ASSESSMENT OF DROUGHT IN SOME STATES OF NORTH-EASTERN NIGERIA

BY

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MEng/SIPET/2018/9010

DEPARTMENT OF CIVIL ENGINEERING

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A THESIS SUBMITTED TO THE POSTGRADUATE SCHOOL, FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGERIA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF ENGINEERING IN CIVIL ENGINEERING (WATER RESOURCES AND ENVIRONMENTAL ENGINEERING)

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ABSTRACT

Drought is one of the most expensive hazards and widespread natural menace, as it occurs in all geographic region of the earth. In Northern Nigeria, studies on drought appraisal have been carried out using rainfall based index which do not take account of other variables and triggers like temperature. Hence, a temperature based index, Standardized Evapotranspiration Index (SPEI) at 3 and 6 months accumulation period was adopted. The study employed the modified Blaney-Morin equation, that is, the Blaney-Morin Nigeria, as its evapotranspiration model for calculating evapotranspiration (PET). The north-eastern part of Nigeria was taken as a case study using hydrometeorolgical data. The analysis of the decadal trend of the rainfall in the study area shows that the last 5 years (2016-2020) witnessed increased rainfall in all the stations with Bauchi having the highest amount of rainfall of 1567.74mm while the analysis of temperature trend shows that monthly temperature was highest in Yola with the peak value of 29.86^{o}C in 2016. The degree of temperature follows an increasing trend in all the stations in the last five years of the study period. The Standardized Anomaly Index further buttressed the likelihood of increased temperature due to global warming as more warming years were observed in the last five years of the study period. The analysis of the drought severity shows that the 3-month time scale demonstrates higher incidences of moderate to severe drought while the 6-month time scale demonstrated a lesser incidence, although, near normal incidences were more pronounced in both timescales. The last five years were shown to be prone to the drought incidences which is likely due to the effect of increased temperature as observed in both accumulation periods; however, the critical years were 2019 and 2020 with moderate to severe drought in the months of August to September for SPEI-3; and October to November for SPEI-6 while the year 2008 was the wettest year across all stations. It was recommended in view of the findings that both accumulation periods can be used for drought monitoring due to the transition from meteorological to hydrological drought, hence, the need for adequate drought monitoring framework for drought preparedness should be put in place.

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CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

Drought is one of the most costly and widespread hazards which cut across all hydro-climatological region and at any time of the year (Faye *et al.*, 2019) bearing with it, severe societal consequences that span various sectors of the economy. It is a temporary natural phenomenon which may originate from lack of precipitation, variability in rainfall and prolong dry spell (Smakhtin and Hughes, 2004), it is commonly also associated with increased evaporation rate (Achugbu and Balogun, 2018). In certain cases, unusual deviation of environmental variables such evapotranspiration, high wind, low relative humidity, temperature, characteristics and duration of rain, intensity and onset may result to drought (Cook *et al.*, 2014; Luo *et al.*, 2017). 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 and Van Lanen, 2013). The events due to climate change and global warming exacerbates the chances of worsening drought in many parts of the world as its likely to enhance its number of occurrences, its magnitude and associated impacts (Zulfiqar *et al.*, 2019).

The event of drought is considered complex, least understood, and difficult to monitor. These complexities arise from four reasons according to Bachmair *et al.* (2016); first, drought develops slowly and its onset and end are not distinct unlike other hazardous phenomena such as flood, pollution and earthquake. This makes it devastating as it gradually increases in severity and tend to persist over a long period of time even after it has stopped (Yue *et al.*, 2018).; second, the definition of drought is not precisely and universally defined; third, its impacts are non-structural and hard to quantify; and fourth, drought's multifaceted nature spreads over a very large area, affecting different parts of the hydrologic cycle, ecosystems and almost all sectors of society. The slow-onset, insidious and creeping devastating nature of the drought phenomenon makes it important for a regular monitoring to ascertain its severity (Adeniyi and Uzoma, 2016).

In Nigeria, the northern part of the country located in the Sudano-Sahel ecological zone (SSEZ) of Africa has been shown to have suffered from severe drought episodes since the Sahelian drought of the early 1970s (Alatise and Ikumawoyi, 2007). The frequent occurrence of droughts in recent decades have become a subject of concern to many researchers most especially the north-eastern Nigeria where there is pronounced occurrence which has resulted to shortage in water resources resulting to crop losses which depends heavily on rainfall, increase in desertification rate, animal mortality, migration and hike in price of food commodity (Adeniyi and Uzoma, 2016; Abdullahi *et al.*, 2016; Hassan *et al.,* 2019). The frequency of drought and its impacts on the lives and the economy of the region through its effects on agricultural production and natural resources therefore call for mitigative and adaptive measures against the natural menace.

Below-normal rainfall activates severe droughts while rising temperature can generally exacerbates drought as revealed by general circulation model which shows that evaporation and transpiration use up to 80% of rainfall (Abramopolous *et al.,* 1988; Faye *et al.*, 2019). Narendra *et al.* (2019) claims that temperature played a significant role in the devasting droughts in central India during the summer of 2015. In the SSEZ, Abdulsalam *et al.* (2014) reveals that elevated temperature due to climate change will increase the occurrence of extreme events of drought and flooding.

Therefore, to monitor and quantify drought in northern Nigeria an index that takes account of temperature information in this present climate change/global warming realities would be a useful tool for drought monitoring and assessment. The focus of this study is to evaluate the extent and degree of drought severity in some northeastern states in Nigeria using the Standardized Precipitation Evapotranspiration Index (SPEI).

1.2 Statement of the Research Problem

Drought and desertification are pronounced in Northern Nigeria as studies have shown several records of its occurrence, recurrence and persistence in the region (Abaje *et al.*, 2013; Olagunju, 2015; Abdullahi *et al.*, 2016; Shiru *et al.*, 2018). The frequent occurrence of drought in the region due to decline in rainfall pattern and the variability of rainfall have made household highly vulnerable (Eze, 2018). The impact of climate change over the years have also exacerbated this condition. In the light of this, the evaluation of drought severity and its impact have been studied using precipitation-based indicators like standardized precipitation index (SPI) and normalized rainfall index (NRI) in Northern Nigeria (Abaje *et al.*, 2013; Achugbu and Balogun, 2018; Eze, 2018) without considering other climatological variables like temperature. Thus, the focus of this study is to evaluate the occurrence of drought using the rainfall-temperature based index.

1.3 Aim and Objectives of the Study

The aim of this study is to carry out an assessment of drought in some states of North-eastern Nigeria.

The objectives are to:

i. assess the climatic trend (rainfall and temperature) in the study area
ii. determine the potential evapotranspiration (PET) of the study area using empirical method (Blaney-Morin Nigeria); and
iii. examine the spatio-temporal variation of drought severity in the study area using SPEI.

1.4 Justification of the Study

In the current climate realities, climate change models have predicted increase in temperature in the 21st century which could worsen drought conditions (Laboratory of Climate Services and Climatology (LCSC), 2020). Thus, in northern Nigeria, frequent severe drought which has largely characterized the region is related to increased temperature (Abubakar and Yamusa, 2013), this was demonstrated to may have hampered crop yield as reported by Sultan *et al.*

(2013). Therefore, a single variable precipitation-based indicator cannot identify the role of temperature increase in future drought conditions, and independently of global warming scenarios, cannot account for the influence of temperature variability. According to Bachmair *et al.* (2016) precipitation-based indices give a wrong conceptualization of drought because it is based on the assumption that droughts are controlled by the temporal variability in precipitation only while other variables like temperature, evapotranspiration (ET) and relative humidity remain stationary. Thus, this study employs a rainfall-temperature based indicator: the Standardized Precipitation Evapotranspiration Index (SPEI), which is an improvement to the Standardized Precipitation Index (SPI).

1.5 Scope of the Study

This work covers drought severity assessment in some North-Eastern states of Nigeria. The hydro-meteorological data that were used for assessment include rainfall, minimum and maximum temperature, relative humidity and ratio of maximum possible radiation to the annual maximum for Bauchi, Gombe and Yola meteorological stations.

CHAPTER TWO

2.0 LITERATURE REVIEW

This chapter would take a close look at what others have done, concepts and literatures which are important towards understanding the basis of this research work

2.1 Drought Definitions

Drought definition differs from region to region, type of discipline and area of interest (or application). Thus, the perception of drought to a meteorologist differs from how a hydrologist, a water manager, an agriculturist and a wild life biologist see drought (Smakhtin and Hughes, 2004). The definition of drought is also of varying perspective within sectors (Sourav *et al.*, 2018). However, Smakhtin and Hughes (2004) opined that most definitions regardless of the area of specialization defines drought relative to some long-term average condition or balance between precipitation and evapotranspiration. In view of this circumstance with dissimilar perspectives of drought by various disciplines, several definitions of drought are thus as follows:

Drought is a treacherous natural hazard characterized by lower-than-normal precipitation that, when prolonged, is insufficient to meet the demands of human activities and the environment (WMO, 2006). It is often referred to as a creeping phenomenon that develops slowly and has a prolonged existence, occasionally over a period of years (WMO, 2006). Drought occurs in both dry and humid regions of the world. It can arise from a range of hydrometeorological processes that suppress precipitation and/or limit surface water or groundwater availability, creating conditions that are significantly drier than normal or otherwise limiting moisture availability to a potentially damaging extent (WMO and GWP, 2016). Palmer (1965) describes it as a prolonged and abnormal moisture deficiency which is associated with sustained periods of significantly lower rainfall, soil moisture, surface water storage, stream flow, and ground water.

Eze (2018) opines that drought occurs when there is significant rainfall deficit that causes hydrological imbalances and affects the land productive systems. It is the severe shortage in the appearance of natural water with respect to normal (Ben-Zvi, 1987). Takeuchi (1974) defines drought as the condition whenever the amount of water which has been expected and relied upon for use in any of man's activities cannot be met for some reason. Meanwhile, Sordo-Ward *et al.* (2017) describes drought as an unusual period of dryness which results from low precipitation or high temperature. This definition concords with Achugbu and Balogun (2018) who suggested that drought may also be due to increased evaporation rate.

A common denominator in all of the definitions is the association of drought to the prolonged deficiency of precipitation. Hence, drought can be defined as the lack of precipitation coupled with increased temperature for a sustained period of time resulting to shortage of water that adversely affect land resources and the ecological systems.

However, the drought definitions are generally categorized into two, they are: conceptual definition and operational definition of drought (Wilhite and Glantz, 1985).

2.1.1 Conceptual definition of drought

This is aimed at defining the basic concepts or gives the general description about the physical processes of drought such as shortage of precipitation (Meteorological drought), soil moisture depletion (Agricultural drought), depletion of surface water (Hydrological drought) and deficit of water for social use associated to water management (Bachmair *et al.*, 2016). Smakhtin and Hughes (2004) argues that the definitions are usually not clearly defined as they do not give quantitative answers to "when", "how long", and "how severe" a drought is and are frequently used as a startup in scientific papers and reports. However, Okesola (2013) opined that the conceptual definition plays a huge role in drought policy formulation as found in Australia where the knowledge of climatic variability is taken into account in drought definition. This is to help farmers make adequate preparations to mitigate the impact.

2.1.2 Operational definition of drought

Operational definitions of drought establish and identify "when", "how long", and "how severe" a drought episode is. It tells of the beginning (onset), end, spatial extent and severity of a drought (Okorie, 2003). Smakhtin and Hughes (2004) also reveals that operational drought definitions are region specific and relies on scientific reasoning after some amounts of hydrometeorological information have been analysed. Operational definition provides precise information regarding to drought to support an effective early warning system. The advantages of this definition include: development of drought policies, design of mitigation strategies and monitoring systems. Operational definitions are expressed in terms of drought indices/indicators (Bachmair *et al.*, 2016).

2.2 Types of Droughts

Zulfiqar *et al.* (2019) classified droughts into four types and the "types" are of different extremes of the same natural and recurring process. Figure 2.1 gives a conceptual depiction of different variables in the hydrologic cycle during drought.

2.2.1 Meteorological drought

Meteorological drought is described as the shortage of precipitation in near or above normal conditions (Achugbu and Anugwo, 2016). Singh (1992) opines that it begins with deficit in precipitation that is usually prolonged and extreme relative to the usual climatic condition. It usually precedes and triggers the other kinds of drought. From the definitions it can be deduced that rainfall is the main driver of meteorological drought. Meteorological drought can however be defined by shortage in precipitation threshold over a predetermined period of time as revealed by Kumar *et al.* (2009) using rainfall deviation from normal in the following countries as thus:

i. In India metrological drought is announced when the total season's rainfall is less than 75% of long-term mean, -50 to -74% deviation as moderate drought and less than 50% as deviation as severe drought

ii. In South Africa, less than 70% of the normal is seen as drought, and when this persists for two consecutive years, an indication for severe drought is raised.

iii. In Poland, rainfall deviation from multi-year mean triggers drought monitoring in Poland.

Meteorological drought therefore can be region specific because the climatic variables responsible for precipitation could differ from region to region.

2.2.2 Agricultural drought

Sepulcre-Canto *et al.* (2012) sees agricultural drought as the consequence of precipitation shortage over a particular timescale that results to a soil moisture deficit that limits water availability for crops to such an extent that yields are reduced. It is lack of water either from meteorological drought or hydrological drought which causes inadequate water to meet crop water requirement (Okesola, 2013). Binbol and Edicha (2012) however sees agricultural drought from the perspective of the availability of soil water to support crops and forage growth than by the departure of normal precipitation over some specified period of time. The sustained period of lower rainfall commonly results to extended periods of unusually low soil moisture which in turn adversely affect the agriculture and natural plant growth (Singh, 1992). Therefore, agricultural drought can be said to occurs when there is insufficient water in the soil to meet a crop water demand leading to crop stress and subsequently loss in crop yield.

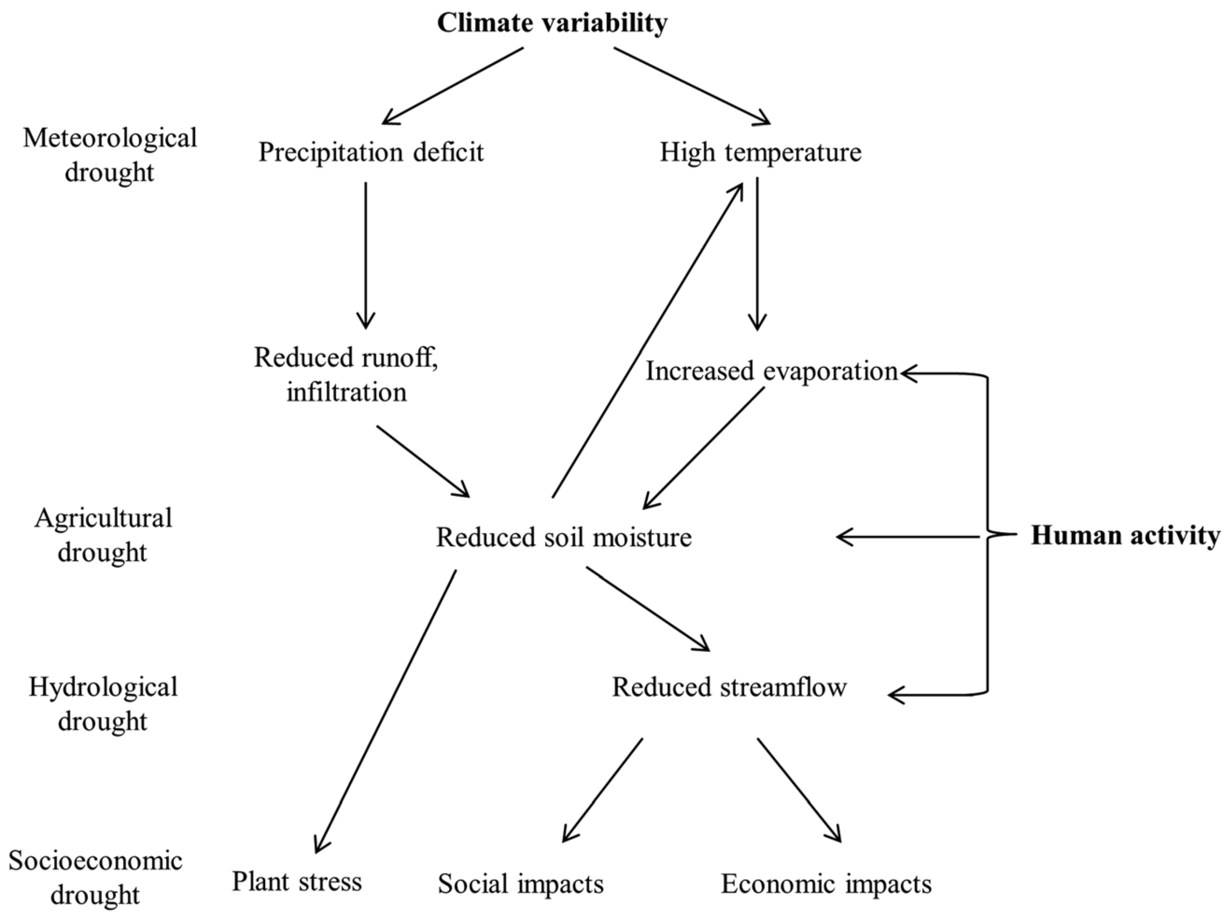


Figure 2.1: Interaction of different variables in the hydrological cycle during drought. (Source: National Drought Mitigation Centre, University of Nebraska-Lincoln, U.S.A.)

2.2.3 Hydrological drought

Hydrological drought occurs when the water reserves available in surface and ground water sources fall below a locally significant threshold. It is a period when water resources both from surface and subsurface sources are inadequate to supply water for use (Binbol and Edicha, 2012). It occurs as the precipitation deficits continues; stream discharge, lake, wetland, reservoirs, aquifers and water tables decline to unusually low levels. Hydrological drought is synonymous with deficit in bulk water supply that includes water levels in streams, rivers, lakes, reservoirs and aquifers (Achugbu and Anugwo, 2016). It tends to show up more slowly because it involves stored water that is used but not replenished. Van Loon and Van Lanen (2013) opines that lack of precipitation, change in climate, human activities and overexploitation of surface water resources are the main factor involved in hydrological drought.

2.2.4 Socio-economic drought

This type of drought occurs when the demand for water exceeds the supply to meet its water needs for socio-economic activities due to weather related deficit (Okesola, 2013). It is the condition that occurs when physical water shortages begin to affect people. It is reflected in the inadequate supply of water to serve local residents (Chin, 2006). Abaje *et al.* (2013) opines that socio-economic drought is associated with the failure of water resources systems to meet the water demands and thus, associating droughts with supply of and demand for an economic good (In this case, water).

Hence, from the above definitions of different drought types, it can be seen that lack or inadequate water is central to all. Precipitation deficit is found among all droughts and each type can lead to the other depending on the severity of water deficit.

2.3 Characteristics of Drought

i. **Severity of drought:** This refers to the departure from the normal of an index. Steinemann *et al.* (2015) classified drought severity levels with nomenclature such as mild, moderate, severe, or extreme drought or level 1, level 2, and level 3. Indices such as the SPI have been developed over the last few decades to quantify the severity of drought by comparing the precipitation levels over a time span to the historical average over the same time period.

ii. **Drought magnitude:** Cech (2002) defines the magnitude of drought as the measure of the cumulative deficit quantity in some quantity over a defined averaging period.

iii. **Duration**: This is the continuous time interval over which the cumulative deficit exceeds a specified threshold value (Cech, 2002). It is important to note that the beginning and end of drought are defined by its threshold limit. Cech (2002) further opines that drought begins when the cumulative deficit exceeds the threshold limit and ends when the cumulative deficit falls below the threshold limit

iv. **Intensity of drought:** This is the cumulative deficit during the drought divided by the duration of drought

v. **Triggers:** Triggers are specific values of an indicator or index that initiate and/or terminate each level of a drought plan and associated mitigation and emergency management responses. In other words, they trigger action and allow for accountability as to who is doing what and when they need to do it (WMO and GWP, 2016)

2.4 Impacts of Drought

The impacts of drought can be broadly categorized into direct and indirect impacts. Direct impacts of drought are felt in the reduction of agricultural activity and productivity, this also include reduction in water level, inadequate supply of potable water, increase in livestock mortality (Adewale, 2019). The indirect impact as a result of the aforementioned direct impact is exposure to water borne diseases, reduced farmer incomes and agricultural business, unemployment, revenue reduction to government and migration (Alhassan *et al.,* 2003). The types of impacts from this broad category are thus:

2.4.1 Environmental impacts

Delayed or prolonged shortage in precipitation have negative effect on the diversity of the ecosystem as it affects wildlife, fish, plant population and water supply (National Drought Mitigation Centre (NDMC), 2021). Organisms such that whose natural habitat are seasonal rivers and water holes may die due to the drying or disappearance of their habitat. Water levels in reservoirs, river flows, ponds and lakes can be greatly reduced as a result of drought leading to reduction in wetlands, ground water and overall water quality (NDMC, 2021). Inadequate soil moisture causes the death of vegetation so that animals that depends on it for their growth either perish or migrate in search of food. Consistent duration of drought also increases the chance for soil erosion, this will contribute to the soils that are unable to sustain plant growth. Other environmental impacts include deforestation, desertification and a higher risk of wildfires due to the dry landscape (NDMC, 2021).

2.4.2 Economic impacts

These are the negative consequence of droughts that cost individuals, governments and corporate bodies financial implications. The economic impact spreads across energy production, agriculture and water supply. Farmers may be in great loss if a drought destroys their crops. And also, if water a farmer's water supply is low, more money would be spent on drilling for new wells. The cost of food may also be expensive due to drought. Businesses that sell boats and fishing equipment may be redundant since the lakes and water bodies on which their wares are used is dried up. The reduction in the volume of water in rivers in hydropower generating dam may result from seasonal drought consequently causing inconsistent power generation and power shedding, this would brew energy crisis in the country consequently lead to spending more money on other fuel sources and this will in turn make the customers pay more (Mohammed *et al.*, 2017)

2.4.3 Social impacts

Social impacts are those that affects human's everyday lives. These are ways in which drought affects people's health (Physical and mental) and overall safety. This type of impact is in the indirect category since it results from the impact on water and food production. Social impacts lead to health problems associated with low water flows and poor water quality; anxiety and depression due to the economic losses caused by drought; health problem related to dust (Respiratory diseases); migration, as people may have to move from place to place in search of food and water; reduced income; fewer recreational activities and loss of human life.

2.5 Causes of Drought

The debates and arguments by researchers on the main causes of drought in the Sahel region have been in high degree yet consensus has not been reached with respect to the processes that result to the naturally occurring menace (Biasutti and Giannini, 2006). However, Epule *et al.* (2013) suggested below, the following mechanisms as the causes of droughts.

2.5.1 Changes in sea surface temperature (SST)

Study on the relationship between the pattern of the sea surface temperature (SST) and Sahelian rainfall using a statiscally based climatological analysis showed that at the emergence of Sahelian droughts of the late 1960s, there was a configuration of global SST which was depicted by warm anomalies in the Southern Hemisphere and cool anomalies in the Northern Hemisphere Oceans (Gleckler *et al.*, 2008). Another study conducted by Zeng (2003) for data spanning between 1930-2000 (70 years) portrayed that the increase in temperature of the Atlantic Ocean weakens the moisture laden West African Monsoon (The WAM is the main source of rainfall in the Sahel) resulting to a southward shift in the Inter-tropical Convergence Zone (ITCZ). This depletes moisture input and reinforces the weakening of the WAM, creating drier conditions with less vegetation and higher albedo (Surface reflectivity) (Zeng, 2003). Epule *et al.* (2013) opines that the trends in SST patterns are responsible for the droughts of the Sahel but added that the consequence of warm waters in the Pacific Ocean (El-Nino) in the Sahel also result to a weakened WAM flow due to the northward shift of the mean sea level pressure along the west African coast thereby creating a dry condition over the Sahel.

2.5.2 Human induced climate change

The National Aeronautics and Space Administration (NASA) (2020) in the definition of climate change alludes it is a wide range of global phenomena which is created mainly by burning fossils (Oil, coal, natural gas) which release heat trapping gases (Carbon dioxide and methane) to the earth atmosphere. Climate change is therefore a change of climate that can be attributed to direct or indirect human activities that alter the composition of the global atmosphere and it includes the natural climate variability monitored over a comparable time periods (United Nations Framework convention on Climate Change (UNFCC), 2011).

Chibueze (2016), Abubakar and Yamusa (2013), and Adegboyega *et al.*(2016) reveals human activities which induces climate change such as deforestation, excessive irrigation, overgrazing and poor cropping methods (This leads to reduction of water in the soil), overexploitation of surface water resources, improper soil conversation techniques and the spewing of green-house gases (GHGs) such as carbon dioxide (CO_2) from bush burning and vehicle exhaust are responsible for drought in northern Nigeria and the Sahelian region at large. This agrees with studies from Tippett (2006) and Epule *et al.* (2013).

In a study conducted by FAO (2010), it was shown that between 2000 and 2010, Africa had a net loss of about 3.4 million hectares of forest reserve per year while the global rate was 13 million hectares per year during the same period. The Sahel emits more GHGs at a rate of 0.9% per capita in 1980 and 0.8% per capita in 2007 while Latin America and Asia had rates of 0.4 and 0.1% per capita in 2007 (FAO, 2010). Roncoli *et al.* (2002) opines that the increase in population between 1960 and 2006 at a growth rate of about 2.2 percent is proportional to the increase in GHG emission in the Sahel and the deforestation rate of about 0.5–0.7%. This human induced phenomenon was found out to be responsible for increased in temperature associated with global warming. According to the reports by Intergovernmental Panel on Climate Change (IPCC) (2013), the global surface mean temperature which has continue to increase up to 1.5°C and beyond is likely due to the rise in anthropogenic greenhouse gas concentration (IPCC, 2013). Green-house gases contribution to global mean surface warming range between 0.5°C to 1.3°C within the period of 1951 to 2010 with increased rise in sea-level; ice mass loss in Greenland, Antarctica, the Arctic and mountain glaciers (NASA, 2020); and extreme weather events such as droughts and flooding (Faye *et al.*, 2019), an increase intensity of storms like tropical cyclones with higher wind speed (IPCC, 2013).

2.5.3 Dust feedback

Ramanathan *et al.* (2001) stated that half of the atmospheric aerosols are contributed by the dust aerosols from the Sahara. Thus, the accumulation in the Sahelian dust in the atmosphere mitigates the occurrence of rainfall by increasing the number of cloud condensation nuclei in warm clouds this is because the dust particles prevent rainfall by forming small cloud droplets that do not reach the size needed to form rain drops and possibly increase evaporation of clouds due to increase absorption of solar radiation (Lohmann and Feichter, 2005). Additionally, Li *et al.* (1996) asserts that dust aerosols can contribute to surface heating by reflecting incoming solar radiation, thus enhancing warming in the troposphere and thereby increasing atmospheric stability, reducing convection and reducing rainfall.

2.6 Methods for Drought Estimation

Drought can be estimated with variety of drought indices in practice (Chin, 2006). Most indices form the basis for the operational definitions of drought as they tell the beginning, ending, intensity and magnitude of drought. Rainfall data are commonly used to estimate drought indices because of long term availability of rainfall record (Smakhtin and Hughes, 2004)

2.6.1 Palmer drought severity index (PDSI)

The PDSI is an index in which temperature, precipitation with local available water content (AWC) also called water-holding capacity of soils is employed to estimate droughts in crop-producing regions of the United States (Palmer, 1965). It can measure both wetness (positive value) and dryness (negative) on the basis of the supply and demand of water balance equation and therefore takes into account prior precipitation, moisture supply, runoff and evapotranspiration demand at the surface (Vicente-Serrano *et al.*, 2010). Its core strength involves the use of soil data and a total water balance technique which makes it quite robust for identifying drought (WMO and GWP, 2016). It has a time scale of between 9 to 12 months, this could be a challenge for short term moisture and agricultural drought detection (Kogan, 1995a).

The computation of PDSI is complex in that it requires a substantial input of serially complete record of meteorological data. In areas where observational networks are scarce, its application may be limited (Smakhtin and Hughes, 2004). Smakhtin and Hughes (2004) further reveals that PDSI may also lag behind several months of emerging drought and so this limits its application in areas of frequently extreme climatic condition. Cech (2002) outlines the PDSI ratings as presented in Table 2.1

Table 2.1: Palmer drought severity index classification

Soil Moisture Algorithm	Weather Conditions
4.0 or more	Extremely wet
3.0 to 3.99	Very wet
2.0 to 2.99	Moderately wet
1.0 to 1.99	Slightly wet
0.5 to 0.99	Incipient wet spell
0.49 to -0.49	Near normal
-0.5 to -0.99	Incipient dry spell
-1.0 to -1.99	Mild drought
-2.0 to -2.99	Moderate drought
-3.0 to -3.99	Severe drought
-4.0 or less	Extreme drought

(Source: Cech, 2002)

2.6.2 Crop moisture index (CMI)

This is an index that was also developed by Palmer (1968) to meet the short falls of PDSI. It measures the short-term soil moisture changes and not long-term changes to monitor weekly crop condition. It uses mean precipitation and mean temperature on a weekly basis and the CMI value of the previous week as it input parameters. The output is weighted; therefore, it can be compared to different climate regime (Smakhtin and Hughes, 2004). The limitation according to Hayes (2013) is that CMI responds quickly to changing condition, this rapid response to changing short term conditions may not be enough to off-set long-term issues, in other words, it may give misleading information about long term conditions

2.6.3 Standardized precipitation index (SPI)

Drought is a multiscalar phenomenon (Narendra *et al.*, 2019). This was revealed in Mckee *et al.* (1993) as the response to water deficit with time by useable water resources which include soil moisture, ground water, snowpack, stream flow and reservoir storage is different. Hence, Mckee *et al.* (1993) introduced the SPI, a multiscalar drought index which employs precipitation as the only input parameter and therefore requires less input data unlike PDSI. Calculation is such that rainfall record of a desired station is fitted to a probability distribution like gamma distribution, which is then converted to a normal distribution so that the mean SPI is zero (Edwards and Mckee, 1997). The advantage of SPI according to Hayes (2013) is easier to use and much more flexible due to its application to multiple timescales or accumulation periods of 1 month up to 72 months. In comparison with PDSI, Bachmair *et al.* (2016) opined that drought characteristics such as intensity, duration and spatial extent are clearly identified by the SPI. In addition the strength of the SPI is that it can identify droughts sooner than the PDSI (Adewale, 2019). The demerits of this index are; it cannot be used to evaluate future climatic scenario since parameters like temperature and evaporation are negligible and also, it assumes that data are normally distributed, this can lead to complications for shorter time periods (Narendra *et al.*, 2019; Faye *et al.*, 2019).The application of SPI as an indicator gives a functional or operational definition of drought for each time scale (Smakhtin and Hughes, 2004). A drought event starts when the SPI value falls below zero and ends when the SPI value is positive. Table 2.2 outlines drought categories according to McKee *et al.* (1993).

Table 2.2: Standardized Precipitation Index classification

SPI numerical range	Drought Conditions
Greater than 2.0	Extremely wet
1.5 -1.99	Very wet
1.0 -1.49	Moderately wet
-0.99 – 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.50 to -1.99	Very dry
Less than -2.0	Extremely dry

(Source: McKee *et al.*, 1993)

Depending on the drought impact in question, SPI values for maximum of 3 months might be useful for basic drought monitoring, maximum of 6 months for monitoring agricultural impacts and values for 12 months or longer for hydrological impacts. The following are the resulting response over different accumulation periods of a meteorological drought as indicated by SPI:

(a) **SPI-1 to SPI-3:** the computation for this timescale reflects short and medium term moisture conditions or immediate impact of precipitation deficit affecting soil moisture, crop stress, snow pack, and flow in smaller creeks (WMO, 2012). The interpretation of SPI-1and SPI-3 may be misleading according to WMO (2012) this is because 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. Also, in areas/regions with a small normal rainfall total for a month, the accumulation periods of 1 to 3 months may be misleading with rainfall values less than normal (WMO, 2012).

(b) **SPI-3 to SPI-6:** The 3 to 6-accumulation period reveals seasonal to medium-term trends in precipitation. WMO (2012) asserts that it is shown 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 September would indicate the amount of precipitation that has fallen during the very important wet season period from April through September in Northern Nigeria. 6-month SPI also provides information regarding the deviation from normal of stream flows and reservoir levels depending on the region and time of the years (WMO, 2012).

(c) SPI-9 to SPI 24: The SPI computed at these time scales provide an indication of inter-seasonal precipitation patterns over a medium time scale duration (9 months) and it also reflects long term precipitation patterns (12 to 24 months). Accumulation periods of these scales are good pointers that dryness is having a significant impact on agriculture when the SPI value is less than -1.5, as well as other sectors of usable water resources these include; reservoir levels, stream flows, and ground water (European Drought Observatory (EDO), 2020).

2.6.4 Standardized precipitation evapotranspiration index (SPEI)

In other to take care of the limitations of the SPI, Vicente-Serrano *et al.* (2010) developed the SPEI, which is based on the calculation of precipitation and potential evaporation. The SPEI uses the basis of SPI but includes a temperature component, allowing the index to account for the effect of temperature on drought development through a basic water balance calculation (also called climatic water balance). The climatic water balance is the difference between precipitation and reference evapotranspiration (ET_o) or potential evapotranspiration ($P - ET_o$) rather than precipitation (P) as the only input parameter. The climatic water balance compares the available water (P) with the atmospheric evaporative demand (ET_o) (Begueria *et al.*, 2013), as a result, it provides a more reliable measure of drought severity than only considering precipitation (Faye *et al.*, 2019). Narendra *et al.* (2019) stated that the SPEI like the SPI can estimate the multi-temporal nature of hydrological, meteorological and agricultural droughts at different time scales. The key strength of this index is the inclusion of temperature along with precipitation data, which allows SPEI to account for the impact of temperature on a drought situation. The output is applicable for all climate regimes, with the results being comparable because they are standardized (Vicente-Serrano *et al.*, 2010). With the use of temperature data, SPEI is an ideal index when looking at the impact of climate change in model output under various future scenarios (Begueria *et al.*, 2013). However, the requirement for a serially complete dataset for both temperature and precipitation may limit its use due to insufficient data being available. However, based on the comparative study between SPEI and SPI, it is suggested that the SPEI is a better indicator for drought assessment and monitoring as it accounts for temperature increase which contributes to some droughts in recent years (Faye *et al.*, 2019).

2.6.5 Rainfall anomaly index (RAI)

Van Rooy (1965) began the development of this index in the early 1960s. The RAI uses normalized precipitation values based upon the station history of a particular location. Comparison to the current period puts the output into a historical perspective. The index addresses droughts that affect agriculture, water resources and other sectors, because of its flexibility analysis at various timescales. The index is simple to calculate, with precipitation as the single input that can be estimated on monthly, seasonal and annual timescales. However, it requires a serially complete dataset with estimates of missing values.

2.6.6 Normalized difference vegetation index (NDVI)

This index was developed from work done by Tarpley *et al.* (1984) and Kogan (1995b) with the National Oceanic and Atmospheric Administration (NOAA) in the United States. The index is an indicator of the status of vegetation health based on the difference between the reflectance of the red or visible red (VIS) and near-infrared (NIR) light band using the spectral reflectivity of solar radiation. A healthy green plant reflects NIR waves and absorbs VIS. The reverse is for an unhealthy plant. The applicability of the index includes drought monitoring, desert encroachment studies, and also for precision farming. The NDVI has a very high resolution and great spatial coverage which facilitates drought monitoring on a regional spatial scale. However, the use of this index has some constraints due to sensor degradation, satellite change and atmospheric noise. Kogan (1995b) suggests that these limitations are error sources found in the use of the index.

2.6.7 Vegetation condition index (VCI)

The index was designed by Kogan (1995a) with NOAA in the United States. VCI is used to identify drought situations and to determine the onset, especially in areas where drought episodes are localized and ill defined. It focuses on the impact of drought on vegetation and can provide information on the onset, duration and severity of drought by noting vegetation changes and comparing them with historical values (Dutta *et al.,* 2014). It can be used in conjunction with NDVI for assessment of vegetation in drought situations affecting agriculture. Its key strength like the NDVI is its high resolution and good spatial coverage. The challenge using the index is that of potential cloud contamination as well as a short period of record.

2.7 Concept of Evapotranspiration

The need for water cut across all sphere of human life; from agricultural practices to domestic and industrial use (Chin, 2006). The impact of climate change/global warming on the available water resources makes it pertinent to understand the rate at which water is being returned to the atmosphere from water bodies, land surfaces, reservoirs and plants bodies (Anyanwu *et al.*, 2017). Adeboye *et al*. (2009) term this process as evapotranspiration.

Evaporation is the process by which liquid water is converted to water vapour and removed from the evaporating surface, while transpiration is the vaporization of liquid water contained in plant tissues and the vapour removal to the atmosphere (FAO, 2010). The combination of the both processes is known as evapotranspiration (ET) or actual evapotranspiration (ET_a), sometimes also called consumptive use (Allen *et al.*, 1998).

2.7.1 Methods of evapotranspiration estimation

The methods of quantifying ET can be broadly classified into direct measurement and indirect measurement (Anyanwu *et al.*, 2017).

The direct methods of estimation of ET include energy balance or budget approach (Adeboye *et al.*, 2009), use of lysimeters (Meissner *et al.*, 2010), atmometers, the soil water budget method (Farahani *et al.*, 2007), the use of pan evaporimeters (Gavilan *et al.*, 2007). The measurement of ET using direct method is most times not feasible as it is expensive and time consuming (Igbadum *et al.*, 2006; Ejieji, 2011). Hence, the estimation is done indirectly using the reference evapotranspiration (ET_o) (Anyanwu *et al.*, 2017).

Indirect measurement of ET includes the application of established models and meteorological data (Echiegu *et al.*, 2016). These models are formulated using simple expressions that relate ET to temperature and/or radiation to models having extensive data requirement (Alexandris *et al.*, 2006). The models maybe classified into three: temperature-based models (Thornthwaite, Blaney-Cridle, Blaney-Morin and McCloud models); radiation-based models (Turc, Hargreaves, Hargreaves-Samani, Priestly-Taylor and the Makkink Formula) and a combination approach based on original Penman model which consists of radiation and aerodynamic part (Ilesanmi *et al.*, 2012). Anyanwu *et al.* (2017) opines that the evaluation of the accuracy of several methods of estimating ET_o is difficult, therefore the physical and dynamic nature of individual formula has to be taken as a guideline in assessing the merits of the formulae.

The Thornthwaite (Th) method requires mean daily temperature (Narendra *et al.*, 2019). The ET_o calculated using this method exaggerates the values in the summer seasons where higher temperatures are dominant, this is consonance with Donohue *et al.* (2010) who posits that with increasing air temperature, the Th-method tends to overestimate ET_o. Furthermore, Van der Schrier *et al.* (2011) asserted that the Th-method underestimates ET_o in the arid and semiarid areas and over estimates ET in the humid areas.

Allen *et al.* (1998) reveals that Penman's model produces good results when applied over different climatic region. As such, the Food and Agriculture Organization (FAO) and the

American Society of Civil Engineers (ASCE) have modified the Penman-Monteith (PM) as FAO56-PM equation and adopted it as the sole equation for determining ET_o (Begueria *et al.*, 2013). The FAO (1998) recommended PM because it closely approximates grass ET_o at the location being assessed, it is physically based, and explicitly incorporates both physiological and aerodynamic parameters. However, the PM model requires data (Solar radiation, temperature, windspeed, and relative humidity) that many meteorological stations do not measure regularly and the long records of these data are most of the times not available (Anyanwu *et al.*, 2017).

Thus, Droogers and Allen (2002) opined that the Hargreaves (Hg) model may be used when some of the extensive data are not available. Like the Th-method, the Hg equation requires daily maximum and minimum temperatures. The Hg equation does not have the setback of Th equation and at monthly and annual scales, the estimates of ETo from the Hg and PM models are similar, although with less than 2mm difference (Droogers and Allen, 2002).

In Nigeria like most developing nations, the data needed for ET_0 estimation using FAO56-PM are most of the time not available (Adeboye *et al.*, 2009). Hence, the modified Blaney-Morin (BM) model popularly known as Blaney-Morin Nigeria (BMN) was developed for the estimation of reference evapotranspiration in Nigeria by Duru (1984). The model parameter includes ratio of monthly radiation to annual radiation, the mean monthly temperature (°C), and the mean monthly relative humidity. The BMN model takes account of the varying relative humidity in Nigeria and the significant role it plays in ET process in the Nigeria region (Anyanwu *et al.*, 2017). Idike (2005) observed that the locations used for evaluating the model are not representative of the ecological zones of the country for which the model was developed. However, the study area in which this study was conducted is located within the region where the model was developed.

2.8 Review of Past Efforts

Studies on drought occurrence and characterization in terms of its severity, timing, duration and location have employed different types of indices to monitor and evaluate drought. The type of impacts relevant in the drought situation of study was crucial in considering and determining the selection of indicators that were employed. Thus, this section spotlights efforts on previously researched works in the area of drought vulnerability assessment, the research findings and the gaps in each paper.

(A) Droughts in the Sudano-Sahelian Ecological Zone of Nigeria: Implications for Agriculture and Water Resources Development

In this work, Abaje *et al.* (2013) appraised the implication of drought in the Sudan-Sahelian region of Nigeria using rainfall data of 60 years period (1949 to 2008) from eight meteorological stations that include Yelwa, Potiskum, Maiduguri, Kano, Gusau, Sokoto, Nguru and Katsina. Drought intensity in the region was investigated using Normalized Rainfall Index (NRI) developed by Turkes (1996) on the basis that precipitation is the main variable for drought assessment.

Research Findings

a. A modified NRI was used to classify drought events in this study because extreme values greater than or equal to 1.76 and less than or equal to -1.76 from the original NRI are not frequent during the study period. Hence, index values of -0.51 to -0.85, -0.86 to -1.31 and -1.31 or less are categorized as mild drought, moderate drought and severe drought respectively.

b. Normal to very wet conditions was witnessed in the 1950s with exception of Yelwa that was affected by moderate drought in the 1950 and 1952.

c. It was revealed that only 38% of the study area was affected by severe droughts in 1968. This therefore means that the catastrophic Sahelian droughts of 1968-1973 did not start simultaneously in the whole of the region. It started in the northern part of the West African Sahel in 1968 and subsequently moved down south until 1973 when it covered the whole region with more severity in Nguru.

d. Between the decadal years of 1970 to 1979, it was found out that mild to moderate drought conditions affected some parts of the zone. 50% coverage of moderate drought and 50% coverage of severe drought characterized the study are in 1973. There was gradual return to normal condition during the rest of the years in the decade except in Sokoto and Potiskum that has persistence of severe drought. Findings show the drought condition was more severe than in previous decade with more widespread. However, it was revealed that the late 1990s and the 2000s witnessed a decline in the number of drought occurrences in the zone.

(B) Spatial-Temporal Characteristic of Drought in Northern Nigeria

Achugbu and Balogun (2018) examined the spatial and temporal characteristics of droughts during the rainy season (May-October) for the study period of 46years from 1965 to 2010. Rainfall data collected from 9 rainfall stations located in Maiduguri, Nguru, Kano, Katsina, Potiskum, Gusua, Sokoto, Bauchi, and Yelwa were employed for drought assessment.

Research Findings

a. The study area covers Sudano-Sahelian zones represented by Sokoto, Kebbi, Zamfara, Katsina, Kano, Jigawa, Bauchi, Yobe and Borno state.

b. Meteorological and agricultural drought were identified using the Standardized Precipitation Index at 3-and-6 months accumulation period as thus:

i. The 3-month SPI reveals the prevalence of meteorological drought for about 25years of the study period (1965-2010) which translates to 54% of the period of study. Findings also revealed persistence of drought years with few wet years from 1965-1995.

ii. The 6-month SPI showed that 20 years of below average rainfall conditions plagued the study period. Between 1966 and 1993, sustained period of dry years was experienced with few non-drought years. This indicated the prevalence of unusual stream flow and reservoir levels.

2.8.1 Research gap

a. Climatic variables like temperature and relative humidity were not taken into account.

b. The study period covers till 2008, hence, the variability in climate in the next ten years after the period of the reviewed studies calls for further evaluation for drought tendency in the study area.

c. Further study is required in other northern states of the SSEZ like Gombe and Adamawa as they are not included in the states covered within the study period.

CHAPTER THREE

3.0 RESEARCH METHODOLOGY

3.1 Overview of the Study Area

Northeastern Nigeria lies on the latitude (8.00-14^{o}N) and longitude (10.3-13^{o}E). Large portion falls within the Sahel and Sudan ecological zones (SSEZ). The area of the region is about 272,451km^2, which covers about 30% of the total landmass of Nigeria (923,768 km^2) (Olatunde, 2013). It borders Jigawa from the west to the Chad Basins in the east. The study region has boundary in the north with Niger Republic and in the extreme north-east with Republic of Chad. Borno, Adamawa, Gombe, Yobe, Bauchi, and Taraba are states of the Nigerian Federation located in the region. Figure 3.1 presents the map of the study area.

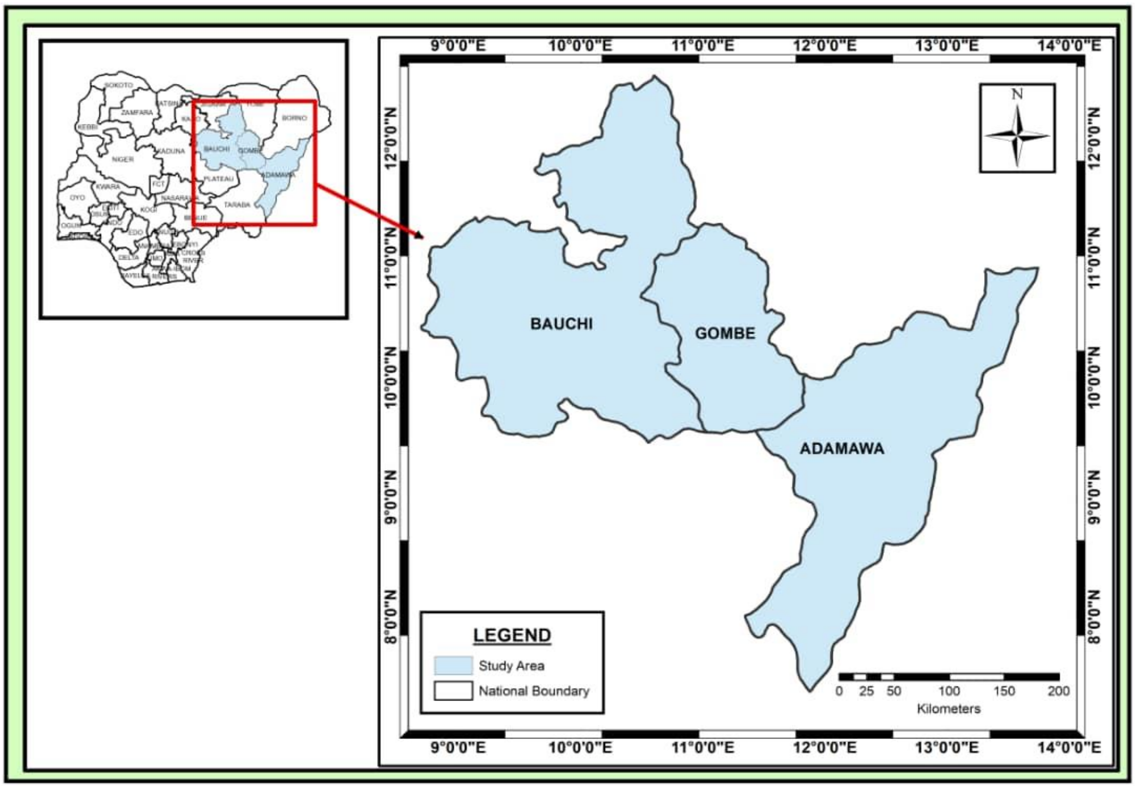


Figure 3.1: Map showing the study area. (Source: GIS Achievers, 2021)

This zone has been described by researchers as the Nigerian dry-land, containing most of the range-land of the country (Abaje, 2007; Binbol and Edicha, 2012). The area is estimated to be about 38% of the total land area of Nigeria and it is the grain belt of the country populated by small scale subsistence farmers and nomadic livestock herders (Abubarkar and Yamusa, 2013). The region's climate is dominated by two distinct seasons; dry season with northeast winds (October–April) and wet season (May-September) with strong southwest winds (Achugbu and Balogun, 2018).

The region is characterized by frequent dry spells causing severe and widespread drought due to large inter-annual difference in rainfall (Adeniyi and Uzoma, 2016; Abaje *et al.*, 2013). The average annual rainfall ranges between 300mm to 1500mm with rain days of between 40 and 100 per year (Olatunde, 2013).The society is agrarian as most of the country's grain and tuber crops are cultivated in the region. People mostly depend on rain-fed farming for their livelihood. Recurrent drought in the region has enormous impacts on both agricultural production and the environment this has led to decreased agricultural production which in turn has led to environmental degradation (Hassan *et al.,* 2019). The coordinate and elevation of selected study area from the Northeast is shown in Table 3.1.

Table 3.1: Coordinate and elevation of selected study area

Station	Elevation(m)	Latitude	Longitude
Yola	599	9◦15' N	12◦30' E
Gombe	461	10◦28 N	11◦11' E
Bauchi	628	10◦18 N	9◦50' E

(Source: www.wikipedia.org/wiki/North_east_Nigeria)

3.2 Data Employed

Secondary data which includes daily rainfall, temperature and relative humidity archived at the Nigerian Meteorological Agency (NiMet) were obtained for a period of 15 years (2006-2020) for each station under investigation.

3.3 Data Analysis

The method of data analysis in this work involved the use of descriptive statistics to help describe the data in a meaningful way. The parameters employed are the arithmetic mean (also known as mean), standard deviation and coefficient of variation. Analyzed data were summarized with the aid of tabulated description (Tables) and graphical description (graphs and charts).

3.3.1 Mean of data

This is equal to the sum of all the values in the data set divided by the number of values in the data set. In this study, the mean was used to summarize data which have daily characteristics into monthly and annual averages. It is expressed in equation 3.1 as thus:

$$\bar{x} = \frac{\Sigma x}{N} \qquad (3.1)$$

Where: $\bar{x}$ is the mean of sample; x is the value of the observed parameter and N is the number of observations (number of days or months or years)

3.3.2 Standard deviation

The standard deviation describes the dispersion of climatic variables from the mean values. It is given in equation 3.2 as:

$$S = \sqrt{\frac{\Sigma(x-\bar{x})^2}{N-1}} \qquad (3.2)$$

Where; S is the sample standard deviation; $\bar{x}$ is the sample mean and N is the number of observations (number of days or months or years)

3.3.3 Coefficient of Variability (CV)

It is the ratio of the standard deviation to the mean. This was used to determine the consistency of the data set. It is expressed in equation 3.3 as:

$$\mathrm{CV} = \frac{\mathrm{S}}{\bar{\mathrm{x}}} \qquad (3.3)$$

Where; CV = coefficient of variation; S = sample standard deviation and $\bar{x}$ = sample mean

3.4 Standardized Anomaly Index Estimation Model

For each of the stations, departures of the annual mean temperature were computed using the SAI model which is a commonly used index for regional climate change studies (Koudahe *et al.*, 2017). Station temperature is expressed as a standardized departure x_i from the long-term mean. A period when below long-term average was dominated is considered as cooling period and a period when above long-term average was most persistent is a warming period. The SAI is given in equation 3.4 as:

$$x_i = \frac{r - r_i}{\sigma} \qquad (3.4)$$

Where, r is the mean temperature of the year, r_i is the long-term mean, and σ is the standard deviation of annual mean temperature for the long-term.

3.5 Estimation of Potential Evapotranspiration (PET)

The PET in this study was estimated on temperature based empirical model developed by Duru (1984); the Blaney-Morin Nigeria (BMN). The PET estimate was obtained using the formula expressed in equation 3.5.

$$\mathrm{PET} = rf\,\frac{(0.45t+8)(H-R^{m})}{100} \qquad (3.5)$$

Where: PET is the Potential evapotranspiration (mm/day); r_f is the ratio of maximum possible radiation to the annual maximum; t is the average temperature (°C); R is the relative humidity (%), and H and m are empirical constants given as 520 and 1.31 respectively.

3.6 Standardized Potential Evapotranspiration Index Computation

The SPEI is a multi-scalar drought index that combines precipitation and temperature as input data as described by Vicente-Serrano *et al.* (2010). The index is based on simple climatic water balance, that is, the difference between precipitation and potential evapotranspiration for each day and as given in equation 3.6. In line with Vicente-Serrano *et al.* (2010), the calculated daily D_i were aggregated at different time scales of 3 and 6 month following the same procedure as SPI.

$$D_i = P_i - PET_i \tag{3.6}$$

Where, D_i is the difference between precipitation and potential evapotranspiration (water balance deficit); P_i is the daily precipitation, and PET_i is the daily potential evapotranspiration.

In this study, a three-parameter log-logistic distribution was used to calculate the SPEI as according to Vicente-Serrano *et al.* (2010), it is found to correlate best with the D series when compared with other selected distributions (Pearson III, lognormal and general extreme values) (Yang *et al.*, 2015). Hence, log-logistic probability density function was used to fit the sequence as follows:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-y}{\alpha}\right)^{\beta-1}\left[1+\left(\frac{x-y}{\alpha}\right)^{\beta}\right]^{-2} \tag{3.7}$$

where α, β and γ are scale, shape and origin parameters of the Log-logistic distribution respectively for the D values in the range (γ> D<∞). The formulars of the parameters were obtained using the L-moment procedure given by Vincent-Serrano *et al.* (2010) as:

$$\beta = \frac{2W_1 - 2W_0}{6W_1 - W_0 - 6W_2} \tag{3.8}$$

$$\alpha = \frac{(W_0 - 2W_1)\beta}{6W_1 - W_0 - 6W_2} \tag{3.9}$$

$$\gamma = W_0 - \alpha\Gamma\left(1+\frac{1}{\beta}\right)\Gamma\left(1-\frac{1}{\beta}\right), \qquad (3.10)$$

where, $\Gamma\left(1+\frac{1}{\beta}\right)$ is the gamma function of $\left(1+\frac{1}{\beta}\right)$, W_s is the probability weighted moments (PWMs).

The probability distribution function of the D series, according to the log-logistic distribution, is then given by:

$$F(x) = \left[1+\left(\frac{\alpha}{x-y}\right)^{\beta}\right]^{-1} \qquad (3.11)$$

The SPEI was then obtained as a standardized value of F(x) using the classical approximation of Abramowitz and Stegun (1965) as given by Vicente-Serrano *et al.* (2010);

$$\text{SPEI} = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \qquad (3.12)$$

where,

$W = \sqrt{-2\ln(P)}$ for $P \leq 0.5$, and P is the probability of exceeding a determined D value

$P = 1 - F(x)$; when $P > 0.5$, $P = 1 - P$

$C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$,

$d_1 = 1.432788$, $d_2 = 0.189269$ and $d_3 = 0.001308$

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

This chapter presents the analysis of the data collected. Furthermore, it shows the results of the findings of the trends in the occurrence of drought events in the study area with reference to the research objectives.

4.1 Variability in Rainfall Pattern

The monthly rainfall distribution over the study area for the period of 2006-2020 is presented in Figure 4.1. The result shows that rainfall begins from April and continues till October. The month of maximum rainfall for all the study area as depicted in Figure 4.1 is August except for Yola whose maximum fell in September (Abaje *et al.*, 2013; Sadiq, 2020).

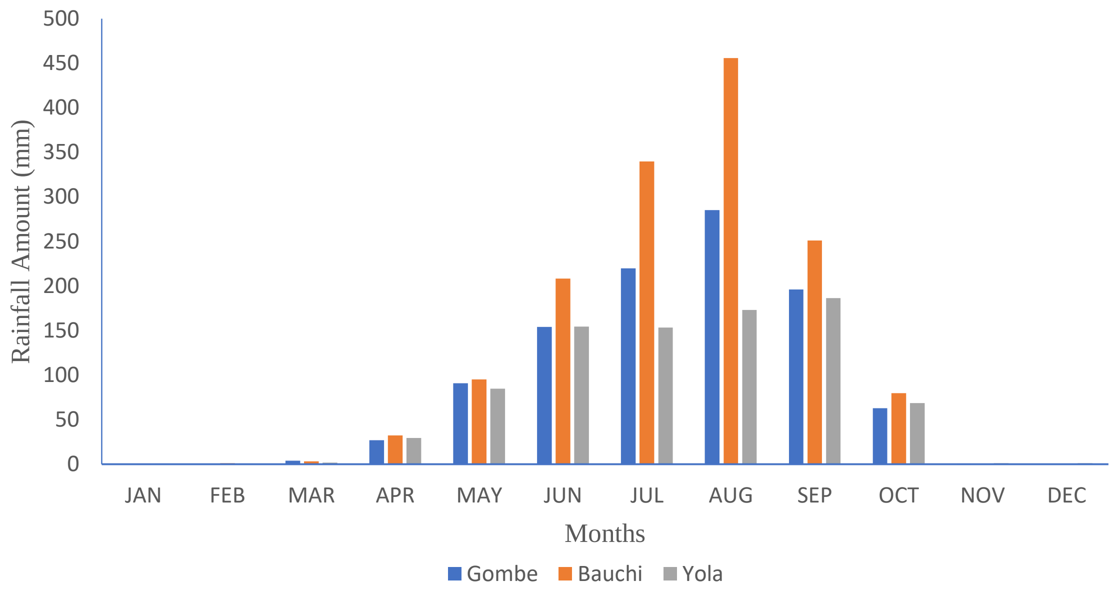


Figure 4.1: Monthly rainfall distribution over the study area

Amongst all the stations, Bauchi received more rainfall in the period of study when compared with other stations. The months of November through March have little or no rainfall and thus can be considered as dry months. For the purpose of agriculture and water resources planning and management, the stations have four months of effective rainfall (June to September) for rain-fed agricultural activities and for recharge of surface and sub-surface reservoirs (Sadiq, 2020).

The interannual rainfall distribution of the stations under investigation is presented in Figure 4.2. It was be observed that Bauchi has the maximum amount of rainfall of 2218.9mm which is followed by Gombe and Yola at 1543.6mm and 1270.2mm respectively.

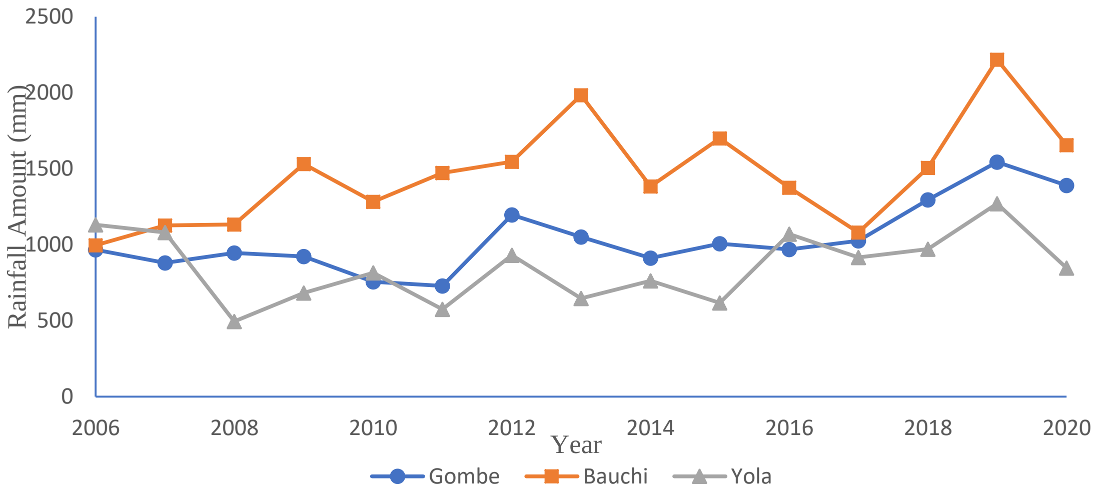


Figure 4.2: Interannual rainfall distribution over the study area

The minimum rainfall record was observed to be 996.3mm in the year 2006, 730mm in 2011 and 495.8mm in 2008 for Bauchi, Gombe and Yola respectively (Table 4.1).

Table 4.1: Descriptive statistics of rainfall distribution over the study period

Station	Minimum (mm)	Maximum (mm)	Mean (mm)	S.D (mm)	C.V (%)
Gombe	730	1543.6	1039.773	226.54	21.79
Bauchi	996.30	2218.9	1466.461	336.08	22.92
Yola	495.80	1270.2	854.35	226.13	26.47

Table 4.2 reveals that the mean annual rainfall for the first decade of the study period was below the long term annual mean as Gombe, Bauchi and Yola stations have values of 937.16mm, 1415.82mm and 774.02mm below their respective long-term. However, there was increase in the amount of rainfall in the latter years of the study period (2016-2020) with mean values of 1245mm, 1567.74mm and 1015mm recorded for Gombe, Bauchi and Yola stations respectively. These values are higher than the long term mean values as seen in Table 4.2

Table 4.2: Decadal descriptive statistics of rainfall distribution

Station	Period	Minimum (mm)	Maximum (mm)	Long term mean (mm)	Decadal Mean (mm)	S.D (mm)	C.V (%)
Gombe	2006 - 2015	730	1197.3	1039.773	937.16	135.82	14.50
	2016 -2020	970	1543.6		1245	243.19	19.53
Bauchi	2006 - 2015	996.3	1984.5	1466.461	1415.82	297.35	21.00
	2016 -2020	1081.12	2218.9		1567.74	420.90	26.85
Yola	2006 - 2015	495.8	1131.4	854.35	774.02	214.56	27.72
	2016 -2020	847.7	1270.2		1015.0	164.36	16.19

The fluctuating pattern of rainfall as described in Table 4.2 by the COV reveals that rainfall in the first decade was less variable compared to the latter years (2016-2020). Gombe was more moderate in terms of high and low pattern in the first ten years compared to other stations, however, in the later years, Yola witnessed more consistency compared to other stations.

4.2 Variability in Temperature Pattern

4.2.1 Interannual variability in temperature

The mean annual temperature presented in Figure 4.3 for Gombe, Bauchi and Yola from 2006 to 2020 portrays Yola to have the highest temperature followed by Gombe and then Bauchi. The year 2016 recorded the maximum value for Yola at 29.86 ^{o}C, Gombe recorded temperature of

28.14 °C in 2015 and Bauchi recorded 27.45 °C in 2010. The minimum temperature for the stations was 28.67 °C in 2015, 26.99 °C in 2017 and 26.39 °C in 2007 for Yola, Gombe and Bauchi respectively. Temperature was steady for Yola in the last five years while a slight decline in temperature was observed for both Gombe and Bauchi stations.

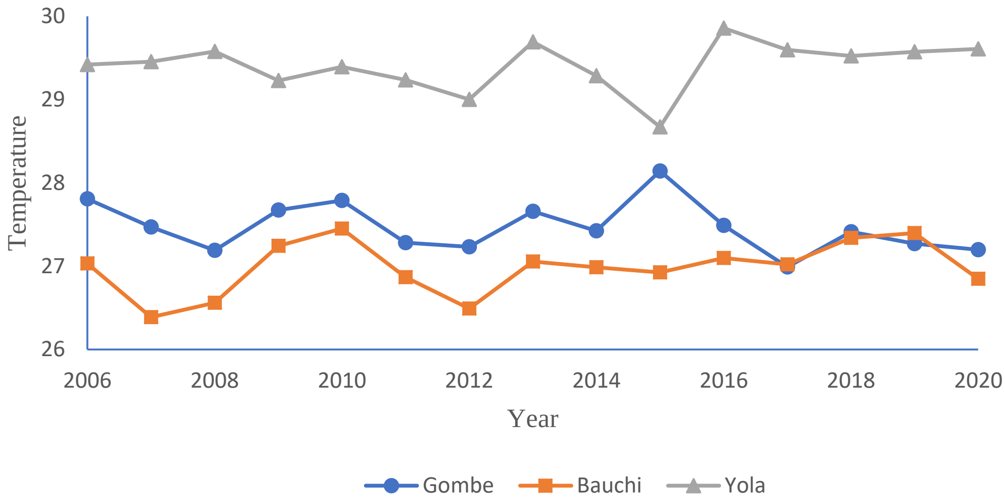


Figure 4.3: Mean annual temperature for Gombe, Bauchi and Yola

4.2.2 Monthly variability in temperature

The variation in the monthly temperature across the stations for the study period is illustrated in Figure 4.4a-4.4e. The monthly temperature was maximum in Yola followed by Gombe and Bauchi.

In the first decade, Figure 4.4a illustrates that the years 2007, 2008 and 2011 witnessed temperature reduction in January while the year 2006 recorded peak temperature except for Yola whose peak was in 2013. An alternating increasing and decreasing trend as illustrated in Figure 4.4a was observed in January for all the stations towards the last five years. Temperature pattern in February as presented in Figure 4.4a reveals that in the first decade, the year 2008 recorded the lowest temperature in Gombe and Bauchi. A remarkable rise in temperature was observed in 2015 after few years of decline. In the last five years, a drop in temperature in 2016 was observed; it increased in 2018 and then subsequently decreased for the latter parts of the study period.

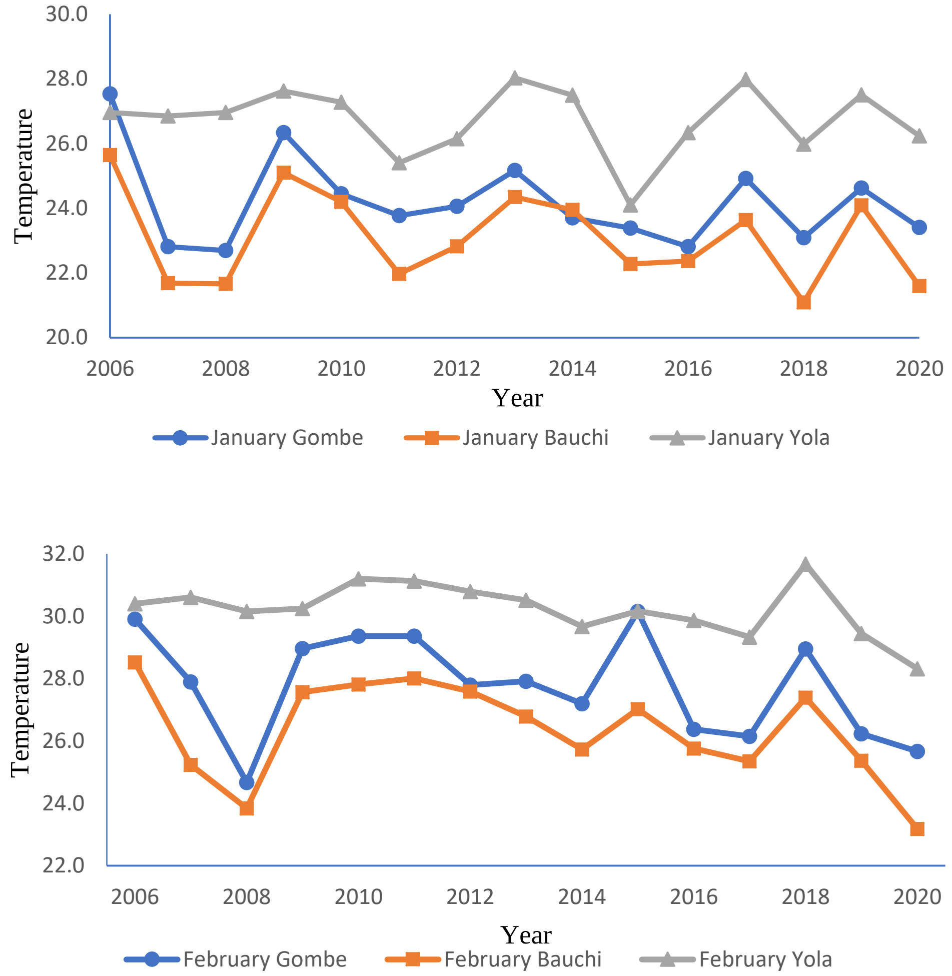
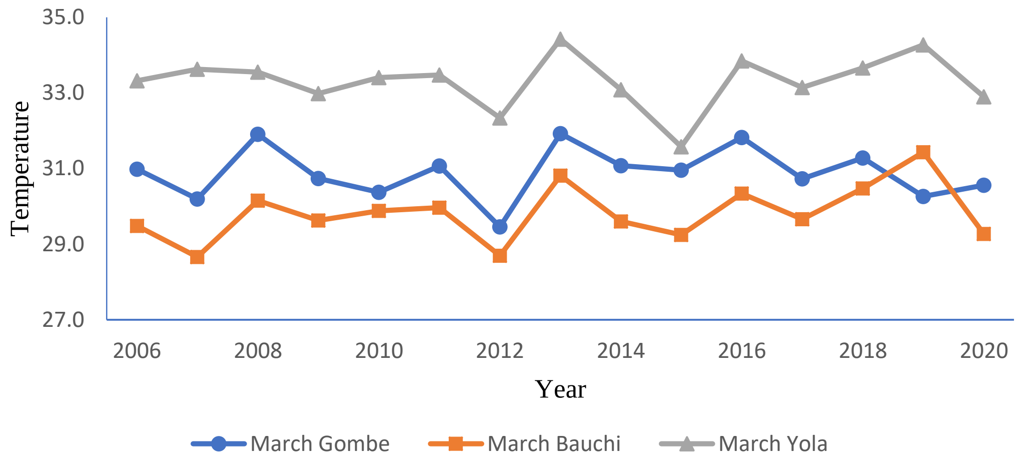


Figure 4.4a: Variation in monthly temperature for January and February

For the month of March, peak values were recorded for all the stations in 2008, 2013, 2016 and 2019 as portrayed in Figure 4.4b. However, the last five years saw a decreasing trend in temperature for Gombe while the contrast was for other stations this is in concordance with (Sadiq, 2020). The month of April witnessed high temperature with peaks in 2010 and 2016, however, the year 2012 in Bauchi as illustrated in Figure 4.4b recorded the lowest value while the latter years saw increasing trend in temperature; this is in harmony with the study by NiMet (2018) that maximum day time temperature was observed in April across the stations.



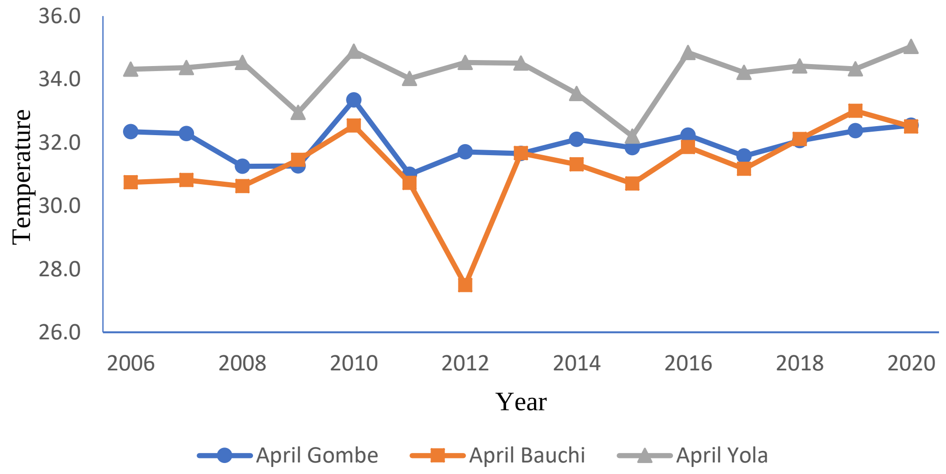


Figure 4.4b: Variation in monthly temperature for March and April

Peak values were recorded in 2010 and 2015 across all stations in the month of May. Subsequently, there was a decrease from 2016 to 2018 for Yola, 2016 to 2017 for Gombe as illustrated in Figure 4.4c. Bauchi witnessed increase from 2016 towards the end of the study period. Temperature pattern for the months of June and July showed a sustained increase and decrease of temperature in the study period as revealed in Figure 4.4c.

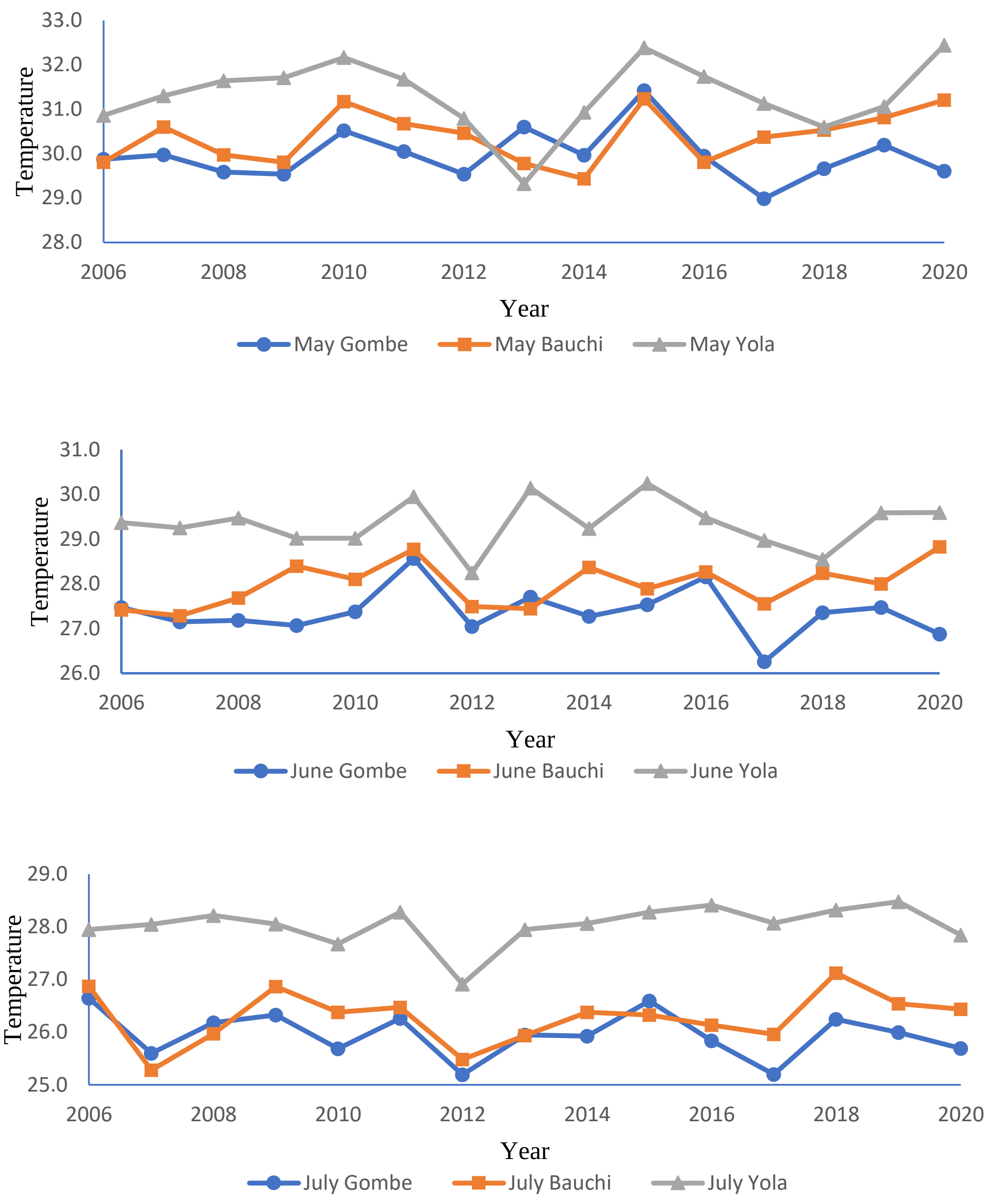


Figure 4.4c: Variation in monthly temperature for May, June and July

The last five years saw a slight increase in trend for the month of August across the stations. In September, uniform temperature was observed from 2010 to 2016 in Gombe while the Bauchi witnessed fluctuating trend the same period. However, there was steady rise from 2015 to 2019 in Bauchi, 2017 to 2019 in Gombe and a drop in temperature across all stations in 2020 as shown in Figure 4.4d.

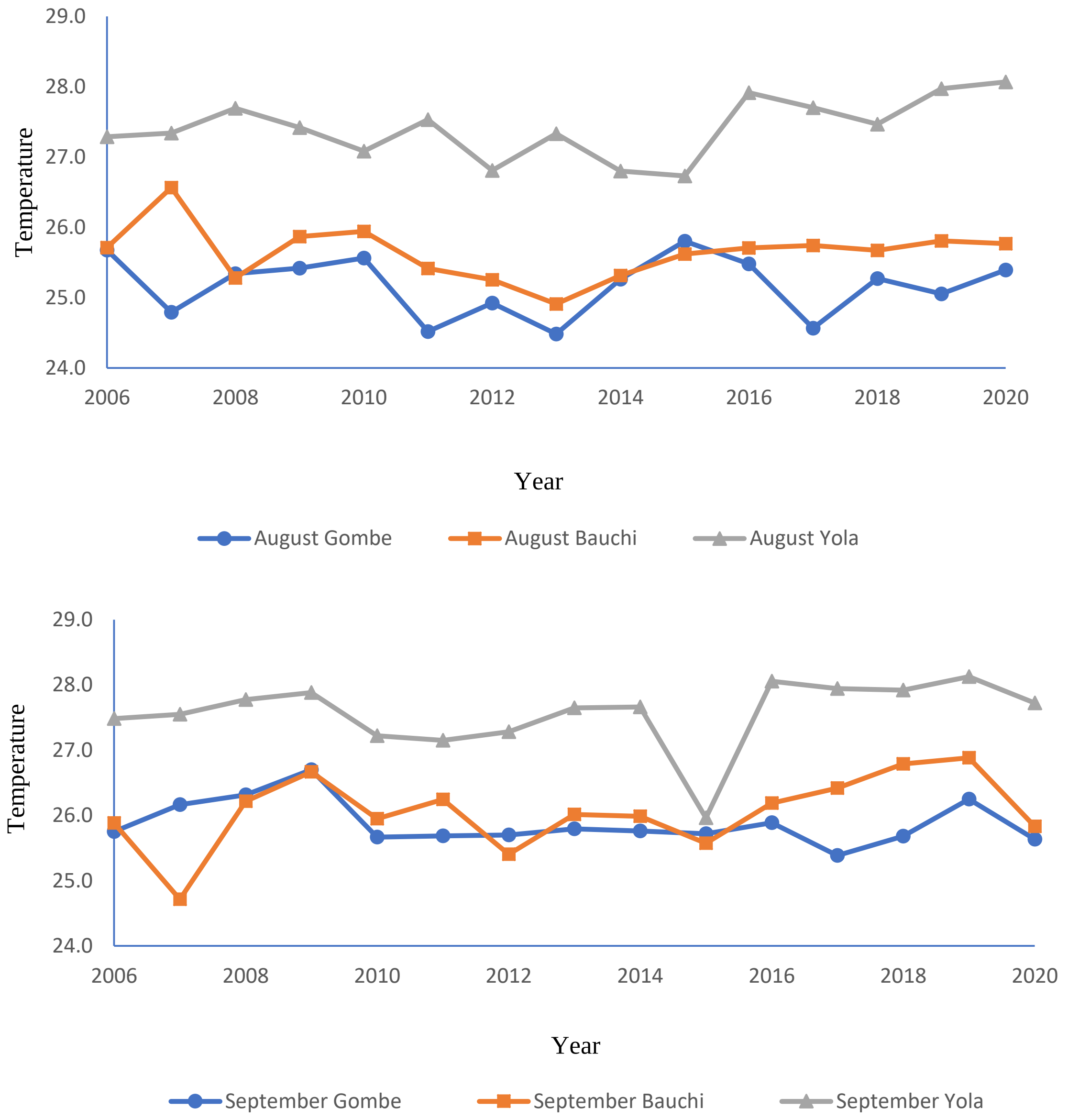


Figure 4.4d: Variation in monthly temperature for August and September

The trend in October reveals a near steady pattern for Yola and Gombe Stations in the first ten years of the study period from 2006 to 2015. However the last five years as depicted in Figure 4.4e, saw a decrease commencing from 2016 in Gombe, alternating rise and fall in Bauchi and a rise and fall in temperature in Yola. The degree of temperature in November for the period of study as portrayed in Figure 4.4e indicates an upward trend in Yola in the latter years of the study period from 2016; Gombe experienced alternating high and low in temperature from 2006 to 2012 while the latter years maintained constant trend; Bauchi experienced rise in temperature in the last five years of the study period. The degree in temperature in the month of December is characterized with upward and downward pattern over the study period. The years 2006, 2009, 2012 were peak years in the first decade, the last five years of study saw peaks in 2017 and 2019. However, fluctuating pattern was observed in the first five years as revealed in Figure 4.4e.

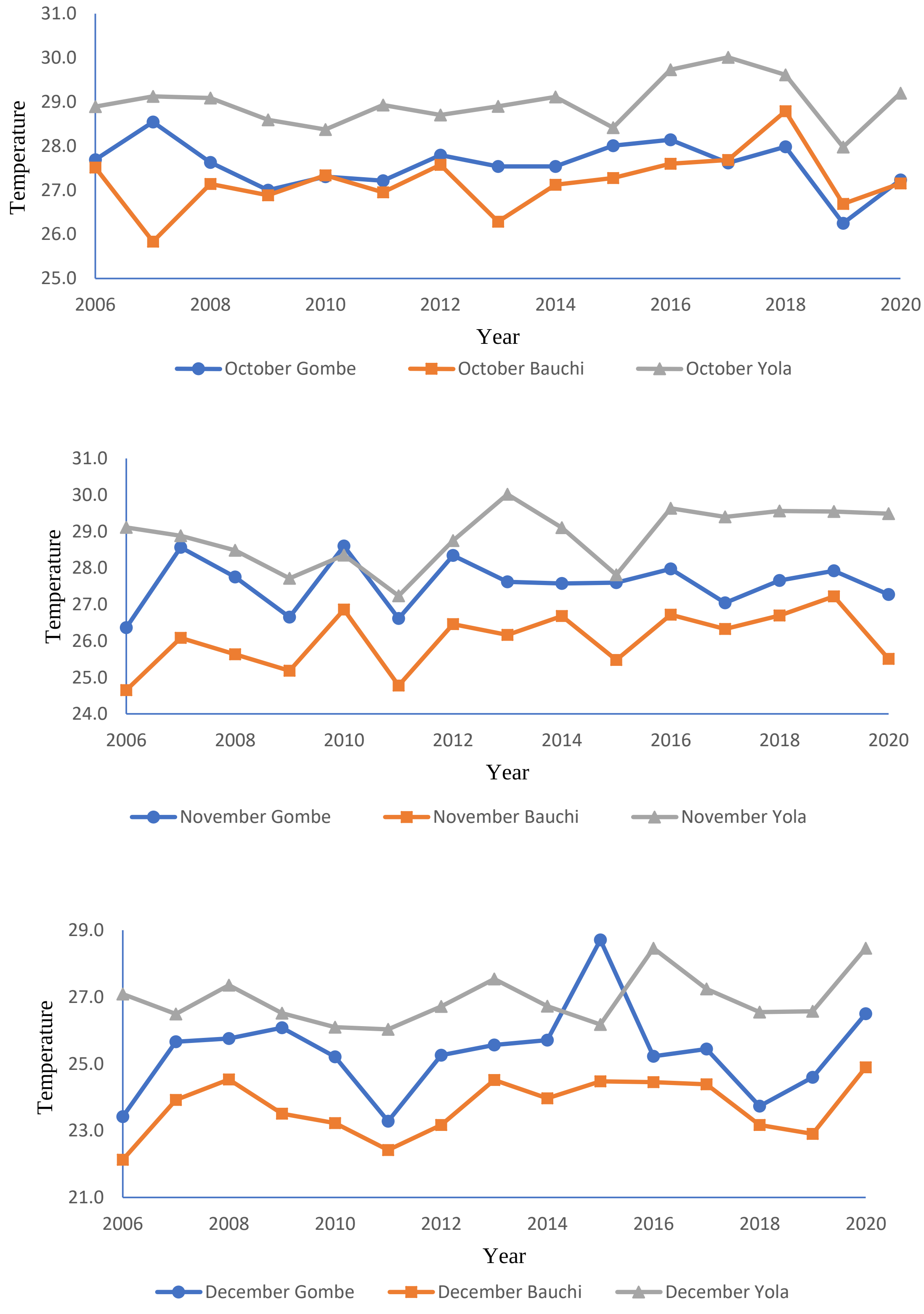


Figure 4.4e: Variation in monthly temperature for October, November and December

4.3 Standardized Anomaly Index

The anomalies of temperature that occurred in Gombe, Bauchi and Yola during the period of study (2006–2020) are described for the minimum and maximum temperatures.

The minimum temperature anomaly of the first decade of study period in Gombe as presented by Figure 4.5 reveals a positive departure from normal which indicates a domination of warmer than normal years (2006, 2007, 2009, 2010, 2012, 2013 and 2015) to colder than normal years (2008, 2011 and 2014). Thereafter, the last five years were all cooling years. The year to year variation contributes 39.21% to the standardized anomaly. In Bauchi, there were alternate periods of cooling and warming as illustrated in Figure 4.5 from 2006 to 2015. Five colder than normal years that occurred in 2007, 2008, 2011, 2012 and 2015 was typical of the first decade while the last five years saw a return to warming years starting from 2016 and extends to 2019. A negative departure in Yola as shown in Figure 4.5 portrays 6 cooling years till the year 2015 which happened to be the coldest year. After 2015, warm years returned and continued till the end of the study period. The year to year variation contributes 9.21% to the standardized anomaly The number of occurrence of warm years were higher than cool years for minimum temperature, this is expressed in Table 4.3.

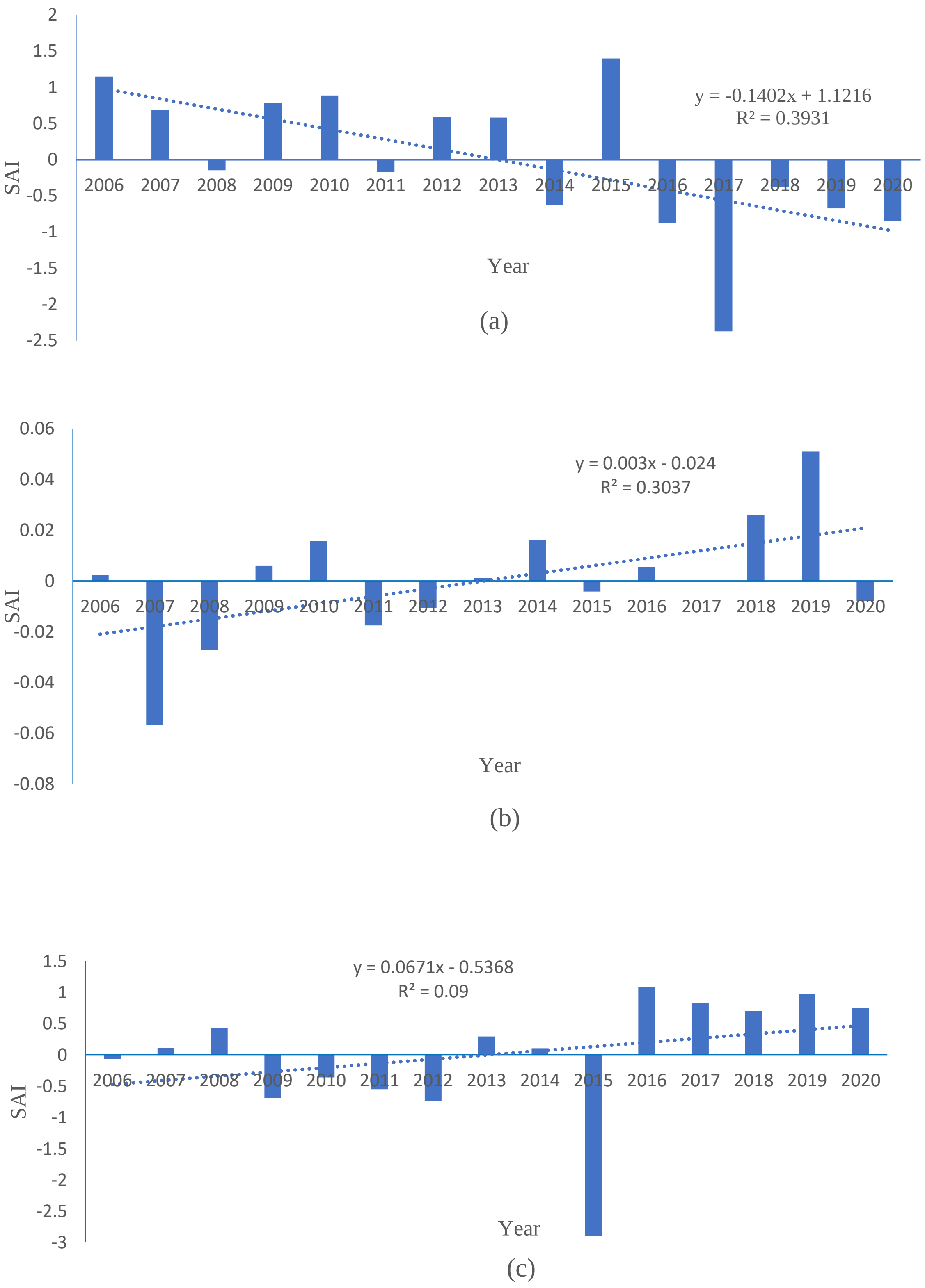
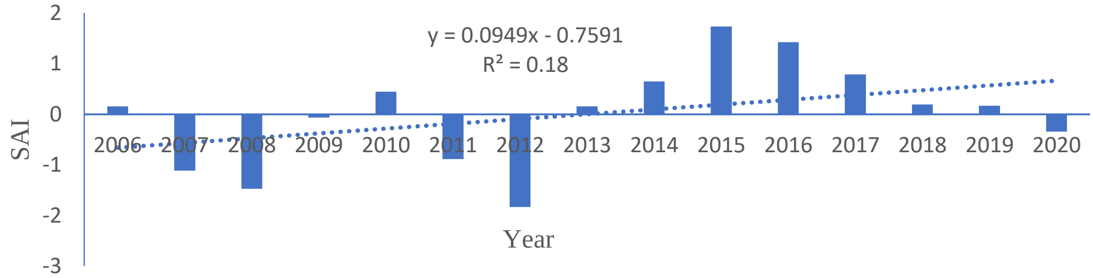
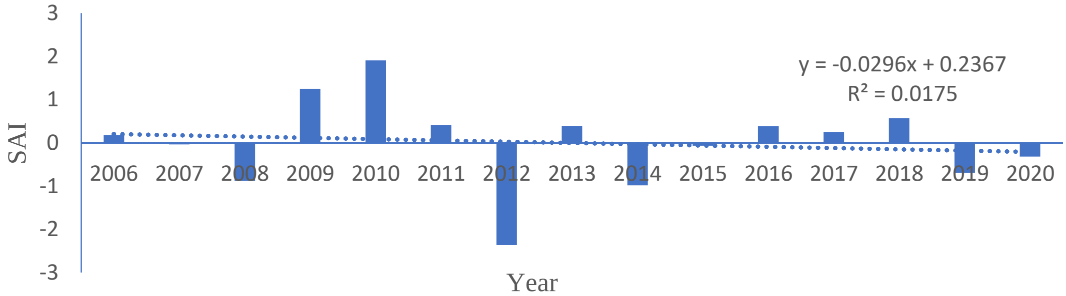


Figure 4.5: Standardized Anomaly Index for Minimum Temperature (a) Gombe (b) Bauchi (c) Yola

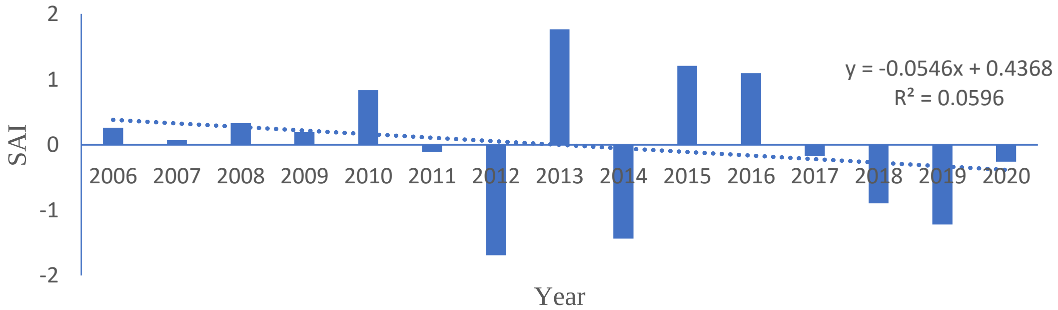
The pattern of the anomalies of the maximum temperature is in contrast with the minimum temperature as illustrated in Figure 4.6. There were alternate warming and cooling years in Gombe from 2006 to 2015. The warming years continued from 2015 to 2019. Bauchi experienced 8 warming years while 7 years were cooling period. Yola experienced 8 warming years which makes up to 53.3% of the study period while the cooling years make up to 46.7% of the period of study.



(a)



(b)



(c)

Figure 4.6: Standardized Anomaly Index for Maximum Temperature (a) Gombe (b) Bauchi (c) Yola

Table 4.3 gives a detailed insight to the numbers of warmer than normal years to the number of colder than normal years for minimum and maximum temperature respectively.

Table 4.3: Frequency of warming and cooling years of the study period

	Minimum Temperature		**Maximum Temperature**	
Station	**Number of Warm Years**	**Number of Cool Years**	**Number of Warm Years**	**Number of cool Years**
Gombe	7 (46.7%)	8 (53.3%)	9 (60%)	6 (40%)
Bauchi	8 (53.3%)	7 (46.7%)	8 (53.3%)	7 (46.7%)
Yola	9 (60%)	6 (40%)	8 (53.3%)	7 (46.7%)

4.4 Determination of Potential Evapotranspiration Using the BMN Model

The result of the PET using the BMN model is presented graphically in Figure 4.7. The method described in equation 3.5 using mean daily temperature, relative humidity and the ratio of maximum possible radiation to the annual maximum for the three stations was adopted for the BMN calculations. Selected months of January to March (dry season) and July to September (wet season) for the entire length of study portrays a periodic pattern of Potential Evapotranspiration as illustrated in Figure 4.7. Maximum PET for all the stations fell in the month of March; this could be attributed to increase in temperature due to dry season in northern Nigeria.

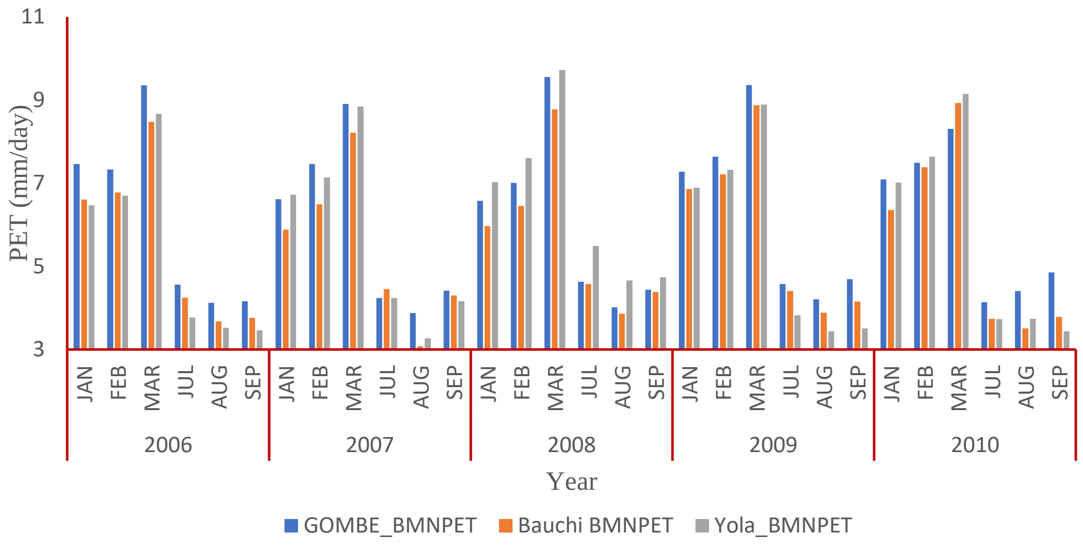


Figure 4.7: Seasonal Potential Evapotranspiration for Selected Months

The months of July to September was found to have low PET values as portrayed in Figures 4.7, A1 and A2; typically these months are characterized by low temperature and the presence of rainy season. In the first-third of the study period, PET was more pronounced in Gombe compared with other stations except in 2010 (Figure 4.7). The years in the two-third of the study period also saw Gombe as the station with pronounced rate of PET, then follows Yola (Figure A1). The last five years in Figure A2 of Appendix A indicates high PET in Yola except for 2018 and 2019 which was recorded for Bauchi.

4.5 Temporal and Spatial Extent of Drought based on SPEI

The temporal variability of droughts was analysed for both 3-month and 6-month timescales for Gombe, Bauchi and Yola for the study period of 15 years between 2006 to 2020. A higher negative value of SPEI suggests more severe drought, and persitence of negative value in the consecutive year for a given time scale depicts the persistence of drought.

The temporal evolution of drought in Gombe using the SPEI-3 shows that the first decade were wet except for 2006 and 2012 while the last five years were dry years (Figure 4.8a). The SPEI values as presented in Appendix H1 reveals that the critical months of July, August, September and October (JASO) in the year 2020 were the most drought prone with values of -1.295, -1.529, -1.628 and -1.165 for JASO respectively.

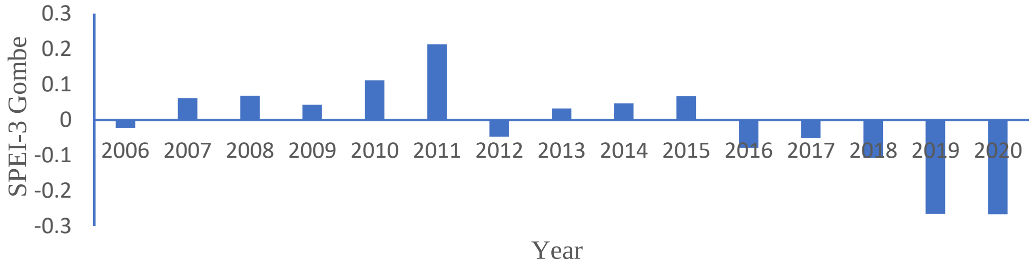


Figure 4.8a: Internannual variability of SPEI-3 Gombe

Bauchi recorded wet years in the first five years, with 2008 being the wettest, the subsequent years of 2011 to 2015 saw a decline into drought years (Figure 4.8b). Three consecutive years of respite from 2016 to 2018 saw a return to wet years (Achugbu and Balogun, 2018), however, a decline to drought episode commenced from 2019 which happened to be the highest drought year with severe drought from August (-1.647) to September (-1.654) and continued till 2020. The magnitude of the drought year is in consonance with Appendix H2.

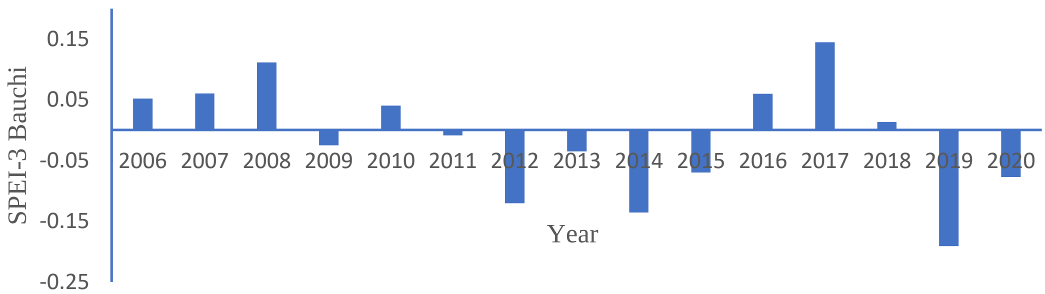


Figure 4.8b: Internannual variability of SPEI-3 for Bauchi

Drought years in Yola as analysed by the 3-month-SPEI were 2006, 2007, 2010, 2012, 2016 through to 2019. Although the drought severity appears to be near normal as shown in Figure 4.8c, the temporal dynamics of the SPEI reveals that 2006 was the most drought prone with drought month of August to September having the magnitude of -1.414 to -1.515 (Appendix H3).

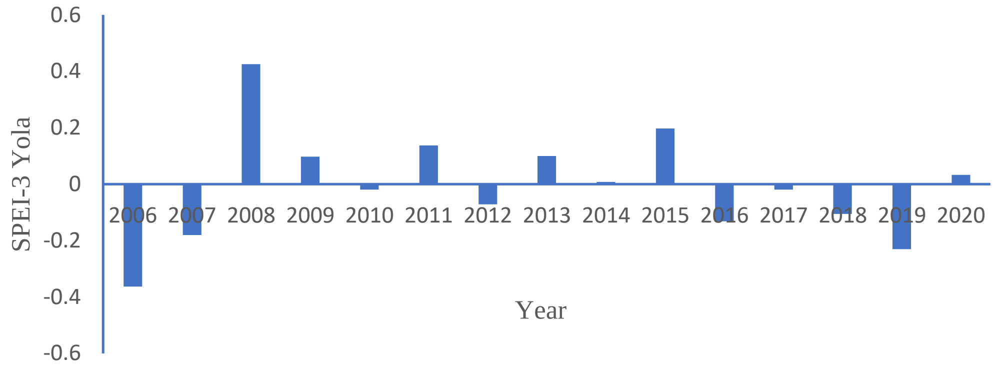


Figure 4.8c: Internannual variability of SPEI-3 for Yola

The Gombe SPEI-6 temporal characteristic takes the pattern of SPEI-3 as portrayed in Figure 4.9a. The first decade indicates wet period while latter years beginning from 2016 through 2020 portrayed years of rainfall deficit from August to November. The drought months (August to November) shows a negative value as presented in Appendix I1. The magnitude of the SPEI for the 6-month resolution period was found to be at peak value in October having values of -1.806 and -1.681 for 2019 and 2020 respectively. The spatio-temporal evolution of the SPEI indicates that 2019 was drought prone year. In Bauchi, Figure 4.9b revealed that the successive years of 2012 to 2015 and 2019 to 2020 were drought years having negative values of SPEI. The drought trajectory shows that the year 2019 was most prone to drought with magnitudes of -1.487,-1.785, and 1.710 for September to November (Appendix I2). Drought years in Yola as analysed by the 6-month-SPEI were 2006, 2007, 2012, 2016 through to 2020 (Figure 4.9c). The temporal evolution of the most prone year to drought has the months September to October as the drought months with October having magnitude of -1.607 and -1.777 in 2006 and 2019 (Appendix I3)

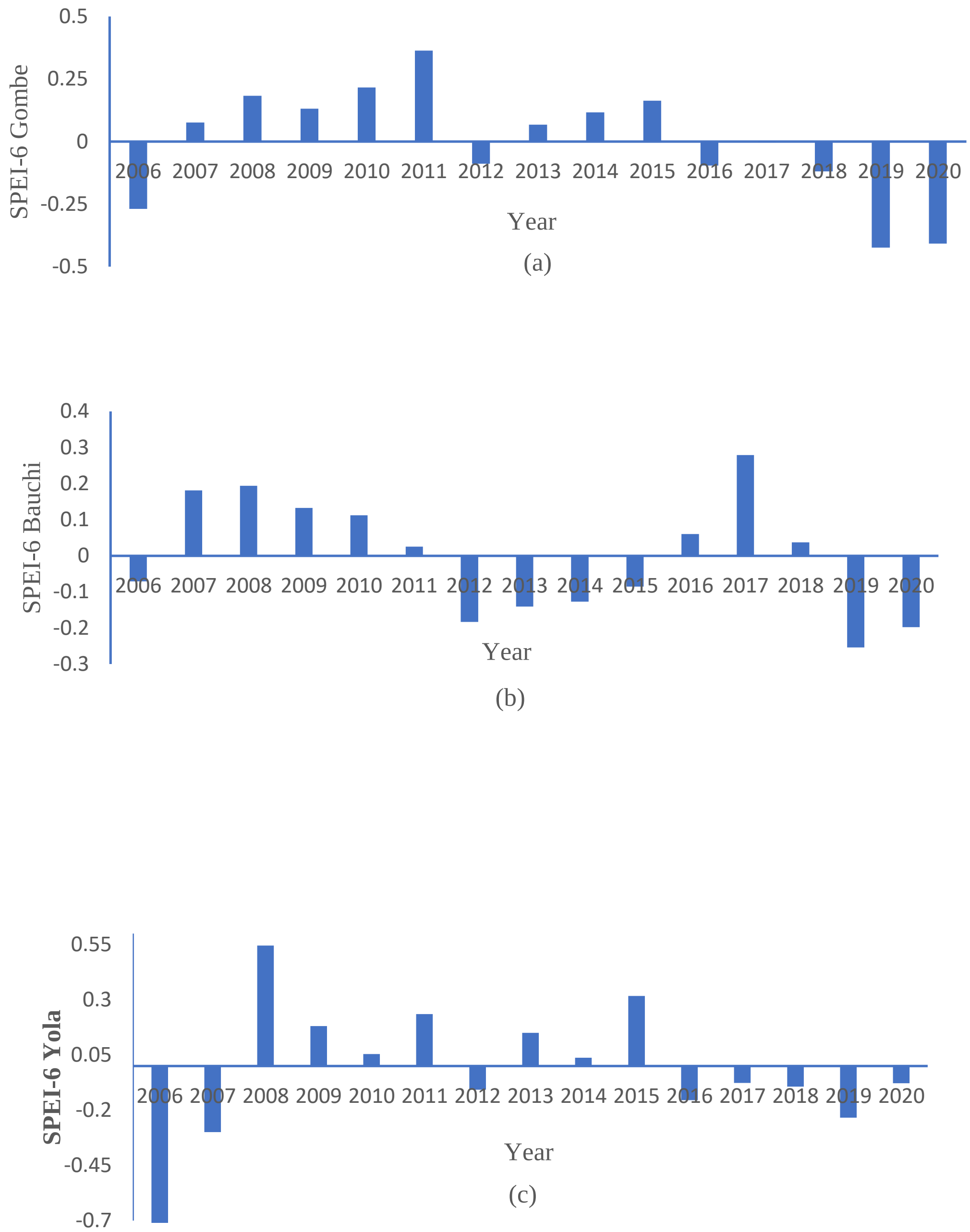


Figure 4.9: Internannual variability of SPEI-6 for (a) Gombe (b) Bauchi (c) Yola

4.5.1 SPEI-3 drought severity analysis

The drought analysis based on 3-month time scale reveals that Gombe suffered 34 cases of moderate to severe drought episodes in the months of July to October as presented in Table 4.4. The 34 drought episodes comprises 29 moderately dry and 5 severely dry conditions which represents 16.29% and 2.81% respectively of the drought cases in the study period. On the other hand, 19 moderately wet cases represent 10.67% of the study period

The SPEI-3 of July as illustrated in Figure B1of Appendix B portrays 3 years of moderate drought observed in 2012, 2019 and 2020. The SPEI-3(August) portrays 5 years of mild drought and 7 years of moderate drought out of which 4 years were successive (2015 to 2018). 3 years of severe drought were also recorded in 2012, 2019 and 2020 (Figure B2). 11 years of moderate drought characterized the month of September out of which there were 7 years of persistent drought (2011 to 2017), however, severe droughts were observed in 2018 and 2020 (Figure B3). In October month, SPEI-3 demonstrates 8 years of moderate drought of which there were two and three years of consecutive droughts found between 2012 to 2013 and 2018 to 2020, this was clearly illustrated by Figure B4 in Appendix B. Hence, most drought prone years according to SPEI categorization were 2018, 2019 and 2020 having magnitudes of -1.682, -1.690 and -1.628 respectively while the wettest years were found to be 2009 and 2010.

The vulnerability analysis in Bauchi indicated there were 36 drought episodes which represents 20.23% of the study period; 29 were moderately dry while seven were severely dry (Table 4.4). The study area experienced 17 moderately wet events that make up 9.55% of the study period. Drought episodes occurred between the months of July to October while other months were observed to be normal (Appendix H2). The drought vulnerability analysis as depicted by Figure C1 in Appendix C revealed that Bauchi experienced 3 years of moderate drought in July (2012, 2013 and 2019) with 12 years of mild drought. The SPEI-3(August) shows 10 years with moderate drought and 3 years of severe drought (2013, 2015, 2019). Ten consecutive droughts years followed from 2011 to 2020 (Figure C2). September witnessed 9 moderately dry years and 4 severe dry years (2013, 2015, 2019 and 2020) as presented by Figure C3. SPEI-3 (October) portrayed 7 years of moderate droughts out of which there were 3 consecutive years of occurrence, from 2018 to 2020. Hence, the years 2013, 2015, 2019 and 2020 with negative values of -1.734, -1.655, -1.654 and -1.515 are the drought prone years according to SPEI classification while the wettest year was found to be 2006, 2008 and 2010.

The analysis of three months accumulation period in Yola as presented in Table 4.4 uncovers 35 cases of dry episodes that represents 19.67% of the study period out of which 32 are moderately dry and 3 are severely dry. SPEI-3 (July) depicts 5 years with moderate drought (out of which there are four consecutive years from 2016 to 2019) and 8 near normal years (Figure D4). SPEI-3 (August) demostrate 4 mild droughts and 11 moderate drought years. SPEI-3(September) shows there were 2 years of mild drought, 11 years of moderate drought and 2 years of severe drought in 2016 and 2019 having magnitude of -1.516 and -1.581 respectively (Figure D3). The SPEI-3 (October) indicates 5 years of moderate drought and a year of severe drought which occurred in 2019 with magnitude of -1.505 on a severe scale. Hence, the most drought prone years were 2006 and 2019 based on SPEI drought severity classification while the wettest years were 2008 and 2013.

In this study, the SPEI-3 reflects a spatio-temporal characteristics of more mild drought conditions to moderate and severe drought occurrence across the stations between the months of July to October as illustrated in Table 4.4.

Table 4.4: Frequency of wet and dry periods in the study area (SPEI-3)

Category	Gombe Duration	Percentage of Occurrence	Bauchi Duration	Percentage of Occurrence	Yola Duration	Percentage of Occurrence
Moderately Wet	19	10.67%	17	9.55%	29	16.29%
Mild wet	76	42.70%	82	46.06%	63	35.40%
Mild dry	49	27.53%	43	24.16%	51	28.65%
Moderately Dry	29	16.29%	29	16.29%	32	17.98%
Severely Dry	5	2.81%	7	3.94%	3	1.69%

4.5.2 SPEI-6 Drought severity analysis

The multiscalar nature of SPEI like the SPI reflects seasonal to medium term trends in precipitation as it impacts stream flows and reservoir levels (WMO, 2012). The analysis of the 6-month resolution indicates that Gombe experienced 25 drought cases; 20 were moderate droughts and 5 were severe droughts (Table 4.5). Moderate droughts makes up to 11.42% of the drought cases while 2.86% makes the severe cases. Analysis of 6-month resolution of the study year for the month of August saw two moderate drought events in 2019 and 2020. SPEI-6 (September) portrays 5 moderate droughts (2012, 2016-2019) and one severe drought in the year 2020 (Figure E2). SPEI-6 (October) witnessed 8 moderate drought and 3 years of consecutive severe drought from 2018 to 2020 indicating the month with the highest severity (Figure E3). SPEI-6 (November) of the study period portrays 10 mildly dry years, 4 moderatly dry years and one severely dry year. The most prone drought month was October which has magnitude of -1.519, -1.809 and -1.681 for 2018 to 2019, while the drought risk year was 2019 having persistent severity from October to November. Wet years were observed to be from 2007 through 2011 and continued in 2014.

Result of analysis presents 27 drought cases that falls into the moderate and severe category in Bauchi station (Table 4.5). 24 cases fell into the moderately dry category and three in the severe drought category which makes up to 13.71%. and 1.72% of the study period respectively while moderate wet period made up to17.14% .

SPEI-6 (August) exhibited 10 mildly dry years and 2 severly dry years. The month of September exhibited 7 moderatly dry years and 5 mildly dry years. SPEI-6 (October) portrayed 6 mildly dry years, 7 moderatly dry years and 2 episodes of severe drought with magnitude of -1.523 and -1.785 in 2013 and 2019 respectively. SPEI-6 (November) was characterized by 5 mildly dry cases, 9 moderatly dry cases and a severe episode which occurred in 2019. The most drought prone year from the vulnerability analysis was found to be 2019 having severity values of -1.785 and -1.710 in October and November while the wettest year were 2006, 2007, 2008, 2009 and 2010.

Yola witnessed 26 drought cases; moderate drought recorded 22 events while severe drought recorded 4 events as potrayed in Table 4.5. The drought events represents 14.86% of the study period while 19.43% represents moderately wet case. It was observed also that the dry condition prevailed through the months of September to December while other months were characterized by normal conditions. SPEI-6 (September) exhibits 7 moderate drought episodes out of which there were 4 consecutive years of drought from 2016 to 2019 (Figure G2). SPEI-6 (October) exhibits drought episodes of 6 near normal years, 7 moderatly dry years and 2 severly dry years (which occur in 2006 and 2019) (Figure G3). The SPEI values of November indicates 7 near normal years, 6 modertly dry years and 2 severely dry years (2006 and 2019). Hence, the crtical drought prone years are 2006 and 2019 occuring in October and November months while the wettest years were 2008, 2009, 2011, 2013, 2014, and 2015

Table 4.5: Frequency of wet and dry periods in the study area (SPEI-6)

Category	Gombe Duration	Percentage of Occurrence	Bauchi Duration	Percentage of Occurrence	Yola Duration	Percentage of Occurrence
Moderately Wet	33	18.86%	30	17.14%	34	19.43%
Mild Wet	54	30.86%	56	32%	52	29.71%
Mild Drought	63	36%	62	35.43%	63	36%
Moderately Drought	20	11.42%	24	13.71%	22	12.57%
Severely Drought	5	2.86%	3	1.72%	4	2.29%

4.6 Summary of Findings and agreement with previous studies

The monthly rainfall distribution over the stations for the period of 2006-2020 reveals that rainfall begins from April and continues till October. Peak rainfall was observed in the month of August with Bauchi having more rainfall than other stations except for Yola whose maximum fell in September. This is in consonance with Abaje *et al.* (2013) that maximum rainfall in the Sahel occurs in August. The temporal distribution of rainfall suggest that there has been an increase in rainfall as the decadal trend depicts an upward rise in the mean rainfall for the last 5 years (2016-2020) compared to the mean of the first decade of the study year. This is in line with Dammo *et al.* (2015); Abashiya *et al.* (2017) and Yusuf and Ekundayo (2019) who opined that rainfall in Bauchi, Gombe and neighbouring states in north eastern Nigeria have witnessed increase in rainfall in recent decades.

The month of April across the three stations was the hottest followed by the month of March while the coldest months are December and January. The cooling period in December and January can be attributed to the harmattan season in the zone. This is in harmony with Binbol and Edicha (2012). Yola was found to be the hottest among the three stations with an upward trend in monthly temperature distribution followed by Gombe which has a downward trend while Bauchi was the least among the stations. The trend in monthly temperature depicts a sustained rise and fall of temperature in all the stations except in April where increase in trend was observed in the last five years of study (2016 – 2020). November temperature was found to be consistent in the last five years in Yola.

The Standardized Anomaly Index for minimum and maximum temperatures depicts period of more warming years than cooling years in the length of study year. This is in consonance with a NiMet (2018) which suggests a rise in temperature for both minimum and maximum temperature in both the Northern and Southern Nigeria. Warming years characterize the last 5 years for Yola and Bauchi while Gombe was cooling periods for minimum temperature. The maximum temperature depicts periods of warming for Gombe in recent years (2016-2019), Bauchi had warming and cooling, while Yola experienced cooling towards the latter part of the study period.

The Potential Evapotranspiration (PET) was found to peak for all the stations in the month of March. This finding is in agreement with the observations made by Echiegu *et al.* (2016) and

NiMet (2018) that high values were obtained during the hottest time of the year which corresponds to the period of insolation usually between February and April. The months of June to September have low PET values. Typically, these months are characterized by low temperature and the presence of rainy season.

The results of the spatio-temporal analysis of drought in the study area using SPEI at both 3-month and 6-month time scale are presented in the Appendices. The results shows similar characteristics for all the 3 stations as the drought severity levels observed in the stations have high dominance of the occurrence of persistent mild drought conditions, which is then followed by few cases of moderate droughts as well as severe drought through the years of study. This is in close agreement with earlier studies that the Sudan Sahel Ecological Zone is drought prone (Achugbu and Balogun, 2018).

The results of the drought analysis shows that the percentage of the normal cases is more than the dry conditions for both time scale across all stations. This is in harmony with the observation made by Abaje *et al.* (2013) that the SSEZ of Nigeria has been experiencing a gradual return to wet years. The result from the study indicated higher frequency of moderate to severely dry cases for the 3-month accumulation period (Table 4.4) compared to the 6-months accumualtion period (Table 4.5). However, there was no evidence of extreme drought events for both resolutions.

For critical drought months of July to November, drought prone years using SPEI-3 were 2018, 2019, and 2020 for Gombe while the wettest years were 2009 and 2010. The years 2013, 2015 and 2019 were dry years for Bauchi and wet years were 2006 and 2008. Yola's drought prone year were 2012 and 2019 while the wettest year was found to be 2008 and 2013. This findings in in consonace with Achugbu and Balogun, (2018). For SPEI-6, drought prone years were found in 2019 and 2020 in Gombe, the years 2013, 2015 and 2019 for Bauchi while for Yola was found to be 2006 and 2019 (Table 4.6)

By implication, the study areas representing the north eastern Nigeria in the last five years were not only liable to shortage in short and medium term moisture which signifies the dominance of meterological drought where agricultural dependent rainfall is ravaged by drought and also shortage in seasonal to medium term moisture condition which signfies the of reduction in stream flow and rerservoir storage.

Table 4.6: Categorization of critical drought in the selected stations

	SPEI-3			SPEI-6		
Station	**Gombe**	**Bauchi**	**Yola**	**Gombe**	**Bauchi**	**Yola**
Duration	2 (August to September, 2020)	2 (August to September, 2013)	2 (September to October, 2019)	2 (October to November, 2019)	2 (October to November, 2019)	2 (October to November, 2006)
		2 (August to September, 2019)		2 (September to October, 2020)		
SPEI value	-1.625 to -1.529	-1.61 to -1.734	-1.518 to -1.505	-1.806 to -1.654	-1.785 to -1.71	-1.607 to -1.51
		-1.654 to -1.647		-1.578 to -1.688		-1.777 to -1.576
Drought category	Severely dry	Severely dry	Severely dry	Severely dry	Severely dry	Severely dry

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The assessment of droughts in parts of north-eastern Nigeria with a view to determining the parts that are most vulnerable has been presented in this study. Hence, the following conclusions were drawn based on the findings:

The rainfall pattern has a fluctuating regime which could be as a result of climate change/global warming; however the last five years have seen a rise in rainfall trend. The alternating rise and fall of monthly temperature that was observed in the period of study resulted to more warming years than cooling years.

The modified Blaney-Morin also called Blaney-Morin Nigeria was found to be suitable for estimating PET for SPEI calculations as it corroborates with result from previous studies using other empirical method.

There were more incidence of mild droughts (near normal) in both 3-month and 6-month temporal accumulation in all the stations, however, the obtained result from the SPEI-6 is indicative of its effectiveness in capturing seasonal to medium term drought patterns as the driest and wettest years were observed. The driest year was observed to be 2006, 2018, 2019, and 2020 while the wettest year was observed to be 2008.

Therefore, this study concludes that the performance of the SPEI for drought monitoring is suitable for use in North East Nigeria as it identifies the multi-temporal nature of drought, captures the influence of temperature and it depicts the severity of drought duration.

5.2 Recommendations

Based on the findings from this study the following recommendations are suggested:

1. Drought should be evaluated using both 3-month and 6-month accumulation period considering the possibility of transition from meteorological to hydrological drought.
2. The impact of climate change/global warming is being reflected, therefore there is a need to carry out further study on the impact it has on drought phenomenon.
3. There is a need for government across all levels to put in place a policy framework for drought management strategies that will include mitigative and adaptive measures to reduce the impact to drought vulnerabilities.

5.3 Contribution to Knowledge

This study employed a evaporation-rainfall based index, the SPEI to assess the drought in the North-Eastern part of Nigeria. The study observed that there were drought signatures in the selected states of study even with the increased rainfall pattern of the last five years of study. Drought evolution trajectory was found to occur in the months of August to November. This study will be beneficial to different water resources users such as the farmers and water supply organization and policy makers to develop adequate plans for early drought preparedness.

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APPENDICES

APPENDIX A

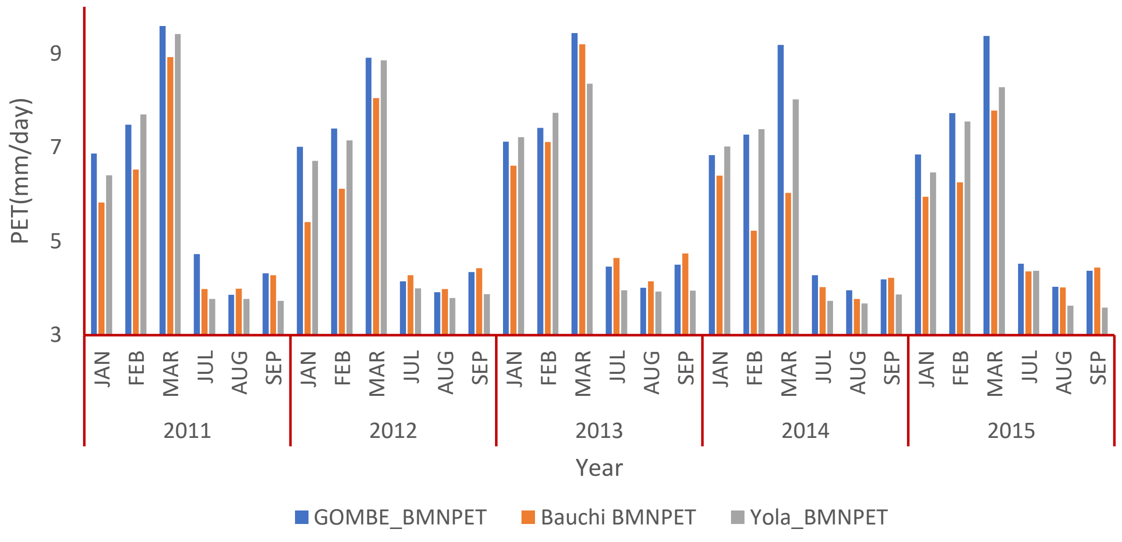

Figure A1: Seasonal Potential Evapotranspiration for selected months (2011-2020)

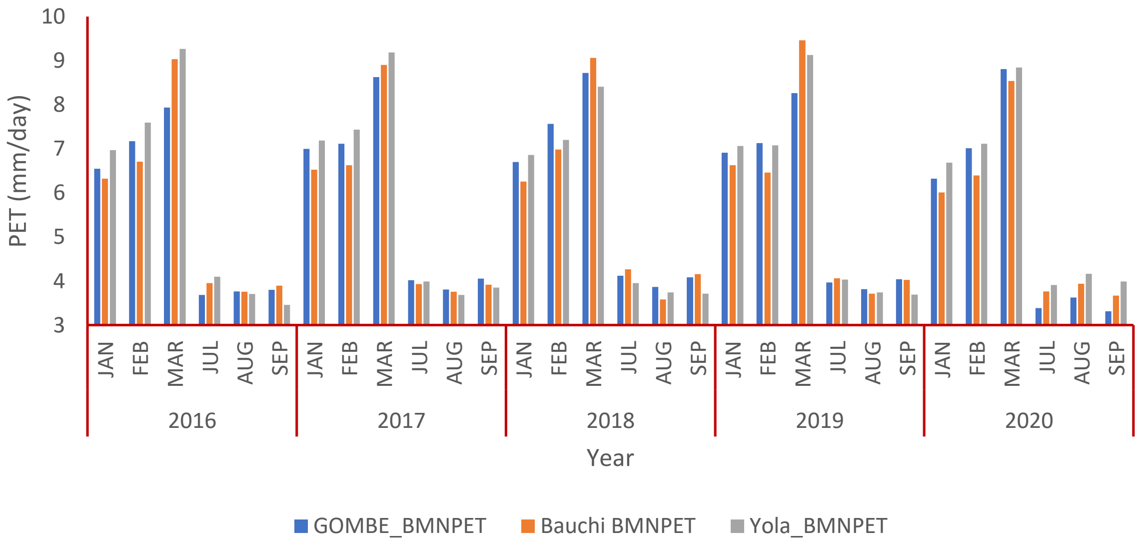

Figure A2: Seasonal Potential Evapotranspiration for selected months (2016-2020)

APPENDIX B

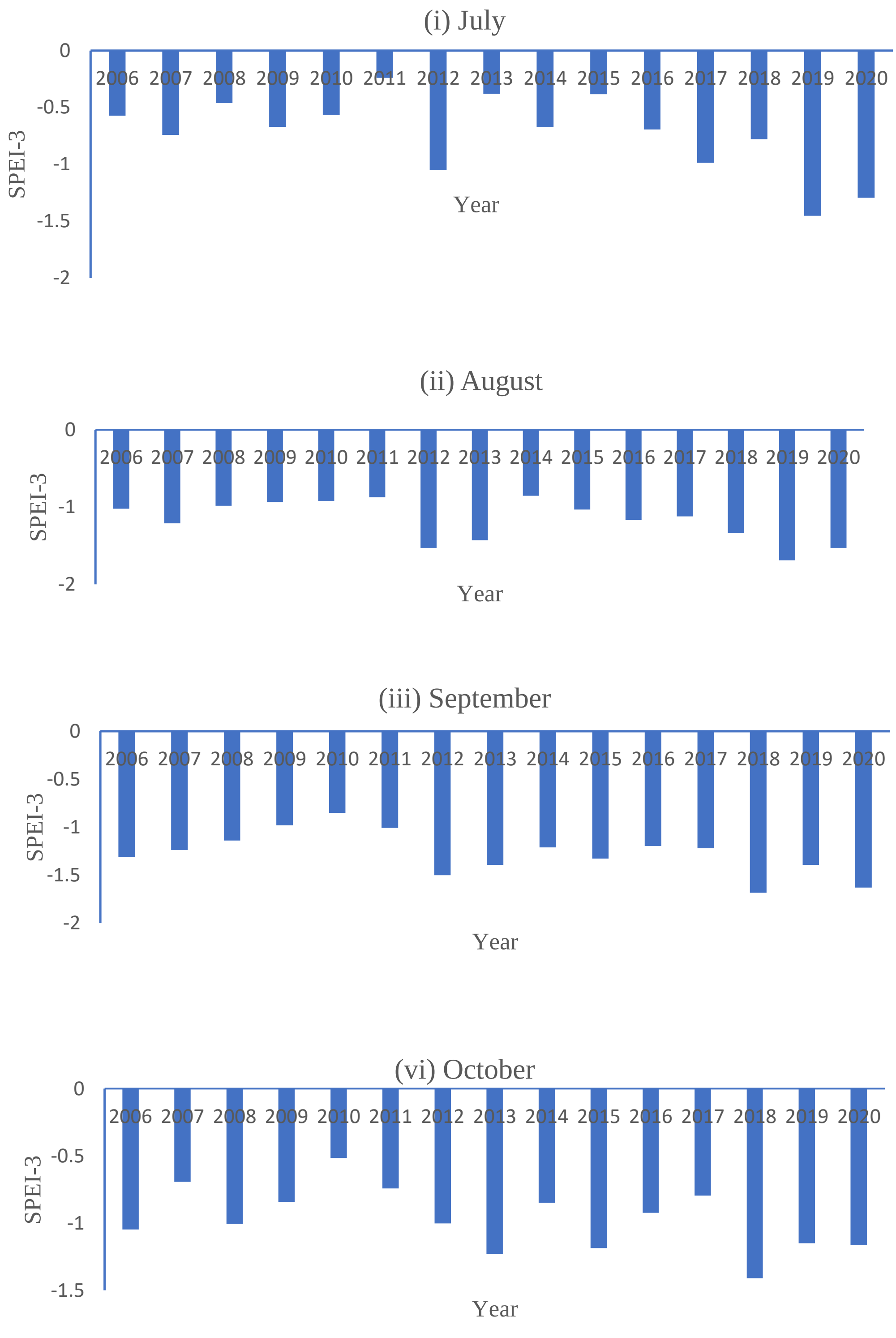

Figure B: Gombe SPEI-3 selected for months: (i) July (ii) August (iii) September (vi) October

APPENDIX C

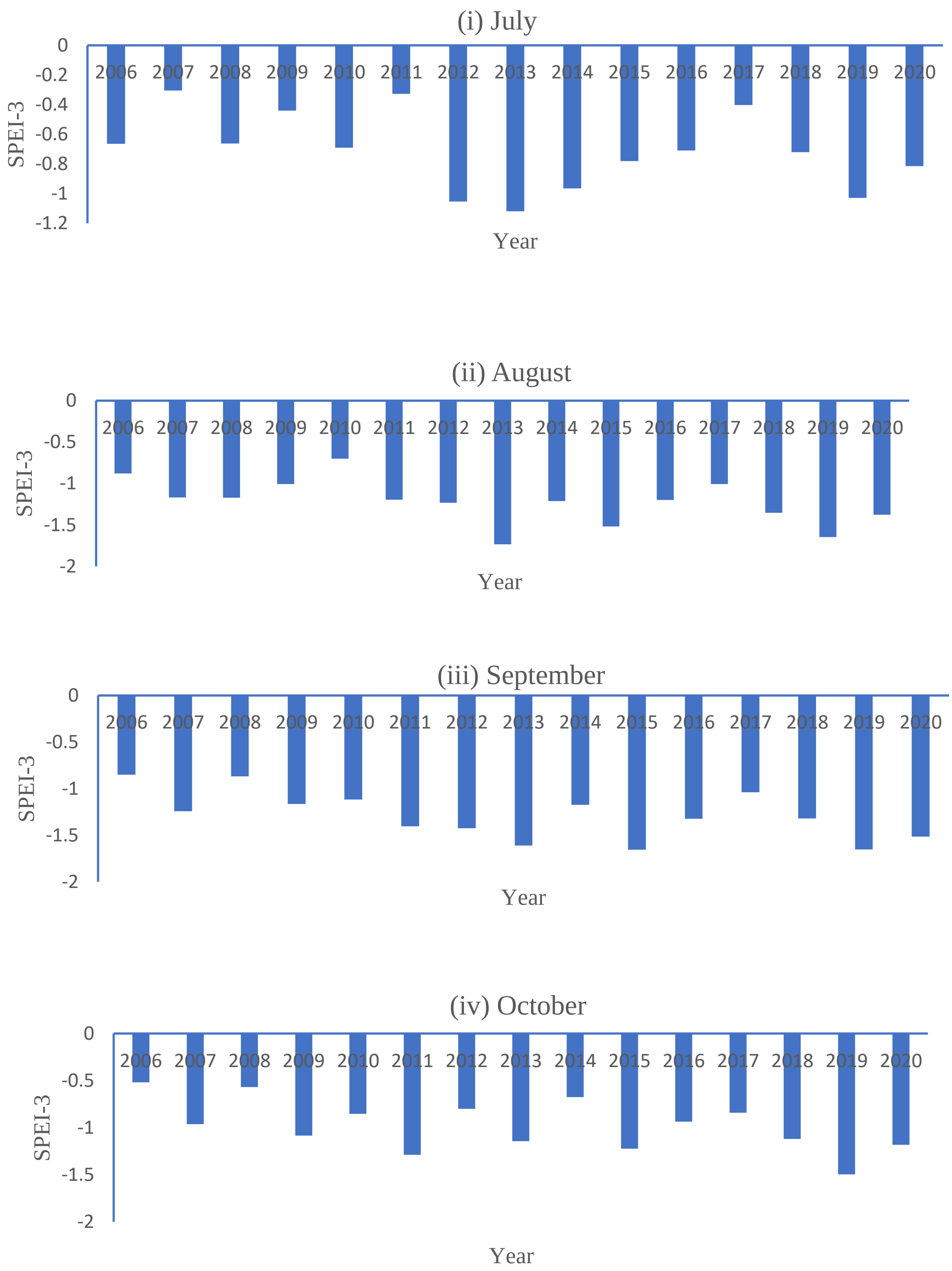

Figure C: Bauchi SPEI-3 selected for months: (i) July (ii) August (iii) September (iv) October

APPENDIX D

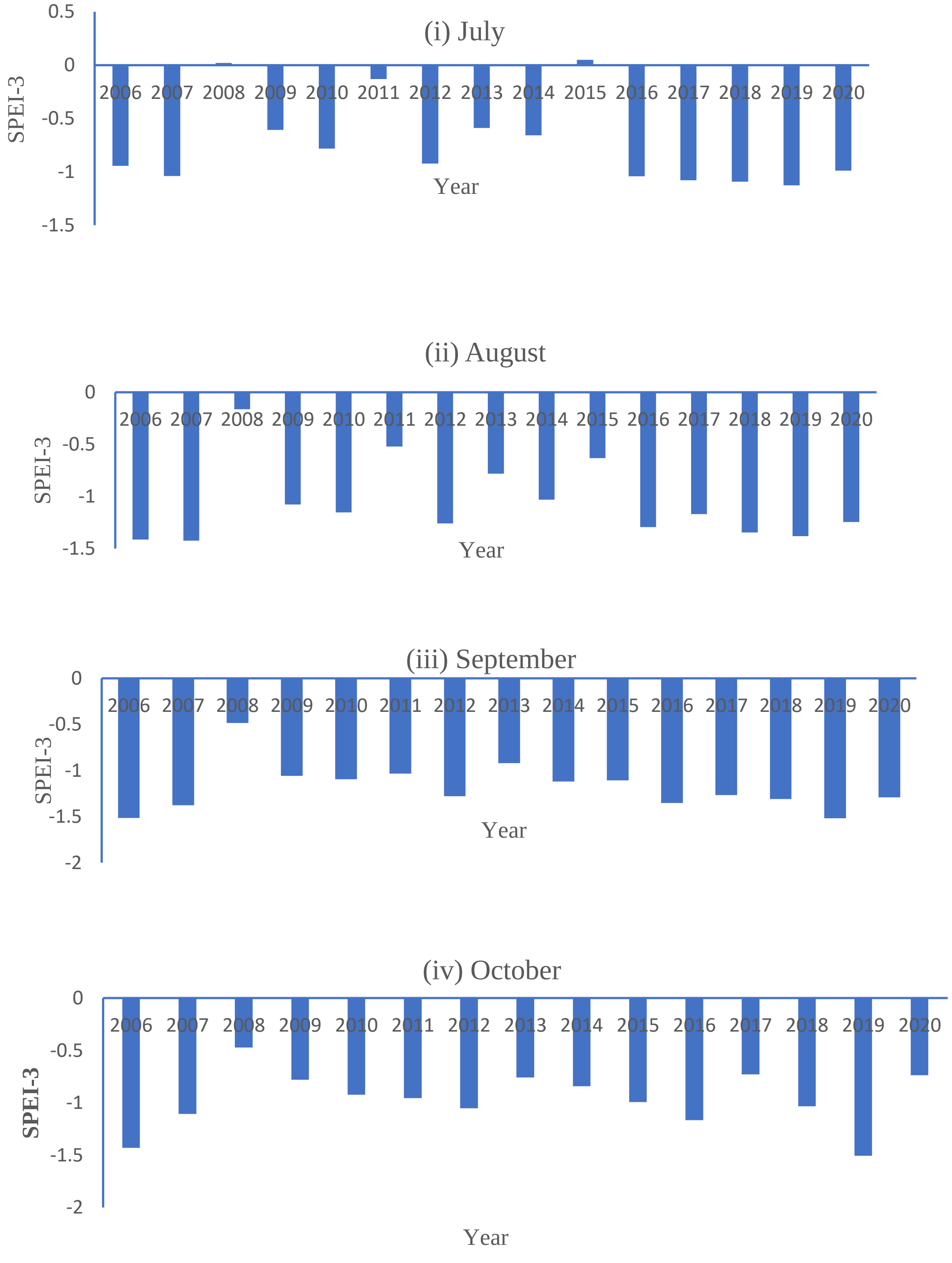

Figure D: Yola SPEI-3 selected for months: (i) July (ii) August (iii)September (iv) October

APPENDIX E

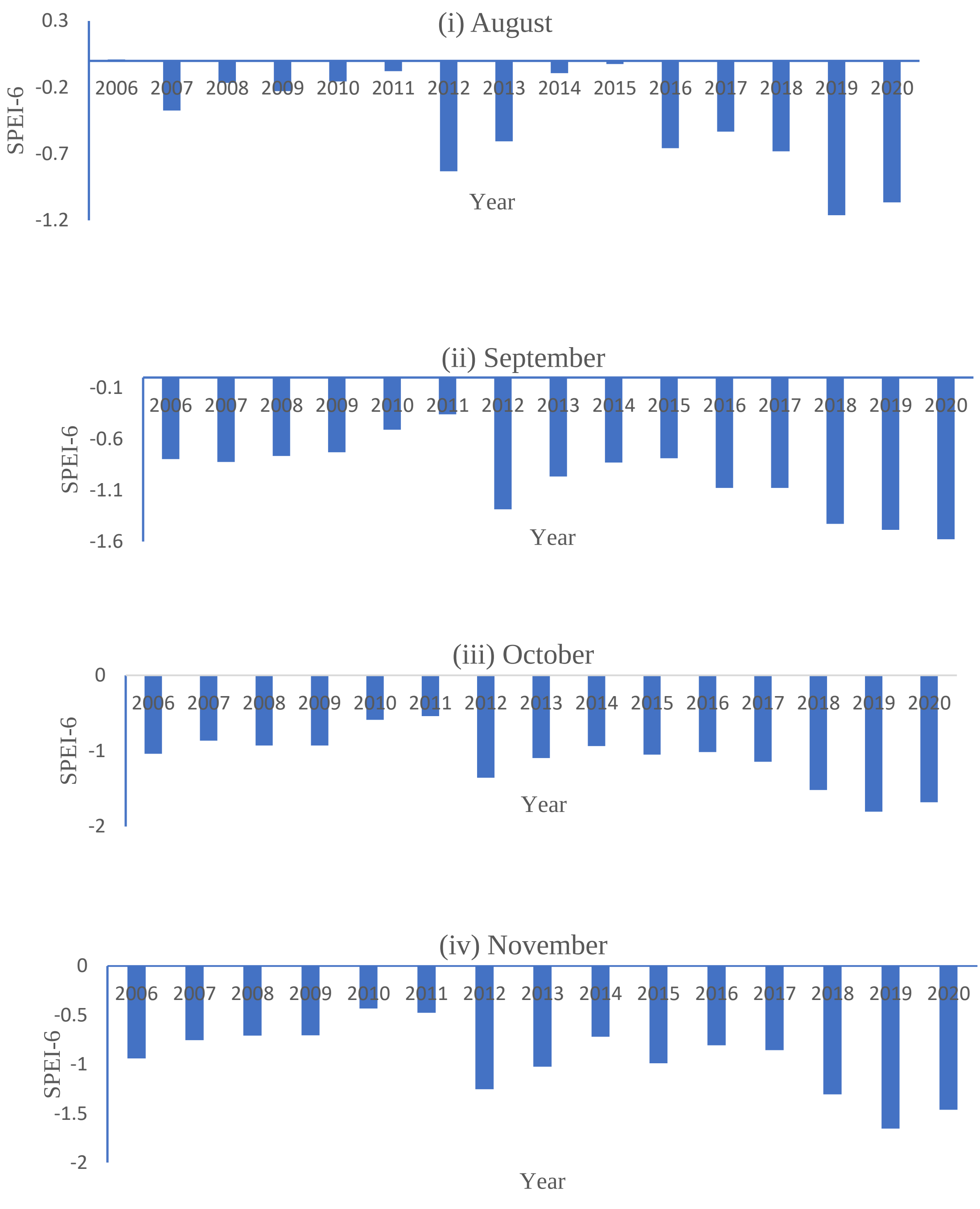

Figure E: Gombe SPEI-6 for selected months: (i) August (ii) September (iii) October (iv) November

APPENDIX F

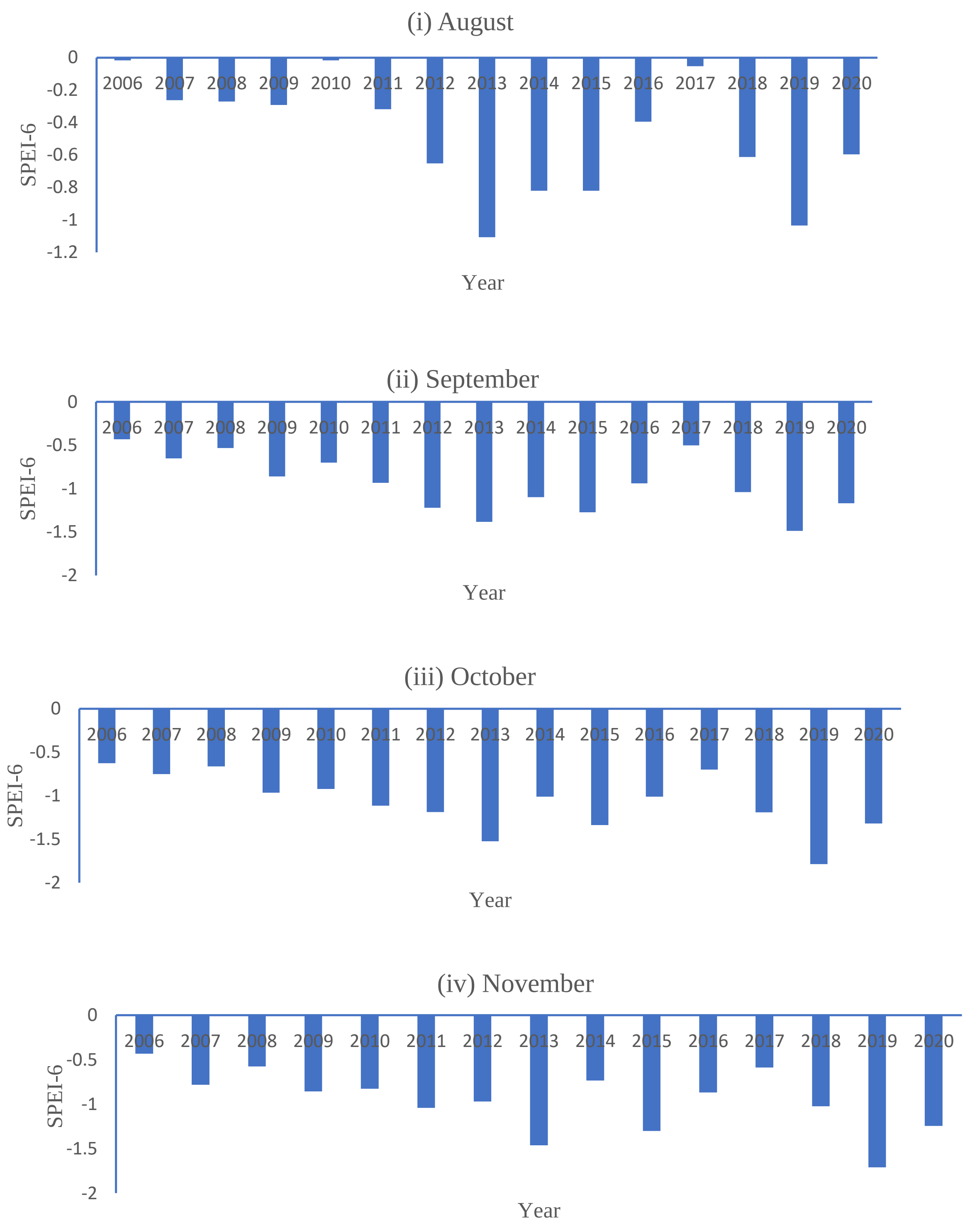

Figure F: Bauchi SPEI-6 for selected months: (i) August (ii) September (iii) October (iv) November

APPENDIX G

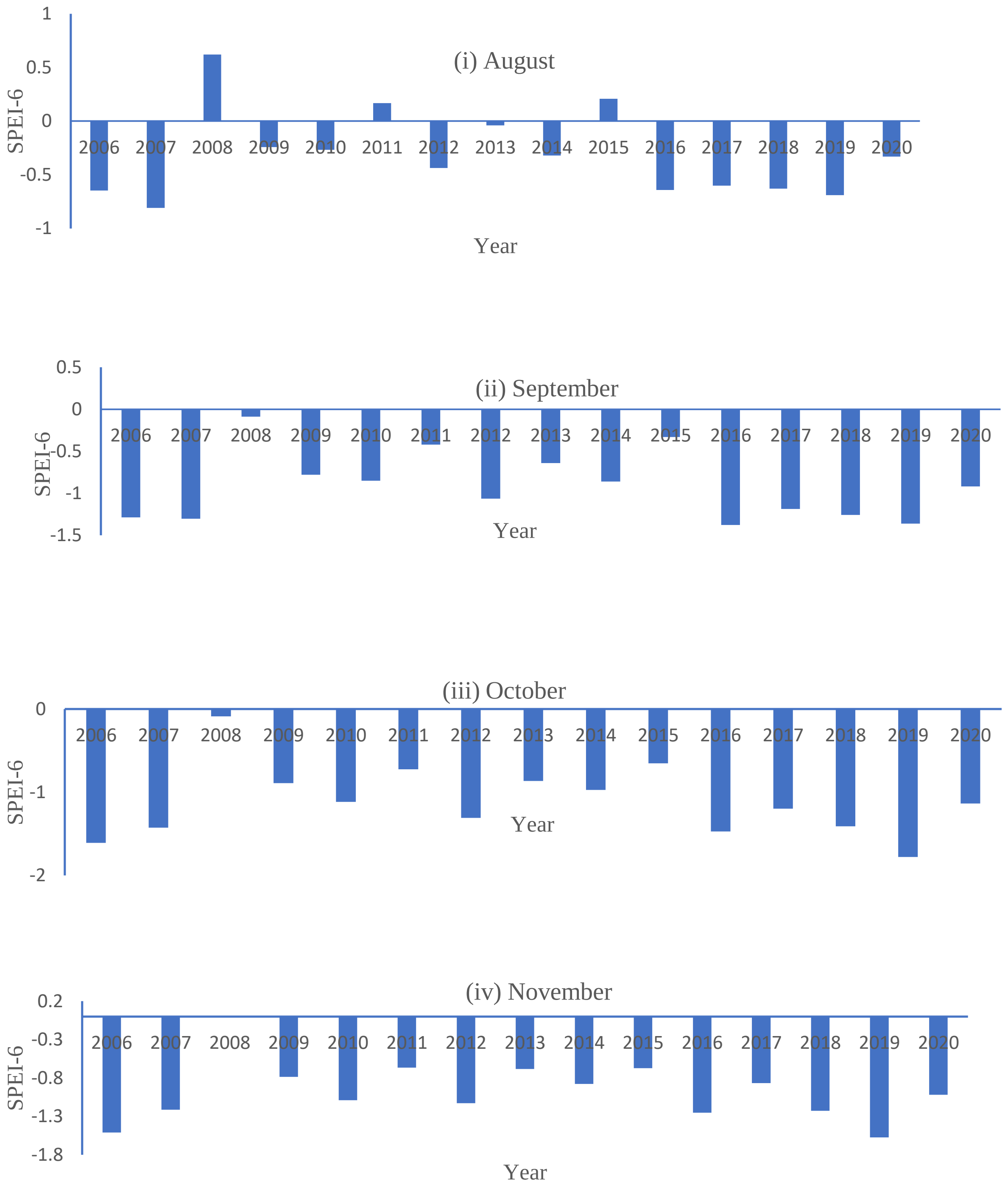

Figure G: Yola SPEI-6 for selected months: (i) August (ii) September (iii) October (iv) November

Appendix H1: Spatio-temporal analysis for SPEI-3 Gombe

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2006			1.320	1.366	1.024	0.106	-0.572	-1.020	-1.308	-1.048	-0.462	0.363
2007	0.640	0.721	0.997	1.051	0.713	-0.113	-0.742	-1.208	-1.236	-0.693	-0.043	0.652
2008	0.699	0.714	1.016	1.109	0.590	0.025	-0.462	-0.983	-1.137	-1.005	-0.151	0.402
2009	0.769	0.832	1.149	1.035	0.373	-0.193	-0.669	-0.935	-0.979	-0.842	-0.220	0.194
2010	0.721	0.845	0.986	0.797	0.477	-0.036	-0.564	-0.920	-0.851	-0.515	-0.023	0.424
2011	0.746	0.736	1.110	1.136	0.968	0.274	-0.240	-0.872	-1.006	-0.741	0.049	0.398
2012	0.764	0.779	1.037	1.031	0.664	-0.187	-1.053	-1.530	-1.499	-1.002	-0.047	0.474
2013	0.688	0.757	1.094	1.083	0.850	-0.028	-0.381	-1.429	-1.393	-1.228	-0.055	0.428
2014	0.724	0.749	1.034	1.040	0.461	0.051	-0.673	-0.854	-1.210	-0.849	-0.359	0.449
2015	0.699	0.814	1.079	1.224	0.980	0.168	-0.382	-1.031	-1.326	-1.186	-0.521	0.292
2016	0.749	0.763	0.788	0.503	0.050	-0.406	-0.694	-1.167	-1.196	-0.923	0.006	0.576
2017	0.757	0.744	0.970	0.896	0.187	-0.371	-0.987	-1.122	-1.218	-0.796	-0.164	0.494
2018	0.703	0.765	0.998	1.096	0.413	-0.014	-0.778	-1.336	-1.682	-1.409	-0.553	0.505
2019	0.708	0.711	0.920	0.937	0.424	-0.757	-1.452	-1.690	-1.391	-1.150	-0.479	0.033
2020	0.663	0.647	0.791	0.786	0.127	-0.469	-1.295	-1.529	-1.628	-1.165	-0.466	0.335

Appendix H2: Spatio-temporal analysis for SPEI-3 Bauchi

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2006			1.183	1.182	0.615	0.024	-0.664	-0.878	-0.851	-0.517	0.069	0.355
2007	0.563	0.627	0.880	0.915	0.860	0.227	-0.304	-1.169	-1.242	-0.962	0.024	0.303
2008	0.504	0.626	0.940	1.096	0.852	-0.109	-0.661	-1.172	-0.870	-0.569	0.196	0.505
2009	0.751	0.842	1.119	0.712	0.357	-0.125	-0.440	-1.006	-1.166	-1.085	-0.400	0.138
2010	0.703	0.808	1.090	1.060	0.701	0.058	-0.690	-0.700	-1.117	-0.851	-0.731	0.150
2011	0.642	0.659	0.948	1.101	0.814	0.086	-0.328	-1.194	-1.404	-1.287	-0.377	0.237
2012	0.531	0.551	0.782	0.698	0.195	-0.216	-1.053	-1.232	-1.426	-0.800	-0.181	0.706
2013	0.794	0.816	1.105	1.183	0.950	-0.053	-1.120	-1.734	-1.610	-1.144	-0.050	0.442
2014	0.819	0.598	0.546	0.236	0.042	-0.503	-0.965	-1.211	-1.174	-0.675	-0.020	0.676
2015	0.733	0.688	0.767	0.813	0.750	0.132	-0.782	-1.517	-1.655	-1.223	-0.146	0.600
2016	0.781	0.779	0.988	1.070	0.652	0.080	-0.709	-1.198	-1.323	-0.936	-0.074	0.610
2017	0.743	0.759	1.026	1.170	0.855	0.025	-0.402	-1.005	-1.038	-0.842	0.035	0.409
2018	0.712	0.767	1.048	1.199	0.649	-0.122	-0.720	-1.352	-1.321	-1.120	-0.010	0.429
2019	0.746	0.737	1.078	1.017	0.733	-0.151	-1.029	-1.647	-1.654	-1.496	-0.628	0.004
2020	0.684	0.668	0.854	1.040	0.775	-0.096	-0.815	-1.378	-1.515	-1.182	-0.367	0.405

Appendix H3: Spatio-temporal analysis for SPEI-3 Yola

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2006			1.116	1.019	0.581	-0.225	-0.943	-1.414	-1.516	-1.430	-0.802	-0.020
2007	0.448	0.663	1.007	0.896	0.297	-0.493	-1.039	-1.425	-1.375	-1.106	-0.250	0.219
2008	0.673	0.837	1.227	1.311	1.140	0.401	0.021	-0.162	-0.486	-0.474	0.023	0.596
2009	0.878	0.881	1.094	1.000	0.656	-0.070	-0.607	-1.078	-1.059	-0.779	-0.056	0.316
2010	0.642	0.813	1.166	1.030	0.744	-0.137	-0.780	-1.153	-1.094	-0.923	-0.456	-0.075
2011	0.528	0.761	1.139	1.272	0.858	0.270	-0.129	-0.522	-1.033	-0.955	-0.550	0.013
2012	0.453	0.693	1.052	1.165	0.648	-0.219	-0.921	-1.259	-1.279	-1.054	-0.372	0.238
2013	0.729	0.904	1.055	1.047	0.516	-0.043	-0.587	-0.781	-0.920	-0.758	-0.291	0.327
2014	0.738	0.883	1.012	0.818	0.441	-0.115	-0.655	-1.033	-1.120	-0.842	-0.275	0.240
2015	0.597	0.802	1.007	1.200	1.075	0.556	0.050	-0.632	-1.109	-0.995	-0.444	0.261
2016	0.692	0.862	1.172	1.046	0.350	-0.662	-1.041	-1.296	-1.353	-1.166	-0.530	0.348
2017	0.722	0.877	1.169	0.986	0.188	-0.455	-1.077	-1.169	-1.267	-0.728	-0.050	0.577
2018	0.751	0.825	1.025	1.019	0.476	-0.517	-1.090	-1.347	-1.310	-1.034	-0.409	0.350
2019	0.742	0.841	1.112	1.077	0.429	-0.363	-1.125	-1.381	-1.518	-1.505	-0.955	-0.121
2020	0.690	0.784	1.045	1.085	0.813	0.062	-0.987	-1.247	-1.292	-0.738	-0.198	0.379

Appendix I1: Spatio-temporal analysis for SPEI-6 Gombe

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2006						1.139	0.417	0.010	-0.796	-1.040	-0.941	-0.670
2007	-0.214	0.189	1.041	1.207	1.087	0.762	0.098	-0.374	-0.824	-0.867	-0.755	-0.439
2008	-0.035	0.664	1.197	1.262	1.022	0.711	0.389	-0.165	-0.764	-0.928	-0.708	-0.441
2009	-0.100	0.495	1.132	1.262	0.966	0.623	0.162	-0.228	-0.730	-0.930	-0.705	-0.372
2010	0.056	0.450	0.942	1.128	1.028	0.655	0.139	-0.156	-0.509	-0.589	-0.432	-0.111
2011	0.155	0.688	1.125	1.296	1.216	1.046	0.581	-0.079	-0.357	-0.540	-0.477	-0.291
2012	-0.048	0.608	1.079	1.258	1.092	0.572	-0.025	-0.832	-1.286	-1.356	-1.254	-0.872
2013	-0.137	0.530	1.144	1.245	1.171	0.863	0.444	-0.607	-0.966	-1.095	-1.023	-0.749
2014	-0.395	0.674	1.092	1.243	0.972	0.737	0.162	-0.094	-0.829	-0.938	-0.720	-0.505
2015	0.038	0.325	1.125	1.313	1.258	0.972	0.512	-0.025	-0.787	-1.052	-0.991	-0.727
2016	-0.328	0.159	0.901	0.995	0.747	0.271	0.089	-0.659	-1.077	-1.017	-0.807	-0.426
2017	-0.013	0.560	1.138	1.193	0.819	0.395	-0.014	-0.534	-1.078	-1.145	-0.856	-0.493
2018	0.095	0.450	1.110	1.258	0.955	0.676	0.084	-0.681	-1.428	-1.519	-1.307	-1.118
2019	-0.643	0.104	1.079	1.188	0.934	0.017	-0.601	-1.162	-1.487	-1.806	-1.654	-1.047
2020	-0.326	0.134	0.603	1.094	0.733	0.220	-0.451	-1.065	-1.578	-1.681	-1.464	-1.110

Appendix I2: Spatio-temporal analysis for SPEI-6 Bauchi

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2006						0.883	0.243	-0.017	-0.431	-0.625	-0.433	-0.118
2007	0.090	0.572	0.987	1.104	1.111	0.920	0.442	-0.263	-0.650	-0.750	-0.781	-0.614
2008	-0.167	0.541	0.987	1.152	1.107	0.599	0.206	-0.271	-0.533	-0.664	-0.576	-0.062
2009	0.136	0.887	1.162	1.101	0.971	0.667	0.232	-0.292	-0.860	-0.964	-0.857	-0.597
2010	-0.224	0.313	0.963	1.228	1.121	0.778	0.161	-0.017	-0.701	-0.921	-0.826	-0.530
2011	0.026	-0.068	0.909	1.218	1.105	0.873	0.507	-0.318	-0.933	-1.115	-1.040	-0.865
2012	-0.571	0.205	0.881	0.993	0.748	0.447	-0.185	-0.652	-1.220	-1.186	-0.968	-0.697
2013	-0.075	0.490	1.248	1.317	1.233	0.712	-0.059	-1.107	-1.382	-1.523	-1.462	-1.084
2014	-0.247	0.628	0.876	0.898	0.540	0.094	-0.307	-0.821	-1.097	-1.011	-0.733	-0.351
2015	0.025	0.690	1.092	1.138	1.090	0.817	-0.047	-0.821	-1.274	-1.336	-1.302	-1.097
2016	-0.372	0.497	1.152	1.267	1.086	0.747	0.147	-0.395	-0.940	-1.011	-0.869	-0.587
2017	-0.023	0.540	1.173	1.289	1.168	0.871	0.476	-0.053	-0.502	-0.700	-0.588	-0.305
2018	0.069	0.617	1.086	1.287	1.079	0.638	0.193	-0.612	-1.041	-1.191	-1.022	-0.663
2019	-0.249	0.573	1.108	1.230	1.104	0.630	-0.011	-1.035	-1.487	-1.785	-1.710	-1.419
2020	-0.814	0.039	0.637	1.212	1.092	0.721	0.021	-0.597	-1.167	-1.319	-1.243	-0.954

Appendix I3: Spatio-temporal analysis for SPEI-6 Yola

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2006						0.601	0.112	-0.646	-1.286	-1.607	-1.510	-1.182
2007	-0.735	0.032	0.639	1.012	0.787	0.284	-0.059	-0.808	-1.301	-1.425	-1.213	-0.796
2008	-0.260	0.370	1.068	1.368	1.364	1.173	0.996	0.620	-0.086	-0.087	-0.004	0.035
2009	0.220	0.593	1.208	1.311	1.123	0.657	0.184	-0.241	-0.779	-0.891	-0.787	-0.420
2010	0.040	0.496	1.089	1.198	1.134	0.654	0.047	-0.268	-0.850	-1.116	-1.089	-0.680
2011	-0.163	0.162	0.835	1.268	1.169	1.047	0.723	0.168	-0.421	-0.724	-0.665	-0.571
2012	-0.239	0.042	0.840	1.167	1.012	0.524	-0.005	-0.437	-1.062	-1.308	-1.130	-0.685
2013	-0.173	0.318	0.980	1.256	1.056	0.653	0.230	-0.039	-0.641	-0.863	-0.683	-0.281
2014	-0.112	0.367	1.008	1.134	1.001	0.576	0.029	-0.321	-0.860	-0.971	-0.879	-0.524
2015	-0.046	0.329	0.954	1.267	1.310	1.137	0.802	0.208	-0.331	-0.650	-0.671	-0.501
2016	-0.135	0.233	1.061	1.235	0.935	0.242	0.030	-0.642	-1.378	-1.469	-1.253	-0.704
2017	-0.294	0.173	1.110	1.218	0.846	0.415	-0.045	-0.601	-1.186	-1.197	-0.866	-0.486
2018	-0.077	0.507	1.159	1.252	0.987	0.275	-0.037	-0.629	-1.258	-1.410	-1.229	-0.656
2019	-0.145	0.249	1.079	1.279	0.970	0.453	-0.040	-0.691	-1.359	-1.777	-1.576	-1.235
2020	-0.693	-0.041	0.591	1.255	1.157	0.718	0.110	-0.330	-0.919	-1.135	-1.021	-0.622