



# Investigating Meteorological Drought in the Northern Region of Nigeria and its Linkage with Climatic Drivers

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## Abstract

Drought is a dearth of water, and a recurrence in all regions, but severe in the semi-arid and arid areas with adverse climatic conditions. There have been quite several studies in the country, but fewer in comparison to flood studies, which is in part due to drought nature as a hazard in the region. Drought creeping presence, the prevalence in arid northern Nigeria, and the water deficient problems have spawned the need for this research.

The study aims to investigate drought events and drivers using the Standardised Precipitation Index and Standardised Precipitation Evapotranspiration Index for assessing drought historicity, principal component analysis to ascertain the spatiotemporal distribution of rainfall and meteorological drought, in addition to wavelet analysis to determine the relationship with climatic drivers in the region. The region is around latitude 6° N and 14° N and between longitude 2° E and 15° E within the Savanna region of Nigeria covering an area of 729, 815 square kilometers. For analyses, gridded rainfall data was collected from 1951-2021 and processed with a 4-step homogeneity test to track the decline in rainfall and the advent of drought in the region.

These analyses showed that drought episodes are a recurring climatic theme in the region, and it was severe in the 1970s, 1980s and continued into the 21st century. Also, principal component analysis and K-means clustering techniques proved that coherence and variation between the regions are a function of the spatial distance between them. Further examination proved that rainfall transits between humid to arid regions, declining in events and intensity as it moves northward of the area. Drought relationship with climatic indices outlines the Tropical South Atlantic as a principal factor with a leading signal of 4-12 months, in the influence of weather conditions, which creates a window in drought management through monitoring.

**Keywords:** Drought; spatiotemporal; characteristics; Northern Nigeria; Principal component analysis; SPI.

## Introduction

Drought is essentially a lack of water at a specific location and period, which accumulates and spreads from one subsystem to the next. However, because of the variance in various locations and times, it is difficult to characterize and measure, making it quite a phenomenon in comparison to other natural hazards, which is why attempts have been made to monitor, assess, and forecast it (Wang et al., 2016). The (American Meteorological Society, 1977) divides drought definitions and types into four categories: meteorological or climatological, agricultural, hydrological, and socioeconomic. According to (Crausbay et al., 2020), new droughts kinds are entering the picture as a result of teleconnection and global warming, human water demand, and activities that shift the ecological status of an environment on a temporary or permanent basis like the recent Millennium drought in Australia [2002-2010] exceeded the threshold of the hydrological ecosystem in the Murray Darling Basin causing cessation of vital functions in the area and costing around 800 million AUD to initiate a transformational adaptation to the drought impact (Herrera-Estrada et al., 2019; Koslowski & Glaser, 1995). (Crausbay et al., 2017) highlighted droughts such as snow droughts, hotter droughts, megadroughts, and human-induced droughts, and stated the novelty and distinction of ecological from agricultural drought. Although drought features a recurrence in nature and affects all ecoclimatic regions, drought has been endemic to the (ASAL) arid and semiarid lands. The ASAL regions in America, and Australia. Asia, Europe, and Africa continents



have been subjected to extreme weather conditions, erratic rainfall variability, and extreme temperatures. This variability has been linked to different climatic patterns such as sea surface temperature, weather systems, Jetstream, etc. This has impacted the hydrological and water-dependent institutions and practices in these regions particularly in West Africa, where there is a heavily skewed rainfed farming practice.

(Seager et al., 2007), posits that climatic projections for the ASAL regions would spot an increasing drought recurrence and decreasing precipitation, and as a consequence, vulnerable regions have the need to understand how to assess and mitigate drought events. In addressing drought in any region, the use of drought indicators has been recommended. Among them are the Standardized Precipitation and Evapotranspiration Index (SPEI) and Standardized Precipitation Index (SPI) which has been recommended by the World Meteorological Organization (WMO) in assessing drought. The SPI and SPEI are widely used because of their ease of computation, and the ability to compute for drought on multiple temporal scales for short-term drought (1-, 3-, and 6- months) and long-term drought (9-, 12-, and 24- months). Although the SPEI improved on the SPI by accounting for evapotranspiration, and according to (Vicente-Serrano et al., 2010) this is important in arid regions and in recent cases of global warming, which in part makes SPEI better in estimating drought about climatic drivers.

Quite several researchers noted that climatic drivers such as sea surface temperature and atmospheric circulation have been known to be associated with cases of drought in a region. And in recent works, Nicholson Zhang has carried out (Henchiri et al., 2021; Nicholson, 1980) that show that El Nino Southern Oscillation, Multidecadal Atlantic Oscillation, Indian Ocean Dipole, Tropical South Atlantic, Arctic Oscillation, etc have been examined as a trigger for the climatic anomaly, particularly their effect on climate and atmospheric systems during the Sahelian drought. Thus, the significance of climatic drivers can't be dismissed in evaluating drought as they are effective in examining and monitoring drought through their influence on rainfall. Methods such as cross-correlation and wavelet analysis have been employed by (Douanla et al., 2022) to explore and establish the relationship between historic droughts and future trends of drought.

Characterizing drought includes and requires understanding the variability of rainfall, since rainfall is the principal element in drought events (Oladipo, 2021; Olukayode Oladipo, 1993) and the spatial temporal variability of drought within the region to establish distinct spatial homogenous domains due to the stochastic nature of drought (Vicente-Serrano et al., 2010; Wilhite, 2021). Recent studies have used principal component analysis (PCA) and K-means non-hierarchy techniques to evaluate the spatial-temporal distribution of rainfall and drought through the application of PCA to the rainfall series and drought indicators. This provides one of the means of breaking down the processes that constitute drought and the necessary mitigation strategies to be employed.

Since the 1970 and 1980 Sahelian drought, the northern region of the country, Nigeria has garnered several research and works to understand the nature of drought, the succeeding impacts, and adaptive measures and strategies in combating it. (Mortimore, 1989; Richards, 1983) worked on a comprehensive drought account of the Sahelian drought, particularly the socioeconomic impacts in the region (Eze, 2018) employed statistical techniques and drought indicators to evaluate drought. While Jude focused on Yobe, a northern state, and the socioeconomic effects of drought to characterize the drought severity, recurrence, and frequency. Recent research carried out by (Ogunrinde, Oguntunde, et al., 2020; Ogunrinde, Olasehinde, et al., 2020) employed the use of principal component analysis to investigate the spatial temporal characteristics of drought in the region, resulting in 4 distinct regions. (Shiru et al., 2018, 2020) have also researched the future trends of rainfall drought, and its relationship with climatic drivers in the region. Also, the comparison between different and multiple drought indicators suitability in assessing drought in the region (Tefera et al., 2019).

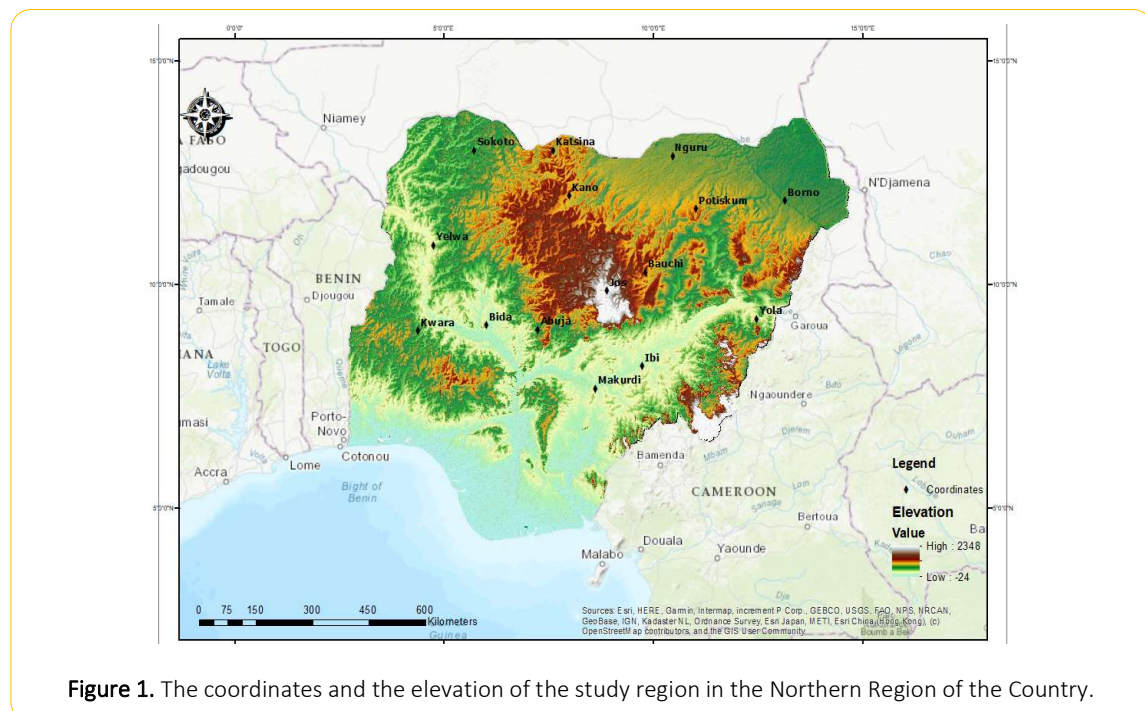
Although the poor monitoring and collection of hydrometeorological data, incurred cost, and lack of complete data have encouraged the use of gridded metrological data time series from the Climate Research Unit (CRU), Tropical Rainfall Measurement Mission (TRMM), and other climatic datasets. These high-resolution gridded

datasets have increased exponentially in use to better understand climate, weather, and environmental systems due to their coverage, diverse variables, degree of accuracy, and accessibility to long temporal climate data for the computation of SPI, SPEI, and other drought indicators. Hence, this has been useful, especially in region with poor data monitoring facilities and records like northern Nigeria. Apart from the gridded dataset subjection to quality control and checks. Several recent studies in the region (Hassan et al., 2020; Mutti et al., 2020; Salehie et al., 2022) have used it, and Hassan in their evaluation of gridded and ground station datasets discovered that among the used gridded products, CRU dataset has the highest association to observational dataset in assessing drought using SPI.

However, most of the research carried out investigate aspects of drought, but this study seeks to understand drought in relationship with climatic drivers, particularly using the wavelet techniques and clustering methods, and taking this into account, this study seeks to take multiple approaches for a high-resolution investigation of the hazard in the region. This study has been carried out to analyze and investigate drought events from 1951-2021. Reconstructing historic drought events and characterization. The study follows multiple approaches towards drought analyses, which includes; (i) characterization and comparison based on the Pearson correlation coefficient using both SPI and SPEI drought indicators, (ii) assessing the homogeneity of the dataset and spatiotemporal variability of rainfall and drought in the region through 4-step approach and principal component analysis techniques, (iii) addressing the homogenous distinct spatial subregions with PCA and K-means clustering technique, and (iv) establishing the relationship between drought and climatic drivers employing cross-correlation method and wavelet spectral analysis.

#### Study Area

The research focuses on the northern region of Nigeria which comprises nineteen states out of the thirty-six states in the federation and shares a boundary with Chad and Niger to the north (Figure 1), Benin to the west, and Cameroon to the east. Northern Nigeria covers an area of about 660,000km<sup>2</sup>, the region terrains shapes and bends into highlands like the Chappal Waddi at 2,419 (m.a.s.l) of Taraba state, the Mambilla Plateau above sea level at 1350 (m.a.s.l) which stretches as far as the border of Cameroon, and the valleys of River Niger and Benue which prevails over the southern parts of the region lowlands (Reuben Kenrick Udo & Toyin O. Falola, 2020).



The temperature in areas like Maiduguri can peak at 480 Celsius, while semi-temperate areas like the Jos plateau vary from 160 to 250 Celsius (Reuben Kenrick Udo and Toyin O. Falola 2020). Within the study period 1951-2021, the mean annual temperature (Figure 2) peaked at 280 Celsius in Borno in the Sahelian zone. The temperature in the northern region is higher compared to the southern region which expresses the spatial variability in temperature, which can be influenced by factors such as atmospheric and climate systems, land use land cover changes and altitude. The rainfall follows similar spatial variability as there is a decreasing transition from the humid south toward the arid northern region. The highest mean annual rainfall reached 2967mm in the subhumid region of Kwara, and the least rainfall in the north-eastern region from extracted coordinates is 712mm in Adamawa. The climate in semi-arid and arid northern Nigeria is characterized and dominated by tropical maritime air mass, which marks out the wet season from April to October, and dry dusty continental air mass; the dry season from October to March. The rainfall in the region is subjected to interannual variability attributed to atmospheric and shifting rain belts [airmass, ITCZ and Jetstream, etc.] which influences its generation and intensity.

#### *Data*

The dataset used for the computation of both the SPEI and SPI which includes; monthly rainfall, monthly mean minimum temperature, monthly mean maximum temperature, and monthly mean temperature within the period of 1951-2021 of the selected coordinates with a spatial resolution of 0.50 provided by the climatic research unit. ([https://crudata.uea.ac.uk/cru/data/hrg/cru\\_ts\\_4.06/ge/](https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.06/ge/)). The dataset has been subjected to quality control and tests for homogeneity and checked for visual errors and missing data in Microsoft Excel packages as well as the XLSTAT add-in.

The retrieved rainfall data was subjected to four homogeneity tests; Buishand range tests (Buishand, 1982), SNHT test (Alexandersson, 1986), Pettitt test, and Von Neumann test (Bingham & Nelson, 1981) ratio detect inhomogeneities in the time series. These four are regarded as absolute homogenous as carried out by (Wijngaard et al., 2003) to determine the quality of data, and this helps to determine trend direction and variation. This is important as it validates the use of time series for further processes, particularly in this study. The method follows multiple steps which include; (i) the usefulness of a time series dataset if one or no tests reject the null hypothesis at 1% (ii) doubtfulness of the time series if two tests reject the null hypothesis (iii) suspicious if three tests or all the four reject the null hypothesis at 1% significance level, except in the case of external factors such as atmospheric circulation and climatic variability.

The climatic dataset was retrieved and monthly data was collected for the same period as the meteorological data 1951-2021 to ensure consistency when computing the correlation between the variables. Climate indices are used to monitor the state of climate systems globally. Climate Indices used in this study include; Tropical South Atlantic index, El Nino 1+2,3,4, & 4, Indian Ocean Dipole, North Atlantic Oscillation index, Atlantic Multidecadal Oscillation index, and Southern Oscillation index. The teleconnection products were checked for quality control and missing data in Microsoft Excel packages, and standardized in the R studio software packages using the scale function to match the drought indices before evaluation of the relationship between the two variables.

#### *Pacific Ocean Indices*

##### *El Nino 1+2 (1951-2021)*

The El Nino is a region within 0-10S, 90W-80W around the equatorial Pacific Ocean and the coast of South America. It forms part of the indices in the El Nino Southern Oscillation (ENSO) used to measure the influence and evolution of the Pacific Ocean.

#### El Nino 3+4 (1951-2021)

The El Nino 3+4 is a region around the equatorial Pacific Ocean with an average sea surface temperature anomaly within 5N to 5S and 170W to 120W. The sea surface temperature is part of the four indices used to monitor and predict global climatic changes.

#### El Nino 4 (1951-2021)

El Nino 4 is the fourth of the El Nino located around 5N - 5S, 160E-150W and used in measuring the ENSO phenomenon for both the La Nina cold phase and the El Nino warm phase of the Pacific Ocean, and their influence on the climatic system.

#### SOI (1951-2021)

The southern oscillation index is featured also on the tropical Pacific Ocean and is different from the El Nino Southern Oscillation, since it measures the strength of the Southern oscillation, while the El Nino indices measure the total effects of the Pacific Ocean. The SOI is calculated based on the difference in the atmospheric pressure between Tahiti and Darwin and expressed as the difference in normalized sea level pressure.

#### *Atlantic Ocean Indices*

The Atlantic Ocean indices like the El Nino Southern Oscillation are used to measure and monitor the aspects and influence of the ocean on climate change.

#### TSA (1951-2021)

The Tropical South Atlantic Ocean Index is defined as an indicator in the Gulf of Guinea, the eastern tropical South Atlantic Ocean. The positive values follow a warmer than average and the negative values indicate a cold sea surface temperature. It is the average between 20 degrees south and 10E- 30W. The index is used to monitor and predict the influence of the sea surface temperature on regional and global climate.

#### NAO (1951-2021)

North Atlantic Ocean Index is based on the atmospheric pressure difference between the Azore's high and subpolar low. Its influence strength and direction of westerly winds and storms over global climate, particularly in Europe.

#### TNA (1951-2021)

The Tropical North Atlantic index indicates the sea surface temperature in the eastern tropical Atlantic Ocean. It is derived from the average of the sea surface temperature in 5.5N – 23.5N to 15W – 57.5W. The TNA is used to monitor the influence of the sea surface temperature on a regional and global scale.

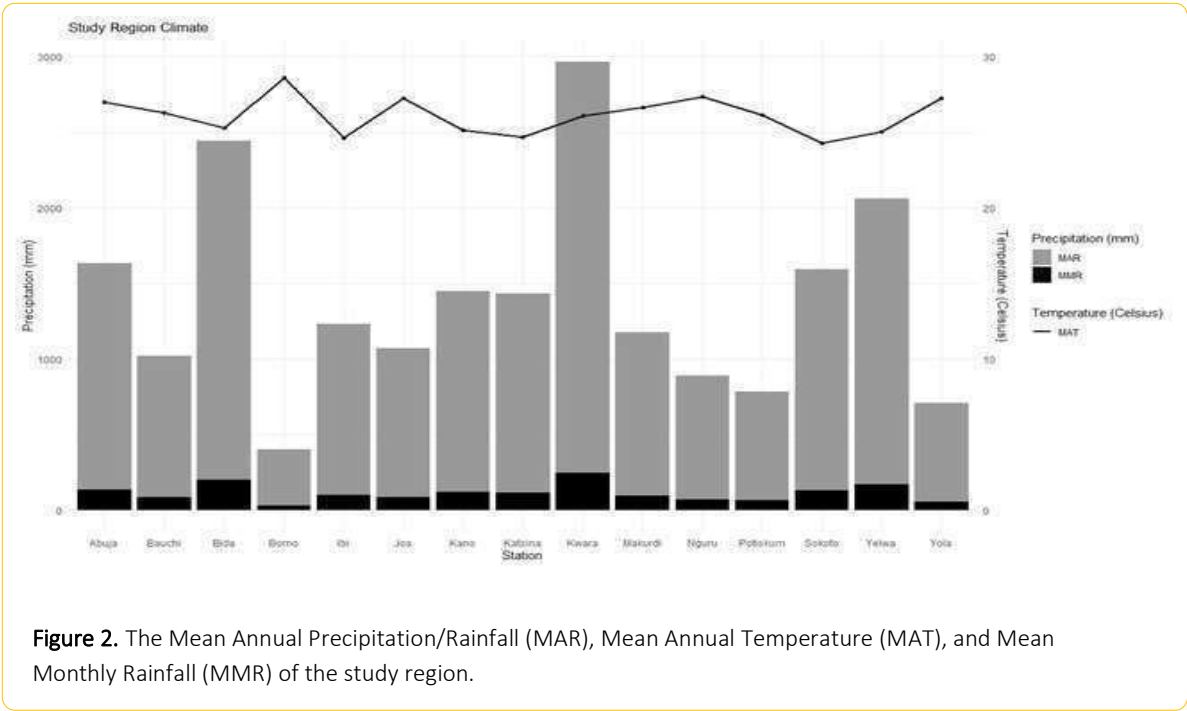
#### AMO (1951-2021)

The Atlantic Multidecadal Oscillation is an index that describes the anomalies of the sea surface temperature of the North Atlantic Ocean. Its values are derived from an average of the North Atlantic, north of the equator from 0 to 70 degrees West longitude in the North Atlantic Ocean. The negative AMO phase is mostly associated with drought and the positive phase is linked to increased rainfall. This enables the forecast of increased and deficit rainfall in regions, global climate scale, and associated climatic patterns and phenomena.

#### IOD (1951-2021)

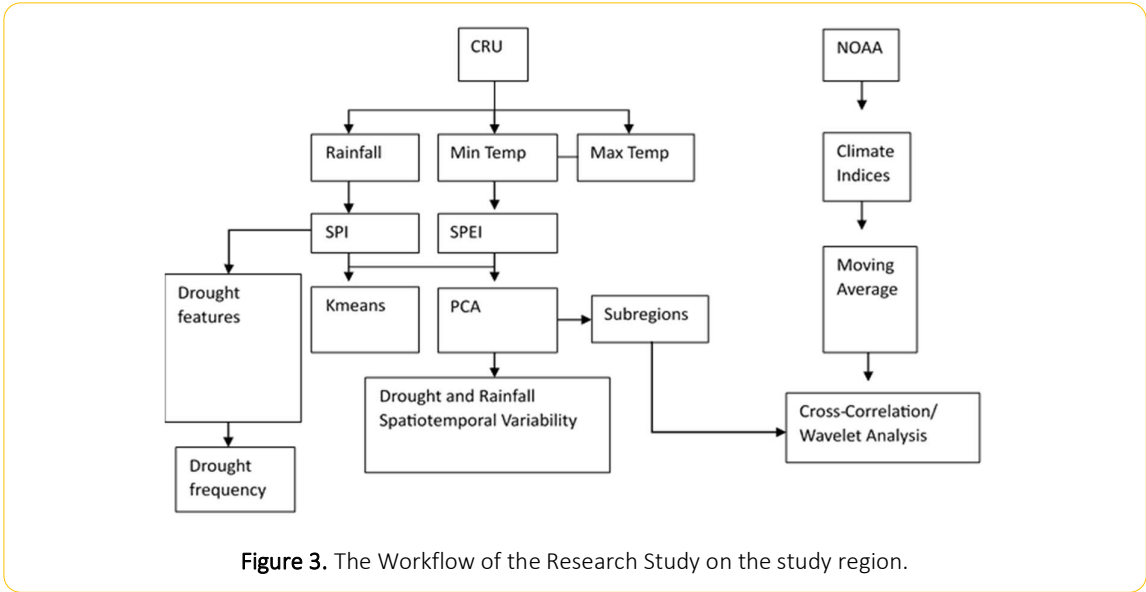
The Indian Ocean Dipole index is one of the characterizing climate systems in Asia continents that have been established to have teleconnection with other ocean oscillations and sea surface temperature i.e., ENSO. The values are derived from the difference between the mean surface temperature in the Western Indian Ocean within 50 degrees 70 degrees on the East, 10 to 10 degrees on the North the mean surface temperature in the

Eastern Indian Ocean 90 to 110 degrees East to 10 to 0 degrees South. The index is used to monitor the influence of sea surface temperature on global and regional scales.



Methods

Drought investigation in the region was carried out in the Northern region of the country, Nigeria within the period 1951-2021 (71 years). The analysis was done on R statistical software (RStudio Team, 2020), ArcMap geospatial software, and Excel Microsoft package. (i) characterization and comparison based on Pearson correlation coefficient using both SPI and SPEI drought indicators, (ii) assessing the spatiotemporal variability of rainfall and drought in the region through principal component analysis techniques, (iii) addressing the homogenous distinct spatial subregions with PCA and K-means clustering technique, and (iv) establishing the relationship between drought and climatic drivers employing cross-correlation method and wavelet spectral analysis.



### Characterization of Drought

Drought is an anomalous phenomenon that is hard to quantify, analyze and monitor. Due to the complexity attributed to drought, many works have developed and evaluated indices for quantifying and monitoring the events of drought, and its kinds. (Zargar et al., 2011) reviewed different indices and their corresponding variables, however, the world meteorology organization considers the use of SPI for drought characterization. (Adeaga, 2013; Olukayode Oladipo, 1985) research in the region has been carried out with SPI and can characterize the hazard even on accumulated timescales for other variables i.e., streamflow and agriculture in the region. The choice and selection of drought monitoring indices depend on the quantity and quality of the availability of the climatic data, objectives of the study, ease of use, and its ability to detect and isolate drought events spatiotemporally (Morid et al., 2006).

**Table 1.** Drought temporal scale and their description.

| SPI Duration | Phenomena                      | Application                                                         |
|--------------|--------------------------------|---------------------------------------------------------------------|
| 1-month      | Short term condition           | Short-term soil moisture and crop stress                            |
| 3- month     | Short to Medium term condition | A seasonal estimation of precipitation                              |
| 6- month     | Medium condition               | Effective estimation of precipitation over distinct seasons         |
| 9- month     | Over a medium term             | Indicates agricultural drought and linked impacts to other sectors  |
| 12- month    | Long term condition            | Linked to surface and subsurface water levels, including reservoirs |

### Standardized Precipitation Index/Standardized Precipitation and Evapotranspiration Index

The SPI and SPEI are the same indexes based on the fundamental structure, except that SPEI accounts for evapotranspiration, accounting for the temperature to its parameters apart from precipitation. Evapotranspiration is much needed for estimating climatic water balance through the difference between precipitation and evapotranspiration, and this helps in accounting for an atmospheric anomaly like climate change. They are both calculated over accumulated precipitation and water balance in timescales (Thomas B. McKee & Department, 1993; Vicente-Serrano et al., 2010) The timescales (Table 1) are reflected in the propagation of the drought from precipitation, soil moisture, streamflow, groundwater, and the ecosystem.

### Computation of Standardized Precipitation Index

1. The calculation of the standardized precipitation index was developed by (Thomas B. McKee & Department, 1993) to fit the accumulated period and frequency distribution usually a minimum of 30 years temporal scale to a probability distribution i.e. (gamma distribution), and its parameters are used to find the cumulative probability function of the observed precipitation before transformation into a mean and variance of 0 and The equation follows:

$$X_{ij}^K = \sum_{t=0}^{k-1} (x_{ij} - t) \quad (1)'$$

Where  $x_{ij}$  is the precipitation,  $i$  is the years specified,  $j$  is the month, and  $k$  is the temporal scale of 1-, 3- 6-, 9-, and 12- months. The short timescale of 6 months and the long 12-month timescale are selected due to their ability to critically reflect soil moisture, streamflow, and groundwater.

- The fitting of gamma distribution (Thomas B. McKee & Department, 1993) to the cumulative precipitation timescale.

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \quad (2)'$$

And the density function for a specified cumulative temporal scale is

$$G(x) = \int_0^x g(x) dx \quad (3)'$$

Then the values are normalized into SPI value

$$SPI = - \left( t - \frac{C_0 + C_1 t + C_1 t^2}{1 + d_1 t + d_1 t^2 + d_1 t^3} \right) \quad (4)'$$

In case  $0 < H(x) \leq 0.5$

$$SPI = - \left( t - \frac{C_0 + C_1 t + C_1 t^2}{1 + d_1 t + d_1 t^2 + d_1 t^3} \right) \quad (5)'$$

In case  $0 < H(x) \leq 1$

P denotes the probability of exceeding the determined D value; the constants are  $C_0 = 2.515517$ ,  $C_1 = 0.802853$ ,  $C_2 = 0.010328$ ,  $d_1 = 1.432788$ ,  $d_2 = 0.189269$ , and  $d_3 = 0.001308$ .

#### Computation of Standardized Precipitation and Evapotranspiration Index

The SPEI calculation accounts for temperature in characterizing drought and it is the difference between precipitation and potential evapotranspiration which is referred to as the climatic water balance (VicenteSerrano et al., 2010).

- The potential evapotranspiration PET of the coordinates is estimated using the Hargreaves-Samani method. The Hargreaves method follows a simple method like the thornthwaite but provides better estimation than thornthwaite and is efficient where there is a paucity of data (Stagge et al., 2015).

$$PET = 0.0023 \times R_a (T_{max} - T_{min})^{0.5} \times \left( \frac{T_{max} - T_{min}}{2} + 17.8 \right) \quad (6)'$$

$R_a$  is the extra-terrestrial radiation controlled by Julian days and Latitudes (MJ/m<sup>2</sup>). The Hargreaves-samani used  $T_{max}$ - $T_{min}$  as a proxy for net radiation.

- The difference between precipitation and potential evapotranspiration of the coordinates is denoted as:

$$D_i = P_i - PET_i \quad (7)'$$

Where  $D_i$  = Climatic water balance of the accumulation period  $i$  = temporal scale of 1-, 3-, 6-, 9- and 12-months.

- The cumulative climatic water balance denoted as  $D_i$  is then fitted to a probability density function on a specified temporal scale. A 3- parameter generalized logistic distribution (Gupta & Kundu, 2010) is fitted

$$\text{to the sequence whose equation is } f(x) = \begin{cases} k \neq 0, z = \frac{\log(1 - \frac{k(x-\xi_g)}{\alpha})}{-k} \\ \frac{\exp(-(1-k)z)}{\alpha(1+\exp(-z))^2} \\ k = 0, z = \frac{x-\xi_g}{\alpha g} \\ -\infty < x < \infty \end{cases} \quad (8)'$$

Where  $\xi$ ,  $\alpha$  and  $K$  are location, scale, and shape parameters.

4. The probability density function of the cumulative water balance is then used to estimate the SPEI values as

$$\text{SPEI} = \left( W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \right) \quad (9)$$

Where  $W = \sqrt{2 \ln(P)}$ .  $P$  represents the probability of a value greater than the  $D_i$ .  $P$  denotes the probability of exceeding the determined  $D$  value; the constants are  $C_0 = 2.515517$ ,  $C_1 = 0.802853$ ,  $C_2 = 0.010328$ ,  $d_1 = 1.432788$ ,  $d_2 = 0.189269$ , and  $d_3 = 0.001308$ .

Both the SPI and SPEI were used in this study to compare and contrast, characterize drought events, and identify the relationship between drought and climatic drivers. Although the SPI and SPEI are similar in versatility, the SPEI accounts for evapotranspiration and it considers climatic water balance in its calculation. while the SPI only uses rainfall time series. In addition, according to using gamma distribution equation (2) and generalized logistic equation (8), both the SPI and SPEI follows the classic probability distribution as recommended by (Santiago Beguería, Sergio M. Vicente-Serrano, Fergus Reig, 1994), and also validated in (Tefera et al., 2019) research in the region. According to the (Table 2), once the value reaches a negative (-1), a drought event is captured, and a return to normal when it reaches (0) (Byun & Wilhite, 1999).

**Table 2.** Characteristics classification of Drought severity Wilhite.

| SPI Value      | Classification |
|----------------|----------------|
| 2.00 or more   | Extremely wet  |
| 1.50 to 1.99   | Severely wet   |
| 1.00 to 1.49   | Moderately wet |
| 0.99 to -0.99  | Near Normal    |
| -1.00 to -1.49 | Moderately dry |
| -1.50 to -1.99 | Severely dry   |
| 2.00 or less   | Extremely dry  |

#### Data Frequency

Furthermore, the frequency of drought of different grades in each coordinate was regarded as the frequency of drought occurrence (Xu and Han, 2018). The calculation formula is as follows:

$$p = \frac{n}{N} \times 100 \quad (10)$$

Where  $p$  is the frequency of drought,  $n$  is the number of droughts in the data sequence, and  $N$  is the number of data series.

#### Climatic Indices

The climate indices were extracted from ([https://psl.noaa.gov/gcos\\_wgsp/Timeseries](https://psl.noaa.gov/gcos_wgsp/Timeseries)) and a moving average of 12- months was applied to the indices. The moving average is estimated to create a relationship between the climate indices and the SPEI-12, which was preferred over the SPI-12, (Li et al., 2020; Stagge et al., 2015)\* have established the significance of SPEI-12 in characterizing the effect of global warming in a region. Each of the subregions obtained from clustering and PCA was compared to the climate indices to investigate their relationship.

### *Clusters and Regionalization*

The characterization of the spatial-temporal pattern distribution of rainfall was assessed across the region coordinates through the principal component analysis technique, in combination with clustering techniques. These techniques have been used in identifying and distinguishing distinct regions in different (Tadić et al., 2021; Usman et al., 2012), and due to the spatial-temporal variability of rainfall in the region, it is essential to evaluate regions that share similar characteristics.

The principal component analysis is a statistical technique used for the dimensionality reduction of a large dataset through the transformation of the original dataset into an uncorrelated set of variables with decreasing order of significance, and the extraction of dominant components (Richman, 1986). The principal component analysis is based on the estimation of the characteristic eigenvalues and eigenvectors. (Richman, 1986) asserts that the analysis of PC can be defined into six basic operational modes which are dependent on the parameters that are selected, variables and individuals, and fixed entities. These modes are identified as O, P, Q, R, S, and T. In meteorological studies (Dabanlı et al., 2017; Omidvar et al., 2016; Sigdel & Ikeda, 1970), the S- mode (data matrix with columns for stations and time for rows) decomposition is considered in determining space-time variation. When a simple rotation is applied to the structure (Richman, 1986), the spatial and temporal variation is smoothened and defined, which makes for a better understanding. The principal component was applied to the coordinates SPI and SPEI across specified temporal series, then rotated using the varimax method to achieve a defined and stable pattern.

To determine the suitability and quality of the data matrix the Bartlett sphericity test (Lovric, 2011) and Kaiser-Meyer-Olkin (KMO) (Kaiser, 1974) measure of sampling were used. The KMO factor adequacy value for the study area was 0.93.. The Bartlett sphericity (Lovric, 2011) test gave a P-value of 0.00, which means the data matrix is significantly correlated.

Clustering analysis is used to group variables with similar observations to identify distinct and homogenous values within the individual rainfall and S time series. Both hierarchical and non-hierarchical clustering techniques were used. The Kmeans, method was applied to the loadings of the principal component analysis; clustering the loadings of principal component analysis have been studied (Espinosa et al., 2019) to give better and more stable results rather than the original series, and they all share similar results.

### *Correlation analysis*

The correlation analysis used both the Pearson product-moment correlation coefficient because of its ability to directly measure the relationship between two variables, and studies have carried out research in the region based on it. Also cross-correlation in investigating the relationship between the indices SPI and SPEI values of the region coordinates on the preferred temporal scales, which was to compare and contrast the relationship between both indicators, and validate the use of SPI.

The cross-correlation function was used to analyze the relationship between the homogenous regions and selected climatic indices. The cross-correlation was done to establish the relationship before further analysis, between the drought index (SPEI), which was preferred over the SPI because it accounts for evapotranspiration, particularly in the cases of global warming and its influence over climatic zones. Both correlations were done under the R studio software. The equation follows.

$$r = \frac{(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (11)'$$

Where,  $r$  is the correlation coefficient  $x_i$  is value of the  $x$ -variable of the first sample,  $\bar{x}$  is the mean of values of the first sample,  $y_i$  is values of the  $y$ -variable of the second sample, and  $\bar{y}$  is mean values of the second sample. Here,  $r$  is the correlation coefficient,  $x_i$  is value of the  $x$ -variable of the first sample,  $\bar{x}$  is the mean of values of the

first sample,  $y_i$  is the values of the  $y$ -variable of the second sample, and  $\bar{y}$  is the mean values of the second sample.

#### Wavelet Analysis

The climate indices and the distinct homogenous regions' drought indicators were further analyzed through wavelet analysis to identify and know their relationship. This informs on a possible means of predicting drought events by identifying their triggers and monitoring the oscillation of the climate indices largely influential for the fluctuation in the region's climate systems.

$$\psi(t) = \pi^{-1/4} e^{i\omega t} e^{-t^2} \quad (12)'$$

Where,  $\psi$  is morlet wavelet,  $\omega$  is dimensionless frequency, and  $t$  is dimensionless time. Here,  $\psi$  is the Morlet wavelet,  $\omega$  is the dimensionless frequency, and  $t$  is the dimensionless time.

The Morlet wavelet analysis was used in this research to evaluate the wavelet transform of the bivariate time series of the regions and climatic drivers. Wavelet analysis is used to shift data from time to a frequency dimension (Daubechies, 1990). The R package used "WaveletComp" uses the Morlet wave transform technique. The Morlet wave transform has been used in several Studies (Guo et al., 2019; Jiang et al., 2021; Zhang et al., 2022) in comparing the relationship between variables, due to its complexity, multiple oscillations, better localization of time-frequency dimension (Addison, 2005) and ability to combine both its positive and negative values into a single broad peak.

## Results

#### Gridded Dataset Homogeneity

The 15 datasets homogeneity test was brought out for clarity, and out of the datasets only 53.33% which denotes majority falls under the first class of "usefulness", while 40% was under the suspect class, and the least group which is the "doubtful" was around 6.6% at 1% significant level (Table 3). It is noteworthy that the majority of the breaks came around the period of the rainfall deviation, and its decline towards drought events of the Sahel. The majority of the coordinates under class 3 of the suspect have or share the same break year in their time series. At least, all the coordinates under the suspect class have two or more similar break years. Coordinates such as Yelwa and Kwara have coherence in their time series break. In addition, the possibility of climatic variability is present and this is further evaluated in this study.

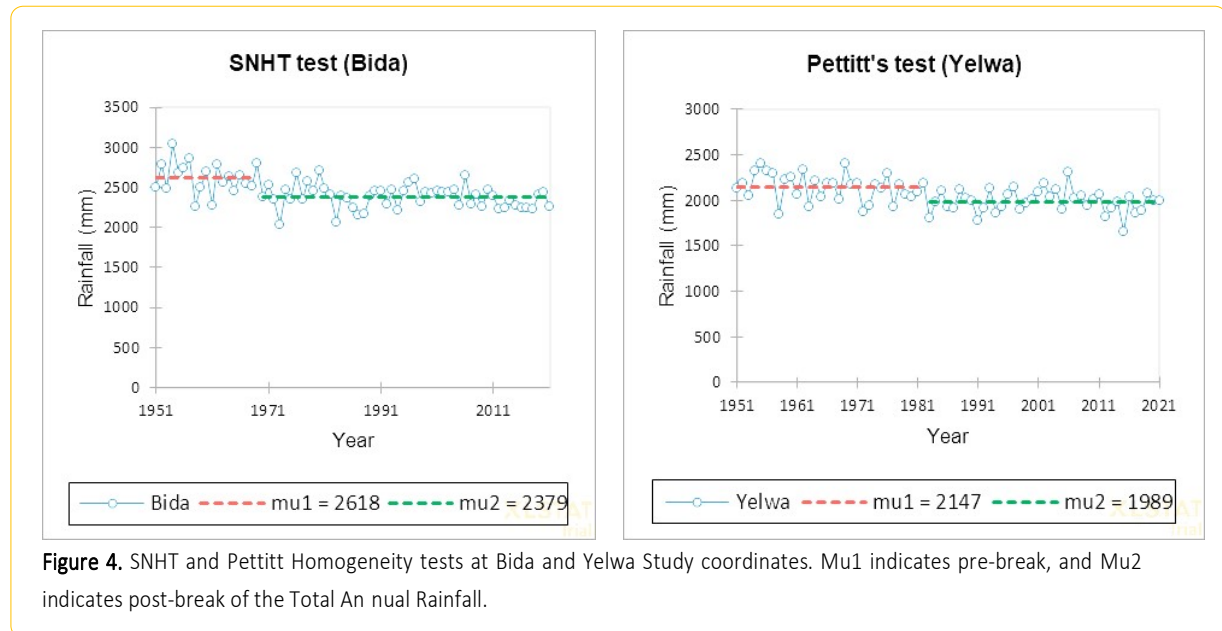
**Table 3.** Homogeneity 4-tests approach for individual coordinates in the region.

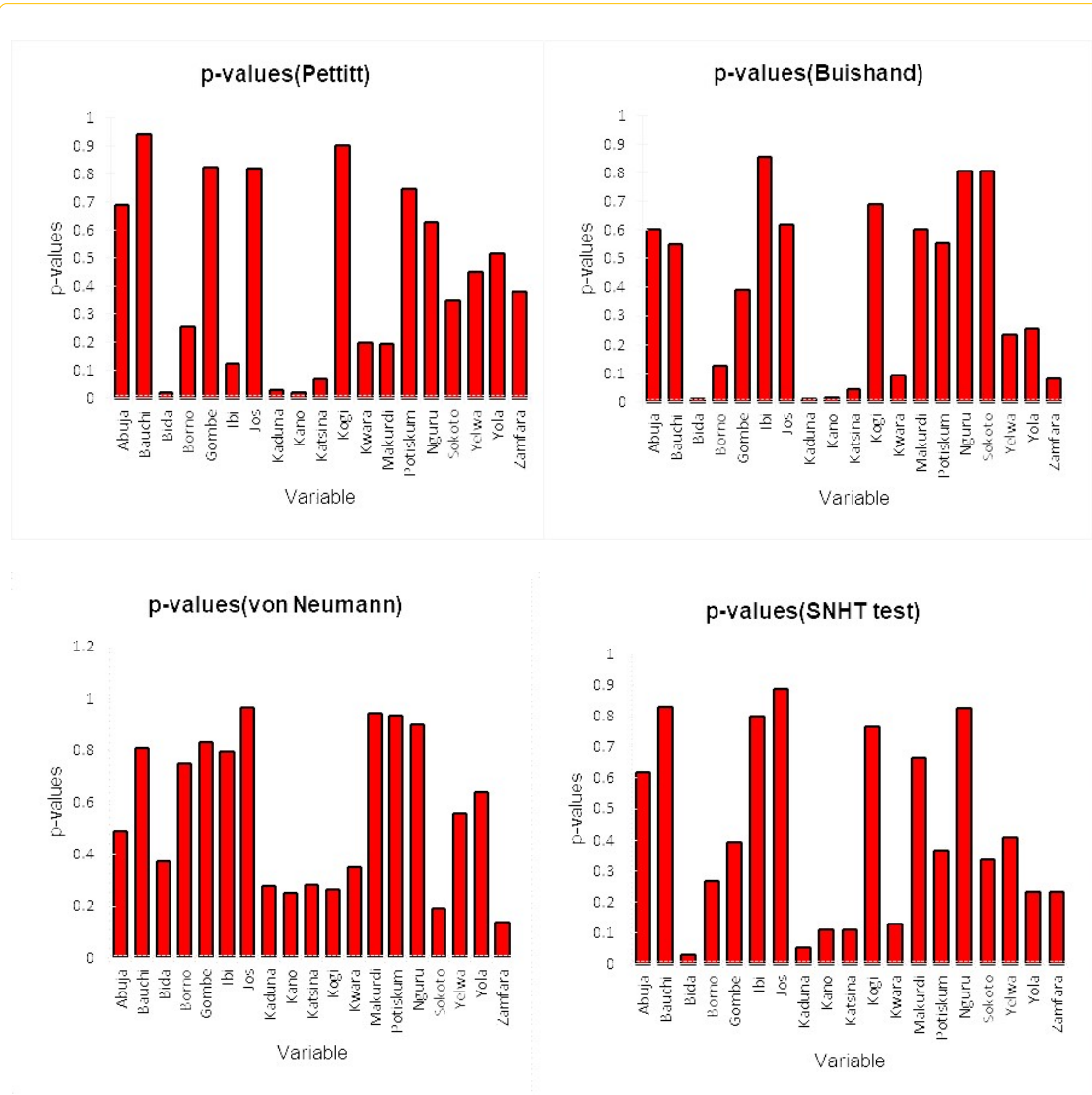
| Coordinates<br>1% sig. level | Pettit | SNHT | Bushaind | Von Neumann |
|------------------------------|--------|------|----------|-------------|
| Abuja                        | 1981   | 1957 | -        | 1981        |
| Bauchi                       | -      | 1969 | 1969     | -           |
| Bida                         | 1981   | 1969 | 1981     | -           |
| Borno                        | -      | -    | -        | -           |
| Ibi                          | -      | -    | -        | -           |
| Jos                          | -      | -    | -        | -           |

**Table 3.** Homogeneity 4-tests approach for individual coordinates in the region (continued).

| Coordinates<br>1% sig. level | Pettitt | SNHT | Bushaind | Von Neumann |
|------------------------------|---------|------|----------|-------------|
| Kano                         | -       | -    | -        | -           |
| Katsina                      | 1971    | -    | 1980     | 1982        |
| Kwara                        | 1971    | 1971 | 1971     | 1971        |
| Makurdi                      | -       | -    | -        | -           |
| Potiskum                     | -       | -    | -        | -           |
| Nguru                        | -       | -    | -        | -           |

Figure 4 depicts the decline and downward shift in the annual total rainfall for Yelwa and Bida. It is also evident that rainfall in the region is extremely variable and clusters as North central regions like Abuja and Bida both had their breaks in 1981. The shift in rainfall events has been understudied and has been attributed to different factors. The long-term displacement of the rainfall belt called intertropical convergence has been identified as one of the possible causes responsible for the advent of the Sahelian drought. To reaffirm this, (Figure 5) shows the rainfall time series taken from (1990 -2021) at a significant level of 1% with a 100% homogeneity throughout the coordinates. This indicates the abrupt shift in inhomogeneity is intrinsic to the study region's subjection to climatic variability.





**Figure 5.** 100% Homogeneous P-value across all individual coordinates using the four tests approach from 1990 – 2021.

#### Comparison between SPI and SPEI

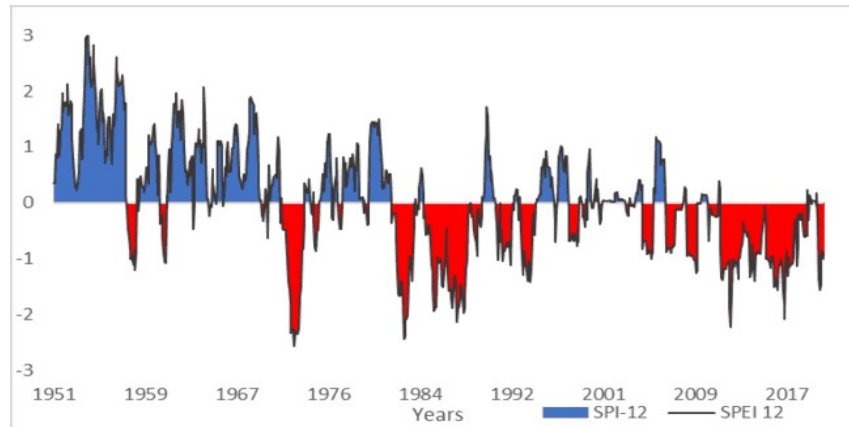
The Pearson correlation between SPI and SPEI across the accumulated periods of each coordinate shows that the significance of evapotranspiration in the computation of SPEI is to some degree essential, as rainfall is the principal component (Oladipo, 2021) in the computation of both SPI and SPEI (Table 4).

Coordinates like Abuja (0.98) and Bida (0.99) (Figure 6 ) have the highest correlation values and coordinates like Nguru (0.65) and Borno (0.77) (Table 4) have the least values. These coordinates (Nguru and Borno) which sit in the Sahelian ecoclimatic region were investigated, and according to (Guigma et al., 2020), have been known to be associated with thermodynamic processes i.e., heat advection and the greenhouse effect. (Shiru et al., 2020) state the significance of evapotranspiration in arid regions.

**Table 4.** SPEI and SPI Pearson Product-Moment Correlation within the study region across different temporal scales.

| Coordinates | 1 month | 3 months | 6 months | 9 months | 12 months |
|-------------|---------|----------|----------|----------|-----------|
| Abuja       | 0.91    | 0.96     | 0.98     | 0.98     | 0.98      |
| Bida        | 0.97    | 0.98     | 0.99     | 0.99     | 0.99      |
| Kano        | 0.80    | 0.87     | 0.95     | 0.95     | 0.96      |
| Nguru       | 0.65    | 0.74     | 0.92     | 0.95     | 0.95      |
| Potiskum    | 0.78    | 0.78     | 0.88     | 0.95     | 0.95      |
| Yelwa       | 0.97    | 0.98     | 0.99     | 0.99     | 0.99      |
| Makurdi     | 0.81    | 0.86     | 0.98     | 0.99     | 0.99      |
| Borno       | 0.77    | 0.75     | 0.80     | 0.89     | 0.93      |
| Jos         | 0.75    | 0.80     | 0.96     | 0.97     | 0.97      |

The northeastern region (Nguru, Potiskum, and Borno) with extreme temperature and low rainfall as indicated by (Ogunrinde et al., 2020) has the lowest correlation. In addition, the increasing correlation value as the temporal scale increases from 1- month to 12- months, is to note the increasing aggregation as drought event pools together and become more definite. However, the estimation of climatic water balance for SPEI which was done using the Hargreaves-Samani equation shows contrasting differences in the semi-arid and arid regions in the northeastern region, when compared to the sub-humid and humid regions.



**Figure 6.** Relationship between SPI and SPEI in Bida. The relationship between the highest correlated SPI and SPEI month in Bida -month temporal timescale.

#### *Characterization of Rainfall Variability in the Region*

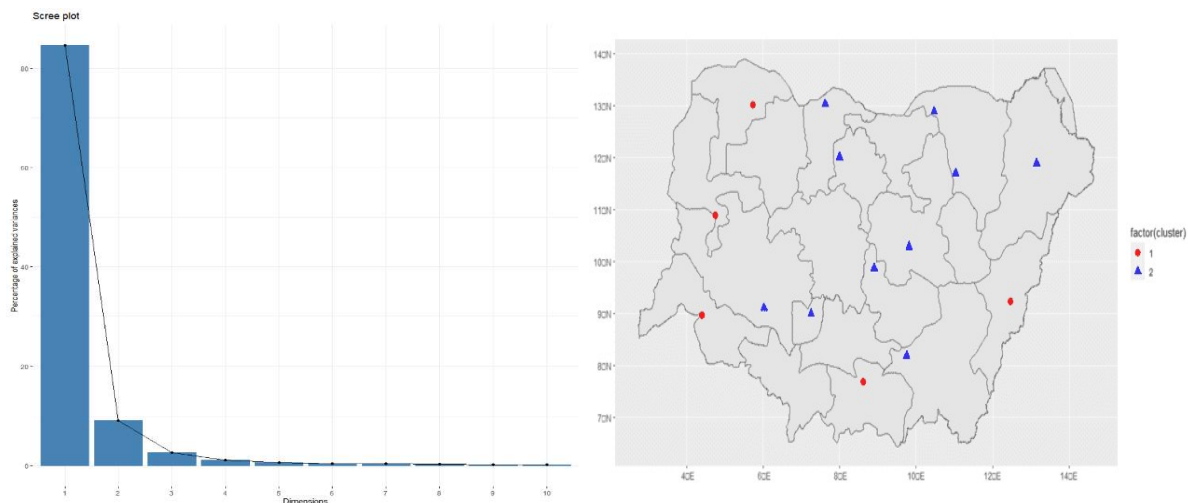
Since rainfall is considered a principal component, the distribution of rainfall in the region highlighting the differences in rainfall intensity and events across the region was investigated with principal component analysis, after checking for suitability as indicated in the section, which was carried out on the rainfall records of individual retrieved coordinates to examine the variability in the distribution of rainfall in the region.

The scree plots (Figure 7) eigenvalues and the rule of thumb in regards to (North et al., 1982) state that the first two principal components should be considered. This is further validated with both the rotated RPC 1 (0.53) and RPC 2 (0.41) and unrotated principal components PC 1 (0.85) and PC 2 (0.09) (Table 5) account for the majority and the cumulative variance (0.94) remain unchanged. The K-means clustering technique also determined the optimal number of components as two. The rotated principal components ensure a stable spatial pattern. The map loadings of the rainfall for RPC 1 (Figure 8) have its highest loading in the North Central towards the North-eastern region and transiting to the North-western region, it grows weaker. While RPC 2 (Figure 8) has its highest loading in the North-western region as it transits toward the North-eastern Region. However, the RPC1 (0.85) accounts for the majority of the loadings, and this accounts for the rainfall variability distribution in the region.

The sub-regional cluster of the rainfall was mapped which shows the distribution of the rainfall cluster using the Kmeans non-hierarchical method also divided the regions into two, resulting in an almost similar pattern to the RPC 1 loadings. The far Northwest and Northcentral (Yelwa, Sokoto, Kwara, Makurdi, and Yola) were partitioned as Region 1, from the Northcentral and Northeast (Abuja, Bida, Jos, Ibi, Katsina, Kano, Nguru, Potiskum, Borno and Zamfara) as region 2. This shows the distribution of rainfall events and intensity as depicted. as it transits towards the semi-arid and arid spots of the study region.

**Table 5.** Rotated and Unrotated Principal Components of Rainfall Distribution within the Study Region.

| Principal Components | Rainfall  |                   |
|----------------------|-----------|-------------------|
|                      | Unrotated | Rotated (Varimax) |
| PC1                  | 0.85      | 0.53              |
| PC2                  | 0.09      | 0.41              |
| Cumulative Variance  | 0.94      | 0.94              |



**Figure 7.** Scree plot of rainfall distribution and the Kmeans cluster spatial distribution across the study region.

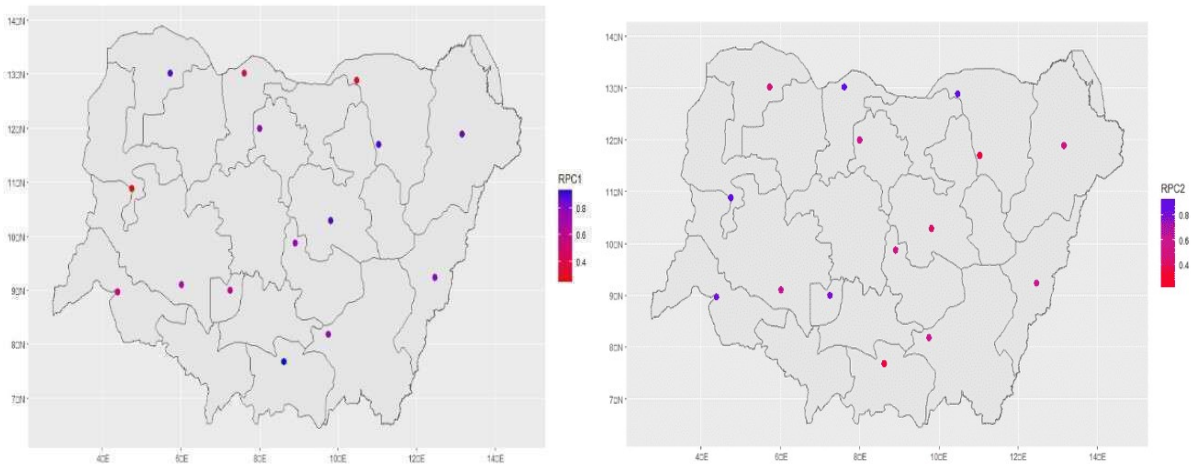


Figure 8. Spatial Distribution of Rainfall Rotated Principal Components 1 and 2 in the Study Region.

*Spatial-temporal characterization of drought coherence of the sites in the region*

The Pearson correlation coefficient shows the correlation among the sites as observable in the drought reconstruction of the SPI-12 (Figure 9). The highest correlation is between Kano and Katsina (0.96), while the lowest is between Yelwa and Borno (0.09). Yelwa shares the least correlation among the sites. Investigating the correlation, the disparities within the sites are contingent on their spaces. The correlation (0.83) and the drought episodes between Jos 1,220 (m.a.s.l) and Ibi (Taraba state) 2,419 (m.a.s.l) indicates that the correlation is not restricted to a certain ecoclimatic region, as both sites are highlands in the Montane region. The matrix shows that there is a discontinuity in coherence as the distance between the coordinates increases towards the northwest and northcentral in Bida, Kwara, and Yelwa, which impinges on the possibility of variation of drought events occurring in subregions.

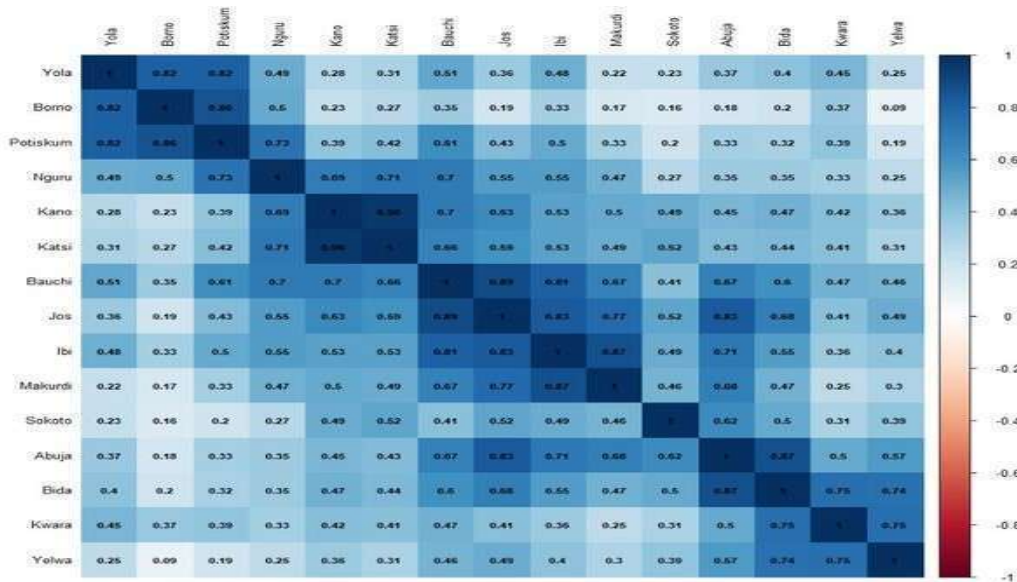


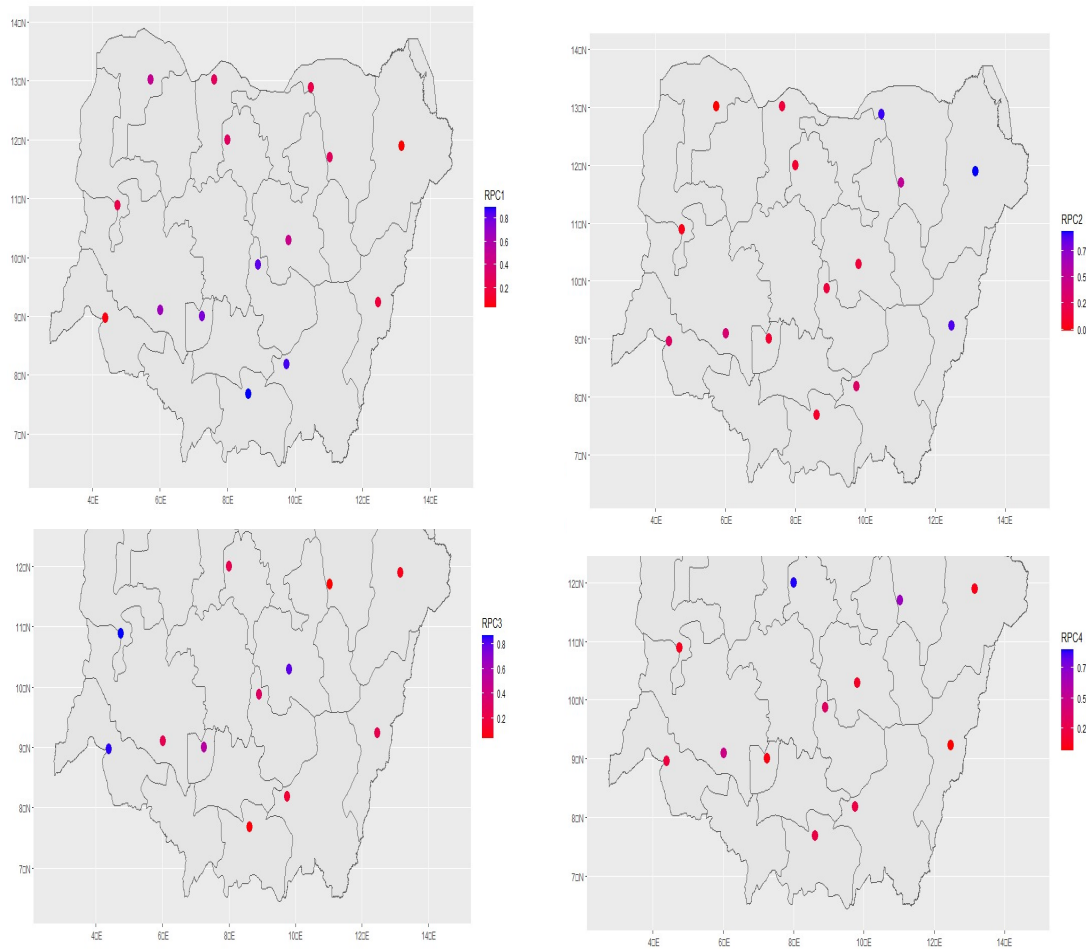
Figure 9. Inter-site Pearson Correlation Coefficient of Standardized Precipitation Index-12.

### *Spatial-temporal characterization of meteorological drought variability in the region*

To address the inter-variability of drought between coordinates, the standardized precipitation index of rainfall records was arranged in the S-mode matrix (time in rows, and stations in columns) on each SPI timescale accumulation period for dimensional reduction using the PCA, then the varimax rotation was applied to the extracted components to obtain a spatially localized and stable pattern, in conjunction with the Kmeans nonhierarchical cluster techniques were used to analyze the variability and similarity of drought within the study region.

However, unlike the rainfall components, using the scree plot and as shown in the (Figure 11), and further verified through Kmeans. the major principal components were 4 which accounts for most of the components out of the 15 computed variables. This confirms the work of (Ogunrinde et al., 2020) of 4 distinct homogenous distinct regions through principal component analysis.

The rotated principal components follow a pattern through which the cumulative variance increases as the timescale accumulates, with the 12- months scale having the highest variance (Table 6) of (0.85), while the 1-month scale has the lowest cumulative variance of (0.81). The rotated and unrotated component values remain unchanged. The mapped loadings of the accumulation periods showed increased variability, which is nucleated towards ecoclimatic regions with the RPC 1 for 12-month timescale (Figure 10) being highest in the upper subhumid north-central.



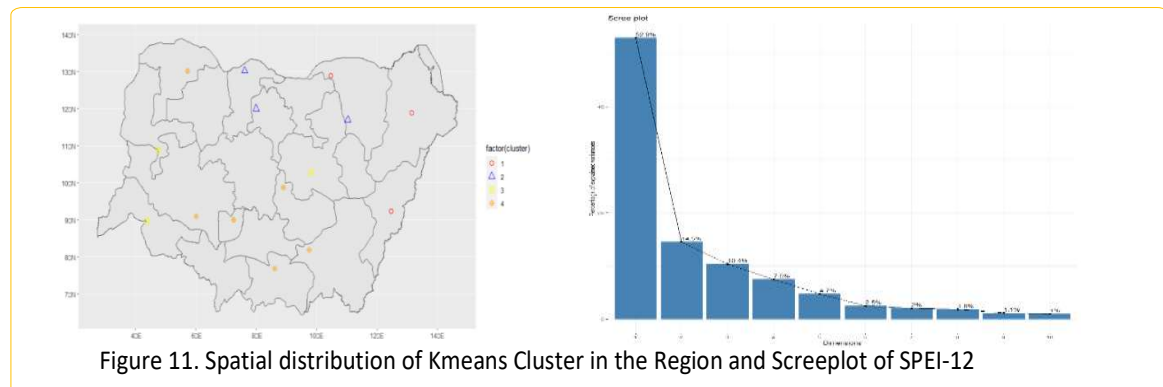
**Figure 10.** Spatial Distribution of Rotated Principal Components Loadings of Standardized Precipitation Index-12.

**Table 6.** Rotated and Unrotated Principal Components of SPI on different temporal scales.

| Standardized Precipitation Index | Principal Components | Unrotated           | Rotated (Varimax) |
|----------------------------------|----------------------|---------------------|-------------------|
| SPI 1                            | PC 1                 | 0.25 0.19 0.18 0.17 | 0.46              |
|                                  | PC 2                 | 0.81                | 0.17              |
|                                  | PC 3                 |                     | 0.10              |
|                                  | PC 4                 |                     | 0.09              |
|                                  | Cumulative Variance  |                     | 0.81              |
| SPI 3                            | PC 1                 | 0.49 0.16 0.09 0.08 | 0.24              |
|                                  | PC 2                 | 0.83                | 0.20              |
|                                  | PC 3                 |                     | 0.19              |
|                                  | PC 4                 |                     | 0.19              |
|                                  | Cumulative Variance  |                     | 0.83              |
| SPI 6                            | PC 1                 | 0.51 0.16 0.10 0.08 | 0.25              |
|                                  | PC 2                 | 0.84                | 0.21              |
|                                  | PC 3                 |                     | 0.20              |
|                                  | PC 4                 |                     | 0.18              |
|                                  | Cumulative Variance  |                     | 0.84              |
| SPI 9                            | PC 1                 | 0.51 0.15 0.11 0.08 | 0.26              |
|                                  | PC 2                 | 0.84                | 0.21              |
|                                  | PC 3                 |                     | 0.19              |
|                                  | PC 4                 |                     | 0.18              |
|                                  | Cumulative Variance  |                     | 0.84              |
| SPI 12                           | PC 1                 | 0.53 0.15 0.10 0.07 | 0.27              |
|                                  | PC 2                 | 0.85                | 0.21              |
|                                  | PC 3                 |                     | 0.19              |
|                                  | PC 4                 |                     | 0.18              |
|                                  | Cumulative Variance  |                     | 0.85              |

#### *Drought Regionalization*

The scree plot and Kmeans nonhierarchal cluster techniques illustrated in the (Figure 11) show the variability of drought in four distinct homogenous regions. It is noteworthy to understand that drought propagation is similar in some regions, and varies in other regions as computed through principal component analysis. Subregions that share similarities are clustered together, and grouped into four distinct regions. Region 1 consists (of Yola, Potiskum, and Borno), Region 2 (Nguru, Kano, and Katsina), Region 3 (Yelwa, Kwara, and Bida) and Region 4 (Abuja, Sokoto, Ibi, Benue, and Jos). The individual regions are further characterized to investigate to recapture and examine drought events on a subregion scale.



**Figure 11.** Spatial distribution of Kmeans Cluster in the Region and Screeplot of SPEI-12

### Drought Characterization

The extracted 15 rainfall records coordinates were extracted and the indicators were used to compute drought on different temporal scales. The 6- month and 12-month temporal scales were both selected to examine the short and long-term drought as both 6- and 12-month have the highest correlation even in arid areas of the region.

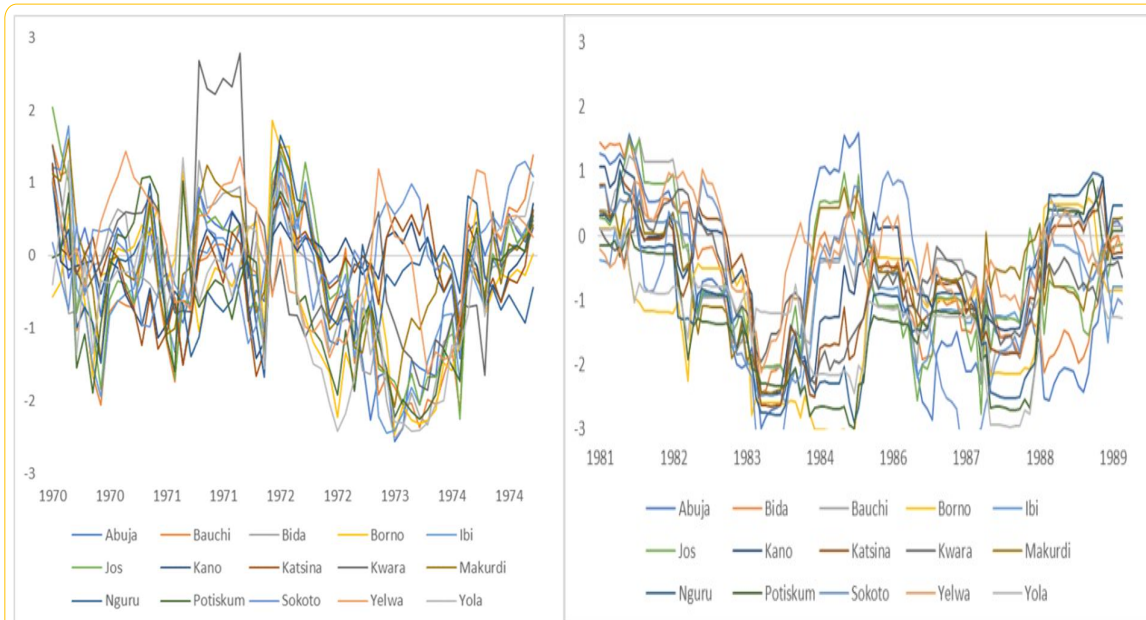
SPI-6 showed an extremely high variability (Figure 12) and captured multiple drought events compared to SPI-12 which can be attributed to the amalgamation of drought events, and this becomes a more defined and pooled. Recapturing of the drought events outlined period with prolonged drought duration and extreme drought severity which includes; 1958-1960, 1970-1974, 1981-1989, and 2011-2019. Indicators were able to recapture the Sahelian drought of the 1970s and 1980s which greatly impacted the Northern region of the country.

Characterizing the meteorological drought events based on onset, duration, severity, and termination further proved that drought is stochastic as there is a variation regionally in its characteristics within the regions. Some of the extreme droughts recaptured include: 1970-1974 and 1981-1989.

#### 1970-1974

In the Sahelian drought of the 1970s and 1980s, which was a flagship drought, using the SPI-6, reconstructing and recapturing the drought event recurred in phases during the period. The SPI-12 values were more defined and split into 3 phases. The first phase onset was in June 1970 with a duration of 1 month in both Borno and Sokoto, before termination in July 1970. The second phase onset was in April, Kano and Katsina with a duration of 2 months and termination on July 1971 (Figure 12). The last phase onset ranges from September 1972 to August 1973 across the coordinates; In April 1973 (Abuja), May 1973 in (Bauchi, Ibi, Jos, Makurdi, and Nguru); September 1972 (Borno, Potiskum, and Yola); October 1972 (Yelwa); August 1973 (Kwara).

The highest duration is 23- months in Borno and 2nd in Potiskum then Yola with 22 months. Peak severity of -2.8 was reached in Yola in June 1973 and termination was reached across all the region with varying cessation in August 1974.

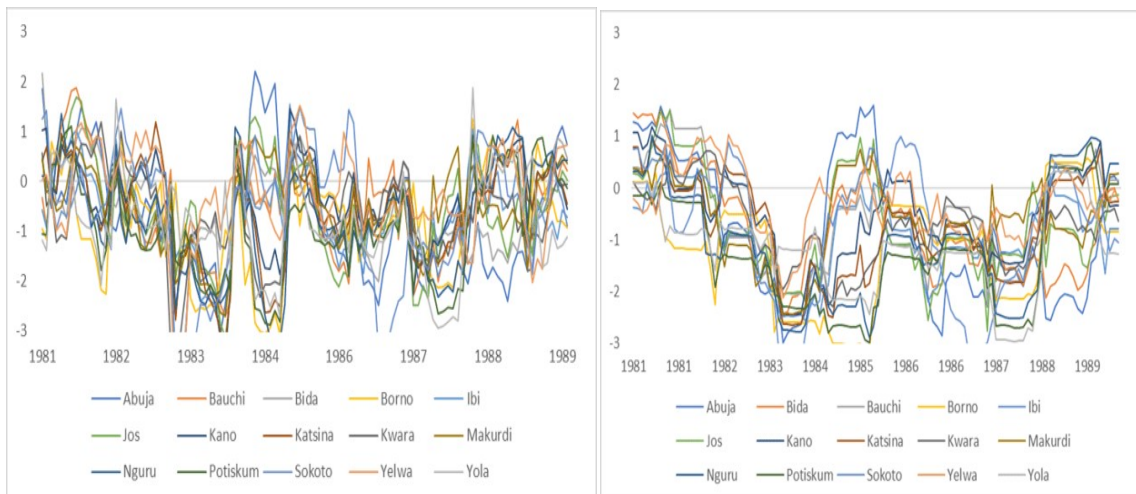


**Figure 12.** Six months reconstructed drought temporal scale of impacted sites, and 12 months temporal scale of impacted sites (1970-1974).

1981-1989

Although the 1970s drought was infamous for its duration and spatial variability, in some studies, (Abaje, I.B, Ati, O.F., Iguisi, E.O., Jidauna, 2013; Charney, 1975; Ozer, 2002), 1980s drought was reported to be more severe.

In this research, using the SPI-6, reconstruction, and observation of the historic drought showed this. The drought is divided into multiple phases with the SPI-6 and the first phase and onset was in Potiskum, Yola, and Borno in ranges from January to February 1981 with a duration of 1- to 2- months, before the wet break punctuation in March 1981. The second phase onset was in April 1981 in Kwara with a duration of 3 months, and a wet break in August 1981 (Figure 13). The third phase onset varied from September 1981 to March 1982 across 5 coordinates Borno, Ibi, Jos, Nguru, Potiskum, and Yola. The highest duration of 6- months and peak severity of -2.2 was in Borno, in February 1982. The fourth phase onset spanned across all 15 coordinates ranging from June 1982 to March 1983. Multiple extreme severity was reached in many of the coordinates; 1st least value was in Yelwa, Kebbi State (-4.5), 2nd Bida (-4.0), 3rd Abuja, Kwara, and Sokoto (-3.9), 4th Kano (-3.6) and 5th Katsina (-3.3). The highest duration was in Makurdi and Potiskum with 18 months. The fifth phase onset was from June 1984 to February 1985 in 9 coordinates (Abuja, Borno, Kano, Katsina, Kwara, Nguru, Potiskum, Sokoto, Yelwa, and Yola) excluding (Bauchi Bida Ibi, and Jos). The phase's first onset was in Borno, Kwara, and Potiskum. Borno, Kwara, and Potiskum all share the highest duration of 6- to 9- months and the peak severity of -3.1 was in Nguru in November 1984. The sixth phase onset was in the range of August 1985 to March 1986 in 12 coordinates (Abuja, Bauchi, Bida, Borno, Ibi, Jos, Katsina, Kwara, Nguru, Potiskum, Makurdi, and Yola) The highest duration of 7- months was in 3 coordinates Bauchi, Jos and Potiskum, and peak severity of -2.1 was in Jos in January 1986. The sixth phase onset ranged from May 1986 to March 1988 across all 15 coordinates. The highest duration was 19- months in Sokoto, and the site had the highest severity of -3.4 in September 1986. The last phase onset was in June 1988 after two punctuated wet breaks in August, October, and November to December 1989 in Sokoto. The highest duration of 11- months was in Abuja, and the peak severity was -2.4 in November 1988. The SPI-6 reconstruction had no effective termination during this event but transited into the next decade (Figure 13).



**Figure 13.** Six months recaptured drought temporal scale of impacted sites, and 12 months temporal scale of impacted sites (1981-1989).

The SPI 12 recapturing of the event followed a definitive pattern into a decadal drought event and found its onset in September 1981 in Borno by September 1983, the drought has reached all the coordinates. The highest duration of 74- months (Table 6) throughout the event was in Potiskum. The peak severity of -3.8 was in Sokoto in October 1983 before termination occurred in November 1989. In this research, this series was the most severe, confirming the works of other studies (Abaje & Friday Ati, 2013; Henchiri et al., 2020; Ibitolu & Balogun, 2019).

Throughout the drought indexing, extreme drought severity and duration appear in certain coordinate and date (Table 7 ) using the SPI-12 to distinguish them from other severity levels as the impact that coalesce from them (Table 1) were enough to cause drought in surface and subsurface water bodies, and propagate to socioeconomic and ecological drought, they were regarded as notable during the recapturing of drought events in the region.

**Table 7.** Drought event(s) with max severity value.

| Drought Event (s) | Coordinates | Drought Severity | Duration month(s) | Severity Date |
|-------------------|-------------|------------------|-------------------|---------------|
| 1958 - 1960       | Abuja       | -2.5             | 11                | March 1959    |
| 1961 - 1962       | Jos         | -2.5             | 13                | August 1961   |
| 1970 - 1974       | Bauchi      | -2.5             | 14                | August 1973   |
|                   | Ibi         | -2.6             | 14                | August 1973   |
|                   | Yola        | -2.8             | 22                | June 1973     |
| 1981-1989         | Abuja       | -2.9             | 56                | October 1983  |
|                   | Borno       | -3.0             | 54                | May 1985      |
|                   | Ibi         | -2.5             | 44                | March 1984    |
|                   | Katsina     | -2.6             | 43                | December 1983 |
|                   | Sokoto      | -3.8             | 39                | October 1983  |
|                   | Potiskum    | -2.9             | 74                | May 1985      |
|                   | Nguru       | -2.9             | 55                | May 1985      |
|                   | Yola        | -2.9             | 66                | March 1988    |
|                   | Jos         | -2.7             | 46                | July 1987     |
| 1990-1993         | Yelwa       | -2.8             | 13                | May 1992      |
| 2004-2007         | Sokoto      | -2.5             | 24                | July 2005     |
| 2011-2019         | Yelwa       | -3.1             | 50                | September     |
|                   | Kano        | -4.1             | 43                | 2015          |
|                   |             |                  |                   | April 2012    |
|                   | Katsina     | -4.3             | 30                | April 2012    |
|                   | Nguru       | -2.6             | 36                | April 2012    |

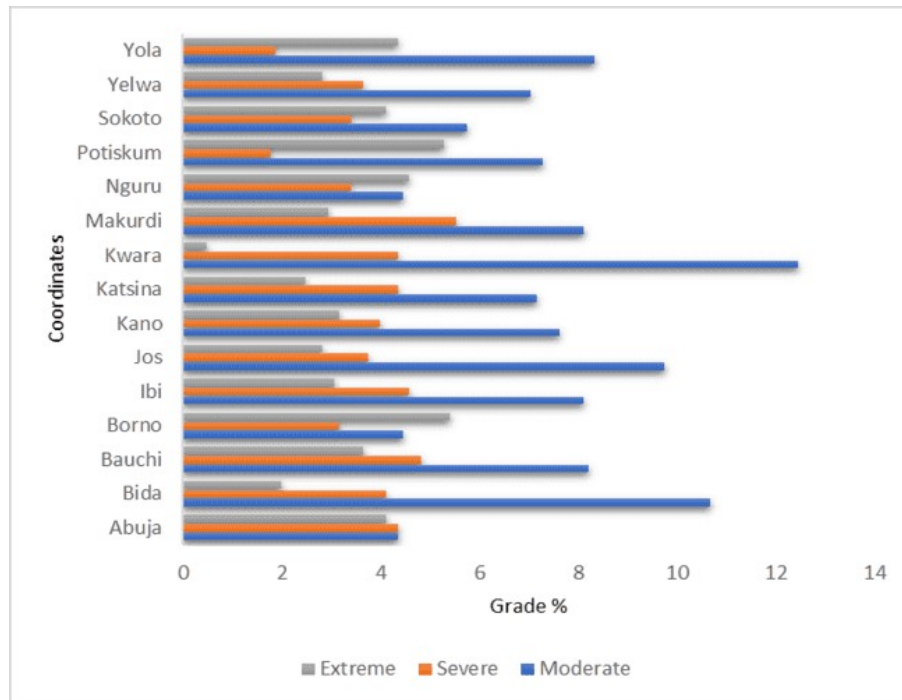
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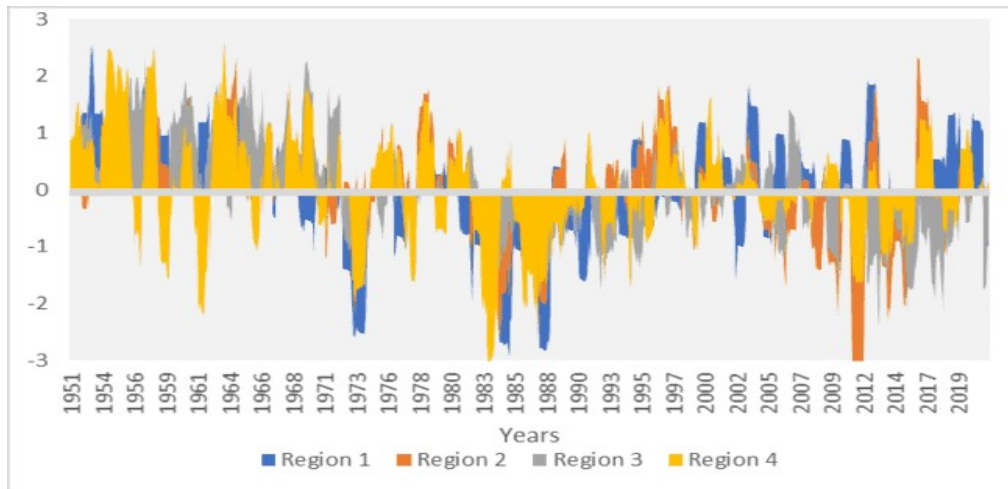


**Figure 14.** Drought Frequency of Standardized Precipitation Index – 12 of the study coordinates from 1951-2021.

#### *Drought characterization of Subregions*

The Kmeans non-hierarchical cluster technique using the silhouette method and PCA affirms the optimal number of clusters as 4. The Kmeans identified 4 distinct homogenous drought subregions in the coordinates. This indicates that drought operates in four subregions in the region. The variability between the four clusters was investigated to determine the coherence and variations between drought episodes in the sub-regional coordinates. The mean rainfall of the four sub-regional clusters was calculated and the SPI-12 was applied to both clusters.

Region 1 consists (of Yola, Potiskum, and Borno), Region 2 (Nguru, Kano, and Katsina), Region 3(Yelwa, Kwara, and Bida) and Region 4 (Abuja, Sokoto, Ibi, Sokoto, Benue, and Jos). Most of the regions were coherent with the benchmark drought of the 1970s, apart from Region 2 until the drought event of the 1980s. The maximum severity of -4.0 was reached in Region 2 in 2012, while the minimum severity of -2.48 was in Region 3 (Figure 15). The Sudan Sahelian ecoclimatic region showed consistently high severities throughout drought events.



**Figure 15.** Temporal Distribution of Standardised Precipitation Index within the Homogenous Subregions.

#### *Relationship between Subregions and Climate Indices*

Analysis was done to identify the link between the distinct homogenous regions, and climate indices, which have been carried out by many studies to be responsible for climatic variability i.e., drought. To identify climate indices that have a principal influence on the course of meteorological drought episodes in the region. The SPEI was adopted as it registers better indexing in regions with extreme heat under the influence of global warming, then cross-correlation and wavelet analysis were used to examine the relationship between climate indices and the distinct regions

In addition, a moving average of 12 months was applied to the climate indices to complement the SPEI-12 of the homogenous regions, before computing the correlation between the variables. Most of the correlation  $r$  between the climate indices and regions were negative, apart from the Southern Ocean Oscillation index, which was positive in all four regions.

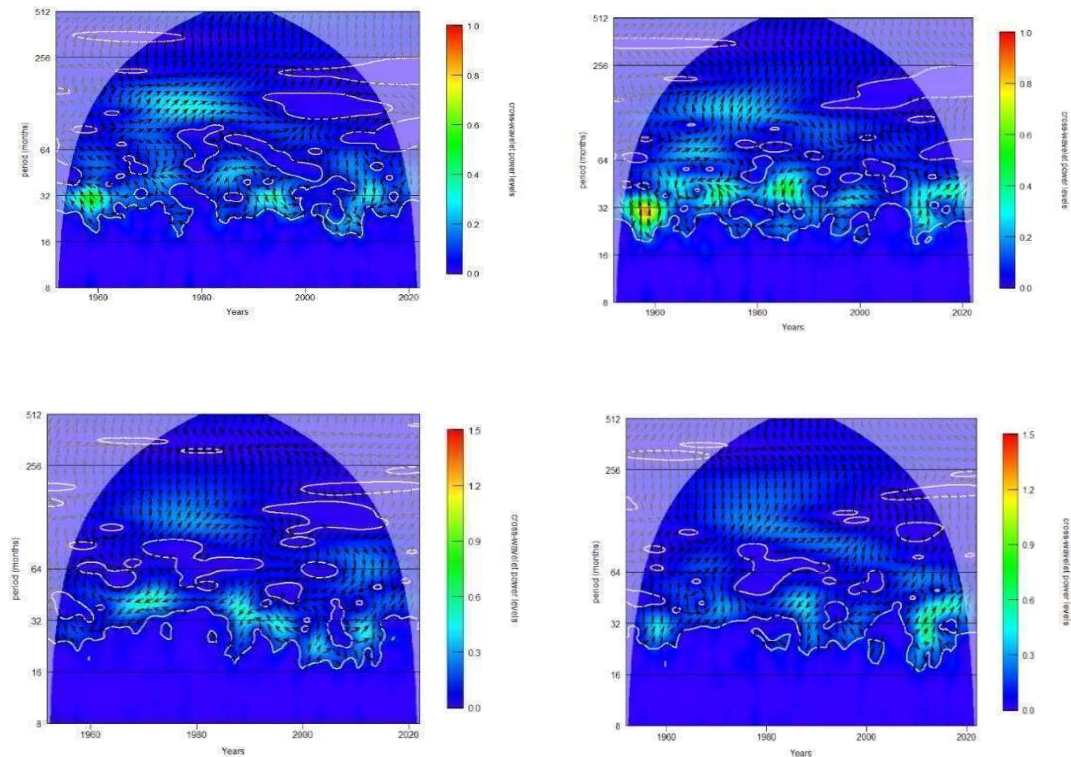
**Table 8.** Cross-Correlation Between Clustered Regions and Climate Indices.

| Climate Indices | Region 1 |        | Region 2 |        | Region 3 |        | Region 4 |        |
|-----------------|----------|--------|----------|--------|----------|--------|----------|--------|
|                 | Lag (r)  | Months | Lag (r)  | Months | Lag (r)  | Months | Lag (r)  | Months |
| TSA             | -0.51    | 9      | -0.33    | 12     | -0.26    | 4      | -0.3     | 12     |
| El Nino 1.2     | -0.45    | -9     | -0.32    | -6     | -0.31    | 0      | -0.22    | -8     |
| El Nino 4       | -0.32    | -5     | -0.21    | 5      | -0.18    | -12    | -0.141   | 5      |
| IOD             | -0.39    | -9     | -0.11    | -1     | -0.04    | 12     | -0.187   | 3      |
| El Nino 3.4     | 0.31     | -6     | -0.22    | -6     | -0.199   | 2      | 0.073    | -12    |
| NAO             | -0.10    | -2     | -0.08    | 4      | 0.117    | 0      | 0.12     | 11     |
| TNA             | -0.06    | 1      | 0.09     | 10     | 0.204    | 12     | -0.19    | -11    |
| AMO             | 0.09     | -12    | 0.08     | 8      | 0.4      | -12    | -0.07    | -10    |
| SOI             | 0.25     | -5     | 0.18     | -7     | 0.18     | 3      | 0.044    | -12    |

A lag of 12- months was used in correlation, as the climate indices oscillation index may not have occurred in the same period. The Tropical Southern Atlantic had the highest correlation (Table 7) of a moderate coefficient indicating a negative phase with  $r$  (-0.51) in region 1 with  $p$ -value < 2.2e-16, and a ranged lag month between 4 to 12 months in all the regions. The ENSO indices observation fairly correlated with the homogenous regions. However, indicating the ENSO has an interrelationship with drought in the regions as conducted by (Leng et al., 2015) in their studies Region 1 has the highest correlation, followed by Region 2 both of which are in the Sahelian region of the study area. Further examination was done between the Tropical South Atlantic and the regions through wavelet analysis.

#### Wavelet Analysis

Tropical South Atlantic analysis showed density concentration in historic drought events in the 1960s to 1980s, greater density is observed in Region 2, while the least density is in Region 3, which were both statistically significant at 0.05 level. The density concentration consistently gathered a signal around 16 – 64 months around 1.3 to 5.3 years in all the regions (Figure 16). However, the wetter region 3 showed lower concentration of power levels in contrast to the rest of the regions. Studies (Gu & Adler, 2004; Joly et al., 2007; Lamb, 1978; Nicholson, 1980; Sun et al., 2010) have examined the influence of TSA on precipitation in the country, and its impact in the drier conditions in the region.



**Figure 16.** Wavelet Analysis between Tropical South Atlantic Index and Standardised Precipitation Evaporation Index-12 between Homogenous Regions 1-4 (1951-2021).

## Discussion

### *Gridded dataset homogeneity*

The rainfall series was subjected to a four-step homogeneity test, and this was able to detect the abrupt shift in the climate change within the period of the 1950s to 1980s, which coincides with the decline in rainfall in the region and the start of the Sahelian drought. In addition, it validates in part the use of gridded dataset in the evaluation of climate studies of the region of study. However, further validation of gridded dataset through the use of ground data has also been implemented in studies in the region that shows the level of correlation and accuracy of the gridded dataset with observational data.

### *Comparison between SPI and SPEI*

Both indices SPI and SPEI were compared to assess the validity of using the SPI and the fitting temporal scale as the primary index to be used for most of the research. The indices showed a positive and good correlation in the computed coordinates. The correlation strength increases as the accumulated temporal scale and the preferred scale for the short and long drought was the 6- and 12-month period, which shows the increased definition of drought pools over time. Although, it is noteworthy to understand that different temporal scale detects drought with different variability, and short-term drought scale 1- month and 3- month detects the higher level of variability which makes them suitable for the slightest indication of drought in a region.

The coordinates such as Bida which is located in the humid region showed a greater correlation than those in the semi-arid and arid regions. This shows the difference in indices as SPEI sensitivity to high-temperature regions through the use of PET, which was estimated using the Hargreaves-Samani method. (Dinka, 1993; 2021; Rahman et al., 2021) have noted its performance and its advantage in semiarid and arid regions. Oladipo (1993) posits the significance of rainfall being the principal variable in characterizing drought, but in areas with extreme weather conditions, the SPEI has been considered more effective, particularly in analyzing agricultural drought but has seen fewer uses in regions due to the case of biases of drought events.

### *Drought characterization*

Both the SPI-6 and SPI-12 were able to capture notable drought events throughout the period. Drought events with at least a severity of -2.5 are extracted (Table 6) . High spatially correlated coordinates such as Kano and Katsina severity ranged from -4.0 to 4.3 in 2012. The 1970s was regarded as the Sahelian drought which saw a decline in the mean rainfall in the region and was regarded as notorious for the spatiotemporal coverage, was captured by the SPI-6 and SPI-12 but according to this study, the 1980s drought was much worse for its severity, duration, and areal extent in the northern region and affirmed by (Mortimore, 1989). The SPI-6 was able to capture partitions and chunks of multiple historic droughts more than the SPI-12 due to the increased variability in the shorter drought temporal scale, the drought pooling, and amalgamation over longer periods. More so, in this study, the drought didn't decrease over the years, nor is it restricted to only the semi-arid and arid regions but its recurrence continued into the 21st century and (Nicholson 2013) affirmed this. Characterization of the time series using SPI-6 and SPI-12 was able to detect severe and extreme drought events in 1958-1960, 1970-1974, 1981-1989 and 2011-2019 while in frequency the extreme drought was prevalent in the northeastern region recurring 46 (5.4%) times in Borno, 45 (5.3%) in Potiskum, 39 (4.6%) in Nguru. Drought severity differences further prove the spatiotemporal difference, and the subregions contrasts.

### *Spatial-temporal characteristics of the study region*

The relationship between the coordinates on SPI-12 was investigated with Pearson product-moment correlation which establishes there exists a strong spatial function between the coordinates, particularly in the arid and semi-arid region, where Kano-Katsina has the strongest correlation of 0.96. Although, all the coordinates have a positive correlation coefficient. further examination carried out using principal component analysis and the K-means clustering technique revealed the decreasing distribution of rainfall, and its variability from the subhumid north-

central towards the extreme north, and the clustering affirms the spatiotemporal distribution of rainfall within the region. However, using both principal component analysis and K-means clustering technique to assess the spatial temporal variability of the SPI-6, and SPI-12 showed four significant loadings and optimal clusters. Clustering the loadings of the principal component was able to ascertain the four distinct homogenous region coordinates coherence and inter variation.

#### Relationship between the climate indices and drought

The drought (climate system) and climate indices follow dynamically related factors such as teleconnection, which is how ENSO during its warm El Nino and cold La Nina phases forces changes in atmospheric circulation globally. The perturbation caused during the ENSO fluctuations is responsible for strong convection that affects both tropics and extratropics. This teleconnectivity has been reported to influence the Indian Ocean. Conversely, it influences the Tropical South Atlantic through a propagation initiated in the central Pacific ENSO fluctuations perturbs the Pacific South America, which in turn links up with the TSA through the South Atlantic Subtropical dipole (Mcphaden et al., 2021). Studies (Rowell, 2001; Yun et al., 2021) have been carried out in the region that links the advent of rainfall decline, drought with the negative phase of TSA and ENSO. In addition, ENSO has been reportedly responsible in part for the sudden abrupt change in climate systems globally in 1957, 1968, 1987, and increasingly into the 21st century, which was observed in the region rainfall homogeneity test.

Investigation of the interrelationship between SPEI-12 of the distinct homogenous regions and the climate indices reveals a correlation between Tropical South Atlantic with a leading signal of 4-12 months, and ENSO influence on drought events, and the wavelet analysis showed the strength of the coherence but its influence was at its strongest in the second region cluster of the extreme northeast with density concentration consistently gathered a signal around 16 – 64 months around 1.3 to 5.3 years particularly during the 1970s and 1980s, while the power levels concentration was weaker in the humid and subhumid region.

This indicates in part an essential element in drought monitoring and prediction which serves as a basis for drought management for water services and infrastructure regulatory bodies in the region.

## Conclusions

Drought investigation was undertaken to evaluate the nature of drought, and its characterization in the region. The objective taken includes:

1. Different indicators have been used to assess drought across different regions and ecoclimatic zones. However, SPI and SPEI are two indicators whose versatility and ease of computation across multiple temporal scales have allowed them to be widely used and accepted, especially the SPI that has been recommended by the WMO (Meteorological et al., 1906; UNCCD et al., 2013) for meteorological studies. In this research, both indicators have been compared as the SPI needs only rainfall records for its computation, and the SPEI uses rainfall and accounts for evapotranspiration. The results showed that in extremely arid regions, the correlation is significant but lower when compared to humid regions, and there is an increasing correlation as the temporal monthly scale increases. Assessing the historic drought which serves as a base for the understanding of drought characterization throughout the region. It is evident that drought in the region's severity follows the distribution of rainfall, and rainfall in the region is affected by different cascading factors. All the extracted 15 coordinates were affected by the 1970s and 1980s drought. However, extreme drought severity in the region is nucleated towards the Sudan Sahelian region where there is a high variability of rainfall, while the whole region observes a sharp decline in precipitation from the 1950s, the Sudan Sahelian suffered greater rainfall deficit in contrast to the humid and subhumid coordinates.

2. The spatiotemporal evaluation was done on the rainfall and meteorological drought distribution. The rainfall spatial distribution is consistent with the works of several authors, its decreasing transition from the south to north, accompanied by the extreme temperature in the northern region. However, the variance and distribution of the meteorological drought showed a function of space proximity in coherence, and its variance chunks and clusters into four distinct homogenous regions.
3. Climatic drivers have been understudied as a chief influence in the climate condition of a region, and successively, a proponent in the event of drought. In this study carried out, different climate indices were used to investigate their influence in historic drought, and the eventuality of drought. The Tropical South Atlantic Indices and ENSO indices showed moderate cross-correlation with the regions and a leading signal of 4-9 months. Further analyses with wavelet analysis showed the negative Tropical South Atlantic antiphase oscillation could have contributed to the Sahelian drought in the region.

In a bid to rectify the problem of drought deficit; water use and misuse, Integrated Water Resources Management (IWRM) is described as a process to redefine the allocation of water resources in a way that creates an interrelation of humans and their ecosystem without depletion and ensures socioeconomic development was introduced in the region. However, the lapses in the policies and legislative acts, political schemes, and inadequate technical capacity retarded the development, and the gaps filled with private stakeholders and water managers are unsettling due to the ownership and authorization crisis. The river basins in the country can be highlighted as the most feasible unit and as proposed by Muller (2019) in studies to enable a functional and operational (IWRM), but it has also faced the same difficulty found in the water policy weakness and lacking institutional, financial structure buried along the ethnoreligious divisions in the country. It is noteworthy that the continued abstraction of Lake Chad and Yobe Basins and resulting insecurity in the northern region prompted and facilitated the consensus in 2008 among stakeholders on a river basin scale which was reflected on a broader scale, and help stabilize the region to some degree.

The problems of the region are distributed across many fronts but the foremost has to do with good governance of water resource management for achieving a sustainable development goal in the country, among the agencies whose importance is vital is the function of the different institutions that monitor, collect and collate hydrometeorological, meteorological, climate and weather, soil moisture, hydrogeological and hydrological data which serves as the basis for accountability, responsiveness, and decision-making, particularly in the case or to prevent a moisture disaster like drought.

Although there are many indicators useful for monitoring, predicting, and forecasting drought triggers and impacts, there is no one size fits all indicators and indices, each indicator follows the spatiotemporal variability attributed to a specific locale. The need for a standard drought indicator linked to drought impact for effective water resource management would serve as a crucial tool in drought monitoring and forecasting.

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