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Flood extrapolation using artificial neural network in coastal region of cross river state, Nigeria

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Abstract
The use of artificial neural network (ANN) is becoming common in the analysis of hydrology and water resource problems. The method of ANN was used in this work to model flood occurrence in Coastal region of Cross River State, Nigeria. Meteorological data were collected from the Nigeria Meteorological Agency (NiMet) and Nigeria Hydrological Survey Agency (NHSA) for over 50 years. Artificial neural networks are known to have capacity for pattern recognition and have been proven to be reliable extrapolative tools for modelling of flood. The Levenberg-Marquardt backpropagation training algorithm was used with Nonlinear Autoregressive with external inputs (NARX) time series tool. Predictions from the neural network model were checked and validated using test of correlation coefficient (R), coefficient of determination (R^2) and the mean square error (MSE) between the observations and predictions. The flood extrapolation from the neural network revealed an increase in water level of Calabar River in the months with extreme rainfall. This consequently in linear response with the catchment characteristics facilitated flooding.

Keywords: ANN- Artificial Neural Network, R- Correlation coefficient, R^2-Coefficient of determination, MSE- Mean Square Error, Calabar

1. Introduction

While many factors contribute to floods, the main cause of floods in Cross River is rainfall. The natural climate phenomenon known as Southern Oscillation has made Cross River's rainfall highly variable compared with other parts of the Nigeria States. When rain falls over Calabar catchment, some rainfall is 'captured' by soil, vegetation and water storages. The remainder flows downhill into waterways. The amount and speed of rainwater that reaches the Calabar River and its tributaries is dependent on the characteristics of the Calabar catchment, particularly its size, shape, vegetation, the way the land is used and the preceding weather conditions. The State Emergency Management Authority (SEMA) in 2018 reported that flood wreaked havoc in Calabar metropolis killing 15 people, destroying over 25 residential houses and rendered hundreds homeless [1, 2]. In 2012, Nigeria experienced the worst flooding in history as a result of heavy rainfall that lasted for several days. The incident affected 30 of the 36 states with 7.7 million people displaced and the estimated economic damages caused by the flood were valued at 2.6 trillion naira [3].

There are various ways by which flood may be defined. It is a temporary covering of land by water in places not usually covered by water [4]. Woodmorapple's definition best suits this work; he defined flooding as the excessive water run-off or the rise in water level in a particular area which is more than what the particular environment can absorb [5]. Generally, when water inundates land that is usually dry, this is called flood. It is an extreme event naturally caused by rising global temperature which results in heavy downpour, thermal expansion of the ocean and glacier melting, resulting in the rise of the sea level thereby causing water to inundate coastal land [6].

ANN is simply a class of mathematical algorithm with network resulting in solutions to a number of specific problems [7]. It is a computer program that is designed to emulate human information processing capabilities such as knowledge processing, speech, prediction, classification and control. It resembles the human brain in two respect: (a) Knowledge is acquired by the network through a learning process (a) inter-neuron connection strength known as synapse are used to store the knowledge [8, 9]. ANN has been widely applied in modelling of many nonlinear hydrologic processes such as numerical weather and global climate model [10, 11], rainfall-runoff model [12, 13, 14], precipitation prediction [15] and flood prediction [16]. The method of ANN was used in this work to extrapolate flood occurrence in Calabar Metropolis, Nigeria [4]. Used ANN in the prediction of river flow at time scale that ranges from one day to one year in River Arno in Italy [17]. Used ANN model in the prediction of maximum and minimum temperature in the summer monsoon over India. The temperature of June, July and August were predicted with the help of January to May data [18]. Used ANN as an effective approach to construct a computationally intelligent system that is able to process non-linear weather conditions in India and the result showed a minimum error using MSE [19]. Using ANN to predict rainfall in Nigeria showed that the correlation coefficient (R) between measured and predicted values was 0.8 with an average value of 0.56 [20]. Employed ANN in his study of Ilorin rainfall in Nigeria. The network yielded 76% and 87% of good forecast and the R of 0.88 was obtained [21]. Utilized ANN for one day a head prediction of temperature. They used multilayer propagation to train and test ten years' meteorological data and the result showed a low MSE [22]. Used one year data of temperature, relative humidity and wind speed for prediction of rainfall. The ANN research showed R and MSE of 0.8230 and 0.0079 respectively. [23]. Used ANN to check different architecture such as Back Propagation Network (BPN), Feed Forward Network (FFN) and

Radial Basic Network (RBN) [24]. Used ANN in modelling of flood in Lagos and the results showed R and R^2 to be 0.9821 and 0.9646 respectively.

1.1 Study area

Calabar is a city found in the southern part of Nigeria. It lies at Latitude 4^0 975'N and Longitude 8^0 34'E with a total area of 406 km² and elevation average of 32 meters above sea level, figure 2. The city is adjacent to Great Kwa River and creeks and the main drainage source is the Calabar River [25] as shown in figure 1.

1.2 Climate and vegetation

The climate is humid sub equatorial with an annual rainfall of about 3000mm, the highest in the country and an annual temperature ranging from $25°C$-$30°C$. The rainfall is almost through the year [25 26].

1.3 Hydrogeologic Setting

The study area is of Coastal plain sand of tertiary to quaternary age, underlain by rocks of the cretaceous Calabar flank and Precambrian Oban massif [27]. The two hydrostratigraphic units in the area are Alluvial Deposit and Coastal Plain Sand Aquifers. The Coastal Plain Sand aquifer is the most extensive and is composed of sand, gravel, and sandstone with clay intercalations. The thickness of the aquifer varies between 35 m in the north and above 100 m in the south with low Static Water Level (SWL). The aquifer is considered to be semi-confined or unconfined, especially in the southern parts of the area. The main groundwater flow direction is from north to south into the Atlantic Ocean [28].

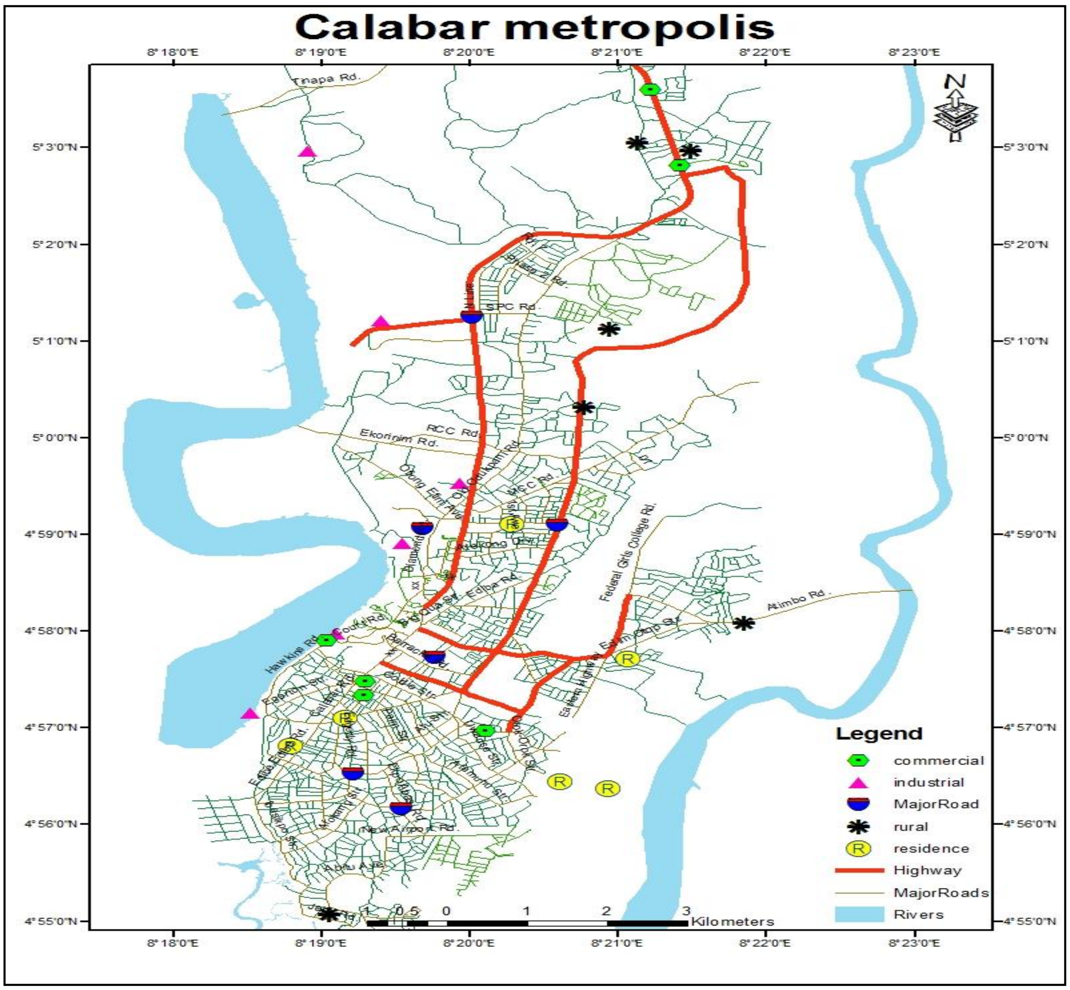

Fig 1: Map of Calabar

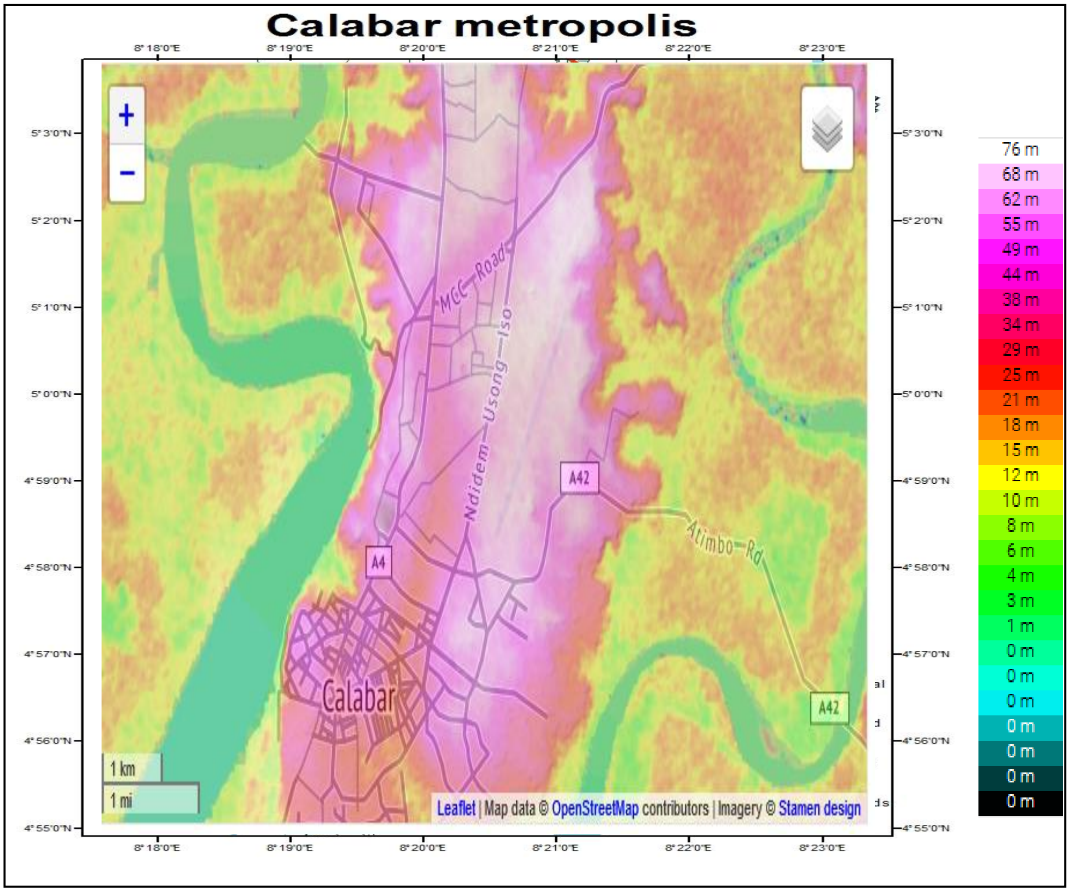

Fig 2: Elevation map of Calabar.

2. Materials and method

2.1 Data collection

The data required for this study are change in water level, rainfall, temperature and relative humidity and were obtained from Nigeria Hydrological Survey Agency and Nigeria Meteorological Agency for a period of 54 years (1962 - 2016).

2.2 Data analysis

With the understanding of Calabar catchment condition, local drainage systems and simple hydro-meterologic knowledge of how much rainfall will run-off on different parts of the Calabar catchment, how much water is needed to cause a flood and how water from different tributaries converges in the Calabar River network. An Artificial Neural Network (ANN) was then used to model the flooding using rainfall, temperature and relative humidity as the input variables. The ANN time series used is the Nonlinear Autoregressive with external input (NARX) and the algorithm applied was the Levenberg-Marquardt with generated network structured (number of input, hidden and output layers) of 3: 10:1. The results were validated using correlation coefficient (R), coefficient of determination (R^2) and mean square error (MSE).

2.2.1 ANN experimental set up

Designing ANN model follows a number of systematic procedures. There are seven basic steps or methodology, these are;

- Collection of the data: firstly the essential data were collected and then the data were prepared.
- Create the network: using different ANN tools the network is created.
- Configure the network: A three layer structure was created (input, hidden and output layer).
- Initialize the weight and biases: weight and biases were initialized for the network.
- Train the network: Training of 70% of the input data was done.
- Validate the network: Validation and testing of the network with the remaining 30% of the data followed.
- Use the network: The network having the lowest or least MSE was selected and used for prediction of future values.

ANN typically has input layer, hidden layer and output layer. In this work, the input layer has 3 neurons which are rainfall, temperature and relative humidity 10 neurons for hidden layer and 1 neuron for the output layer (predicted change in water level). The performance indexes used to validate the result are R, R^2 and MSE. Table 1 is the summary of ANN parameters used.

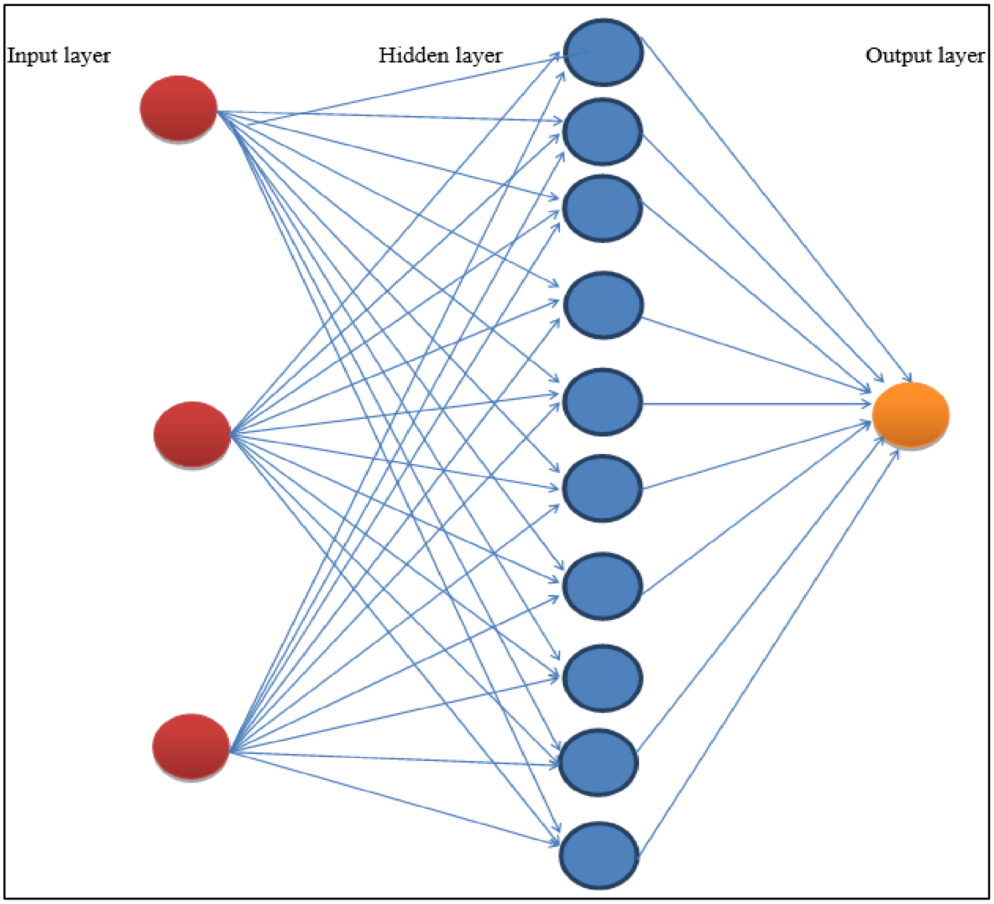

Fig 3: Schematic diagram of neural network architecture

Table 1: Summary of ANN parameters used

S/N	Parameter	Value
1	Epoch	3
2	No of hidden layer neurons	10
3	Training algorithm	Levenberg-Marquardt
4	ANN time series tool	NARX

3. Results and discussion

The swampy aquic soils of the deltaic coastal plain that is usually flooded during the rainy season characterises the study area is caused by the artificial obstacle (urbanisation) in waterways. The build-up sediment and alteration of size and nature of Calabar River by development encroachment are all linearly prone to cause flooding in the area. Figure 4 is the regression plot analysis network structure showing the correlation coefficient (R) while table 2 is the summary of the ANN model. The correlation coefficient (R) indicates the strength and the direction of the linear relationship existing between two variables. For this research, R establishes the relationship between the actual values (rainfall, temperature and relative humidity) and the ANN predicted values of change in water level. In general R is 0.9705; this value tells the relationship between the actual values and the predicted values, after training, validation and testing had taken place as shown in figure 4. It can be seen that there is a perfect fit values of regression analysis of approximately equal to one: meaning there is a strong relationship or perfect relationship between the actual values and the ANN predicted values. The actual and the target values here represent the 54 years of water level for Calabar River. The coefficient of determination (R^2) enables us to know the percentage of variation of water level in Calabar River caused by rainfall, temperature and relative humidity. The R^2 is 0.9418; meaning that the variation in water level is 94% influenced by rainfall, temperature and relative humidity. It can also be noted that the higher in value of these meteorological parameters the higher the influence it will have on the water level. Figure 5 is the Mean Square Error (MSE) plot; this is simply a measure of the difference between the ANN predicted values (target) and the actual values error. The best validation performance as shown in this figure is 0.017077 at epoch 3. This value indicates that the training, validation and testing data set came close at a particular epoch or period; resulting in the given value. MSE indicates the closeness to or wideness from the perfection of a prediction; as the smaller the value the better the predictability. The actual and ANN predicted changes in water level from 1962-2016 closely agreed as shown in Figure 6. Figure 7 shows the monthly average rainfall and change in water level of the observed years. The rainfall was converted to meters so both can be in the same unit. The months of June and July shows a higher rainfall of about 3.7m (3700mm) to 3.6m (3600mm) resulting in a high rise in the water level as shown in plotted graph. These are the months with expected higher rainfall that will greatly increase the water level of Calabar River indicating that an increase in rainfall is proportional to increase in water level. The histogram trend in figures 8 and 9 show the monthly average water level and rainfall from 2010 to 2020 (from 2017- 2020 is the forecast period). The highest change in water level is about 3.4m in 2020. Rainfall trend shows a uniform peak of about 610mm from 2017 to 2020 with the months of June to July showing the highest rainfall. This result confirmed that extreme rainfall is expected in May to July which is in line with the results of other investigator such as [19]and [30] work which showed that there is a gradual increase in rainfall trend of Calabar Metropolis. The ANN forecast trend of change in water level and rainfall in Figure 8 and 9 is said to be a quality forecast as previous prediction on ANN by [21] was accurate and a better time series predictive tool compare to other linear modelling software.

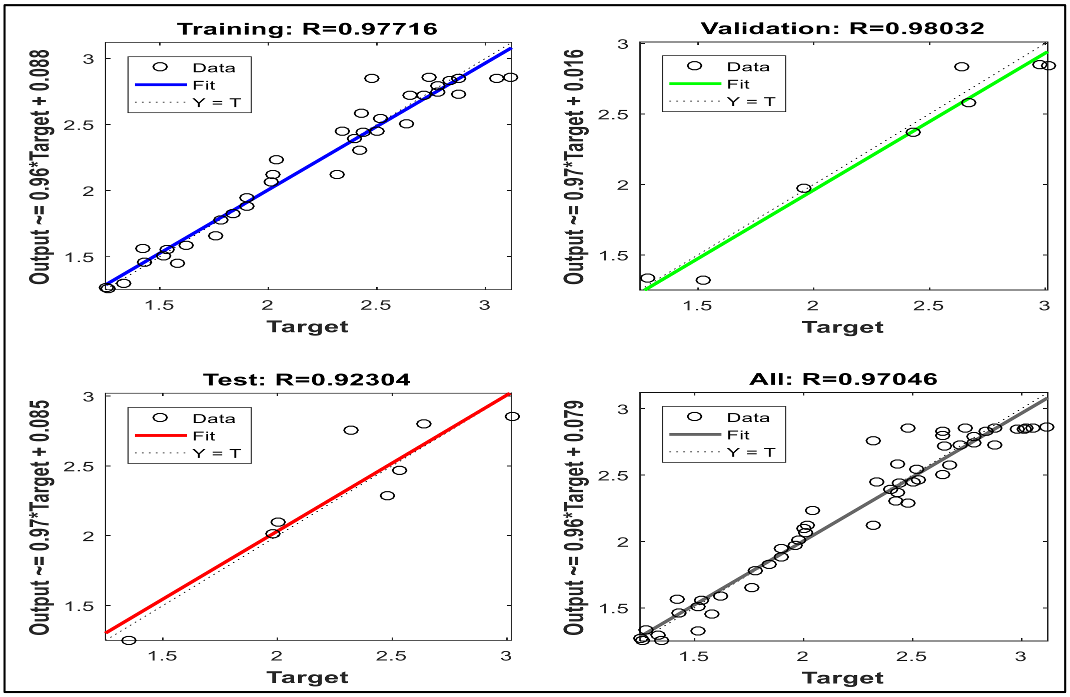

Fig 4: Regression plot analysis network structure

Table 2

Sample partition	Data (year)	Percentage (%)	R	R^2	MSE
Training	38	70	0.97716	0.95484	0.017077
Validation	8	15	0.98032	0.96102	0.008712
Testing	8	15	0.92304	0.85200	0.032655
Total	54	100			

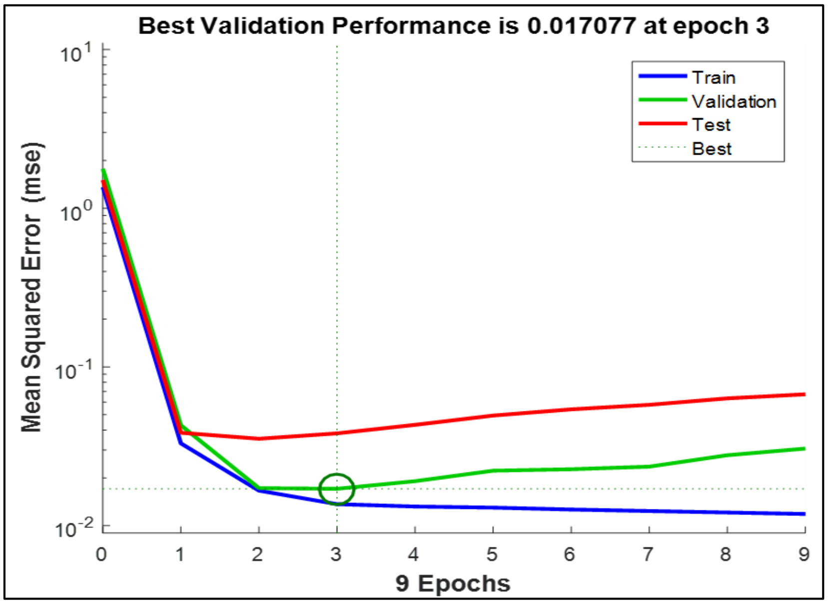

Fig 5: Mean square error (MSE)

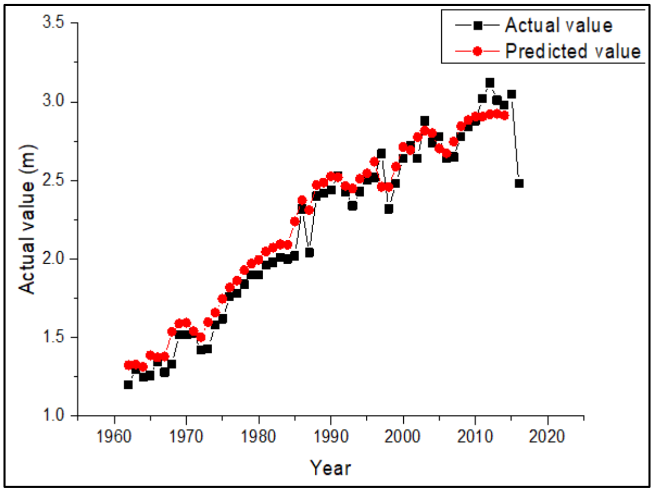

Fig 6: Actual and ANN predicted change in water level for Calabar River

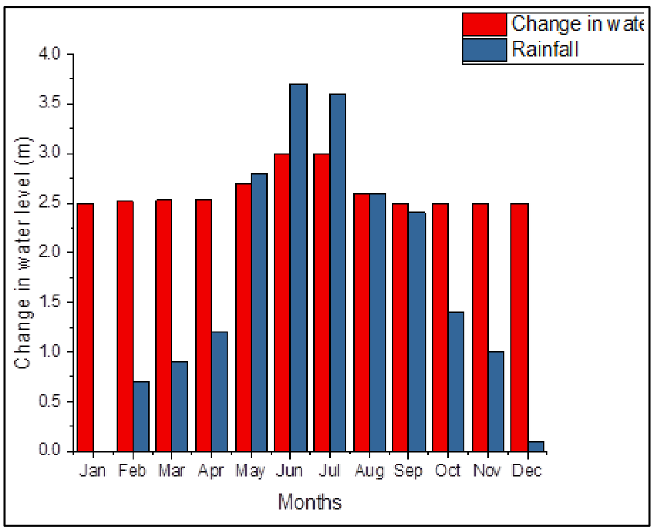

Fig 7: Bar chart showing monthly average change in water level and rainfall

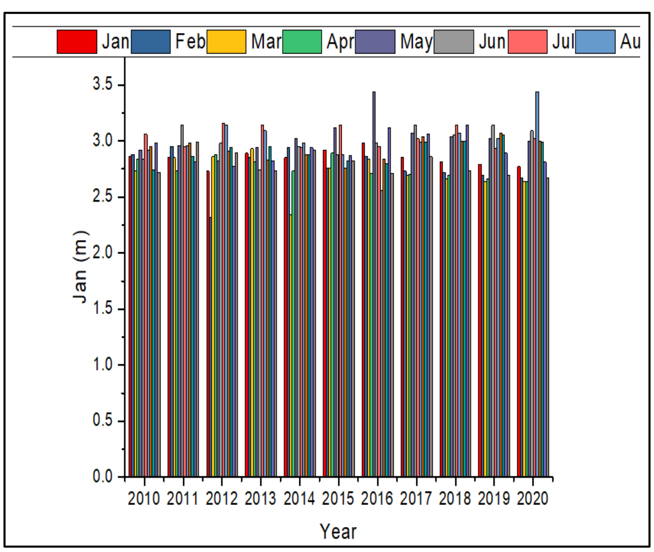

Fig 8: Trend showing monthly average change in water level

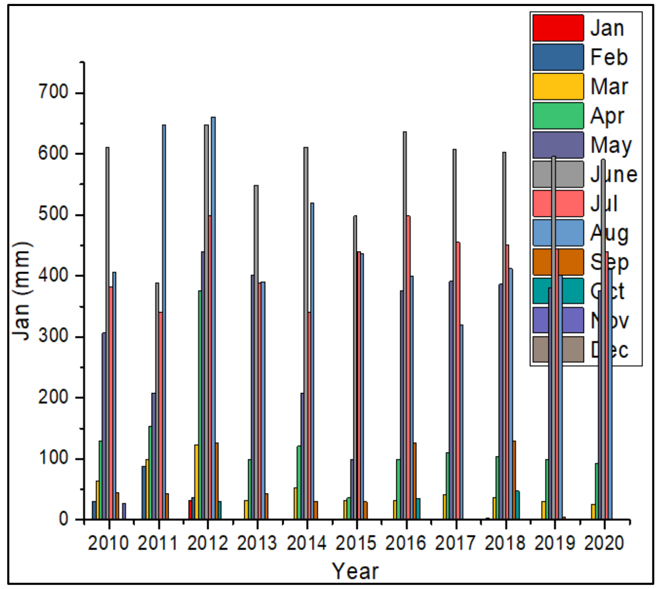

Fig 9: Trend showing monthly average rainfall

5. Conclusion

In this study, an ANN model was developed to run real time change in water level prediction for Calabar River with lead time of 4 years in advance (from 2017-2020). 54 years data of rainfall, temperature, relative humidity and change in water level were used for the modelling, 38 years of these data (from 1962-2000) were used to train the ANN model and the remaining 16 years (2001-2016) were used for validation and testing. Using the Levenberg-Marquardt as the training algorithm, the model was validated with R, R^2 and MSE to be 0.9705, 0.9418 and 0.0170 respectively. The ANN model results revealed that there was a strong positive relationship between the actual and the predicted change in water level, R^2 showed that the variation in water level was 94% influenced by rainfall, temperature and relative humidity. The MSE was used as indicator to measure the performance of the network during training, validation and testing.

When rain falls on Calabar catchment the amount of rainwater that reaches the waterways depends on the characteristic of the catchment, particularly its size, shape and land-use. The Calabar River characteristic such as size and shape, the vegetation in and around the river and the presence of structures in and adjacent to the waterway all affect the level of water in the waterway. The study shows that the months with heavy downpour from June to July (although there was a slight increase in May) also have high water levels. These months have more rainfall exceeding the maximum water level of the area which might lead to flooding. The trend of change in water level of Calabar River also shows an increase in the forecast year in 2020. The trend of rainfall from 2017 to 2020 shows values of 600mm and above. The increase in rainfall, the rise in water level, catchment condition, local drainage systems and low elevations, all project a high stream flow volume which can facilitate flooding during these months in Calabar city.

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