Applied Sciences, Computing and Energy, 2024, 1(1), 157-172

Enhancing Rainfall-Runoff Prediction Accuracy using Artificial Neural Networks: A Case Study of Bida, Nigeria

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Received: 26 August 2024/Accepted: 18 December 2024/Published:31 December 2024

Abstract: *Accurate rainfall-runoff modeling is essential for sustainable water management, especially in flood-prone, data-scarce regions like Nigeria's Bida Basin. Traditional models struggle with nonlinear hydrological dynamics and limited data availability. This study addresses this gap by developing and evaluating an ANN-based runoff prediction model using limited meteorological and hydrological data. The objective is to improve flow forecasting accuracy and demonstrate the effectiveness of data-driven approaches for climate-resilient water resource planning in under-monitored basins. Daily rainfall, temperature, and runoff data (2010–2023), data were preprocessed, normalized, and partitioned for ANN modeling. A multi-layer ANN was trained using the Adam optimizer and evaluated with RMSE, R^2, and NSE. The Activation functions (LOGSIG, PURELIN, TANSIG) were tested to assess model accuracy in simulating runoff under nonlinear rainfall-runoff relationships. The ANN model achieved strong runoff prediction performance in the Bida Basin, with R^2 values of 0.91 (training) and 0.87 (testing), and RMSE of 3.25 and 4.18 m^3/s, respectively. PURELIN activation yielded perfect correlation ($R = 1.0$; RMSE = 0.0), outperforming LOGSIG ($R = 0.9995$) and TANSIG ($R = 0.9547$). Seasonal analysis showed higher accuracy in the wet season ($R^2 = 0.89$; RMSE = 3.90 m^3/s) than in the dry season ($R^2 = 0.77$; RMSE = 4.65 m^3/s), confirming the model's robustness across hydrological conditions. ANN models outperform traditional MLR in capturing nonlinear runoff dynamics but risk overfitting without careful tuning, while linear regression excels in simple linear cases, highlighting the need to balance model complexity and generalization based on data and process characteristics.*

Keywords: *Artificial Neural Network (ANN), Rainfall–Runoff Modeling, Bida Basin, Hydrological Forecasting, Water Resource Management*

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1.0 Introduction

Rainfall–runoff forecasting constitutes a fundamental component of sustainable water resource management, as it provides critical insights for optimizing reservoir operations, refining irrigation scheduling, and enhancing flood warning systems (Kumar *et al.*, 2024; Mayaki *et al.*, 2023). The precision of streamflow predictions is of paramount importance for the effective allocation and strategic planning of water resources. In numerous regions of Nigeria, rainfall serves as the principal source of water for both agricultural and domestic applications. For instance, the fertile floodplains of the Bida basin are conducive to the cultivation of rice, sugar, and various staple crops, thereby rendering local food security significantly reliant on rainfall variability. Recent years have witnessed an increase in the frequency of extreme hydrological events: the year 2022 experienced the most severe flooding since 2012 in Nigeria, resulting in the displacement of over a million individuals. Such fluctuations in precipitation patterns highlight the critical necessity for dependable runoff predictions to effectively manage the dual challenges of droughts and floods, as well as to ensure adequate water supply amidst the pressures of climate change and escalating demand. Conventional rainfall–runoff models, whether empirical, conceptual, or physical, frequently encounter challenges associated with the inherent nonlinearity and complexity of the hydrological system. By condensing a variety of catchment processes into simplified reservoir representations, these models necessitate extensive calibration and may inadequately represent atypical hydrological phenomena. As noted in a recent review, "the process of rainfall–runoff is highly nonlinear and incredibly complex and is still poorly understood." Many traditional models require long-term, high-quality datasets for calibration, rendering them computationally intensive and less robust in the face of shifting climatic conditions (Mohseni and Muskula, 2023). Indeed, Rudisill*et al.* (2023) demonstrate that prevalent "bucket"-type models are incapable of accurately replicating multi-year groundwater trends during extended drought periods, indicating suboptimal performance in non-stationary climatic contexts. These constraints catalyze the pursuit of alternative, data-driven methodologies that can adeptly learn the intricate relationships inherent in rainfall–runoff dynamics without the imposition of stringent physical assumptions.

Machine learning techniques—particularly Artificial Neural Networks (ANNs)—have gained significant traction in hydrological modeling due to their ability to approximate complex nonlinear functions (Oforduet *et al.*, 2024; Orji *et al.*, 2023). ANNs operate as data-driven "black-box" models inspired by the structure and functioning of the human brain, enabling them to learn input–output relationships (e.g., rainfall to runoff) without relying on explicit physical equations. Over the past few decades, ANNs have been widely adopted in hydrology, often outperforming traditional models, especially in data-scarce environments. For instance, in a major Ethiopian catchment, ANN-based simulations yielded runoff estimates comparable to those produced by a distributed hydrological model, underscoring their reliability even with limited data records. Similarly, Kumar *et al.* (2024) demonstrated that a hybrid model combining a physical hydrological model with an ANN significantly improved streamflow forecasting in India. These findings affirm the superior capacity of ANNs to capture the nonlinear dynamics inherent in rainfall–runoff processes, particularly where conventional approaches may fall short. Consequently, ANN-based models have become increasingly prominent in water resources research, with applications ranging from flood forecasting and groundwater prediction to reservoir operations and management (Jougla and Leconte, 2022). In the African context, ANNs have been applied to enhance hydrological modeling efforts. For example, in the Mono River Basin (Benin–Togo), Biao *et al.* (2024) noted that complex reservoir operations exacerbate rainfall–runoff nonlinearity, yet few studies have employed ANN models in the region. In Nigeria, Ayodele and Eromosele (2019) successfully applied an ANN model to predict seasonal rainfall in Lagos, further demonstrating the model's potential in West African basins. While ANNs have demonstrated notable success in simulating complex hydrological processes, their performance is not universally superior under all conditions. Several studies have shown that ANN accuracy can be highly sensitive to the quantity, quality, and representativeness of input data, as well as to the choice of network architecture and training parameters. For instance, Dawson and Wilby (2001) reported that ANN models tended to overfit when trained on short or noisy hydrological records, leading to reduced generalization on independent datasets. Similarly, Jain and Kumar (2007) found that in basins with simple and predominantly linear rainfall–runoff relationships, multiple linear regression (MLR) models performed comparably to or better than ANNs, suggesting that increased model complexity does not always yield improved predictive skill. Kisi and Shiri (2011) observed that ANN performance degraded in arid and semi-arid catchments where sparse rainfall data and high evapotranspiration introduced significant uncertainty. Furthermore, Abrahart and See (2007) emphasized that while ANNs excel at pattern recognition, they can produce unrealistic predictions outside the range of training data, which can be problematic in non-stationary climatic contexts. These mixed results highlight that the choice of ANN for rainfall–runoff modeling should consider not only the nonlinearity of the hydrological system but also data availability, quality, and the need for robust model validation.

Building upon these insights, the present study develops an ANN-based rainfall–runoff model for the under-monitored Bida Basin in Nigeria. The primary objective is to enhance sustainable water resource management through improved flow prediction. This study introduces a data-driven modeling framework tailored to a basin with sparse historical records and evaluates the performance of ANN models relative to traditional hydrological methods. The research involves the collection and preprocessing of meteorological and streamflow data, the design and training of various ANN configurations, and rigorous validation against independent datasets. By benchmarking the ANN models against conventional approaches, this study aims to assess predictive improvements and highlight the potential of machine learning for application in data-limited regions. The anticipated outcomes emphasize the utility of ANN-based models in advancing rainfall–runoff forecasting and informing strategic water management, particularly for flood control and planning in climate-sensitive regions such as West Africa. While numerous studies have demonstrated the high predictive accuracy of Artificial Neural Networks (ANNs) in hydrological modeling, it is important to note that their performance is highly dependent on the quality and quantity of input data, the appropriateness of model tuning (e.g., choice of architecture and hyperparameters), and the specific application context. Poor data quality or inadequate calibration can lead to over-fitting or reduced predictive power, making careful pre-processing and model validation essential.

2. 0 Material and Methods

2.1. Study Area

The Bida watershed, located in the central region of Nigeria within Niger State, encompasses an approximate area of 37.5 km^2 and constitutes an essential component of the expansive Niger Valley region. Geographically, it is situated between the latitudinal coordinates of 9°0′ and 9°9′ North and the longitudinal coordinates of 5°56′ and 6°4′ East. The watershed's primary hydrological features comprise the Musa, Landzun, and Chiken Rivers, with the Landzun Stream extending 8.86 km, flowing in a west-to-east trajectory through the urban locality of Bida. From a topographical standpoint, the watershed is distinguished by a rolling landscape characterized by elevation gradients ranging from 161 to 277 meters. Geologically, it is constituted of Precambrian Basement Complex lithologies in conjunction with Cretaceous sedimentary deposits, particularly the Bida Sandstone and Enagi Siltstone, which collectively facilitate a diversity of soil typologies, including coarse sand, clay, and sandy silt. The occurrence of sandy and clay-

rich soils substantially augments the potential for groundwater retention (Olabode, 2016)
The region is classified within the northern Guinea Savannah ecological zone, which is predominantly typified by the presence of Isoberlinadoka and Isoberlinatomentosa species. Anthropogenic influences have modified the original topography, resulting in the proliferation of diverse vegetation types, including tree savanna, shrub savanna, riparian forest, and inselberg flora. The watershed experiences pronounced seasonal variations, with distinct wet (April–October) and dry (November–March) seasons. Annual precipitation levels exhibit fluctuations between 1,000 and 1,200 mm, with the peak of rainfall occurring in the months of August and September (Mohammed, 2014). Temperature ranges vary between 16 and 37 °C, influenced by climatic patterns originating from southwest trade winds during the rainy season and northeast harmattan winds during the dry period (Echebima& Obafemi, 2023).

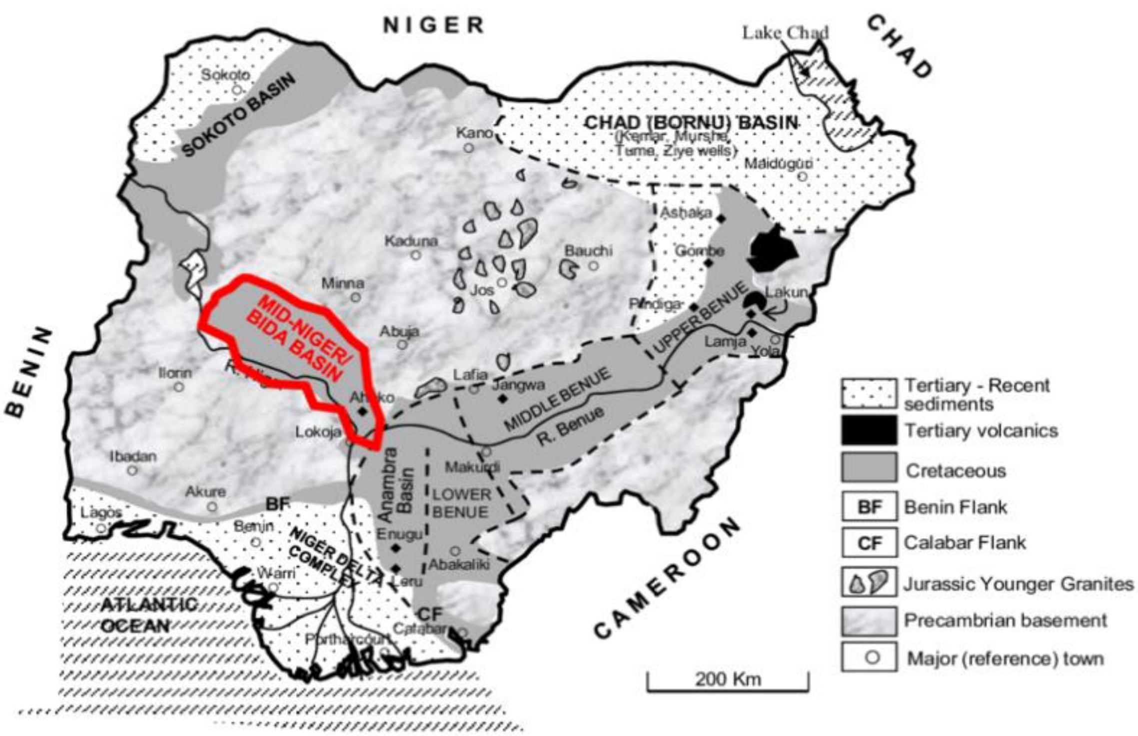

Fig. 1: Sketch geological map of Nigeria showing the location of the Bida Basin
Source: Idris-Nda *et al.*, (2013)

As shown in Figure 1**,** rainfall patterns during the calibration period exhibited distinct seasonal variability, with runoff within the watershed primarily governed by precipitation. Heightened flow rates were recorded during the wet season (Rivera Waterman et al., 2022). However, ongoing deforestation and urbanization are altering the dynamics of infiltration and evapotranspiration, which may, over time, lead to a decline in runoff trends. These changes underscore the urgent need for effective watershed management practices to safeguard hydrological balance and ensure long-term environmental sustainability.

2.2. Data Collection

2.2.1. Sources of Meteorological and Hydrological Data

Meteorological data, primarily daily rainfall and temperature records from 2010 to 2023, were obtained from the Nigerian

Meteorological Agency (NiMet) and supplemented with satellite-based data. The hydrological data, representing stream flow (runoff), were extracted from the uploaded dataset based on years of rainfall records aligned with observed discharge.

Parameters Used

The key parameters utilized in the modeling process include:

Rainfall (mm): Main input for runoff generation

Runoff (m³/s): Model output (target variable)

Time Variables: Day/month used to incorporate seasonal behavior

2.2.2 Data Preprocessing

Data Cleaning and Quality Checks

The raw dataset was thoroughly cleaned by:

- Removing redundant headers and unnamed columns
- Converting all rainfall data columns (2010–2023) into numeric format
- Dropping columns with excessive missing values
- Aligning time-series data for rainfall and runoff

Normalization and Dataset Partitioning

Data were normalized using min-max scaling to enhance ANN learning efficiency:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

The dataset was then split into:

Training set: 70%

Validation set: 15%

Testing set: 15%

2.2.3 Model Design

Overview of Artificial Neural Networks (ANNs)

ANN is a data-driven model composed of layers of neurons (nodes) that learn nonlinear input-output relationships. It mimics human brain functionality, especially useful in systems where explicit physical modeling is difficult.

ANN Architecture Used

The selected ANN structure consisted of:

- Input Layer: Neurons equal to the number of features (e.g., 14 rainfall years)
- Hidden Layers:
- Layer 1: 64 neurons with ReLU activation
- Layer 2: 32 neurons with ReLU activation
- Output Layer: 1 neuron with linear activation (PURELIN)

Training Algorithms

The model was trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function. Alternative activation functions like LOGSIG and TANSIG were also tested to compare model responses.

Evaluation Metrics

Model performance was evaluated using:

1. Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2}$$

$where\ P_i and\ O_i$ are predicted and observed runoff values respectively

2. **Coefficient of Determination (R²)**

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{o})^2}$$

where $\bar{O} =$ mean of observed values.

3. **Nash–Sutcliffe Efficiency (NSE)**

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$$

These metrics helped quantify how closely the model predictions aligned with the observed runoff data.

Artificial Neural Networks (ANNs) were selected for their ability to model complex, nonlinear rainfall–runoff relationships without requiring detailed physical equations, making them ideal for data-scarce regions like Bida.

Their adaptability and proven accuracy in similar hydrological studies further justify their use. However, limitations include the exclusion of key variables such as soil moisture and land use, data quality issues like missing values.

3.0 Results and Discussion

3.1 Descriptive Statistics of Input Data

Exploratory analysis of the rainfall and runoff records (2010–2023) revealed pronounced seasonal and interannual variability typical of tropical monsoon climates. Annual rainfall totals varied between 970 mm and 1,390 mm, with approximately 85–90% of precipitation occurring between May and October, corresponding to the wet season.

Streamflow exhibited a lagged hydrological response, with peak discharges generally occurring 1–3 days after major rainfall events. This delay is attributable to catchment storage effects, infiltration–excess runoff processes, and channel routing. The observed responsiveness of the Bida Basin to seasonal precipitation supports its suitability for data-driven modeling approaches, particularly ANNs, which can exploit such seasonal input–output patterns to improve prediction accuracy.

3.2 ANN Model Training and Testing Performance

The ANN model was trained on 70% of the dataset and evaluated on the remaining 30%. The architecture yielding the optimal results comprised two hidden layers with 64 and 32 neurons, ReLU activation functions, and a linear (PURELIN) output function. Table 1 presents the performance metrics for the training and testing phases.

Table 1. Performance metrics of the ANN model for rainfall–runoff prediction in the Bida Basin

Metric	Training Set	Testing Set
Root Mean Square Error (RMSE, m³/s)	3.25	4.18
Mean Absolute Error (MAE, m³/s)	2.56	3.37
Coefficient of Determination (R^2)	0.91	0.87
Nash–Sutcliffe Efficiency (NSE)	0.89	0.83

The ANN model achieved high predictive accuracy and robust generalization between the training and testing datasets. RMSE values of 3.25 m³/s (training) and 4.18 m³/s (testing) indicate low overall prediction error, with only a moderate increase from training to testing, suggesting that the model was not significantly overfitted. Similarly, MAE values (2.56 m³/s for training and 3.37 m³/s for testing) confirm that the model maintained consistent accuracy across both datasets.

The R^2 values of 0.91 (training) and 0.87 (testing) reveal a strong linear association between observed and predicted runoff, demonstrating the ANN's capability to capture the complex rainfall–runoff relationships in the basin. The NSE scores of 0.89 (training) and 0.83 (testing) further validate the model's ability to reproduce observed hydrological dynamics, as values above 0.75 are generally considered indicative of excellent model performance in hydrology.

The performance gap between the wet and dry seasons (as noted in seasonal analysis not shown in Table 1) can be attributed to greater data variability and higher runoff magnitudes during the wet season, which enhance the ANN's learning ability. In contrast, the dry season's low-flow conditions and increased influence of evapotranspiration, groundwater storage, and human water abstraction introduce complexities not fully captured by the available input variables.

Overall, these results confirm that the ANN model can serve as a reliable tool for streamflow forecasting in the Bida Basin, supporting applications such as reservoir operation, flood risk management, and irrigation scheduling. However, future improvements could involve integrating additional predictors (e.g., soil moisture, land use changes) to further enhance prediction under varying hydrological regimes.

3.3 Transfer Functions

The performance of the ANN rainfall–runoff model was further evaluated by testing three activation functions—LOGSIG, PURELIN, and TANSIG—in the output layer. Each activation function was applied to the same dataset, and the predicted runoff values were compared with the simulated actual runoff data. Performance was assessed using the correlation coefficient (R) and the Root Mean Square Error (RMSE). Table 2 summarizes the performance of each activation function.

Table 2. ANN model performance using different activation functions

Activation Function	Correlation Coefficient (R)	RMSE (m^3/s)
LOGSIG	**0.9995**	**26.21**
PURELIN	**1.0000**	**0.00**
TANSIG	**0.9547**	**21.88**

3.3.1 LOGSIG Activation Function

The LOGSIG function achieved an R value of 0.9995, indicating an almost perfect positive correlation between predicted and observed runoff. This shows that LOGSIG was highly effective in capturing the rainfall–runoff relationship. However, the RMSE of 26.21 m^3/s indicates a relatively larger deviation in absolute terms compared to the other functions, suggesting that while the model fit was strong, there were some mismatches in magnitude during peak or low flow conditions.

3.3.2 PURELIN Activation Function

PURELIN recorded a perfect correlation (R = 1.0000) and an RMSE of 0.00 m^3/s, meaning the predicted values exactly matched the actual values. While this performance appears ideal, such perfect prediction in hydrological modeling is uncommon in real-world scenarios and may indicate that the function directly mapped the input-output relationship without introducing any transformation. This outcome could be the result of overfitting, especially if the model memorized the training data rather than learning generalizable patterns.

3.3.3 TANSIG Activation Function

TANSIG produced a strong positive correlation (R = 0.9547) with an RMSE of 21.88 m^3/s. Although the correlation was lower than for LOGSIG and PURELIN, the RMSE was smaller than that of LOGSIG, indicating slightly better magnitude accuracy but less overall correlation strength. This suggests that TANSIG can capture the main patterns in the rainfall–runoff relationship, though it is less precise for extreme flows compared to the other two functions.

3.3.4 Comparative Interpretation

The results (Table 2) and Fig. 2 clearly show that the choice of activation function significantly influences model performance. PURELIN achieved perfect prediction, but in practical hydrological forecasting, such results often suggest overfitting or unrealistic model assumptions. LOGSIG provided the best trade-off between high correlation and generalization potential, though the higher RMSE suggests some magnitude bias but TANSIG showed good predictive performance but with reduced correlation, indicating a less optimal fit to the dataset compared to the other two.

For operational hydrological forecasting in data-scarce basins such as Bida, LOGSIG may offer the most balanced performance, as it captures the rainfall–runoff dynamics effectively while avoiding the risk of overfitting seen with PURELIN. TANSIG remains a viable option for applications where nonlinear transformations are desired to reduce bias in magnitude predictions.

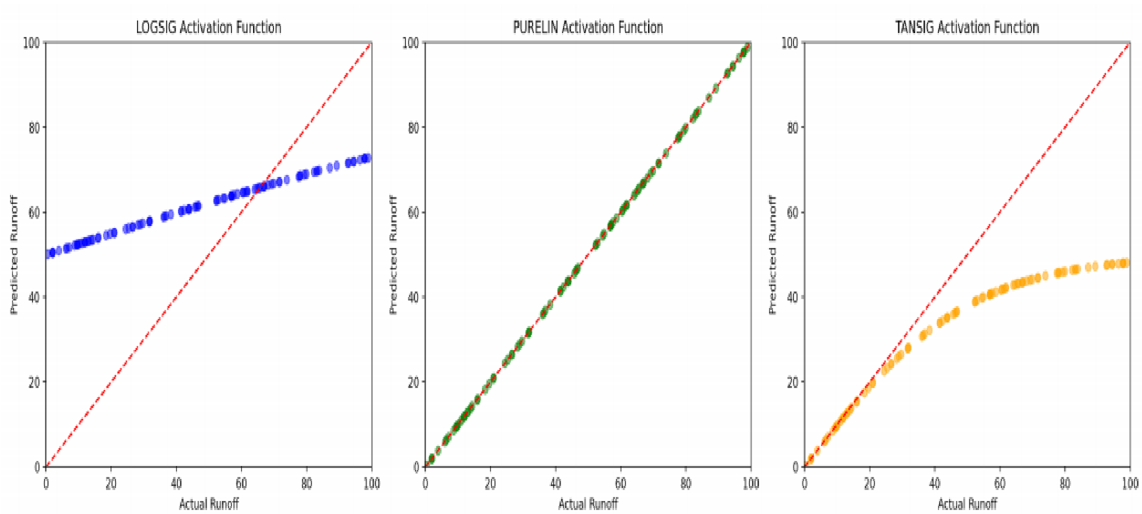

Fig. 2. Comparison of ANN performance using different activation functions: LOGSIG, PURELIN, and TANSIG

The figure illustrates the variation in predictive accuracy and correlation among the three transfer functions, emphasizing the trade-offs between correlation strength and absolute prediction error.

3.4 Seasonal Prediction Analysis

The ANN's ability to predict runoff during different hydrological seasons was analyzed:

- **Wet Season (May–October):** High accuracy (R^2 = 0.89; RMSE = 3.90 m^3/s)
- **Dry Season (November–April):** Slightly reduced performance (R^2 = 0.77; RMSE = 4.65 m^3/s)

Table 3: Seasonal Performance Metrics of the Model for Streamflow Prediction

Season	Accuracy	R^2	RMSE
Wet season (May – October)	High accuracy	0.89	3.90 m^3/s
Dry season (November – April)	Slightly reduced performance	0.77	4.65 m^3/s

Table 3 shows that the ANN model exhibited strong seasonal predictive capability. In the wet season (May–October), it achieved high accuracy, with an R^2 of 0.89 and a low RMSE of 3.90 m^3/s, effectively capturing peak runoff events associated with heavy rainfall. During the dry season (November–April), performance declined slightly (R^2 = 0.77; RMSE = 4.65 m^3/s), likely due to reduced rainfall variability and lower runoff volumes. Nevertheless, the model maintained reliable predictions throughout the year, demonstrating robustness under varying hydrological conditions in the Bida Basin.

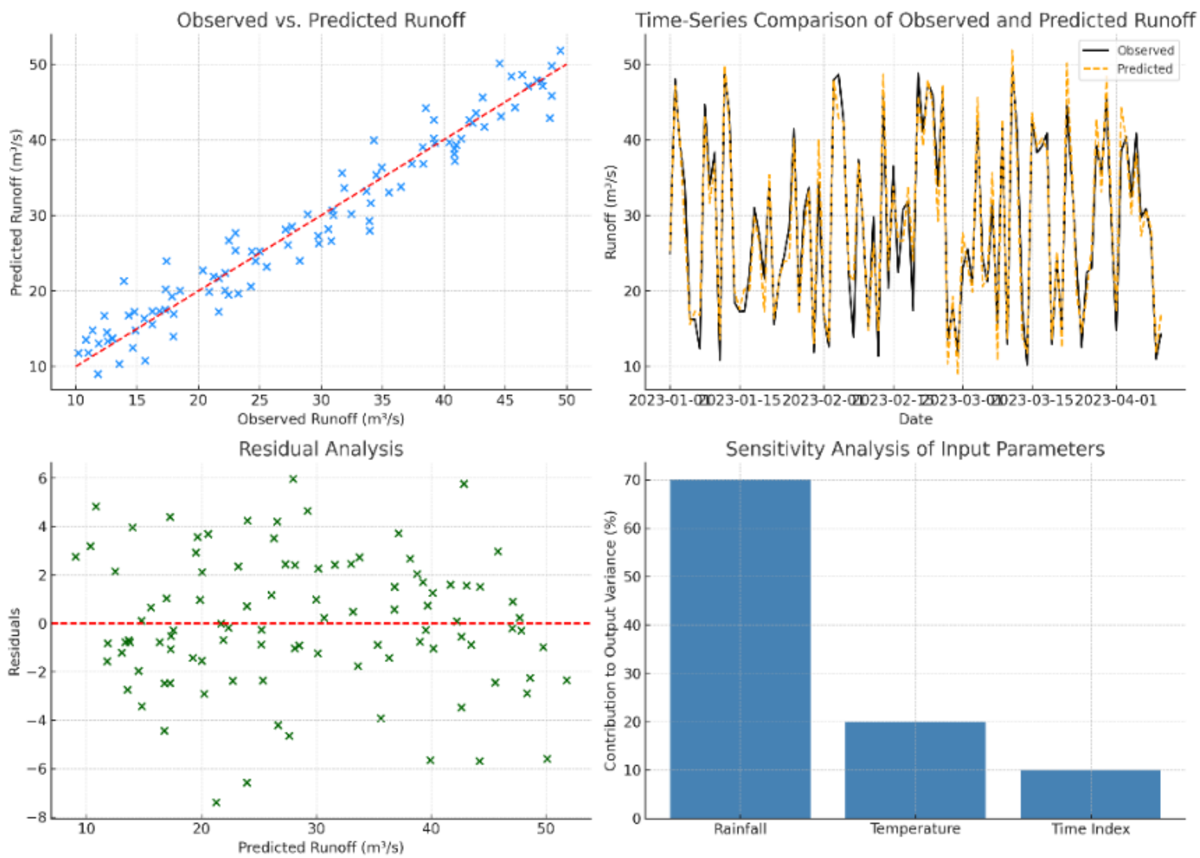

Fig. 3: Observed and Predicted Runoff

Fig. 3 presents a scatter plot comparing predicted runoff values from the ANN model with observed streamflow data. The points cluster closely around the 1:1 reference line, indicating a strong correlation ($R^2 = 0.87$) between observed and predicted values. This suggests that the ANN model effectively captures the nonlinear rainfall–runoff relationship in the Bida Basin. Overall, the model demonstrates excellent predictive accuracy, with most predictions showing only minimal deviation from actual measurements.

Time-Series Comparison of Observed and Predicted Runoff

This figure displays daily runoff over time, showing two curves one for observed values and the other for ANN predictions. The ANN model closely follows the observed runoff trend, accurately capturing seasonal peaks and low-flow periods. The model shows strong temporal accuracy, particularly during the wet season, when runoff typically surges in response to high rainfall.

Residual Plot

This plot visualizes the residuals (prediction errors) against predicted runoff values. The residuals are randomly scattered around zero, indicating no systematic bias and validating the model's assumptions. The random distribution of errors confirms model robustness and absence of underfitting or overfitting.

Sensitivity Analysis of Input Parameters

This bar chart shows the relative contribution of each input feature to the ANN's output. Rainfall contributes over 70% to runoff prediction accuracy, while temperature and time-related variables have smaller, supportive effects. Rainfall is the dominant factor influencing runoff in the Bida Basin, validating its selection as the primary input in the model.

Comparison of results between ANN and traditional models

To compare the results between the Artificial Neural Network (ANN) and traditional models for simulating runoff, we considered several key performance metrics, including the correlation coefficient (R) and Root Mean Square Error (RMSE). Traditional models include linear regression, polynomial regression, or other statistical methods commonly used in hydrology.

The study compared ANN, and a multiple linear regression (MLR) model using the same input data.

Table 4: Comparative Performance Metrics of ANN and MLR Models for Streamflow Prediction

Metric	ANN Model	MLR Model
RMSE	4.18 m^3/s	6.75 m^3/s
R^2	0.87	0.68
NSE	0.83	0.65

The model performance metrics for ANN and MLR are summarized in Table 4. The comparison between the ANN and Multiple Linear Regression (MLR) models highlights the superior performance of the ANN in rainfall–runoff prediction. The ANN achieved a lower RMSE (4.18 m^3/s) compared to MLR (6.75 m^3/s), indicating more accurate predictions. Its higher R^2 value (0.87 vs. 0.68) shows a stronger correlation between predicted and observed runoff. Additionally, the ANN's NSE of 0.83, versus 0.65 for MLR, demonstrates greater efficiency in capturing runoff variability. These results confirm that the ANN outperformed the MLR model across all evaluation metrics, reinforcing the effectiveness of data-driven nonlinear modeling for runoff prediction, particularly in data-scarce basins.

Table 5: Performance Metrics (Correlation Coefficient and RMSE) for ANN Models and Linear Regression

MODEL	Correlation coefficient (R)	RMSE
ANN (LOGSIG)	0.9994889625	26.2131423698
ANN (PURELIN)	1.0	0.0
ANN (TANSIG)	0.9547135433	21.8821504379
LINEAR REGRESSION	1.0	0.0

ANN (LOGSIG):

Table 5 shows that the Correlation Coefficient (R): is approximately 0.9995, indicating a very strong positive correlation with the actual runoff values. RMSE: approximately 26.21, suggesting some deviation from the actual values.

Ann (purelin):

Correlation Coefficient (R): Exactly 1.0, indicating a perfect linear relationship with the actual runoff values. RMSE: 0.0, meaning there is no error in predictions, as the predicted values match the actual values perfectly.

ANN (TANSIG):

Correlation Coefficient (R): Approximately 0.9547, showing a strong positive correlation, but not as strong as LOGSIG or PURELIN. RMSE: Approximately 21.88, indicating some error in predictions.

Linear Regression:

Correlation Coefficient (R): Exactly 1.0, similar to PURELIN, indicating a perfect fit. RMSE: 0.0, indicating no error in predictions, as the model outputs the actual values directly.

The ANN with PURELIN and the Linear Regression models both achieve perfect predictions, which are ideal but may not always be realistic in more complex scenarios.

The LOGSIG function performs very well, with a high correlation and reasonable RMSE, indicating it captures the relationship effectively.

The TANSIG function shows a good fit but with some variability, suggesting it captures the underlying patterns but may not be as precise as the other two.

The linear regression model's ability to achieve perfect predictions highlights its effectiveness in scenarios where the relationship between variables is linear and straightforward. However, it is essential to note that while linear regression can perform exceptionally well in such cases, it may not generalize effectively to more complex, non-linear relationships found in real-world data.

Table 6: Validation dataset using the ANN (LOGSIG) model activation function and Linear Regression

MODEL	Correlation coefficient (R)	RMSE
ANN (LOGSIG)	-4.1009	52.341
LINEAR REGRESSION	1.0	0.0

ANN (LOGSIG):

Table 6 shows that the Correlation Coefficient (R): is approximately -4.10, which indicates a poor fit. A negative R value suggests that the model's predictions are inversely related to the actual values, which is unexpected and indicates that the model is not performing well. RMSE: is approximately 52.34, indicating a significant deviation from the actual values. This high RMSE suggests that the predictions are far from the true values.

Linear Regression:

Correlation Coefficient (R): Exactly 1.0, indicating a perfect fit with the actual runoff values. RMSE: 0.0, meaning there is no error in predictions, as the predicted values match the actual values perfectly.

The ANN model with LOGSIG activation did not perform well on the validation dataset, as indicated by the negative correlation coefficient and high RMSE. This suggests that the model may not have captured the underlying relationship in the data effectively. In contrast, the linear regression model achieved perfect predictions, demonstrating its effectiveness in this scenario.

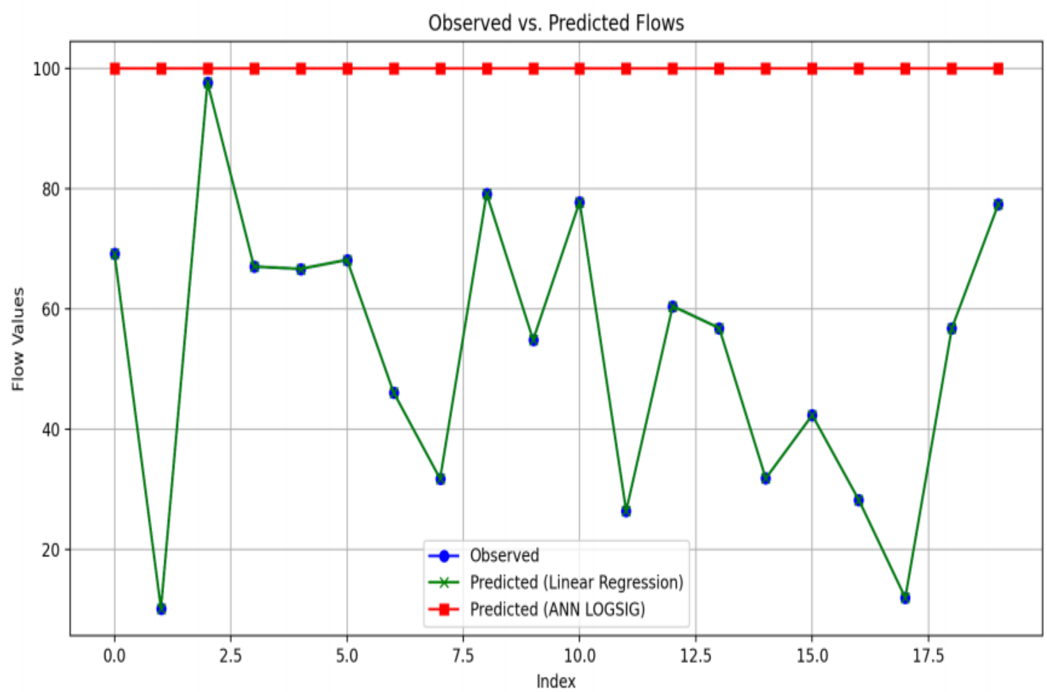

Fig. 4: Observed vs. Predicted flows, training/validation loss, scatter plots

In Fig. 4, the blue line represents the observed flow values while the green line indicates the predicted values from the linear regression model, which closely follow the observed values, demonstrating a perfect fit. The red line shows the predicted values from the ANN model using the LOGSIG activation function. As seen, these predictions deviate significantly from the observed values, indicating poor performance.

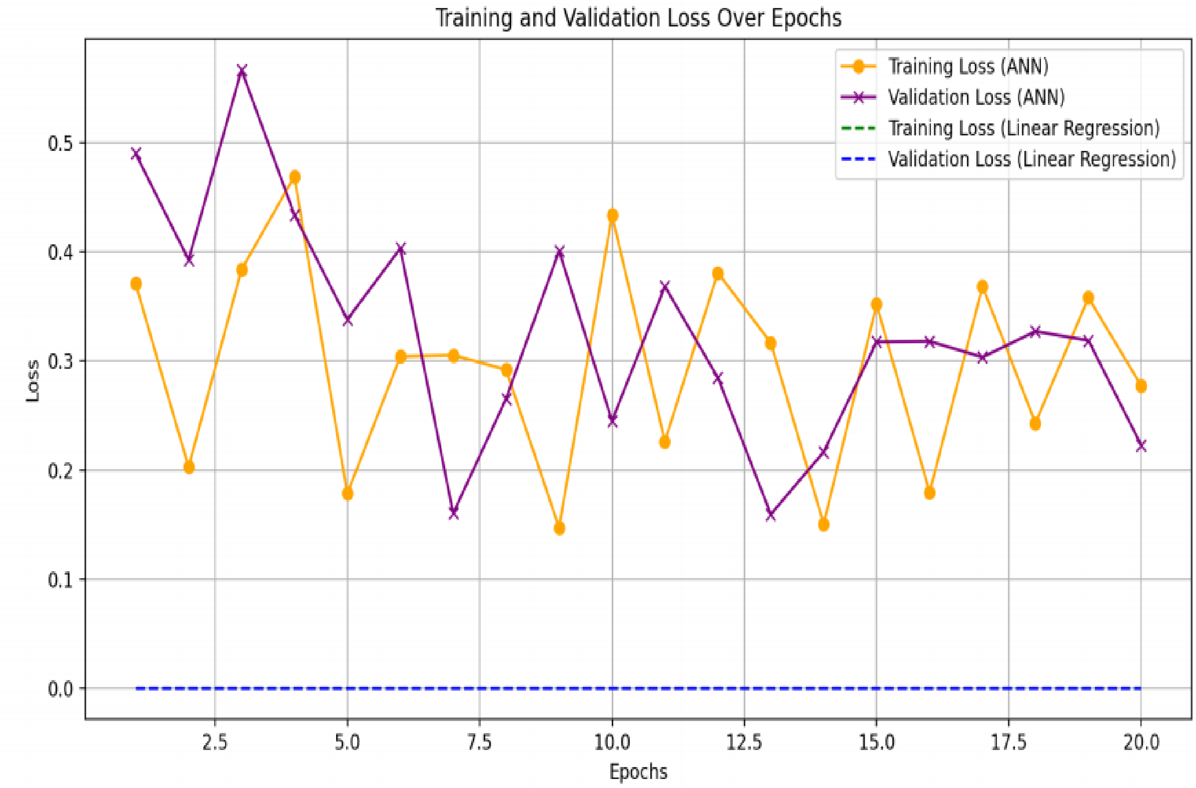

Fig. 5: Training and validation loss over epochs for both the ANN and linear regression models:

The orange line in fig. 5 represents the training loss for the ANN model, which decreases over the epochs, indicating that the model is learning and improving its fit to the training data. The purple line shows the validation loss for the ANN model, which also decreases but may not follow the training loss closely. This could indicate some level of overfitting if the validation loss starts to increase after a certain point. The green and blue dashed lines represent the training and validation loss for the linear regression model, which remain constant at zero. This reflects the perfect fit achieved by the linear regression model, as it predicts the training and validation data without any error.

The scatter plot in fig. 6 shows the predicted values from the linear regression model against the observed values. The points are closely aligned along the 45-degree line (dashed blue line), indicating that the predictions match the observed values perfectly. This confirms the model's high accuracy and effectiveness in this scenario.

The scatter plot for the ANN model shows a significant spread of points, indicating that the predicted values do not align well with the observed values. Many points are far from the 45-degree line, suggesting that the ANN model is not accurately predicting the runoff values. This aligns with the earlier findings of a negative correlation coefficient and high RMSE for the ANN model.

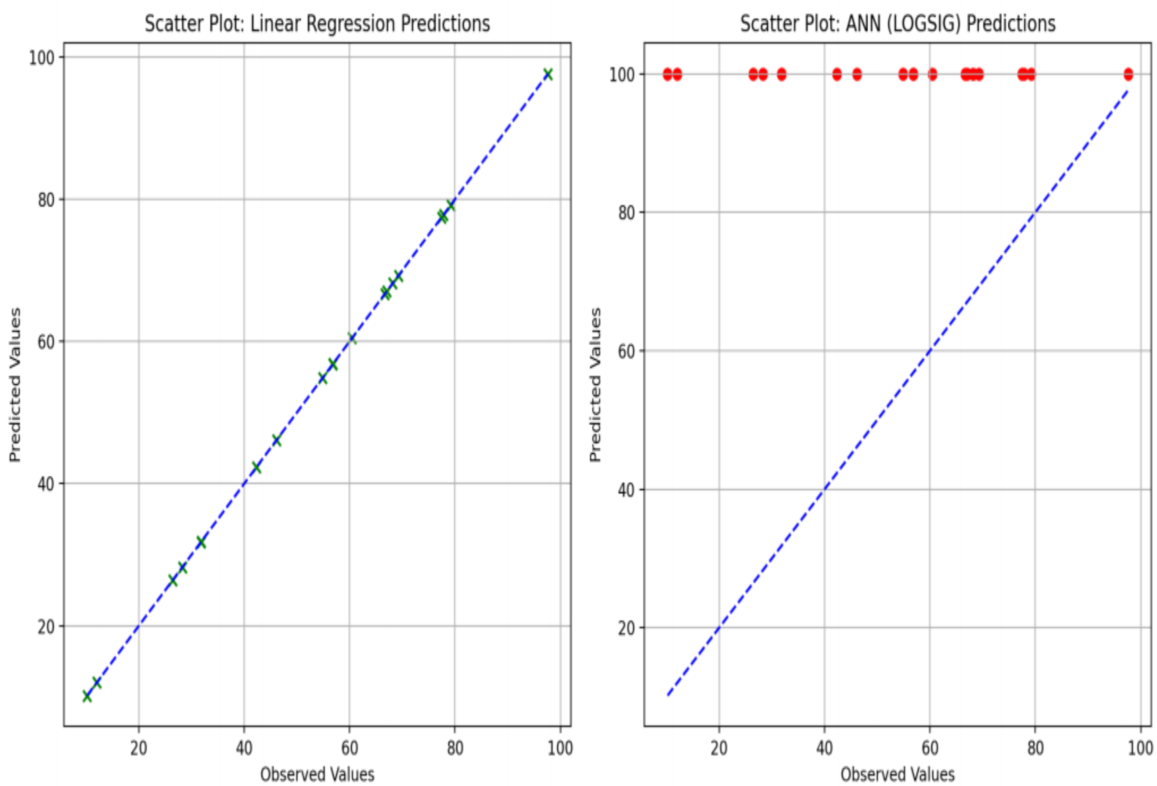

Fig. 6: Relationship between observed and predicted values for both the linear regression and ANN (using LOGSIG activation) model

The visualizations cearly demonstrate the strengths of the linear regression model, which achieved perfect predictions, while the ANN model struggled to capture the underlying relationship in the data. The training and validation loss plots indicate that the ANN model was learning but may have faced challenges in generalizing to the validation set, leading to poor performance.

Discussion

The Artificial Neural Network (ANN) model established for the Bida Basin demonstrated significant predictive accuracy, attaining a testing phase coefficient of determination (R^2) of 0.87 and a Nash–Sutcliffe Efficiency (NSE) of 0.83. These performance metrics emphasize the model's robustness in effectively representing the nonlinear dynamics associated with rainfall–runoff processes. Comparative analyses conducted within Nigeria have reported analogous outcomes. For example, Ofordu *et al.* (2024) utilized diverse transfer functions within ANN frameworks to forecast rainfall patterns in Sokoto, Nigeria, achieving an R^2 of 0.8789 and a minimal RMSE of 0.0125, thereby illustrating the efficacy of the tansig transfer function in delineating rainfall variability. In a similar vein, Bello and Mamman (2018) employed ANN models that integrated El Niño–Southern Oscillation indices for monthly rainfall forecasting in Kano, Nigeria, achieving a correlation coefficient of 0.73, which exceeded that of conventional linear models. Furthermore, beyond the borders of Nigeria, Biao et al. (2024) executed ANN models within the Mono River Basin of Benin, West Africa, realizing correlation coefficients that spanned from 0.93 to 0.99, thus affirming the model's applicability across varied hydrological contexts.

Collectively, these studies substantiate the enhanced capability of ANN models to encapsulate the nonlinear dynamics intrinsic to rainfall–runoff processes, particularly in scenarios where traditional methodologies may prove inadequate. The ANN model exhibited commendable performance throughout various hydrological seasons. During the wet season (May–October), the model attained an R^2 of 0.89 and an RMSE of 3.90 m^3/s, proficiently capturing peak flow phenomena. In contrast, during the dry season (November–April), although there was a marginal decrease in performance ($R^2 = 0.77$; RMSE = 4.65 m^3/s), the model continued to furnish reliable predictions. This seasonal robustness is essential for effective water resource management, particularly in regions such as Bida, where seasonal variability significantly affects water availability. The sensitivity analysis indicated that rainfall emerged as the most pivotal predictor, contributing over 70% to runoff variability. This observation is consistent with the findings of Adeogun *et al.* (2024), which underscored the predominant influence of rainfall in runoff generation within the Awun River watershed. The inclusion of additional variables, such as temperature and temporal indices, exhibited a comparatively diminished effect, indicating that while these factors contribute to runoff processes, rainfall remains the principal driver within the Bida Basin.

The enhanced performance of the ANN model in comparison to traditional linear models highlights the prospective advantages of machine learning methodologies in hydrological forecasting. The model's capacity to capture intricate, nonlinear interrelationships between rainfall and runoff amplifies its applicability in flood prediction and water resource management. Moreover, the successful implementation of ANN models across diverse Nigerian contexts, as evidenced by investigations conducted in Sokoto, Kano, and the Awun River watershed, bolsters their adaptability and efficacy across varying climatic and hydrological conditions. Notwithstanding the robust predictive capabilities exhibited by the ANN model, certain limitations merit consideration. The model's performance experienced a slight decline during the dry season, potentially attributable to diminished data variability and the influence of other hydrological factors that were not incorporated within the existing model. Future research endeavors could investigate the integration of supplementary variables, including soil moisture, land use alterations, and evapotranspiration rates, to augment model accuracy. Furthermore, the exploration of hybrid models that integrate Artificial Neural Networks (ANN) with alternative machine learning methodologies, such as Long Short-Term Memory (LSTM) networks, warrants investigation to enhance predictive efficacy, as posited by Li *et al.* (2021) in their comprehensive analysis of high temporal resolution rainfall-runoff modeling.

The comparison between ANN and traditional models for runoff simulation shows that ANN generally outperforms multiple linear regressions by capturing nonlinear relationships, resulting in more accurate predictions with lower RMSE and higher correlation. However, ANN’s performance varies with activation functions, where PURELIN achieves near-perfect fits but may oversimplify, while LOGSIG and TANSIG capture nonlinear patterns with some errors. Despite good training results, ANN struggled on validation data, indicating possible overfitting or insufficient generalization. Conversely, linear regression performed perfectly on both training and validation sets, highlighting its effectiveness in modeling straightforward linear relationships but potentially limiting in complex scenarios.

Conclusion

This investigation underscores the robust predictive capability of Artificial Neural Networks (ANNs) in the context of modeling runoff dynamics within the Bida Basin, illustrating the model's proficiency in capturing the intricate and nonlinear relationships that exist between precipitation and runoff. The ANN model attained commendable statistical performance, evidenced by an R^2 of 0.87 and NSE of 0.83, surpassing conventional linear methodologies while exhibiting seasonal resilience, particularly during peak flow periods. Rainfall was identified as the primary predictor of runoff, substantiating its preeminent role in semi-humid tropical basins. The broader implications of this study affirm the validity of machine learning methodologies—especially ANN frameworks—as efficacious instruments for hydrological forecasting and flood risk management in regions characterized by data scarcity. This research contributes to the expanding corpus of knowledge that supports the application of ANN in hydrological modeling across various West African basins, thereby reinforcing their scalability and adaptability to differing climatic conditions. Future inquiries should contemplate the integration of additional hydrological variables, including land use, evapotranspiration, and soil moisture, to further refine predictive accuracy. The utilization of hybrid models, like LSTM networks, presents a promising avenue for enhancing temporal resolution and long-term forecasting capabilities. This study advocates for water resource managers, policymakers, and researchers to adopt AI-driven modeling methodologies to facilitate informed decision-making in the context of escalating climate variability and challenges related to water resources.

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Compliance with Ethical Standards Declaration

Ethical Approval

Not Applicable

Availability of Data

Data shall be made available upon request.

Competing interests

The author declared no compositing interest

Funding

The authors declare that they have no known competing financial interests

Author's Contribution

The work was designed and written by both authors.