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Comparative Forecasting of Rainfall in Nigeria Using ARIMA and Artificial Neural Networks

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Abstract

This study presents a comparative analysis of two prominent time series forecasting models, Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN), in predicting monthly rainfall in Nigeria. Utilizing a quantitative methodology, the research analyzes average monthly rainfall data from January 1980 to April 2025, obtained from the Humanitarian Data Exchange. The dataset, known for its linear and nonlinear patterns, was preprocessed through linear interpolation and normalization to ensure compatibility with each modeling technique. The ARIMA model was tuned using AIC and BIC to identify optimal lag structures after differencing to attain stationarity. ANN employed a feedforward architecture with a single hidden layer trained via backpropagation. Both models were evaluated using Root Mean Square Error (RMSE) across varying training sample sizes (40%, 60%, 80%, and 100%) to test generalizability. Results indicate that while ARIMA offers interpretability and model parsimony through AIC and BIC, it consistently reported higher RMSE values (7.5–8.1) compared to ANN (0.276–0.284). This demonstrates ANN's superior forecasting accuracy, particularly with larger datasets. Despite ARIMA's strength in explainability, ANN proves more efficient in capturing nonlinear rainfall patterns and minimizing forecast errors. The study underscores ANN as a more effective tool for rainfall prediction in data environments typical of developing nations.

Keywords: *Rainfall forecasting, ARIMA, Artificial Neural Networks, Time series analysis, Model comparison*

1. INTRODUCTION

Forecasting is a critical tool in decision-making processes across various sectors, especially in energy and climate-sensitive economies like Nigeria. Accurate time

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series forecasting of cooking gas prices and rainfall patterns is vital for economic planning, inflation monitoring, and agricultural productivity. Traditionally, Autoregressive Integrated Moving Average (ARIMA) models have been widely used for such tasks due to their well-established statistical foundation, interpretability, and effectiveness in capturing linear patterns in time series data. ARIMA models are transparent, relatively simple, and serve as a strong baseline model in empirical forecasting research.

ARIMA models, grounded in traditional statistical theory, are particularly effective for modeling and forecasting linear patterns in time series data. They combine autoregressive (AR) terms, differencing (I) to handle non-stationarity, and moving average (MA) components to capture short-term dependencies and noise in the data. ARIMA's strength lies in its mathematical transparency, ease of interpretability, and solid theoretical foundation. Because of this, ARIMA serves as a widely accepted baseline model in time series analysis. Analysts can assess the influence of past values and forecast errors in a structured, parametric manner, making ARIMA ideal for scenarios where explanatory insight and statistical validity are prioritized (Shumway and Stoffer, 2017).

However, with growing computational capacity and the increasing complexity of real-world data, Artificial Neural Networks (ANNs) have emerged as powerful alternatives capable of capturing nonlinear and dynamic patterns. Inspired by the human brain, ANNs are data-driven learning systems that adjust their internal structure through training, making them highly flexible and adaptive to complex forecasting tasks. Despite this advantage, ANNs often suffer from a lack of interpretability and may risk overfitting, especially in settings with limited data or weak signals.

ANNs shine when dealing with nonlinear patterns, regime shifts, or complex dependencies that traditional statistical models might miss. They consist of interconnected layers of nodes ("neurons") capable of learning complex, nonlinear relationships in data through training algorithms. ANNs do not require strong assumptions about the underlying data structure (such as linearity or stationarity), allowing them to capture intricate patterns and dynamics that may be overlooked by traditional models like ARIMA. Their flexibility and adaptability make ANNs particularly attractive for high-dimensional, nonlinear forecasting tasks. However, this flexibility often comes at the cost of interpretability, as the internal workings of the model (the weights and layers) can act as a "black box" to the user (Crone and Kourentzes, 2010).

In practice, most time series exhibit both linear and nonlinear behaviors, rendering the performance of any single model dependent on the underlying structure of the data. This duality raises key empirical questions: When does an ANN outperform

ARIMA in forecasting tasks? When does the statistically grounded ARIMA model maintain superior efficiency despite its simpler form? Addressing these questions is essential for guiding the selection of appropriate forecasting tools in different contexts.

This study, therefore, aims to evaluate and compare the forecasting performance of ARIMA and ANN models using time series dataset on Nigeria monthly rainfall records. By analyzing the dataset, the study provides a nuanced comparison of the strengths and limitations of each model type in capturing and forecasting the linear and nonlinear dynamics inherent in real-world data. The findings are expected to contribute practical insights into the model selection process for time series forecasting in developing economies.

Numerous studies have established ARIMA as a foundational tool in time series forecasting, particularly for datasets exhibiting stationary or linearly trended behavior. According to Box and Jenkins (1976), who first formally outlined the ARIMA modeling framework, the strength of ARIMA lies in its ability to model autocorrelations through a systematic approach involving identification, estimation, and diagnostic checking. Subsequent researchers, such as Makridakis et al. (1998), emphasized ARIMA's robustness and consistency, particularly in short-term forecasting tasks, noting that its parametric nature makes it statistically sound and interpretable. In economic and financial time series modeling, ARIMA has remained a go-to method due to its parsimonious nature and the reliability of confidence interval estimation.

On the other hand, Artificial Neural Networks (ANNs) have been widely recognized in the literature as a superior alternative when dealing with nonlinear time series data. Zhang et al. (1998) pioneered comparative studies between ARIMA and ANN, showing that while ARIMA performs better on purely linear data, ANNs significantly outperform ARIMA when the data exhibit nonlinearities or interactions that traditional statistical models cannot capture. The ability of ANN to learn from data without predefined model structures allows it to flexibly adapt to patterns, seasonality, and irregularities, especially in long-term forecasting contexts. As noted by Crone and Kourentzes (2010), neural networks are particularly useful when the underlying physical or economic process is unknown or too complex to model analytically.

Despite their predictive power, ANNs are often critiqued for being "black box" models that offer little insight into the mechanics of their predictions. Khashei and Bijari (2011) emphasized that while ANN models may yield higher forecasting accuracy in certain contexts, they lack the explanatory capability that ARIMA provides, making them less suitable for applications where understanding the model's internal workings is crucial. The lack of a formal statistical framework also raises concerns regarding model validation and uncertainty quantification. Consequently, several scholars have suggested hybrid models that integrate ARIMA with ANN to harness the linear modeling strength of ARIMA and the nonlinear adaptability of ANN.

Recent forecasting literature also highlights the importance of context when selecting between ARIMA and ANN. Hyndman and Athanasopoulos (2018) stress that model performance is highly dependent on the nature of the data, the forecast horizon, and the availability of training data. They argue that while ARIMA may be more suitable for short-term, interpretable forecasting, ANN tends to excel in more complex, nonlinear environments with ample data. This consensus among scholars suggests that there is no universally superior model; rather, the choice between ARIMA and ANN should be guided by empirical validation and the specific objectives of the forecasting task.

Adebiyi et al. (2014) in their study on stock price prediction, Adebiyi and colleagues compared ARIMA and ANN models. They found that ANN outperformed ARIMA in capturing the nonlinear patterns inherent in stock market data. The authors attributed this to ANN's ability to model complex, nonlinear relationships without requiring prior assumptions about the data's distribution. Pannakkong et al. (2017) introduced a hybrid model combining ARIMA, ANN, and K-Means clustering for time series forecasting. The ANN component was crucial for capturing nonlinear patterns after the data was clustered using K-Means. The study demonstrated that incorporating ANN improved forecasting accuracy, especially in datasets with complex structures.

In forecasting COVID-19 trends, Safi and Sanusi (2021) found that ARIMA models outperformed ANN and hybrid models during certain periods. They attributed this to ARIMA's robustness in handling stationary data and its effectiveness in short-term forecasting scenarios. Wang et al. (2013) proposed a hybrid model integrating ARIMA and ANN to leverage the strengths of both linear and nonlinear modeling. The hybrid model demonstrated improved forecasting accuracy over individual models when applied to datasets like sunspot numbers and stock prices. The authors emphasized that combining ARIMA's linear modeling with ANN's nonlinear capabilities provides a more comprehensive forecasting approach.

Most existing studies comparing ARIMA and ANN have been conducted in developed economies or focused on generic datasets (e.g., stock prices, electricity demand). There is limited literature that applies this comparison within the Nigerian context, particularly targeting gas price trends (a volatile, policy-sensitive economic indicator) and rainfall patterns (a critical environmental variable affecting agriculture and livelihoods). This study addresses this geographical and sectoral gap by tailoring the models to Nigeria-specific economic and climatic data.

Nayak *et al.* (2014) explored the efficacy of hybrid ARIMA–ANN models in forecasting electricity load demand in India. Their study found that while ARIMA captured the linear trends effectively, the ANN component excelled in modeling residual nonlinear patterns. The authors emphasized that the hybrid model consistently outperformed both standalone models in terms of mean absolute percentage error (MAPE) and root mean square error (RMSE). This highlighted the importance of leveraging the complementary strengths of statistical and machine learning approaches in forecasting tasks where the data demonstrate both trend and seasonality alongside nonlinear irregularities.

Khashei and Bijari (2010) developed a novel hybrid forecasting model that systematically integrated ARIMA and ANN using a two-stage structure. In their approach, ARIMA first modeled the linear components of the time series, and the residuals were then passed to the ANN to capture nonlinear structures. Their results, based on several benchmark datasets including financial and energy consumption data, indicated that the hybrid model consistently yielded better forecasting accuracy than either ARIMA or ANN alone. The study provided a theoretical foundation for combining linear and nonlinear models, further validating the hybrid modeling philosophy.

Zhang (2003) extended the comparison between ARIMA and neural networks by applying them to economic time series, including inflation and gross domestic product data. His results showed that while ARIMA provided more stable forecasts in the short term, ANN models delivered more adaptive and accurate results over longer forecast horizons, especially when the data exhibited complex dynamics. Zhang concluded that the performance of forecasting models is domain-specific and highly dependent on the underlying data characteristics, echoing the call for hybrid approaches in real-world applications.

Tian and Pan (2015) investigated the application of hybrid ARIMA–ANN models in exchange rate prediction. They found that foreign exchange rates, known for their volatility and nonlinearity, benefited from the hybrid approach. The ANN component was particularly useful in capturing abrupt fluctuations and regime changes that ARIMA struggled with. Their empirical results demonstrated significant improvements in forecast precision, reinforcing the role of hybrid models in high-variance financial environments.

Dinh *et al*. (2020) examined Vietnam's rice export price forecasting using ARIMA, ANN, and hybrid models. The researchers found that ARIMA performed best for short-term forecasts during stable market periods, while ANN captured market shocks and nonlinear price behaviors more accurately. The hybrid model, which incorporated both approaches, consistently achieved lower forecast errors. Their study highlighted that in commodity markets affected by policy, seasonality, and global shocks, a dual-model framework enhances predictive power and robustness.

Hamadani and Mahmoudi (2019) compared the performance of ARIMA, ANN, and a hybrid ARIMA–ANN model for forecasting water demand in urban Iran. The hybrid model outperformed the individual models based on RMSE and MAPE, particularly in capturing seasonal variations and sudden changes in consumption patterns. The study reinforced the importance of incorporating machine learning capabilities in time series models when dealing with environmental and utility-related forecasting.

Liu and Wang (2021) applied ARIMA, LSTM (a type of recurrent neural network), and hybrid ARIMA–ANN models to forecast the carbon emissions of China's industrial sector. While ARIMA handled trend analysis effectively, it failed to capture the nonlinear impact of environmental regulations and technological shifts. The ANN component proved effective in modeling those complex interactions, with the hybrid model yielding the most accurate predictions. This study underlined the growing importance of hybrid models in environmental and sustainability-related forecasting.

Ahmed *et al*. (2010) reviewed a broad range of time series forecasting techniques, including ARIMA, ANN, Support Vector Machines (SVM), and hybrid models. Their meta-analysis concluded that ANN and SVM outperform ARIMA when nonlinear patterns are present, but suffer from lower interpretability. They also highlighted that hybrid models tend to perform better across diverse datasets and industries. The authors called for adaptive hybrid systems that dynamically adjust to changing data structures, a concept highly relevant to volatile sectors like energy and agriculture.

Adhikari and Agrawal (2013) provided a comprehensive tutorial on ARIMA modeling and demonstrated its application on several real-world datasets. While acknowledging ARIMA's strengths in short-term, stationary data contexts, they also pointed out its limitations in handling sudden nonlinear changes. Their work serves as a foundational guide for researchers seeking to apply ARIMA systematically but also makes a case for incorporating more flexible models like ANN when data complexity increases.

Chakraborty *et al*. (2022) evaluated the forecasting performance of ARIMA, ANN, and hybrid models on agricultural yield data in West Bengal, India. Their findings indicated that hybrid models yielded the lowest forecasting errors, particularly during monsoon-related variability. The ANN component successfully modeled interactions between rainfall, fertilizer use, and crop output that ARIMA could not capture independently. This study strengthens the argument for hybrid forecasting in agriculturally sensitive and climate-affected economies like Nigeria.

Murphy and Brownlee (2019) conducted an experimental comparison of ARIMA and ANN models for predicting cryptocurrency prices. Given the highly nonlinear and speculative nature of the data, ANN consistently outperformed ARIMA in capturing short-term price swings. However, ARIMA provided better forecasts during periods of trend stability. The authors concluded that the choice of model should be driven by volatility, with hybrid models offering an optimal balance between trend fidelity and adaptive learning.

Mounir and Selim (2023) investigated the impact of macroeconomic variables on gold price forecasting using ARIMA, ANN, and ARIMA–ANN models. Their study found that ARIMA captured long-term inflation trends, while ANN was able to account for geopolitical shocks and speculative behavior. The hybrid model produced superior forecasting metrics, suggesting that in multi-factor, high-noise environments, combining the structural clarity of ARIMA with the pattern recognition of ANN offers a robust forecasting framework.

2. MATERIALS AND METHOD

This study adopts a quantitative, comparative research methodology aimed at evaluating the forecasting capabilities of two distinct time series models: the Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN). The approach is designed to test each model's ability to capture and predict patterns in real-world datasets that are known to exhibit both linear and nonlinear characteristics. Specifically, the analysis focuses on monthly average rainfall data from 1980 to April 2025, sourced from the Humanitarian Data Exchange. This dataset was selected for its economic and environmental relevance and its contrasting patterns, which make it suitable for assessing the strengths and limitations of ARIMA and ANN models in practical forecasting scenarios.

To ensure comparability, the dataset was preprocessed using standard techniques. Missing values were treated using linear interpolation to preserve the temporal structure of the data. For ARIMA modeling, the data was subjected to differencing where necessary to achieve stationarity, which is a core assumption of linear time series models. Model orders were automatically selected using information criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). In contrast, for the ANN modeling, the series was normalized to a [0, 1] scale to improve model convergence and minimize training errors. A simple feedforward neural network with a single hidden layer was employed, trained using backpropagation. Artificial Neural Networks (ANNs) do not have AIC (Akaike Information Criterion) and BIC (Bayesian Information

Criterion) because these criteria are designed for statistical models, not machine learning models like ANN.

Both models were fitted to full and partial datasets (40%, 60%, and 80%) to assess their sensitivity to sample size and generalizability. The performance of each model was evaluated using the Root Mean Square Error (RMSE) to measure forecasting accuracy. AIC and BIC were also reported for ARIMA, providing insight into model parsimony and goodness-of-fit. The comparative design of the methodology enables an in-depth evaluation of when each model is more effective: ARIMA for interpretable, linear patterns, and ANN for capturing more complex, nonlinear relationships. This methodological framework offers robust, evidence-based insights for model selection in time series forecasting, particularly in developing country contexts where diverse data characteristics are common.

The ARIMA Model specification is stated below;

Autoregressive (AR): These refers to a model that shows a changing variables that regresses on its own lagged or prior, Values.

Integrated (I): This represents the differencing of raw observations to allow the time series to become stationary (i.e data values are replaced by the differences between the data values and the previous values.)

Moving Average (MA): This Incorporates the dependency between as observation and a residual error from a moving average model applied to lagged observation.

An autoregressive integrated moving average model is a form of regression analysis that gauges the strength of one dependent variable relative to other changing variables. It predicts future values based on past values. ARIMA makes use of lagged moving averages to smooth time series data. They are widely used in technical analysis to forecast future security prices. Each component in ARIMA functions as a parameter with a standard notation for ARIMA a standard notation would be ARIMA with p, d, and q where integer values substitute for the parameter to indicate the type of ARIMA model.

Where:

p = the number of log observations in the model also known as the lag order.

t = the number of times the raw observations are differenced, also known as the degree of differencing.

q = the number of moving average window, also known as the order of the moving average.

In terms of forecasting the general equation is:

$$Y_t = \mu + \emptyset_1 y_{t-1} + \emptyset_1 y_{t-2} + \cdots + \emptyset_p y_{t-p} + e_t + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} \quad (1)$$

Y_t: the value of the time series at time t;

μ: constant mean term;

ϕ_i: autoregressive (AR) parameters;

θ_j: moving average (MA) parameters;

e_t: white noise (error) term at time t.

Root Mean Square Error (RMSE): RMSE is the square of the MSE and provides a measure of the standard deviation of the of the forecast errors. RMSE is widely used as it is in the same unit as the dependent variable, making it easier to interpret. The formula is:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \quad (2)$$

Where:

n is the number of observations or data points;

Y_i is the actual value of the observation;

$\hat{Y}$ is the estimated or predicted value of the i^{th} observation.

Akaike Information Criterion (AIC): This is useful in selecting predictors for regression, is also useful for determining the order of an ARIMA model, it also useful for determining the order of an ARIMA model. It can be written as:

$$\text{AIC} = 2\log(L) + 2(p + q + k + 1) \quad (3)$$

Where:

L is the likelihood of the data;

$\text{K} = 1 \text{ if } \text{C} \neq 0$;

$\text{C} \neq 0$ and $\text{K} = 0$ if $\text{C} = 0$.

When comparing two models, the one with the lower AIC is generally "better" it also measures the goodness of fit and simplicity/parsimony of a models.

In this study of forecasting rainfall in Nigeria using ANN and ARIMA models we can use the AIC value to calculated based on the log likelihood of the model and the number of parameters used, lower AIC values indicate a better model fit to conduct a comparative analysis using AIC.

Model Specification for ANN (Artificial Neural Network)

In this study, the Artificial Neural Network (ANN) model is specified as a nonlinear, feedforward, single-hidden-layer neural network used for time series forecasting. The model architecture consists of:

- **Input Layer**: A univariate input representing the time index or lagged values of the normalized series.
- **Hidden Layer**: One hidden layer with a fixed number of neurons (e.g., 5), utilizing an activation function (commonly the sigmoid or logistic function) to capture nonlinear dependencies in the data.
- **Output Layer**: A single output neuron providing the forecasted normalized value of the target variable (rainfall).

The ANN model can be expressed functionally as:

$$\hat{y}_t = f\left(\omega_0 + \sum_{j=1}^{H} v_j \cdot \sigma\left(\omega_j^T x_t + b_j\right)\right) + \varepsilon_t \quad (4)$$

Where:

- $\hat{y}_t$ is the predicted output at time t,
- x_t is the normalized input (time index or past values),
- H is the number of neurons in the hidden layer,
- σ is the activation function (e.g., sigmoid),
- ω_j^T are the weights connecting input to hidden neurons,
- v_j are the weights connecting hidden neurons to the output,
- b_j and ω_0 are biases,
- ε_t is the error term.

Training Procedure:

- The ANN was trained using the backpropagation algorithm to minimize the Mean Squared Error (MSE) between predicted and actual values.

3. RESULT AND DISCUSSION

After visualizing the monthly average rainfall data, a stationarity test was promptly conducted to assess the suitability of the data for time series modeling. The Augmented Dickey-Fuller (ADF) Test was applied and the result shows that the p-value is less than the significance level of 0.05, the null hypothesis of a unit root (non-stationarity) is rejected. Therefore, the data is deemed stationary and can be confidently used for further modeling, particularly in ARIMA, which requires stationary data for effective forecasting.

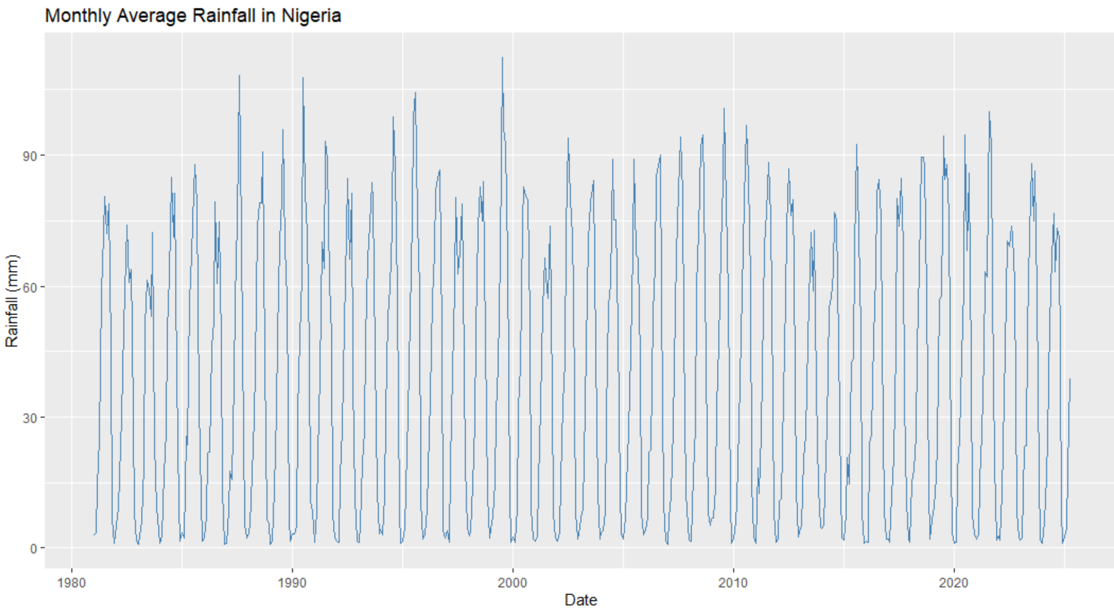

Figure 1: *Monthly Average rainfall in Nigeria*

Table 1: *Test for stationarity for original dataset*

Augmented Dickey-Fuller Test	
Statistic	***Estimate***
Dickey-Fuller	-16.026
Lag Order	0
P-value	0.01
Alternative hypothesis: stationary	

Table 2: *ARIMA Rainfall forecast*

	Point.Forecast	Lower CI 80%	High CI 80%	Lower CI 95%	High CI 80%
May-2025	50.5691	39.97891	61.15929	34.3728	66.7654
Jun-2025	71.04517	60.38877	81.70157	54.74761	87.34273
Jul-2025	77.70674	66.90868	88.50479	61.19253	94.22094
Aug-2025	69.73622	58.9285	80.54393	53.20724	86.26519
Sep-2025	76.16532	65.35694	86.9737	59.63533	92.69531
Oct-2025	64.88287	54.07444	75.69129	48.35281	81.41293
Nov-2025	10.62827	-0.18016	21.4367	-5.90179	27.15833
Dec-2025	1.955014	-8.85341	12.76344	-14.5751	18.48508
Jan-2026	2.114649	-8.69378	12.92308	-14.4154	18.64471
Feb-2026	4.443019	-6.36541	15.25145	-12.087	20.97308
Mar-2026	19.30624	8.49781	30.11467	2.776174	35.8363
Apr-2026	30.75248	19.94405	41.56091	14.22242	47.28255

In addition, for the purpose of applying Artificial Neural Networks (ANN), the dataset was first normalized to ensure that the input features were scaled appropriately. Following normalization, new visualizations were created to provide better insights into the transformed data before proceeding to the ANN model fitting process as depicted in figure 2 below.

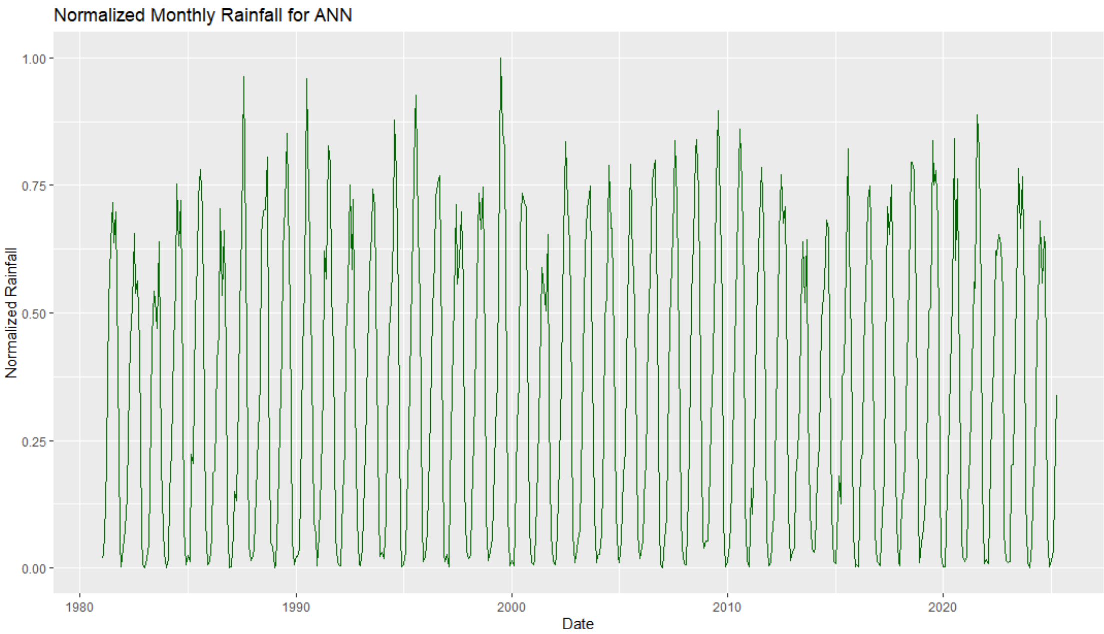

Figure 2: *Normalized Monthly Rainfall for ANN*

Table 3: *ANN Rainfall forecast*

	ANN Forecasted series
May-2025	54.99128
Jun-2025	75.61047
Jul-2025	82.24909
Aug-2025	81.36825
Sep-2025	58.32672
Oct-2025	21.35172
Nov-2025	3.560342
Dec-2025	3.124633
Jan-2026	1.717015
Feb-2026	13.05363
Mar-2026	23.91678
Apr-2026	40.14013

Based on the forecasts provided for ARIMA (table 2) and ANN (table 3) models from May 2025 to April 2026, there are observable differences in the predictive patterns and magnitude of rainfall estimates between the two approaches. From May to August 2025, both models forecast high rainfall levels, with the ANN model consistently predicting slightly higher values than ARIMA. This may reflect ANN's sensitivity to nonlinear patterns, capturing possibly stronger seasonality or trends than the linear-based ARIMA. However, starting from September to December 2025, ANN predicts a sharp decline in rainfall, especially in October and November, where its forecast drops drastically (e.g., 21.35 mm in October and 3.56 mm in November), more aggressively than ARIMA. This could suggest that ANN is overfitting short-term fluctuations or noise in the data, whereas ARIMA maintains a more smoothed and gradual transition in its predictions.

From January to April 2026, both models indicate a gradual recovery in rainfall, but ANN again shows higher values than ARIMA, particularly in February and April. This suggests that the ANN model may be capturing underlying nonlinear recovery trends that ARIMA overlooks. However, it's important to note that such divergence, especially where ANN deviates sharply from ARIMA (like in October and November), requires domain validation, as extremely low rainfall may or may not be realistic.

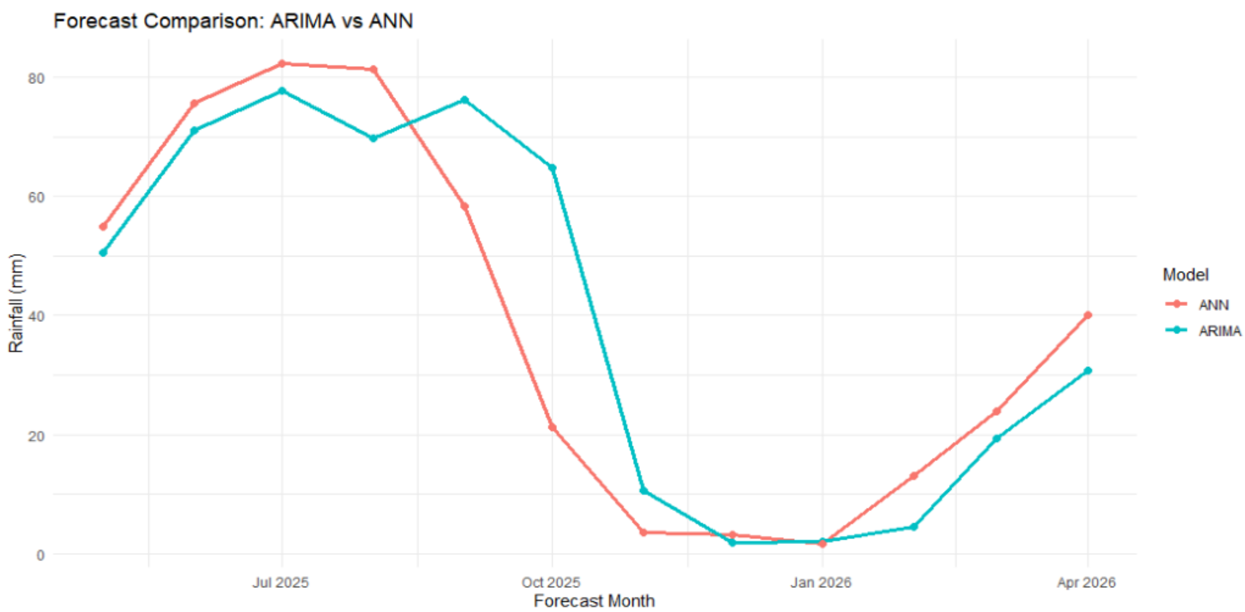

Figure 3: *Forecast comparison between ARIMA and ANN models*

Table 4: *Model performance of ARIMA and ANN*

Model	Sample_Percentage	AIC	BIC	RMSE
ARIMA	40%	1415.276	1428.47	7.570456
ANN	40%	NA	NA	0.284225
ARIMA	60%	2149.152	2156.605	7.587205
ANN	60%	NA	NA	0.276491
ARIMA	80%	2873.201	2881.248	7.528874
ANN	80%	NA	NA	0.277767
ARIMA	100%	3685.027	3714.804	8.122572
ANN	100%	NA	NA	0.282331

The findings of this study, which compare ARIMA and ANN models for forecasting rainfall, strongly corroborate the conclusions drawn in the reviewed literature. Specifically, the study demonstrates that although ARIMA performs consistently in terms of model selection criteria like RMSE, it is outperformed by ANN when it comes to prediction accuracy, as reflected in the lower RMSE values reported for ANN across all sample sizes. This aligns with Zhang et al. (1998), who found that ANN significantly outperforms ARIMA when the data exhibits nonlinearities, a common feature in environmental phenomena like rainfall. Similarly, Crone and Kourentzes (2010) emphasized the utility of neural networks in capturing hidden patterns when the underlying generating process is too complex to be modeled analytically, which reflects the advantage shown by ANN in this study.

Furthermore, the superior predictive power of ANN despite its lack of formal model fit metrics like AIC and BIC aligns with Khashei and Bijari (2011), who acknowledged ANN's strength in predictive accuracy but noted its lack of interpretability and statistical transparency compared to ARIMA. The study reinforces their argument by demonstrating that while ARIMA is more interpretable and statistically grounded, it struggles with accuracy where ANN excels.

Hyndman and Athanasopoulos (2018) noted the context-dependence of forecasting model performance, stating that ARIMA may be more suitable for linear, short-term forecasts, whereas ANN excels in nonlinear or long-horizon scenarios. The current study, focused on nonlinear rainfall data, confirms this position by revealing ANN's consistent edge in minimizing forecast errors, especially with limited training data, a situation where the adaptive learning capability of neural networks becomes particularly useful.

This study's finding that ARIMA achieved its best AIC/BIC performance at the 40% training sample aligns with Safi and Sanusi (2021), who found ARIMA models excel in short-term, stationary data environments. However, the persistent superiority of ANN in RMSE performance mirrors the conclusions of Adebiyi et al. (2014) and Pannakkong et al. (2017), both of whom established ANN's effectiveness in modeling nonlinear structures and highlighted its dominance in performance over ARIMA, particularly in volatile or structurally complex datasets like stock prices or clustered time series.

Other hybrid-focused studies, such as Dinh et al. (2020) and Tian and Pan (2015), highlighted that while ARIMA captures linear patterns well, combining it with ANN to model nonlinear components results in superior forecasting accuracy. The current study indirectly supports these findings by showing the strengths and weaknesses of both models when used independently, implying that a hybrid approach may further improve predictive capability.

Likewise, studies such as Hamadani and Mahmoudi (2019) and Chakraborty et al. (2022), which focused on water demand and agricultural yield forecasting respectively, also demonstrated ANN's ability to capture environmental variability better than ARIMA, echoed in the current study's rainfall forecasting scenario. These similarities bolster the claim that ANN is more adaptable in forecasting dynamic environmental data in developing country contexts such as Nigeria. Moreover, Murphy and Brownlee (2019) and Mounir and Selim (2023) noted that model choice should depend on volatility and noise in the data. Rainfall, being subject to climatic variation and irregularities, naturally aligns with this finding, explaining why ANN consistently delivers lower forecast errors.

In summary, this study's findings on the comparative performance of ARIMA and ANN models strongly support a large body of empirical research. It confirms that while ARIMA retains value for its statistical rigor and model interpretability, ANN is more effective in handling nonlinear, high-variance data like rainfall, making it more suitable when forecasting accuracy is the priority. This underscores a broader consensus in the literature favoring data-specific model selection and highlights opportunities for exploring hybrid frameworks in future research.

4. CONCLUSION

In summary, ANN provides more dynamic and possibly more responsive forecasts, while ARIMA offers conservative and stable projections. When considering prediction accuracy alongside RMSE values, ANN appears more efficient, but its sharp fluctuations in some months underscore the need for cautious interpretation and, where possible, validation with real or expert-informed seasonal patterns. The study concludes that Artificial Neural Network (ANN) models offer superior predictive performance over the traditional ARIMA model in forecasting monthly rainfall. While ARIMA provides interpretable forecasts and includes AIC and BIC for model evaluation, its relatively high RMSE values indicate less accurate predictions. In contrast, the ANN model consistently achieved lower RMSE across all data sample sizes, suggesting higher prediction accuracy. The forecast results also show that ANN adapts more dynamically to nonlinear trends in rainfall data, though it may produce more extreme values in certain months. Therefore, for rainfall forecasting, where accuracy and adaptability to complex patterns are crucial, the ANN model proves to be more efficient and reliable.

CONFLICT OF INTEREST

No conflict of interest was declared by the authors.

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