Rainfall prediction in Nigeria using Artificial Neural Networks

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Abstract: Rainfall data from the Nigerian Meteorological Agency, Oshodi, Lagos collected over thirty (30) years and from twenty three weather measuring stations spread across Nigeria have been used for the study. By applying stochastic and data reduction procedures the data was filtered to fast track the actual variables to be used for modeling rainfall. There were a total of 360 monthly mean data points for each station. The first 300 data points representing 25 years were used for training the network. The remaining 60 data points representing 5 years were used to cross validate the model. Each set of data was trained for 5 different sets of epochs. The number of epochs was chosen at intervals of about 500, 1000, 1500 2000 and 3000 epochs. By varying the weights and learning cycles, 5 different sets of predicted values were obtained. The predicted values were then correlated with actual values for corresponding periods. We obtained correlation coefficients between measured and predicted values up to 0.80 with an average value of 0.56. Compared on latitudinal basis, the coefficients were in ascending order from south to North. This means that the predictability of rainfall using Neuro Xl was better at higher latitudes.

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1. Introduction

Precipitation is any form of water (either liquid or solid) that falls from the atmosphere and reaches the ground, such as rain, snow, or hail. In Nigeria the major form of precipitation is rainfall. Because of its location in the low pressure zone of the earth and its proximity to the Atlantic Ocean, the country experiences heavy rainfall especially in the southern part of the country and less in its northern border. Nigeria thus has many water-related problems such as flooding and drought including desertification (Udo et al 2008; Ewona et al 2008; Obot et al 2010; Agbor et al 2013, Osang et al 2013; Udoimuk et al 2014).

Significant changes in rainfall have been reported both in pattern and seasonality. Rainfall is an important index in climate change considerations. The possibility for rapid and irreversible changes in the climate system exists, but there is a large degree of uncertainty about the mechanisms involved and hence also about the likelihood or time-scales of such transitions. The frequency of extreme precipitation events is projected to increase almost everywhere. Precipitation extremes are projected to increase more than the mean and the intensity of precipitation events are projected to increase also (IPCC, 2007; Ewona et al 2009, 2013; Ushie, et al 2014; Osang et al 2013; Udoimuk et al 2014).

However, Oladipo (1995) reported that decline in the rainfall in Nigeria started in the beginning of the 1960s when a decade of relatively wet years ended. According to him, the persistence of below-mean rainfall in the last two decades before 1995 in Nigeria is an indication of an abrupt change in climate. The agricultural sector is highly sensitive to rainfall pattern especially in southern Nigeria where rain-fed agriculture is mainly practiced (NOAA, 2008; Osang et al 2013; Udoimuk et al 2014). Chantasut, et al (2011) have use neural networks to undertake historical rainfall data mining covering the period 1941-1999 from 245 rainfall monitor stations in Thailand. The aim was to use data mining techniques for water resources management which is helpful in predicting rainfall quantitatively. Such treatment is helpful in crop planting decisions and reservoir water resource allocation (Ewona et al 2008; Osang et al 2013; Obi et al 2013; Ushie et al 2014; Ojar et al 2014; Ewona et al 2014).

Artificial Neural Networks (ANNs) has been increasingly applied in various aspects of science and engineering because of its ability to model both linear and non-linear systems without the need to make assumption as are implicit in most traditional statistical approaches Chantasut, et al (2011). It can explain complex data and more multi-layer components when the problem has more complex relationships. For hydrological modeling problems, ANNs have been used in modeling rainfall. (Lee, et al, 1998) have compared rainfall predictions made with neural networks and linear regression model. Results showed that the artificial neural networks produced good predictions while the linear models produced poor predictions. Chayanis, et al, (2003) worked with the prediction of monthly rainfall at Chiangmai station in Chao Phraya river basin using neural networks. Sixteen rainfall monitoring stations in Chao Paraya river basin, the Sea Surface Temperature (SST) areas around Thailand and the Southern

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Oscillation Index (SOI) were employed as the predictors. In an additional study, ANNs have been used in forecasting model of Chao Phraya river flood levels in Bangkok (Tingsanchali, 2000), neural network models for river flow forecasting (Danh, et al, 1999). The quantitative prediction of monthly rainfall in Nigeria by back propagation neural network is examined.

After being trained on historical Georgia statewide weather data, Shank (2006) made dew point temperature predictions for up to 12 hours. The study used three-layer back propagation, ANNs and weather data combined for three years from 20 locations in Georgia. An iterative search found that in addition to dew point temperature, important weather related ANN inputs included relative humidity, solar radiation, air temperature, wind speed, and vapor pressure (Shank, 2006). Experiments also showed the best models included 60 nodes in the ANN hidden layer, a ±0.15 initial range for the ANN weights, a 0.35 ANN learning rate, and a duration of prior weather related data used as inputs ranging from 6 to thirty hours based on the prediction period. The evaluation of the final models with weather data from 20 separate locations and a different year showed that the one-hour prediction had a mean absolute error (MAE) of 0.550 °C, the four-hour prediction model had a MAE of 1.234 °C, the eight-hour prediction had a MAE of 1.799 °C, and the 12-hour had a MAE of 2.280 °C. These final models adequately predicted on previously unseen weather data including difficult freeze and heat stress extremes (Shank, 2006). By varying the learning rate from 0.5 to 0.01 and setting a goal of 10^{-4}, Shank obtained an MSE around 10^{-3} after 100 000 epochs.

Knutti et al (2003) presented a neural network based climate model that increases the efficiency of large climate model ensembles by several orders of magnitude. Using the observed surface warming over the industrial period and estimates of global ocean heat uptake as constraints for the ensemble, the method estimates ranges for climate sensitivity and radiative forcing that are consistent with observations.

Anticipated and continuous warming of the climate system increases the need for accurate climate projections. The problem, however, is associated with the large uncertainties in these model projections. Sometimes the problem is that these estimates are based on expert judgment rather than on objective quantitative methods. Further, important climate model parameters are still given as poorly constrained ranges that are partly inconsistent with the observed data (Knutti et al, 2003).

2. **Data preparation.**

- Monthly mean data that were missing were estimated by interpolation or other means.
- A year with missing data for more than two consecutive months was excluded in the analysis. This followed the method applied by Dugas and Heuer (1985).
- Only years that contain an unbroken chain of data were used for correlation analysis and formulation of the model.
- The monthly mean data were spread out as one continuous string of data from month 1 year 1 to month 12 year n. Where n is the number of years used in the study of the parameter in question to enable trend analysis to be performed on them using SPSS statistical package and artificial neural networks.
- The data were finally normalized, a step necessary for intelligent modeling and simulation with digital computer.

The next step in data preparation is in terms of detection and replacement of outliers. We define an outlier as a data point which is twice the value of the sum of the two corresponding periods lying before and or after the outlier for a periodic data set. In general, it is replaced by the mean observation of successive corresponding periods before and after and outlier. But if the outlier is in the first or last cycle of a periodic set of data, the replacement is considered in terms of two successive periods for the

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first cycle or two preceding periods for the last cycle. This is presented in equations 1- 4. For a cycle of twelve months, which is the case for almost all meteorological data, x_i is an outlier if

- $x_i \succ (x_{i-12} + x_{i-24})$
- or $x_i \succ (x_{i+12} + x_{i+24})$
- or $x_i \succ (x_{i-12} + x_{i+12})$ 1
- X_i is therefore replaced by
- $x_{i'} = \dfrac{x_{i+12} + x_{i-12}}{2}$ 2
- or $= \dfrac{x_{i+12} + x_{i+24}}{2}$ for an outlier in the first cycle 3
- or $= \dfrac{x_{i-12} + x_{i-24}}{2}$ for an outlier in the last cycle. 4

3. Method

360 monthly mean rainfall data points, representing a thirty year period were used for the analysis. The first 300 data points representing 25 years were used for training the network. The remaining 60 data points representing 5 years were used to cross validate the model. Each set of data was trained for 5 different sets of epochs. The number of epochs were chosen at intervals of about 500, 1000, 1500 2000 and 3000 epochs. By varying the weights and learning cycles, 5 different sets of predicted values were obtained. The predicted values were then correlated with actual values for corresponding periods. The predicted values were then correlated with actual values for corresponding periods. This is cross validation. This is one way to avoid poor or over learning of the network. The values of the correlation coefficients were used to determine the most suitable network among the five different settings and learning processes. It follows then that the higher the correlation coefficient the

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lower the error and the higher the ability of the network to predict unknown values of the parameter. Such values obtained for the highest correlation coefficients were termed optimum values for the network. The number of epochs and the weight that produce optimum values were noted.

4. Network parameters

The artificial neural network (ANN) employed for the analysis was used in conjunction with Excel software to model three hundred and thirty data sets covering ten meteorological parameters and twenty-three weather stations in Nigeria. Table 1 shows the initial settings used with the network.

Table 1: Initial settings for the ANN

S/N	Property	Value
1	Maximum number of epochs	3000
2	Minimum weight	between 0.001 and 0.0001
3	Initial weight	0.3
4	Learning rate	0.3
5	Momentum	0.6
6	Number of neurons in the hidden layer	0 or 1
7	Activation function	zero-based log sigmoid function or hyperbolic tangent function

A time plot of optimum predicted values and actual values were obtained. The procedure was repeated for all ten parameters that met the minimum requirement used in data reduction. The analysis was carried out in all 23 stations chosen for the study.

5. RESULTS

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In general the network could not account for the extreme rainfall in the months of August and September judging from the general variation in the other meteorological parameters used for modeling it. This can be seen as poor fit between predicted and actual data between month 6 which is June and Month 10 that is October in Figure 1 to 4. These months are noted for having heavy cloudiness in this part of the world as reported by Udo (2002) and Ewona and Udo (2008). Clouds are the most unpredictable of all meteorological data. It is not surprising that the network could predict rainfall less accurately at this time. This is probably responsible for lower correlations coefficient between predicted and actual values. Correlation coefficients were generally between 0.20 and 0.80. The network however faired better in the middle belt as can be seen in the graphs at Lokoja. Apart from Lagos all other Southern stations recorded poor correlation values between the two set of values. This can be seen in table 2 where the stations have been listed in descending order of latitudes.

Table 2: Table showing ANN parameters used and correlations between actual and predicted values for northern zone.

S/N	Station	No. of Parameters	Epoch	Weight	Correlation between actual and predicted values
1	Yelwa	4	500	0.0012	0.58
2	Sokoto	4	1000	0.0001	0.77
3	Katsina	3	1539	0.0024	0.69
4	Kano	4	3000	0.0001	0.73
5	Bauchi	6	507	0.0003	0.48
6	Maiduguri	6	633	0.0010	0.76
7	Yola	7	17	0.0010	0.79
8	Minna	6	501	0. 0006	0.80
9	Lokoja	6	1000	0.0002	0.63
10	Jos	8	996	0.0002	0.76

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11	Ibi	5	505	0.0005	0.59
12	Ilorin	5	1509	0.0044	0.64
13	Lagos	4	506	0.0088	0.20
14	Ibadan	6	500	0.0005	0.45
15	Ondo	6	505	0.0071	0.37
16	Benin	6	3000	0.0030	0.46
17	Warri	7	2001	0.0007	0.46
18	Calabar	5	3000	0.0037	0.43
19	Enugu	3	1521	0.0003	0.69
20	Owerri	2	3000	0.0013	0.52
21	P/Harcourt	2	2030	0.0019	0.65

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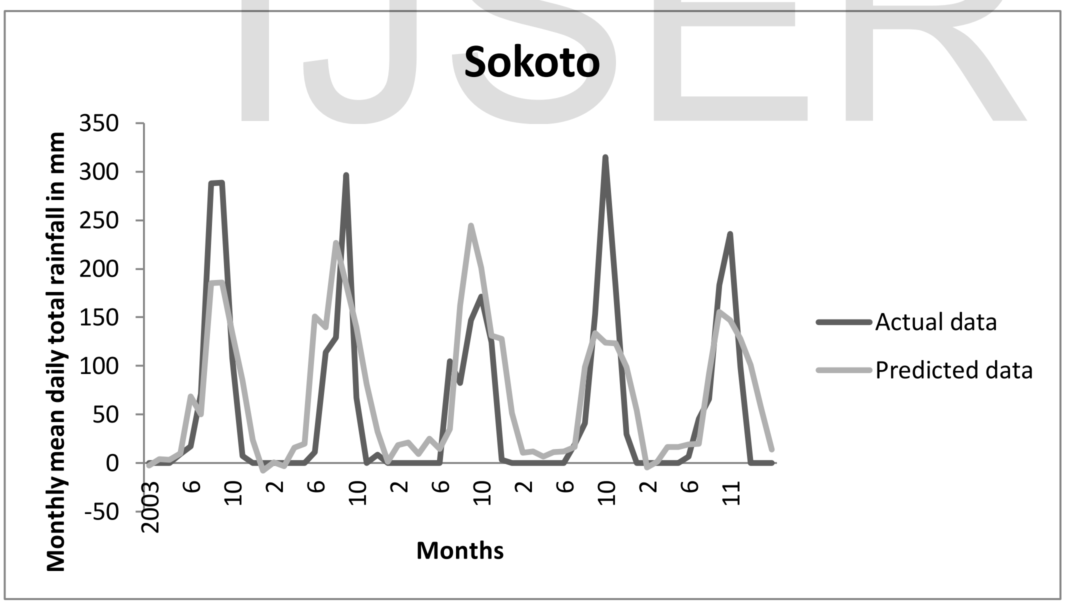

FIG.1. Monthly mean daily total rainfall and ANN predicted values for Sokoto between February 2003 and January 2008

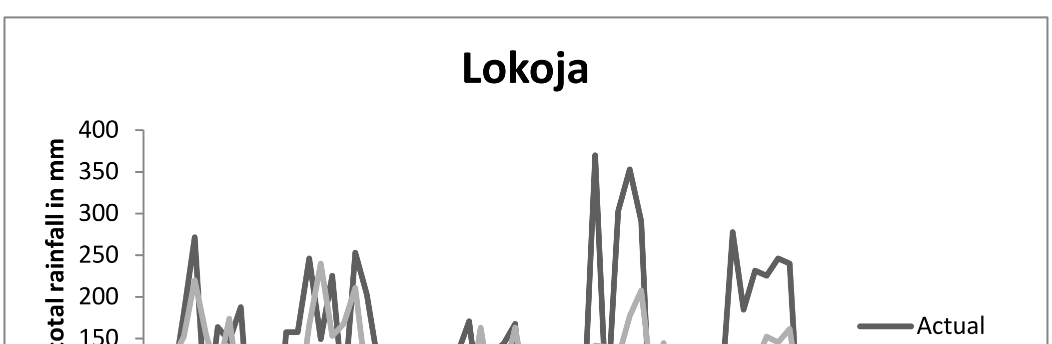

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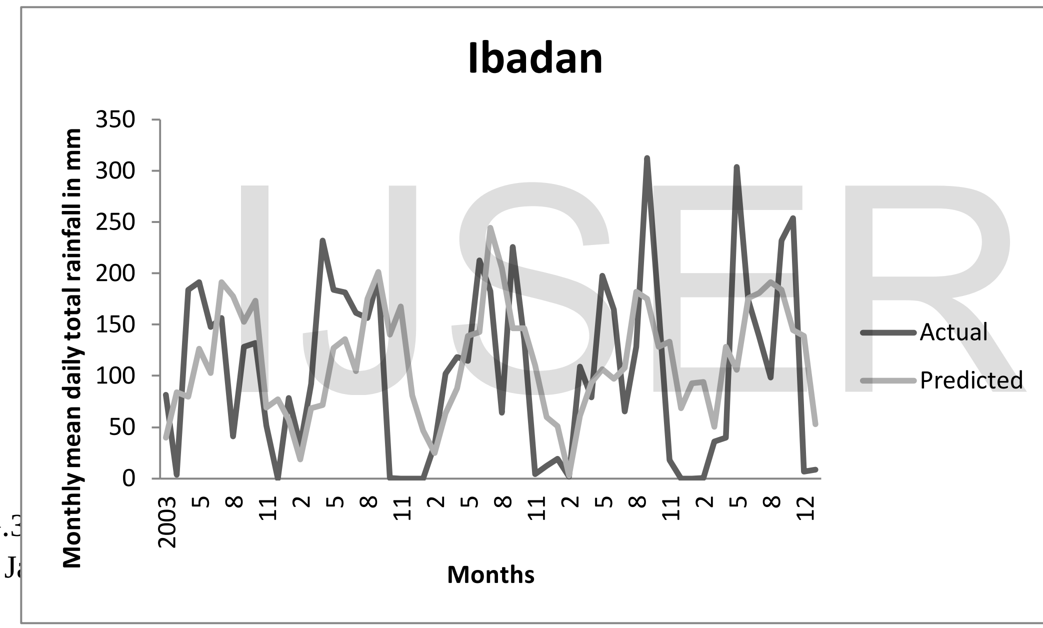
FIG.2 Monthly mean daily total rainfall and ANN predicted values for Lokoja between February 2003 and January 2008



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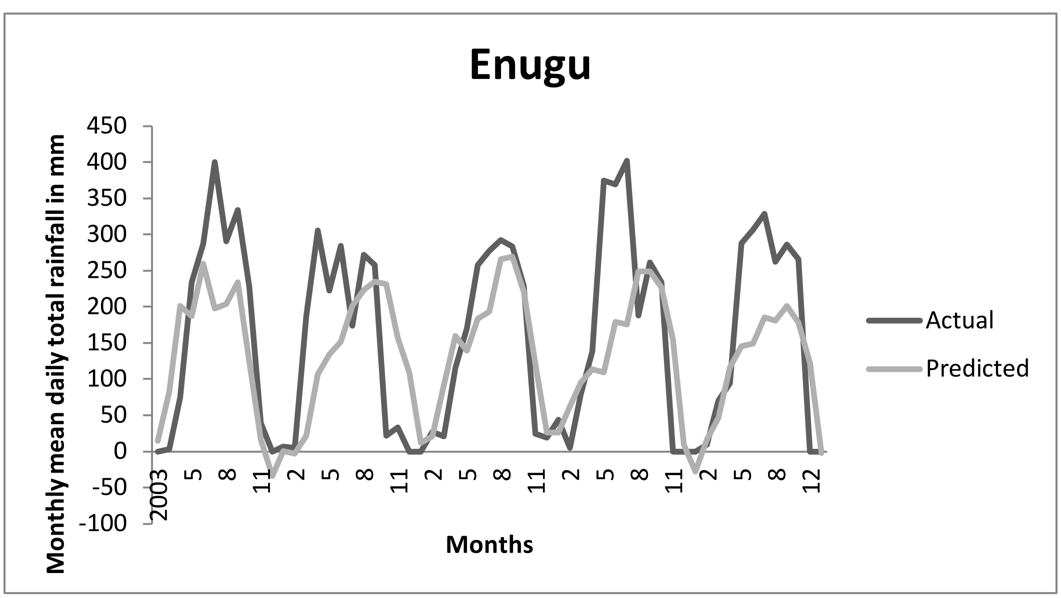

FIG.4 Monthly mean daily total rainfall and ANN predicted values for Enugu between February 2003 and January 2008.

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