

Spatiotemporal Precipitation Trends and Hybrid Machine Learning Prediction in the Humid Rainforest Climatic Zone of Nigeria

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ABSTRACT

This study investigated the spatiotemporal trends and hybrid machine learning prediction of precipitation in Nigeria's humid rainforest climatic zone using 45 years (1981–2025) of monthly rainfall data from Calabar, Yenagoa, Benin City, and Ikeja. Data obtained from the NASA POWER database were analyzed using statistical, spatial, and machine learning techniques. The Mann–Kendall test and Sen's slope estimator assessed the significance and magnitude of rainfall trends, while Kernel Density Estimation (KDE) and spatiotemporal analyses evaluated spatial variability. Hybrid machine learning models, Random Forest–Support Vector Regression (RF–SVR) and Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM), were employed for precipitation prediction. Model performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Results revealed decreasing but non-significant rainfall trends at Calabar, Yenagoa, and Ikeja, while Benin City exhibited a significant increasing trend. Spatial analysis demonstrated considerable variability in precipitation characteristics across the study area. RF–SVR outperformed CNN–LSTM, with RMSE values of 0.1765–0.4608 and MAE values of 0.1433–0.3658, compared with RMSE values of 1.5639–1.7747 and MAE values of 1.2868–1.5055 for CNN–LSTM. CNN–LSTM forecasts for 2026–2035 indicated decreasing precipitation at Calabar, Yenagoa, and Ikeja, but an increasing trend at Benin City. RF–SVR predicted decreasing precipitation at Calabar, relative stability at Yenagoa, moderate variability at Benin City, and substantial interannual variability at Ikeja, without a significant long-term decline by 2035. These findings highlight rainfall variability as an important concern for agriculture, water resources, food security, and sustainable development in Nigeria's humid rainforest zone.

Keywords:

Spatiotemporal trends,
Humid Rainforest Zone,
Machine Learning Prediction,
Precipitation.

INTRODUCTION

The humid rainforest climatic zone in Nigeria, which includes the coastal states of Lagos, Ogun, Ondo, Edo, Delta, Bayelsa, Rivers, Cross River, and parts of Akwa Ibom, is characterized by high annual rainfall >2000mm, high humidity, and dense vegetation (Adejuwon, 2012). The zone supports agriculture, fisheries, forestry, and large urban populations, making it extremely sensitive to changes in rainfall patterns.

Studies in Nigeria show that rainfall in the southern humid zone has become increasingly variable over the

last 5 decades. Olaniran (2002) noted that rainfall anomalies in Nigeria are driven by shifts in the Inter-Tropical Convergence Zone (ITCZ) and ocean-atmosphere interactions, leading to more frequent floods in wet years and drought stress in dry years. Similarly, Abaje *et al* (2014) observed that extreme rainfall events in southern Nigeria have intensified, causing soil erosion, flooding, and loss of nutrients from farmlands. At the regional level, Akinsanola and Ogunjobi (2017) analyzed rainfall variability from 1981–2015 and reported significant spatiotemporal differences, with coastal areas

experiencing more intense rainfall events compared to inland areas. This spatial heterogeneity implies that a one-size-fits-all approach to adaptation will not be effective for the rainforest zone. The livelihood implications are severe. In the humid rainforest, women farmers depend heavily on rain-fed agriculture and fishing (Olaniran, 2002). Flooding washes away fertilizers and topsoil, while extreme dry spells reduce crop yields and fish availability, thereby increasing food prices and reducing purchasing power.

Traditional statistical models often fail to capture the non-linear and complex interactions driving precipitation trends in tropical regions. The advent of machine learning has provided new tools for climate prediction. Tao *et al.* (2018) demonstrated that hybrid machine learning models outperformed conventional models in forecasting hydrological extremes in the Niger River Basin, including parts of Nigeria. For precipitation trends, ML techniques such as Random Forest, Support Vector Machines, and Neural Networks have shown promise in downscaling and predicting trend events at local scales where observational data are sparse.

Iyeme *et al.* (2024) investigated the long-term variations in temperature and precipitation across Nigeria's climatic zones using data from Calabar, Ibadan, Kano, and Kukawa to represent the tropical monsoon, tropical savannah, semiarid and desert climate respectively. The findings of the study revealed that precipitation trends varied by region, with Calabar showing a monthly decrease of -1.26 mm/year, while Kukawa exhibited an unexpected significant increase, which suggest potential greening in the desert.

Agbo (2025) used innovative trend analysis of precipitation changes over Nigeria a case study of locations across the Niger and Benue Rivers, analyzed the trends in 40 years (1981-2020) of total monthly and annual precipitation data from six selected locations in Nigeria, using both the Mann-Kendall (MK) and new Sen's innovative trend analysis (ITA) method. The ITA test results showed that only Kainji has an increasing trend in total annual and wet season precipitation, especially for high precipitation values, whereas other locations show decreasing trends for maximum precipitation values.

Danbatta *et al.* (2025) used hybrid time-series and machine-learning techniques to study monthly rainfall forecasts in five northern Nigerian locales. To describe the nonlinear and periodic features of rainfall, the study used Fourier-series components, polynomial functions, and artificial neural networks (ANN). The outcomes demonstrated that the hybrid machine-learning approach outperformed a number of traditional forecasting techniques. The study shows how data-driven nonlinear modelling and traditional time-series representations can be combined to estimate rainfall in areas with significant seasonal variability.

Similarly, for the purpose of predicting daily rainfall in a few African cities, including Abuja, Samson and Aweda (2025) evaluated single and hybrid deep learning models. ANN, recurrent neural networks (RNN), long short-term memory (LSTM), and combinations like RNN-ANN and LSTM-ANN were all assessed by the researchers. Their results showed that model performance differed significantly between regions, proving that no single architecture works well in all African climate conditions. The results for Abuja specifically showed how LSTM-ANN hybridization may be used to predict rainfall. This result is significant because it suggests that rainfall prediction in some West African environments could be enhanced by combining models that can learn temporal dependencies with models that can approximate nonlinear functions.

In northern tropical Africa, Walz *et al.* (2024) investigated data-driven and physics-based methods for 24-hour precipitation forecasting. Their research showed that data-driven models may produce accurate precipitation forecasts and that merging data from data-driven and physical methods might yield further gains. Because rainfall is regulated by interrelated atmospheric and oceanic processes that may not be fully captured by rainfall history alone, this development is especially pertinent to West Africa.

At the regional scale, Dioha *et al.* (2025) applied different machine-learning methods to precipitation simulations and projections across West Africa using NEX-GDDP-CMIP6 data. Their results showed that machine learning algorithms can replicate key features of observed precipitation and can be used to study future changes under various climate scenarios. However, rather than full hybrid deep-learning structures, the study mainly concentrated on specific ML methods. This suggests a chance for additional study using integrated models that take advantage of the complementing advantages of various algorithms.

Calabar, Yenagoa, Benin City and Ikeja were selected as representative meteorological stations for the humid rainforest zone of southern Nigeria based primarily on their geographical distribution, climatic characteristics and ability to capture the major west-east and coastal-inland climatic gradients within the region. While recent research has specifically used Calabar, Yenagoa, Benin City, and Ikeja to examine climate variability within the coastal rainforest environment, earlier climatological studies in Nigeria have shown the value of stations like Ikeja, Benin City, and Calabar for representing the rainforest ecological region (Obi *et al.*, 2026).

The eastern coastal region of the humid rainforest zone is represented by Calabar, which has a humid tropical climate and comparatively high annual rainfall, both of which are indicative of considerable maritime impact. Yenagoa is representative of the central Niger Delta area, where the lowland rainforest ecosystem is characterized

by high atmospheric moisture and significant yearly rainfall. Benin City serves as a helpful contrast to the more heavily marine areas and represents the inland portion of the rainforest belt. The western part of the humid coastal rainforest habitat is represented by Ikeja, which is situated in southwest Nigeria. As a result, the four stations offer a geographically dispersed network that covers the study region's western, central-inland, central-delta, and eastern regions. Their combined spread makes it more difficult to describe the climate of the humid rainforest from a single localized station and makes it possible to look at common temporal patterns and spatial variations in rainfall.

Despite the advances in machine learning, there is limited application of hybrid machine learning models specifically for predicting precipitation trends across the humid rainforest climatic zone of Nigeria. Most existing studies have focused on national or Sahelian trends, leaving a gap in high-resolution, zone-specific projections.

Most studies on precipitation trends in Nigeria are national in scope or focused on the northern regions. Few have isolated the humid rainforest zone for detailed spatiotemporal analysis. Application of hybrid machine learning for predicting precipitation trends is still limited in Nigeria's coastal rainforest, despite its demonstrated success in the Niger Basin and globally. There is inadequate integration of extreme rainfall indices with ML-based projection for 2021-2050 to support local adaptation planning. This gap justifies the need for the present study on spatiotemporal trend and machine learning prediction of precipitation across the humid rainforest climatic zone of Nigeria.

MATERIALS AND METHODS

This study employed a combination of non-parametric statistical methods (Mann-Kendall test and Sen's slope estimator), hybrid machine learning models (RF- SVR and CNN- LSTM) to analyze and predict precipitation extremes across Nigeria. While model performance was evaluated using MAE, RMSE, and R^2 . Microsoft Excel software was used. Data visualization was carried out by the python programming language. All graphical representation and some statistical analyses were implemented. Packages in python programming like sklearn, seaborn, matplotlib, etc, were utilized for representations including box plots.

The Mann Kandal Trend Test

The Mann-Kendall (MK) test is a robust test that determines whether a time series data has a substantial

monotonic upward or downward trend. Since it is a non-parametric test, data does not need to meet the assumption of normality. The test is also less sensitive to sudden breaks instigated by non-homogenous time series. This test is based on two hypotheses: the null hypothesis (H_0) which indicates no trend (no change in the series mean) and the alternative hypothesis (H_1) which indicates the presence of a monotonic trend (a rise or decrease in the mean over time). The Mann-Kendall test uses the time series of n data points and considers x_i and x_j as two data subsets where $i = 1, 2, 3, \dots, n-1$ and $j = i + 1, i + 2, i + 3, \dots, n$. Data values are evaluated as an ordered time series. Each data value is compared to the subsequent data values. If the data value of a subsequent period exceeds that of the previous period, the S statistic is increased by one. In contrast, S is reduced by one if the data value of a subsequent period of time is less than a previously sampled data value. The total of all these increments and decrements yields the final value of S (Drapela & Drapelova, 2011). The Mann-Kendall test statistic (S) is thus, calculated as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n s_i(x_j - x_i)$$

A positive value of S implies an upward trend, while a negative value signifies a downward trend (Silver & Lundquist, 2025). If the time series is sufficiently long (number of data values, $n \geq 10$), the S statistics behave essentially normally, and the test is done using a normal distribution with the mean $E(S)$ and variance $V(S)$ as indicated in eqn(3) and eqn(4).

The Non-Parametric M-K Test

The S statistics is usually used for a time series having below 10 data points calculated statistically as (Kisi & Ay, 2014).

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(x_j - x_k) \quad (1)$$

Where;

$$\text{sgn}(x_j - x_k) = \begin{cases} +1; & \text{if } (x_j - x_k) > 0 \\ 0; & \text{if } (x_j - x_k) = 0 \\ -1, & \text{if } (x_j - x_k) < 0 \end{cases} \quad (2)$$

n here is the number data values studied in the series, for this study that number is 45 years. If n is 45 or more like in this case, the normal approximation is used (the Kendall Z -value). To get this value, we need to calculate the variance of S ($VAR(S)$) (Chattopadhyay, *et al.*, 2016)

$$VAR(S) = \frac{1}{18} [n(n-1)(2n+5) \sum_{p=1}^g t_p - (t_p-1)(2t_p+5)] \quad (3)$$

The equation takes into account the several tied values (equal values); n is the number of data values, g here is representing the number of these equal trend values or

$$Z = \frac{S-1}{\sqrt{\text{VAR}(S)}}; \quad S > 0; \quad S = 0 \frac{S+1}{\sqrt{\text{VAR}(S)}}; \quad S < 0 \quad (4)$$

We have a decreasing trend if Z is negative and an increasing trend if Z is positive.

Slope Estimator

Sen (1968) derived a method for the estimation of the Kendall Tau. Kendall Tau is a non-parametric measure of the strength and direction of a monotonic relationship (trend), it shows how well data are increasing or decreasing trend over time. This method has its application in the estimation of the slope of a linear trend, which arises from a linear equation as;

$$f(t) = Qt + B \quad (5)$$

Here is a function of time which represents the time series, which can be increasing or decreasing, t is the date (time) values, B is a constant and Q is the slope. Q can be gotten by the equation.

$$Q_{i=\frac{j-k}{j-k}}$$

Here at time j and k , $j > k$ and $i = 1, 2, \dots, N$, the values of the data pairs are represented by and we can determine the median of the N values of Q_i by (Atta-ur and Dawood, 2017);

$$Q = \begin{cases} Q_{[(N+1)/2]} & \text{if } N \text{ is odd} \\ 1/2 [Q_{[N/2]} + Q_{[(N+2)/2]}] & \text{if } N \text{ is even} \end{cases} \quad (6)$$

When the value of Q_i is positive, one can discern that there is an increasing trend, and similarly a decreasing trend shows that the value of Q_i is negative. No trend is indicated by a zero value.

The Kernel Density Estimator

The general form of the kernel estimator that employs the full smoothing matrix as noted by Deheuvels in 1977.

$$f(x) = \frac{1}{n|H|^{1/2}} \sum_{i=1}^n k\left(\frac{x-X_i}{H^{1/2}}\right), \quad (7)$$

where $K(\cdot)$ is a kernel function, n is sample size, H is bandwidth matrix (smoothing matrix), $|H|$ is the determinant of the smoothing matrix, x is range of the observations and X_i are the sets of observations. The bivariate kernel estimator using the product approach is

$$f(x) = \frac{1}{n h_x h_y} \sum_{i=1}^n k\left(\frac{x-X_i}{h_x}, \frac{y-Y_i}{h_y}\right) = \frac{1}{n h_x h_y} \sum_{i=1}^n k\left(\frac{x-X_i}{h_x}, \frac{y-Y_i}{h_y}\right) \quad (8)$$

where $h_x > 0$ and $h_y > 0$ are the smoothing parameters in X and Y directions, x and y are ranges of the variables in

groups, p represents the number of data values in the p^{th} group.

We can now compute the Kendall test statistics (Z -value) by adopting $\text{VAR}(S)$ and S .

the different axes and $K(x, y)$ is bivariate kernel estimator (Wand & Jones, 1995; Silverman, 2018) The multivariate product kernel of Eq. (1) with different smoothing parameter for the respective axes is given as

$$f(x) = \frac{1}{n h_1 h_2 \dots h_d} \sum_{i=1}^n k\left(\frac{x_1-X_{i1}}{h_1}, \frac{x_2-X_{i2}}{h_2}, \dots, \frac{x_d-X_{id}}{h_d}\right) \quad (9)$$

Where d represents the dimension of the kernel function.

Box plot

The box plot which is also called, box and whisker plot includes, the median, the interquartile range and the outer range. The median is the middle observation in a ranked dataset (or mean of the two middle observations for an even numbered dataset) and is a measure of the central tendency of the data, the interquartile range The box represents the middle 50% of the ranked data and is drawn from the lower quartile value to the upper quartile value (i.e., the 25th to 75th percentile). The lower (upper) quartile is computed by taking the median of the lower (upper) half of the ranked data. The whiskers represent an outer range and are drawn as vertical lines extending outward from the ends of the box.

Lower extreme/minimum ($Q_1 - 1.5 \cdot \text{IQR}$), Lower quartile (Q_1), median (Q_2), upper quartile (Q_3) and upper extreme ($Q_3 + 1.5 \cdot \text{IQR}$).

Hybrid Machine Learning Model

Hybrid machine learning is an approach that combines two or more machine learning models, statistical techniques or computational methods in to a single, framework in order to improve prediction accurately, efficiency and reliability. Instead of relying on only one model, hybrid models take advantage of the strengths of different methods while reducing their weakness.

Random Forest Support Vector Regression Model (RF-SVR)

RF-SVR is typically used to leverage the feature selection capability of random forest to enhance the predictive accuracy of SVR. RF act as a pre-processor for input variable selection, or in a stacking ensemble where RF and SVR predictions are combined, usually for time series forecasting or complex regression task.

R.F. builds a forest decision trees T and calculate the importance of variable in based on the decrease in mean

squared error (MSE) when that variable is permitted (Cherkassky & Ma, 2004).

Tree prediction $\bar{Y}_t = \text{Tree}(x)$

Trial Rf prediction (Ensemble)

$$\bar{Y}_{Rf} = \frac{1}{T} \sum_{t=1}^T 1 \bar{Y}_t$$

Variable importance (V1mm)

$$V1mm = \frac{1}{T} \sum_{t=1}^T \text{permutation error}(t, m)$$

Where higher V1mm indicates higher importance, allowing for feature pruning.

Support vector regression maps the selected features into a high-dimensional space to find a non-linear regression function $f(x)$ that fits within a ϵ -insensitive tube.

$$\min_{w, b, \epsilon, \varepsilon} \frac{1}{2} \|W\|^2 + C \sum_{i=1}^n (\varepsilon_i + \varepsilon_i)$$

$$Y_1 - 1. \emptyset(x_i) - b \leq \epsilon + \varepsilon_i$$

$$w. \emptyset(x_i) + b - Y_1 \leq \epsilon + \varepsilon_i$$

$$\varepsilon_i, \varepsilon_i \geq 0$$

Where $\|W\|^2$ is model complexity, C is the penalty parameter, ϵ is the insensitive error margin and $\emptyset$ is the kernel function.

$$f(x) = \sum_{i=1}^n (x_i + x_i) k(x_i, x) + b$$

Where; $k(x_i, x)$ is the kernel function

Rf hybrid is sometime used as an additional input feature or used in conjunction with SVR to improve results.

SVR handles complex non-linear structures well, while Rf manages features selection and reduces noise

Rf reduces overfitting by averaging and SVR optimizes for the margin, enhancing generalization

Convolutional Neural Network – Long Short Term Memory

(CNN- LSTM) is a hybrid model that combines the spatial features extraction capabilities of convolutional neural Network (CNN) with the temporal sequence modelling strengths of long short-term memory (LSTM) networks. This is designed to handle spatiotemporal data, such as video analysis, stock to recasting, or sensor data, where both spatial relationships and time base dependencies exist. CNN act as a feature extractor. They process input (e.g. image frames or time series) using convolutional and pooling layers to extract key spatial features, reducing the input dimensionality.

LSTM receive the sequence of extracted features from the CNN and learn Long Term temporal dependencies between them to predict the final output.

CNN extracts feature from the input data (or consecutive sequences) to identify patterns

$$Y_t = \sigma(W_{cnn} * X_t + b_{cnn})$$

X_t = input at time t

W_{cnn} = filter weight

$*$ = convolution operation

bccn = Bias

σ = Activation function

Y_t = Extracted spatial feature vector

LSTM, the sequence of features Y_t is passed to the LSTM. The LSTM update its memory cells to retain or forget information

Forget gate (F_t) decides what information to discard from the cell state.

$$F_t = \sigma(W_f \cdot [h_{t-1}, Y_t] + b_f)$$

Input gate (i_t) determines which new information to store in the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, Y_t] + b_i)$$

Candidate cell gate (C_t) creates a candidate for the new memory

$$C_{tt} = \tanh(W_c \cdot [h_{t-1}, Y_t] + b_c)$$

Cell states update (C_t) updates the long term memory

$$C_t = f_t \times C_{t-1} + i_t \times C_{tt}$$

Output gate (O_t) decides which part of the cells states to output.

$$O_t = \sigma(W_o \cdot [h_{t-1}, Y_t] + b_o)$$

Hidden state (h_t). The short-term memory (output)

$$h_t = o_t \times \tanh(c_t)$$

This structure allows the network to learn both, for example, the spatial arrangement of a sensor network and how the data from those sensors evolves over time.

Matrix Evaluation

Evaluation metrics are quantitative measures used to assess how well a model performs on a given task. They tell you how good (or bad) your model is at making predictions or generating outputs. We need evaluation metrics to objectively measure how well a machine learning model performs on a given task. Without them, there would be no reliable way to understand whether the model is making accurate predictions or meaningful outputs. Evaluation metrics provide a standardized way to compare different models, track improvements during training, and make informed decisions about deployment. They also help identify specific strengths and weaknesses such as whether a model is good at precision but poor at recall which is critical when optimizing for real-world use cases.

Mean Absolute Error (MAE)

MAE is a regression metric that calculates the average absolute difference between predicted and actual values is given by the formula

$$MAE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (10)$$

MAE computes the mean of the absolute differences between predicted and observed values. By eliminating

the sign of the errors, MAE provides a direct measure of the average magnitude of prediction error.

The RMSE measures the square root of the average squared differences between observed and predicted values. It gives greater weight to large errors due to the squaring process and is therefore sensitive to outliers.

The MSE quantifies the average directional deviation between predicted and observed values. It indicates whether a model systematically overestimates (positive MBE) or underestimates (negative MBE) the observations. MAE represents the average absolute difference between predicted and observed values

Mean Squared Error (MSE)

MSE measures the average squared difference between predicted and actual values. By squaring the errors, it gives more weight to larger mistakes, which makes it useful when you want to penalize big errors more. Given by

$$MSE = (1/n) \times \sum (\text{actual} - \text{predicted})^2. \quad (11)$$

A smaller MSE means better model performance.

Root Mean Squared Error (RMSE)

RMSE is simply the square root of MSE, which brings the error metric back to the same unit as the target variable. Which is given as

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}. \quad (12)$$

RMSE represents the square root of the mean of squared differences between predicted and observed values. Because of the errors are squared before averaging, RMSE gives greater weight to large deviations and is therefore sensitive to outliers.

Y is observed (measured) value at observation i , y is Predicted value at observations I , n is a total number of observations, i is index of individual observation.

Study Area

The study area covers selected locations in the humid rainforest climatic zone, including Calabar, Yenagoa, Benin City and Lagos. Nigeria is located in West Africa, lying approximately between latitudes 4°N and 14°N and longitudes 3°E and 15°E, and it exhibits strong spatial and temporal variability in climate due to its latitudinal extent and atmospheric circulation patterns (Ayoade, 2003)

The southern part of the country, including Calabar, Yenagoa, Benin City, and Lagos, falls within the humid tropical rainforest and coastal zone. This region is characterized by high annual rainfall (2000–4000 mm), high humidity, and relatively small temperature variability. The influence of the Atlantic Ocean and the dominance of the maritime tropical air mass contribute to frequent precipitation and occasional extreme rainfall events (Adefolalu 2007).

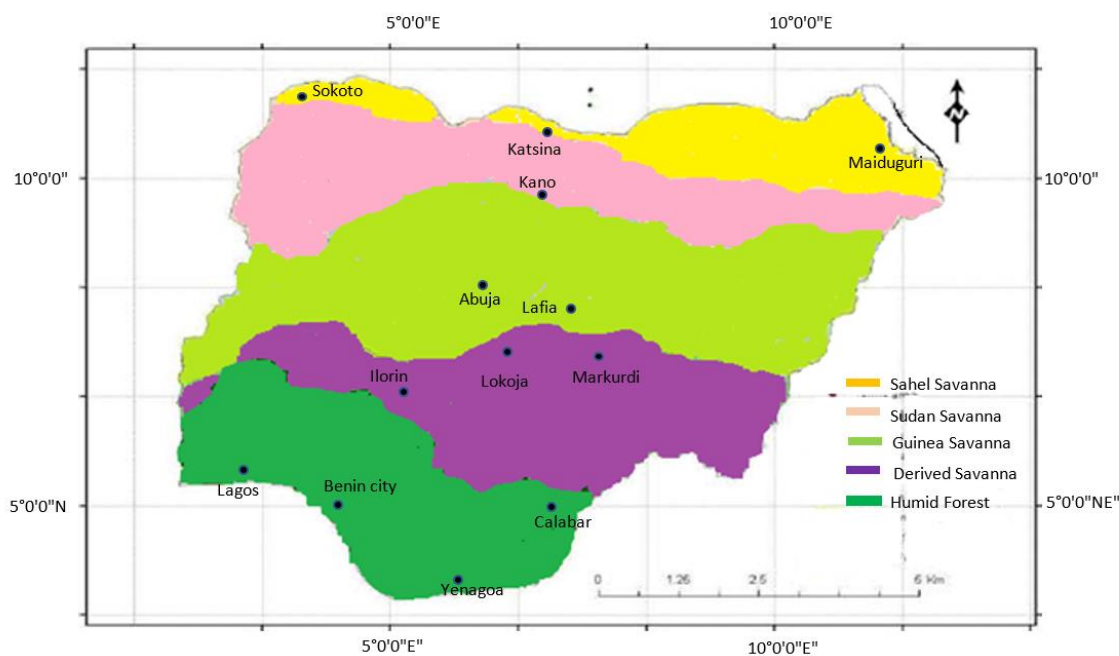


Figure 1: Map of Nigeria showing the study area, showing the various climatic zones with Humid Rainforest zone (Nicholson, 2013)

Data Source and Method of Analysis

Monthly and annual precipitation data for four (4) locations in the humid rainforest zone of Nigeria were obtained from the NASA POWER database for a 45 – year's period (1981 – 2025) for precipitation.

RESULTS AND DISCUSSION

Seasonal variation of precipitation in Humid Rainforest Zone is presented (Figure 2 – Figure 6).

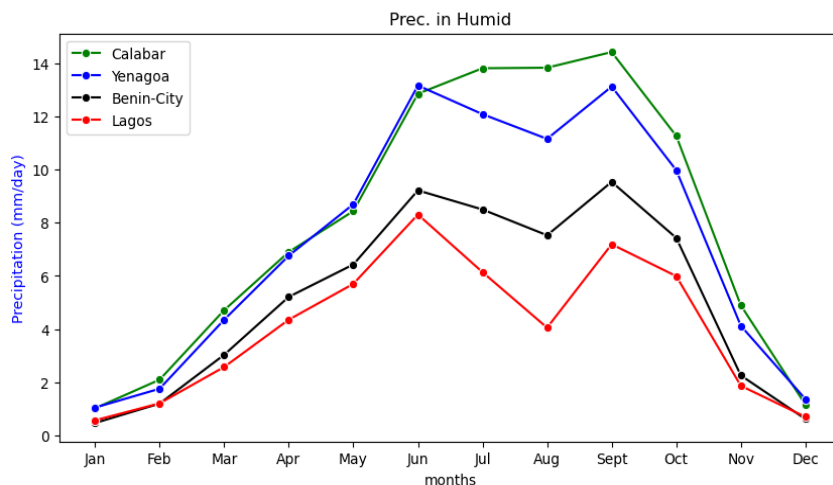


Figure 2: Monthly plot for Precipitation in Humid Rainforest Zone

Figure 2 represent the comparative seasonal precipitation distribution across Calabar, Yenagoa, Benin City, and Lagos reveals a coherent spatial rainfall structure characteristic of the humid climatic zone of southern Nigeria. The observed seasonal rainfall behaviour reflects the dominant influence of Atlantic moisture inflow associated with the southwest monsoon circulation and the seasonal migration of the Intertropical Discontinuity, which governs precipitation distribution across the region.

The rainfall distribution across all stations shows a progressive increase from the dry-season minimum in January (0.5–1.1 mm/day) to the early wet-season transition in March (2.6–4.7 mm/day) and intensifies further through April (4.4–6.9 mm/day) and May (5.7–8.7 mm/day). This consistent increase across all locations confirms the onset of southwest monsoon activity across southern Nigeria during the late boreal spring period.

Peak rainfall conditions occur between June and September across all stations, although with noticeable spatial differences in magnitude. Calabar records the highest rainfall intensities during this period, increasing from approximately 12.9 mm/day in June to a peak of about 14.5 mm/day in September, confirming its position as one of the wettest coastal locations in Nigeria.

Similarly, Yenagoa experiences strong rainfall intensities ranging between 13.3 mm/day in June and 13.2 mm/day in September, indicating persistent atmospheric moisture availability across the Niger.

Following the September rainfall maximum, precipitation decreases steadily across all stations during October (6.0–11.3 mm/day) and declines sharply toward November (1.9–4.9 mm/day) and December (0.6–1.4 mm/day), marking the seasonal withdrawal of southwest monsoon circulation

From the perspective of precipitation-extreme detection and hybrid machine-learning prediction modelling, the months between June and September represent the most critical period for rainfall-extreme characterization across all stations within the humid climatic zone. During this interval, precipitation consistently exceeds 8 mm/day across most locations, indicating the period of maximum hydro-climatic vulnerability within southern Nigeria.

The comparative precipitation structure across Calabar, Yenagoa, Benin City, and Lagos demonstrates a coherent regional rainfall regime characterized by strong wet-season persistence, a mid-season August break signature, and a pronounced eastward rainfall intensification gradient.

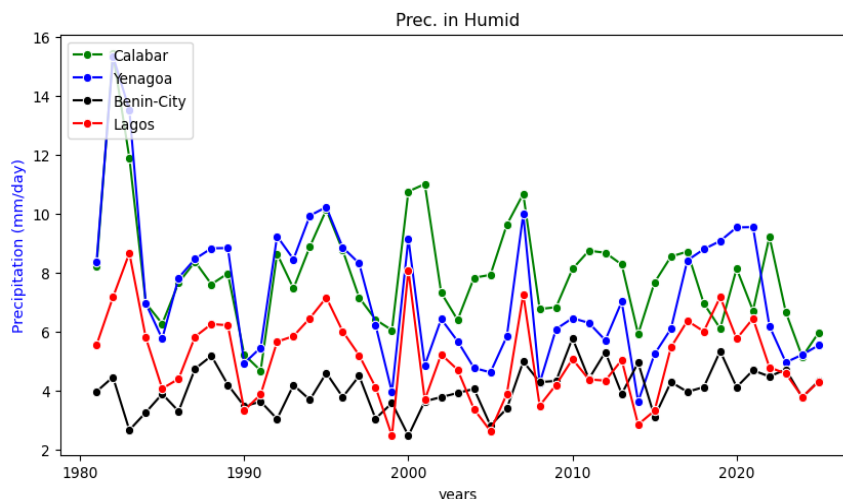


Figure 3: Annual trend of Precipitation in Humid Rainforest zone

Figure 3 show the long-term interannual variability of precipitation across Calabar, Yenagoa, Benin City, and Lagos between 1981 and 2024 reveals important spatial contrasts and temporal fluctuations that characterize precipitation behaviour within the humid climatic zone of southern Nigeria. These variations reflect the influence of southwest monsoon dynamics associated with the seasonal migration of the Intertropical Discontinuity, mesoscale convective systems, and regional ocean atmosphere interactions along the Gulf of Guinea coastline.

Across the four stations, precipitation exhibits pronounced interannual variability rather than a strictly monotonic long-term trend, indicating that rainfall behaviour within the humid coastal belt is largely controlled by seasonal monsoon strength and short-term atmospheric variability. However, clear spatial contrasts exist in rainfall magnitude and variability intensity across the study locations.

Calabar consistently records the highest precipitation magnitudes among the four stations throughout the study period, with rainfall values fluctuating approximately between 4.5 mm/day and 12.0 mm/day, and several notable wet anomalies occurring around 2000, 2007, 2010, and 2022, when precipitation exceeded 10 mm/day. Conversely, relatively dry anomalies appear around 1991, 1998, and 2015, when rainfall declined toward approximately 5.0–6.0 mm/day. These fluctuations reflect strong sensitivity of eastern coastal rainfall regimes to variations in Atlantic moisture inflow and convective activity.

Similarly, Yenagoa exhibits substantial interannual rainfall variability, with precipitation values ranging approximately between 4.0 mm/day and 15.5 mm/day,

representing the largest variability amplitude among the four stations. A particularly strong wet anomaly occurs during the early 1980s, especially around 1982, when precipitation exceeds 15 mm/day, followed by alternating wet and dry phases throughout the late 1980s and early 1990s. Additional wet anomalies are observed around 1995, 2008, and 2020, indicating episodic intensification of southwest monsoon activity across the Niger Delta region.

Benin City, representing the transitional Derived Guinea Savanna climatic zone, records comparatively lower precipitation magnitudes than the coastal stations, with rainfall values fluctuating between approximately 2.5 mm/day and 6.0 mm/day across the study period. Wet anomalies are observed around 1988, 1995, 2008, and 2019, whereas dry anomalies occur around 1983, 1991, and 2014, reflecting moderate but persistent interannual rainfall variability influenced by both maritime and continental atmospheric processes.

Lagos records the lowest precipitation magnitudes among the four stations, with rainfall values ranging approximately between 2.5 mm/day and 8.5 mm/day throughout the study interval. A notable wet anomaly occurs around 1983, when rainfall exceeds 8.5 mm/day, while relatively dry conditions appear around 1998, 2006, and 2015, indicating strong sensitivity of western coastal rainfall regimes to localized atmospheric circulation variability and urban-modified surface conditions.

A comparison of precipitation variability across the four stations reveals a clear east–west rainfall gradient within the humid climatic zone of southern Nigeria. Specifically, precipitation magnitude generally increases eastward from Lagos through Benin City and Yenagoa

toward Calabar. This spatial gradient reflects enhanced moisture transport efficiency and stronger convective activity across the eastern Gulf of Guinea coastal sector compared with the western coastal region.

Temporal analysis further indicates that rainfall variability across the humid climatic zone becomes more irregular after the late 1990s, with alternating wet and dry anomalies occurring more frequently across all stations. This behaviour suggests increasing rainfall variability

associated with changing monsoon dynamics and regional climate variability across West Africa.

From the perspective of precipitation-extreme characterization, the early 1980s and late 2000s represent the most rainfall-active periods across the humid climatic zone, particularly in Yenagoa and Calabar, where precipitation magnitudes reached their highest values. Conversely, the early 1990s and mid-2010s represent relatively dry intervals across several stations within the study area.

Table 2: Mann-Kendall and Sen's slope Test for Precipitation from the period of 1981-2025

Location	Kendall's Tau	Mann Kendall's Statistic (S)	Test Statistic (Z)	p-value (Two-tailed)	Intercept	Sen's slope (Q)	Test Interpretation	Trend
Calabar	-0.13	-130.0	-1.26	0.20	8.41	-0.02	FALSE	decreasing
Yenagoa	-0.17	-174.0	-1.69	0.09	7.60	-0.05	FALSE	decreasing
Benin-City	0.23	233.0	2.27	0.02	3.61	0.02	TRUE	Increasing
Ikeja	-0.12	-121.0	-1.17	0.24	5.63	-0.02	FALSE	decreasing

Table 2 present the Mann-Kendall and Sen's slope results for precipitation during the period 1981–2025 reveal considerable spatial variability in rainfall trends across the humid rainforest, tropical savanna, and semi-arid climatic zones of Nigeria. The results indicate that while some locations experienced increasing precipitation trends, others showed statistically significant decreases, reflecting the influence of regional climatic variability and environmental changes.

Within the Humid Rainforest zone, Calabar recorded a negative Kendall's Tau value of -0.13 with Mann-Kendall statistic (S) of -130 and Z-statistic of -1.26 . The p-value of 0.20 indicates that the decreasing trend is not statistically significant. The Sen's slope value of -0.02 mm/year suggests a slight reduction in precipitation over

time. Similarly, Yenagoa showed a weak decreasing trend with $\text{Tau} = -0.17$, $Z = -1.69$, and Sen's slope of -0.05 mm/year. However, the p-value of 0.09 indicates that the trend is not significant at the 95% confidence level. Ikeja also exhibited a non-significant decreasing trend with $\text{Tau} = -0.12$ and Sen's slope of -0.02 mm/year. In contrast, Benin-City recorded a statistically significant increasing rainfall trend with $\text{Tau} = 0.23$, $Z = 2.27$, and p-value = 0.02 . The Sen's slope of 0.02 mm/year indicates gradual rainfall increase within the period. These results suggest that precipitation changes within the humid rainforest zone are spatially inconsistent, although slight rainfall reduction dominates most coastal stations except Benin-City.

KDE Plots in the Humid Rainforest Climatic Zone

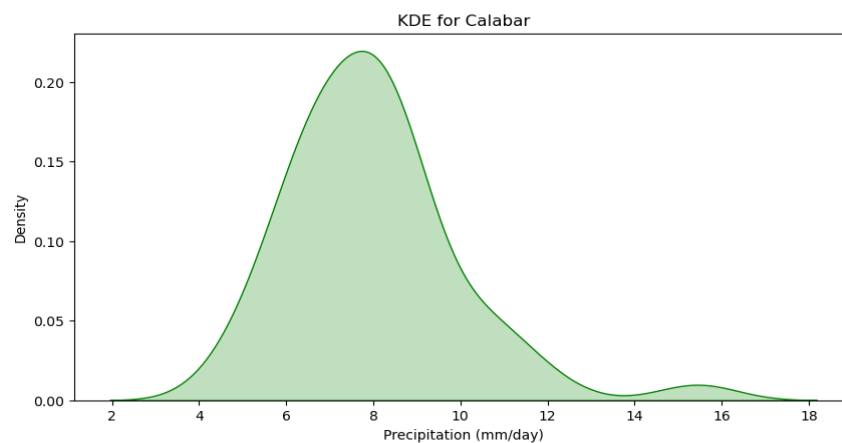


Figure: 4(a): KDE plot for Precipitation in Calabar (Humid Rainforest zone)

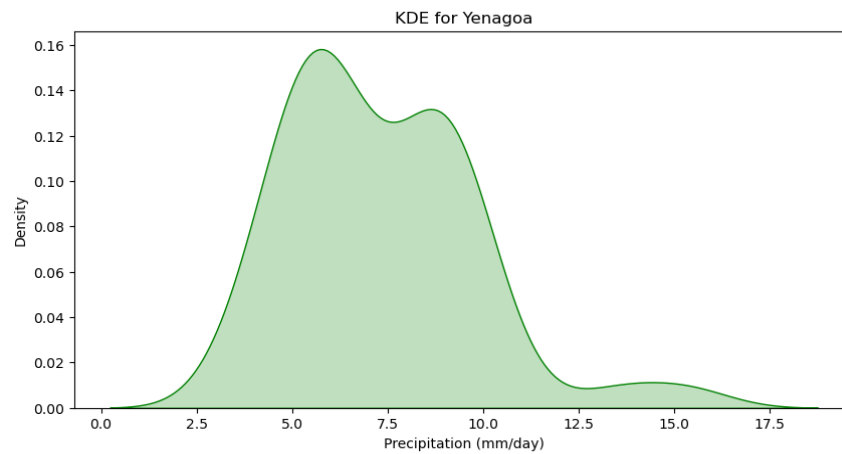


Figure: 4(b): KDE plot for Precipitation in Yenagoa (Humid Rainforest zone)

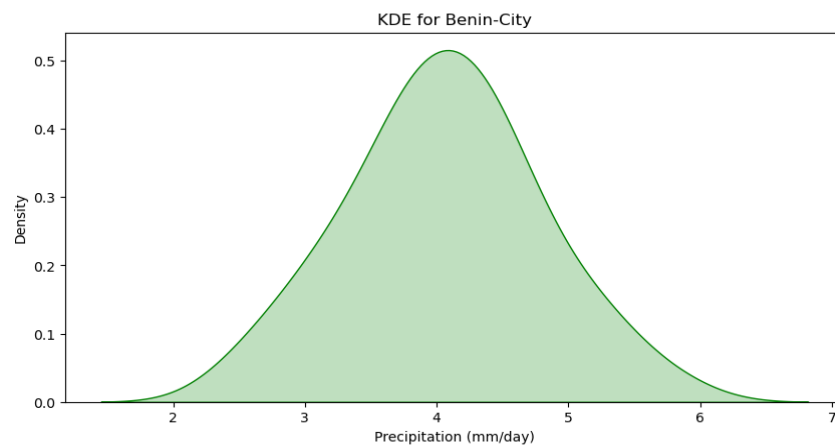


Figure: 4(c): KDE plot for Precipitation Benin-City (Humid Rainforest zone)

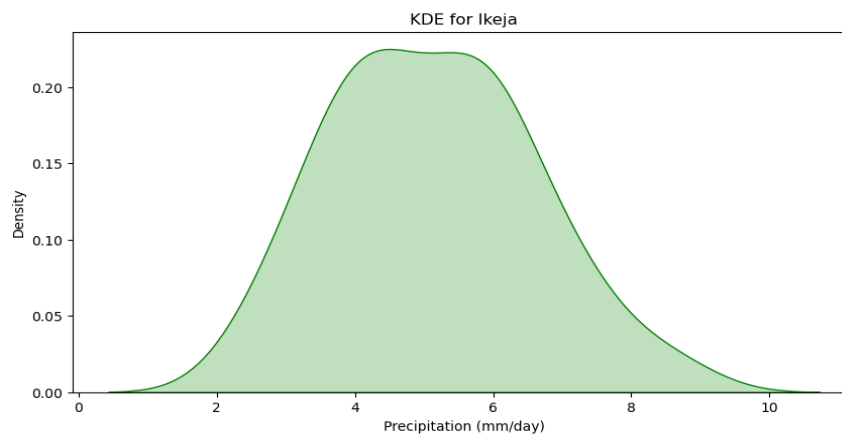


Figure: 4(d): KDE plot for Precipitation in Ikeja (Humid Rainforest zone)

Figure 4(a), (b), (c) and (d) show the Kernel Density Estimate (KDE) analysis of precipitation in the Humid Rainforest tropical of Nigeria.

According to the KDE, the average daily precipitation in Calabar is 8 mm, with a predominant range of 4–12 mm. The distribution is right-skewed, with severe rainfall occurring infrequently and moderate rainfall occurring

frequently. The little rise in density of 15–16 mm per day indicates sporadic extreme precipitation events that deviate from the background regime. Two different dominating rainfall mechanisms are indicated by the bimodal distribution of Yenagoa's daily precipitation, with modes at around 5.8 and 8.7 mm/day. A small heavy-tail population of 14–15 mm/day represents uncommon extreme precipitation events, while the majority of events fall between 2.5 and 12 mm/day. In contrast to the unimodal distribution seen for Calabar, the bimodal structure indicates more variability in rainfall-generating systems. Precipitation in Benin City has a limited range of 1.5–6.5 mm/day with a unimodal, near-normal distribution centered at roughly 4.1 mm/day. In contrast to the wider and bimodal distributions seen for Calabar and Yenagoa, the high peak density (0.51) indicates little day-to-day variability and a relatively constant rainfall regime. The lack of a heavy tail suggests a restricted incidence of extreme precipitation events. Instead of a single distinguishable mode, Ikeja precipitation has a wide, flat-topped unimodal KDE centered about 4.3–5.6 mm/day, showing a range of equally likely moderate rainfall amounts. In comparison to the bimodal and heavy-tailed distributions of the Niger

Delta stations (Calabar, Yenagoa), the distribution is right-skewed and ranges from 0.5 to 10.5 mm/day. It is more variable than the narrow, sharply peaked distribution of Benin-City.

Overall, the statistical distribution of daily precipitation in Calabar, Yenagoa, Benin City, and Ikeja shows significant spatial heterogeneity, according to the KDE analysis. Benin City displays a somewhat concentrated rainfall regime, while Calabar and Yenagoa display wider rainfall distributions and more pronounced upper-tail behaviour. Ikeja is in the middle, with a wide, comparatively level distribution of mild rainfall. Although the KDE cannot determine the physical reasons of the distinct rainfall regimes, the strong bimodality at Yenagoa implies their cohabitation. These results are consistent with earlier research showing significant spatial variability and erratic rainfall distribution throughout southern Nigeria (Akinbobola *et al.*, 2023). In order to comprehend precipitation variability, extreme rainfall behavior, and related hydrometeorological concerns, station-specific research is crucial. The results therefore show that rainfall features within the humid rainforest zone are spatially diverse.

RF-SVR Hybrid Model in the Humid Rainforest Zone

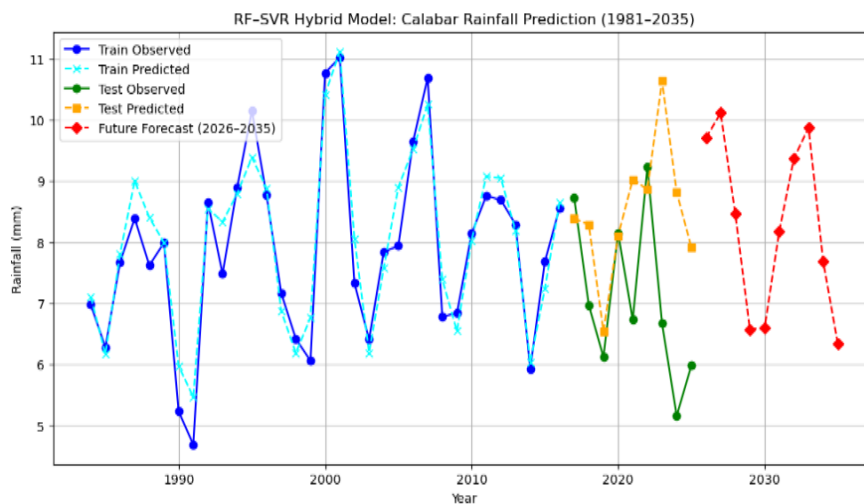


Figure: 5(a): RF-SVR Hybrid model prediction of precipitation in Calabar (Humid Rainforest zone)

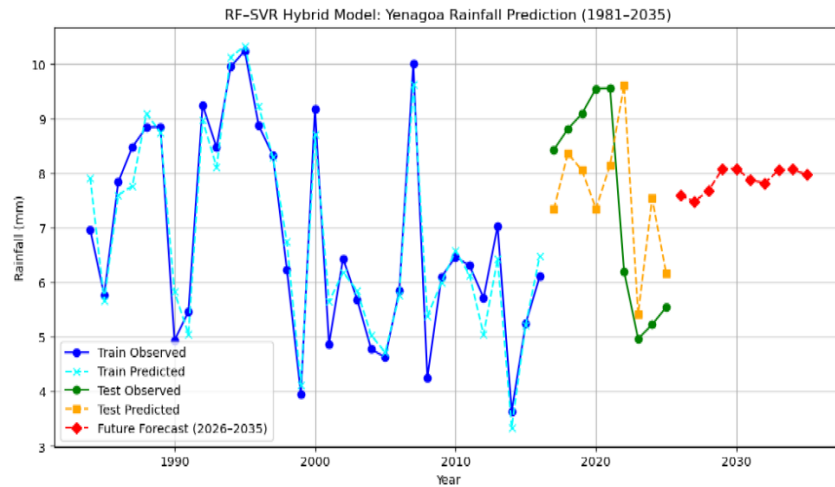


Figure: 5(b): RF-SVR Hybrid model prediction of precipitation in Yenagoa (Humid Rainforest zone)

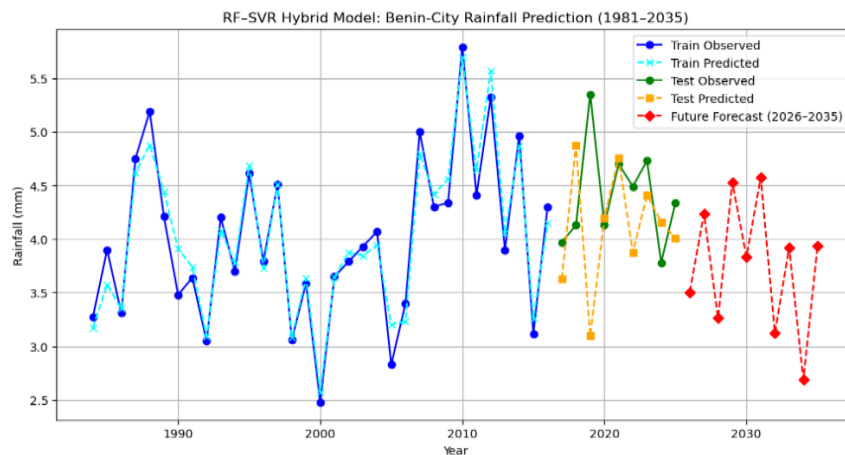


Figure: 5(c): RF-SVR Hybrid model prediction of precipitation in Benin-City (Humid Rainforest zone)

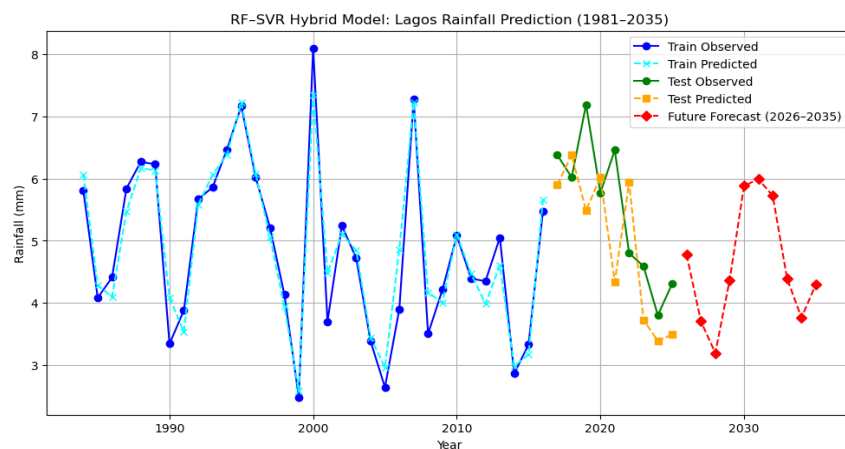


Figure: 5(d): RF-SVR Hybrid model prediction of precipitation in Ikeja (Humid Rainforest zone)

Figure 5(a) presents the rainfall prediction for Calabar using the hybrid Random Forest Regression–Support Vector Regression (RF–SVR) model for the period 1981–2035. The model combines the nonlinear learning capability of Random Forest with the strong generalization ability of Support Vector Regression to improve rainfall prediction accuracy within the humid tropical rainforest zone. Model evaluation during the training period (1981–2015) shows that the predicted rainfall values closely matched the observed rainfall pattern, successfully reproducing major peaks and troughs around 1995, 2001, 2007, and 2012. This indicates strong capability of the hybrid model in learning historical rainfall variability.

During the testing phase (2016–2025), the RF–SVR model maintained satisfactory agreement with observed rainfall values, although slight overestimations occurred in some years such as 2022 and 2024. Despite these minor deviations, the model effectively captured the general rainfall variability pattern, confirming its robustness for hydroclimatic prediction. Future rainfall projections for 2026–2035 indicate moderate interannual variability, with rainfall values ranging between approximately 6.4 mm/day and 10.1 mm/day. Wetter conditions are projected around 2027, 2028, and 2032, while relatively lower rainfall is expected around 2029, 2030, and 2035. Overall, the forecast suggests persistent humid conditions with oscillatory rainfall behavior and no significant long-term declining trend over Calabar through 2035.

Figure 5(b) represent the RF–SVR hybrid model effectively captured the historical rainfall variability and future precipitation trends in Yenagoa between 1981 and 2035. During the training phase (1981–2016), rainfall exhibited strong interannual fluctuations ranging from approximately 3.6 mm to 10.2 mm. Peak rainfall values above 10.0 mm were observed during the mid-1990s and around 2007, while the lowest rainfall occurred around 2014 at approximately 3.6 mm. The predicted rainfall closely matched the observed values, indicating that the RF–SVR model successfully captured the nonlinear rainfall variability and temporal behavior of the region.

In the testing phase (2017–2025), rainfall varied between about 5.0 mm and 9.6 mm. The model generally reproduced the observed trends, although slight underestimations and overestimations occurred during some years. Despite these differences, the predictions remained within the observed variability range, demonstrating satisfactory model performance.

Future rainfall projections for 2026–2035 indicate relatively stable and persistently high rainfall conditions, ranging from approximately 7.5 mm to 8.1 mm. The

forecast suggests no significant long-term rainfall decline, reflecting continued humid climatic conditions in Yenagoa. However, sustained high rainfall may increase the risks of flooding, erosion, and drainage-related environmental challenges in the coastal Niger Delta region.

Figure 5(c) represent the RF–SVR hybrid model prediction for rainfall in Benin-City (1981–2035) demonstrates the effectiveness of the combined Random Forest and Support Vector Regression techniques in reproducing historical rainfall variability and forecasting future precipitation trends. During the training period (1981–2016), observed rainfall values fluctuated between approximately 2.5 mm and 5.8 mm, indicating considerable interannual variability. Peak rainfall values above 5.0 mm were recorded around the late 1980s, 2007, and 2010–2012, while lower values near 2.5–3.0 mm occurred around 2000 and 2005. The predicted rainfall closely matched the observed series, successfully capturing major peaks and declines, which indicates that the hybrid model effectively learned the nonlinear rainfall characteristics of the region.

During the testing phase (2017–2025), rainfall varied between about 3.8 mm and 5.4 mm. The predicted values generally followed the observed trend, despite slight overestimations and underestimations in some years, demonstrating satisfactory predictive performance. Future projections for 2026–2035 indicate moderate rainfall variability, with forecast values ranging between approximately 2.7 mm and 4.6 mm. The forecast suggests alternating wetter and drier years, reflecting continued climatic variability in Benin-City. The RF–SVR model shows strong capability for rainfall prediction and indicates persistent but fluctuating precipitation conditions in the humid rainforest region.

Ikeja (Figure 5d) from 1981 to 2035, the RF–SVR hybrid model showed a strong capacity to simulate the annual rainfall variations in Lagos. The predicted values closely followed the real data during the training period (1981–2016), capturing significant peaks like the 8.1 mm high in 2000 and lows like the 2.5 mm in 1999, suggesting an excellent model fit. The model replicated the general trend and the 2019 peak of around 7.2 mm during the testing phase (2017–2025), albeit with somewhat larger variations than during training. According to the forecast for 2026–2035, rainfall is expected to be very variable between years, ranging from approximately 3.2 mm to approximately 6.0 mm, with no discernible long-term upward or downward trend. This implies that rather than a steady change in the rainfall regime, Lagos will probably see alternating wet and dry years. The findings suggest that rather than reacting to a unidirectional trend,

climate adaptation initiatives in Lagos should focus on controlling rainfall variability and related flood and drought hazards.

CNN-LSTM Hybrid Model Prediction of Precipitation in the Humid Rainforest Zone

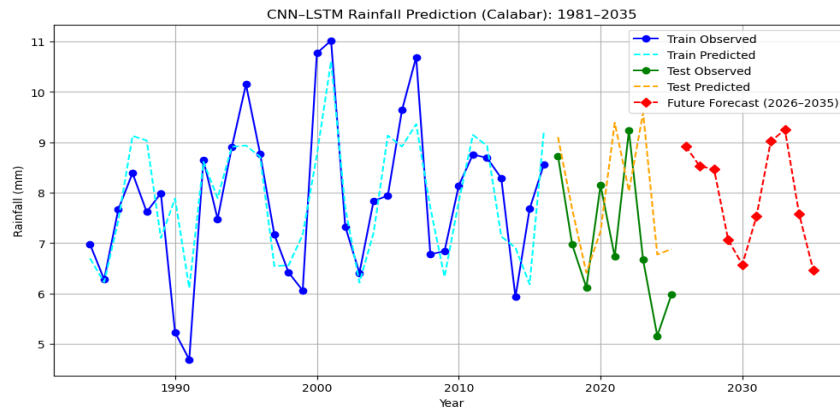


Figure 6(a): CNN-LSTM Hybrid model prediction of precipitation in Calabar (Humid Rainforest zone)

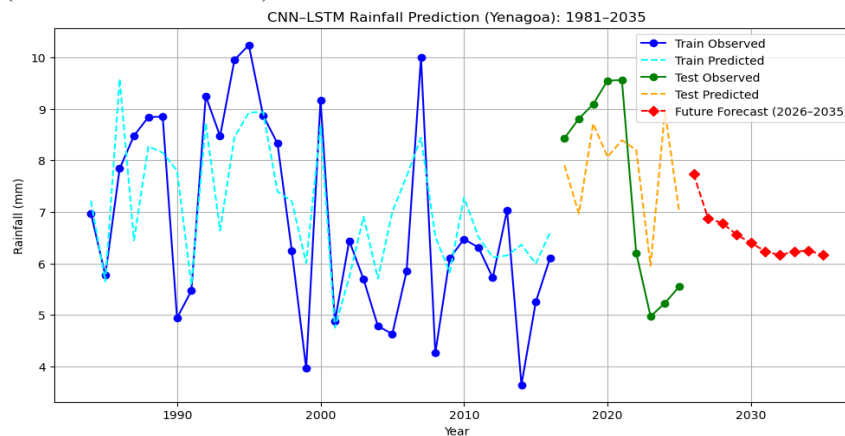


Figure 6(b): CNN-LSTM Hybrid model prediction of precipitation in Yenagoo (Humid Rainforest zone)

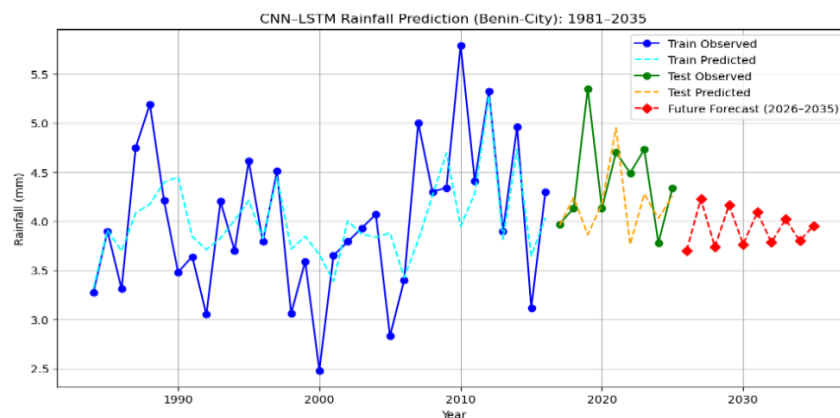


Figure: 6(c): CNN-LSTM Hybrid model prediction of precipitation in Benin-City (Humid Rainforest zone)

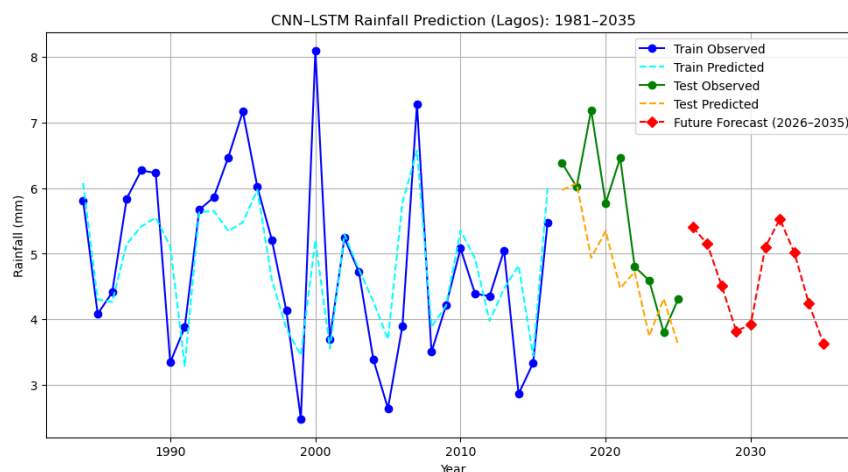


Figure: 6(d): CNN-LSTM Hybrid model prediction of precipitation in Ikeja (Humid Rainforest zone)

Hybrid CNN-LSTM Model Prediction of Precipitation in the Humid Rainforest Zone

The CNN–LSTM precipitation prediction in the humid rainforest zone of Nigeria for the period 2025–2035 reveals distinct spatial and temporal rainfall behaviors associated with the Humid Rainforest.

In the Humid Rainforest zone, comprising Calabar, Yenagoa, Benin-City, and Ikeja, the CNN–LSTM model projects generally high rainfall condition, although varying trends are observed among the locations. Calabar (Figure 6a) exhibits a fluctuating rainfall pattern with an overall decreasing tendency from approximately 9.0 mm/day in 2025 to about 6.5 mm/day by 2035. Despite the decline, rainfall remains relatively high, consistent

with the persistent humid coastal climate of southeastern Nigeria. Yenagoa (Figure 6b) also shows a gradual decrease in precipitation from approximately 7.8 mm/day to 6.2 mm/day by 2035, indicating a possible reduction in moisture intensity over the Niger Delta region. Benin-City (Figure 6c) maintains moderate interannual fluctuations but shows a slight increasing trend from about 3.7 mm/day to 4.0 mm/day by 2035, suggesting relatively stable rainfall conditions with slight enhancement in precipitation. Ikeja (Figure 6d) records the most pronounced decline within the humid rainforest locations, decreasing from approximately 5.5 mm/day to 3.5 mm/day by 2035, indicating a potential weakening of rainfall intensity over the coastal southwestern.

Table 3: Model Evaluation

Locations	RF-SVR		CNN-LSTM	
	RMSE	MAE	RMSE	MAE
Calabar	0.4608	0.3658	1.5639	1.2868
Yenagoa	0.4486	0.3494	1.7747	1.5055
Benin-City	0.1765	0.1433	0.5859	0.37969
Ikeja	0.3615	0.2666	1.0980	0.8072

Model Evaluation

Table 3 presents the performance evaluation of the RF–SVR and CNN–LSTM models using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) in the Humid Rainforest zone of Nigeria. The results reveal that the RF–SVR hybrid model generally outperformed the CNN–LSTM model in predicting precipitation across almost all locations, as indicated by the consistently lower RMSE and MAE values.

In the Humid Rainforest zone, Calabar recorded RMSE and MAE values of 0.4608 and 0.3658 respectively for the RF–SVR model, whereas the CNN–LSTM model produced significantly higher errors of RMSE = 1.5639 and MAE = 1.2868. Similarly, Yenagoa showed lower RF–SVR errors (RMSE = 0.4486; MAE = 0.3494) compared to CNN–LSTM values of RMSE = 1.7747 and MAE = 1.5055. Benin-City exhibited one of the best performances among all stations, where RF–SVR achieved RMSE = 0.1765 and MAE = 0.1433, while

CNN–LSTM recorded higher errors of RMSE = 0.5859 and MAE = 0.37969. Ikeja also followed the same pattern, with RF–SVR producing lower RMSE (0.3615) and MAE (0.2666) relative to CNN–LSTM values of RMSE = 1.0980 and MAE = 0.8072. These results indicate that RF–SVR was more effective in capturing the rainfall variability within the humid coastal environment. The findings therefore suggest that the RF–SVR hybrid approach is more suitable for rainfall prediction in the study area compared to the CNN–LSTM model.

CONCLUSION

This study successfully investigated the spatiotemporal trends and hybrid machine learning prediction of precipitation trends in the humid rainforest zone of Nigeria using long-term climatic data from 1981 to 2025. The analysis of precipitation showed strong spatial and temporal variability across the zone, with no uniform increasing or decreasing trend. The results revealed decreasing but non-significant rainfall trends at Calabar, Yenagoa, and Ikeja, while Benin City exhibited a significant increasing trend. Spatial analysis demonstrated considerable variability in precipitation characteristics across the study area. RF-SVR outperformed CNN-LSTM, with RMSE values of 0.1765–0.4608 and MAE values of 0.1433–0.3658, compared with RMSE values of 1.5639–1.7747 and MAE values of 1.2868–1.5055 for CNN-LSTM. CNN-LSTM forecasts for 2026–2035 indicated decreasing precipitation at Calabar, Yenagoa, and Ikeja, but an increasing trend at Benin City. RF-SVR predicted decreasing precipitation at Calabar, relative stability at Yenagoa, moderate variability at Benin City, and substantial interannual variability at Ikeja, without a significant long-term decline by 2035. These findings highlight rainfall variability as an important concern for agriculture, water resources, food security, and sustainable development in Nigeria's humid rainforest zone.

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