinen *et al*., 2006). The performance of this method highly relies on the number of independent variables, type of dependent variables and shape of the regression line. In essence, the wide range of regression analysis used for time series forecasting includes logistic regression and log linear regression.

2.12.2 Stochastic modeling: ARIMA and SARIMA

Stochastic models have been widely used for scientific applications, including analyzing and modeling of the hydrologic time series. The advantages of stochastic models include better consideration of the serial linear correlation characteristic of time series; capability to search systematically for identification; estimation and diagnostic check for model development; and SARIMA requires only a few parameters to describe non-stationary time series for both within and across seasons. Two important and popular classes of stochastic models are the ARIMA and the SARIMA (Karimi *et al.* 2019). For both variants of these stochastic models, they contain three important parameters; namely the autoregressive order of p, the dth difference of the time series zt and the moving average order of q, where iterative tuning has to be carried out to generate a robust model.

2.12.3 Probabilistic modeling: Markov Chain (Mc)

Markov chain is a memory less random process in which, if a present state has been known or given, the future and the past are independent of each other. It is a mathematical technique to obtain the probabilities of the system using a set of transition probabilities from one state to another. Generally, when the transitional probability is dependent on the conditions in the previous m time periods, it is called an mth order Markov chain.

2.12.4 Artificial intelligence-based models

Artificial neural networks are flexible, nonlinear models that resemble the structure of a nerve system. They can adapt the data inserted and analyze and discover patterns from it. Theoretically, by giving an adequate amount of nonlinear processing units, neural networks are able to gain experiences and learn to estimate any complex functional relationship accurately (Mishra & Singh, 2010). The ANNs learn based on a black-box process, the main factors affecting the performance of the model are input adequacy, network architecture and model validation. The network of ANNs is constructed from three major components: input layer, hidden layer and output layer. Thus, ANNs have the clear advantage of not needing to define the procedures or processes between the inputs and outputs.

Studies have shown that the ANN is outperforming other traditional non-AI based models with the advantages of less statistical training and its nonlinear property. The availability of different variants is another advantage of using ANN to cope with different needs and situations compared with the other methods. One of its draw backs is the fact that the „black-box‟ nature of ANN causes it to be lacking in interpretation of the model‟s functional behavior.

2.12.5 Fuzzy logic (FL)

Fuzzy logic was conceptualized by Zadeh (1965) and is defined as a handy way to map an input space to an output space (Adhikary and Mallick, 2015). Among the several advantages of using fuzzy logic, the most relevant for our subject matter is the fact that it can model imprecise data and nonlinear functions of arbitrary complexity and that it is based on a natural language.

2.12.6 Support vector regression (SVR)

SVMs seek to minimize the generalization error, while ANNs and other empirical risk minimization-based learning algorithms seek to minimize training error. SVMs can be categorized into two types: support vector classification (SVC) and support vector regression (SVR), where SVR is the preferable type for forecasting tasks.

2.12.7 Hybrid models

Hybrid models are a new category of hydrology modeling which has emerged in the last decade. To the best knowledge of the authors, the first drought forecasting hybrid model used in the hydrology field since 2007 was introduced by (Mishra *et al.* 2007). The hybrid models can be grouped into two variants, first, the hybrid between machines learning models and, second, the hybrid between data pre-processing techniques and machine learning models.

2.12.8 Dynamic modeling

Dynamic modeling is an approach which utilizes real time data to describe a phenomenon over time. Due to the rapid development of remote sensing in drought monitoring and impact assessment, the availability of drought related real time variables has also increased Unlike the statistical drought forecasting models that use long-term conventional gauge observations, dynamic drought modeling is highly dependent on the real time remote sensing data.

2.13 Drought Early Warning Systems

A drought early warning system‟s main purpose is to warn local communities when there is risk of a drought, improving preparedness and decreasing risks associated with crop and food loss. This technology is particularly important for agriculture and water resource management. Effective warning systems require drought monitoring using appropriate drought indicators, meteorological data and forecasts, a warning signal, public awareness and education, institutional cooperation, and data sharing arrangements. The unpredictable weather patterns resulting from climate change, such as the occurrence of increasingly severe droughts, make this technology important for climate change adaptation efforts in many countries. Assessing risks and vulnerabilities and improving preparedness for natural disasters can minimize threats and avoid expensive relief efforts following such an event. An early warning system combined with the slow onset of a drought can give sufficient lead-time to local decision makers to mitigate drought threats, for example by arranging for emergency food supply, planning water harvesting programs or introducing improved dry-land farming initiatives.

2.14 Drought Indices and Indicators

Drought risk management involves hazards, exposure, vulnerability and impact assessment, a drought early warning system (DEWS), and preparedness and mitigation (Nhamo *et al*., 2019). It is important that drought indicators or indices accurately reflect and represent the impacts being experienced during droughts. As droughts evolve, the impacts can vary by region and by season. Drought Indicators are variables or parameters used to describe drought conditions. Examples include precipitation, temperature, stream flow, groundwater and reservoir levels, soil moisture and snowpack.

Drought indices are typically computed numerical representations of drought severity, assessed using climatic or hydro meteorological inputs including the indicators. They can also be described as assimilate data on rainfall, snowpack, stream flow, and other water supply indicators into a comprehensible big picture They aim to measure the qualitative state of droughts on the landscape for a given time period. Indices are technically indicators as well. Table 2.1 shows the indices/indicator categorized by type and grouped into the following classifications: (a) meteorology, (b) soil moisture, (c) hydrology, (d) remote sensing and (e) composite or modeled.

Table 2.1: Different indices (Meteorology) and indicators with their respective parameters

Meteorology	Input Parameters	Additional information
Aridity Anomaly Index (AAI)	P, T, PET, ET	Operationally available for India
Deciles	P	Easy to calculate; examples from Australia are useful
Keetch–Byram Drought Index (KBDI)	P, T	Calculations are based upon the climate of the area of interest
Percent of Normal Precipitation	P	Simple calculations
Standardized Precipitation Index (SPI)	P	Highlighted by the World Meteorological Organization as a starting point for meteorological drought monitoring
Weighted Anomaly Standardized Precipitation (WASP)	P, T	Uses gridded data for monitoring drought in tropical regions
Aridity Index (AI)	P, T	Can also be used in climate classifications
China Z Index (CZI)	P	Intended to improve upon SPI data
Crop Moisture Index (CMI)	P, T	Weekly values are required
Drought Area Index (DAI)	P	Gives an indication of monsoon season performance
Drought Reconnaissance Index (DRI)	P, T	Monthly temperature and precipitation required
Effective Drought Index (EDI)	P	Program available through direct contact with originator
Hydro-thermal Coefficient of Selyaninov (HTC)	P, T	Easy calculations and several examples in the Russian Federation
NOAA Drought Index (NDI)	P	Best used in agricultural applications
Palmer Drought Severity Index (PDSI)	P, T, AWC	Not easy to use due to complexity of calculations and the need for serially complete data
Palmer Z Index	P, T, AWC	One of the many outputs of PDSI calculations
Rainfall Anomaly Index (RAI)	P	Serially complete data required
Self-Calibrated Palmer Drought Severity Index (sc-PDSI)	P, T, AWC	Not easy to use due to complexity of calculations and serially complete data required
Standardized Anomaly Index	P	Point data used to describe regional
Agricultural Reference Index for Drought (ARID)	P, T, Mod	Produced in south-eastern United States of America and not tested widely outside the region
Crop-specific Drought Index (CSDI)	P, T, Td, W, Rad, AWC, Mod, CD	Quality data of many variables needed, making it challenging to use
Reclamation Drought Index (RDI)	P, T, S, RD, SF	Similar to the Surface Water Supply Index, but contains a temperature component

Table 2.2: Different indices (soil moisture) and indicators with their respective parameters

Soil Moisture	Input Parameters	Additional Information
Soil Moisture Anomaly (SMA)	P, T, AWC	Intended to improve upon the water balance of PDSI
Evapotranspiration Deficit Index (ETDI)	Mod	Complex calculations with multiple inputs required
Soil Moisture Deficit Index (SMDI)	Mod	Weekly calculations at different soil depths; complicated to calculate
Soil Water Storage (SWS)	AWC, RD, ST, SWD	Owing to variations in both soil and crop types, interpolation over large areas is challenging

Table 2.3: Different indices (Hydrology) and indicators with their respective parameters

Hydrology	Input parameters	Additional Information
Palmer Hydrological Drought Severity Index (PHDI)	P, T, AWC	Serially complete data required
Standardized Reservoir Supply Index (SRSI)	RD	Similar calculations to SPI using reservoir data
Standardized Streamflow Index (SSFI)	SF	Uses the SPI program along with streamflow data
Standardized Water-level Index (SWI)	GW	Similar calculations to SPI, but using groundwater or well-level data instead of precipitation
Streamflow Drought Index (SDI)	SF	Similar calculations to SPI, but using streamflow data instead of precipitation
Surface Water Supply Index (SWSI)	P, RD, SF, S	Many methodologies and derivative products are available, but comparisons between basins are subject to the method chosen
Aggregate Dryness Index (ADI)	P, ET, SF, RD, AWC, S	No code
Standardized Snowmelt and Rain Index (SMRI)	P, T, SF, Mod	Can be used with or without snowpack information

Table 2.4: Different indices (Remote Sensing) and indicators with their respective parameters

Remote Sensing	Input Parameters	Additional Information
Enhanced Vegetation Index (EVI)	Sat	Does not separate drought stress from other stress
Evaporative Stress Index (ESI)	Sat, PET	Does not have a long history as an operational product
Normalized Difference Vegetation Index (NDVI)	Sat	Calculated for most locations
Temperature Condition Index (TCI)	Sat	Usually found along with NDVI calculations
Vegetation Condition Index (VCI)	Sat	Usually found along with NDVI calculations
Vegetation Drought Response Index (VegDRI)	Sat, P, T, AWC, LC, ER	Takes into account many variables to separate drought stress from other vegetation stress
Vegetation Health Index (VHI)	Sat	One of the first attempts to monitor drought using remotely sensed data
Water Requirement Satisfaction Index (WRSI and Geo-spatial WRSI)	Sat, Mod, CC	Operational for many locations
Normalized Difference Water Index (NDWI) and Land Surface Water Index (LSWI)	Sat	Produced operationally using Moderate Resolution Imaging Spectroradiometer data
Soil Adjusted Vegetation Index (SAVI)	Sat	Not produced operationally

Table 2.5: Different indices (Modelling) and indicators with their respective parameters

Composite or Modelled	Input Parameters	Additional Information
Combined Drought Indicator (CDI)	Mod, P, Sat	Uses both surface and remotely sensed data
Global Integrated Drought Monitoring and Prediction System (GIDMaPS)	Multiple, Mod	An operational product with global output for three drought indices: Standardized Soil Moisture Index, SPI and Multivariate Standardized Drought Index
Global Land Data Assimilation System (GLDAS)	Multiple, Mod, Sat	Useful in data-poor regions due to global extent
Multivariate Standardized Drought Index (MSDI)	Multiple, Mod	Available but interpretation is needed
United States Drought Monitor (USDM)	Multiple	Available but interpretation is needed

Key to variables:

AWC = available water content,

CC = crop coefficient,

CD = crop data,

ER = ecoregion,

ET = evapotranspiration,

GW = groundwater,

LC = land cover,

Mod = modelled,

Multiple = multiple indicators used,

P = precipitation,

PET = potential evapotranspiration,

Rad = solar radiation,

RD = reservoir,

S = snowpack,

Sat = satellite,

SF = streamflow,

ST = soil type,

WD = soil water deficit

T = temperature,

Td = dew point temperature,

W = wind data

2.15 Standardized precipitation Index

Droughts are apparent after a long period with a shortage of precipitation or without any precipitation (Vicente-Serrano *et al*., 2020). Many definitions and related mathematical tools for their quantification have been developed. Among the most widely used are the traditional Palmer drought severity index and the standardized precipitation index (McKee *et al*., 1993). The PDSI is a soil moisture algorithm that includes terms for water storage and evapotranspiration, whereas the SPI is a probability index that is based solely on precipitation. It was formulated by (McKee *et al*., 1993) to give a better representation of abnormal wetness and dryness than does the PDSI. The SPI can be defined as the number of standard deviations by which a normally distributed random variable deviates from its long-term mean.

In recent decades, many studies using the SPI were undertaken. Using the SPI extended to the Northern Hemisphere, (Bordi and Sutera 2001) showed that there are some interesting spatially remote teleconnections that link the tropical Pacific Ocean with the European area. Lloyd-Hughes and Saunders (2002) found that trends in SPI values indicate significant change in the proportion of Europe experiencing extreme and/or moderate drought conditions during the twentieth century.

SPI analysis satisfactorily explained the recurrent floods in the past 25 years that have affected the southern Cordoba Province in Argentina (Seiler *et al*., 2002). Livada and Assimakopoulos (2007) used the SPI to detect spatial and temporal drought events over Greece and found mild to moderate drought reduction from north to south and from west to east on 3- and 6-month time scales over the 51-yr time period of the study. In that study, the frequency of occurrence of severe and extreme drought conditions was very low on the 12-month time scale. The SPI was also used in China to study drought/wetness episodes in the Pearl River basin, and the results were helpful for basin-scale water resource management under a changing climate (Zhang *et al*., 2009).

Its main weaknesses are dependence on the normalization procedure (the probability density function used) and poor definition in arid regions that experience many months with zero precipitation (Wu *et al*., 2007). For Africa in particular, there are only a few studies on drought monitoring by use of climate indices. (Ntale and Gan 2003) used the SPI as a drought indicator in the East African region and compared its performance with the PDSI and the Bhalme–Mooley index. The identification of droughts in Zimbabwe by Manatsa *et al*. (2017) on the basis of SPI estimation from the regionally averaged rainfall for 1900–2000 revealed that the most extreme droughts of the twentieth century were recorded in 1991 and 1992. (Yuan *et al*., 2013) more recently used dynamical models to obtain probabilistic seasonal drought forecasts in Africa.

2.15.1 Characteristics

Uses historical precipitation records for any location to develop a probability of precipitation that can be computed at any number of timescales, from 1 month to 48 months or longer. As with other climatic indicators, the time series of data used to calculate SPI does not need to be of a specific length. (Guttman 1998, 1999) noted that if additional data are present in a long time series, the results of the probability distribution would be more robust because more samples of extreme wet and extreme dry events are included. SPI can be calculated on as little as 20 years‟ worth of data, but ideally the time series should have a minimum of 30 years of data, even when missing data are accounted for.

SPI has an intensity scale in which both positive and negative values are calculated, which correlate directly to wet and dry events. For drought, there is great interest in the „tails‟ of the precipitation distribution, and especially in the extreme dry events, which are the events considered to be rare based upon the climate of the region being investigated.

Drought events are indicated when the results of SPI, for whichever timescale is being investigated, become continuously negative and reach a value of −1. The drought event is considered to be ongoing until SPI reaches a value of 0. McKee *et al*. (1993) stated that drought begins at an SPI of −1 or less, but there is no standard in place, as some researchers will choose a threshold that is less than 0, but not quite −1, while others will initially classify drought at values less than −1.

Owing to the utility and flexibility of SPI, it can be calculated with data missing from the period of record for a location. Ideally, the time series should be as complete as possible, but SPI calculations will provide a „null" value if there are insufficient data to calculate a value, and SPI will begin calculating output again as data become available. SPI is typically calculated for timescales of up to 24 months, and the flexibility of the index allows for multiple applications addressing events that affect agriculture, water resources and other sectors (Abubakar & Yamusa 2013).

2.15.2 Short- versus long-term Standardized Precipitation Index values

2.15.2.1 1-month SPI

A 1-month SPI map is very similar to a map displaying the percentage of normal precipitation for a 30-day period (Da Silva *et al.*, 2021). In fact, the derived SPI is a more accurate representation of monthly precipitation because the distribution has been normalized. For example, a 1-month SPI at the end of November compares the 1-month precipitation total for November in that particular year with the November precipitation totals of all the years on record. Because the 1-month SPI reflects short-term conditions, its application can be related closely to meteorological types of drought along with short-term soil moisture and crop stress, especially during the growing season (Kumar *et al.*, 2021). The 1-month SPI may approximate conditions represented by the Crop Moisture Index, which is part of the Palmer Drought Severity

Index suite of indices. Interpretation of the 1-month SPI may be misleading unless climatology is understood. In regions where rainfall is normally low during a month, large negative or positive SPIs may result even though the departure from the mean is relatively small. The 1-month SPI can also be misleading with precipitation values less than the normal in regions with a small normal precipitation total for a month.

2.15.2.2 3-month SPI

The 3-month SPI provides a comparison of the precipitation over a specific 3-month period with the precipitation totals from the same 3-month period for all the years included in the historical record. In other words, a 3-month SPI at the end of February compares the December–January– February precipitation total in that particular year with the December–February precipitation totals of all the years on record for that location. Each year data is added, another year is added to the period of record, thus the values from all years are used again. The values can and will change as the current year is compared historically and statistically to all prior years in the record of observation.

A 3-month SPI reflects short- and medium-term moisture conditions and provides a seasonal estimation of precipitation. In primary agricultural regions, a 3-month SPI might be more effective in highlighting available moisture conditions than the slow-responding Palmer Index or other currently available hydrological indices (Sajeev *et al*., 2021).

It is important to compare the 3-month SPI with longer timescales. A relatively normal or even a wet 3-month period could occur in the middle of a longer-term drought that would only be visible over a long period. Looking at longer timescales can prevent misinterpretation believing that a drought might be over when in fact it is just a temporary wet period. Continuous and persistent drought monitoring is essential to determine when droughts begin and end. This helps avoid “false alarms” when going into and coming out of drought. Having a set of “triggers” in place, which are tied to actions within a drought plan, can help ensure this (WMO, 2012).

As with the 1-month SPI, the 3-month SPI may be misleading in regions where it is normally dry during any given 3-month period. Large negative or positive SPIs may be associated with precipitation totals not very different from the mean. This caution can be explained with the Mediterranean climate of California and around northern Africa and southern Europe, where very little rain falls or is expected over distinct periods of the year. Because these periods are characterized by little rain, the corresponding historical totals will be small, and relatively small deviations on either side of the mean could result in large negative or positive SPIs. Conversely, this time period can be a good indicator for some monsoon regions around the world (Sajeev *et al*., 2021).

2.15.2.3 6-month SPI

The 6-month SPI compares the precipitation for that period with the same 6-month period over the historical record. For example, a 6-month SPI at the end of September compares the precipitation total for the April–September period with all the past totals for that same period.

The 6-month SPI indicates seasonal to medium-term trends in precipitation and is still considered to be more sensitive to conditions at this scale than the Palmer Index. A 6-month SPI can be very effective in showing the precipitation over distinct seasons. For example, a 6-month SPI at the end of March would give a very good indication of the amount of precipitation that has fallen during the very important wet season period from October through March for certain Mediterranean locales. Information from a 6-

month SPI may also begin to be associated with anomalous stream flows and reservoir levels, depending on the region and time of year (Edossa *et al*., 2010).

2.15.2.4 9-month SPI

The 9-month SPI provides an indication of inter-seasonal precipitation patterns over a medium timescale duration. Droughts usually take a season or more to develop. SPI values below -1.5 for these timescales are usually a good indication that dryness is having a significant impact on agriculture and may be affecting other sectors as well. Some regions may find that the pattern displayed by the map of the Palmer Index is closely related the 9-month SPI maps. For other areas, the Palmer Index is more closely related to the 12-month SPI. This time period begins to bridge a short-term seasonal drought to those longer-term droughts that may become hydrological, ormulti-year, in nature (Edossa *et al*., 2010).

2.15.2.5 12-month up to 24-month SPI

The SPI at these timescales reflects long-term precipitation patterns. A 12-month SPI is a comparison of the precipitation for 12 consecutive months with that recorded in the same 12 consecutive months in all previous years of available data. Because these timescales are the cumulative result of shorter periods that may be above or below normal, the longer SPIs tend to gravitate toward zero unless a distinctive wet or dry trend is taking place. SPIs of these timescales are usually tied to stream flows, reservoir levels, and even groundwater levels at longer timescales. In some locations, the 12-month SPI is most closely related with the Palmer Index, and the two indices can reflect similar conditions (Edossa *et al*., 2010).

The SPI based on short-term precipitation data can be calculated using the following two indirect methods: (1) using long series of precipitation data from the surrounding area to complete short series of precipitation data, before calculating the SPI; (2) calculating relevant climatic variables (such as the distribution parameters for precipitation) based on the precipitation data for stations with long sequences in the surrounding area, before spatially interpolating the climatic variables to obtain the climatic variables for the stations with short-term precipitation data, and then calculating the SPI. The spatial consistency of climate variables is better than a single data record, so the second of these two methods is preferable. Previous studies also support the usego of the second calculation scheme. For example, (McRoberts and Nielsen-Gammon 2012) used the Pearson III type distribution function to obtain precipitation data for stations, before interpolating the data to a 4-km grid as the distribution parameter for this point. The precipitation data for the grid point were estimated based on the reflected waves from the radar. The SPI index was then calculated for each grid point and comparative analysis showed that the high-resolution SPI results agreed well with the SPI results calculated using the traditional method. (DeGaetano *et al*. 2015) used the gamma distribution function as the fitting function for precipitation. The feasibility of using the gamma distribution function for spatial interpolation was systematically investigated and the results showed that spatial interpolation of the distribution parameters is a reasonable approach.

2.15.3 Advantages

Using precipitation data only is the greatest strength of SPI, as it makes it very easy to use and calculate. SPI is applicable in all climate regimes, and SPI values for very different climates can be compared. The ability of SPI to be computed for short periods of record that contain missing data is also valuable for those regions that may be data poor or lacking long-term, cohesive datasets. The program used to calculate SPI is easy to use and readily available. NDMC provides a program for use on personal computers that has been distributed to more than 200 countries around the world. The ability to be calculated over multiple timescales also allows SPI to have a wide breadth of application. Many articles relating to SPI are available in the science literature, giving novice users a multitude of resources to rely on for assistance.

2.15.3 Disadvantages

With precipitation as the only input, SPI is deficient when accounting for the temperature component, which is important to the overall water balance and water use of a region. This drawback can make it more difficult to compare events of similar SPI values but different temperature scenarios. The flexibility of SPI to be calculated for short periods of record, or on data that contain many missing values, can also lead to misuse of the output, as the program will provide output for whatever input is provided. SPI assumes a prior distribution, which may not be appropriate in all environments, particularly when examining short-duration events or entry into, or exit out of, drought. There are many versions of SPI available, implemented within various computing software packages other than that found in the source code distributed by NDMC. It is important to check the integrity of these algorithms and the consistency of output with the published versions.

2.15.4 Spatial and Temporal Flexibility of SPI

There is no single definition of drought (Wilhite and Glantz, 1985). We can generally group them into meteorological, agricultural, hydrological and socioeconomic droughts. Drought is a very complex hazard to define and detect. It spans multiple sectors and timescales. Just as there is no single definition of drought, there is no single drought index that meets the requirements of all applications.

That said, a real strength of the SPI is its ability to be calculated for many timescales, which makes it possible to deal with many of the drought types described above. The ability to compute the SPI on multiple timescales allows for temporal flexibility in the evaluation of precipitation conditions in relation to water supply.

As mentioned earlier, the SPI was designed to quantify the precipitation deficit for multiple timescales, or moving averaging windows. These timescales reflect the impacts of drought on different water resources needed by various decision-makers. Meteorological and soil moisture conditions (agriculture) respond to precipitation anomalies on relatively short timescales, for example 1-6 months, whereas streamflow, reservoirs, and groundwater respond to longer-term precipitation anomalies of the order of 6 months up to 24 months or longer. So, for example, one may want to look at a 1- or 2-month SPI for meteorological drought, anywhere from 1-month to 6-month SPI for agricultural drought, and something like 6-month up to 24-month SPI or more for hydrological drought analyses and applications (WMO, 2012).

The SPI can be calculated from 1 month up to 72 months. Statistically, 1–24 months is the best practical range of application (Guttman, 1999). This 24-month cutoff is based on Guttman‟s recommendation of having around 50–60 years of data available. Unless one has 80–100 years of data, the sample size is too small and the statistical confidence of the probability estimates on the tails (both wet and dry extremes) becomes weak beyond 24 months. In addition, having only the minimum 30 years of data (or less) shortens the sample size and weakens the confidence. Technically, one could run the SPI on less than 30 years of data bearing in mind, however, the statistical limitations and weaker confidence pointed out above.

In 2009, WMO recommended SPI as the main meteorological drought index that countries should use to monitor and follow drought conditions (Hayes, 2011). By identifying SPI as an index for broad use, WMO provided direction for countries trying to establish a level of drought early warning. Therefore, in this study, both 3 and 6 months‟ time scale SPIs were used in the assessment of drought vulnerability in Minna meteorological station.

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Description of study area

The study area is Minna, the capital city of Niger State located between Latitude 9° 5000' and 9° 5625' N and Longitude 6° 373' and 6° 4375' E (Figure 3.1). The soil type on the study area was in a textural class of gravelly sand up to the depth of 80 – 90 cm. The area is characterized with low and erratic rainfall of between 1000 to 1200 mm as total annual rainfall with peaks in July and August. Seventy years" monthly precipitation data has been collected from Nigerian Meteorological Agency (NiMet) for the study area from 1950 to 2019. Variations in the annual precipitation data has been collected from Nigerian Meteorological Agency (NiMet) for the study area from 1950 to 2019. Variations in the annual precipitation for seventy years from 1950 to 2019 are as shown in Figure 3.2

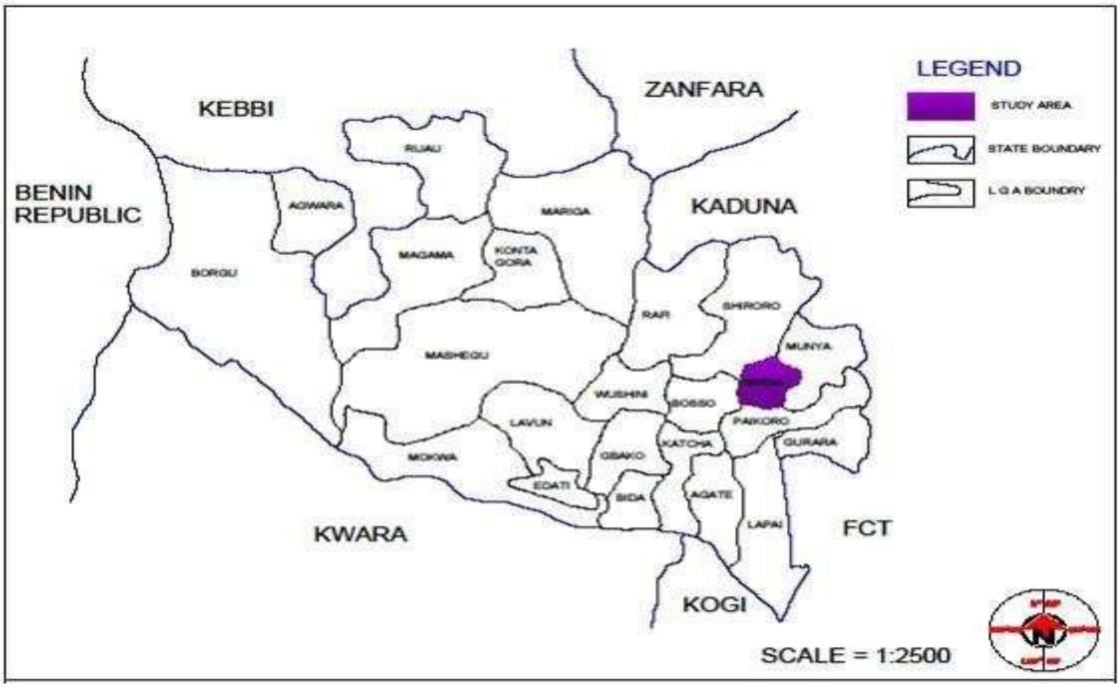

Figure 3.1: Map of Niger State showing the study area

3.2 Rainfall Anomaly Index of the study area

From the precipitation data, the Annual Rainfall Anomaly Index (RAI) can be calculated to analyze the frequency and intensity of the dry and rainy years in the study area. In addition, the monthly RAI was calculated for specific years of the historical series aiming to analyze the distribution of rainfall in the years. RAI, developed and firstly used by Van-rooy (1965) and adapted by Freitas (2005), constitutes the following equations:

RAI = 3 $\left[\frac{N - \bar{N}}{\bar{M} - \bar{N}}\right]$, For positive anomalies

RAI = - 3 $\left[\frac{N - \bar{N}}{\bar{M} - \bar{N}}\right]$, For negative anomalies

Where: N = current monthly/yearly rainfall, in order words, of the month/year when RAI will be generated (mm); $\bar{N}$ = monthly/yearly average rainfall of the historical series (mm); $\bar{M}$ = average of the ten highest monthly/yearly precipitations of the historical series (mm); $\bar{X}$= average of the ten lowest monthly/ yearly precipitations of the historical series (mm); and positive anomalies have their values above average and negative anomalies have their values below average. All calculations were done using excel spread shit.

Table 3.1 Classification of rainfall anomaly index

RAI range	Classification
Above 4	Extremely humid
2 to 4	Very humid
0 to 2	Humid
-2 to 0	Dry
-4 to -2	Very dry
Below -4	Extremely dry

Source: Freitas (2005)

In order to obtain the rainfall anomaly index of Minna the annual rainfall data of Minna was obtained from Nigeria Meteorological Centre (Nimet) for this study.

The average of ten highest yearly rainfalls (figure 3.2), ten lowest yearly rainfalls is obtained from the rainfall data acquired while the average of the current rainfall data is also calculated which is inputted into the rainfall anomaly index to calculate the anomaly index for each year.

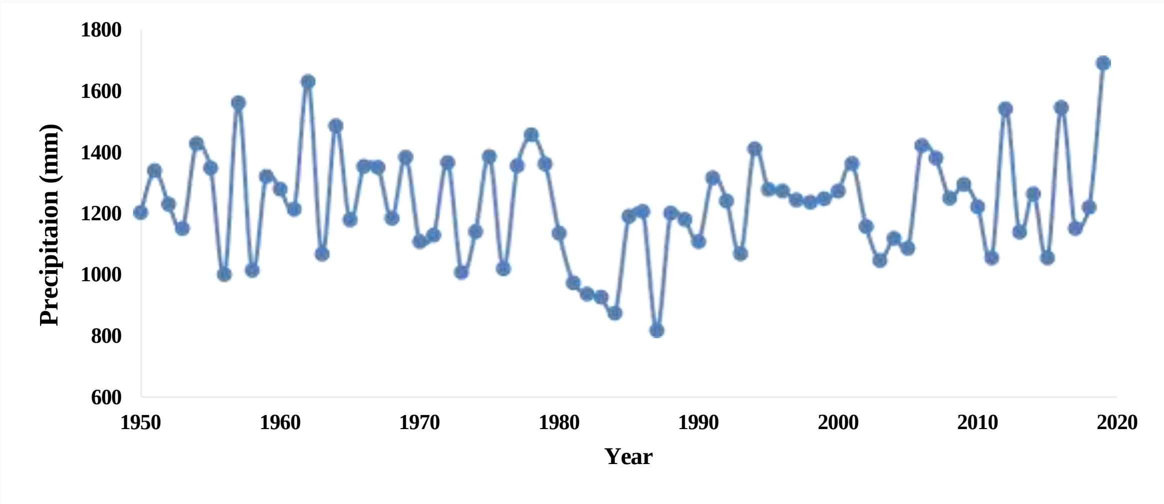

Figure 3.2: Annual Precipitation (mm) from 1950 to 2019 for Minna Station

3.3 Standardized Precipitation Index

For the purpose of this research emphasis was placed on Standardized Precipitation Index (SPI) for reasons stated below. Drought is much more complicated than other natural disasters (Wilhite *et al*., 2014). There is no uniform definition for drought (Mishra and Singh 2010) but it is often divided into four categories comprising meteorological drought, hydrological drought, agricultural drought, and socio-economic drought (Kalura *et al*., 2021). In drought research, a drought index is a highly effective tool for quantifying information such as the severity, duration, frequency, and spatial extent of a drought (Wilhite *et al*., 2014). However, due to the complexity of the drought problem, various drought indices have been proposed for the quantitative characterization of droughts, and hundreds of different drought indices are available (Mishra and Singh 2010). The basic data typically used for calculating these indices include precipitation, temperature, wind speed, evapotranspiration, soil type, soil moisture, and crop types. In the absence of basic data, it is difficult to calculate drought indices that require different data types. In general, meteorological drought indices require relatively few data types, and thus they are more readily popularized and applied, and is also easier to develop high-resolution drought indices based on them. Among the many meteorological drought indices, the standardized precipitation index (SPI) designed by McKee (McKee *et al.,* 1993) is the most popular drought analysis tool (Zhang *et al.,* 2009; Yang et al.,2018; Odewale *et al.,* 2019) because calculating the SPI index only requires precipitation data, and it is independent of geographic and topographic features, as well as using a variable time scale. Therefore, the World Meteorological Organization recommends the SPI index as the main meteorological drought index for tracking meteorological drought (Hayes *et al*., 2011 Abdulrazzaq *et al*., 2019). High-density precipitation observation data are required to construct a high-resolution SPI indicator. However, before calculating the SPI, an appropriate probability distribution function must be selected to fit the long-term precipitation data.

3.3.1 Input parameters of SPI

Most users apply SPI using monthly datasets, but computer programs have the flexibility to produce results when using daily and weekly values. The methodology of SPI does not change based upon using daily, weekly or monthly data.

3.3.2 Applications of SPI

Based on Karavitis *et al*. (2011) findings, for the calculation of the SPI, the first step is to find the probability density function which best describes the distribution of the precipitation data over the different time scales. This pattern is applied separately for each month. The ability of SPI to be calculated at various timescales allows for multiple applications. Depending on the drought impact in question, SPI values for 3 months or less might be useful for basic drought monitoring, values for 6 months or less for monitoring agricultural impacts and values for 12 months or longer for hydrological impacts. SPI can also be calculated on gridded precipitation datasets, which allows for a wider scope of users than those just working with station-based data.

The SPI was designed to quantify the precipitation deficit for multiple timescales. These timescales reflect the impact of drought on the availability of the different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale. Groundwater, streamflow and reservoir storage reflect the longer-term precipitation anomalies. For these reasons, McKee and others (1993) originally calculated the SPI for 3-, 6-,12-, 24- and 48-month timescales.

The SPI algorithm development and application was achieved by the following rationale. The first step is to find the probability density function which best describes the distribution of the precipitation data over the different time scales. This pattern is applied separately for each month. Variable time scales of 1, 3, 6, 12, 24 months can be selected for the estimation of the index, which represents arbitrary time scales for precipitation deficits in relation to SPI application premises (Wu *et al.*, 2007). Each of the data sets is fitted to the gamma probability density function with shape parameter α and scale parameter β to define the relationship of probability to precipitation. With the equal-probability transformation the gamma cumulative distribution function converges to the standardized normal cumulative distribution function with a mean of zero and standard deviation of unity Karavitis *et al.* (2011). This standardization gives the advantage of having consistent values in space and time for the frequency of extreme dry and wet events. More explicitly a continuous random variable X follows a gamma distribution if the p.d.f. of X is:

$$g(x,\alpha,\beta) = \frac{1}{\beta^{\alpha} * \Gamma(\alpha)} x^{\alpha-1} * e^{-x\,\beta} \qquad (3.1)$$

For x ≥ 0,
otherwise g(x) = 0,

where the parameters α and β satisfy α > 0, β > 0. For α > 0 the gamma function Γ(α) is defined by

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} e^{-x} dx \qquad (3.2)$$

Adjusting the gamma distribution to the data set needs the α and β parameters to be estimated through the maximum likelihood estimation using the approximation of :

$$\alpha^{\wedge} = \frac{1}{4A}[1 + \sqrt{\frac{4A}{3}}] \qquad (3.3)$$

$$\beta^{\wedge} = \frac{\bar{x}}{\alpha^{\wedge}} \qquad (3.4)$$

Where for n observations

$$A = \ln(\mathrm{x}) - \sum \frac{\ln(x)}{n} \qquad (3.5)$$

Integrating the probability density function with respect to x and attach α and β parameters yields the cumulative probability distribution function G(x):

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}^{\hat{\alpha}}\Gamma(\hat{\alpha})}\int_0^x x^{\hat{\alpha}} e^{-x\,\hat{\beta}} \qquad (3.6)$$

substituting t for $\frac{x}{\hat{\beta}}$ yields the incomplete gamma function:

$$\mathrm{G}(x) = \frac{1}{(a)}\int_0^x t^{a-1}e^{-1}\,dt \qquad (3.7)$$

The gamma distribution is undefined for x = 0 and q = P(x = 0) > 0, where P(x = 0) is the probability of zero (null) precipitation. Thus, the cumulative probability distribution function becomes:

$$H(x) = q + (1 - q) * G(x) \qquad (3.8)$$

McKee and others (1993) used the classification system shown in the SPI value table below (Table 3.1) to define drought intensities resulting from the SPI. They also defined the criteria for a drought event for any of the timescales. A drought event occurs any time the SPI is continuously negative and reaches an intensity of -1.0 or less. The event ends when the SPI becomes positive. Each drought event, therefore, has a duration defined by its beginning and end, and an intensity for each month that the event continues. The positive sum of the SPI for all the months within a drought event can be termed the drought"s "magnitude" (Edossa *et al*., 2010).

Table 3.2: Category of standardized precipitation index (SPI) based on range values

SPI	**Range Category**
+ 2 to more	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 to less	Extremely dry

The drought events based on the precipitation obtained from Minna basin were assessed using SPI (McKee et al., 1993). This index is based on the cumulative probability of the considered precipitation as presented in equation 3.8:

Xst = The mean value of the precipitation quantity,

N = The precipitation measurement number and

Xi = The quantity of precipitation in the sequence of data

$If\ x\ =\ 0$, then the cumulative probability becomes

$H(x) = q + (1-q)G(x) and$

$Q\ =$ the probability of precipitation as zero (0)

The 3-month SPI was calculated for Minna rainfall station using monthly rainfall data for the period of 1950–2019. The SPI is determined by normalizing the precipitation for a given station after it has been fitted to a probability density function as described by Edwards and McKee (1997), and Guttman (1998). Positive SPI values indicate greater than median precipitation, and negative values indicate less than median precipitation, drought, according to the SPI, starts when the SPI value is equal or below -1.0 and ends when the value becomes positive.

3.4 Data collection and analysis

The 3,6 and 12-month SPIs were calculated for Minna rainfall station using monthly rainfall data for the period of 1950 – 2019. The rainfall data was obtained from Nigeria Meteorological Agency, Abuja and calculations were done using excel spread sheet.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Rainfall Anomaly of the study area

Figure 4.0 shows the results of the rainfall anomaly index analysis of the study area. The analysis of the rainfall anomaly index of the study area revealed positive values for all the years under review. The occurrence of positive values for the years averaged between 0 to 1.32 with the highest in 1987 which falls under the humid conditions based on the categorization of the rainfall anomaly index. This implies the vulnerability to drought was low with insignificant threat to the unset of drought due to the humid conditions. The table of the annual rainfall anomaly is presented as Appendix IV

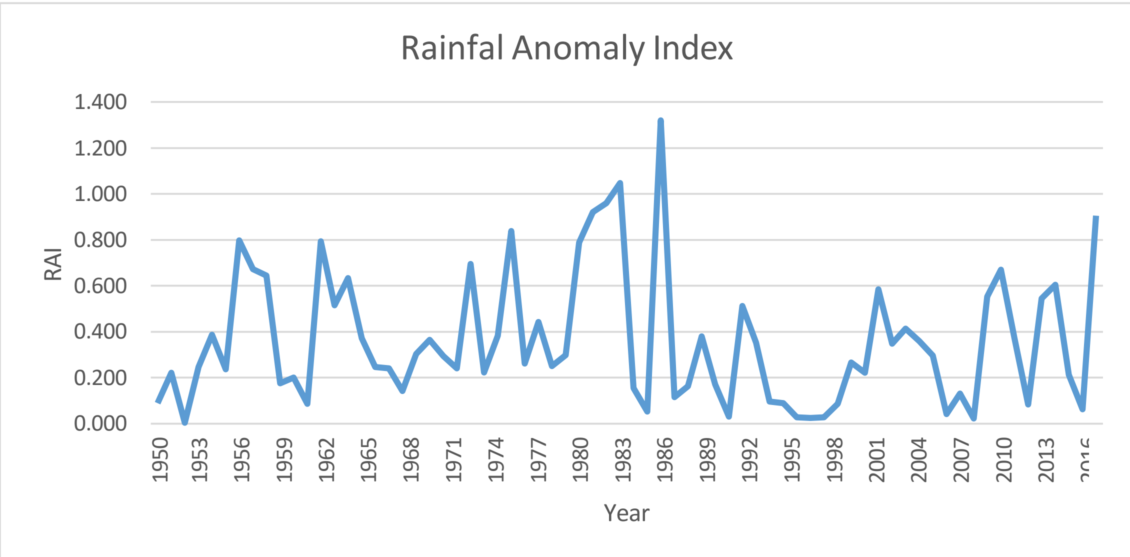

Figure 4.0: Rainfall Anomaly Index of the study area

4.2 SPI-3 Analysis

The results of SPI for 3-month time scale drought estimation for the study area is presented as Appendices Ia and Ib. From the table, the drought months for consideration are June to November as months of December to May are mostly regarded as dry season months.

The SPI diagrams for different drought months (June to November) have been presented to show the pattern and trends of SPI during these years (Figures 4.1 to 4.3). The 3-month SPI for the months of August to November shows the temporal dynamics of below and above normal precipitation distribution in Minna. It can be seen that during the drought years of 1976, 1982, 1984 and 1987, negative SPI values were observed in the study area and this indicates that there was rainfall deficit in these areas particularly during the drought months of June–November.

In these drought years of 1976, 1982, 1984 and 1987, the spatial patterns of 3-month SPI across crucial months (June-November) shows negative SPI values, with the area having an SPI value above −3.0. Thus, the spatio-temporal evolution of the SPI clearly indicates that 1982 was the most drought-prone year taking into consideration the magnitude and extent of a negative SPI value (-3.993) which is consistent with Gore and Sinha, (2002). From the results, the month of June recorded this highest value of 3-month SPI across the years under study. 1973 and 1976 were also seen as having high SPI values ranging from −3.0 to −3.35, especially in the months of July, September and October. However, during the wet years of 1957, 1962, 2001 and 2019, the observed 3-month SPI values across the drought months of June-November are mostly positive, ranging from 2.00 in 1962 to 2.49 in 2016 which shows that these years were wet years which is in consonance with Figure 4.3.

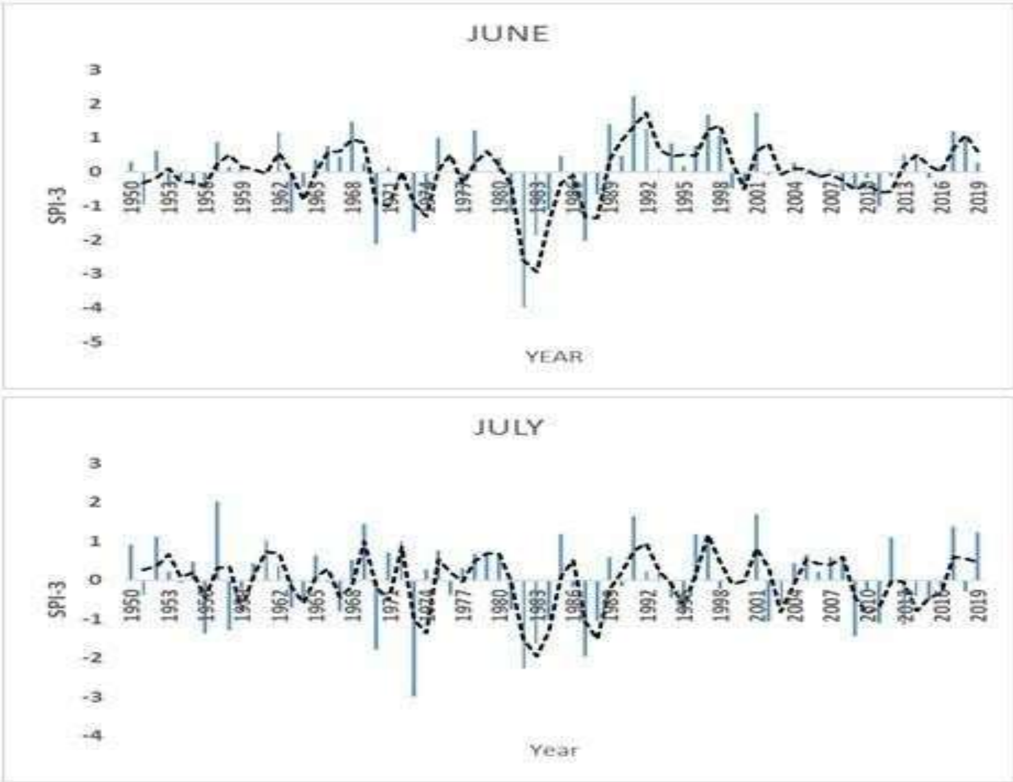

Figure 4.1: SPI-3 diagrams for JUNE & JULY in the study area

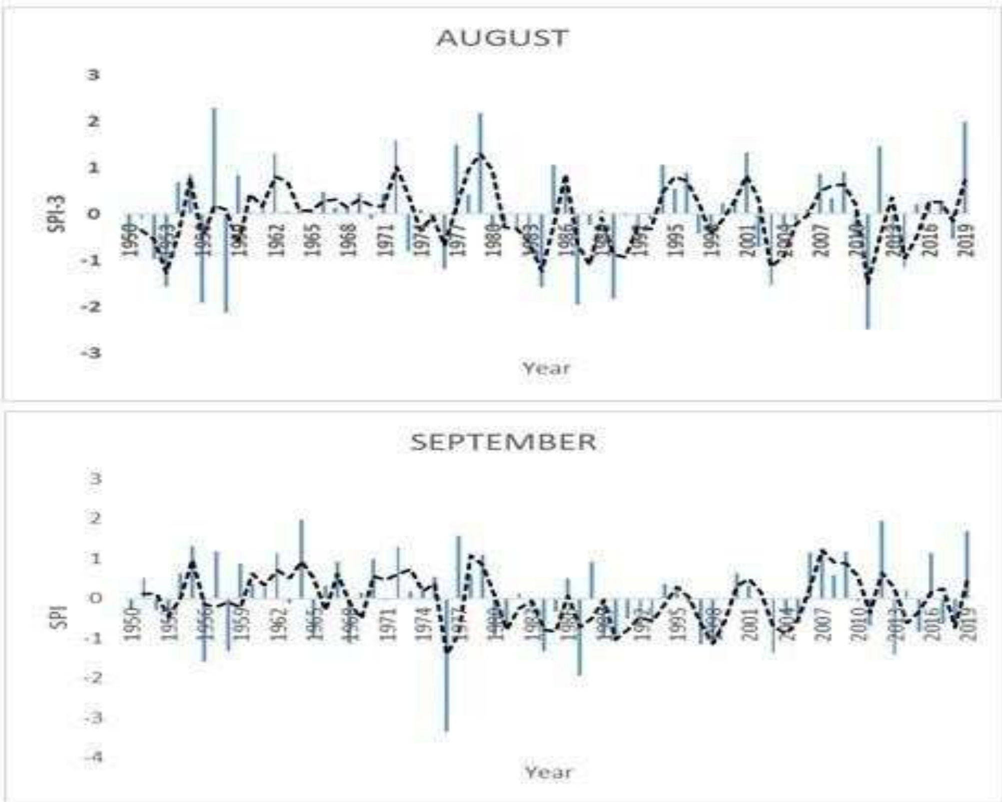

Figure 4.2: SPI-3 diagrams for AUG & SEP in the study area

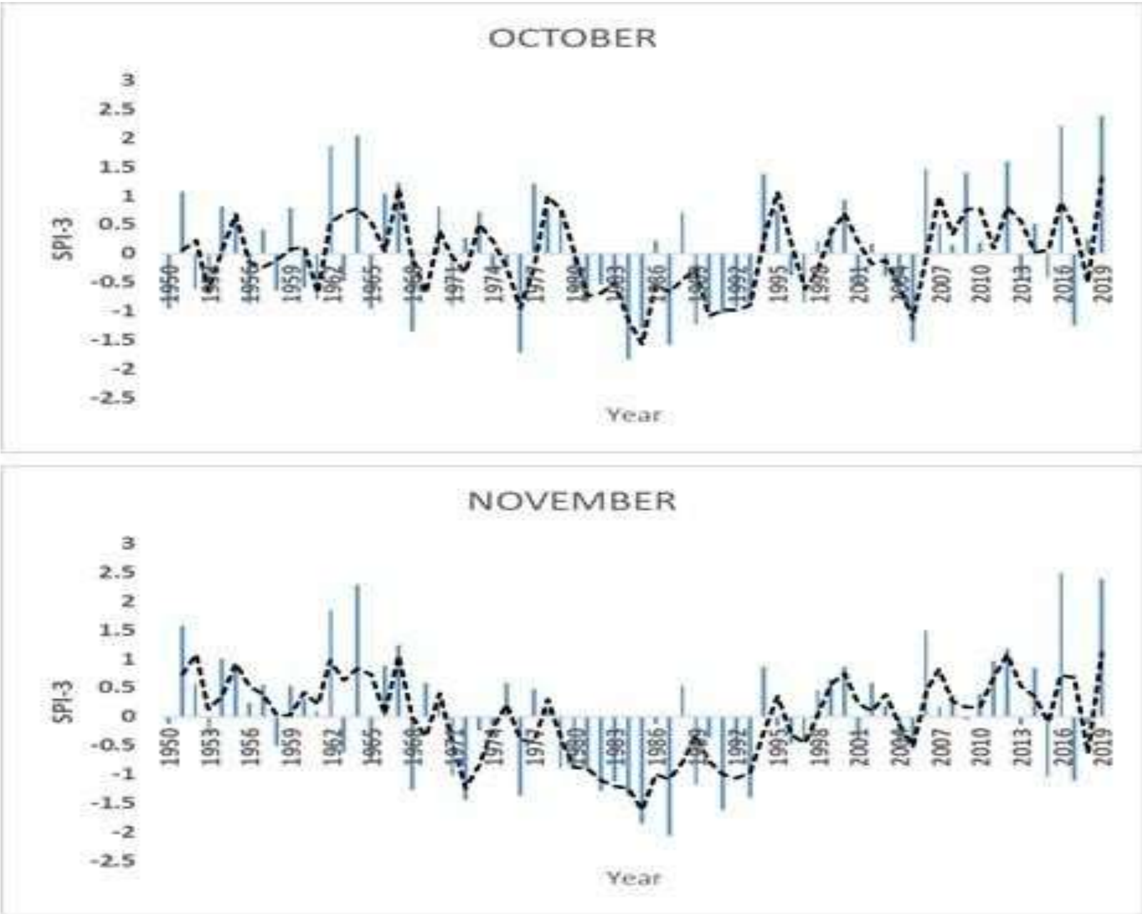

Figure 4.3: SPI-3 diagrams for October & November in the study area

4.3 SPI-6 Analysis

The results of SPI for 6-month time scale drought estimation for the study area is presented as Appendices IIa and IIb.

The SPI-6 diagrams for different drought months (June to November) are as shown in Figures 4.4 to 4.7. The drought years of 1970 - 1973 and 1983 were observed to have negative SPI values in the study area which indicates that there was rainfall deficit in the study area during the months of June to November. The drought years of 1970, 1973, 1982 and 1983 6 months SPI across the drought months show negative SPI values with the area having an SPI value above -2. The spatio-temporal evolution of the SPI indicates that 1983 has the most drought – prone year considering the magnitude and extent of a negative SPI value of -2.393 which is consistent with Gore and Sinha (2002). From the results, June has the highest value of 6 months SPI across the year under consideration. 1970 and 1973 were observed to have a near normal precipitation conditions and moderately dry conditions with the highest SPI 6 months" value of -1.285 and -1.119 in 1970 and 1973 respectively while the periods with high SPI values were observed in the months of June for both years.

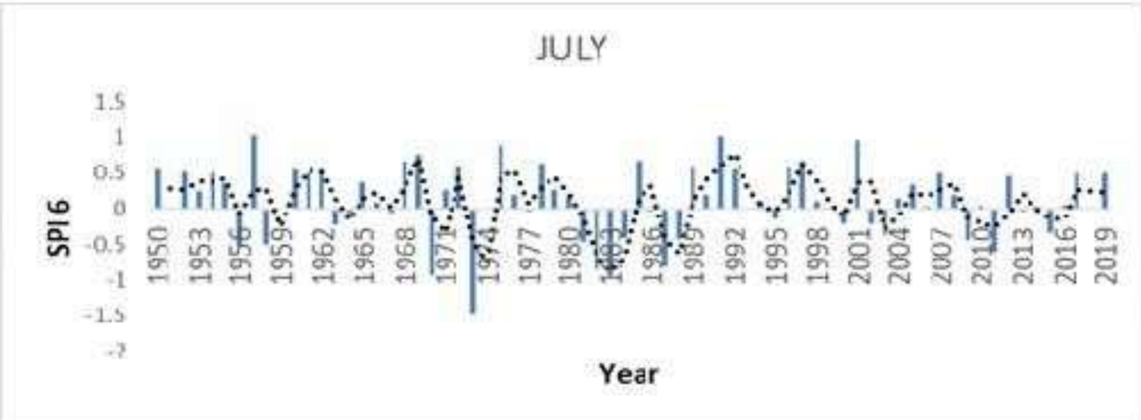

Figure 4.4: SPI-6 diagrams for June and July in the study area

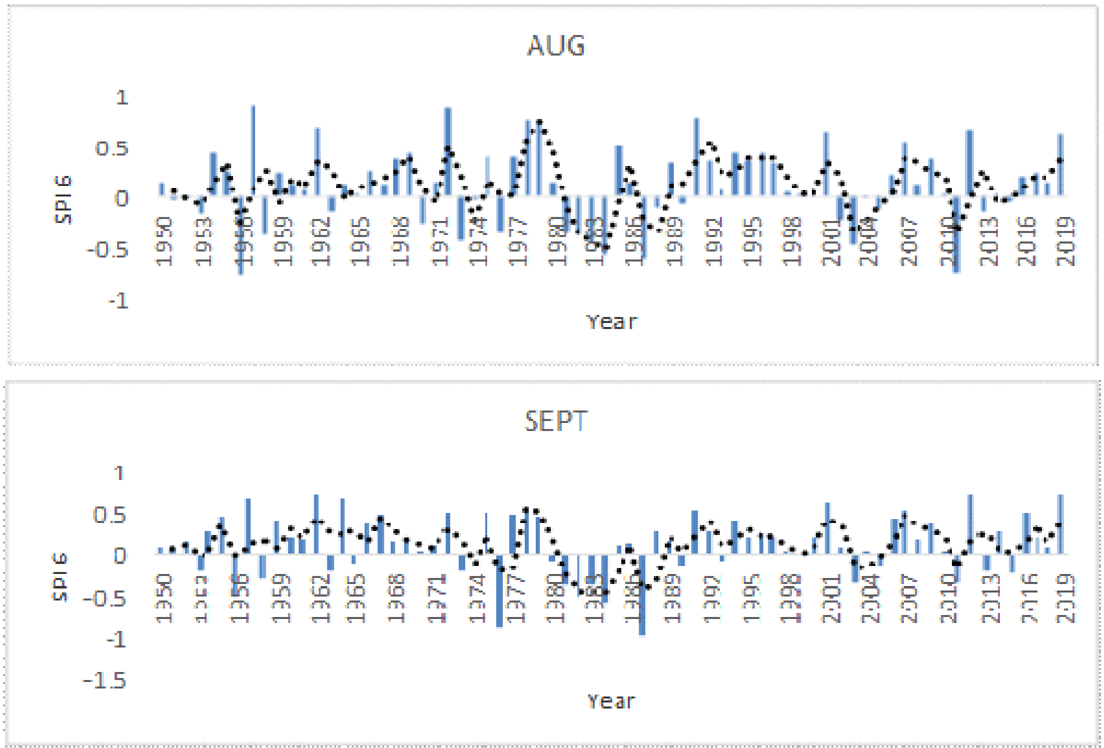

Figure 4.5: SPI-6 diagrams for AUG & SEP in the study area

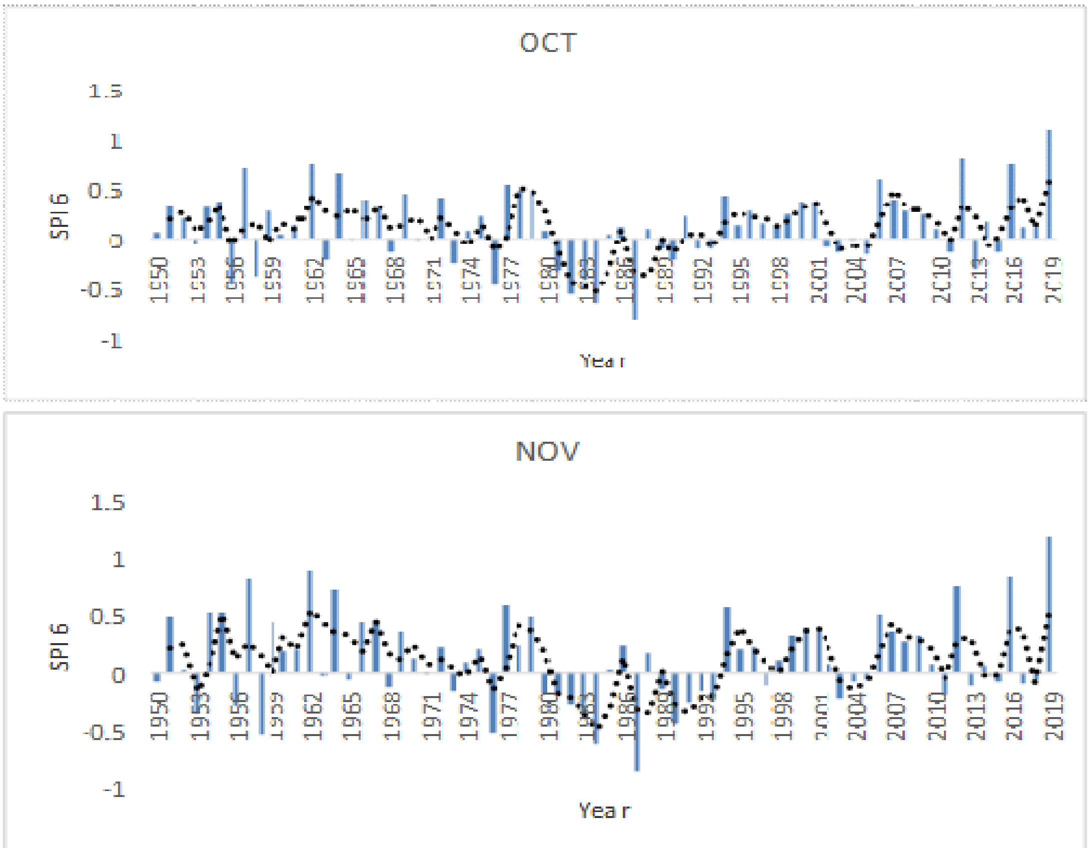

Figure 4.6: SPI-6 diagrams for October and November in the study area

4.4 SPI-12 Analysis

The SPI-12 diagrams for the drought months of June to November are presented in Figures 4.7 to 4.9. In the drought years of 1973, 1981, 1982, 1983, 1984 and 2006 the spatial patterns of 12 months SPI across crucial months (June to November) show negative values with the areas having an SPI of -0.809 which clearly indicates that the spatio-evolution of the SPI clearly shows that 1987 was the most drought prone year even though based on the SPI categorization of drought intensities the drought during that year is about near normal. From the result the month of September recorded the highest value across the year under consideration. 1973 and 1982 were also observed to have SPI values ranging from -0.4 to -0.6 especially in the month of June. However, during the wet years of 1952, 1957, 1962, 1978, 1967, 2017 and 2019 the observed 12 month SPI across the drought months of June to November are mostly positive ranging from 0.8 in 1962 and 1 in 2019 which shows that these years are near normal and moderately wet years. The results of SPI for 12-month time scale drought estimation for the study area is presented as Appendices IIIa and IIIb.

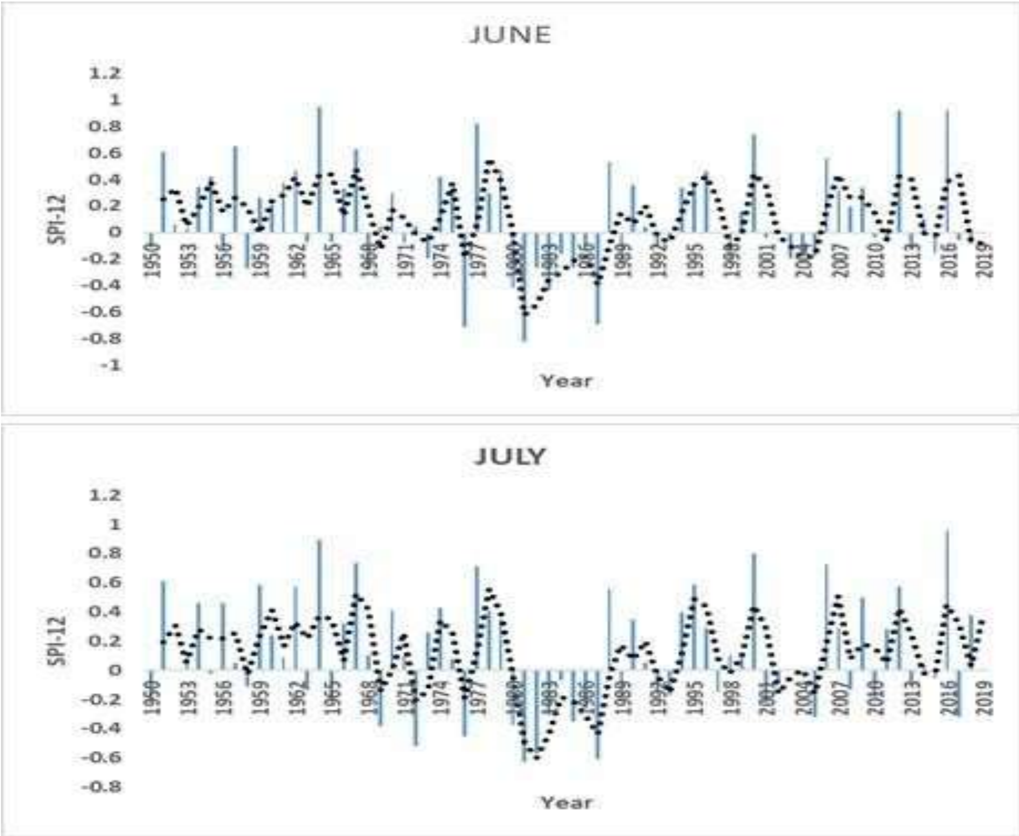

Figure 4.7: SPI-12 diagrams for June & July in the study area

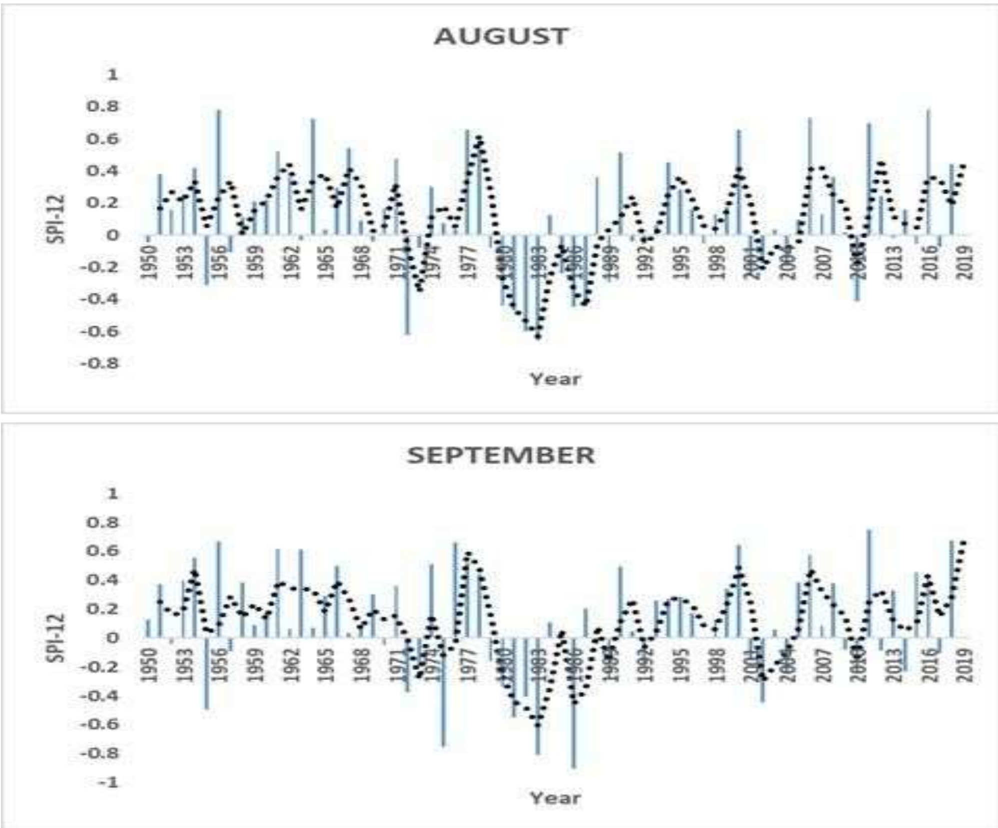

Figure 4.8: SPI diagrams for August & September in the study area

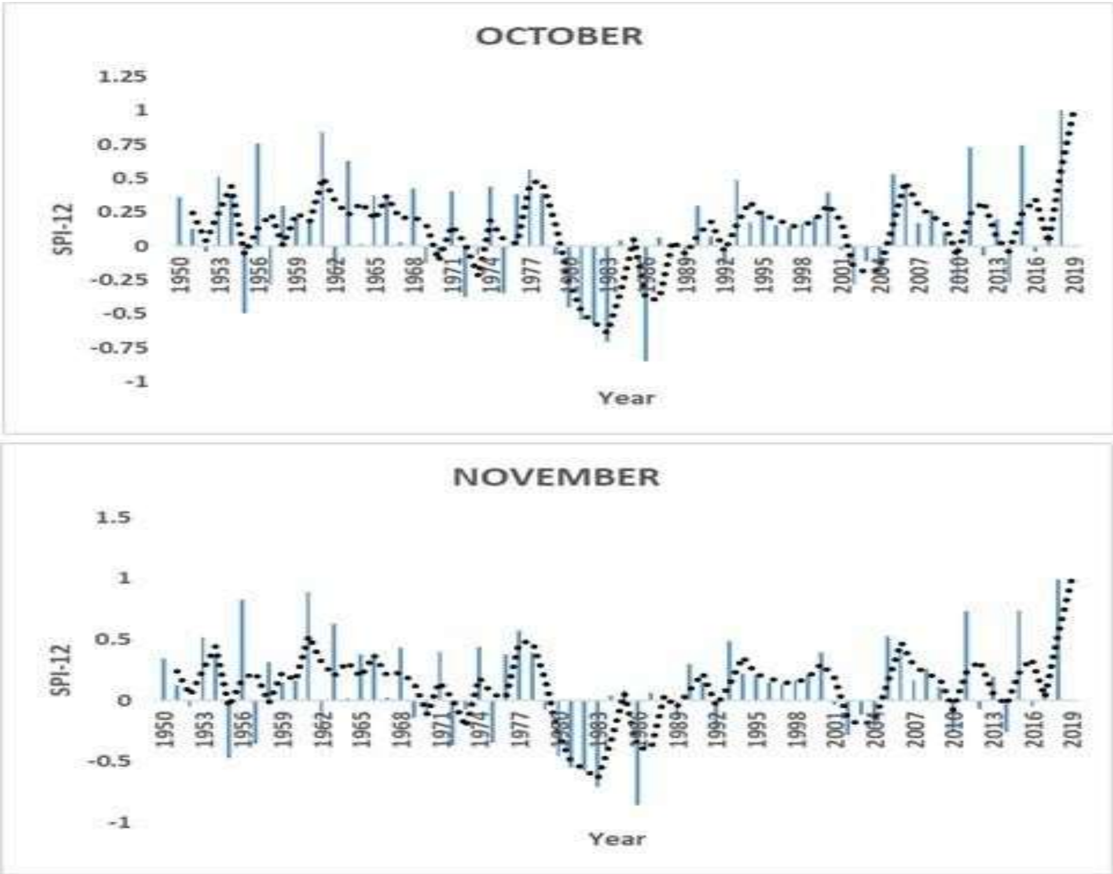

Figure 4.9: SPI diagrams for October & November in the study area

4.5 Drought Vulnerability Assessment

Drought vulnerability assessment was conducted for the study area during the months of June to November from 1951 to 2019 using 3_month SPI, 6_month SPI and 12_month SPI. The result of 3 months" time scale in the month of June as shown in Figure 4.10 reveals that there was 10 episodes of drought with the highest at -3.99 in 1982 and -2.0 in 1987. Therefore, according to the standardized precipitation index categorization 1982 and 1987 experienced extreme drought which implies high risk to drought vulnerability. Subsequently the 3 months SPI showed that there were considerable rains with the highest positive SPI value of 2.21 in 1991 while 1997 had 1.66 and 1.76 in 2001 implying low risk in these years.

The results of 6 months SPI of June revealed 4 episodes of extreme drought across cases with the highest negative SPI value of -2.39 in 1982 which implies high risk to drought vulnerability while other years under consideration experienced mostly near normal to moderately dry weather conditions which in turn reduces their vulnerability to droughts. 1991 had the most wet conditions with a positive SPI value of 1.43 and 2001 was observed to have 1.13 SPI value.

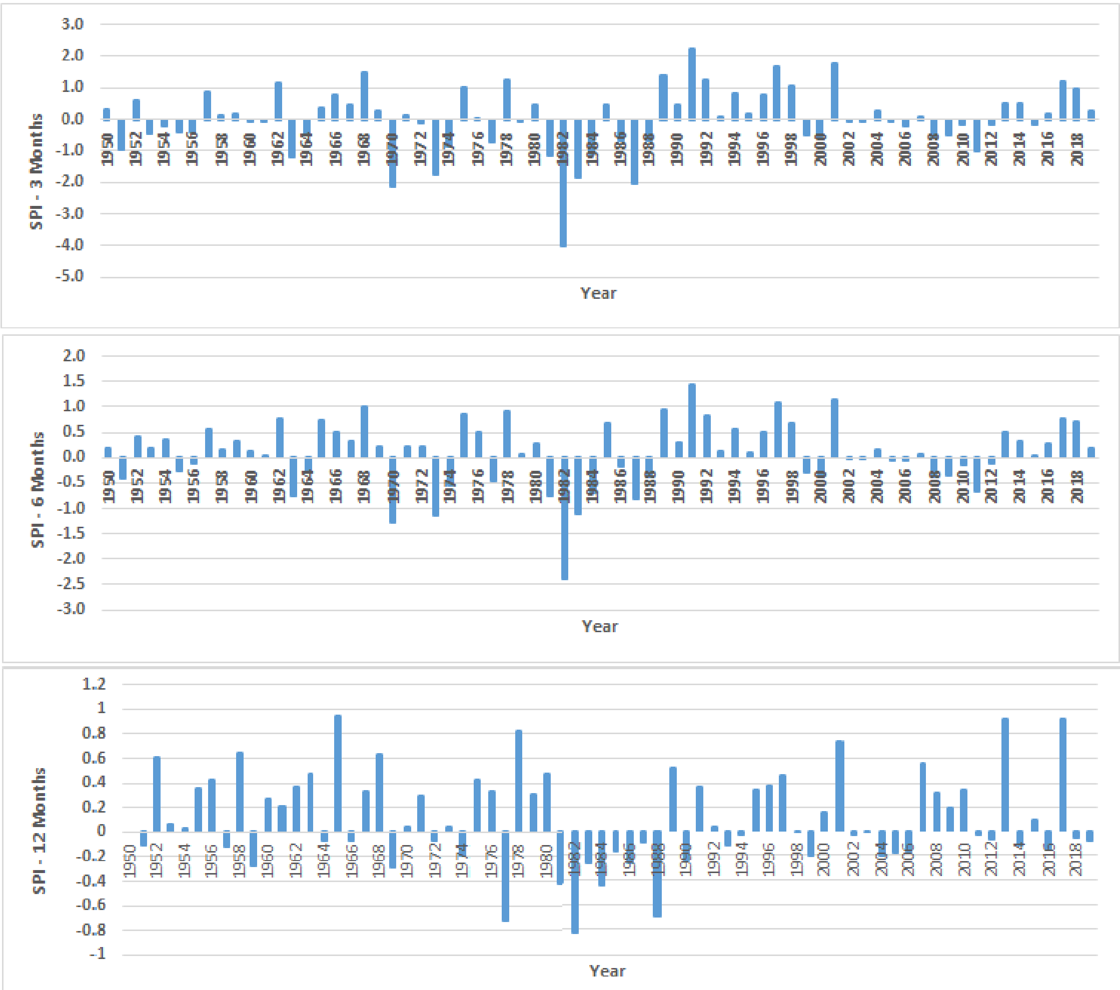

Figure 4.10: Drought vulnerability assessment of June

The analysis for 3 months SPI of the month of June revealed that there was one drought episodes that occurred in 1982 with a negative SPI value of -2.4 showing extreme dry weather highly vulnerable to drought, while 1982 and 1987 had -2 and -2.2 SPI values respectively which put them in the extremely dry condition and vulnerable to drought.

The rainy season was mostly within moderate conditions with the exception of 2001, 1997, 1991 and 1968 with respective positive SPI values 1.5, 1.5, 2.0 and 1.5 which indicated their categories to fall between extremely wet in 1991 and very dry conditions for the other years.

The result of 6 SPI analysis shown in Figure 4.11 revealed that drought was experienced in the month of June. While 1970,1973 and 1983 were indicative of moderate drought while extreme drought occurred in 1982. The analysis also revealed moderate rains were experienced in all the years before reaching its peak in 1991.

The 12 months SPI analysis showed that near normal weather conditions were experienced through-out the years under review with the highest negative SPI reached in 1992 even though it fell within the moderate conditions. Consequently, the positive SPI values were indicative of near normal conditions which implied to have considerable low drought vulnerability to drought.

The 3 months SPI analysis of July, as shown in Figure 4.11, exhibited four episodes of drought in the years 1973, 1982 and 1987 indicative of extremely dry weather condition highly vulnerable to drought. 1970 showed SPI values category of severe dryness which implied high vulnerability to drought and 1983 was indicative of moderate dryness showing vulnerability to drought. The rest of the years fell in the near normal conditions which implied low risk to drought. However, the years were observed to have positive SPI values indicative of moderately wet conditions with a peak in 1957 where it was observed to be extremely wet.

The 6 months SPI analysis revealed that only one drought episode occurred in 1973 with moderately to near normal wet conditions for the years under review which implies low vulnerability to drought.

The 12 months SPI showed no episode of drought in the years under review with a highest negative SPI value recorded in 1982 indicative of near normal conditions. Furthermore, the rainy condition fell was indicative of moderately wet according to the analysis. This implies that the vulnerability to drought is low.

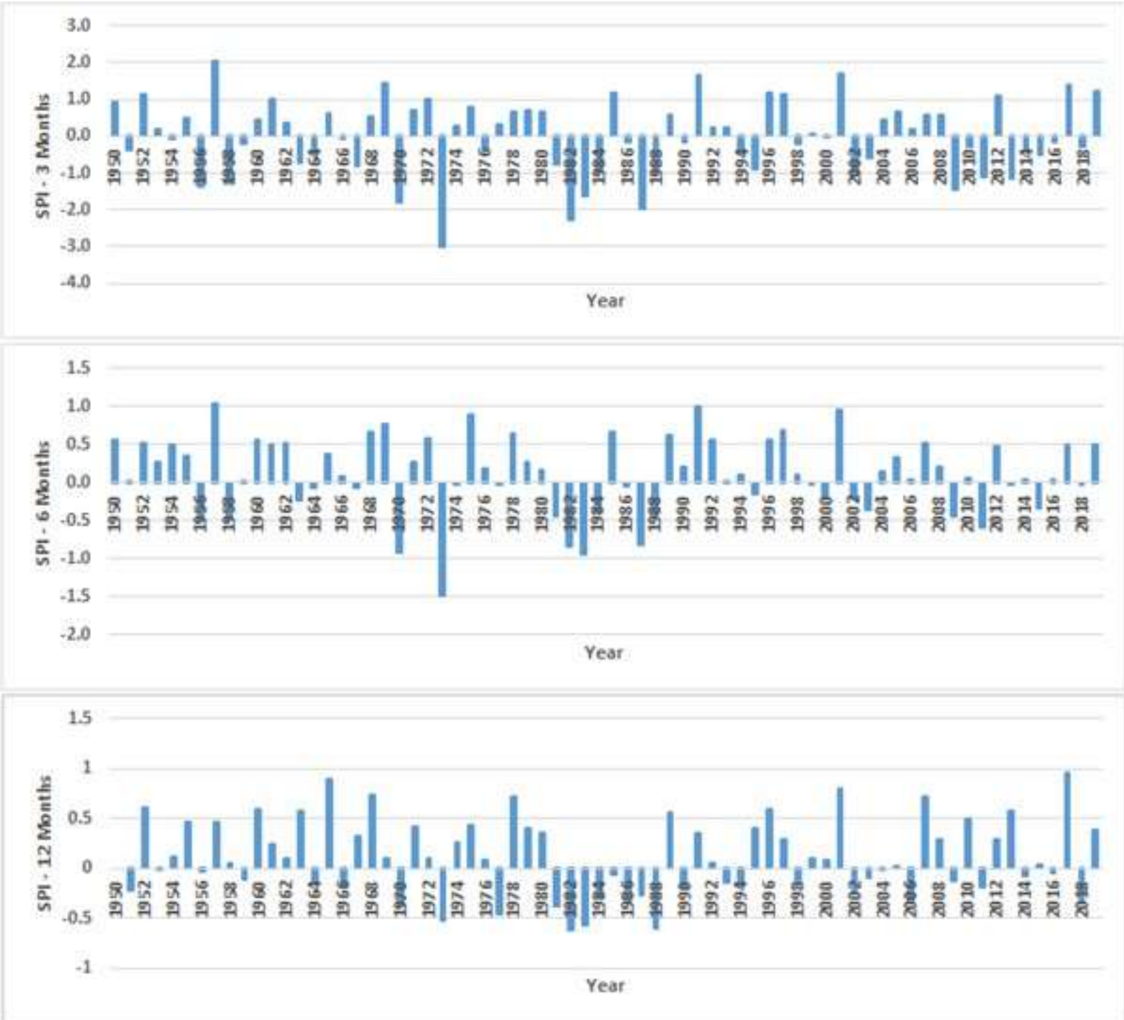

Figure 4.11: Drought vulnerability assessment of July

From Figure 4.12, four episodes of drought occurred according to result of the analysis of the 3 months SPI of August. The droughts were recorded in 1970, 1981, 1982 and 1983. 1973 was indicative of moderate conditions with low risk to drought while the analysis revealed that the rest of the years had low vulnerability to drought due to the fact that their SPI values averaged within 0-1.4.

Subsequently,1991 and 1978 are indicative of extremely wet conditions, 1992, and 1997 are indicative of very wet conditions while the remaining years fell under moderately wet to near normal conditions which implies low risk to drought.

The 6 months‟ drought analysis revealed that there were no drought episodes recorded. The maximum negative SPI value of -0.6 was recorded in 1956 which is categorized under near normal conditions. This implies that vulnerability to drought is almost nonexistent. Likewise, the positive SPI conditions of the month fall within near normal conditions.

According to the 12 months SPI analysis no drought was recorded amongst the year under review. The analysis revealed negative SPI values indicative of near normal conditions for the years in question which implies a low risk to drought occurrences.

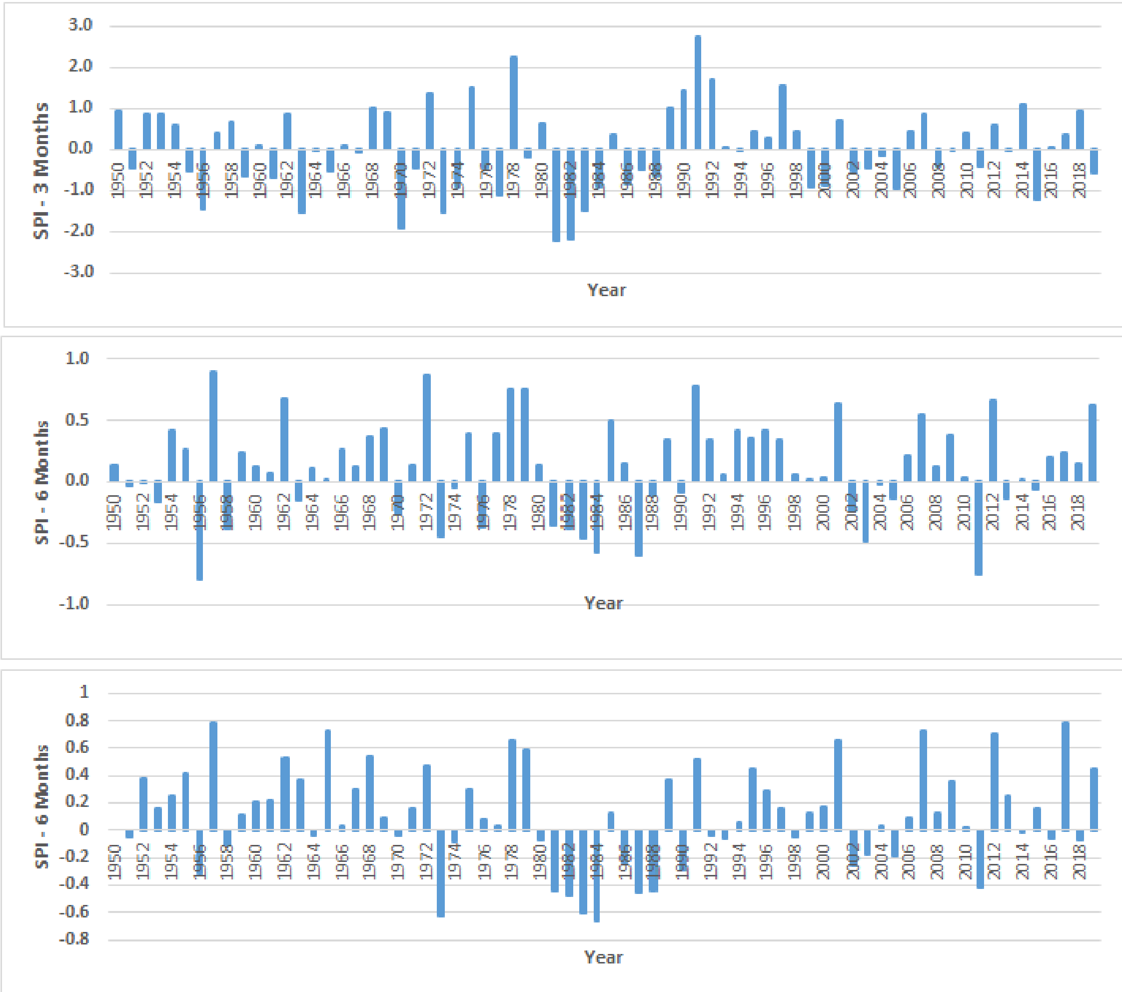

Figure 4.12: Drought vulnerability assessment of August

For September SPI analyses, as shown in Figure 4.13, the analysis of the 3 month SPI revealed that four drought episodes occurred in the years 1970, 1981, 1982 and 1991 having the highest SPI value indicative of extreme dryness and high vulnerability to drought occurrences. The rest of the years averaged a negative SPI value indicative of near normal and moderately dry conditions which implies low risk vulnerability to drought. Furthermore, the analysis also disclosed that most of the positive SPI values for most of the years were characteristic of near normal conditions with the exception of 1991 and 1978 that were indicative of extremely wet conditions while 1972, 1975, 1990, 1992 and 1997 showed characteristics SPI values for very wet conditions. 6 months SPI study affirmed that no drought was experienced for all the years thereby recording a low vulnerability to drought.

From the analysis of the 12 months SPI, it was observed that the highest negative SPI value in the month of September was observe in the year 1987 categorized as near normal while the other years were found to have average negative SPI values ranging from -0.3 to -0.77 which signifies near normal condition thereby implies a low risk of drought.

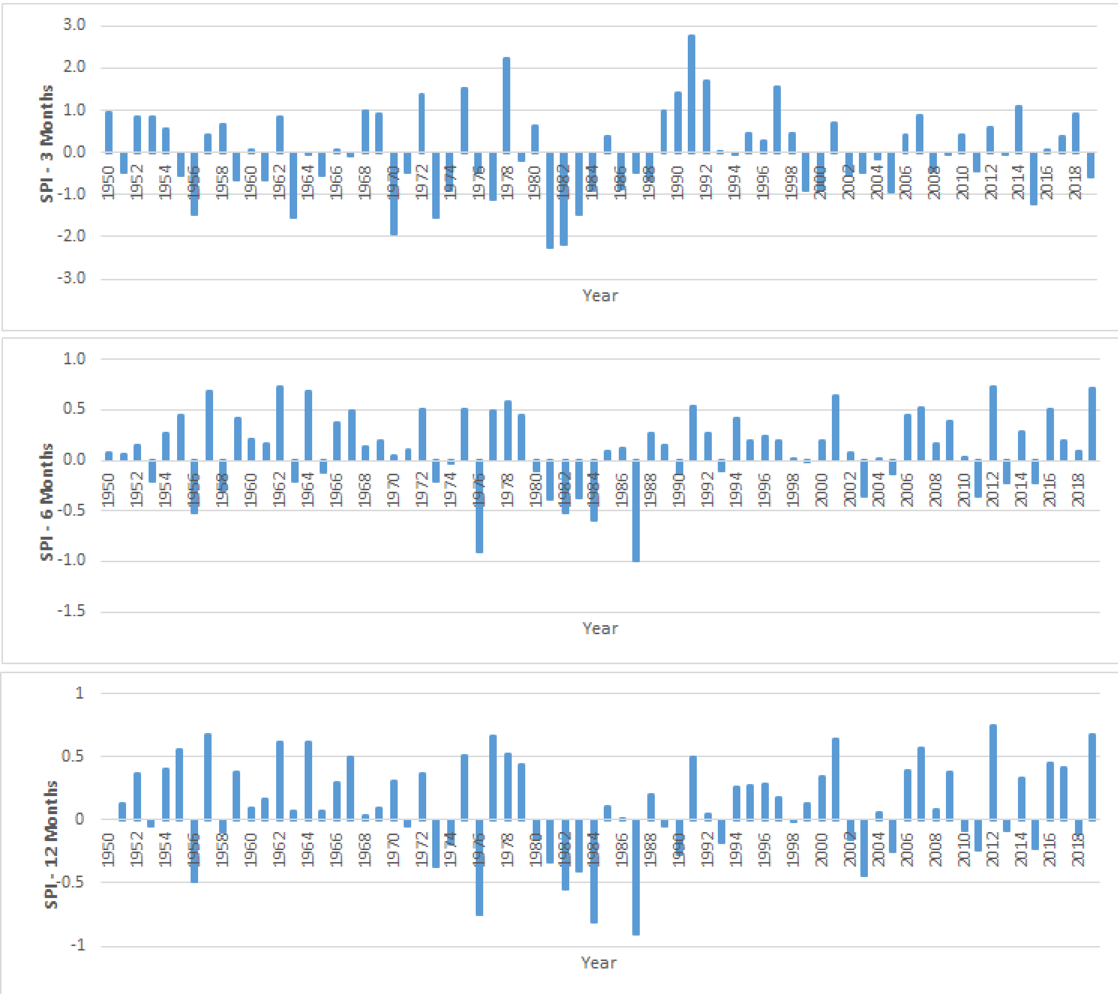

Figure 4.13: Drought vulnerability assessment of September

The 3 months SPI analysis depicted that 1981 and 1982 were indicative of extremely dry condition which would make them highly vulnerable to drought (Figure 4.14). 1970 also showed SPI values characteristic of severely dry conditions and which made it vulnerable to drought. The wet season of the years generally have average positive values characteristic of moderately wet conditions which reached its peak in 1978 and 1991 which were observed to have extreme wet conditions.

It was observed from the analysis of the 6 months SPI that no drought episodes occurred, near normal conditions was indicative of all the years while near normal conditions were observed for from the positive SPI values observed which implies a low risk to drought.

The analysis of 12 months SPI revealed that the condition of the years is near normal with a peak value observed in 1987 which also fell in the aforementioned category and a peak value of moderately wet condition was observed in 2019 while the other years were observed to have positive SPI values indicative of near normal conditions. This implies the vulnerability to drought is low.

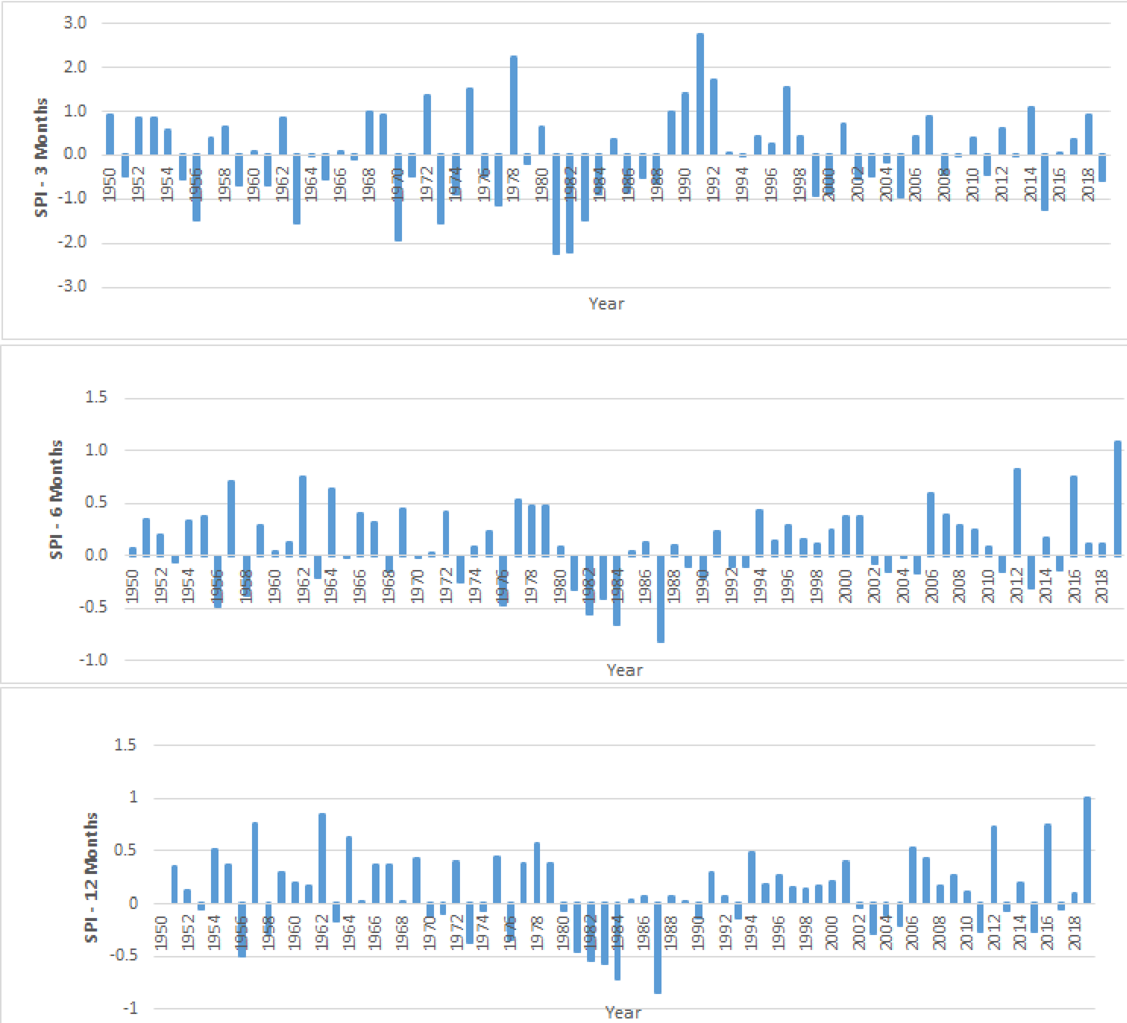

Figure 4.14: Drought vulnerability assessment of October

4.6 Correlation Between SPI and RAI

Figure 4.15 shows the correlation between RAI and SPI 3, 6, and 12. From the analysis of the graph it was observed that the RAI increases as the SPI decrease especially in the case of SPI 6 and SPI 12 which fell within similar range and margins of the rain fall data used for the analysis of SPI and that of the RAI margins. SPI 12 was found to be more accurate as it confirms with the anomaly observed in the rain fall data.

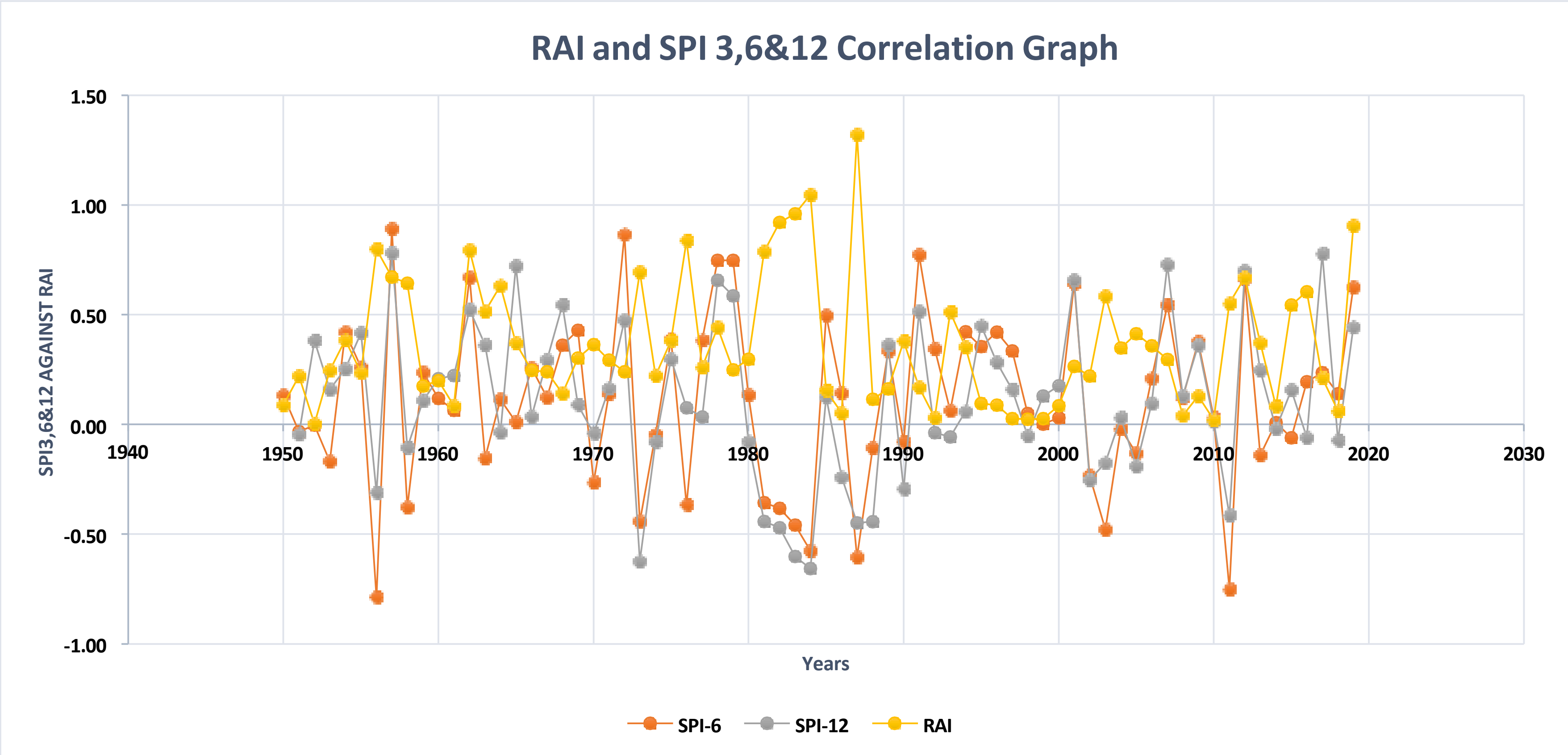

Figure 4.15: RAI and SPI 3,6 & 12 Graph

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

At the end of this research, the following conclusions were drawn;

The assessment of drought vulnerability of Minna has been presented in this study using 70 years‟ rainfall data. This study has also shown the appraisal and the usefulness of the SPI to check the variability in meteorological drought at seasonal scale in semi-arid parts of Nigeria in which Minna is found.

The SPI at a 12-month time-scale was found effective in capturing seasonal drought patterns over space and time in Minna. This is evident from the obtained results as the driest and the wettest years were observed with the SPI at a 12-month scale.

1987 was observed as the driest year with the worst drought using SPI at a 12-month scale while 2019 was observed to be the wettest year. Therefore, the present study concludes that the 12-month SPI of June to November represents the good indicator of any drought vulnerability assessment of any drought-prone areas.

The analysis established the fact that there was a correlation between SPI and RAI which was further confirmed by SPI 12 due to inverse relationship between it and the RAI.

5.2 Recommendations

Drought contingency plans generally call for certain measures to be initiated when a drought indicator reaches a predefined level. Trigger levels can be refined through computer modeling or other decision making aids to strike an acceptable balance between the frequency of drought declarations and the effectiveness of an early response. Combined with drought contingency planning, this may lead to holistic drought management strategies. Therefore, drought management strategies should include sufficient capacity for contingency planning before the onset of drought, and appropriate policies to reduce vulnerability and increase resilience to drought. Effective information and early warning systems based on indicators such as the SPI are the foundation for overall effective drought adaptation plans.

5.3 Contribution to Knowledge

The study has now made it possible to ascertain the vulnerability of cities, regions or states using the SPI analysis and the correlation with RAI to further confirm their potential drought conditions. The study has also been able to establish an approach of determining the drought vulnerability of cities by analyzing SPI 3, 6 and 12 SPI and checking the correlation with RAI that in turn helps in selecting the most suitable SPI to use in determining the drought vulnerability of cities or towns. This study can further be used in the development or improvement of weather model or indices that can be used to analyze drought‟s severity and its magnitude during and after each episode for planning and preparedness purposes.

REFERENCES

Abdulrazzaq, Z. T., Hasan, R. H. & Aziz, N. A. (2019). Integrated TRMM data and standardized precipitation index to monitor the meteorological drought. *Civil Engineering Journal*, *5*(7), 1590-1598.

Abubakar, I.U. & Yamusa, M. A. (2013) Recurrence of drought in Nigeria: Causes, effects and mitigation. International Journal of Agriculture and Food Science Technology, 4(3), 169– 180.

Adhikary, D. D., & Mallick, D. K. (2015). A fuzzy-logic based relay selection scheme for multi-hop wireless sensor networks. In *2015 1st International Conference on Next Generation Computing Technologies (NGCT)* (285-290). IEEE.

Ahmed, S. M. (2020). Impacts of drought, food security policy and climate change on performance of irrigation schemes in Sub-saharan Africa: The case of Sudan. *Agricultural Water Management*, *232*, 106064.

Alberta Water Portal Society (APWPS). (2014) Impacts of Drought https://albertawater.com/impacts-of-drought (accessed 28/07/2021)

Antwi-Agyei, P., Fraser, E.D.G., Dougill, A.J., Stringer, L.C. and Simelton, E. (2012) Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socioeconomic data. *Applied Geography*, 32, 324–334.

Azare, I. M., Abdullahi, M. S., Adebayo, A. A., Dantata, I. J. & Duala, T. (2020). Deforestation, desert encroachment, climate change and agricultural production in the Sudano-Sahelian Region of Nigeria. *Journal of Applied Sciences and Environmental Management*, *24*(1), 127-132.

Aguirre, B. A., Hsieh, B., Watson, S. J. & Wright, A. J. (2021). The experimental manipulation of atmospheric drought: Teasing out the role of microclimate in biodiversity experiments. *Journal of Ecology*, *109*(5), 1986-1999.

Bordi, I. & Sutera, A. (2001). Fifty years of precipitation: some spatially remote teleconnnections. *Water Resources Management*, *15*(4), 247-280.

Chevrier, B., Lespez, L., Lebrun, B., Garnier, A., Tribolo, C., Rasse, M., Guérin, G., Mercier, N., Camara, A., Ndiaye, M. & Huysecom, E. (2020). New data on settlement and environment at the Pleistocene/Holocene boundary in Sudano-Sahelian West Africa: Interdisciplinary investigation at Fatandi V, Eastern Senegal. *PloS one*, *15*(12), 0243129.

Cook, B.I., J.S. Mankin., K. Marvel., A.P. Williams., J.E. Smerdon., & K.J. Anchukaitis, (2020). *Twenty-first Century drought projections in the CMIP6 forcing scenarios. Earth's Future*, 8(6), e2019EF001461.

Cooper, P. J. M., Dimes, J., Rao, K. P. C., Shapiro, B., Shiferaw, B. & Twomlow, S. (2008). Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change?. *Agriculture, ecosystems & environment*, *126*(1-2), 24-35.

Crystal, J. B. (2009). A Survey of Drought Impacts and Mitigation Planning in Kentucky Masters Theses & Specialist Projects. Western Kentucky University https://digitalcommons.wku.edu/cgi/viewcontent.cgi? (accessed 30/10/2021)

Da Silva, A. S. A., Menezes, R. S. C., Telesca, L., Stosic, B. & Stosic, T. (2021). Fisher Shannon analysis of drought/wetness episodes along a rainfall gradient in Northeast Brazil. *International Journal of Climatology*, *41*, E2097-E2110.

Dar, M. H., Waza, S. A., Shukla, S., Zaidi, N. W., Nayak, S., Hossain, M. & Singh, U. S. (2020). Drought Tolerant Rice for Ensuring Food Security in Eastern India. Sustainability, 12(6), 2214.

DeGaetano, A. T., Belcher, B. N., & Noon, W. (2015). Temporal and spatial interpolation of the standardized precipitation index for computational efficiency in the dynamic drought index tool. *Journal of Applied Meteorology and Climatology*, *54*(4), 795-810.

Dikshit, A., Pradhan, B. & Alamri, A. M. (2020). Short-term spatio-temporal drought forecasting using random forests model at New South Wales, Australia. *Applied Sciences*, *10*(12), 4254.

Edossa, D. C., Babel, M. S. & Gupta, A. D. (2010). Drought analysis in the Awash river basin, Ethiopia. *Water resources management*, *24*(7), 1441-1460 USA.

Edwards, D. C., McKee, T. B. (1997). Characteristics of 20th century drought in the United States at multiple time scales. *Atmospheric Science Paper No. 634, Climatology Report* 97−2, Department of Atmospheric Science, Colorado State University.

Eze, J. N. (2018). Drought occurrences and its implications on the households in Yobe state, Nigeria. Geoenvironmental Disasters, 5(1), 18.

Farahmand, A., Reager, J. T. & Madani, N. (2021). Drought Cascade in the Terrestrial Water Cycle: Evidence from Remote Sensing. *Geophysical Research Letters*, e2021GL093482

Freitas, M. (2005). A decision support system for monitoring meteorological droughts in semiarid regions, *Review Technology*, (19), 84-95.

Gore, P. G. & Ray, K. S. (2002). Variability in drought incidence over districts of Maharashtra. *Mausam*, *53*(4), 533-538.

Guiqin, J., Fuliang, Y., & Yong, Z. (2012). An analysis of vulnerability to agricultural drought in China using the expand grey relation analysis method. *Procedia Engineering*, *28*, 670-676.

Guttman, N. B. (1998). Comparing the palmer drought index and the standardized precipitation index. *Journal of the American Water Resources Association*, 34, 113 – 121.

Guttman, N. B. (1999). Accepting the standardized precipitation index: A calculation algorithm. *Journal of the American Water Resources Association*, 35, 311 – 322.

Hao, Z., Singh, V. P., & Xia, Y. (2018). Seasonal drought prediction: advances, challenges, and future prospects. Reviews of Geophysics, 56(1), 108-141.

Hassan, A. G., Fullen, M. A. & Oloke, D. (2019). Problems of drought and its management in Yobe State, Nigeria. *Weather and Climate Extremes*, *23*, 100192.

Hayes, M., Svoboda, M., Wall, N. & Widhalm, M. (2011). The Lincoln declaration on drought indices: universal meteorological drought index recommended. *Bulletin of the American Meteorological Society*, *92*(4), 485-488.

Heikkinen, R. K., Luoto, M., Araújo, M. B., Virkkala, R., Thuiller, W. & Sykes, M. T. (2006). Methods and uncertainties in bioclimatic envelope modelling under climate change. *Progress in Physical Geography*, *30*(6), 751-777.

IPCC (2001). Third assessment report (ar3). Cambridge University Press, Cambridge.

IPCC (2007). Fourth assessment report (ar4). Cambridge University Press, Cambridge.

IPCC (2014). *Climate Change 2001—Impacts, Adaptation, and Vulnerability*, Summary for Policymakers and Technical Summary of the Working Group II Report. IPCC, Geneva, 89 pp.

Kalura, P., Pandey, A., Chowdary, V. M. & Raju, P. V. (2021). Assessment of Hydrological Drought Vulnerability using Geospatial Techniques in the Tons River Basin, India. *Journal of the Indian Society of Remote Sensing*, 1-15.

Karavitis, C. A., Alexandris, S., Tsesmelis, D. E. & Athanasopoulos, G. (2011). Application of the standardized precipitation index (SPI) in Greece. *Water*, *3*(3), 787-805.

Karimi, M., Melesse, A. M., Khosravi, K., Mamuye, M. & Zhang, J. (2019). Analysis and prediction of meteorological drought using SPI index and ARIMA model in the Karkheh River Basin, Iran. In *Extreme Hydrology and Climate Variability* (pp. 343-353). Elsevier.

Khan, M. M. H., Muhammad, N. S. & El-Shafie, A. (2020). Wavelet based hybrid ANN-ARIMA models for meteorological drought forecasting. *Journal of Hydrology*, *590*, 125380.

Kiem, A. S., Johnson, F., Westra, S., Van Dijk, A., Evans, J. P., O‟Donnell, A. & Jakob, D. (2016). Natural hazards in Australia: droughts. Climatic Change, 139(1), 37-54.

Kim, H., Park, J., Yoo, J. & Kim, T. W. (2015). Assessment of drought hazard, vulnerability, and risk: A case study for administrative districts in South Korea. *Journal of Hydro-environment Research*, *9*(1), 28-35.

Kogo, B. K., Kumar, L. & Koech, R. (2021). Climate change and variability in Kenya: a review of impacts on agriculture and food security. *Environment, Development and Sustainability*, *23*(1), 23-43.

Kumar, U., Singh, S., Bisht, J. K. & Kant, L. (2021). Use of meteorological data for identification of agricultural drought in Kumaon region of Uttarakhand. *Journal of Earth System Science*, *130*(3), 1-13.

Lange, B., Holman, I. & Bloomfield, J. P. (2017). A framework for a joint hydro-meteorological-social analysis of drought. *Science of the Total Environment*, 578, 297-306.

Leng, G., Tang, Q. & Rayburg, S. (2015). Climate change impacts on meteorological, agricultural and hydrological droughts in China. *Global and Planetary Change*, *126*, 23-34.

Livada, I. & Assimakopoulos, V. D. (2007). Spatial and temporal analysis of drought in Greece using the Standardized Precipitation Index (SPI). *Theoretical and Applied Climatology*, *89*(3), 143-153.

Livneh, B. & Hoerling, M. P. (2016). The physics of drought in the US central Great Plains. *Journal of Climate*, 29(18), 6783-6804.

Lloyd- Hughes, B., & Saunders, M. A. (2002). A drought climatology for Europe. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, *22*(13), 1571-1592.

Luo, L., Apps, D., Arcand, S., Xu, H., Pan, M., & Hoerling, M. (2017). Contribution of temperature and precipitation anomalies to the California drought during 2012–2015. *Geophysical Research Letters*, 44(7), 3184-3192.

Mahmood, R. & Jia, S. (2019). Assessment of hydro-climatic trends and causes of dramatically declining stream flow to Lake Chad, Africa, using a hydrological approach. *Science of The Total Environment*, *675*, 122-140.

Manatsa, D., Mushore, T. & Lenouo, A. (2017). Improved predictability of droughts over southern Africa using the standardized precipitation evapotranspiration index and ENSO. *Theoretical and Applied Climatology*, *127*(1-2), 259-274.

Mbuli, C. S., Fonjong, L. N. & Fletcher, A. J. (2021). Climate Change and Small Farmers‟ Vulnerability to Food Insecurity in Cameroon. *Sustainability*, *13*(3), 1523.

Mishra, A. K. & Desai, V. R. (2005). Drought forecasting using stochastic models. *Stochastic Environmental Research and Risk Assessment*, *19*(5), 326-339.

Mishra, A. K. & Singh, V. P. (2010). A review of drought concepts. *Journal of hydrology*, *391*(1-2), 202-216.

Mishra A., Desai V. & Singh V. (2007) Drought forecasting using a hybrid stochastic and neural network model. *Journal of Hydrologic Engineering 12*, 626–638.

McKee, T. B., Doesken, N. J. & Kleist, J. (1995). Drought monitoring with multiple time scales. *Proceedings of the Ninth Conference on Applied Climatology*, 233–236. American Meteorological Society, Boston.

McKee, T. B., Doesken N. J. & Kleist, J. (1993). The relationship of drought frequency and duration to time scale. *Proceedings of the Eighth Conference on Applied Climatology*, 179–184. American Meteorological Society, Boston.

McRoberts, D. B. & Nielsen-Gammon, J. W. (2012). The use of a high-resolution standardized precipitation index for drought monitoring and assessment. *Journal of Applied Meteorology and Climatology*, *51*(1), 68-83.

Medugu, N. I., Majid, M. R. & Johar, F. (2011). Drought and desertification management in arid and semi-arid zones of Northern Nigeria. *Management of Environmental Qualit,*Bradford 22(5), 595-611.Dol:1108/14777831111159725.

Mohammed, Y. S., Mustafa, M. W., Bashir, N. & Ibrahem, I. S. (2017). Existing and recommended renewable and sustainable energy development in Nigeria based on autonomous energy and microgrid technologies. *Renewable and Sustainable Energy Reviews*, *75*, 820-838.

Mortimore, M. J. & Adams, W. M. (2001). Farmer adaptation, change and „crisis‟ in the Sahel. *Global Environmental Change*, *11*(1), 49-57.

Nasra I. (2020). Effect of Drought on Smallholder Farmers in Somaliland https://www.researchgate.net/publication/34555958 (accessed 10/08/2021)

National Drought Mitigation Centre (NDMC) (2021). Types of Drought. https://drought.unl.edu/Education/DroughtIn-depth/TypesofDrought.aspx (accessed 08/08/2021)

Nhamo, L., Mabhaudhi, T. & Modi, A. T. (2019). Preparedness or repeated short-term relief aid? Building drought resilience through early warning in southern Africa. *Water Sa Journal*, *45*(1), 75-85.

Ntale, H. K. & Gan, T. Y. (2003). Drought indices and their application to East Africa. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, *23*(11), 1335-1357.

Obahoundje, S., Ta, M. Y., Diedhiou, A., Amoussou, E. & Kouadio, K. (2021). Sensitivity of Hydropower Generation to Changes in Climate and Land Use in the Mono Basin (West Africa) using CORDEX Dataset and WEAP Model. *Environmental Processes*, 1-25.

Odewale, O. & Adebola, A. (2019). Integration of standardized precipitation index and drought severity index for assessment of drought in the Sudano-Sahelian ecological zone of Nigeria. *Climate Change. 5*, 188–199

Odusola, A. (2021). Agriculture as the Fulcrum of Inclusive Development in Africa. In *Africa's Agricultural Renaissance* (pp. 15-54). Palgrave Macmillan, Cham.

Oladipo, E. O. (1993). Some aspects of the spatial characteristics of drought in northern Nigeria. Natural Hazards, 8(2), 171-188.

Olaniyi, O. A., Ojekunle, Z. O. & Amujo, B. T. (2013). Review of climate change and its effect on Nigeria ecosystem. *International Journal of African and Asian Studies-An Open Access International Journal*, *1*, 57-65.

Olaniyi, W. A. (2021). The proposed Eko Atlantic City project, Victoria Island, Lagos: Preliminary impact assessment of land reclamation on the aquatic lives and climate change. *Nigerian Journal of Animal Production*, *48*(4), 194-200.

Oluwatayo, I. B. & Ojo, A. O. (2018). Walking through a tightrope: the challenge of economic growth and poverty in Africa. *The Journal of Developing Areas*, *52*(1), 59-69.

Piedallu, C., Gégout, J.C., Ary B. and Seynave, I. (2011) Mapping soil water holding capacity over large areas to predict potential production of forest stands. *Geoderma*, 160, 355–366.

Qin, Y., Yang, D., Huimin L., Kai, X. and Xiangyu, X. (2014) Comparative analysis of drought based on precipitation and soil moisture indices in the Haihe Basin of North China during the period of 1960–2010. *Journal of Hydrology*, 9: 61–74

Reside, A. E., Briscoe, N. J., Dickman, C. R., Greenville, A. C., Hradsky, B. A., Kark, S., Kearney, M.R., Kutt, A.S., Nimmo, D.G., Pavey, C.R. and Read, J.L, & Fisher, D. O. (2019). Persistence through tough times: fixed and shifting refuges in threatened species conservation. *Biodiversity and Conservation*, *28*(6), 1303-1330.

Saber, A., James, D. E., & Hannoun, I. A. (2020). Effects of lake water level fluctuation due to drought and extreme winter precipitation on mixing and water quality of an alpine lake, Case Study: Lake Arrowhead, California. *Science of The Total Environment*, *714*, 136762.

Sajeev, A., Deb Barma, S., Mahesha, A. & Shiau, J. T. (2021). Bivariate drought characterization of two contrasting climatic regions in India using copula. *Journal of Irrigation and Drainage Engineering*, *147*(3), 05020005.

Seiler, R. A., Hayes, M. & Bressan, L. (2002). Using the standardized precipitation index for flood risk monitoring. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, *22*(11), 1365-1376.

Smakhtin, V. U. & Hughes, D. A. (2004). Review, automated estimation and analyses of drought indices in South Asia (Vol. 83). Iwmi.

Swann, A. L. (2018). Plants and drought in a changing climate. *Current Climate Change Reports*, *4*(2), 192-201.

Sykes, A. O. (1993). An introduction to regression analysis. https://chicagounbound.uchicago.edu (accessed 14/09/2021)

United Nations International Strategy for Disaster Reduction (2004). Living with Risk. A Global Review of Disaster Reduction Initiatives, United Nations, Geneva.

Van Loon, A. F., Gleeson, T., Clark, J., Van Dijk, A. I., Stahl, K., Hannaford, J. & Hannah, D. M. (2016). Drought in the Anthropocene. Nature Geoscience, 9(2), 89.

Van Loon, A. F. & Laaha, G. (2014) Hydrological drought severity explained by climate and catchment characteristics. *Journal of Hydrology*, 19: 1–12.

Van-rooy, M. P. (1965). A Rainfall Anomaly Index (RAI), Independent of the Time and Space, *Notos*.14, 43-48

Vardharajula, S., Zulfikar Ali, S., Grover, M., Reddy, G. & Bandi, V. (2011). Drought-tolerant plant growth promoting Bacillus spp.: effect on growth, osmolytes, and antioxidant status of maize under drought stress. Journal of Plant Interactions, 6(1), 1-14.

Vicente-Serrano, S. M., Quiring, S. M., Pena-Gallardo, M., Yuan, S. & Dominguez-Castro, F. (2020). A review of environmental droughts: Increased risk under global warming. *Earth-Science Reviews*, *201*, 102953.

Vicente-Serrano, S.M., Beguería, S., Gimeno, L., Eklundh, L., Giuliani, G., Weston, D., El Kenawy, A., López-Moreno, J.I., Nieto, R., Ayenew, T. & Konte, D. (2012) Challenges for drought mitigation in Africa: The potential use of geospatial data and drought information systems. *Applied Geography*, 34, pp.471-486.

Weng, W., Becker, S. L., Lüdeke, M. K. & Lakes, T. (2020). Landscape matters: Insights from the impact of mega-droughts on Colombia's energy transition. *Environmental Innovation and Societal Transitions*, *36*, 1-16.

Wilhelmi, O. V. & Wilhite, D. A. (2002). Assessing vulnerability to agricultural drought: a Nebraska case study. *Natural Hazards*, *25*(1), 37-58.

Wilhite, D. A. & Glantz, M. H. (1985). Understanding: the drought phenomenon: the role of definitions. *Water International*, *10*(3), 111-120.

Wilhite, D. A. (2005) Drought and Water Crises Science, Technology, and Management Issues. Taylor and Francis, Boca Raton, Florida: CRC Press.

Wilhite, D. A., Svoboda, M. D. & Hayes, M. J. (2007). Understanding the complex impacts of drought: A key to enhancing drought mitigation and preparedness. *Water resources management*, *21*(5), 763-774.

Wilhite, D. A., Sivakumar, M. V. & Pulwarty, R. (2014). Managing drought risk in a changing climate: The role of national drought policy. *Weather and Climate Extremes*, *3,* 4-13.

World Meteorological Organization (2012). *Standardized Precipitation Index User Guide.* No. 1090 www.Library.wmo.int (accessed 25/07/2021)

Wu, H., Svoboda, M. D., Hayes, M. J., Wilhite, D. A. & Wen, F. (2007). Appropriate application of the standardized precipitation index in arid locations and dry seasons. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, *27*(1), 65-79.

Yaduvanshi, A., Srivastava, P. K. & Pandey, A. C. (2015). Integrating TRMM and MODIS satellite with socio-economic vulnerability for monitoring drought risk over a tropical region of India. *Physics and Chemistry of the Earth, Parts A/B/C*, *83*, 14-27.

Yang, P., Xia, J., Zhan, C.; Zhang, Y., Hu, S. (2018). Discrete wavelet transform-based investigation into the variability of standardized precipitation index in Northwest China during 1960–2014, *132*, 167–180

Yuan, X., Wood, E. F., Chaney, N. W., Sheffield, J., Kam, J., Liang, M., & Guan, K. (2013). Probabilistic seasonal forecasting of African drought by dynamical models. *Journal of Hydrometeorology, 14*(6), 1706-1720.

Zadeh, L. A. (1965). Fuzzy sets. Information and control, 8(3), 338-353

Zargar, S. M., Gupta, N., Nazir, M., Mahajan, R., Malik, F. A., Sofi, N. R., Shikari, A.B. & Salgotra, R. K. (2017). Impact of drought on photosynthesis: Molecular perspective. *Plant Gene*, *11*, 154-159.

Zhang, Q., Xu, C. Y. & Zhang, Z. (2009). Observed changes of drought/wetness episodes in the Pearl River basin, China, using the standardized precipitation index and aridity index. *Theoretical and Applied Climatology*, *98*(1), 89-99.

APPENDICES

APPENDIX Ia: SPI 3 Month time scale for study area

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1950			-0.524	0.357	0.929	0.293	0.923	-0.570	-0.269	-0.957	-0.117	0.389
1951	0.746	0.524	0.991	0.499	-0.471	-0.965	-0.385	-0.113	0.507	1.061	1.569	1.709
1952	0.539	0.594	-0.292	-0.400	0.844	0.610	1.111	-0.975	-0.299	-0.605	0.574	0.295
1953	0.444	2.059	1.981	0.476	0.841	-0.422	0.203	-1.559	-0.632	-0.704	-0.312	0.336
1954	0.444	0.524	2.062	1.739	0.569	-0.186	-0.074	0.678	0.629	0.807	1.000	1.185
1955	0.632	0.524	-0.230	0.361	-0.544	-0.409	0.475	0.847	1.304	0.566	0.827	-0.123
1956	0.444	0.768	0.786	0.198	-1.470	-0.415	-1.383	-1.914	-1.595	-0.871	0.235	0.583
1957	1.843	1.528	-0.524	0.240	0.408	0.867	2.020	2.298	1.176	0.408	0.549	1.259
1958	2.135	0.942	0.199	0.079	0.645	0.132	-1.290	-2.129	-1.336	-0.645	-0.498	-0.334
1959	1.101	1.052	1.105	0.218	-0.664	0.186	-0.222	0.839	0.861	0.787	0.527	-1.069
1960	1.334	0.524	0.840	1.230	0.071	-0.030	0.430	0.035	0.365	-0.583	0.309	0.253
1961	1.991	1.781	0.239	-0.168	-0.670	-0.070	1.016	0.308	0.286	-0.805	0.105	-0.340
1962	0.444	0.524	-0.524	1.216	0.838	1.170	0.360	1.313	1.132	1.869	1.843	1.680
1963	1.451	0.711	-0.072	0.144	-1.533	-1.203	-0.723	0.061	-0.119	-0.468	-0.601	0.027
1964	0.444	0.524	-0.172	0.328	-0.018	-0.444	-0.474	0.077	1.973	2.031	2.270	0.213
1965	1.580	2.250	2.315	0.058	-0.539	0.375	0.631	0.068	-0.950	-0.960	-0.793	-0.162
1966	0.444	0.524	-0.524	0.212	0.067	0.763	-0.057	0.482	0.327	1.029	0.875	0.522
1967	0.444	0.524	-0.105	0.925	-0.076	0.447	-0.807	0.145	0.910	1.222	1.240	-0.534
1968	0.444	0.524	0.037	1.506	0.993	1.479	0.523	0.164	-1.140	-1.352	-1.259	-0.562
1969	0.444	0.524	0.158	0.210	0.909	0.253	1.449	0.460	0.135	-0.017	0.592	1.763
1970	0.780	0.524	0.184	-1.077	-1.931	-2.118	-1.783	-0.101	0.972	0.804	0.216	-1.398
1971	0.444	0.768	0.623	-0.873	-0.472	0.131	0.716	0.432	-0.063	-0.911	-1.024	-2.046
1972	0.444	0.524	1.410	0.339	1.358	-0.117	0.993	1.588	1.296	0.272	-1.443	-1.285
1973	0.444	0.524	-0.208	-1.024	-1.542	-1.759	-3.007	-0.813	0.170	0.730	-0.248	-1.176
1974	0.444	0.524	-0.145	-1.651	-0.901	-0.877	0.284	0.095	0.197	-0.292	-0.152	0.058
1975	0.444	1.164	1.226	1.863	1.505	0.991	0.768	-0.186	0.542	-0.199	0.583	-0.617
1976	0.444	2.353	2.218	1.163	-0.471	0.006	-0.377	-1.182	-3.352	-1.709	-1.375	1.667
1977	0.444	0.524	-0.524	-2.453	-1.119	-0.708	0.301	1.502	1.567	1.209	0.480	-0.283
1978	0.444	0.524	0.667	1.146	2.224	1.229	0.676	0.425	0.615	0.762	0.123	0.231
1979	0.688	0.524	0.431	-0.823	-0.202	-0.017	0.697	2.176	1.084	0.748	-0.892	-0.128
1980	0.821	0.524	-0.524	-2.078	0.619	0.428	0.665	-0.311	-0.937	-0.637	-0.873	0.475
1981	0.444	0.524	-0.524	-1.133	-2.243	-1.163	-0.749	-0.258	-0.658	-0.836	-0.916	-0.258
1982	0.444	0.524	0.325	0.379	-2.191	-3.994	-2.286	-0.357	0.116	-0.535	-1.279	-0.203
1983	0.444	0.524	0.287	-1.713	-1.488	-1.866	-1.643	-0.886	-0.258	-0.483	-1.120	-1.838
1984	0.444	0.524	-0.253	-0.072	-0.903	-1.112	-0.997	-1.578	-1.324	-1.831	-1.366	-0.717
1985	0.444	0.524	1.889	0.356	0.361	0.469	1.177	1.068	-0.340	-1.294	-1.861	-1.475
1986	0.444	0.524	1.229	-0.139	-0.860	-0.662	-0.182	0.646	0.490	0.227	-0.117	-0.542
1987	0.656	0.524	1.672	-0.061	-0.493	-2.023	-1.961	-1.947	-1.947	-1.582	-2.054	-0.185
1988	0.935	0.945	0.209	-0.063	-0.660	-0.668	-1.053	-0.235	0.919	0.703	0.525	-1.729
1989	0.444	0.524	0.031	1.217	0.988	1.393	0.582	0.076	-0.985	-1.238	-1.180	-0.815
1990	0.444	0.524	-0.524	0.862	1.412	0.464	-0.166	-1.818	-1.086	-0.922	-0.365	0.307

APPENDIX Ib: SPI 3 Month time scale for study area

1991	0.444	0.524	-0.524	0.941	2.742	2.218	1.646	-0.027	-0.511	-1.047	-1.618	-1.869
1992	0.444	0.524	-0.393	1.525	1.692	1.264	0.235	-0.525	-0.470	-0.919	-0.512	-0.481
1993	1.741	0.524	0.347	-1.151	0.025	0.061	0.219	-0.118	-0.648	-0.883	-1.399	-0.951
1994	0.444	0.524	0.031	0.931	-0.008	0.833	-0.454	1.057	0.371	1.375	0.854	0.986
1995	0.444	0.524	-0.524	0.746	0.434	0.155	-0.889	0.558	0.185	0.738	-0.156	0.716
1996	1.363	0.524	-0.524	-0.289	0.260	0.781	1.188	0.885	-0.116	-0.378	-0.466	0.273
1997	0.444	0.524	-0.208	0.459	1.551	1.670	1.144	-0.420	-1.161	-0.847	-0.442	0.167
1998	0.444	0.524	-0.524	0.609	0.438	1.067	-0.222	-0.455	-1.129	0.221	0.469	1.119
1999	0.444	0.864	0.066	-0.422	-0.909	-0.496	0.012	0.237	0.004	0.471	0.650	1.348
2000	0.487	0.571	-0.459	-2.636	-0.891	-0.531	-0.043	0.318	0.631	0.938	0.854	0.637
2001	0.444	0.524	-0.524	0.624	0.688	1.761	1.693	1.322	0.330	-0.543	-0.407	-2.192
2002	0.444	0.524	-0.066	0.792	-0.549	-0.087	-1.059	-0.704	0.004	0.166	0.590	-0.477
2003	0.444	0.790	-0.066	-1.133	-0.467	-0.072	-0.573	-1.549	-1.378	-0.393	0.187	0.665
2004	0.460	0.524	-0.524	-0.771	-0.157	0.256	0.421	-0.268	-0.434	-0.737	-0.465	-0.624
2005	0.444	0.524	-0.524	-0.139	-0.953	-0.086	0.641	-0.147	-0.617	-1.526	-0.550	-0.081
2006	1.328	1.255	0.239	-0.852	0.416	-0.194	0.202	0.096	1.163	1.459	1.475	0.880
2007	0.444	0.524	-0.223	0.814	0.868	0.060	0.585	0.876	1.245	0.515	0.163	-0.199
2008	0.444	0.524	-0.524	-0.941	-0.429	-0.561	0.592	0.353	0.582	0.146	0.375	0.468
2009	0.444	0.524	-0.524	0.533	-0.003	-0.499	-1.446	0.909	1.174	1.392	-0.060	-0.485
2010	0.444	0.524	-0.524	0.559	0.408	-0.181	-0.286	-0.495	-0.066	0.188	0.395	0.905
2011	0.444	0.620	-0.375	-0.948	-0.435	-1.009	-1.107	-2.485	-0.688	0.012	0.973	0.809
2012	0.444	0.524	-0.524	-0.704	0.593	-0.138	1.089	1.455	1.953	1.591	1.178	0.699
2013	1.489	1.383	0.930	1.445	-0.028	0.515	-1.162	-0.747	-1.419	-0.468	-0.136	0.809
2014	0.444	0.524	-0.524	0.665	1.073	0.514	-0.398	-1.146	0.205	0.513	0.840	-0.137
2015	0.444	0.524	0.721	-1.094	-1.235	-0.182	-0.501	0.205	-0.847	-0.414	-1.049	-0.351
2016	0.607	0.524	0.837	0.273	0.043	0.169	-0.171	0.298	1.144	2.204	2.488	1.714
2017	0.444	0.524	-0.524	-2.129	0.363	1.195	1.381	0.218	-0.654	-1.246	-1.113	-2.038
2018	0.444	1.129	0.506	0.236	0.914	0.952	-0.287	-0.534	-0.787	0.262	-0.144	0.298
2019	0.755	0.620	-0.375	-0.995	-0.586	0.267	1.214	1.987	1.683	2.379	2.385	2.321

Appendix IIa: SPI 6 Month time scale for study area

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1950						0.183	0.553	0.133	0.075	0.063	-0.073	0.040
1951	-0.376	-0.002	0.607	0.480	-0.338	-0.403	0.002	-0.034	0.062	0.340	0.484	0.641
1952	0.659	1.061	1.476	-0.425	0.642	0.403	0.512	-0.004	0.145	0.203	0.010	0.010
1953	-0.217	0.786	1.011	0.365	1.171	0.188	0.255	-0.169	-0.211	-0.054	-0.364	-0.117
1954	-0.269	-0.124	1.084	1.556	0.430	0.347	0.499	0.420	0.261	0.325	0.515	0.566
1955	0.533	0.699	0.992	0.313	-0.393	-0.251	0.352	0.260	0.448	0.374	0.512	0.609
1956	0.396	0.618	0.102	0.103	-0.999	-0.111	-0.508	-0.789	-0.516	-0.473	-0.299	-0.442
1957	-0.178	0.423	0.388	0.805	0.636	0.557	1.031	0.892	0.676	0.703	0.818	0.799
1958	0.507	0.474	1.136	0.879	0.581	0.142	-0.496	-0.378	-0.296	-0.384	-0.549	-0.532
1959	-0.175	-0.144	0.083	0.387	-0.306	0.322	0.009	0.237	0.419	0.288	0.437	0.302
1960	0.587	0.402	-0.610	1.340	0.062	0.137	0.547	0.119	0.206	0.036	0.183	0.274
1961	-0.009	0.543	0.234	0.632	0.074	0.019	0.502	0.064	0.171	0.126	0.201	0.145
1962	-0.322	0.137	-0.486	1.063	0.629	0.754	0.514	0.670	0.733	0.750	0.888	0.875
1963	1.156	1.245	1.477	0.511	-1.067	-0.745	-0.231	-0.154	-0.203	-0.205	-0.025	0.035
1964	-0.146	-0.306	-0.074	0.225	-0.004	-0.268	-0.078	0.114	0.678	0.640	0.729	0.941
1965	1.252	1.824	1.147	0.522	0.446	0.741	0.362	0.011	-0.115	-0.014	-0.066	-0.342
1966	-0.403	-0.427	-0.317	0.116	0.059	0.489	0.081	0.256	0.379	0.398	0.435	0.308
1967	0.638	0.621	0.397	0.789	-0.047	0.313	-0.062	0.123	0.493	0.309	0.452	0.385
1968	0.739	0.850	-0.529	1.336	0.743	0.990	0.668	0.361	0.138	-0.144	-0.137	-0.490
1969	-0.608	-0.719	-0.515	0.114	0.681	0.214	0.764	0.429	0.195	0.444	0.358	0.513
1970	0.116	0.443	1.595	-0.864	-1.420	-1.285	-0.935	-0.263	0.038	-0.013	0.126	0.319
1971	0.520	0.237	-0.978	-0.912	-0.279	0.201	0.268	0.139	0.102	0.021	-0.016	-0.191
1972	-0.377	-0.572	-0.796	0.236	1.013	0.207	0.581	0.866	0.503	0.410	0.228	0.472
1973	0.242	-0.835	-1.287	-1.055	-1.131	-1.119	-1.495	-0.444	-0.202	-0.244	-0.165	-0.011
1974	0.482	-0.084	-1.166	-1.652	-0.657	-0.544	-0.005	-0.044	-0.030	0.081	0.086	0.171
1975	-0.053	0.094	0.445	1.673	1.264	0.840	0.881	0.388	0.502	0.225	0.199	0.216
1976	-0.005	0.894	0.572	1.013	0.553	0.503	0.189	-0.367	-0.902	-0.470	-0.524	-0.733
1977	-0.795	-0.792	1.413	-2.417	-0.818	-0.468	-0.033	0.386	0.486	0.530	0.595	0.699
1978	0.732	0.373	-0.081	0.997	1.653	0.899	0.629	0.748	0.585	0.477	0.235	0.374
1979	0.513	0.149	0.272	-0.721	-0.140	0.078	0.264	0.748	0.450	0.478	0.494	0.514
1980	0.517	-0.489	-0.285	-1.515	0.467	0.271	0.156	0.134	-0.097	0.080	-0.183	-0.209
1981	-0.234	-0.477	0.286	-1.159	-1.650	-0.765	-0.455	-0.356	-0.382	-0.319	-0.179	-0.238
1982	-0.338	-0.504	-0.190	0.274	-1.612	-2.393	-0.844	-0.383	-0.523	-0.554	-0.283	0.094
1983	-0.181	-0.732	-0.155	-1.711	-1.091	-1.108	-0.936	-0.459	-0.375	-0.408	-0.389	-0.262
1984	-0.153	-0.632	-1.803	-0.153	-0.659	-0.708	-0.400	-0.576	-0.596	-0.660	-0.626	-0.592
1985	-0.859	-0.786	0.288	0.251	0.277	0.675	0.667	0.497	0.096	0.047	0.007	-0.265
1986	-0.578	-1.097	-0.629	-0.216	-0.626	-0.163	-0.044	0.142	0.115	0.125	0.236	0.204
1987	0.232	-0.002	0.258	-0.062	-0.355	-0.801	-0.825	-0.604	-1.001	-0.815	-0.874	-0.753
1988	-0.678	-1.119	-0.165	0.069	-0.349	-0.366	-0.423	-0.107	0.263	0.091	0.172	0.269
1989	0.467	0.401	-1.571	1.064	0.740	0.935	0.608	0.334	0.156	-0.099	-0.145	-0.463
1990	-0.549	-0.670	-0.936	0.729	1.053	0.294	0.191	-0.080	-0.132	-0.205	-0.440	-0.305

Appendix IIb: SPI 6 Month time scale for study area

1991	-0.383	-0.158	0.128	0.804	2.035	1.435	1.001	0.774	0.530	0.235	-0.260	-0.376
1992	-0.449	-0.944	-1.892	1.354	1.260	0.821	0.554	0.344	0.266	-0.104	-0.157	-0.196
1993	-0.220	-0.250	-0.375	-0.095	0.028	0.116	0.003	0.062	-0.101	-0.099	-0.242	-0.338
1994	-0.363	-0.807	-0.901	0.795	0.004	0.574	0.088	0.423	0.410	0.427	0.571	0.420
1995	0.819	0.608	0.769	0.620	0.330	0.093	-0.149	0.354	0.188	0.135	0.204	0.289
1996	0.565	-0.026	0.514	0.138	0.202	0.501	0.563	0.420	0.245	0.282	0.222	0.080
1997	-0.098	-0.221	0.146	0.349	1.156	1.095	0.672	0.335	0.189	0.149	-0.114	-0.364
1998	-0.344	-0.206	-0.005	0.491	0.333	0.686	0.101	0.050	0.021	0.114	0.104	-0.130
1999	0.215	0.411	0.981	-0.484	-0.558	-0.275	-0.003	0.001	-0.017	0.241	0.318	0.359
2000	0.348	0.483	1.117	-2.492	-0.641	-0.348	-0.206	0.030	0.190	0.372	0.390	0.454
2001	0.590	0.608	0.440	0.505	0.518	1.137	0.953	0.642	0.638	0.371	0.352	-0.025
2002	-0.185	-0.184	-2.008	0.664	-0.397	-0.028	-0.207	-0.234	0.074	-0.083	0.077	0.006
2003	0.186	0.473	-0.509	-1.159	-0.268	-0.018	-0.371	-0.478	-0.362	-0.149	-0.229	-0.338
2004	-0.106	0.189	0.466	-0.808	-0.106	0.159	0.140	-0.021	0.014	-0.008	-0.080	-0.202
2005	-0.286	-0.221	-0.755	-0.216	-0.695	-0.064	0.333	-0.131	-0.127	-0.156	-0.068	-0.190
2006	-0.593	-0.122	-0.064	-0.271	0.528	-0.061	0.027	0.210	0.442	0.587	0.505	0.718
2007	0.863	0.997	0.709	0.684	0.651	0.053	0.504	0.544	0.522	0.384	0.360	0.573
2008	0.369	0.174	-0.352	-0.976	-0.307	-0.373	0.202	0.122	0.167	0.279	0.278	0.402
2009	0.176	0.307	0.280	0.419	0.007	-0.332	-0.446	0.377	0.385	0.247	0.318	0.505
2010	0.828	0.034	-0.623	0.443	0.311	-0.125	0.060	0.031	0.029	0.090	0.076	0.230
2011	0.198	0.328	0.710	-0.984	-0.294	-0.652	-0.601	-0.751	-0.360	-0.141	-0.203	-0.036
2012	0.105	0.682	0.602	-0.751	0.448	-0.098	0.463	0.664	0.728	0.818	0.750	1.010
2013	1.017	0.952	0.843	1.581	0.278	0.492	-0.035	-0.141	-0.217	-0.302	-0.121	-0.319
2014	-0.146	-0.014	0.602	0.543	0.803	0.327	0.038	0.008	0.279	0.165	0.045	0.142
2015	0.368	0.598	0.063	-1.122	-0.904	0.022	-0.333	-0.061	-0.224	-0.138	-0.083	-0.333
2016	-0.106	-0.587	-0.061	0.223	0.041	0.261	0.044	0.194	0.510	0.754	0.841	0.887
2017	1.253	1.633	1.457	-2.108	0.278	0.769	0.502	0.236	0.194	0.114	-0.092	-0.453
2018	-0.553	-0.496	-1.508	0.138	0.832	0.702	-0.016	0.140	0.088	0.112	-0.071	-0.187
2019	0.258	-0.010	0.140	-0.818	-0.405	0.175	0.492	0.625	0.714	1.087	1.191	1.241

Appendix IIIa: SPI 12 Month time scale for study area

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1950												0.070
1951	0.084	0.084	0.150	0.102	-0.138	-0.110	-0.220	-0.045	0.129	0.360	0.349	0.349
1952	0.367	0.367	0.307	0.284	0.555	0.608	0.611	0.381	0.371	0.128	0.127	0.127
1953	0.139	0.275	0.287	0.226	0.278	0.064	-0.001	0.159	-0.044	-0.044	-0.043	-0.044
1954	-0.030	-0.177	-0.020	0.171	-0.225	0.031	0.108	0.252	0.397	0.512	0.518	0.518
1955	0.535	0.534	0.390	0.342	0.388	0.347	0.459	0.417	0.553	0.373	0.366	0.366
1956	0.382	0.392	0.424	0.367	0.297	0.423	-0.025	-0.312	-0.494	-0.492	-0.473	-0.388
1957	-0.377	-0.387	-0.436	-0.369	-0.118	-0.112	0.458	0.781	0.671	0.759	0.826	0.765
1958	0.802	0.800	0.800	0.788	0.838	0.648	0.050	-0.107	-0.092	-0.285	-0.355	-0.356
1959	-0.370	-0.334	-0.285	-0.350	-0.555	-0.269	-0.109	0.108	0.383	0.296	0.312	0.312
1960	0.327	0.298	0.310	0.455	0.396	0.264	0.588	0.209	0.093	0.197	0.151	0.228
1961	0.266	0.266	0.212	0.097	0.171	0.204	0.242	0.222	0.169	0.169	0.170	0.091
1962	0.081	0.082	0.081	0.252	0.306	0.371	0.090	0.523	0.619	0.841	0.887	0.888
1963	0.907	0.911	0.915	0.789	0.643	0.468	0.576	0.363	0.065	-0.172	-0.232	-0.232
1964	-0.221	-0.227	-0.223	-0.196	-0.030	-0.072	-0.139	-0.036	0.612	0.629	0.628	0.629
1965	0.704	0.788	0.805	0.680	0.732	0.948	0.891	0.723	0.070	0.016	0.017	0.016
1966	-0.039	-0.143	-0.173	-0.020	-0.052	-0.072	-0.192	0.036	0.294	0.375	0.375	0.375
1967	0.391	0.391	0.401	0.475	0.375	0.328	0.324	0.293	0.498	0.370	0.370	0.370
1968	0.386	0.386	0.390	0.475	0.549	0.631	0.734	0.545	0.036	0.027	0.028	0.028
1969	0.041	0.042	0.046	-0.149	0.029	-0.283	0.101	0.089	0.093	0.422	0.434	0.434
1970	0.451	0.450	0.451	0.360	0.099	0.040	-0.385	-0.041	0.302	-0.124	-0.138	-0.138
1971	-0.126	-0.113	-0.102	-0.112	0.052	0.298	0.411	0.164	-0.047	-0.093	-0.092	-0.092
1972	-0.079	-0.090	-0.020	0.029	0.215	-0.075	0.101	0.476	0.363	0.401	0.401	0.401
1973	0.417	0.416	0.331	0.314	0.012	0.044	-0.521	-0.623	-0.375	-0.372	-0.371	-0.371
1974	-0.360	-0.358	-0.357	-0.387	-0.280	-0.194	0.257	-0.080	-0.194	-0.067	-0.066	-0.066
1975	-0.053	-0.011	0.024	0.322	0.366	0.422	0.431	0.298	0.514	0.439	0.439	0.439
1976	0.456	0.584	0.545	0.340	0.287	0.328	0.077	0.075	-0.751	-0.343	-0.342	-0.343
1977	-0.332	-0.541	-0.542	-0.642	-0.634	-0.714	-0.454	0.035	0.665	0.379	0.379	0.379
1978	0.395	0.394	0.437	0.635	0.890	0.823	0.710	0.657	0.521	0.565	0.573	0.574
1979	0.591	0.590	0.579	0.402	0.177	0.299	0.405	0.586	0.440	0.386	0.392	0.392
1980	0.408	0.407	0.377	0.364	0.527	0.469	0.355	-0.076	-0.159	-0.063	-0.079	-0.079
1981	-0.066	-0.065	-0.066	-0.031	-0.443	-0.415	-0.377	-0.442	-0.338	-0.454	-0.453	-0.454
1982	-0.443	-0.441	-0.410	-0.302	-0.435	-0.824	-0.625	-0.471	-0.548	-0.548	-0.546	-0.547
1983	-0.537	-0.534	-0.537	-0.709	-0.459	-0.267	-0.571	-0.602	-0.404	-0.572	-0.570	-0.572
1984	-0.562	-0.559	-0.583	-0.445	-0.483	-0.439	-0.304	-0.656	-0.807	-0.709	-0.707	-0.708
1985	-0.699	-0.696	-0.528	-0.641	-0.484	-0.161	-0.069	0.125	0.108	0.041	0.041	0.041
1986	0.055	0.055	-0.007	0.005	-0.117	-0.262	-0.351	-0.239	0.002	0.068	0.076	0.076
1987	0.090	0.091	0.130	0.099	0.139	-0.097	-0.264	-0.448	-0.906	-0.851	-0.859	-0.861
1988	-0.824	-0.820	-0.985	-0.820	-0.847	-0.691	-0.608	-0.444	0.202	0.064	0.064	0.064
1989	0.055	0.056	0.071	0.219	0.306	0.528	0.553	0.362	-0.044	0.019	0.020	0.020
1990	0.033	0.034	0.018	-0.020	0.119	-0.233	-0.205	-0.295	-0.272	-0.138	-0.137	-0.138

Appendix IIIb: SPI 12 Month time scale for study area

1991	-0.125	-0.124	-0.124	-0.111	0.184	0.359	0.345	0.515	0.495	0.300	0.300	0.300
1992	0.316	0.316	0.318	0.407	0.082	0.043	0.051	-0.038	0.045	0.068	0.148	0.148
1993	0.162	0.162	0.188	-0.134	-0.139	-0.112	-0.137	-0.057	-0.175	-0.144	-0.229	-0.230
1994	-0.218	-0.216	-0.231	-0.010	-0.219	-0.035	-0.167	0.060	0.262	0.487	0.487	0.487
1995	0.504	0.503	0.489	0.481	0.568	0.339	0.397	0.450	0.274	0.176	0.225	0.225
1996	0.240	0.240	0.240	0.131	0.216	0.380	0.584	0.283	0.283	0.262	0.214	0.214
1997	0.229	0.229	0.236	0.303	0.451	0.462	0.290	0.158	0.174	0.154	0.154	0.154
1998	0.169	0.169	0.161	0.189	-0.034	-0.006	-0.150	-0.052	-0.007	0.138	0.138	0.138
1999	0.152	0.169	0.169	0.049	-0.016	-0.199	0.102	0.129	0.125	0.162	0.162	0.162
2000	0.178	0.162	0.162	0.096	0.167	0.156	0.083	0.176	0.339	0.215	0.216	0.216
2001	0.229	0.229	0.229	0.412	0.447	0.736	0.800	0.657	0.641	0.394	0.394	0.394
2002	0.410	0.409	0.421	0.432	0.238	-0.037	-0.226	-0.253	-0.155	-0.030	-0.029	-0.030
2003	-0.016	-0.003	-0.016	-0.197	0.011	-0.011	-0.091	-0.174	-0.442	-0.280	-0.278	-0.279
2004	-0.268	-0.279	-0.280	-0.243	-0.231	-0.198	-0.003	0.032	0.060	-0.115	-0.115	-0.115
2005	-0.103	-0.101	-0.102	-0.050	-0.208	-0.181	0.006	-0.190	-0.247	-0.214	-0.213	-0.188
2006	-0.150	-0.148	-0.149	-0.204	0.050	-0.171	-0.319	0.095	0.386	0.529	0.529	0.508
2007	0.504	0.503	0.509	0.648	0.576	0.557	0.724	0.728	0.573	0.429	0.429	0.429
2008	0.446	0.445	0.439	0.291	0.260	0.318	0.292	0.129	0.085	0.167	0.167	0.167
2009	0.182	0.182	0.182	0.309	0.243	0.194	-0.131	0.360	0.379	0.260	0.260	0.260
2010	0.275	0.275	0.275	0.280	0.339	0.337	0.495	0.015	-0.080	0.108	0.108	0.108
2011	0.122	0.126	0.126	-0.011	0.004	-0.035	-0.188	-0.413	-0.238	-0.262	-0.261	-0.262
2012	-0.250	-0.251	-0.252	-0.231	-0.084	-0.069	0.281	0.699	0.751	0.731	0.730	0.730
2013	0.799	0.797	0.800	1.007	0.719	0.919	0.570	0.246	-0.083	-0.070	-0.070	-0.070
2014	-0.120	-0.118	-0.121	-0.247	0.073	-0.120	-0.078	-0.019	0.330	0.195	0.195	0.195
2015	0.210	0.210	0.257	0.059	-0.126	0.105	0.036	0.157	-0.228	-0.268	-0.260	-0.261
2016	-0.249	-0.247	-0.240	-0.130	-0.071	-0.155	-0.054	-0.059	0.452	0.743	0.737	0.738
2017	0.756	0.754	0.707	0.634	0.801	0.917	0.955	0.778	0.411	-0.045	-0.044	-0.045
2018	-0.032	0.007	0.007	0.111	0.105	-0.058	-0.322	-0.074	-0.107	0.092	0.105	0.105
2019	0.119	0.086	0.086	0.023	-0.148	-0.084	0.378	0.444	0.673	1.002	0.991	0.992

Appendix IV: Annual rainfall anomaly

Year	Annual anomaly	Year	Annual anomaly	Year	Annual anomaly	Year	Annual anomaly
1950	0.087	1967	0.240	1985	0.153	2002	0.220
1951	0.221	1968	0.141	1986	0.052	2003	0.585
1952	0.003	1969	0.303	1987	1.321	2004	0.348
1953	0.246	1970	0.364	1988	0.115	2005	0.413
1954	0.386	1971	0.293	1989	0.162	2006	0.358
1955	0.236	1972	0.240	1990	0.379	2007	0.295
1956	0.798	1973	0.694	1991	0.170	2008	0.041
1957	0.672	1974	0.222	1992	0.030	2009	0.130
1958	0.644	1975	0.382	1993	0.512	2010	0.021
1959	0.175	1976	0.838	1994	0.352	2011	0.552
1960	0.200	1977	0.261	1995	0.095	2012	0.669
1961	0.085	1978	0.442	1996	0.087	2013	0.373
1962	0.794	1979	0.249	1997	0.026	2014	0.082
1963	0.515	1980	0.297	1998	0.023	2015	0.544
1964	0.633	1981	0.788	1999	0.027	2016	0.604
1965	0.370	1982	0.920	2000	0.085	2017	0.212
1966	0.246	1983	0.960	2001	0.265	2018	0.061
		1984	1.047			2019	0.905