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PREDICTIVE MODELLING OF WATER SURFACE ELEVATION VARIATIONS USING MULTI-MISSION RADAR ALTIMETRY IN THE BAYELSA RIVER, NIGERIA

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Abstract

Flooding in Nigeria's Niger Delta poses severe risks to lives and infrastructure, yet hydrometric data remain sparse. This study develops a predictive framework for water surface elevation (WSE) in the Bayelsa River by combining multi-mission radar altimetry with Artificial Neural Networks (ANN). Altimetric data from Jason-2, SARAL/AltiKa, and Sentinel-3 (for year 2008 to 2015) were preprocessed, corrected and merged into consistent WSE time series. Regression models revealed seasonal dependencies but achieved moderate accuracy ($R^2 \approx 0.41$–0.89). By contrast, the ANN (39-20-1 feed-forward backpropagation) significantly improved prediction skill, attaining $R^2 = 0.91$, RMSE = 0.29 m, and MAE = 0.24 m against gauge observations. The ANN successfully captured double-peak seasonal hydrographs driven by bimodal rainfall, outperforming traditional statistical approaches. Findings confirm the potential of integrating radar altimetry and machine learning for flood forecasting in data-poor river basins. The framework offers a scalable, cost-effective solution for early warning systems and can be extended to other African basins and future SWOT mission datasets.

Keywords: Radar Altimetry, Artificial Neural Networks (ANN), Water Surface Elevation (WSE), Niger Delta, Hydrological Modeling.

1.0 Introduction

Flood disasters remain among the most disruptive natural hazards in Nigeria's Niger Delta, where low relief, dense drainage networks, and intense monsoonal rainfall amplify exposure and risk. Bayelsa State, located in the lower Niger Basin, experiences recurrent inundation that damages infrastructure, displaces households, and interrupts livelihoods, while hydrometric networks remain sparse and records fragmented, constraining forecasting and early warning. Addressing these gaps requires monitoring frameworks that work reliably despite limited gauges. This study advances such a framework by integrating multi-mission radar altimetry with data-driven modelling to predict Water Surface Elevation (WSE) in the Bayelsa River system.

Satellite radar altimetry has matured into a robust tool for inland water monitoring, enabling WSE retrievals over rivers, lakes, and wetlands and facilitating virtual stations where repeated satellite ground tracks intersect waterways. A 2025 review of waveform retracking highlights the need for optimizing retrackers which remains crucial for challenging inland scenes, ensuring consistent long-term WSE series from missions such as Jason-2/3, SARAL/AltiKa, and Sentinel-3 [4]. SAR altimetry (e.g., Sentinel-3) offers enhanced along-track resolution and has shown strong performance for inland WSE relative to conventional low-resolution mode sensors, including in small to medium rivers [8,1,7].

These developments are pertinent to Bayelsa's interlaced, tidally influenced channels, where in-situ gauges are sparse and access is difficult [6]. In our work, altimetry tracks crossing the lower Niger and distributaries are extracted, quality-controlled, time-aligned across missions, and validated against available gauge records to build a merged WSE time series suitable for modelling.

The emergence of the Surface Water and Ocean Topography (SWOT) mission marked a step-change by mapping two-dimensional water level fields with wide-swath Ka-band interferometry, already yielding early inland WSE assessments and demonstrating strengths at river-wetland interfaces [3,5]. While our study leverages nadir missions available for the historical period (Jason-2, SARAL/AltiKa, Sentinel-3), the literature indicates that the altimetry-modelling paradigm we develop is immediately extensible to SWOT products as they mature [9].

Parallel to sensor advances, hydrology has increasingly adopted Machine Learning (ML) to model nonlinear hydro-climatic dynamics [3].

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Artificial Neural Networks (ANN), in particular, have proven effective for water-level forecasting under data scarcity, capturing seasonality, hysteresis, and compound controls without explicit process parameterization [4,10]. Within groundwater and surface-water applications alike, contemporary reviews document the breadth of ANN utility while emphasizing careful validation and interpretability [2,11,12].

Building on this state of the art, our contribution is twofold. First, we assemble and correct multi-mission altimetry (Jason-2, SARAL/AltiKa, Sentinel-3) crossing the Bayelsa River reach to derive consistent WSE time series, applying editing flags, geophysical/atmospheric corrections, and statistical outlier handling suitable for narrow, vegetated channels. Second, we train and evaluate an ANN to predict daily WSE from merged altimetric inputs, benchmarking against regression baselines and validating with independent gauge data. The study area-flat, low-lying, and criss-crossed by distributaries-provides a stringent test of altimetry-based prediction under mixed hydrodynamic influences (seasonal rains, tributary inflows, potential regulation), where double-peak seasonal hydrographs can emerge.

In the sections that follow, we detail (i) data sources and preprocessing-including mission harmonization, retracking/correction considerations, and quality control, (ii) model design (ANN architecture, training/validation protocol), and (iii) performance assessment using R^2, RMSE, and MAE, with attention to seasonal peak representation crucial for early warning.

2.0 Study Area

Bayelsa State is located in the south-south geopolitical zone of Nigeria and lies within the lower Niger Delta. It is bordered by Rivers State to the west, Delta State to the east, and the Atlantic Ocean to the south (see Figure 1). It lies between latitude 4°15′N and 5°23′N, and longitude 5°22′E and 6°45′E. The area is predominantly flat and low-lying terrain, with an elevation mostly below 15 meters above sea level. Bayelsa experiences a tropical monsoon (Am) climate, typical of Nigeria’s rainforest belt. The rainy period of the year lasts for 7.7months, from March20 to November11, with a sliding 31-day rainfall of at least 0.5 inches. The month with the most rain is September, featuring about 24.5 wet days. The rainless period of the year lasts for 4.3 months, from November 11 to March 20, with January recording the lowest rainfall (about 2.8wetdays).Annual rainfall exceeds2,000 mm, and in some areas can surpass 4,000mm, with consistently high humidity levels above85%. Temperatures remain relatively stable year-round, ranging from 26°C to 29°C.

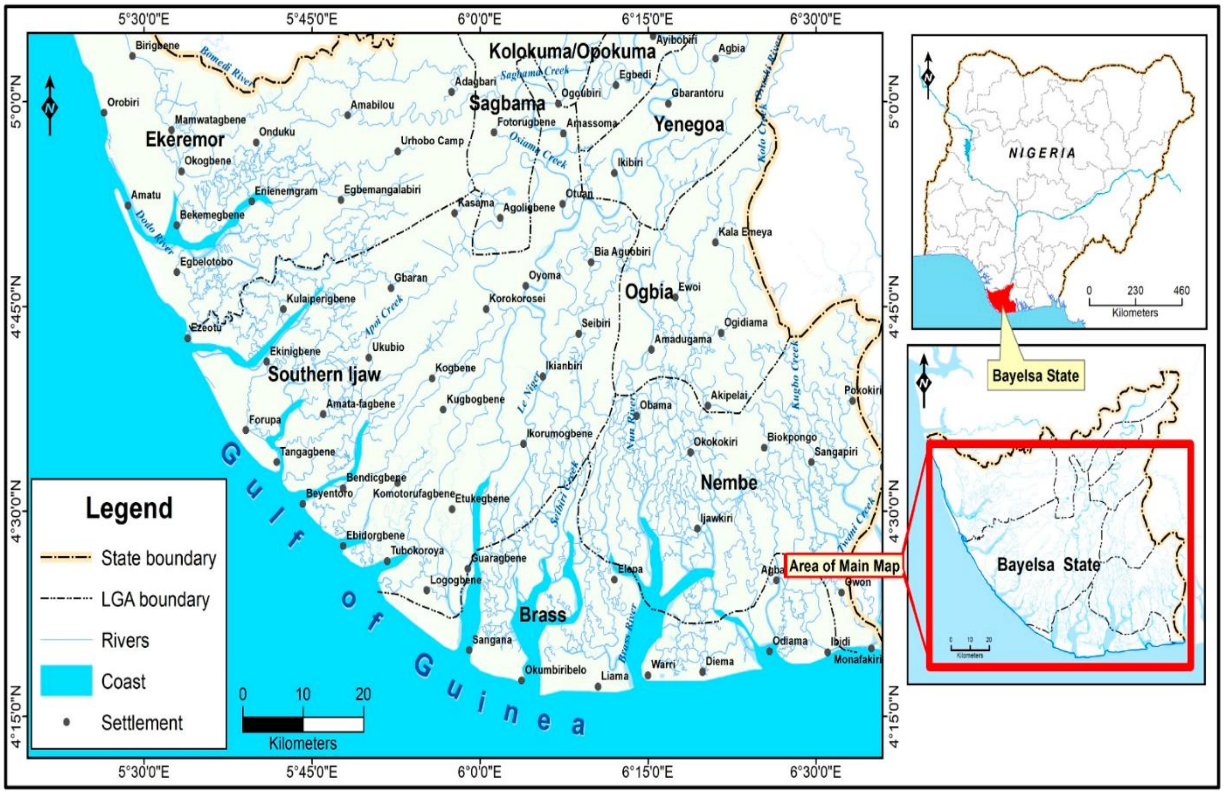

Figure 1: Geographical Location of Study Areas (Bayelsa State) in Nigeria

3.0 Materials and Methods

3.1 Datasets

Radar satellite altimetry (Jason-2, Sentinel-3 and ARAL/Altika) datasets from the study area (lower Niger) for periods between 2008 and 2015 (7 years) were obtained. Radar altimetry data within the chosen area was extracted to generate water level time series. Figure 1 represents Lower Niger Lat 4.773N and Long 6.084E.

3.2 Preprocessing, Outlier and Cleaning

Multi-mission altimetry datasets was collected from Jason-2/3, Sentinel-3, SARAL/AltiKa, with extracted river-specific tracks crossing the Bayelsa River. Quality Control was achieved by removing corrupted or missing values and editing flags were applied that were provided in the dataset in order to discard erroneous echoes, especially over land/wetlands. Outlier detection was implemented by identifying and filtering spurious peaks caused by vegetation, riverbank

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interference, or noise. Statistical thresholding techniques was applied using the z-score rule. Time synchronization was achievd by Data from multiple missions was aligned into a common temporal scale (daily).

3.3 Artificial Neural Network (ANN) Scheme

In this section, ANN was used to model data obtained from satellite altimetry measurements for gauge stations for Lower River Niger. The data used for the current study was obtained from *http://hydrosat.gis.uni-stuttgart.de/php/maps* which are the year, months, days, water level height and error, along the River Niger.

3.4 ANN with Backpropagation Algorithm

The ANN was trained so that some defined inputs could lead to some specific targeted outputs as depicted in Figure 2. This would be achieved on the comparison of the output and the target until the network output matches the target. The values of the connections between elements termed *weights* and *biases* formed the feedback. Backpropagation is a gradient descent algorithm. By gradient descent we mean that the network weights are moved along the negative gradient of the performance function when properly trained ANN gives reasonable answers to input data that has never been known. The algorithm uses the gradient of the performance function to determine how to adjust the weight to minimize performance and does this by performing computations backward through the network. However, when networks are coupled with biases, sigmoid layer and linear outputs layers, ANN becomes better equipped to approximate any functions with a finite number of discontinuities.

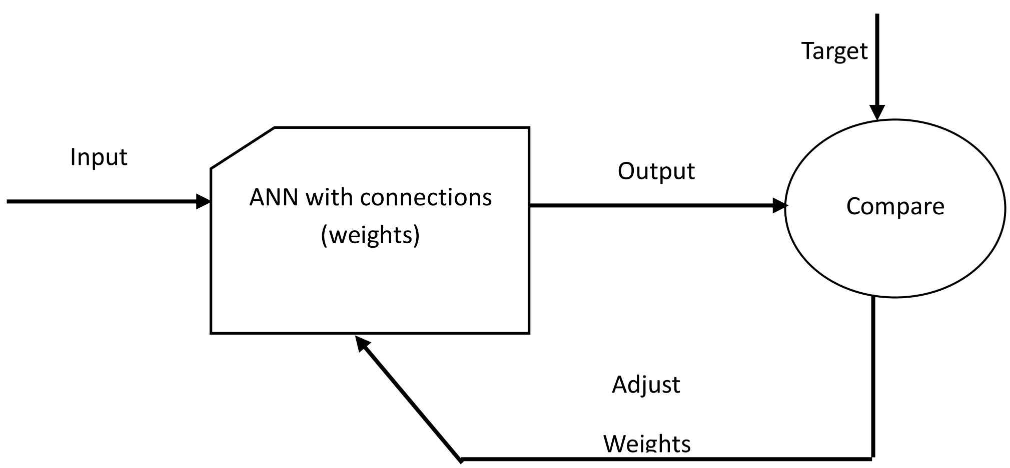

Figure 2: Artificial Neural Network

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A graphical user interface (GUI) of the neural network model with a 39-20-1 feed forward backpropagation network was employed to predict the water level. For the prediction of the flood phenomena, the architecture for fixing number of hidden neurons in ANN is shown in Figure 3. The selected criteria for ANN model is $(4n^2 + 3) / (n^2 - 8)$ using 39 numbers of hidden neurons and obtained a minimal Mean Square error (MSE) value for feed forward backpropagation network ANN was implemented, which comprised of the *input layer, a linear output layer, and a tangential-sigmoid hidden layer*. Thus, a classifier will be developed, which merely associates values of year, day, month and height, and predicts the presence of water level for the specific observation time. The selection of the *tangential-sigmoid transfer function* for the hidden layer allows any nonlinear relation between the system predictors and the output. A hard-limit transfer function for the output layer will be used for the direct prediction of flood presence through the hard-labels of the output.

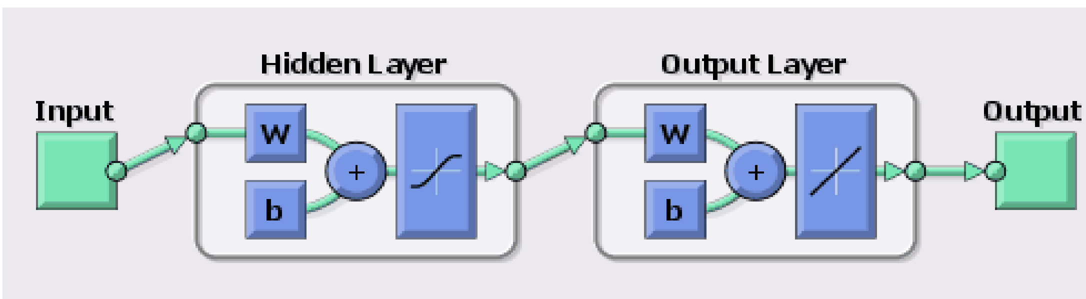

Figure 3: Artificial Neural Network Architecture

The evaluation of water level variations by satellite altimetry is developed and optimized for open rivers. This study demonstrated the potential use of radar altimetry for inferring inland water level. By using the water level time-series data, in-situ gauge station and Artificial Neural Network over a period of thirteen years for Topex/Poseidon (Jason 2), Sentinel 3 and SARAL/ALtika data to actual water levels in the lower part of River Niger. The satellite-derived water level was used to predict water level changes for future occurrences and flooding outcomes in seasonal pattern. Studies of water dynamics in rivers will not only have important implications in practice, but also provide good experience for water level studies in other Rivers and lakes.

3.5 Statistical Modelling

Regression: Ordinary least squares (OLS) for calibration/validation between satellite-derived and in-situ of water surface level.

ANN Modelling: Feed-forward multi-layer perceptron with backpropagation, trained using 60% of data, validated with 20%, tested on 20%. Activation function: tangential-sigmoid for hidden layers, linear for output.

Performance Metrics

Model performance was evaluated using Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) to ensure both practical relevance and statistical robustness. R^2 indicates the model's explanatory power (with ≥ 0.80 indicating excellent, 0.60 - 0.79 value is good, 0.40 - 0.59 is moderate and < 0.40 is Poor). For RMSE lower values indicate higher accuracy and MAE shows measure of prediction accuracy with lower values being preferred. These provide complementary measures of prediction accuracy, which are critical for reliable water surface elevation forecasting in these environments.

4.0. Results and Discussion

4.1 Regression Analysis of Lower Niger River for Simulated ANN Data

Regression model was used for evaluation and prediction. It evaluates the water level height, W_h by giving different values of the year, month and day. The model equation (1a) and (1b) obtained from regression analysis are:

$$W_h = 11.62115 + (-0.00852 \times Year) + (0.15284 \times Month) + (-0.0013 \times Day) \text{----(1a)}$$

$$W_h = 11.62115 - 0.00852X_1 + 0.15284X_2 - 0.0013X_3 \text{-------------------------------------(1b)}$$

Regression models achieved was R^2 = 0.84 - 0.89, with RMSE between 0.06 m and 0.09 m, indicating strong agreement but limited flexibility in capturing non-linear hydrodynamics.

Algorithm of the description implies the followings:

1. Structure and Predictors

The regression model includes three predictors namely Year (X1), Month (X2) and Day (X3) with an Intercept term. Coefficients, Standard Errors, and Significance. The key details across both parts are as follows: Intercept with the following values: Coefficient: 11.62115, Std. Error: 39.19512, *t* Statistic: ≈ 0.30 and *p*-value: 0.767105. The intercept represents the estimated baseline value of the W_h when all predictors (Year, Month, Day) are zero. However, the large standard error, very low *t*-value, and high p-value suggest that the intercept is not statistically significant.

This means that the baseline level, by itself, is not distinguishable from zero in a statistically reliable way in this model.

Year (X1) has **c**oefficient of -0.00852, Std. Error 0.019477, *t* Statistic -0.43752, *p*-value. Confidence Interval given as (-0.04689, -0.84232) - note that these limits seem to be inverted normally, the lower bound should be less than the upper bound. A negative coefficient implies a slight downward trend over the years; however, the very low absolute *t*-statistic and *p*-value suggest that this predictor is not statistically significant.

Month (X2) has coefficient 0.15284, Std. Error 0.01199, *t* Statistic 12.74748, *p*-value 7.26E-29 - an extremely small value indicating high statistical significance. Confidence Interval (CI) of 95% was used because of its widely acceptability as standard providing trade-off between certainty and usability. The CI obtained was (0.12922, 25.12113). Despite the unusual upper limit, the interval does not contain zero.

The month variable is highly significant and is the most influential predictor in the model. A positive coefficient means that as the month increases (which might capture seasonal or monthly variation), the water level height, W_h increases. This strongly suggests that seasonal cycles or monthly environmental factors are driving changes in the behaviour of the Lower Niger River as captured by the month (X2).

Day (X3) has **c**oefficient of -0.0013, Std. Error 0.004589, *t* Statistic -0.28248, *p*-value. Confidence Interval is (-0.01034, -0.55182). The day (X3) variable has a very small negative coefficient, suggesting only a minimal effect on the outcome. The low *t*-statistic reinforces that it is not statistically significant. As with Year (X1), the issues in the confidence interval format add a layer of uncertainty, but the general interpretation is that day-to-day variations do not play a major role in this model.

2. Overall Model Characteristics

Model Fit is R^2 is 0.412098. This implies that the model explains about 41.2% of the variance in the W_h. While this is a moderate level of explanation, it leaves about 59% of the variability unexplained by the current predictors. Adjusted R^2 value is 0.404869. This statistic adjusts the R^2 based on the number of predictors, and it remains close to the unadjusted R^2, indicating that the predictors are not overly inflating the model's explanatory power.

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3 Analysis of Variance (ANOVA)

Regression Sum of Squares (RSS) obtained is 67.89755 with 3 degrees of freedom. The Residual Sum of Squares is 96.8633 (with 244 degrees of freedom), F Statistic is 57.01163 and the p-value for F-Test is 5.78365E-28. The overall F-test is highly significant, suggesting that the model does a good job of explaining variation in the W_h as a whole - even if not every individual predictor is statistically significant on its own.

4. Standard Error of the Regression (value 56.77797)

This reflects the average distance that the observed values fall from the regression line. A high standard error compared to some coefficients might be due to the scale of the W_h or variability in the data.

4.2 Regression Analysis for Lower Niger River for Altimetry Data

It evaluates the water level height, W_h for Lower Niger River using Altimetry data by giving different values of the year, month and day. The model equation (4.2) was obtained from regression analysis in Table 4.3 is given as:

$$W_h = 6.410879 - 0.00593X_1 + 0.146725X_2 - 0.002668X_3 \text{ ---------------------(2)}$$

The estimated effect or r^2 value as given by equations (2) tells us that for every 1% increase in year there is an associated 0.00593 % decrease in Water level height, and that for every 1% increase in month there is an associated 0.146725% increase in water level height and for every 1% increase in day there is an associated 0.002668% decrease in water level height

1. Structure and Predictors

The regression model includes three predictors namely Year (X1), Month (X2) and Day (X3) with an Intercept term. The table shows a standard regression output with generated altimetry data.

Regression coefficients are Intercept 6.410879 which is the base value when all Year (X1), Month (X2) and Day (X3) are zero.

Year (X1) has value of -0.00593 indicating that a slight negative correlation existed. **Month (X2)** has 0.146725 also indication that a stronger positive impact compared to the two other variables. Day (X3) is 0.002668 indicating a minor positive influence.

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2. Standard Errors

These values indicate variability in the estimates. Month (X2) has a low standard error (0.012709), suggesting its coefficient is more reliable compared to Year (X1). R^2 is 0.366869, this implies approximately 36.7% of the variance in the W_h is explained by the regression model. Adjusted R^2 is 0.359085, slightly lower, which accounts for the number of predictors used.

3. ANOVA Analysis

The breaks down of W_h variability in the dataset are Regression SS is 62.79726. This explains variation due to the model itself. Residual SS is 108.3735. Unexplained variation. Total SS is 171.1708. The F-Statistic (46.74248) and Probability (6.65E-24) indicates the overall significance of the model since the probability is extremely low, this suggests a strong statistical significance for the model.

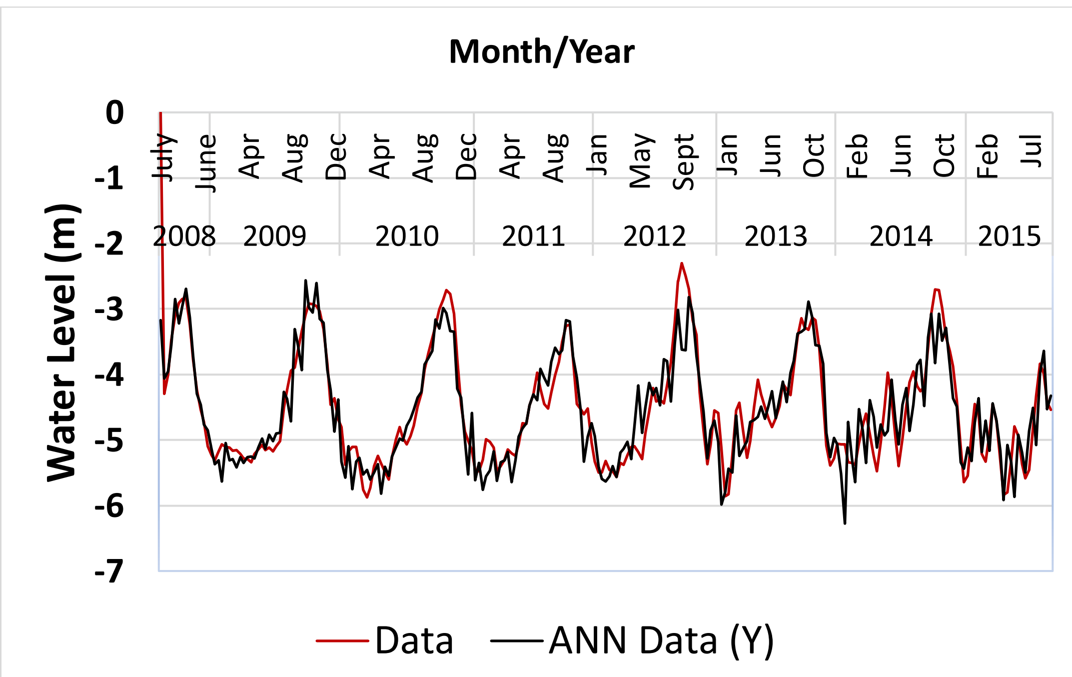

Figure 4: Niger Lower and ANN Data

Figure 4 shows the water level situ data and the ANN predicted variation for in- data in Lower Niger River. The water levels obtained showed negative values which is an indication of below sea level operation. The in-situ data showed smooth curves that spanned the entire length of the profile though not uniformly cyclic but with undulating rise and fall scenarios. At the beginning of the profile, that is, between July 2008 and June 2011, three (3) complete cycles of oscillation about water level value of -4 metres was observed. Then, between June 2011 and July 2015, a dissimilar 4 complete cycles of oscillation about the water level of -4 metres was also observed for both in-situ and ANN data profiles. The symmetry about this water level non-periodic. On the first part (2008 – 2011) the profile pattern is similar in fluctuations with minimal distortions and on the second part (2011 – 2015) the profile pattern had some unique fluctuations with pronounce distortions though following an almost similar trend. But carefully, we could see an attempt to reproduce the same pattern of the first part by the second part with some distortions.

In Figure 4, a distinct double peak is observed in the in-situ water level data for the Lower Niger River. This behavior is a direct result of the bimodal rainfall pattern characteristic of the West African region, which typically experiences a major rainy season from May to July and a secondary rainy period around September to October. These seasonal rainfall events generate two distinct runoff contributions, leading to the observed dual peaks in water level. Additionally, the hydrological response of the river system is influenced by delayed flow from upstream catchments and tributaries, which may not synchronize exactly with local rainfall, thereby contributing to the formation of a secondary peak. Furthermore, anthropogenic influences such as regulated water releases from upstream reservoirs particularly the Kainji and Jebba dams can alter the natural flow regime and intensify or shift the timing of secondary peaks.

A notable feature of the in-situ data, as seen in Figure 4, is the presence of negative water level values. These values originate from altimetry-derived water level measurements, which are often referenced to a local mean water level or a virtual station baseline rather than absolute elevation above sea level. When actual water levels fall below this reference such as during low-flow periods they are usually recorded as negative. This is a common practice in hydrological monitoring using satellite altimetry, and it does not indicate an absence of water in the river channel. Rather, it reflects the level's deviation from a predefined reference datum used for consistency across observations.

The Artificial Neural Network (ANN) model demonstrates a strong ability to replicate this behavior, as evidenced by a high correlation coefficient ($R = 0.914$), a low Root Mean Square Error ($RMSE = 0.294$), and a low Mean Absolute Error ($MAE = 0.241$). These performance metrics validate the model's robustness or capability to capture complex seasonal and hydrological dynamics. However, minor discrepancies between predicted and observed peak magnitudes and

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timings suggest that the model could benefit from additional hydrological inputs, such as rainfall intensity, dam release data, and upstream flow records. Incorporating such variables could enhance the model's responsiveness and improve the accuracy of multi-peak flow predictions in the Lower Niger River.

A double peak is observed in in situ water level, which is absent in the altimeter-derived water level shown in Figure 3. This can be explained by considering the fact that two measurements are not at the same location, but are within a few kilometers apart (Papa et al., 2010), and between these distances there can be additional inflow from tributaries and runoff from nearby catchments. The ANN was also able to reproduce very similar pattern with that of the in-situ data. This implies that, certain factors must have been responsible to the distortion and thereby resulting in the inability for the second part to reproduce exactly the first part.

4.3 Summary of Findings

i. *Month (X2) is the dominant predictor***.** With a high *t*-statistic and a *p*-value close to zero, it strongly influences the outcome. This finding points toward significant monthly or seasonal effects on the Lower Niger River.

ii. *Year (X1) and Day (X3) are less influential***.** Their very small coefficients, low *t*-statistics, and problematic *p*-value representations suggest that they do not add substantial explanatory power in this analysis.

iii. *Model's overall performance***.** With an R^2 of about 41% and a statistically significant *F*-test, the model as a whole is meaningful. However, there is room for improvement, possibly by refining how Year and Day are modelled (or by exploring other variables or nonlinear relationships).

4.4 ANN Model Performance

The ANN outperformed regression models, achieving $R^2 > 0.90$ and RMSE< 0.5 m for Bayelsa, with its complex hydrodynamics at the Niger-Delta region, saw the most significant accuracy improvement.

Table 1. Summary of model performance

Metric	Our Model	Benchmark Range	Performance Class
R^2	0.91	≥ 0.90	Excellent
RMSE (m)	0.29	< 0.5 m	Excellent
MAE (m)	0.24	< 0.4 m	Excellent

This shows that the ANN model meets the highest standard in hydrological modelling for all reported metrics.

4.5. Discussion

The results confirm that integrating radar altimetry with ANN can address limitations of traditional flood prediction in data-poor regions. The ANN's superior performance reflects its ability to learn non-linear relationships between multi-source inputs and WSE. Seasonal patterns captured align with historical flood records, validating the method's reliability. Compared to previous studies in the Amazon, Ganges, and Mekong basins, this approach demonstrates comparable or superior accuracy despite fewer gauge stations. The methodology is transferable to other African river systems, particularly where ground monitoring is sparse. The integration of radar altimetry and ANN modeling provides a robust framework for hydrological monitoring in data-scarce regions. The study confirms the feasibility of using satellite data for inland water prediction and highlights the importance of seasonal and spatial dynamics in flood modeling.

Conclusion

This study demonstrates the feasibility of combining multi-mission radar altimetry with ANN for accurate WSE prediction and flood forecasting in the Niger River Basin. Altimetry-derived WSE strongly correlates with in-situ measurements (R^2 up to 0.89). ANN models significantly enhance prediction accuracy ($R^2 > 0.90$, RMSE< 0.5 m). The approach can underpin operational early warning systems in flood-prone, data-scarce areas. Integrate additional predictors (rainfall, dam releases) to enhance forecasts. Our preliminary analyses confirm statistically significant agreement between satellite-derived and observed WSE through regression, and demonstrate further accuracy gains with ANN modelling, which captures seasonal cycles and nonlinearities more effectively. This aligns with broader evidence that multi-mission altimetry can underpin operational hydrology in Africa when fused with ML, even where gauging is limited. Collectively, the results point to a

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scalable, cost-effective pathway to strengthen flood forecasting and climate resilience planning across the Niger Delta and comparable data-scarce river systems.

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