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Full Length Research Article

ASSESSMENT OF DROUGHT SEVERITY IN NORTHERN NIGERIA USING MULTI-INDEX DROUGHT INDICATORS (1980–2023)

[1]R.B. Raji, [1]J.K. Aremu, [1]A. Umar, [1]O.A. Oluwole, [2]A. Amao, *[3]B.B. Mustapha

[1]Department of Geography, Nigerian Defense Academy, Kaduna
[2]Department of Geosciences, King Fahd University of Petroleum and Minerals
[3]Department of Geography, Kaduna State University, Kaduna

*Corresponding Author Email Address: bashariyamustaphababa@gmail.com

ABSTRACT

Drought is one of the most persistent climate-related hazards affecting Northern Nigeria, with significant implications for agricultural productivity, water resources, ecosystem stability, and food security. Despite increasing drought occurrence, most previous studies have relied on single drought indices, limiting comprehensive understanding of drought dynamics under changing climatic conditions. Therefore, this study assessed the temporal, seasonal, and spatial characteristics of drought in Northern Nigeria from 1980 to 2023 using a multi-index approach. Monthly hydro-climatic variables, including precipitation, maximum and minimum temperature, potential evapotranspiration, actual evapotranspiration, soil moisture, and runoff, were obtained from the TerraClimate dataset (approximately 4-km spatial resolution), while observed rainfall and temperature records from the Nigerian Meteorological Agency were used for validation. Drought conditions were evaluated using the Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Evaporative Demand Drought Index (EDDI). Data were analysed using descriptive statistics, frequency analysis, temporal trend analysis, seasonal analysis, spatial mapping, comparative analysis, and Pearson correlation implemented in Python and ArcGIS 10.4. The findings revealed pronounced temporal and spatial variability in drought severity, with severe drought conditions occurring during the early 1980s and intensifying again after 2020. Near-normal conditions were the dominant drought class, although recurrent moderate-to-extreme drought events were observed throughout the study period. Spatial analysis identified persistent drought hotspots across the northwestern and southern parts of Northern Nigeria, while EDDI showed that increasing atmospheric evaporative demand significantly intensified drought conditions. The study concludes that integrating multiple drought indices provides a more reliable assessment of drought dynamics than a single indicator. It is recommended that multi-index drought monitoring be incorporated into national drought early warning systems to strengthen climate adaptation, agricultural planning, and sustainable water resource management in Northern Nigeria.

Keywords: Drought; Northern Nigeria; Palmer Drought Severity Index; Standardized Precipitation Index; Standardized Precipitation Evapotranspiration Index; Evaporative Demand Drought Index; Climate change.

INTRODUCTION

Drought is one of the most devastating and complex natural hazards worldwide, affecting more people than any other climate-related disaster because of its slow onset, prolonged duration, and widespread environmental, economic, and social consequences (Pizzorni et al., 2024). According to the United Nations Convention to Combat Desertification, drought affected more than 1.84 billion people between 2000 and 2019, while the World Meteorological Organization reported that drought accounted for approximately 34% of all disaster-related deaths in Africa over the past five decades (Tsegai et al., 2023). In addition to its human toll, drought has caused global economic losses exceeding US$124 billion and continues to threaten food production, water security, biodiversity, and sustainable development (United Nations, 2022). The increasing concentration of greenhouse gases has intensified climate change, resulting in rising temperatures, altered precipitation patterns, and increased atmospheric evaporative demand, all of which have contributed to more frequent and severe drought events across many parts of the world (Bolan et al., 2024). Globally, drought significantly disrupts agricultural productivity, freshwater availability, hydropower generation, ecosystem services, and rural livelihoods (Rahman et al., 2025). The Food and Agriculture Organization of the United Nations estimates that drought accounts for more than one-third of agricultural production losses from natural hazards worldwide (Bertram, 2016). Beyond agriculture, prolonged drought accelerates land degradation, reduces groundwater recharge, increases wildfire risks, degrades vegetation, threatens biodiversity, and contributes to food insecurity, forced migration, and conflicts over limited natural resources (Tefera et al., 2024). These impacts are particularly severe in developing countries, where economies and livelihoods are highly dependent on climate-sensitive sectors.

Africa is among the continents most vulnerable to drought because of its high climatic variability, widespread reliance on rain-fed agriculture, and limited adaptive capacity(Apraku et al., 2021). Approximately 95% of agricultural production in sub-Saharan Africa depends on rainfall, making millions of households highly susceptible to prolonged precipitation deficits and increasing temperatures (Dlamini et al., 2026). Recurrent droughts across the Sahel, the Horn of Africa, and Southern Africa have resulted in widespread crop failures, livestock mortality, water scarcity, malnutrition, and humanitarian crises (Lombe et al., 2024). Climate projections further indicate that drought frequency, duration, and severity are expected to increase across many parts of the continent, posing serious threats to food security, poverty reduction, and sustainable environmental management (Bhardwaj & Mishra, 2026).

Nigeria has experienced increasing drought occurrences in recent decades, particularly across its northern region, where climatic conditions are characterized by high temperatures, low and highly variable rainfall, and increasing evapotranspiration (Ogunrinde et al., 2023). Northern Nigeria encompasses the Sudan and Sahel ecological zones. It is one of the country's major agricultural regions, with a substantial proportion of the population depending directly on rain-fed farming and livestock production for their livelihoods (Baba et al., 2026). Historical drought episodes, including those of 1972–1973 and 1983–1984, caused severe agricultural losses, environmental degradation, water shortages, and socio-economic disruptions (Ayugi et al., 2022). More recently, rising temperatures, declining soil moisture, erratic rainfall patterns, and increasing atmospheric evaporative demand have further intensified drought conditions, threatening agricultural productivity, water resources, ecosystem resilience, and regional food security (Mustapha Baba et al., 2022). These challenges underscore the importance of accurately assessing drought severity to support effective drought monitoring, early warning systems, and climate adaptation strategies.

Accurate assessment of drought severity requires using multiple drought indices, as individual indices capture different components of the drought process (Shalwee et al., 2025). The Standardized Precipitation Index (SPI) measures precipitation deficits; the Standardized Precipitation Evapotranspiration Index (SPEI) incorporates both precipitation and atmospheric evaporative demand; the Palmer Drought Severity Index (PDSI) evaluates long-term soil moisture and hydrological conditions, while the Evaporative Demand Drought Index (EDDI) identifies drought development through anomalies in atmospheric evaporative demand. Integrating these complementary indices provides a more comprehensive understanding of drought severity than relying on a single drought indicator (Homdee et al., 2016).

Despite the increasing number of drought-related studies conducted in Nigeria, important knowledge gaps remain. Most previous studies have relied on a single drought index, particularly SPI, which evaluates only precipitation anomalies and does not adequately account for the influence of rising temperatures and evaporative demand under changing climatic conditions (Bello et al., 2026; Shiru et al., 2020). Furthermore, many studies have focused on individual states or specific river basins, thereby limiting a comprehensive understanding of drought severity across Northern Nigeria (Jimoh et al., 2023). Comparative assessments involving multiple drought indices that simultaneously capture meteorological, hydrological, and atmospheric drought conditions remain limited. Consequently, there is insufficient evidence regarding the consistency, complementarity, and effectiveness of PDSI, SPI, SPEI, and EDDI in characterizing drought severity across the region. Addressing these gaps is essential for improving drought monitoring, strengthening early warning systems, and supporting evidence-based climate adaptation and sustainable water resource management.

Therefore, this study aims to assess the severity of drought in Northern Nigeria from 1980 to 2023 using multiple standardized drought indices. Specifically, the study evaluates the temporal characteristics of drought severity using PDSI, SPI, SPEI, and EDDI, compares their effectiveness in characterizing drought conditions, and identifies the seasonal patterns of drought severity across the region. The findings are expected to provide robust scientific evidence for improving drought early warning systems, climate adaptation planning, sustainable water resource management, and agricultural resilience in Northern Nigeria.

MATERIALS AND METHODS

Study Area

The study was conducted in Northern Nigeria, comprising the nineteen states located within the North-West, North-East, and North-Central geopolitical zones. The region lies between latitudes 6°N and 14°N and longitudes 3°E and 15°E, covering about 568,000 km², representing approximately 79% of Nigeria's total land area (Figure 1). Northern Nigeria encompasses three major ecological zones, namely the Sahel Savannah, Sudan Savannah, and Guinea Savannah, each characterized by distinct climatic conditions (Baba et al., 2022). The climate is tropical with a unimodal rainfall pattern extending from May to October and a prolonged dry season from November to April under the influence of the Harmattan winds. Annual rainfall decreases from over 1,500 mm in the Guinea Savannah to less than 500 mm in the Sahel, whereas mean annual temperature generally ranges between 25°C and 35°C (Isa et al., 2023). The region is predominantly dependent on rain-fed agriculture and livestock production, making it highly susceptible to recurrent droughts driven by rainfall deficits, rising temperatures, declining soil moisture, and elevated atmospheric evaporative demand (Musa et al., 2022; Mustapha et al., 2025).

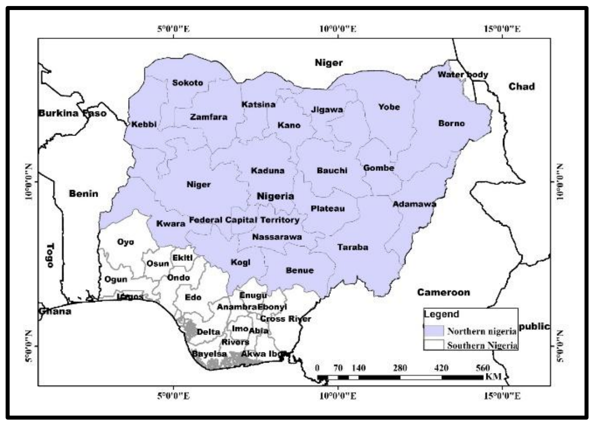

Figure 1: Map of the study area

Data Sources

Monthly hydro-climatic data covering the period from 1980 to 2023 were obtained from the TerraClimate dataset at approximately 4-km spatial resolution. The variables extracted included precipitation, maximum and minimum temperature, potential evapotranspiration (PET), actual evapotranspiration (AET), soil moisture, runoff, climatic water deficit, and water balance variables required for drought assessment. Ground-based monthly rainfall and temperature observations obtained from the Nigerian Meteorological Agency were used to validate and supplement the gridded climate datasets. The combined use of gridded and station observations improved the spatial representation and reliability of hydro-climatic conditions across Northern Nigeria.

Data Pre-processing

All climatic datasets were subjected to quality control before analysis. Missing observations and anomalous values were screened using consistency checks and descriptive statistics. Monthly observations were aggregated into annual and seasonal datasets where required for temporal analyses. Climatic variables were standardized to ensure consistency among different datasets and facilitate the computation of drought indices. Potential evapotranspiration and climatic water balance variables were derived from the processed climatic datasets before drought index

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computation. All datasets were converted into a common spatial reference system and raster resolution to ensure compatibility during spatial analysis.

Computation of Drought Indices

Drought severity was assessed using four complementary drought indices representing different components of the hydro-climatic system. The Standardized Precipitation Index (SPI) was computed following the methodology proposed by Lorenzo et al. (2024) using long-term monthly precipitation records. Monthly precipitation totals were fitted to a gamma probability distribution and subsequently transformed into a standard normal distribution to obtain standardized precipitation anomalies. SPI was calculated at multiple accumulation periods to characterize short-, medium-, and long-term meteorological drought conditions.

The Standardized Precipitation Evapotranspiration Index (SPEI) was calculated using the climatic water balance (precipitation minus potential evapotranspiration). The water balance series was fitted to a log-logistic distribution and standardized to produce SPEI values. Unlike SPI, SPEI incorporates the effects of atmospheric evaporative demand and therefore provides a more accurate characterization of drought severity under changing climatic conditions.

The Palmer Drought Severity Index (PDSI) was computed using precipitation, temperature, soil moisture, runoff, recharge, moisture loss, and potential evapotranspiration in a two-layer soil-water balance model. Potential evapotranspiration was estimated using the Thornthwaite approach, while soil water balance coefficients were calibrated to reflect the climatic characteristics of Northern Nigeria. PDSI was selected because it integrates both meteorological and hydrological processes and effectively represents cumulative drought severity over extended periods.

The Evaporative Demand Drought Index (EDDI) was derived from monthly atmospheric evaporative demand estimated from potential evapotranspiration. Monthly anomalies in evaporative demand were standardized relative to the long-term climatology to quantify atmospheric moisture stress. Positive EDDI values indicate above-normal evaporative demand and increasing drought severity, whereas negative values indicate wetter-than-normal atmospheric conditions. EDDI was incorporated because of its ability to detect rapidly developing (flash) droughts before substantial precipitation deficits become evident. This methodological step was included to support the extensive EDDI analyses presented in the results.

Drought Severity Classification

The computed drought indices were classified into standard drought severity categories based on the classification scheme recommended by the National Oceanic and Atmospheric Administration. The categories included Near Normal, Incipient Dry Spell, Mild Drought, Moderate Drought, Severe Drought, Extreme Drought, and Exceptional Drought. These classifications were used to determine annual frequencies, monthly distributions, seasonal characteristics, and long-term changes in drought severity across Northern Nigeria.

Temporal Analysis

Temporal variations in drought severity were evaluated using monthly and annual time-series analyses covering the period 1980 to 2023. Annual frequencies of drought occurrence were calculated for each drought index to quantify changes in drought occurrence through time. Smoothed trend curves were generated to identify long-term drought evolution and multi-decadal variability. Monthly drought characteristics were also examined to identify seasonal drought behaviour and recurrent drought episodes throughout the observation period. These analyses correspond directly to the annual frequency plots, monthly distributions, and time-series analyses presented in Chapter Six.

Seasonal Analysis

Seasonal drought characteristics were investigated by grouping monthly observations into the dry (Harmattan) and wet seasons. Seasonal averages of SPI, SPEI, PDSI, and EDDI were calculated to evaluate differences in drought severity between climatic seasons. Seasonal analyses enabled assessment of intra-annual drought variability and the influence of rainfall seasonality on drought development across Northern Nigeria. The resulting seasonal statistics formed the basis for the seasonal trend analyses presented in the results.

Spatial Analysis

Spatial variability in drought severity was examined by calculating long-term mean values of each drought index for every raster grid across Northern Nigeria. Geographic Information Systems (GIS) techniques were employed to generate spatial distribution maps illustrating regional variations in drought severity. Spatial analysis facilitated the identification of drought hotspots and differences in drought intensity among the Sahel, Sudan, and Guinea Savannah ecological zones. These procedures correspond to the mean drought distribution maps reported in the results.

Statistical Analysis

Descriptive statistical techniques were employed to summarize the characteristics of each drought index using means, standard deviations, frequencies, percentages, and probability distributions. Histograms and boxplots were used to examine the distribution and variability of drought indices, while frequency analyses quantified the occurrence of different drought severity classes. Comparative analyses were conducted to assess similarities and differences among SPI, SPEI, PDSI, and EDDI in their representation of drought conditions. Pearson correlation analysis was used to examine the relationship between potential evapotranspiration and EDDI, thereby evaluating the contribution of atmospheric evaporative demand to drought development. Smoothed trend analyses were further employed to identify long-term changes in drought severity throughout the study period. All statistical analyses were performed using Python, while spatial analyses and cartographic outputs were generated using ArcGIS 10.4.

Validation of Drought Indices

The reliability of the computed drought indices was evaluated by comparing the identified drought events with historically documented drought episodes reported in previous studies and national climate records. Agreement among SPI, SPEI, PDSI, and EDDI was assessed by examining their ability to detect major historical drought events affecting Northern Nigeria, including the severe droughts of the early 1980s and the recent post-2010 drought episodes. This validation enhanced confidence in the suitability of the selected drought indices for representing drought severity across the study area.

RESULTS

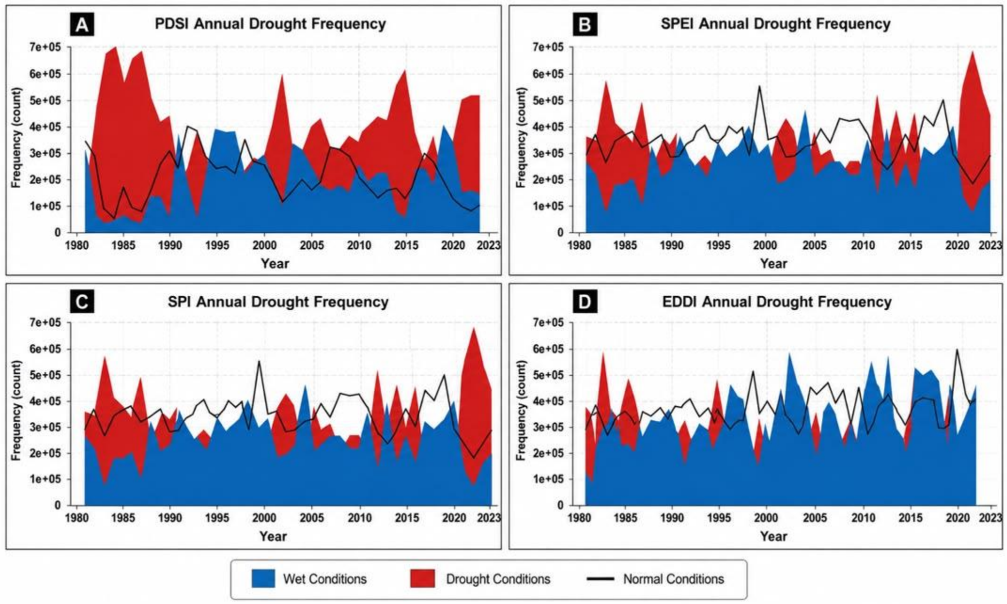

Figure 2: Annual Drought Dynamics Based on PDSI, SPEI, SPI and EDDI

Figure 2 shows the annual frequency of drought, wet and normal conditions in Northern Nigeria from 1980 to 2023 using four widely applied drought indices: (A) PDSI, (B) SPEI, (C) SPI and (D) EDDI. Although the four indices differ in their formulation, they exhibit comparable temporal variability and collectively demonstrate pronounced interannual fluctuations in drought occurrence throughout the study period.

The Palmer Drought Severity Index (PDSI) (Figure 2A) indicates that severe drought conditions dominated the early 1980s, with particularly high drought frequencies between 1982 and 1988. A relatively wetter period was observed during the early to mid-1990s, followed by alternating wet and dry conditions around the late 1990s and early 2000s. Drought conditions intensified again after 2010, reaching another major peak around 2014–2016 before remaining relatively elevated towards 2023. Normal conditions fluctuated considerably throughout the study period but generally occupied an intermediate position between wet and drought conditions.

The Standardized Precipitation Evapotranspiration Index (SPEI) (Figure 2B) shows a similar temporal pattern but with relatively smoother transitions between wet and dry years. Drought events occurred intermittently during the 1980s and became less dominant during the 1990s and early 2000s, when wet conditions were comparatively more frequent. However, drought frequency increased substantially after approximately 2015, culminating in the highest drought occurrence during 2022–2023.

The Standardized Precipitation Index (SPI) (Figure 2C) similarly identifies substantial drought activity during the early 1980s, followed by alternating wet and dry phases throughout the study period. Compared with PDSI, SPI reflects more frequent transitions between climatic states, indicating its greater responsiveness to precipitation variability. Nevertheless, the index reveals a pronounced increase in drought frequency during the final years of the record, with the highest drought frequency occurring in 2022.

The Evaporative Demand Drought Index (EDDI) (Figure 2D) presents a somewhat different temporal behaviour. Wet conditions became increasingly dominant after approximately 2000, reflecting increasing atmospheric evaporative demand, while drought conditions occurred as intermittent but intense episodes. Although EDDI identifies fewer prolonged drought periods than PDSI, it clearly captures increasing climatic variability during the last decade of the study period. The four indices consistently demonstrate that Northern Nigeria experienced major drought episodes during the early 1980s, relatively wetter conditions during parts of the 1990s and early 2000s, and a renewed increase in drought frequency after 2010, particularly between 2018 and 2023. Among the four indices, PDSI portrays greater drought persistence, whereas SPI and SPEI exhibit higher year-to-year variability, and EDDI emphasizes increasing atmospheric moisture demand during recent decades.

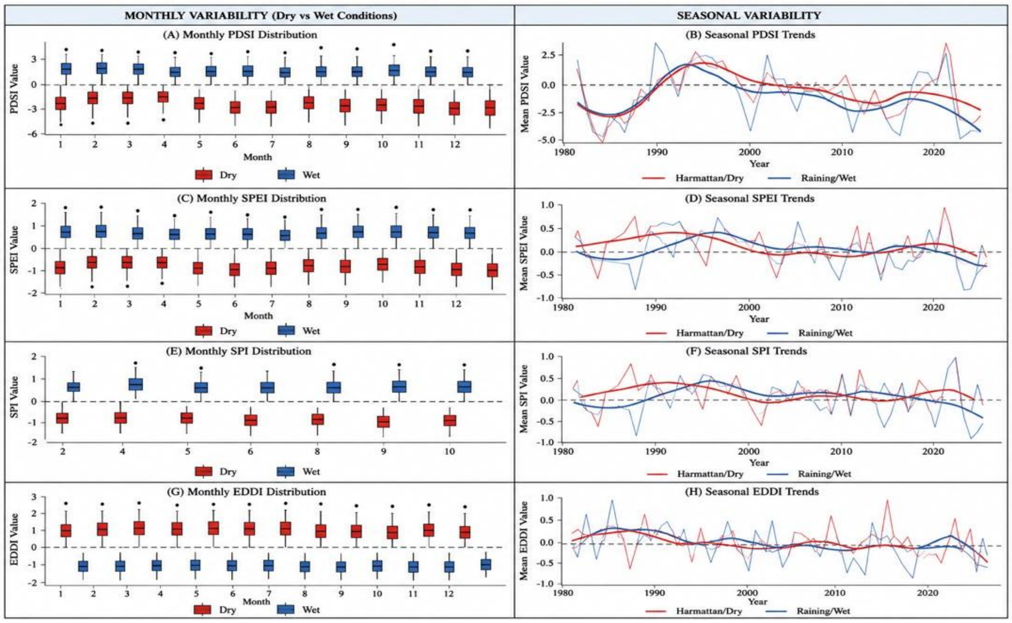

Figure 3: Monthly and Seasonal Variability of Drought Indices

Figure 3 shows the monthly and seasonal variability of drought conditions in Northern Nigeria using four drought indices: (A–B) PDSI, (C–D) SPEI, (E–F) SPI, and (G–H) EDDI. The boxplots illustrate the monthly distribution of dry and wet conditions, while the seasonal trend plots compare the Harmattan/Dry and Raining/Wet seasons from 1980 to 2023. The PDSI (Figures 3A–B) exhibits pronounced seasonal variability. The monthly boxplots show that wet conditions consistently record positive PDSI values throughout the year, whereas dry conditions remain negative in all months. The greatest variability in drought intensity occurs between May and September, when median drought values become more negative and the interquartile ranges widen, indicating stronger and more persistent drought conditions. Seasonal trends reveal that both the Harmattan/Dry and Raining/Wet seasons experienced severe drought in the early 1980s before recovering in the early 1990s. However, both seasons show a gradual decline after approximately 2000, with drought intensity increasing again after 2015, particularly during the rainy season.

The SPEI (Figures 3C–D) shows lower monthly variability than PDSI. Wet conditions consistently maintain positive values between approximately 0.5 and 1.0, while dry conditions remain moderately negative throughout the year. Seasonal trends indicate relatively stable moisture conditions during the 1990s, followed by increasing fluctuations after 2005. Both seasons show declining SPEI values towards the end of the study period, suggesting increasing drought stress associated with rising evapotranspiration.

The SPI (Figures 3 E–F) shows less dispersion than both PDSI and SPEI. Monthly distributions show consistently positive values during wet months and negative values during dry months, with the greatest variability between June and September. Seasonal trends fluctuate around the long-term mean, with wetter conditions during the early and mid-1990s, followed by increasing dryness after approximately 2018. The SPI indicates more rapid transitions between wet and dry conditions than the other indices.

The EDDI (Figures 3G–H) displays an inverse pattern compared with the moisture-based indices because it measures atmospheric evaporative demand. Monthly boxplots show higher positive EDDI values during dry conditions and negative values during wet conditions. Seasonal trends indicate relatively stable evaporative demand during the early years of the study but reveal increasing fluctuations after the mid-2000s. Although long-term changes are modest, the increased variability after 2010 suggests greater atmospheric moisture demand in recent decades.

The four indices consistently demonstrate clear seasonal differences between wet and dry conditions. PDSI exhibits the greatest seasonal variability and drought persistence; SPI responds most rapidly to precipitation fluctuations; SPEI reflects the combined influence of precipitation and evapotranspiration; while EDDI captures changes in atmospheric evaporative demand. Despite these methodological differences, all indices indicate increasing climatic variability and a tendency toward more severe drought conditions during the latter part of the study period.

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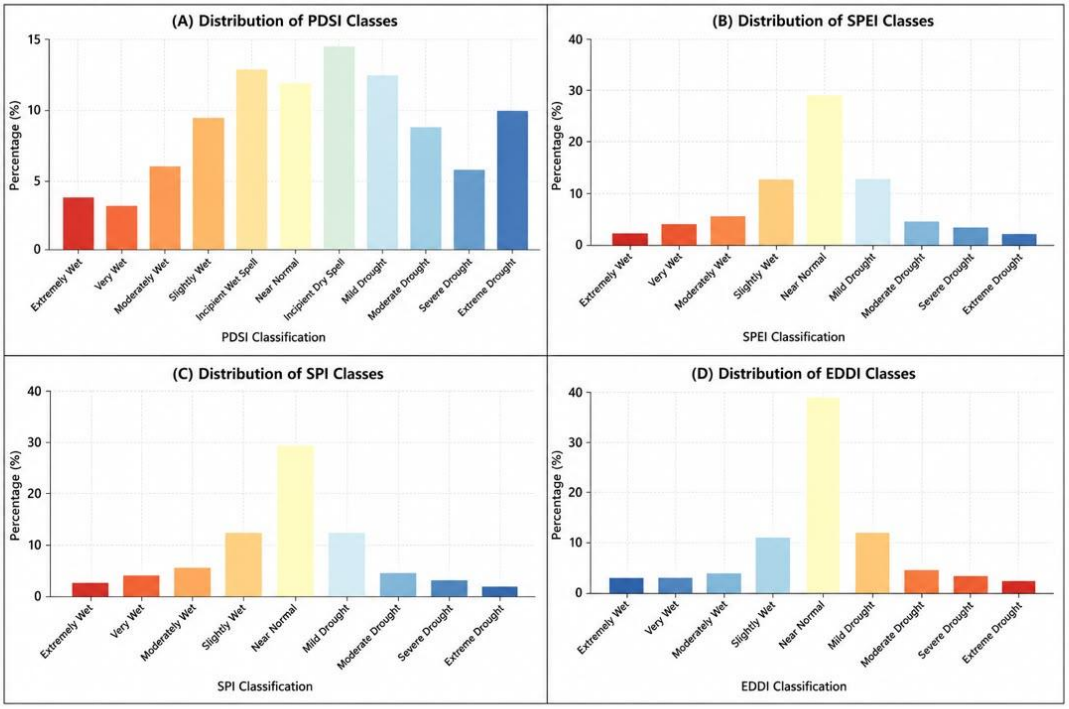

Figure 4: Drought Class Distribution Based on Multiple Drought Indices

Figure 4 shows the percentage distribution of drought and wetness classes derived from the four drought indices: (A) PDSI, (B) SPEI, (C) SPI, and (D) EDDI. Although the indices differ in their computational approaches, they consistently indicate that near-normal conditions dominate the long-term climatic regime, while extreme drought and extreme wet conditions occur relatively infrequently. The PDSI classification (Figure 4A) exhibits the greatest diversity of drought categories. Near-normal conditions account for approximately 12% of all observations, while incipient dry spell represents the most frequent class (approximately 14–15%), closely followed by incipient wet spell (about 13%). Mild drought contributes approximately 12%, whereas moderate, severe, and extreme drought collectively account for nearly 25% of observations. Wet classes occur less frequently, with slightly wet conditions approaching 10%, while extremely wet conditions represent less than 5%.

The SPEI classification (Figure 4B) is dominated by near-normal conditions, which account for nearly 29% of observations. Slightly wet conditions account for approximately 13%, followed by mild drought at about 13%. Moderate, severe, and extreme drought collectively contribute less than 10%, indicating that prolonged severe moisture deficits are relatively uncommon when precipitation and atmospheric evaporative demand are considered simultaneously.

Similarly, the SPI classification (Figure 4C) identifies near-normal conditions as the dominant category, representing approximately 29–30% of observations. Slightly wet and mild drought classes each contribute approximately 12%, whereas moderate, severe, and extreme drought classes each account for less than 5% individually. This distribution indicates that precipitation anomalies are generally moderate, with extreme rainfall departures occurring relatively infrequently.

The EDDI classification (Figure 4D) also shows a predominance of near-normal atmospheric evaporative demand, accounting for approximately 39% of all observations. Mild drought contributes about 12%, while slightly wet conditions account for approximately 11%. Moderate, severe, and extreme drought each represent less than 5%, suggesting that exceptionally high atmospheric moisture demand occurs infrequently despite increasing climatic variability.

The four drought indices consistently indicate that near-normal climatic conditions constitute the largest proportion of observations, while mild drought and slightly wet conditions are the next most common categories. Although severe and extreme drought events occur less frequently, their presence across all indices confirms the periodic occurrence of significant drought episodes within Northern Nigeria.

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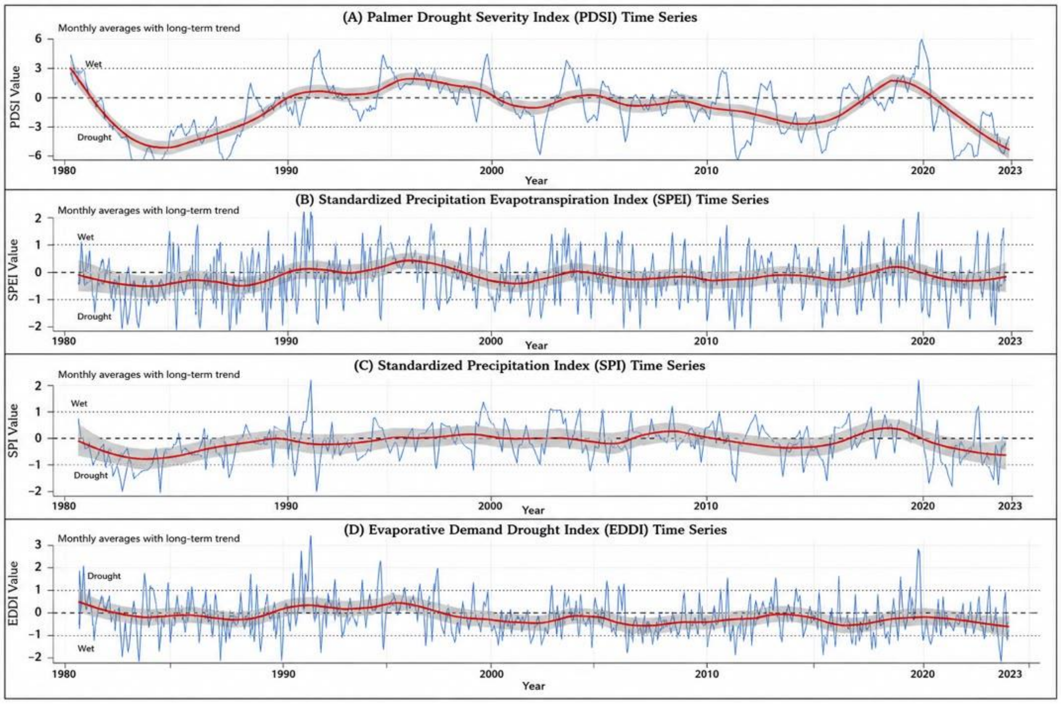

Figure 5: Long-Term Evolution of Drought Indices

Figure 5 shows the long-term evolution of drought conditions across Northern Nigeria from 1980 to 2023 using four drought indicators: (A) Palmer Drought Severity Index (PDSI), (B) Standardized Precipitation Evapotranspiration Index (SPEI), (C) Standardized Precipitation Index (SPI), and (D) Evaporative Demand Drought Index (EDDI). The time series displays monthly variability (blue line) together with the smoothed long-term trend (red curve), enabling assessment of both short-term fluctuations and long-term drought evolution.

The PDSI time series (Figure 5A) exhibits the largest variability among the four indices, with values ranging from approximately −6 to +6. A pronounced drought period occurred during the early to mid-1980s, when the smoothed trend declined sharply below **−5**, representing one of the most severe drought episodes in the study period. Conditions gradually improved during the early 1990s, with positive moisture anomalies peaking between 1993 and 1998. Moderate drought conditions re-emerged after 2000 before another wet phase occurred around 2018–2020. However, the trend declined rapidly after 2020, indicating an intensification of drought conditions toward 2023.

The SPEI time series (Figure 5B) demonstrates comparatively smaller fluctuations, generally remaining between −2 and +2. The smoothed trend indicates mild drought conditions in the early 1980s, followed by a gradual recovery in the 1990s. Between 2000 and 2015, the index fluctuated near normal conditions, with relatively small departures from zero. A brief improvement occurred around 2018–2020, after which the trend shifted slightly downward, showing increasing atmospheric water deficit in recent years.

Similarly, the SPI time series (Figure 5C) shows moderate interannual variability, with values predominantly ranging between −2 and +2. The early 1980s experienced below-normal precipitation, followed by gradual recovery during the late 1980s and 1990s. Rainfall conditions remained relatively stable throughout much of the 2000s, with occasional wet and dry episodes. Following a short wet period around 2018–2020, the SPI trend declined after 2020, indicating renewed precipitation deficits.

The EDDI time series (Figure 6.4D) reflects changes in atmospheric evaporative demand rather than precipitation alone. The index shows considerable short-term variability throughout the study period but a relatively stable long-term trend. Slightly positive values during the early 1990s indicate elevated evaporative demand, while a gradual decline is observed after 2000. The smoothed trend remains close to zero for much of the record but becomes increasingly negative after 2020, suggesting rising atmospheric moisture stress associated with enhanced evaporative demand.

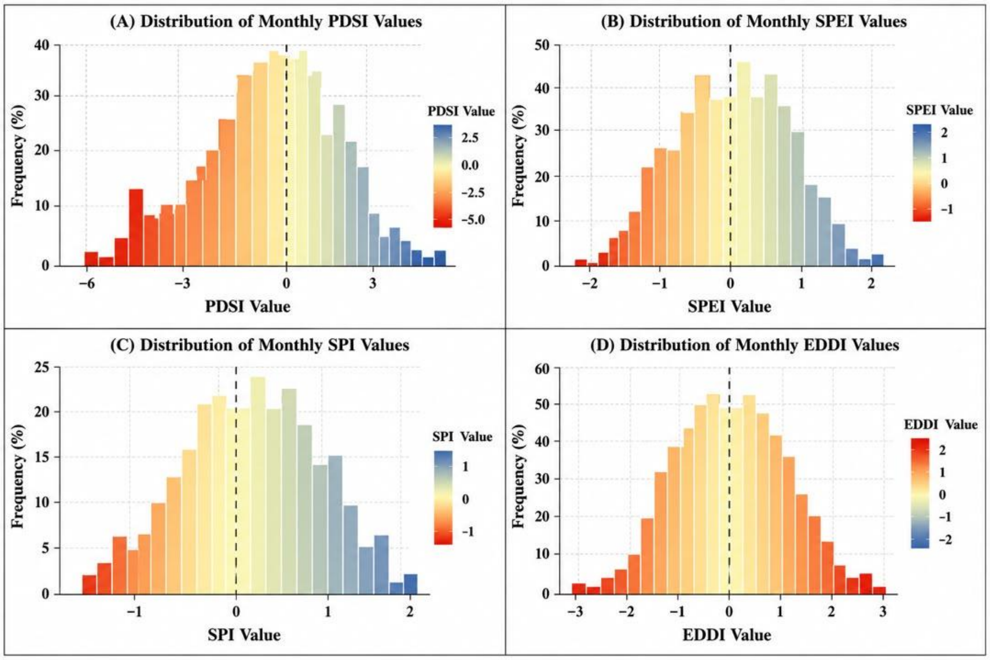

Figure 6: Statistical Distribution of Drought Indices

Figure 6 shows the statistical distributions of monthly drought values derived from the Palmer Drought Severity Index (PDSI), Standardized Precipitation Evapotranspiration Index (SPEI), Standardized Precipitation Index (SPI), and Evaporative Demand Drought Index (EDDI). The histograms illustrate the frequency distribution of each drought index over the study period (1980–2023), with the dashed vertical line indicating the neutral (zero) condition that separates dry and wet anomalies. The PDSI histogram (Figure 6A) exhibits the widest distribution, with values extending from approximately −6.0 to +5.0. The distribution is centred near zero but shows a noticeable concentration of observations between −2.5 and +1.5, indicating that moderate dry and near-normal conditions dominated the study period. The extended negative tail reflects several severe drought episodes, while fewer observations occurred under extremely wet conditions. The SPEI distribution (Figure 6B) is approximately symmetric around the zero threshold, with most observations occurring between −1.0 and +1.0. The highest frequencies are concentrated close to normal conditions, while relatively few months experienced extreme drought or exceptionally wet conditions. This narrower distribution suggests lower variability compared with PDSI. Similarly, the SPI histogram (Figure 6C) displays a nearly normal distribution centred close to zero, with the majority of observations lying within −1.0 to +1.0. The balanced spread of wet and dry values indicates that precipitation anomalies were generally moderate throughout the study period, although isolated extreme events are evident at both ends of the distribution.

In contrast, the EDDI histogram (Figure 6D) is also centred around zero but exhibits a relatively broader spread extending from approximately −3.0 to +3.0. The highest frequencies occur near neutral conditions, while both positive and negative extremes are represented by relatively few observations. The broader tails indicate greater variability in atmospheric evaporative demand compared with precipitation-based drought indices. All four drought indices show unimodal distributions centred around the neutral condition, indicating that near-normal hydroclimatic conditions occurred most frequently during the study period. However, PDSI demonstrates the greatest variability, whereas SPI and SPEI exhibit comparatively narrower distributions. EDDI occupies an intermediate position, reflecting the influence of atmospheric moisture demand on drought variability.

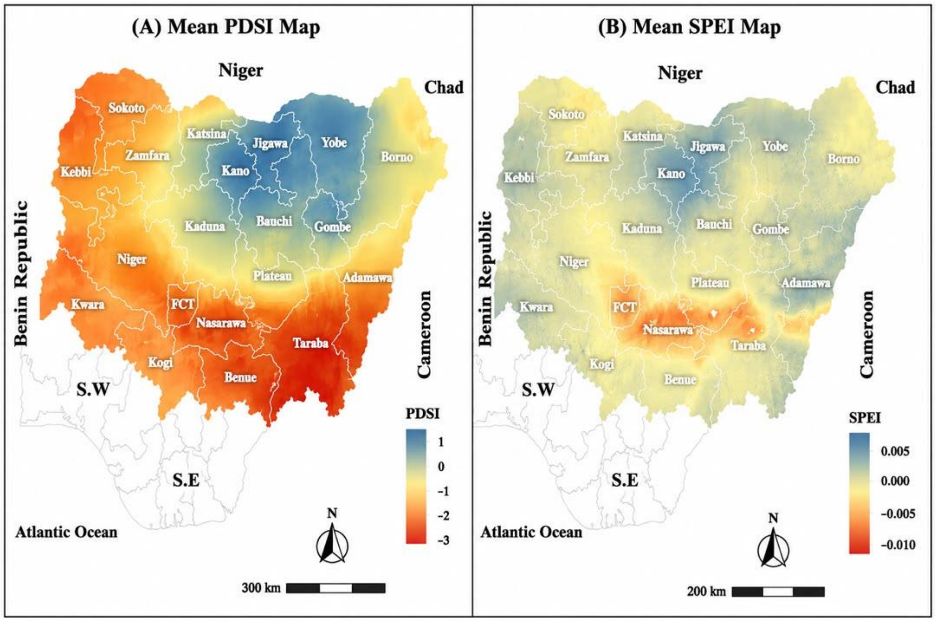

Figure 7: Spatial Patterns of Mean Drought Conditions

Figure 7 shows the spatial distribution of long-term mean drought conditions across Northern Nigeria using the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Evapotranspiration Index (SPEI) for the period 1980–2023. The maps reveal considerable spatial variability in drought intensity, highlighting distinct geographical differences in long-term moisture conditions. The mean PDSI map (Figure 7A) reveals a pronounced north–south gradient in drought severity. Positive PDSI values (blue shades), indicating relatively wetter conditions and improved soil moisture availability, are concentrated across the northeastern and central parts of the study area, particularly around Kano, Jigawa, Yobe, Bauchi, and Gombe States. Conversely, strongly negative PDSI values (orange to red shades), representing persistent moisture deficits, dominate the northwestern and southern margins of the region. The most pronounced drought conditions occur across Kebbi, Sokoto, Zamfara, Niger, Nasarawa, Benue, Taraba, and parts of the Federal Capital Territory (FCT), indicating sustained long-term depletion of soil moisture in these areas.

The mean SPEI map (Figure 7B) exhibits a more spatially uniform pattern than the PDSI map. Most parts of Northern Nigeria are characterized by values close to zero (yellow-green shades), indicating generally near-normal climatic water balance over the study period. Nevertheless, localized negative SPEI values are observed across the Federal Capital Territory, Nasarawa, Taraba, and parts of Benue, suggesting areas where precipitation deficits combined with elevated evaporative demand have produced relatively drier conditions. Slightly positive SPEI values occur over portions of Jigawa, Kano, Yobe, Bauchi, Gombe, Adamawa, and Kebbi, reflecting relatively favourable moisture conditions.

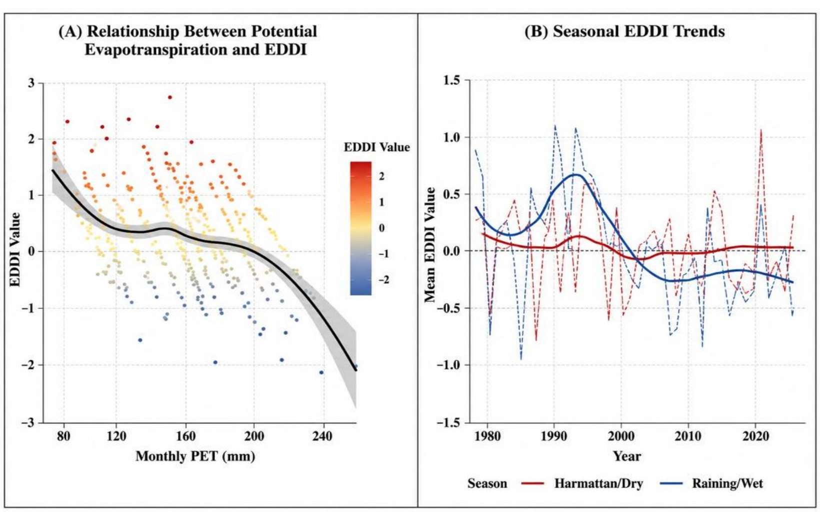

Figure 8: Relationship Between Potential Evapotranspiration and Atmospheric Drought

Figure 8 shows the relationship between potential evapotranspiration (PET) and the Evaporative Demand Drought Index (EDDI) together with the seasonal evolution of EDDI during the study period (1980–2023). Panel (A) illustrates the association between monthly PET and EDDI values, while Panel (B) compares seasonal EDDI variability during the Harmattan/Dry and Raining/Wet seasons. The scatterplot in Figure 8A demonstrates a clear nonlinear inverse relationship between PET and EDDI. At relatively low PET values (approximately 80–120 mm), EDDI values are predominantly positive, indicating comparatively lower atmospheric moisture stress. As PET increases, EDDI declines progressively toward zero, then becomes increasingly negative beyond approximately 200 mm. At the highest PET values (above 230 mm), EDDI decreases sharply to values below −2, indicating severe atmospheric drought conditions. The fitted smoothing curve confirms a strong negative relationship, suggesting that increasing evaporative demand substantially intensifies drought severity.

The seasonal EDDI time series (Figure 8B) indicates considerable year-to-year variability in both seasons. During the Raining/Wet season, EDDI exhibits greater interannual fluctuations, particularly during the late 1980s and early 1990s, when positive anomalies exceeded 0.6. Thereafter, the smoothed trend gradually declined, becoming predominantly negative after approximately 2000 and remaining below zero throughout much of the recent period. In contrast, the Harmattan/Dry season displays relatively smaller seasonal variability. The smoothed trend remains close to the neutral condition throughout most of the study period, although short-lived positive and negative anomalies occur intermittently. Despite these fluctuations, a slight decline is evident after the late 1990s, showing increasing atmospheric moisture demand during the dry season.

DISCUSSION

The multi-index assessment conducted in this study demonstrates that drought dynamics in Northern Nigeria have undergone significant temporal changes over the last four decades, with pronounced drought episodes occurring during the early 1980s and renewed intensification after approximately 2020. The temporal consistency observed across PDSI, SPI, SPEI, and EDDI indicates that drought variability in the region is driven by interacting meteorological, hydrological, and atmospheric processes rather than precipitation deficits alone. The severe drought conditions observed during the early 1980s coincide with the well-documented Sahelian drought, widely attributed to weakened West African monsoon circulation, anomalous sea surface temperatures, and large-scale land–atmosphere feedback. These findings agree with those of Peña-Angulo et al. (2025); Wane et al. (2025); and Okpara et al. (2026), who reported that the 1970s and 1980s represented one of the most severe drought periods in the climatological history of the Sahel, and with more recent studies that identified the early 1980s as a period of exceptional hydroclimatic stress across West Africa.

The relatively wetter conditions observed during the 1990s and early 2000s are also consistent with previous studies that reported partial recovery of Sahel rainfall following the prolonged twentieth-century drought (Biasutti, 2019; Giannini & Kaplan, 2019; Mohino et al., 2011). For example, Biasutti attributed this recovery to strengthening monsoon activity and changes in tropical Atlantic sea surface temperature gradients (Kingtse et al., 2001). Nevertheless, despite this apparent rainfall recovery, the present study shows that drought conditions intensified again after 2020 across all four drought indices. This observation shows that rainfall recovery alone is insufficient to offset the increasing influence of rising temperatures and atmospheric evaporative demand on drought development. Similar conclusions have been reached in recent hydroclimatic studies, which demonstrate that warming has become a dominant driver of drought severity by accelerating evapotranspiration and reducing effective water availability even where precipitation remains relatively stable (Gebrechorkos et al., 2025).

One of the most important findings of this study is the contrasting behaviour of the four drought indices. Although all indices identified the principal drought episodes, their sensitivities differed considerably because each represents a different component of the hydrological cycle. The PDSI consistently exhibited greater drought persistence than SPI and SPEI because it incorporates cumulative soil moisture storage, evapotranspiration, runoff, and recharge processes within a water balance framework. This aligns with the original conceptualization of PDSI by Mingwei et al. (2014), and subsequent studies have demonstrated that Palmer-based indices are particularly effective for evaluating long-duration agricultural and hydrological droughts.

In contrast, SPI responded more rapidly to precipitation anomalies and therefore captured short-term meteorological droughts more effectively than prolonged moisture deficits. This behaviour agrees with the recommendation of the World Meteorological Organization that SPI remains one of the most appropriate indicators for operational meteorological drought monitoring because of its simplicity and standardized statistical properties. However, the present findings also demonstrate that SPI underestimated drought severity in recent decades compared with SPEI, particularly during warm periods. Similar observations have been reported in recent comparative studies, which show that SPEI generally identifies greater drought duration and severity than SPI because it incorporates potential evapotranspiration and thus reflects the increasing role of temperature in drought evolution under climate change (Salami & Togo, 2026).

The stronger response of SPEI during recent decades highlights the increasing importance of atmospheric evaporative demand in drought development. Unlike SPI, which assumes precipitation is the principal driver of drought, SPEI accounts for the climatic water balance by incorporating both precipitation and potential evapotranspiration. Consequently, SPEI detected more severe drought conditions after 2000 despite only modest changes in precipitation. This finding corroborates previous investigations that demonstrated the superiority of SPEI in representing drought under warming climates, particularly in semi-arid environments where evapotranspiration exerts strong control over soil moisture dynamics (Afamondji et al., 2026).

The EDDI results provide additional evidence that atmospheric processes are becoming increasingly important drivers of drought in Northern Nigeria. The inverse relationship observed between potential evapotranspiration and EDDI indicates that increasing atmospheric moisture demand substantially intensifies drought severity. This finding is consistent with the work of Ogunrinde et al. (2026) and Hobbins et al. (2016), who demonstrated that EDDI detects flash droughts and atmospheric drying earlier than precipitation-based indices because it responds directly to anomalies in evaporative demand. More recent studies in arid and semi-arid environments have similarly concluded that EDDI frequently identifies more pronounced drying trends than SPI (Ogunrinde et al., 2026; Tu et al., 2026).

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Conclusion

This study provides a comprehensive multi-index assessment of drought dynamics across Northern Nigeria during the period 1980–2023 by integrating the Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Evaporative Demand Drought Index (EDDI). The combined use of these complementary drought indicators enabled the characterization of drought evolution from meteorological, agricultural, hydrological, and atmospheric demand perspectives, thereby providing a more robust understanding of regional drought behaviour than could be achieved using a single index.

The findings demonstrate that drought variability in Northern Nigeria is characterized by pronounced temporal, seasonal, and spatial heterogeneity. Although near-normal climatic conditions dominated the long-term record, recurrent moderate-to-extreme drought events occurred throughout the study period, with particularly severe episodes in the early 1980s and a renewed intensification of drought conditions after approximately 2020. While SPI and SPEI primarily reflected fluctuations in precipitation and climatic water balance, PDSI captured prolonged soil moisture deficits, and EDDI highlighted the increasing role of atmospheric evaporative demand. The convergence of these independent drought indicators toward drier conditions during recent years provides compelling evidence that drought risk is increasing across the region.

Seasonal analyses further revealed that drought behaviour differs substantially between the Harmattan and rainy seasons. The rainy season exhibited greater interannual variability, whereas the Harmattan season showed comparatively persistent atmospheric moisture stress. The observed decline in recent seasonal trends suggests that increasing evaporative demand associated with rising temperatures is progressively amplifying drought severity, even where rainfall variability alone may not fully explain observed conditions.

Spatial analysis identified distinct drought hotspots across the northwestern and southern parts of Northern Nigeria, whereas relatively favourable moisture conditions persisted over parts of the northeastern and central regions. These spatial differences highlight the influence of regional climatic gradients, land surface characteristics, and atmospheric processes on drought development. Such heterogeneity underscores the necessity of geographically targeted drought mitigation and water resource management strategies rather than uniform regional interventions.

The statistical distributions of the four drought indices further emphasize their complementary characteristics. PDSI exhibited the greatest variability because of its cumulative representation of soil moisture dynamics, whereas SPI and SPEI showed comparatively stable standardized distributions centred around normal climatic conditions. EDDI captured substantial fluctuations in atmospheric moisture demand, providing an effective early indicator of rapidly developing drought conditions. Together, these results confirm that no single drought index adequately represents the complexity of drought processes across Northern Nigeria.

From a scientific perspective, this study demonstrates the value of integrating multiple drought indices to improve drought characterization in semi-arid environments. The complementary strengths of PDSI, SPI, SPEI, and EDDI provide a comprehensive framework for monitoring drought onset, persistence, severity, and recovery under changing climatic conditions. Such an integrated approach enhances confidence in drought assessment while improving the capacity for early warning and climate risk evaluation.

The implications of these findings extend beyond drought monitoring. Increasing atmospheric evaporative demand, coupled with recurrent precipitation deficits and declining soil moisture, poses growing challenges to agricultural productivity, water resource sustainability, ecosystem resilience, and food security across Northern Nigeria. Consequently, drought preparedness strategies should move beyond precipitation-based monitoring by incorporating soil moisture and atmospheric demand indicators into operational drought early warning systems. Strengthening climate-resilient agricultural practices, improving water conservation measures, and integrating multi-index drought information into national adaptation policies will be essential for reducing future drought vulnerability. This study provides a scientifically rigorous baseline for understanding the evolution of drought in Northern Nigeria under contemporary climate variability. The multi-index framework developed herein offers an important methodological contribution for regional drought assessment. It provides valuable evidence to support climate adaptation planning, sustainable water resources management, and informed decision-making in drought-prone environments. Future research should integrate high-resolution satellite observations, land surface models, and machine learning approaches to improve drought prediction and enhance the operational capability of drought early warning systems across West Africa.

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