

Article

Assessment of Seasonal Rainfall Drought Indices, Nyala City Sudan

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Abstract: Drought is an unpredictable hydrological phenomenon, and climate change has made it difficult to predict and analyze droughts. Nyala city airport metrological station rainfall records from 1943 to 2017 (75 years) were investigated. Four statistical drought indices were used; the standardized precipitation index (SPI), the rainfall anomaly index (RAI), the rainfall decile percent index (RDI), and the percent normal precipitation index (PNI). The study analyzes, assesses, compares, and determines the proper drought index. Results show that annual normal drought class (DC4) percentages for PNI, RDI, and RAI are not significantly different at an average of 42% and 65.3% for SPI at a frequency of 49 years. In comparing the average monthly and yearly drought frequency values and considering the historical dry and wet droughts, results showed the indices performance rank as: SPI, RAI, RDI, and PNI. Result reveals that the SPI was superior in all analyses, but it had some defects in detecting monthly dry drought when precipitation is dominated by rare or zero values (start and end of the rainy season). This was concluded and revealed by conducting a zone chart showing the deviations of standard deviation about the mean. Thus, the SPI index outperforms the other three indices.

Keywords: seasonal; drought; assessment; frequency; precipitation; drought indices; RDI; NPI; RAI; SPI



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1. Introduction

Climate change has recently had devastating consequences all around the world, including unprecedented floods, droughts, extreme temperatures, and other natural disasters. Drought is one of the most important climatic factors that indicate climate change. Rainfall deficit (drought) is a hydrological phenomenon that occurs without explicit warning [1,2]. The analysis and the prediction of rainfall drought have been of great concern due to the global climate changes. Drought and rainfall variations analysis has a significant concern, especially in arid and semi-arid environments [3–5].

Drought can be defined as a period of abnormally dry weather, resulting in vegetation cover condition changes [6–8]. It is a temporary feature of a climatic anomaly phenomenon that leads to a lack or poor distribution of the rainfall (precipitation) amount to below known normal average precipitation or restricted distribution in a region (area). Drought is a natural hazard that may significantly affect human activities and the environment [9–11]. Drought is commonly characterized as a protracted period of a season, a year, or several years of shortfall precipitation relative to a region's statistical multi-year average, resulting

in water scarcity for some activity, community, or environmental sectors [12]. On the other hand, drought is a multifaceted calamity, and it can be described in terms of meteorological, agricultural, hydrological, and socio-economic [11,13,14], as follows: (1) Meteorological: an event in which the long-term rainfall average is surpassed. (2). Agricultural: a lack of soil moisture to meet the needs of a specific crop at a specific period. It is commonly used following a meteorological drought and occurs before a hydrological drought. (3). Hydrological: a scarcity of surface and subsurface water supplies. (4). Socio-economic: whenever lower precipitation and water availability impact human activities.

As a result, determining the severity of the drought is critical for assessing the repercussions and reducing the expected effects [15]. Drought is a climatic condition that occurs with different frequencies, severity, and duration in almost all climatic areas [16]. Drought is considered a transitory difference in water availability characterized by lower-than-average precipitation with unexpected or highly difficult to anticipate, resulting in depleting water resources. Drought is a hazard and also a disaster. It is considered a hazard since it is an unforeseeable occurrence that is part of the naturally changing climatic system. Disaster because the water supply interruption to the natural and agricultural ecosystems and other human activities is caused by the collapse of the precipitation regime [17,18].

For example, recent studies have shown that the SPI has several advantages, including being relatively simple, spatially, and sequentially coherent and enabling the identification of drought conditions at various scales, such as the Palmer drought severity index [19]. The constant drop in rainfall has been one of the most significant climate fluctuations in the African Sahel since the late 1960s [20]. The Sahel is characterized by high climatic changes and erratic rainfall ranging from 200 to 600 mm, with coefficients of variation ranging from 15% to 30%. It was also revealed that rainfall decreased by 29 to 49% in the Sahel region from 1968 to 1997 compared to the baseline period of 1931 to 1969.

The most crucial of these classes for water resource management is hydrological drought assessment. The drought index is essential for tracking drought conditions [21]. Drought indices aid decision-making by recognizing drought features such as severity, length, and frequency. The most common hydrological indices are runoff, streamflow, discharge, and groundwater [22]. Determining a suitable drought index requires more attention [23] because it is vital to assessing drought risk.

Sudan suffered from severe droughts during the 20th century, with the most destructive ones occurring in 1913, 1940, and 1954 and affecting large portions of the nation. A total of 1.5 million inhabitants were impacted between 1913 and 1940, and 4.5 million people experienced hunger in year 1984. The driest dry spell, which was followed by localized mass starvation, happened between 1980 and 1984. In 1967–1973, 1987, 1989, 1991, 1993, and 2000, localized and less severe droughts (affecting one and five states) were also noted [23,24]. Drought and starvation relationship in Sudan: policy implications research report 88, International Food Policy Research Institute noted that rainfall levels in Sudan had decreased over the previous three decades, with average annual rainfall falling between 1960 and 1969 and 1970 and 1970 and 1979 and by 17.7% between 1970 and 1979 and 1980 and 1986. Additionally, yearly variations in precipitation around a trend line appear to have gotten worse, particularly in arid and semi-arid regions. In western Sudan, the average coefficient of variation rose from 16% in the 1960s to 21% in the 1970s and 32% in the 1980s [24].

Drought and rainfall variations analysis has a significant concern, especially in arid and semi-arid environments. A few researchers conducted drought studies, most of their works were within a specific region and for specific drought consequences. The dry conditions changed over Sudan at various temporal and spatial dimension scales; the drought severity index (DSI) data obtained from both the Kordofan and Darfur regions plagued by drought from 2001 to 2005, where most regions were affected by drought from 2008 to 2011, demonstrating that DSI could be used for agricultural drought monitoring as well as an alternate indicator for crop yield estimation over Sudan at various levels [25,26].

This study aims to analyze, evaluate, assess, and detect drought frequency and drought class. Thus, to understand and assess the hydrological characteristics, the drought wet and dry classes and their frequencies, and the historical trends value and variability, this study will be of great knowledge value and guidance for future at-site and regional research in Nyala and the region around it (South Darfur State).

2. Materials and Methods

2.1. The Study Area

Nyala (Coordinates 12.0365 N–24. 8765 E, Elevation of about 670 m above sea level) is the capital city of the South Darfur State in the South West of Sudan, as shown in Figure 1, and the second-largest city in Sudan concerning population, economy, and agricultural domination. It shares borders with North Darfur State, West Darfur State, Central Darfur State, East Darfur State, the Republic of South Sudan, the Central African Republic, and Chad. The city suffers from severe water and water infrastructure problems caused by drought and insufficient water management tools. Nyala city has climate seasons (rainfall trend); a dry season from November to February, a hot season from March to May, and a wet season from June to October. Therefore, it is extremely dry in May and November, and the peak of the wet season is in July and August [27].

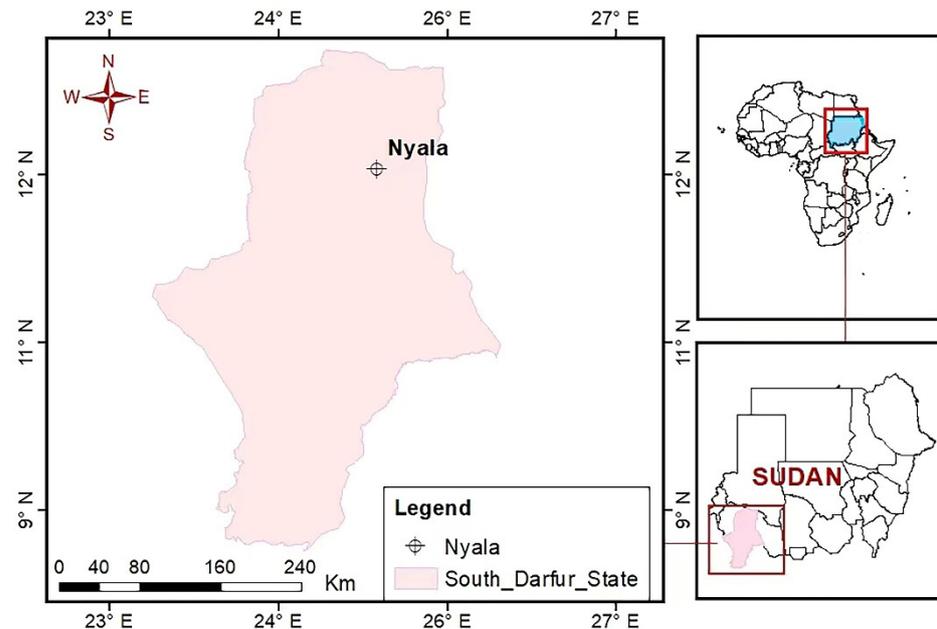


Figure 1. Locations of Nyala City in South Darfur, Sudan.

Thousands of internally displaced people (IDPs) gather around the town in search of safety and peace, which increases the city population and requires all water-using sectors to share the only water source (the Wadi-Nyala basin) as the common source of water demand for all water-using sectors. Understanding and assessing drought frequency and their occurrences regime and features will help water resources management guide them to put strategic planning that assists in evaluating and mitigating the consequences of drought in various water usage sectors.

2.2. Dataset and Methodology

The station rainfall (precipitation) data used in this study are extended for 75 years (1943–2017). The water harvesting center/University of Nyala provided a daily dataset for the period from 1943–2000; originally, these data were acquired by the center from Sudan National meteorological center (SNMC), and the rest of the period dataset (2001–2017) monthly precipitation was acquired and collected from both, the SNMC Nyala office and

the center of agricultural research, ministry of agriculture and animal resources, South Darfur State, Nyala. A quick homogeneity test was carried out for the dataset, including the spatial homogeneity test, consistency tests, long-term systematic shifts, and time series trend tests. Then the data were grouped into; monthly data, including the rainy six months (May, June, July, August, September, and October), the successive addition of month to month rains, and the total rainfalls or annual rainfall. The statistical tests and data processes were carried out using MINITAB statistical software in concord with excel.

2.3. Seasonal Hydrological Characteristics

The seasonal hydrological characteristics are determined using the following basic statistics:

The Mean:-

The mean is the sum of all recorded observations (precipitation data) divided by the number of the observations, the formula:

$$\bar{p} = \frac{\sum_i^n p_i}{n} \quad (1)$$

The median:-

The median is the middle value of a recorded observation sample (precipitation data) arranged in order of magnitude.

The standard deviation (St. Dev):-

The standard deviation is the measure of the spread of a sample recorded observations (precipitation data), the formula:

$$S = \sqrt{\left\{ \sum_{i=1}^n (p_i - \bar{p})^2 / (n - 1) \right\}} \quad (2)$$

The variance:-

Variance measures how far the sample recorded observations (precipitation data) are spread about the mean. The sample variance equals the standard deviation squared, S^2 .

The distribution shape:-

The distribution shapes are the skewness and the kurtosis.

Skewness is a measure of asymmetry (B1). A negative value implies skewness left, while a positive value represents right skewness. A zero value may not always imply symmetry. The kurtosis (B2) of a distribution is one measure of how dissimilar it is from the normal distribution. A positive score usually means the distribution has a sharper peak, thinner shoulders, and fatter tails than the normal distribution. A negative number indicates that the distribution is flatter in the peak, thicker in the shoulders, and thinner in the tails than the normal distribution. The formulas for the skewness (B1) and the kurtosis (B2) are as follow:

$$B1 = \frac{n \sum_{i=1}^n \left[\frac{p_i - \bar{p}}{S} \right]^3}{[(n - 1)(n - 2)]} \quad (3)$$

$$B2 = \left\{ \frac{n(n + 1) \sum_{i=1}^n [(p_i - \bar{p}) / S]^4}{(n - 1)(n - 2)(n - 3)} \right\} - \left\{ \frac{3(n - 1)}{(n - 2)(n - 3)} \right\} \quad (4)$$

where, n is the number of recorded observations, p_i is the i^{th} observation.

In all above estimations of the hydrological characteristics, $n = 75$ for all analysis periods, p_i stands for annual, monthly, and annual parts precipitations, and \bar{p} stands for the average mean of the specified period of precipitation. The period stands for the different rainfall periods used in this study; (1) the yearly rainy analysis period based on total annual rainfall, (2) the monthly rainy analysis period based on monthly rainfall (6 months of rainfall, May to October), and (3) the successive accumulation of the monthly rainfalls.

2.4. The Standardized Precipitation Index (SPI)

SPI relies solely on the precipitation dataset and requires less data and calculation time [28]. The mean SPI is zero after a long-term precipitation history at the chosen station is attached to a probability distribution (e.g., gamma distribution), which is then converted into a normal distribution. SPI can be calculated in various time steps (e.g., 1 month, 3 months, 48 months) and detect impending droughts earlier than the Palmer index. With a zero mean and unit standard deviation, SPI is identical to the impartial z-score [29]. The effects of a precipitation shortfall on multiple water resource mechanisms can be measured by combining different time scales under the same index. The SPI is calculated by multiplying the variation among the normalized seasonal precipitation and the long-term seasonal mean by the standard deviation [30,31]:

$$SPI = \frac{(P_{ij} - \bar{P})}{\sigma} \quad (5)$$

where P is the seasonal precipitation at the i th gauge site and j th observation, \bar{P} is the long-term seasonal mean, and σ is its standard deviation.

2.5. The Rainfall Anomaly Index (RAI)

The rainfall anomaly index is an index that uses the mean of the ten extremes to calculate positive and negative RAI indices [32]. Let \bar{M} be the mean of the ten highest precipitation records for the under study, \bar{P} the mean precipitation of all records for the period, and P the precipitation for the specific year. Then the positive RAI (for the anomalies) for that year is:

$$RAI = 3 \left\{ \frac{P - \bar{P}}{\bar{M} - \bar{P}} \right\} \quad (6)$$

For the negative RAI, let \bar{m} be the mean of the ten lowest precipitation records for the period under study. Then the negative RAI (for negative anomalies) for that year is

$$RAI = -3 \left\{ \frac{P - \bar{P}}{\bar{m} - \bar{P}} \right\} \quad (7)$$

2.6. The Rainfall Deciles Index (RDI)

With RDI, total monthly precipitation long-term records are first sorted in descending order to generate a cumulative frequency distribution. This index, proposed by Gibbs and Maher (1967), divides the distribution into ten parts known as deciles [33]. The first decile is the precipitation value that is not greater than the lowest ten percent of all precipitation values in a record; the second decile is between the lowest ten and twenty percent, and so on. Precipitation values from the current or previous months can be evaluated to these deciles and interpreted in terms of them [30]. The equation for calculating drought is then given as:

$$P_i = \frac{i}{n + 1} * 100 \quad (8)$$

where, P_i is the probability of rain in ranked number i th and n is a number of rainfall data.

The computational easiness of the percentile approach is a benefit, but its simplicity can lead to shortcomings. Droughts can be overcome when rainfall is close to or above normal. Even though the average annual precipitation is insignificant and does not end the water crisis, minor precipitation can activate the first stopping rule during periods when little or no precipitation normally falls [15]. Since the commencement of the drought, the total rainfall can be considered using a third supplemental rule [34]. This rule states that a meteorological drought is declared if the total precipitation of water deficit months exceeds the first deciles.

2.7. The Normal Precipitation Index (PNI)

This index computes the deviation of rainfall from its long-term mean value. The normal value is 100% and can be calculated for a month, a season, or a year. At different locations, the same PNI may have different specific impacts. The PNI is a relatively simple measure of precipitation deficit and differs from region to region [35]. The PNI is one of the most basic indicators used to assess drought, and it is effective in drought and wet time series and during a specific season [30,36].

The formula for calculating the index is as follows:

$$PNI = \frac{P_i}{\bar{P}} * 100 \tag{9}$$

where, P_i is the annual rainfall and \bar{P} is the long-term rainfall mean.

Table 1 presents an aggregated range for drought indices classes. As shown in Table 1, the SPI and the RAI almost have similar range numerical values. In contrast, the RDI and the PNI have similar range percentage values, and the numerical and the percentage values are categorized into similar classes (aggregated). The study conducts three seasonal drought analyses (monthly, successive cumulative monthly, and annual). Equations (1) through (9) were applied in all analyses with P_i , \bar{P} , and n standing for the concerned analysis, precipitation, average mean precipitation, and record length.

Table 1. DC and drought indices limit values for SPI, RAI, RDI, and PNI.

PNI (%)	RDI (%)	RAI	SPI	Drought Class [DC]
≥110 *	≥90	≥3	≥2	Extremely wet [7-EW]
	80_90	2.0_2.99	1.5_1.99	Very wet [6-VW]
	70_80	1.0_1.99	1.0_1.49	Moderately wet [5-MW]
80_110	30_70	0.99_−0.99	0.99_−0.99	Normal [4-N]
55_80	20_30	−1.0_−1.99	−1.0_−1.49	Moderately dry [3-MD]
40_55	10_20	−2.0_−2.99	−1.5_−1.99	Severely dry [2-SD]
≤40	≤10	≤−3	≤−2	Extremely dry [1-ED]

* represents the three PNI wet classes (EW, VW, and MW).

3. Results and Discussion

Table 2 shows the hydrological characteristics of the rainfall data considered in this study. The results show the effect of the accumulated precipitations for standard deviation and the skewness. The monthly and the annual standard deviations results showed that, in August and July, the rainfall patterns were highly varied (65.68 and 50.89) compared to other month’s rainfall variations; thus, May and October variations (19.59 and 19.62) were significantly not different, and same remarks seem for June and September variations (35.29 and 36,86). For the skewness, all the monthly rainfalls were positively skewed; May and October were high with 1.42 and 1.41, respectively, June and September were 1.01 and 0.97, respectively, and July and August were 0.85 and 0.40, respectively.

Table 2. Seasonal (monthly and annual) hydrological characteristics.

Min.	Max.	Skewness	Variance	St-Dev.	Median	Mean	Month
0.00	85	1.42 [1.42] *	383.94	19.59 [19.59] *	16	19.19	May
0.00	158	1.01 [1.00] *	1245.28	35.29 [42.16] *	44	47.44	June
30	298	0.85 [0.52] *	2590.29	50.89 [64.25] *	123	127.11	July
13	329	0.40 [−0.15] *	4314.16	65.68 [100.1] *	132	140.29	August
5	199	0.97 [0.17] *	1358.45	36.86 [105.9] *	66	69.89	September
0.00	81	1.41 [0.18] *	385.11	19.62 [101.9] *	13	18.59	October
197	648	0.18	10,385.60	101.9	427	423.00	Annual

* Skewness and St. Dev., estimated from successive precipitation additive of the month(s) and the next followed month.

On the other hand, step-by-step accumulation of monthly rainfalls improved the overall skewness patterns, resulting in an annual positive skewness of 0.18. This can be explained by the skewness decreasing from 1.42 to 1 when June rainfalls were added to May rainfalls. In the same way, the skewness decreased from 1 to 0.52, from 0.52 to -0.15 , from -0.15 to 0.17, and from 0.17 to 0.18 when July, August, September, and October rainfalls were added successively to each other. Rainfall accumulations in June, July, and August contributed 0.42, 0.48, and 0.67 points to the negative skewness of the rainy season, respectively, while September and October rainfalls each contributed 0.32 and 0.01 points each to the positive skewness of the rainy season, respectively. This shows that the overall effect of monthly rainfall accumulations ends with a positive result, as also shown in Figures 2–4.

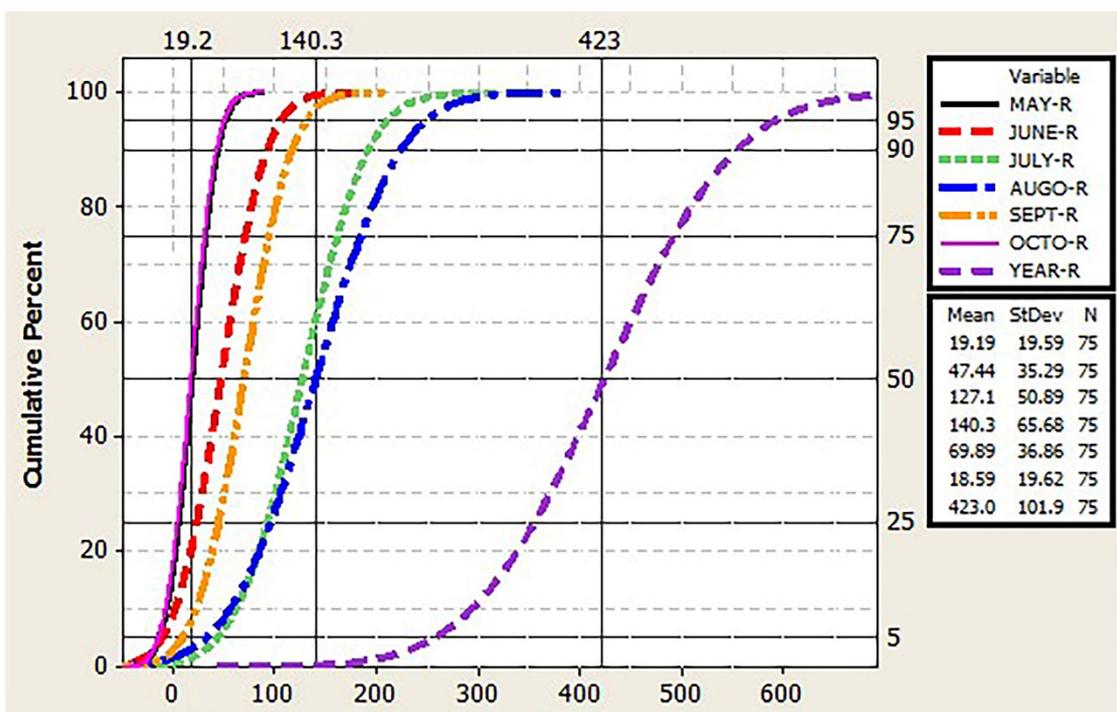


Figure 2. Monthly precipitations cumulative percent histogram.

Table 3 shows that the annual normal DC4 percentages for PNI, RDI, and RAI are not significantly different at an average of around 42%, with frequencies of 33, 30, and 29 years, respectively. In contrast, the percentage for SPI is 65.3%, with a frequency of 49 years. When the two tails drought classes (total dry; DC1, DC2 and DC3, and total wet; DC5, DC6, and DC7) are investigated, the results suggest that RDI, RAI, and SPI are likely to be positively skewed (total dry) with occurrence percentages of 40%, 35%, and 20%, respectively. Still, PNI is negatively skewed (total wet) with an occurrence percentage of 32% (24% dry, 44% normal, and 32% wet). Additionally, the total wet periods and percentages for PNI, RDI, RAI, and SPI are 24 (32%), 16 (21%), 19 (25%), and 11 (15%), respectively. Moreover, the cumulative dry periods and percentages for PNI, RDI, RAI, and SPI are 18 (24%), 30 (40%), 26 (35%), and 15 (20%), respectively. The above result indicates that the PNI may not be considered to perform well for modeling the data in the case studied because it shows a negatively skewed frequency pattern. In contrast, the original data show a positively skewed pattern (Table 2). Another piece of evidence supporting this was that the PNI index shows no extremely dry period (ED), whereas the real experienced data and visualized situation does (two well-known EDs in 1984 and 2002). The RDI was also shown to be substantially positively skewed (40% dry, 39% normal, and 21% wet), with an 11-year (14.7%) ED duration, despite this not being the case. As a result, the RDI index may not

be considered a good model for the instance investigated. Furthermore, the former was a more trustworthy model when comparing the remaining two indices (SPI and RAI). It outperformed the RAI, as evidenced by the hydrological properties of the data in Table 2 and the DC of Table 3, columns 2 and 4 distributions. Finally, the overlapping of the time series in Figure 5 shows a clear tracking for drought classes and frequency, which validates that SPI is superior to other indices.

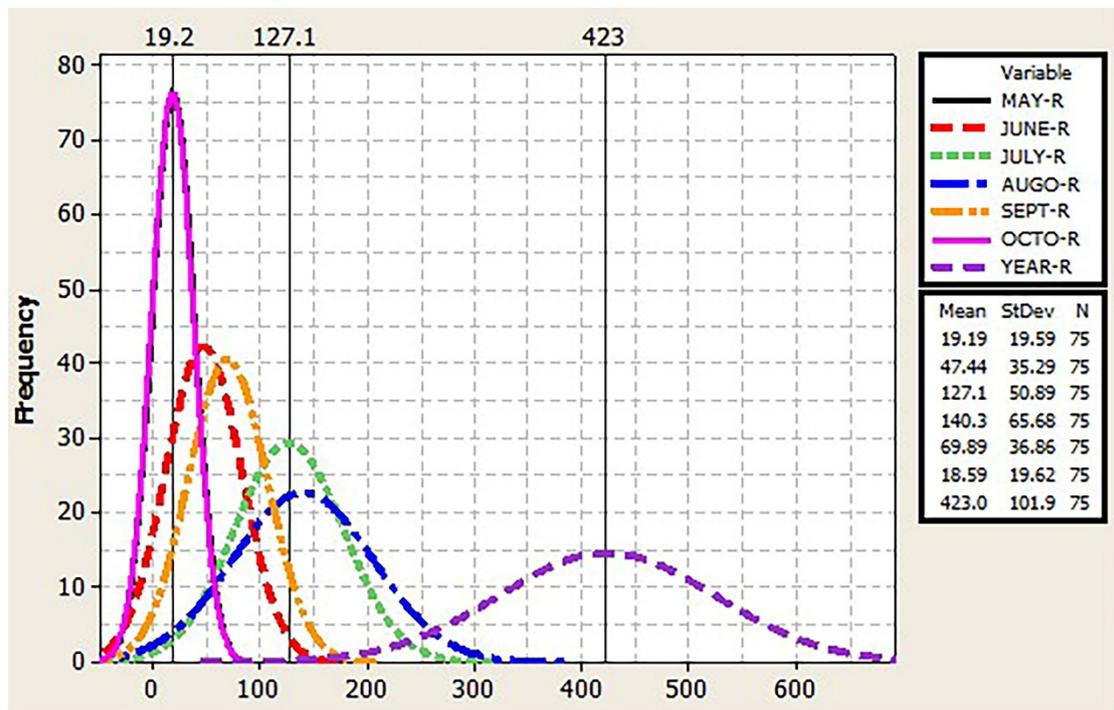


Figure 3. Seasonal (monthly and annual) precipitations frequency histogram.

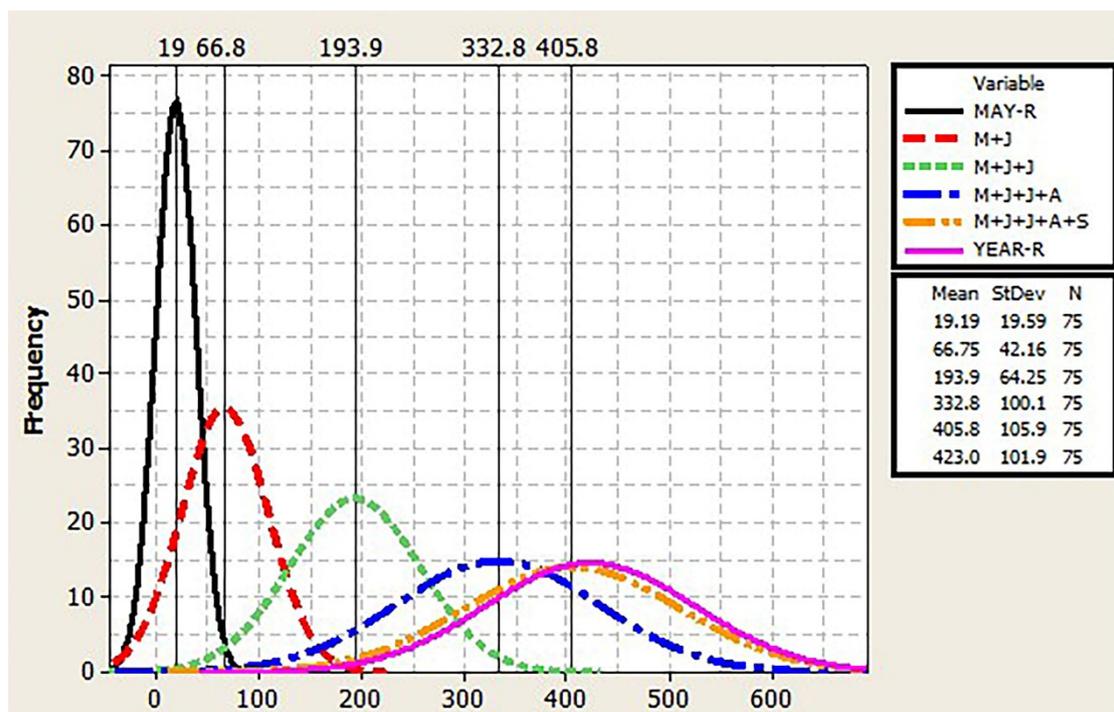


Figure 4. Seasonal monthly accumulated precipitations frequency histogram.

Table 3. Drought class DC, annual frequencies and their percentages for SPI, RDI, RAI, and PNI.

Drought Class (DC)	SPI	RDI	RAI	PNI
7 E.W.	2 [2.67%]	4 [5.33%]	5 [6.67%]	
6 VW	5 [6.67%]	6 [8.00%]	6 [8.00%]	24 * [32.00%]
5 MW	4 [5.33%]	6 [8.00%]	8 [10.67%]	
4 N	49 [65.33%]	29 [38.67%]	30 [40.00%]	33 [44.00%]
3 MD	11 [14.67%]	9 [12.00%]	11 [14.67%]	16 [21.33%]
2 VD	2 [2.67%]	10 [13.33%]	11 [14.67%]	2 [2.67%]
1 ED	2 [2.67%]	11 [14.67%]	4 [5.33%]	0 [0.00%]
Total Wet%	11 [15%]	16 [21%]	19 [25%]	24 [32%]
Normal%	49 [65%]	29 [39%]	30 [40%]	33 [44%]
Total Dry%	15 [20%]	30 [40%]	26 [35%]	18 [24%]
Total period	75	75	75	75

* represents the three PNI wet classes (EW, VW, and MW).

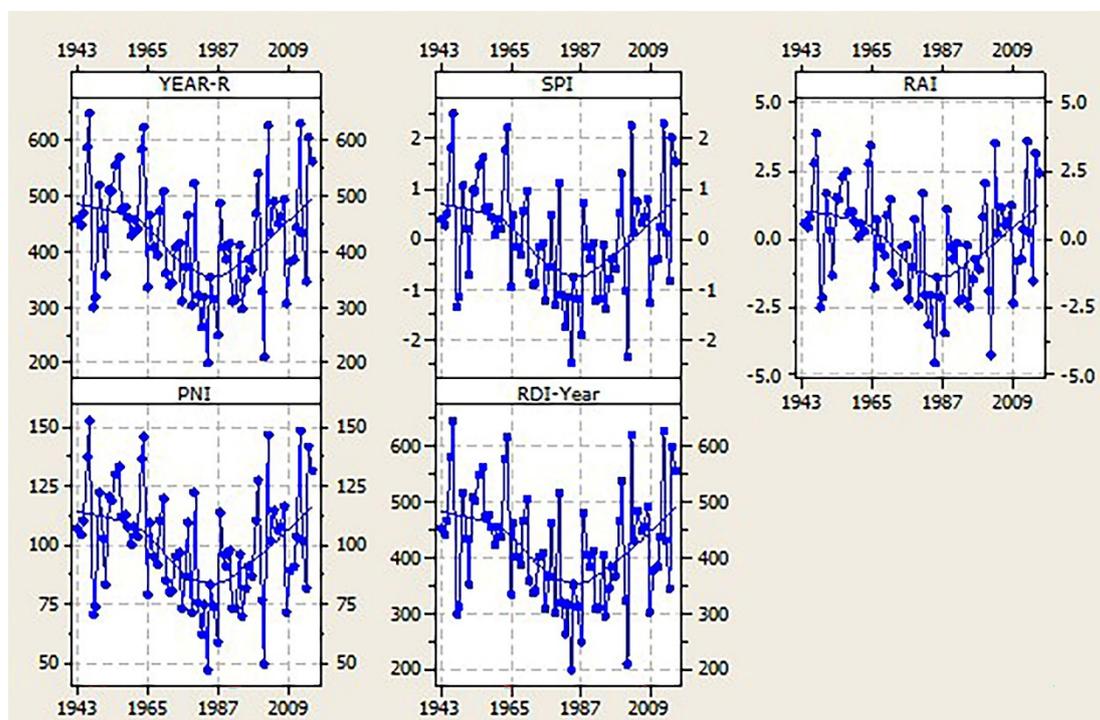


Figure 5. Annual time series plots of observed rainfall, RDI, SPI, PNI, and RAI.

Table 4 illustrates the monthly and annual frequency of the indices for the analysis period (1943–2017). The four indices revealed average monthly drought frequencies for wet, normal, and dry periods of 14, 76, and 10, respectively, for SPI; 14, 31, 55, for RDI; 21, 40, 38, for RAI; and 35, 23, 41, for PNI. By comparing the average index values to the yearly values and taking into account the historic droughts of 1984 and 2002, as well as the historical wets of 1947, 1965, 2003, and 2013, the index performances for the case study may be ranked as SPI, RAI, RDI, and PNI. On the other hand, Table 5 shows that the SPI index performs well in successive month precipitation accumulations and yearly precipitation. However, it lags in recognizing the dry drought classes (ED, VD, and MD) due to dominance and the presence of infrequent or zero precipitation values, particularly at the beginning and conclusion of the rainy season months (May and October). The SPI detects no dry frequency despite the period having a drought. However, the SPI formula is based on subtracting precipitation mean from precipitation. Zeros and rare rain play a significant role in increasing the season’s variance.

Table 4. Seasonal (monthly and annual) drought frequencies for SPI, RDI, RAI, and PNI.

Drought Class (DC)	[SPI, RDI, RAI, PNI]							
	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8
		May	June	July	August	September	October	Annual
7 EW		6, 3, 6	3, 3, 3	3, 4, 4	2, 4, 3	2, 2, 4	6, 2, 5	2, 4, 5
6 VW		1, 2, 2	6, 3, 6	2, 5, 5	3, 5, 4	4, 4, 5	0, 2, 2	5, 6, 6
5 MW		2, 2, 3, 28 *	2, 3, 5, 28 *	5, 5, 7, 23 *	6, 5, 15, 30 *	4, 5, 8, 26 *	6, 2, 8, 25 *	4, 6, 8, 24 *
4 N		66, 20, 32, 10	52, 24, 31, 17	53, 28, 35, 29	53, 25, 30, 18	55, 26, 30, 20	64, 18, 25, 9	49, 29, 30, 33
3 MD		0, 7, 8, 6	12, 8, 9, 6	9, 8, 12, 15	8, 9, 12, 14	7, 9, 17, 18	0, 7, 8, 9	11, 9, 11, 16
2 VD		0, 9, 11, 4	0, 10, 16, 4	3, 10, 7, 5	3, 10, 7, 3	3, 11, 6, 5	0, 9, 17, 4	2, 10, 11, 2
1 ED		0, 32, 13, 27	0, 24, 5, 20	0, 15, 5, 3	0, 17, 4, 10	0, 18, 5, 6	0, 35, 10, 28	2, 11, 4, 0
Wet%		12-9-14-37	15-12-19-37	13-19-21-31	15-19-29-40	13-15-23-34	16-8-20-33	15-21-25-32
N%		88-27-43-14	69-32-41-23	71-37-47-39	70-33-40-24	74-34-40-27	84-24-33-12	65-39-40-44
Dry%		0-64-43-49	16-56-40-40	16-44-32-30	15-48-31-36	13-51-37-37	0-68-47-55	20-40-35-24

* represents the three PNI wet classes (EW, VW, and MW).

Table 5. Monthly cumulative precipitations SPI drought frequencies.

DC.	Seasonal Cumulative Precipitation SPI Frequencies					
	M [1]	M [1 + 2]	M [1 + 2 + 3]	M [1 + 2 + 3 + 4]	M [1 + 2 + 3 + 4 + 5]	M [1 + 2 + 3 + 4 + 5 + 6]
7 EW	6	4	2	2	2	2
6 VW	1	2	4	2	7	5
5 MW	2	5	6	4	4	4
4 N	66	51	52	56	49	49
3 MD	0	13	8	5	9	11
2 VD	0	0	2	5	2	2
1 ED	0	0	1	1	2	2
	Drought occurrences percentage [Wet (MW + VW + EW), Normal, Dry (MD + VD + ED)]					
Wet%	12	15	16	10	17.5	15
N%	88	68	69	75	65	65
Dry%	0	17	15	15	17.5	20

Furthermore, detailed explanations of columns 2 to 7 of Table 4 demonstrate and affirm with the greater justification that the SPI index is the best of the three indexes. For example, Column 5 (August) indicated that the total wet, normal, and dry periods are as follows: The wet SPI, RDI, RAI, and PNI values were 11, 14, 22, and 30; the normal SPI, RDI, RAI, and PNI values were 53, 25, 30, and 18; and the dry SPI, RDI, RAI, and PNI values were 11, 36, 23, and 27. As previously stated, August rainfall, with its valuable hydrological characteristics, impacted shaping the hydrologic regime of the data under consideration [37]. It appears to have a well-known influence on shifting the positively skewed rainfall direction to the negatively skewed approach. Thus, hydrologically, it is considered the wettest and most fruitful month over the years, and for this reason, it has been considered for a more detailed explanation. Thus, the PNI result was 30 (40%) wet years, 27 (36%) dry years, and only 18 (24%) normal years, the RAI result was 22 (29%) wet years, 23 (31%) dry years, and 30 (40%) normal years, the RDI result was 14 (19%) wet years, 36 (48%) dry years, and 25 (33%) normal years, and the SPI result was 11 (15%) wet years, 11 (15%) dry years, and 53 (70%) normal years. As a result, the PNI and RDI produced inconsistent and contradictory results regarding the dry period percentages in the semi-arid savanna region(s). In contrast, the RAI index produced relatively comparable results. Furthermore, when the seasonal monthly drought frequencies of the three indices are compared for the remaining hydrological months, the results clearly indicate and justify a discrepancy with the hydrological data characteristics (Table 4).

Table 5 shows the analysis of monthly cumulative rainfall for the reliable index SPI. The letter M represents a month in this table, and the numbers 1 through 6 represent May

through October. As a result, the outcome gives the annual rainfall (last column) when the successive rainfall is completed. The results show that May and October had relatively limited influence on drought frequencies, with August, July, and September being the most prominent months [25]. August and July increased typical DC frequency percentages (68 to 69 to 75), while June and September saw a fall (88 to 68 and 75 to 65). In contrast, October altered the results by raising dry DC percentages (17.5 to 20), reducing wet DC percentages (17.5 to 15), and leaving the usual DC percentage unchanged (65). Monthly drought analysis plays an essential role in water resource planning and management, particularly for agricultural water demand [3,26] (in irrigation or crop water requirements).

There are no significant differences in the mean, standard deviation, or peaks of May and October precipitation [27,37], as shown in Figure 3. Precipitation frequency patterns in June and September are depicted the same way but with slight differences in their peaks and substantial variations in their means (47.5 and 69.9). There are no notable differences between the two (1.01 and 0.97). July and August (the two mid-months) differed significantly from the rest of the year, with the latter having a mean of 127.1 and a standard deviation of 50.9. Both were positively skewed at 0.85 and 0.4, respectively. Figure 4 illustrates the effect of monthly accumulated precipitation on frequency histograms for the cumulative rainfall data for the SPI index drought frequencies.

Moreover, the time series for annual precipitation based on the variations of the series around the standard deviation of the ground precipitation data was analyzed based on the deviation zones or ranges around the hydrological mean of the data, Figure 6. Thus, throughout the study period (1943–2017), the pattern indicates the occurrence of (1) 2 extremely drought years for a zone below the mean -2 Stdev. (1984 and 2002); (2) 2 extremely wet years for zone above the mean $+2$ Stdev. (1949 and 2013), as shown in Figure 6, there are alarms on the red circles, the first 2 are positive, and the last 2 are negative hydrological, this matches with historical rain characteristics; (3) 13 precipitations occur within the zone between -1 Stdev., and -2 Stdev.; (4) 9 precipitation occurs within the zone between $+1$ Stdev. and $+2$ Stdev.; (5) negative precipitation trend [38] started in the mid 60 towards its lowest in the early 80, then turned positive by the end of 80. Since that time, it tells to know the general future for the trend pattern is positively oriented. Standard deviation zone chart results coincided with the SPI index result, as remarked before, and this result reveals the superiority of the SPI over other indices.

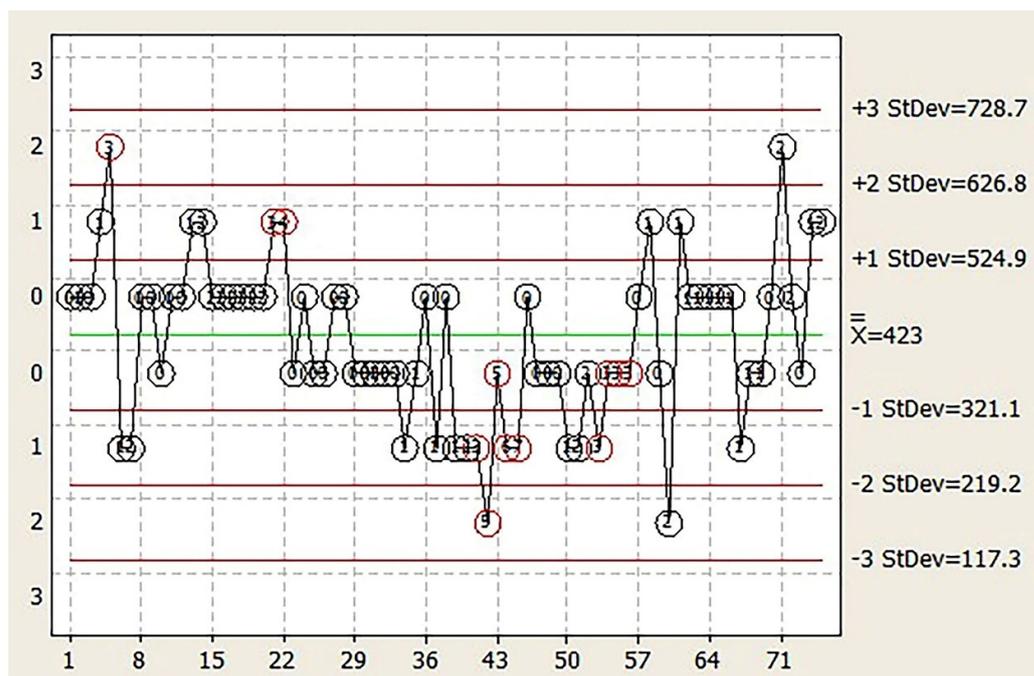


Figure 6. Zone chart for data series (deviation of the standard deviation about the mean).

Most previous drought analysis studies used daily, monthly, and/or annual precipitation data. Besides the monthly and annual data, this study also conducted the successive cumulative monthly precipitation data using the SPI drought index. Using successive cumulative monthly precipitations improves the monthly approach by providing results for the specified month(s) and the following month(s) and capturing annual results by the end of the rainy season. For more detailed explanations, see Tables 3–5. Furthermore, it gives and justifies another more practical approach for the drought index (SPI), in that the SPI index can be used not only for monthly or annual analysis but also as a more useful approach for successive cumulative monthly precipitation (rainfall). The evidence is that it gives and considers a clear weighted effect for each month on how the month shapes the hydrological regime features throughout the rainy season. For this study, the shaping effect appears as the specified month's effect on the most important hydrological characteristics; the skewness, the standard deviation, the drought frequency, and its percentage, etc. It also estimates the points or percentages of gains and losses in the hydrological regime features (positive and negative shifts). It can play an essential role and provide good guidance in water resources planning and management. As a result, it will assist water resource planners and users in predicting and estimating monthly fluctuations in precipitation, as well as the precipitation surplus and deficit, particularly in agricultural water usage concerning specific crop types and crop(s) and irrigation water requirements. Thus, this study justifies and reveals that the SPI index is the best of the other three indices for the case of Nyala. The SPI index can be used with successive cumulative monthly precipitation. The subsequent application results cover both the monthly and annual time scales and provide a clear explanation of the month(s) influences on the hydrological regime in detail. Finally, this study results also confirm that not the monthly but the subsequent cumulative monthly drought analysis plays an essential role in water resource planning and management, particularly for agricultural water demand (in irrigation or crop water requirements).

4. Conclusions

The study estimates, evaluates, assesses, and compares the performances of four drought indices: the SPI, the RDI, the RAI, and the PNI. Thus, the following conclusions for drought detection in Nyala city and region are drawn.

1. The SPI and the RAI indices performed similarly for drought detection with minor variations. Furthermore, a comparative assessment of the long-term historical data, hydrological characteristics, and their frequency of occurrences are considered. This reveals that the SPI index is more reliable than the RAI index.
2. The PNI and the RDI indices performed similarly for drought detection in some drought classes, especially for the normal class (DC 4–N). Still, they showed high variations in drought extremes (dry and wet periods). Results also demonstrate that both the PNI and the RDI declare extremely dry drought frequency more than the real situations in the long-term historical frequency. Furthermore, the PNI index also aggregates the three wet period classes (EW, VW, and MW) into one class (≥ 110). This complicates the assessment in detailed comparison features.
3. Generally, the SPI revealed the best for annual data drought detection, followed by the RAI, the RDI, and the PNI. Therefore, SPI seems to be a more reliable index to evaluate droughts for the site investigated.
4. Further studies are recommended for this study to use the Decile Index (DI), Indian Ocean Dipole (IOD), El Niño–Southern Oscillation (ENSO), SPI, and the RAI to clearly explain the multiannual variability of temperature and precipitation. A combination of precipitation-based and remote sensing-related indices can offer an advantage for drought evaluation and assessment.
5. It may be useful to conduct seasonal—monthly based drought assessment in conjunction with different water usage scenarios, especially in irrigation and crops water requirements. Such studies are useful and can guide water resources planners and

managers to understand the seasonal fluctuations and variations to mitigate drought effects and their consequences impacts on various water usage sectors.

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