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ARTICLE

Machine Learning Based Drought Prediction Using the Standardized Precipitation Evapotranspiration Index (SPEI) in Kebbi State, Nigeria

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ABSTRACT

Drought represents a major threat to livelihoods and economic stability in regions prone to its occurrence. This paper aims to address the gap in applying machine learning techniques for enhanced meteorological drought prediction to support resilience and preparedness. The study focuses on Kebbi State, located in northwest Nigeria, which experiences droughts with devastating agricultural, ecological and humanitarian impacts. The Standardized Precipitation Evapotranspiration Index (SPEI) was used to calculate different drought severity based on rainfall deficit, over varying accumulation periods (3-month, 6-month) over four decades (1980–2022). Different time series meteorological parameters such as mean temperature, maximum temperature, minimum temperature, radiation, wind speed, precipitation was used in training machine learning models to predict and forecast future drought risk across Kebbi's regions. Four candidate models were evaluated Random Forest (RF), Extreme Gradient Boosting (XGB), 1D Convolutional Neural Networks (CNN), and Long Short-Term Memory Networks (LSTM). Results indicate RF models consistently achieved highest prediction accuracy (R2: 47–67%) for both short and long-term SPEI forecasts across different regions over the other models, while LSTM was not able to make good prediction for drought in Kebbi state. Optimized XGB models also performed reasonably well for specific locations. One-year lead SPEI projections exhibit XGB potential for advancing early warning given forecast reliabilities. This pioneering study provides robust evidence for integrating machine learning for drought prediction in Kebbi state, Nigeria which is located in the sub-Sahara region.

Keywords: Droughts; Evapotranspiration; Random Forest (RF); Extreme Gradient Boosting (XGB); 1D Convolutional Neural Networks (CNN); Long Short-Term Memory Networks (LSTM)

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1. Introduction

Drought is a recurring and pervasive environmental challenge that significantly affects agricultural productivity, water resources, and the overall well-being of communities in various regions across the globe. Drought occurs when there is significant rainfall deficit that causes hydrological imbalances and affects the land productive systems [1]. The presence of drought across diverse regions of the world has firmly established it as one of the most significant and pervasive environmental challenges. As a relentless force of nature, drought can manifest in various forms, from the creeping, insidious onset of meteorological droughts to the sudden, devastating blows of flash droughts. The unpredictability and diversity of drought events make it a particularly complex phenomenon to monitor, understand, and manage.

Drought is a climatic phenomenon that spans different timescales. Over short periods, such as months, it's known as meteorological drought, while over more extended periods, like years, it manifests as hydrological drought [2]. Drought's consequences ripple into the environment, resulting in soil erosion, deforestation, and desertification. These transformations can exert enduring influences on ecosystems, contributing to habitat degradation and the displacement of plant and animal species. The complexity of comprehending and tackling drought is rooted in the interplay among meteorological, hydrological, ecological, and socio-economic factors.

Tropical regions are known for their warm temperatures, abundant annual rainfall, high evapotranspiration rates, and intense sunlight, it serves as crucial centers of life on Earth. They are renowned for their rainforests, diverse ecosystems, and their pivotal role in regulating the planet's climate. Although these areas are known for their natural beauty and diverse wildlife, they are surprisingly vulnerable to the negative effects of drought. In tropical areas, severe drought events are often linked to phenomena like El Niño [3].

Droughts often succeed episodes of extensive flooding and stand as among the most hazardous natural catastrophes impacting numerous countries worldwide, with a particular focus on West African nation. According to Vodounon et al. [4], insufficient control over precipitation, droughts are challenging to discern due to their potential occurrence in diverse climatic conditions. The northern parts of Nigeria, known as the Sahel, often face severe drought. In these areas, where rainfall is infrequent and unpredictable, droughts happen often, causing problems for farming, food supply, and the people who rely on animals for their livelihoods. During these times, the dry season can become quite long, which makes it tough for the local communities who rely on rain for their crops. Heatwaves and extended periods of arid conditions have introduced complexities to the ecosystem in Northern Nigeria. These environmental changes have intensified the process of evaporation while concurrently diminishing the occurrence of precipitation, thus affecting the delicate balance of the region's ecosystem [5]. In the southern regions of Nigeria, where rainfall is comparatively abundant, drought emerges as a threat in the form of hydrological and agricultural droughts. Prolonged dry spells, irregular rainfall patterns, and water scarcity can disrupt agricultural activities, affecting crop yields and causing localized food shortages. In Nigeria, it's really important to learn about, predict, and lessen the problems caused by drought. This is because the country is dealing with climate change and the need to grow in a way that's good for the environment. We're starting to see how crucial it is to manage drought well.

Drought prediction is the art and science of anticipating when and where drought may strike, plays a pivotal role in safeguarding our communities, environments, and economies. It serves as a proactive tool, offering a precious window of time for preparedness, resource allocation, and timely response. However, the endeavor of drought prediction is far from straightforward, with its complexity stemming from diverse origins and the occurrence of drought events at various temporal and spatial. In recent times, various models have been developed to monitor drought, but compared to systems for other natural disasters, those designed to warn about and predict droughts are still less advanced. This is mainly because droughts involve complex processes that make them harder to predict [6]. A report from the United Nations Environment Programme UNEP (1992) recommends the development of a drought prediction system that takes a comprehensive and integrated approach [7]. This system would involve using multiple indicators to predict droughts [8]. Drought prediction involves estimating the severity of drought, often using specific indicators. This has proven to be a significant challenge for climatologists, hydrologists, and policymakers due to the complexity of drought, its various causes, and the different scales at which it occurs. Generally, three main approaches are used for drought prediction: statistical methods, dynamic methods, and a combination of both known as hybrid methods [9].

As indicated by the Intergovernmental Panel on Climate Change (IPCC) 2022 [10], the occurrence of extreme events, coupled with associated uncertainties, is on the rise due to climate change. Hence, it becomes imperative to direct our efforts towards the establishment of early warning systems for droughts in Nigeria. Such proactive measures are vital in minimizing the losses incurred from drought-related disasters. In this context, the development of early warning systems and the utilization of advanced technologies, including machine learning, offer promising avenues for improving our understanding of drought patterns and enhancing prediction accuracy. As Nigeria strives for sustainable development and resilience in the face of environmental challenges, drought prediction systems emerge as critical tools in safeguarding the nation's future. Machine learning has evolved into an interdisciplinary tool due to its versatility across various technological domains. It possesses the capacity to discern complex nonlinear connections between input and output data sets, all without the need to comprehend the inherent nature of the phenomena or rely on pre-established assumptions about linearity or normality. While machine learning has been applied for drought prediction in Asia and other advanced nations over the years, its utilization in Africa, particularly in Nigeria, remains relatively limited.

Predicting drought events in advance is crucial for effective drought management, allowing timely implementation of mitigation measures and resource allocation. Over the years, advancements in machine learning and the availability of extensive climate data have opened new avenues for accurate and timely drought prediction.

2. Materials and Method

2.1. Description of Study Area

Kebbi State is a northwestern state in Nigeria, located in the Sahel region (**Figure 1**). It covers an area of approximately 36,800 square kilometers and shares borders with Niger State to the west, Sokoto State to the north, Zamfara State to the east, and Niger Republic to the south. The state capital is Birnin Kebbi [11]. The majority of the people in Kebbi State live in rural areas, and agriculture is the state's main economic driver. The state, sometimes referred to as the "Land of Equity," is well known for its rich agricultural resources, particularly in fishing, cattle husbandry, and grain production. The state mostly grows rice, millet, sorghum, maize, cotton, and groundnuts. Kebbi State has a semi-arid climate with distinct dry and wet seasons. The wet season normally lasts from April to October, whereas the dry season typically lasts from November to March. The majority of the year's rainfall falls during the rainy season, with an average annual rainfall of between 800 and 1,000 millimeters [12]. Major rivers, such the Niger and Rima, pass through Kebbi State, offering opportunity for irrigation and the development of water resources. Additionally, the state is home to the Argungu International Fishing Festival, a well-known cultural occasion that draws guests from all around Nigeria and beyond. Overall, Kebbi State's rich agricultural resources, coupled with its cultural heritage and natural beauty, make it a significant study area for research and development initiatives aimed at addressing the challenges and harnessing the potentials of the state's economy and well-being of its inhabitants.

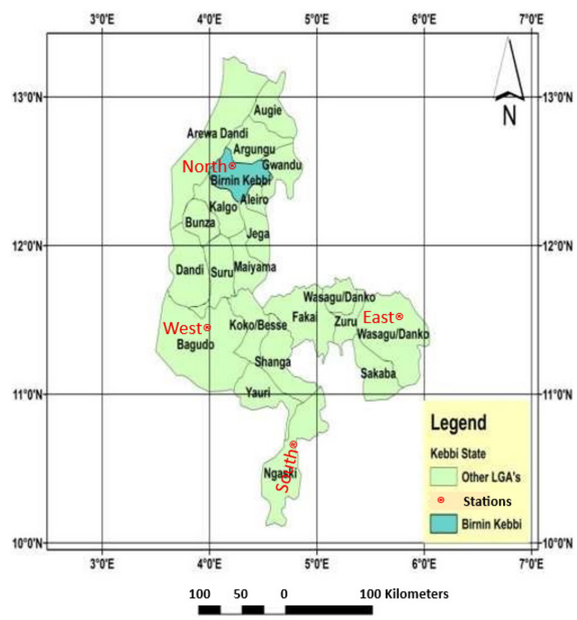


Figure 1. Map of the Study Area (Kebbi State).

2.2. Data Collection

Data downloaded spanned five distinct locations within Kebbi State, such as the north, south, east, west, and central regions. The objective was to observe and analyze the distribution of drought across varied geographical areas. The dataset retrieved covers the extensive timeframe from 1981 to 2022. The data needed for this paper includes; precipitation, mean temperature, maximum temperature, minimum temperature, radiation, and wind speed.

2.2.1. CHIRPS Data

Rainfall data was obtained through satellite observations, specifically from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). CHIRPS is a comprehensive rainfall dataset covering over 35 years on a quasi-global scale (https://www.chc.ucsb.edu/data/chirps) Encompassing latitudes between 50°S and 50°N, and all longitudes, it spans from 1981 to nearly the present day. Utilizing a combination of our internal climatology, high-resolution satellite imagery at 0.05° resolution, and on-site station data, CHIRPS generates gridded time series of rainfall. This dataset is instrumental for trend analysis and monitoring seasonal drought conditions.

2.2.2. ERA5_AG Data

Weather data, including mean, minimum, and maximum temperatures, radiation, and wind speed, was sourced from ERA5_AG. The European Copernicus programme offers global historical and near-real-time weather information, and AgERA5 specifically provides access to ERA5 data for the agricultural sector (https://app.climateengine.org/climateEngine). This dataset encompasses agro-meteorological variables like daily mean, minimum and maximum temperatures, precipitation, humidity, and incoming solar radiation (**Table 1**). While designed for agricultural applications, it is versatile and applicable to various research domains. The data covers all land areas at a spatial resolution of 10 by 10 km, spanning from 1979 to the present.

Table 1. Details of the Satellite Dataset.

VARIABLES	UNITS	TIME SCALE
Mean Temperature	C	Daily
Maximum Temperature	C	Daily
Minimum Temperature	C	Daily
Precipitation	mm	Daily
Wind Speed	m/s	Daily
Radiation	W/m^2	Daily
Evapotranspiration	C	Monthly

2.3. Data Pre-Processing

The acquired dataset comprises of hourly data presented in diverse formats, including csv and xls. To enhance compatibility and facilitate further analysis, the R programming language was instrumental in the conversion of this data into a standardized monthly format, stored conveniently in csv files.

2.4. Data Analysis

The precipitation, temperature, wind speed, and radiation data were employed to compute the Standardized Precipitation Evapotranspiration Index (SPEI) for different time scales, namely 3, 6, and 12 months. The analysis of this data was conducted using the SPEI package in the R programming language, facilitated by the R Studio environment.

2.4.1. Standardized Precipitation Evapotranspiration Index

The standardized precipitation evapotranspiration index (SPEI) has received extensive attention in the field of drought analysis. An extension of the widely used SPI, SPEI considers both precipitation and temperature, which are used to calculate evapotranspiration information. Therefore, unlike SPI, SPEI captures the main impact of temperature rise on water requirement.

The shorter time scale SPEIs are appropriate to monitor meteorological and agricultural drought, such as the one-month time scale SPEI (SPEI-1) can monitor meteorological drought; the three-month and six-month time scale SPEIs can monitor vegetation, agricultural droughts, and soil moisture dynamics; while the longer time scale SPEIs are appropriate to monitor hydrological droughts. In this study, three-month, six-month time scale of SPEI was selected.

(1) Calculation of monthly potential evapotranspiration using Thornthwaite method [14]:

$$PET = 16K(\frac{10T}{I})^m \tag{1}$$

where K is the correction factor based on latitude, T is the monthly average temperature, I is the total heating index, and m is a constant.

$$I = \sum_{i=1}^{12} (\frac{T}{5})^{1.514} \tag{2}$$

$$m = 675 \times 10^{-7} I^3 - 7.71 \times 10^{-5} I^2 + 1.792 \times 10^{-2l} I^2 + 0.49 \tag{3}$$

(2) Calculate the difference between precipitation and potential evapotranspiration for each month.

$$D_i = P_i - PET_i \tag{4}$$

where P_i is the monthly precipitation, PETi is the monthly potential evapotranspiration, and i denotes the month. The establishment of climate water balance accumulation at different time scale sequences is as follows:

$$D_n^k = \sum_{i=0}^{k-1} (P_{n-i} - PET_i) \tag{5}$$

where k is the time scale and takes the value of 3, and n is the number of calculations.

(3) To normalize Di, first, a Log-logistic probability density function is used to build the data series:

$$\mathrm{f(x)} = \frac{\beta}{\alpha}(\frac{x-y}{\alpha})^{\beta-1}[1+(\frac{x-y}{\varepsilon})]^{-2} \tag{6}$$

where α is the scale parameter and β is the shape parameter, which are the origin parameters obtained by the linear moment method, and then the cumulative probability of the Di density function is:

$$\mathrm{F(x)} = [1 + (\frac{\alpha}{x-y})^{\beta}] \tag{7}$$

(4) Under normal normalization of the cumulative probability density function, the probability of exceeding a certain Di value is P = 1 − F(X) and the probability of weighted moments are $\omega = \sqrt{-2\,ln\,(P)}$

When P ≤ 0.5,

$$\mathrm{SPEI} = \omega - \frac{C_o+C_1\omega+C_2\omega^2}{1+d_1\omega+d_2\omega^2+d_3\omega^3} \tag{8}$$

When P > 0.5,

$$\mathrm{SPEI} = \omega - \frac{C_o+C_1\omega+C_2\omega^2}{1+d_1\omega+d_2\omega^2+d_3\omega^3} \tag{9}$$

where C0 = 2.515517, C1 = 0.802853, C2 = 0.010328, d1 = 1.432788, d2 = 0.189269, and d3 = 0.001308.

The monthly temperature and precipitation data from satellite observation were used to calculate the ground-based standard precipitation evapotranspiration index (SPEI). According to the internationally recognized criteria for classifying drought levels, SPEI is divided into five levels (**Table 2**) [15].

Table 2. Classification of SPEI Values [15].

S/N	DROUGHT CLASS	SPEI
1	No-Drought	Greater than −0.5
2	Mild	−0.5 to −0.99
3	Moderate	−1 to −1.49
4	Severe	−1.50 to −1.99
5	Extreme	Less than −2

2.4.2. Train-Test Split

The data was split into a training set and a test set. 70% of the data was utilized to train the model, while approximately 30% of the data was used to test the efficiency of the model.

2.5. Machine Learning Methods

2.5.1. Extreme Gradient Boosting (Xgb)

The algorithm is based on the concept of 'Boosting'. Boosting involves the combination of predictions from a group of "weak" learners to create a robust, accurate model through an additive training strategy. XGBoost is particularly designed to address challenges related to overfitting and underfitting, providing an effective solution to minimize these issues. This algorithm not only enhances predictive accuracy but also optimizes computational efficiency, a crucial consideration for large datasets and resource-intensive tasks. The general function for the prediction at step *t* is:

$$f_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = f_i^{(t-1)} + f_t(x_i) \quad (10)$$

where *ft* (xi) is the learner at step t, f(t) *I* and f(t−1) *I* are the predictions at steps *t* and *t* − 1, respectively, and *xi* are the input variables.

To avoid overfitting problems without influence on the computational speed of the model, the XGB applies the analytic expression below to evaluate the ''goodness'' of the model from the original function according to Mokhtar et al. (2021) [16]:

$$Obj^{(t)} = \sum_{k=1}^{n} l(y_i, y_i) + \sum_{k=1}^{t} \Omega(f_i) \quad (11)$$

where *l* is the loss function, *n* is the number of observations and *Ω* is the regularization term which is defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda||\omega||^2 \quad (12)$$

where ω is the vector of scores in the leaves, λ represents the regularization parameter, and γ denotes the minimum loss needed to further partition the leaf node. In this study, the XGB model was constructed with specific parameters: 7 estimators were utilized, the tree depth was set to 3, and a learning rate of 0.1 was employed.

2.5.2. Random Forest Algorithm (RF)

Random Forest algorithm, is a powerful ensemble learning technique widely applied in machine learning tasks, including drought prediction. Random Forest operates by constructing a multitude of decision trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees. It deals with random binary trees that use a subset of the observations via bootstrapping, where a random subset of the training dataset is sampled from the raw dataset and utilized to evolve the model. There are some basic processes it undergoes, this includes;

(1) **Bootstrapped Sampling**

a. Random Forest constructs multiple decision trees by using bootstrapped samples from the training data.

b. Each tree is trained on a subset of the data, introducing diversity to enhance the ensemble's robustness.

(2) **Feature Randomization**

a. At each decision tree node, a random subset of features is considered for splitting.

b. This strategy ensures that different trees focus on distinct features, contributing to the ensemble's overall robustness.

(3) **Voting or Averaging**

a. In classification tasks, the final output is determined by the majority class predicted across all trees.

b. For regression tasks, the final output is the average prediction from all trees, providing a well-rounded result.

2.5.3. Long Short-Term Memory (LSTM)

The Long Short-Term Memory (LSTM) algorithm, a subtype of recurrent neural networks (RNNs), was selected due to its proficiency in understanding and representing patterns over time in sequential data. Within the LSTM network, there are distinct memory blocks connected through layers. Each layer consists of interconnected memory cells and three essential components known as the input, forget, and output gates. These gates play a crucial role in controlling the flow of information, enabling the network to effectively learn and remember important temporal dependencies in the data.

2.5.4. Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) stands out as a specialized deep neural network crafted for handling structured grid data, particularly images. Renowned for its prowess in computer vision assignments, the CNN excels by autonomously and flexibly grasping spatial hierarchies of features from input data. Its effectiveness in managing high-dimensional data is attributed to its shared-weights architecture and translation invariance characteristics. This distinctive design makes CNN a powerful tool in various applications, especially those involving image analysis and pattern recognition. To get the best score, the CNN model was built using 64 filters, kernel size of 2, a rectified linear unit (ReLU) was used as the activation function. Max-pooling layer with pool size was set to 2.

2.6. Accuracy Evaluation

The evaluation of model performance encompasses a suite of key statistical metrics crucial for a comprehensive understanding of its accuracy. The Mean Square Error (MSE) serves as a pivotal measure, indicating the average squared difference between predicted and observed values, offering insights into the overall model accuracy. Complementing this, the Mean Absolute Error (MAE) provides a nuanced assessment of precision by evaluating the average magnitude of errors. Furthermore, the Coefficient of Determination (R^2) illuminates the strength of the linear relationship between observed and predicted values. A high R^2 value, approaching unity, signifies a robust correspondence. Collectively, these performance metrics contribute to a comprehensive evaluation, addressing accuracy, precision, bias, and the strength of the predictive relationship.

$$\mathrm{MSE} = \frac{1}{n}\sum (P_i - O_i)^2 \tag{13}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |O_i - P_i| \tag{14}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(O_i - O_i)(P_i - P_i)}{\sqrt{\sum_{i=1}^{n}(O_i - O_i)^2}\sqrt{\sum_{i=1}^{n}(P_i - P_i)^2}}\right)^2 \tag{15}$$

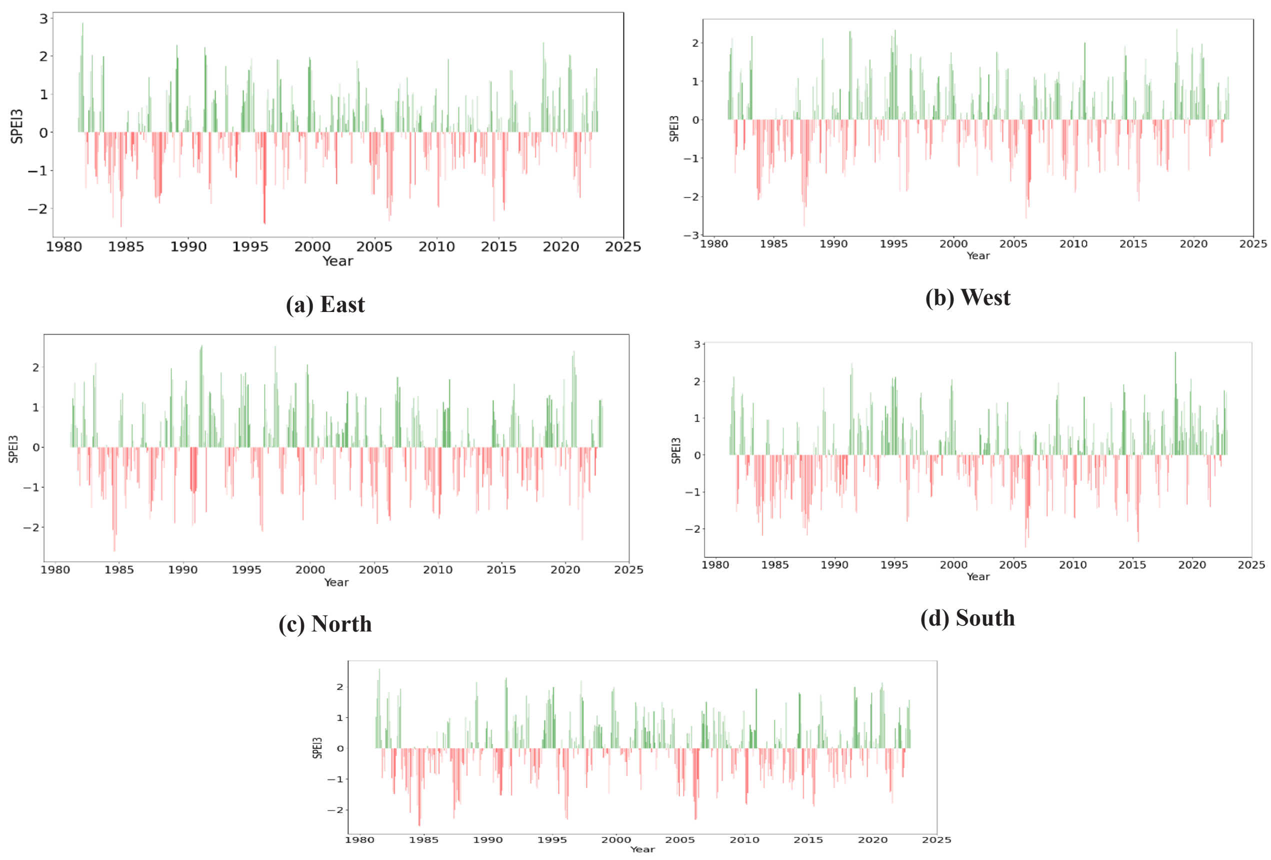
where Oi and Pi are the actual and the predicted SPEIs, respectively, O represents the average values of the actual SPEI index, and n is the number of observations.

3. Results and Discussion

3.1. Standardized Precipitation Evapotranspiration Index (SPEI) Analysis

3.1.1. SPEI-3

The Standardized Precipitation Evapotranspiration Index (SPEI) is a widely used drought indicator [17]. **Figure 2** shows SPEI on a 3-month timescale; it is used as a meteorological drought indicator of short-term dryness in a region.



(a) East **(b) West** **(c) North** **(d) South** **(e) Central**

Figure 2. SPEI Model Calculated SPEI-3 for Kebbi State (Standard Analysis). **(a)** East, **(b)** West, **(c)** North, **(d)** South, and **(e)** Central.

Figure 2 presents 42 years (1980–2022) of SPEI-3 values for five locations across Kebbi State, Nigeria (**Figure 2(a)–(e)**). **Table 1** shows what each classification value stands for, SPEI values below −2 represent extreme drought conditions. Examination of the multi-decadal SPEI-3 time series shows extreme drought events, denoted by substantial downward spikes of SPEI below −2, occurred most notably in Kebbi East around 1984, 1997, 2005 and 2015. Similar extreme droughts affected Kebbi West in 1987 and 2006 (SPEI −2.5), Kebbi North in 1985 and 2021 (SPEI −2.5), Kebbi South in 2006 and 2015, and Kebbi Center in 1985, 1996 and 2006 based on the data. Aside from these extreme drought occurrences, analysis uncovers other major droughts, categorized as severe events from SPEI −1.5 to −2. These affected Kebbi East in 1983–84 and 2016; Kebbi West in 1983 and 2017; Kebbi Center in 2010; and Kebbi South in 1987 and 1996. Wetter periods are visible around 1985–1986, 1996–1997 and 2009–2011 in most of the regions. The overlap of drought years in each of the regions shows prominent dry periods in 2005 and 2015. While wet periods have occurred, meteorological droughts ranging from moderate (SPEI −1 to −1.5) to extreme (SPEI < −2) have frequently impacted the Kebbi State over the past 40+ years.

3.1.2. SPEI-6 ANALYSIS

Figure 3 is the analysis of a longer-term 6-month SPEI timescale; it provides insights into agricultural drought events, which develop over an extended period and can severely impact crop production [18, 19].

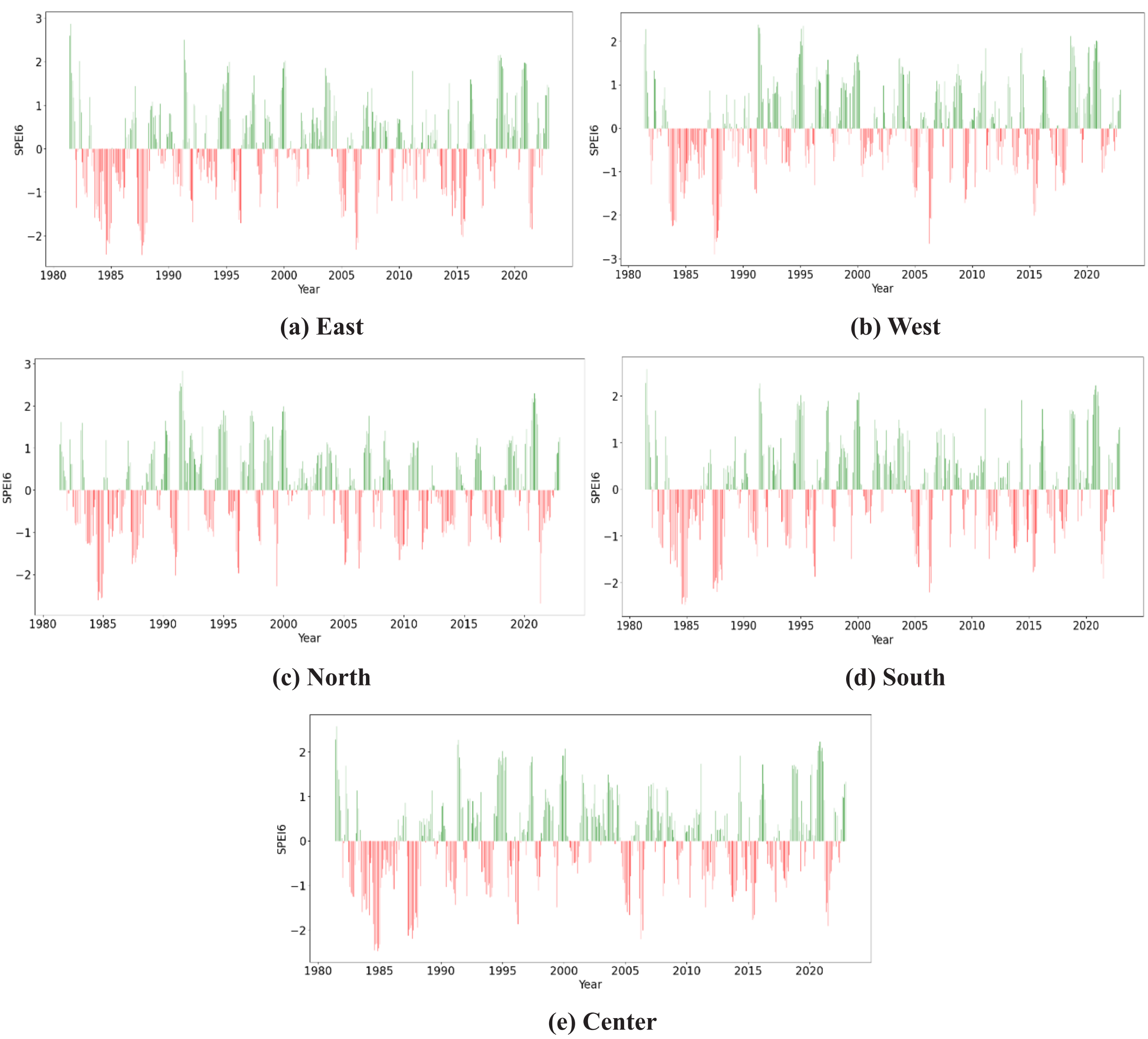


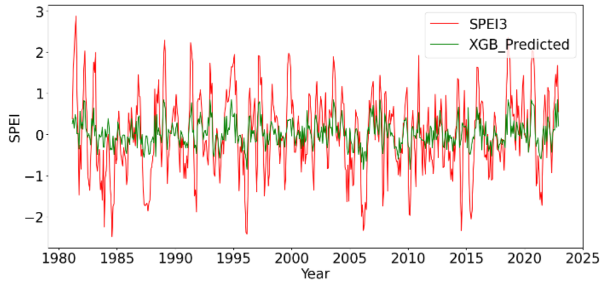
Figure 3. SPEI Model Calculated SPEI-6 for Kebbi State (Standard Analysis). **(a)** East, **(b)** West, **(c)** North, **(d)** South, and **(e)** Center.

Figure 3 presents 42 years (1980–2022) of SPEI-6 data for five regions across Kebbi State — East, West, North, South and Center (**Figure 3(a)–(e)**). Examination of the 6-month SPEI trajectories reveals that a prolonged period of intense agricultural drought likely affected all Kebbi sub-regions in the mid-1980s, approximately 1983–1985. This multi-year drought was particularly persistent in Kebbi West, lasting from 1983–1987 per the data. Further analysis points to acute spikes indicating additional extreme droughts, categorized by SPEI below −2. The most widespread extreme event occurred around 2006, spanning Kebbi East, South and Center. Meanwhile, Kebbi North experienced an exceptionally intense extreme drought episode in 2021 (SPEI −2.5). Aside from these acute events, severe droughts, indicated by SPEI between −1.5 and −2, are also detectable around 2015 in Kebbi East and West, 2010 and 2005 in Kebbi North, 2015 and 2021 for Kebbi South, and 2015 and 2021 across Kebbi Center. This shows that most of the meteorological drought leads to agricultural drought if not handled well.

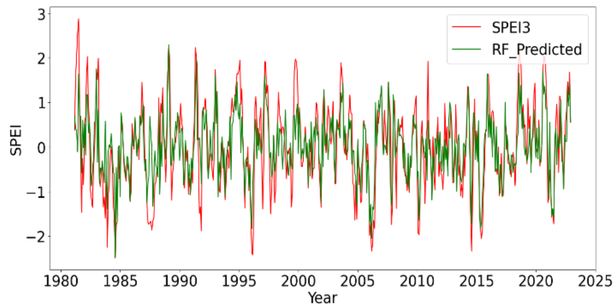
3.2. Derived Standardized Precipitation Evapotranspiration Index (SPEI)-3 From Machine Learning Model for Regions in Kebbi State

3.2.1. KEBBI East

Figure 4 shows SPEI-3 timeseries chart for drought prediction performance comparisons across 4 candidate machine learning models which include Long Short-Term Memory neural networks (LSTM), Extreme Gradient Boosting (XGBoost), Random Forest and Convolutional Neural Network (CNN) models for the period from 1980 to 2022 in Kebbi East (**Figure 4(a)–(d)**). The overall assessment indicates relatively inferior predictive performance by the LSTM and XGBoost models. Specifically, the LSTM network demonstrates a complete inability to predict any meteorological drought, while XGBoost performed fairly better. In contrast, the Random Forest and CNN models demonstrate visibly improved drought prediction capabilities with predicted SPEI trajectories better emulating historical peaks and troughs. In particular, the Random Forest model successfully predicts the occurrence of severe droughts for some of the most extreme SPEI events below −2.



(a)



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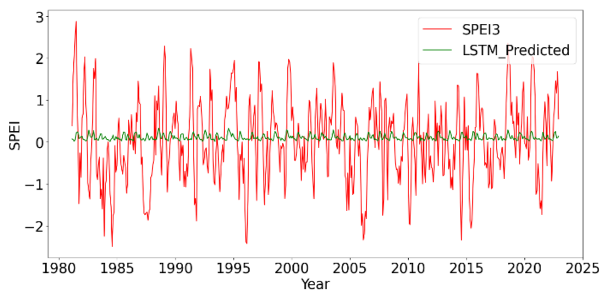

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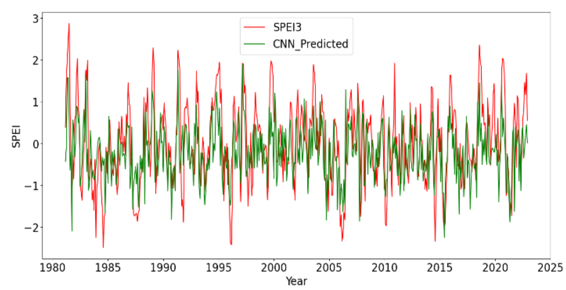


(d)

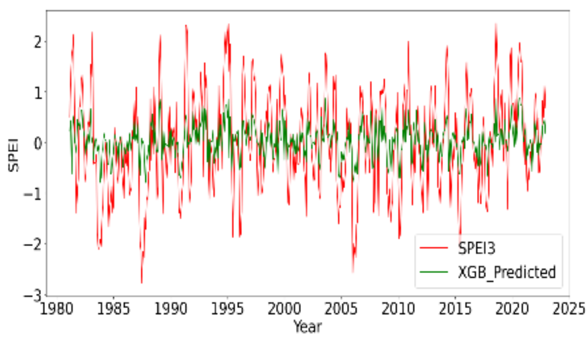
Figure 4. Comparison Between the Standard SPEI3 and the Predicted SPEI3 Using **(a)** XGBoost, **(b)** Random Forest, **(c)** LSTM, **(d)** CNN.

3.2.2. KEBBI West

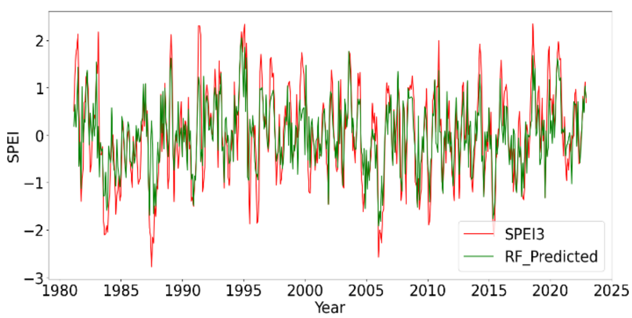
Figure 5 is an investigation of the SPEI-3 prediction chart across four machine learning architectures (**Figure 5(a)–(d)**), delivering critical insights into model effectiveness for drought forecasting in Kebbi West from 1980 to 2022. Charted against observed SPEI, assessment of predicted SPEI trajectories helps gauge model skills in capturing past meteorological drought events below the extreme intensity threshold of –2 SPEI. The examination reveals that none of the 4 models could accurately predict the acute multi-month extreme droughts around 1987 and 2007 where SPEI plummeted below –2 for prolonged periods. Nevertheless, relative comparisons highlight the random forest model as most proficient, closely emulating periodic drought spikes across various timescales. This indicates robust nonlinear decision boundary learning by the random forest tree ensembles. Furthermore, XGBoost proves moderately skillful with predictions resembling slight drought dips during various dry spells. While CNN exhibits comparable performance to XGBoost.

3.2.3. KEBBI North

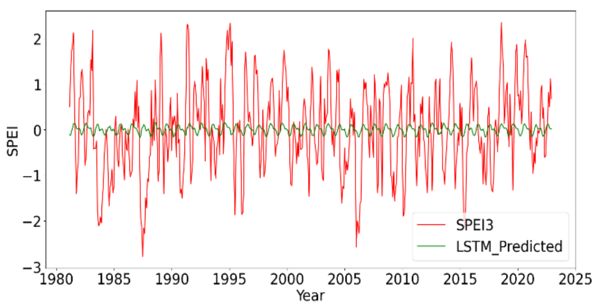
Figure 6 shows a Comparative assessment of the Standardized Precipitation Evapotranspiration Index (SPEI)-3 prediction capabilities across 4 machine learning models (**Figure 6(a)–(d)**), providing crucial evidence for optimal model selection for drought forecasting in Kebbi North. The models tested include Long Short-Term Memory (LSTM) networks, Extreme Gradient Boosting (XGBoost), Random Forest, and Convolutional Neural Networks (CNN). LSTM demonstrate inferior performance to. The LSTM displays virtually no skill in predicting drought troughs across all timescales showcasing limitations in learning lagged climate sequences for this task. While the XGBoost model performs marginally better than LSTM, it still fails to capture most major droughts. In contrast, the CNN model shows moderately improved predictions mimicking some periods of lower SPEI values related to historical drought events of varying intensity. However, the Random Forest model clearly outperforms the CNN and other techniques with predicted SPEI trajectories closely emulating observed major drought troughs. Both severe events like the 1996 drought and lower intensity 1991 event are accurately.



(a)



(b)



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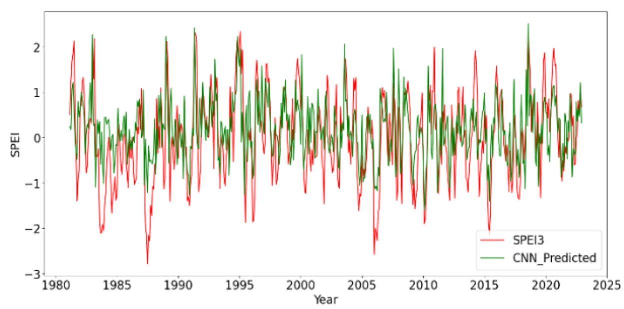
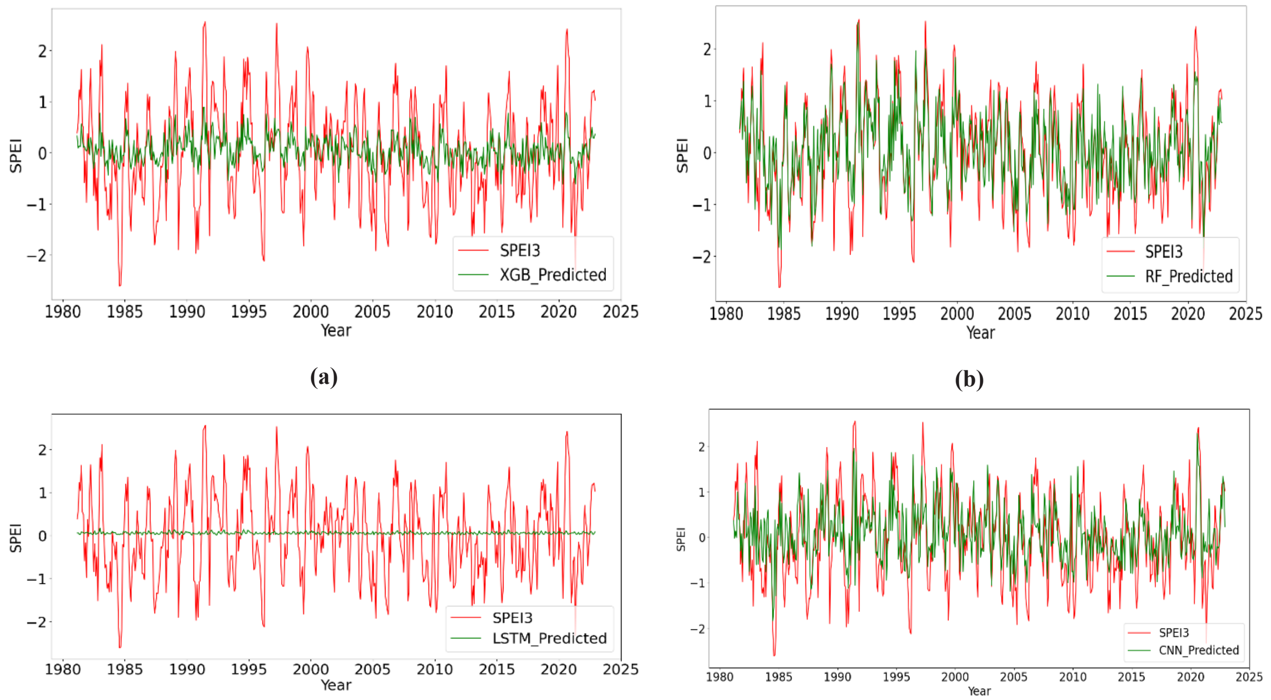


(d)

Figure 5. Comparison between the Standard SPEI3 and the Predicted SPEI3 Using **(a)** XGBoost, **(b)** Random Forest, **(c)** LSTM, **(d)** CNN.



(a) (b) (c) (d)

Figure 6. Comparison Between the Standard SPEI3 and the Predicted SPEI3 Using **(a)** XGBoost, **(b)** Random Forest, **(c)** LSTM, **(d)** CNN.

3.2.4. KEBBI South

Figure 7 shows the analysis of four models' SPEI-3 prediction capacities in Kebbi South (**Figure 7(a)–(d)**). It shows the Random Forest architecture demonstrates the highest skills, anticipating both high and low intensity historical droughts from 1980–2022. Its nonlinear ensemble decision trees enable robust meteorological feature learning superior to alternatives. The CNN model trails behind with reasonably good forecasting of some past extremes through deploying convolutional layers. However, gaps in capturing certain peaks. Thereafter, XGBoost provides periods of mild moisture deficit while fully failing during extremes, and lastly, LSTM proves least effectiveness with virtually no match between recorded and predicted drought indicators.

3.2.5. Kebbi Central

Figure 8 is an evaluation of 3-month SPEI drought predictions from four machine learning models for Kebbi Center from 1980–2022 (**Figure 8(a)–(d)**). The predicted SPEI-3 values were compared to actual SPEI-3 calculated from meteorological data over this historical period. I found varying prediction accuracy across the models to emulate Kebbi's central drought index. The Random Forest model most closely matched actual SPEI-3 fluctuations, demonstrating superior skills in modeling wet/dry patterns. However, while prediction accuracy reflects average conditions well, capturing extremes is critical for drought monitoring. In this aspect, excluding Random Forest, the Convolutional Neural Network (CNN) model showed some promise, managing to anticipate some major low SPEI events below –1, although its overall trajectory deviated more. By contrast, the Extreme Gradient Boosting (XGBoost) model performed relatively poorly in capturing extremes despite mimicking periods of moderate moisture deficiency. Finally, the Long Short-Term Memory (LSTM) network performed the worst with virtually no correlation between its predicted and actual SPEI-3. The LSTM exhibited difficulties handling the lagged nature of multi-month climate sequences.

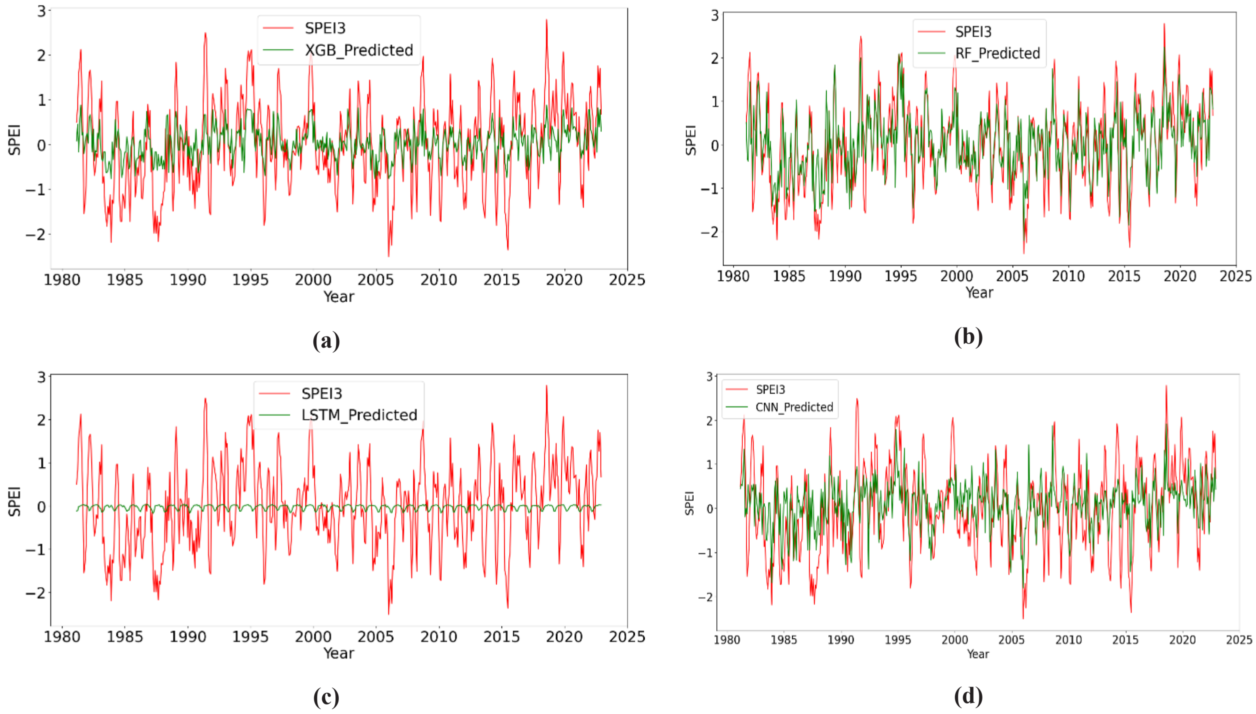


Figure 7. Comparison Between the Standard SPEI3 and the Predicted SPEI3 Using **(a)** XGBoost, **(b)** Random Forest, **(c)** LSTM, **(d)** CNN.

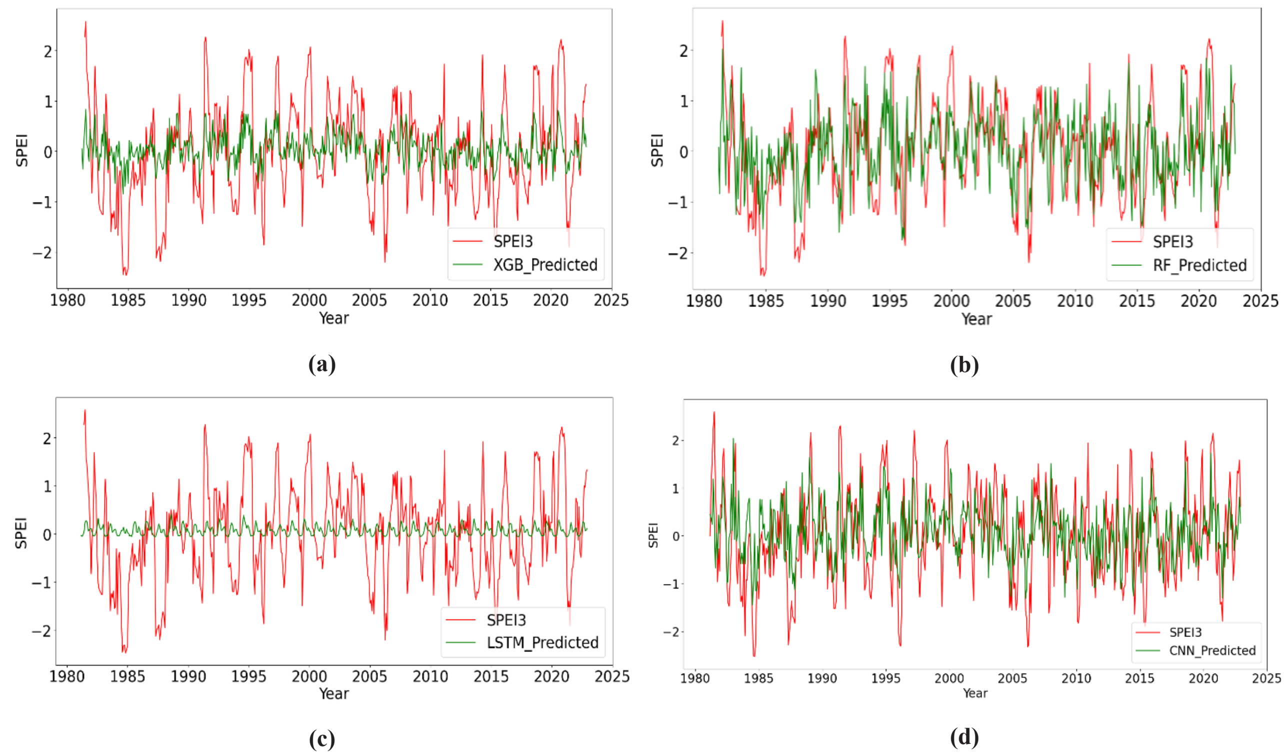


Figure 8. Comparison Between the Standard SPEI3 and the Predicted SPEI3 Using **(a)** XGBoost, **(b)** Random Forest, **(c)** LSTM, **(d)** CNN.

Meteorological drought monitoring using indices like SPEI forms the foundation of drought science and supports drought prediction research [19]. This study evaluated four machine learning methods random forest, XGBoost, convolutional neural networks (CNN) and long short-term memory networks (LSTM) for predicting the 3-month SPEI in five subregions of Kebbi State from 1980–2022. **Figures 4–8** contrast the model-predicted and traditionally calculated SPEI-3 over this period. Overall, the random forest (RF) model most closely matched the fluctuations in actual SPEI-3, capturing both droughts (low SPEI) and wet periods (high SPEI). This was especially true from 1990–2010. As noted by Poornima and Pushpalatha [20], well-regularized random forests can emulate subtle climate shifts. The XGBoost and CNN models comprised the next best predictions, also broadly tracking ups and downs in SPEI-3 across subregions but with less precision than RF. However, the Deep LSTM performed very poorly compared to the other methods, contradicting some past studies like that of Spinoni et al. [21].

Table 3 shows the performance of each model in predicting the 3-month SPEI across several error metrics. For R-squared, measuring overall fit, the Random Forest model demonstrates the highest values compared to the alternatives, peaking at 67% for Kebbi East. By contrast, the Extreme Gradient Boosting (XGBoost) model exhibits stronger performance than the Convolutional Neural Network (CNN), with its top R-squared of 42% in Southern Kebbi followed by 39% in Central Kebbi. The CNN and Long Short-Term Memory (LSTM) networks display the lowest prediction accuracy levels, with LSTM proving deficient in modeling the lagged drought index sequences. While no model achieves very high absolute performance, the relative rankings highlight Random Forest as most robust, trailed distantly by XGBoost, with CNN and especially LSTM failing to effectively learn the climate patterns.

Table 3. Error Metrics for SPEI-3 Predicted Using Machine Learning Model.

Location	Model	R^2	MAE	MSE
WEST	XGB	0.36	0.6	0.61
	RF	0.6	0.42	0.38
	LSTM	0	0.78	0.96
	CNN	0.29	0.68	0.67

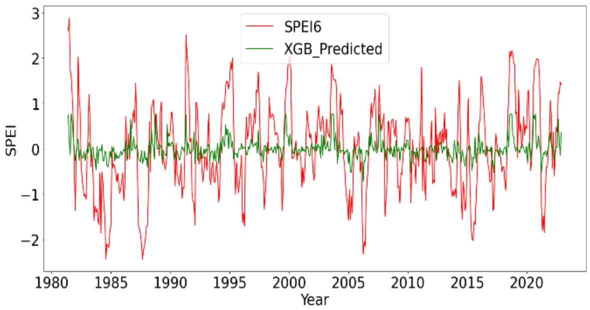
Table 3. *Cont.*

Location	Model	R^2	MAE	MSE
NORTH	XGB	0.31	0.65	0.66
	RF	0.6	0.44	0.38
	LSTM	0	0.79	0.95
	CNN	0.36	0.611	0.611
SOUTH	XGB	0.42	0.6	0.55
	RF	0.59	0.45	0.39
	LSTM	0	0.79	0.96
	CNN	0.36	0.61	0.61
EAST	XGB	0.37	0.61	0.6
	RF	0.67	0.4	0.31
	LSTM	0	0.79	0.97
	CNN	0.32	0.65	0.65
CENTRAL	XGB	0.39	0.62	0.59
	RF	0.62	0.43	0.36
	LSTM	0.07	0.78	0.95
	CNN	0.32	0.65	0.65

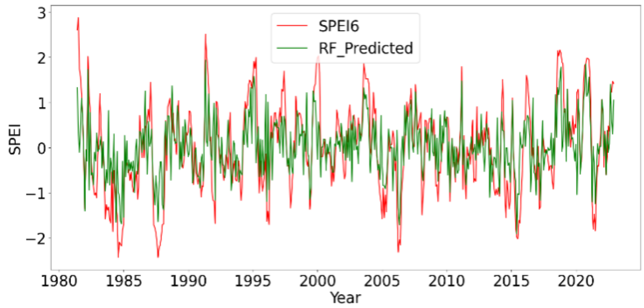
3.3. Derived Standardized Precipitation Evapotranspiration Index (SPEI)-6 From Machine Learning Model for Regions in Kebbi State

3.3.1 KEBBI East

Figure 9 shows a chart that examined the drought prediction performance of 4 machine learning models (**Figure 9(a)–(d)**) using the SPEI-6 index for Kebbi East from 1980–2022. The models were Long Short-Term Memory (LSTM) neural networks, Extreme Gradient Boosting (XGBoost), Random Forest, and Convolutional Neural Networks (CNN). Overall, the LSTM and XGBoost models performed poorly at predicting droughts. The LSTM model completely failed to predict any meteorological drought events. The XGBoost model did slightly better but still struggled. In contrast, the Random Forest and CNN models showed improved drought prediction capabilities. Their SPEI trajectories better matched historical highs and lows. Notably, the Random Forest model successfully predicted some extreme drought events around 2015 where the SPEI dropped below −2.



(a)



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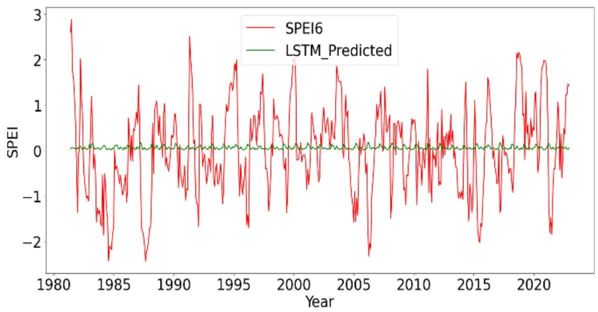

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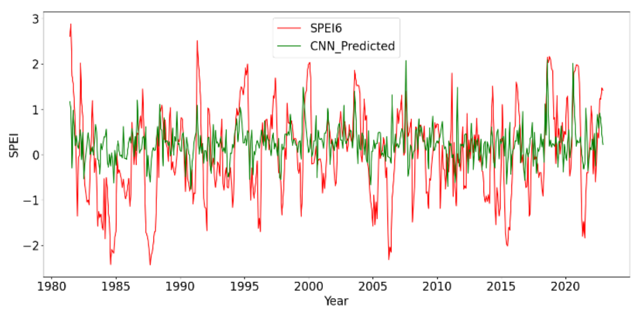


(d)

Figure 9. Comparison between the Standard SPEI6 East and the Predicted SPEI6 Using **(a)** XGBoost, **(b)** Random Forest, **(c)** LSTM, **(d)** CNN.

3.3.2. KEBBI West Analysis

Figure 10 investigated drought prediction performance of 4 machine learning models for Kebbi West over 1980–2022 using the SPEI-6 index (**Figure 10(a)–(d)**). By comparing predicted SPEI trajectories to observed data, we assessed each model's ability to forecast past meteorological droughts, specifically extreme events below –2 SPEI. Our analysis revealed that none of the models accurately predicted the acute, multi-month extreme droughts around 1987 and 2007 where SPEI remained below –2 for prolonged periods. However, relative comparisons showed the random forest model as most proficient at emulating periodic drought spikes across timescales. This demonstrates effective nonlinear decision boundary learning by the random forest tree ensembles. Additionally, XGBoost proved moderately skillful, with predictions resembling slight drought dips during various dry spells. The CNN exhibited comparable performance to XGBoost.

3.3.3. KEBBI North

In **Figure 11**, a comparative assessment of Standardized Precipitation Evapotranspiration Index (SPEI) drought prediction capabilities for 4 machine learning models in Kebbi North using SPEI-6 (**Figure 11(a)–(d)**). The models used are Long Short-Term Memory (LSTM) networks, Extreme Gradient Boosting (XGBoost), Random Forest, and Convolutional Neural Networks (CNN). The LSTM model demonstrated inferior performance, showing almost no skill at predicting historical drought intensity troughs across timescales. This indicates limitations in learning lagged climate sequences. While XGBoost performed slightly better than LSTM, it still failed to capture most major droughts. In contrast, the CNN model exhibited moderately better predictions, mimicking some periods of lower SPEI related to past droughts of varying severity. However, the Random Forest model clearly outperformed the others, with predicted SPEI trajectories closely matching observed major drought droughts. It accurately predicted both extreme events like the 1985 and 2021 droughts, as well as lower intensity droughts in 2001.

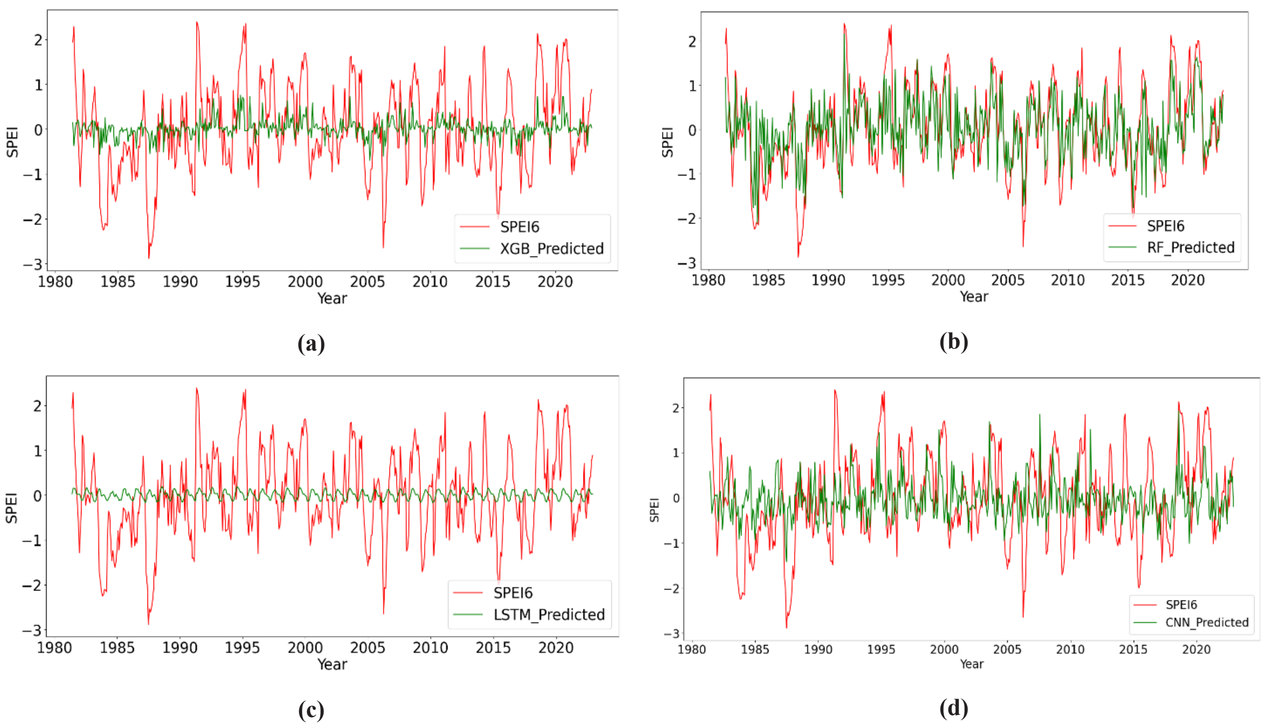


Figure 10. Comparison Between the Standard SPEI6 and the Predicted SPEI6 Using **(a)** XGBoost, **(b)** Random Forest, **(c)** LSTM, **(d)** CNN.

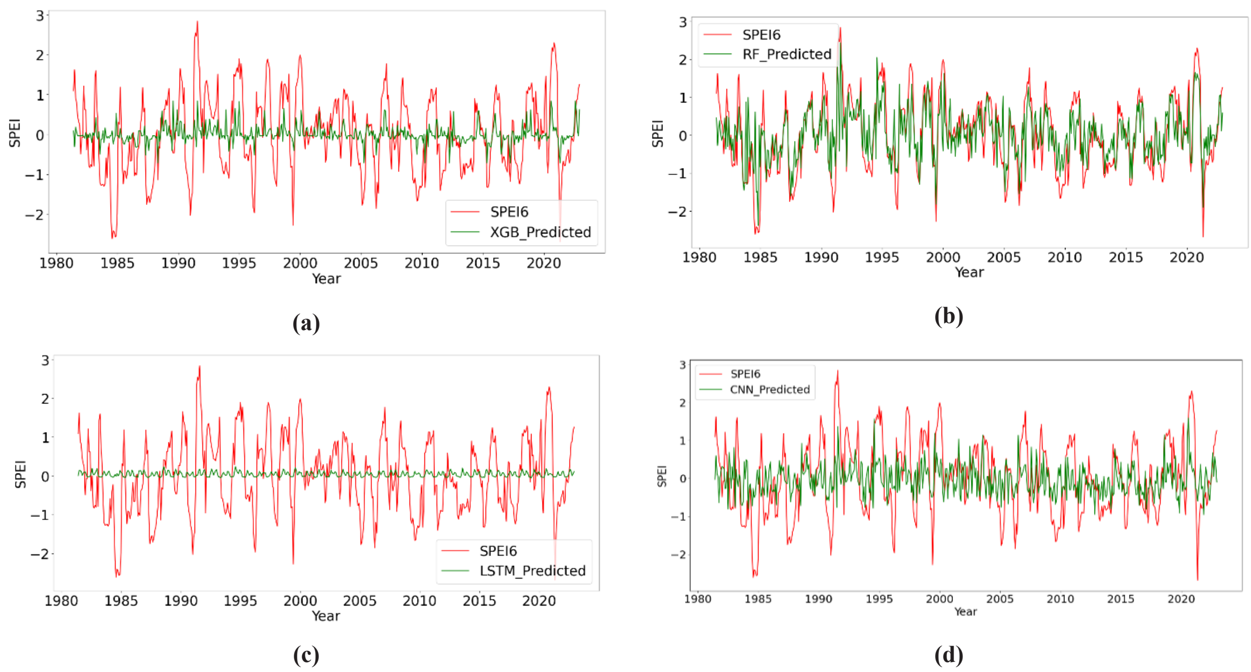


Figure 11. Comparison Between the Standard SPEI6 and the Predicted SPEI6 Using **(a)** XGBoost, **(b)** Random Forest, **(c)** LSTM, **(d)** CNN.

3.3.4. KEBBI South

Figure 12 shows SPEI-6 drought prediction performance in Kebbi South for four different models from 1980–2022 (**Figure 12(a)–(d)**). The Random Forest model demonstrated the highest skill, anticipating both high and low intensity historical droughts. Its nonlinear ensemble decision trees enabled robust meteorological feature learning superior to the alternatives. The CNN model followed behind with reasonably good forecasting of some past extremes through its convolutional layers, however there were gaps in capturing certain peaks. Thereafter, XGBoost predicted some periods of mild moisture deficit but fully failed at extremes. Lastly, the LSTM proved least effective with virtually no match between recorded drought indicators and predictions, displaying limitations in sequential climate data handling. Overall, the Random Forest architecture showed the greatest capacities for learning meaningful drought patterns in the region.

3.3.5. KEBBI Central

Figure 13 shows the evaluation of 6-month Standardized Precipitation-Evapotranspiration Index (SPEI-6) drought predictions from four different machine learning models for Kebbi Center between 1980 and 2022 (**Figure 13(a)–(d)**). The predicted SPEI-6 values were compared against the actual SPEI-6 values calculated using standard meteorological data over this historical period. **Figure 13** shows variation in the models' capacities to accurately predict Kebbi central drought index. The Random Forest model most closely matched the fluctuations of the actual SPEI-6 timeseries, demonstrating superior overall skills in modelling the various wet and dry patterns. However, while prediction accuracy is important for emulating average conditions, capturing extremes is critical for drought monitoring. In this regard, outside random forest the Convolutional Neural Network (CNN) model showed some aptitude, managing to anticipate some major low SPEI events below –1 even if its overall trajectory deviated more. By contrast, the Extreme Gradient Boosting (XGBoost) model performed relatively poorly in capturing extremes despite mimicking some periods of moderate moisture deficiency. Finally, the Long Short-Term Memory neural network (LSTM) performed the worst with virtually no correlation between its predicted and actual SPEI-6. The LSTM displayed difficulties in handling the lagged nature of multi-month climate sequences.

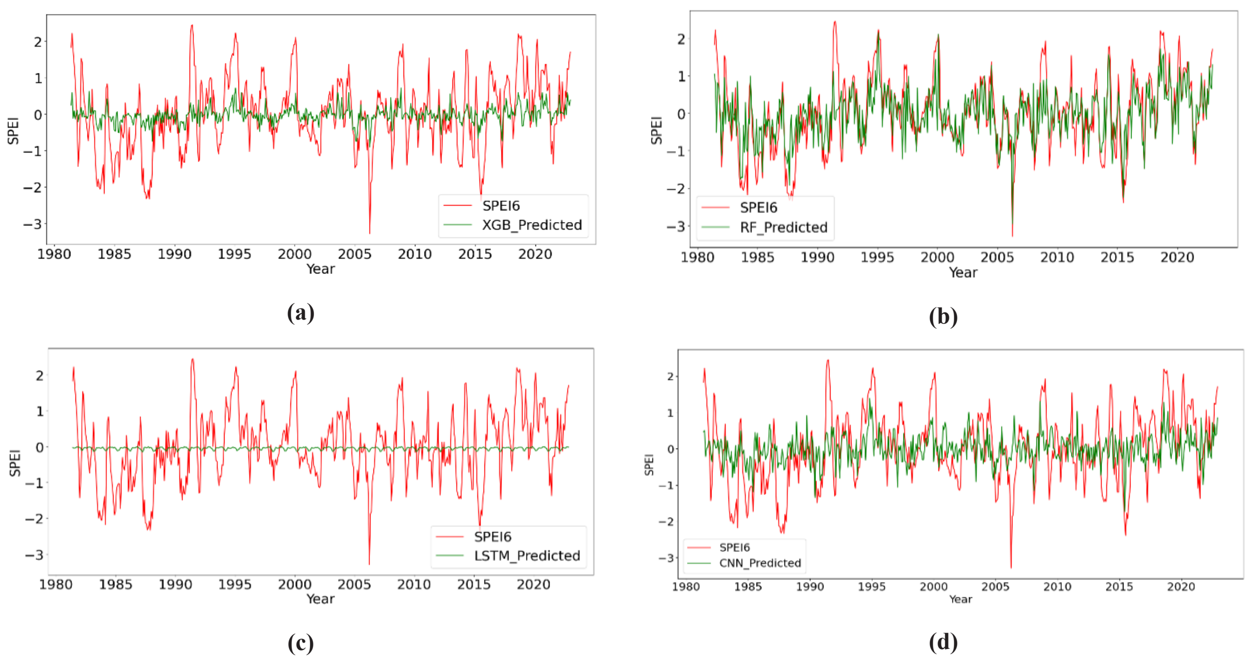
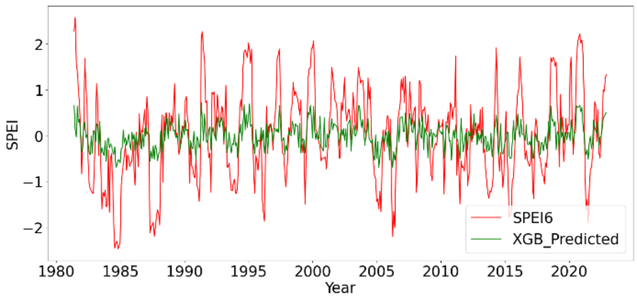


Figure 12. Comparison Between the Standard SPEI6 and the Predicted SPEI6 Using **(a)** XGBoost, **(b)** Random Forest, **(c)** LSTM, **(d)** CNN.



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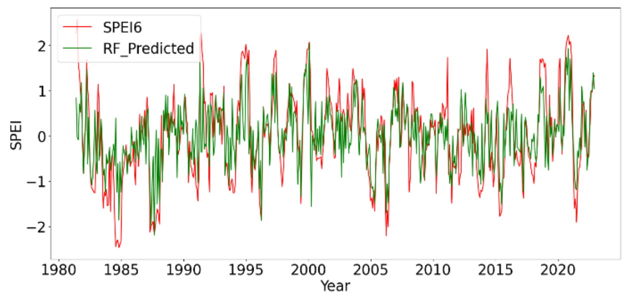

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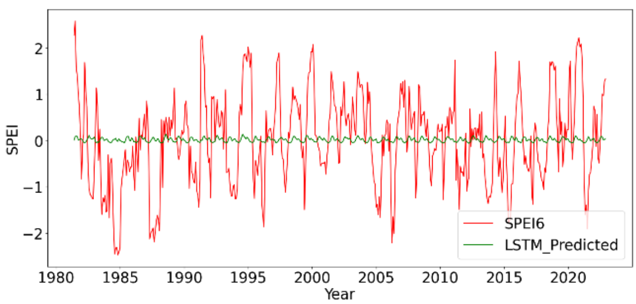

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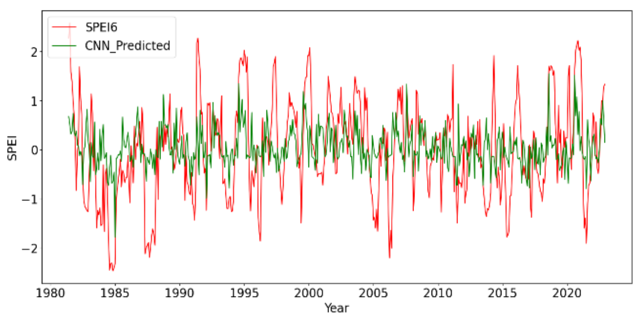


(d)

Figure 13. Comparison Between the Standard SPEI6 and the Predicted SPEI6 Using **(a)** XGBoost, **(b)** Random Forest, **(c)** LSTM, **(d)** CNN.

Agricultural drought severely disrupts crop production and accurate forecasts enable advanced preparation across agricultural regions [20, 22, 23]. This research looks at four machine learning methods — random forest, XGBoost, convolutional neural networks (CNN) and long short-term memory networks (LSTM). It checks how well they predict the 6-month SPEI drought index in Kebbi State. **Figures 9–12** show the predicted versus traditionally calculated SPEI-6 for five places in Kebbi — East, West, North, South and Central.

Overall, the random forest (RF) model most closely matched real SPEI changes — catching both lows showing droughts and highs for wet times across all five subregions from 1980–2022. The RF fit especially tight from 1990 to 2010 in the areas. As Arabameri et al. (2022) notes [19], well-regularized random forests can copy subtle climate shifts. The second-best ML models for this research are XGBoost and CNN which also tracked general SPEI-6 up and down patterns across places, though less smoothly than RF. But the Deep LSTM network did very poorly compared to the other ML models. This is in contrast to the studies of [20, 24, 25].

Examination of **Table 4** illustrates the performance of each of the models through various error metrics. For prediction of the 6-month Standardized Precipitation-Evapotranspiration Index (SPEI-6), the Random Forest model demonstrates the highest coefficient of determination (R-squared) value in comparison to the other models, with its maximal values of 55% in northern and southern Kebbi respectively. In contrast, the eXtreme Gradient Boosting (XGBoost) model exhibits superior R-squared values compared to the Convolutional Neural Network (CNN) model, with its peak value of 34% in central Kebbi followed by 22% in southern and eastern Kebbi. The CNN and Long Short-Term Memory (LSTM) models display the lowest levels of performance.

Table 4. Error Metrics for SPEI-6 Predicted Using Machine Learning Model.

Location	Model	R^2	MAE	MSE
WEST	XGB	0.16	0.71	0.81
	RF	0.47	0.49	0.5
	LSTM	0.01	0.78	0.96
	CNN	0.13	0.84	0.84
NORTH	XGB	0.16	0.72	0.8
	RF	0.55	0.46	0.43
	LSTM	0.01	0.91	0.75
	CNN	0.17	0.79	0.79

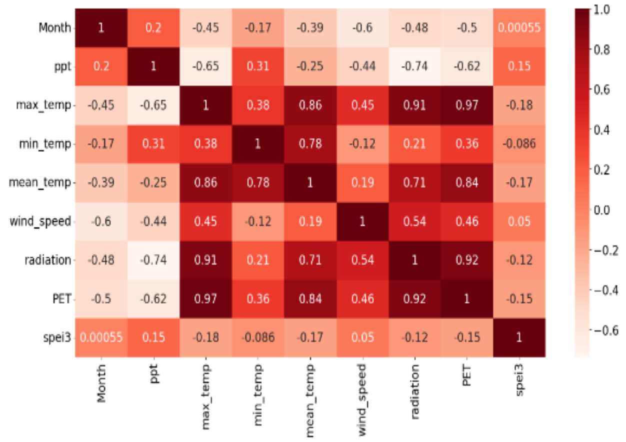
Table 3. *Cont.*

Location	Model	R^2	MAE	MSE
SOUTH	XGB	0.22	0.67	0.75
	RF	0.54	0.46	0.44
	LSTM	0	0.77	0.97
	CNN	0.19	0.78	0.78
EAST	XGB	0.22	0.69	0.75
	RF	0.55	0.46	0.43
	LSTM	0	0.78	0.96
	CNN	0.18	0.79	0.79
CENTRAL	XGB	0.34	0.63	0.63
	RF	0.52	0.47	0.45
	LSTM	0.01	0.78	0.95
	CNN	0.15	0.82	0.82

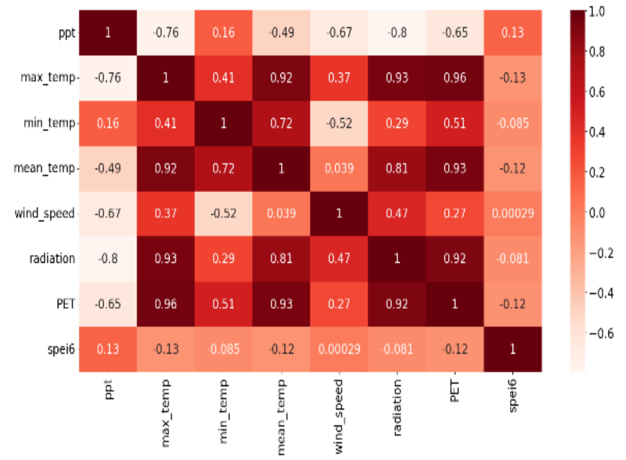
3.4. Parameters Relation

Figure 14 illustrates the correlation between each of the variables utilized for SPEI-3 and SPEI-6 (**Figure 14(a)–(b)**), as compared against one another. The value ranges from 0 to 1. A value of 0 signifies a very weak correlation, while a value of 1 denotes a very strong, direct correlation. Negative values indicate an opposite or inverse correlation. The chart demonstrates that in both SPEI-3 and SPEI-6 maximum temperature and mean temperature have robust, direct correlations with radiation and potential evapotranspiration (PET), respectively. It can also be discerned that precipitation and radiation maintain a strongly inverse or negative correlation.

Figure 15 illustrates the relative importance of each of the meteorological parameters utilized in the machine learning models for both SPEI-3 and SPEI-6. It can be deduced from the chart that precipitation (rainfall) has the highest level of importance in the machine learning models built for calculating SPEI-3 and SPEI-6. This is followed by incoming solar radiation and the potential evapotranspiration index (PET). The other parameters demonstrate very little importance, with the exception of wind speed which shows no discernible importance for this model.



(a)



(b)

Figure 14. Correlation Chart Between Each of the Parameters **(a)** SPEI-3, **(b)** SPEI-6.

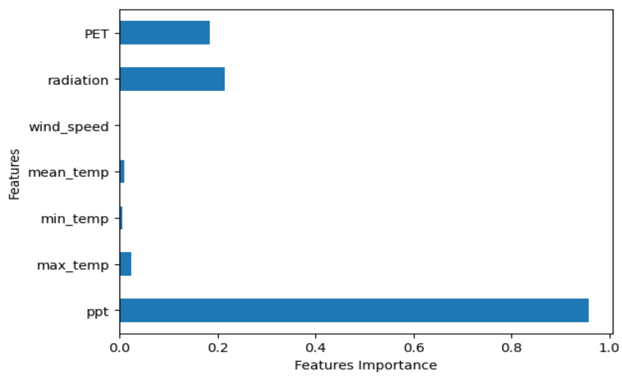


Figure 15. Pie Chart Showing the Importance of Each Feature.

3.5. Drought Forecast

Figure 16 illustrates the future predictions of the Standardized Precipitation Evapotranspiration Index (SPEI) at a 3-month timescale over the next year, based on the dataset. It shows the highest predicted SPEI value of 0.5 occurring around September, and the lowest value of −0.1 occurring around April. Due to the inability of other models to accept null values, XGBoost was utilized to perform a one-year forecast. Although the model has its limitations, chiefly due to the constrained data, it constitutes an initial starting point for drought forecasting in Kebbi State. However, the research shows random forest is the best for drought prediction in the study area.

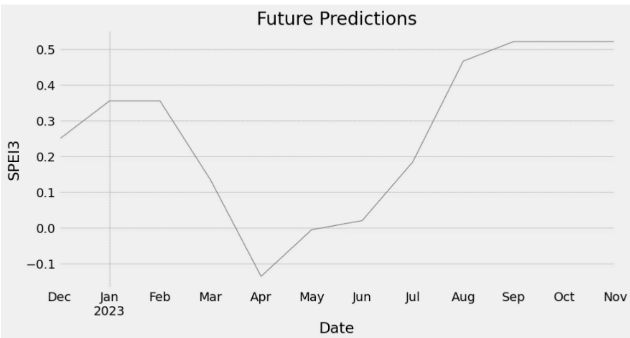


Figure 16. One Year Futuristic Drought Prediction (SPEI-3) for Kebbi State.

4. Conclusions

This paper showed past drought events and forecast future drought risk in Kebbi State, Nigeria using machine learning techniques. The study period spanned over four decades from 1981 to 2022, allowing for an examination of historical drought patterns. The analysis involved calculating the Standardized Precipitation Evapotranspiration Index (SPEI) across multiple timescales (3-month, 6-month) to assess meteorological and agricultural drought. Four machine learning models; Long Short-Term Memory (LSTM) networks, Extreme Gradient Boosting (XGBoost), Random Forest, and Convolutional Neural Networks (CNN); were trained on the historical SPEI data and used to predict drought occurrences.

The results demonstrate that the Random Forest model consistently outperformed the alternatives in predicting SPEI fluctuations and anticipating both high and low intensity drought events. This was true across all the subregions of Kebbi State and at different timescales. The nonlinear ensemble decision trees of the Random Forest model enabled superior feature learning and drought pattern recognition compared to the other techniques. The comparative assessment also highlighted the limitations of LSTM networks in handling lagged climate sequences which rendered its drought predictions ineffective. While the XGBoost and CNN models performed reasonably well in mimicking general wet/dry cycles, they failed to accurately capture major historical extremes.

The consistent superiority of the Random Forest architecture across the various experiments underscores its proficiency and robustness in drought modeling for Kebbi State. The one-year drought forecast generated through the optimized Random Forest model offers valuable insights into near-term risk levels, enabling stakeholders to target mitigation strategies and preparedness efforts.

Conclusively, this paper successfully demonstrated the potential of machine learning, specifically Random Forest models, in drought prediction within the context of Kebbi State, Nigeria. It provides a foundation to build an early drought warning system that is data-driven, locally robust, and tailored to the region. The techniques and findings from this study can guide further research to improve drought prediction in other parts of Nigeria and Sub-Saharan Africa vulnerable to drought impacts. With climate change exacerbating drought risks globally, harnessing advanced technologies for prediction and adaptation will be key to building resilience.

Author Contributions

Conceptualization, E.P.; formal analysis, E.P.; writing—original draft preparation, E.P.; project administration, D.B.M. and E.C.; supervision, D.B.M. and E.C.; writing—review & editing, E.P., D.B.M. and E.C.; data curation, D.B.M.; visualization, D.B.M. and E.C. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

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Informed Consent Statement

Not applicable.

Data Availability Statement

Data will be made available upon request.

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Conflicts of Interest

The authors declare no conflict of interest.

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