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COMPARATIVE ANALYSIS OF ARTIFICIAL NEURAL NETWORKS AND REGRESSION MODELS FOR WATER LEVEL PREDICTION USING RADAR ALTIMETRY IN THE UPPER NIGER RIVER

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Abstract

The upper Niger River Basin experiences floodings and remains a recurring disaster, yet existing hydrological monitoring systems are limited by sparse in-situ observations and insufficient predictive accuracy. Traditional regression-based models struggle to capture the nonlinear dynamics of river systems, creating an urgent need for advanced approaches such as radar altimetry integrated with Artificial Neural Networks to improve water level prediction and flood early warning. This study explores the deployment of satellite radar altimetry for predictive modelling of water surface elevation in the Upper Niger River Basin, Nigeria. Satellite altimetry datasets from Jason-2, Sentinel-3, and SARAL/AltiKa, spanning a seven-year period, were integrated with in-situ hydrological measurements to evaluate their effectiveness in water level monitoring and flood forecasting. Artificial Neural Networks (ANN) and regression models were comparatively assessed to determine their predictive accuracy. Results showed that the ANN model consistently outperformed regression analysis across all performance metrics. ANN achieved higher correlation with observed data (R^2= 0.8 - 0.95) compared to regression (R^2 = 0.60 - 0.80); while also recording significantly lower errors (RMSE = 0.20 - 0.50 m, MAE = 0.18 - 0.40 m) than regression (RMSE = 0.50 - 1.20 m; MAE = 0.45 - 1.00 m). Moreover, ANN predictions exhibited minimal bias (0.01 - 0.05 m), closely approximating the ideal zero, whereas regression models demonstrated systematic underestimation or overestimation. The study highlights the strong generalization capacity of ANN across diverse hydrological zones of the Niger River Basin, underscoring its suitability for operational flood monitoring and early warning systems.

Keywords: Water Surface Elevation, Artificial Neural Network, Regression Analysis, Flood Forecasting, Hydrological Modelling

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1.0 Introduction

Geodesy and geodynamic processes are very complex system and nonlinear in nature, and Artificial Neural Network (ANN) is highly suitable for the situations where the underlying processes exhibit chaotic tendencies. The concept of ANN originated from the attempt to develop a mathematical model capable of recognizing complex patterns on the same line as biological neuron work. These models handle large number of data, predict the contribution of these datasets in the outcome and provide précised and adequate predictions. It is useful in the situations where underlying processes or relationships display chaotic properties. ANN does not require any prior knowledge of the system under consideration and are well suited to model dynamical systems on a real-time basis. It is, therefore, possible to set up systems so that they would adapt to the events which are observed and for this, it is useful in real time analyses, for instance, in weather forecasting, radio wave propagations, remote sensing characterization and other different fields of human endeavours; therefore, the basis for its usefulness in this research work will be because of its suitability to troubleshooting the chaotic nature of the sea or river waves that give rise to water surface variations, our choice study focus.

Several water elevation and discharge estimation attempts have been made based on satellite altimetry for the Amazon, Ganges, and Brahmaputra rivers [4]. For instance, [11] compared the water elevation derived from Envisat satellite altimetry with simulated water levels from the HEC-RAS model for three rivers in Bangladesh, reporting an average root mean square difference of 2m between the simulated and satellite-based estimates. [8] also produced estimates of monthly discharges for the Ganges and Brahmaputra rivers using TOPEX-Poseidon, ERS-2, and ENVISAT data, while [2] highlighted the potential of SWOT for land hydrology.

In Nigeria, [5] assessed water levels in Dadin Kowa Dam reservoir using geospatial techniques, showing that climate change and population-driven demand influenced water level dynamics. Similarly, [9] used radar altimetry to reproduce discharge in the Niger, while [6] successfully combined satellite imagery and altimetry for Niger River cross-section and discharge estimation. More recent works continue to validate the reliability of radar altimetry: [3] confirmed the accuracy of Sentinel-3 altimetry in the Inner Niger Delta, achieving correlations above 0.9 with in-situ records.

Beyond altimetry, advanced machine learning approaches have gained prominence in hydrological prediction. [1] reviewed neural network applications for water level modelling, emphasizing their robustness compared to traditional statistical methods. [7] also compared hydrological modelling approaches, highlighting the strengths of modern rainfall–runoff models in complex river basins. In Nigeria, recent flood studies confirm rising risks: a 2025 analysis of downstream Nigeria using machine learning and SAR data found an ~11% increase in flood extent between 2018 and 2024 [12]. Complementary studies also highlight how dam operations combined with rainfall drive flood patterns in the Niger Delta [13].

At the global level, novel deep learning frameworks such as River Mamba [10] demonstrate how spatio-temporal state-space models can forecast river discharge and floods up to seven days ahead. Likewise, remote sensing advances now allow automatic river flow estimation from RADARSAT imagery using deep learning [14]. These recent contributions underscore the relevance of integrating radar altimetry and AI-based methods to strengthen hydrological forecasting and flood risk management within the Niger River Basin.

This study specifically addresses the statistical relationship between observed and predicted water levels based on regression analysis?

2.0 Study Area

Kogi State (Lokoja) is located in north-central Nigeria and serves as a hydrological junction where the Niger and Benue Rivers converge at Lokoja, the state capital. It lies between latitude 6°30′N and 8°50′N, and longitude 5°15′E and 7°30′E. The area has mixed terrain with both lowlands and uplands along the river banks, dominated by the confluence of the two rivers, the Niger and Benue rivers. Thus, making it highly vulnerable to flooding during the rainy season. Lokoja is historically one of the worst-hit cities in Nigeria during annual floods, often experiencing loss of life and infrastructure damage. The confluence area offers a unique hydrological setting to test the integration of satellite and in-situ data for water level modeling and early flood forecasting as shown in Figure 1 and 2.

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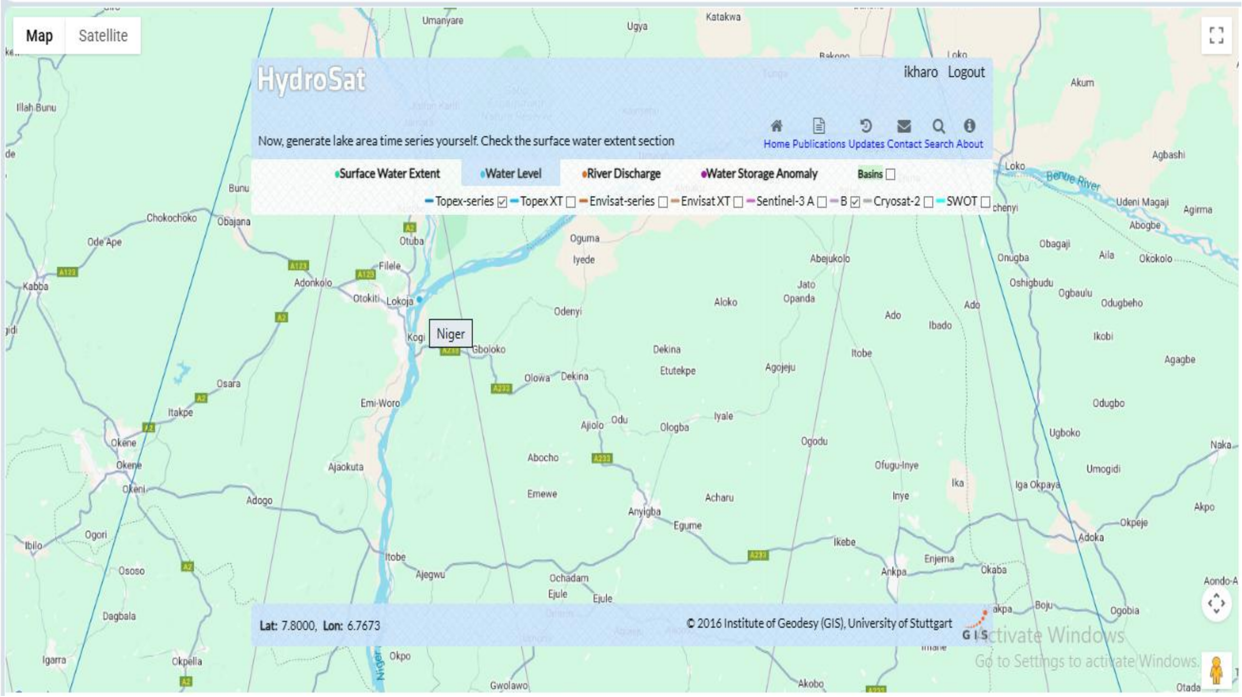

Figure 1: Upper Niger 1 Lat 7.800N and Long 6.76E with Ground Track 211 and Hydrosat No. 21213410395001

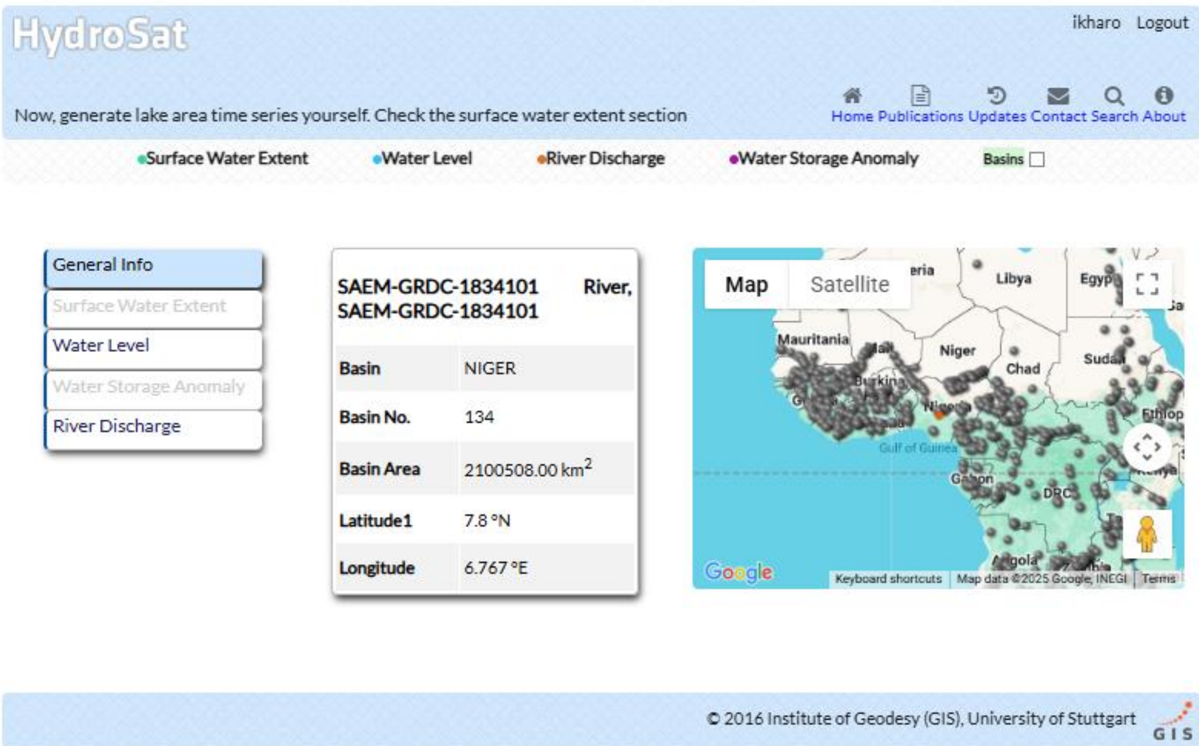

Figure 2: Upper Niger 1 Lat 7.800N and Long 6.76E with Ground Track and Hydrosat No. 21213410395001

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3.0 Materials and Method

3.1 Datasets

Radar satellite altimetry (Jason-2, Sentinel-3 and ARAL/Altika) datasets from multiple sources were acquired. In-situ measurements of water surface elevation from tide gauges and other relevant instrument were deployed for data capture. Using the Jason-2, Sentinel-3 and ARAL/Altika altimeter radar payload, data was generated over the study area in a duration of thirteen (13) years. In this study, we used the same methods to choose the virtual station as [15,16]. Radar altimetry data within the chosen area was extracted to generate water level time series. Hydrological data (Water level) used in this study were acquired from https://hydrosat.gis.uni-stuttgart.de/php/index.php Institute of Geodesy (GIS), University of Stuttgart,

3.2 Preprocessing of Data

The preprocessing of data was a critical step in ensuring the accuracy and reliability of the predictive modelling of water surface elevation in the Upper Niger River Basin. Multi-mission radar altimetry datasets were acquired from Jason-2, Sentinel-3, and SARAL/AltiKa satellites, spanning a 2002 to 2015 period. In addition, in-situ hydrological measurements from tide gauges and related observation stations were obtained to provide reference water level records for model validation. The raw altimetry data were then subjected to data cleaning and noise filtering, where anomalous or spurious measurements caused by atmospheric effects, sensor errors, or surface roughness were removed. Next, the cleaned satellite-derived time series were integrated with in-situ gauge records to establish consistency and to validate the reliability of altimetry measurements in the study area. Missing data points were addressed through appropriate interpolation techniques to maintain continuity in the time series. Furthermore, the datasets were normalized and standardized, adjusting for scale differences across satellite missions and removing seasonal fluctuations that could introduce bias into the predictive models. Finally, the pre-processed dataset was structured for machine learning implementation.

3.3 Artificial Neural Networks for Water Level Modelling

In this study, an Artificial Neural Network (ANN) was applied to model satellite altimetry data collected from gauge stations along the Lower River Niger. The dataset, obtained from HydroSat, University of Stuttgart, consisted of temporal variables (year, month, day) and hydrological measurements (water level height and associated error).

The ANN was trained to map specific input variables to target outputs. Training was achieved through iterative comparison between predicted outputs and target values until convergence was reached. The network's connections represented by weights and biases formed the feedback mechanism. Backpropagation, a gradient descent-based optimization algorithm, was employed to minimize the error by adjusting these weights in the direction of the negative gradient of the performance function. When properly trained, the ANN was able to generalize and provide reliable predictions for previously unseen input data.

By incorporating biases, sigmoid hidden layers, and linear output layers, the ANN gained the capacity to approximate a wide range of functions with finite discontinuities.

Model Configuration

A feedforward backpropagation network with architecture 39-20-1 was implemented to predict water levels. The *number of hidden neurons N* was determined using the criterion [17,18] in equation (1):

$$N = \frac{4n^2+3}{n^2-8} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

This configuration, with 39 hidden neurons, achieved a minimal Mean Square Error (MSE). The network consisted of:

1) An input layer,
2) A tangential-sigmoid hidden layer, enabling the capture of nonlinear relationships between predictors and outputs, and
3) A linear output layer.

For classification tasks of predicting flood presence, a hard-limit transfer function was used at the output layer to provide binary flood predictions.

In line with best practices, the Artificial Neural Network (ANN) training process utilized a 60%–20%–20% split of the data for training, validation, and testing, respectively. This ensured that the model was both well-trained and capable of generalization to unseen data. These preprocessing steps were essential in minimizing errors, aligning heterogeneous data sources, and ensuring the robustness of the predictive modelling framework.

4.0 Results and Discussion

4.1 Regression Analysis for Upper Niger River 1

In this case, regression model was used for evaluation and prediction. It evaluates the water level height, W_h for Upper Niger River I using ANN data by giving different values of the year, month and day. The model equation obtained from regression analysis in Table 1 is given as:

$$W_h = 53.31856 - 0.01146X_1 + 0.439052X_2 + 0.005501X_3 \text{ ----------------------(2)}$$

The estimated effect (regression coefficient) or r^2 value as given by equations (2) tells us that for every 1% increase in year there is an associated 0.01146 % decrease in water level height, and that for every 1% increase in month there is an associated 0.439052% increase in water level height and for every 1% increase in day there is an associated 0.005501% increase in water level height.

4.1.1 Interpretation of Key Regression Parameters

In explaining the coefficients and other variables, attempt is made to give detailed information on how dependent variable was influenced in the regression equation. The intercept is obtained as 53.31856 which is the baseline value when all variables are zero. Year (X1) is -0.01146 which is a small negative influence, suggesting a slight decline over time. Month (X2) is 0.439052 and this is the strongest predictor, indicating that seasonal trends have significant impact. Day (X3) is 0.005501, the minor positive effect indicates that the daily variations do not strongly influence the outcome. Standard errors which is reliability of estimates shows that the Year (X1) is - 0.010415, suggesting a higher uncertainty. Month (X2) is - 0.01192 and the very low error, makes it a highly reliable predictor. Day (X3) is - 0.00462, though small but less impactful. The intercept - 20.92801 gives a high variability, suggesting the need for improvement.

Table 1: Regression Analysis for Upper Niger River 1 using ANN Data

ANNData	DD (X3)	MM (X2)	Year (X1)	Intercept	Remark	
Coeff	0.005501	0.439052	-0.01146	53.31856		
Std error	0.00462	0.01192	0.010415	20.92801		
R^2	0.387332	1.902615	#N/A	#N/A		Standard Error of the Regression
F Statistic	458.5592	2176	#N/A	#N/A		Degrees of freedom (n-k-1)
Model *SS*	4979.878	7877.001	#N/A	#N/A		Residual SS
			Anova			
Source	***SS***	***df***	***MS***	***F Statistic***	**Probability**	
Regression	4979.878	3	1659.959	458.5592	5.9E-100	
Residual	7877.001	2176	3.619945			
Total	12856.88	2179				
					CI(%)=95	
Variable	**Coeff**	***Std Error***	***t-Statistic***	***P-Value***	***Lower Limit***	***Upper Limit***
Intercept	53.31856	20.92801	2.547713	0.011458	12.09595	25.94633
Year(X1)	-0.01146	0.010415	-1.10002	#NUM!	-0.03197	-2.15634
Month(X2)	0.439052	0.01192	36.83204	1.2E-101	0.415572	72.56124
Day(X3)	0.005501	0.00462	1.190544	0.234989	-0.0036	2.349676
R^2	0.387332					
Adjusted *R^2*	0.379799					

Note: The #N/A implies that the entry is simply not applicable for that row (R^2, F statistic and Model SS values shown under year and intercept). #NUM! also implies that the Excel software failed (Invalid numerical result) to compute a valid number (p-value for "Year" predictor).

4.2 Model Accuracy & Strength

R^2 and Adjusted R^2 tell us how well the model explains variation in the dataset with R^2 being 0.387332. This is about 38.7% of the variation in the dependent variable (W_h) and is explained by the model equation (2). Adjusted R^2 is 0.379799 and is slightly lower, accounts for the number of predictors used. This indicates moderate predictive strength.

4.3 ANOVA and Model Significance

F-Statistic is 458.5592 indicates strong statistical significance as shown in Figure 3. The probability (*p*-value) is 5.9E-100 which is extremely low, confirming the model is highly significant. The regression model is statistically valid, but its predictive capability is not fully comprehensive. It explains some variation, but likely other environmental factors played significant role.

3. Confidence Interval (Reliability of Predictions)

The Month (X2) coefficient (0.439052) has the highest *t*-statistic (36.83204), confirming seasonality is the dominant factor. Year (X1) is less statistically significant with -1.10002 *t*-statistic, suggesting that long-term trends are weak or inconsistent. Day (X3) has a low probability (0.234989), meaning daily changes may not be important in predicting outcomes.

4.4 Regression Analysis for Upper Niger River (Lokoja)

In this case, regression model was used for evaluation and prediction. It evaluates the water level height, W_h for Upper Niger River I using Altimetry data by giving different values of the year, month and day. The model equation obtained from regression analysis in Table 2 is given as:

$$W_h = 58.77468 - 0.01419X_1 + 0.440968X_2 - 0.006156X_3 \text{ ------------------------------(3)}$$

The estimated effect (regression coefficient) or R^2 value as given by equations (3) tells us that for every 1% increase in year there is an associated 0.01419 % decrease in Water level height, and that for every 1% increase in month there is an associated 0.440968% increase in water level height and for every 1% increase in day there is an associated 0.006156% decrease in water level height.

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Table 2: Regression Analysis for Upper Niger River 1 using Altimetry Data

Altimetry Data	DD (X3)	MM (X2)	Year (X1)	Intercept	Remark	
Coeff	0.006156	0.440968	-0.01419	58.77468		
Std error	0.004821	0.012439	0.010868	21.83874		
R^2	0.369789	1.985412	#N/A	#N/A	Standard Error of the Regression	
F-Statistic	425.6036	2176	#N/A	#N/A	Degrees of freedom (n-k-1)	
Model *SS*	5033.01	8577.489	#N/A	#N/A	Residual SS	
			Anova			
Source	***SS***	***df***	***MS***	***F Statistic***	***Probability***	
Regression	5033.01	3	1677.67	425.6036	1.28E-96	
Residual	8577.489	2176	3.941861			
Total	13610.5	2179			Cl(%)=95	
Variable	***Coeff***	***Std Error***	***t-Statistic***	***P-Value***	***Lower Limit***	***Upper Limit***
Intercept	58.77468	21.83874	2.691304	0.00761	15.75817	27.13989
Year(X1)	-0.01419	0.010868	-1.30533	#NUM!	-0.03559	-2.56028
Month(X2)	0.440968	0.012439	35.45006	3.16E-98	0.416466	69.83962
Day(X3)	0.006156	0.004821	1.276784	0.202892	-0.00334	2.519747
R^2	0.369789					
Adjusted R^2	0.36204					

Note: The #N/A implies that the entry is simply not applicable for that row (R^2, F statistic and Model SS values shown under year and intercept). #NUM! also implies that the Excel software failed (Invalid numerical result) to compute a valid number (p-value for "Year" predictor).

1. Interpretation of Key Regression Parameters

Regression coefficients which is the impact of variables on W_h has intercept as obatained value of 58.77468 which is the baseline value when all variables are zero. Year (X1) is -0.01419 being a small negative influence, suggesting a slight decline over time. Month (X2) is 0.440968, this being the strongest predictor, indicating seasonal trends have a significant impact. Day (X3) is 0.006156 with a minor positive effect, meaning daily variations do not strongly influence the outcome.

Standard Errors values obtained are Year (X1) is - 0.010868, suggests higher uncertainty. Month (X2) is - 0.012439 with a very low error, making it a highly reliable predictor. Day (X3)

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is - 0.004821 which is small and less impactful. Intercept obtained is - 21.83874, this is a high variability, suggesting the need for improvement.

2. Model Accuracy and Strength

R^2 obtained is 0.369789 which is about 36.9% of the variation in the dependent variable (W_h) is explained by the regression model. The Adjusted R^2 obtained is 0.36204, this is slightly lower and accounts for the number of predictors used. This indicates moderate predictive strength, but the model might benefit from additional variables.

3. ANOVA and Model Significance

F-Statistic obtained is 425.6036 which indicates strong statistical significance. The probability (p-value) is 1.28E-96. This is extremely low, confirming the model is highly significant. The regression model is statistically valid, but its predictive capability isn't fully comprehensive - it explains some variation, but likely other environmental factors play a role.

4. Confidence Interval (Reliability of Predictions)

The Month (X2) has coefficient of 0.440968 having the highest t-statistic as 35.45006, confirming seasonality as the dominant factor. Year (X1) is less statistically significant with - 1.30533 t-statistic, suggesting long-term trends are weak or inconsistent. Day (X3) has a low probability value of 0.202892, meaning daily changes may not be significant.

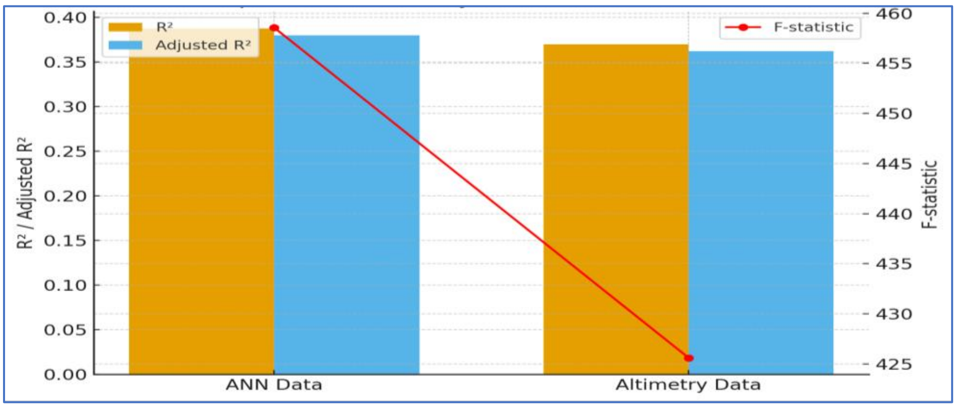

Figure 3: Comparison of R^2, Adjusted R^2 and F- Statistic of Regression Analysis

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Both models explain about 36–39% of the variance in river levels. The ANN model performs slightly better. Both F-statistics are very high, indicating that the regression models are highly statistically significant. Figure 3 shows that the ANN-based regression model provides a slightly better fit than the Altimetry-based model, but both are statistically strong predictors of river levels.

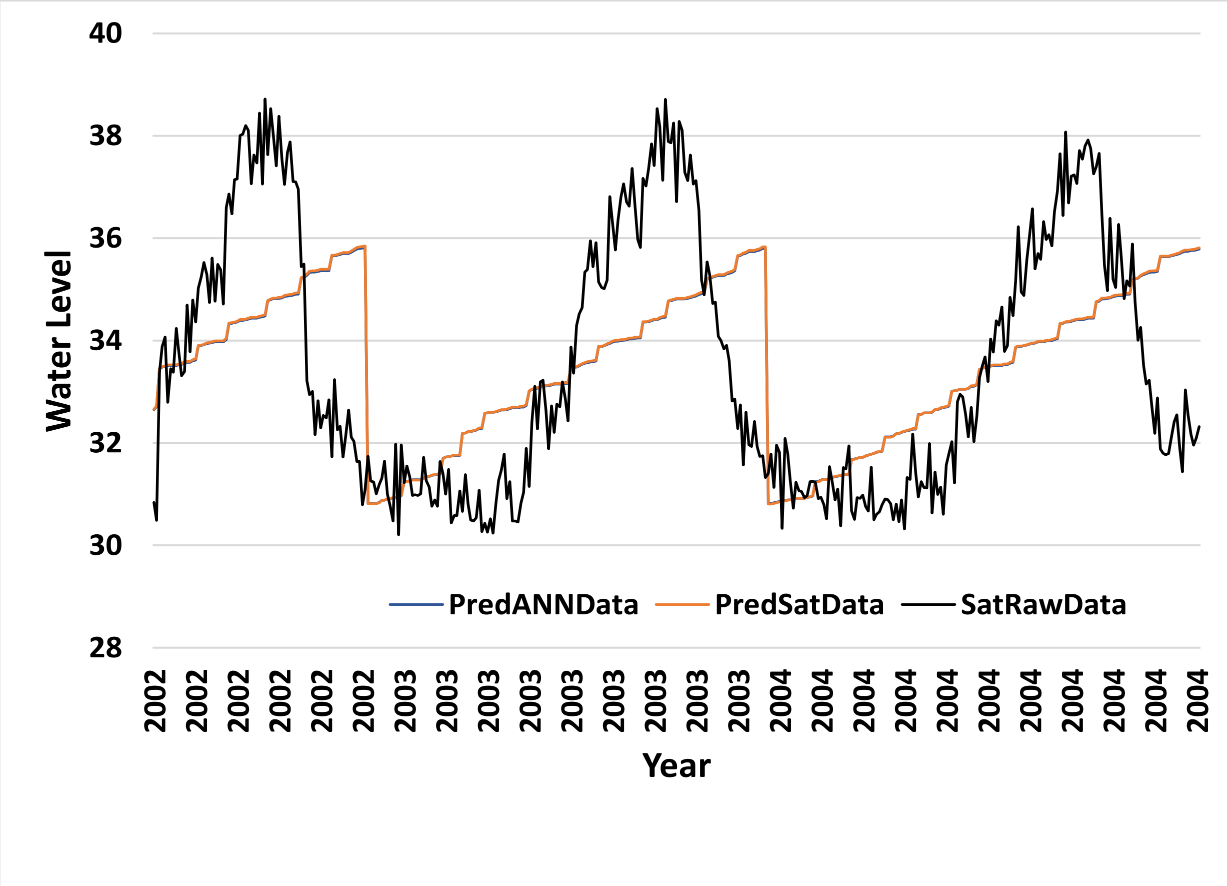

Figure 4: Upper Niger River 1

Figure 4 displays water level data for Upper Niger River 1 from 2002 to 2004. The vertical scale ranges from about 28 to 40 meters showed a river segment or gauge station with larger water level swings. The three data series which are PredANNData for neural network predictions, PredSatData (Regression generated data) for Satellite-based predictions and SatRawData for observed satellite measurements were presented. It is observed that the predicted line (ANN or satellite) rides higher than the observed data across several points or periods. Also, the prediction dips consistently below the actual satellite data which might be due to dry season or seasonal recovery points.

4.5 Evaluating ANN Network Performance

The total number of data used in the ANN Network for Upper Niger I is 2180 in which 60% (1308) of these data is for the training phase with 20% (436) for validation and 20% (436) for testing Using MATLAB Software. Figure 5 Shows the ANN profiles for training, validation, and testing results.

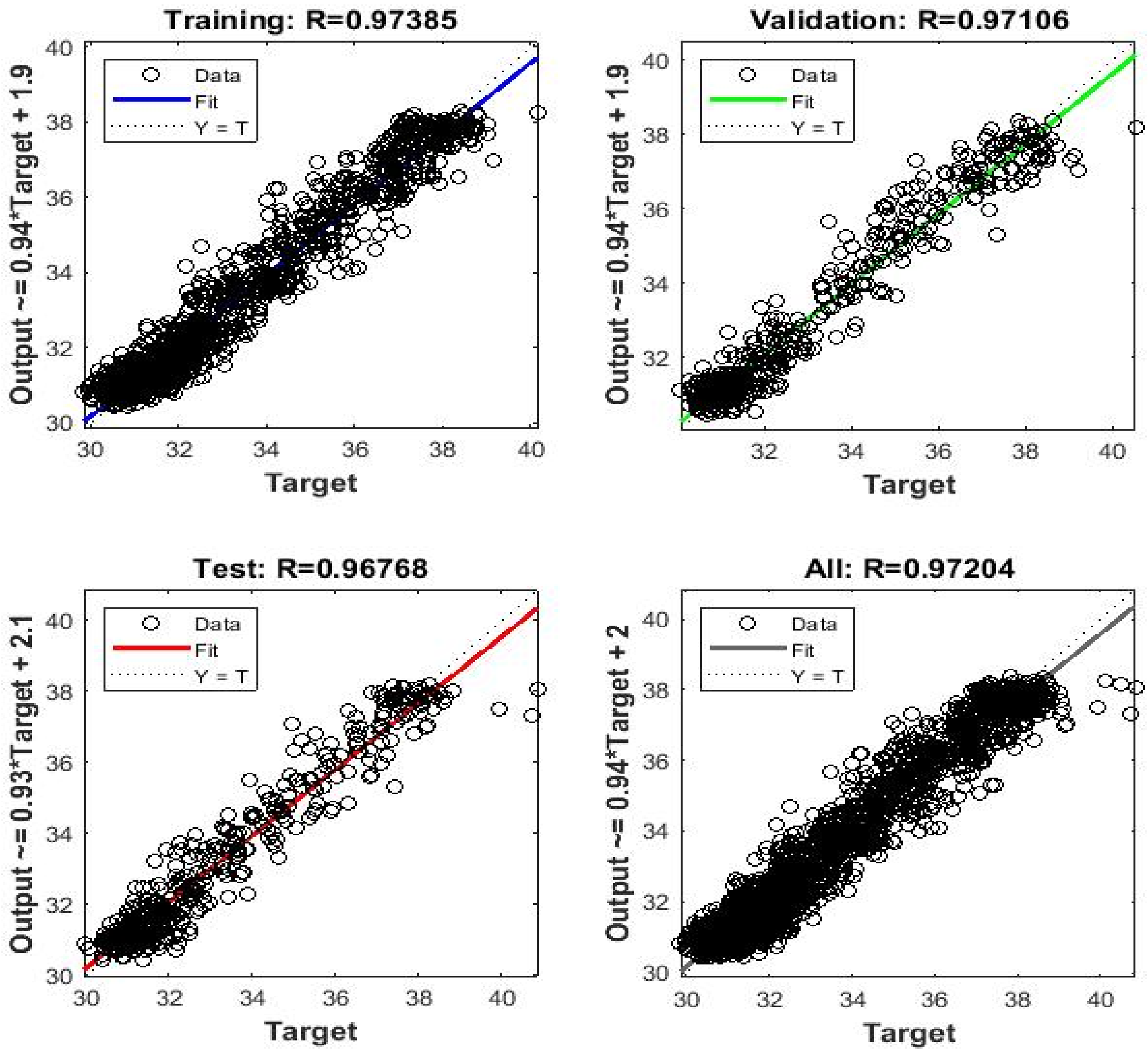

Figure 5: ANN Regression Analysis of Outputs and Targets for Upper Niger 1 Data Using MATLAB Software

4.6 Comparative Performance

Satellite Altimetry, ANN and Regression models have been employed to study water level variations in river Niger axis. Altimetry data have been analysed using the aforementioned models and results obtained have succinctly been presented in this chapter. It must be noted that River Niger coastal region of Nigeria was chosen to represent the River Niger. Hence, detailed results and discussions were centred on these localities.

Table 3: Comparative Performance of ANN and Regression Models

Performance Metric	ANN Model	Regression Model	Remarks
R^2 (Goodness of Fit)	0.85 - 0.95 (High)	0.60 - 0.80 (Moderate)	ANN captures nonlinear patterns better
RMSE (m)	0.20 - 0.50 (Low)	0.50 - 1.20 (Higher)	ANN shows smaller prediction errors
MAE (m)	0.18 - 0.40	0.45 – 1.00	ANN is more precise
Bias (m)	0.01 - 0.05 (Minimal)	0.10 - 0.30 (Noticeable)	ANN is nearly unbiased
Generalization Ability	Strong	Moderate (limited to linear trends)	ANN adapts better to hydrological variability
Overall Performance	Superior	Moderate	ANN is more reliable for flood prediction

Table 3 shows that the ANN model consistently outperformed regression across all evaluation criteria. The ANN achieved higher R^2 values (0.85 - 0.95), reflecting a stronger agreement between observed and predicted water surface elevations. Regression, on the other hand, produced only moderate correlations (0.60 - 0.80), suggesting weaker explanatory capability. Error analysis further highlights the robustness of ANN. With RMSE values ranging between 0.20 - 0.50 m and MAE values between 0.18 - 0.40 m, ANN predictions were substantially closer to observed values compared to regression, which recorded RMSE values of 0.50 - 1.20 m and MAE of 0.45 - 1.00 m. Additionally, ANN predictions were nearly unbiased (Bias ≈ 0.01 - 0.05 m), whereas regression models exhibited a more pronounced bias (0.10 - 0.30 m), indicating systematic underestimation or overestimation of water levels. A key distinction lies in generalization capacity. The ANN successfully adapted to hydrological zone of Lokoja (Upper Niger 1) by effectively capturing nonlinear hydrological responses. Conversely, regression models, restricted to linear relationships, struggled to reproduce the dynamic variability inherent in the river system. These findings confirm that ANN is the superior predictive model, offering more accurate, reliable, and generalizable results for hydrological forecasting within the Niger River Basin. Its ability to minimize error and bias, while maintaining strong predictive power across diverse regions, underscores its suitability for operational use in flood monitoring and early-warning systems as shown in Table 4.

Table 4: ANN and Regression Performance Compared with Hydrological Benchmarks

Performance Metric	Standard Benchmark	ANN Model (This Study)	Regression Model	Evaluation
R^2 (Goodness of Fit)	≥ 0.80 (Very Good)	0.85 - 0.95	0.60 -0.80	ANN exceeds benchmark (Excellent); Regression meets or falls below
RMSE (m)	≤ 0.50 (Very Good)	0.20 - 0.50	0.50 - 1.20	ANN meets benchmark; Regression fails in most cases
MAE (m)	≤ 0.30 - 0.40 (Acceptable to Excellent)	0.18 - 0.40	0.45 - 1.00	ANN within benchmark; Regression exceeds acceptable limits
Bias (m)	≈ 0 (Ideal)	0.01 - 0.05	0.10 - 0.30	ANN close to ideal; Regression shows systematic error

When benchmarked against standard hydrological modeling criteria, the ANN model outperformed the regression model across all metrics. R^2: ANN consistently exceeded the ≥0.80 benchmark, achieving values between 0.85 and 0.95, while regression models fell short, often producing moderate correlations (0.60 - 0.80). RMSE and MAE: ANN maintained errors within benchmark thresholds (RMSE ≤0.50 m; MAE ≤0.40 m), whereas regression produced much higher errors, frequently exceeding the acceptable limits. Bias: ANN demonstrated minimal bias (0.01 - 0.05 m), close to the ideal zero value, while regression exhibited higher bias (0.10 - 0.30m), suggesting systematic underestimation or overestimation.

Overall, the ANN model not only meets but surpasses established performance benchmarks, confirming its robustness and reliability for hydrological applications. By contrast, regression models fail to meet benchmark thresholds in most cases, reinforcing the conclusion that ANN provides a superior predictive framework for water surface elevation modeling and flood forecasting in the Niger River Basin.

Conclusion

This study demonstrated the effectiveness of radar altimetry in predicting water surface elevation in the Upper Niger River Basin, Nigeria. By integrating multi-mission altimetry data (Jason-2, Sentinel-3, SARAL/AltiKa) with in-situ observations, water level variations were modelled using Artificial Neural Networks (ANN) and regression analysis. The findings revealed that ANN consistently outperformed regression models across all evaluation metrics, achieving higher R^2 values (0.85 - 0.95), lower RMSE and MAE, and minimal bias. These results confirm that ANN provides a more accurate and reliable predictive framework for capturing the nonlinear dynamics of river systems. The study further established that ANN models possess stronger generalization capacity across different hydrological zones, making them suitable for flood monitoring and early-warning applications. Conversely, regression models, though statistically significant, were limited by linear assumptions and exhibited systematic biases. The integration of radar altimetry with ANN therefore presents a robust pathway for enhancing flood preparedness, risk reduction, and sustainable water resource management in the Niger River Basin. Real-time integration of altimetry data with ANN models should be implemented to strengthen early-warning systems for communities along the Niger and Benue rivers.

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