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Monthly rainfall prediction using artificial neural network: A case study of Kano, Nigeria

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ABSTRACT

Rainfall continues to be the major source of moisture for agricultural activities over Nigeria, therefore accurate and timely rainfall prediction is essential for food availability and improved water resources management over this region. In this study, Artificial Neural Network (ANN) was applied to predict monthly rainfall over Kano, Nigeria. Three months lagged climate indices for monitoring El Niño–Southern Oscillation (ENSO) namely; Southern Oscillation Index (SOI), Niño1+2, Niño3, Niño3.4 and Niño4 monthly values for 37 years were used as predictors. A Linear Model (LM) was first developed to serve as a yardstick. The ANN was trained using neuralnet package in R statistical software, 25 years data (1981-2005) was used for model training while the remaining 12 years data (2006-2017) was used for model evaluation. Results indicated that both ANN and LM replicated the actual pattern of monthly rainfall, although with some disparities. ANN has a correlation coefficient value of 0.73 which is higher than 0.70 recorded by LM, a lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were also observed for ANN as compared with LM. Therefore indicating ANN is more preferable and could confidently be used with ENSO indices for subsequent monthly rainfall prediction over Kano, Nigeria.

1. INTRODUCTION

The contribution of Agriculture to Gross Domestic Product (GDP) of Nigeria is on the increase, as of the third quarter of 2017, the agricultural sector has contributed about 29.15% to the overall GDP, making it the second largest contributing sector to Nigeria's economy after Oil [1].

Rainfall is one of the most important climatic variable over West Africa as it remains the major source of moisture for agricultural activities over this region. Rainfall climatology obtained from surface rain gauges shows a strong spatial and temporal variability form the Sahel-Northern Nigeria down to Guinea coast. Values ranges from about 400mm/year in the North to about 3000mm/year in the South.

Large scale climate phenomena described by climate indices has been attributed to rainfall variability most parts of the world e.g. over Australia [2-3], India [4] and West Africa [5]. Slight northward pull of the Intertropical Convergence Zone (ITCZ) above its mean position during a La Niña event is accompanied by decrease in temperature and rise in mean precipitation while a slight southward pull of the Intertropical Convergence Zone (ITCZ) below its mean position during a El Niño event is accompanied by increase in temperature and decrease in mean precipitation over Nigeria [6].

Several past studies have applied statistical methods for rainfall prediction over Nigeria. Akinbobola et al. [7] applied Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) models to predict monthly rainfall over some selected meteorological stations over Nigeria. The results indicated that SARIMA model is a reliable method for rainfall prediction over the country. Egbuawa et al. [8] investigated the contributions of ENSO to rainfall variability across Nigeria. Positive correlation coefficient observed between rainfall values and Southern Oscillation Index (SOI) indicated that rainfall variation in Nigeria is analogous with ENSO related circulation. The study further suggested that introduction of ENSO indices could improve rainfall forecast over Nigeria. Adeniyi and Dilau [9] generated a seasonal rainfall prediction model using regression model over 21 stations in Nigeria. Using 53 years monthly rainfall and Sea Surface Temperature of the tropical oceans as predictors, they concluded that SST of the tropical oceans is linearly related to June, July, August and September (JJAS) seasonal rainfall over Nigeria.

Furthermore, ANN has been widely used in preference to linear models due to its ability to detect complex and non-linear relationships between climatic. Ewona et al. [10] applied ANN using a 30-year data to predict rainfall over 23 stations in Nigeria. The results indicated more accurate rainfall predictability at higher latitudes over the country. Using consecutive rainfall depths data as input, Abdulkadir et al. [11] evaluated the performance of Neural Networks in predicting rainfall pattern in some selected stations in Nigeria. Significant values of correlation coefficients were obtained after model validation, suggesting that ANN can be used for quantitative rainfall prediction over this region. Although some variability was observed in model accuracy as a result of changes in the number of neurons used in model training.

However, over Nigeria, previous research has not considered the effect of one or more climate indices as predictors of monthly rainfall using ANN. Therefore, the main aim of this study is to employ climate indices used for monitoring El Niño–Southern Oscillation (ENSO) namely; Southern Oscillation Index (SOI), Niño1+2, Niño3, Niño3.4

and Niño4 in forecasting monthly rainfall over Kano, Nigeria using ANN. In order to provide reasonable prediction lead time for decision making, the predictors have a three months lag.

2. STUDY AREA

Kano is located in the Sudano-Sahelian Northern part of Nigeria and has a land area of about 20,131 km^2. It also has a mean annual rainfall of about 800 mm/year. The station used is located at Lat. 12.05°N and Lon. 8.53°S with an elevation of 481m above mean sea level. The study area and station location are shown in Figure 1.

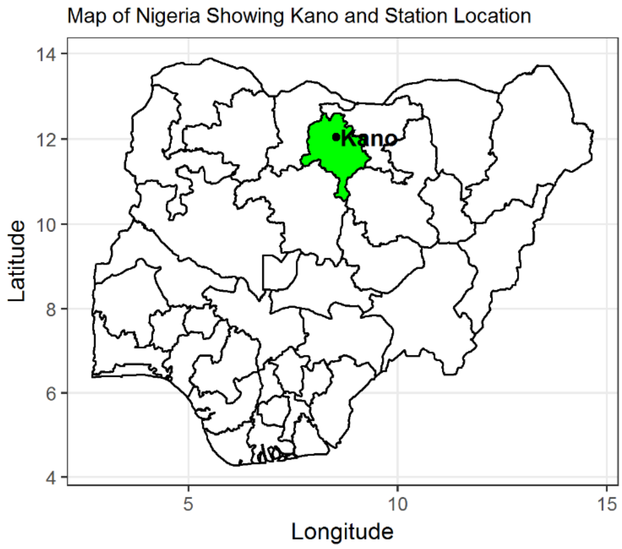

Figure 1. Map of Nigeria showing station location in Kano

3. MATERIALS AND METHODS

3.1 Data

The data used in this study include monthly rainfall of data of Kano meteorological station obtained from Nigerian Meteorological Agency for 37 years (1981-2017).

The monthly climate indices used are;

a. Southern Oscillation Index (SOI) which is a standardized sea level pressure differences between Tahiti (149.23°W, 17.78°S) and Darwin (130.83°E, 12.45°S) for the period of 1951 to present.

b. Nino1+2 is an index used to monitor SST over tropical pacific, it corresponds with region of coastal South America (0-10°S, 90°W-80°W).

c. Nino3 is same as Nino1+2 but for the region (5°N-5°S, 150°W-90°W).

d. Nino3.4 is same as Nino1+2 but for the region (5°N-5°S, 170°W-120°W).

e. Nino4 is same as Nino1+2 but for the region (5°N-5°S, 160°E-150°W).

These climate indices are used to represent the ENSO phenomena. Monthly values of the above mentioned variables were obtained from Climate Prediction Center (CPC) (http://www.cpc.ncep.noaa.gov/data/indices) for 37 years from 1981-2017 to coincided with the available monthly rainfall data for the area under study.

3.2 Method

3.2.1 Linear regression

Linear regression is one of the simplest and widely used statistical method for rainfall forecasting. It is used to predict the value of a single "response" variable as a linear function of one or more "predictor" variables. Linearity is assumed between the response and predictor variables. It is represented mathematically by:

$$Y = a_1X_1 + a_2X_2 + \cdots + a_nX_n + K \quad (1)$$

where Y is value of the response variable and X_1, X_2,..., X_n are values of the predictor variables and a_1, a_2, ..., a_n are the regression coefficients and K is constant (intercept on the Y axis).

3.2.2 Artificial neural network

Artificial Neural Network (ANN) is a statistical method designed to simulate the way biological human brain processes information. ANNs learn by detecting patterns and relationship within the provided input and desired output variables. It is an effective modeling approach that is used in weather and climate prediction. Figure 2 shows structure of ANN.

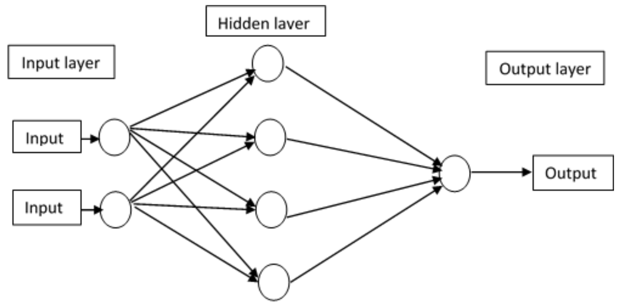

Figure 2. Structure of artificial neural network

The number of neurons in the input layer corresponds to the number of input variables provided in the network, which are then passed to the hidden layer. The hidden layer has arbitrary number of layers with arbitrary number of neurons and the output layer provides the output variables.

In this study, monthly values of SOI, Nino1+2, Nino 3, Nino 3.4 and Nino4 are used as predictor variables for both the Linear Regression Model (LM) and Artificial Neural Network (ANN), while the response variable to be predicted is Monthly rainfall values in mm/month over Kano. The predictor variables (SOI, Nino1+2, Nino3, Nino3.4 and Nino4) are lagged by three months before the models were developed. To avoid over fitting, data from 1981-2005 was used to for model generation while 2006-2017 was used for model evaluation. LM and ANN models are developed via the *lm* and *neuraltnet* functions available in R statistical software. The model evaluation was carried out using Correlation Coefficeint (r), Mean Absolute Error (*MAE*) and Root Mean Square Error (*RMSE*).

4. RESULTS AND DISCUSSION

A time series plot of monthly values of Nino1+2, Nino3, Nino3.4, Nino4 and Rainfall (monthly rainfall over Kano) for the year 1981-2005 is shown in Figure 3. This particular period is considered as the training period. It was observed that Nino1+2, Nino3, Nino3.4 and Nino4 indices exhibit a similar trend, although with some disparities. Higher values of monthly rainfall were observed from 1996-2005 as compared to earlier years (1981-1995).

For the traditional Linear Model (LM), after model evaluation, a correlation coefficient *r* value of 0.70 was observed between the Actual monthly rainfall values and the Predicted monthly rainfall values over Kano for the evaluation period (2006-2017). A scatter plot of Actual versus Predicted monthly rainfall is shown in Figure 4. MAE and RMSE values of 72.21 and 106.0 are also observed for LM respectively. There is an improvement in correlation coefficient by 0.03 when ANN was applied. MAE and RMSE values of 64.73 and 100.77 are reported, respectively. A higher *r*, lower MAE and RMSE produced by ANN results indicate higher accuracy as compared with the LM.

Annual rainfall variability over Kano can be clearly seen in Figure 6 and Figure 7. The months of June, July, August and September are considered rainy season over this region, with highest in the month of August. Figure 6 shows a comparison between Actual and LM Predicted monthly rainfall with a three month lead time while Figure 7 shows a comparison between Actual and ANN Predicted monthly with a three month lead time. Both LM predicted and ANN predicted monthly rainfall follow the same rainfall patter as depicted by actual monthly rainfall for the evaluation period of 10 years (2006-2017). However, both models tend to under estimate monthly rainfall values when compared with actual monthly rainfall. High monthly rainfall values in the mid of 2008 and 2012 was failed to be replicated by both models. Finally, these results clearly show that ANN predicted monthly rainfall fitted the pattern of the actual rainfall better therefore indicating its superiority over LM.

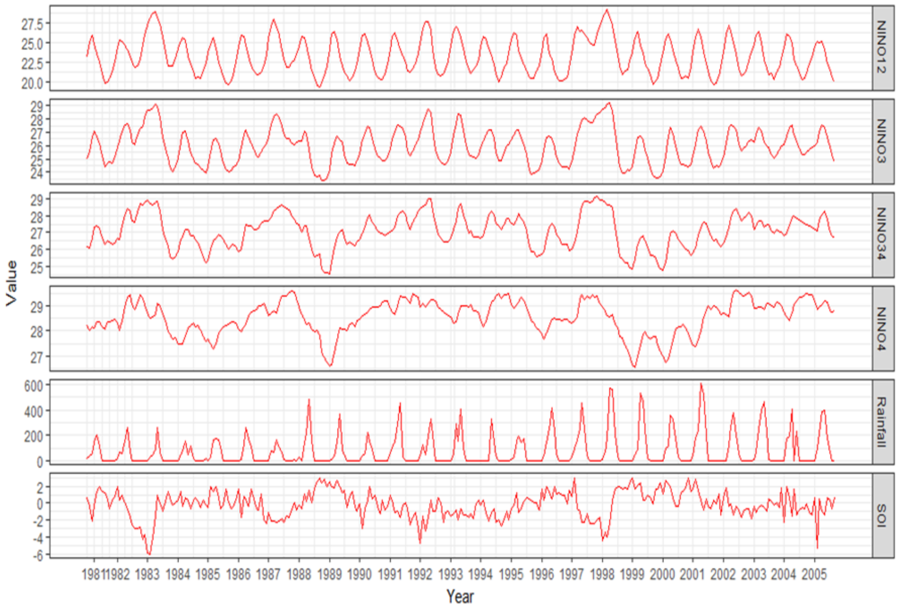

Figure 3. Time series plot of monthly values of SOI, Nino1.2, Nino3, Nino3.4, Nino4 and Kano rainfall for the period of 1981 to 2015

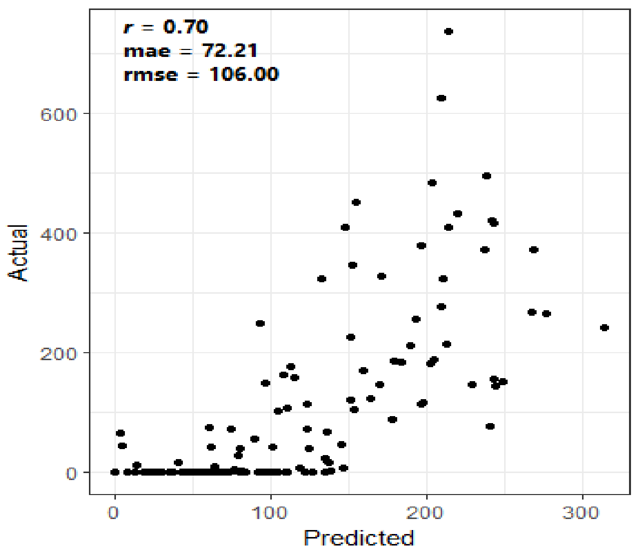

Figure 4. A scatter plot of LM predicted versus Actual monthly rainfall over Kano, Nigeria

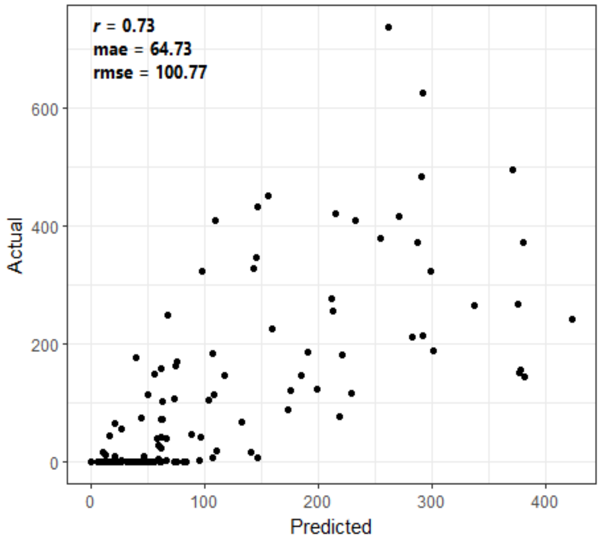

Figure 5. A scatter plot of ANN Predicted versus Actual monthly rainfall over Kano, Nigeria

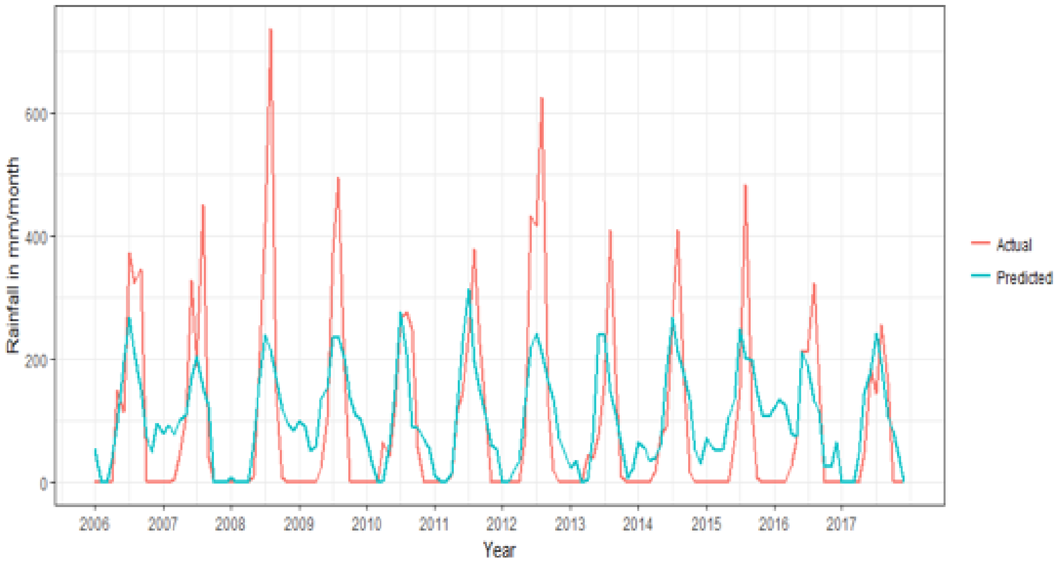

Figure 6. Time series of actual versus linear model (LM) predicted monthly rainfall in mm/month for the period 2006-2017 over Kano, Nigeria

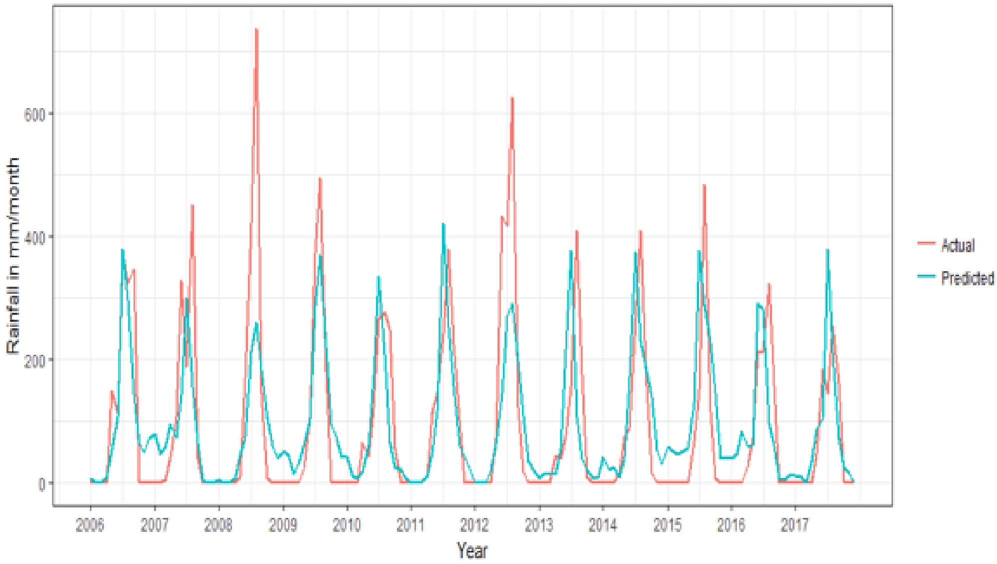

Figure 7. Time series of actual versus Artificial Neural Network (ANN) predicted monthly rainfall in mm/month for the period 2006-2017 over Kano, Nigeria

5. CONCLUSIONS

In this study, an attempt has been made to forecast monthly rainfall over Kano, Nigeria using Artificial Neural Network. Large scale climate indices representing ENSO namely; SOI, NINO12, NINO3, Nino3.4 and Nino4 were been used as predictors. The predictors were lagged by three months in order to provide a three months prediction lead time. Furthermore, linear model was developed using Linear Regression with the same predictors in order to provide a benchmark. Both ANN and LM reproduced with some level of accuracy the monthly rainfall trend over Kano. However, ANN was observed to have higher correlation coefficient, lower RMSE and MAE than the LM when compared with actual monthly rainfall over Kano during the validation period (2006-2017). This indicates that forecast made using ANN was more accurate. Although this method could confidently be used for monthly rainfall prediction over the study region, further studies should be carried out over other regions due to wide spatial and temporal variability of rainfall in Nigeria.

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