EVALUATION OF SPATIO-TEMPORAL CHARACTERISTICS OF METEOROLOGICAL DROUGHT OVER SELECTED STATIONS IN NORTH-WESTERN REGION OF NIGERIA

BY

SALIU, IBRAHEEM ISHOLA
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ABSTRACT

Global warming has resulted in extreme variability in climate change leading to development of extreme related conditions; one out of these extreme conditions is drought. In the light of this, this study evaluated spatio-temporal characteristics of meteorological drought over selected stations in North-Western region of Nigeria. To be able to address this issue, the study employed three (3) meteorological indices namely: SPI, SnsPI and SPAI to characterise meteorological drought at different timescales of 3, 6 and 12 months. At 6-month timescale for the SnsPI model, the percentages of severe conditions were recorded as: Gusau (11.5%), Kaduna (10.64%), Kano (8.45%), Katsina (4.23%), Sokoto (12.76%), Yelwa (15%) and Zaria (16.67%) while the SPI recorded the percentages of severe conditions as follows: Gusau (13.8%), Kaduna (9.86%), Kano (2.61%), Katsina (9.86%), Sokoto (4.17%), Yelwa (6.58%) and Zaria (7.80%). So also, the SPAI severe conditions recorded as: Gusau (2.29%), Kaduna (6.29%), Kano (3.37%), Katsina (1.29%), Sokoto (4.30%), Yelwa (3.90%) and Zaria (2.29%). Similarly, the results of the principal component analysis showed that the first two components contributed largely to the total cumulative variance with values: PC1 (69.18) and PC2 (52.29). Based on the results, it could be concluded that the non-stationary standardised precipitation index (SnsPI) is more effective than any other rainfall-based indices for drought analysis. Similarly, based on the regionalisation patterns drawn, it could be concluded that the entire North-Western zone can be classified to three (3) homogenous zones.

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CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

Drought is a very common disaster in most countries of the world, particularly in the arid and semi-arid regions (Achugbu and Anugwo, 2016). It is defined as a “period of insufficient rainfall either in time or in space” caused by low rainfall, often associated with high rates of evaporation. This causes crop failure, enough to cause a severe shortage of food in a rural population (Li *et al*., 2019). The underlying causes of most droughts can be related to changing weather patterns which manifested through the excessive buildup of heat on the earth’s surface, meteorological changes which result in a reduction of rainfall, and reduced cloud cover, all of which results in greater evaporation rates (Abubakar and Yamusa, 2016). The impacts of drought in general include mass starvation, famine and cessation of economic activity especially in areas where rain fed agriculture is the main stay of the rural economy (Olatunde and Aremu, 2013). Different types of drought can be distinguished, (e.g., which are meteorological, Agricultural, hydrological and socio-economic drought.

Drought is a complex phenomenon which varies spatially and temporally in its extent, duration, frequency and severity. It becomes important to study the drought distribution characteristics on the time and space of a region and cause of the drought for the design and management of water resource systems (Hisdal, 2003; Rhee and Carbone, 2007; Bao *et al*., 2011). Spatial and temporal analysis can also help to assess the exposure of water resources, vegetation patterns and the entire environment to drought.

Several indices have been developed to evaluate the water supply deficit in relation to the time duration of precipitation shortage (Van Loon, 2014). Drought indices are indicators used to characterize drought to assist decision makers for taking measures for mitigating its effects (Zargar *et al*., 2011). Some of the most popular indices used in drought estimation include the Standardised Precipitation Index (SPI), the Standardised Precipitation Anomaly Index (SPAI), and Standardised non-stationary Precipitation Index (SnsPI). These indices have different significances depending on their characteristics based on robustness, transparency, sophistication, extendibility and dimensionality (Oguntunde *et al.*, 2017). Different researchers have suggested various drought indices best suited for a particular area based on their respective merits. Zhang *et al*. (2017) showed from his studies that Standardised Precipitation Index (SPI) is more feasible than other types of indices because of its versatile nature and flexibility for different timescales. The use of standardised drought indices, such as the SPI, as an operational basis of drought monitoring systems has been increasing in many parts of the world. Recommendations for the use of the SPI, and those indices that share its properties, do not take into account the limitations that this type of indices can exhibit under the influence of multi-decadal climate variability (Núñez *et al*., 2014).

Russo *et al.* (2013) developed a non-stationary Gamma distribution with its scale parameter linearly varying with time and then calculated a Standardised non-stationary Precipitation Index (SnsPI) to describe precipitation changes in Europe. In order to validate its reliability, the SnsPI was compared with the traditional SPI in respect of temporal and spatial assessment of historical droughts (Cavus and Aksoy, 2019). When an assessment of drought is required from social repercussion point of view, the SPI may not reflect the social consequences caused by deficit/surplus rainfall across both the high and low rainfall months. For instance, a rainfall deficit of 8.4mm in January (traditionally dry month) and 68.73mm in August (wet season) result in more or less similar values of SPI (Chanda and Maity, 2015). However, the consequences attributable to the rainfall deficit corresponding to a SPI value of (-2) in a traditionally dry period (January) are very different from the same corresponding to the similar SPI value in a climatologically wet period (August). The two events maybe statistically equally frequent, but have vastly contrasting socioeconomic impacts. Such issues may lead to practical difficulties while planning drought response activities (Pei *et al.*, 2020). This leads to the development of the Standardised precipitation Anomaly Index (SPAI) which can address the aforementioned challenges. The anomaly index may be able to differentiate between the aforementioned rainfall deficits (8.4mm in January and 68.73mm in August), which constitutes the motivation behind the development of the new index (González-Hidalgo *et al.*, 2018). The choice of these metrics is predicated on the need to ascertain the robustness of using only rainfall-based indexes for drought quantification taking cognisance of drought state transition and the spatio-temporal variability in rainfall pattern across the region with implications for relevant stakeholders; majorly, agricultural and hydropower generation (i.e., reservoir management with respect to inflow for resolving demand and supply requirements).

Despite the avalanche of available studies in this regard, majority of these works, especially in the case of drought analysis, establish homogenous meteorological drought areas for effective regionalisation is limited. In addition, no comprehensive studies focusing on drought scenarios have ever been exquisitely documented for North-western region of Nigeria.

1.2 Statement of the Problem

Inadequate documentation on meteorological drought state transition vis-à-vis climate change dynamics (Achugbu and Anugwo, 2016), high spatiotemporal variability associated with rainfall of the northern Nigeria (Aremu and Olatunde, 2012) and the vulnerability status of the rainfall of North-western region of Nigeria (Bibi *et al.*, 2014).

1.3 Aim and Objectives

The aim of this study is to evaluate spatio-temporal characteristics of meteorological drought over selected stations in North-Western region of Nigeria.

The objectives of the study are to:

i. determine trend and characterise the drought field

ii. establish homogenous meteorological drought areas for effective regionalisation

iii. compute drought intensity based on rainfall deficit for selected return periods

1.4 Justification of the Study

i. Pervasive and creeping nature of drought

ii. Lack of a comprehensive, robust singular drought index due to the spatiotemporal variability of the drought phenomena- conditioned on relevant evaluation criteria such as dimensionality, tractability, robustness and transparency.

iii. Researches on drought all over the World have shown that drought analysis gives important information on water deficit and its impact on agriculture and the hydrology of an area, which is a pre-requisite for mitigating drought and the planning of new water project. Therefore, a shift in focus to the provision of information in this direction is vital (Vicentra-Serrano *et al.*, 2012; Masih *et al.*, 2014).

1.5 Scope of the Study

The extent of coverage of the study is limited to the evaluation of spatiotemporal characteristics of meteorological drought over selected states in North-Western region of Nigeria. The study employed the use of secondary data for analysis. The limitation of this study is basically the lack of extensive and continuous data pool as well as the integrity of available data which affect result.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Concept of Drought

Drought is a normal, recurrent feature of climate, although it is erroneously considered as a rare and random event (Bao *et al*., 2011). It differs from aridity, which is restricted to low rainfall regions and is a permanent feature of climate. Drought should be considered relative to some long-term average conditions of the balance between precipitation and evapotranspiration (i.e., evaporation plus transpiration) in a particular area. It is also related to the timing (principal season of occurrence, delays in the start of the rainy season, occurrence of rains in relation to principal crop growth stages) and the effectiveness (i.e., rainfall intensity, number of rainfall events) of the rains (Hannaford *et al*., 2010). However, these are only conceptual definitions that are unable to give an operational definition of drought. There are two main definitions of drought: conceptual and operational.

2.1.1 Conceptual definition of drought

Conceptual definitions, formulated in general terms, help people understand the concept of drought. For example, drought is a protracted period of deficient precipitation resulting in extensive damage to crops, further resulting in loss of yield. Conceptual definitions may also be important in establishing drought policy (Masih *et al.*, 2014).

2.1.2 Operational definition of drought

An operational definition of drought helps people to identify the beginning, end, and degree of severity of a drought (Kirono, 2011). This definition is usually made by comparing the current situation to the historical average, often based on a 30-year period of record (according to World Meteorological Organization recommendations).

2.2 Types of Drought

Vangelis *et al.,* (2013) explained that drought is multidimensional with lots of contributory factors in any region but its beginning usually points to lack of precipitation which may or may not affect soil moisture, streams, groundwater, ecosystems and human beings depending on how severe it is. This therefore, points to the identification of different drought types which reflects the perspective of various water sectors.

According to Zarch *et al.* (2011), drought can be classified 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.

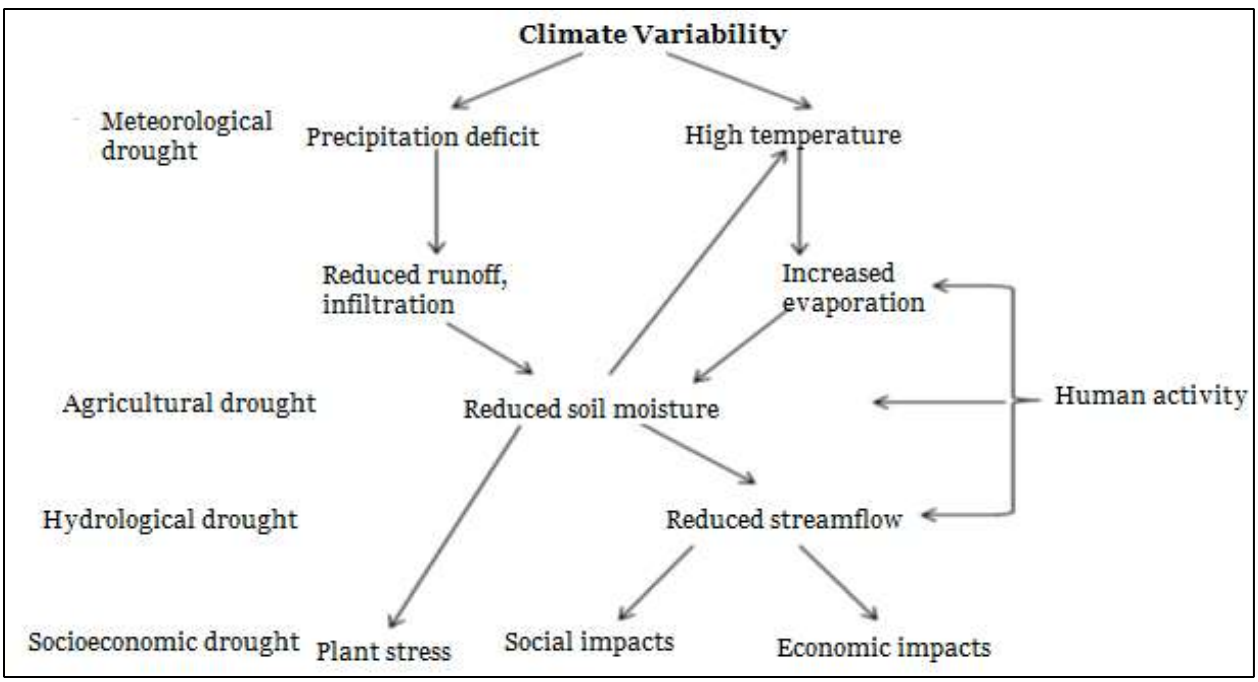

Figure 2.1: Interaction of different variables in the hydrological cycle during drought.

Source: (Hisdal *et al.,* 2003)

2.2.1 Meteorological: Meteorological drought refers to a precipitation deficiency, possibly combined with increased potential evapotranspiration, extending over a large area and spanning an extensive period of time (Achugbu, and Anugwo, 2016).

2.2.2 Agricultural (soil moisture drought): Soil moisture drought is a deficit of soil moisture (mostly in the root zone), reducing the supply of moisture to vegetation. Soil moisture drought is also called agricultural drought, because it is strongly linked to crop failure (Sepulcre-Canto *et al.*, 2012).

2.2.3 Hydrological: Hydrological drought is associated with the effects of periods of precipitation (including snowfall) shortfalls on surface or subsurface water supply (i.e., streamflow, reservoir and lake levels, groundwater). The frequency and severity of hydrological drought is often defined on a watershed or river basin scale. Hydrological with respect of the land use although climate is a primary contributor to hydrological drought, other factors such as changes in land use (e.g., deforestation), land degradation, and the construction of dams all affect the hydrological characteristics of the basin(McEvoy *et al.*, 2012).

2.2.4 Socio-economic: Socioeconomic drought is associated with the impacts of the three above-mentioned types. It can refer to a failure of water resources systemstomeetwaterdemandsandtoecologicalor health-related impacts of drought.

2.3 Causes of Drought in Northern Nigeria

The causes of drought can be the nature of the changing weather patterns which often seen via uncontrolled buildup of heat on the earth's surface, meteorological changes which result in a reduction of rainfall, and reduced cloud cover, all of which results in greater evaporation rates. Another cause is the over active participation of human activities which affects the climatic condition of the land and forest. These human activities are bush burning, deforestation, overgrazing and poor cropping methods, reduction of water retention in the soil, and improper soil conservation techniques, which lead to soil degradation. According to a research done by Lester, (2006), between 1950 and 2006, the Nigerian livestock population grew from 6 million to 66 million, which was an 11-fold increase. Meanwhile, the needs of livestock exceeded the carrying capacity of its grasslands. Hence, overgrazing and over-cultivation of land was converting 351,000 hectares of land space into desert annually. That made the rate of land degradation acute when used for farming practices on marginal land such as arid and semi rid lands, hilly and mountainous areas and wetlands. Large numbers of inhabitants of the drought prone areas are small arable farmers, who depend mostly on the highly variable rainfall for crop cultivation and maintenance of their herds (Abdullahi *et al.,* 2006).

2.3.1 Effects of drought in Northern Nigeria

Generally speaking, drought has a vast effect on mass starvation, famine and cessation of economic activity especially in areas where rainfed agriculture is the main stay of the rural economy (Mendicino *et al.,* 2000). Forced human migration and environmental refugees, deadly conflicts over the use of dwindling natural resources, food insecurity and starvation, destruction of critical habitats and loss of biological diversity, socio-economic instability, poverty and climatic variability through reduced carbon sequestration potential are common knowledge of the causes of drought (Asadizarch *et al*., 2011). Several researches have been conducted on the effect of drought and they have come to terms that drought especially in Africa and with particular reference to Nigeria assert that several challenges such as the widespread poverty, the fact that Nigeria's economy depend on climate-sensitive sectors mainly rain fed agriculture, poor infrastructure, heavy disease burdens, high dependence on and unsustainable exploitation of natural resources, and conflicts are major reasons why drought often harm the Northern region of Nigeria (Aremu and Olatunde, 2012). Other forms of effect of drought was identified in the work done by Jibrin, (2010) such as low or no crop yields resulting in low food security index; mass famine; death of livestock; low groundwater levels resulting in dry wells (which needed to be dug deeper and deeper to obtain water for drinking); drying of lakes and dams; loss of biodiversity and impoverishment of ecosystem;

acute shortage of water for domestic use and for livestock; decline in GDP; migration into urban areas; separation of families; and increased indebtedness.

2.3.2 Short term measures for combating drought and its effects

(i) Drought Information Dissemination and Relief Measures

Dissemination of information to the farmers, animal herders and other stakeholders should be done regularly and as at when due. This is to inform them of an impending drought, its likely intensity and the measures to be adopted by the citizens to mitigate its effects. Also, relief measures for example, distribution of food, water and drugs should be done immediately drought sets in (Van loon, 2014).

(ii) Strategic Irrigation

This measure includes installing drip irrigation that directs water to the roots of crops. Irrigation of land should also be done in the morning to minimize evaporation. Though large-scale irrigation of land is advisable especially during drought and in arid regions as in the study region, however, marginal lands as found in the South Chad irrigation project area should not be irrigated to avoid ecological damage and land degradation (Jibrin, 2010). Irrigation of lands outside arid areas should also be intensified to make food available and abundant all year round. Land cultivation where the soil permits should be mechanized as tilling of soils with crude implements like hoes and cutlasses especially during drought make land cultivation tedious and uninteresting.

(iii) Good Land Husbandry

Drought tolerant and resistant crops and short season varieties of cereals like sorghum and millet as well as succulent plants should be planted (Mishra and Singh, 2010). Regular weeding is also recommended as unwanted plants use up lots of water. Also the adaptation of a trap crop based cropping system and seed treatment with sodium chloride ($NaCl$) should be explored to reduce the menace of Striga (witch weed) mentioned earlier under effects of drought on weeds (Gebrehiwot *et al.*, 2011). Pesticides and insecticides should be applied to kill off insect, birds and locust that breed extensively during drought. The collaborative effort of various tiers of government should be intensified in this regard (Dai, 2011).

(iv) Herd and Pasture Management

There is the need by animal herders in this region to adopt modern animal rearing methods for example ranching and rotational grazing. (It involves the subdivision of the grazing land or ranch into sections called paddocks and the rotation of animals from one paddock to another to ensure that no part of the land is overgrazed). Land can be improved on through reseeding (Cunderlik and Burn, 2003). There is also the need to alert the herders beforehand of an impending drought and educate them of the various herd management methods that include reduction in herd numbers to balance the land carrying capacity to avoid over grazing. Other methods include weaning of calves during drought, herd segregation and parasite control.

(v) Construction of Wells, Boreholes and Ponds

This measure includes refurbishing old and shallow wells and boreholes and also digging new ones to tap into the groundwater to immediately relieve the populace of the need for water in areas affected by drought, although, this on the long run has some negative effects on the environment (Zhang *et al.*, 2017). Also, ponds can be constructed to boost fishing activities in areas where drought has drastically reduced the amount of water in rivers and lakes (for example Lake Chad). In fact, the construction and management of the ponds should be taught to fishermen that face the prospect of losing their means of livelihood due to drought. There is also the need to expand and conclude the programme embarked on earlier for the establishment of small scale hydropower dams in conjunction with United Nations Industrial Development Organisation (Aremu and Olatunde, 2012).

(vi)Soil and Water Conservation and Management

The soil water of the region can be conserved and managed through the combination of the following practices; carefully planned crop rotation (help to minimize erosion), terracing, minimum tillage of the soil, litter management, shelter belts construction, use of organic fertilizers (to enhance soil composition and improve water retention) thereby combating drought (Rossi *et al.*, 1992).

The use of Green Infrastructure (G.I) in cities, towns and villages in the study region will help to reduce the actual and potential impact of radiation especially in reducing evaporation of water from soils and water bodies. It will also help to stabilize and protect the soil against water and wind erosion and also to combat the anthropogenic causes of drought and desertification (Eldouni *et al.*, 2007).

2.3.3 Long term measures for combating drought and its effects

i. Upgrading and Empowerment of Nigerian Meteorological Agency (NIMET)

   There is the need to adequately fund, equip and empower NIMET to carry out its constitutionally mandated functions. NIMET public enlightenment department also needs to be more proactive by giving out information as early as possible to stakeholders if possible, using their local dialects (Estrela, 2011).

ii. Establishment of National Drought Monitoring and Mitigation Agency (NDMMA)

   In order to effectively carryout the monitoring, mitigation and adaptation of measures to combat droughts in the study region, there is the need to establish an organization to coordinate and implement these measures (Strupczewski *et al.*, 2001). The proposed organisation can be called the “National Drought Monitoring and Mitigation Agency” (NDMMA). The body should be a parastatal of the federal ministry of environment. Corresponding bodies should also be established at the state and local government levels.

iii. The agency (NDMMA) will be charged with the responsibility of collecting data on the effects of droughts on the people for future reference and use. The agency should also be responsible for the amelioration of the impacts and effects of drought on the people and the environment. This is because the present National Emergency Management Agency (NEMA) at least at the federal level is finding it difficult to successfully carryout this task. There is also the need to establish the “drought fund” to be administered by the agency (NDMMA). This is because the present ecological fund barely makes an impact in funding the mitigation of drought effects in the study region.

iv. Weather and Microclimate Modification

Cloud seeding which is the artificial technique to induce rainfall to ameliorate the low amount of rainfall in the region may be introduced. The down side to this approach is its high cost and logistics on such a large scale (Bornaccorso *et al.,*2003).

v. Transvasement (Inter-basin Transfer of Water)

It involves the construction of canals and pipelines or the redirection of rivers to or through drought-stricken areas to ameliorate droughts (Zhang *et al.*, 2017). That is the large-scale transfer of water from area of surplus (Southern Nigeria) to areas of deficit (study region).

vi. Xeriscaping or Hard Landscaping

This is the type of landscaping that uses limited amount of water. It includes using decorative rocks, sculptures, trellises, wood decking, cobble lines, stepping stones and cemented screed blocks and also drought resistant plants to replace water loving plants as they required little or no water especially on farmlands and buildings (Tallaksen *et al.*,2009).

vii. Water Banking

This measure involves the temporary transfer of water from those who are willing to lease it those who are willing to pay to use it. In this method, people who hold water rights agree to temporarily let others use their allocation of water in return for a fee, for example from one irrigation farmer to another. The disadvantage of this method is that wealthy individuals may corner the available water and consideration may not be given to environmental needs (Tsakiris *et al.,* 2007).

viii. Water Recycling

Waste water from toilets/sewage and other house hold sources can be recycled in which water is being diverted to tunnels and then sent to water recycling plants. The recycled water may not be for drinking, but may be used for toilets, irrigation of farmlands and also in chemical and manufacturing processes (Bao, 2011).

ix. Dams

There is the need to refurbish the existing dams in the study region, especially those that are used for irrigation of farmlands so as to ensure that they perform optimally according to their installed capacity. New irrigation dams should also be constructed to alleviate water shortages for man, animals and crops. Therefore, there is the need to expediate action on the construction of the proposed KafinZaki dam in Bauchi state and the Zauro project in Kebbi State (Mika *et al.*, 2005).

x. Insurance and Food Storage

There is the need to re-organise and make more effective the Nigerian Agricultural Insurance Corporation. This will enable it to be able to effectively insure the small-scale farmers and animal herders against the impacts of drought occurrence in their various agricultural activities. There is also the need to construct, enlarge and complete the strategic food and grains reserves in the country by the various tiers of governments (Wu *et al.,* 2007). These are to serve as reservoirs that are to be used to combat the likely food shortages during droughts. Insecticides and pesticides can be applied to farmlands invaded by pests, insects and birds in a collaborative effort by the people and governments in the study region. The insects (grasshoppers) can be aggressively hunted and converted to food as being done in the north-eastern part of the country (Wells *et al*., 2004).

2.4 Indicators and Drought Indices

2.4.1 Indicators

Indicators are variables or parameters used to describe drought conditions. Examples include precipitation, temperature, streamflow, groundwater and reservoir levels, soil moisture and snowpack (Achugbu and Anugwo, 2016).

2.4.2 Droughts indices

Indices are typically computed numerical representations of drought severity, assessed using climatic or hydro-meteorological inputs (Bao *et al.,* 2011). They aim to measure the qualitative state of droughts on the landscape for a given time period. Indices are technically indicators as well. Monitoring the climate at various timescales allows identification of short-term wet periods within long-term droughts or short-term dry spells within long-term wet periods. Indices can simplify complex relationships and provide useful communication tools for diverse audiences and users, including the public. Indices are used to provide quantitative assessment of the severity, location, timing and duration of drought events (Núñez *et al.,* 2013). Severity refers to the departure from normal of an index. A threshold for severity may be set to determine when a drought has begun, when it ends and the geographic area affected (Elagib and Elhag, 2016).

The timing and duration are determined by the approximate dates of onset and cessation. The interaction of the hazard event and the exposed elements (people, agricultural areas, reservoirs and water supplies), and the vulnerabilities of these elements to droughts, determines the impacts. Vulnerabilities may have been exacerbated by previous droughts, which, for example, might have triggered the sale of productive assets to meet immediate needs. The timing of droughts may be as significant as their severity in determining impacts and outcomes (Peters, 2003). A short, relatively low severity, intra-season drought, if it occurs during the moisture sensitive period of a stable crop, can have a more devastating impact on crop yield than a longer, more severe drought occurring at a less critical time during the agricultural cycle. Thus, drought indices – in combination with additional information on exposed assets and their vulnerability characteristics – are essential for tracking and anticipating drought-related impacts and outcomes (Thorntwaite, 1984). Indices may also play another critical role, depending on the index, in that they can provide a historical reference for planners or decision-makers (Storch and Zwiers, 2009). This provides users with a probability of occurrence, or recurrence, of droughts of varying severities. Importantly, however, climate change will begin to alter historical patterns. Information derived from indicators and indices is useful in planning and designing applications (such as risk assessment, DEWSs and decision-support tools for managing risks in drought-affected sectors), provided that the climate regime and drought climatology is known for the location (Wagan *et al.,* 2015). In addition, various indictors and indices can be used to validate modelled, assimilated or remotely sensed indicators of drought. There are several indices that measure how much precipitation for a given period of time has deviated from historically established norms (Li *et al.,* 2009).

Although none of the major indices is inherently superior to the rest in all circumstances, some indices are better suited than others for certain uses (Heim, 2002). In the international publications different indices have been discussed and applied. Among these are:

a. Percent of Normal

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

$$I = \frac{<P>}{<P>_{30}} \times 100 \qquad (2.1)$$

Values of the index less than 100 means drought conditions exist.

a. Deciles

The distribution of the time series of the cumulated precipitation for a given period is divided into intervals each corresponding to 10% of the total distribution (decile). Gibbs and Maher (1967) proposed to group the deciles into classes of events as listed in table 2.1:

Table 2.1: Deciles categorization values

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

Source: (Olatunde and Aremu, 2013)

c. Palmer Drought Severity Index (PDSI)

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

Table 2.2: Index classification of PDSI values

PDSI	CLASS
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
-1.9 to 1.99	Mild drought
-2.0 to -2.99	Moderate drought
-3.0 to 3.99	Severe drought
-4.0 or less	Extremely drought

Source: (Mishra and Singh, 2010)

d. Surface Water Supply Index (SWSI)

The Surface Water Supply Index (SWSI) was developed to complement the Palmer Index. It is designed for large topographic variations across a region and it accounts for snow accumulation and subsequent runoff. The procedure to determine the SWSI for a particular basin is as follows: monthly data are collected and summed for all the precipitation stations, reservoirs, and snowpack/streamflow measuring stations over the basin. Each summed component is normalized using a long-term mean. Each component has a weight assigned to it depending on its typical contribution to the surface water within that basin. Like the Palmer Index, the SWSI is centered on zero and has a range between -4.2 and +4.2. The SWSI suffers the same limitations discussed for the PSDI.

e. Standardised Precipitation Index (SPI).

The SPI was developed by McKee *et al.* (1993). It was designed to quantify the precipitation deficit for multiple time scales. These time scales reflect the impact of a drought on the availability of the different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale. Groundwater, streamflow, and reservoir storage reflect the longer-term precipitation anomalies. For these reasons, McKee *et al*. (1993) originally calculated the SPI for 3, 6, 12, 24, and 48-month time scales. The calculation of the index needs only precipitation record. It is computed by considering the precipitation anomaly with respect to the mean value for a given time scale, divided by its standard deviation. The precipitation is not a normal distribution, at least for time-scales less than one year.

Therefore, the variable is adjusted so that the SPI is a gaussian distribution with zero mean and unit variance. A so adjusted index allows comparing values related to different regions. Moreover, because the SPI is normalized, wet and dry climates can be monitored in the same way. The index calculation is based on the following expressions:

$$\begin{aligned} SPI &= +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), t = \sqrt{ln\left(\frac{1}{H(P)^2}\right)} \quad per\ 0 < H(P) < 0.5 \\ SPI &= -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), t = \sqrt{ln\left(\frac{1}{(1 - H(P))^2}\right)} \quad per\ 0.5 < H(P) < 1 \end{aligned} \tag{2.2}$$

where P is the cumulated precipitation for the given time-scale, H(P) is the cumulative probability of the observed precipitation and c_0, c_1, c_2, d_1, d_2, d_3 are mathematical constants. The classification shown in the following table is used to define drought intensities resulting from the SPI computation:

Table 2.3: Drought intensities classification table resulting from SPI computation

SPI Values	Class
>2	Extremely Wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
0.99 to −0.99	Near normal
-1 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
<-2	Extremely dry

Source: (Chanda and Maity, 2015)

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:

(i) 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-1 and 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).

(ii) 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).

(iii) SPI-9 to SPI 24: The SPI computed at these time scales provide an indication of inter-seasonal precipitation patterns over medium time scale duration (9 months) and it also reflects long term precipitation patterns (12 to 24months). 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 (EDO, 2020).

(f) Reconnaissance Drought Index

Origins: Work was initiated by Tsakiris and Vangelis at the National Technical University of Athens, Greece.

Characteristics: Consists of a drought index that contains a simplified water balance equation considering precipitation and potential evapotranspiration. It has three outputs: the initial value, the normalized value and the standardised value. The standardised DRI value is similar in nature to SPI and can be compared to it directly. DRI is more representative than SPI, however, as it considers the full water balance instead of precipitation alone.

Input parameters: Monthly temperature and precipitation values.

Applications: Cases where impacts on agriculture or water resources are a primary concern.

Strengths: The use of potential evapotranspiration gives a better representation of the full water balance of the region than SPI provides, which will give a better indication of the drought severity. Weaknesses: Potential evapotranspiration calculations can be subject to errors when using temperature alone to create the estimate. Monthly timescales may not react quickly enough for rapidly developing droughts (Tsakiris and Vangelis, 2005).

(g) Rainfall Anomaly Index

Characteristics: 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.

Input parameters: Precipitation.

Applications: Addresses droughts that affect agriculture, water resources and other sectors, as RAI is flexible in that it can be analysed at various timescales.

Strengths: Easy to calculate, with a single input (precipitation) that can be analysed on monthly, seasonal and annual timescales.

Weaknesses: Requires a serially complete dataset with estimates of missing values. Variations within the year need to be small compared to temporal variations (Kraus, 1977).

(h) Standardised Anomaly Index

Origins: Introduced by Kraus in the mid-1970s and was examined closely by Katz and Glantz at the National Center for Atmospheric Research, United States, in the early 1980s. SAI was developed based on RAI, and RAI is a component of SAI. They are similar, but both are unique.

Characteristics: Based upon the results of RAI, and was developed to help identify droughts in susceptible regions, such as the West African Sahel and north-east Brazil.

Deviations are then averaged over all stations in the region to obtain a single SAI value.

Input parameters: Precipitation at monthly, seasonal or annual time steps.

Applications: Identifying drought events, especially in areas frequented by drought.

Strengths: Single input, which can be calculated for any defined period.

Weaknesses: Only uses precipitation, and calculations are dependent on quality data (Katz and Glantz, 1986; Kraus, 1977).

(i) Crop Moisture Index

Origins: As part of original work done by Palmer in the early 1960s, CMI is usually calculated weekly along with the Palmer Drought Severity Index (PDSI) output as the short-term drought component in which the impact on agriculture is considered.

Characteristics: As some of the drawbacks associated with PDSI became apparent, Palmer responded to them with the development of CMI. It is intended to be a drought index especially suited to drought impacts on agriculture, in that it responds quickly to rapidly changing conditions. It is calculated by subtracting the difference between potential evapotranspiration and moisture, to determine any deficit.

Input parameters: Weekly precipitation, weekly mean temperature and the previous week's CMI value.

Applications: Used to monitor droughts in which agricultural impacts are a primary concern.

Strengths: The output is weighted, so it is possible to compare different climate regimes. Respond quickly to rapidly changing conditions.

Weaknesses: As it was developed specifically for grain-producing regions in the United States, CMI may show a false sense of recovery from long-term drought events, as improvements in the short term may be insufficient to offset long-term issues (Palmer, 1968).

(l) Normalized Difference Vegetation Index

Origins: Developed from work done by Kogan, (1995) with the National Oceanic and Atmospheric Administration (NOAA) in the United States.

Characteristics: Uses the global vegetation index data, which are produced by mapping 4 km daily radiance. Radiance values measured in both the visible and near-infrared channels are used to calculate NDVI. It measures greenness and vigour of vegetation over a seven-day period as a way of reducing cloud contamination and can identify drought-related stress to vegetation.

Input parameters: NOAA AVHRR satellite data.

Applications: Used for identifying and monitoring droughts affecting agriculture.

Strengths: Innovative in the use of satellite data to monitor the health of vegetation in relation to drought episodes. Very high resolution and great spatial coverage.

Weaknesses: Data processing is vital to NDVI, and a robust system is needed for this step. Satellite data do not have a long history (Kogan, 1995; Tarpley *et al*., 1984).

(m) Standardised Precipitation Evapotranspiration Index (SPEI)

Characteristics: As a relatively new drought index, 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. SPEI has an intensity scale in which both positive and negative values are calculated, identifying wet and dry events. It can be calculated for time steps of as little as 1 month up to 48 months or more. Monthly updates allow it to be used operationally and the longer the time series of data available, the more robust the results will be.

Input parameters: Monthly precipitation and temperature data. A serially complete record of data is required with no missing months.

Applications: With the same versatility as that of SPI, SPEI can be used to identify and monitor conditions associated with a variety of drought impacts.

Strengths: The inclusion of temperature along with precipitation data 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 standardised. 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.

Weaknesses: The requirement for a serially complete dataset for both temperature and precipitation may limit its use due to insufficient data being available. Being a monthly index, rapidly developing drought situations may not be identified quickly. The computation of SPEI requires the potential evapotranspiration (PET) and rainfall data. The following steps were used to compute the SPEI values. The first step is to estimate potential evapotranspiration (PET) using Hargreaves model. The difference (D) between the Precipitation (P) and PET for the month i was computed as shown in equation (2.3).

$$D_i = P_i - PET_i \tag{2.3}$$

The calculated Di can be done on many timesteps (Vicente-Serrano *et al.*, 2010). The in a given month j and year I depends on the chosen time steps, k. i.e. the accumulated difference for one month in a particular year. A 12-month time step is as follows:

$$X_{i,j}^{k} = \sum_{i-13-k-j}^{12} D_{i-1,1} + \sum_{i=1}^{j} D_{i,1} \qquad if \;\; j < k, and$$

$$X_{i,j}^{k} = \sum_{i=j-k+1}^{j} D_{i,1}\, , if \; j \geq k \tag{2.4}$$

$Di$is then fitted to a three-parameter log-logistic distribution. The probability density function (PDF) of a three parameter Log-logistic distributed variable is expressed as:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1} (1 + (\frac{x-\gamma}{\alpha})^{\beta})^{-2} \tag{2.5}$$

Where α,β, and γ are scale, shape and origin parameters, respectively, for D values in the range (γ>D>∞). The parameters of the log-logistic distribution can be obtained using different procedures. Among them, the L-moment procedure is the most robust.

$$F(x) = (1 + (\frac{\alpha}{x-\gamma})^{\beta})^{-1} \quad (2.6)$$

Having obtained F(x), the SPEI is obtained in a standardised form of F(x).

2.5 Approaches to Rainfall Regionalisation

The conventional practice is to delineate regions based on physiography and or political/administrative boundaries (Gong *et al.*, 2021). To delineate effective homogeneous zones, a well regionalisation approaches have been developed over the past decades. This includes those based on:

i. Correlation Analysis between time series corresponding to all pairs of rain gauges in the study area. The first step is to pair gauges that have the highest correlation in rainfall as identical. The second are those greater than certain specified threshold and this is repeated until all gauges are assigned to the tentative groups. This approach to regionalisation found application in countries like Nigeria, United Kingdom, Tanzania and Sierra-Leone. The major challenge of regionalizingbasedoncorrelationapproachisthatthedelineatedregionsaresensitivetot hechoice of threshold value employed.

ii. The Principal Component Analysis (PCA) often referred as eigenvector or Empirical Orthogonal Function or Singular Decomposition Principal Components (PC) are orthogonal to each other which are derived through correlation and/or covariance matrix of rainfall in the study area (Jolliffe *et al.*, 2002). This approach involves plotting the un-rotated PC. The first PCs that accounted for significant percentage of the total variance loading on the map of the study area, or representing stations at point in two-dimensional space leading PCs. In regionalizing extreme rainfall, regions at frequency (growth) curves of rainfall extremes are constructed for each of the delineated regions using pooled information from the region by fitting regional regression relationship between PCs and the parameters of the distribution. This approach had been applied to precipitation data from various parts of the world including Africa, United Kingdom, Mexico, Austria, India Switzerland, Italy and Spain. This becomes cumbersome when large PCs account for significant percentage of total variance to address this problem PCA based on sequential sieving of stations was proposed for regionalisation. This procedure involves identification of first major sequential region by grouping sites that are highly correlated with the first significant PC. Those grouped sites are omitted and reduced dataset and subjected to PCA.

iii. Common Factor Analysis (CFA)

This approach to regionalisation involves application of factor analysis to inter-site correlation matrix to arrive at a common factor and specific factors. The analysis assumes a basic model for data that allows for accounting for specific variance which is not possible with PCA. The specific variance is related to local forcing that influence rainfall variability at the individual gauges in the study area and is different from the forcing that is common to a group of gauges (Keith, 1993).

In PCA, specific variance is distributed among all the loadings, indicating that the sum of localized effect is spread over the modes. In CFA, the variance is not manifested on any of the loadings. The common factor optimized to maximize variance shared by stations (Communality).

iv. Cluster Analysis Procedure

Cluster analysis is used in delineating interpreting patterns in data of explanatory influencing rainfall or loading PCs result from PCA (Rousseeuw, 1987). Each gauge is represented by a vector that comprises of explanatory variables which are referred to as attributes. The practice is to consider attributes as statistics computed from rainfall records. The statistic includes mean annual/seasonal/monthly and daily rainfall. When such statistics (attributes) form the basis for regionalisation, adequate number of sites with sufficiently long period of contemporaneous observation is necessary to form meaningful region and cannot be delineated in ungauged area that are not necessarily contiguous in geographical space. This approach finds its application in United States of America, Spain, Australia, South Africa, Lesotho, India and China.

Spectra variability refers to variation among Power Spectra Density (PSD) of standardised anomaly rainfall time series.

v. Hierarchical Regionalisation Approach

This explicitly account for spatial variability in moment of predict and (extreme rainfall). It is based on the hypothesis of higher order moment (e.g., skewness and kurtosis) of extreme rainfall data that do not display significant spatial variability over a larger area than relatively lower order moment (coefficient of variation) which in turn is assumed to vary more slowly over space than the first-order moment. Frequency of analysis at the target sites is used to estimate distribution parameters controlling the higher (lower) order moment.

2.6 Drought Severity and Terminologies

The already known concepts related to the drought process are the dry period length, drought duration, drought severity and drought intensity (Vangelis *et al.*, 2011). Also, the frequency or return period is used to characterise the drought. These concepts are defined as follows:

(a) Dry period length (L): The cluster which consists of consecutive negative values of SPI is referred to as the dry period length Figure (2.2). It begins in a month with a negative SPI and

(a) Dry period length (L):

The cluster which consists of consecutive negative values of SPI is referred to as the dry period length Figure (2.2). It begins in a month with a negative SPI and continues until a positive SPI value is obtained in the time series. A dry period is shown mathematically as in Equation (2.29)

$$A = \{SPI | SPI < 0\} \qquad (2.29)$$

where s(A) is the number of elements of set A that shows the length of the dry period as (Equation (2.30))

$$L = s(A) \qquad (2.30)$$

(b) Drought duration (D): Duration of droughts in an L-month long dry period.

(c) Drought severity (S): The accumulation of negative SPI values preceded and followed by positive SPI clusters is called severity. The severity of a drought D month-long is calculated by Equation (2.31).

$$S = \sum_{i=1}^{D} SPI_i, \quad SPI_i \in A \qquad (2.31)$$

In other words, it is the largest absolute value of the cumulative drought index (SPI in this study) in the dry period considered (Equation (2.32)):

$$S = \sum_{i=1}^{D} SPI \qquad (2.32)$$

(d) Drought intensity (I): The intensity is obtained by dividing the severity of the drought by its duration (Equation (2.33)):

$$I = \frac{S}{D} \qquad (2.33)$$

(e) Return period (or frequency): The return period of a drought is defined as the average time between two consecutive drought events. The drought frequency decreases with the increasing return period. In this study, the following definitions of (Cavus and Aksoy, 2019) are also considered:

(f) Critical drought severity: When more than one drought is recorded for any year, drought with the maximum severity is taken as the critical drought. No critical drought is assigned to a year in which drought is not observed.

(g) Within-period drought: Any drought with duration shorter than the dry period length is called within-period drought. For example, in a dry period of 3 months, there are three 1-month droughts and two 2-month droughts. Similarly, there are two 1-month droughts in a dry period of 2 months (Figure 2.2).

(h) Singular drought: Drought that extends over the dry period length is called a singular drought (Heim, 2002). For example, there exists a 1-month singular drought in a dry period of 1 month; a 2-month singular drought in a dry period of 2 months; a 3-month singular drought in a dry period of 3 months and so on. The length of dry period becomes the same as the drought duration for singular droughts while the former is larger than the latter for within-period droughts.

(i) No drought year: Any year with no negative run of SPI is considered a year with no drought (Clausen and Pearson, 1995). Thus, the critical drought severity is not calculated for such years; a zero value is assigned to the critical drought severity instead. It should be emphasized that drought is a process which is different than a dry period. It occurs any time when the value of the drought index (SPI in this study) takes a negative value. The drought can be as short as 1 month and as long as the dry period length. However, the critical drought concept introduced in this study considers the most severe drought of the year and eliminates all other milder droughts observed in the same year. The critical drought concept is meteorological station-based and therefore, area under the drought episodes are not considered (González-Hidalgo *et al*., 2018)

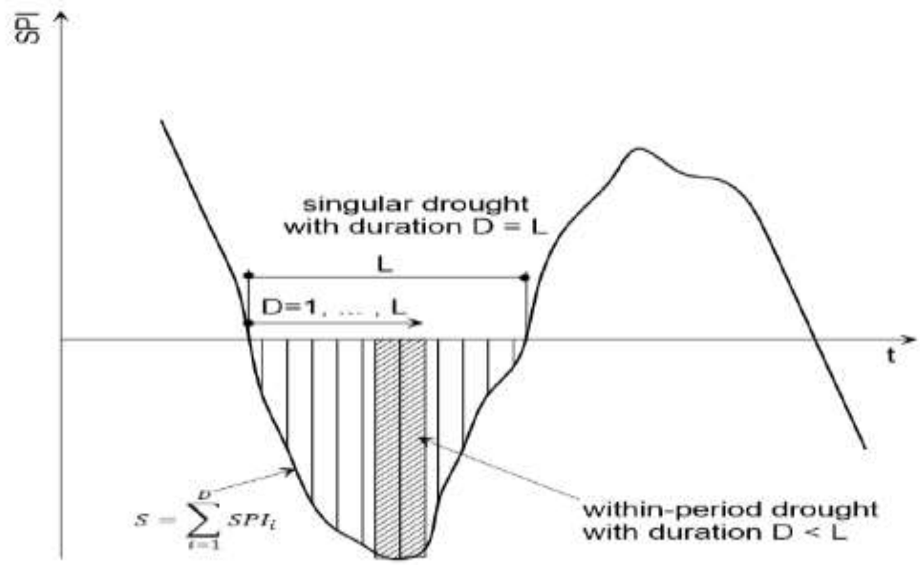

Figure 2.2: Dry period length (L), drought duration (D), and drought severity (S).

Source: (Dai, 2011)

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Materials and Study Area

3.1.1 Study Area

Northwest zone of Nigeria which comprises of the selected stations (Gusau, Kaduna, Kano, Katsina, Sokoto, Yelwa and Zaria)is located between Latitudes $9^{o}02^{1}$N and 13^{o} 58^{1}N and Longitudes $3^{o}08^{1}$E and 10^{o} 15^{1}E Figure(3.1). The area so defined covers a land area approximately 91, 633.75 squared miles Table(3.1). Northwest zone of Nigeria shares borders with Niger Republic in the northern part, Benin and Niger Republic in the Western part, Niger State and FCT to the south, and Yobe, Bauchi and Plateau States to the East.The climate of Northwest zone of Nigeria is the tropical wet-and-dry type (Koppen's Aw climate). The wet season lasts from April through October with a peak in August, while the dry season extends from November of one calendar-year to April of the next (Abaje*et al*., 2012). The annual average rainfall varies from about 1733 mm at the extreme southern part of the zone to about 600 mm at the extreme northern part (Abaje*et al.*,2016).

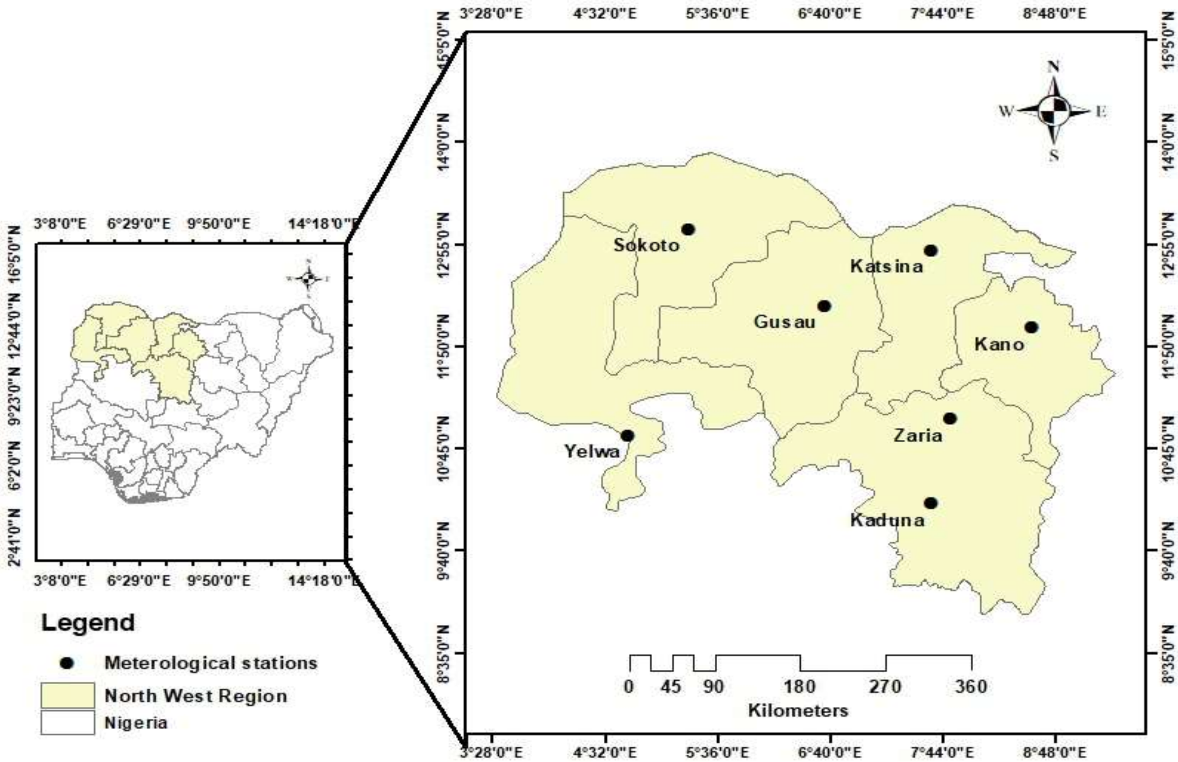

Figure 3.1: Map of North-Western region of Nigeria showing the study meteorological stations

The climate is dominated by the influence of the relative warm and moist tropical maritime (mT) air mass, which originates from the Atlantic Ocean associated with Southwest winds in Nigeria; and the relatively cool, dry and stable tropical continental (cT) air mass that originates from the Sahara Desert and is associated with the dry, cool and dusty Northeast Trades known as the Harmattan (Vasiliades *et al.*, 2011). These two air masses (mT and cT) me*et al*ong a slanting surface called the Inter-tropical Discontinuity (ITD). The movement of the ITD northwards across northern part of this zone in August (around latitude 21 to 22^{o}N) marks the height of the rainy season in the whole zone while its movement to the southernmost part around January/February (approximately at 6^{o}N) marks the peak of the dry season in the zone (Abaje *et al.*, 2017). The movement of the ITD is very irregular, varying according to the season from 2^{o} to 5.6^{o} of latitude per month, and the southward retreat of the ITD is faster than its northward advance. While the northward advance is at the rate of about 160 km per month, that of the southward retreat is at about 320 km per month. This accounts for the rather gentle onset of the rainy season in the zone and its rather abrupt end (Abaje, 2016). The highest average air temperature normally occurs during the hot season (March to May) while the lowest average air temperature occurs during the cold season (December to February) (Abaje *et al*., 2017).

Table 3.1: Land area of North-western zone by states

States	**Latitude (°)**	**Longitude (°)**	**Acres**	**Square miles**
Kaduna	10.50774	7.44101	10,450,326	16,594.14
Kano	12.00136	8.51475	4,988,880	7,921.88
Katsina	12.97245	7.58434	5,796,006	9,203.52
Yelwa	10.883	4.75000	9,098,310	14,447.27
Sokoto	13.06137	5.24632	6,844,950	10,869.14
Gusau	12.1459	6.71333	9,331,026	14,816.80
Zaria	11.08554	7.71995	139, 100	17, 781
Total			**46, 648, 598**	**91, 633.75**

Source: (Abaje *et al*., 2012)

3.2 Methods

3.2.1 Data collection

Daily rainfall data (15 years) for seven stations, Kaduna, Sokoto, Gusau, Kano, Katsina, Zaria and Yelwa were collected from the Nigerian Meteorological Agency (NIMET) by the Drought Early Warning System (DEWS) Team of Futminna. Before the datasets were used for the analysis, they were subjected to quality control test. Some of which are days with missing values and possible outliers, which might have occurred due to human or measuring equipment errors.

3.2.2 Preliminary data analysis

Based on the digest of the specific nature of the problems that drives the motivation for the study, there is the utmost need to ensure that the available data obtained for the study are of non-varying length so as to forestall compensatory information loss and by extension, enhance data quality assurance; i.e., reduce the possibilities of severe perturbations by considering stochastic characteristics like statistical moments. Specifically to this end, linear trend and statistical change point detection tests were carried out.

1) Linear trend and mutation detection

Trend and mutation detection of rainfall time-series has gained popularity among researchers for their usefulness in tracking the extent and magnitude of climate change and variability (IPCC, 2007).

Linear trend test and statistical change point (SCP) or Mutation detection: The overall objective here was to examine the rainfall data for regular movement in the time series through which the values are on the average, either increasing or decreasing. This is informed by the fact that the presence of a trend, either local or global could in effect be a part of low-frequency oscillatory movement induced by climatic factors or through changes in landuse and catchment characteristics (Yue and Wang, 2004).

Thus for this study, linear trend and mutation analysis were conducted by employing the following methods, respectively:

(a) Linear trend: (i) Mann–Kendall Test for annual and monthly series (ii) Sen’s Slope Estimator

(b) Statistical Change Point or Mutation: (i) Petitts' Test, and (ii) Sequential Mann–Kendall (SQ-MK) test.

(a) Linear Trend Analysis

(i)Mann-Kendall test for annual series

In the implementation of this approach, to remove the impact of serial correlation, the annual data series was pre-whitened as noted by (Wang *et al*., 2005). Thus, the annual series was pre-whitened by employing equation (3.1)

$$M_i = x_i - \Phi x_{i-1} \tag{3.1}$$

where,

M_i is the pre-whitened series value, x_i is the original series value, and Φ, the estimated lag-one (1) serial correlation value.

To fully implement the Mann-Kendall approach, the mean daily series (temperature and precipitation, respectively) were aggregated to annual mean values. The null hypothesis (H_o) for this test was that the series: $x_1 \ldots, x_N$ come from a population where the random variables are independent and identically distributed (IID). The test statistic S was expressed according as

$$S = \sum_{i=1}^{N-1} \sum_{k=i+1}^{N} \operatorname{sgn}(x_k - x_i) \tag{3.2}$$

where

$$\operatorname{sgn}(x) = \begin{cases} +1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases}$$

Mann-Kendall test statistic tau, τ is computed as

$$\tau = \frac{2S}{N(N-1)} \tag{3.3}$$

and

$$\sigma_s^2 = \frac{1}{18}\left[\begin{array}{l} N(N-1)(2N+5)- \\ \sum_{i=1}^{m} p_i(p_i-1)(2p_i+5) \end{array}\right] \tag{3.4}$$

Here, m is the number of tied groups in the data set andp_i, the number of data points in the i^{th} tied group. Similarly too, under the null hypothesis, the quantity z was taken to be standard normally distributed. Based on this,

$$z' = \begin{cases} (S'-1)/\sigma_{s'} & S' > 0 \\ 0 & S' = 0 \\ (S'+1)/\sigma_{s'} & S' < 0 \end{cases} \tag{3.5}$$

(ii) Mann - Kendall test for monthly or seasonal series

In line with Hirsch *et al*. (1982), the Kendall test in this regard allows for seasonality in the observations collected over a time period was employed; to do this, the Mann-Kendall test was computed on each season.

Thus, let the monthly or seasonal series be represented by the matrix

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix} \tag{3.6}$$

Here, p is the number of seasons for n years under consideration; similarly, let the matrix

$$R = \begin{pmatrix} R_{11} & R_{12} \cdots & R_{1p} \\ R_{21} & R_{22} \cdots & R_{2p} \\ \vdots & \vdots & \vdots \\ R_{n1} & R_{n2} \cdots & R_{np} \end{pmatrix} \tag{3.7}$$

denote the ranks corresponding to the observations in x where the n observations for each season are ranked among themselves. Thus, each column of R is a permutation of (1, 2,…., n). Specifically, the rank matrix R_{ij} was computed as

$$R_{ij} = \frac{1}{2}\left[n + 1 + \sum_{k=1}^{n} \operatorname{sgn}\left(x_{ij} - x_{kj} \right) \right] \tag{3.8}$$

The Mann-Kendall test statistic for each season is

$$S_i = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \operatorname{sgn}\left(x_{ji} - x_{ki} \right) \tag{3.9}$$

where, n is water years, i = number of seasons and a season here is defined as one calendar month, and S_i, the S-statistic in the Mann - Kendall test for season i (i = 1, 2, …, 12)

$S^{'} = \sum_{i=1}^{p} S_i$, p = seasons; $\sigma^2{}_{s'} = \sum_{i=1}^{p} Var\left(S_i \right)$

To account for serial correlation, as in monthly flow or discharge processes, the variance of S' is defined (Otache, 2008) as

$$\sigma^2{}_{s'} = \sum_{i=1}^{p} Var\left(S_i \right) + \sum_{g=1}^{p-1} \sum_{h=g+1}^{p} \sigma_{gh} \tag{3.10}$$

where the covariance matrix σ_{gh} is expressed as

$$\hat{\sigma}_{gh} = \frac{1}{3}\left[K_{gh} + 4\sum_{i=1}^{n} R_{ig} R_{ih} - n\left(n+1 \right)^2 \right] \tag{3.11}$$

$$K_{gh} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}\left[\left(x_{jg} - x_{ig} \right)\left(x_{jh} - x_{ih} \right) \right] \tag{3.12}$$

This is for a “no missing” data situation, and g and h are different seasons, respectively. The test statistic Z' which is standard normally distributed, is evaluated as

$$z' = \begin{cases} \left(S' - 1\right) / \sigma_{s'} & S' > 0 \\ 0 & S' = 0 \\ \left(S' + 1\right) / \sigma_{s'} & S' < 0 \end{cases} \tag{3.13}$$

(iii) Sen's slope estimator

The Sen's slope Estimator was employed to determine the magnitude of change of trend; in this case, the analysis was done by considering the implications of potential climate change nuances. The magnitude of the computed slope indicates the extent of the trend as to whether it is increasing or decreasing. This was determined according as in Equation (3.14).

$$T_{(i)} = \frac{x_{(j)} - x_{(k)}}{j - k} \tag{3.14}$$

where, x is the variable of interest; i.e., stage or discharge series on an annual basis. Accordingly, the slope magnitude in the overall was computed by using the statistic β given in equation

$$\begin{cases} \beta = \quad \frac{T(N+1)}{2} \text{ if N is odd} \\ \frac{T(N)}{2} + \frac{T(N+2)}{2} \text{ if N is even} \end{cases} \tag{3.15}$$

where, N is the length of the data series.

(b) Statistical Change Point (SCP) or Mutation Detection

The change point or mutation detection was done by employing the Pettit's test and Sequential Mann-Kendall test (SQ-MK test).

(i) Pettit's test

This test, developed by Pettit (1979) is a non-parametric test. As reported by Getahun *et al*. (2021), the basic reason for adopting this approach or test is that it is more sensitive to breaks in the middle of the time series. The algorithm for the implementation of the test is according as:

a. Compute U_k statistic using the following formula

$$U_k = 2\sum_{i=o}^{n} m_i - k(n+1) \quad (3.16)$$

where, m_i is the rank of the i^{th} observation when the values $x_1,\ x_2,\ \ldots.x_n$ in the series are arranged in ascending order and k takes values from 1, 2, ..., n.

b. Define the statistical change point test (SCP) as follows,

$$K = \max_{1 \le k \le n} |U_k| \quad (3.17)$$

when, U_k attains maximum value of k in a series, then a change point will occur in the series. The critical value is obtained by:

$$K_\alpha = [-\text{In}\ \alpha\ (n^3 + n^2)\ /\ 6]^{1/2} \quad (3.18)$$

where n is number of observation and α is level of significance which determines the critical value.

(ii) Sequential Mann – Kendall test (SQ – MK test)

The SQ-MK test proposed by Samy *et al.* (2019) was used for determining the approximate year of the beginning of a significant trend.

Procedure:

(a) The test sets up two series, a progressive one u(t) and a backward one or retrogade $u'(t)$. If they can cross each other and diverge beyond the specific threshold value, then there is a statistically significant trend. In other words, the point where they cross each other indicates the approximate year at which the trend begins.

Remark: Let U(t) be a standardised variable that has zero mean and unit deviation such that its sequential behaviour fluctuates around zero level. u (t) is the same as the z values that are found from the first to last data point. It considers the relative values of the terms in the time series $(x_1,\ x_2,\ \ldots.x_n)$.

The algorithm for its implementation is according as:

(b) Compute the magnitudes of x_j annual mean series (j = 1,…, n) with x_k, (k = 1, . . , j-1).

At each comparison, count the number of cases $x_j > x_k$and denote same as n_j.

(a) The test statistic t is given by the equation (3.19)

$$t_j=\sum_1^j n_j \tag{3.19}$$

(b) The mean and variance of the statistic are:

$$e(t) = \frac{n\,(n-1)}{4} \tag{3.20}$$

and

$$\text{Var } t_j = \frac{j(j-1)(2j+5)}{72} \tag{3.21}$$

(e) Compute the sequential values of u as

$$u(t) = \frac{t_j - e(t)}{\sqrt{var\ (t)}} \tag{3.22}$$

(f) Similarly, compute the values of $u'(t)$ in a backward manner. In doing so, start from the end of the series.

(g) Determine the point of intersection of the curves. The intersection of the curves showing the forward (u) and backward (u') represents the time when a trend or change starts; the critical value for 95% level is ± 1.96.

3.3 Detailed Study Design

3.3.1 Characterization of meteorological drought field

This was achieved using the following indices:

(a) Standardised Precipitation Index (SPI)

(b) Standardised Precipitation Anomaly Index (SPAI) and,

(c) Non-stationary Standardised Precipitation Index (SnsPI)

a. Standardised Precipitation Index (SPI)

The SPI is a common indicator of drought, which does not require information about land surface conditions and needs only precipitation amount to compute droughts. It is a normalized score and represents an event departure from the mean, expressed in standard deviation units. SPI is simple, spatially invariant, and probabilistic in nature and can be applied to analyse different types of drought phenomenon, such as meteorological, agricultural, and hydrological drought. The findings of several researchers (e.g., Szalai and Szinell, 2000; Chanda and Maity, 2015 andPei *et al*., 2020) revealed extensively that SPI is suitable for evaluating most types of drought events as it allows for drought analysis on different temporal accumulations. In practice, the computation of SPI index in a given year i and a calendar monthj, for a time scale k requires (McKee *et al*., 1993; Wu *et al*., 2007) the following steps:

i. Computation of cumulative precipitation series $X_{ij}^{k}(i = 1, \dots\dots, n)$ for the particular period of interest j, where each term is the sum of precipitation of $k - 1$ past consecutive months.

ii. Fitting of cumulative probability distribution (usually gamma distribution function) on aggregated monthly precipitation series. The gamma PDF is defined as,

$$g(x) = \frac{1}{\beta^{\alpha}\gamma(\alpha)} x^{\alpha-1} e^{\frac{-x}{\beta}} \tag{3.23}$$

Where β is a scale parameter, α is a shape parameter, which can be estimated using method of maximum likelihood and $\gamma(\alpha)$ is the gamma function at α. The estimated parameters can be used to find the cumulative probability distribution of observed precipitation event for the given month and particular time scale. The cumulative probability is obtained by integrating equation (3.23), i.e.

$$G(x) = \int_0^x g(x)dx = \int_0^x \frac{1}{\beta^{\alpha}\gamma(\alpha)} x^{\alpha-1} e^{\frac{-x}{\beta}} d(x) \tag{3.24}$$

iii. As two-parameter gamma function is not defined for zero values, and precipitation distribution may contain zeros, a mixed distribution function (zeros and continuous precipitation amount) is employed, and the CDF is given by the following:

$$\mathrm{F(x)} = \mathrm{q} + (1 - \mathrm{q})\mathrm{G(x)} \tag{3.25}$$

Where $\mathrm{G(x)}$ is the distribution function for nonzero precipitation probability from the historical time series.

iv. Because precipitation is not normally distributed, an equiprobability transformation is carried out from the cumulative distribution function (CDF) of mixed distribution to the CDF of the standard normal distribution with zero mean and unit variance, which is given as follows:

$$\mathrm{SPI} = \varphi[\mathrm{F(x)}] \tag{3.26}$$

This transformed probability is theSPI. A positive value of SPI indicates that precipitation is above average and a negative value denotes below average precipitation.

A drought period is assumed as a consecutive number of months where SPI values remains below a threshold of -0.8. Based on SPI range, drought period can be classified as moderate drought (-0.8 to -1.2), severe drought (-1.3 to -1.5), extreme drought (-1.6 to -1.9), and exceptional drought (-2 or less) conditions. Drought length or duration (D) is taken as the number of consecutive intervals (months) where SPI remains below this threshold value. Because the drought event is defined at aggregation of monthly time scale, the minimum duration of drought is 1month. Drought severity (S) is the cumulative values of SPI within the drought duration. For convenience, severity of drought event i, $\mathrm{Si}(\mathrm{i} = 1,2,\ldots)$ is taken to be positive, which is given by (McKee *et al*., 1993)

$$\mathrm{S_i} = -\sum_{\mathrm{i}=1}^{\mathrm{D}} \mathrm{SPI_i} \tag{3.27}$$

where $\mathrm{SPI_i}$ is value of ith period SPI for a D duration drought event.

b. Standardised Precipitation Anomaly Index (SPAI)

In the computation of SPAI, the precipitation anomalies were used instead of raw precipitation values. The anomalies of the precipitation are given by

$$y_{i,j} = x_{i,j} - x'_i \tag{3.28}$$

Where$y_{i,j}$ is precipitation anomalies for the ith year and jth year time step of the year: $x_{i,j}$is the precipitation value for the ith year and jth time step of the year. x'_i is the long term mean precipitation for the jth time step of the year. Noteworthy is that the unit of the rainfall anomaly series is the same as that of the rainfall series. This needs to be standardised to convert to the scale of Z score. It is explained as follows.

i. After obtaining the anomalies, a single probability distribution is fitted to the entire anomaly series (y). Gussian, t-location-scale, three parameter gamma or empirical distributions are various options to model the anomaly series.

ii. It is noted that because anomalies are not lower bounded by zero, the gamma distribution (commonly used in SPI computation) is not applicable here (Chanda and Maity, 2015). Though Gussian distribution might be most preferable among the alternatives, considering the higher order moments of rainfall anomaly series, it may not pass the statistical test(s) of distribution fitting. If a sufficiently long dataset (> 30-35 years) is available, am empirical distribution would be a good choice. Whereas goodness-of-fit tests are mandatory for parametric distributions, such as t-location-scale distribution and three parameter gamma distribution, the empirical distribution estimates the true underlying CDF of the points in the sample. To obtain the empirical CDF of the rainfall anomaly series (y), the Weibull's plotting position formula is found to be the best (Makkonen, 2006) and is expressed by

$$p = \frac{m}{N+1} \tag{3.29}$$

Where p is the cumulative probability, m is the rank of dataset arranged in descending order, and N is the sample size as explained before, i.e., the total number of the time steps in the dataset.

iii. After fitting the empirical distribution, the quantile values corresponding to each anomaly values are obtained. These quantile values, ranging from 0 to1. Maybe designated as the reduced variates of the rainfall anomalies. These reduced variates are transformed to standard normal variates (Z), i.e., the numbers on the real line which would correspond to the values of reduced variates in a standard normal distribution are determined. The obtained standard normal variates are (Z) are the required SPAI. Similar to the SPI, SPAI values also range between -∞ and +∞ where negative (positive) values reflect drier (wetter) conditions

c. Non-Stationary Standardised Precipitation Index (SnsPI)

It is worthwhile to present here a brief explanation of the methodology of computation of the Standardised non-stationary Precipitation Index (SnsPI), as it was developed to incorporate the variability of long precipitation datasets which cannot be appropriately handled by the SPI. The SnsPI is obtained by fitting the precipitation data to a non-stationary gamma distribution with a fixed shape parameter but a time varying scale parameter. This is implemented by expressing the mean of the rainfall series in terms of a time-dependent linear equation. The SnsPI may be computed at different temporal scales. Because we have considered monthly case in the case of SPI and SPAI, the same maybe considered here as well. Hence, if X_t represents the monthly rainfall series for a particular month, say January, and μ_t represents the nonstationary mean rainfall for that month, then

$$E(X_t) = \mu_t = b_1 + b_2 t \tag{3.30}$$

Where b_1 and $b_2$are constants; and t is time step. Thus, the mean rainfall for the month of January is not a constant; rather it is a function of time. The next step is to express this non-stationary monthly rainfall series as a gamma distribution, which is also used in the case of SPI. Thus $X_t \sim Gamma(\alpha, \beta_t)$, where α and $\beta_t$are the shape and scale parameters, respectively. The scale parameter β_t maybe expressed as

$$\beta_t = \frac{\mu_t}{\alpha} \tag{3.31}$$

If there zero rainfall values at the monthly scale, then a mixed distribution, consisting of a concentrated probability and a gamma distribution, maybe considered, as explained in the case of SPI. Subsequently, for each of the 12 monthly rainfall series, the cumulative distribution is transformed to standard normal variates (Z) to obtain the month-wise SnsPI series, which are then recognized into a chronological series.

3.4 Development of a Regionalised Spatiotemporal Drought Patterns

The principal component analysis (PCA) is a common way of identifying patterns in climatic data and expressing the data in such a way as to highlight their similarities and differences (Smith, 2002). The conventional practice is to delineate regions based on physiography and or political/administrative boundaries (Gong *et al.,* 2021). Others define the PCA method as a technique applied to multivariate analysis for dimensionality reduction, emphasizing patterns on data and relations between variables and between variables and observations (Lins, 1985; Tipping and Bishop, 1999; Jolliffe, 2002; Kahya *et al*., 2008a, 2008b). The original inter-correlated variables could be reduced to a small number of new linearly uncorrelated ones that explain most of the total variance (Bonaccorso *et al*., 2003). Some aspects in the use of PCA could be found, such as:

(i) PCAs are not affected by the lack of independency in the original variables;

(ii) Normality is desirable but not essential; and

(iii) Only an excessive number of zeros could cause problems, which in the applications envisaged is not a concern (Hair *et al*., 2005). The PCA method does not require normalized data sets as long as the data are not excessively skewed; since the drought indices are normalized variables, following the calculation procedure, there were no needs to previously transform data, nevertheless some normality assessment has been made previously to the PCA application (Kalayci and Kahya, 2006).

Furthermore, principal Component Analysis (PCA) can be used in the study of climatology and meteorology to further analyze data into monthly, annual, decadal and seasonal segment. Variability that exists between variability (Gong *et al.*, 2021) and can reduce a large number of interrelated variables from a multivariate data table to few variables (principal components). These variables correspond to a linear combination of the originals. The number of principal components is less than or equal to the original variables. The information in a given data set corresponds to the total variation it contains. The goal of PCA is to identify directions (or principal components) along which the variation in the data is maxima. It reduces the dimensionality of a multivariate data to two or three components that can be visualized graphically with minimal loss of information. PC transform, the matrix of the variables (X) is centered by subtracting its mean, and then the covariance matrix of x is obtained as follows:

$$S_{XX} = E(X^T X) \tag{3.32}$$

Where E is operator's expectation, knowing that the principal component is not invariant underscaling. Orthogonal decomposition of S_{XX} is given without loss of generality.

$$S_{XX} = U_X D_X U_X^T \tag{3.33}$$

Where the U_X is the matrix having the orthogonal eigenvectors of S_{XX} and D_X = diag (λ_1……. λ_k) represent the diagonal matrix of the eigenvalues of S_{XX} in decreasing order of magnitude. (Mavromatis and Stathis, 2011). The PC is given as below

$$V_X = X\ U_X \tag{3.34}$$

Where V_X of columns represent individual PC

3.5 Drought Intensity Based on Rainfall Deficit for Selected Return Periods

The probability of drought occurrence was determined based on the computation of absolute empirical probability. Considering that the return period of a given severity for particular drought duration was estimated using the equations below;

$$F(x) = 1 - \frac{1}{T} \tag{3.35}$$

$$F'(x) = \frac{1-\frac{1}{T}-p}{1-p} \tag{3.36}$$

Where T denotes the return period of a given drought severity and $F(x)$ represents the cumulative probability distribution function for zeros values and $F'(x)$ for non-zeros values.

CHAPTER FOUR

4.0 RESULT AND DISCUSSION

4.1 Trend and Drought Field Characterisation

4.1.1 Mann-Kendall test for annual and monthly rainfall

Tables 4.1(a and b) showed the Mann-Kendall test results for annual and monthly rainfall respectively, at 95% level of significance, the null hypothesis of no trend is rejected if |Z|>1.96. The Z-values for the months in all stations lie between the set Z-statistic value ($Z = \pm 1.96$), hence there were insignificant trend in the rainfall data for all the stations considered (Gusau, Kano, Kaduna, Katsina, Sokoto, Yelwa and Zaria). This implies that the rainfall data is free of potential persistence biases (noise) and can be used for computation.

Annual trends of precipitation using the Mann-Kendall test (Zs) presented in Table 4.1a. A significantly increasing trend in annual precipitation series was detected in all the stations at the 5% significance level between the year 2006 and 2020.

The results of the monthly Mann-Kendall test (Zs) test at the 5% significance level between 2006 and 2020 are presented in Table 4.1b. Positively significant trends in precipitation were observed in all stations. These trends indicate that there are fluctuations in the precipitation pattern all over Nigeria. Most of the changes occurred in the months of April, June, August and September. Similar findings were documented by Oguntunde *et al.* (2011) on rainfall trends in Nigeria; they noted that trends in the Sahelian region and regions south of 6ºN in the Niger Delta were insignificant at $p < 0.05$.

Table 4.1a: Mann-Kendall test for mean annual rainfall for all stations

Stations	Z-values	τ
Gusau	0.00	0.18
Kaduna	0.00	0.18
Kano	0.00	0.15
Katsina	0.00	0.16
Sokoto	0.00	0.17
Yelwa	0.00	0.2
Zaria	0.00	0.2

Table 4.1b: Monthly Mann-Kendall test for all stations

Month	Gusau		Kaduna		Kano		Katsina		Sokoto		Yelwa		Zaria	
	Z-value	τ	Z-value	τ	Z-value	τ	Z-value	τ	Z-value	τ	Z-value	τ	Z-value	τ
Jan	0.29	0.64	0.19	0.42	0.19	0.42	0.19	0.42	0.30	0.68	0.30	0.68	0.19	0.42
Feb	0.23	0.51	0.08	0.15	0.08	0.15	0.08	0.15	0.20	0.46	0.20	0.46	0.08	0.15
March	0.29	0.64	0.23	0.51	0.23	0.51	0.23	0.51	0.25	0.55	0.25	0.55	0.23	0.51
April	0.13	0.29	0.23	0.51	0.23	0.51	0.23	0.51	0.19	0.42	0.19	0.42	0.23	0.51
May	0.25	0.55	0.13	0.29	0.13	0.29	0.13	0.29	0.27	0.60	0.27	0.60	0.13	0.29
June	0.21	0.46	0.21	0.46	0.21	0.46	0.21	0.46	0.10	0.20	0.10	0.20	0.21	0.46
July	0.12	0.26	0.14	0.31	0.14	0.31	0.14	0.31	0.25	0.55	0.25	0.55	0.14	0.31
August	0.17	0.37	0.17	0.37	0.17	0.37	0.17	0.37	0.21	0.46	0.21	0.46	0.17	0.37
Sept	0.1	0.20	0.12	0.26	0.12	0.26	0.12	0.26	0.13	0.29	0.13	0.29	0.12	0.26
Oct	0.16	0.35	0.03	0.04	0.03	0.04	0.03	0.04	0.10	0.20	0.10	0.20	0.03	0.04
Nov	0.11	0.24	0.11	0.24	0.11	0.24	0.11	0.24	0.04	0.07	0.04	0.07	0.11	0.24
Dec	0.15	0.33	0.14	0.31	0.14	0.31	0.14	0.31	0.11	0.24	0.11	0.24	0.14	0.31

At 95% level of Significance

4.1.2 Sen's slope estimator

The Sen's slope estimator was employed to determine the change per unit time of trend in rainfall data collected. Figures 4.1(a-g) painted a vivid picture of the magnitude of slope in the rainfall series. Positive and negative sign indicated an upward and downward slope respectively.

Insignificant changes in the annual rainfall data were recorded in all stations, some of the years showed increasing (upward) trend while some experienced decreasing trends (Animashaun *et al.*,2020). In Figure 4.1a, the following years 2007, 2008, 2009, 2011, 2012, 2014, 2017, 2018, 2019, and 2020 witnessed increasing slope magnitude while the years 2006, 2010, 2013, 2015, and 2016 showed non-significant decreasing trend of rainfall data in Gusau meteorological station.

Figure 4.1b showed that the following years 2006, 2009, 2010, 2012, 2013, 2014, 2015, 2017, 2018, 2019, and 2020 experienced increasing slope magnitude while 2007, 2008, 2011 witnessed insignificant decreasing trend of rainfall data for Sokoto meteorological station. On the other hand, 2007, 2010, 2011, 2013, 2015, 2019, and 2020 in Figure 4.1c witnessed increasing slope magnitude while 2006, 2008, 2009, 2012, 2014, 2016, 2017, and 2018 showed non-significant decreasing trend of rainfall data in Kano meteorological station. Also, Figure 4.1d revealed that year 2006, 2009, 2011, 2014, 2016, 2017, 2019, and 2020 experienced an increasing slope magnitude while 2007, 2008, 2010, 2012, 2013, 2015 and 2018 showed non-significant decreasing trend of rainfall data in Katsina meteorological station. In Figure 4.1e, the years 2008, 2009, 2011, 2012, 2015, 2019 and 2020 showed an increasing slope magnitude while 2006, 2007, 2010, 2014, 2016, 2017 and 2018 experienced insignificant decreasing trend of rainfall data in Kaduna meteorological station.

Figure 4.1f showed that years 2006, 2007, 2013, 2015, 2016, 2017, 2019, and 2020 experienced increasing slope magnitude while 2008, 2009, 2010, 2011, 2012, 2014 and 2018witnessed non-significant decreasing trend of rainfall data in Yelwa meteorological station. Finally, Figure 4.1g revealed that years 2006, 2008, 2009, 2011, 2013, 2015, 2018, 2019, and 2020 showed increasing slope magnitude and 2007, 2010, 2012, 2014, and 2017 experienced non-significant decreasing trend of rainfall data in Zaria meteorological station. The explanation above concurred with study performed by (Achugbu and Anugwo, 2016).

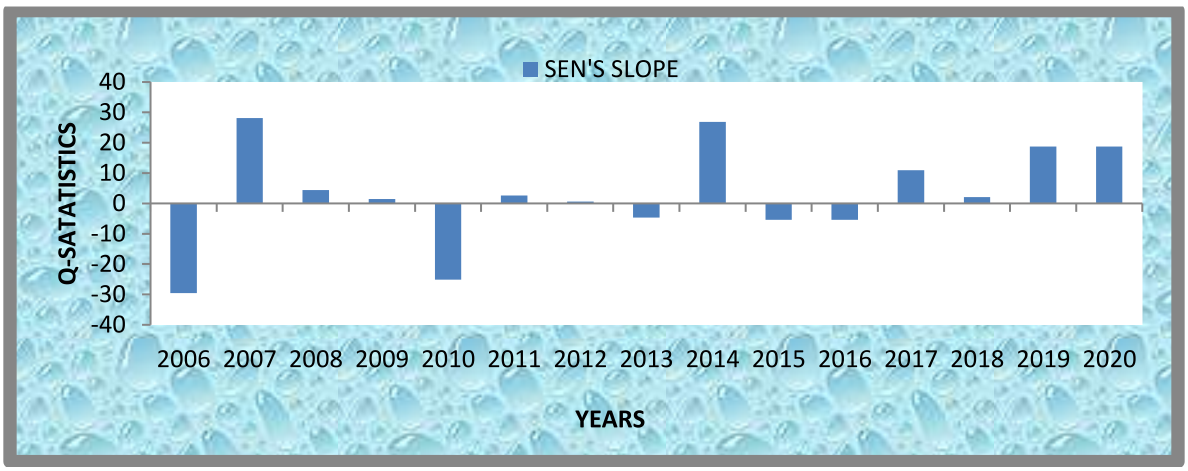

Figure 4.1a: Sen’s slope chart (Gusau)

Figure 4.1b: Sen’s slope chart (Sokoto)

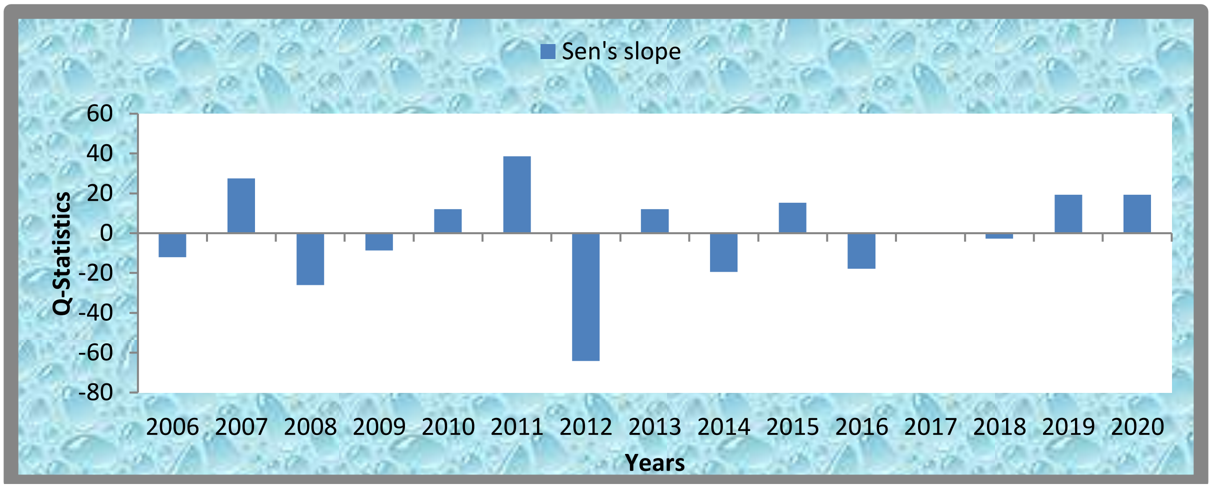

Figure4.1c: Sen’s slope chart (Kano)

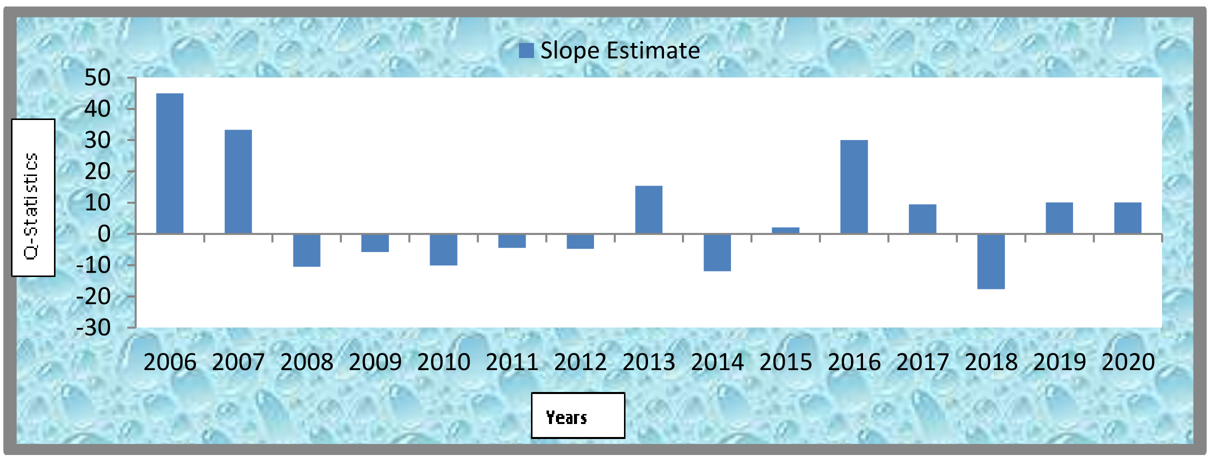

Figure 4.1d: Sen’s slope chart (Yelwa)

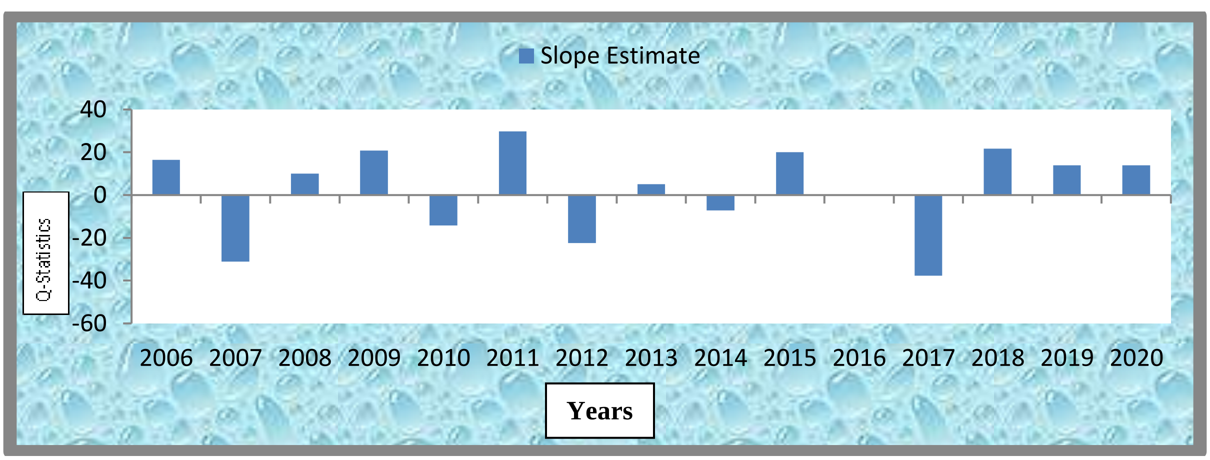

Figure4.1e: Sen’s slope chart (Zaria)

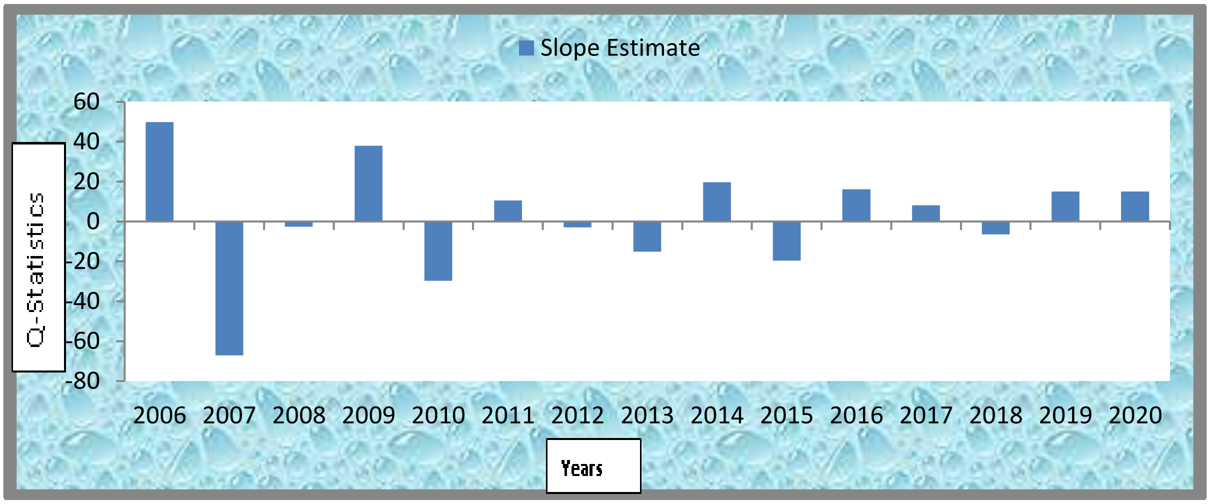

Figure 4.1f: Sen's slope chart (Katsina)

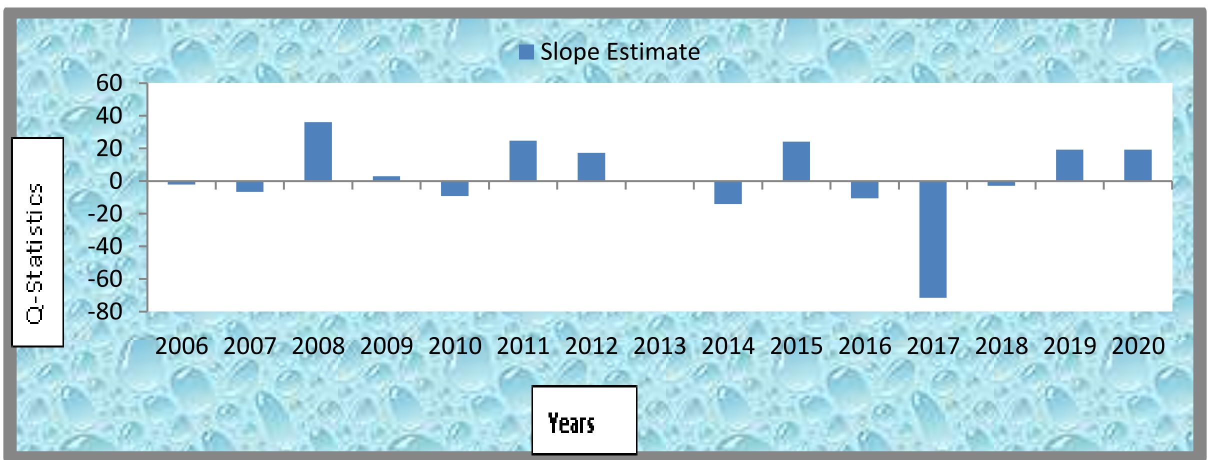

Figure4.1g: Sen's slope chart (Kaduna)

4.1.3 Statistical Change Point Detection

4.1.3.1 Pettit's result

The Pettit test was performed to detect a single change-point in the annual series of rainfall data during the period (2006 - 2020). It tests the H_o: The data are homogeneous, against the alternative: a change point exists (i.e., there is a date at which there is positive shift in data) as shown in Table 4.2. Analysis of the annual rainfall indicated that there were change points in all stations. In Table (4.2), change points were recorded in Gusau in 2010, Kaduna in 2012, Kano and Zaria in 2011, Katsina, Sokoto and Yelwa in 2009 with decreasing and increasing trend as in the case of Mann-Kendall test discussed above. This test concurred with the findings of (Getahun *et al*., 2021).

Table 4.2: Pettit's results for all stations

Years	Gusau	Kaduna	Kano	Katsina	Sokoto	Yelwa	Zaria
	U(k)	U(k)	U(k)	U(k)	U(k)	U(k)	U(k)
2006	1782.32	2562.2	2210.48	1249.55	1308.42	1249.55	2401.88
2007	1270.32	2050.2	1698.48	737.55	796.42	737.55	1889.88
2008	758.32	1538.2	1186.48	225.55	284.42	225.55	1377.88
2009	246.32	1026.2	674.48	-286.45	-227.58	-286.45	865.88
2010	-265.68	514.2	162.48	-798.45	-739.58	-798.45	353.88
2011	-777.68	2.2	-349.52	-1310.4	-1251.5	-1310.4	-158.12
2012	-1289.6	-509.8	-861.52	-1822.4	-1763.5	-1822.4	-670.12
2013	-101.6	-1021.8	-1373.5	-2334.4	-2275.5	-2334.4	-1182.1
2014	-2313.6	-1533.8	-1885.5	-2846.4	-2787.5	-2846.4	-1694.1
2015	-2825.6	-2045.8	-2397.5	-3358.4	-3299.5	-3358.4	-2206.1
2016	-3337.6	-2557.8	-2909.5	-3870.4	-3811.5	-3870.4	-2718.1
2017	-3849.6	-3069.8	-3421.5	-4382.4	-4323.5	-4382.4	-3230.1
2018	-4361.6	-3581.8	-3933.5	-4894.4	-4835.5	-4894.4	-3742.1
2019	-4873.6	-4093.8	-4445.5	-5406.4	-5347.5	-5406.4	-4254.1
2020	-5385.6	-4605.8	-4957.5	-5918.4	-5859.5	-5918.4	-5918.4

4.1.3.2 Sequential Mann-Kendall

The SQ-MK test is used for determining the approximate year of the beginning of a significant trend. This test sets up two series; a progressive one $U(t)$ and a backward one $U'(t)$. In Figures 4.2 (a-g) presented below, change points were recorded in Gusau, Kano, Yelwa, Katsina and

Kaduna rainfall data and these coincide to the year 2006 in Gusau meteorological station, 2006, 2007 and 2015 in Kano meteorological station, 2011, 2012, 2013, and 2019 in Yelwa meteorological station, 2007, 2008, 2010, 2012, 2014, 2016, and 2017 in Katsina meteorological station. In Kaduna meteorological station, changes were recorded in 2006, 2012, 2018 and 2019. These depicted that there was a change in the pattern of rainfall distribution in the stations (Ogungbenro and Morakinyo, 2014). Sokoto and Zaria recorded no change points in the rainfall distribution as shown in Figures 4.2(b and g). Their respective statistics showed that there was insignificant trend as they fall between the set Z-values ($Z = \pm 1.96$).

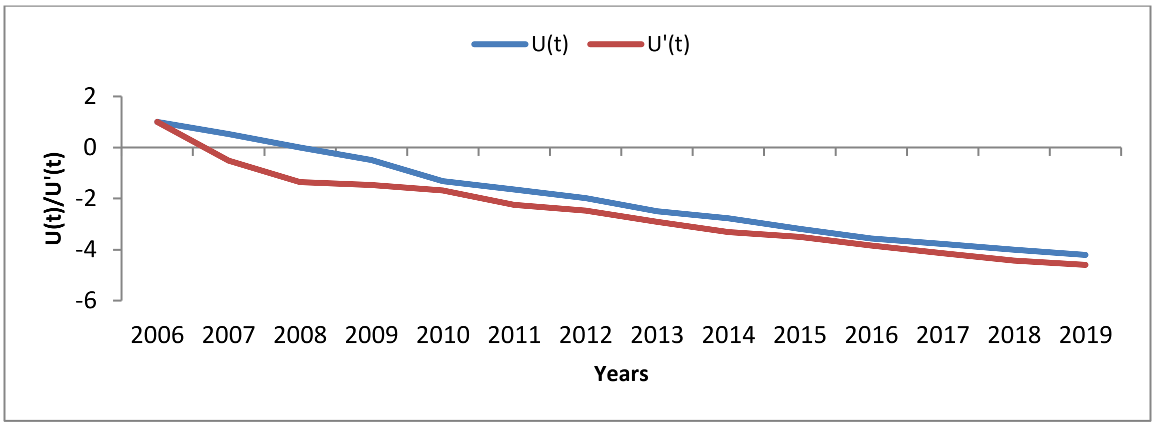

Figure 4.2a: SQ-MK chart (Gusau)

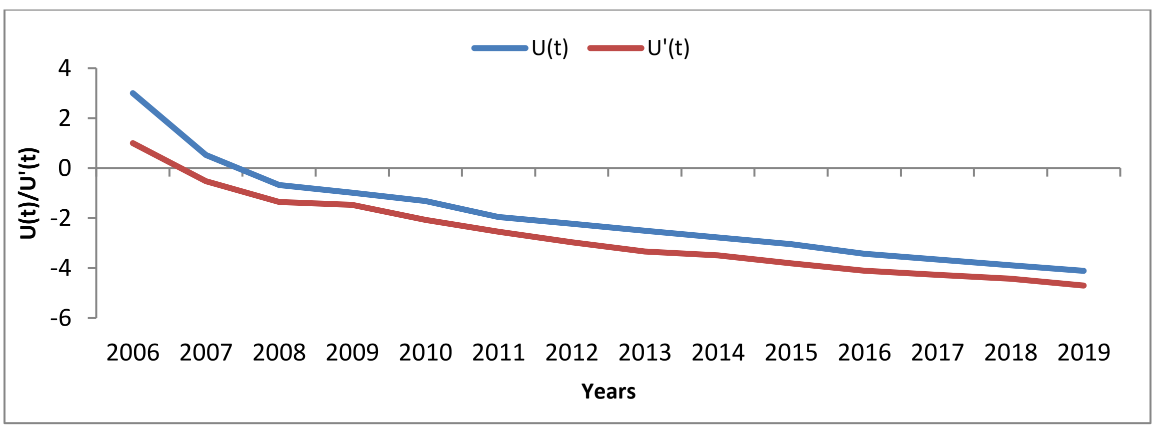

Figure 4.2b: SQ-MK chart (Sokoto)

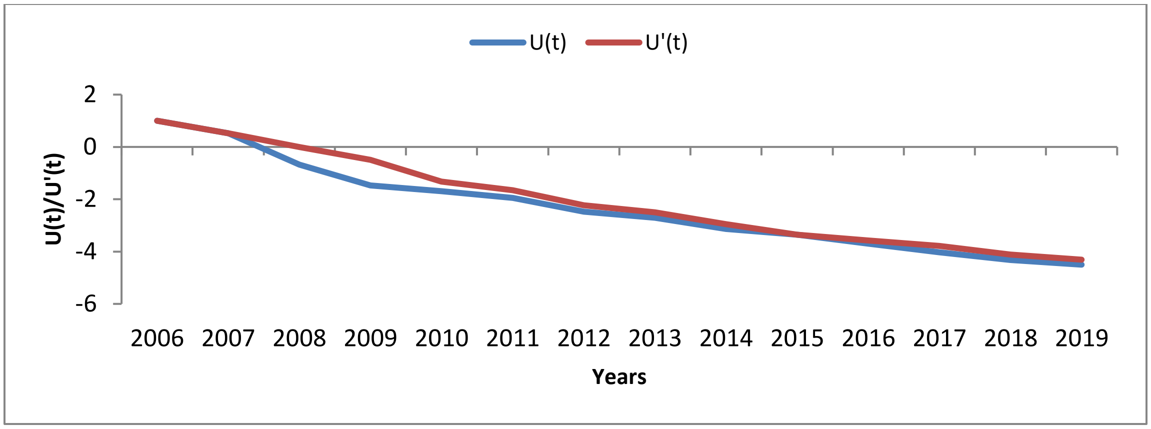

Figure4.2c: SQ-MK chart (Kano)

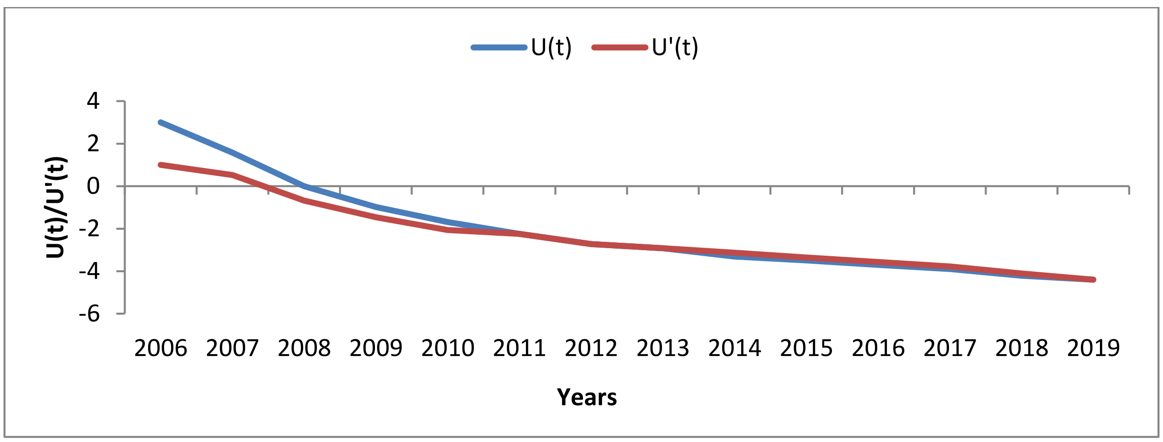

Figure 4.2d: SQ-MK chart (Yelwa)

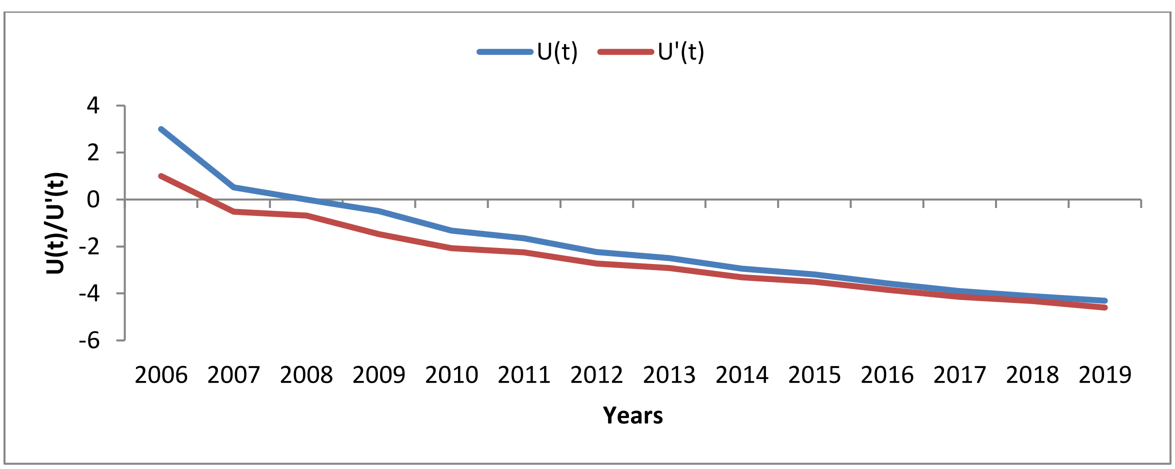

Figure 4.2e: SQ-MK chart(Zaria)

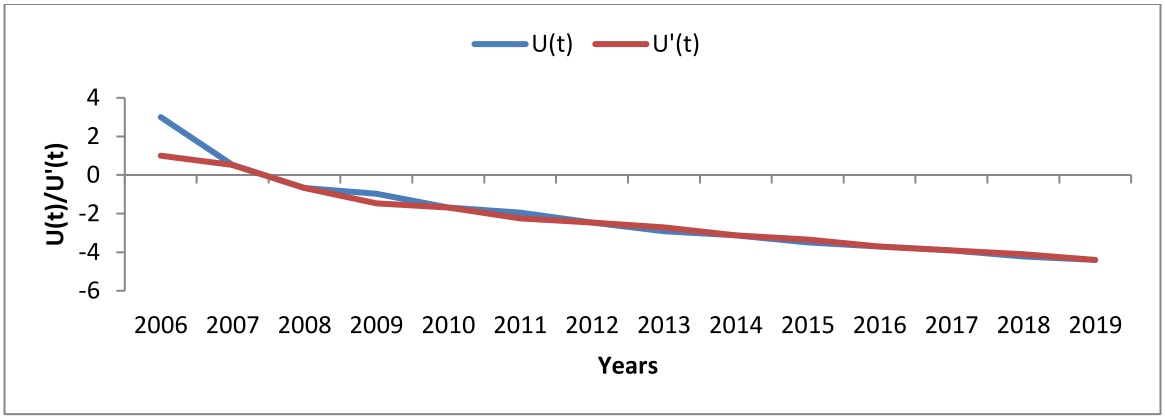

Figure 4.2f: SQ-MK chart (Katsina)

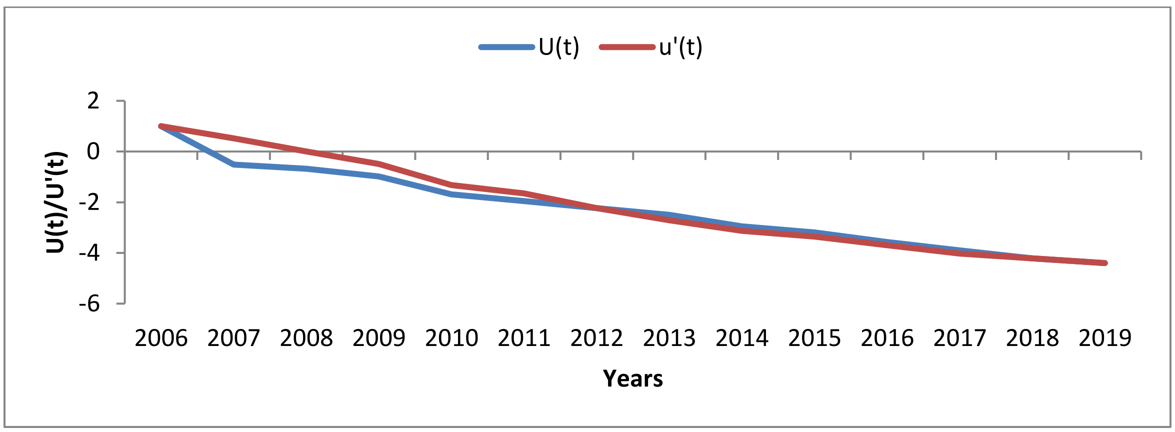

Figure 4.2f: SQ-MK chart (Kaduna)

4.1.4Characterization of meteorological drought field

4.1.4.1 Mean annual standardised precipitation index

Figures 4.3(a-g) showed the mean annual SPI values for selected stations in North-Western region of Nigeria. The SPI values were computed on the basis of three accumulations (3-month, 6-month and 12-month time scales). The SPI charts revealed the fluctuation in amount of rainfall recorded over a long period of time. The negative values indicated years with droughts ranging from near normal to extremely dry condition. The figures revealed the percentage distribution of the extremely dry, dry and wet years for the period 2006 to 2020. In agreement with the findings of other researchers (e.g. Oguntunde *et al*., 2011; Bibi *et al*., 2014), rainfall variability in Nigeria is characterized by many fluctuations and could be categorized into phases/periods, it is evident hat all the stations had a mixture of both dry and wet years.

In Figures 4.3 (a-g), there were equal distributions of wet and dry spells in Sokoto, Kaduna, and Zaria while wet spells outweighed dry spells in Kano, Gusau, and Katsina. Yelwa experienced more of the dry spells than the wet spells.

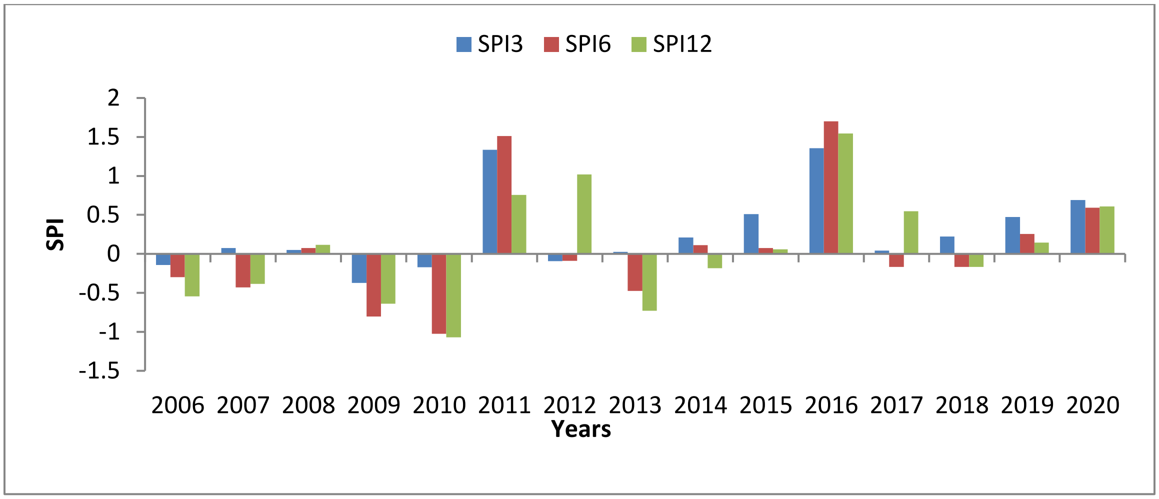

Figure 4.3a: Mean Annual SPI chart (Sokoto)

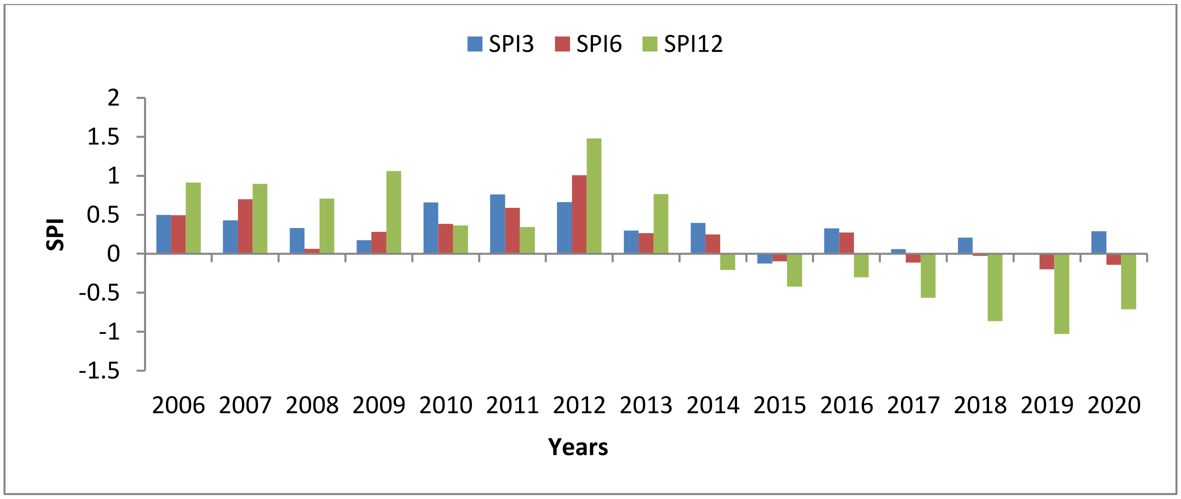

Figure 4.3b: Mean Annual SPI chart (Kano)

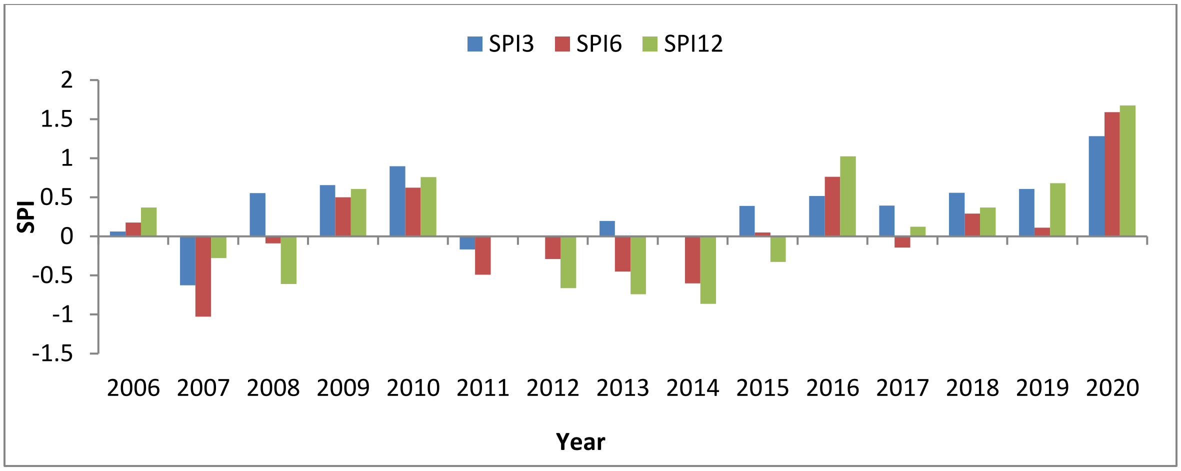

Figure 4.3c: Mean Annual SPI chart (Gusau)

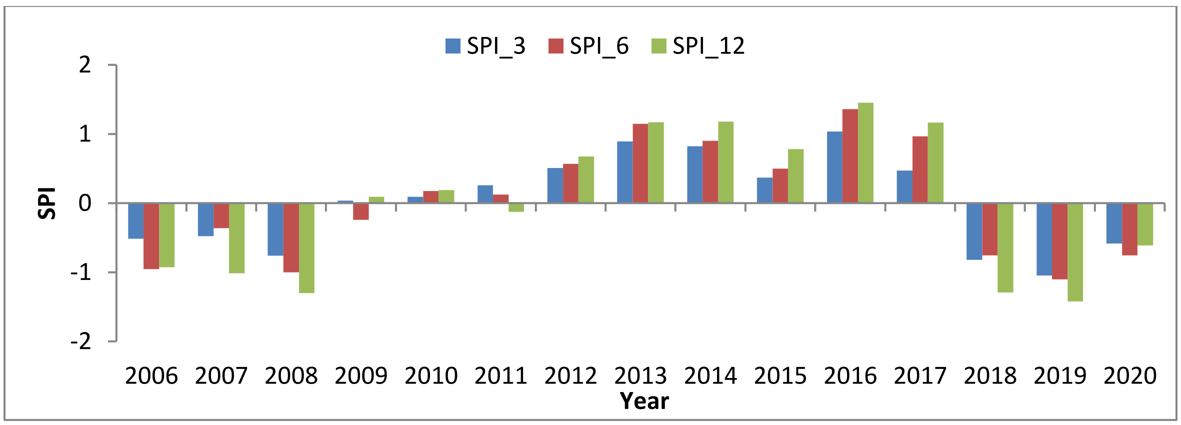

Figure 4.3d: Mean Annual SPI chart (Kaduna)

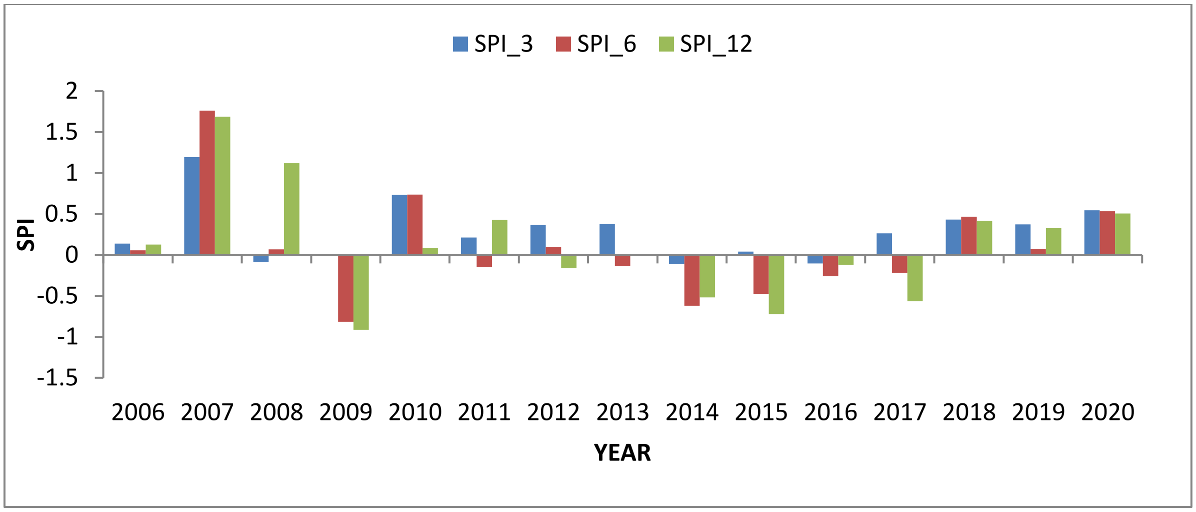

Figure 4.3e: Mean Annual SPI chart (Katsina)

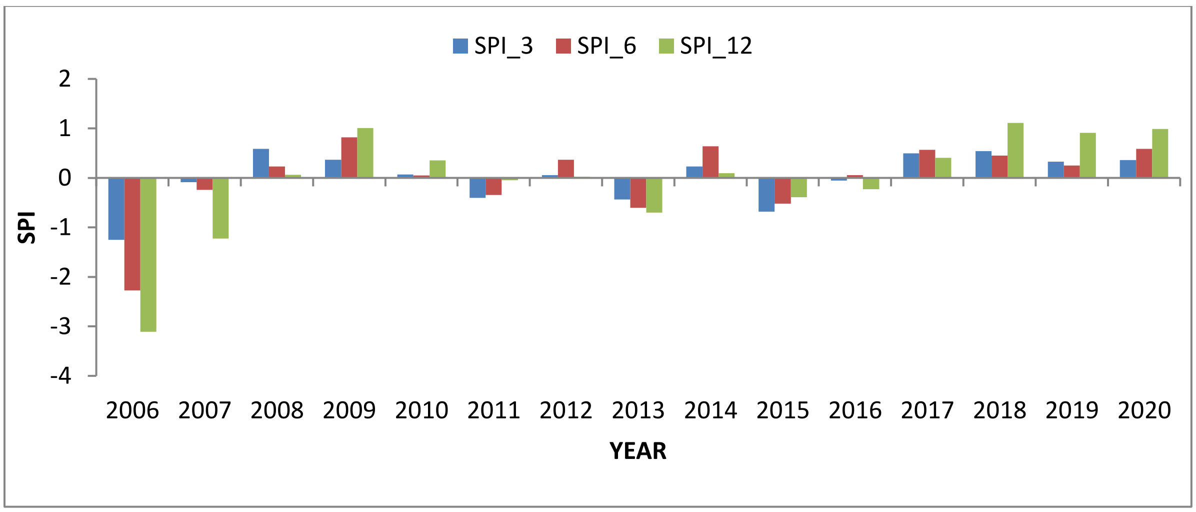

Figure 4.3f: Mean Annual SPI chart (Yelwa)

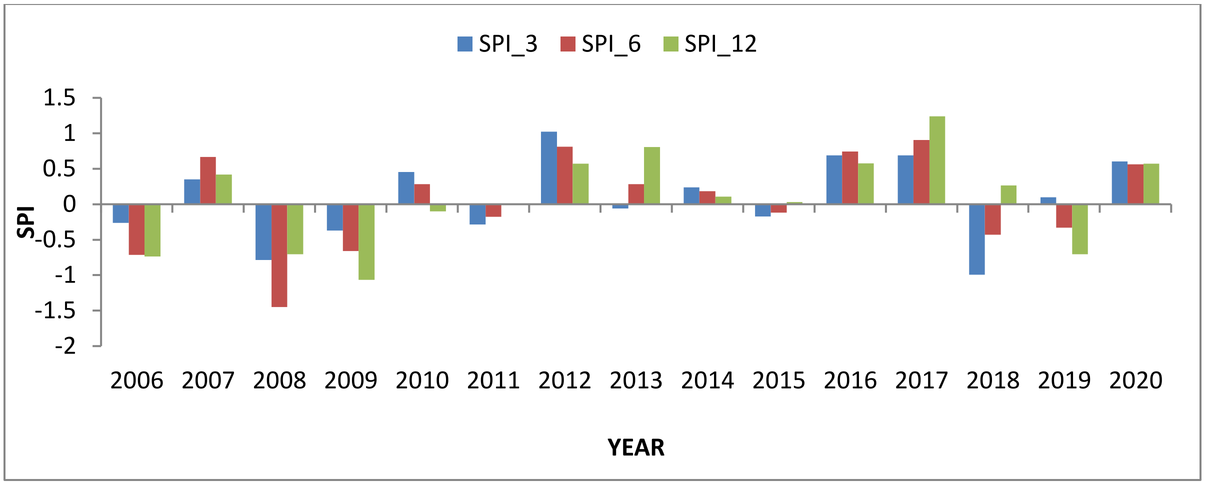

Figure 4.3g: Mean Annual SPI chart (Zaria)

4.1.4.2Mean annual Non-Stationary standardised Precipitation Index

Figures 4.4(a-g) indicated the mean annual SnsPI charts for selected stations. The SnsPI values were computed on the basis of three accumulations (3-month, 6-month and 12-month time scales) as in the case of SPI. The index (SnsPI) showed the amount of fluctuation in amount of rainfall recorded over a long period of time where the negative values indicate years with rainfall distribution ranging from near normal to extremely dry condition. It was shown that the wet spells outweigh the dry spells in all the stations reaching an extremely wet conditions occurring between 2009 and 2019. The results revealed that the zone (North-Western)is generally replete with normal and extremely wet events occurring between 2009 and 2019 while some of the years experienced near normal conditions between 2006 and 2018, and 2020.

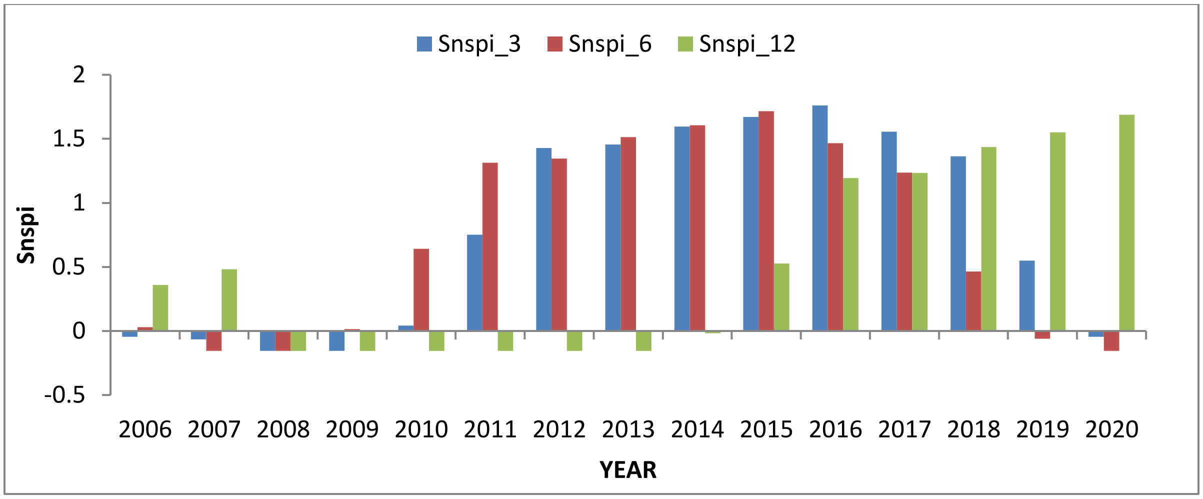

Figure 4.4a: Mean annual SnsPI chart (Gusau)

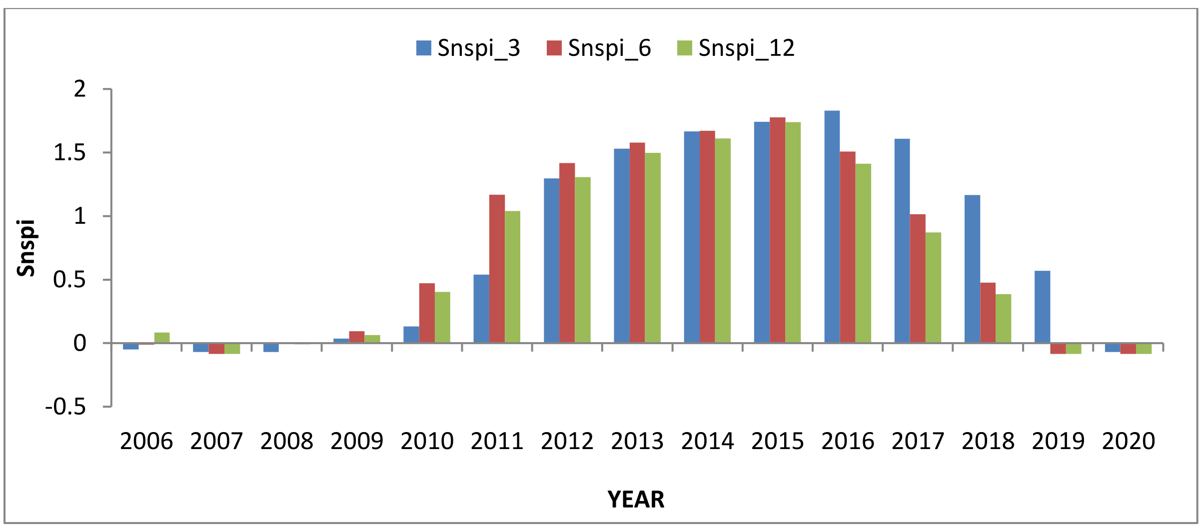

Figure 4.4b: Mean annual SnsPI chart (Kano)

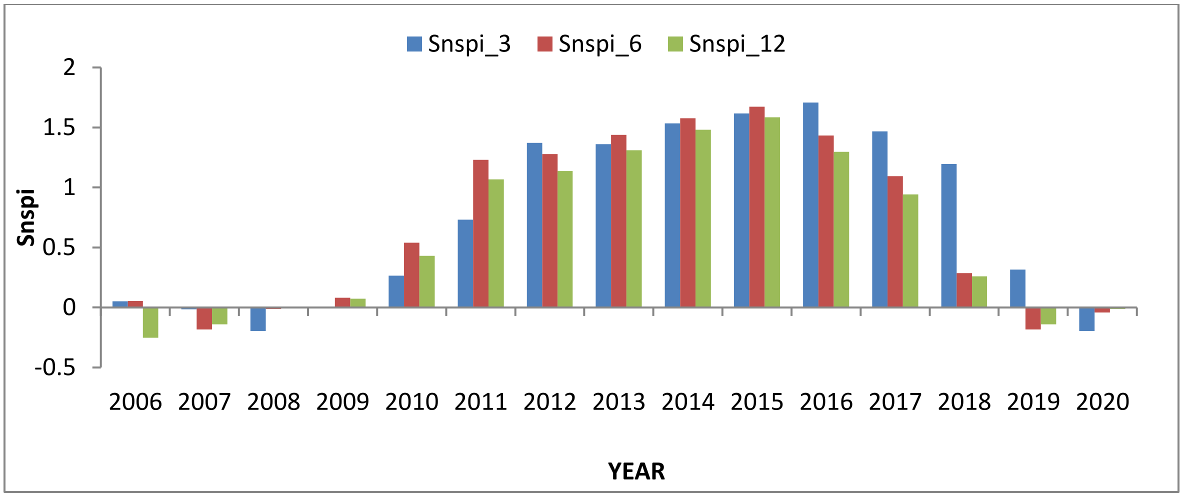

Figure 4.4c: Mean annual SnsPI chart (Sokoto)

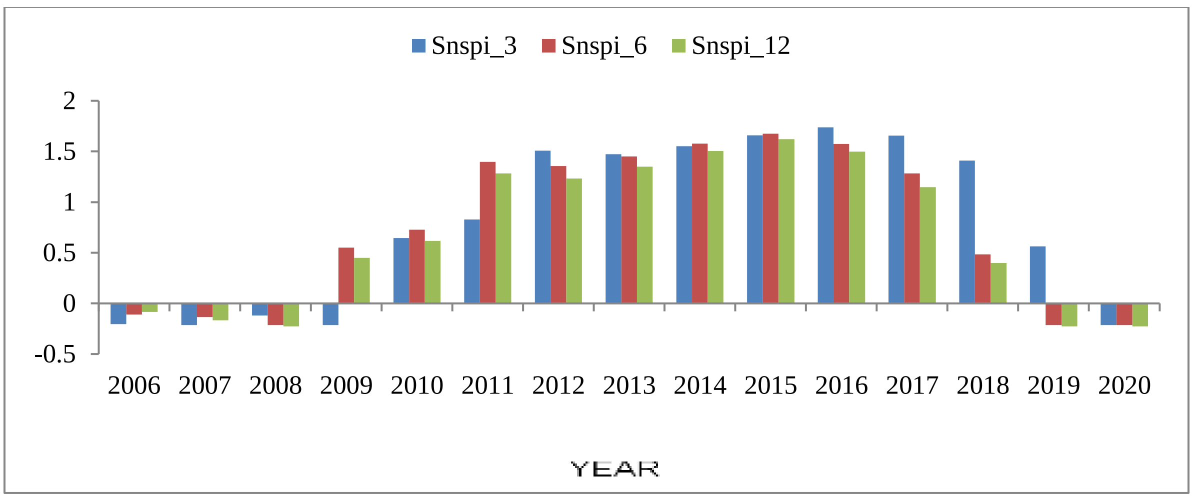

Figure 4.4d: Mean annual SnsPI chart (Kaduna**)**

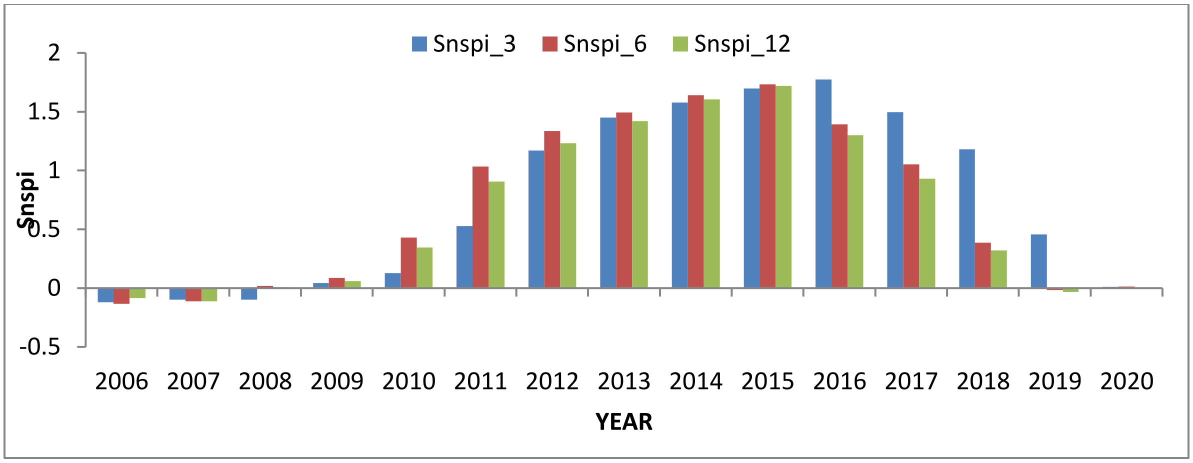

Figure 4.4e: Mean annual SnsPI chart (Katsina**)**

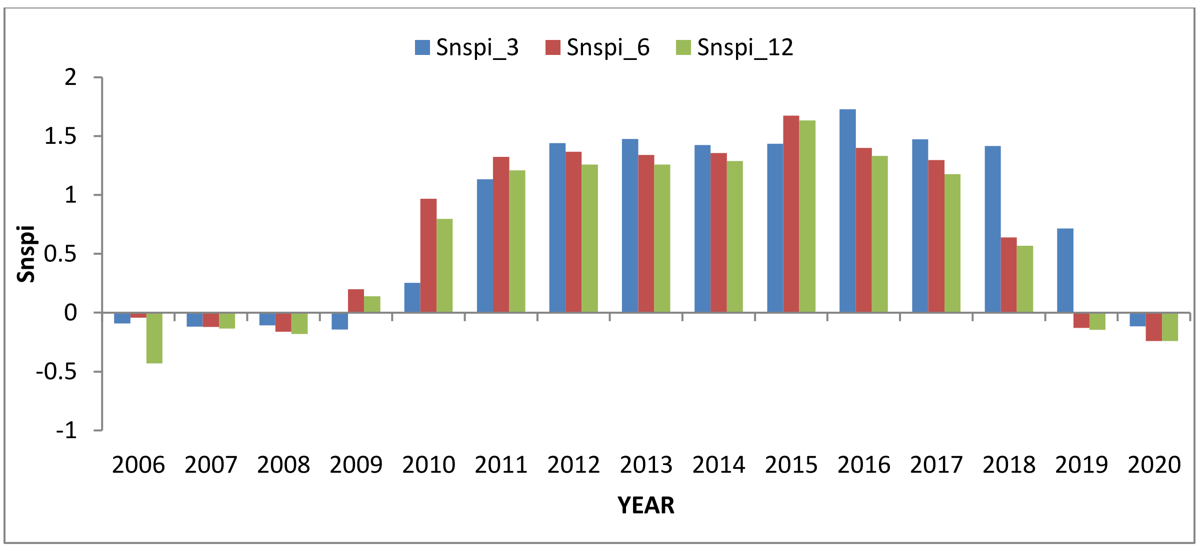

Figure 4.4f: Mean annual SnsPI (Yelwa)

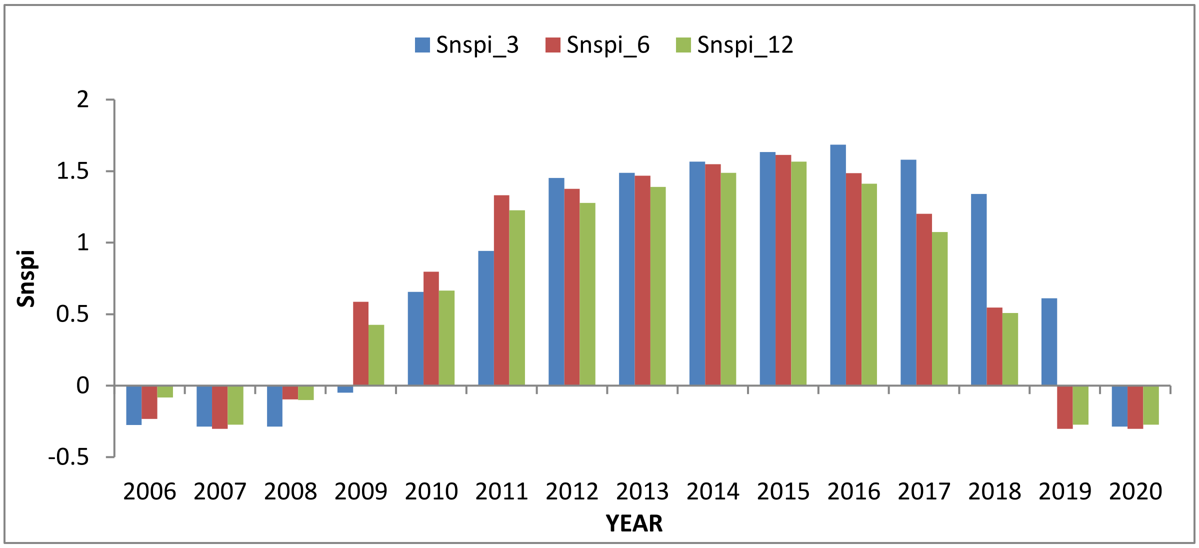

Figure 4.4g: Mean annual SnsPI chart (Zaria)

4.1.4.3 Mean annual standardised precipitation anomaly index

The Figures 4.5(a-g) below showed the mean annual SPAI charts for selected stations. The SPAI values were computed on the basis of three accumulations (3-month, 6-month and 12-month time scales) as in the case of SPI and SnSPI. Standardised Precipitation Anomaly Index (SPAI) was used for the analysis of the drought effect of annual rainfall in the various stations. The index indicated the amount of fluctuation in rainfall data recorded over a long period of time where the negative values indicated years with shortfall in the amount of rainfall. As shown in Figure 4.5(a-g), the dry spells outweighed the wet spells in all the stations with the intensities close to extremely dry conditions and occur between 2010 and 2017 in almost all the stations and concurred with (Ogunrinde *et al.*, 2019). The results revealed that the zone is generally replete with severe and prolonged drought events occurring in (2010-2017) as said earlier. Some of the years still experience normal to very wet conditions and could be seen between 2006-2009 and 2018-2020 in this zone.

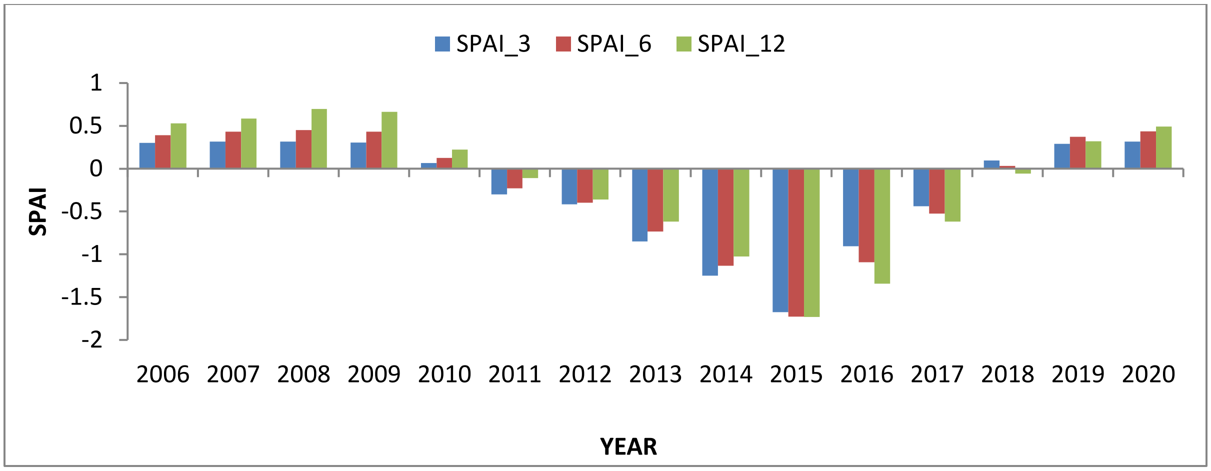

Figure 4.5a: Mean annual SPAI chart (Gusau)

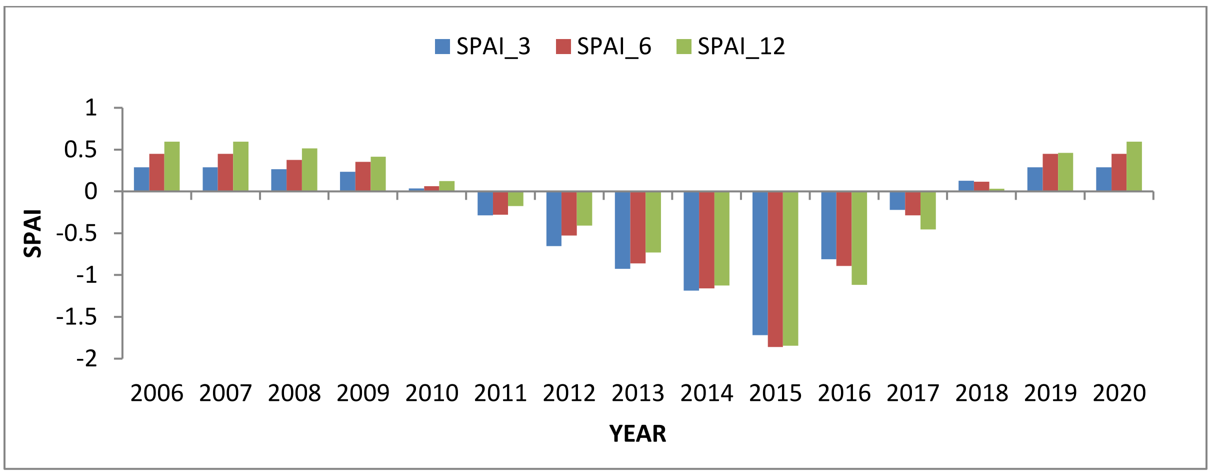

Figure 4.5b: Mean annual SPAI chart **(**Kano)

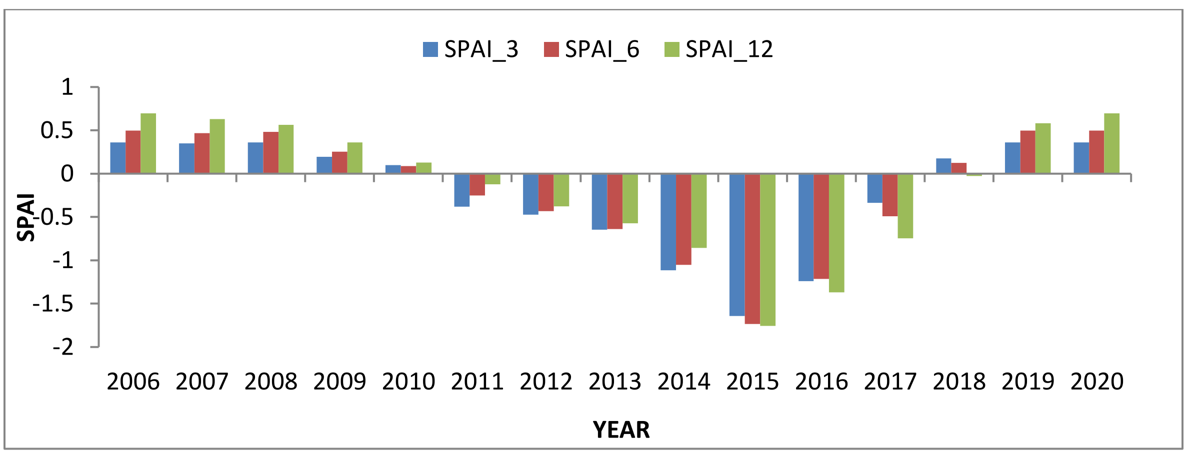

Figure 4.5c: Mean annual SPAI chart (Kaduna)

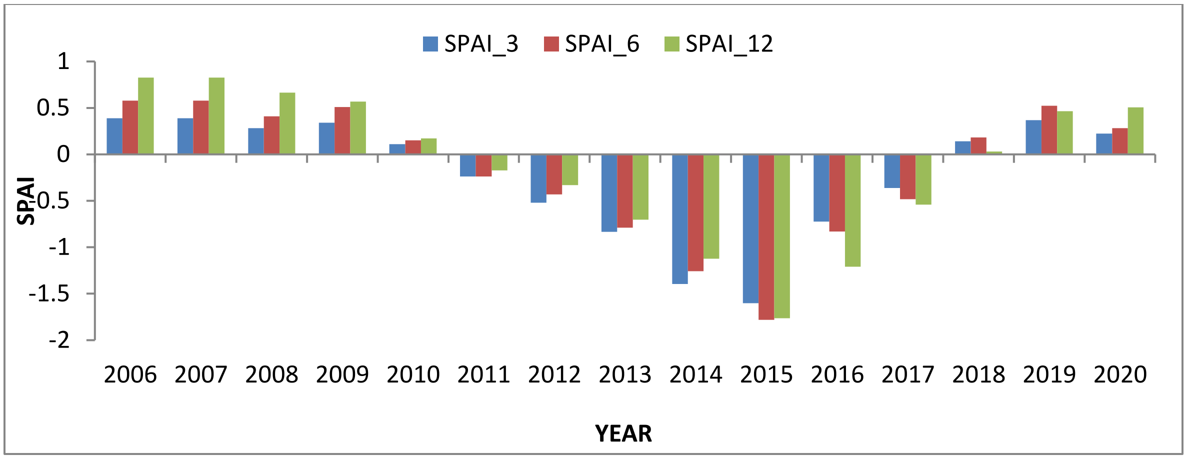

Figure 4.5d: Mean annual SPAI chart Katsina

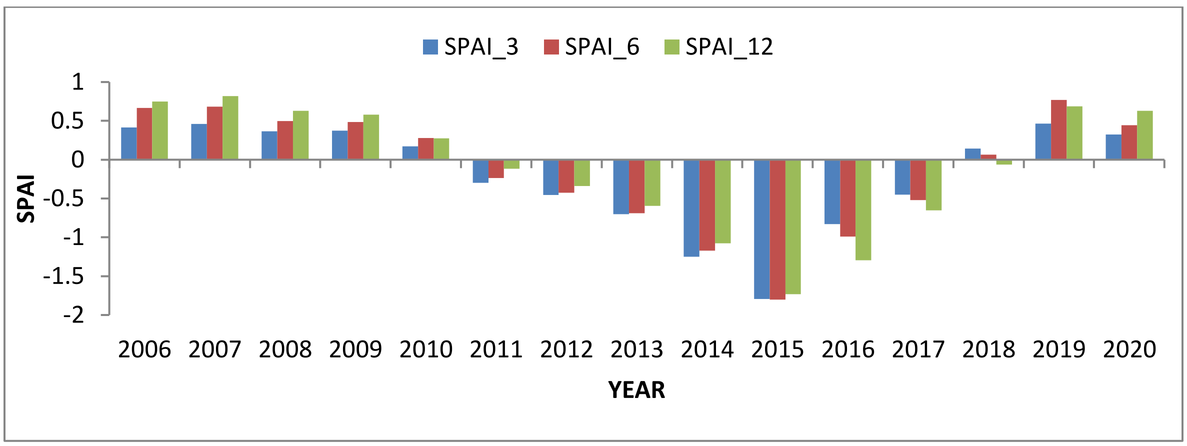

Figure 4.5e: Mean annual SPAI chart (Sokoto)

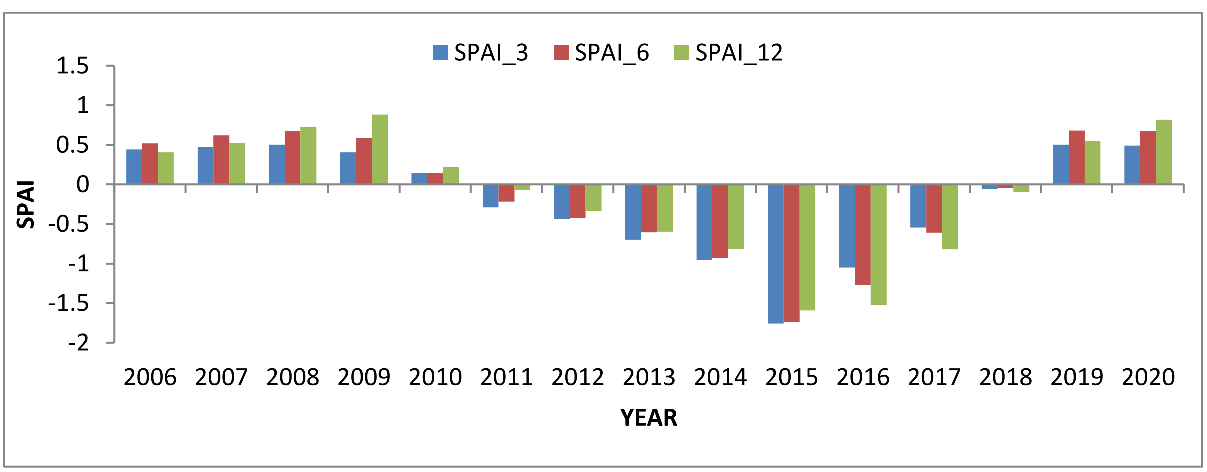

Figure 4.5f: Mean annual SPAI chart (Yelwa)

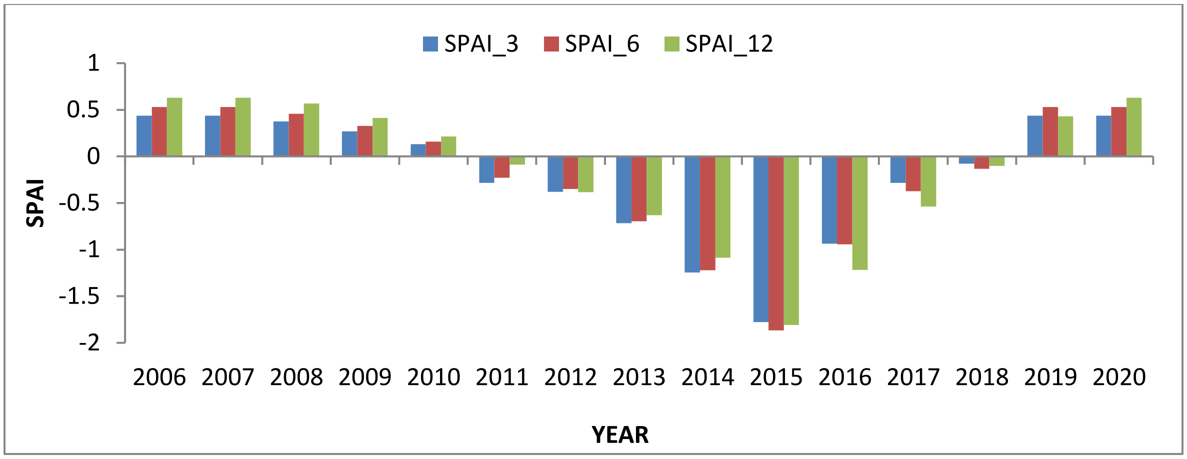

Figure 4.5g: Mean annual SPAI chart (Zaria)

4.1.5 Categorization of meteorological droughts

4.1.5.1 Categorization using Standardised Precipitation Index (SPI)

The Tables 4.3(a-g) showed the drought intensity summary for all stations at 3, 6 and 12 months time scales using Standardised Precipitation Index (SPI). The categorisation was done on the basis of extremely wet, very wet, moderately wet, near normal, moderately dry, severely dry, extremely dry. Across the stations, there was uniform occurrence of extremely wet, very wet, moderately wet and severely dry conditions. For instance, Sokoto recorded 6 times extremely wet conditions, 37 times very wet conditions, 93 times near normal conditions, 9 times moderately dry condition, a month for both severely dry and extremely dry conditions respectively for the past 15years under a 3_month timescale Table (4.13). The same conditions with little variation in the frequency of occurrence were recorded under the timescale of 6 and 12 with some stations recording a near normal condition for the past 15 years. Generally, all the stations recorded the same drought conditions but with little variation in the frequencies of occurrence.

Table 4.3a: Summary of Gusau drought intensity

Drought Intensity	Index Threshold	SPI_3		SPI_6		SPI_12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	3	2.4	0	0	0	0
Very wet	1.5 to 1.99	28	22.4	17	11.81	4	2.78
Moderately Wet	1.0 to 1.49	77	61.6	105	72.92	129	89.58
Near Normal	-0.99 to 0.99	0	0	0	0	0	0
Moderately dry	-1 to -1.49	13	10.4	20	13.88	11	7.64
Severely dry	-1.5 to -1.99	4	3.2	2	1.38	0	0
Extremely dry	<-2	0	0	0	0	0	0
Total		**125**	**100**	**144**	**100**	**144**	**100**

Table 4.3b: Summary of Kaduna drought intensity

Drought Intensity	Index Threshold	SPI_3		SPI_6		SPI_12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	4	2.89	1	0.704	0	0
Very wet	1.5 to 1.99	28	20.28	32	22.54	43	29.86
Moderately Wet	1.0 to 1.49	94	68.11	93	65.49	80	55.56
Near Normal	-0.99 to 0.99	0	0	0	0	1	0.69
Moderately dry	-1 to -1.49	6	4.34	14	9.86	20	13.89
Severely dry	-1.5 to -1.99	4	2.89	2	1.41	0	0
Extremely dry	<-2	2	1.44	0	0	0	0
Total		**138**	**100**	**142**	**100**	**144**	**100**

Table 4.3c: Summary of Kano drought intensity

Drought	Index	SPI_3		SPI_6		SPI_12	
Intensity	**Threshold**	**Freq**	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	2	1.50	1	0.65	11	7.28
Very wet	1.5 to 1.99	23	17.29	10	6.54	9	5.96
Moderately	1.0 to 1.49						
Wet		107	80.45	138	90.19	116	76.82
Near Normal	-0.99 to 0.99	0	0	0	0	0	0
Moderately dry	-1 to -1.49	0	0	4	2.61	15	9.93
Severely dry	-1.5 to -1.99	1	0.75	0	0	0	0
Extremely dry	<-2	0	0	0	0	0	0
Total		**133**	**100**	**153**	**100**	**151**	**100**

Table 4.3d: Summary of Katsina drought intensity

Drought	Index	SPI_3		SPI_6		SPI_12	
Intensity	**Threshold**	**Freq**	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	3	2.65	6	3.95	10	6.41
Very wet	1.5 to 1.99	20	17.70	17	11.18	16	10.25
Moderately	1.0 to 1.49						
Wet		81	71.68	113	74.34	122	78.20
Near Normal	-0.99 to 0.99	0	0	0	0	0	0
Moderately dry	-1 to -1.49	6	5.30	15	9.86	8	5.13
Severely dry	-1.5 to -1.99	1	0.88	1	0.66	0	0
Extremely dry	<-2	2	1.77	0	0	0	0
Total		**113**	**100**	**152**	**100**	**156**	**100**

Table 4.3e: Summary of Sokoto drought intensity

Drought Intensity	Index Threshold	SPI_3		SPI_6		SPI_12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	6	4.08	10	6.94	14	9.59
Very wet	1.5 to 1.99	37	25.17	10	6.94	4	2.74
Moderately Wet	1.0 to 1.49	93	63.26	116	80.55	116	79.45
Near Normal	-0.99 to 0.99	0	0	1	0.69	0	0
Moderately dry	-1 to -1.49	9	6.12	6	4.17	12	8.21
Severely dry	-1.5 to -1.99	1	0.68	0	0	0	0
Extremely dry	<-2	1	0.68	1	0.69	0	0
Total		**147**	**100**	**144**	**100**	**146**	**100**

Table 4.3f: Summary of Yelwa drought intensity

Drought Intensity	Index Threshold	SPI_3		SPI_6		SPI_12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	1	0.66	0	0
Very wet	1.5 to 1.99	9	8.26	18	11.84	22	14.67
Moderately Wet	1.0 to 1.49	86	78.89	121	79.61	123	82
Near Normal	-0.99 to 0.99	0	0	0	0	0	0
Moderately dry	-1 to -1.49	8	7.33	10	6.58	5	3.33
Severely dry	-1.5 to -1.99	5	4.58	2	1.32	0	0
Extremely dry	<-2	1	0.91	0	0	0	0
Total		**109**	**100**	**152**	**100**	**150**	**100**

Table 4.3g: Summary of Zaria drought intensity

Drought Intensity	Index Threshold	SPI_3		SPI_6		SPI_12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	1	0.71	0	0
Very wet	1.5 to 1.99	15	15.15	20	14.18	29	21.17
Moderately Wet	1.0 to 1.49	74	74.75	107	75.89	99	72.26
Near Normal	-0.99 to 0.99	0	0	0	0	0	0
Moderately dry	-1 to -1.49	6	6.06	11	7.80	8	5.84
Severely dry	-1.5 to -1.99	3	3.03	1	0.71	1	0.73
Extremely dry	<-2	1	1.01	1	0.71	0	0
Total		**99**	**100**	**141**	**100**	**137**	**100**

4.1.5.2 Categorization of droughts using Standardised Non-Stationary Precipitation Index (SnsPI)

Tables 4.4(a-g) revealed the summary of drought intensity for all stations at 3, 6 and 12_month timescale using Standardised Non-stationary Precipitation Index (SnsPI). The categorization was done on the basis of extremely wet, very wet, moderately wet, near Normal, moderately dry, severely dry, extremely dry. Across the stations, there was uniformly occurrence of near normal condition, moderately wet and extremely dry conditions. For instance, Gusau recorded 101 numbers of near moderately wet condition, 22 and 8 numbers of near normal and extremely dry conditions respectively for the past 15years under a 3_month timescale Table (4.13). The same conditions with little variation in the frequency of occurrence were recorded under the timescale of 6 and 12 for the past 15 years. Generally, all the stations recorded the same drought conditions but with little variation in the frequencies of occurrence.

Table 4.4a: Summary of Kano drought intensity

Drought Intensity	Index Threshold	SnsPI_3		SnsPI _6		SnsPI _12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	103	72.53	103	72.54	103	74.64
Near Normal	-0.99 to 0.99	27	19.01	27	19.01	30	21.74
Moderately dry	-1 to -1.49	0	0	0	0	0	0
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	12	8.45	12	8.45	5	3.62
Total		**142**	**100**	**142**	**100**	**138**	**100**

Table 4.4b: Summary of Gusau drought intensity

Drought Intensity	Index Threshold	SnsPI _3		SnsPI _6		SnsPI _12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	101	77.10	101	73.19	70	56.91
Near Normal	-0.99 to 0.99	22	16.79	21	15.22	33	26.83
Moderately dry	-1 to -1.49	0	0	0	0	0	0
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	8	6.11	16	11.59	20	16.26
Total		**131**	**100**	**138**	**100**	**123**	**100**

Table 4.4c: Summary of Kaduna drought intensity

Drought Intensity	Index Threshold	SnsPI _3		SnsPI _6		SnsPI _12	
		Freq	%	Freq	%	Freq	%
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	106	78.52	105	74.47	105	74.47
Near Normal	-0.99 to 0.99	21	15.56	21	14.89	21	14.89
Moderately dry	-1 to -1.49	0	0	0	0	0	0
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	8	5.93	15	10.64	15	10.63
Total		**135**	**100**	**141**	**100**	**141**	**100**

Table 4.4d: Summary of Katsina drought intensity

Drought Intensity	Index Threshold	SnsPI _3		SnsPI _6		SnsPI _12	
		Freq	%	Freq	%	Freq	%
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	97	69.78	98	69.01	98	69.01
Near Normal	-0.99 to 0.99	39	28.06	38	26.76	38	26.76
Moderately dry	-1 to -1.49	0	0	0	0	0	0
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	3	2.16	6	4.23	6	4.22
Total		**139**	**100**	**142**	**100**	**142**	**100**

Table 4.4e: Summary of Sokoto drought intensity

Drought Intensity	Index Threshold	SnsPI _3		SnsPI _6		SnsPI _12	
		Freq	%	**Freq**	%	**Freq**	%
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	102	75.56	101	71.63	101	70.63
Near Normal	-0.99 to 0.99	21	15.56	22	15.60	29	20.28
Moderately dry	-1 to -1.49	0	0	0	0	0	0
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	12	8.89	18	12.76	13	9.09
Total		**135**	**100**	**141**	**100**	**143**	**100**

Table 4.4f: Summary of Yelwa drought intensity

Drought Intensity	Index Threshold	SnsPI _3		SnsPI _6		SnsPI _12	
		Freq	%	**Freq**	%	**Freq**	%
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	106	75.71	106	75.71	107	81.06
Near Normal	-0.99 to 0.99	13	9.29	13	9.29	13	9.85
Moderately dry	-1 to -1.49	0	0	0	0	0	0
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	21	15	21	15	12	9.09
Total		**140**	**100**	**140**	**100**	**132**	**100**

Table 4.4g: Summary of Zaria drought intensity

Drought Intensity	Index Threshold	SnsPI _3		SnsPI _6		SnsPI _12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	110	82.71	111	77.08	110	76.92
Near Normal	-0.99 to 0.99	9	6.77	9	6.25	12	8.39
Moderately dry	-1 to -1.49	0	0	0	0	0	0
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	14	10.53	24	16.67	21	14.69
Total		**133**	**100**	**144**	**100**	**143**	**100**

4.1.5.3Categorization of droughts using Standardised Precipitation Anomaly Index (SPAI)

Tables (4.19-4.25) revealed the drought intensity summary for all stations at 3, 6 and 12 months using Standardised Precipitation Anomaly Index (SPAI). The categorisation was done on the basis of extremely wet, very wet, moderately wet, near normal, moderately dry, severely dry, extremely dry. Across the stations, there was uniformly occurrence of near normal condition, moderately dry and extremely dry conditions. For instance, Kano recorded 166 numbers of near normal condition, 8 and 4 numbers of moderately extremely dry conditions respectively for the past 15years under 3_month timescale Table (4.19). The same conditions with little variation in the frequency of occurrence were recorded under the timescale of 6 and 12 for the past 15 years.

Table 4.5a: Summary of Kano drought intensity

Drought	Index	SPAI_3		SPAI_6		SPAI_12	
Intensity	**Threshold**	**Freq**	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	0	0	0	0	0	0
Near Normal	-0.99 to 0.99	166	93.26	163	93.14	150	88.76
Moderately dry	-1 to -1.49	8	4.49	8	4.57	15	4.73
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	4	2.25	4	2.29	4	2.37
Total		**178**	**100**	**175**	**100**	**169**	**100**

Table 4.5b: Summary of Gusau drought intensity

Drought	Index	SPAI_3		SPAI_6		SPAI_12	
Intensity	**Threshold**	**Freq**	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	0	0	0	0	0	0
Near Normal	-0.99 to 0.99	164	93.26	163	93.14	157	92.90
Moderately dry	-1 to -1.49	10	4.49	8	4.57	6	3.73
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	4	2.25	4	2.29	6	2.37
Total		**178**	**100**	**175**	**100**	**169**	**100**

Table 4.5c: Summary of Kaduna drought intensity

Drought Intensity	Index Threshold	SPAI_3		SPAI_6		SPAI_12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	0	0	0	0	0	0
Near Normal	-0.99 to 0.99	156	87.63	160	91.43	157	92.90
Moderately dry	-1 to -1.49	18	10.11	8	4.57	8	4.73
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	4	2.25	11	6.29	4	2.37
Total		**178**	**100**	**175**	**100**	**169**	**100**

Table 4.5d: Summary of Katsina drought intensity

Drought Intensity	Index Threshold	SPAI_3		SPAI_6		SPAI_12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	0	0	0	0	0	0
Near Normal	-0.99 to 0.99	162	93.26	163	93.14	157	92.90
Moderately dry	-1 to -1.49	12	4.49	8	4.57	8	4.73
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	4	2.25	4	2.29	4	2.37
Total		**178**	**100**	**175**	**100**	**169**	**100**

Table 4.5e:Summary of Sokoto drought intensity

Drought Intensity	Index Threshold	SPAI_3		SPAI_6		SPAI_12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	0	0	0	0	17	10.06
Near Normal	-0.99 to 0.99	160	89.89	163	93.14	140	82.84
Moderately dry	-1 to -1.49	14	7.89	8	4.57	8	4.73
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	4	2.25	4	2.29	4	2.37
Total		**178**	**100**	**175**	**100**	**169**	**100**

Table 4.5f: Summary of Yelwa drought intensity

Drought Intensity	Index Threshold	SPAI_3		SPAI_6		SPAI_12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	0	0	0	0	17	10.06
Near Normal	-0.99 to 0.99	166	93.26	163	93.14	140	82.84
Moderately dry	-1 to -1.49	8	4.49	8	4.57	8	4.73
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	4	2.25	4	2.29	4	2.37
Total		**178**	**100**	**175**	**100**	**169**	**100**

Table 4.5g: Summary of Zaria drought intensity

Drought Intensity	Index Threshold	SPAI_3		SPAI_6		SPAI_12	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Extremely Wet	>2	0	0	0	0	0	0
Very wet	1.5 to 1.99	0	0	0	0	0	0
Moderately Wet	1.0 to 1.49	0	0	0	0	0	0
Near Normal	-0.99 to 0.99	156	87..65	161	92	157	92.90
Moderately dry	-1 to -1.49	18	10.49	10	5.71	8	4.73
Severely dry	-1.5 to -1.99	0	0	0	0	0	0
Extremely dry	<-2	4	2.25	4	2.29	4	2.37
Total		**178**	**100**	**175**	**100**	**169**	**100**

4.2Developing a Regionalised Spatio-temporal Drought Patterns

4.2.1 Spatio-temporal maps for Standardised Precipitation Index (SPI)

Figures 4.6(a-c) showed the spatio-temporal maps of all stations at timescales of 3,6 and 12 months respectively. The patterns showed the most affected areas with drought conditions as well as stations with average rainfall conditions as in the study of Wagan *et al.* (2015) in China. In Figure 4.7a, all stations recorded near normal conditions (SPI ranging between -0.99 and 0.99) with Zaria, Yelwa and Kaduna recording close values to moderately dry conditions while Gusau, Kano, Sokoto and Katsina recorded values close to moderately wet conditions. All stations in Figure 4.6b recorded near normal conditions (SPI ranging between -0.99 and 0.99 according to the stated standardised values in Table 2.3) with close values to moderately dry conditions in Yelwa, Kaduna, Zaria and Sokoto while close conditions to moderately wet situations experienced in Katsina, Gusau and Kano meteorological stations at 6_month timescale. In Figure 4.6c, Yelwa and Kaduna recorded moderately dry conditions with extreme condition in Yelwa.

Sokoto, Zaria, Katsina, Gusau and Kano experienced moderately wet conditions (SPI ranging between 1.00 and 1.49) for the past 15years.

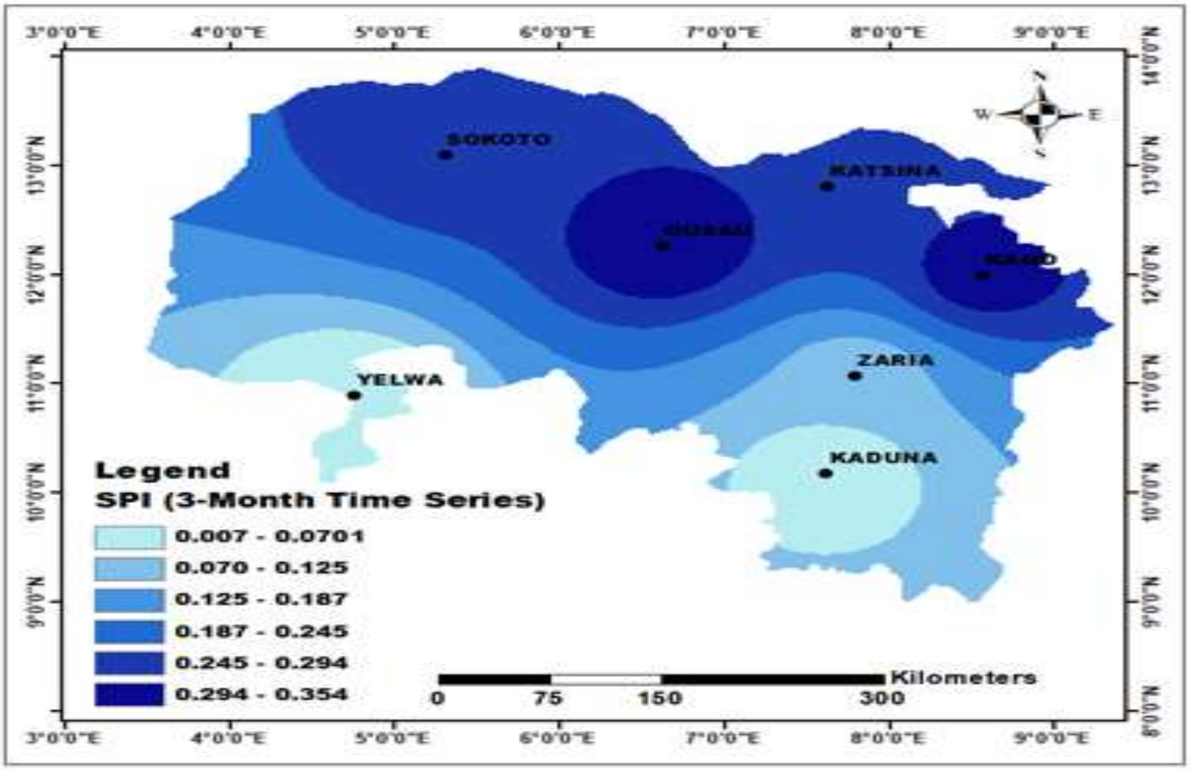

Figure 4.6a: 3-months Mean Annual SPI spatial map for all stations

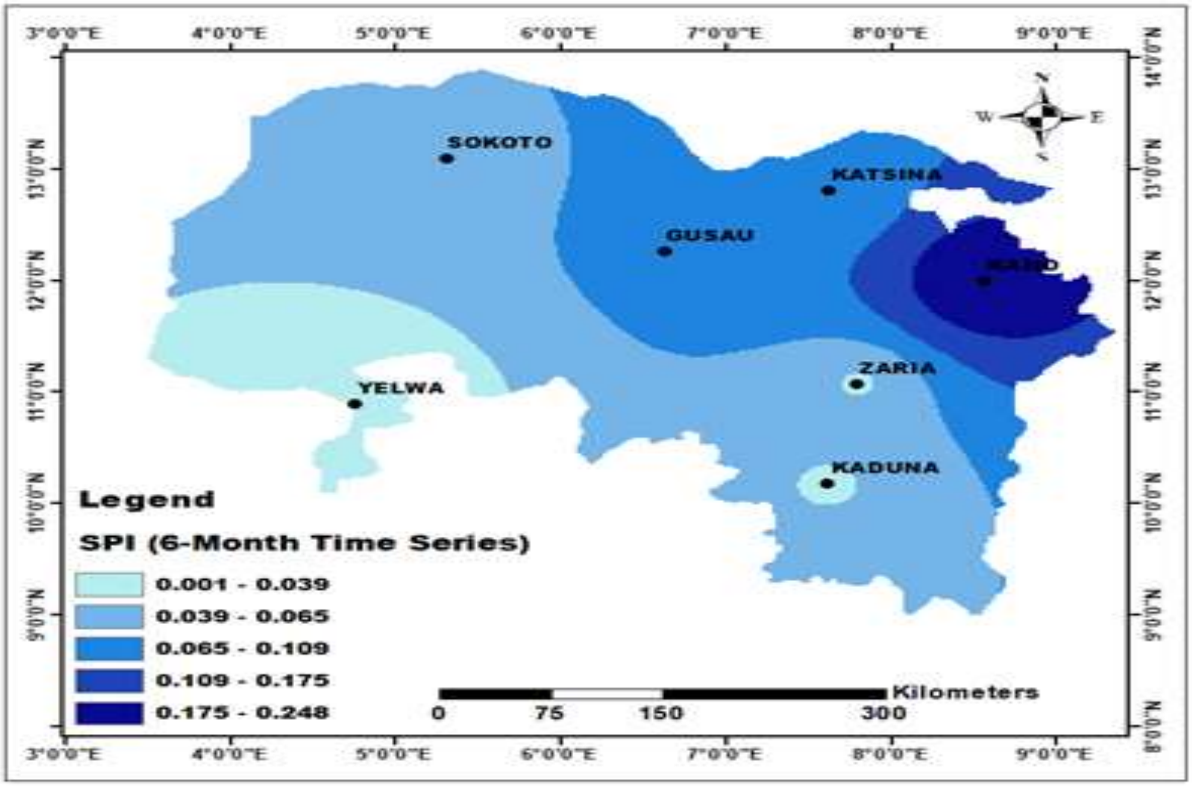

Figure 4.6b: 6-months Mean Annual SPI spatial map for all stations

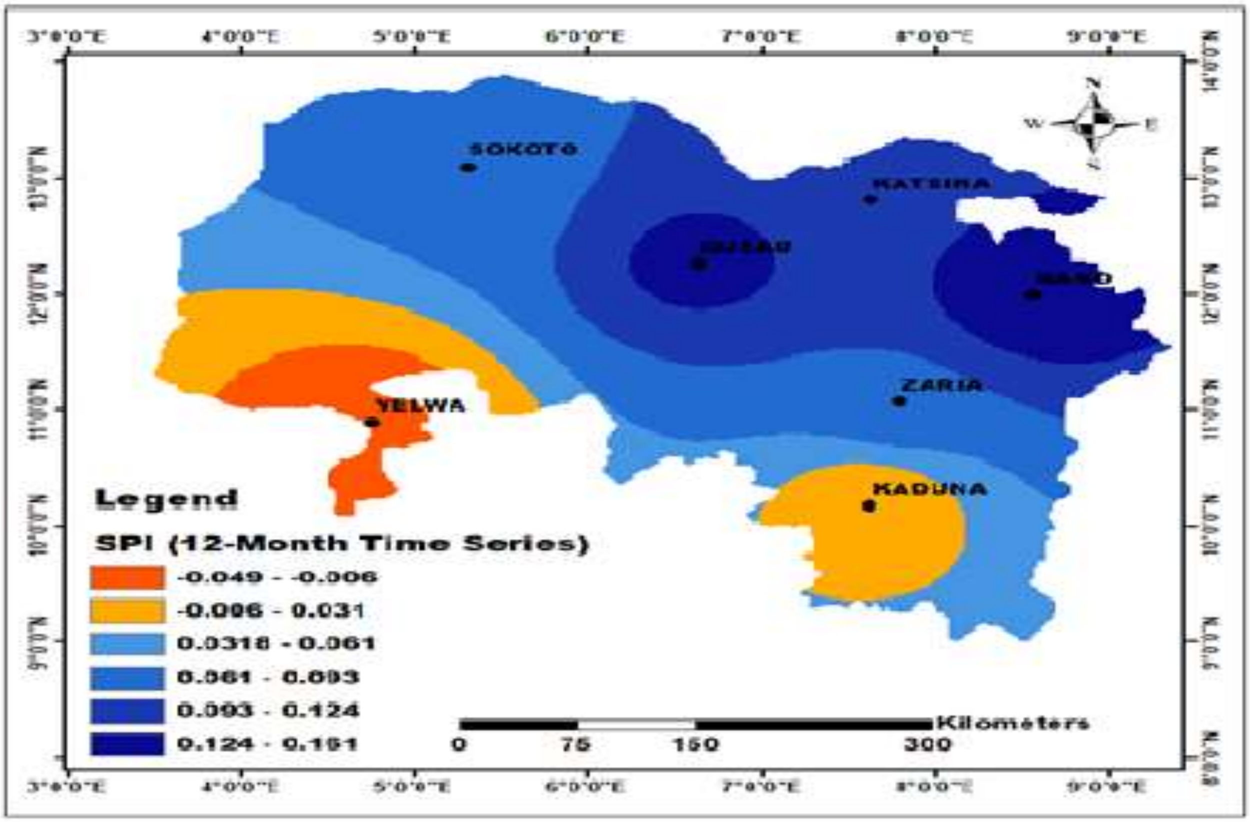

Figure 4.6c: 12-months Mean Annual SPI spatial map for all stations

4.2.2 Spatio-temporal Maps using Standardised Non-stationary Precipitation Index

Figures 4.7(a-c) revealed the spatio-temporal maps at timescales of 3, 6 and 12months respectively. The maps showed the most affected areas with drought and also areas with average rainfall conditions. Across all stations, near normal (SnsPI ranging between -0.99 and 0.99 according to the stated standardised values in Table 2.3) conditions were experienced with Sokoto, Katsina, and Gusau recording values close to moderately dry conditions while Zaria, Kano, Yelwa and Kaduna recorded values closely related to moderately wet condition in all the timescales considered.

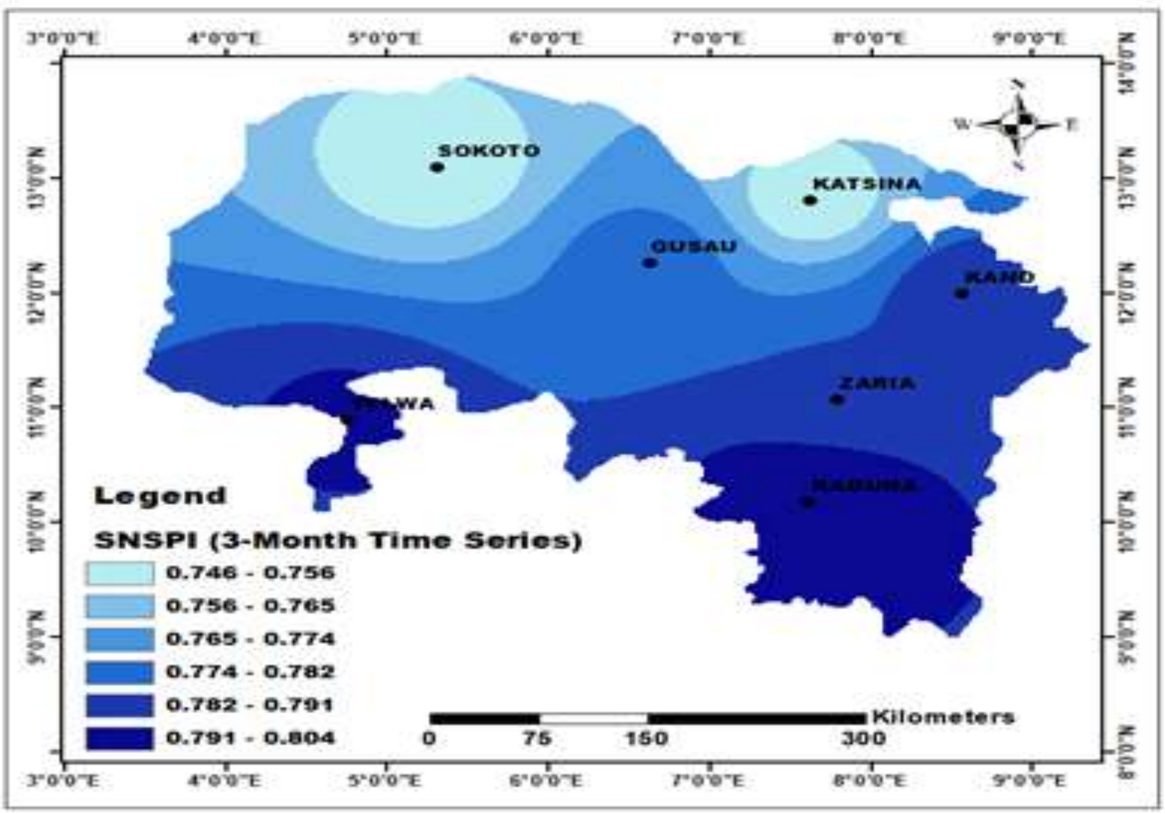

Figure 4.7a: 3-months Mean Annual SnsPI spatial map for all station

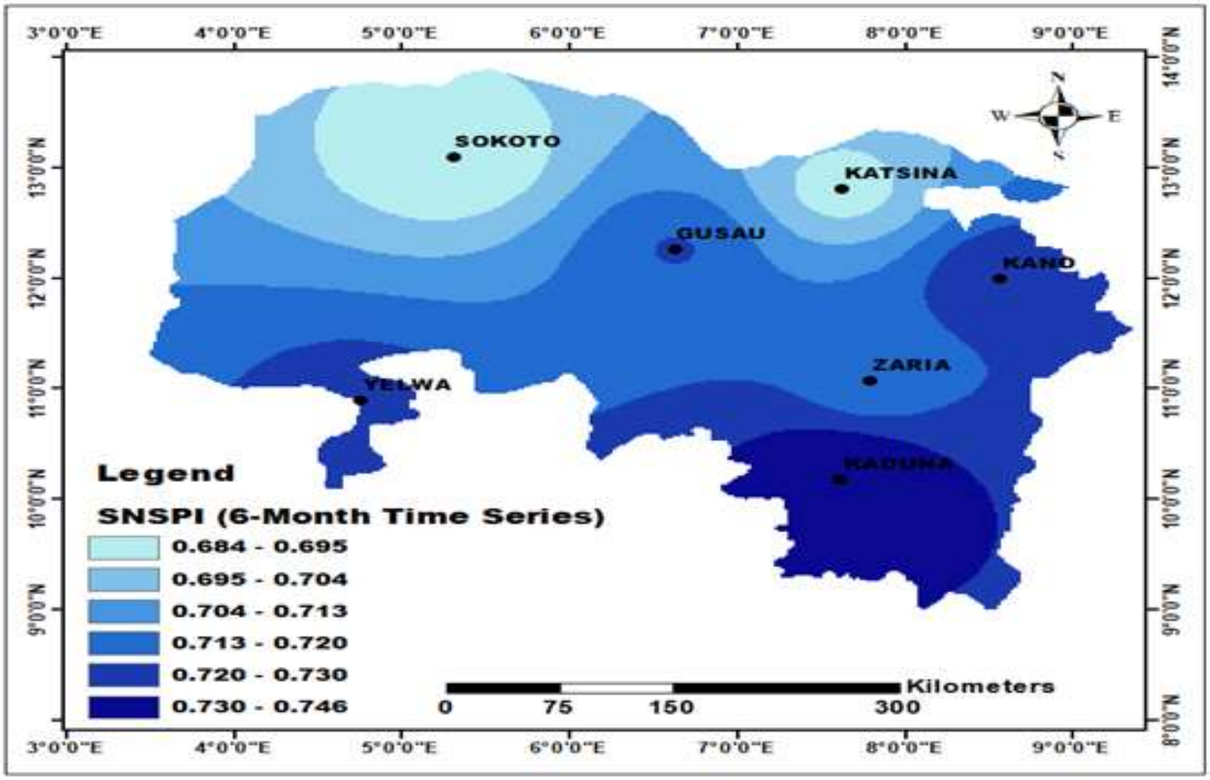

Figure 4.7b: 6-months Mean Annual SnsPI spatial map for all the stations

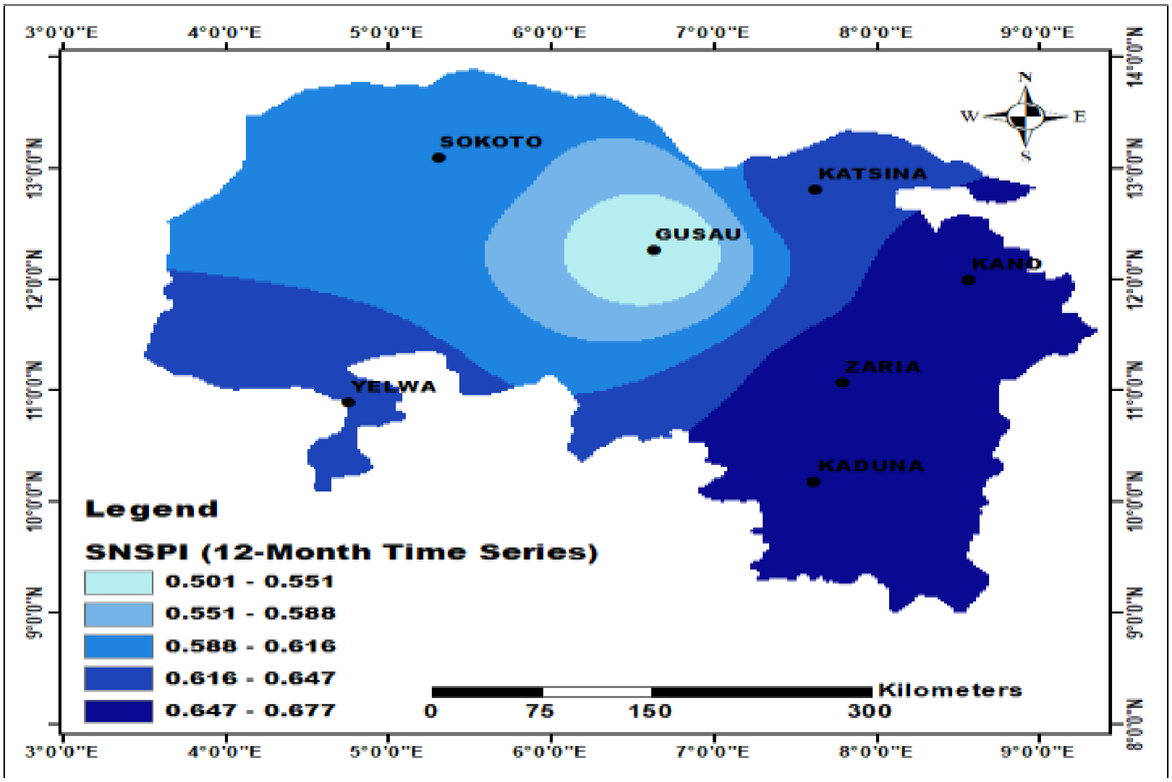

Figure 4.7c: 12-months Mean Annual SnsPI spatial map for all the stations

4.2.3 Spatio-temporal maps using Standardised Precipitation Anomaly Index

Figures 4.7(a-c) showed the spatio-temporal maps at timescales of 3, 6 and 12months respectively. The maps showed the most affected areas with drought and also areas with average rainfall conditions (Baltas, 2015). Across the spatial maps, near normal conditions were recorded with Gusau, Kano, Kaduna and Katsina showing conditions closely related to moderately dry conditions while Sokoto, Yelwa and Zaria recording values close to moderately wet conditions at all the timescales considered for the past 15years.

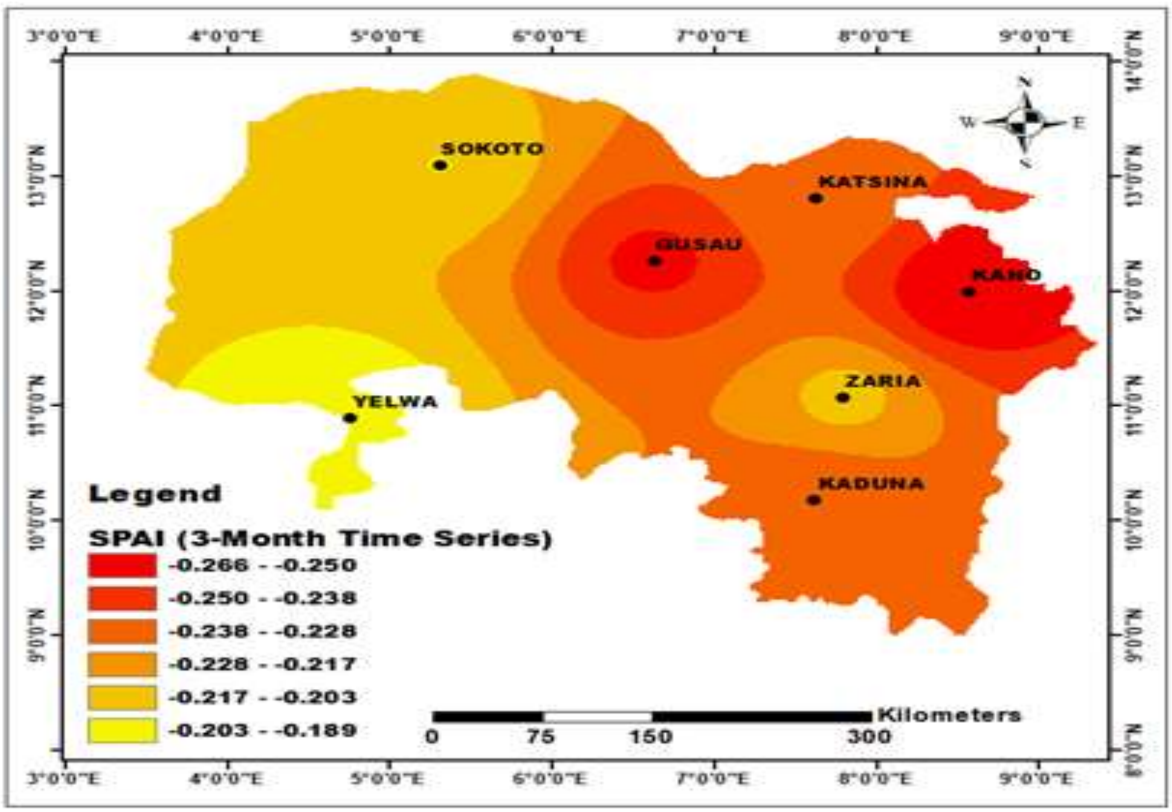

Figure 4.8a: 3-months Mean Annual SPAI spatial map for all stations

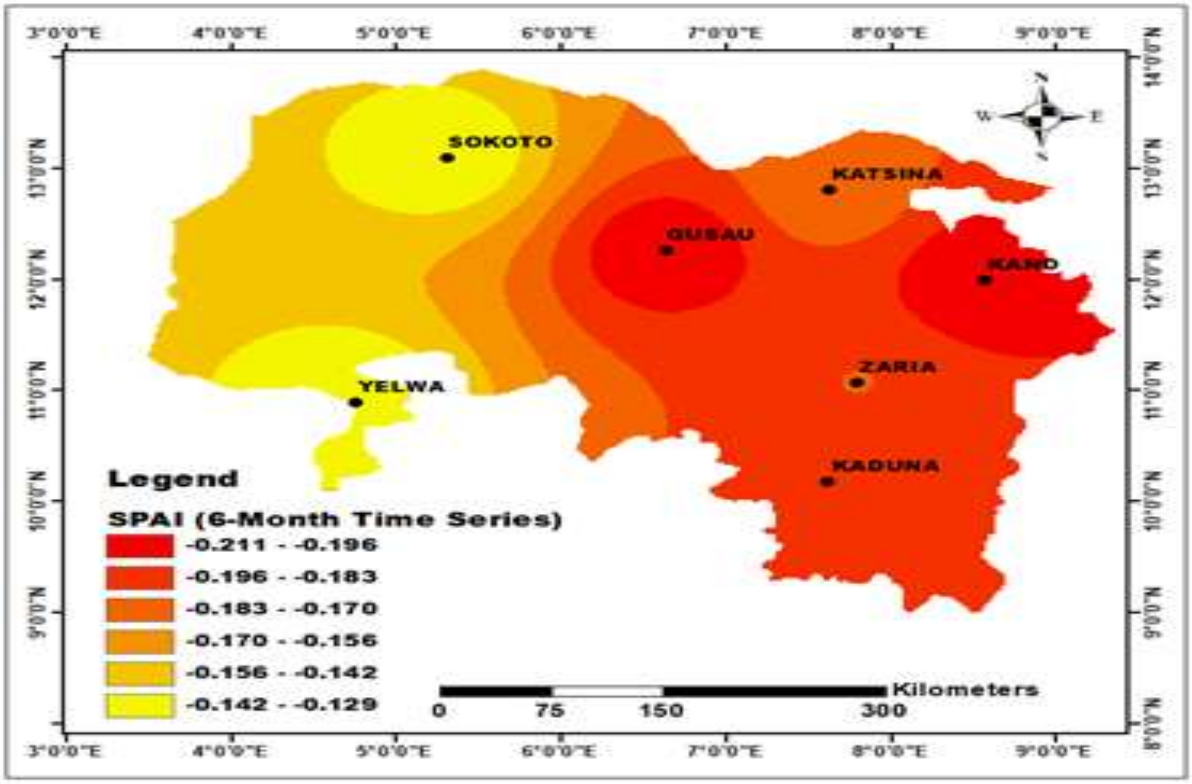

Figure 4.8b: 6-months Mean Annual SPAI spatial map for all stations.

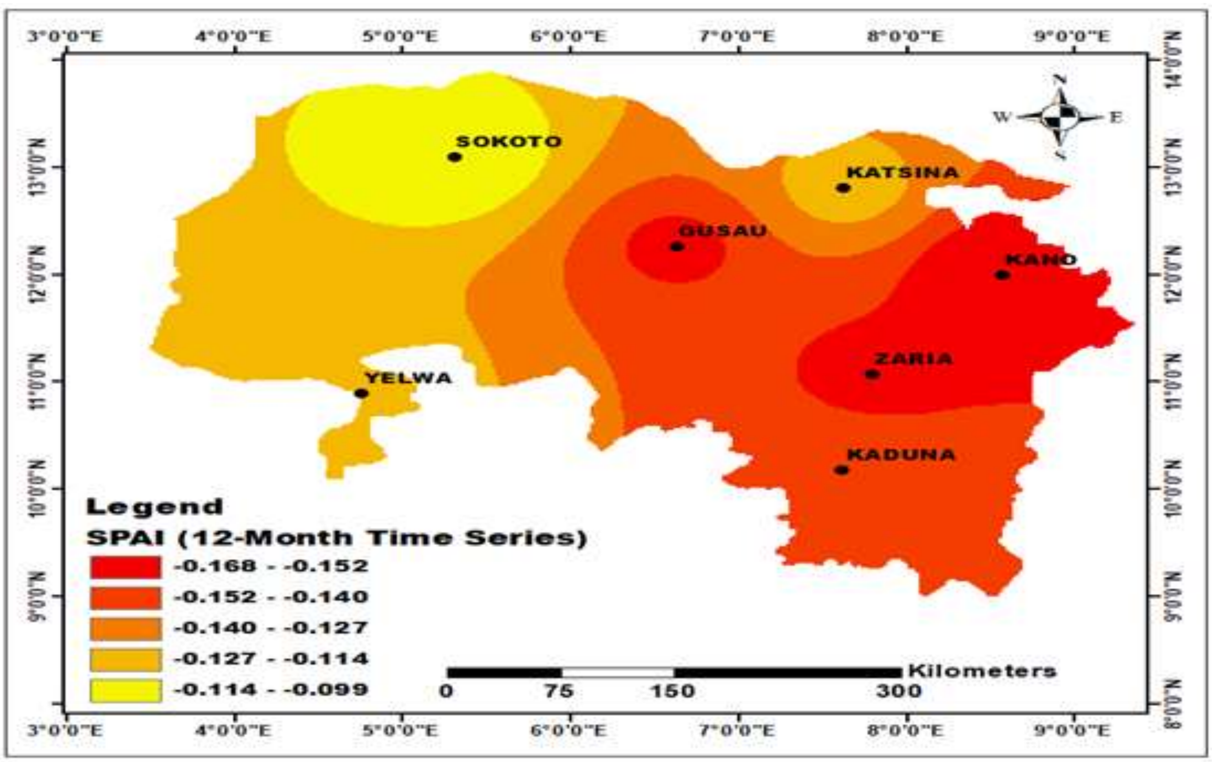

Figure 4.8c: 12-months Mean Annual SPAI spatial map for all stations

4.2.4 Regionalisation of Drought into Coherent Zones

4.2.4.1 Results of principal component analysis of drought

Figure (4.9) showed the screeplot diagram of the three components of the PCA and their respective contributions. PCA of the SnsPI fields revealed that the first principal components (PC1) have not only the largest, but also the most dominant contributions to the total variance after the orthogonal linear transformation SnsPI_6 drought estimates. The principal components PC1, PC2 and PC3 explained 69.18%, 52.29% and 27.22% of the total cumulative variance respectively with the first principal component contributing largely to the entire zones Figure (4.9).The first result of the principal components function, contain the coefficients of the linear combination of the original values that generate the principal components. The coefficients are known as factor loadings. The first three PCs revealed the contributions of the PC as Table 4.6.

According to PCA, the first Empirical Orthogonal Function (EOF) explained of the total variance. The first principal component (PC1) showed variation (Table 4.6) affecting the region as a whole, with maximum loading distributed across the stations, hence represents rainfall i.e., all places wet or all places dry. All factor exhibited both positive and negative correlation with the principal component. The correlation coefficient between the drought at any point and the principal component was obtained from the product of the factor loading and square root of the eigenvalue.

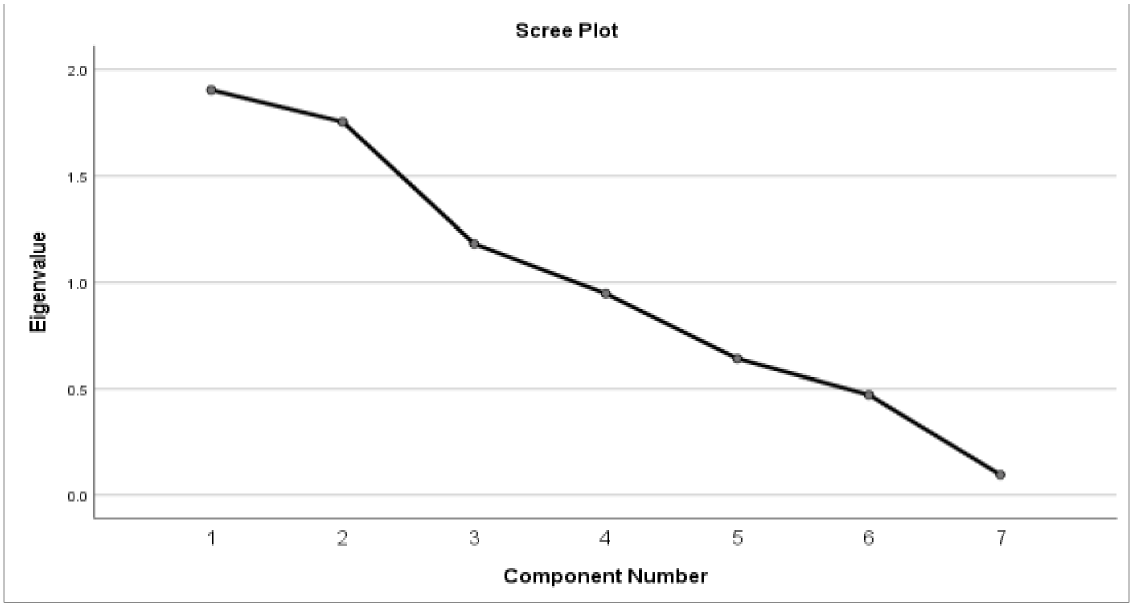

Figure 4.9: Scree Plot diagram

Table 4.6: Principal components coefficients of the drought estimates

Station	**PC1**	**PC2**	**PC3**
Gusau	0.028	0.476	0.014
Kano	0.116	-0.445	0.117
Kaduna	-0.364	-0.145	0.367
Sokoto	-0.354	0.048	0.067
Katsina	0.639	0.008	0.167
Yelwa	0.026	0.399	0.299
Zaria	0.094	0.044	0.567
Cumulative Variance %	**69.18**	**52.29**	**27.22**

The geographical distribution pattern of loading of the first three principal component (PC1, PC2 and PC3) computed for monthly drought total series of the seven stations within the stations are shown in Figures(4.10, 4.11 and 4.12) respectively. It is seen in Figure 4.10 that Sokoto, Gusau and Kano recorded the highest drought severity (dry spell condition) while Kaduna and Zaria recorded wet spell condition. In Figure (4.11), Kano had the highest drought severity condition while Gusau recorded the least drought condition corresponding to extremely wet conditions. Other stations recorded between mild drought and near normal conditions as shown in the map.

Finally in Figure (4.12), Sokoto recorded the highest severity condition corresponding to extremely dry condition and Katsina with the least wet condition among the stations under consideration.

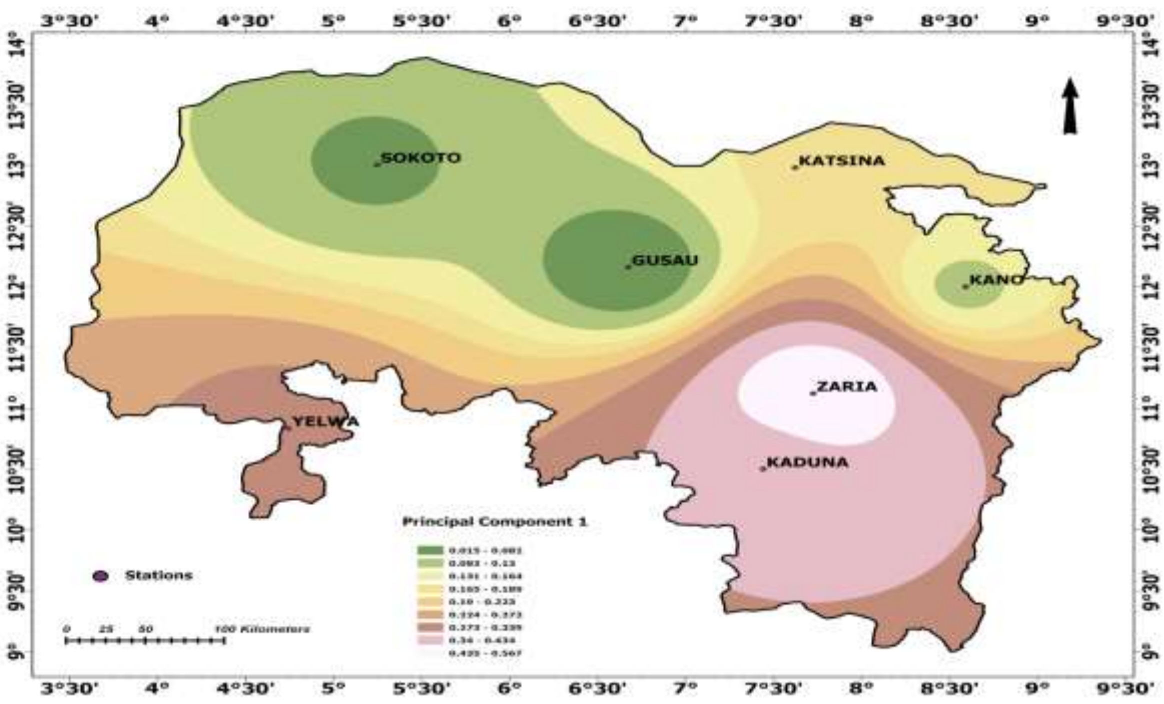

Figure4.10a: Principal Component 1

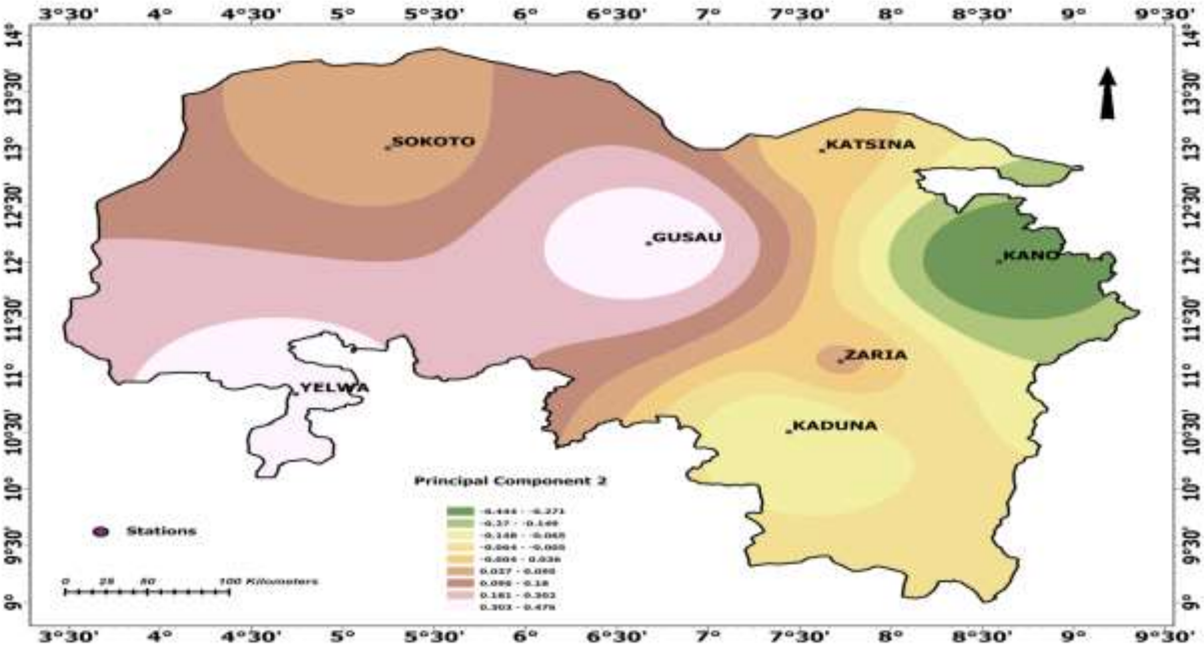

Figure 4.10b: Principal Component 2

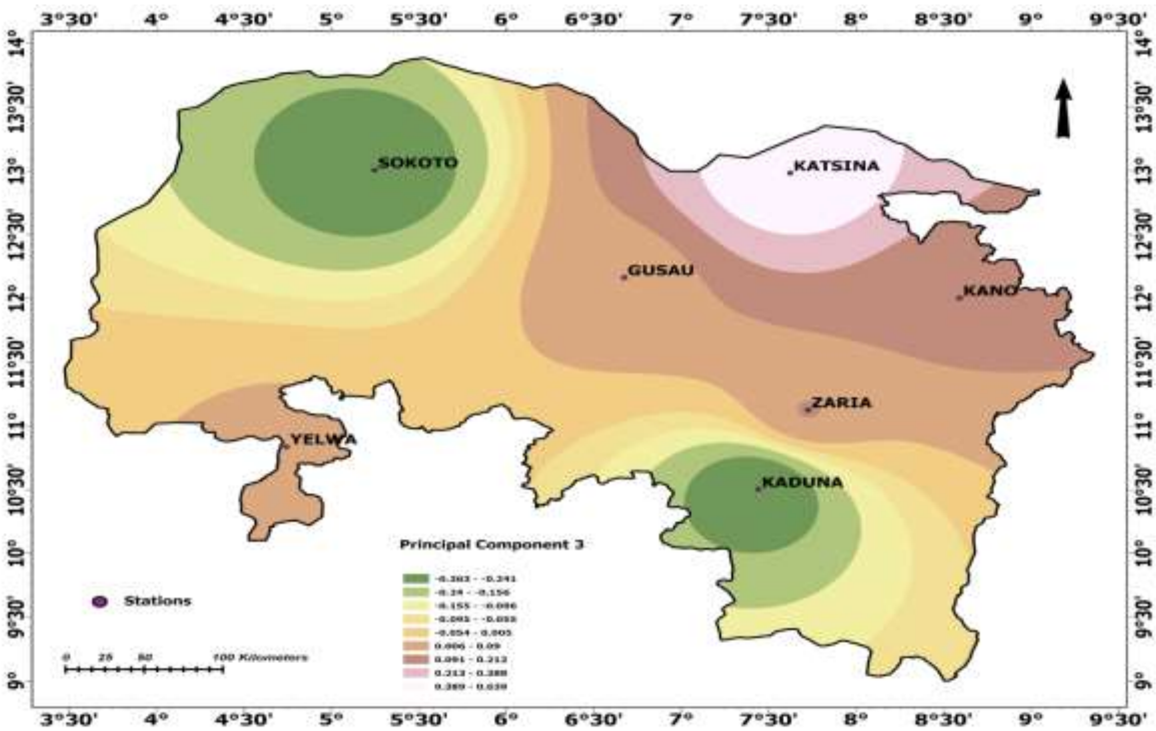

Figure 4.10c: Principal Component 3

To investigate the relationship among variables as shown in Figure 4.7each variable (station) can be represented by the factor loadings for two principal components (dimensions). All variables are plotted with respect to the PC1 and PC2 and shows both negative and positive correlation with the PC1 and PC2.

Table 4.7: Factor loadings

Station	F1	F2	F3
Gusau	-0.4874	-0.5118	0.3426
Kano	0.6089	0.5667	-0.1060
Kaduna	0.8129	-0.4296	-0.1906
Sokoto	0.1550	-0.4781	-0.2517
Katsina	0.0531	0.6055	0.7026
Yelwa	0.0235	-0.5770	0.4762
Zaria	0.7803	-0.2431	0.4832

The factor loading map F1, F2 and F3 showed the relationship among variables. The loading map after varimax rotation are shown in Figure 4.13and 4.14 respectively. I

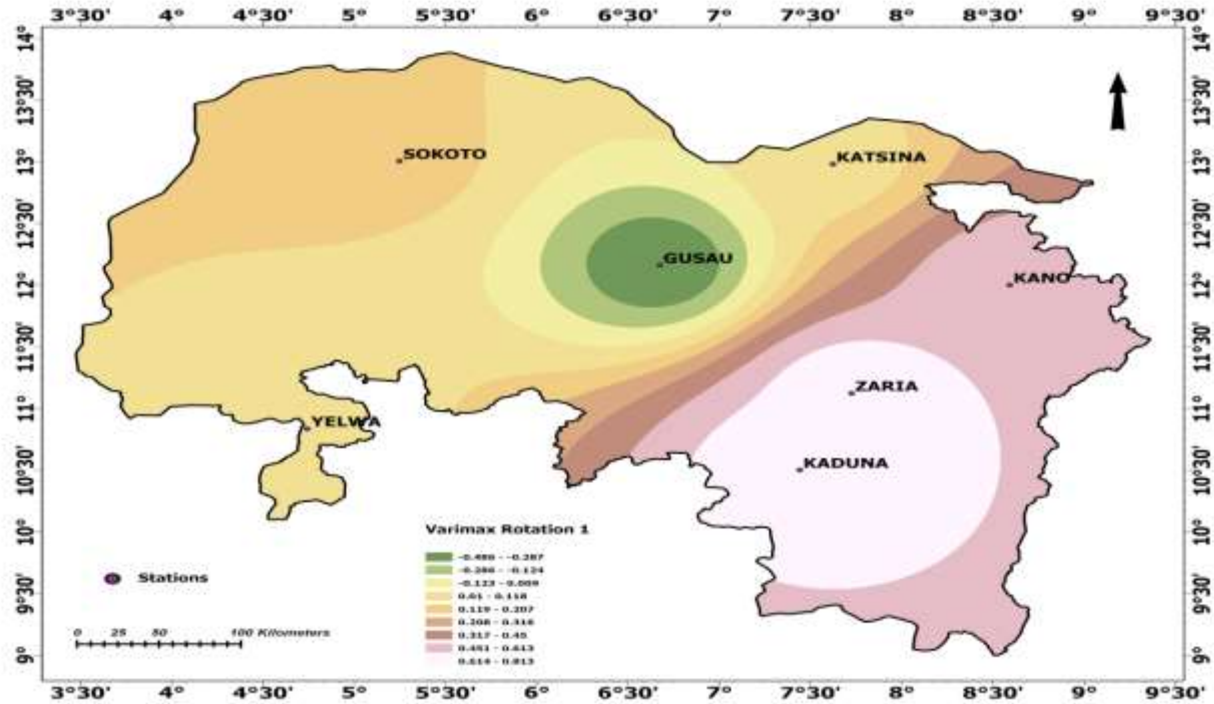

Figure 4.11a: Factor loading D1

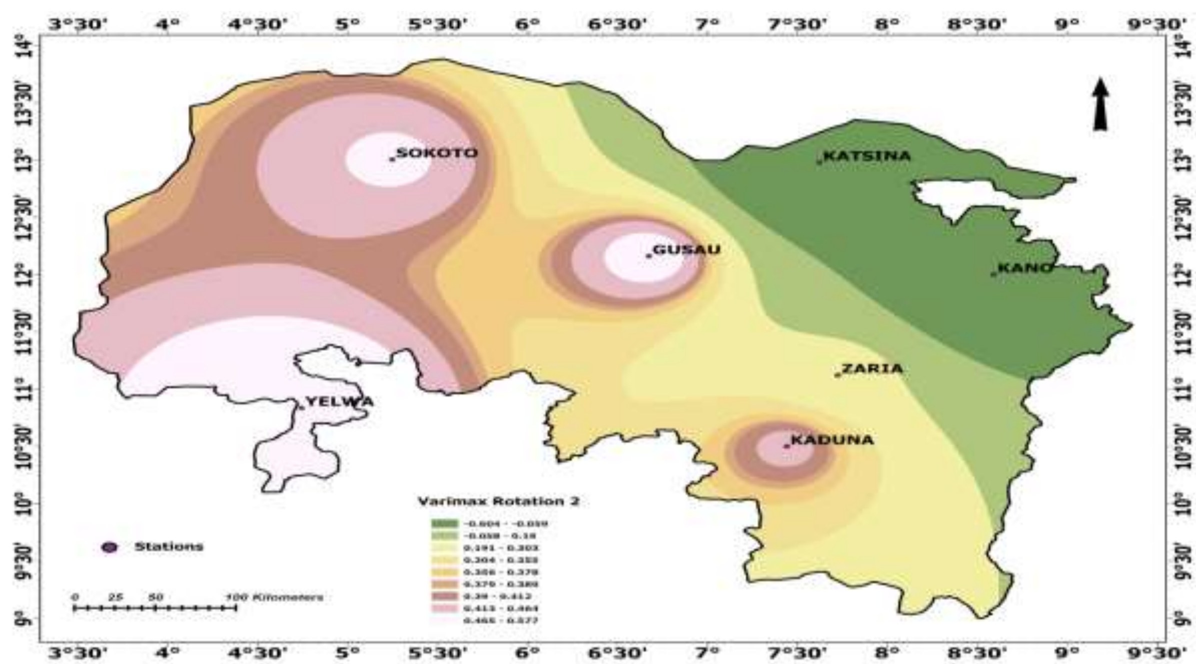

Figure 4.11b: Factor loading F2

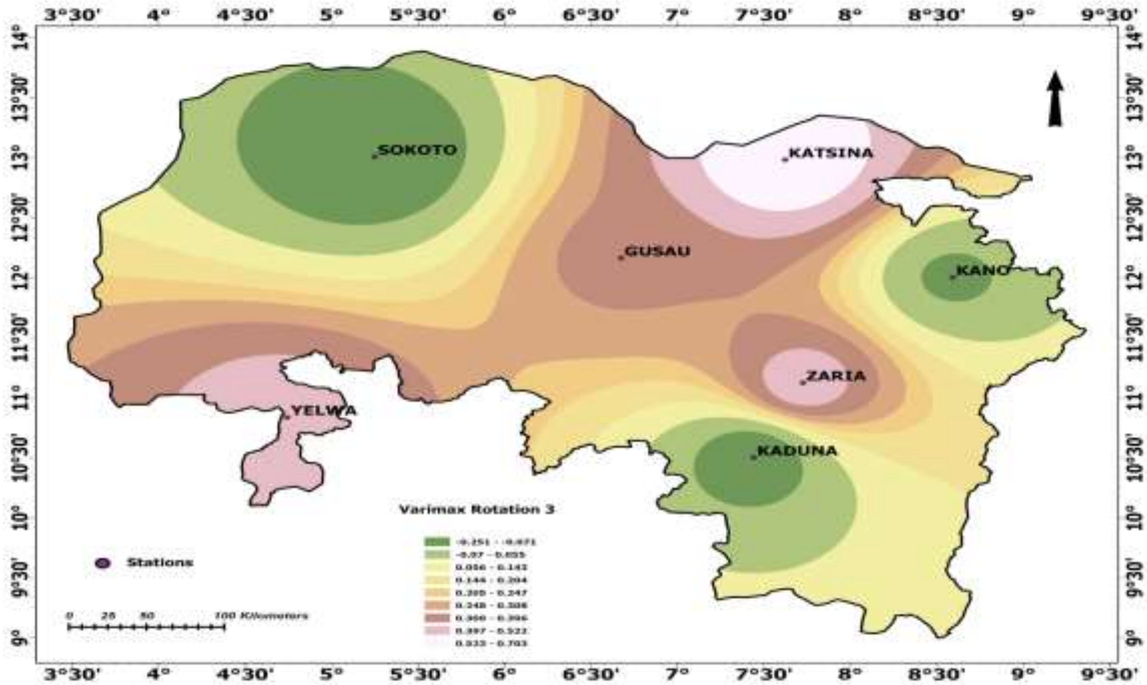

Figure 4.11c: Factor loading F3

4.2.4.2 Regionalisation of coherent drought estimates

The characteristics of rotated PCs were used to delineate coherent homogeneous region of rainfall variation over the study area. By selecting a loading magnitude for which sharp gradient on different rotated PC, a loading Magnitude of 0.4 was used for delineation of homogeneous zones.

The factor loading F1 and F2 was analysed using the K-means Cluster analysis. F3 was not considered because it has less than 0.4000 in magnitude. K-means cluster analysis showed 2 clusters; cluster 1 has three stations or observations while cluster 2 has four observations as shown in Table 4.8a and cluster centroid of F1 and F2 in Table 4.8 (a and c)

Table 4.8a: Cluster Analysis

Variables	No of Stations	Cluster sum of Squares	Average distance from centroid	Maximum distance from centroid
F1	3	0.235	0.261	0.385
F2	4	1.241	0.545	0.701

Table 4.8b: Cluster Centroid

Variable	Cluster 1	Cluster 2	Grand Centroid
F1	-0.1030	0.5638	0.2780
F2	-0.5223	0.1249	-0.1525

Table 4.8c: Distance between cluster centroids

Cluster 1	0.0000	0.9292
Cluster 2	0.9292	0.0000

4.3 Drought Intensity for Selected Return Periods Using SPI Model

In this objective (3), the selected stations of the North-Western region of Nigeria were investigated based on the rainfall deficit. SPI was applied to monthly rainfall data at the stations (k=3month) timescale. Critical drought severity was calculated for return periods of 1,2,3,4 and 5 for 3, 6 and 12 months duration (Table 4.9). From the critical severity, the rainfall deficit of 3, 6 and 12 month drought durations and 1,2,3,4 and 5-year return periods were determined. The drought intensity values were also obtained as the ratio of the drought severity and duration. In Table (4.9) it is clearly seen how the drought values increase as the drought durations and return periods increase from 1 to 2, 3, 4 and 5. At (D= 3month), drought boundary changes between

17.4mm (1-year return period drought in Kaduna meteorological station) and 21.4mm (1-year return period in Sokoto meteorological station). The above indicated that more severe rainfall deficit tend to occur in Sokoto meteorological station for all return periods while lower rainfall deficit is prone to Kaduna at the same return periods. Similarly, for the drought of D= 6 month-duration, drought boundary changes between 6.46mm (1-year return period drought in Kaduna meteorological station) and 46.26mm (1-year return period in Sokoto meteorological station) and this implied that more severe rainfall deficit tend to occur in Sokoto meteorological station for all return periods while lower rainfall deficit is prone to Kaduna at the same return periods. At (D = 12 month), drought boundary changes between Yelwa and Sokoto meteorological stations with lowest rainfall deficit of 47.11mm in Yelwa (at 1-year return period) and highest rainfall deficit of 85.31mm in Sokoto (at 5-year return period). This revealed that more severe rainfall deficit tend to occur in Sokoto meteorological station for all return periods while lower rainfall deficit is prone to Yelwa at the same return periods. The above explanations concur to (Cavus and Aksoy, 2019).

Table 4.9: SnsPI Drought intensity based on rainfall deficit corresponding to 1, 2, 3, 4 and 5-year return periods at k = 3_month timescale

	D=3months	D = 6months			D = 12months				
R.P / Stations	1	1	2	3	1	2	3	4	5
Gusau	19.8	11.2	43.5	44.2	55.10	57.89	57.90	58.33	59.67
Kaduna	17.4	6.46	28.1	33.4	56.4	58.14	59.39	59.70	59.90
Kano	19.4	7.46	32.1	35.4	58.4	63.14	63.39	69.10	72.1
Katsina	19.5	8.34	34.15	41.5	61.11	65.14	66.45	67.19	68.15
Sokoto	21.41	13.43	45.19	46.26	56.20	76.10	83.54	84.10	85.31
Yelwa	19.9	12.3	44.10	45.78	47.11	55.90	56.81	67.81	75.1
Zaria	17.8	6.78	31.1	36.4	50.4	51.14	56.39	57.70	57.90

4.3.1Implications for water resources development

The spatio-temporal variability identified by PCA has immediate implications for water resources management in all the stations considered. In the Figure (4.16), it is revealed that the stations experienced both dry and wet spells conditions with the wet spells condition outweighing the dry spells. Figure (4.16) showed the extent of the drought-affected area for the past 15 years for 6-month SPI fields. It provides further verification for the results of the PCA and the inferred implications. The extent of the drought is on the basis of mild, moderate, severe and extreme. It is seen that Kano, Kaduna and Sokoto recorded the highest drought conditions mostly under the PC1 and PC2. Conclusively, the large extent of droughts and the long accumulated duration of consecutive drought events call for concerted and dedicated efforts in water resources management across the stations.

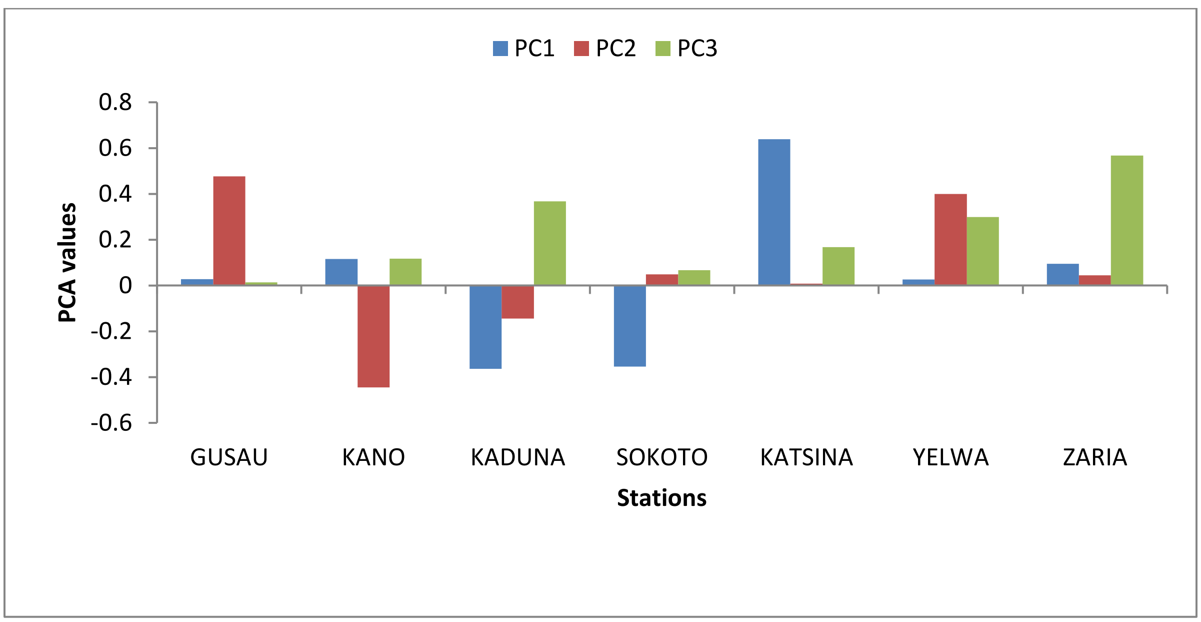

Figure 4.12: Temporal evolution of drought-affected areas in the stations

CHAPTER FIVE

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSIONS

This study examined the spatio-temporal characteristics of meteorological drought over selected stations in North-Western region of Nigeria with the following objectives: To determine trend and characterise the drought field, establish homogenous meteorological drought areas for effective regionalisation and to compute the drought intensity based on rainfall deficit for selected return periods.

Based on the analysis done, the following conclusions were drawn;

The trend results for all stations showed statistically insignificant trend as their respective values lie within the set Z-statistic value $(Z = \pm 1.96)$ at 95% level of significance. In the meteorological drought characterisation, the typology of the meteorological drought was analysed in terms of its characteristics such as mild, moderate, severe and extreme and this was done using three (3) different rainfall-based indices. Based on the analysis, it is apparent that despite the fact that annual timescale maybe long, it can be employed to obtain information on the temporal evolution of drought most importantly, regional behavior. Monthly timescale can be more appropriate if emphasis is on evaluating the effects of drought in situations relating to water supply, agriculture and water abstractions.

On the basis of the spatio-temporal patterns drawn, drought incidents such as mild, moderate, severe and extreme were recorded in Sokoto, Yelwa, Gusau and Kano with minimal effects of extreme conditions in other stations. Also, the drought summary tables revealed the frequencies and percentages of occurrence of droughts for all stations with the nonstationary standardised precipitation index being the best amongst the rainfall-based drought indices.

Conclusively, the identified patterns (PCA and Factors loading) across the stations highlighted the challenging nature of drought management in the country and the need for a well-coordinated water resources planning and drought preparedness, as well as effective and efficient emergence responses during drought events.

5.2 Recommendations

The following recommendations are made based on the study;

i. In view of the observed shortcomings of both indices, especially the SPI, the Standardised Precipitation Evapotranspiration Index (SPEI) should be looked into and too, other indexes that take into consideration the implications of global warming by incorporating potential evapotranspiration may be deemed more suitable for drought studies in Northern Nigeria.

ii. Research on spatiotemporal variability of meteorological drought on the basis of identifying the best probability distribution functions that fit the SPI, SPAI and other drought matrices should be looked into.

iii. In light of the findings, the lack of an adoptable threshold for drought quantification is a critical limitation hence there is need to establish a regional threshold vis-a-vis the employment of an only rainfall-based metrics for drought study may not be a veritable option but consideration should be given to other indexes that use variables that impact on regional water balance.

5.3 Contribution to Knowledge

Based on the conclusion drawn, the study has contributed in the following measures;

i. This study has established that the non-stationary standardised precipitation index is more effective than any other rainfall-based indices for drought analysis.

ii. This work established that for meteorological drought analysis for Northern Nigeria, 6-month time tuning resolution is the best.

iii. This study also established that each state crispy delineation/partition of Northern Nigeria into distinct hydrological areas in the face of prevailing climate change may not be viable but rather regionalisation should be taken into cognizance for fuzzy (degree of membership probability) nature of hydroclimatic variable usually employed for drought analysis.

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