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Research Article

Predicting Rainfall Variability and Cereal Crop Yields Using Climatic Oscillation Indices and Machine Learning in Northwestern Nigeria

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ABSTRACT

Northwestern Nigeria, a semi-arid Sahelian environment, is highly vulnerable to rainfall variability due to its strong dependence on rain-fed agriculture. This study evaluated the predictive capability of Artificial Neural Network (ANN) and Random Forest (RF) machine learning models in forecasting annual rainfall variability and aggregate cereal crop yields using some large-scale climate oscillation indices, specifically the El Niño-Southern Oscillation (ENSO), North Atlantic Oscillation (NAO), and the Atlantic Multi-decadal Oscillation (AMO). Historical data (2000-2024) were sourced from the National Aeronautics and Space Administration (NASA) Prediction of Worldwide Energy Resource (POWER) database for rainfall, the National Agricultural Extension and Research Liaison Services (NAERLS) for crop yields, and the National Oceanic and Atmospheric Administration (NOAA) for climate indices. Data preprocessing included temporal aggregation, normalisation, and quality control procedures before model development. The models were trained and validated using a chronological 80:20 data split, while predictive performance was evaluated using the coefficient of determination (R^2), Mean Squared Error (MSE), and Mean Absolute Error (MAE). Results showed that the ANN model achieved slightly superior rainfall prediction performance (R^2 = 0.811; MAE = 101.82 mm), while the RF model produced higher predictive accuracy for aggregate cereal crop yields (R^2 = 0.893; MAE = 0.04375 T/Ha). The findings demonstrate the effectiveness of machine learning approaches in modelling complex climate-crop interactions across northwestern Nigeria. However, limitations associated with the relatively short temporal dataset and the exclusion of agronomic variables are acknowledged. The study highlights the potential application of machine learning models in climate-informed agricultural forecasting, early warning systems, and climate adaptation planning within vulnerable semi-arid regions.

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1 Introduction

Northwestern Nigeria, encompassing states such as Kano, Katsina, Jigawa, Zamfara, Sokoto, Kebbi, and Kaduna (Figure 1), constitutes one of the country's most agriculturally active zones with rainfed farming serving as the dominant source of livelihood and food production (Abdullahi & Marafa, 2023; Olayide et al., 2023; Prince et al., 2023). Major staple cereals cultivated across the region include rice, millet, and sorghum, which are highly sensitive to fluctuations in rainfall amount, timing and distribution (Ekpoh & Nsa, 2011; Ogundele et al., 2024; Oguntunde et al., 2014; Rilwanu & Adamu, 2022). However, increasing climatic variability in recent decades has intensified the vulnerability of agricultural systems across the semi-arid Sahelian environment of northern Nigeria (Adejuwon & Ogundiminegha, 2019; Ekpoh & Nsa, 2011; Ogundele et al., 2024). Variations in seasonal rainfall characteristics have contributed to recurrent droughts, dry spells, floods, and shortened growing seasons, thereby disrupting crop productivity and threatening regional food security (Abdullahi & Marafa, 2023; Adeniyi et al., 2009; Ogundele et al., 2024; Oguntunde et al., 2014; Prince et al., 2023).

Climate variability across many parts of the world has been strongly linked to large-scale ocean-atmosphere interactions (Lukwasa et al., 2022; Masao, 2024; Shi et al., 2017) known as climate oscillations or teleconnections. Among the most influential of these are the El Niño-Southern Oscillation (ENSO), the Atlantic Multidecadal Oscillation (AMO), and the North Atlantic Oscillation (NAO), all of which influence atmospheric circulation, temperature regimes, monsoon dynamics, and precipitation variability across several climatic regions (Nassah et al., 2022; Nicholson, 2013; Nye et al., 2014). ENSO has been associated with droughts and floods across Africa, Asia, and America through its modulation of global atmospheric circulation systems (Nicholson, 2013; Okumura, 2019; Singh et al., 2021). Similarly, the AMO influences sea surface temperature anomalies over the North Atlantic Ocean and has been linked with rainfall variability and monsoon intensity over West Africa and the Sahel (Borgel et al., 2020; Martin & Thorncroft, 2014; Nye et al., 2014). The NAO also exerts considerable influence on atmospheric pressure gradients and moisture transport processes affecting rainfall variability across the

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Sahelian belt (Barcikowska et al., 2018; Chinazor, 2021; Ding et al., 2023; Nassah et al., 2022).

Several studies have examined the relationship between climatic oscillations, rainfall variability and crop yields at global and regional scales. Raj et al. (2020) investigated ENSO impacts on tea production and rainfall variability in South India, while Schillerberg et al. (2019) explored the influence of climate oscillations on maize and wheat yields in the United States. Nobre et al. (2019) linked large-scale climatic variability with sugar beet production across Europe, whereas Cao et al. (2024) demonstrated the role of ENSO phases in influencing wheat production in Australia. In Africa, studies have also highlighted the importance of climate teleconnections in shaping rainfall variability across the Sahel region (Lukwasa et al., 2022; Martin & Thorncroft, 2014; Nassah et al., 2022; Nicholson, 2013; Takele et al., 2020; Tullu, 2024).

Within Nigeria, existing studies have largely concentrated on the influence of ENSO on rainfall variability and temperature patterns (Ati et al., 2010; Bello & Mamman, 2018; Hashidu & Badaru, 2021; Igbawua et al., 2024; Salau et al., 2016; Shehu et al., 2016). However, many of these studies either focused on isolated locations or treated Nigeria as a homogeneous climatic entity despite its strong regional climatic contrasts. More importantly, limited attention has been given to the combined influence of multiple climate oscillation indices, such as ENSO, AMO, and NAO, on rainfall variability and cereal crop yields in northwestern Nigeria as a distinct agroecological region. This represents a significant knowledge gap because climatic conditions over the Sahel are influenced by complex interactions among multiple ocean-atmosphere systems rather than a single teleconnection mechanism. Integrating ENSO, AMO, and NAO, therefore, provides a more comprehensive representation of the large-scale climatic drivers affecting rainfall variability and crop yields across the region.

Another important gap in the literature is the limited application of advanced machine learning approaches in modelling climate-crop relationships in northwestern Nigeria. Conventional statistical approaches often struggle to adequately capture the complex nonlinear interactions between climatic oscillations, rainfall variability, and crop yields. Machine learning techniques such as Artificial Neural Networks (ANN) and Random Forest (RF) regression models have increasingly demonstrated strong predictive capabilities in climatic and agricultural studies due to their ability to model nonlinear relationships and high-dimensional interactions (González-González & Corrales-Suastegui, 2024; Kumar et al., 2007; Uddin et al., 2022). While Bello and Mamman (2018) successfully applied ANN to rainfall prediction in Kano, Nigeria, studies that integrate multiple teleconnection indices with machine learning approaches to simultaneously predict rainfall variability and cereal crop yields across northwestern Nigeria remain conspicuously absent. Those that integrate multiple teleconnection indices with machine learning approaches to simultaneously predict rainfall variability and cereal crop yields across northwestern Nigeria remain scarce.

This study, therefore, applies Artificial Neural Network (ANN) and Random Forest (RF) models to predict annual rainfall variability and aggregate cereal crop yields in northwestern Nigeria using ENSO, AMO, and NAO indices as climatic predictors for the period 2000-2024. The study specifically compares the predictive performance of the two machine learning models and evaluates their suitability for climate-informed agricultural forecasting and decision support in the semi-arid environment of northwestern Nigeria.

2 Materials and Methods

2.1 Study Area

The study was conducted in northwestern Nigeria, comprising seven states, namely Kano, Kaduna, Katsina, Jigawa, Kebbi, Sokoto, and Zamfara States (Figure 1). The region lies approximately between longitudes 3°00′E and 12°00′E and latitudes 9°00′N and 14°00′N, covering an estimated land area of about 212,350 km² (National Bureau of Statistics (NBS), 2010). The region is characterised by rapid population growth and intense agricultural activities. Based on recent projections from the National Population Commission (NPC), the combined population of the seven states exceeds 48 million people, making it one of the most densely populated and agriculturally active regions in Nigeria (NBS, 2020). Agriculture constitutes the major source of livelihood for the predominantly rural population, with rain-fed farming serving as the dominant agricultural system. Figure 1 shows the administrative boundary of Nigeria with a delineation of the study area.

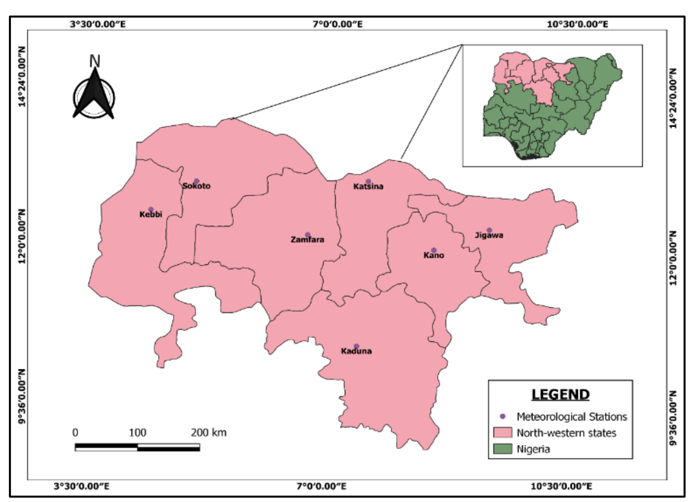

Figure 1: The Study Area (North-western Nigeria)

Climatically, northwestern Nigeria experiences a tropical continental climate characterised by distinct wet and dry seasons controlled largely by the seasonal migration of the Inter-Tropical Discontinuity (ITD) (Gbode et al., 2019; Olalere et al., 2021). Mean annual rainfall generally ranges between approximately 500 mm in the extreme northwestern Sahelian areas and about 1200 mm in the southern Guinea savannah margins, particularly over Kaduna State. The rainy season typically lasts between May and October, although onset and cessation dates vary spatially and temporally across the region (Gbode et al., 2019; Oguntunde et al., 2014; Olalere et al., 2021). The dominant farming season generally coincides with the rainy season, with planting activities commonly commencing between May and June, and harvesting occurring between September and November, depending on crop type and local climatic conditions (Ogundele et al., 2024; Oguntunde et al., 2014; Rilwanu & Adamu, 2022).

Table 1 presents the spatial coordinates and annual rainfall characteristics of the selected stations across northwestern Nigeria for the period 2000-2024. The values indicate considerable spatial variability in rainfall distribution across the study area, with Kaduna recording the highest mean annual rainfall and Jigawa the lowest. The regional mean annual rainfall for northwestern Nigeria was approximately 870.44 mm, reflecting the region's semi-arid climate. The coefficients of variation further indicate substantial interannual rainfall variability across the selected stations, highlighting the climatic vulnerability of the region's predominantly rain-fed agricultural systems.

Table 1: Spatial Coordinates and Annual Rainfall Characteristics of the Selected Stations (2000 – 2024)

Station	Longitude (°E)	Latitude (°N)	Mean Rainfall (mm)	Maximum (mm)	Minimum (mm)	Coefficient of Variation (%)
Kaduna	7.44	10.52	1791.77	6360.63	664.45	73.54
Kano	8.52	12.00	647.62	1845.69	268.95	53.65
Katsina	7.53	13.00	749.82	1784.55	374.41	48.14
Kebbi	4.37	12.47	806.43	2202.76	553.71	39.54
Sokoto	5.02	12.92	721.20	1403.83	421.88	37.57
Zamfara	6.67	12.17	741.55	1542.85	300.59	34.79
Jigawa	9.32	12.33	623.09	1693.74	237.30	54.14
Regional Mean (Northwestern Nigeria)	-	-	870.44	2199.82	427.90	46.41

Note: Values represent annual rainfall characteristics derived from NASA-POWER rainfall datasets for the period 2000-2024.

Northwestern Nigeria forms part of the semi-arid Sudan and Sahel savannah ecological zones of West Africa. Figure 2 shows the major agroecological zones within northwestern Nigeria, comprising the Sahel Savannah, Sudan Savannah, and Guinea Savannah zones. The Sahel Savannah occupies the extreme northern margins of the region and is characterised by low annual rainfall amounts, short growing seasons, and sparse vegetation cover. The Sudan Savannah dominates a substantial portion of the study area and supports extensive cereal cultivation under semi-arid climatic conditions. The Guinea Savannah zone, located mainly in the southern parts of Kaduna, Zamfara, and Kebbi States, experiences relatively higher rainfall amounts and longer growing seasons, thereby supporting more intensive agricultural activities (Adedibu et al., 2022). The spatial distribution of these agroecological zones significantly influences rainfall variability patterns and agricultural productivity across the region.

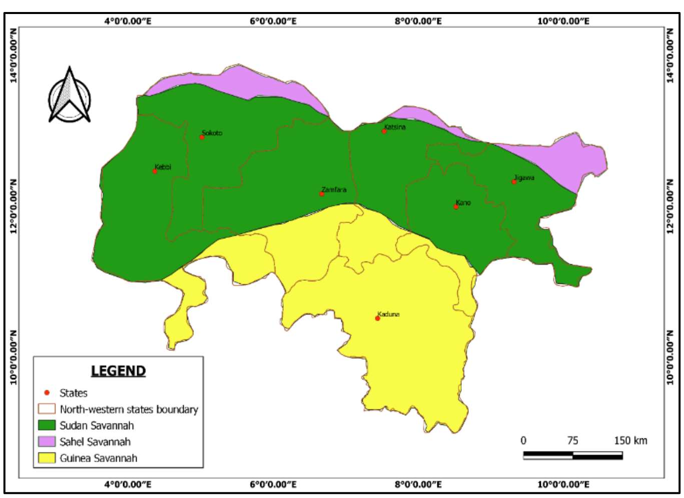

Figure 2: Agroecological Zones of Northwestern Nigeria
Source: Modified from (Adedibu et al., 2022)

2.2 Data Types and Sources

This study utilised climatic oscillation indices, rainfall, and crop yield datasets covering northwestern Nigeria from 2000 to 2024, corresponding to the period for which consistent crop yield data were available across the study area. Three major large-scale climate oscillation indices, namely the El Niño-Southern Oscillation (ENSO), North Atlantic Oscillation (NAO), and Atlantic Multidecadal Oscillation (AMO), were used as predictor variables. Monthly climate oscillation index data were obtained from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Centre and the Physical Sciences Laboratory database (https://psl.noaa.gov/data/climateindices/list/).

Rainfall data were obtained from the National Aeronautics and Space Administration Prediction of Worldwide Energy Resources (NASA-POWER) database (https://power.larc.nasa.gov/data-access-viewer/). The NASA-POWER dataset was selected because of its long-term temporal consistency, wide spatial coverage, accessibility, robustness and extensive application in hydroclimatic and agrometeorological studies across data-sparse regions (Darman et al., 2024; Rodrigues & Braga, 2021; Tayyeh & Mohammed, 2023). Seven representative locations corresponding to the geographical coordinates of the Nigerian Meteorological Agency's (NiMet) synoptic stations distributed across the study area were selected. Although observed station datasets from NiMet provide high-quality measurements, their limited accessibility and cost constraints necessitated the use of NASA-POWER rainfall data. An exploratory comparison between NASA-POWER rainfall estimates and available station-based rainfall characteristics showed almost similar monthly and annual rainfall distribution patterns across the study region, supporting the reliability and suitability of the dataset for this study.

Annual crop yield data for major cereal crops, including millet, sorghum, and rice, were obtained from the National Agricultural Extension and Research Liaison Services (NAERLS), Nigeria. Aggregate annual cereal crop yield values were computed from the combined yields of the selected cereal crops across the study region.

2.3 Data Preprocessing and Quality Control

Quality control procedures were conducted to ensure data consistency and reliability before model development. Missing climatic and rainfall observations within the study period were minimal and were handled using linear interpolation where necessary. Monthly climatic indices and rainfall datasets were screened for inconsistencies, outliers, and duplicate records before analysis.

To address differences in temporal resolution between climatic indices and annual crop yield data, monthly ENSO, AMO, and NAO indices were aggregated into annual mean values corresponding to each study year. Similarly, monthly rainfall totals were aggregated into annual rainfall totals for consistency with the annual crop yield records. This temporal harmonisation enabled direct comparison and modelling of climatic predictors against annual rainfall variability and crop yield outcomes. Input variables were subsequently normalised using Min-Max scaling to improve model efficiency and minimise bias associated with differences in variable magnitudes. Normalisation transformed all predictor variables into comparable numerical ranges prior to machine learning model training.

2.4 Model Development and Validation

Artificial Neural Network (ANN) and Random Forest (RF) regression models were developed to predict (hindcast) annual rainfall variability and aggregate cereal crop yields from 2000 to 2024 using ENSO, AMO, and NAO indices as predictor variables. These machine learning approaches were selected because of their ability to model complex nonlinear relationships between climatic drivers and environmental variables without strict assumptions regarding data distribution (Kagabo et al., 2024). Future projections beyond 2024 were not conducted, as the study focused on historical predictive modelling based on available climatic and crop yield datasets. Predictions into the future would require new climate indices data for those years, which would only be generated using climate model projections.

The complete dataset was divided into training and testing subsets using an 80:20 ratio. The split was conducted chronologically to preserve the temporal structure of the climatic and crop yield datasets and to minimise information leakage between training and testing phases. The training dataset was used for model learning and calibration, while the testing dataset was used for independent model evaluation and validation. Model performance was evaluated using the coefficient of determination (R^2), Mean Squared Error (MSE), and Mean Absolute Error (MAE), which collectively assessed prediction accuracy, model fit, and magnitude of prediction errors.

2.5 Artificial Neural Network (ANN) model

The Artificial Neural Network (ANN) model was employed to predict annual rainfall variability and aggregate cereal crop yields from the selected climate oscillation indices (ENSO, AMO, and NAO). By simulating the structure and function of the human brain, ANNs can learn from historical data, adapt to changing climatic conditions, and provide accurate predictions (Bello & Mamman, 2018; Kumar et al., 2007). This makes them highly suitable for climate modelling, where the relationships between climatic indices, rainfall and crop yields are inherently complex and nonlinear.

The ANN architecture consisted of an input layer, five hidden layers, and an output layer. The input layer received the normalised climatic predictor variables, while the output layer generated predictions for annual rainfall and aggregate cereal crop yields. The five hidden layers utilised the Rectified Linear Unit (ReLU) activation function to capture nonlinear relationships between climatic oscillations and the predicted variables. The five hidden layers contained 64, 128, 128, 64, and 32 neurons, respectively. The conceptualised ANN structure used in this study is presented in Figure 3.

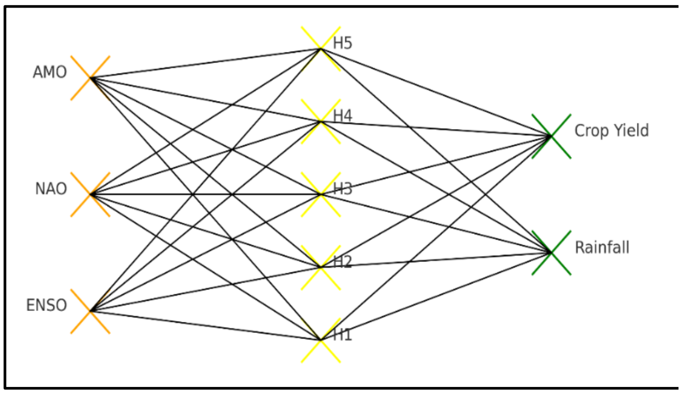

Figure 3: Conceptualised Artificial Neural Network (ANN) Structure

The network architecture was optimised iteratively to improve predictive performance and minimise model error. The ANN model was implemented as a multi-output regression framework in which annual rainfall variability and aggregate cereal crop yields were simultaneously predicted through two output neurons within the output layer. Training and validation losses progressively converged during model training, indicating stable learning behaviour and minimal overfitting within the training process. The ANN model was trained using the Adam optimiser with a learning rate of 0.001 over 500 epochs. Mean Squared Error (MSE) was adopted as the loss function during training. To reduce the risk of overfitting, validation monitoring was conducted during model training, and model performance was evaluated using independent testing datasets derived from the chronological 80:20 data split.
The ANN model is mathematically expressed as Equation (1):

$$\hat{Y} = f\left(\sum_{j=1}^{m} woj . g\left(\sum_{i=1}^{n} wji . X_i + b_j\right) + b_0\right) \quad (1)$$

Where:
$\hat{Y}$ = the predicted rainfall and crop yield values
X_i = the input features representing climatic indices (ENSO, NAO, and AMO)
wji = the weights connecting the input layer neuron i to the hidden layer j
b_j = the bias term for the neuron j in the hidden layer
$g(.)$ = the activation function (rectified linear unit or sigmoid) for the hidden neuron
woj = the weights connecting the hidden layer neuron j to the output layer
b_0 = the bias term for the output layer
$f(.)$ = the activation function for the output layer (often a linear function in regression tasks).

2.6 Random Forest (RF) Regression Model

The Random Forest (RF) regression model was also employed to predict rainfall variability and aggregate cereal crop yields based on the climatic oscillation indices. RF is an ensemble machine learning approach that combines multiple decision trees to improve prediction accuracy and minimise overfitting. Random forest constructs multiple decision trees during training and outputs the average prediction of the individual trees (Meenal et al., 2021; Simon et al., 2023). This method is particularly well-suited for analysing climatic data because it effectively handles missing values, captures feature interactions, and provides feature importance rankings, helping to identify the most influential climatic factors driving rainfall variability. Given its versatility and high predictive performance, RF is a justified choice for climate impact assessments and adaptive decision-making in the agricultural sector (Meenal et al., 2021; Simon et al., 2023). The prediction $\hat{Y}$ for crop output and rainfall is given by the average of predictions from all the trees, and it is mathematically expressed as Equation (2):

$$\hat{Y} = \frac{1}{N}\sum_{i=1}^{N} \hat{Y_i} \quad (2)$$

Where:
$\hat{Y}$ = the final predicted value of rainfall or crop yield
$\hat{Y_i}$ = Prediction from the i-th decision tree
N = the total number of trees in the random forest ensemble

The RF model in this study was developed using 100 decision trees with a maximum tree depth of 10 and a minimum sample leaf size of 2. Bootstrap aggregation was implemented during training, while out-of-bag (OOB) validation was utilised to evaluate model stability and generalisation performance. Feature importance analysis was also conducted to assess the relative contribution of ENSO, AMO, and NAO to rainfall variability and crop yield prediction. However, because RF models may produce overly optimistic predictions when trained on limited datasets, independent test validation was conducted to minimise overfitting and assess model robustness. A conceptualised structure of the random forest regression model for rainfall and crop yield prediction is depicted in Figure 4.

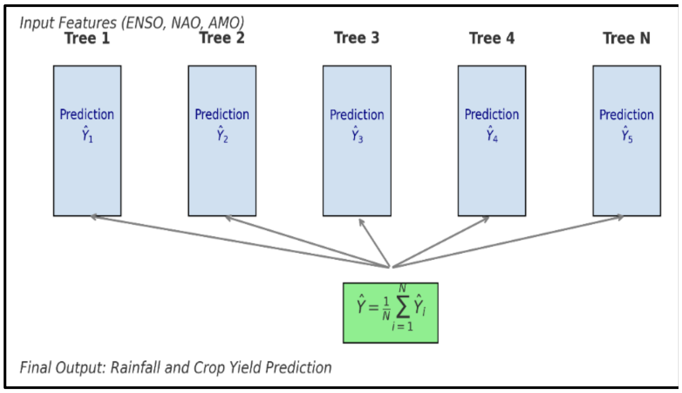

Figure 4: Conceptual Structure of a Random Forest Regression Model

2.7 Performance Evaluation Metrics

The predictive performance of the ANN and RF models was evaluated using the coefficient of determination (R^2), Mean Squared Error (MSE), and Mean Absolute Error (MAE). These metrics were selected because they collectively assess model fit, prediction accuracy, and the magnitude of prediction errors. The coefficient of determination is expressed as Equation (3):

$$R^2 = 1 - \frac{\sum(Y_i - \hat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2} \quad (3)$$

Where:

R^2 = coefficient of determination
Y_i = observed value
$\hat{Y}_i$ = predicted value
$\bar{Y}$ = mean observed value

The prediction models were trained using the backpropagation algorithm, where the network adjusts its weights based on the error between the predicted and actual rainfall and crop yield values. The goal was to minimise this error over the set of training data. Mean Squared Error (MSE) was used as the loss function for regression tasks, which was minimised during training and is expressed as Equation (4):

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (\hat{Y}_i - Y_i)^2 \quad (4)$$

Where:

MSE = Mean squared error
N = number of observations (training samples)
$\hat{Y}_i$ = predicted value of rainfall or crop output for the ith observation
Y_i = observed (actual) value of rainfall or crop yield for the ith observation

In addition to the Mean Squared Error (MSE), the Mean Absolute Error (MAE) was used as a performance metric to evaluate the accuracy of the prediction models for rainfall and crop yields. MAE measures the average magnitude of the errors between predicted and observed values without considering their direction (that is, positive or negative errors are treated equally). A lower MAE value indicates a better fit of the prediction model to the observed data. See Equation (5).

$$MAE = \left(\frac{1}{n}\right) \times \sum\left|Y_i - \hat{Y}_i\right| \quad (5)$$

Where:

MAE = Mean absolute error
Y_i = observed value
$\hat{Y}_i$ = predicted value
n = number of observations

3 Results

3.1 ANN Prediction of Rainfall Variability and Crop Yields in the Study Area

The Artificial Neural Network (ANN) model's prediction of annual rainfall variability and aggregate cereal crop yields in northwestern Nigeria for the period 2000 to 2024 is depicted in Figure 5. The left panel displays the observed and predicted rainfall values, while the right panel presents the observed and predicted total cereal crop yields. The ANN model demonstrates a generally strong ability to replicate the temporal patterns of rainfall variability, with close alignment between observed and predicted values from 2000 through 2019. However, notable underestimation of rainfall amounts is observed during extreme rainfall years, particularly between 2020 to 2022 and 2024, indicating that while the model captures general trends effectively, it struggles with predicting extreme climatic anomalies. In terms of crop yield prediction, the ANN model also performed reasonably well, successfully capturing the general oscillations in yield trends over the study period. Nevertheless, the model consistently underpredicted during years of exceptionally high yields, notably around 2010 and 2017. Nonetheless, the overall temporal agreement between observed and predicted values indicates satisfactory predictive capability of the ANN model.

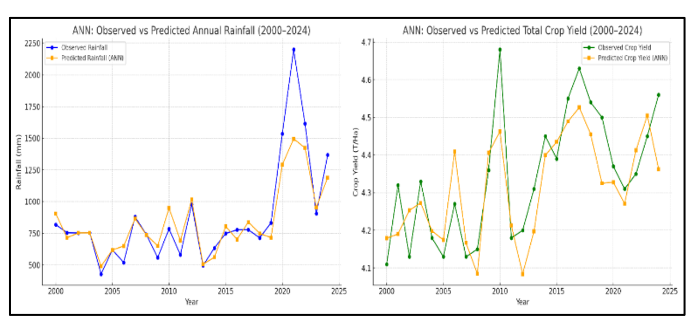

Figure 5: Comparison of ANN-Predicted and Observed Rainfall and Crop Yields in Northwestern Nigeria (2000-2024)

The predictive performance of the Artificial Neural Network (ANN) model for annual rainfall variability and total cereal crop yields in northwestern Nigeria between 2000 and 2024 has been collectively assessed in Figure 6 and Table 2. The scatter plots shown in Figure 6 visually compare observed and predicted values. For rainfall variability (left panel), the scatter distribution indicates a moderate positive alignment with the 1:1 reference line, although a degree of dispersion is evident, particularly for years characterised by extreme rainfall anomalies. The right panel, representing total crop yield predictions, exhibits a less tight clustering of points along the 1:1 line, indicating that the ANN model achieved relatively higher predictive accuracy for rainfall than for crop yields.

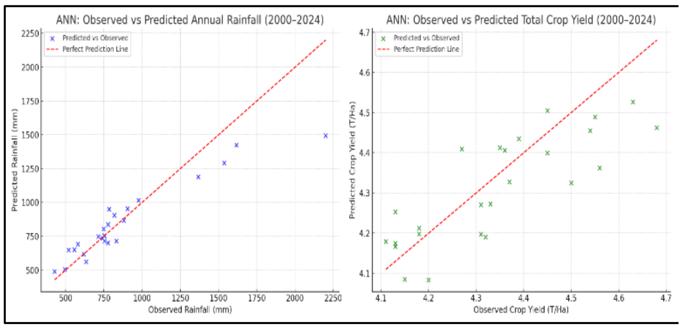

Figure 6: Scatter Plots of Observed vs ANN-Predicted Annual Rainfall and Crop Yields in Northwestern Nigeria (2000–2024)

These visual interpretations are quantitatively supported by the testing performance metrics reported in Table 2. For rainfall prediction, the coefficient of determination (R^2) was 0.811, demonstrating that approximately 81.1% of the variance in observed rainfall was captured by the ANN model. The Mean Squared Error (MSE) and Mean Absolute Error (MAE) for rainfall prediction were 29,627.40 mm² and 101.82 mm, respectively, highlighting that moderate-sized prediction errors were particularly pronounced during extreme rainfall years. For crop yield prediction, the ANN model achieved a lower R^2 value of 0.635, indicating that about 63.5% of the variability in observed yields was explained by the model. The MSE and MAE for crop yield prediction were 0.00998 T²/Ha² and 0.085 T/Ha, respectively, suggesting moderate-sized prediction errors. The corresponding Mean Squared Error (MSE) and Mean Absolute Error (MAE) values further indicate acceptable model accuracy across the testing dataset.

Table 2: Testing Performance Metrics for ANN Prediction of Rainfall Variability and Crop Yields in Northwestern Nigeria (2000-2024)

Metric	Rainfall Prediction (ANN)	Crop Yield Prediction (ANN)
R-squared (R^2)	0.810889387	0.635070815
Mean Squared Error (MSE)	29627.39924mm²	0.009998242 (T/Ha)²
Mean Absolute Error (MAE)	101.8200742mm	0.084947928 T/Ha

Note: Performance metrics were computed using independent test datasets.

Figure 7 presents the ANN training and validation loss curves during model training. Both curves progressively converged with increasing epochs, indicating stable model learning behaviour and minimal overfitting during the training process.

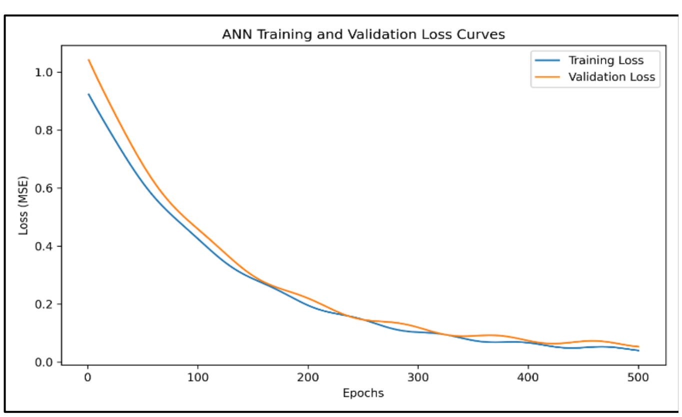

Figure 7: ANN Training and Validation Loss Curves during Model Training

The residual errors associated with ANN predictions are presented in Figure 8. The residual plot indicates that most prediction errors were distributed relatively not so far away from zero across the study period, although slightly larger residuals occurred during years associated with extreme rainfall and crop yield conditions.

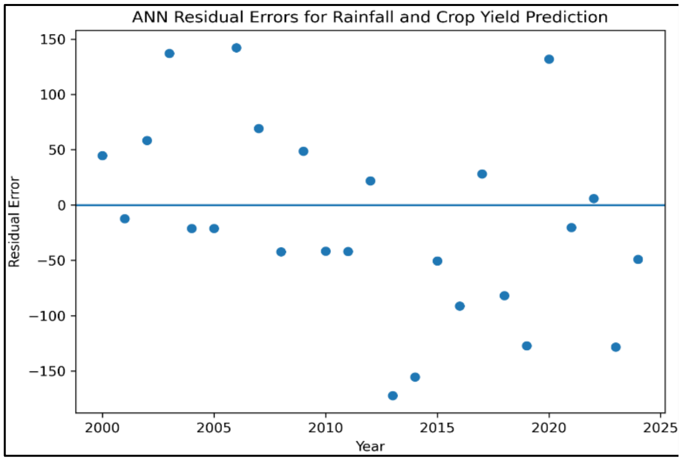

Figure 8: ANN Residual Errors for Rainfall and Crop Yield Prediction (2000-2024)

3.2 RF Prediction of Rainfall Variability and Crop Yields in the Study Area

The Random Forest (RF) model predictions versus observed values of annual rainfall and aggregate cereal crop yields in northwestern Nigeria for the period 2000 to 2024 are presented in Figure 9. The left panel displays the comparison between observed and RF-predicted rainfall values. Just like the ANN model, the results demonstrate that the RF model effectively captured the temporal patterns of rainfall variability, with predicted values closely following observed values across most of the study period. Minor underestimations were observed during years of exceptionally high rainfall, particularly in 2020 to 2023 and 2022, suggesting that while the RF model performs strongly, slight challenges remain in precisely modelling extreme rainfall anomalies. Nonetheless, the overall predictive accuracy for rainfall variability was notably high. The right panel depicts the RF model's performance in predicting total cereal crop yields. The Figure shows a remarkable alignment between predicted and observed crop yields, with the curves nearly overlapping throughout the 25 years. Only slight deviations are visible during peak-yield years (2010, 2016 to 2019, and 2024) and in some lower-yield years (2002, 2004 - 2005, 2007 - 2008), indicating very small prediction errors.

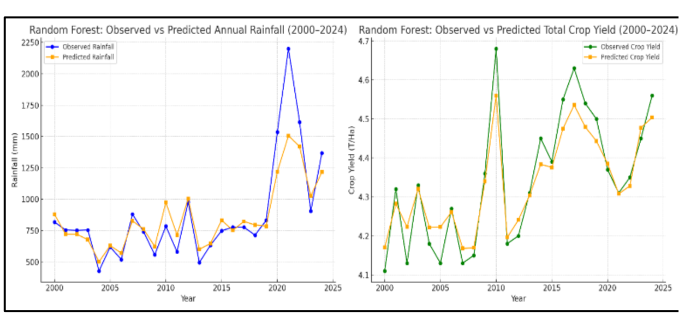

Figure 9: Comparison of RF-Predicted and Observed Rainfall and Crop Yields in Northwestern Nigeria (2000–2024)

The predictive performance of the Random Forest (RF) model for annual rainfall variability and total cereal crop yields in northwestern Nigeria from 2000 to 2024 was jointly evaluated in Figure 10 and Table 3. The scatter plots shown in Figure 10 visually compare observed and RF-predicted values. For rainfall variability (left panel), the points are moderately clustered around the 1:1 line, indicating a strong positive relationship between observed and predicted values, although some dispersion is visible, especially at the extremes. The right panel, depicting total crop yield predictions, shows a near-perfect clustering of points along the 1:1 reference line, reflecting outstanding prediction accuracy with minimal deviations across the study period.

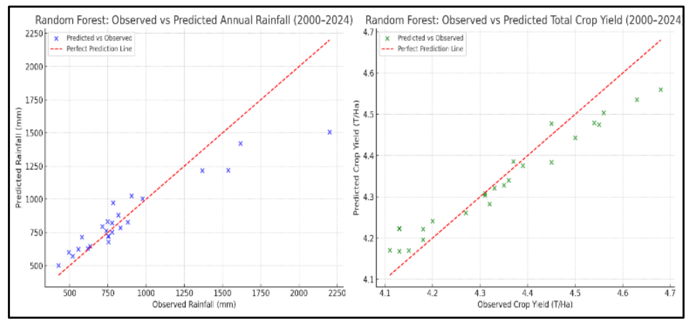

Figure 10: Scatter Plots of Observed vs RF-Predicted Annual Rainfall and Crop Yields in Northwestern Nigeria (2000-2024)

The quantitative testing performance metrics in Table 3 substantiate these visual observations. The coefficient of determination (R^2) for rainfall prediction was 0.8036, meaning that the RF model explained approximately 80.4% of the variability in observed rainfall. The associated Mean Squared Error (MSE) and Mean Absolute Error (MAE) were 30,776.05 mm^2 and 108.35 mm, respectively, indicating moderate predictive errors, particularly during periods of extreme rainfall. In contrast, crop yield prediction achieved an R^2 of 0.8929, indicating that nearly 89.3% of the variability in observed yields was captured by the RF model. The MSE and MAE for crop yield predictions were impressively low, at 0.002935 (T/Ha)^2 and 0.04375 T/Ha, respectively.

Table 3: Testing Performance Metrics for RF Prediction of Rainfall Variability and Crop Yields in Northwestern Nigeria (2000-2024)

Metric	Rainfall Prediction	Crop Yield Prediction
R-squared (R^2)	0.803557565	0.89286841
MSE	30776.054 mm^2	0.002935166 (T/Ha)^2
MAE	108.3489044 mm	0.043752 T/Ha

Note: Performance metrics were computed using independent test datasets

The feature importance analysis for the RF model is presented in Figure 11. The results indicate that ENSO contributed most strongly to rainfall variability prediction, while AMO and NAO also demonstrated important contributions to the predictive performance of the model.

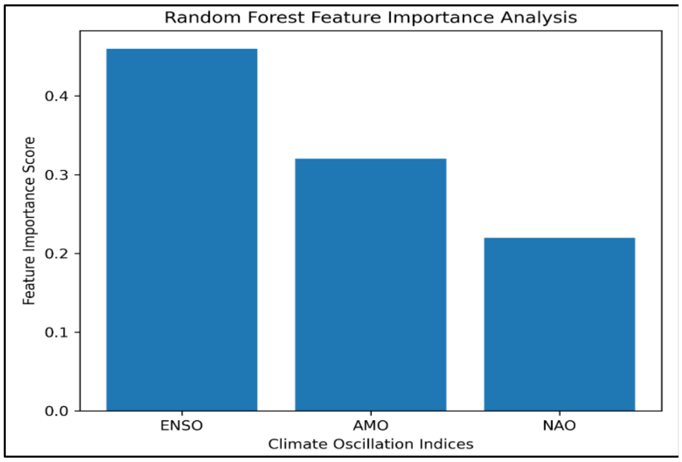

Figure 11: Random Forest Feature Importance Analysis over Northwestern Nigeria (2000 – 2024)

Figure 12 presents the RF residual error distribution across the study period. Most residual errors were not very far away from zero across the study period, although slightly larger residuals occurred during years associated with extreme rainfall and crop yield conditions, indicating strong predictive consistency and limited model bias throughout the testing period.

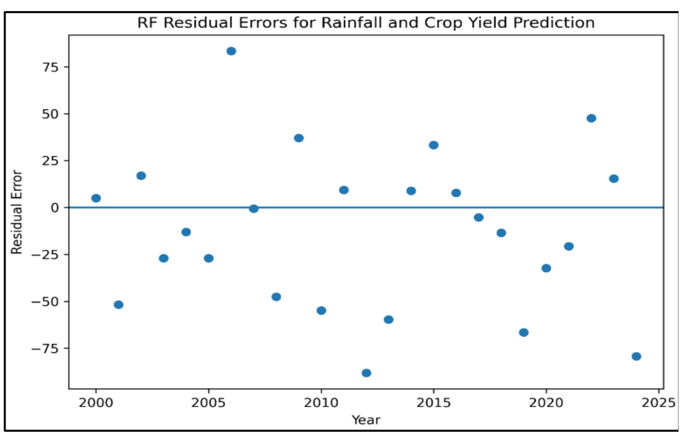

Figure 12: RF Residual Errors for Rainfall and Crop Yield Prediction (2000 – 2024)

4 Discussion

4.1 Performance of ANN and RF Models

The findings of this study demonstrate that both the Artificial Neural Network (ANN) and Random Forest (RF) models possess strong capability for predicting rainfall variability and aggregate cereal crop yields in northwestern Nigeria using the selected large-scale climate oscillation indices. However, differences were observed in the predictive strengths of the two machine learning approaches. The ANN model produced slightly better performance in rainfall prediction, whereas the RF model demonstrated superior performance in crop yield prediction. This difference may be attributed to the ability of Random Forest algorithms to effectively capture complex nonlinear interactions and threshold responses between climatic predictors and crop yields through ensemble learning techniques (Uddin et al., 2022). The superior crop yield prediction performance of the RF model further suggests that large-scale climatic oscillations exert substantial influence on cereal crop yields across the semi-arid environment of northwestern Nigeria. Although agronomic variables such as soil properties, fertiliser application, crop management practices, and pest conditions were not incorporated into the modelling framework, the RF model was still able to capture a considerable proportion of crop yield variability. This indicates that rainfall variability associated with climate oscillations remains a major controlling factor influencing cereal crop productivity within the study area.

4.2 Physical Interpretation of Climate-Crop Relationships

The predictive relationships identified in this study are physically plausible within the broader climatological context of the West African Sahel. Previous studies have established that ENSO strongly influences atmospheric circulation and rainfall variability across West Africa through modifications in tropical convection and moisture transport processes (Egbuawa et al., 2017; Hashidu & Badaru, 2021; Henchiri et al., 2021; Nicholson, 2013; Salau et al., 2016; Umar & Kehinde, 2020). El Niño conditions are frequently associated with suppressed rainfall and drought occurrences across parts of the Sahel, whereas La Niña conditions often enhance rainfall activity (Egbuawa et al., 2017; Nicholson, 2013; Umar & Kehinde, 2020). Similarly, the Atlantic Multidecadal Oscillation (AMO) influences sea surface temperature anomalies over the North Atlantic Ocean, thereby modulating monsoon intensity and moisture advection into the West African region (Martin & Thorncroft, 2014; Nye et al., 2014; Ta et al., 2016).

The North Atlantic Oscillation (NAO) also contributes to variations in atmospheric pressure gradients and circulation dynamics, affecting rainfall distribution across the Sahelian belt (Borgel et al., 2020; Chinazor, 2021; Ding et al., 2023; Nassah et al., 2022). The combined integration of ENSO, AMO, and NAO in this study therefore provided a more comprehensive representation of the large-scale climatic controls governing rainfall variability and cereal crop yields in northwestern Nigeria. Since cereal crop production in the region depends heavily on seasonal rainfall availability, fluctuations in these climatic oscillations may substantially influence planting dates, soil moisture conditions, crop growth duration, and final yield outcomes.

4.3 Underprediction of Extremes and Model Uncertainty

Despite the strong predictive performance achieved by both machine learning models, certain limitations were observed. The ANN model tended to underpredict extreme rainfall and exceptionally high crop yield years. This behaviour may be associated with the smoothing characteristics of neural network models, where rare extreme events are often inadequately represented within relatively short training datasets because the extreme deviations are often compressed toward the mean during prediction (Bello & Mamman, 2018; Kumar et al., 2007; Yilmaz & Kaynar, 2011). The limited occurrence of climatic extremes within the historical record may therefore constrain the model's ability to fully learn highly anomalous atmospheric conditions.

Furthermore, climatic systems are characterised by substantial temporal complexity and memory effects, which may not be completely captured using annual climatic indices alone. The slight underestimation of extremes may therefore reflect limitations in representing highly nonlinear hydroclimatic feedback mechanisms within the modelling framework.

Although the RF model achieved very high crop yield prediction accuracy, the possibility of residual uncertainty still exists. Crop yields are influenced not only by climatic variability but also by several agronomic and socioeconomic factors, including soil fertility, fertiliser application, seed quality, irrigation practices, pest infestation, and farm management strategies, which were not incorporated into the present study.

4.4 Comparison with Previous Studies

The findings of this study are generally consistent with previous studies that have demonstrated the effectiveness of machine learning approaches in climatic prediction. Bello and Mamman (2018) reported strong ANN performance in rainfall prediction over Kano, Nigeria, while Uddin et al. (2022) demonstrated the effectiveness of Random Forest models in predicting extreme rainfall indices using large-scale atmospheric predictors. Similarly, González-González and Corrales-Suastegui (2024) observed that machine learning techniques effectively captured precipitation variability associated with ENSO conditions in Mexico.

The present findings also support earlier studies highlighting the influence of large-scale climate oscillations on rainfall variability across the Sahel and West Africa (Egbuawa et al., 2017; Hashidu & Badaru, 2021; Henchiri et al., 2021; Igbawua et al., 2024; Martin & Thorncroft, 2014; Nassah et al., 2022; Nicholson, 2013; Shehu et al., 2016; Ta et al., 2016). However, unlike many previous studies that focused primarily on single climatic oscillations or isolated climatic variables, this study integrated ENSO, AMO, and NAO simultaneously within a comparative machine learning framework for both rainfall variability and cereal crop yield prediction across northwestern Nigeria. The study therefore contributes to improving climate-informed agricultural forecasting and adaptive planning within semi-arid agroecological systems.

5 Conclusion

This study evaluated the capability of Artificial Neural Network (ANN) and Random Forest (RF) machine learning models in predicting annual rainfall variability and aggregate cereal crop yields in northwestern Nigeria using ENSO, AMO, and NAO from 2000 to 2024. The findings revealed that both models demonstrated strong predictive capability, although their performances varied across the predictands. The ANN model produced slightly better rainfall prediction performance, whereas the RF model achieved superior accuracy in predicting aggregate cereal crop yields. These results demonstrate the significant influence of large-scale climate oscillations on rainfall variability and crop yields within the semi-arid environment of northwestern Nigeria. The study further highlights the potential application of machine learning approaches in climate-informed agricultural forecasting, early warning systems, and climate adaptation planning across vulnerable agroecological regions. However, certain limitations should be acknowledged. The modelling framework was based on a relatively short temporal dataset and did not incorporate important agronomic variables such as soil characteristics, fertiliser application, irrigation practices, pest conditions, and crop management techniques, which may also influence crop yields.

Future studies should therefore consider the integration of hybrid machine learning and process-based modelling approaches, the incorporation of additional environmental and agronomic predictors, and the extension of predictive frameworks to seasonal forecasting and broader food security applications across the West African Sahel.

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