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Evaluation of Drought Indices in the Niger Basin, West Africa[1]

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Abstract

The Niger River Basin (NRB) in West Africa is drought-prone. This study evaluates and compares the performance of three drought indices in the Upper Niger subwatershed, two of which drought managers in the region are already used to, the Standardized Rainfall Anomaly Index (SAI) and Bhalme and Mooley Drought Index (BMDI). The third one is the Standardized Precipitation Index (SPI). A time series of the three indices were derived using 52 years growing season monthly station rainfall (April-October), regionalized into areal rainfall. The calculated statistical relationships of the indices provides diagnostics for their performance evaluation based on six decision criteria, whose weightings were determined using pairwise comparison of the Analytic Hierarchy Process (AHP) approach. Two-parameter gamma distribution is the best fit and most suitable for transformation of rainfall distribution in the region. SPI requiring equiprobablity transformation of the data, satisfied the normality assumption, whereas it was violated by others. The three drought indices showed similar temporal trends in all the time scales, with the historical extreme climatic anomalies in the basin well captured. Results further showed that SPI, which is more robust and sensitive to dryness, identified 42 and 17 moderate and extreme drought events respectively, against 35 and 7 captured by the SAI and BMDI that are less robust. In this paper, we find that SPI ranked first among other meteorological drought index in the Niger River basin, having the highest priority weight of 0.6123, with the inconsistency in the pairwise comparison with the tolerable limit (i.e. CR $\leq$ 0.1).

Keywords: Drought indices, evaluation, Analytic-Hierarchy-Process, Rainfall, gamma distribution

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1. Introduction

In 2009 drought experts drawn from 22 countries and organizations such as United States Drought Mitigation Center (NDMC), the World Meteorological Organization (WMO), the United States National Oceanic and Atmospheric Administration (NOAA), and the United Nations Convention to Combat Desertification (UNCCD), among others, met at the University of Nebraska Lincoln to review drought indices in use around the world and to assess their capacity and suitability for a number of applications. At the end of the workshop, the group issued the Lincoln Declaration in which they stated among others that "the National Meteorological and Hydrological Services(NMHSs) around the world are encouraged to use the SPI to characterize meteorological droughts and provide this information on their websites, in addition to the indices currently in use"(WMO, 2009, 2012). This declaration was subsequently endorsed by the 16th World Meteorological Organization Congress in 2011. Given both pedigree and imprimatur, the SPI rapidly emerged as the quasi-official meteorological drought index around the world and numerous authors have espoused its strengths and desirable characteristics (e.g. Edwards and McKee, 1997; Guttman, 1998; Hayes *et al*., 2011; Blain, 2012). Notably, it has the ability to compare drought events in regions with different climates, as well as at different or multiple time scales (Moorhead, et al., 2015). Thus, the SPI has brought standardization to an important area of drought research hitherto characterized by region-specific and often disparate indices, which often lead to confusion about how to properly utilize and interpret them (Quiring, 2009). Furthermore, the index is probability-based, computationally simple and sensitive to dryness (Hayes et al., 2011; Blain, 2012).

However, a number of studies have shown that SPI underestimates the intensity of drought / wetness when the rainfall is very low / very high relative to the actual rainfall and rainfall deviation (Naresh Kumar et al., 2009). By implication, very low (i.e. – 2.0 or less) or very high (i.e. + 2.0 or more) values of SPI do not correspond to very low or very high rainfall. The authors attributed this problem of the underestimation of dryness/wetness to non-normality found between the lower and upper ranges of the SPI. Turkes and Tatli (2009) also noted that the SPI underestimates the probabilities of occurrence of extreme precipitation (both drought and wet conditions) in Turkey when compared to the modified time-varying SPI. In the Modified SPI, the authors estimated the scale parameter by dividing the long-term average by shape parameter. Historically, researchers and drought managers within the drought-prone Niger River Basin, West Africa, have utilized the Standardized Rainfall Anomaly Index (SAI; also called the Lamb Index, (Tarhule and Lamb, 2003; Dai et al., 2004) or the Sahelian Standardized Rainfall Index (Ali and Lebel 2009). Another index also used, albeit less widespread, in the basin is the Bhalme and Mooley Drought Index (BMDI; Oladipo, 1993, 1995; Aremu and Olatunde, 2012; Olatunde, 2013). Each of these indices calculates drought differently.

The WMO call for the adoption of the SPI provides an opportunity to evaluate the relative performance of these three indices at various rainfall time scales in the Niger Basin, West Africa. Such evaluation serves the following purposes: First, to have a better overview of the individual performance relative to other indices of the same category. Second, to ascertain the indices suitability for detecting, monitoring and early warning of the different aspects of drought of concerns, and whether they make sense for the problem in context. Third, to show the ability of the indices to consistently detect spatial and temporal variations during drought events. Fourth, to highlight the level of differences in the severity of identified drought, if any, between non-probability-and probability-based indices that depend on historical rainfall distribution as input for drought characterization. This paper is structured as follows: section two describes the background to the study, which highlights the strengths and weaknesses of the evaluation criteria. In sections three and four, which are the study area, methodology including indices performance evaluation criteria and results and discussion respectively; while the conclusion appears in section five.

2.0 Background to Study

Drought is simultaneously the most damaging of all natural hazards (Pulwarty et al., 2014) and the least understood. A creeping phenomenon, it begins innocuously and becomes noticeable only through its impacts over a region (Wilhite, 2006; ARCS 2007). The end of drought is similarly difficult to predict (Moorhead et al., 2015), and what constitutes drought varies from one region to another (WMO, 2006). By representing drought as a single numeric value, drought indices greatly facilitate analysis and comparison over time and space. Used in combination with an appropriate threshold, all relevant drought characteristics, namely onset, drought magnitude, intensity and cessation, can be derived (Yevjevich, 1967; Dracup et al., 1980; Agnew and Chappell, 2000; Paulo and Pereira, 2006).

Considering that each index calculates drought differently, it is often useful to compare several indices using the same regional data. To do so, Yevjevich et al. (1978) proposed eight quantitative criteria, namely, (i) Characteristics, statistical properties and variability of droughts indices, (ii) Detailed analysis of a major historical drought, (iii) Indices adaptation to the local climate, (iv) Unbounded index values, (v) Spatial invariability, (vi) Flexible time scale, (vii) Data requirements and availability, and (viii) Interpretability. Review of these criteria is available in literature (Ntale and Gan , 2003). In recognition of the desirable properties of an ideal drought index, proposed by Redmond(1991, 2002) (i.e. drought Indices should not be too complex; nor overly simplified; should offer improved information over raw values; its values should be open-ended(because, unprecedented behavior yields unprecedented values); statistical properties and sensitivities thoroughly evaluated before operational usage;

Historical time series of data must be readily available, recent values must be quickly computable and compactible for routine practical usage etc.). Quiring (2009) used six qualitative criteria namely (1) robustness; (2) tractability; (3) scalability; (4) sophistication; (5) transparency; and (6) dimensionality. It was originally proposed by Keyantash and Dracup, (2002). The rationale behind each evaluation criterion is given below.

Robustness: refers to the degree of sensitivity of the indices to any perturbation in the process; as well as the ability of the indices to measure drought over a wide range of climatic conditions (Keyantash and Dracup, 2002). It further refers to the ability of the index to be spatially and temporally comparable (Narasimhan and Srinivasan, 2005), and indices not easily affected by seasonality (e.g. summer and winter values should be comparable anytime). A robust index should also be correlated with and sensitive to drought impacts and discriminate among drought impacts (Quiring, 2009). It is a very important decision criterion for a drought index. Though, a robust index may not be necessarily the most appropriate index to use, especially if it cannot be calculated easily using readily available data. This is a critical limitation of the criteria that needs to be recognized while assigning weight.

Tractability: measures whether the drought index can be practically calculated easily, using readily available data (Keyantash and Dracup, 2002). Hence, it refers to the simplicity of the computational algorithm of the indices. It is extremely important that an ideal drought index should be easy to calculate using readily available data (Quiring, 2009). Therefore, a tractable drought index should provide affirmative answers to such questions as: Is the data requirement of the index easily met? Is the drought index easy to compute? Is the index useful in the context of the drought problem in the concerned or vulnerable area? So this criterion is as important as the robustness.

Transparency: It evaluates the rationale behind the index construction, its clarity and whether the index is understandable to both the scientific community, decision-makers, the affected public and / or user community. For example, a good drought index should be scientifically defensible and useful (Quiring, 2009). It also represents the general utility of the drought index (Keyantash and Dracup, 2002).

Sophistication: It evaluates the indices for scientific merit; especially, it judges whether the indices accurately represent important physical aspects of the drought event. The decision criterion depends on the quality of the available data and fundamental accuracy of the assessment method, including the validity of inherent assumptions in the index. However, the main limitation to sophisticated approach, is that it requires more data, which makes the approach less transparent and tractable (Quiring, 2009).

Hence, for the purpose of operational use, an index that is easy to use and easy to understand will have more credit than a sophisticated index that is difficult to calculate (Quiring, 2009).

Extendability: It measures the degree to which an index can be extended across time. Hence, a good index should be open-ended, and extendable to place current and future drought events into historical context (Quiring, 2009). The approach considers how readily available are the data to capture both past and future are events.

Dimensionality: It refers to the connection of the drought index with the physical world (Keyantash and Dracup et al., 2002). An ideal drought index should have a unit that has physical meaning (i.e. mm of soil water, percent of normal precipitation) rather than strictly dimensionless unit.

The major task in this method is therefore, how to measure each of these evaluation criteria. This is achieved by assigning weight to each of the criteria. Usually, the purpose of assigning weight to parameters affecting drought is to convey the importance of each parameter relative to other parameters (Keyantash and Dracup, 2002; Quiring, 2009). Therefore, we defined weight as a value assigned to an identified evaluation criterion, which indicates its importance relative to other criteria under consideration (Jacek, 1999). The larger the assigned weight, the more important is such criterion in the overall utility of the drought index.

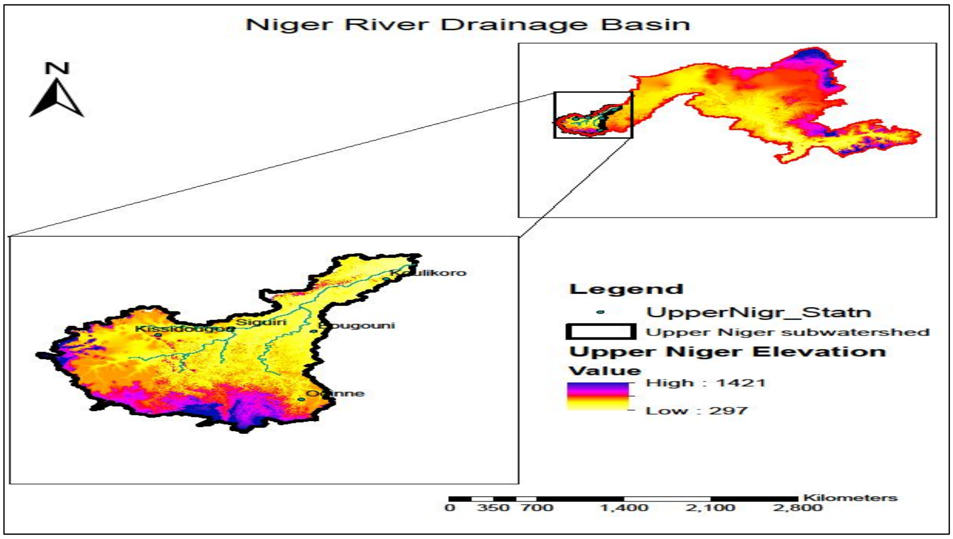
There has been a number of decision criteria weighting procedures proposed in literature, which are often based on experts' judgement, field observations, previous experience and knowledge (Hwang and Yook, 1981; Keeney and Raiffa, 1993; Baker et al., 2002); however, the most popular procedures include pairwise comparison, rating, ranking and trade-off analysis. Others include; average weight method, deviation weight method, optimal weight method, entropy weight method. Often they differ in terms of their degree of easiness to use, accuracy and understanding on the part of the decision-makers. Since weighting of drought parameters by arbitrary means could induce subjectivity and this have to be removed to eliminate biases, there is need for an unbiased procedure. To deal with such uncertainty in the relative importance of weightings, we adopted the use of pairwise comparison approach in this study, in the context of Analytic Hierarchy Process (AHP) proposed by Saaty (1980).

2.1 The Analytic Hierarchy Process (AHP) Method

The AHP is a methodology for structuring, measurement and synthesis, and generally based on the well-defined mathematical structure of consistent matrices and their associated right-eigenvector's ability to generate true or approximate weights (Saaty, 1980, 1994). Basically, the AHP approach structures a complex problem by decomposing the problem into goal (problem definition), decision criteria, and / or alternatives, then compares the criteria, or alternatives with respect to a criterion, in a natural, pairwise mode. To achieve this, the AHP uses a fundamental scale of absolute numbers (1 – 9) that has been proven in practice and validated by physical and decision problem experiments (Forman and Gass,2001).This fundamental scale captures individual preferences with respect to quantitative and qualitative attributes just as well or better than other scales (Saaty, 1980, 1994). The method converts the individual preferences into ratio scale weights, and the resultant weights used to compare and rank the alternatives, thereby assisting the decision-maker in making a choice. The AHP has been applied to a wide range of problem situations such as the allocation of scarce resources, forecasting and selecting among competing alternatives in a multi-objective environment (Forman and Gass, 2001); as well as in drought vulnerability assessment(Babaei et al 2013) and water resources management(Yilmaz and Harmancioglu, 2010). The method has the advantage of considering only two criteria at a time. It is easy to use, precise and with high trustworthiness (Jacek, 1999). Despite its wide applicability, the axiomatic foundation of the AHP carefully delimits the scope of the problem environment (Saaty, 1986).

3.0 Study Area and Methodology

This paper focuses on the Upper Niger subwatershed, also called West Africa's water tower (Fig. 1). The basin area is 120,000 km^2 with a mean elevation of 463m (Vetter et al., 2015). The figure also describes the topography of the Niger basin and the distribution of the rainfall stations. Annual rainfall averages is 1300 mm (1960-2010). The rainfall is highly seasonal, concentrated within the months of April to October. Eighty percent of the rain is received within the months of July, August, and September. The dominant land cove or vegetation are forest, savanna and cropland. Temperature is high all year round 28.6^{o}C (1901 – 2006) (Tarhule et al., 2014).



3.1 Methods

The data analyzed consists of monthly rainfall totals at 6 stations for the period 1950-2001, located within the Upper Niger subwatershed. This period of analysis was selected to put the pre-drought periods (humid), the major droughts of 1970s and 1980s in the basin, and the recovery periods of 1990s into historic context; and test the ability of the indices to represent the variabilities in the time series. The data was obtained from the database of the Global Historical Climatology Networks (GHCN-NOAA). The point station rainfall data were first areally regionalized using the Thiessen Polygon approach in ArcGIS (v10) software to determine the area of influence of each individual station (Kasei et al., 2010). This regionalized rainfall was then accumulated into five different time scales (1, 3, 6, 9 and 12 months) and used to derive a time series of the SAI, SPI and BMDI at various time scales.

The SAI uses the normalization procedure introduced by Kraus (1977). Lamb (1982) showed that the index can be regionalized as follows:

$$x_i = \frac{1}{N}\sum_{i=1}^{Ni}\frac{r_{ik}-\overline{r_i}}{\sigma i} \quad \text{.......... (1)}$$

Where r_{ik} is seasonal total rainfall at station i, $\overline{r_i}$ and σi are respectively mean and standard deviation of the seasonal rainfall. While simple conceptually and analytically, the SAI has been found useful because the standardization process reduces rainfall at stations with different characteristics (amounts, timing, and distributional patterns) and locations to a common unit, making it directly comparable.

The main limitations of the SAI are that the method assumes rainfall data follows a Gaussian distribution; thus, applying the Z-score transforms the distribution to standard normal distribution. This assumption is not always satisfied, especially at time scales of months or finer.

Like the SAI, the Bhalme and Mooley Drought Index (BMDI; Bhalme and Mooley, 1980), uses monthly precipitation as the sole climatological input for assessing drought intensity. It models the percentage departure of monthly precipitation from the long-term averages weighted by the reciprocal of the coefficient of variation (Agwata, 2014). To estimate the BMDI, the monthly statistical properties of the precipitation time series such as mean (μ) and standard deviation (σ) is first computed, and the moisture index (M) is obtained from:

$$M = 100\,\frac{x-\mu}{\sigma} \quad (2)$$

Usually, the anomalies for nonhomogeneous areas or larger areas having different climatic conditions are not comparable. To overcome such problems, the common practice is to normalize the difference (anomalies) using the standard deviation of the precipitation series (Dunkel, 2009) as shown in equation 2. Fig. 2 illustrates the concept of the BMDI procedure. It is based on the idea that the extreme drought condition from the monthly highest accumulated negative M could be given by the least-squares regression equation which describes the relationship between accumulated M and duration, k. Based on such regression analysis, the BMDI duration factor coefficients 0.21 and 132 were calculated for the study area. The duration factor is location specific, and depends on the regression coefficients, the slope and intercept. The general form of the BMDI applied in this study is as expressed below;

$$I_k = 0.2I_{k-1} + M_k/132 \quad (3)$$

where I_k and I_(k-1) are drought intensities for the kth and (k-1)th months respectively, M_k is the moisture index for kth month. Conceptually, BMDI is a simplified version of the well-known and widely used Palmer Drought Severity Index (PDSI) (Alley, 1984; Ntale and Gan, 2003). While the BMDI provides satisfactory measures of the current condition of agricultural drought (Bhalme and Mooley, 1980; Oladipo, 1985; Ntale and Gan, 2003), it has sensitivity to, and therefore frequently overestimates, wet conditions.

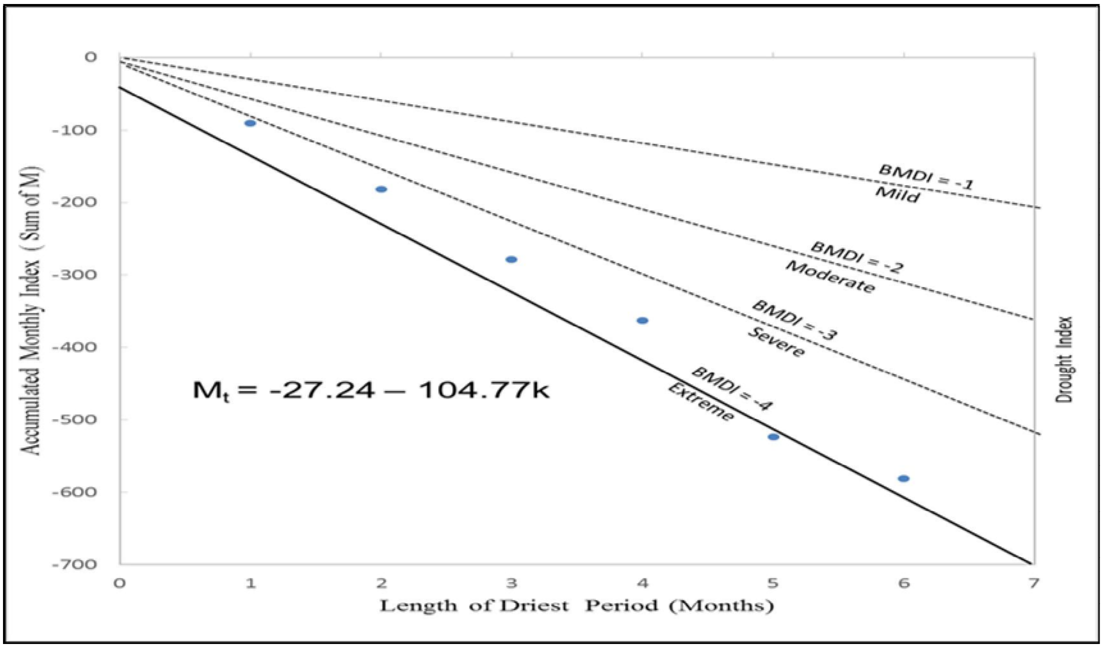


Fig. 2: Plot of cumulative moisture index M versus period k (months) for four levels of drought episodes

The Standardized Precipitation Index (SPI) is a probability-based drought index developed by McKee et al. (1993). Similar to the SAI, the SPI calculates the number of standard deviations at which the observed cumulative rainfall at a given time scale deviates from the long-term mean. Yet, unlike the SAI, the SPI does not assume normality, providing instead an opportunity for researchers to base the standardization procedure on the most appropriate statistical probability distribution underlying the data series. With the SPI method, values at different locations and climes can be computed at a different time scale; such as 1, 3, 6, 12, 24 and 48 months, which separates the different types of drought (McKee et al., 1993) i.e. meteorological, agricultural and hydrological droughts.

Three general steps involved in the computation of SPI are as follows: (i) selection of monthly long-term precipitation record (30 years or more), and accumulate the time series to desired time scales, (ii) determining the probability distribution that best describes the data and compute the probability density function (PDF) (iii) transforming the CDF of the selected distribution into a standard normal distribution, which is achieved through inverse normal distribution(Turkes and Tatli, 2009).

The precipitation time series in the study area exhibit strong non-stationarity (Tarhule et al, 2013). Therefore to calculate the SPI, it is necessary to transform the time series first so that its distribution is nearly normal (WMO, 2000). Guided by previous studies (Guttman 1998, 1999; Guenang and Kamga, 2014), we fitted five different distribution functions (i.e. Lognormal, Exponential, Log-logistic, Weibull and Gamma) to the monthly rainfall series using Mathwave and evaluated the goodness of fit using Chi-square. The results (Appendix 1) showed that the best fitting distribution is the gamma type two distribution.The probability density function (pdf) of the gamma distribution is (McKee et al. 1993):

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \text{ for } x>0 \qquad (4)$$

where: $\alpha > 0$, $\beta > 0$, $x > 0$

The cumulative distribution function (CDF or (G(x)) is expressed as;

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}^{\hat{\alpha}}\Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}} e^{-x}/\hat{\beta} \qquad (5)$$

$$G(x) = \frac{1}{\Gamma(\hat{\alpha})} \int_0^x \frac{x^{\hat{\alpha}}}{\beta^{\hat{\alpha}}} e^{-x/\hat{\beta}} dx \qquad (6)$$

By substituting $t = \frac{x}{\beta}$, equation 3 yields the incomplete gamma function, expressed as below:

$$G(x) = \frac{1}{\Gamma(\alpha)} \int_0^x t^{\hat{\alpha}-1} e^{-t} dt \qquad (7)$$

where

α, β, x is the shape parameter, scale parameter and precipitation amount respectively.

For $\alpha > 0$, the gamma function $\Gamma(\alpha)$ is a quantity defined by eqn. 5

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} e^{-x} dx \qquad (8)$$

where,

$\Gamma(\alpha)$ is the gamma function, x is precipitation amount.

Fitting the gamma distribution to the rainfall data requires estimating α and β. These parameters were estimated using Maximum Likelihoods (Thom (1958) :

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \qquad (9)$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{\alpha}} \qquad (10)$$

Where

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \quad \text{...(11)}$$

where α and β are the parameters of the distribution, A is the difference between the logs of arithmetic and geometric means, $\bar{x}$ is the mean of the cumulative precipitation, n is number of precipitation observations. The SPI is computed using the program code developed by U.S. National Drought Mitigation center (US-NDMC).The program code is freely available at http://drought.unl.edu/Monitoring Tools / DownloadableSPIProgram.aspx.

It would be a relatively straightforward matter to compare the three drought indices if the theoretical range of index values were the same- that is, if it could be assumed that a -1 on the SPI scale is directly comparable to -1 on the BMDI scale. Because this is not the case, we opted instead to specify a threshold rainfall deficit on the raw data and then estimated the index value corresponding to that deficit. The specified thresholds are as shown in Table 1. These thresholds were obtained using percentile ranking approach as applicable in the U.S. Drought Monitor (Svoboda et al 2002). We define drought of moderate or worst intensities with 20th percentile or less. The 20th percentile threshold defines a non-exceedance probability of drought that occurs once in 5 years. This threshold represents rainfall deficit of 63%, 38% 23%, 22%, 29%, 21% and 40% for the months of April, May, June, July, August, September, and October respectively, from the long-term average(1950-2001), which is in agreement with the findings of Downing et al (1987). Report on the assessment of 1980s drought prepared for the U.S. Agency for International Development (USAID) to aid decision on humanitarian intervention by the U.S. Government, documented that 20% to 40 % deficits of rainfall below the long-term average in West Africa as well as other parts of the continent leads to drought of moderate intensity, while deficits over 40% below the average results in severe drought (Downing et al., 1987). In this region also, monthly rainfall frequently less than 25% of the long-term average (i.e. more than 75% below the average) has been found to cause significant livestock deaths, especially over Senegal, Mauritanian and Gambia. Arguably, this livestock died as a result of dearth of forage and water due prevailing drought then.

Table 1 Monthly Drought severity classification based on non-exceedance probability

Month	Category	Threshold Values SPI	SAI	BMDI	Corresponding Rainfall values (mm)	Frequency	Percentile Trigger
	Mild (D0)	>= -0.61	>= -0.56	>= -0.43	3.55	Once in 3 yr	21-30%
	Moderate(D1)	-0.62 to -0.70	-0.57 to -0.73	-0.44 to -0.55	2.55	Once in 5 yr	11-20%
April	Severity(D2)	-0.71 to -1.07	-0.74 to -0.90	-0.56 to -0.68	1.56	Once in 10 yr	6-10%
	Extreme (D3)	-1.08 to -1.56	-0.92 to -0.94	-069 to -0.71	1.30	Once in 20 yr	3-5%
	Exceptional(D4)	< -1.56	-0.95 to -1.02	-0.72 to -0.77	0.82	Once in 50 yr	0-2%
	Mild (D0)	>= -0.54	>= -0.61	>= -0.54	15.15	Once in 3 yr	21-30%
	Moderate(D1)	-0.55 to -1.00	-0.62 to -0.96	-0.55 to -0.70	12.40	Once in 5 yr	11-20%
May	Severity(D2)	-1.01 to -1.38	-0.97 to -1.19	-0.71 to -1.01	10.53	Once in 10 yr	6-10%
	Extreme (D3)	-1.39 to -1.83	-1.20 to -1.46	-1.02 to -1.14	8.41	Once in 20 yr	3-5%
	Exceptional(D4)	< -1.83	-1.47 to -1.56	-1.15 to -1.26	7.59	Once in 50 yr	0-2%
	Mild (D0)	>= -0.72	>= -0.70	>= -0.62	32.81	Once in 3 yr	21-30%
	Moderate(D1)	-0.73 to -0.90	-0.71 to -0.85	-0.63 to -0.74	31.16	Once in 5 yr	11-20%
June	Severity(D2)	-0.91 to -1.02	-0.86 to -0.97	-0.75 to -0.82	29.88	Once in 10 yr	6-10%
	Extreme (D3)	-1.03 to -1.07	-0.98 to -1.01	-0.83 to -0.85	29.48	Once in 20 yr	3-5%
	Exceptional(D4)	-1.08 to -1.50	-1.02 to -1.31	-0.86 to -1.08	26.16	Once in 50 yr	0-2%
	Mild (D0)	>= -0.58	>= -0.62	>= -0.49	77.75	Once in 3 yr	21-30%
	Moderate(D1)	-0.59 to -0.96	-0.63 to -0.95	-0.50 to -0.75	70.88	Once in 5 yr	11-20%
July	Severity(D2)	-0.97 to -1.24	-0.96 to -1.18	-0.75 to -0.97	65.93	Once in 10 yr	6-10%
	Extreme (D3)	-1.25 to -1.55	-1.19 to -1.42	-0.98 to -1.03	60.90	Once in 20 yr	3-5%
	Exceptional(D4)	-1.56 to -1.75	-1.43 to -1.53	-1.04 to -1.26	58.52	Once in 50 yr	0-2%
	Mild (D0)	>= -0.64	>= -0.67	>= -0.79	97.00	Once in 3 yr	21-30%
	Moderate(D1)	-0.65 to -0.95	-0.68 to -0.93	-0.80 to -1.38	86.94	Once in 5 yr	11-20%
August	Severity(D2)	-0.96 to -1.30	-0.94 to -1.18	-1.39 to -1.86	77.59	Once in 10 yr	6-10%
	Extreme (D3)	-1.31 to -1.48	-1.19 to -1.32	-1.87 to -2.07	72.34	Once in 20 yr	3-5%
	Exceptional(D4)	-1.49 to -1.58	-1.33 to -1.38	-2.08 to -2.20	70.13	Once in 50 yr	0-2%
	Mild (D0)	>= -0.51	>= -0.53	>= -0.51	58.21	Once in 3 yr	21-30%
	Moderate(D1)	-0.52 to -0.76	-0.54 to -0.76	-0.52 to -0.78	53.84	Once in 5 yr	11-20%
September	Severity(D2)	-0.77 to -1.30	-0.77 to -1.19	-0.79 to -1.00	45.77	Once in 10 yr	6-10%
	Extreme (D3)	-1.31 to -1.49	-1.20 to -1.31	-1.01 to -1.33	43.42	Once in 20 yr	3-5%
	Exceptional(D4)	-1.50 to -1.68	-1.32 to -1.44	-1.34 to -1.39	41.03	Once in 50 yr	0-2%
	Mild (D0)	>= -0.59	>= -0.60	>= -0.51	13.00	Once in 3 yr	21-30%
	Moderate(D1)	-0.60 to -0.73	-0.61 to -0.71	-0.52 to -0.71	11.77	Once in 5 yr	11-20%
October	Severity(D2)	-0.74 to -1.18	-0.72 to -0.92	-0.72 to -0.81	9.49	Once in 10 yr	6-10%
	Extreme (D3)	-1.19 to -1.20	-0.93 to -0.99	-0.82 to -0.93	8.78	Once in 20 yr	3-5%
	Exceptional(D4)	-1.21 to -1.58	-1.0 to -1.16	-0.94 to -0.99	6.99	Once in 50 yr	0-2%

3.2 Drought Indices Performance Evaluation Criteria

To evaluate the performance of the three indices, the statistical relationships of the drought indices were first calculated to provide diagnostics for their performance evaluation. As a result, the following analyses were carried out: (i) time series analysis to explore the effect of the different time scales on the frequency, duration and severity of drought; (ii) Pearson correlation analysis between SPI and SAI, SPI and BMDI, and SAI and BMDI; (iii) linear regressions between SPI and SAI, SPI and BMDI, and SAI and BMDI; (iv) comparison of identified drought characteristics; and (iv) Comparison of drought indices during major historical drought events of 1970s and 1980s.

The next step in determining which drought indices is the most appropriate for monitoring drought conditions in the Niger River basin is to evaluate all the three candidate drought indices using modified version of the evaluation criteria proposed by Quiring (2009).

The approach was originally developed by Keyantash and Dracup (2002) to select the most appropriate agricultural, meteorological, and hydrological drought indices for monitoring drought in Oregon. The revised version of their approach is adopted in this study to select the most appropriate meteorological index for monitoring drought at the basin. We judge the overall utility of each of the candidate drought indices using six evaluation criteria identified based on the ideal characteristics of drought index (Redmond, 1991; Keyantash and Dracup, 2002; Narasimhan and Srinivasan, 2005).

These six qualitative criteria are robustness, tractability, scalability, sophistication, transparency, and dimensionality. Following the identification of the evaluation criteria, the next challenge is how to determine their weights, and the weights of the candidate indices based on these criteria. Usually, weights are assigned to the evaluation criteria by the researchers or decision-makers based on their knowledge, experience and perception of the problem (Yilmaz and Hamrmancioglu, 2010). In this study, the Saaty's pairwise comparison method of the Analytic Hierarchy Process (AHP) (Saaty, 1980) approach is used in the weightings of the criteria and the each of the candidate drought indices. The AHP is a method of converting subjective judgements of the researcher to a set of weights by pairwise comparisons between all criteria. Fig. 3 is a conceptual diagram of how Saaty's method has been applied in structuring the problem of evaluating the three drought indices, the SAI, BMDI and SPI. As evidenced from the conceptual framework, the six evaluation criteria have to be weighted first, to establish their relative importance. Then, using the candidate indices weightings corresponding to each of the evaluation criteria and the relative importance of the criteria, the candidate indices are ranked and evaluated accordingly. The Saaty's method consists of three major steps, namely; (i) the generation of pairwise comparison matrix, (ii) the criterion weight computation, and (iii) the consistency ratio estimation.

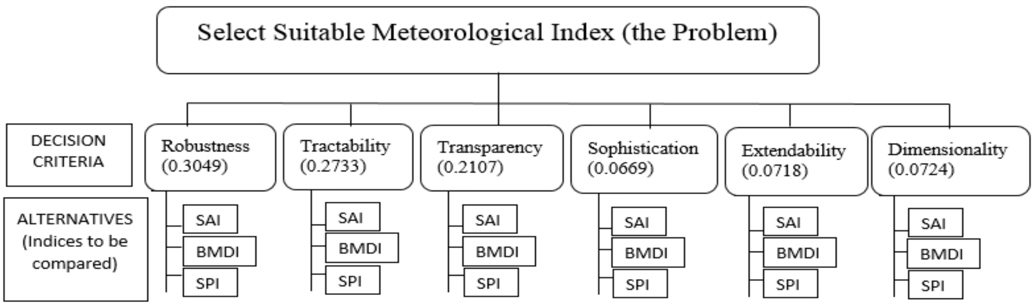


Fig. 3 Framework for the Saaty's Pairwise comparison of AHP approach of Criteria Evaluation

3.2.1 The Development of Pairwise Comparison Matrix

The major problem with pairwise comparison method is how to quantify a choice that is subjectively made by the researcher or decision-maker in numerical terms during their evaluation. Usually, this comparisons are quantified using a standard scale proposed by Saaty (1980), which has values ranging from 1 to 9 (Table 2) to rank the researcher's choice. According to Saaty's scale, the values of the pairwise comparisons are members of the set: {9, 8, 7, 6, 5, 4, 3, 2, 1, 1/2, 1/3, 1/4, 1/5, 1/6, 1/7, 1/ 8, 1/9}. This scale numbers indicate how many times more important or dominant one element is over another element with respect to the defined criterion or property with respect to which they are being compared (Saaty, 2008). To generate the pairwise comparison matrix, the elements of the matrix are randomly determined according to the scale proposed by Saaty (1980). Since the entries into the matrix are randomly selected, this implies that each of the two elements being compared have equal chance (probability) of being ranked better than the other. These elements consist of ranks (1 – 9) assigned to the preferred choice out of the two elements being compared using the Saaty's Scale numbers (Xu et al 2008; Dijkstra, 2010).

In real life decision-making process, the problem of choice is always extremely difficulty, because of conflicting objectives (Pazek and Rozman, 2000); even when numbers are obtained from a standard scale (Saaty, 2008). There is still a problem of linking the difference between the two elements being compared to the Saaty's scale of ranking or scoring decisions. For example, how to measure the differences to ascertain that one element is moderately, strongly or very strongly more important than the other is still a challenge. To overcome this problem, in this study, we prepared a summary table of collection of information, comprising the ideal drought index desirable properties, statistical relationships of the indices and questionnaires connected to each evaluation criteria, to offer explanation to the decisions leading to the pairwise comparison ranking and weighting assignments (Table 3).

The answers to the questionnaires informed by the combination of the information in the table provided the diagnostics for the random selection of the pairwise comparison ranks quantifying the researcher's judgement. As an illustrative example, suppose index A in the Table 3 is strongly better or highly ranked than index B, and index C is the least desired one as far as robustness criteria is concerned. By implications, when index A is compared to index B, the researcher has determined that index A is to be classified between "moderately to strongly important" and very strongly to very important than index B. Thus, the corresponding comparison assumes the value of 5. A similar interpretation is given for the rest of the entries in the matrix. According to Saaty (1986), this matrix must have the following three properties:

Reciprocity: It states that if $a_{jk} = x$, then $a_{kj} = 1/x$, with $1/9 \leq x \leq 9$. Where a_{jk} represents the comparison between element j and element k. By implications, once the upper triangular matrix is determined during the comparison process, the lower triangular matrix can be defined by $a_{kj} = 1/x$.

i. Homogeneity: It states that if the elements j and k are considered to be equally important then,

$$a_{jk} = a_{kj} = 1 \text{ and } a_{jj} = 1 \text{ for all } j$$

ii. Consistency: $a_{jl} * a_{lk} = a_{jk}$ is satisfied for all $1 \leq j, k, l \leq n$

With regard to the reciprocity property, only n (n-1) / 2 comparison are needed to build a matrix with a dimension of n x n, for a property to reciprocate. For example, the comparison matrix is said to be reciprocal, if the criterion A is twice as preferred to criterion B, then it can be concluded that B is preferred only one-half as much as criterion A. As a result, if criterion A is given a score of 2, relative to criterion B, then criterion B should receive a score of 1/ 2 when compared to criterion A. By applying this logic, the upper right and lower left side of the pairwise comparisons matrix are derived in this study. With regards to homogeneity property, the diagonal element of the matrix is assigned the score of 1, which represents equally preferred criteria when comparing anything to itself. A times, consistency infrequently occurs due to innate subjectivity of the decision-maker, which significantly affects the pairwise comparison. This property is meant to show an existing inconsistencies in the comparisons. According to Saaty (1986), the degree of inconsistency is measured by calculating the Consistency Ratio (CR) of the matrix.

Table 2 Fundamental Saaty's Scale for Pairwise Comparison

Intensity of Importance	Definition / Interpretation	Explanantion
1	j and k are Equally Important	Two activities contribute equally to the objective
2	j is slightly to moderately important than k	
3	j is moderately more important than k	Experience and judgement slightly favor one activity over another
4	j is moderately to strongly more important than k	
5	j is stronglyl more important than k	Experience and judgement strongly favor one activity over another
6	j is strongly to very strongly more important than k	
7	j is very strongly more important than k	An activity is favored very strongly over another; its dominance is proved in practice
8	j is very strongly to extremely more important than k	
9	j is extremely or absolutely more important than k	The evidence favoring one activitiy over another is of the highest possible order of affirmation

Table 3: presentation of information to aid decision on weight assignment (Note: Y = Yes, N =No)

Index Desirable properties	Statistical Relationship	Evaluation Criteria	SAI Y/N	BMDI Y/N	SPI Y/N	Remarks
1. Not too complex; 2. Not overly Simplified; 3. Offers improved information over raw values; 4. Historical data readily available;	1. Most of the time, negative anomalies of ≤ -2 were captured by SPI ; while positive anomalies of ≥ 2 were captured by SAI and BMDI (boxplot analysis);	Robustness: Answers questions such as; 1. Index Sensitivity (Less sensitive or highly sensitive)? 2. Index has the ability to measure drought over different climatic conditions? 3. Index spatially and temporally comparable? 4. Index not affected by seasonality? 5. Index data input readily available?	N Y Y Y N	N Y Y Y N	Y Y Y Y Y	BMDI is most sensitive, while SPI is least sensitive; SPI ranked much better than SAI, and BMDI least desired
5. Both social and economic impacts are proportional to the values of the index; 6. Index value open-ended;	2. Sensitivity: % of changed values of index, SPI (12%), SAI (29%), BMDI (43%)	Tractability: Answers questions such as; 1. Index easy to calculate using readily available data? 2. Index overly simplified? 3. Index highly skillful in detecting drought severity of the area? 4. Index satisfies normality assumptions?	Y Y N N	Y N N N	Y N Y Y	SAI is overly simplified, with normality assumption violated(and less useful); SPI ranked highest
7. Normalized to background climate; 8. Non-dimensional unit;	3. W-Shapiro-Wilk normality test: SPI satisfies assumption, SAI and BMDI violates it.	Transparency: Answers questions such as; 1. Index is understandable to both scientific community, and the public? 2. Index is scientifically defensible and generally useful?	N N	N N	Y Y	SAI and BMDI are difficult to perceive, and explain to the public,& ranked behind SPI
9. Facilitates spatial comparison across very different settings; 10. Statistical properties thoroughly evaluated before operational usage;	4. Time series: Indices identified similar temporal trends and major droughts events;	Sophistication: Answers questions such as; 1. Index has conceptual or scientific merit? 2. Index accurately represents drought? 3. Fundamental accuracy of assessment method widely acceptable? 4. Index satisfies inherent normality assumption?	N N N N	N N Y N	Y Y Y Y	SPI has most scientific merit, satisfies fundamental laws and has high utility. BMI better than SAI
11. Sensitivities thoroughly evaluated before operational usage;		Extendability: Answers questions such as; 1. Index is open-ended? 2. Index has ability to detect past, current and future drought events?	Y Y	Y Y	Y Y	All indices are extendable and can adjust to unprecedented future values; & ranked equally
12. Measures of placement within the historical context are invaluable and frequently requested, typically as percentile	5. B/w 1950 - 2001,Extreme drought identified: 7 (SAI and BMDI) ,17 (SPI), Equal severe drought detected	Dimensionality: Answers questions such as; 1. Index is computed from variable with Physical fundamental units (e.g. rainfall)? 2. Index is dimensionless, normalized, and / or probabilistic renditions? 3. Impacts of drought proportional to the values of indices?	Y Y N	Y Y N	Y Y Y	All indices are derived from a variable with physical unit; but magnitude of drought is higher in SPI, so impacts will be more. SPI slightly ranked higher than SAI and BMDI

3.2.2 The Computation of the Criterion Weighting

To compute the criteria weightings, the following mathematical operations are involved.

i. The summation of the values in each column of the pairwise comparison matrix
ii. Dividing each element in the matrix by its column sum total, which results in the normalization of the pairwise comparison matrix.
iii. Then, the average of the elements in each row of the normalized matrix is calculated. These averages provide an estimate of the relative weightings of the criteria being compared. These averages are also referred to as eigenvectors.

3.2.3 The Estimation of the Consistency Ratio (CR)

The Consistency Ratio (CR) is defined as the ratio of Consistency Index (CI) to random Index (RI) (Saaty, 1986). The purpose of the consistency test, is to test the null hypothesis (H_0) that the relative importance ratios in the pairwise comparison are randomly selected from the Saaty's 17 value scale {9, 8, 7, 6, 5, 4, 3, 2, 1, 1/2, 1/3, 1/4, 1/5, 1/6, 1/7, 1/ 8, 1/9} (by implications $H_0 < 0.1$ and $H_1 > 0.1$; where H_1 id alternative hypothesis). Considering the that pairwise comparison matrices were generated without any concern for consistency, Saaty (2005) suggested as a rule of thumb to accept the inconsistency when CR < 0.10, indicating that the pairwise comparison matrix is of reasonable level of consistency; whereas CR > 0.10, indicates inconsistent judgements. In such cases, the revision of the original values in the pairwise comparison matrix is advised (Saaty. 1986). The CI is known to provide a measure of departure from consistency, that is, the difference between the maximum eigenvalue (λmax) of the pairwise comparison matrix and the eigenvalue (n) of perfectly consistent matrix. This is expressed as below.

$$CI = (\lambda max - n) / (n - 1) \quad (12)$$

Where λmax is the maximum of the eigenvalues (i.e. the average value of the consistency vector), and n is the number of evaluation criteria parameters. The RI value is read from a statistical table that is proposed by Saaty (1980). This is presented in Table 4.

Table 4 Random Inconsistency Indices (RI) for n = 1,2 …..15 proposed by Saaty(1980)

No. of criteria(n)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Random index(RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.6

The following mathematical operations are involved in the determination of CR:

i. The sum of the weighted vector is determined by multiplying the obtained weight of the first criterion by the first column of the original pairwise comparison matrix, followed by the multiplication of the second weight criterion with the second column. The process is continued for n criterion and finally, summed up for each row.

ii. Then, the consistency vector is determined by dividing the weighted sum vector by the criterion weights earlier calculated.

Following this procedure, weights were assigned to the six evaluation criteria in this study as shown in Table 5. Subsequently, by repeating the process, the three indices (SAI, BMDI and SPI) were evaluated against each of these criteria.

Table 5 Drought Index Evaluation Criteria and their Relative Importance

Criterion	Relative Importance (%)
Robustness	30
Tractability	27
Transparency	21
Sophistication	7
Extendability	7
Dimensionality	7

4.0 Results and Discussion

As seen in the boxplot of Fig. 4 various statistical properties of SPI, SAI and BMDI have been highlighted for different time scales. The critical examination of the indices' behavior on the individual months (April- October), revealed few differences in their means and variances. These differences were further subjected to significance test, using t-test and F-test distributions respectively. Results showed that the observed differences in the means and variances of the time series of the indices are in general not statistically significant at 95% confidence interval. The distribution of each index time series presented in Fig. 5 show that SPI, which required equi-probabilty transformation, identified anomalies that describe a near normal distribution, while SAI and BMDI anomalies describe a skewed distribution. This result prompted the need for testing the normality of the indices' time series, using the Shapiro-Wilk normality test in SPSS statistical software, with the null hypothesis that the data (time series) are Gaussian. As evidenced from the results, SPI had highest test (W)-statistics values > 0.959 (Table 6), signifying that time series significantly followed Gaussian distribution at 95% confidence interval, whereas the SAI and BMDI showed significant departure from normality due to either skewness or kurtosis or both.

The temporal behavior of the SAI, BMDI and SPI values is presented in Figs. 6 and 7, the negative values in these standardized anomalies indicate drier than long-tern average periods and positive values indicate wetter periods. Generally, the figure shows similar temporal trends by the three drought indices in all the time scales, with 1, 3, 6, and 12 months' time scales displayed in the figure.

The pre-drought humid periods of 1950s, the major drought periods of 1970s and 1980s and the recovery periods of 1990s in the Niger basin were well identified. Also, on short-term scales such as 3-months SAI, BMDI and SPI series, the drought severities were highly variable, and on several occasions becoming less than -1 and greater than 1, corresponding to the 20th percentile threshold depending on the month. Arguably, these observed variations are due to a seasonal component always present in the rainfall data. Furthermore, there is no recognizable long-term trend component.

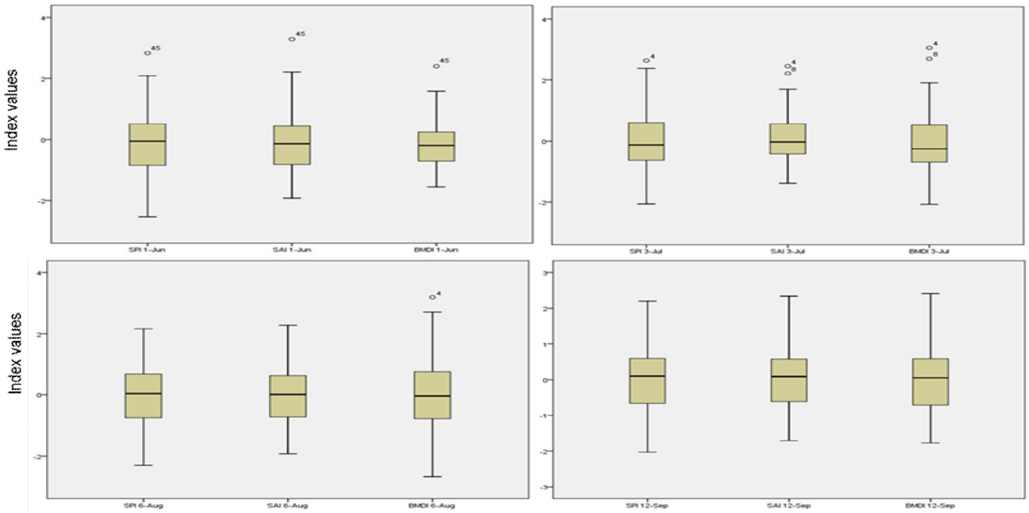


Fig. 4 Boxplot showing the statistical properties of the three indices at different time scales and months

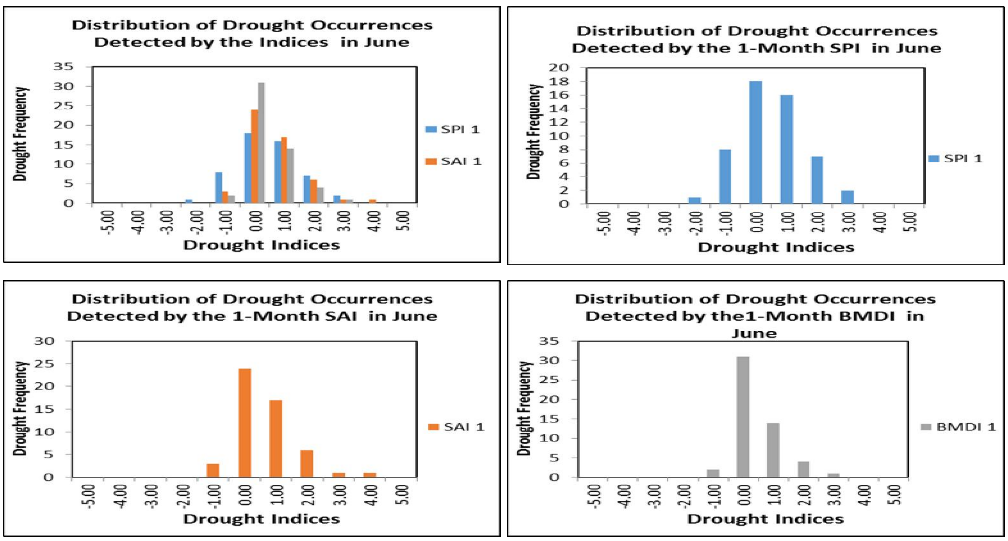
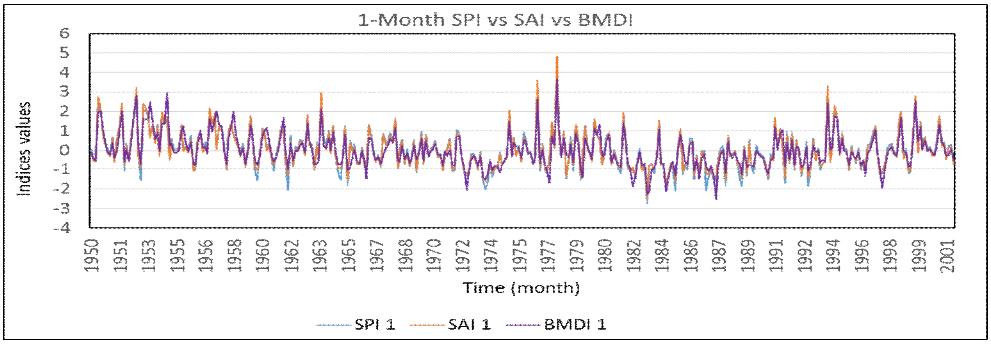


Fig. 5 Typical distributions of the drought event identified by the indices during the month of June



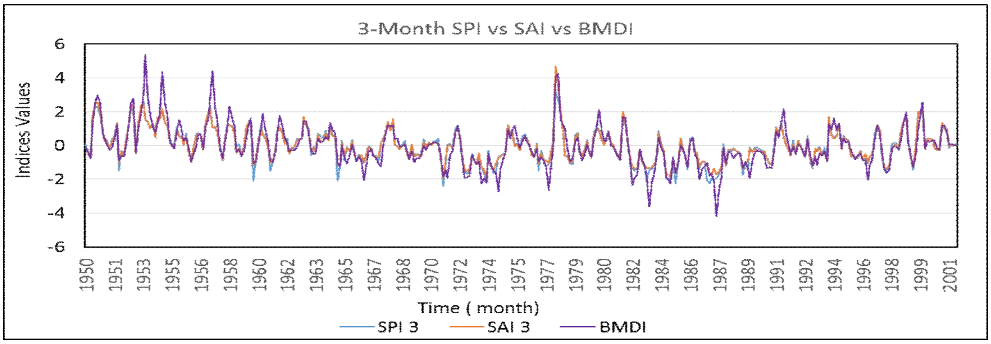
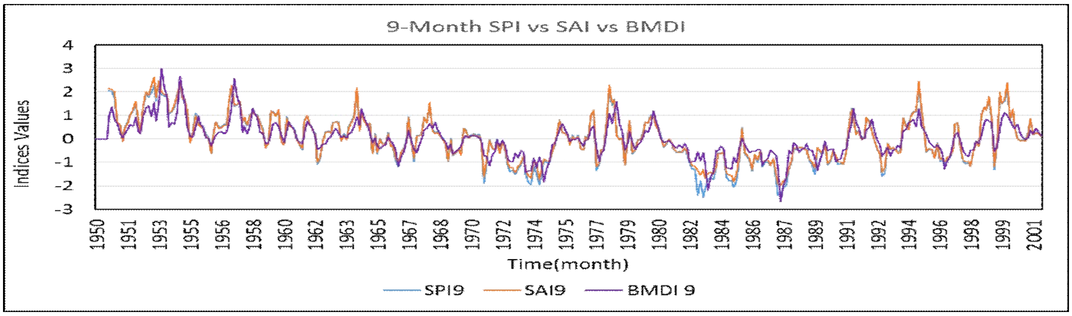


Fig. 6 Time series of 1, and 3- Months SAI, BMDI and SPI over the upper Niger basin



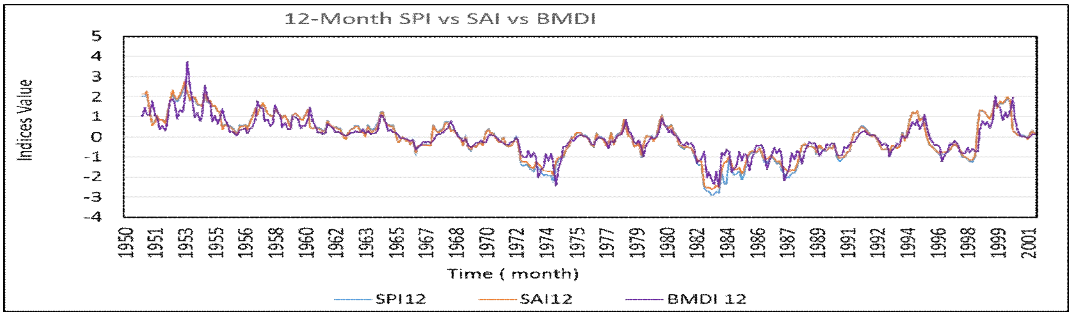


Fig. 7:Time series of 9, and 12 - Months SAI, BMDI and SPI over the upper Niger basin

Table 6 Comparison of the Normality test Results between SPI SAI and BMDI

	SPI		SAI		BMDI	
Month	W-statistics	Significance	W-statistics	Significance	W-statistics	Significance
Apri	0.959	0.198	0.78	0	0.78	0
May	0.982	0.604	0.968	0.169	0.968	0.177
June	0.967	0.163	0.932	0.005	0.932	0.005
July	0.981	0.555	0.968	0.18	0.963	0.101
Aug	0.985	0.76	0.962	0.097	0.972	0.262
Sep	0.982	0.634	0.947	0.022	0.966	0.149
Oct	0.96	0.078	0.846	0	0.893	0

Table 7 Pearson correlation coefficients (r) of the SPI vs SAI, SPI vs BMDI and SAI and BMDI

Events	Cases	1-Month	3-Month	6-Month	9-Month	12-Month
	SPI vs SAI	0.982	0.981	0.987	0.996	0.997
All	SPI vs BMDI	0.901	0.895	0.88	0.893	0.907
	SAI vs BMDI	0.913	0.905	0.887	0.888	0.904
	SPI vs SAI	0.970	0.996	0.992	0.998	0.999
Dry	SPI vs BMDI	0.979	0.974	0.984	0.976	0.969
	SAI vs BMDI	0.942	0.973	0.967	0.968	0.965
	SPI vs SAI	0.95	0.953	0.973	0.997	0.996
Wet	SPI vs BMDI	0.97	0.934	0.944	0.949	0.959
	SAI vs BMDI	0.99	0.97	0.951	0.973	0.965

The indices statistical relationships tested by fitting a linear regression trend to their time series, showed a slope nearly equal to zero, signifying the absence of a significant trend. A drought event begins when the indices' values become continuously negative below an established threshold and ends when the indices' values become continuously positive above the threshold. The drought severity becomes the cumulative of the indices' values within the drought duration. In this way Figs. 6 and 7 can be used to estimate the drought severity or magnitude and the duration. Further results show that the three indices were significantly correlated (see the Pearson correlation coefficient in Table 7). The correlation between SPI and SAI increases as the time scales increases.

However, the correlation between SPI and BMDI, and between SAI and BMDI slightly decreases as the time scale increases, except for the 12-month time scale as evidenced in the three event categories considered in table 6 (i.e. All, dry and wet event). In the event column of Table 7 'All' indicates normal, dry and wet conditions included in the time series; 'Dry' indicates events whose SPI values are negative; 'Wet' indicates events whose SPI values are positive. In addition, during dry events the indices show higher correlation than during the wet events. These notable patterns are supported by several previous studies (Wu et al., 2001; Choi et al., 2013).

The regression analysis shows a monotonic increasing relationship among all of the various indices (Fig. 8). In comparison with SAI, the SPI has a higher slope of 0.9619 and 0.9203 and R^2 (coefficients determinant) of 0.9436 and 0.957 for the shorter time scale 3 and 6 months; unlike the decreased slope of 0.8803 and 0.8585 and R^2 of 0.96 and 0.9609 for longer time scales of 9 and 12 months. Hence, as the slope decreases, the R^2 increases. Also, the scatter diagrams of SPI versus the SAI in Fig. 8 show that the SAI generally appears more positive or wetter than the SPI in both time scales. For example, when the SPI is -2.35, the corresponding SAI is -1.93, and when SPI is + 3.14, the corresponding SAI is + 4.84. Such relationship was not found in the case of scatter diagram of SAI and BMDI 9, graph not displayed. The 1-month time scale was not considered in this comparison because the occurrence of monthly rainfall deficiency is a common feature of climate; as a result the 1-month time step may not describe the drought situation very well.

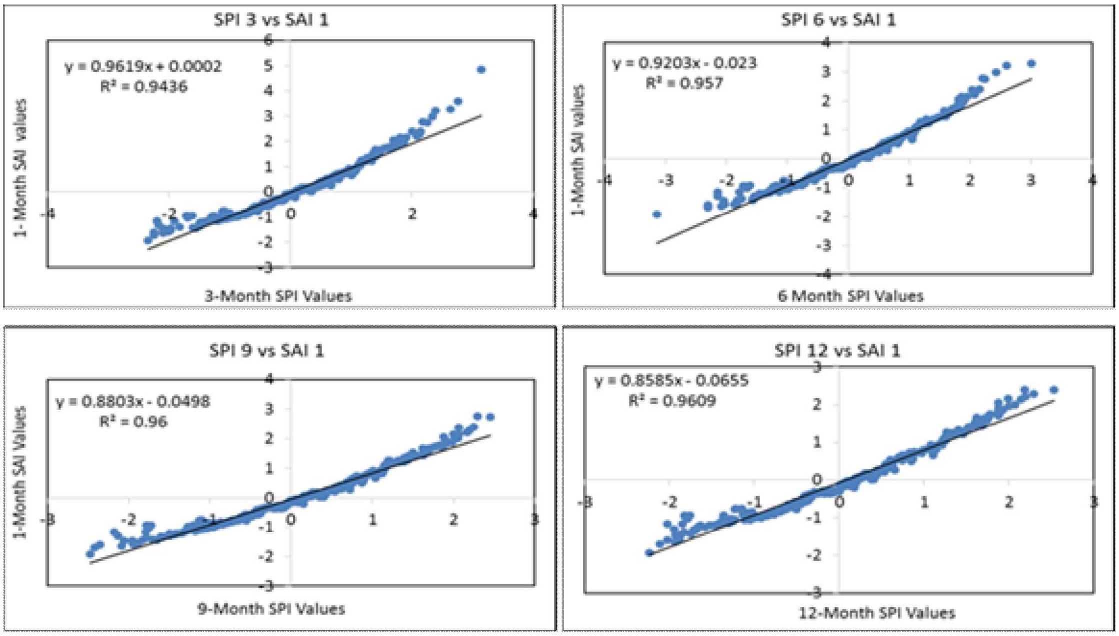


Fig. 8 The scatter diagram of SAI, BMDI and SPI

As further seen in Fig. 9 under different percentile thresholds, over the past 50 years (1950-2001), SAI and BMDI captured the occurrence of 14 exceptional drought events while SPI captured 11(approx. 21% less). In terms of extreme droughts occurrence, however, SAI and BMDI identified 7, while SPI identified 17 (approx. 59% more). The three indices captured 21 equal number of severe drought events. In terms of moderate droughts, SPI, SAI, and BMDI captured 42, 35, and 35 events respectively. Most of the time, therefore, SPI identified the highest number of occurrences of drought. Table 8 shows the details of the monthly drought events as identified by each of the indices. The numbers in the parentheses represent the wetness frequency. Some of the drought events captured by SPI were not identified by SAI and BMDI, such as 1966, 1974, 1985 droughts.

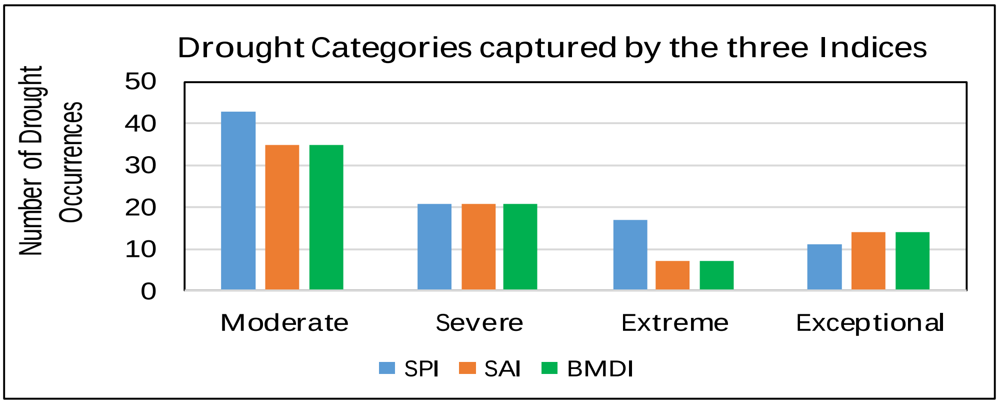


Fig. 9 Frequency of drought intensities category captured by the various indices

Table 8 Monthly distribution of drought occurrences and their intensities cate

Month	20th Percentile			10th Percentile			5th Percentile			2nd Percentile		
	Moderate Drought			Severe Drought			Extreme Drought			Exceptional Drought		
	SPI1	SAI 1	BMDI 1	SPI1	SAI 1	BMDI 1	SPI1	SAI 1	BMDI 1	SPI1	SAI 1	BMDI 1
Apr	6(15)	5(13)	5(13)	5(7)	3(1)	3(1)	4(1)	1(1)	1(1)	1(1)	2(1)	2(0)
May	5(21)	5(19)	5(15)	2(2)	3(0)	3(3)	3(4)	1(2)	1(2)	1(1)	2(1)	2(1)
Jun	4(15)	5(15)	5(12)	6(2)	3(2)	3(0)	1(0)	1(0)	1(1)	2(3)	2(2)	2(1)
Jul	6(14)	5(13)	5(10)	2(5)	3(4)	3(5)	2(3)	1(2)	1(1)	2(1)	2(1)	2(1)
Aug	5(20)	5(18)	5(16)	3(1)	3(0)	3(1)	1(0)	1(4)	1(4)	2(0)	2(0)	2(0)
Sep	8(16)	5(15)	5(16)	3(5)	3(0)	3(3)	2(0)	1(5)	1(0)	1(4)	2(0)	2(1)
Oct	9(16)	5(13)	5(17)	0(3)	3(2)	3(0)	4(0)	1(0)	1(0)	2(2)	2(0)	2(0)

The ability of the indices to represent major historical droughts in the basin were investigated, and results show that all the three indices at 3 months' time scale, and from July 1972 to May, 1975 (34 months duration period) were experiencing a dry period (for 3-month time scale) (Fig. 10); but with 9-month time scale, the period of the dryness is from Mid-1971 to July 1975(50 months duration periods). The maximum negative values of the 3-month SPI, were -2.20 for October 1973, while SAI and BMDI were -1.86 and -2.20 respectively; and for the 9-month SPI is -2.47 for May, 1974, while SAI and BMDI were -2.04 and -1.27 respectively. However, for the same time scales 3 and 9 months, from September 1981 to end of 1989 (99 months duration period), was dry period (for 3-month time scale); though the 1980s drought continued into 1990s), (Fig. 11); with 9 month time scale however, from June 1982 to end of 1989 (90 months duration period), was dry period. The maximum negative values of the 3-month SPI is -2.24 for May 1985, while SAI and BMDI were-1.68 and -1.76 respectively. SPI indicates more severe drought than SAI and BMDI most of the time in all the time scales, except in the 3-months' time scale where BMDI indicates more severe drought than other indices.

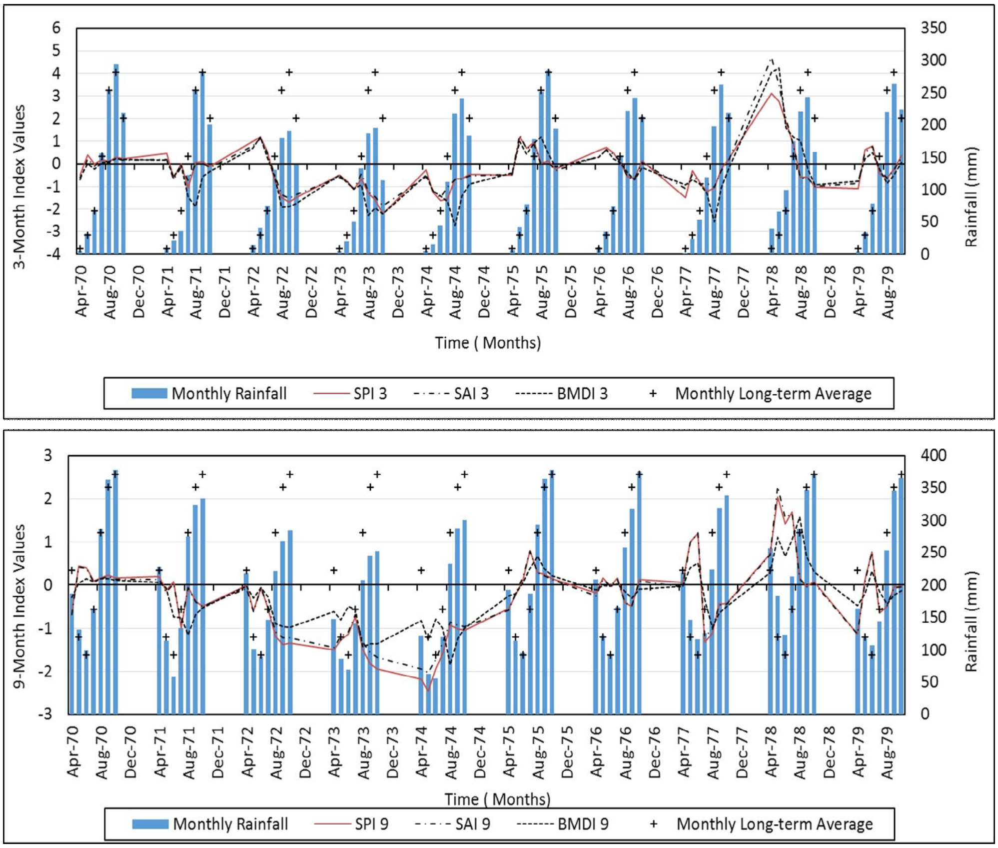


Fig. 10 Comparison of 1970s SAI, BMDI and SPI along with rainfall at different time scales

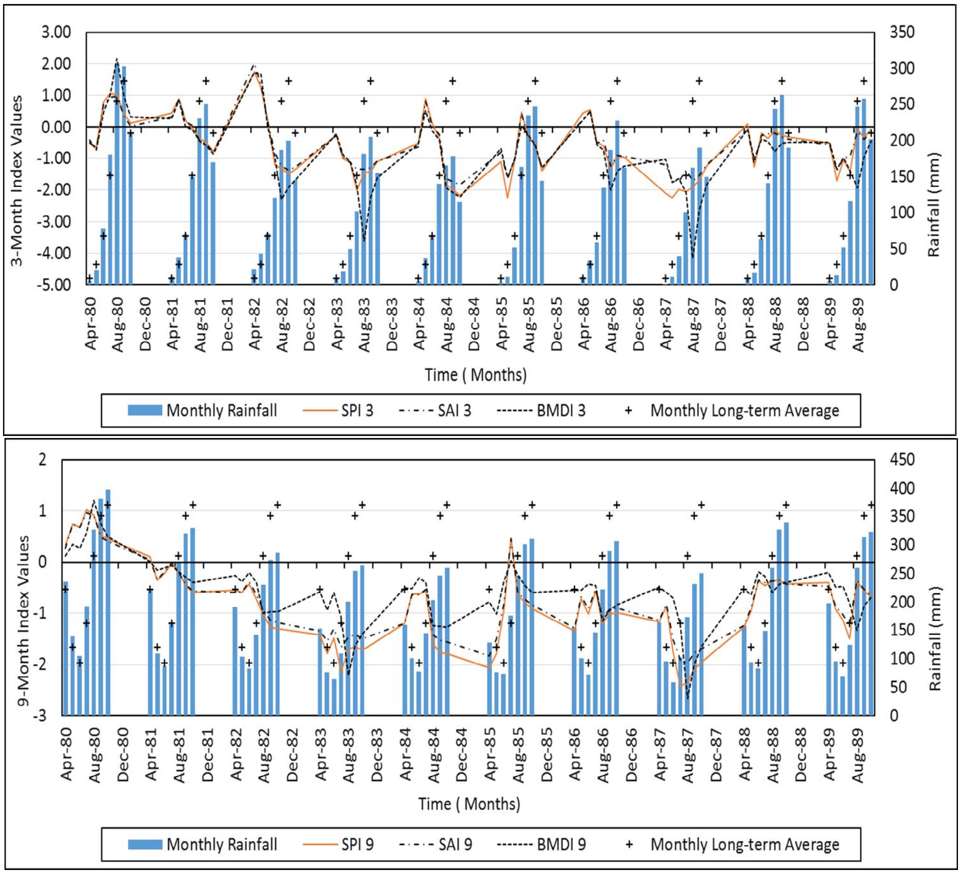


Fig. 11 Comparison of 1980s SAI, BMDI and SPI along with rainfall at different time scales

4.1 Performance Evaluation of the three Drought Indices

The results of the weightings of the six evaluation criteria carried out using Saaty's pairwise comparison of the Analytic Hierarchy Process (AHP) approach showed that robustness criterion has the highest weight of 30% due to its relative importance. This is closely followed by tractability and transparency with relative weightings of 27% and 21% respectively. Then sophistication, extendability and dimensionality criteria had equal weights of 7% each (Table 4). The results of the acceptable inconsistency level in the pairwise comparison of the criteria adjudged by the computed values of Consistency Index (CI) and Consistency Ratio values (CR) were 0.0091 and 0.0074 respectively; which are less than 0.1. Saaty proposed that for CR< 0.1, the level of inconsistency in assigning the pairwise comparison rank is tolerable (Saaty, 1980, 1986, 2005). This weighting is slightly different from the relative weights used by Quiring (2009).

For instance, Quiring (2009) obtained the same relative weight of 30% for robustness, but had 25%, 15%, and 10% each for tractability, transparency, and sophistication, extendability and dimensionality respectively; as against 27%, 21 and 7% obtained in this paper. With the weightings of the evaluation criteria achieved, the performance of each of the three indices SAI, BMDI and SPI was subsequently evaluated following the same procedures for the criteria evaluation. Table 8 is the pairwise comparison matrix of the ranks assigned to each indices, for each of the six criteria. The normalized pairwise comparison matrix is obtained by dividing each element in the matrix by its column sum. The results of the eigenvector that defines the index weight for the criteria in consideration obtained by averaging across the rows of the normalized pairwise matrix is shown in Table 9. The product of the obtained values of the eigenvector and the relative importance weight of the respective six evaluation criteria produced the final weightings and rankings of the indices and result showed that SPI is the most highly ranked meteorological drought index in the Niger River basin, followed by SAI which slightly ranked ahead of BMDI (Table 10). Overall, the SPI had a rating of 0.6123. The emergence of SPI as the most ranked meteorological drought index is supported by works of Quiring, (2009) and Keyantash and Dracup, (2002). SPI was also identified as the most appropriate index for monitoring meteorological drought in Iran (Morid et al., 2006).

Table 8 showing the pairwise comparison matrix generated for each of the six criteria

Pairwise Comparison Matrix- Robustness

INDICES	SAI	BMDI	SPI
SAI	1	3.0000	0.3333
BMDI	0.333333	1	0.2000
SPI	3	5.0000	1
Total	**4.333333**	**9.0000**	**1.5333**

Pairwise Comparison Matrix- Tractability

INDICES	SAI	BMDI	SPI
SAI	1	0.5000	0.2000
BMDI	2	1	0.5000
SPI	5	2.0000	1
Total	**8**	**3.5000**	**1.7000**

Pairwise Comparison Matrix- Transparency

INDICES	SAI	BMDI	SPI
SAI	1	1.0000	0.2500
BMDI	1	1	0.2000
SPI	4	5.0000	1
Total	**6**	**7.0000**	**1.4500**

Pairwise Comparison Matrix- Sophistication

INDICES	SAI	BMDI	SPI
SAI	1	1.0000	0.2000
BMDI	1	1	0.3333
SPI	5	3.0000	1
Total	**7**	**5.0000**	**1.5333**

Pairwise Comparison Matrix- Extendability

INDICES	SAI	BMDI	SPI
SAI	1	1.0000	1.0000
BMDI	1	1	1.0000
SPI	1	1.0000	1
Total	**3**	**3.0000**	**3.0000**

Pairwise Comparison Matrix- Dimensionality

INDICES	SAI	BMDI	SPI
SAI	1	1.0000	0.3333
BMDI	1	1	0.3333
SPI	3	3.0000	1
Total	**5**	**5.0000**	**1.6667**

Table 9 The Eigenvectors obtained for SAI, BMDI and SPI for each of the Decision Criteria

Index	Robustness	Tractability	Transparency	Sophistication	Extendability	Dimensionality
SAI	0.260	0.129	0.161	0.158	0.333	0.200
BMDI	0.106	0.277	0.149	0.187	0.333	0.200
SPI	0.633	0.595	0.690	0.655	0.333	0.600
CI	0.019	0.003	0.057	0.015	0.000	0.000
CR	0.033	0.005	0.098	0.025	0.000	0.000

Table 10 Meteorological Index Evaluation

Index	Weighting	Ranking
SAI	0.1974	2
BMDI	0.1903	3
SPI	0.6123	1

5.0 Conclusion

Drought is simultaneously the most damaging of all natural hazards and the least understood. This study, therefore, evaluates and compares the performance of three drought indices, the Standardized Rainfall Anomaly Index (SAI), Bhalme and Mooley Drought Index (BMDI) already used by the local drought managers and standardized Precipitation Index (SPI) based on rainfall. Two-parameter gamma distribution was used to transform the skewed rainfall data, because it best fit the rainfall frequency distribution in the region. Prior to the indices evaluation, their statistical relationships were first explored. SPI requiring equiprobablity transformation of the data, satisfied the normality assumption, whereas it was violated by SAI and BMDI.

The three drought indices showed similar temporal trends in all the time scales, the 1, 3, 6, and 12 months' time scales respectively. Also, the pre-drought humid periods of 1950s, the major drought periods of 1970s and 1980s and the recovery periods of 1990s in the Niger basin were well identified. Based on variable monthly 20th percentile thresholds, SPI identified 42 and 17 moderate and extreme drought events respectively, against 35 and 7 captured by SAI and BMDI over the past 50 years (1950-2001). The SAI time series generally appears more positive or wetter than the SPI in both time scales; and vice-versa with that of SPI. When the SPI is -2.35, the corresponding SAI is -1.93, and when SPI is + 3.14, the corresponding SAI is + 4.84. Such relationship was not found in the case of SAI and BMDI.

The three indices were evaluated based on six qualitative decision criteria, using an appropriate weighting system that accounts for the relative importance of each criterion, and results show that SPI is the most ranked meteorological drought index in the Niger River basin with a priority weight of 0.6123. On the basis of the computed consistency index and consistency ratio values, the weighting judgment is acceptable; because the null hypothesis is accepted.

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Appendix1: Comparing five statistical distributions over the upper Niger subwatershed

I - Month Time Scale

Distribution Name	Parameters Estimate	Goodness of Fit: Chi-Squared Rank
Lognormal	σ = 1.39, μ=4.14	16
Exponential	λ = 0.015	9
Log-Logistic	α= 1.31, β=74.71	17
Weibull	α= 1.01, β=4.08	12
Gamma	α= 0.53, β=132.82	6

3 - Months' Time Scale

Distribution Name	Parameters Estimate	Goodness of Fit: Chi-Squared Rank
Lognormal	σ = 1.65, μ=4.81	12
Exponential	λ =0.0047	16
Log-Logistic	α= 1.10, β=152.85	14
Weibull	α= 0.88, β=66.65	10
Gamma	α= 0.80, β=265.13	8

6 - Months' Time Scale

Distribution Name	Parameters Estimate	Goodness of Fit: Chi-Squared Rank
Lognormal	σ = 1.35, μ=5.51	12
Exponential	λ =0.0024	6
Log-Logistic	α= 1.36, β=301.08	15
Weibull	α=1.11, β=443.01	10
Gamma	α=1.77, β=238.81	16

12 - Months' Time Scale

Distribution Name	Parameters Estimate	Goodness of Fit: Chi-Squared Rank
Lognormal	σ = 0.19, μ=6.72	14
Exponential	λ =0.001	19
Log-Logistic	α= 9.21, β=825.86	3
Weibull	α=26.46, β=902.54	13
Gamma	α=28.25, β=29.79	6