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ORIGINAL PAPER

Comparative analyses of standardised precipitation index and moisture quality index for wet and dry periods monitoring over the savanna zones of Nigeria

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Abstract
This study evaluated the suitability of a monsoon quality index (MQI) within the timescales of 6 months and 12 months, as an alternative to the standardised precipitation index (SPI), in assessing rainfall conditions over the rainfall-sensitive, food-producing savanna zones of Nigeria. The results revealed varied correlation between commensurate rainfall variability classes depicted by the indices at the two timescales (ranging from −0.719 for near normal and fair rainfall pairs to 0.249 for extreme drought and extremely poor rainfall pairs) due to MQI's emphasis on intraseasonal dry spells. The findings also showed that while the MQI did better at depicting the south to north variability in rainfall, it over-generalised the wet and dry events by implying very sharp drops in rainfall quality between the southerly and northerly locations. It was thus reclassified into a modified monsoon quality index (mMQI) to correct the over-generalisation. The trend analysis of the frequency of wet and dry episodes for the mMQI and SPI demonstrated agreement in a declining tendency in dry periods and a rising tendency in wet periods. While further studies are recommended to assess differences and similarities between the SPI and mMQI for other rainfall regimes, it is clear that the mMQI has shown viability in analysing wet and dry events in Nigeria's savanna zones and is able to do so even with just 1 year of data. The requirement for long-term records to compute the SPI makes it relatively weak for environments where data records may be sparse and of varying lengths.

Keywords Drought · SPI · MQI · mMQI · Rainfall · Wet periods · Dry periods

Abbreviations

AU	African Union
ADI	Aggregated drought index
CZI	China-Z index
DI	Deciles index
GCOS	Global Climate Observing System
IDSI	Integrated drought severity index
MQI	Monsoon quality index
mMQI	Modified monsoon quality index
RDI	Reconnaissance drought index
RFA	Rainfall anomaly
SPI	Standardised precipitation index
SPEI	Standardised precipitation evapotranspiration index
SRI	Standardised runoff index
UNECA	United Nations Economic Commission for Africa
VCI	Vegetation condition index

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Background to the study

As a continent, Africa has inadequate and inefficient meteorological observation networks (GCOS/UNECA/AU 2006). The inefficiency in meteorological observation networks makes it challenging to address some climate-sensitive critical issues such as poverty reduction and national development, which are being held back by the variability and other climate extremes. Parker et al. (2012) agreed with this assertion in observing that the density and coverage of existing African climate data observation

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networks are generally low and sparse. The United Nations Economic Commission for Africa Climate Policy Centre (Assessment of Africa's climatic records and recording networks including strategies for rescuing of climatic data 2011) has added that even the existing substantial useful data in Africa are not in databases thus, potentially limiting their availability and integrity over time. For this reason, even though climate and weather recording in Africa started during the colonial era with a few meteorological stations on the continent (Griffiths and Peterson 1997), large-scale studies using observed data have been near-impossible. Be that as it may, Parker et al. (2012) suggests that climate scientists must consider the possibility of using the now-available gridded satellite data over Africa, with care and caution.

While data scarcity challenges persist in Africa, the demand for accurate climatic information grows with the most demanded climatic information in Africa being rainfall and its attributes. This is especially so in Sub-Saharan Africa, where rain is a significant natural determinant of agriculture, and the most relevant attributes of rainfall are the two extremes of variability (drought and floods). The droughts constitute the most significant threat to rain-fed agriculture (Usman et al. 2005). Similarly, Norrgård (2017) averred that the intermittent droughts that have affected the Sahel region and other semi-arid areas across Sub-Saharan Africa since the end of the 1960s are associated with rainfall variability. Therefore, a better understanding of past rainfall variability is of great importance for Sub-Saharan Africa's future development.

Bayissa et al. (2018) argued that the performance of rainfall monitoring indices varies from one area to another due to varying data quality and length. Previous studies have also suggested that comparative analysis of rainfall monitoring indices has long been of research interest in different parts of the world. Pei et al. (2020) compared the standardised precipitation index (SPI) and standardised precipitation evapotranspiration index (SPEI) at various timescales in Inner Mongolia, China. Their finding showed that the SPEI was more suitable than the SPI for drought monitoring. On its part, Oloruntade et al. (2017) assessed meteorological and hydrological droughts in the Niger-South Basin, Nigeria and reported more agreement between the standardised runoff index (SRI) and SPEI than between the SRI and the SPI. Xiang-Xiang et al. (2017) analysed spatial and temporal variation of drought characteristics in the Huang-Huai-Hai Plain, China. The finding showed that standardised precipitation evapotranspiration index and the Penman-Monteith equation (SPEI-PM) performed better than SPI and SPEI. Soleimani et al. (2013) studied the comparison of SPI's temporal and spatial trends, deciles index (DI) and China-Z index (CZI) as important drought indices using inverse distance weight method in Taleghan watershed. Their finding shows that SPI as a tool was more reliable in forecasting rainfall events in comparison to the DI and CZI indices. Nohegar et al. (2015) researched the suitability of SPI and aggregated drought index (ADI) in Minab Watershed, Iran. Mpelasoka et al. (2008) compared suitable drought indices for climate change impacts assessment over Australia. Khalili et al. (2011) compared the SPI and reconnaissance drought index (RDI) for meteorological drought indices in different climatic zones. Bandyopadhyay and Saha (2016) compared SPI, rainfall anomaly (RFA), vegetation condition index (VCI) and NDVI anomaly index (NAI) in Gujarat, India. Findings of these comparative studies in rainfall monitoring indices have shown mixed results across the world, indicating that the identification of an appropriate rainfall monitoring index for a specific area is essential for mitigating and preparing for rainfall-related hazards.

It is for this reason that a monsoon quality index (MQI) for rainfall variability monitoring over the Sahel and sub-humid parts of Sub-Saharan Africa, developed by Usman (2000), deserves close scrutiny. Although this noble effort is noted and cited in several studies (Usman et al. 2005; Abdulkadir et al. 2013, 2015; Usman and Abdulkadir 2014; Garba et al. 2018), not much has been done to ascertain its comparative advantages relative to the globally accepted SPI. In this regard, this study's primary objective is to compare the performance and evaluate SPI and MQI application at both the seasonal and the annual timescales, in monitoring rainfall variability in the light of the long-term rainfall data paucity in Sub-Saharan Africa. The comparative treatment also guided needed modifications to the existing MQI for rainfall monitoring at various latitudinal bands, underscoring the point that regional peculiarities remain instrumental in the choice of rainfall monitoring indices.

Material and methods

Data used and study area location

The comparison of SPI and MQI for wet and dry periods' anomalies was based upon 13 globally referenced meteorological stations in Nigeria's savanna zones (Fig. 1) for 1970–2015. The observed daily rainfall data were acquired from the Environmental Management Programme, Federal University of Technology, Minna, Nigeria. The stations represent conditions within the drier Sahelian (Yelwa, Maiduguri, Kano, Gusau, Katsina, Nguru and Sokoto stations) and the relatively wetter sub-humid savanna (Bida, Yola, Minna, Jos, Bauchi and Kaduna stations) zones. The start of rainfall is earliest at stations across the Guinea savanna zone (start of the rains range from 25th May to 9th June each year). In contrast, the stations across the Sudano-Sahelian savanna zone have a late start of the rains (start of the rains range from 4th July to 18th August each year).

Table 1 represents the spatial and climatic information of the selected stations. It is a summary of information on latitude (Lat), longitude (Lon), maximum rainfall (Max),

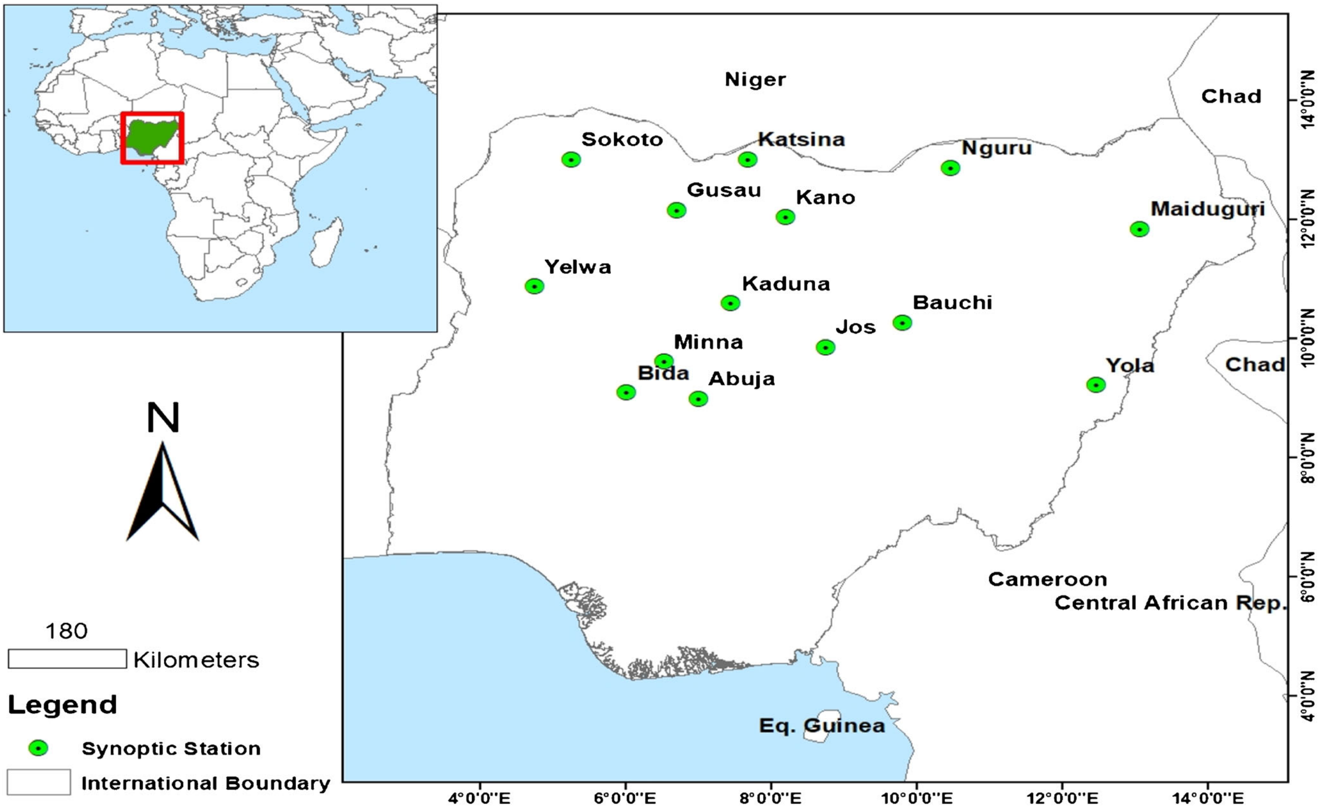

Fig. 1 Geographical location of study areas and the synoptic stations in Nigeria's savanna zones

minimum rainfall (Min), mean, standard deviation (Std. Dev.) and coefficient of variation (CV) for each observation station. Minna recorded the highest mean annual rainfall, attributable to the influence of its latitudinal position. Nguru, located in the north-eastern part of the study area, recorded the lowest mean annual rainfall. Each station has inter-annual rainfall variability, but this is generally less than 50% for all the stations. The coefficient of variation shows that the variability is highest (47.38%) at Bauchi, while as expected, the lowest variability (10.41%) was recorded at Jos. The difference in variability between these locations despite their proximity is very likely as a result of Bauchi's location on the leeward side of the Jos Plateau, and therefore less consistently swept by the moisture-laden south-westerly (monsoon) winds of the rainy season, especially at the beginning and at the end of the rainfall season.

Table 1 Spatial and climatic information of the selected stations

Station	Lat	Lon	Max	Min	Mean	Std. Dev.	CV
Bida	9.1	6.02	1547	304.1	1118.83	223.55	19.98
Yola	9.23	12.47	1164.2	495.8	870.95	143.94	16.53
Minna	9.62	6.53	2772.7	1260.3	2066.2	288.37	13.96
Jos	9.87	8.75	1582.7	814.7	1255.72	130.78	10.41
Yelwa	10.88	4.75	1564.6	255.9	940.81	252.27	26.81
Bauchi	10.28	9.82	2030.3	29.91	952.97	451.49	47.38
Kaduna	10.6	7.45	1655.2	793.4	1223.65	190.9	15.6
Maid	11.85	13.08	1073.9	26.13	541.08	194.26	35.9
Kano	12.05	8.2	1789	414	948.87	352.89	37.19
Gusau	12.17	6.7	1503.8	615.9	882.72	181.97	20.62
Nguru	12.88	10.47	654.1	2.8	398.38	131.31	33.93
Sokoto	13.02	5.25	1146.7	372.9	635.29	151.99	32.96
Katsina	13.02	7.68	1310.2	259.8	563.82	191.31	23.9

Data quality control

Research suggests that data quality control is a requirement for climate analysis (Zhang et al. 2017). We found 1 year (2.17%) missing data in each of Bida, Yelwa, Bauchi Kaduna Maiduguri, Kano, Gusau and Sokoto stations. Previous studies agree that less than 5% of missing data has no significant impact on climate data analysis (Byakatonda et al. 2019; Zhang et al. 2017). Consequently, the missing data did not count in data analysis. We used R ClimDex package in R software to search and correct outliers in line with its established use as a standard for data quality control.

Methods of data analysis

The SPI developed by Mckee et al. (1993) tracks dry and wet events on different timescales, i.e. 1, 3, 6, 9, 12 and 24 months, and is flexible for the period chosen. Owing to its reliability and ability to address drought at multiple time steps for various climatic regions, the SPI has been used extensively in various parts of the world (e.g., Shahid 2010; Zhao et al. 2012; Jain et al. 2015). It provides a comparison of precipitation over a specific period with the precipitation totals from the same period for all the years included in the historical record. Therefore, it facilitates the temporal analysis of wet and dry phenomena but requires continuous long-term data of at least 30 years to compute. It does not allow for missing data. For this study, the SPI is calculated for the timescales of 6 months (SP-6) and 12 months (SP-12).

The method for calculating the SPI index is:

$$g(x) = \frac{1}{\beta^{\alpha} \cdot \Gamma(\alpha)} x^{\alpha-1} \cdot e^{-\frac{x}{\beta}}, x > 0 \tag{1}$$

where α: form parameter; β: scale parameter; x: precipitation quantity and $\Gamma(\alpha)$ is a gamma function defined by the following statement:

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

Parameters α and β are determined by the method of maximum probability for a multiyear data sequence, i.e.:

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

$$A = \ln(x_{ST}) - \frac{\sum_{i=1}^{n} \ln(x_i)}{n} \tag{4}$$

$$\beta_{pro} = \frac{x_{ST}}{\alpha_{pro}} \tag{5}$$

where x_{ST}: mean value of precipitation quantity, n: precipitation measurement number and x_i is the quantity of precipitation in a sequence of data.

The obtained parameters are further applied to determining a cumulative probability of certain precipitation for a specific period on a temporal scale of all the observed precipitation. The cumulative probability can be presented as:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta_{pro}^{\alpha_{pro}} \cdot \Gamma(\alpha_{pro})} \int_0^x x^{\alpha_{pro}-1} e^{-\frac{x}{\beta_{pro}}} dx \tag{6}$$

Since the gamma function has not been defined for $x = 0$, and the precipitation may amount to zero, the cumulative probability becomes:

$$H(x) = q + (1-q)G(x) \tag{7}$$

where q: the probability that the quantity of precipitation equals zero, which is calculated using the following equation:

$$q = \frac{m}{n} \tag{8}$$

where m: a number signified how many times the precipitation was zero in a temporal sequence of data and n is precipitation observation number in a sequence of data.

The calculation of the SPI is performed based on the next equation (Lloyd-Hughes and Saunders 2002; Milanovic et al. 2014):

$$SPI = \left\{ \begin{array}{ll} -\left(t - \frac{C_0 + C_1 t + C_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), & 0 < H(x) \le 0.5 \\ +\left(t - \frac{C_0 + C_1 t + C_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), & 0.5 < H(x) \le 1.0 \end{array} \right\} \tag{9}$$

where t is determined as:

$$t = \left\{ \begin{array}{ll} \sqrt{\ln \frac{1}{(H(x))^2}}, & 0 < H(x) \le 0.5 \\ \sqrt{\ln \frac{1}{(1-H(x))^2}}, & 0.5 < H(x) \le 1.0 \end{array} \right\} \tag{10}$$

C_0, C_1, C_2, d_1, d_2 and d_3 are coefficients whose values are as follows: $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$ and $d_3 = 0.001308$.

The SPI is classified as in Table 2.

Based on the threshold values in Table 1, a season or year is counted as wet or dry when the SPI is ≥ 1.0 or ≤ -1.0.

The MQI developed by Usman (2000) for rainfall monitoring in the savanna areas is a rainfall-only and non-mean-based index. The daily rainfall is aggregated into 5-day intervals (pentads). The annual rainfall total, seasonal rainfall total (May–October), highest monthly rainfall total and the number of breaks (pentad totals of < 5mm) for each hydrologic growing season are taken into consideration. It was computed, as shown in Eq. 11:

$$MQI = \left(\frac{r_{mm} * Nb_i}{R_i^2}\right) \tag{11}$$

where:

i year identifier
r_{mm} highest monthly rainfall total

Table 2 Standardised precipitation index (SPI) classification values by McKee et al. (1993)

Category	SPI values	Probability of occurrence (%)
Extremely wet	2.00 and above	2.3
Severely wet	1.50–1.99	4.4
Moderately wet	1.00–1.49	9.2
Near normal	−0.99–0.99	34.1
Moderate drought	−1.00 to −1.49	9.2
Severe drought	−1.50 to −1.99	4.4
Extreme drought	−2.00 and less	2.3

R annual rainfall total
Nb number of 'breaks' in rainfall. A break is taken as any pentad period with < 5 mm of rain.

The index is small if the annual amount is high and the rains are not concentrated in any 1 month. Thus, the smaller the index, the better the seasonal rainfall. As shown in Table 3 for the intended comparative analysis, the index was computed at seasonal and annual timescales.

Based on threshold values in Table 3, a season or year is counted as wet or dry when the MQI < 0.005 and $\geq$ 0.01, respectively.

The frequencies of wet and dry periods for SPI and MQI were correlated using the Pearson product-moment correlation coefficient to establish their relationships at the two timescales.

The Mann-Kendall test (Mann 1945; Kendall 1975) is applied to detect trends in the frequency of wet and dry episodes in both SPI and MQI indices. The test identifies essential hydro-meteorological time series (for example Deka et al. 2015; Hoscilo et al. 2015; Jones et al. 2015; Sushant et al. 2015; Katsanos et al. 2017). The confidence levels of α = 0.001, 0.01, 0.05 and 0.1 are taken as the starting point to classify the significance of upward and downward trends.

Results and discussion

Seasonal standardised precipitation index

The seasonal (6 months) SPI pattern of observation stations are represented in Fig. 2. The findings show a general fluctuation in wet and dry episodes at all the stations. The pattern indicates that rainfall was well below average in the late 1970s and 1980 to 1990. The patterns of wet and dry episodes are consistent with the findings of Dong and Sutton (2015), Evan et al. (2015), Ifabiyi and Ojoye (2013) and Nkiaka et al. (2016) over Nigeria and the Sahelian region of West Africa. The remaining years depicted rainfall well above normal across the study area.

Table 4 shows the percentage of the SPI's wet and dry frequency classes from May to September (season) for the savanna zones. In about 17.78% of the years, the SPI class fell under the wet category at Bauchi, Kaduna and Kano stations. Equal seasonal percentage frequencies of dry and wet episodes were observed at Minna, Maiduguri, Gusau and Nguru stations. In contrast, a high seasonal percentage frequency of wet spells was observed at Bauchi, Kaduna and Katsina stations, indicating that the anomalies of rainfall in the study area are not uniformly distributed and that local factors may be influencing the rainfall in each observation station. The finding is supported by D'Orangeville et al. (2018) submission that drought timing and the atmospheric water demand are the local determinants of drought. Philip et al. (2020) also opined that local precipitation is the driver of agricultural drought.

Table 3 Monsoon quality index classification values by Usman (2000)

MQI values	Category
$\geq$0.015	Very poor
$\geq$0.01 < 0.015	Poor
$\geq$0.005 < 0.01	Fair
$\geq$0.001 < 0.005	Good
<0.001	Very good

Annual standardised precipitation index

Figure 3a–d represents the annual SPI of the observation stations. This figure depicts seven (7) categories of SPI patterns for the various stations, with oscillations between wet and dry episodes. The general pattern indicates that conditions are generally near normal. This general pattern contrasts with the findings by Azimi and Azhdary Moghaddam (2020) that found a steeper mild drought than a near-normal drought condition in Iran. Findings reveal a high annual SPI percentage frequency of dry episodes at Bida, Yola, Minna, Yelwa, Bauchi, Kaduna, Maiduguri, Kano, Sokoto and Katsina for the period under review. Equal annual SPI percentage frequencies were observed in dry and wet episodes at Nguru, while high annual SPI percentage frequency of wet episodes was observed at Jos and Gusau. The general pattern shows that the Sudano-Sahelian region known to have the lowest mean annual rainfall is now less prone to dry events. On the other hand, stations in the sub-humid areas (Guinea savanna) are now more prone to dry events. A study by Li et al. (2019) found a similar pattern in the Yangtze River Basin, possibly suggesting perceptible local and/or regional shifts in climatic regimes that may be masked by known global patterns.

Table 5 shows the percentage of SPI's wet and dry frequency classes from January to December (annual). The findings reveal that Bida, Yola, Minna, Yelwa, Bauchi, Kaduna, Maiduguri, Kano, Sokoto and Katsina stations have higher annual SPI percentage frequency of dry episodes to wet episodes for the period under review. Nguru recorded equal annual SPI percentage frequency of drier and wetter episodes, and Jos and Gusau had higher annual SPI percentage frequency of wet episodes to dry episodes. In general, there are similarities in the wet and dry periods for seasonal and yearly SPI.

Seasonal moisture quality index (MQI)

Figure 4**a**–**d** shows the temporal pattern of seasonal MQI. The results reveal very high variability in the quality of the seasonal rainfall over the study locations. The variability

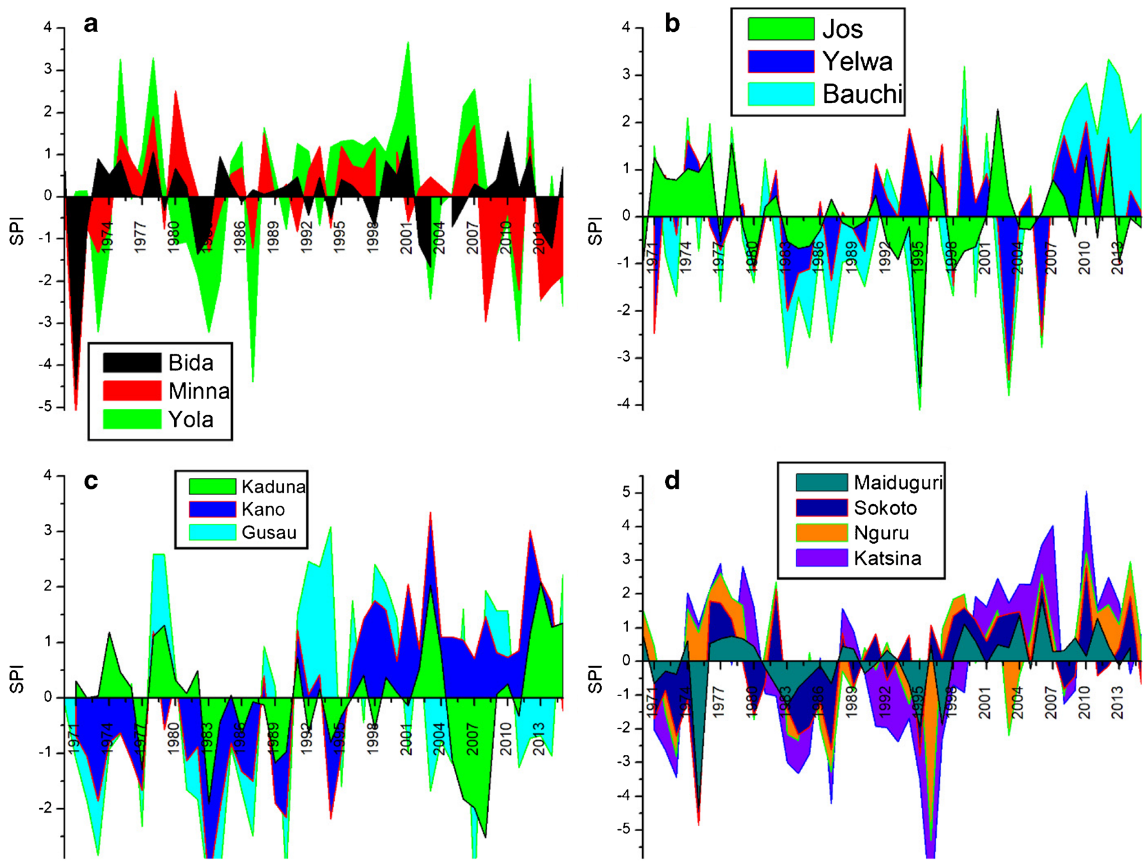

Fig. 2 **a**–**d** Seasonal standardised precipitation index series of the observation stations

transcended all the five classes of MQI, with the least variability experienced at Jos and Minna stations while the highest variability is detected at Maiduguri and Nguru stations. Jos and Minna, it is to be noted, are in the Guinea savanna zone where rainfall is higher, while the Maiduguri and Nguru stations are in the Sudano-Sahelian savanna where rain is the least. The Yelwa station's variability was high between the 1980s and 1990s while it was higher at Katsina between 2000 and 2010. The general pattern indicated that more southerly stations (Bida, Yola, Minna, Jos, Bauchi and Kaduna) had good to the very good seasonal rainfall. The stations in the Sudano-Sahelian ecological zone, except for Maiduguri and Nguru, had the bulk of seasonal rainfall quality in the range of fair to good. Maiduguri and Nguru stations in the extreme north-eastern part recorded much higher percentages of very poor seasonal rainfall quality.

Table 4 Percent (%) seasonal SPI frequency of wet and dry periods

Stations	Wet	Normal	Dry
Bida	2.22	88.89	8.89
Yola	10.87	73.91	15.22
Minna	10.87	78.26	10.87
Jos	17.02	68.09	14.89
Yelwa	6.67	82.22	11.11
Bauchi	17.78	66.67	15.56
Kaduna	17.78	66.67	15.56
Maiduguri	8.89	82.22	8.89
Kano	17.78	62.22	20
Gusau	13.04	71.74	15.22
Sokoto	15.56	66.67	17.78
Nguru	4.35	91.3	4.35
Katsina	15.56	73.33	11.11

The percentage of the frequency of seasonal quality of the rainfall is represented in Table 6. The table indicated that the quality of the seasonal rainfall in the Guinea ecological zone is good to very good with isolated cases of poor and very poor. On the other hand, the Sudano-Sahelian ecological zone stations had rainfall quality in the range of fair to good, except for Maiduguri and Nguru where seasonal rainfall quality is mostly very poor.

Annual moisture quality index (MQI)

Figure 5**a**–**d** represents the temporal variability of annual MQI. The figure indicated apparent differences between seasonal rainfall and yearly rainfall. Although the variability follows a similar pattern with seasonal rain, the rainfall quality

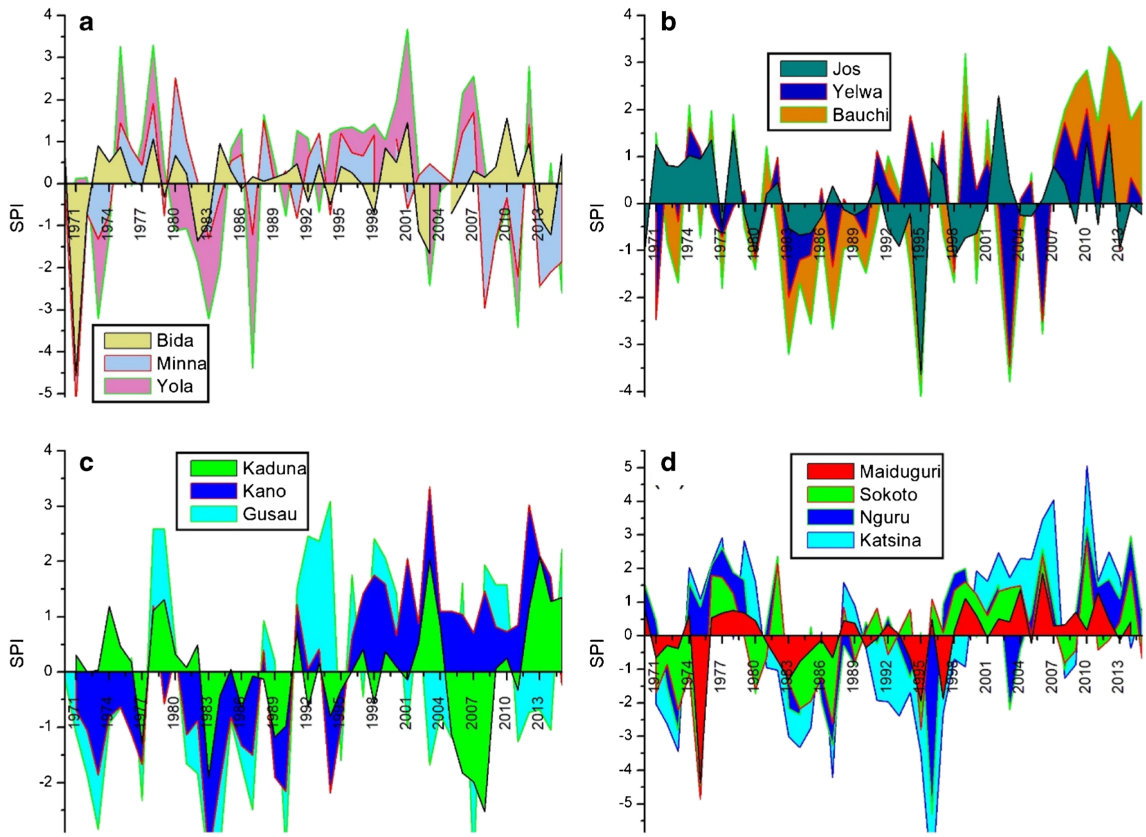

Fig. 3 **a**–**d** Annual standardised precipitation index series of the observation stations

becomes progressively worse off beyond the growing season of May to October in each year.

Table 7 shows the annual frequency percent of the annual MQI. As indicated, the bulk of the Guinea ecological zone stations has the quality of their rainfall in fair class, with Yola station being an exception. It is important to note that Bida and Kaduna had only 2.2% to 4.4% rainfall in a good class. Generally, the Sudano-Sahelian ecological zone stations had a higher percentage of the quality of rainfall in poor to very poor categories, indicating that the relatively long dry season affects the quality of rain when considered.

Table 5 Percent (%) annual SPI frequency of wet and dry periods

Stations	Wet	Normal	Dry
Bida	6.67	82.22	11.11
Yola	13.04	71.74	15.22
Minna	11.36	77.27	11.36
Jos	14.89	76.6	8.51
Yelwa	6.67	82.22	11.11
Bauchi	17.78	64.44	17.78
Kaduna	17.78	66.67	15.56
Maiduguri	8.89	82.22	8.89
Kano	20.00	60.00	20.00
Gusau	13.04	76.09	10.87
Sokoto	15.56	66.67	17.78
Nguru	4.35	91.3	4.35
Katsina	11.36	77.27	11.36

Comparison of SPI and MQI indices

The study compared the SPI and MQI indices' seven (7) and five (5) respective classes and reclassified the latter into seven (7) classes (Table 8).

Table 9 depicts the seasonal frequency of SPI and MQI. Pearson correlation coefficients were computed between paired time series using all SPI and MQI indices classes at 95% confidence level. For example, severity values estimated using SPI seasonal rainfall were paired with severity values calculated using MQI seasonal rainfall. The SPI and MQI correlation indicated the extreme drought and extremely poor rainfall pairs had a coefficient of 0.249, severe drought and very poor rainfall pairs had a coefficient of −0.233, moderate drought and poor rainfall pairs had a coefficient of 0.073. The near normal and fair pairs had a correlation coefficient of −0.719. The moderately wet and good rainfall pairs had a coefficient of −0.455, severely wet and very good rainfall pairs had a coefficient of 0.237 and extremely wet and extremely good rainfall pairs had a coefficient of −0.386. The coefficient values generally indicate that there is a weak relationship between the SPI and MQI, especially in the case of

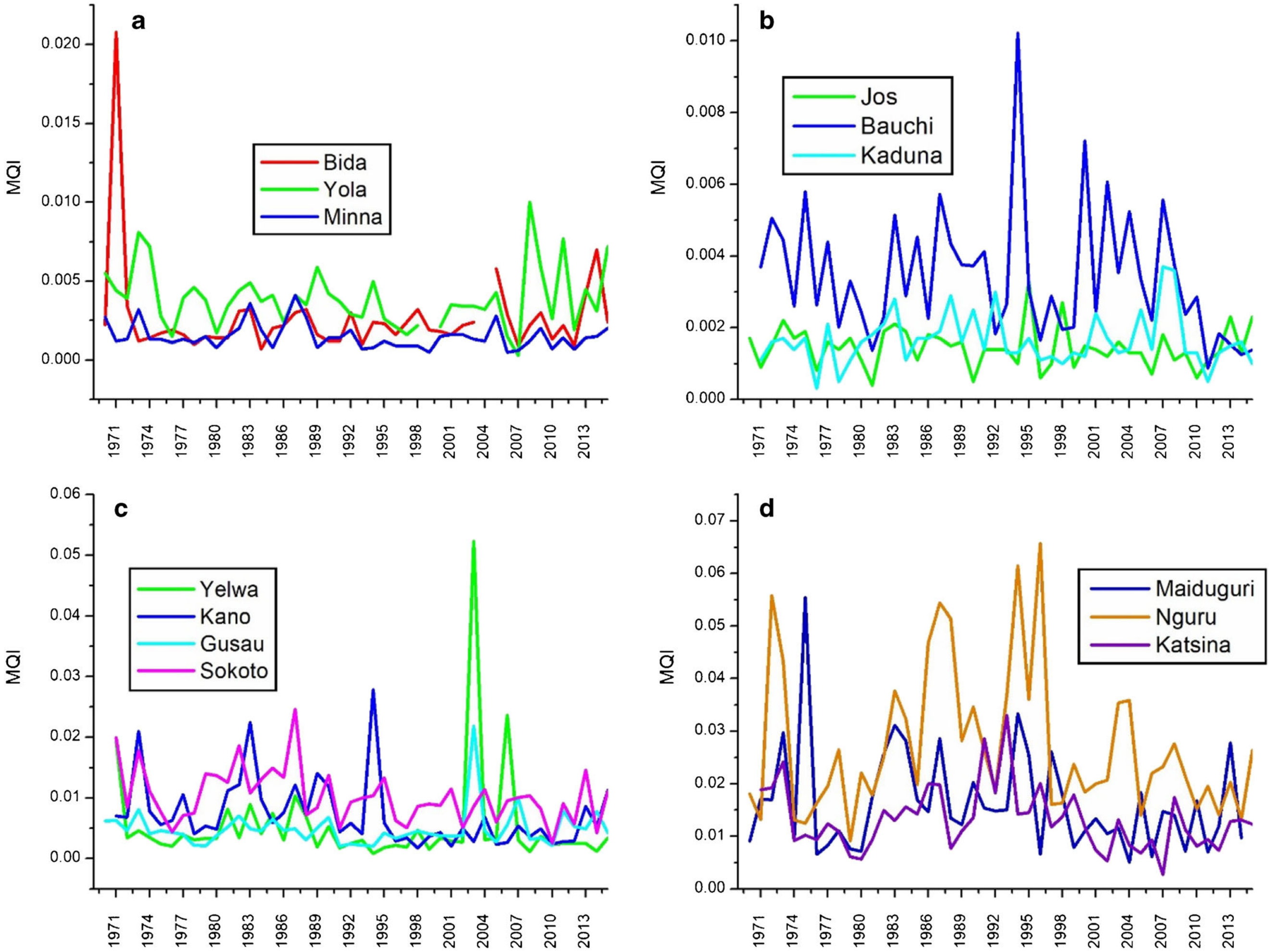

Fig. 4 **a**–**d** Seasonal moisture quality index series

extreme classes. The relatively high negative correlation between the near normal and fair pairs does suggest the existence of consistency in the differing treatment of a constant feature of the seasonal rains in any given season. The considered opinion of this study is that this is related to the consideration given to the number of breaks in rainfall receipt (an indicator of rainfall distribution) by the MQI. As other studies (Pei et al. 2020; Moghimi and Zarei 2019; Uddin et al. 2020; Harisuseno 2020; Zarei et al. 2019) have shown, such varied relationships between SPI and other indices are to be expected.

Table 6 Percentage (%) of seasonal MQI classes

Stations	Wet	Fair	Dry
Bida	93.3	4.4	2.2
Yola	80.5	17.4	2.2
Minna	100	0	0
Jos	100	0	0
Yelwa	80	11.1	8.9
Bauchi	80	17.8	2.2
Kaduna	8.9	91.1	0
Maiduguri	0	28.9	71.1
Kano	42.2	35.6	37.7
Gusau	69.6	28.3	2.2
Sokoto	6.7	46.7	46.7
Nguru	0	2.2	97.8
Katsina	2.2	31.1	66.7

Considering the percent seasonal and annual frequency of SPI in Table 3 and Table 4, the SPI indicates no apparent difference in the occurrence of wet and dry episodes for seasonal and annual rainfall. The result explains SPI's limitation as it compares the mean rainfall over a period with the total rainfall from the same period for all the years included in the historical record (Mohammed et al. 2018). It follows that if the record of rainfall was to change, the SPI values for the same study area would change.

The MQI, on the other hand, showed a remarkable difference between the quality of seasonal rainfall (Table 6) and the quality of annual rainfall (Table 7). The MQI result implies that it is possible to have good seasonal rainfall within a poor year and vice versa. This is more realistic as the bulk of the

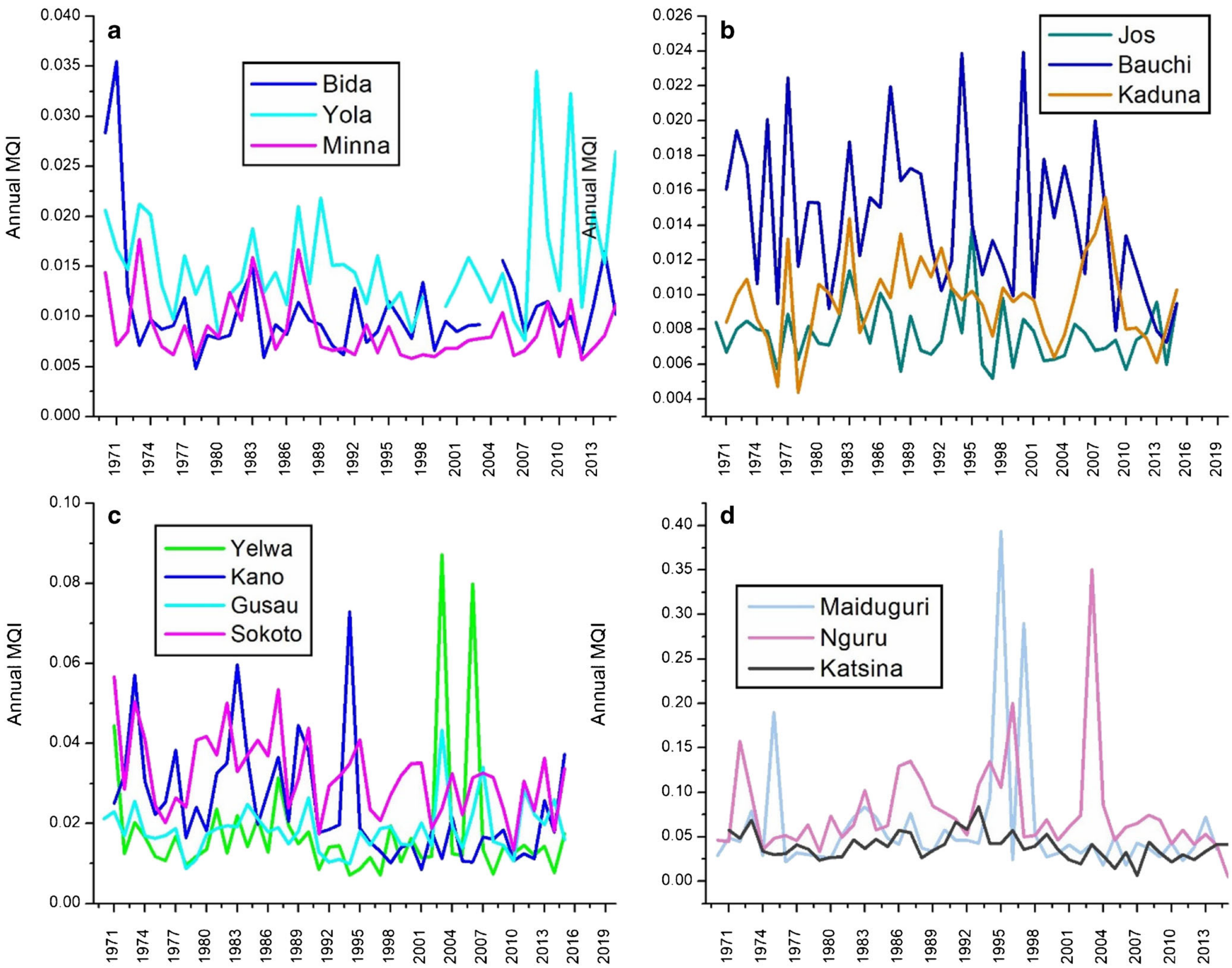

Fig. 5 **a–d** Annual moisture quality index series

rain in the study area is concentrated in the rainy season between May and October. A similar comparative analysis by Li et al. (2019) found that the Penman-Monteith (PM) method performed better than the SPI in the Yangtze River Basin. The transition in the pattern of wet and dry events from the southerly stations (Guinea savanna) to the northern part (Sudano-Sahelian Savanna) is also realistically captured by the MQI. Another clear difference is that SPI requires the use of a climatological mean. Once any two mean periods are different, the SPI values for the same location in the same year would be different. This limiting requirement does not apply to the MQI. The MQI can be computed even with just 1 year of data. Additionally, the SPI is a measure of departure from the long-term mean, while the MQI is a combined measure of the amount and spread of the rains, each year, independent of any other years in the data period (Table 10).

Table 7 Percent (%) of annual MQI classes

Stations	Wet	Fair	Dry
Bida	2.2	60	37.8
Yola	0	13	87
Minna	0	76.1	23.9
Jos	0	91.5	8.5
Yelwa	0	15.6	84.4
Bauchi	0	20	80
Kaduna	4.4	48.9	46.6
Maiduguri	0	0	100
Kano	0	2.2	97.8
Gusau	0	4.3	95.7
Sokoto	0	0	100
Nguru	0	2.2	97.8
Katsina	0	2.2	97.8

A year registered as very wet (by SPI) because it recorded rainfall amount well above normal may not necessarily be good for agriculture if the rainfall received was not adequately spread throughout the season. Another year with less annual total rainfall may be better if the rain received is better spread through the season. In both cases, the MQI moderates the

Table 8 Wet and dry categories of SPI and MQI indices based on the index value

Category	SPI values	Category	MQI
Extreme drought (Ed)	≤−2.00	Extremely poor (Ep)	≥0.02
Severe drought (Sd)	−1.50 to −1.99	Very poor (Vp)	≥0.015 < 0.02
Moderate drought (Md)	−1.00 to −1.49	Poor (P)	≥0.01 < 0.015
Near normal (Nn)	−0.99–0.99	Fair (F)	≥0.005 < 0.01
Moderately wet (Md)	1.00–1.49	Good (G)	≥0.001 < 0.005
Severely wet (Sw)	1.50–1.99	Very good (Vg)	≥0.0005 < 0.001
Extremely wet (Ew)	≥2.00	Extremely good (Eg)	<0.0005

influence of the total rainfall with its intraseasonal spread. It is also noteworthy that the SPI is a direct indicator, whereas the MQI is indirect. In other words, the higher the SPI, the better the rainfall year. For the MQI, the reverse is the case.

In general, and from the foregoing, the MQI is considered better suited to the analysis of seasonal rainfall in aid of agriculture in Nigeria's savanna zones.

Although there is a remarkable advantage of MQI over SPI in seasonal rainfall analysis, Tables 6 and 7 show a potential weakness in MQI's indication of a sharp drop in the quality of rainfall between the southerly latitude (Guinea ecological zone below latitude 11° N) and northerly latitude (Sudano-Sahelian ecological zone, ≥11° N). The drop in rainfall quality suggests that the MQI over-generalised the rainfall events across ecological zones with distinct rainfall regimes. This is important because what is 'poorly distributed' rainfall may not necessarily have the same impacts everywhere. Abdulkadir et al. (2013) indicated that rainfall characteristics in the Sudano-Sahelian ecological zone are more arid (relative permanent low rainfall) than a drought. Consequently, the nature of crops cultivated and their water requirement differ from one ecological zone to another. Amikuzuno and Donkoh (2012) and Defrance et al. (2020) had suggested that sorghum, millet, maize and groundnut are the most grown crops in the Sudano-Sahelian savanna zone of West Africa, while Egbebiyi et al. (2019) and Sultan and Gaetani (2016) have identified yam, cassava and mango as the most important crops grown in the Guinea zone of West Africa. In effect, society is said to adapt to changes as and when it is necessary to survive (Antwi and Sedegah 2018). That people have lived in these areas for years, with agriculture as their preponderant primary economic activity, shows that data treatment may require more fine-tuning.

It is, therefore, fundamental to redefine the MQI along the latitudinal lines. Hänsel et al. (2015) similarly modified rainfall anomaly index (RAI) in Central Eastern Europe to allow comparative analysis with SPI. Table 11 represents the monsoon quality index's modified classes referred to as modified monsoon quality index (mMQI) along latitudinal lines.

mMQI and its frequency of wet and dry periods are presented in Table 12. The table reveals a more balanced distribution of rainfall quality across the different ecological zones, providing a basis as posited by Khan et al. (2018) for choosing an appropriate index for a specific region to identify

Table 9 Seasonal frequency counts and comparison of SPI and modified MQI

Stn	Ed	Sd	Md	Nn	Mw	Sw	Ew	Eg	Vg	G	F	P	Vp	Ep
Bida	3	0	1	40	1	0	0	0	5	37	2	1	0	1
Yola	1	3	3	34	3	2	0	1	0	37	8	0	0	0
Minna	1	3	1	36	2	2	1	2	11	33	0	0	0	0
Jos	1	1	5	32	5	3	0	2	8	37	0	0	0	0
Yelwa	3	0	2	37	1	1	1	0	1	35	5	4	1	2
Bauchi	0	1	6	30	4	2	2	0	1	35	8	1	0	0
Kaduna	2	1	1	37	3	1	0	3	2	40	0	0	0	0
Maid	2	2	3	30	5	3	0	0	0	0	13	19	8	11
Kano	0	2	7	28	4	3	1	0	0	19	16	8	0	3
Gusau	1	1	5	33	3	0	3	0	0	32	13	1	0	1
Sokoto	1	2	5	30	5	0	2	0	0	4	20	18	3	1
Nguru	2	0	0	42	2	0	0	0	0	0	1	7	12	27
Katsina	2	1	2	33	5	1	1	0	0	1	14	19	8	4

Table 10 Annual frequency counts and comparison of SPI and modified MQI

Stn	Ed	Sd	Md	Nn	Mw	Sw	Ew	Eg	Vg	G	F	P	Vp	Ep
Bida	1	1	3	37	2	1	0	0	0	1	27	13	2	2
Yola	2	2	3	33	5	1	0	0	0	0	6	22	9	9
Minna	1	3	3	34	3	1	1	0	0	0	35	8	3	0
Jos	1	1	2	36	4	2	1	0	0	0	43	4	0	0
Yelwa	3	0	2	37	1	2	0	0	0	0	7	23	7	8
Bauchi	0	0	8	29	4	2	2	0	0	0	9	17	14	5
Kaduna	1	3	3	30	6	0	2	0	0	2	23	19	1	0
Maid	1	2	1	37	3	1	0	0	0	0	0	0	2	43
Kano	0	2	7	27	6	2	1	0	0	0	1	10	13	21
Gusau	0	2	3	35	3	1	2	0	0	0	2	12	19	13
Sokoto	0	4	4	30	4	1	2	0	0	0	0	1	3	41
Nguru	2	0	0	42	2	0	0	0	0	1	0	0	0	45
Katsina	2	1	2	35	2	2	1	0	0	0	1	1	1	42

rainfall events' severity. The more balanced rainfall variability patterns depicted by the mMQI relative to the MQI is consistent with Hänsel et al. (2015), which found the modified rainfall anomaly index (mRAI) to provide more sufficient results for evaluating rainfall in Central Eastern Europe, than the RAI.

Trends of wet and dry periods

Table 13 represents the trend analysis of the wet and dry periods for the entire study area. The trend value reveals an insignificant declining trend in the dry seasonal frequency of SPI, while a significant declining trend in the seasonal dry frequency of MQI is shown. SPI's wet seasonal frequency reveals a significant rising trend, while the MQI's reveals an insignificant rising trend. Similarly, SPI's annual dry frequency reveals an insignificant downward trend, while the MQI shows a significant downward trend similar to the finding by Abaje et al. (2012) and Achugbu and Anugwo (2016) of decreasing drought trend over Kano in northern Nigeria's Sudano-Sahelian zone. Previous studies suggest this finding signals the recovery of the rainfall regime from the great Sahelian drought of the 1970s (Ekpoh and Nsa 2011).

SPI's annual wet frequency reveals a significant upward trend, while the MQI's shows an insignificant upward trend. Although there are differences in the wet and dry event patterns by the two indices, their similarity indicates that the frequency of dry periods is on the decline, and that of the wet periods is on the rise. Moghimi and Zarei (2019) found a similar pattern in an evaluation of the performance of seven indices in arid regions.

Table 11 Modified classes of MQI

	<latitude 11° N	≥latitude 11° N
Extremely poor	≥0.02	≥0.025
Very poor	≥0.015 < 0.02	≥0.02 < 0.025
Poor	≥0.01 < 0.015	≥0.015 < 0.02
Fair	≥0.005 < 0.01	≥0.01 < 0.015
Good	≥0.001 < 0.005	≥0.005 < 0.01
Very good	≥0.0005 < 0.001	≥0.001 < 0.005
Extremely good	<0.0005	<0.001

Conclusion

Two drought indices, the SPI and MQI, with the timescales of 6 months (seasonal) and 12 months (annual) have been compared in Nigeria's savanna zones. Both indices have shown quite different and incoherent results through their application to thirteen (13) observation stations distributed across the savanna zones having Guinea and Sudano-Sahelian climates. The results indicated a weak correlation between the frequency of SPI and MQI classes. An analysis of the time series of wet and dry period frequencies, based on the SPI and MQI, showed that MQI results depicted the savanna zones' wet and dry conditions more realistically than the SPI. Though the advantages of the MQI over SPI were manifest, the study detected an over-generalisation of wet and dry events using the MQI. To correct the over-generalisation, the MQI was reclassified to accurately capture the wet and dry conditions across Guinea and Sudano-Sahelian savanna zones. The reclassification gave rise to a modified monsoon quality index (mMQI). A similarity in the behaviour of the indices (SPI and mMQI) is the declining tendency in dry periods and a rising tendency in wet periods at the two-time scales of 6 months and

Table 12 Frequency of mMQI

	Extremely good	Very good	Good	Fair	Poor	Very poor	Extremely poor
Bida	0	5	37	2	1	0	1
Yola	1	0	37	8	0	0	0
Minna	2	11	33	0	0	0	0
Jos	2	8	37	0	0	0	0
Yelwa	0	1	35	5	4	1	2
Bauchi	0	1	35	8	1	0	0
Kaduna	3	2	40	0	0	0	0
Maiduguri	0	0	13	13	8	1	10
Kano	0	18	17	7	0	2	1
Gusau	0	32	13	0	0	1	0
Sokoto	0	3	20	18	3	1	0
Nguru	0	0	1	6	11	8	20
Katsina	0	1	14	18	7	3	2

1 year. The trends confirmed the findings of previous studies such as Ifabiyi and Ojoye (2013), Okonkwo et al. (2015) and Ibrahim et al. (2020) that the study regions have recovered from the great Sahelian droughts of the late 1960s and early 1970s. In conclusion, the Nigeria savanna rainfall is similar to the savanna rainfall of Sub-Saharan African countries. The mMQI as an enhanced rainfall regime analysis tool may therefore aid sustainable rain-fed agriculture and general water resources management in Sub-Saharan Africa's savanna zones where similar variability patterns have been reported and where observation data paucity is a shared challenge. The mMQI is highly recommended as it has the advantage of tracking the wet and dry conditions, even with just 1 year of data, as against the long-term record needed to calculate the SPI. More studies are required to assess the differences and similarities of the SPI and mMQI for other rainfall regimes as a prelude to adopting the latter as the best-fit index for rainfall variability monitoring in arid, semi-arid and sub-humid ecological zones, especially where observed data availability is sparse.

Table 13 Trends of dry and wet episodes in the study areas for SPI and MQI

Time scales	Years		No. of year	Test Z
SPI-6 dry	1970	2015	46	−0.1687
MQI-6 dry	1970	2015	46	−1.96*
SPI-6 wet	1970	2015	46	3.060**
MQI-6 wet	1970	2015	46	1.50
SPI-12 dry	1970	2015	46	−0.969
MQI-12 dry	1970	2015	46	−1.87+
SPI-12 wet	1970	2015	46	2.949**
MQI-12 wet	1970	2015	46	0.2

**Significant trend at $\alpha = 0.01$; *Significant trend at $\alpha = 0.05$, +Significant trend at $\alpha = 0.1$

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Availability of data and material Data for this study is available on request.

Code availability Available on request.

Declarations

Conflict of interest The authors declare no competing interests.

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