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Exploring the Effectiveness of Modified Z Score for Drought Monitoring: A Comparative Study using Innovative Comparison Analysis

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Abstract

Monitoring meteorological drought requires reliable methods to determine when, how long, and how severe drought events are. Although several drought indices exist, questions persist regarding their suitability, comparability, and effectiveness across different climatic contexts. This study aimed to evaluate the effectiveness of modified Z-Score (mZS) with respect to Rainfall Anomaly Index (RAI), and Z-Score Index (ZSI) using rainfall data (1977 – 2020) of Dadin-Kowa Town in Gombe State Nigeria. This study suggested Innovative Comparison Analysis (ICA), to evaluate the performance of mZS with the other indices under review. Sen's Slope of Innovative Trend (Slope of IT), Mann–Kendall Test, and Sen's Slope were used for further evaluation of the trend reported by the indices under review. The result revealed that mZS, RAI, and ZSI consistently identified an increasing trend in rainfall across annual, growing seasonal, and monthly scales except for May, which showed a decreasing trend in Dadin-Kowa from 1977 to 2020. The ICA demonstrated a strong agreement between mZS and ZSI, and a relatively moderate agreement between mZS and RAI. The study concludes that mZS proved effective and statistically comparable to the established indices. Its consistent alignment with other indices highlights its potential for broader application in localized drought monitoring. It is recommended that Future drought monitoring frameworks in any given ecological setting should consider integrating mZS.

Keywords: Anomaly, Dadin-Kowa, Drought, Meteorological, modified Z Score, Z Score

1.0 Introduction

Rainfall plays a significant role in the provision of environmental services. It recharges surface and underground water, supplies vegetation, agriculture, and other living organisms beneath the surface, and puts down the skin temperature and that of the air near the surface of the earth. However, abnormal departures of rainfall affect the aforementioned environmental services which results in meteorological drought. This form of drought is governed by low rainfall (below the normal trend) and increased air temperature. Some of the signs of drought occurrence after fallen of rainfall below normal include an increase in solar radiation, temperature, evapotranspiration decline in cloudiness, and humidity [1], [2], others include a decrease in soil moisture, stream flow, dam/lake storage and underground water level (hydrological drought). However, if the incidence persists over time agricultural and socio-economic droughts will manifest from the lingering effect of the aforementioned forms of drought.

Researchers have defined drought based on variables and regional perception [3], [4], [5], [6], that the events should be fully defined concerning the long-term mean behavior [7]. Several studies were conducted as a result of the occurrence and reoccurrence of drought in Northern Nigeria [8], [9], [10], [11]. Drought events can't be avoided [7], but preparedness and early warning mechanisms can be put in place to inform the administrative and decision-making instruments and manage their impact.

Precipitation is common in exploring meteorological drought [12], [13] using some specific indices namely: Rainfall Anomaly Index RAI, [14], Deciles Index DI [15], Standardized Precipitation Index SPI [16], Bhalme and Mooley Drought Index BMDI [17], Drought Severity Index DSI [18], Effective Drought Index EDI [19], Percent of Normal Index PNI [20], National Rainfall Index NRI [21], Reconnaissance Drought Index RDI [22]. Several researchers have evaluated the performance of some of the aforementioned drought indices. For instance, [23] explored the performance of SPI, ZSI, and CZI in some selected areas in China on a scale of 1, 3, 6, 9, and 12 months and reported that the indices performed well in identifying and evaluating drought. [24] compare SPI, RAI, and Z-Score and reported a similar performance on a 12-month scale, [25] explored the performance of seven indices, the result revealed that SPI, CZI, and Z-Score had similar behavior in detecting drought and identifying slow onset of the phenomenon, [26] tested the performance of RDI and SPI in Iran's different climatic conditions and reported an overall similar behavior. [27] Evaluated six indices in Iran's different climatic zones and concluded that ZSI, CZI, and MCZI could be employed in the prediction of meteorological drought. Notwithstanding, [28] evaluated the performance of PNPI, RAI, and SPI in which they reported separate classes of drought events. [29] Reported that time scale plays a significant impact on the performance of the drought indices and that there is no specific index for a region and time scale. The objectives of this study include: (i) Assess the effectiveness of the modified Z-Score index for monitoring meteorological drought with respect to RAI, and ZSI, (ii) Introduce Innovative Comparative Analysis for performance test between two data sets/indices, (iii) Explore the trend characteristic of rainfall around Dadin-Kowa and its environs.

2.0 Materials and Method

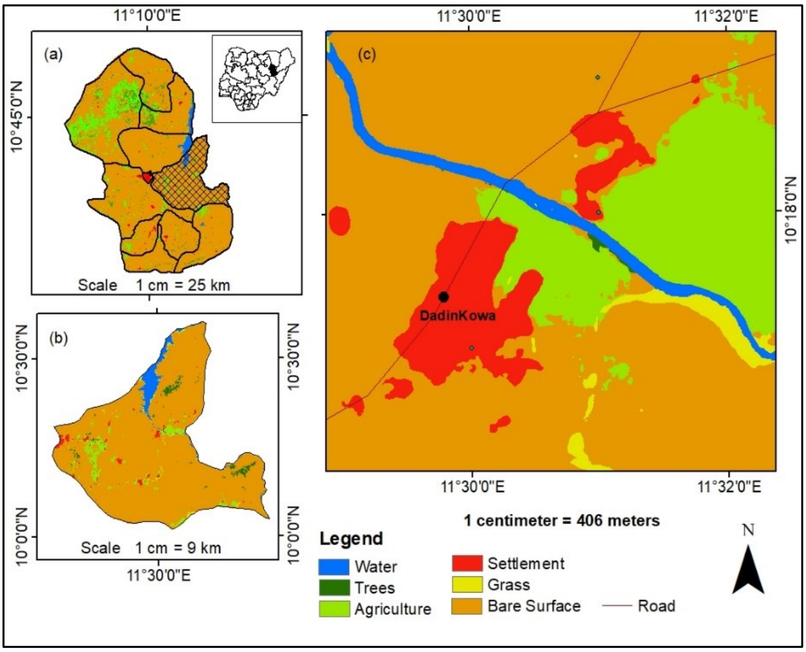
2.1 Study Area

Dadin Kowa is the study area presented in Figure 1. The study area is relatively situated about 37 km East of Gombe Metropolis, in Yamaltu-Deba Local Government Area of Gombe State. The climate is influenced by the movement of the two air masses which lead to the occurrence of district seasons. The rainy season in the study area generally spans between May and October. The rainfall peaks occur either in July or August of every year. The study area had the annual mean, minimum, and maximum rainfall from 1977 to 2020 of about 842.7mm, 506.4 mm (1987), and 1119mm (2000) respectively. The study area also recorded a total of 2,490 rainy days from 1977 to 2020 with approximate mean, minimum, and maximum rainy days of 57 days, 38 days (1991), and 69 days (1982). The dry season covers the rest of the months that is November to April of every year. The hottest period spans between March and April, just before the onset of the rainy season, with the highest monthly maximum temperature of 42^0C from 1983 to 2020. The degree of temperature around this period is interrupted in May by the onset of the first rainfall. The lowest temperature in the study area is recorded between December – January at the peak of the Harmattan with the lowest monthly minimum temperature of 13^0C during 1983 – 2020. The minimum temperature of the study area particularly the annual mean, minimum and maximum temperatures from 1983 to 2020 stood at about 21.4^0C, 17.8^0C (2018), and 23.6^0C (2009) respectively. The study area also recorded the maximum temperature particularly the annual mean, minimum and maximum temperatures from 1983 to 2020 stood at about 34.7^0C, 31.1^0C (1986), and 36.4^0C (1990) respectively. The mean temperature of the study area particularly the annual mean, minimum and maximum temperatures from 1983 to 2020 stood at about 28^0C, 25.7^0C (2015), and 29.5^0C (2009) respectively. The major occupations of people living in the study area are farming, fishing, and trading. The presence of the Dadin-Kowa dam in the area plays a significant role in fishing and irrigation, especially twice a year. The major crops cultivated in both irrigation and rainfed include: rice, sorghum, millet, cowpea, ground nut, beni seed, melon, bambara nut, and maize.

Figure 1: Land use land cover of the study area (a) Gombe State, Nigeria, (b) Yamaltu Deba L.G.A., (c) Dadin-Kowa Town

2.2 Methods

In this article, monthly rainfall data from 1977 to 2020 was obtained from Dadin-Kowa Meteorological Station of Upper Benue River Basin Development Authority, Dadin-Kowa Area Office in Yamaltu-Deba L.G.A. Gombe State, Nigeria.



2.2.1 Modified Z-Score

This study intends to explore the potential and effectiveness of modified Z-score in meteorological drought monitoring. The rationale for this investigation lies in its theoretical advantages and statistical robustness, which may enhance its application in drought monitoring. The approach involves adapting the concept and renaming the core variables to align with rainfall data. As formulated in Equation (1), mZS quantifies deviations from the median rainfall, offering a potentially more stable measure of anomaly compared to traditional mean-based indices. This study seeks to determine the reliability and responsiveness of mZS in identifying drought events, particularly their frequency, severity, and temporal trends, and to evaluate whether it can serve as a suitable alternative or complement to conventional drought indices. The study suggested mZS thresholds for the classification and interpretations of meteorological drought which range from extremely wet = ≥ 1.5, severely wet = 1.0 to 1.49, moderately wet = 0.5 to 0.99, near normal = 0.49 to -0.49, moderately dry = -0.5 to -0.99, severely dry = -1.0 to -1.49, extremely dry = ≤ -1.5.

$$\text{mZS} = \frac{0.6745\ (P - \acute{P})}{MAD_P} \tag{1}$$

Where: 0.6745 = constant, P = rainfall in year$_i$, season$_i$, or month$_i$, $\acute{P}$ = median value of rainfall in year$_i$, season$_i$, or month$_i$, MAD_P = median absolute deviation of rainfall in year$_i$, season$_i$, or month$_i$.

The Justification for the selection of RAI and ZSI as benchmark indices for evaluating the performance of the mZI is based on their wide application [30], [31], [23], [24], statistical robustness, and relevance to the climatic context of semi-arid regions like Dadin-Kowa.

Both RAI and ZSI are anomaly-based indices that offer standardized metrics for detecting meteorological drought, making them suitable for comparative analysis with mZI. RAI is particularly for rainfall-based drought studies, making it sensitive to extremely dry and wet years. This is important in a region like Dadin-Kowa, where rainfall variability significantly influences agricultural and hydrological outcomes. On the other hand, ZSI is based on standard statistical deviation from the mean and is known for its application in climate time series analysis. Its use allows for direct statistical comparison with mZI, Furthermore, both indices have been applied in similar ecological contexts, [1], [2], [27], [32], [33], which provide a relevant basis for evaluating how well mZI reflects drought signals in Dadin-Kowa. Comparing mZI against RAI and ZSI helps establish its validity, sensitivity, and added value in drought detection.

2.2.2 Z-Score (ZSI)

ZSI determines the deviation of rainfall from its normal trend. According to [32], the ZSI index is relatively unknown as a drought index. However, researchers have applied it in drought monitoring: [1], [23], [24], [25], [27]. Z-score is given in equation (2)

$$Z\ Score = \frac{Pi - \bar{P}}{\sigma} \qquad (2)$$

Where: Pi = rainfall in $year_i$, $season_i$, or $month_i$, $\bar{P}$ = average rainfall (climatology) in $year_i$, $season_i$ or $month_i$, σ = standard deviation of rainfall in $year_i$, $season_i$ or $month_i$.

2.2.3 Rainfall Anomaly Index

RAI was first developed by [14]. It is widely used [1], [2], [28], [30], [31], [33], [34]. The index uses positive anomaly and negative anomaly. If the observed rainfall is more than the mean rainfall, the RAI is said to be positive (equation 2) and if the observed rainfall falls below the mean, then the RAI is said to be negative (equation 3). RAI can be used to evaluate monthly, seasonal, or yearly rainfall and explore the intensity and frequency of dry and rainy conditions of a given geographical region. RAI classification includes: ≥ 3.0 = extremely wet, 2.0 – 2.99 = very wet, 1.0 – 1.99 = moderately wet, 0.50 – 0.99 = slightly wet, 0.49 – -0.49 = near normal, -0.50 – -0.99 = slightly dry, -1.0 – -1.99 = moderately dry, -2.0 – -2.99 = Very wet, ≤ -3.0 = extremely dry [14]. The Index is given in equations 3 and 4.

$$RAI = 3\,\frac{N - \bar{N}}{M - \bar{N}} \qquad \text{For Positive Anomaly} \qquad (3)$$

$$RAI = -3\,\frac{N - \bar{N}}{X - \bar{N}} \qquad \text{For Negative Anomaly} \qquad (4)$$

Where: N = rainfall in $year_i$ $season_i$ or $month_i$, $\bar{N}$ = mean rainfall in $year_i$, $season_i$ or $month_i$, M = mean of the ten highest rainfall in $year_i$, $season_i$ or $month_i$ recorded for the positive anomaly, X = mean of the ten lowest rainfall in $year_i$, $season_i$ or $month_i$ recorded for the negative anomaly, Positive anomaly =$N \geq \bar{N}$, and Negative =$N < \bar{N}$.

Slope of Innovative Trend Analysis (S)

The indicator determines the relationship between the first and second halves of a given parent data Trend indicator (S) [35], is given as:

$$S = \frac{2(\bar{y}_2 - \bar{y}_1)}{n} \quad (5)$$

y_1 = mean of the first half of sub-series, y_2 = mean of the second half of the sub-series, n = number of observations, 2 is constant.

2.2.4 Mann-Kendal Trend Test

Mann–Kendall Test is a widely used method for trend detection especially in long-term hydro-meteorological data [36], [37]. It is given in equation (6):

$$Z_{MK} = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, & if\, S > 0 \\ 0, & if\, S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, & if\, S < 0 \end{cases} \quad (6)$$

ZMK = > 0
Trend increases

ZMK = < 0
Trend decreases

Where: S = test statistics, Var (S) = Variance Statistics

Mann Kendall statistic S of the series is given in equation (7)

$$S = \sum_{j=1}^{n-1} \sum_{j=k+1}^{n} \text{sgn}\,(x_j - x_k) \quad (7)$$

Where: n = total number of data, x_j and x_k = data points of time i and j,
The sign function is denoted as sgn (x_j - x_k) and is given in equation (8),

$$\text{Sgn}\,(x_j - x_k) = \begin{cases} +1, if\,(x_j - x_k) \\ 0, if\,(x_j - x_k) \\ -1, if\,(x_j - x_k) \end{cases}$$

The variance S is computed using equation (9)

$$Var(S) = \frac{1}{18}\, n(n-1)(2n+5) \sum_{f=1}^{h} t_f\,(t_f - 1)(2_f + 5) \quad (9)$$

2.2.5 Sen's Slope Estimator

Sen's slope estimator (Q) determines the magnitude of the trend of a given data, along with the Mann–Kendall test. The estimator (slope Q) calculates the slopes for all the pairs of ordinal time points by using the median of these slopes as a determinant of the overall slope, using equation (10). Mann Kendal and Sen's Slope tests were conducted using XLSTAT software.

$$Q_i = \begin{cases} T_{(n+1)/n}, & n \text{ is odd} \\ \frac{1}{2}\,(T_{n/2} + T_{(n+1)/_{n,}} & n \text{ is even} \end{cases} \tag{10}$$

Where Q is Sen's slope estimator

$$T_i = \frac{x_j - x_k}{j - k}, i = 1, 2, 3, \dots\dots\dots, n, j > k \tag{11}$$

2.2.6 Innovative Comparison Analysis (ICA)

ICA is a novel statistical tool adapted and modified from Sen's Innovative Trend Analysis (ITA) [58], by transforming its conceptual design from a univariate trend detection tool into a comparative analytical tool. ICA enables a comparative evaluation of two distinct time series from a common variable, displaying their agreement or deviation over time in a visual and graphical illustration on a Cartesian coordinate system (Figure 2a). It consists of two reference lines the x-axis and the y–axis, with their intersection at (0, 0). The plot area is divided into two triangles separated by a 1:1 line, a straight line placed diagonally at an angle of 45°, the triangle above the 1:1 line is known as an overestimating triangle and the triangle below the 1:1 line is known as an underestimating triangle. ICA can be constructed by placing the individual series into separate columns i.e. first series (observed or reference data is plotted on the x-axis) and the second series (expected or test data plotted on the y–axis). Both series are sorted in descending order before plotting. The two series are then plotted against each other on a Cartesian coordinate system to present a single scatter point. The length of the reference lines (x and y axes) must be the same so that the plot area is divided equally into overestimating and underestimating triangles by a 1:1 line at an angle of 45^0 (Figure 2a). In this case, the scatter points of ICA, are concentrated above (below) a 1:1 line, which means the expected data over-estimated the observed data (under-estimated). In case, the entire scatter points fall on the 1:1 line or with insignificantly random deviations from the line, the association is said to be perfect.

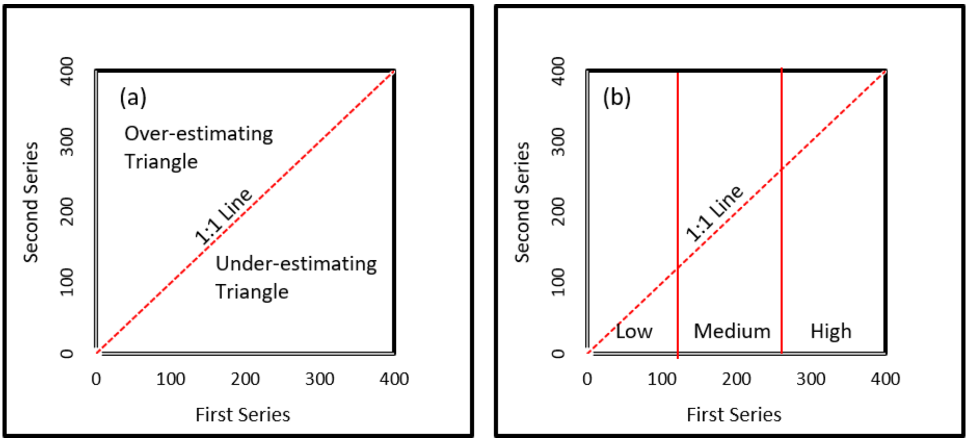


Figure 2: illustration of ICA and its components (a) ICA, (b) ICA Clusters

The ICA evaluates the variability of a given dataset, such as rainfall, by classifying the time series into three distinct clusters namely: low, medium, and high based on the magnitude of values. This classification provides both a visual and analytical tool for identifying rainfall behavior over a specified period (Figure 2b).

Low Cluster: This cluster comprises the lowest rainfall values within the time series. Scatter points are located in the lower section of the 1:1 line, representing dry periods characterized by low rainfall. This cluster helps to assess whether drought conditions are becoming more frequent and severe over time.

Medium Cluster: This cluster includes the average rainfall values in the time series. The corresponding scatter points appear around the central region of the 1:1 line, indicating periods of normal rainfall. The trend observed in this cluster offers a hint as to whether the area under study is becoming wetter or drier over time.

High Cluster: This cluster consists of the higher rainfall values in the time series. Scatter points in this group are positioned in the upper part of the 1:1 line, reflecting periods of above-normal rainfall. This cluster is useful in determining whether instances of high rainfall are becoming more frequent (thereby signaling an increased risk of flooding) or not.

2.2.7 Scientific Values of ICA

1) The novelty of the Innovative Comparative Analysis lies in its transformation of Sen's ITA from assessing the direction and magnitude of change in a univariate or single time series into a comparative analytical tool capable of evaluating the behavior of multiple data over time.
2) ICA provides a visual framework that translates time series into clusters depicting the agreement or divergence between the datasets. It improves result communication for both technical and non-technical audiences. This is critical in informing stakeholders,

such as policymakers and local planners, who rely on clear evidence to implement drought mitigation strategies.

3) ICA offers a novel methodological tool for a multi-cluster comparative approach for evaluating data or indices that can be extended beyond meteorological drought. It introduces a replicable framework that future studies can adopt or refine, contributing to methodological advancement in climate analytics.
4) ICA builds upon class-based analysis (e.g., low, medium, and high rainfall conditions), enabling researchers to examine how indices respond under different drought severities. These clusters help identify how the index behaves with respect to minor anomalies in extreme clusters or events.
5) ICA provides a structured method for assessing how well one index reflects local drought realities compared to others. ICA allows for categorical agreement analysis. This gives researchers a better understanding of where indices align or diverge especially under different rainfall regimes or drought severities. In this study, ICA helped to reveal the comparative effectiveness of mZS against established indices like RAI and ZSI.
6) ICA has a key strength in its adaptability across spatial and temporal scales be it region, localized drought assessments like single station in Dadin-Kowa, ICA offers a robust tool for analyzing annual, seasonal, or monthly trends, enabling researchers to derive measures that are appropriate for both long-term planning and short-term drought response.

3.0 Result and Discussions

The outcome of mZS analysis revealed a positive trend of annual rainfall at Dadin-Kowa over 1977-2020 with a trendline of 0.1697. The longest period of drought for the annual rainfall was three consecutive years, the result further showed reoccurrence in these periods which are: 1977-1979, 1981-1983, and 1985-1987. Among the above-mentioned years, the year 1987 was the driest year with an mZS value of -3.2 (extremely dry). On the other hand, the longest period of wet years can be identified between 2003 and 2010. The year 2000 was the wettest year with an mZS value of 2.4 (extremely wet) as in Table 1.

The result further revealed a positive trend of rainfall in the growing seasons during the period under review with a trendline of 0.1729. There were seven consecutive growing seasons from 1981-1987 with rainfall lower than normal which marked the longest period of drought within the growing seasons under consideration. The growing season of the year 1987 was ranked the driest season with an mZS value of -2.3 (extremely dry) as in Table 1. On the other hand, there were eight consecutive wet growing seasons from 2003 – 2010 with adequate rainfall which marked the longest period of wet seasons within the growing seasons under consideration. The growing season of the year 2000 was the wettest season with an mZS value of 2.0 (severely wet) as in Table 1.

A negative trend of rainfall was observed in May for the period under review with a trendline of 0.0371. On the other hand, a positive trend of rainfall was observed in June, July, August, September, and October for the period under review with a trendline of 0.1513, 0.0028, 0.1159, 0.0049, and 0.0169 respectively.

Rainfall Anomaly Index

The RAI assessment also revealed an increasing trend of annual rainfall in the study area during the period under review with a trendline of 0.172. The longest period of drought occurrence for the annual rainfall was three consecutive years, the result further showed reoccurrence in these periods which were: 1977-1979, 1981-1983, and 1985-1987. Among the drought years, the year 1987 was the driest year with an RAI value of -5.9 (extremely dry) as in Table 1. On the other hand, the longest period of wet years can be identified between 2003 and 2010. The year 2000 was the wettest year with an RAI value of 5.3 (extremely wet) as in Table 1.

The result further showed an increasing trend of rainfall for the growing seasons during the period under review with a trendline of 0.1701. The longest period of drought occurrence was seven consecutive seasons during the years 1981-1987. It was observed that the growing season of the year 1987 was the driest of the growing seasons under focus with an RAI value of -5.4 (extremely dry) as in Table 1. On the other hand, there were eight consecutive wet seasons were observed between the years 2003-2010.with adequate rainfall which marked the longest period of wet seasons within the growing seasons under consideration. The growing season of the year 2000 was classified as the wettest season of all growing seasons under review with RAI of 5.2 (Extremely wet) as in Table 1.

Decreasing trend of rainfall was observed in the month of May for the period of 1977-2020 with trendline of 0.0322. On the other hand, positive trend of rainfall was observed in the months of June, July, August, September and October for the period under review with trendline of 0.154, 0.0028, 0.1159, 0.0047, and 0.0134 respectively.

Table 1: Comparison of the Wettest and Driest years between MZS, RAI, and Z Score

	mZS		RAI		ZSI	
Variables	**Wettest**	**Driest**	**Wettest**	**Driest**	**Wettest**	**Driest**
Annual	2000 (2.4)	1987 (-3.2)	2000 (5.3)	1987 (-5.9)	2000 (2.2)	1987 (-2.6)
Growing Season	2000 (2.0)	1987 (-2.3)	2000 (5.2)	1987 (-5.4)	2000 (2.1)	1987 (-2.5)
May	1997 (3.3)	2002 (-1.6)	1997 (6.5)	2002 (-4.2)	1997 (3.0)	2002 (-1.6)
Jun	2017 (3.8)	1979 (-1.6)	2017 (6.8)	1979 (-4.4)	2017 (3.2)	1979 (-1.5)
July	2003 (2.0)	2013 (-1.4)	2003 (4.9)	2013 (-4.4)	2003 (2.1)	2013 (-1.9)
August	2019 (1.5)	1997 (-1.3)	2019 (4.5)	1997 (-4.7)	2019 (2.0)	1997 (2.0)
September	1988 (2.2)	2016 (-2.1)	1988 (5.3)	2016 (-5.3)	1988 (2.3)	2016 (-2.3)
October	2009 (3.8)	2017 (-1.4)	2009 (6.0)	2017 (-3.9)	2009 (3.0)	2017 (-1.3)

Z-Score

The outcome of the ZSI analysis revealed a positive trend of annual rainfall at Dadin-Kowa over 1977-2020 with a trendline of 0.1729. The result further showed that the longest period of drought for the annual rainfall was three consecutive years, the result further showed the reoccurrence of these conditions which are: 1977-1979, 1981-1983, and 1985-

1987. Among the above-mentioned years, the year 1987 is the driest year with a ZSI value of -2.6 (extremely dry) as in Table 1. On the other hand, the longest period of wet years can be identified from 2003 – 2010. The year 2000 was the wettest year with a ZSI value of 2.2 (extremely wet) as in Table 1.

The result further revealed a positive trend of rainfall for the growing seasons during the period under review with a trendline of 0.1697. There were seven consecutive growing seasons from 1981-1987 with rainfall lower than normal which marked the longest period of drought within the growing seasons under consideration. The growing season of the year 1987 was ranked the driest season with a ZSI value of -2.5 (extremely dry) as in Table 1. On the other hand, there were eight consecutive wet growing seasons from 2003 – 2010 with adequate rainfall which marked the longest period of wet seasons within the growing seasons under consideration. The growing season of the year 2000 was the wettest season with a ZSI value of 2.1 (extremely wet) as in Table 1.

Negative trend of rainfall was observed in the month of May for the period under review with trendline of 0.0371. On the other hand, positive trend of rainfall was observed during the months of June, July, August, September and October for the period under review with trendline of 0.1513, 0.0028, 0.1159, 0.0049, and 0.0169 respectively.

Correlation Analysis

The Graphical correlation was constructed using of scatter with smooth line and area charts in Figure 3 & 4 respectively. There exists a slight gap between mZS and RAI in Figure 4 than between mZS and ZSI in Figure 3. In the foregoing, ICA was suggested in this paper to further evaluate the residual gap that exists between the indices under focus.

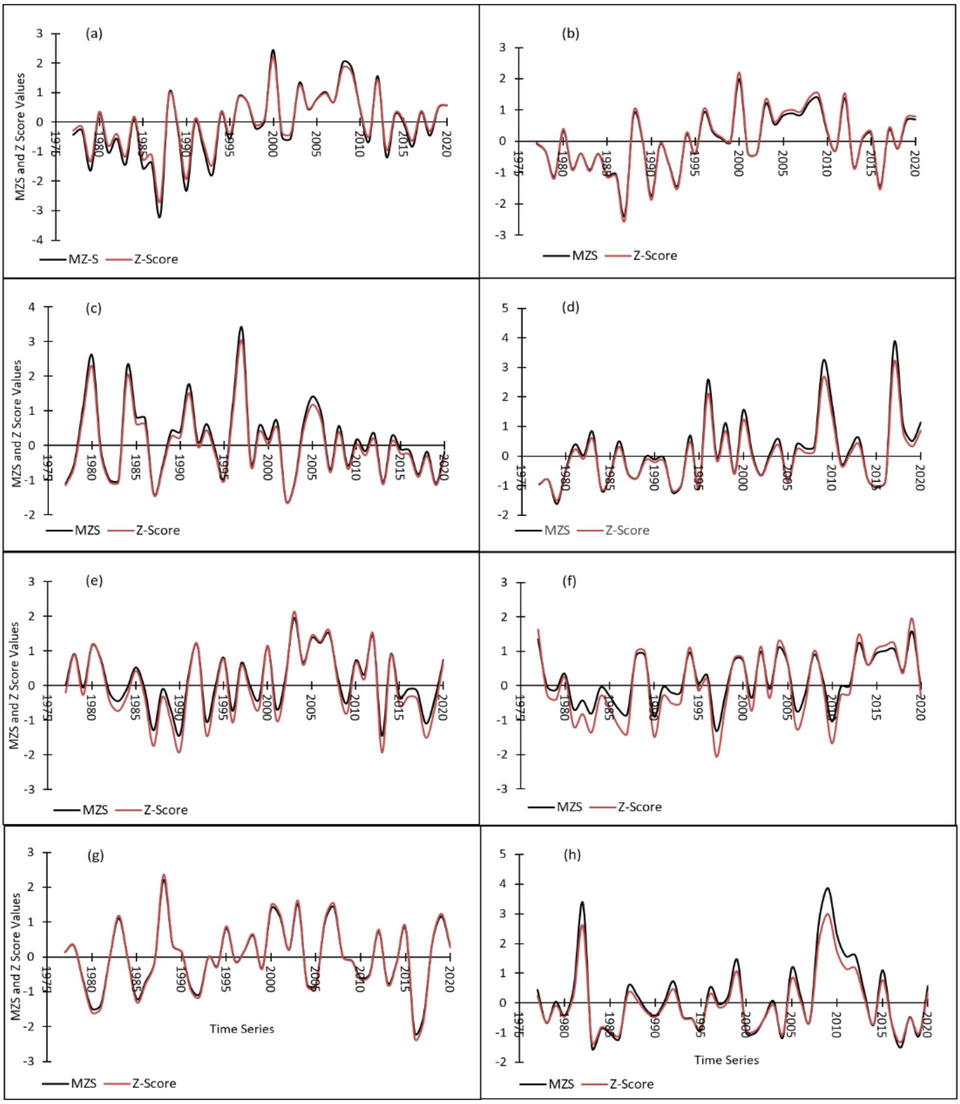


Figure 3: Presented correlation assessment between mZS and ZSI using scatter with smooth line chart: (a) Annual, (b) Growing Season, (c) May, (d) June, (e) July, (f) August, (g) September and (h) October.

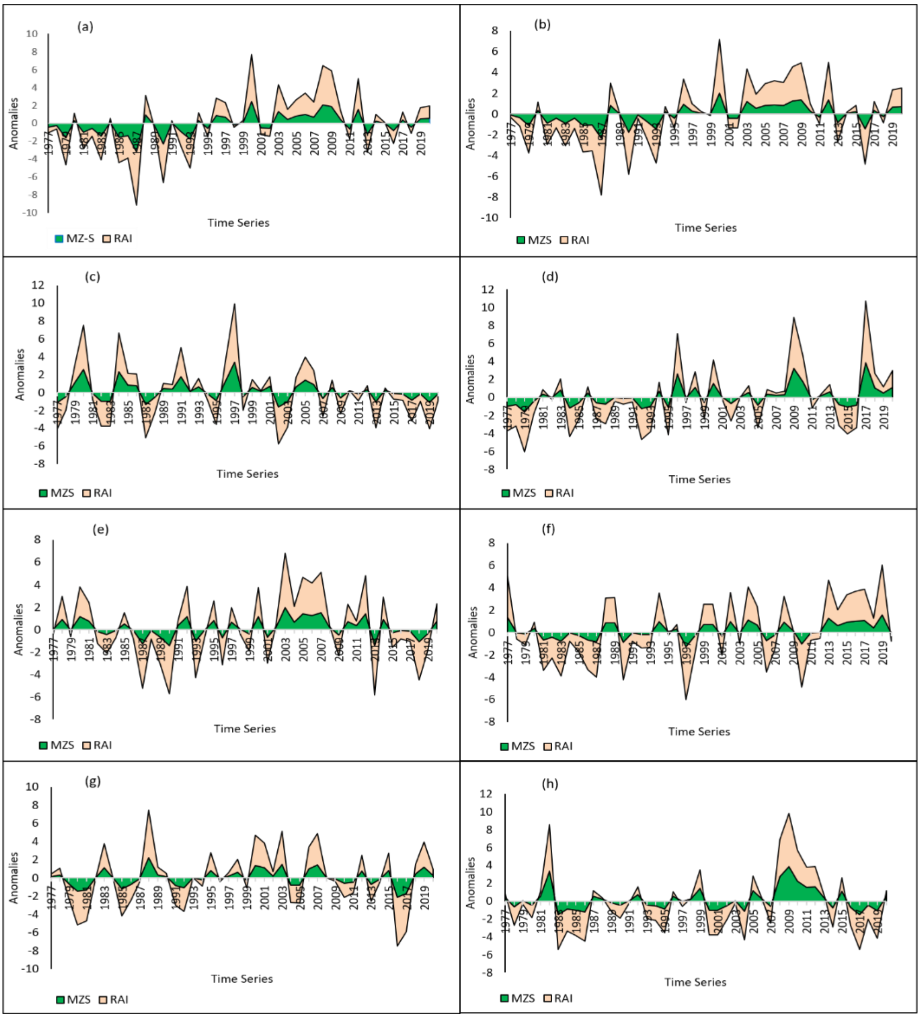


Figure 4: Presented correlation assessment between mZS and RAI using stacked area chart: (a) Annual, (b) Growing Season, (c) May, (d) June, (e) July, (f) August, (g) September and (h) October.

Innovative Comparison Analysis

Figure 5, presents the ICA between mZS and ZSI which reveals that mZS performed very well, as a significant proportion of the scatter points lies directly on a 1:1 line, particularly within the entire medium cluster, and partially within the low and high clusters. Among various periods assessed, the ICA for the growing season and the month of September in Figure 5b and g, demonstrated a near-perfect relationship with only minimal deviation observed. In the low cluster, the mZS slightly overestimated the lower values compared to ZSI, while the insignificant deviation of scatter points was also observed in the high cluster, the ZSI slightly overestimated the higher value of mZS.

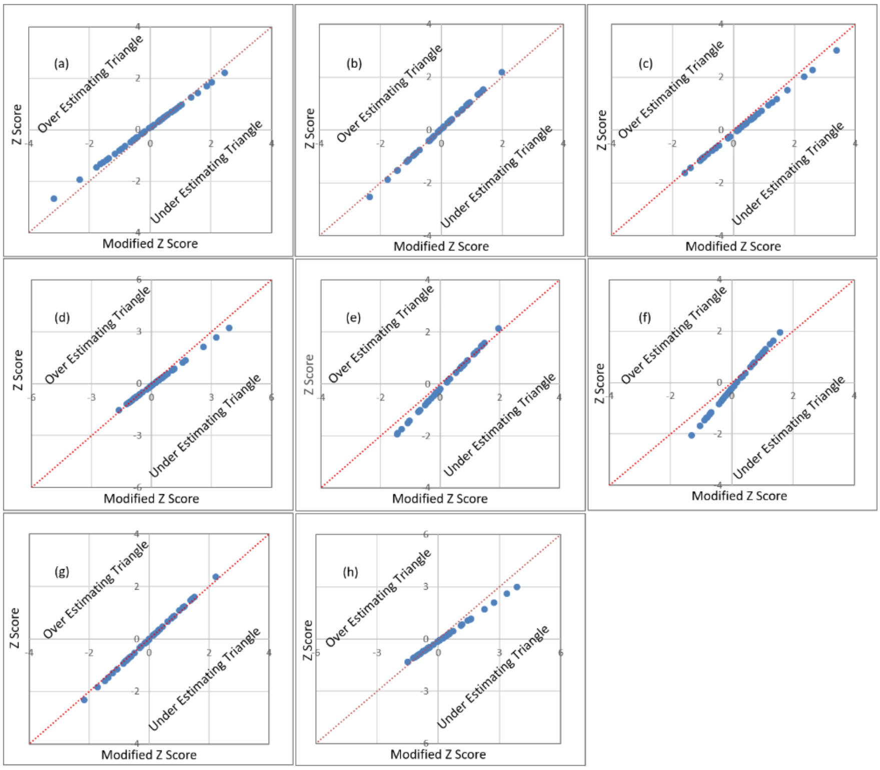


Figure 5: Present a very good comparison assessment between mZS and ZSI (a) Annual, (b) Growing Season, (c) May, (d) June, (e) July, (f) August, (g) September, (h) October

The ICA of May, June, and October (Figure 5c, d, and h), revealed a slight deviation of scatter points within in high cluster, attributed to the mZS slightly overestimating the higher values of ZSI. Similarly, the ICA for the annual dataset and the months of July and August (Figure 5a, e, and f), showed minor deviation in both low and high clusters. The Annual ICA the low cluster exhibited slight deviation of scatter points where mZS underestimated the lower values of ZSI. Conversely, in the high cluster, the mZS slightly overestimated the higher values of ZSI. The ICA of July and August portrayed a slight deviation of a few scatter points into the low cluster based on the account that the mZS slightly overestimated the lower values of ZSI. Whereas in the high cluster, there observed slight deviation of very few scatter points on the fact that ZSI overestimated slightly the higher values of mZS. The strong alignment between the indices across the clusters informs the suitability of mZS, as a statistically reliable tool for metrological drought monitoring and evaluation. The insignificant deviation observed in the lower and upper rainfall extremes points to the potential of mZS to serve as a more sensitive indicator for detecting drought onset or excess rainfall. This sensitivity can be harnessed in providing stakeholders with more timely information for decision-making in agriculture, water allocation, etc.

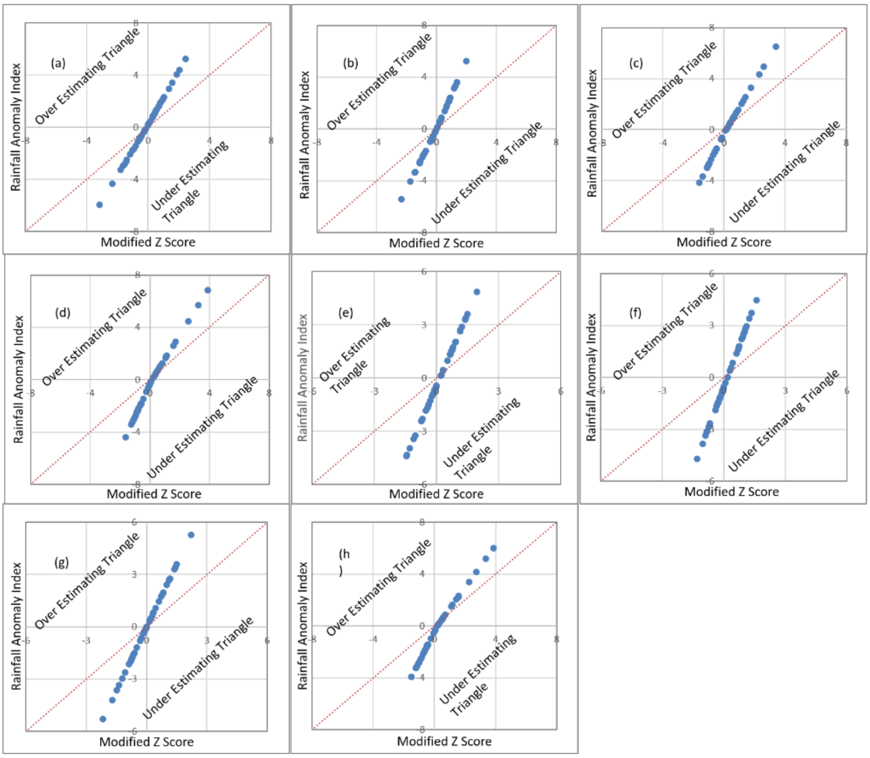


Figure 6: Present the comparison assessment between mZS and RAI (a) Annual, (b) Growing Season, (c) May, (d) June, (e) July, (f) August, (g) September, (h) October

Figure 6, presented the ICA result between mZS and RAI which pointed out that there exists a residual gap between the two indices. This is evidenced by the fact that very few scatter points align with the 1:1 line, primarily within the medium cluster, while points in the low and high clusters deviate significantly. This pattern of deviation appeared to be consistent across all ICA plots in Figure 6. The scatter point deviation in the low cluster suggests that RAI underestimated the lower values of mZS. Conversely, the deviation in the high cluster indicates that RAI overestimated the higher values of mZS. The significance of these findings indicated that mZS relies on the median and median absolute deviation as its central metrics which provides a statistically robust approach to detect anomalies in highly variable datasets like rainfall. This is particularly relevant in regions like Dadin-Kowa, where rainfall distribution is highly variable and often interrupted by extreme wet and dry years. On the other hand, RAI uses the mean of the entire data and the mean of the ten highest and lowest of the data, which makes it highly sensitive to outliers. This methodological difference explains why RAI tends to diverge more significantly from mZS in the low and high clusters of the ICA. In other words, this amplification of outliers by RAI particularly in the high and low extremes leads to an overestimation of wet conditions and an underestimation of dry events or vice versa. mZS relies on the constant value and median absolute deviation to moderate the influence of outliers, in turn, offers a more stable anomaly detection tool. The ICA results reflect this clearly in the low cluster where RAI underestimates drought severity compared to mZS, while in the high cluster, it overestimates the wet conditions. This disparity is particularly significant in drought monitoring where sensitivity to marginal but critical deviations in rainfall is essential for early warning and mitigation. RAI requires a modification of distributional assumptions to perform better in semi-arid or tropical climates where the rainfall pattern is highly variable. However, mZS does not rely on near-normal distribution, making it more flexible and adaptable to a wider range of climatic environments. This dictates the more consistent placement of mZS values on a 1:1 line in the medium cluster of the ICA plots and its divergence from RAI in the low and high clusters where the impact of distributional skew becomes most pronounced.

Table 2: Trend Analysis of Modified Z Score

		Modified Z-Score			Z Score			Rainfall Anomaly			
Variables	**Observation**	**SIT**	**SS**	**Z**	**SIT**	**SS**	**Z**	**SIT**	**SS**	**Z**	**TD**
Annual	44	0.05	0.03	0.27	0.04	0.03	0.27	0.10	0.07	0.27	▲
Growing	44	0.03	0.03	0.29	0.04	0.03	0.29	0.09	0.07	0.29	▲
May	44	-0.02	-0.14	-0.17	-0.01	-0.01	-0.14	-0.04	-0.03	-0.14	▼
June	44	0.03	0.03	0.26	0.02	0.02	0.26	0.06	0.07	0.26	▲
July	44	0.01	0.003	0.02	0.01	0.004	0.02	0.04	0.008	0.02	▲
August	44	0.02	0.02	0.24	0.04	0.02	0.24	0.07	0.06	0.24	▲
September	44	0.008	0.01	0.08	0.009	0.01	0.08	0.02	0.02	0.08	▲
October	44	0.02	0.01	0.06	0.01	0.008	0.06	0.03	0.01	0.06	▲

NB: SS – Sen's Slope, SIT – Slope of Innovative Trend, Z – Z Statistic, TD – Trend Direction

Table 2, presents the trend analysis conducted on the indices under consideration proving the previous result presented by the individual index. This increase in rainfall in the annual and growing season rainfall across the period under study suggests a notable shift in the hydrological regime in Dadin-Kowa and is consistent with [38]. This trend has significant implications for water resource availability in the region which enhances groundwater recharge, improves river flows, and sustains the capacity of Dadin-Kowa Dam, which serves purposes ranging from irrigation to hydroelectric power generation. For the agricultural sector, higher rainfall during the main growing season (June to October) provides favorable conditions for crop development, potentially supporting higher yields and allowing for the cultivation of water-intensive crops. However, the benefits of increased rainfall are highly dependent on its intra-seasonal distribution; erratic or intense rainfall events can result in runoff, soil erosion, or localized flooding, undermining the potential gains. Thus, while the upward trend appears promising, it necessitates careful management to ensure that the additional water resources translate into sustainable use. [38] Stressed that the current trend of rainfall in Gombe and its environment may affect soil moisture, flooding, and ecological changes.

The observed decreasing trend of rainfall in May is concerning, as this month marks the onset of the rainy season in the study area and is critical for land preparation and early planting. A reduction of rainfall in May across the forty-three years under review implies a delayed onset of the growing season, which can disrupt the planting calendar, especially for crops that require early sowing. This delay shortens the effective growing period, potentially exposing crops to terminal drought toward the end of the season. Farmers who rely on consistent May rainfall may face increased uncertainty, reduced yields, or even crop failure if timely planting is missed. Additionally, this decline in early rains might necessitate a shift in agronomic practices, such as using short-duration or drought-tolerant crop varieties, adjusting planting schedules, and integrating soil moisture conservation techniques. From a policy perspective, these shifts underline the importance of early warning systems and climate-smart agricultural advisories that account for changes in seasonal rainfall dynamics.

4.0 Conclusion and Recommendations

This study assessed the effectiveness of the mZS in monitoring meteorological drought, particularly in the semi-arid context of Dadin-Kowa, northeastern Nigeria. The mZS demonstrated strong alignment with established indices such as the ZSI and RAI, showing a consistent upward trend in rainfall during the annual period, growing season, and key months (June to October), except May, which exhibited a declining trend. The proposed ICA proved useful in evaluating the behavioral association between indices, revealing a strong agreement between mZS and ZSI, and a relatively moderate between mZS and RAI.

However, the limitation of this study is that it is based on a single weather station, which is restricted to a given area. Additionally, the application of ICA, while methodologically innovative, is still in early development and may benefit from broader validation across different ecological zones and datasets. Future research should explore multi-station, regional-scale assessments, incorporate other drought indices such as SPI, EDI, etc., and test the ICA across diverse environmental variables. In conclusion, while mZS appears effective as a context-sensitive and statistically robust indicator, its broader applicability requires further empirical scrutiny to uphold scientific integrity and support informed environmental decision-making.

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