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Characterisation of Meteorological Drought in Northern Nigeria Using Comparative Rainfall-Based Drought Metrics

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Abstract

Meteorological droughts occur when there is deficiency in rainfall; *i.e.* rainfall availability is below some acclaimed normal values. Hence, the greater challenge is to be able to obtain suitable methods for assessing drought occurrence, its onset or initiation and termination. Thus, an attempt was made in this paper to evaluate the performance of Standardised Precipitation Index (SPI) and Standardised Precipitation Anomaly Index (SPAI) to characterise drought in Northern Nigeria for purposes of comparison and eventual adoption of probable candidate index for the development of an Early Warning System. The findings indicated that despite the fact that the annual timescale may be long, it can be employed to obtain information on the temporal evolution of drought especially, regional behaviour. However, monthly timescale can be more appropriate if emphasis is on evaluating the effects of drought in situations relating to water supply, agriculture and groundwater abstractions. The SPAI can be employed for periodic rainfall time series though; it accentuates drought signatures and may not necessarily dampen high fluctuations due to implications of high climatic variability considering the stochastic nature and state transition of drought phenomena. On the other hand, the temporal evolution of SPI and SPAI were not coherent at different temporal accumulations with differences in fluctuations. However, despite the differences between the SPI and SPAI, generally at some timescales, for instance, 6-month accumulation, both spatial and temporal distributions of drought characteristics were seemingly consistent. In view of the observed shortcomings of both indices, especially the SPI, the Standardised Nonstationary Precipitation Index (SnsPI) 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.

Keywords

Characterisation, Timescale, Meteorological, Drought, Metrics

1. Introduction

In a precise but simple manner, drought as a climate phenomenon is a situation of unavailability of water typified by precipitation below normal. Thus by extension, drought means scarcity of water; therefore, it affects various sectors of the human society in a deleterious number of ways [1]. The phenomena of drought attract different meanings with attendant action plans or reactions for preparedness, response, and mitigation depending on the spectrum of the society; to the hydrologist, basically, it connotes below average water levels in the streams, lakes, reservoirs and the like [1]; precisely, it is some complex phenomena. As opined by [2], not only are the appurtenant climate events like high temperatures, rainstorms, and droughts come with pastels of consequences and hazards but rather are becoming increasingly frequent [3]; this pattern has become discernibly evident through this decade in Northern Nigeria with intermittent change in the pattern of both rainfall and temperature regimes. Thus, it suffices to note as reported by [4] that droughts are the world's costliest natural disasters; this climate phenomenon has caused an average of 6 - 8 billion US Dollars in global damages annually and affected more people than any other form of natural disasters [5]. For instance, in 2011, the worst drought in nearly 60 years occurred in Eastern Africa; this led to severe water and food shortages [2] and 12.4 million people were affected by the ensuing famine while about 30,000 children died in Somalia [6]. As noted by [7] as well as [8], drought events will however increase in the 21st century though not in all parts of the world; the severity and duration will differ across all parts of the world, some may not experience it while others may. As such, drought warnings, preparedness and assessments should be considered as strategic policy objective for actionable plans.

Since precipitation is the primary input to the watershed system, unavailability of precipitation in good measure leads to all forms of drought [9] [10]. Precipitation in itself can be reduced due to over-seeding of clouds by dust particles from the Earth's surface, an increase in albedo, a decrease in the availability of biogenic nuclei for rain drop formation caused by reduced plant cover and similar factors [1] [11]. Hence, considering the consequences and the pervasive nature of drought, it is important to assess all forms (such as meteorological, hydrological and agricultural) of drought and in particular, meteorological drought [4]; in this regard, taking cognisance of its severity, duration and frequency is essentially critical. Meteorological droughts are assumed to occur when rainfall is below the range of values considered as normal (at least greater than 0.8 mm for wet spell) [1]. It has been documented that meteorological drought transitions to other forms of droughts like agricultural and hydrological droughts [2].

In view of the complexity of drought, its precise quantification is not easy but a difficult geophysical endeavour [4]. Numerous specialised indices have been proposed to do this; for an extensive listing of available indices, refer to World Meteorological Organisation: [9] and [12]. These include the Standardised Precipitation Index (SPI), Standardised Precipitation Anomaly Index (SPAI), Standardised Nonstationary Precipitation Index (SnsPI), and Standardised Precipitation Evapotranspiration Index (SPEI), Rainfall Anomaly Index (RAI), etc. These indexes have the characteristics of multiple timescales (precisely, monthly and annual) which can represent various drought typology and do reflect the variations in drought characteristics [13]; that is, by analysing spatial and temporal evolutional characteristics at both single and multiple timescales but to varying degrees of robustness. For instance, though the SPI has been widely employed in drought studies, there are certain aspects of it that limits its comprehensive use [10]. It is noted that a small deficit in precipitation may be reflected as large negative SPI value for the locations with small variation in precipitation [14] [15]. Against this backdrop, it suffices to note as reported by [10] that a small precipitation deficit (in this context, surplus) in a season with low precipitation variation and a large precipitation deficit (surplus) in a season with high precipitation variation may each be reflected as large negative (positive) SPI values; this implies that these dry (wet) events may be statistically similar, but they may perhaps not lead to similar social consequences in life of the people for a particular area [10]. As such, the goal of this study, patterned after [10], is to investigate the spatio-temporal differences of meteorological characteristics identified by the SPI and SPAI at different timescales; this is imperative considering that the characteristics of multiple timescales in drought monitoring has not been sufficiently examined [2]. The whole essence is to determine the best probable timescale for adoption in terms of drought event frequency, duration and intensity using SPI or SPAI for general drought monitoring across Northern Nigeria. 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).

2. Materials and Methods

2.1. Study Area and Data

2.1.1. Study Area

Figure 1 below shows the stations in Northern Nigeria with meteorological

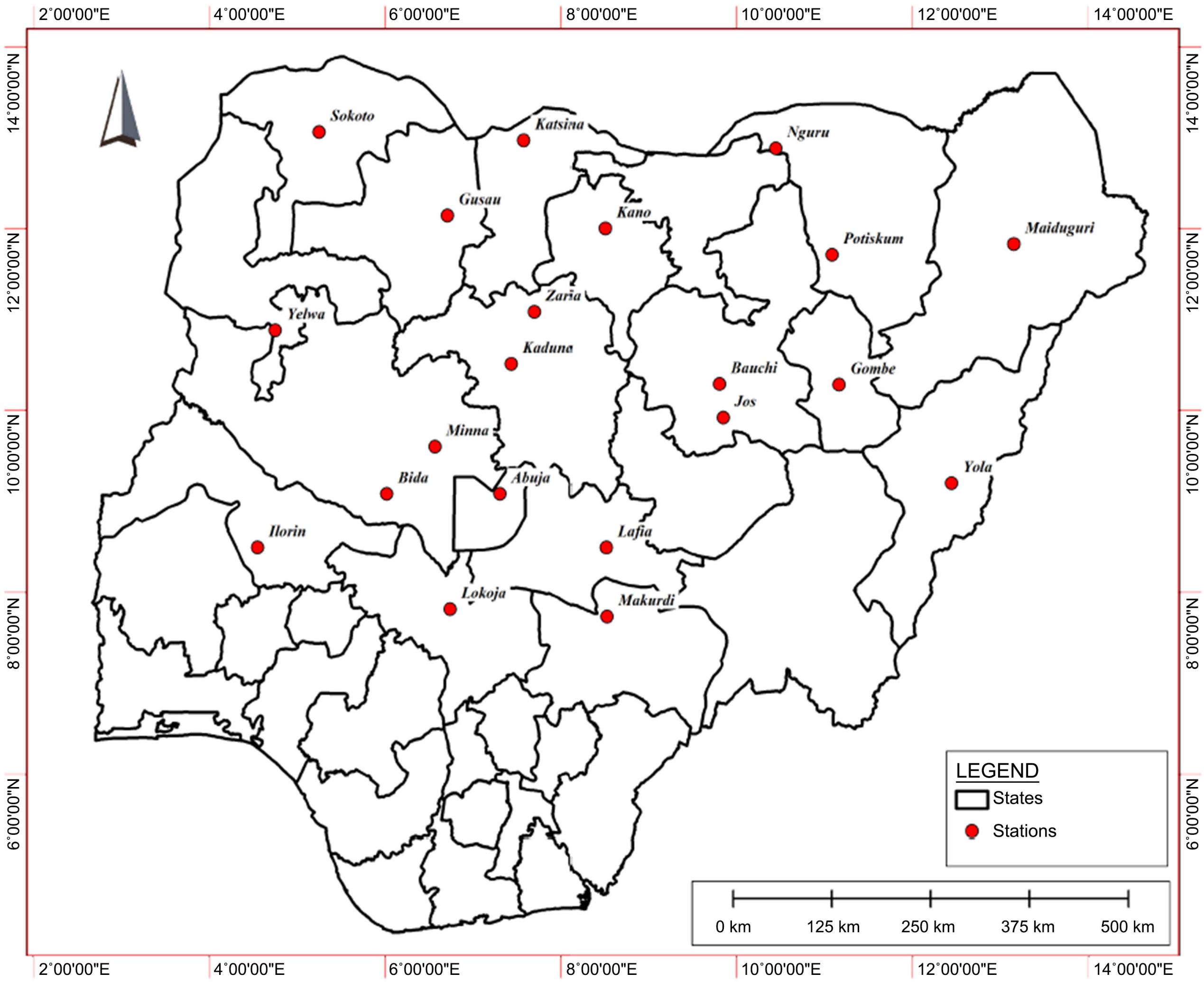


Figure 1. Map of Nigeria showing the geographical location of the Stations in Northern Nigeria.

data that was deployed for this study. One of the main characteristics of the stations is that length of rainfall data (daily aggregated to monthly series) differs across the entire region; though some stations have equal length of temporal coverage but the extent of continuity is not the same. It is pertinent to state that, both wet and dry season periods across the entire region differ in terms of amount of rainfall; water year starts from April to March (corresponding to wet season which covers the crop growing season) while dry season is from November to March. There has been a seeming variability in the pattern of rainfall trend over the last ten years; this lead to variations in beginning and cessation of the rainfall across the region with incessant dry spells or little dry season.

2.1.2. Data Source/Mobilisation and Data Processing

For the purpose of employing the SPI and SPAI in this study, Daily rainfall time sequence for varying stations across the Hydrological Areas (HA_s) in Northern Nigeria was obtained from Nigerian Meteorological Agency (**NiMet**). The data period span through the year 1950 to 2020 with varying time base. Thus, the data for this time period is employed for effective comparison of the metrics adopted. However, for this period the entire data, precisely the daily time sequence for each station was screened for continuity and consistency. Based on this, data sequence with substantial length of missing values were discountenanced (*i.e.*, the year removed or ignored) while those found to exhibit discernible inconsistency/coherence were also removed; this explained the varying length of data for the stations. In addition to **Figure 1**, **Table 1** shows the stations with their respective geographic coordinates with corresponding statistical properties of the annual rainfall series over the entire period: 1950-2020. Statistical tests, in this regard, Kolmogorov-Smirnov (K-S) and Chi-square tests implemented in XLSTAT-2014 were employed to examine whether rainfall series across Northern region majorly follow the gamma distribution; this is to establish the basis for the implementation of SPI.

Table 1. Selected hydrological stations with characteristic details.

Stations	Geographic coordinates		Statistical properties of rainfall series (covering varying periods between 1950-2020) on long-term basis					
	Latitude	Longitude	Mean (mm)	Max (mm)	Min (mm)	Standard deviation	Skewness	Kurtosis
Abuja	9.08	7.31	133.13	513.80	0.00	126.08	0.68	−0.46
Bauchi	10.29	9.81	122.20	715.70	0.00	170.40	1.54	1.76
Bida	9.08	6.02	102.46	489.30	0.00	118.11	0.94	−0.07
Gombe	10.28	11.17	86.65	578.30	0.00	113.13	1.48	2.03
Gusau	12.14	6.71	76.48	473.40	0.00	103.76	1.49	1.92
Ilorin	8.49	4.55	132.84	615.40	0.00	138.61	1.07	0.76
Jos	9.92	9.85	104.54	429.00	0.00	109.98	0.74	−0.54
Kaduna	10.51	7.44	102.47	546.8	0.00	130.89	1.27	0.90
Kano	12.00	8.51	90.75	738.60	0.00	140.72	1.86	3.44
Katsina	12.97	7.58	58.72	359.10	0.00	83.69	1.50	1.48
Lafia	8.49	8.52	131.76	663.70	0.00	142.62	1.07	0.88
Lokoja	7.81	6.74	109.97	438.20	0.00	106.92	0.63	−0.50
Maiduguri	11.83	13.16	64.60	461.50	0.00	103.41	1.80	2.68
Makurdi	7.73	8.53	105.52	372.50	0.00	104.76	0.61	−0.87
Minna	9.60	6.57	110.34	480.60	0.00	121.06	0.80	−0.45
Nguru	12.88	10.45	50.89	518.50	0.00	88.86	2.20	5.40
Potiskum	11.71	11.09	57.04	402.60	0.00	86.73	1.75	2.60
Sokoto	13.06	5.25	60.68	357.60	0.00	82.30	1.45	1.61
Yelwa	10.88	4.75	89.50	465.80	0.00	114.31	1.31	1.07
Yola	9.20	12.45	71.19	296.80	0.00	82.86	0.85	−0.57
Zaria	11.08	7.70	97.13	348.50	0.00	104.09	0.65	−0.83

2.2. Methods

2.2.1. Standardised Precipitation Index (SPI)

The conceptualisation of SPI allows for the quantification of precipitation shortfalls/deficits on multiple time scales. This is based on the realisation that shorter (at least 1-month) or longer (around 24 or 48-month) time scales probably could indicate the transient non-coherence or delay in the response of different water resources to precipitation anomalies. The findings of several researchers (e.g., [2] [10] [16]; etc.) revealed extensively that SPI is suitable for evaluating most types of drought events as it allows for drought analysis on different temporal accumulations. Based on these findings, streamflow could best be described by SPIs with time scale of 2 - 6 months with agricultural drought proficiently quantified by SPI on the scale of 2 - 3 months. Thus in this study, SPI was employed as drought index in the light of its robust attributes. Here, a drought event occurs for a time period when the value of SPI is continuously negative and ends when it becomes positive; in other words, the beginning of positive values connotes beginning of recovery phase and thus complete cessation.

2.2.2. Computation of Standardised Precipitation Index (SPI)

The SPI was calculated by fitting a probability density function (pdf) to the frequency distribution of precipitation and then summed over the time scale of interest; this was precisely done separately for each calendar month (over the entire period of the data), and in this case, a gamma distribution was employed. Each pdf was then transformed into a standardised normal distribution. The gamma distribution was defined by its pdf as in Equation (1).

$$g(x)=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}x^{\alpha-1}\mathrm{e}^{-x/\beta}\quad \text{for } x>0 \tag{1}$$

where $\alpha(>0)$ is a shape factor, $\beta(>0)$ is a scale factor, and $x>0$ is the amount of precipitation. $\Gamma(\alpha)$ is the gamma function defined as in Equation (2).

$$\Gamma(\alpha)=\int_0^{\infty} y^{\alpha-1}\mathrm{e}^{-y}\mathrm{d}y \tag{2}$$

To fit the distribution to the data requires that both α and β are to be expressly determined. Based on the recommendations of [17], these parameters can be determined using maximum likelihood approximation of [18] as contained in [19] and evaluated as defined in Equations (3-5).

$$\hat{\alpha}=\frac{1}{4A}\left(1+\sqrt{1+\frac{4A}{3}}\right) \tag{3}$$

$$\hat{\beta}=\frac{\overline{x}}{\hat{\alpha}} \tag{4}$$

where,

$$A=\ln(\overline{x})-\frac{\sum_{i=1}^{n}\ln(x_i)}{n} \tag{5}$$

for n observations (A is in mm units), and $\bar{x}$ is the long-term mean of the series.

These parameters were used to determine the cumulative probability ($G(x)$) of the precipitation event for each month; this was on the basis of the adopted temporal scale of interest (*i.e.*, 3-month, 6-month, and 12-month).

$$G(x)=\frac{1}{\Gamma(\hat{\alpha})}\int_0^x t^{\hat{\alpha}-1}e^{-1}dt \tag{6}$$

However, noting that the gamma function is undefined for $x=0$ and a precipitation distribution may contain zero values, the cumulative probability (CDF) was then evaluated as in Equation (7).

$$H(x)=\begin{cases} q & x=0 \\ q+(1-q)G(x) & x>0 \end{cases} \tag{7}$$

where q is the probability of zero precipitation. The CDF, $H(x)$ is thus converted to the normal random variable Z; Z has a mean of zero and variance one. The computed normalised values become the SPI values. To achieve this transformation, the approximate conversion provided by [20] as reported in [16] is employed. This is given as in Equations (8-9).

$$Z=\text{SPI}=\begin{cases} -\left(k-\dfrac{c_0+c_1k+c_2k^2}{1+d_1k+d_2k^2+d_3k^3}\right) & \text{for } 0<H(x)\le 0.5 \\ +\left(k-\dfrac{c_0+c_1k+c_2k^2}{1+d_1k+d_2k^2+d_3k^3}\right) & \text{for } 0.5<H(x)<1 \end{cases} \tag{8}$$

$$\begin{cases} k=\sqrt{\ln\left[\dfrac{1}{\left(H(x)\right)^2}\right]} & \text{for } 0<H(x)\le 0.5 \\ k=\sqrt{\ln\left[\dfrac{1}{\left(1-H(x)\right)^2}\right]} & \text{for } 0.5<H(x)<1 \end{cases} \tag{9}$$

For this computation, 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; these values are as in [19]. The drought field was characterised based on **Table 2** below.

Table 2. Characterisation of drought event based on SPI.

SPI values	Class
>2	Extremely wet
1.5 - 1.99	Very wet
1.0 - 1.49	Moderately wet
−0.99 to 0.99	Near normal/mild
−1.0 to −1.49	Moderately dry
−1.5 to −1.99	Severely dry
<−2	Extremely dry

Source: [10].

2.2.3. Standardised Precipitation Anomaly Index (SPAI)

1) Theoretical basis for the adoption of SPAI

Though, SPI is generally reported to have robust adaptability in time and space (e.g. [2]), certain aspects of it encumbers its general application. As reported in [21], in dry seasons, where there is a high preponderance of zero values, *i.e.* no rainfall, the SPI values are lower bounded and fail to adequately indicate a drought occurrence. In this context too, it is noted that SPI is not suitable for a long data series (e.g., [2] [10]; spanning hundreds of years) whose nature changes significantly during a period of study [10]. To address this seeming shortcoming, [22] had earlier recommended the need for a modification of SPI. This culminated in the development of Standardised nonstationary precipitation index (SnsPI) and Standardised precipitation anomaly index (SPAI). Besides the aforementioned, in the views of [10], when an evaluation of drought is needed on the basis of social-economic implications, SPI may not reflect the social consequences caused by deficit/surplus rainfall across both the high and low rainfall month(s). Thus, SPAI is designed to successfully differentiate the consequences resulting from shortages/surplus of rainfall amount.

2) Computation of SPAI

The calculation of SPAI uses precipitation anomalies instead of raw precipitation values. In this regard, the anomalies were computed as in Equation (10).

$$\varphi_{i,j} = \left(\omega_{i,j} - \bar{\omega}_j\right) \tag{10}$$

where $\varphi_{i,j}$ is precipitation anomaly for the *i*th year and *j*th time step of the year, $\omega_{i,j}$ the precipitation value for the *i*th year and *j*th time step of the year while $\bar{\omega}_j$ stands for the long-term mean precipitation for the *j*th time step of the year. When the anomalies were obtained, a single probability distribution was fitted to the entire anomaly series, here in $\varphi_{i,j}$. Since anomalies are not lower bounded by Zero, based on the submission of [10], the gamma distribution may not be appropriate; secondly, considering the higher order moments of rainfall anomaly series it may not pass statistical tests [10]. Thus, to obtain cumulative probability function: CDF, the Weibull's plotting formula given by [23] as in Equation (11) was adopted.

$$p = \frac{\beta}{N+1} \tag{11}$$

Here, p is the cumulative probability of the rainfall anomaly series, β the rank of the dataset sorted in descending order and N is the sample size. After fitting the CDF, the quantiles for each anomaly values were thus obtained; these reduced variates were then transformed to standard normal variates as in the SPI. The standard normal variates obtained hence constitute the SPAI. To allow for a wider range of assessment, both the SPI and SPAI were computed for temporal periods of accumulation of 3-month, 6-month and 12-month, respectively; in this regard, the periods cover 1950-2020, 1952-2020, 1971-2016, and 1981-2016 for the stations considered.

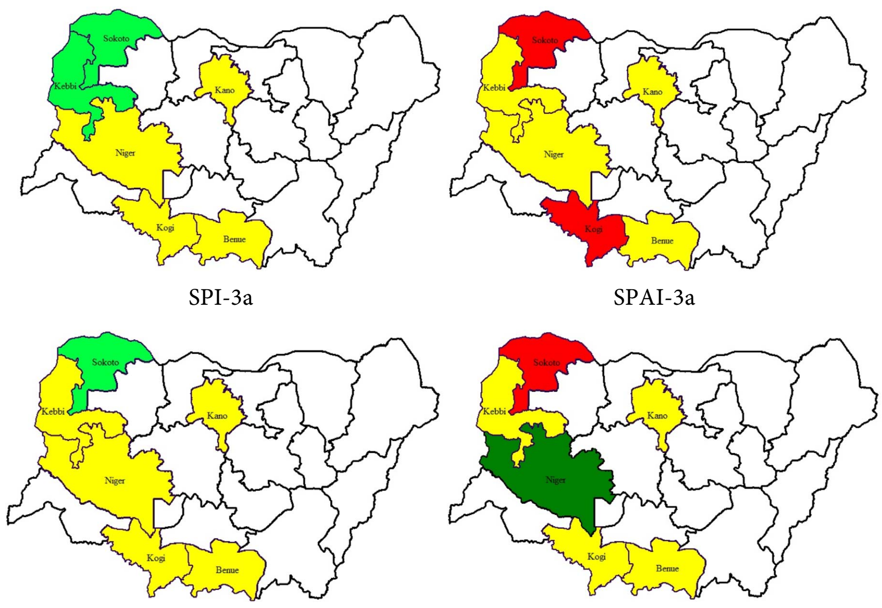
In general, to be able to evaluate the performance of these indexes or metrics, their respective performances in terms of temporal and spatial distribution of drought characteristics were explored; the objective is to put the issues arising thereof in perspectives. The stations selected for this phase of the analysis included Maiduguri, Kano, Minna, and Sokoto; these stations were selected randomly to appreciate implications of the variability in rainfall from the Sahel/montane region through to the Sudan and Guinea Savanna of Northern Nigeria as epitomised by vegetation conditions or differential. For each temporal accumulation considered, both SPI and SPAI values for the months covering the beginning and ending years of the last decade in the data sequence were used.

3. Discussion

3.1. Spatial Variations in the SPI and SPAI

Spatial Distribution of Drought Characteristics

Figure 2a, **Figure 2b** shows the differences in the drought characteristics as reflected by SPI and SPAI for different temporal accumulations. To evaluate the spatial distribution in characteristics, emphasis is on the beginning and ending of the last decade of the time series; specifically, for the stations with 1950-2020 data, the beginning and ending as alluded refer to the years 2011 and 2020 whereas for the stations with 1971-2016, it is the years 2007 and 2016. The contrast in drought pattern is visibly evident considering the respective drought signatures. In **Figure 2a**, as for drought frequency at different timescales, there is no coherence in the distribution; mild drought pattern dominates all through for SPI at 3, 6, and 12-month timescales though not without isolated cases of no drought and moderate drought conditions. On the other hand, for SPAI, there is an admixture of drought pattern from mild drought to extreme with dominance of mild drought signature.



SPI-3a SPAI-3a

SPI-6a SPAI-6a

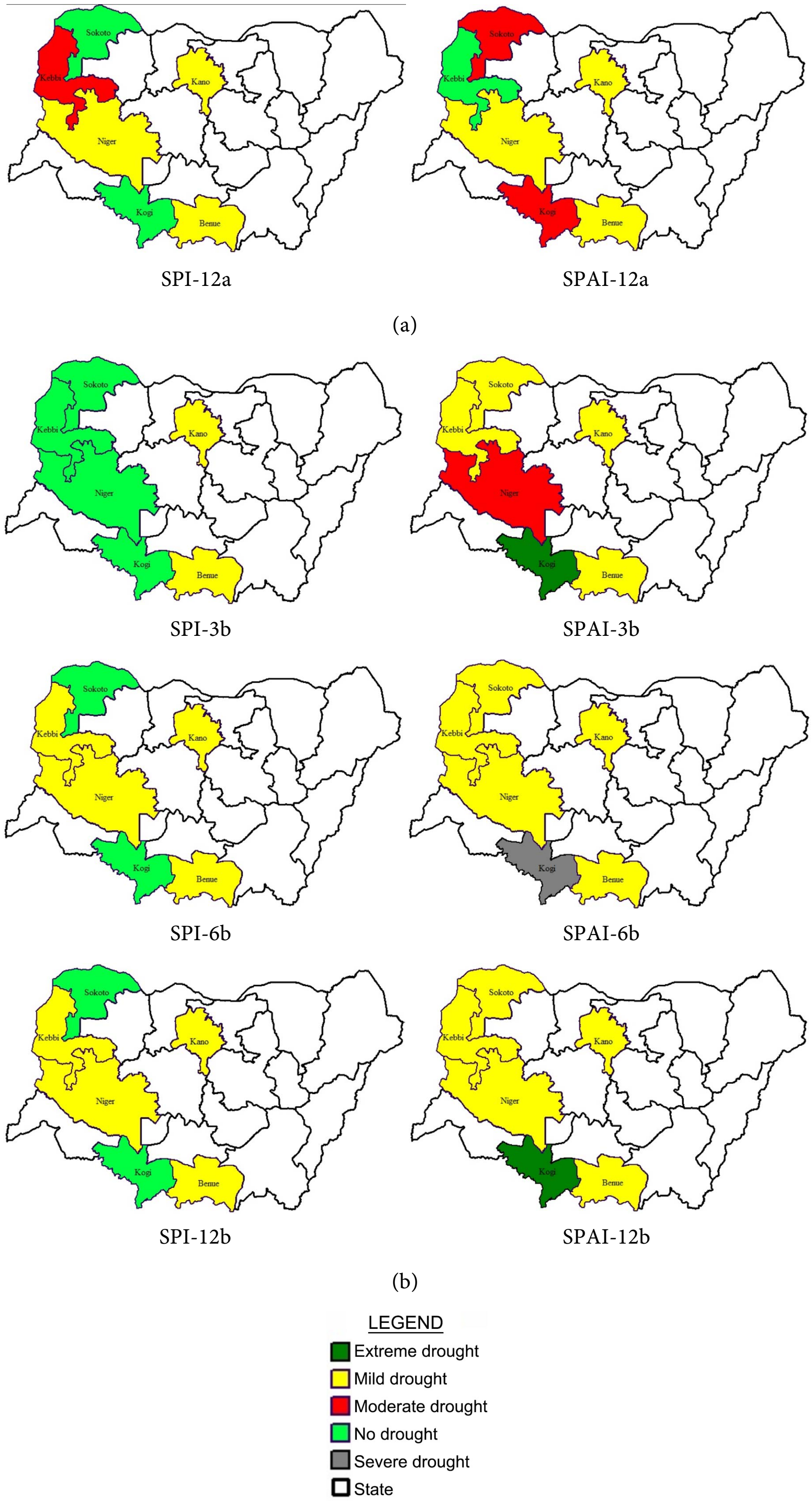


Figure 2. Spatial drought pattern for different temporal accumulations for the beginning (a) and ending (b) of the last decade in the periods under reckoning for selected stations considering 3-month, 6-month and 12-month timescales.

The characteristic trend in the SPAI is the reversal in drought pattern in some instances compared to the case with the SPI; for instance, the case for Niger where at 6-month timescale, there is complete contrast with mild drought in SPI and extreme drought condition with SPAI. This difference in severity in drought condition could be largely attributable to the underlying conceptual formulation of the two models and by extension due in part to irregularity or climatic variability for this period under reckoning. Despite this though, there is seeming coherence in spatial drought pattern in the last part of the decade as noted in **Figure 2b** for all the timescales; this is inferred to connote a certain stability in climatic variability towards the last phase of the decade of the time series employed; *i.e.*, the decade under discourse for emphasis. Despite this though, the findings as in **Figure 2a** and **Figure 2b** bring to the fore two basic things: 1) the change in drought characteristics as indicated by the two indexes revealed the creeping nature of drought; for instance, the slow state transition from no drought to mild drought condition as shown here. 2) variability or pure volatility in rainfall regime could lead to volatility in initiation, recovery, relapse, and cessation of drought. As noted, enhancement of clarity of drought incidence whether it is at incipient stage or moderate to severe condition depends on the power of the Index employed for drought quantification. Here, the SPAI was able to show this clearly. But on the other hand, whichever way one may want to look at the scenario, performance of the indexes could give room for conflict as to designing drought action plans as the indication of no drought condition may not necessarily connote the total absence of drought signature, though it could be latent. This is exemplified for instance by the "Green" turning to "Yellow" and "Green" becoming "dark Green or "Yellow" to "Red"; basically showing how according to either SPI or SPAI, drought condition is changing. This could further be understood by looking at SPI-6 and SPAI-6, SPI-12 and SPAI-12 for Kogi as **Figure 2b**; the contrast here is high; the only plausible reason for this could be that at higher temporal accumulation, closer data values become redundant and their overall impact become negligible due to spurious correlation.

To capture the spatial distributions in drought characteristics in an efficient manner, **Figure 3** below details the distribution in terms of "***low***" and "***high***" spatial concentration (***the low and higher connote the degree of drought intensity***) based on 3-month temporal accumulation for both SPI and SPAI. In both cases, the frequency of mild and moderate drought as defined in **Table 2**, dominates with lower concentrations of severe and extreme drought intensities as is indicated by the percentage values; precisely, the range of percentage values portray the intensity of respective drought characteristics (***low*: <2% - 5% *spatial coverage*; *high*: >5% - 35% *spatial coverage***) across the stations in all instances as shown in **Figure 3**; *i.e.*, in relative terms. The change pattern here explains the coherence in drought conditions as in SPI and SPAI for the selected stations with no significant change in drought frequency. To a large extent, this is similar with the case in **Figure 2**.

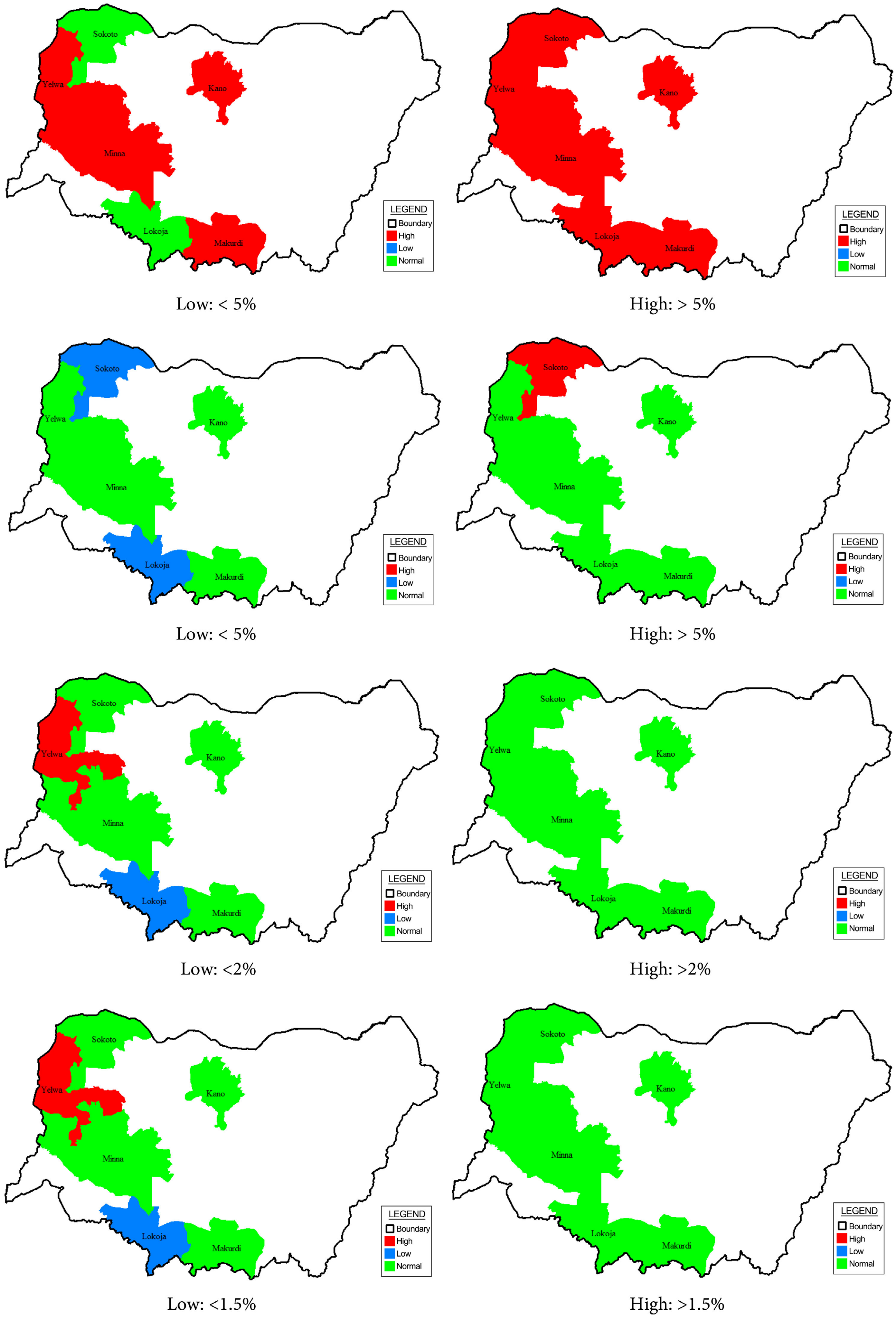


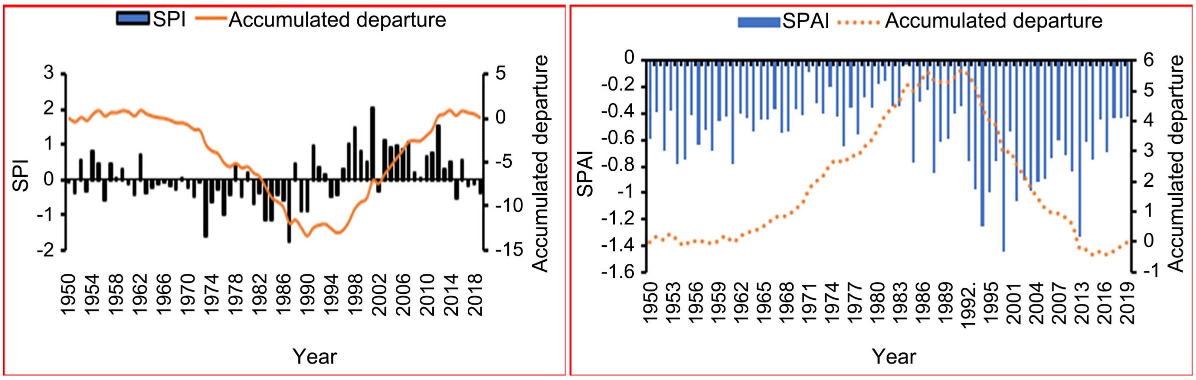
Figure 3. An exemplar of change in drought characteristics based on 3-month temporal accumulation.

3.2. Temporal Variations in SPI and SPAI

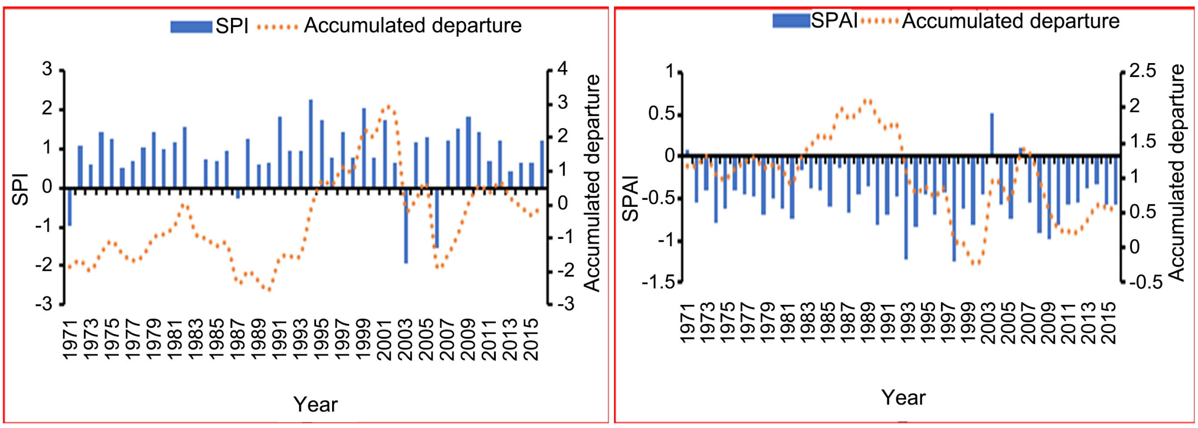
Temporal Evolution of the SPI and SPAI Computed Drought Characteristics

Figures 4(a)-(e) below shows the temporal drought evolution over an annual cycle and change characteristics for selected stations based on SPI and SPAI. Basically, it depicts the inter-annual variation; as shown in Figure 4(a), the SPI exhibited an extensive decline for the period of 1982 to 1986, with 1986 the dividing line as the point where the conditions changed from seeming drought to normal conditions of no drought. It displayed positive trend for most of 1987 to 2014. But for SPAI, the scenario is entirely different for Figure 4(a); as could be seen, the accumulative value of SPAI rises and peaked at both 1989 and 1995 and declined afterwards effectively; precisely, the accumulated departure depicts the transition from no drought condition to drought and vice versa over the entire time period covered characterised by initiation, cessation and relapse of drought. This indicates that the frequency of drought over an annual cycle is increasing. However, the frequency of drought characteristics as in Figures 4(a)-(e) clearly shows that the SPAI tends to accentuate drought signature more than the SPI as evidenced here. For instance, the drought severity differential in Figure 4(c) attests to this; but in Figure 4(d) and Figure 4(e), the variations appear to be smooth with slight decreases in volatility as reflected by the difference on the right. Here, the vertical axis reflects the severity of drought as computed by both the SPI and SPAI and not a ratio. This pattern largely indicates the long-term characteristics of drought as in the views of [2]. The variations as noted are similar at this timescale, 6-month, however, there is evidence of slight differences in the fluctuation value; this connotes differences in drought frequencies and severity (***severity exemplified by the spikes***).

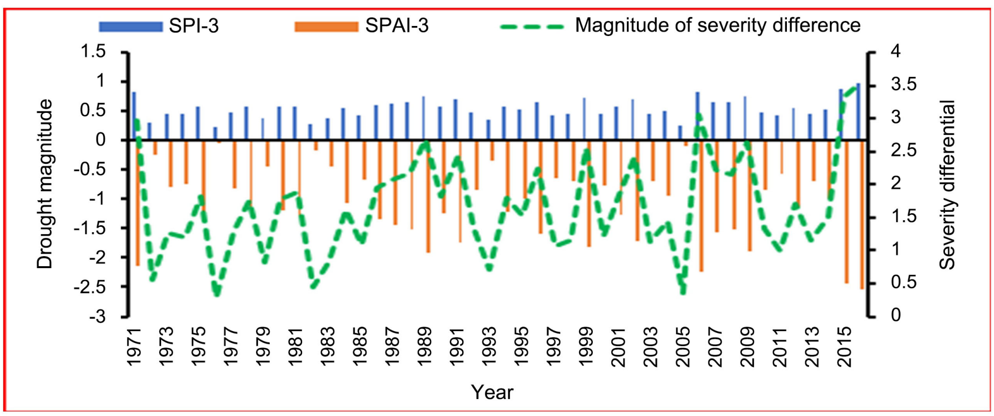
In addition, Tables 3(a)-(e) and Tables 4(a)-(c) show the frequencies and incidence probabilities of drought characteristics, and monthly variations in the SPI and SPAI for the growing seasons (May-October). For all the timescales, the probability of drought incidence tends to be close with the lowest in SPI-3 of 10% and 11%, respectively for Sokoto and Lokoja stations while SPAI is 50% all through in the overall and SPI-12 of 0% (Sokoto) and SPI-6 of 11% (Sokoto). Here, the zero (0%) percentage value indicates the absence of a specific drought signature (for instance, mild, moderate, severe or extreme) as defined in [10]. Despite this, Tables 4(a)-(c) bring to the fore the monthly variations in the characteristics of the SPI and SPAI for the growing season where there is high availability of rainfall though, there are changes in rainfall amount and frequency regime. The variations clearly indicate the implications of seasonality as to the frequency of drought incidence; this is more evident in months of August through October in all instances based on 3-month temporal accumulation. It is imperative to note that at higher temporal accumulations, the frequency of drought incidence may not be same, especially with increase in the time series and too, considering change in climatic variability.


SPI
Accumulated departure
SPI
Accumulated departure
Year
SPAI
Accumulated departure
SPAI
Accumulated departure
Year

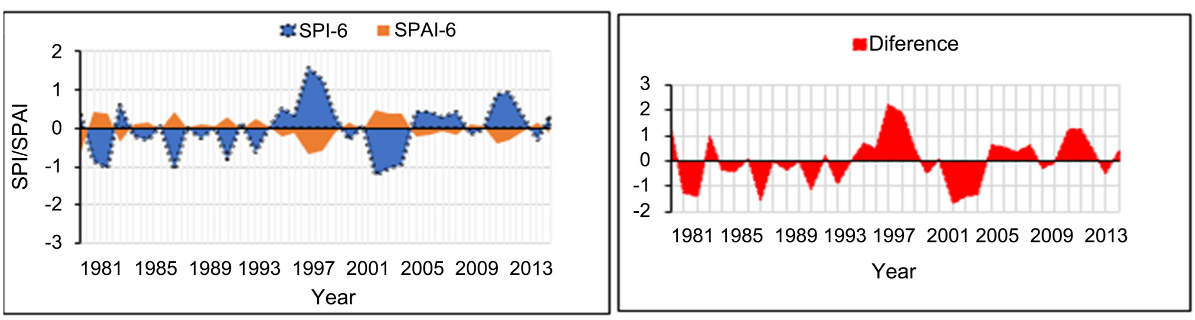
(a)


SPI
Accumulated departure
SPI
Accumulated departure
Year
SPAI
Accumulated departure
SPAI
Accumulated departure
Year

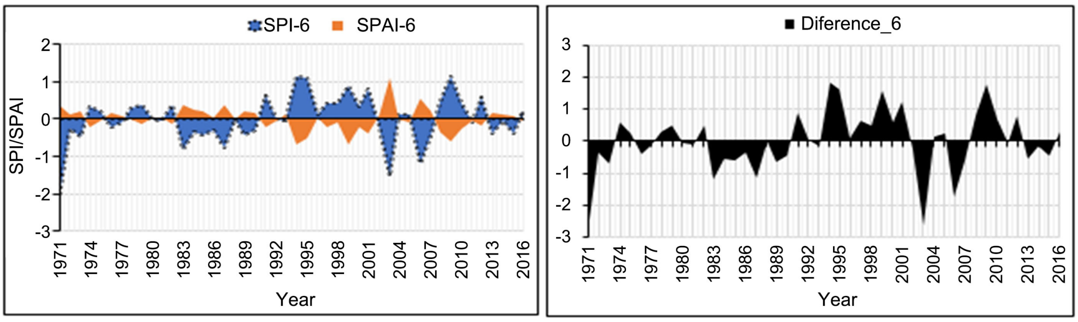
(b)


SPI-3
SPAI-3
Magnitude of severity difference
Drought magnitude
Severity differential
Year

(c)


SPI-6
SPAI-6
SPI/SPAI
Year
Diference
Year

(d)



(e)

Figure 4. Temporal drought evolution over an annual cycle and change characteristics for selected stations ((a): SPI-3 and SPAI-3 for Kano), ((b): SPI-3 and SPAI-3 for Yelwa), and ((c): SPI-3 and SPAI-3 for month of September in Lokoja), ((d) and (e): 6-month accumulation with difference for Makurdi and Yelwa).

Table 3. Detection and severity of drought incidences by the drought metrics: SPI and SPAI (total number of dry months) for selected stations (1950-2020).

(a) Kano (1950-2019)

Drought Index	Number of months and percent occurrence					
	Extreme	*Severe*	*Moderate*	*Mild*	*Normal*	*Total and % number of drought incidence/probability*
SPI-3	12	27	42	231	526	312 (*37*)
SPAI-3	19	37	77	286	419	419 (*50*)
SPI-6	15	35	51	308	426	409 (*49*)
SPAI-6	19	36	77	286	417	418 (*50*)
SPI-12	20	41	49	296	423	406 (*49*)
SPAI-12	19	41	73	282	414	415 (*50*)

(b) Minna (1950-2019)

Drought Index	Number of months and percent occurrence					
	Extreme	*Severe*	*Moderate*	*Mild*	*Normal*	*Total and % number of drought incidence/probability*
SPI-3	18	27	52	245	496	342 (*41*)
SPAI-3	19	37	77	286	414	419 (*50*)
SPI-6	5	9	17	309	495	340 (*41)*
SPAI-6	19	36	77	286	417	418 (*50*)
SPI-12	0	0	0	316	513	316 (*38*)
SPAI-12	18	37	76	284	414	415 (*50*)

(c) Yelwa (1971-2016)

Drought Index	Number of months and percent occurrence					
	Extreme	*Severe*	*Moderate*	*Mild*	*Normal*	*Total and % number of drought incidence/probability*
SPI-3	14	46	36	91	363	187 (*34*)
SPAI-3	12	24	51	188	275	275 (*50*)
SPI-6	18	20	36	164	309	238 (*43*)
SPAI-6	12	24	50	188	274	274 (*50*)
SPI-12	20	12	17	71	321	220 (41)
SPAI-12	15	21	51	186	268	*273* (*50*)

(d) Lokoja (1971-2016)

Drought Index	Number of months and percent occurrence					
	Extreme	*Severe*	*Moderate*	*Mild*	*Normal*	*Total and % number of drought incidence/probability*
SPI-3	1	1	23	37	488	62 (***11***)
SPAI-3	12	24	51	188	275	275 (***50***)
SPI-6	10	21	38	219	259	288 (***53***)
SPAI-6	12	24	50	188	273	274 (***50***)
SPI-12	7	20	53	209	252	289 (***53***)
SPAI-12	12	24	49	186	270	*271* (***9***)

(e) Makurdi (1981-2016)

Drought Index	Number of months and percent occurrence					
	Extreme	*Severe*	*Moderate*	*Mild*	*Normal*	*Total and % number of drought incidence/probability*
SPI-3	8	14	29	161	218	212 (***49***)
SPAI-3	9	19	40	147	215	215 (***50***)
SPI-6	11	19	45	123	229	198 (***46***)
SPAI-6	9	19	39	147	214	214 (***50***)
SPI-12	11	7	26	74	170	118 (***28***)
SPAI-12	9	19	38	147	208	213 (***49***)

Table 4. Monthly distribution of drought characteristics over annual period for selected stations (*May-October*: *Growing Season*).

(a)

Station	**Month**	**Drought Index**	**Drought Characteristics**			
Kano (1950-2019)			***Mild***	***Moderate***	***Severe***	***Extreme***
	May					
		SPI-3	21	4	6	1
		SPAI-3	24	0	0	0
	June					
		SPI-3	18	10	3	2
		SPAI-3	62	0	0	0
	July					
		SPI-3	28	6	3	1
		SPAI-3	56	11	1	2
	August					
		SPI-3	21	6	4	1
		SPAI-3	20	24	18	8
	Sept					
		SPI-3	26	5	3	3
		SPAI-3	20	26	15	9
	Oct					
		SPI-3	21	4	3	3
		SPAI-3	51	16	3	0

(b)

Station	Month	Drought Index	Drought Characteristics			
Sokoto (1952-2019)			*Mild*	*Moderate*	*Severe*	*Extreme*
	May					
		SPI-3	7	0	0	1
		SPAI-3	15	0	0	0
	June					
		SPI-3	0	0	0	0
		SPAI-3	52	0	0	1
	July					
		SPI-3	0	0	0	0
		SPAI-3	53	10	1	1
	August					
		SPI-3	0	0	0	0
		SPAI-3	21	28	12	4
	Sept					
		SPI-3	0	0	0	0
		SPAI-3	16	25	17	7
	Oct					
		SPI-3	0	0	0	0
		SPAI-3	52	8	4	1

(c)

Station	Month	Drought Index	Drought Characteristics			
Minna (1950-2019)			*Mild*	*Moderate*	*Severe*	*Extreme*
	May					
		SPI-3	27	4	3	2
		SPAI-3	17	0	0	0
			June			
		SPI-3	25	4	2	3
		SPAI-3	62	0	0	0
	July					
		SPI-3	22	7	3	2
		SPAI-3	59	9	1	0
	August					
		SPI-3	22	2	6	2
		SPAI-3	31	29	8	2
	Sept					
		SPI-3	22	8	2	1
		SPAI-3	22	16	19	13
	Oct					
		SPI-3	27	5	4	0
		SPAI-3	37	20	9	0

The implications of the results presented call for some levels of concerns. Between the SPI and SPAI in all instances, there is noticeable lack of closeness or coherence in the number of drought incidences, though slight in some cases and staggering in others; clearly visible by probability of drought occurrence as shown in parentheses in **Table 3**. It is clear that the length of data employed for drought analysis does not translate directly to the possible amount of drought incidence, though essential. What is thus critical is the extent of climatic variability in a time period. For instance, the combined average percentage probabilities for SPI-3 and SPAI-3 based on **Table 3(a)** and **Table 3(b)** are SPI-3: 39%; SPAI: 50% while for **Table 3(c)** and **Table 3(d)** they are 22.5% and 50%, respectively. The differences over an annual cycle and months or seasons could lead to different socioeconomic implications that may require thorough knowledge of local climate for evidence-based policy decisions. The SPAI variations here, tend to be high as compared to that of SPI as it failed to dampen high fluctuations probably due to the variability in rainfall pattern. As noted all through, at higher temporal accumulations: 6 and 12-month (See **Tables 3(a)-(e)**), it is evident here in accord with the findings of Chanda and Maity (2015) that SPAI may not work well at high temporal accumulations; this might be due to the high temporal overlap in accumulated rainfall totals.

4. Conclusion

In this study, the typology of meteorological drought was analysed in terms of its characteristics such as mild, moderate, severe and extreme. This was done by using two drought metrics for purposes of comparative drought incidence quantification. Based on the analysis, it is clear that despite the fact that the annual timescale may be long, it can be employed to obtain information on the temporal evolution of drought especially, regional behaviour. However, monthly timescale can be more appropriate if emphasis is on evaluating the effects of drought in situations relating to water supply, agriculture and groundwater abstractions. Worthy of note is that SPAI can be employed for periodic rainfall time series though, it accentuates drought signatures and may not necessarily dampen high fluctuations due to implications of high climatic variability. The temporal evolution of drought characteristics as computed based on SPI and SPAI were not coherent at different temporal accumulations with differences in fluctuations; in addition, the length of data may not necessarily determine the frequency of drought incidence but rather climatic variability. However, despite the differences between the SPI and SPAI, generally at some timescales, for instance, 6-month accumulation, both spatial and temporal distributions of drought characteristics were seemingly consistent and thus either one could be adopted for meteorological drought quantification in Northern Nigeria using 6-month accumulation but generalisations of results should be done with cautious optimism. In light of the findings, the lack of an adoptable threshold for drought quantification is a critical limitation hence there is a 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.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Panu, U.S. and Sharma, T.C. (2003) Challenges in Drought Research: Some Perspectives and Future Directions. *Hydrological Sciences Journal*, 47, 19-30. https://doi.org/10.1080/02626660209493019

[2] Pei, Z., Fang, S., Wang, L. and Yang, W. (2020) Comparative Analysis of Drought Indicated by the SPI and SPEI at Various Timescales in Inner Mongolia, China. *Water*, **12**, Article No. 1925. https://www.mdpi.com/journal/water

[3] Coumou, D. and Rahmstorf, S. (2012) A Decade of Weather Extremes. *Nature Climate Change*, **2**, 491-496. https://doi.org/10.1038/nclimate1452

[4] Keyantash, J. and Dracup, J.A. (2002) The Quantification of Drought: An Evaluation of Drought Indices. *Bulletin of the American Meteorological Society*, **83**, 1167-1180. https://doi.org/10.1175/1520-0477-83.8.1167

[5] Wilhite, D.A. and Glantz, M.H. (1985) Understanding: The Drought Phenomenon: The Role of Definitions. *Water International*, **10**, 110-120. https://doi.org/10.1080/02508068508686328

[6] Maxwell, D. and Fitzpatrick, M. (2012) The 2011 Somalia Famine: Context, Causes, and Complications. *Global Food Security*, **1**, 5-12. https://doi.org/10.1016/j.gfs.2012.07.002

[7] Cook, B.I., Smerdon, J.E., Seager, R. and Coats, S. (2014) Global Warming and the 21st Century Drying. *Climate Dynamics*, **43**, 2607-2627. https://doi.org/10.1007/s00382-014-2075-y

[8] Sheffield, J. and Wood, E.F. (2008) Projected Changes in Drought Occurrence under Future Global Warming from Multi-Model, Multi-Scenario, IPCC AR4 Simulations. *Climate Dynamics*, **37**, 79-105. https://doi.org/10.1007/s00382-007-0340-z

[9] Heim Jr., R.R. (2002) A Review of Twentieth-Century Drought Indices Used in the United States. *Bulletin of the American Meteorological Society*, **83**, 1149-1166. https://doi.org/10.1175/1520-0477-83.8.1149

[10] Chanda, K. and Maity, R. (2015) Meteorological Drought Quantification with Standardised Precipitation Anomaly Index for the Regions with Strongly Seasonal and Periodic Precipitation. *Journal of Hydrologic Engineering*, **20**, Article ID: 06015007. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001236

[11] Cordery, I. and Opoku-Ankomah, Y. (1994) Atlantic Sea Surface Temperatures and Rainfall Variability in Ghana. *Journal of Climate*, **7**, 551-558. https://doi.org/10.1175/1520-0442(1994)007<0551:ASSTAR>2.0.CO;2

[12] WMO (2006) Drought Monitoring and Early Warning: Concepts, Progress and Future Challenges. World Meteorological Organisation, Geneva.

[13] Mishra, A.K. and Singh, V.P. (2010) A Review of Drought Concepts. *Journal of Hydrology*, **391**, 202-216. https://doi.org/10.1016/j.jhydrol.2010.07.012

[14] Lloyd-Hughes, B. and Saunders, M.A. (2002) A Drought Climatology for Europe. *International Journal of Climatology*, **22**, 1571-1592. https://doi.org/10.1002/joc.846

[15] Mallya, G., Tripathi, S., Kirshner, S. and Govindaraju, R.S. (2013) Probabilistic Assessment of Drought Characteristics Using Markov Model. *Journal of Hydrologic Engineering*, **18**, 834-845. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000699

[16] Szalai, S. and Szinell, C. (2000) Comparison of Two Drought Indices for Drought Monitoring in Hungary—A Case Study. In: Vogt, J.V. and Somma, F., Eds., *Drought and Drought Mitigation in Europe. Advances in Natural and Technological Hazards Research*, Vol. 14, Springer, Dordrecht, 161-166. https://doi.org/10.1007/978-94-015-9472-1_12

[17] Edwards, D.C. and McKee, T.B. (1997) Characteristics of 20th Century Drought in the United States at Multi Timescales. Climatology Report No. 97-2.

[18] Thon, H.C.S. (1958) A Note on Gamma Distribution. *Monthly Weather Review*, **86**, 117-122. https://doi.org/10.1175/1520-0493(1958)086<0117:ANOTGD>2.0.CO;2

[19] Mishra, A.K. and Desai, V.R. (2005) Spatial and Temporal Drought Analysis in the Kansabati River Basin, India. *International Journal of River Basin Management*, **3**, 31-41. https://doi.org/10.1080/15715124.2005.9635243

[20] Abramowitz, M. and Stegun, I.A. (1965) Handbook of Mathematical Functions: with Formulas, Graphs, and Mathematical Tables. Dover Publications Inc., New York.

[21] Wu, H., Svoboda, M.D., Hayes, M.J., Wilhite, D.A. and Wen, F. (2007) Appropriate Application of the Standardised Precipitation Index in Arid Locations and Dry Seasons. *International Journal of Climatology*, **27**, 65-79. https://doi.org/10.1002/joc.1371

[22] Russo, S., Dosio, A., Sterl, A., Barbosa, P., and Vogt, J. (2013) Projection of Occurrence of Extreme Dry-Wet Years and Seasons in Europe with Stationary and Non-stationary Standardized Precipitation Indices. *Journal of Geophysical Research: Atmospheres*, **118**, 7628-7639. https://doi.org/10.1002/jgrd.50571

[23] Makkonen, L. (2006) Plotting Positions in Extreme Value Analysis. *Journal of Applied Meteorology and Climatology*, **45**, 334-340. https://doi.org/10.1175/JAM2349.1