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Research Article

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Drought Prediction and Trend Analysis in Minna Using Support Vector Machine and Decision Tree Models: A Comparative Study of SPEI and SPI Indices

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ABSTRACT

This research explores the complex relationships between precipitation, temperature, and evapotranspiration in Minna, with an emphasis on understanding climatic variability. The study utilizes the Standardised Precipitation Index (SPI) and Standardised Precipitation Evapotranspiration Index (SPEI) to examine trends and predict drought conditions across various time scales. A comparative analysis was conducted using machine learning algorithms, specifically Support Vector Machines (SVM) and Decision Trees (DT), to evaluate their effectiveness in predicting drought conditions. By investigating the dynamic interactions among these climatic variables, this study aims to contribute to a better understanding of drought dynamics in the region. In addition, correlation analyses using Pearson, Spearman, and Kendall's Tau were conducted to explore empirical relationships between the indices. Regression metrics and innovative trend analysis were also applied to identify underlying patterns in the drought series before machine learning implementation. Preliminary results show that the probabilities for moderately dry, severely dry, and extremely dry conditions range from 0.058–0.16, 0.09–0.157, and 0.01–0.12, respectively, indicating a notable risk of moderate to severe drought events in the region. Correlation between SPI and SPEI is generally weak at shorter time scales (3- and 6-month), with values below 0.2, but improves moderately at the 9-month scale (Kendall's Tau = 0.312). Trend analysis reveals a near-balanced occurrence of wet and dry conditions across time scales, with strong agreement ($r > 0.95$) between computed indices and observed trends. Both SVM and DT models performed well in predicting SPI-3 and SPEI-3, especially under near-normal conditions. However, model performance declined under moderate, severe, and extreme drought scenarios. Future research should focus on integrating advanced machine learning approaches, such as ensemble techniques and deep learning, with a broader array of hydroclimatic and land surface variables to enhance prediction accuracy and support more informed decision-making by stakeholders.
Keywords: Drought, Precipitation, Temperature, Agriculture, Timescale

INTRODUCTION

As a pressing global issue, climate change has severe implications for human societies and ecosystems. Droughts, which can be triggered by climate change or human factors, are recurring natural hazards that challenge water management, agricultural productivity, and ecosystem resilience (Majid *et al.*, 2023). Globally, droughts are increasing in frequency and intensity as reported by Mohammed *et al*. (2024). Mohammed *et al.* (2024) highlighted that droughts result from reduced water availability over a particular period and region. The variability in precipitation is a key factor in triggering either droughts or floods, underscoring the importance of precipitation in shaping these natural hazards. Wilhite's (2000) study examined the precipitation-drought relationship, providing crucial insights for improving water management, environmental conservation, agricultural productivity, and socioeconomic growth in targeted areas. The research concluded that droughts, resulting from inadequate precipitation, constitute a natural hazard with disastrous consequences. According to Hirabayashi *et al.* (2008), recognizing patterns in precipitation and drought can substantially enhance water resource management, environmental conservation, agricultural productivity, and socioeconomic development. Similarly, Paulo *et al*. (2012) examined drought characteristics, including frequency, severity, and duration, in various climate regions. Research by Cai *et al*. (2014) highlighted drought as a highly impactful climatic extreme affecting vast populations. Furthermore, Ravinesh *et al*. (2016) noted that warmer and drier conditions intensify drought impacts, which are further compounded by growing water demands driven by population expansion and increased industrial, agricultural, and energy activities

Atedhor (2016) emphasised that droughts are recurring disasters in northern Nigeria, including Minna, with severe events occurring in recent years, such as the 2019 drought that affected 55.75 km² (13.94% of the region). Understanding drought patterns is essential for developing effective management strategies and agricultural planning. By analysing these patterns, policymakers and stakeholders can make informed decisions to mitigate drought impacts and promote sustainable agriculture. Accurate drought predictions are critical for effective management and mitigation, enabling informed adaptation measures (Wilhite *et al.*, 2014; Mishra and Singh, 2010). Drought complexity and localised characteristics hinder the development of a single, universally applicable model. The dynamic nature of drought demands region-specific approaches, as a one-size-fits-all model can lead to inadequate mitigation strategies (Almedeij, 2015). Drought modelling faces challenges such as input selection, index choice, and regional variability in impacts (Mishra and Desai, 2005). To establish a robust predictive framework, it is essential to test different models and account for regional differences. As droughts evolve across various dimensions (Mpelasoka et al., 2008), predictive models must be adaptable, requiring region-specific predictors and approaches (Almedeij *et al.*, 2015). SPI is a popular drought index linked to soil moisture and groundwater levels. Various studies have investigated SPI-based drought forecasting using data-driven models in different geographic locations, such as ANN, ANFIS, SVM, and ARIMAX. These studies, including those by Cancelliere *et al.* (2007), Jalalkamali *et al.* (2015), and Belayneh and Adamowski (2012), showcase the application of SPI-based forecasting in regions like Sicily, Iran, and Ethiopia. SPI has drawbacks in drought prediction because it exclusively considers precipitation, neglecting the impact of other important variables such as temperature and evapotranspiration (Vicente-Serrano *et al.*, 2010). Nevertheless, researchers have successfully applied data-driven models like ANN, SVM, and RF to forecast SPI in various contexts (Bishal *et al.*, 2024; Belayneh *et al.*, 2014). These studies demonstrate the potential of SPI-based models, but also underscore the importance of considering multiple variables to enhance drought prediction accuracy. Hybrid approaches may offer a more comprehensive understanding of drought dynamics In light of the foregoing, it is glaring that drought analysis in the context of ML is completely dominated by the application of SPI. Even though Chukwu (2024) noted that drought is characterised by multiple independent variables: precipitation, temperature and evapotranspiration. Understanding precipitation, temperature, and evapotranspiration dynamics and interactions is Sine qua non for effective analysis and water resource planning and must be factored in any surmised drought analysis. Suffices to know, there is a limited illumination on empirical relationship between different accumulation time interval that is SPI-3, SPI-6 and SPI-9 verses SPEI-3, SPEI-6 and SPEI-9 as this give thorough impression of spatial-temporal distribution of drought, for instance Chukwu (2024) opined each time scale a gives a fore gleam of probable drought type prevalent in a supposed region and possible transition, that is either from meteorological to hydrological or agricultural. Such has not been verified in connection with different machine learning. In the general horizon of hydroclimatic extremes modelling and studies have adversely experienced neglect, on drought class modelling and possible predictions. Considering this there is no qualitative studies that have successfully imposed Support vector machine (SVM) and decision tree (DT) algorithms on different time scales/indices of drought series, nor determines appropriate model that tallies with a particular time scale or index explicitly, with it associated real time implication in the studied area. In addition, SVM and decision tree (DT) are perceived as the most plausible algorithms for classification. for instance, recent studies have highlighted the effectiveness of Support Vector Machine (SVM) as a machine learning algorithm for tackling complex data challenges. SVM and Decision Trees (DT) have been noted for their advanced validation capabilities, geometric interpretability, and accurate statistical analysis, which can be achieved with relatively small training datasets. Furthermore, the use of kernel functions in SVM has been shown to play a vital role in optimizing dataset classification, making it a valuable tool for precise data analysis (Kushwaha *et al.*, 2021; Achirul-Nanda *et al*., 2018; and Sihag *et al*.,2018)

Yet these stances have not been verified with computed drought series in the studied area. to the best of the author's knowledge, there is no documented case of such nor any similar work proposed to address the aforementioned gap. In recognition of this, this research is tilted towards satisfying the identified gaps. Hence, actualised the following objectives; (1) established empirical relationship between computed SPI and SPEI at different time scales as well as identified trend pattern for the series (2) developed and evaluated the performance of SVM and DT models in predicting drought events at various time scale and (3) identified the most effective timescale that agrees with studied machine learning models, hence unveiled the most common drought type probably prevailing in the studied area for effective planning.

MATERIALS AND METHODS

Study Location

Minna Metrological

Minna is capital of Niger State (Figure 1) is located between latitude 9° 34’– 9° 37’N and longitude 6° 36’– 6° 39’E. Annual rainfall of 578 mm, onset of rainfall in Minna is mostly March-April and ends towards October-November, with a mean temperature of 34° (Musa *et al*, 2012). This region falls under the Guinea Savanna zone, characterised by a mix of short grasses and sparse tree cover, typical of Nigeria's tropical climate. The area experiences two distinct seasons: a wet season and a dry season (Musa *et al*, 2012). Figure 1 shows a detail view of the study location.

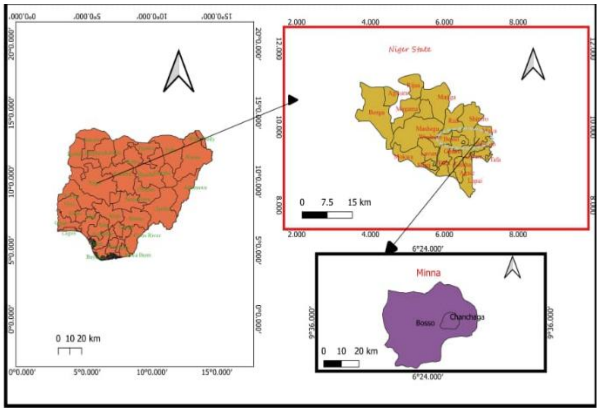

Figure 1. Study Location Map

Hydroclimatic Characteristics and Data Mobilisation

Minna climate is classified as a tropical savanna (Köppen Aw), typical of Nigeria's Middle Belt region. The city experiences two distinct seasons: a dry season from November to April, characterized by arid and dusty conditions due to Harmattan winds, and a wet season from May to October, marked by high humidity and monsoonal rainfall. Throughout the year, temperatures remain high, ranging from hot to extremely hot. While the peak of the rainy season brings slightly lower temperatures, the elevated humidity levels often make conditions feel just as, if not more, uncomfortable than during the hotter dry months (Christopher et al., 2020). For this research, rainfall data spanning 35 years were sourced from the Nigerian Meteorological Agency (NiMet) and the Nigeria Hydrological Services Agency (NIHSA), including daily, monthly, and annual records. Figure 2 provides a detailed summary of the analytical methods applied in this study.

Standardised Precipitation Evapotranspiration Index (SPEI)

Research has shown that simplified methods for estimating potential evapotranspiration (PET) can produce reliable results when used with drought indices like the Palmer Drought Severity Index (PDSI) (Mavromatis, 2007). The Thornthwaite method is a popular choice for calculating PET due to its simplicity and requirement of only monthly mean temperature data (Boroneant *et al*., 2011). This study uses specific drought classification criteria, outlined in Table 1. To calculate the SPEI, climatic water balance was normalised using a log-logistic probability distribution (Toromani *et al*., 2011). SPEI was computed for 3-, 6-, and 9-month periods using average monthly precipitation and temperature data:

The probability density function is defined as $f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)\left[1+\left(\frac{x-\gamma}{\alpha}\right)\right]^{-2}$ (1a)

where α, β, and γ represent the scale, shape, and origin parameters, respectively. The corresponding probability distribution function is $F(x) = \left[1+\left(\frac{\alpha}{x-\gamma}\right)\right]^{-1}$.

Therefore, $\mathrm{SPEI} = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}$, (1b)

where W is determined based on the probability value P. For $P \leq 0.5$, $W = \sqrt{-2\ln(P)}$, and for $P > 0.5$, $W = \sqrt{-2\ln(1-P)}$. The coefficients C_0, C_1, C_2, d_1, d_2, and d_3 are predefined constants.

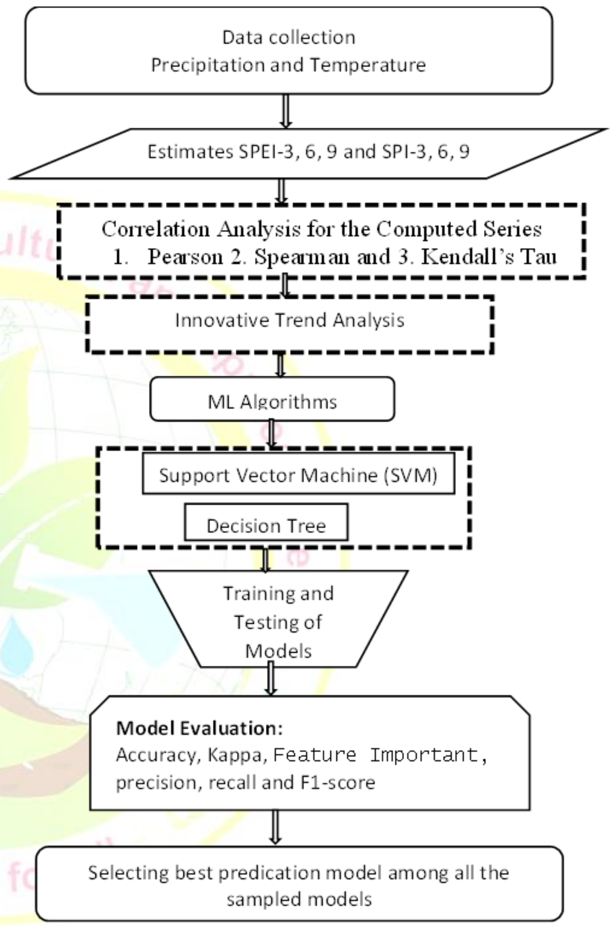

Figure 2. Flowchart of the methodologies employed Determination of Drought Signatories

Standardised Precipitation Index (SPI)

The SPI was calculated by fitting a gamma probability density function to the average monthly rainfall frequency. The SPI was computed for 3-, 6-, and 9-month accumulation periods, with drought classification criteria outlined in Table 1. The calculation involved determining the cumulative probability of the observed data series using the gamma distribution parameters. The framework used is based on the following equations

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

$$H(x) = q + (1-q)G(x)$$

G(x) represents the cumulative probability distribution, and H(x) accounts for the probability of zero values. The resulting cumulative probability was then transformed into a standard normal variable Z, yielding the SPI value with a mean of zero and a standard deviation of one. This was in accordance with Jimoh *et al.* (2023)

$$Z = SPI = \begin{cases} -[t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} & for\ 0 < H(x) \leq 0.5 \\ +[t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} & for\ 0.5 < H(x) < 1.0 \end{cases} \quad (2a)$$

$$t = \begin{cases} \left[in\left(\frac{1}{(H(x))^2}\right)\right]^{1/2} & for\ 0 < H(x) < 0.5 \\ \left[in\left(\frac{1}{(1.0 - H(x))^2}\right)\right]^{1/2} & for\ 0.5 < H(x) < 1.0 \end{cases} \quad (2b)$$

$$\begin{cases} c_0 = 2.515517, & c_1 = 0.802853 \\ c_2 = 0.010328, & d_1 = 1.432788 \\ d_2 = 0.189269, & d_3 = 0.001308 \end{cases}$$

Table 1. Classification of Drought based on SPI and SPEI

Category	SPI values
Extreme dry	SPI ≤ -2
Severely dry	-2< SPI ≤ -1.5
Moderately dry	-1.5 < SPI ≤ -1
Near normal	-1 < SPI ≤ 1
Moderately wet	1 < SPI ≤ 1.5
Very wet	1.5 < SPI ≤ 2
Extreme drought	SPI > 2

Jimoh *et al.*(2023)

Empirical Relationship between SPIs and SPEIs Series and Trend pattern

Pearson Correlation Coefficient

The Pearson correlation coefficient (r) measures the strength and direction of the linear relationship between two continuous variables Zou (2003), such as SPEI and SPI. In this study, it was used to assess the relationship between SPEI and SPI at different time scales (3, 6, and 9 months). As illustrated in the transformed equation below

$$r = \frac{\sum(SPEI_i - \overline{SPEI}_i)(SPI_i - \overline{SPI}_i)}{\sum(SPEI_i - \overline{SPEI}_i)^2 \sum(SPI_i - \overline{SPI}_i)^2} \quad (3)$$

The coefficient ranges from -1 to 1, indicating the degree of correlation: 1 (perfect positive linear relationship), -1 (perfect negative linear relationship), or 0 (no linear relationship). The correlation strength can be classified as strong (|r| ≥ 0.7), moderate (0.5 ≤ |r| < 0.7), or weak (|r| < 0.5) (Dancey and Reidy, 2017)

Spearman's Rank Correlation Coefficient

To address the limitations of Pearson correlation, which assumes normality and can be affected by outliers, this research used Spearman's rank correlation coefficient.

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \quad (4)$$

This method is suitable for non-normal data and calculates the correlation between variables based on their ranks. The Spearman correlation coefficient (ρ) ranges from -1 to 1, indicating the strength and direction of the relationship: ρ > 0 (positive relationship), ρ < 0 (negative relationship), or ρ ≈ 0 (no significant relationship). The correlation strength can be classified as strong (|ρ| ≥ 0.7), moderate (0.5 ≤ |ρ| < 0.7), or weak (|ρ| < 0.5) (Myers and Well, 2003)

Kendall's Tau

Kendall's Tau statistic was in addition used to analyse the relationship between variables, particularly suitable for small sample sizes and non-normal data.

$$\tau = (Nc - Nd)/\sqrt{(Nc + Nd + Nt) * (Nc + Nd + Nu)} \quad (5)$$

The Tau value indicates the direction and strength of the relationship: τ > 0 (positive relationship), τ < 0 (negative relationship), or τ ≈ 0 (no significant relationship). The strength of the correlation was further classified by Gibbons and Chakraborti (2011) as strong (|τ| ≥ 0.6), moderate (0.3 ≤ |τ| < 0.6), or weak (|τ| < 0.3).

Innovative Trend Analysis (ITA)

The ITA method involved dividing the SPI series into two equal halves, sorting them in ascending order, and plotting them on a 1:1 line. Points above the line indicate a positive trend, while those below indicate a negative trend. Points on the line suggest no trend. The trend analysis categorizes points into low, medium, and high values, providing insight into the drought series' behavior. By calculating the average values of both halves, the trend and its magnitude can be determined. (Esit, 2023; Sethi *et al*., 2023). The trend in the drought series and its magnitudes was driven by calculating the average values of both halves in a time series denoted as Y_1 and Y_2 According to Pande *et al.* (2020);

$$s = \frac{2(\bar{Y}_2 - \bar{Y}_1)}{n} \quad (2a)$$

Where S is the slope of the trend, $\bar{Y}_2$ and $\bar{Y}_2$denotes the averages of both halves, and n is the total number of samples in the series. Then, the confidence limit and magnitude of the trend was calculated using the innovative trend analysis index ITA_i (Wu and Qian, 2017), as shown in equation (2b)

$$\text{ITA}_i = \frac{1}{n}\sum_{i=1}^{n} \frac{10(y_i - x_i)}{X^i} \quad (2b)$$

Where x_i and y_i are the values of the first ordered sub-series and the second sub-series, and X′ is the average of x_i. The confidence limit is represented by:

$$Cl_{(I-\alpha)} = 0 \pm S\sigma_s \quad (2c)$$

Where α is the percent of significant level, S is the standard deviation value, and σ_s It is the slope of the standard deviation.

Application of Machine Learning Models Imposed on Different Time Scales

Support Vector Machine Algorithms

For both regression and classification tasks, SVM is a powerful supervised learning method. SVM employs the kernel trick to map the initial input space into a higher-dimensional feature space, which facilitates the linear separation of non-linearly separable data (Poornima, 2019). The transformed equation, modelled after Mohamadi (2020), was implemented in R.

SVM Formulation

$\{(SPI_1$ or $SPEI_1,\ y_1)$, $(SPI_2$ or $SPEI_2,\ y_2)$, ..., $(SPI_n,\ y_n)\}$

where $SPI_i/SPEI_i$ is the SPEI/SPI values and y_i is the corresponding drought class label (e.g., mild, moderate, severe, etc.)

SVM Optimisation Problem

The SVM optimisation problem was formulated as:

minimize: ||w||^2 / 2 + C * $\sum(\xi_i)$

subject to: y_i* (w^T * SPI_i or $SPEI_i$+ b) ≥ 1 - ξ_i

where w is the weight vector, b is the bias term, ξ_i is the slack variable, and C is the regularisation parameter.

Kernel Functions

The kernel function can be used to map the input SPI values into a higher-dimensional space:

K(SPI_i or $SPEI_i$, SPI_j or $SPEI_j$) = Φ(SPI_i or $SPEI_i$)^T * Φ(SPI_j or $SPEI_j$)

where Φ is the mapping function.

Decision Tree Algorithm

The submissions of Sharma *et al*. 2020 and Foyez *et al*. 2022 were transformed and adhered to the computation, hence by using R programming language packages for DT for the studied region, thus:

1. Entropy

H(/SPEI/SPI) = - ∑ (p * log2(p))

where p is the proportion of each drought class (e.g., mild, moderate, severe, etc.) based on SPEI/SPI values at different time scales.

2. Information Gain

IG (SPEI/SPI, threshold) = H(SPI) - ∑ (|SPI-j|/|SPI| * H(SPI-j))

Where SPEI-j or SPI-j is the subset of SPI or SPEI values after splitting at a specific threshold, and |SPEI-j|/|SPEI| or |SPI-j|/|SPI| is the proportion of SPI or SPEI values in each subset.

3. Gini Index

Gini(SPEI/SPEI) = 1 - ∑ (p^2)

where p is the proportion of each drought severity class based on SPI/SPEI values.

RESULTS AND DISCUSSION

Detection of Drought Signatures and Implications of Variable Time Scales

The probability distributions of drought classes in Minna, as presented in Table 1, offer a nuanced understanding of the region's hydroclimatic features. Across different time scales (SPEI-3, SPI-3, SPEI-6, SPI-6, SPEI-9, and SPI-9), therefore, reveals a predominance of near-normal conditions, providing valuable insights into the drought dynamics of the area. The dominance of near normal conditions across all time scales (probabilities ranging from 0.518 to 0.615) is consistent with previous studies that have noted the relative stability of climatic conditions in certain regions (Trenberth *et al*., 2007). However, the presence of drought conditions, even if less frequent, warrants attention due to their potential impacts on ecosystems and human activities (Wilhite, 2000). The observed decrease in drought probabilities with increasing time scales (e.g., SPEI-3 to SPEI-9), that is, the seemingly, variability of probabilities across timescales, indicating that the duration of analysis influences the assessment of drought likelihood. For instance, SPEI-3 and SPI-3 (3-month) show slightly different probabilities compared to SPEI-9 and SPI-9 (9-month), highlighting how short-term vs. longer-term accumulations of precipitation (and evapotranspiration in SPEI's) affect drought classification. Mishra and Singh (2010), suggested that shorter-term droughts accumulation are more common and often more manageable than longer-term droughts accumulation. The differences between SPEI and SPI probabilities highlight the importance of considering evapotranspiration in drought assessments, as SPEI accounts for both precipitation and evapotranspiration, providing a more comprehensive view of drought conditions (Vicente-Serrano *et al*., 2010). In addition, supports the use of multiple indices for a nuanced understanding of drought dynamics (Keyantash and Dracup, 2002).

Overall, the **drought Probabilities taken a cursory** look at the dry categories, the probabilities for moderately dry ranging from 0.058 to 0.16, for severely dry from 0.09 to 0.157, and for extremely dry from 0.01 to 0.12. This shows that dry conditions, particularly moderately and severely dry, have a non-negligible chance of occurring in Minna. Extremely dry conditions are the least probable among the dry categories, but are still present. However, the notable presence of severely dry and extremely dry conditions across different time scales underscores the vulnerability of Minna to significant drought events. This finding is consistent with studies emphasising the potential for severe drought impacts on agriculture, water resources, and ecosystems (IPCC, 2013).

Table 1. Probability Distributions of Different Drought Classes

Class	SPEI-3	SPI-3	SPEI-6	SPI-6	SPEI-9	SPI-9
Extreme Wet	0	0	0	0	0	0
Severely Wet	0.024	0.04	0.024	0.05	0.019	0.04
Moderately Wet	0.085	0.11	0.084	0.17	0.087	0.14
Near Normal	0.518	0.57	0.518	0.52	0.615	0.55
Moderately Dry	0.096	0.11	0.096	0.16	0.058	0.14
Severely Dry	0.157	0.14	0.157	0.09	0.154	0.11
Extremely Dry	0.12	0.03	0.12	0.01	0.067	0.02

Empirical Relationship between SPI and SPEI at Varying Time Scales

Table 2a presents the results of correlation analyses conducted to assess the relationship between the SPI and SPEI at 3, 6, and 9-month timescales. Three correlation methods were employed: Pearson, Spearman, and Kendall's Tau, each providing a slightly different perspective on the association between the two indices. **Weak correlation at shorter timescales** consistently across all three correlation methods, which indicates the association between SPI and SPEI at shorter timescales (3 and 6 months) was weak. The Pearson correlation coefficients range from 0.119 to 0.139, Spearman's coefficients are 0.112 and 0.036, and Kendall's Tau values are 0.075 and 0.018. These values indicate a limited linear relationship and suggest that at these shorter durations, SPI and SPEI may capture different aspects of hydroclimatic variability. At the 9-month time scale, the correlation between SPEI and SPI strengthens, with Kendall's Tau coefficient indicating a moderate relationship (0.312). This implies that as the time scale increases, the difference between SPEI and SPI becomes less pronounced, and the indices tend to capture similar drought patterns.

The discrepancy in correlation strength across timescales can be attributed to the differing roles of temperature and evapotranspiration, which SPEI incorporates but SPI does not. At shorter timescales (3 and 6 months), precipitation patterns may exhibit greater variability accounted by the influence of temperature or evapotranspiration. Consequently, SPI, which solely relies on precipitation, may diverge from SPEI. Over longer timescales (9 months), the cumulative effect of temperature and evapotranspiration on moisture or precipitation deficits becomes less pronounced, leading to *a* stronger agreement between SPEI and SPI. As Tamrakar *et al.* (2024) highlight, understanding the interplay between precipitation and evapotranspiration is crucial for accurate drought assessment. Longer timescales inherently involve cumulative effects; at 9 months, both SPI and SPEI reflect the accumulated precipitation deficit or surplus over a more extended period. This temporal aggregation can smooth out short-term fluctuations and reveal a more coherent relationship between the two indices (Tamrakar *et al*. 2024). For long-term drought planning and water resource management, the increasing correlation at longer timescales suggests that SPI and SPEI tend to converge in their assessment of prolonged dry or wet conditions. However, even at longer timescales, the correlation is not perfect, and SPEI may offer additional insights due to its inclusion of temperature effects, particularly in a region like Minna, where temperature can play a significant role in water availability. The findings of studies such as Patel and Bhatt (2018), which emphasise the importance of considering both SPI and SPEI in drought monitoring across diverse climatic zones in India, should be upheld.

To further explore the relationship between SPI and SPEI at different timescales, a simple linear regression analysis was conducted, the results of which were presented in the following Table 2b he results provide additional insights into the dynamics between these two drought indices. The previous discussion focused on correlation coefficients (Pearson, Spearman, and Tau), which primarily measure the strength and direction of the association between SPI and SPEI. The regression analysis complements this by providing a linear model that predicts the value of one index based on the other, along with statistical measures. The findings from the regression analysis largely corroborate the earlier observation of weak relationships between SPI and SPEI, particularly at shorter timescales. For example, the R values (Pearson correlation coefficient) in the regression Table 2b (0.100 to 0.139) align with the "weak" correlations reported in the previous table. This consistency reinforces the interpretation that SPI and SPEI, weakly related, capture distinct aspects of drought, especially over shorter durations, where temperature and evapotranspiration may not exert as dominant influence in longer periods. The R-squared values were low, indicating that SPI explains only a small proportion of the variance in SPEI (1% to 1.9%). This suggests that SPEI captures unique aspects of drought dynamics not accounted for by SPI, potentially due to the influence of evapotranspiration (Beguería *et al*., 2014). It is glaring from Table 2b that the p-values are non-significant across all time scales, indicating that the relationships between SPEI and SPI are not statistically significant. This is equally consistent with the preponderance of weak correlations and low explanatory power observed in the data.

Innovative Trend Pattern and Associated Implication

Table 3 presents the results of the innovative trend test for SPEI and SPI at varying time scales (3, 6, and 9 months). SPEI-9 and SPI-9 show a neutral trend, which possibly connote stable state. The negative trend slopes for SPEI-3, SPI-3, and SPI-6 suggest strongly drying regime, a situation likely to initial drought and most often attributed to changes in precipitation and evapotranspiration patterns. Nicholson (2013) highlighted that the onset and drought propagation are likely to be preceded by decreasing trend. The high correlation values (>0.95) indicate strong relationships between the indices and the trend, which equally implies that the chosen indices were appropriate and were able to capture the seasonal variability inherent in the series, thus reinforcing the **reliability** of the observed drought trends. **Beguería et al (2014) reaffirmed that**.

Table 3 revealed that the slope standard deviations associated with the identified drought trends were notably low, that is, 0.000, 0.000, 0.093, 0.001, 0.000 and 0.000 SPEI-3, SPI-3, SPEI-6, SPI-6, SPEI-9 and SPI-9, respectively. This consistency in the slope standard deviation values suggests that the observed trends, whether increasing or decreasing, exhibit a degree of reliability and are not greatly influenced by short-term fluctuations or extreme events (Sen, 2012). However, this contrasts with studies that have reported higher variability in drought trends, often attributed to the influence of El Niño-Southern Oscillation (ENSO) or other climatic oscillations, which can introduce significant non-linearity in long-term data (Wang and Swail, 2001). The relative stability observed in these studies suggests that the identified drought trends are more likely to be indicative of a gradual shift, potentially linked to longer-term climatic changes, rather than being dominated by interannual variability. From Table 3, it is clear that the trend results varied across time scales, highlighting the importance of considering multiple time scales when analysing drought trends. This finding is consistent with previous studies that have emphasised the importance of considering multiple time scales when assessing drought trends (Vicente-Serrano *et al*., 2010). Figures 3 and 4 show a blend of increased and decreased trends across the studied area. For instance, SPI at shorter timescales (3, 6 and 9 months) shows admixed of negative and positive trends while SPEI-3 and SPEI-9 indicate an increasing trend, as opposed to SPEI-6, which shows excessive downward trend. The divergence between SPI and SPEI trends suggests that temperature, evapotranspiration and precipitation play an increasingly important role in drought patterns as a function of time scale. Overall, the innovative trend test provides valuable insights into drought trends in the region. The results suggest a balanced trend of drying and wetting for the indices across the time scales at the neighbourhood of 50 % to 50%.

Applications of Machine Learning Models for Drought Predictions

Support Vector Machine Model

Table 4 presents the performance metrics of a Support Vector Machine (SVM) model for drought classification using different time scales (SPI-3, SPI-6, SPI-9, SPEI-3, SPEI-6, and SPEI-9). The metrics include specificity, positive predictive value (PPV), negative predictive value (NPV), balanced accuracy, kappa, accuracy, F-score, recall, precision, and feature importance. Table 4 reveals varying performance of the SVM model across different drought classes and timescales. For instance, for SPI-3, the model demonstrates high accuracy (0.850 to 1.000) in classifying near normal and moderately wet conditions, with perfect Specificity, PPV, and NPV. However, the performance is poor for very dry, very wet, and extreme wet classes, with 0.000 values for PPV and NPV, indicating the model's difficulty in correctly identifying these extreme conditions. SPI-6 shows a similar trend, with high accuracy for near normal conditions but poor performance for extreme drought and wet classes. The performance for SPI-9 also follows the same pattern. SPEI-3 shows a slightly different trend with a good classification of very dry, near normal, and moderately wet conditions. This suggests that the SVM model appeared to be more proficient at classifying near-normal and moderate conditions than at accurately capturing extreme drought or wet events. This could be attributed to the imbalanced nature of the dataset, where extreme events are less frequent, posing a challenge for the model to learn and generalise effectively, as reported by Chawla *et al*. (2002). In tandem with the submission of McCuen (2016) and Chawla *et al*. (2002) the seemingly, high accuracy for near normal conditions could be due to its prevalence in the dataset, providing the model with sufficient examples to learn from, the poor performance in classifying extreme events is likely due to the limited number of such occurrences, leading to under-representation and inadequate learning by the SVM model. This is a common issue in classification problems where class imbalance exists. In addition, the variations in model performance can be attributed to the complexity of drought phenomena, which involves non-linear interactions between climatic variables. The choice of model parameters, data preprocessing techniques, and the specific climatic context of the study area can also influence the results (Breiman 2001).

In light of the foregoing, it is challenging to definitively declare one timescale as best with a clear, consistent superiority across all metrics and classes. However, SPI-3 and SPEI-3 show relatively higher accuracy and balanced performance across more classes compared to SPI-6 and SPI-9. SPI-3 particularly demonstrates high accuracy for near-normal and moderately wet classes. SPEI-3 also shows a good classification of very dry, near normal, and moderately wet conditions. Guttman (1999) opined that shorter timescales (3-month) might capture immediate drought impacts more effectively, reflecting the direct influence of recent precipitation patterns, which was perceived in the studied region, therefore, validating SPEI-3 and SPI-3 as the most balanced and appropriate time scale for SVM functionality in connection with the studied region. Breiman (2001) showed that SVM can be effective in classifying near normal, moderate dry and very dry drought conditions, but less accurate for extreme events. Therefore, SVM models, particularly those using SPI-3 and SPEI-3, can contribute to drought monitoring systems in Minna, providing timely information for water resource management and aiding in decisions related to water allocation for irrigation, especially during near-normal conditions, where accurate prediction is crucial for sustainable agriculture. A Thorough Comparison of SPI-3, SPI-6, and SPI-9 shows a general trend of decreasing

performance in capturing extreme events as the timescale increases. This suggests that the SVM model is more adept at short-term drought classification using SPI, and the seemingly small differences in the performance between SPI-3 and SPEI-3 highlight the importance of considering both precipitation and temperature in drought modelling. Guttman (1999) reiterated that longer timescales (6-month and 9-month) might smooth out immediate effects, potentially obscuring the model's ability to detect rapid-onset droughts.
In accordance, with Chukwu (2024) submitted that each accumulation interval or time scale portend prevailing drought type in the region, for instance and SPI-3, SPI-6 and SPI-9, gives an idea of; short and medium moisture deficit (agricultural drought), streamflow and reservoir deficit (hydrological drought) and short and medium moisture deficit precipitation deficit (meteorological drought) respectively. Based on this, it can be inferred in connection with SVM and SPI-3/SPEI-3 that the predominant drought type is agricultural drought, with a consequent threat to food security. Similar droughts have been recorded in Nigeria, more pronounced in the northern regions, with varying frequencies and intensities (Federal Ministry of Environment National Drought Plan, 2018).

Table 2a. Correlation of the Computed Indices

Indices	Pearson	Remarks	Spearman	Remarks	Tau	Remark
SPEI-3 and SPI-3	0.119	weak	0.112	weak	0.075	weak
SPEI-6 and SPI-6	0.139	weak	0.036	weak	0.018	weak
SPEI-9 and SPI-9	0.255	weak	0.293	weak	0.312	moderate

Table 2b. Regression Metrics of the Computed Indices

Indices	R	R-squared	Intercept	t-stat	p-value	Standard Error
SPEI-3 and SPI-3	0.100	0.01	0.061	-0.468	0.320	0.931
SPEI-6 and SPI-6	0.139	0.019	0.011	-0.196	0.423	0.928
SPEI-9 and SPI-9	0.102	0.010	0.017	0.112	0.455	0.899

Table 3. Innovative Trend Component across Multiple Scales

Parameters	SPEI-3	SPI-3	SPEI-6	SPI-6	SPEI-9	SPI-9
Trend Slope	-0.001	-0.001	-2.599	-0.003	0.000	0.000
Trend Indicator	-8.617	-9.296	-1.320	-12.481	3.902	-284.279
Slope Standard Deviation	0.000	0.000	0.093	0.001	0.000	0.000
Correlation	0.967	0.991	0.962	0.959	0.989	0.988
Lower Confidence Limit (90%)	-0.008	-0.000	-0.153	-0.001	-0.004	-0.003
Upper Confidence Limit (90%)	0.008	0.000	0.153	0.001	0.004	0.000
Lower Confidence Limit (95%)	-0.009	-0.000	-0.182	-0.001	-0.0004	-0.000
Upper Confidence Limit (95%)	0.009	0.000	0.182	0.001	0.0004	0.000
Lower Confidence Limit (99%)	-0.001	-0.000	-0.239	-0.001	-0.000	-0.000
Upper Confidence Limit (99%)	0.001	0.000	0.239	0.001	0.000	0.000

Table 4. Overview of the Performance of SVM

		Classification Matrics				Evaluation Matrics					
Class	Indices	Specificity	PPV	NPV	Bal. Accuracy	Kappa	Accuracy	F-Score	Recall	Precision	Feature Imp.
Extreme Dry	SPI-3	0.000	0.000	0.000	0.000	0.703	0.850	0.000	0.000	0.000	0.463
Very Dry		1.000	0.000	0.090	0.500			1.000	1.000	1.000	
Moderately Dry		0.882	0.500	0.938	0.775			1.000	1.000	1.000	
Near Normal		0.857	0.929	1.000	0.929			0.960	1.000	0.923	
Moderately Wet		1.000	1.000	1.000	1.000			1.000	1.000	1.000	
Very Wet		1.000	0.000	0.000	0.000			0.000	0.000	0.000	
Extreme Wet		1.000	0.000	0.000	0.000			0.000	0.000	0.000	
Extreme Dry	SPI-6	1.000	0.000	0.957	0.500	0.664	0.783	0.000	0.000	0.000	0.588
Very Dry		0.9546	0.500	1.000	0.977			1.000	1.00	1.000	
Moderately Dry		1.000	1.000	1.000	1.000			0.000	0.000	0.000	
Near Normal		1.000	1.000	0.818	0.929			1.000	1.000	1.000	
Moderately Wet		0.818	0.200	1.000	0.909			0.000	0.000	0.000	
Very Wet		1.000	1.000	0.999	0.667			0.000	0.000	0.000	
Extreme wet		1.000	0.000	0.000	0.000			0.000	0.000	0.000	
Extreme Dry	SPI-9	1.00000	0.000	0.957	0.500	0.609	0.783	0.000	0.000	0.000	0.467
Very Dry		0.955	0.000	0.955	0.477			0.000	0.000	0.000	
Moderately Dry		0.947	0.667	0.900	0.724			0.571	0.500	0.667	
Near Normal		0.778	0.867	0.875	0.853			0.897	0.929	0.867	
Moderately Wet		0.9500	0.750	1.000	0.975			0.857	1.000	0.750	
Very Wet		1.000	0.000	0.000	0.000			0.000	0.000	0.000	
Extreme wet		1.000	0.000	0.000	0.000			*0.000*	*0.000*	0.000	
Extreme Dry	SPEI-3	1.000	0.000	0.000	0.000	0.649	0.850	0.000	0.000	0.000	0.475
Very Dry		1.000	1.000	1.000	1.000			1.000	1.000	1.000	
Moderately Dry		1.000	0.000	0.900	0.500			0.000	0.000	0.000	
Near Normal		0.667	0.875	1.000	0.833			0.933	1.000	*0.875*	
Moderately Wet		1.000	1.000	1.000	1.000			1.000	1.000	*1.000*	
Very Wet		0.000	0.000	0.95	0.500			0.000	0.000	0.000	
Extreme Wet		0.00	0.000	0.000	0.000			0.000	0.000	0.000	
Extreme Dry	SPEI-6	1.000	0.000	0.000	0.000	0.736	0.895	0.000	0.000	0.000	0.3611
Very Dry		1.000	1.000	0.944	0.750			1.000	1.000	1.000	
Moderately Dry		0.944	0.000	0.944	0.472			0.800	0.667	1.000	
Near Normal		0.800	0.933	1.000	0.900			0.957	1.000	0.917	
Moderately Wet		1.000	1.000	1.000	1.000			1.000	1.000	1.000	
Very Wet		1.000	0.000	0.000	0.000			0.000	0.000	0.000	
Extreme wet		1.000	0.000	0.000	0.000			0.000	0.000	0.000	
Extreme Dry	SPEI-9	1.000	0.000	0.00	0.000	1.000	1.000	0.000	0.000	0.000	0.443
Very Dry		1.000	1.000	1.000	1.000			1.000	1.000	1.000	
Moderately Dry		1.000	1.000	1.000	1.000			0.00	0.000	0.000	
Near Normal		1.000	1.000	1.000	1.000			0.941	0.941	0.941	
Moderately Wet		1.000	1.000	1.000	1.000			0.667	1.000	0.500	
Very Wet		1.000	0.000	0.000	0.000			0.00	0.000	0.000	
Extreme Wet		1.000	0.000	0.000	0.000			0.000	0.000	0.000	

Table 5. Overview of the Performance of DT

Class	Indices	Classification Matrics				Evaluation Matrics					
		Specificity	PPV	NPV	Bal. Accuracy	Kappa	Accuracy	F-Score	Recall	Precision	Feature Imp.
Very Dry	SPI-3	0.9474	0.500	1.000	0.973	0.863	0.950	0.667	1.000	0.500	1109.130
Moderately Dry		1.000	0.000	0.95	0.500			0.000	0.000	0.000	
Near Normal		1.00	1.000	1.000	1.000			1.000	1.000	1.000	
Moderately Wet		0.947	0.500	1.000	0.973			0.667	1.000	0.500	
Very Wet		1.000	0.000	0.950	0.500			0.000	0.000	0.000	
Near Normal	SPI-6	1.000	1.000	1.000	1.000	0.889	0.9545	1.000	1.000	1.000	1622.469
Moderately Wet		0.9412	0.833	1.000	0.970			0.909	1.00	0.833	
Very Wet		1.000	0.00	0.956	0.500			1.000	0.000	0.000	
Extreme Dry	SPI-9	1.000	0.000	0.000	0.000	0.849	0.952	0.000	0.000	0.000	220.725
Very Dry		0.950	0.500	1.00	0.975			-	-		
Moderately Dry		1.000	0.000	0.952	0.500			0.000	0.000	0.000	
Near Normal		1.000	1.000	1.000	1.00			1.000	1.000	1.000	
Moderately Wet		1.000	0.000	0.000	0.000			0.857	1.000	0.75	
Very Dry	SPEI-3	1.000	1.000	1.000	1.000	0.857	0.950	1.000	1.000	1.000	228.155
Moderately Dry		1.000	1.000	1.000	1.000			1.000	1.000	1.000	
Near Normal		1.000	1.000	1.000	1.000			1.000	1.000	1.000	
Moderately Wet		0.947	0.500	1.000	0.974			0.667	1.000	0.5	
Very Wet		1.00	0.000	0.950	0.500			0.000	0.000	0.000	
Extreme Wet		1.00	0.000	0.95	0.500			-	-	-	
Very Dry	SPEI-6	1.000	1.000	1.000	1.000	0.868	0.947	1.000	1.000	1.000	191.028
Moderately Dry		1.000	0.944	0.500	0.972			0.667	1.000	0.500	
Near Normal		1.000	1.000	0.800	0.9667			0.966	0.933	1.000	
Moderately Wet		1.000	1.000	1.000	1.000			1.000	1.000	1.000	
Very Dry	SPEI-9	1.000	1.000	1.000	1.000	1.000	1.000	1.000		1.000	189.482
Near Normal		1.000	1.000	1.000	1.000		0.965	1.000		1.000	
Moderately Wet		1.000	1.000	1.00	1.00		1.000	1.000		1.000	

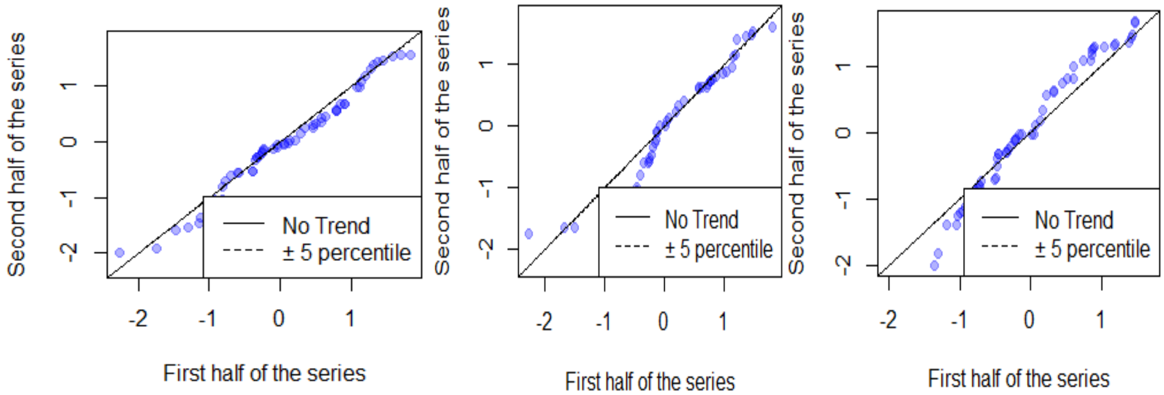

Figure 3: Innovative Trend Pattern for (a) SPI-3 (b) SPI-6 (c) SPI-9

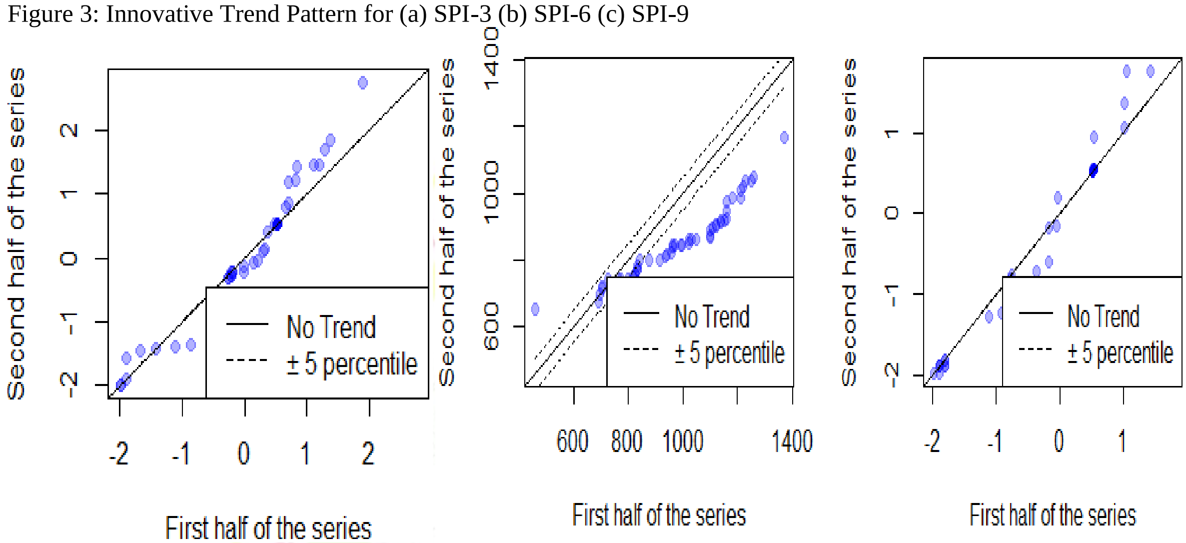

Figure 4. Innovative Trend Pattern for (a) SPEI-3 (b) SPEI-6 (c) SPEI-9

Decision Tree Model

Table 1 presents the performance metrics of the Decision Tree (DT) model in classifying drought categories. The Table was structured to show class (drought categories), Indices (SPI or SPEI with time scales). The near normal class consistently achieves perfect classification metrics (1 for Specificity, PPV, NPV, Balanced Accuracy, Accuracy, F-Score, Recall, and Precision) across SPI-3, SPI-6, and SPI-9. Similar pattern was maintained with SPE-3 and varied with SPEI-6 and resurface in SPEI-9. The incidence of near normal appeared to be predominate in all the time scales sampled across the indices. This indicates the DT model exhibited high accuracy in identifying and predicting near normal conditions. For the SPI-3 index, the model demonstrates high specificity (0.9474 to 1) for very dry, moderately dry, and moderately wet categories. The SPEI-3 captured very dry incident with high accuracy (1) for very dry and moderately wet categories but poor performance for extreme dry (0 accuracy, F-Score, Recall, and Precision) and moderately dry (0 F-Score, Recall, and Precision). Additionally, SPEI-3 show a perfect metrical value of 1 for Specificity, PPV, NPV, Balanced Accuracy, Accuracy, F-Score, Recall, and Precision for moderate dry and gradually decreases with moderate wet. SPI-3 and SPEI-3 shows similar characteristics for Specificity, PPV, NPV, Balanced Accuracy, Accuracy, F-Score, Recall, and Precision for very wet, though with very weak validation metric values that hove around zero, which signify very low probability. Such latent pattern indicates the reliability and repetitiveness of the model to point out probable very wet period though at very low tune. Against this backdrop, the model ability cut across diverged drought event and non-event. The SPI-6 shows a strong prediction for normal with perfect metric of 1 and somewhat fluctuate between moderate wet and very wet. While in SPEI-6 shows a perfect metrics of 1 for moderate dry and moderate wet and decreases with moderate dry. The Incident of repeated very dry captured by SPEI may be attributable to SPEI index in cooperating evapotranspiration series in it computation. For SPI-9, the model shows a decline in accuracy for the extreme dry class (accuracy 0.952) compared to SPI-3 and SPI-6, and also shows zero values for PPV, Recall, and F-Score in several categories.

Considering all this, it can be inferred that short-term indices (SPI-3, and to some extent, SPEI-3) show more potential. It tend to have higher accuracy overall, but the Decision Tree model struggles with precision for specific drought categories. This suggests that while the model can generally identify drought conditions, it has difficulty in correctly classifying the *class* of those drought conditions. The high Recall for some categories indicates that when a drought event occurs, the model is likely to capture it. **Longer-term indices (SPI-9) perform poorly with DT in this context.** The model's inability to predict anything beyond near normal for SPI-9 suggests that DT might not be suitable for modelling drought at this time scale, or that the model needs significant refinement (e.g., hyperparameter tuning, feature engineering) to handle longer-term drought patterns. It can be inferred, DT performs better with SPEIs series and is more explicit with SPI-3 and SPEI-3. Suffices to know that Short-term indices (SPI-3, SPEI-3) may better capture rapid-onset droughts or immediate impacts of precipitation/temperature (Chukwu, 2024). This emphasises the relative performance of time scales within a specific DT modelling exercise. Tamraka *et al*. (2024) opined that DT can learn complex relationships between input variables and categories. Hence, it can capture non-linear patterns, which is important in drought analysis. Sequel to these studies, model performance varies across drought categories and time scales. Near normal conditions are consistently well-predicted, while extreme and moderate drought/wet categories show a mixed grilled. This is probably because drought datasets are often imbalanced, with fewer instances of extreme events compared to normal conditions. This imbalance can bias models towards the majority class (near normal), leading to poor performance on minority classes (extremes). The sporadicity observed across computed series, that is, non-uniformity of the model to output all drought classes across multi-scales and indices, could be accounted by the fact that SPI (McKee, 1993) and SPEI (Vicente-Serrano *et al.*, 2010) capture different drought aspects. SPI focuses on precipitation deficits, while SPEI includes temperature and evapotranspiration. Performance differences may arise from these inherent differences and the importance of temperature in the study area.

In Overall, the performance patterns of both models revealed multiple points of convergence, which is strong agreement on near normal, for example, both SVM and DT accurately and consistently classify the near normal drought category, likely due to its prevalence in the dataset, enabling better training performance. Shared limitations in extremes; neither model handles extreme drought or wet categories effectively. This is symptomatic of class imbalance, a structural limitation that hampers their ability to learn sufficient decision boundaries for minority events. In a similar instance, both models achieve superior performance with a short-term time scale (SPI-3 and SPEI-3). This finding aligns with established knowledge that short-term indicators are better suited to detect immediate hydrometeorological changes (Guttman, 1999; Chukwu, 2024). SVM displays marginally better classification precision for moderate classes (moderately dry, moderately wet), while DT shows greater overall reliability in reproducing perfect scores for near normal and very dry and slightly better adaptability with SPEI derived indices. DT offers greater consistency in classification performance, particularly under short-term indices (SPI-3, SPEI-3) was due to its capacity to model non-linear relationships and adapt to complex climatic patterns. For operational deployment in drought-prone regions like Minna, short-term indices should be prioritised, and model refinement strategies such as resampling techniques, ensemble learning, and feature engineering should be employed to better capture the intricacies of extreme drought conditions. These findings will serve as a foundational step in developing robust drought early warning systems that are both timely and context sensitive, especially in regions where food security and water availability are closely tied to climate variability.

The DT and SVM models showed high accuracy in predicting common drought classes such as *near normal and moderately dry*, evidenced by consistent alignment between observed and predicted labels. However, Table 6 shows a few misclassification instances, which occurred predominantly in extreme drought categories, likely due to class imbalance within the dataset.

Table 6. Misclassification

Observed	Predicted
Decision Tree	
SPI-3	
Moderate dry	Extreme dry
Moderately Wet	Extreme wet
SPEI-3	
Very wet	Moderate wet
Moderately Wet	Extremely Wet
Support Vector Machine	
SPI-3	
Near normal	Moderate dry
Very dry	Moderate dry
SPEI-3	
Moderate dry	Extreme dry
Very dry	Moderate dry

CONCLUSION

This study provides a comparative analysis of drought patterns and prediction in Minna, Nigeria, through the application of both traditional drought indices (SPI and SPEI) and machine learning models (SVM and Decision Tree). Finding have clearly shown that both algorithms have repeated unveiled prevalence of moderate dry, near normal and very dry and remain erratic on the predictions of extremes, this may not be considered as limitation as earlier drought signatories detection carried out, shows that the probabilities for moderately dry ranging from 0.058 to 0.16, for Severely dry from 0.09 to 0.157, and for extremely dry from 0.01 to 0.12. This indicates that dry conditions, particularly moderately and severely dry, have a non-negligible chance of occurring in Minna. Extremely dry conditions are the least probable among the drought categories, but still present.

However, the notable presence of severely dry and extremely dry conditions across different time scales underscores the vulnerability of Minna to significant drought events. In addition, subtle look at the model's performance across different drought categories and timescales shows SVM and Decision Tree algorithms demonstrated a capacity for accurately classifying near-normal conditions, their effectiveness diminished in the identification of more extreme drought states. Specifically, shorter timescales (SPI-3 and SPEI-3) were shown to exhibit superior performance, characterised by higher accuracy and a more balanced suite of evaluation metrics, compared to their longer-term counterparts. This suggests that, within the hydroclimatic context of Minna, shorter accumulation periods are more salient in capturing the immediate influence of precipitation and evapotranspiration dynamics on drought evolution. These results underscore the inherent challenges in drought characterisation and prediction within a region marked by complex hydroclimatic interactions. The analysis highlights the critical importance of integrating both precipitation and temperature data, as encapsulated in the SPEI, to achieve a more holistic understanding of drought phenomena. Furthermore, the study demonstrates that while machine learning techniques hold considerable promise for drought analysis, their successful application hinges on careful consideration of input variable selection, timescale dependencies, and the specific climatic context. The observed variability in model performance across drought categories, particularly the difficulty in accurately classifying extreme events, points to the need for further refinement of modelling approaches and potentially the incorporation of additional relevant predictors. The implications of these findings for water resource management and agricultural planning in Minna are significant. The identification of SPI-3 and SPEI-3 as the most informative timescales for drought monitoring can contribute to the development of more effective early warning systems, facilitating the implementation of timely and targeted interventions to mitigate the adverse impacts of drought. Moreover, the comparative assessment of machine learning models provides a foundation for the development of improved drought prediction tools. Future research should prioritise the exploration of advanced machine learning methodologies, such as ensemble modelling and deep learning, and the integration of a broader range of hydroclimatic and land surface variables, to enhance the robustness and accuracy of drought predictions and to provide more actionable information for stakeholders and decision-makers.

CONFLICT OF INTEREST

The author here declares that there is no conflict of interest in the publication of this article.

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