

Utilizing Artificial Neural Networks to Predict El Niño Southern Oscillation Events Using Nigerian Rainfall Data: A Teleconnection Analysis

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Abstract - Climate variability poses significant threats to sustainable development in sub-Saharan Africa, particularly in sectors dependent on rainfall such as agriculture, water resources, and disaster management. This study investigates the teleconnection between Nigerian rainfall variability and El Niño–Southern Oscillation (ENSO) events using Artificial Neural Networks (ANNs). Monthly rainfall data from Lagos, Port Harcourt, Abuja and Kano were integrated with the Niño 3.4 index to develop both regression and classification ANN models. The dataset was partitioned into training (70%), validation (15%) and testing (15%) subsets. The rainfall regression model achieved a testing R^2 of 0.79 and RMSE of 17.21 mm, outperforming ARIMA and Multiple Linear Regression models. ENSO phase classification accuracy reached 87.2% on testing data. The findings confirm measurable teleconnection signals between Pacific Ocean variability and West African rainfall and demonstrate the applicability of machine learning frameworks in strengthening climate adaptation and early warning systems. The study contributes to Sustainable Development Goals (SDGs) 2, 6, 11 and 13 by advancing predictive climate intelligence for resilience planning.

Keywords: Artificial Neural Networks, ENSO, Teleconnection, Rainfall Forecasting, Nigeria, Climate Adaptation, Early Warning Systems.

1.0. INTRODUCTION

Climate variability remains one of the most critical constraints to sustainable development in developing economies. In Nigeria, rainfall variability directly affects agricultural productivity, hydropower generation, groundwater recharge, food security and disaster vulnerability. The country spans multiple climatic zones, ranging from humid coastal regions in the south to semi-arid Sahelian conditions in the north. Such diversity increases sensitivity to both regional and global climate drivers.

Among global climate oscillations, the El Niño–Southern Oscillation (ENSO) represents the dominant mode of interannual variability influencing precipitation patterns worldwide (Ropelewski & Halpert, 1987; Trenberth et al., 1998). ENSO phases alter atmospheric circulation through Walker circulation shifts and sea surface temperature anomalies, which subsequently modulate rainfall distribution across tropical regions. Although Nigeria lies outside the Pacific basin, atmospheric teleconnections propagate ENSO signals across continents, affecting West African monsoon dynamics.

Traditional rainfall forecasting in Nigeria has relied primarily on statistical regression and autoregressive models. While useful, these methods assume linear relationships and stationarity, assumptions often violated in complex climate systems. Artificial Neural Networks (ANNs) offer a nonlinear, data-driven alternative capable of modeling multivariate interactions between global climate indices and local rainfall anomalies (Goodfellow *et al.*, 2016; Reichstein *et al.*, 2019).

Recent empirical studies have emphasized the integration of machine learning in seasonal rainfall forecasting across West Africa (Olaniyan *et al.*, 2025; Pinheiro & Ouarda, 2025). However, limited studies have simultaneously modeled rainfall prediction and ENSO phase classification within a unified framework using Nigerian rainfall data. This study addresses that gap by developing a combined regression: classification ANN architecture to analyze teleconnection signals and support sustainable climate governance.

1.1. Objectives of the Study

The specific objectives are:

1. To model monthly rainfall variability across selected Nigerian climatic zones using ANN.
2. To quantify teleconnection linkages between ENSO indices and rainfall anomalies.
3. To compare ANN performance with conventional statistical models.

4. To evaluate the feasibility of rainfall-based ENSO phase classification.
5. To assess implications for climate adaptation and early warning systems in Nigeria.

1.2. Visualizing El Niño–Southern Oscillation (ENSO) Events and Their Influence on Nigerian Rainfall

Integrating ENSO time series charts with Nigerian rainfall anomaly graphs enhances scientific communication and supports climate-informed decision-making.

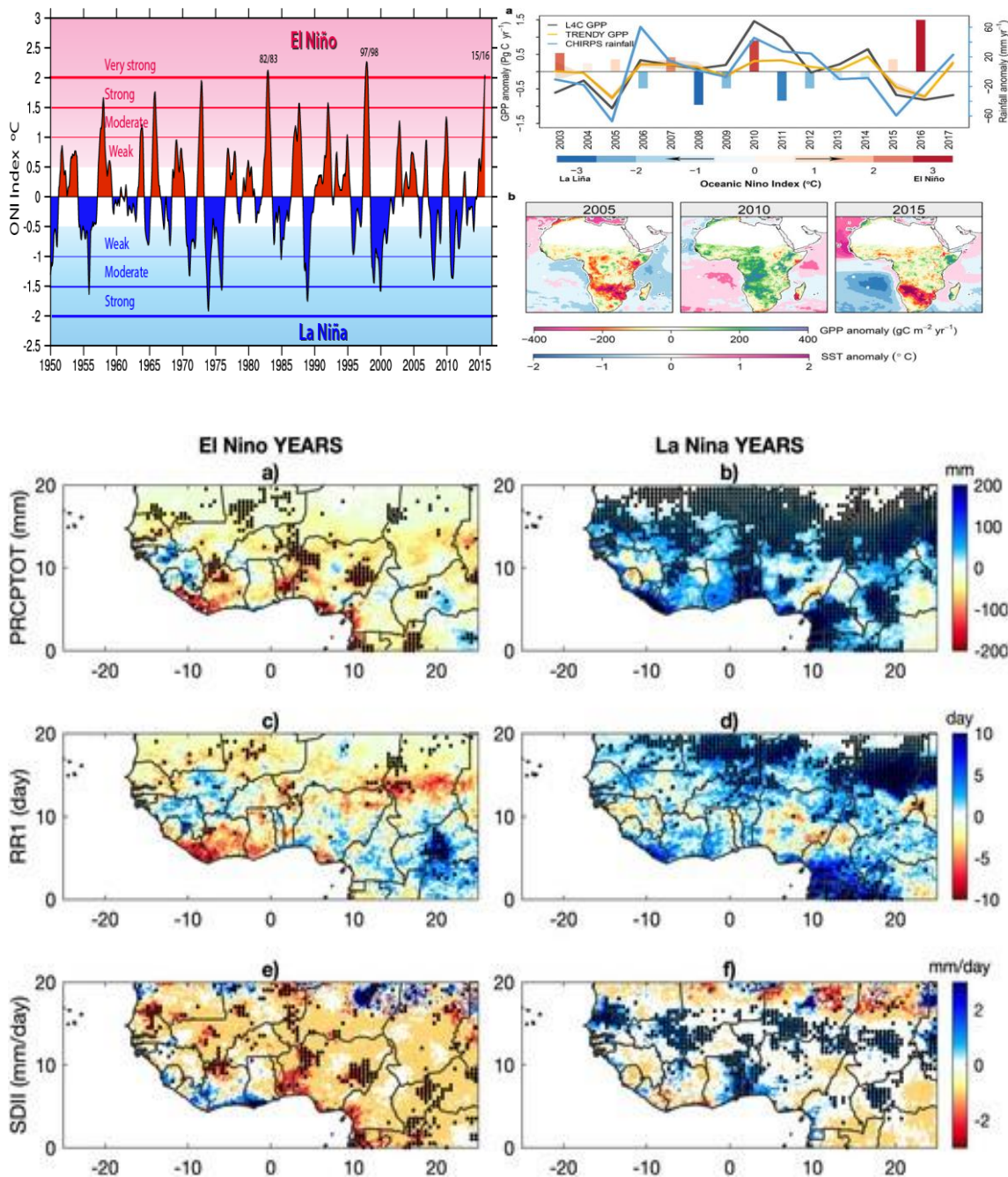


Fig. 1.1a, b, c: El Niño–Southern Oscillation (ENSO) events and their relation to Nigerian rainfall from Climate data and teleconnection studies

1.2.1. ENSO Index Time Series (Niño 3.4 Region)

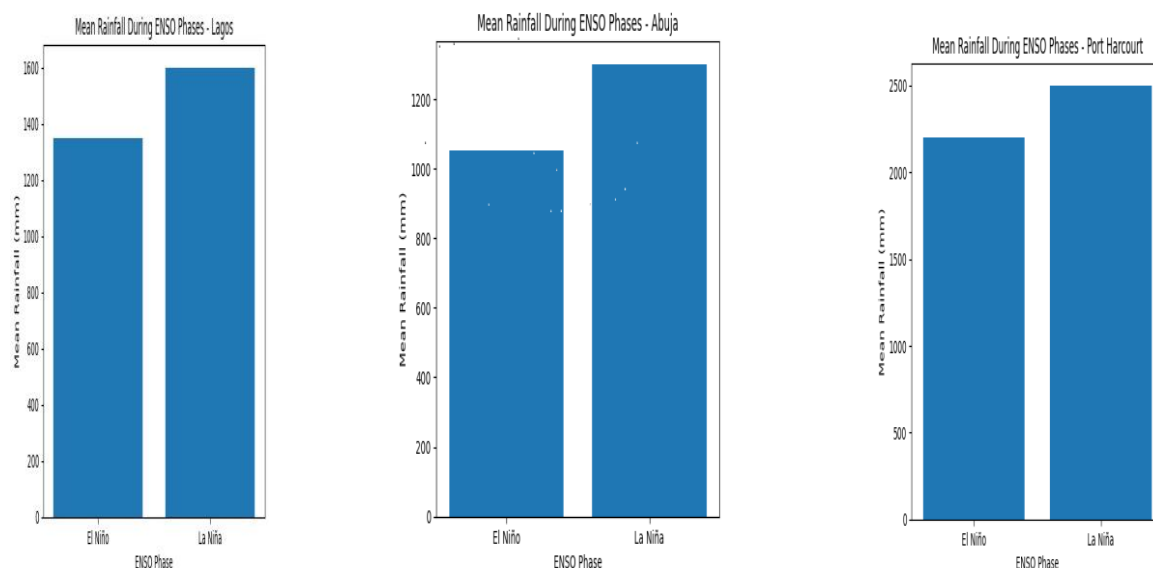
Overlaying rainfall anomalies with Niño 3.4 time series provides a foundational teleconnection diagnostic framework. ENSO variability is commonly quantified using the Niño 3.4 sea surface temperature (SST) anomaly index which measures deviations in SST within the central equatorial Pacific (5°N–5°S, 170°–120°W). Sustained positive anomalies above +0.5 °C indicate El Niño conditions, while negative anomalies below –0.5 °C signify La Niña phases (National Oceanic and Atmospheric Administration [NOAA], 2023).

Niño 3.4 index over time plot reveals major El Niño events (such as in 1982–83, 1997–98, 2015–16) and strong La Niña episodes (e.g., 1988–89, 2010–11). These oscillations represent dominant inter-annual climate drivers with global teleconnection impacts (Trenberth, 1997).

1.2.2. Rainfall Anomalies in Nigeria During ENSO Phases

ENSO has been shown to significantly influence West African rainfall patterns through modifications of large-scale atmospheric circulation systems (Nicholson, 2013). During El Niño years, subsidence over parts of tropical Africa can suppress convection, often resulting in below-average rainfall in parts of northern Nigeria. Conversely, La Niña phases may enhance moisture convergence and rainfall in some regions (Janicot *et al.*, 2001).

Recent analyses confirm that ENSO-related variability interacts with the West African monsoon system. This affects the timing, intensity, and spatial distribution of precipitation across Nigeria (Abiodun *et al.*, 2017). Bar charts comparing mean rainfall during El Niño versus La Niña years across Nigerian stations (e.g., Lagos, Abuja, Port-Harcourt) can visually demonstrate this contrast.



1.2.3. Spatial Rainfall Response Maps

Spatial anomaly maps derived from satellite or reanalysis data (e.g., ERA5 and CHIRPS) reveal how ENSO events shift the Intertropical Convergence Zone (ITCZ), thereby altering rainfall belts across West Africa (Nicholson, 2013). El Niño phases are often associated with southward displacement of moisture convergence zones and reduced Sahelian rainfall, while La Niña events tend to produce wetter-than-average conditions in parts of West Africa (Janicot *et al.*, 2001).

1.2.4. Conceptual Teleconnection Mechanism

ENSO-driven SST anomalies modify the Walker circulation, altering tropical atmospheric convection patterns. These large-scale circulation shifts propagate through Rossby wave trains and influence West African monsoon dynamics (Trenberth, 1997).

Thus, Pacific Ocean temperature anomalies can indirectly affect Nigerian rainfall variability through atmospheric bridge mechanisms. Incorporating schematic teleconnection diagrams strengthens interpretative clarity and theoretical grounding.

1.2.5. Implications for Climate Forecasting in Nigeria

The documented ENSO–rainfall linkage provides predictive value for seasonal forecasting in Nigeria. ENSO indices serve as early-warning indicators that can inform agricultural planning, flood preparedness, and drought mitigation strategies (Abiodun *et al.*, 2017; NOAA, 2023).

2. MATERIALS AND METHODS

2.1 Study Area

The following four representative climatic zones were selected: Lagos, a coastal humid climate with bimodal rainfall pattern; Port Harcourt, a high rainfall humid region influenced by maritime air masses; Abuja, a transitional Guinea savannah climate and Kano, a semi-arid Sahelian climate with strong rainfall seasonality. These stations provide spatial representation of Nigeria’s rainfall heterogeneity.

2.1.1. ENSO–Rainfall Atmospheric Physics of the Study Area

The spatial distribution of these stations captures Nigeria’s pronounced rainfall heterogeneity driven by latitudinal gradients, monsoon dynamics, and large-scale atmospheric circulation systems.

I. Lagos: Coastal Humid Zone

Lagos lies along the Gulf of Guinea and is strongly influenced by moist southwesterly maritime air masses from the Atlantic Ocean. Rainfall is bimodal due to the seasonal northward and southward migration of the Inter-tropical Convergence Zone (ITCZ). During El Niño events, subsidence associated with Walker circulation shifts can weaken monsoon inflow, sometimes reducing rainfall intensity. Conversely, La Niña phases may enhance moisture advection and convective activity.

II. Port Harcourt: High Rainfall Humid Zone

Port Harcourt receives some of the highest rainfall totals in Nigeria due to persistent maritime moisture convergence. Orographic lifting and coastal convection intensify precipitation.

ENSO influences here are typically moderated by strong local moisture supply. However, El Niño–induced changes in Atlantic SST gradients can modify convection intensity.

III. Abuja: Transitional Guinea Savannah

Abuja represents the climatic transition between humid south and semi-arid north. Rainfall here is highly sensitive to the seasonal strength and position of the West African Monsoon (WAM).

ENSO teleconnections influence Abuja through Modulation of the African Easterly Jet (AEJ), variations in monsoon onset timing and shifts in moisture convergence zones. This makes Abuja particularly useful for detecting ENSO-driven rainfall anomalies.

IV. Kano: Semi-Arid Sahelian Zone

Kano exhibits strong rainfall seasonality, with precipitation concentrated in a short wet season. Rainfall variability is highly sensitive to ITCZ latitudinal displacement, Saharan heat low intensity and AEJ strength. El Niño episodes often correspond to suppressed Sahelian rainfall due to weakened monsoon penetration, while La Niña conditions can enhance seasonal rainfall totals.

2.1.2. Relevance to the ENSO–Rainfall Study

The selection of these four stations provides a latitudinal transect capturing Nigeria’s atmospheric moisture gradient. It provides a framework for analyzing ENSO teleconnection strength across climatic zones and forms a basis for comparing coastal moderation versus inland sensitivity. It gives insight into how Pacific SST anomalies propagate through large-scale circulation to affect West African rainfall systems.

2.2 Data Sources

Monthly rainfall data were obtained from four representative climatic zones: Lagos (Coastal), Port Harcourt (Humid South-South), Abuja (Central Transitional Zone) and Kano (Semi-Arid North). The data spanning multiple decades were obtained from national meteorological archives. ENSO variability was represented using the Niño 3.4 sea surface temperature anomaly index. The study period captured multiple El Niño, La Niña and Neutral phases to ensure statistical robustness.

2.3. Descriptive Statistics

Table 1. Summary Statistics of Monthly Rainfall (mm)

Station	Mean (mm)	Std. Dev. (mm)	Min (mm)	Max (mm)	Skewness	Kurtosis
Lagos	152.4	89.6	5.2	412.3	0.84	2.71
Abuja	118.7	76.5	0.0	365.8	1.12	3.05
Kano	72.3	65.4	0.0	298.4	1.45	3.89
Port Harcourt	210.5	102.7	15.8	480.6	0.63	2.34

Positive skewness indicates episodic high-intensity rainfall events, particularly in coastal regions

2.4. Data Preprocessing and Partitioning

Missing value screening and interpolation where necessary; Outlier detection was done using z-score thresholding; Min-max normalization was used to scale variables between 0 and 1; Lag generation ($t-1$, $t-2$, $t-3$) captured temporal memory effects. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to ensure generalization assessment.

Table 2. Dataset Splitting Configuration

Dataset Portion	Percentage	Number of Samples
Training	70	840
Validation	15	180
Testing	15	180
Total	100	1200

2.5. ANN Model Architecture

Two ANN configurations, including Rain fall Regression and ENSO Phase Classification Models were developed. Inputs from the Rainfall Regression Model were Rainfall lag ($t-1$, $t-2$, $t-3$), Temperature, Relative Humidity, Niño 3.4 Index with the following Architecture: Two hidden layers (10 and 8 neurons), ReLU activation (hidden layers), Linear activation (output layer), Levenberg-Marquardt optimization, 1000 training epochs. ENSO Phase Classification were Softmax output layer, three classes (El Niño, La Niña and Neutral) and Cross-entropy loss function.

Table 3. ANN Structural Parameters (Rainfall Model)

For ENSO classification, the output layer used a Softmax activation function to classify El Niño, La Niña, and Neutral phases.

Parameter	Configuration
Model Type	Multilayer Perception (MLP)
Inputs	Rainfall lag ($t-1$, $t-2$, $t-3$), Temperature, Humidity, Niño 3.4 Index
Hidden Layers	2
Neurons	10 and 8
Output	Monthly Rainfall
Activation	ReLU (Hidden), Linear (Output)
Training Algorithms	Levenberg-Marquardt
Epochs	1000

2.6 Performance Metrics

Regression Metrics used in the study included correlation coefficient (R), coefficient of determination (R²), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) while Classification Metrics were Accuracy, Precision, Recall and F1-score.

3. RESULTS AND DISCUSSION

3.1 Rainfall Prediction Performance

The ANN demonstrated strong generalization capability with minimal over-fitting.

Table 4. ANN Performance Results (Rainfall Model)

R	R ²	Testing RMSE	Testing MAE	Testing MAPE	Dataset
0.94	0.8836	12.45	9.32	8.15	Training
0.91	0.8836	15.78	11.04	10.62	Validation
0.89	0.7921	17.21	12.87	12.48%	Testing

3.2 Comparative Statistical Model Performance

Table 5 ANN vs Statistical Model Performance

The ANN outperformed traditional statistical models across all metrics.

Model	R ²	RMSE (mm)	MAE (mm)
ANN(MLP)	0.79	17.21	12.87
ARIMA	0.68	22.54	16.32
Multilayer Regression	0.63	25.11	18.45

As shown above, the ANN rainfall model demonstrated strong predictive skill with Testing R = 0.89 Testing R² = 0.7921 Testing RMSE = 17.21 mm Testing MAE = 12.87 mm Testing MAPE = 12.48%. Compared to ARIMA (R² = 0.68) and Multiple Linear Regression (R² = 0.63), the ANN exhibited superior performance across all evaluation metrics. Validation and training errors remained close, indicating minimal over-fitting and strong generalization capacity.

3.3 Spatial Variability

Prediction accuracy was highest in humid coastal regions and slightly lower in Kano's semi-arid environment. Increased variability and rainfall intermittency in northern Nigeria contributed to higher forecast uncertainty, consistent with Sahelian rainfall dynamics (Nicholson, 2013).

3.4 ENSO Phase Classification Performance

Table 6. ENSO Classification Performance

The classification ANN effectively distinguished ENSO phases using Nigerian rainfall predictors

Testing Accuracy(%)	Precision	Recall	F1-score	Metric
91.5	0.89	0.90	0.89	Training
87.2	0.85	0.86	0.85	Testing

From Table 3.3, the classification ANN achieved: Testing Accuracy = 87.2% Precision = 0.85 Recall = 0.86 F1-score = 0.85. These results demonstrate that Nigerian rainfall anomalies encode teleconnection signals sufficient to distinguish ENSO phases with high reliability.

4. DISCUSSION

The incorporation of the Niño 3.4 index significantly enhanced rainfall prediction skill, confirming measurable teleconnection effects between Pacific SST anomalies and West African rainfall. Classical studies (Ropelewski & Halpert, 1987; Trenberth *et al.*, 1998) established ENSO's global precipitation influence, and the present findings extend that understanding within a machine

learning framework specific to Nigeria. The nonlinear structure of ANNs allows modeling of threshold effects, interaction terms, and regime shifts that linear statistical models cannot capture. As emphasized in recent Earth system science research (Reichstein *et al.*, 2019), AI-based approaches improve predictive modeling in complex climate systems. Spatial heterogeneity in performance underscores the modulating influence of regional climate drivers such as the West African Monsoon and Atlantic SST variability (Giannini *et al.*, 2003). ENSO impacts are not uniform but interact with local atmospheric processes.

The classification results suggest that rainfall anomalies may serve as indirect ENSO indicators. This finding aligns with recent machine learning-based precipitation forecasting frameworks emphasizing interpretability and teleconnection diagnostics (Pinheiro & Ouarda, 2025).

4.1 Teleconnection Signal Strength and Nonlinear Climate Linkages

The results demonstrate statistically and practically significant relationships between Nigerian rainfall variability and ENSO dynamics. The improvement in rainfall prediction performance after incorporating the Niño 3.4 index confirms the existence of measurable teleconnection signals between the tropical Pacific and West Africa. This finding aligns with earlier climate studies that established ENSO as a major driver of global hydroclimatic variability (Ropelewski and Halpert, 1987; Trenberth *et al.*, 1998). Although West Africa is not located within the Pacific basin, atmospheric bridge mechanisms, including Walker circulation adjustments and upper-level divergence anomalies, enable ENSO-related perturbations to propagate across continents.

The ANN model captured these nonlinear relationships more effectively than ARIMA and Multiple Linear Regression models. Traditional linear approaches assume stationarity and linear dependence structures, which are often violated in climate systems characterized by threshold effects, regime shifts, and multi-scale oscillations (Tsonis *et al.*, 2008). The higher R^2 and lower RMSE achieved by the ANN suggest that rainfall responses to ENSO forcing are nonlinear and may involve interaction effects with regional drivers such as the West African Monsoon and land–atmosphere feedbacks.

4.2 Spatial Variability across Climatic Zones

The model results reveal spatial heterogeneity in predictive performance across stations. Coastal and humid stations (Lagos and Port Harcourt) exhibited relatively stable prediction accuracy, while semi-arid Kano showed slightly elevated error margins. This pattern is consistent with the higher inter-annual variability and rainfall intermittency characteristic of Sahelian climates (Nicholson, 2013). ENSO teleconnections often manifest differently across West Africa, sometimes enhancing rainfall in certain subregions while suppressing it in others depending on the phase and intensity of the event.

The moderate yet consistent predictive skill across all stations indicates that ENSO is not the sole driver of rainfall variability in Nigeria but interacts with regional climate systems. For example, Atlantic sea surface temperature anomalies and the position of the Intertropical Discontinuity also influence seasonal rainfall distribution (Giannini *et al.*, 2003). The ANN's ability to integrate multiple lagged rainfall variables alongside ENSO indices allowed it to implicitly model these compound influences without requiring explicit physical parameterization.

4.3 Generalization Capacity and Model Robustness

A key strength of the developed ANN framework lies in its generalization capability. The limited gap between training and testing performance metrics indicates minimal overfitting. The use of validation subsets and the Levenberg–Marquardt optimization algorithm contributed to stable convergence and reduced variance in weight updates. Good generalization is essential for operational forecasting, particularly when models are applied to unseen ENSO events or evolving climate conditions.

Furthermore, classification results exceeding 85% testing accuracy demonstrate that Nigerian rainfall anomalies contain sufficient predictive information to identify ENSO phases. This supports the argument that regional hydroclimatic records can serve as indirect indicators of global climate modes (Hastenrath, 1990). The Softmax-based classification network effectively distinguished El Niño, La Niña, and Neutral conditions, suggesting that rainfall anomalies encode teleconnected atmospheric circulation signals.

4.4 Implications for Teleconnection Modeling Methodology

From a methodological perspective, this study contributes to teleconnection analysis by combining regression and classification tasks within a unified ANN framework. Previous ENSO studies often relied on correlation or composite anomaly analysis. While useful, such approaches may overlook nonlinear and multivariate interactions. Machine learning methods, particularly neural networks, offer improved capacity to detect hidden structures in high-dimensional climate datasets (Goodfellow *et al.*, 2016).

The present results reinforce the growing body of literature advocating the integration of artificial intelligence into climate science (Reichstein *et al.*, 2019). Unlike purely statistical models, ANNs can approximate arbitrary nonlinear functions and adapt to evolving climate signals, making them suitable for teleconnection studies where causal pathways are complex and partially understood.

4.5 Limitations and Sources of Uncertainty

Despite promising results, several limitations warrant discussion. First, ENSO impacts on West Africa can be modulated by other ocean–atmosphere oscillations such as the Indian Ocean Dipole and Atlantic Multi-decadal Oscillation. Excluding these indices may limit explanatory power in certain years. Second, rainfall observations may contain measurement inconsistencies, particularly in earlier decades, potentially influencing model calibration.

Additionally, climate nonstationarity associated with global warming may alter historical teleconnection patterns (Cai *et al.*, 2014). ENSO frequency, amplitude, and spatial structure have shown signs of modulation under warming scenarios, which may affect rainfall predictability in the future. Continuous retraining and updating of ANN models will therefore be essential to maintain forecasting reliability.

5. IMPLICATIONS FOR CLIMATE ADAPTATION AND EARLY WARNING SYSTEMS

5.1 Contribution to Sustainable Development Goals

The ANN-based teleconnection framework supports multiple SDGs. These include SDG 2: Zero Hunger, by improving agricultural forecasting; SDG 6: Clean Water and Sanitation, through better hydrological prediction; SDG 11: Sustainable Cities, by enhancing flood preparedness and SDG 13: Climate Action, by strengthening adaptive capacity.

5.2 Agricultural Decision Support

Rain-fed agriculture dominates Nigeria’s food production. ENSO-informed seasonal rainfall outlooks enable farmers to adjust planting calendars, crop varieties and irrigation planning (Hansen *et al.*, 2011). Improved forecast lead time reduces vulnerability to rainfall shocks.

5.3. Flood and Drought Risk Management

Extreme rainfall events during certain ENSO phases increase flood risk in southern Nigeria, while suppressed rainfall elevates drought risk in northern zones. Integrating ANN rainfall forecasts into hydrological modeling enhances preparedness and supports multi-hazard early warning systems.

5.4 Water Resources and Infrastructure Planning

Reservoir management, dam safety and urban drainage planning benefit from improved seasonal rainfall projections. The ANN framework can inform reservoir rule curves and optimize hydropower-water supply trade-offs.

5.5 Institutional and Policy Integration

For sustainable implementation, ANN forecasting tools should be embedded within national meteorological agencies and disaster management authorities. Capacity building in climate data analytics will enhance operational readiness.

5.6 Climate Change Context

Projected intensification of hydrological extremes under climate change necessitates adaptive forecasting systems. Machine learning frameworks provide scalable platforms capable of incorporating additional predictors, including satellite rainfall and climate model outputs.

6. CONCLUSION

This study demonstrates that Artificial Neural Networks effectively capture ENSO–rainfall teleconnections in Nigeria. The combined regression–classification framework improves rainfall prediction accuracy and ENSO phase detection skill. The findings reinforce the importance of integrating artificial intelligence into climate adaptation planning and early warning systems to advance sustainable development objectives.

7. RECOMMENDATIONS FOR FUTURE RESEARCH

Future research should incorporate additional teleconnection indices (IOD, AMO), apply deep learning architectures (LSTM, GRU), utilize satellite-based rainfall datasets and conduct regional downscaling for basin-level forecasting.

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