

Performance of Random Forest and Support Vector Machine Models for Drought Prediction in Kano, State, Northwest Nigeria

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Abstract

Drought significantly impacts water resources, ecosystems, and human livelihoods, particularly in northern Nigeria, where rainfed agriculture is predominant. The effects, including reduced water supply, poor water quality, crop failure, environmental hazards, and civil unrest, are worsened by climate change, which increases drought frequency and severity. Monitoring the spatiotemporal dynamics of drought—severity, magnitude, intensity, duration, and extent—is critical for early warning, prevention, and preparedness. This study evaluates the effectiveness of machine learning models—Random Forest (RF) and Support Vector Machine (SVM)—in predicting drought events in Kano State. Historical meteorological data (2012–2023) from the Visual Crossing Weather (VCW) dataset were validated using Nigeria Meteorological Agency (NIMET) data at a 0.05 confidence level. Key variables included precipitation, temperature, solar radiation, and indices such as SPI Gamma, SPEI, and Fisk Distribution. Results indicated irregular rainfall patterns, with a recovery from 2018. SPI3 Gamma and Pearson indices identified dry periods (2013–2018) and wet periods (2019–2022), while SPEI provided a more comprehensive drought assessment by integrating evapotranspiration. The RF model outperformed SVM in accuracy (66.8% vs. 65.7%) and precision (60.3% vs. 45.4%), effectively reducing false positives. Recall scores were comparable (66%), indicating both models reliably identified drought events. Random Forest (RF) and Support Vector Machine (SVM) performed well and in the absence of hydroclimatic data, the models offer valuable insights for improving climate resilience and drought preparedness in Kano State.

Keywords: machine learning, random forest, support vector machine, drought, prediction, climate change

INTRODUCTION

Climate change and natural climate variability are primary drivers of extreme weather events, including heavy rainfall and droughts, which significantly disrupt ecosystems and human livelihoods (Schubert & Lim, 2012; O’Gorman, 2015). At regional scales, climate variability stems from anomalies in large-scale oceanic and atmospheric circulations, which

alter atmospheric transport patterns and contribute to localized weather extremes (Schwing et al., 2010; Cabos et al., 2020). These climatic drivers, associated with distinct patterns and regional configurations, often induce contrasting weather conditions due to their asymmetric physical characteristics (Hoerling et al., 1997; Montroy et al., 1998). Northern Nigeria is particularly vulnerable to such extremes due to its geographical location, characterized by low rainfall and significant

variability. The region's dry conditions are largely influenced by the dominance of low-level cyclonic circulations over parts of the Western Asian landmass, which enhance the penetration of northeasterly winds from the Sahara Desert (Nicholson, 2013; Shiru et al., 2019). Moreover, Nigeria's diverse ecoregions experience distinct rainfall patterns, driven by the seasonal migration of the Inter-Tropical Convergence Zone (ITCZ) and anomalies in sea surface temperatures (SSTs) in adjacent oceans (Folland et al., 1991; Raj et al., 2019). These factors, combined with the West African Monsoon system's dynamics, significantly influence rainfall distribution and variability across the country (Akinsanola & Zhou, 2020). Climate change exacerbates these conditions, particularly in northern Nigeria, where rising temperatures increase evapotranspiration rates, further intensifying droughts. Between 1960 and 2006, Nigeria's average annual temperature rose by 0.8°C, with a steeper increase since 1980 and the most pronounced changes occurring in the northern region (USAID, 2019; World Bank Group, 2021). Projections suggest that by 2060, mean annual temperatures could rise by 1.1 to 2.5°C, with the northern region facing the highest increases (USAID, 2019). Concurrently, precipitation has declined, averaging a decrease of 3.5 mm per month per decade during the same period (USAID, 2019).

This climatic instability has severe socio-economic repercussions, particularly for food security. Sub-Saharan Africa, including Nigeria, faces alarming levels of malnutrition due to decreased agricultural productivity and rising temperatures. Reports indicate that food insecurity affects 36–40 million people in West Africa, with high poverty and illiteracy rates

compounding the region's vulnerability (Sultan & Gaetani, 2016; FAO et al., 2019). Furthermore, over 94% of arable lands in the Sudano-Sahel region rely on rainfed agriculture, which is increasingly threatened by erratic rainfall patterns (Abrams, 2018; Lemi and Hailu, 2019). Droughts manifest through various spatiotemporal characteristics, including severity, magnitude, intensity, duration, and geographic extent, necessitating robust monitoring mechanisms for early warnings and mitigation measures (Yang et al., 2017). Traditional rainfall data from precipitation gauges, while accurate, often suffer from limited spatial coverage and high maintenance costs, making satellite-based data a preferred alternative for drought monitoring (Xie et al., 2022).

Recent advancements in Machine Learning (ML) have shown promise in addressing these challenges. ML models, such as artificial neural networks (ANNs), Random Forests (RF), support vector machines (SVMs), and long short-term memory (LSTM) networks, have demonstrated high accuracy and precision in drought prediction (Citakoglu and Coşkun, 2022; Deo et al., 2017; Kisi et al., 2019). Other models, including decision trees (DT), adaptive neuro-fuzzy inference systems (ANFIS), and k-nearest neighbors (KNN), have also proven effective for drought monitoring (Kikon Deka, 2022; Lotfirad et al., 2021; Yaseen et al., 2021). Bhusal et al. (2022) emphasized that ML models can enhance prediction accuracy without requiring explicit design for specific purposes, making them versatile tools in drought assessment. However, their application in Nigeria remains underexplored (Oyounalsoud et al., 2024), underscoring the

need for research on ML-based drought prediction in the region.

This study bridges this gap by evaluating the performance of two ML models, Random Forest (RF) and Support Vector Machine

(SVM), in predicting drought events in Kano State. Through this effort, the study seeks to contribute to developing accurate and efficient tools for drought monitoring and preparedness in northern Nigeria.

Materials and Methods

Geographical description of study area

The study was conducted in Kano State, located in the northern region of Nigeria. Geographically, the state is situated between latitudes 10°48'N and 12°30'N, and longitudes 7°59'E and 9°11'E (Fig. 1). Kano State is

bordered to the north by the Republic of Niger, to the south by Bauchi State, to the east by Jigawa State, and to the west by Kaduna and Katsina States.

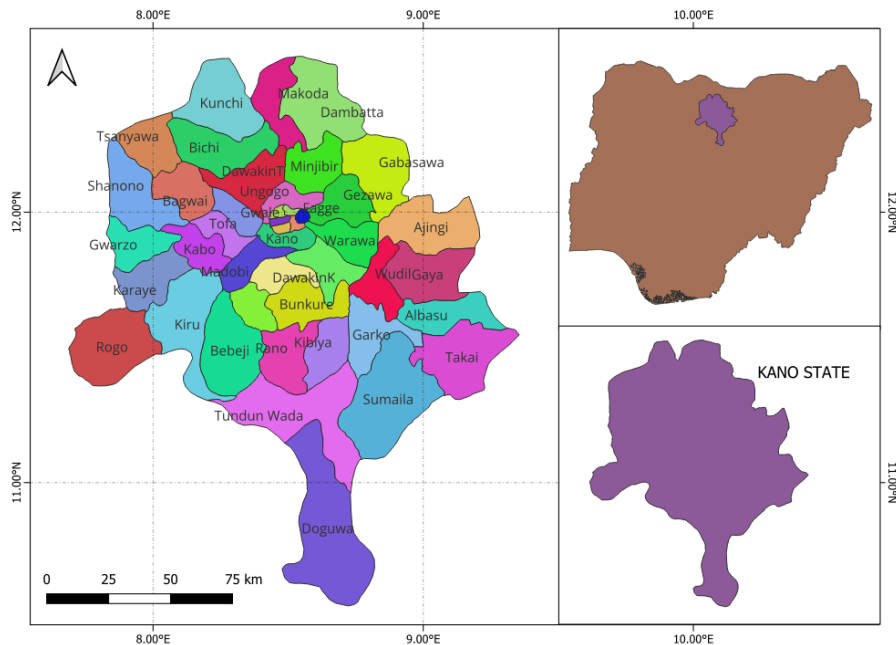


Fig. 1: Study Area, Kano State, Nigeria

Climate of the Study Area

The climate of the study area falls within the tropical savanna or tropical wet and dry (Aw) climate zone. This climate type is characterized by distinct wet and dry seasons, with the rainy season lasting approximately five months. Rainfall amounts decrease from the southern part of the region to the north, with the southern

areas receiving over 1,000 mm of rainfall annually, while the northern parts receive less than 800 mm. In drought years, rainfall can drop below 450 mm, as seen during the 1972/73 period (Abdulhamid, 2000). The rainy season is brief, lasting only three to four months, with erratic distribution. Rainfall in the region typically follows a unimodal pattern, with a peak usually occurring in August (Buba, 2009).

Consequently, water availability is a critical issue in the area.

Temperature in the study area is generally warm to hot throughout the year, averaging around 25°C with a variation of $\pm 7^\circ\text{C}$ (Olofin & Tanko, 2002). Temperatures remain relatively high from March to October and cooler from November to February. Humidity levels are significantly influenced by the movement of the Inter-Tropical Discontinuity (ITD). During the rainy season, relative humidity (RH) can rise up to 90%, while in the harmattan season (November to March), RH may drop as low as 20%, reflecting the influence of the tropical maritime air mass (TM).

Relief and Vegetation

The study area spans approximately 42,592 km² (Mamman et al., 2002). The topography of the region is dominated by high, undulating plains interspersed with subdued interfluves (Mortimore, 1970). The relief varies in elevation from 500 m to 1,000 m, with shallow yet wide valleys that extend for several tens of kilometers, characterized by gently sloping valley sides.

The vegetation in the study area is predominantly Sudan–Sahel Savanna, which is a mixture of woodlands and grasslands, with trees and grasses interspersed in varying degrees (Mamman et al., 2002). The natural vegetation has been largely cleared for agricultural purposes (Ahmed, 2010), resulting in the loss of many native species. The remaining natural vegetation consists of trees that rarely exceed 20 meters in height, including species such as *Acacia albida*, *Tamarindus indica*, *Butryospermum* spp., *Parkia clappertoniana*, among a few others.

Grasses are also present, though they are sparse and typically do not exceed one meter in height at maturity, often drying out during the dry season. In many areas, cultural vegetation has replaced the natural flora, with exotic species becoming predominant (Bichi, 2016).

Economic Activities

Agriculture is the primary land use activity in the study area, encompassing both rain-fed and irrigation-based farming systems. The region's farming practices are primarily focused on subsistence and commercial agriculture. The key crops grown during the rainy season (rain-fed agriculture) include sorghum, millet, groundnut, and rice, while dry season crops (irrigated agriculture) feature wheat, rice, maize, tomatoes, and onions. In addition to agriculture, other significant land use activities in the area include residential areas, markets, schools, government offices for administration, motor parks, holiday resorts, communication networks, roads, and forest reserves (Olofin, 1987).

Data Collection

For this drought prediction project, daily weather data spanning from 2012 to 2023 was collected from the Visual Crossing Weather (VCW) dataset via www.visualcrossing.com. The data used for this study includes key meteorological variables such as precipitation, temperature, humidity, and other factors influencing drought conditions. To verify the reliability of the VCW dataset, the daily precipitation and temperature data were aggregated into mean monthly values and compared with corresponding mean monthly data from the Nigerian Meteorological Agency (NIMET) for the period 2000–2006, based on

data availability. The correlation was tested at a 0.05 significance level.

SPI Drought Index Calculation: The Standardized Precipitation Index (SPI) was calculated using the acquired precipitation data. The SPI is a commonly used index that quantifies the severity of meteorological drought based on observed precipitation.

Data Compilation: Following the calculation of the SPI, the meteorological data, SPI values, Standardized Precipitation and Evapotranspiration Index (SPEI) values, and historical drought events were compiled into a comprehensive dataset. This dataset forms the foundation for the development of our machine learning model.

Data Analysis

Test for reliability of Visual Crossing weather Dataset

To test for reliability of Visual Crossing weather datasets, the Pearson's Product Moment Correlation statistics was performed at

0.05 level of significance for the degree of association between estimated values and measured rainfall, temperature data from NIMET. The equation is given as follows;

$$r_{xy} = \sqrt{\frac{\Sigma(x - \bar{x})(y - \bar{y})}{\Sigma(x - \bar{x})^2 \Sigma(y - \bar{y})^2}} \quad (1)$$

Where r_{xy} is the correlation coefficient x and y were the 2 sets of observation

All the analysis were performed using excel mathematical tool at 0.05 level of significance (95% confidence level). The rule of thumb is the closer correlation coefficient to unit value (1.00) the more reliable Visual Crossing weather datasets for used for the study (Figs 2 and 3). The student t test was used to establish the significance of the coefficient.

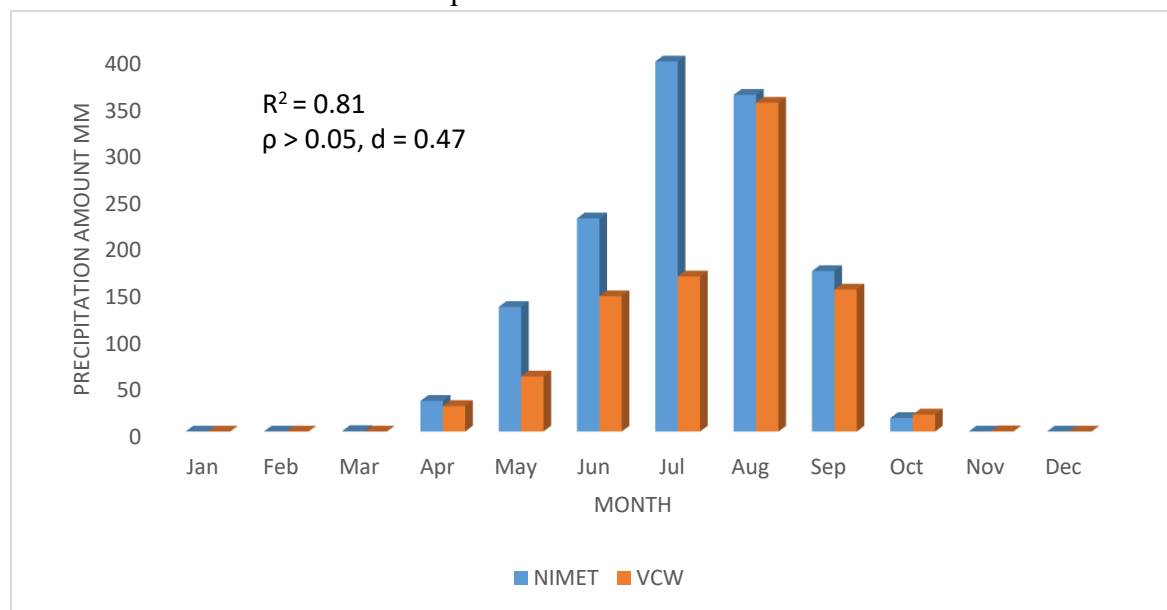


Fig. 2: Statistical relationship between NIMET mean monthly rainfall data and VCW dataset
 Positive relationship is significant at $p > 0.05$, $d = 0.47$

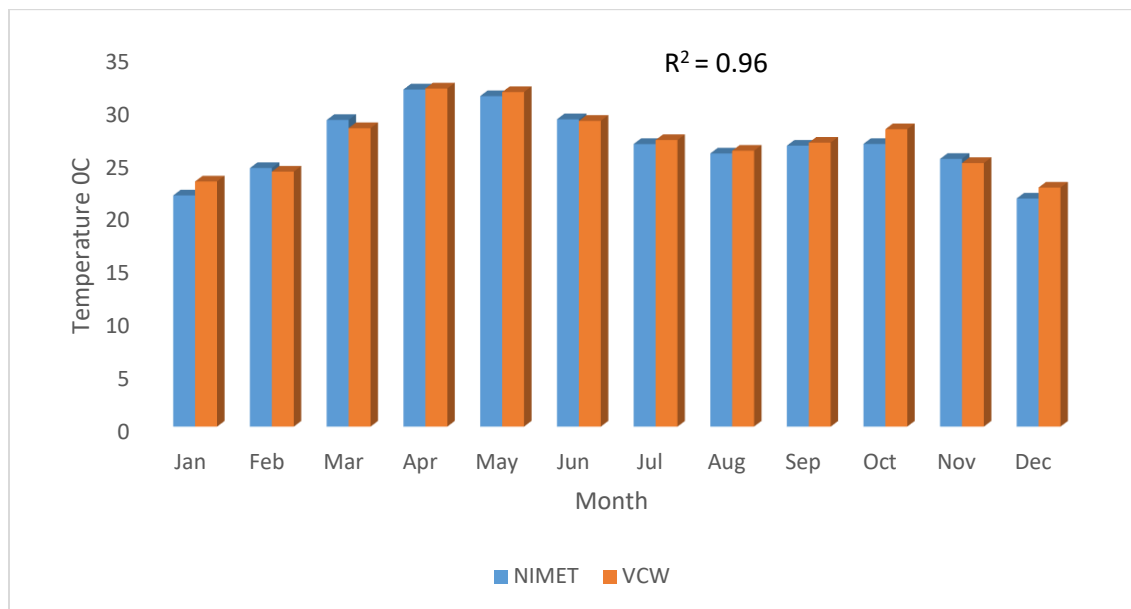


Fig. 3: Statistical relationship between NIMET mean monthly Temp data and VCW dataset
Positive relationship is significant at $p > 0.05$, $d = 0.37$

Ensemble Method

Ensemble learning involves the strategic creation and combination of multiple models, such as classifiers or experts, to address a specific computational intelligence problem (Gandhi, 2022). One of the most commonly used ensemble learning techniques is Random Forest, which is applied in tasks such as classification and regression. During the training process, Random Forest generates multiple decision trees. For classification, it selects the class that is most frequently predicted by the majority of the trees. Random Forest is a form of Bootstrap Aggregation, or bagging, an ensemble machine learning algorithm. The "forest" in Random Forest refers to a collection of decision trees that, when considered individually, may act as "weak" classifiers and produce poor predictions. However, when combined, these trees generate a more robust and accurate

prediction. In essence, ensemble methods like Random Forest leverage the strengths of multiple models to improve predictive accuracy.

The Random Forest model employs two key techniques: a) Bagging: this technique involves creating multiple subsets of the original training data by random sampling with replacement, with each subset in the dataset used to build a decision tree and the final prediction is obtained by aggregating the predictions of all trees. B) Feature Randomization: During the construction of each decision tree, only a random subset of features is considered at each split, reducing the correlation between trees and makes the model more robust to noisy and irrelevant features.

Working Principles of Support Vector Machines

The SVM model operates by: (a) preprocessing and normalizing input data as such noise and irrelevant information that may affect the model are removed in this stage; (2) mapping data to a higher-dimensional feature space using an RBF kernel function; (3) learning the optimal separating hyperplane by solving a quadratic optimisation problem that minimises classification error while maximising the margin between the hyperplane and support vectors; and (4) classifying unseen data based on its position relative to the learned hyperplane.

Data Preprocessing

Data preprocessing is a very important step in this study because the quality of the data directly affects how well the model performs. At this stage data cleaning was done. This involved dealing with missing values, outliers, and inconsistencies in the dataset. Missing values can reduce the accuracy of predictions, so they were identified and handled using suitable methods such as deleting incomplete records, replacing values with averages, or estimating them using techniques like regression or K-Nearest Neighbors (KNN). Outliers, which can distort the model, were detected using statistical methods such as Z-scores and IQR, as well as visual tools like box plots. Any inconsistencies in the data, such as incorrect labels or data types, were also corrected to ensure reliability.

Next, data transformation was carried out to make the data more suitable for modelling. This included scaling the data to improve model performance. Where variables had different ranges, normalization was applied to bring values within a range of 0 to 1. For data that followed a normal distribution, standardization

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was used to adjust values so they have a mean of 0 and a standard deviation of 1.

By properly preprocessing the data, we ensured that the model receives accurate and consistent inputs that reflect the real meteorological conditions and drought events in the study area.

Feature Selection

Feature selection helps to identify the most important variables that contribute to drought prediction. This step improves the model's performance and also makes it easier to understand.

We began by identifying which features were most relevant to drought events. Variables such as rainfall, temperature, humidity, and SPI values were considered important because of their strong relationship with drought. Their importance was evaluated using statistical methods like correlation and mutual information, as well as feature importance scores from machine learning models. Correlation analysis was carried out to measure how strongly each variable is related to drought events. Features with higher correlation were considered more useful. In addition, mutual information was used to capture both linear and non-linear relationships between variables and drought occurrence.

Machine learning techniques, particularly the Random Forest model, was used to determine feature importance. Based on these results, feature selection methods such as recursive feature elimination and forward or backward selection was applied to choose the most relevant variables.

Where the dataset contained many variables, dimensionality reduction techniques like Principal Component Analysis (PCA) and

Linear Discriminant Analysis (LDA) were used to reduce complexity while retaining important information. This process ensured that only the most relevant features were used, improving model accuracy and reducing unnecessary complexity.

Model Development

Model development is the main stage of the study, where machine learning algorithms were used to predict drought events in the study area. The dataset was divided into training and testing sets while the training set was used to build the model and the testing set was used to assess how well the model performs. The Random Forest algorithm was applied because it combines multiple decision trees, making it more reliable and less prone to overfitting. The model was then trained to learn the relationship between input variables and drought events. Hyperparameter tuning was carried out to improve model performance. This involved selecting the best values for parameters such as the number of trees and tree depth. Techniques like grid search were used to test different parameter combinations, while cross-validation ensured that the model performs well on unseen data.

Finally, the model was validated using the testing dataset. Its predictions were compared

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with actual values, and performance was measured using metrics such as accuracy, precision, recall, and F1-score. Cross-validation was also applied to ensure the model is stable and reliable.

Through this process, a robust model was developed that can effectively predict meteorological drought events in Kano State while remaining interpretable and reliable.

Results and Discussion

Daily time series of precipitation distribution in mm from the year 2012-2023 is presented in Fig. 4. Rainfall distribution over Kano is highly variable and marked by annual lows and highs. However precipitation amount was very low before 2018 when a sign of rainfall recovery becomes evident. This recovery is consistent with findings by Gbode et al. (2019) and Ogunrinde et al. (2019), who similarly documented an increasing rainfall trend in Kano and the broader Sahel region from the late 1990s onwards. The low precipitation years (2013–2017) correspond to heightened drought risk, as limited rainfall reduces soil moisture and increases dependence on irrigation, imposing significant stress on the predominantly rainfed agricultural systems of Kano State.

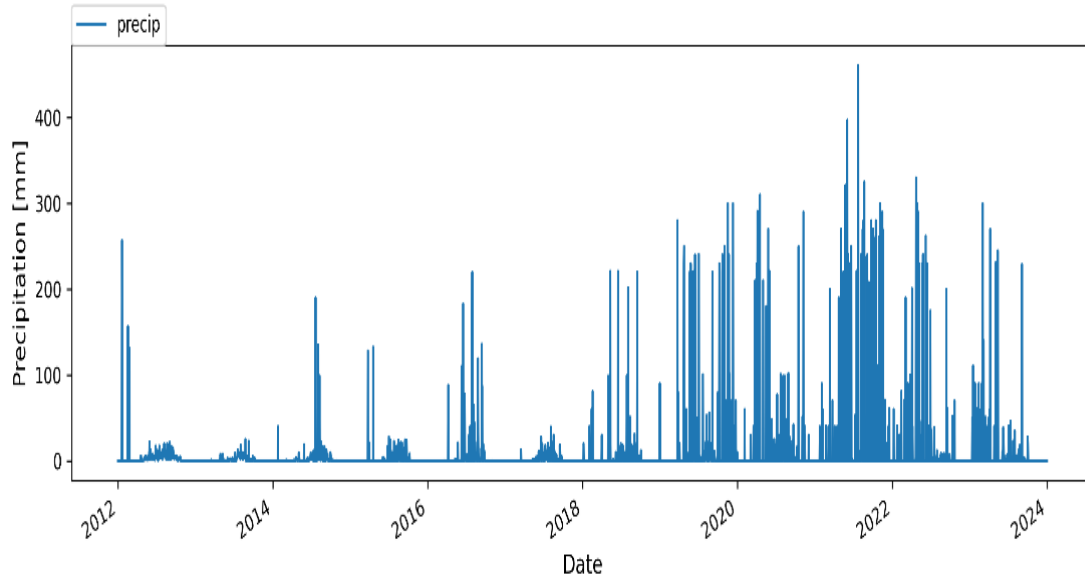


Figure 4. Precipitation Chart

Distribution of relative humidity in percentage (%) between the relative humidity and time (from 01-01-2012 to 31-12-2023). Fig. 5. The chart shows the relationship

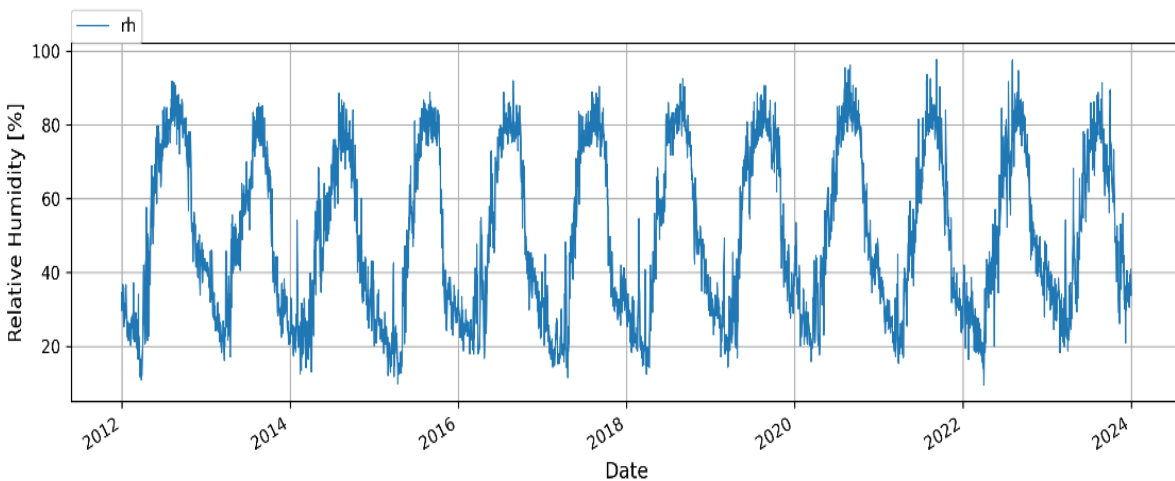


Figure 5: Relative Humidity Chart

The cyclical pattern of relative humidity, fluctuating between approximately 20% during the dry harmattan season (November–March) and up to 90% during the peak rainy season (June–September), reflects the seasonal influence of the Inter-Tropical Discontinuity (ITD) and the alternating dominance of tropical continental and tropical maritime air masses over Kano State. The declining RH trend observed during the drier years (2013–2017) corresponds to reduced moisture availability and heightened evapotranspiration demand,

conditions directly associated with increased drought risk. The recovery in RH values from 2018 onwards aligns with the rainfall recovery observed in Figure 4 and is corroborated by the SPI and SPEI analysis presented subsequently.

Both Solar radiation and temperature distribution show evidence of rising trends (Figs. 6 and 7). Okemini (2015) also reported

that Kano State is warming at an average annual rate of 0.011°C and becoming wetter at a rate of 21.26 mm per annum. Precipitation and RH control moisture supply and demand, while rising temperature signifies increasing evaporative demand and enhanced evapotranspiration, leading to soil moisture depletion and reduced surface runoff, thereby intensifying drought (Fig.8).

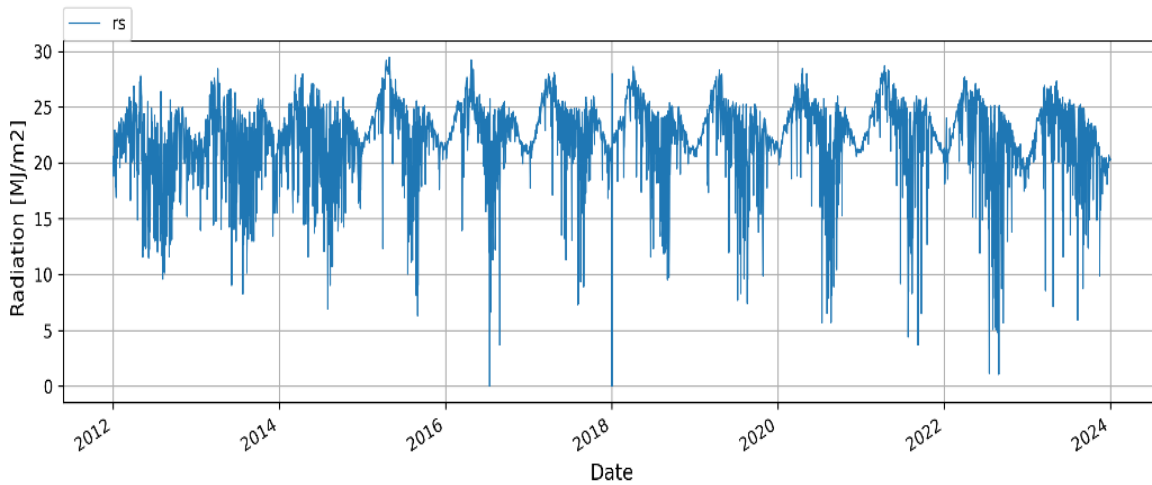


Figure 6: Solar Radiation Chart

Figure 6 shows that solar radiation in Kano State exhibits a cyclical annual pattern, with values ranging from approximately 5 30 MJ/m² to 30 MJ/m². Higher radiation is recorded during the dry season (October–March), when cloud cover is minimal. This elevated radiation during dry periods contributes to increased potential evapotranspiration (PET), thereby

exacerbating soil moisture deficits and intensifying drought conditions. The consistently high radiation levels observed throughout the 2012–2023 period, combined with the rising temperature trend, underscore the growing evaporative demand that characterizes Kano State’s evolving climate.

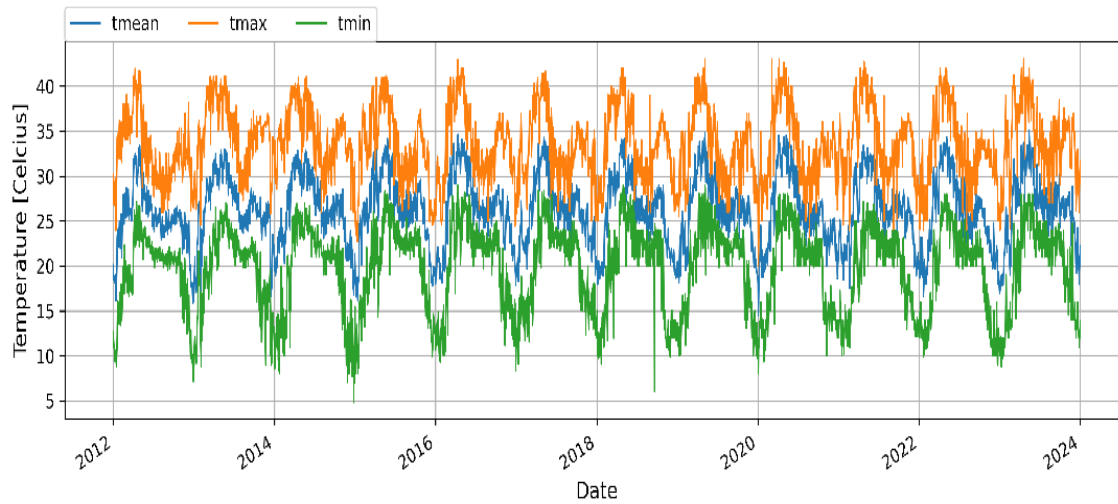


Figure 7: Min and Max temperature

Figure 7 shows that maximum temperatures in Kano State consistently exceed 35°C during the pre-rainy season months of March–May, while minimum temperatures drop to approximately 10°C during the harmattan period (November–January). Both minimum and maximum temperature series exhibit an upward trend over the 2012–2023 period, consistent with the broader regional warming documented by

Okemini (2015). These rising temperatures amplify evapotranspiration demand, contributing to enhanced soil moisture loss during dry periods. In the context of the study, this warming trend is a critical driver of increased drought severity in Kano State, as confirmed by the SPEI analysis which integrates temperature-driven evapotranspiration into its drought assessment.

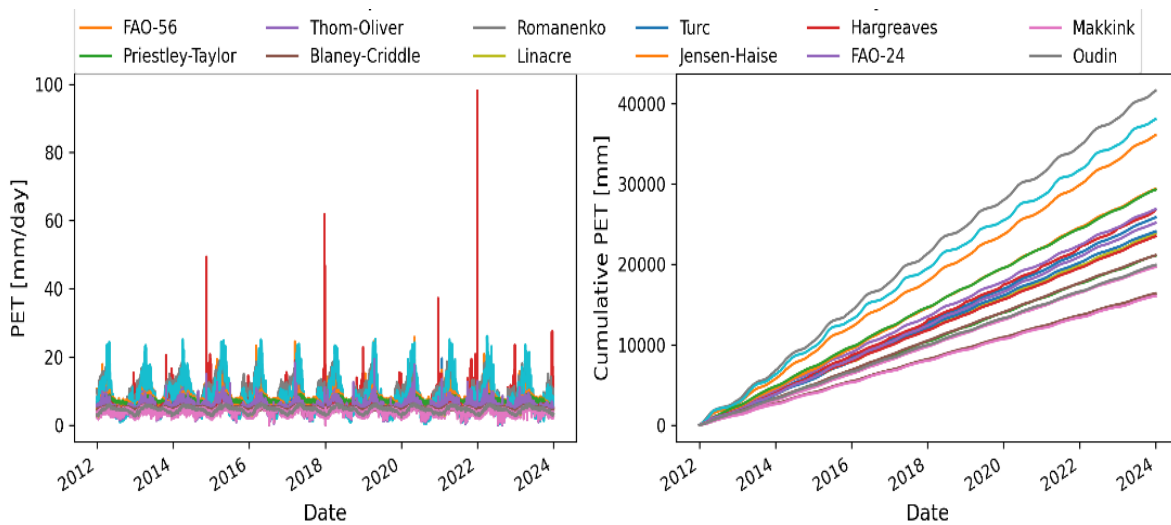


Figure 8: PET Chart for various distributions

The chart below represents the SPI index for the year 2012-2023. For this project, SPI3 was used, which represents 3months/ 90days timescale Two popular SPI methods are represented below which is Gamma method and Pearson method (Fig. 9 and 10). The SPI3 Gamma and Pearson Charts Figures 9 and 10

show that Kano had more dry periods from 2013-2018 and the state has more wet periods from 2019-2022. The common method of SPI that is mostly considered is the gamma method, the SPI index values from the gamma method are represented in the chart below

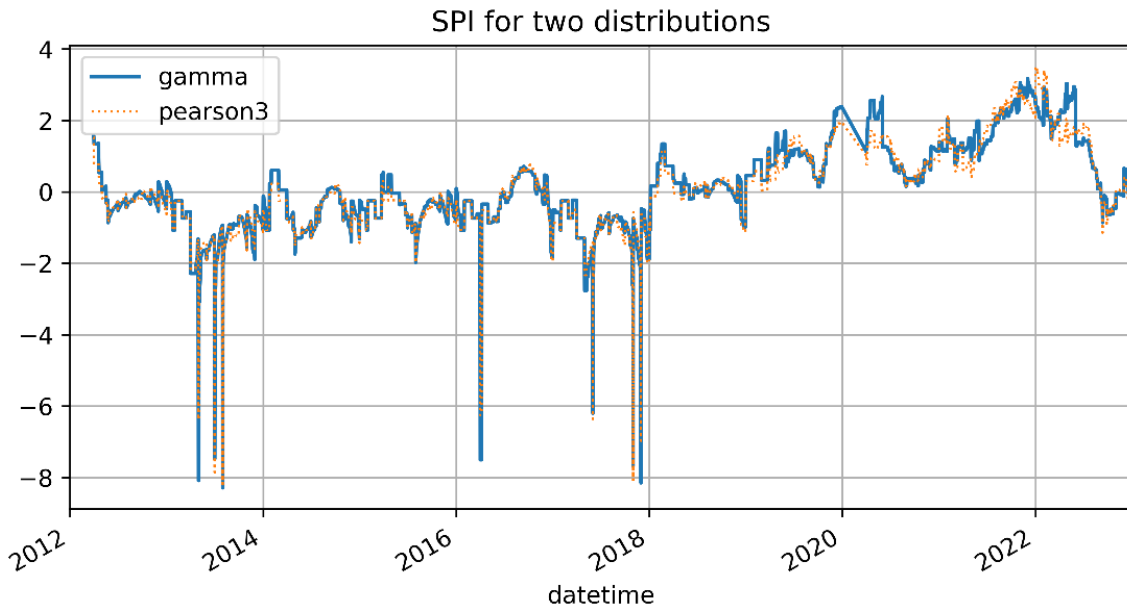


Figure 9: SPI3 Gamma and Pearson Chart

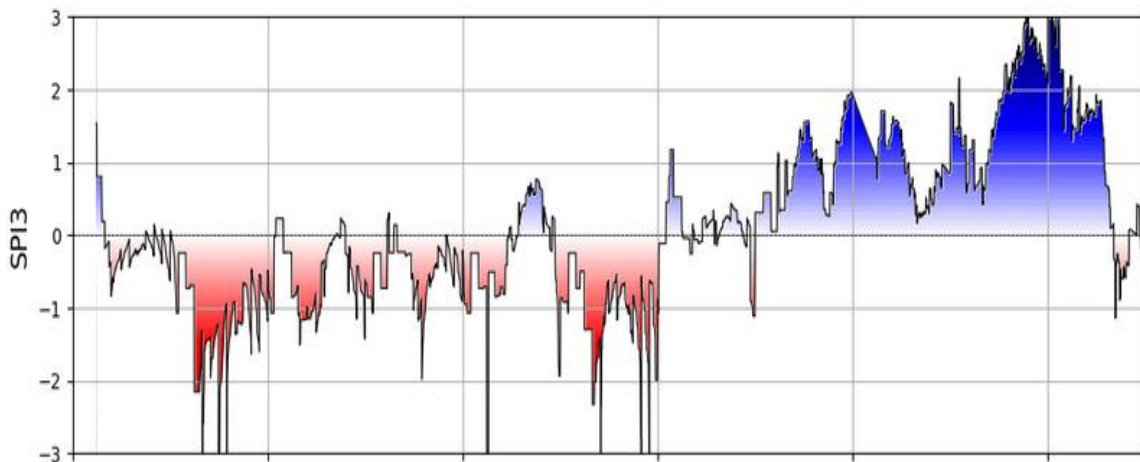


Figure 10: SPI3 Gamma Method

The SPEI was calculated for using one month/30 days' timescale, which can also be

called SPEI1. The method that was used to calculate this index is known as fisk method.

Figs 11 and 12 represent the SPEI index with respect to time (which is from the year 2012-2023)

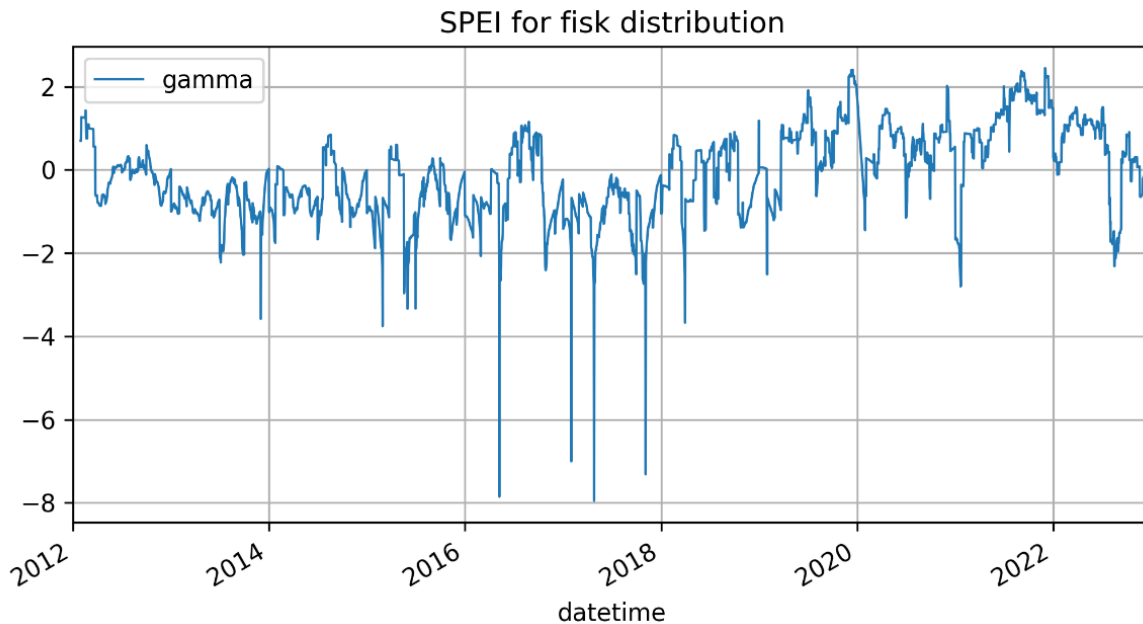


Figure 11: SPEI Chart – Fisk Distribution (A)

The SPEI chart in Figure 11 reveals frequent and pronounced negative SPEI values (indicating drought conditions) during 2012–2018, with the most severe negative anomalies occurring around 2016–2018. This corroborates the dry period identified by the SPI analysis. From 2019 onwards, SPEI values shift towards positive anomalies, reflecting increased moisture availability consistent with the observed rainfall recovery. Importantly, the

SPEI captures the additional influence of elevated temperatures on evapotranspiration demand, rendering it a more comprehensive drought indicator than SPI alone for the semi-arid climate of Kano State. These findings imply that even in years with moderate rainfall, high temperatures can sustain drought-like conditions, underscoring the need for temperature-sensitive drought indices in climate monitoring for the region.

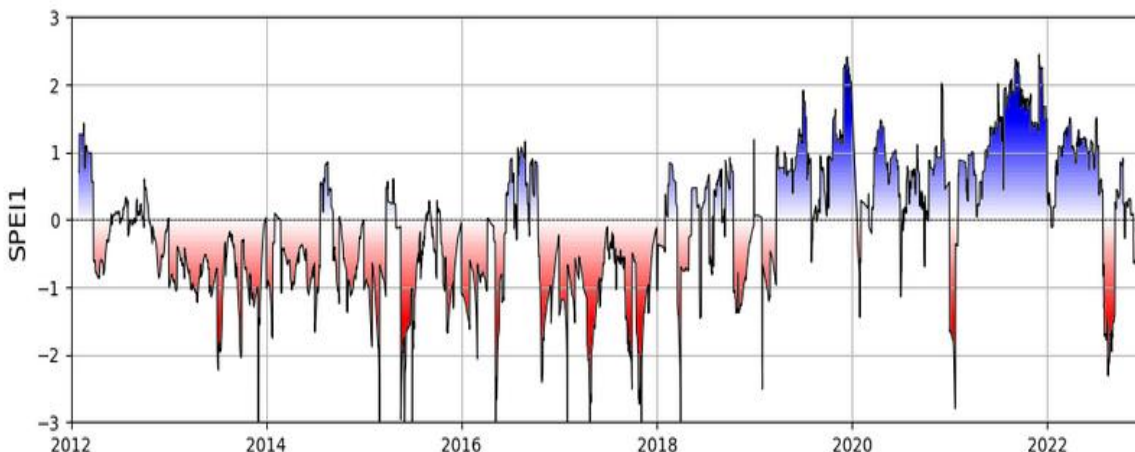


Figure 12: SPEI1 Chart – Fisk Distribution (B)

Table 1: Result of Model Evaluation

	RANDOM FOREST MODEL	SVM MODEL EVALUATION RESULTS
Accuracy	66.82%	65.67%
Precision	60.28%	45.38%
Recall:	66.82%	65.67%
F1 Score:	59%	52.58%

Accuracy: This is the proportion of correct predictions made by the model. In this case, the Random Forest model has a slightly higher accuracy (66.8%) compared to the SVM model (65.7%).

Precision: This metric tells you the proportion of positive predictions that were actually correct. The Random Forest model again has a better precision score (60.3%) than the SVM model (45.4%). This means the Random Forest model was better at avoiding false positives drought prediction.

It is acknowledged that a precision of 60.3% for the Random Forest model and 45.4% for the SVM model are modest results that do not meet the ≥ 70 –80% threshold typically expected for operationally reliable drought early warning systems. These scores are contextualised by the

constraints of the study: the dataset covers a single station over 12 years (2012–2023), limiting training data volume and drought-class balance; the SPI- and SPEI-based drought labels are subject to their own uncertainty; and drought is a complex, multi-scale phenomenon inherently difficult to predict from meteorological variables alone at short timescales. The precision scores are, however, comparable to those reported for ML-based drought prediction in data-scarce regions in the literature (Piri et al., 2023; Felsche and Ludwig, 2021), and represent a useful baseline for future improvement through expanded datasets, additional stations, and deep learning approaches.

Recall: Recall indicates the proportion of actual positive cases that were correctly

identified by the model. Both models have similar recall scores (around 66%).

F1 Score: This metric is a harmonic mean between precision and recall, giving equal importance to both. A higher F1 score is generally desirable. Here, the Random Forest model has a clear advantage with an F1 score of 59.0% compared to the SVM model's F1 score of 52.6% indicating a better overall balance between false positives and false negatives.

In practical terms for Kano State, the Random Forest model's superior precision means it generates fewer false drought alarms—an important advantage, as false alarms erode institutional and public trust in early warning systems, leading to 'cry-wolf' fatigue among farmers and water resource managers. The comparable recall scores (~66%) for both models indicate that they are equally capable of detecting actual drought events, ensuring that genuine drought occurrences are not systematically missed. For a region where over 70% of the population depends on rainfed agriculture, even a model with moderate accuracy can support proactive drought preparedness actions—including early seed distribution, water conservation advisories, and pre-positioning of food stocks—that meaningfully reduce the socio-economic impacts of drought on vulnerable farming communities in Kano State.

Overall, the Random Forest model seems to be a better choice based on these metrics.

Discussion

The annual rainfall recovery observed in this study is consistent with previous research on northern Nigeria. For instance, Gbode et al. (2019) reported a significant increasing trend in

the annual total precipitation (PRCPTOT) index across various stations, including those in the Guinea Coast, Bauchi in the Savannah, and Kano and Maiduguri in the Sahel. Similarly, the positive trend in PRCPTOT over Kano was also noted by Gbode et al. (2015). This recovery has been linked to the influence of localized rainfall and convective activities associated with the presence of the Hadejia and Jama'are river wetlands (Adeyeri et al., 2019). Druyan (2011) also identified a recovery in seasonal precipitation accumulations across the Sahel from the 1990s to the 2000s, although not to the levels observed prior to the severe droughts of the 1970s and 1980s.

While the IPCC (2013) indicated a drying trend in West Africa based on a longer time series from 1951 to 2012, Ibrahim et al. (2014) reported an increase in both annual total precipitation and the frequency of wet days, contributing to a partial recovery of rainfall in the Sahel. This recovery has been attributed not only to natural variability (Mohino et al., 2011) but also to anthropogenic factors such as greenhouse gas emissions (Haarsma et al., 2005; Ackerley et al., 2011; Biasutti, 2013; Dong and Sutton, 2015). Ogunrinde et al. (2019) observed that Kano State experienced a decreasing rainfall trend between 1981 and 1995, followed by an increase in rainfall in the subsequent decades (1996–2015).

Rainfall variability in Nigeria has been connected to various climatological and dynamical factors influencing the drastic changes in rainfall distribution (Omotosho, 2008; Ogungbenro and Morakinyo, 2014). Studies have also examined the dynamics behind dry periods in the Sahelian zone, highlighting the role of the latitudinal location of the African Easterly Jet in the region's

rainfall production mechanism (Nicholson, 1986; Omotosho, 2008; Oluleye, 2009). The Intertropical Discontinuity (ITD), which separates tropical continental (cT) and tropical maritime (mT) air masses, plays a critical role in shaping rainfall patterns and drought occurrences in Nigeria and West Africa (Ilesanmi, 1971; Odekunle et al., 2005; Ayanlade, 2009). The movement of the ITD affects spatial and temporal rainfall variability, with rainfall decreasing from regions of lower latitudes to those of higher latitudes. Other factors influencing long-term rainfall variability in West Africa and Nigeria include the tropical easterly jet (TEJ), sea-surface temperature anomalies (SSTA), biogeophysical feedback mechanisms, and the El Niño Southern Oscillation (ENSO) (Bello, 1998; Olaniran, 2002; Oguntunde et al., 2011).

The observed precipitation variability in this study has significant implications for water availability. Rainfall is the primary climatic variable affecting hydrological processes and climate-induced changes in both environmental and human systems (Mohamed et al., 2022). Variations in its spatial and temporal distribution can significantly influence ecosystems and water resource management (Mathew et al., 2021). Climate change, especially changes in rainfall patterns and temperatures in sub-Saharan Africa, is expected to increase the frequency of both droughts and flooding (IPCC, 2014).

An increase in temperature will accelerate the hydrological cycle, leading to greater evapotranspiration when water is available. However, in the absence of precipitation, this can exacerbate drought conditions by promoting surface dryness (Omonijo and Okogbue, 2014; Whitman et al., 2015; Shiru et

al., 2019; Ideki and Weli, 2019; Ogunrinde et al., 2019). This is evident in the Sudan Savannah Region of Nigeria, which has experienced significant rainfall variability over the past 40 years, characterized by reductions in mean annual rainfall (Dai et al., 2004; Ekpoh and Nsa, 2011). The region is part of the Sudan-Sahel ecological zone of West Africa, which has been affected by recurrent climatic anomalies such as droughts, dust storms, and floods since the early 1970s (Camberlin and Diop, 2003; Ekpoh and Nsa, 2011).

The persistence of drought in the Sudano-Sahelian regions of Nigeria has been linked to stagnated anti-cyclonic circulation patterns in the tropical atmosphere, which prevent the usual rise of the tropical Hadley Cell circulation (Kalu, 1987; Kamara, 1986). These atmospheric conditions are influenced by heat sources such as warm ocean surfaces and equatorial rainforests, which impact tropical circulation patterns (Lockwood, 1979; Nicholson and Tucker, 1998). Consequently, rainfall patterns in West Africa, including northern Nigeria, exhibit both annual and longer-term variations, influenced by distant locations through teleconnections (Nicholson, 1993).

Climate change is expected to affect all four dimensions of food security in Nigeria, including food availability, access, stability, and utilization (Ikhatua, 2010). Environmental challenges due to unplanned urbanization, such as rising temperatures, are particularly prevalent in major Nigerian cities (Mohammed et al., 2014; Adenle et al., 2023). In Kano city, for example, urban microclimate temperatures have increased by nearly 2°C between 1980 and 2018 due to rapid urban expansion and poor urban planning (Asonibare et al., 2024).

Model evaluations in this study showed an accuracy rate of over 65% for both models, with precision rates of 60.3% for the Random Forest model and 45.4% for the Support Vector Machine (SVM) model. Both models exhibited similar recall scores (around 66%). The Random Forest model had an F1 score of 59.0%, while the SVM model achieved an F1 score of 52.6%. These findings support the efficacy of these models in drought prediction and align with previous studies that highlight the effectiveness of machine learning (ML) algorithms in improving drought forecasting (Piri et al., 2023; Danandeh Mehr et al., 2023; Felsche and Ludwig, 2021).

In other regions, similar ML-based models have been employed for drought prediction. For example, Malik et al. (2020) developed a fuzzy logic model, the coactive neuro-fuzzy inference system (CANFIS), to predict the SPI at various time scales in India, showing that CANFIS outperformed traditional regression models and AI techniques. Khan et al. (2020) tested a hybrid model that combined wavelet transformation, ARIMA, and an artificial neural network (ANN) to predict future droughts in Malaysia. The hybrid model surpassed the standalone ANN, achieving an R^2 of 0.914, compared to 0.423 for the ANN. Mehr et al. (2022) developed a hybrid model combining convolutional neural networks and long short-term memory networks for short-term prediction in Turkey, achieving root mean square errors (RMSE) between 0.043 and 0.075. Recent studies have also applied various machine learning models such as ANNs, random forests, LSTM, and SVM for drought prediction (Deo and Şahin, 2015; Fahimi et al., 2017; Rhee and Im, 2017; Parajuli et al., 2024).

Conclusion and Recommendations

The continuous rise in surface temperature, driven by climate change, has profound implications for the hydrological cycle, with drought being one of the key indicators of this warming trend. The Intergovernmental Panel on Climate Change (IPCC) projects a global mean temperature increase of 1 to 3 degrees Celsius (1.8 to 5.4 degrees Fahrenheit) above pre-industrial levels, which may bring both beneficial and harmful impacts depending on the region (IPCC, 2021). Drought, a hydro-climatological phenomenon, is defined by temporary and recurring water shortages, which can last from weeks to several months or even years. This phenomenon is dynamic in nature; regions may simultaneously experience wet and dry spells depending on the timescale considered. For example, in northern Nigeria, dry or wet conditions may persist for short periods, but over the long term, the opposite may occur. Such variability negatively affects the onset and duration of farming operations, subsequently impacting agricultural outputs.

Agriculture plays a pivotal role in the economic development of West Africa, contributing approximately 50% to the GDP, with smallholder farmers being the largest group within the agricultural sector. In Nigeria, particularly in the northern regions, over 70% of the population relies on agriculture for their livelihoods. Unfortunately, this agricultural dependence is predominantly on rainfall, which dictates the timing and duration of farming activities. Consequently, the increasing frequency, intensity, severity, and geographic spread of droughts due to global warming exacerbate the challenges faced by farmers. This, in turn, hinders the achievement of key Sustainable Development Goals (SDGs),

particularly those related to eradicating poverty and hunger.

Understanding the characteristics of drought in northern Nigeria is crucial for developing effective management and preparedness strategies. This study aimed to evaluate the effectiveness of two machine learning (ML) models—Random Forest (RF) and Support Vector Machine (SVM)—for predicting drought conditions in Kano State. The findings revealed an erratic rainfall pattern, with evidence of rainfall recovery starting from 2019. Both solar radiation and temperature values were observed to be high. The analysis of two common drought indices, the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI), showed that SPEI provided more accurate results, as it accounts for additional variables such as temperature and evapotranspiration, unlike SPI, which only considers precipitation. The SPEI chart indicated that drought conditions were more prevalent from 2012 to 2018, with reduced drought conditions observed from 2019 to 2022.

Both the Random Forest and SVM models were successfully developed to predict drought occurrences, utilizing input variables such as temperature, precipitation, and humidity. Upon comparing the performance of the two models, it was concluded that the Random Forest model outperformed the SVM model across all evaluation metrics. Although the models demonstrated satisfactory results, further research is needed to expand the understanding of other drought characteristics, such as severity, magnitude, spatial spread, and intensity. The present study was limited to a single region, Kano State, and relied on rainfall

data from a single source. Thus, future studies should explore different optimization techniques for ML model parameters, which hold promise for improving prediction capabilities.

Additionally, applying these algorithms to a larger sample of meteorological stations and agro-climatic regions across the country would help assess the generalizability of the methodologies to other parts of Nigeria. To achieve this, access to continuous, long-term observation time-series rainfall data is essential for improving the accuracy and robustness of drought predictions.

Declaration

AI Use Declaration: Artificial Intelligence (AI) writing assistance tools were used in the preparation of this manuscript solely for drafting and language editing purposes, specifically in the initial structuring of the methodology subsections and parts of the model development narrative. All scientific content, data analysis, interpretation of results, and conclusions are the original work of the authors. The AI-generated text has since been identified, substantially revised, and replaced with author-specific content as part of the revision process in response to reviewer feedback. The authors take full responsibility for the integrity and accuracy of all content presented in this manuscript.

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