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EVALUATION OF CLIMATE CHANGE IMPACT ON RUNOFF IN THE KAINJI LAKE BASIN USING ARTIFICIAL NEURAL NETWORK MODEL (ANN)

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Abstract: This paper presents an evaluation of the impacts of climate change on the runoff in the Kainji Lake basin. Hydro-meteorological data used include the minimum and maximum temperature, evaporation, precipitation, runoff and water level were subjected to artificial neural network (ANN) model. The model results revealed a positive relationship between the actual and forecasted runoff for all the selected locations and their correlation coefficient of 0.62, 0.57, 0.55 and 0.57 for Lokoja, Kaiji, Baro and Idah respectively. Runoff values were predicted for the stations and the mean annual predicted runoff were subjected to trend analysis in order to determine their variation. The percentage variations are estimated as -9.75%, +4.58%, -12.07% and - 6.48% for Lokoja, Kainji, Idah and Baro respectively. The trend analysis indicated that the runoff at Lokoja, Baro and Idah are negative while that of Kainji exhibit positive trend. This implies that there is tendency for runoff to decrease at Lokoja, Baro and Idah stations while increases at Kainji. The study revealed that climate change has positive impact on the reservoir inflow at Kainji damand subsequently assure more water for hydropower generation.

Key words: *Kainji lake basin, climate change, river niger, hydro-meteorological variable*

1.0 Introduction

Impact of climate change on River Niger is a very crucial issue due to its effect on runoff into the hydropower reservoirs within its catchment. Climate change is caused by natural and anthropogenic factors due to emission of greenhouse gases. Climate change affects man and his environment and constantly modifies temperature and precipitation thereby alters quantity and quality of runoff in the River basin. Flooding or drought may be resulted from climate change in the environment. Climate change in IPCC usage refers to a change in the state of the climate that can be identified by changes in the mean and the variability of its properties that persists for an extended period typically decades or longer. It refers to any change in climate over time whether due to natural variability or as a result of human activity (IPCC, 2007).There is growing concern that the NigerRiver Basin (NRB) system is vulnerable to climatevariability. The projected impacts of climate change may induce some potential risks to an investment plan for building new water infrastructures in the basin. For this reason water resource managers and policy makers seek the best possible sources of climate change projections to assist their decision making.The changes in climate variables such as precipitation and temperature have hydrological impacts that will influence reservoir management. From the same perspective, water supplies, flood, irrigation and hydropower production will be affected at various levels (Minville *et al*., 2010).

Solaimani (2009) assessed rainfall-runoff prediction based on ANN in Jarahi Watershed in Iran. The study was aimed at modelling the rainfall-runoff relationship in the catchment area using monthly hydro-meteorological data such as precipitation, temperature and runoff for the period of seventeen years (1983 - 2000). Poff *et al*., (1996) employed ANN to evaluate the hydrological responses of two streams with different hydro-climatological data in the north-eastern of the United State of America. Harun *et al*. (2002) carried out a study using ANN for rainfall-runoff relationship on the Sungai Lui catchment in Malaysia. The hydro-meteorological data used are daily precipitation and runoff for the period of five years (1993-1997). The data used or the analysis consists of two sets: the data for the first three years (1993-1995) were used for model calibration while the data for the remaining two years (1996-1997) were used for the model validation. The result showed that the ANN model predicts the runoff accurately.

Pulido-Calvo *et al*. (2012) carried out study on Water Resources Management in the Guadalquivir River Basin, Southern Spain using ANN model to simulate the inflow and outflow in a water resources system under shortage of water using hydro-meteorological data from various gauging stations. Weekly data were used for the analysis for the period of eight years, data of six years were used for model calibration and the remaining two years data were for the validation. The results demonstrated that the neural approach approximated the behaviour of various components of the water resources system in terms of various hydrologic cycle processes and management rules. Demirel and Booij (2009) studied the identification of an appropriate low flow forecast model for the Meuse River in Netherlands based on the comparison of output uncertainties of different models. Three models were developed for the Meuse River such as multivariate, linear regression and ANN models. The uncertainty in the three models is assumed to be represented by the difference between observed and simulated discharge. The data used for the study are discharge, precipitation and evapotranspiration for thirty years (1968-1998). Twenty years data was used for the model calibration while ten years data was used for validation of the result. The results show that the ANN low flow forecast model performed slightly better than the other statistical models when forecasting low flows for a lead time of seven days.

Neural network was used to model the impacts of climate change on water supplies in Colorado Arkansas River basin under two GCM-based climate change scenarios. Historical and future climate scenarios were used respectively to calibrate and validate the ANN model and to run simulations for the ANN-generated water supply under changing climatic conditions. The climate data include historical data from 1895 to 1993 and projections from two GCM-based scenarios for 1994–2099. The behaviour of the water supplies under climate change was compared to the behaviour of supplies with no climate change that is baseline. The model was trained with the historical climatic data and tested if it would perform satisfactorily with data that were not used during training. The results of the study gave insights into changes in monthly and seasonal water supplies under two GCM scenarios. Based on the analysis, the region is sensitive to climate change and water supply is sensitive to changes in precipitation projections. The two GCM scenarios gave different indications about the direction of the effect of climate change on water supply. The region is expected to be relatively wet under the HAD scenario with the growing season having sufficient water supplies but relatively dry under the CCC scenario with the growing season having shortages in water supply (Elgaali and Garcia, 2007). ANN model was used forsimulation of climate change impacts on streamflow in the Bosten lake basin in China. The objective of the assessment is to show the impact of meteorological parameters: precipitation and temperature on the streamflow. The relationship between temperature and pan evaporation was used to derive evaporation which was then used to estimate streamflow response to climate change. The model was trained using error propagation algorithm. The data were divided into three sub-sets two trained periods from 1977-1990 and 1995-2001 and a validation period from 1991-1994 and additional validation was made using monthly mean value from 1978-2001. In conclusion, it was observed that large portion of the streamflow in the basin are from snowmelt. They also suggested that the limited flow in the River basin can be improved if the region current warming and moistening trends continue (Chen *et al*., 2008).

Dibike and Solomatine (1999) assessed the River flow forecasting using ANN model in the Apure river basin in Venezuela. Two types of ANN architectures namely multilayer perceptron network (MLP) and radial basis function networks (RBF) were implemented. The data used for the analysis are weekly precipitation, evapotranspiration and runoff for the period of five years (1981-1985). The model was calibrated (or trained) with the first three years (1981-1983) and validated (or tested) with the remaining two years (1984-1985). The performances of these networks were compared with a conceptual rainfall-runoff model and they were found to be slightly better for the River flow forecasting problem. The main difference between RBF and MLP networks are as follows (Akbarpour, 2004): (i) The RBF network has one hidden layer and activation functions of neurons and is Gussian function with particular centre and spread (ii) There are no weights between input layer and hidden layer of RBF and the distance between each pattern and center vector of each neuron in hidden layer is used as an input of

Gussian activation function and (iii) In RBF network, activation functions of output neurons are simple linear functions and because of this reason linear optimum algorithms can used.

Olomoda (2011) reported that for the past five decades, the Niger basin has been affected by series of climatic changes causing extreme low flows along the river. For example in June 1985 the river Niger was completely dry in Niamey. This phenomenon was almost repeated in June 2002 when the flow recorded fell among the lowest in 50 years. The Niger basin theoretical area of about 2 million km^2 has also been reduced to an active catchment area of about 1,500,000 km^2. Ojoye (2012) reported that study had also shown that impact of climate change was noticed in the River Niger when the annual yield of the River at Kainji reservoir had steadily decrease from 46 x 10^9 m^3 in 1970 to 26 x 10^9 m^3 at the peak of 1973 drought. Also there has been drastic reduction in electricity generation at Kainji hydropower station over the years and this may be due inter alia to shortage of water in the reservoir.

It is imperative therefore to study the impact of climate change on the Kainji Lake and to predict the future climatic change impact in the River basin at some selected locations in the study area using hydro-meteorological parameters analyzed with artificial neural network (ANN) model.The aim of this paper therefore is to evaluate climate change impact on the runoff in the Kainji Lake basin by modeling hydro-meteorological parameters with ANN model and prediction of future runoff for trend analysis in order to study runoff variation.

2.0 Material and Methods

2.1 Study Area

River Niger has a total length of about 4,200 km and is the third longest river in Africa and the 9thworld largest river basin. The river Niger basinhas catchment area of about 2 million Km^2 covering 10 Countries namely Algeria, Benin Republic, Burkina Faso, Cameroon, Chad, Ivory Coast, Guinea, Mali, Niger and Nigeria is shown in the Figure1. The river is the source of water for over 100 million people and is also the major sources of hydropower to most of the Countries in its basin. Two out of the three hydropower stations in Nigeria were constructed on the river Niger namely: Kainji and Jebba hydropower stations. The river provides habitat for over 130 aquatic species such fish varieties, hippopotamus, crocodiles, sea-cows and birds. Its unique vegetal cover, lakes and reservoirs provides humid zones for these species (Olomoda, 2011). Figure 2 is map of Nigeria showing Kainji dam on Niger River.

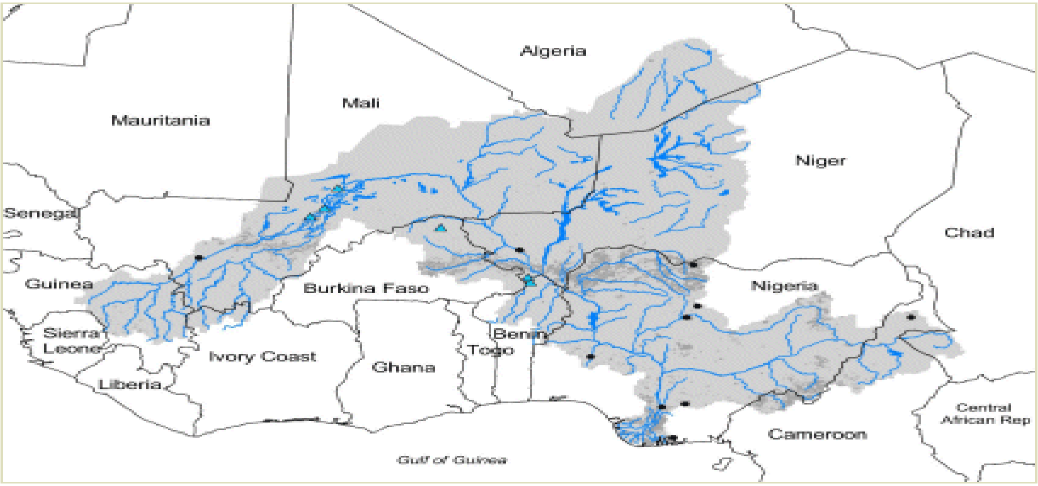

Figure 1: River Niger basin and the contributing countries

Figure 2: Map of Republic of Nigeria showing Kainji dam on River Niger

Kainji hydroelectric power dam was constructed across the river Niger and it is the first hydropower station in Nigeria. River Niger is divided into upper Niger, middle Niger and lower Niger. Kainji dam is located on the middle Niger and it is fed by many river tributaries such as Malando, Danzaki and Sokoto-Rima Rivers. Kainji hydropower dam was built between 1964 and 1968 and the operation was commenced in 1969. The characteristic of Kainji reservoir is presented in Table 1.

Table 1: Salient features of Kainji reservoir

Parameters	Characteristics
Latitude	9° 50' N
Longitude	4° 40' E
Maximum Capacity	15 x 10^9 (m^3)
Minimum Capacity	3 x 10^9 (m^3)
Surface Area	1270 km^2
Length	135 km
Maximum Width	30 km
Maximum Elevation (m.a.s.l)	141.9 m

Source: Salami and Nnadi (2012)

2.2 Data Collection

The data required for this study are hydro-meteorological data which were obtained for a period of 30-50 years. The meteorological data include precipitation, evaporation, minimum and maximum temperature while the hydrological data are the runoff and water level. The meteorological data were obtained from Nigerian Meteorological Agency (NIMET) and meteorological unit of Kainji hydropower station. The hydrological data such as runoff and water level for the River Niger at various gauge stations were obtained from the Nigerian National Inland Waterways Agency (NIWA). The gauging stations located along river Niger Basin is presented in Table 2.

Table 2: Geographical location of gauging stations and year of records

Location	Coordinate		Year of records
	Latitude (°N)	Longitude (°E)	
Lokoja	7° 48' 30.7"	6° 44' 14.5"	1960-2011
Kainji	9° 50' 00"	4° 40' 00"	1970-2011
Baro	8 ° 35' 27"	6 ° 27' 41"	1960-2001
Idah	7 ° 05 ' 00"	6 ° 45' 00'	1960-2001

2.3 Data Analysis

2.3.1 Artificial Neural Networks Model

Artificial neural networks (ANNs) model are collection of non-linear mapping structures based on the function of human brain. They are powerful modeling tools used especially when the underlying data relationship is not known. The model can identified and learn correlation patterns between input data set and corresponding target values. ANNs imitate the learning process of human brain and can process problems involving non-linear and complex data. ANN is a computational structure that is inspired by observed process in natural network of biological neurons in the human brain. It consists of simple computational units called neurons that are highly interconnected. The model is very suitable where the training data is readily available and are now being increasingly recognised in the area of classification and prediction where regression model and other related statistical techniques have traditionally been employed.

ANNs are recognised as a powerful tool for data analysis. They are constructed with layers of units termed multilayer ANNs. A layer of units composed of units that perform similar function. There are three layers in the ANN model namely: the input units, the hidden layer and the output layer corresponding to the dependent variables. Input layer is a unit where data are introduced to the model, hidden layer is a unit where the data are processed while the output layer is the unit where the result for a given input are produced (Harun *et al*., 2002). ANNs model normally use learning techniques to train data before analysis. The data required for the ANN model calibration is normally larger than the one required for model validation/testing and forecasting/predicting. As a rule of thumb about two-third of the input and output data are required for model calibration while the remaining data are used for the validation and testing (Al Shamisi *et al*., 2011).

The most widely used learning technique is back propagation algorithm. Back propagation algorithm uses the earlier generated output data to adjust the network weighs in order to minimise the error in the predicted training data. Equations 1 to 3 (Chen *et al*., 2008) are the ANN expressions modeladopted for this study.

$$y = f(u_j) \tag{1}$$

$$u_i = \sum w_i x_i - \theta_j \tag{2}$$

$$f(u) = \frac{1}{1 + \exp(-u)} \tag{3}$$

where:

y = runoff output ; f = logistic sigmoid function; u_j = interconnected neuronsw_i = weight of $x_i (i = 1,2,3, \dots n)$; x_i = input variables; θ_j = critical value

Artificial Neural Network (ANN) was used to assess the impact of the meteorological parameters of precipitation, temperature and evaporation on the hydrological parameters such as river runoff and water level at Lokoja, Kainji, Baro and Idah. Equations 1 to 3 are the ANN expressions model adopted. The ANN model in the statistical package for social science (SPSS) and 'Alyuda forecaster XL' softwares were used for the analysis. The model was trained, validated and tested with the available hydro-meteorological parameters in the selected stations using error back propagation algorithm and momentum in order to speed up its convergence to a minimum error (Chen *et al*., 2008). The input parameter required for ANN model analysisare monthly mean temperature, precipitation and evaporation while output parameter is the runoff at various locations.

2.3.2 ANN Model Calibration

The data available for the study were not of equal durations in all the locations, hence different calibration periods were employed in the calibration of the ANN model. The ANN model for Lokoja was calibrated with 35 years hydro-meteorological data (1960-1994), Kainji was calibrated with 30 years hydro-meteorological data (1970-1999), Baro and Idah data were respectively calibrated with 30 years hydro-meteorological data (1960-1989).

2.3.3 ANN Model Validation

The ANN model for Lokoja station was validated with the 10 years hydro-meteorological data (1995-2004) while 7 years (2000-2006) for Kainji station and 5 years (1990-1994) for Baro / Idah stations respectively.

2.3.4 ANN Model Testing

The ANN model for the Lokoja station was tested with 7 years hydro-meteorological data (2005-2011),5 years hydro-meteorological data (2007-2011) for Kainji station and for Baro and Idah stations 7 years hydro-meteorological data (1995-2001) were used.

2.3.5 ANN Model Analysis

The ANN model analyses for the hydro-meteorological parameters at the selected locationsrevealed correlation coefficient of 0.62, 0.57, 0.55 and 0.57 for Lokoja, Kainji, Baro and Idah gauging stations respectively. Figures 3 - 6 depict the actual and forecast runoff, while Figures 7 - 10 depict the scatter plots of forecast and actual runoff.

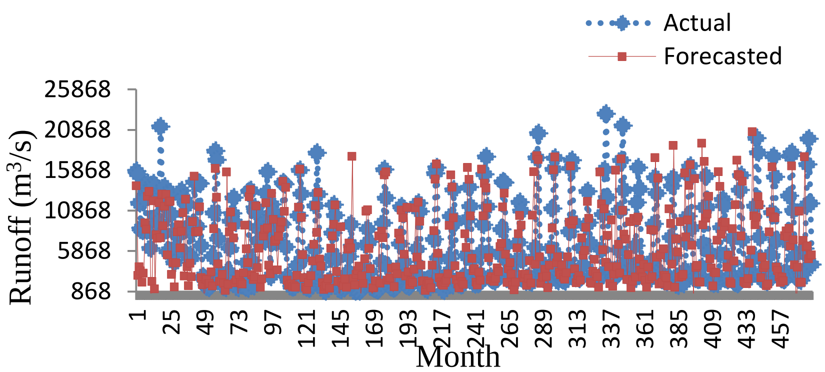

Figure 3: Actual and forecasted runoff for Lokoja

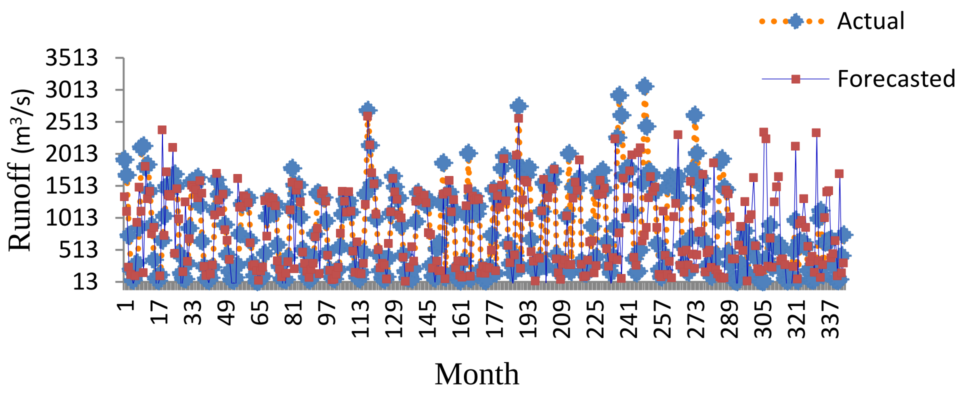

Figure 4: Actual and forecasted runoff for Kainji

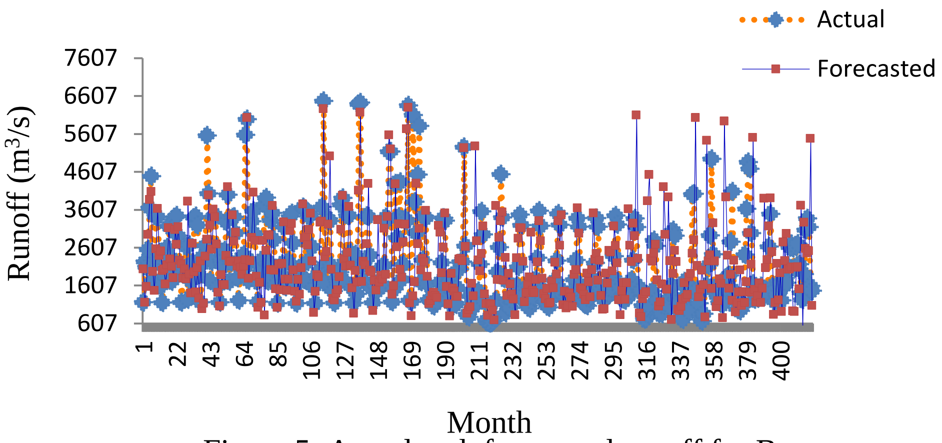

Figure 5: Actual and forecasted runoff for Baro

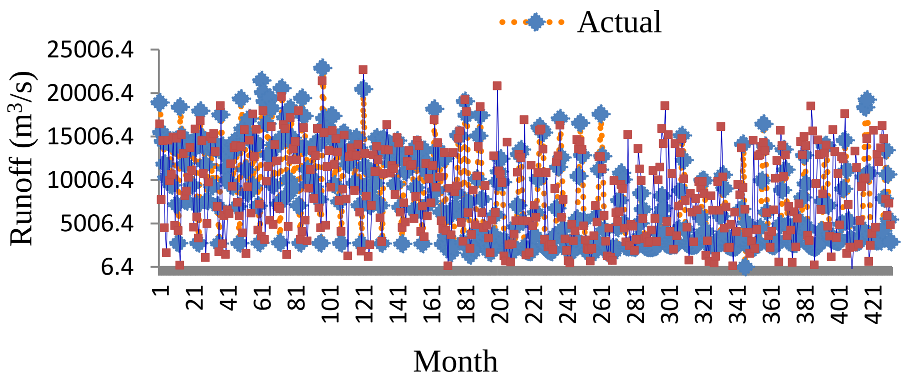

Figure 6: Actual and forecasted runoff for Idah

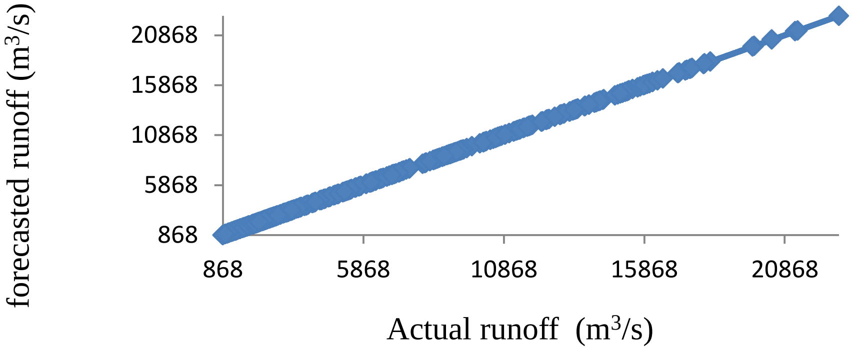

Figure 7: Scatter plot of forecasted and actual runoff for Lokoja

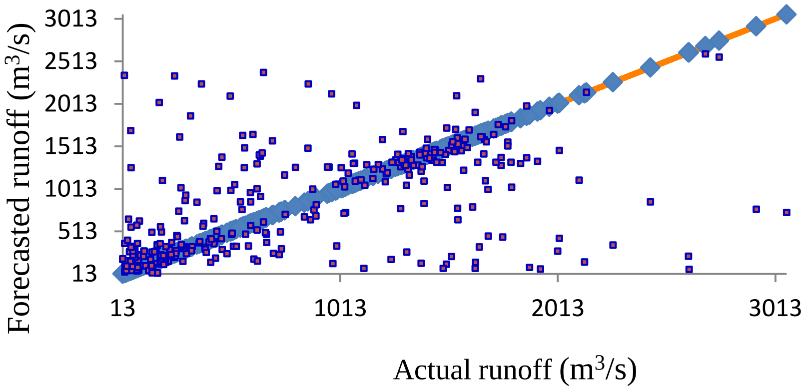

Figure 8: Scatter plot of forecasted and actual runoff for Kainji

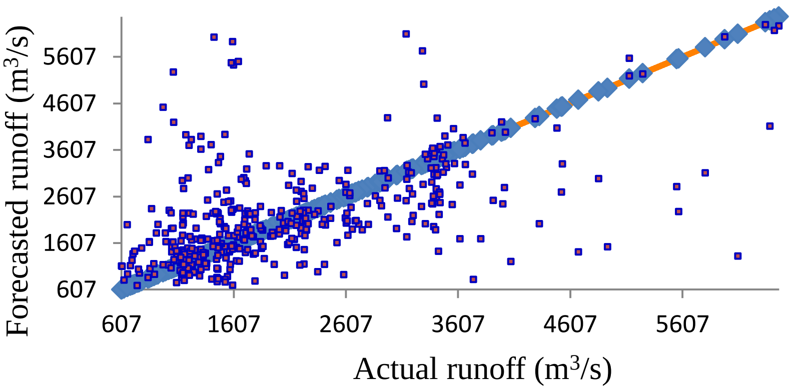

Figure 9: Scatter plot of forecasted and actual runoff for Baro

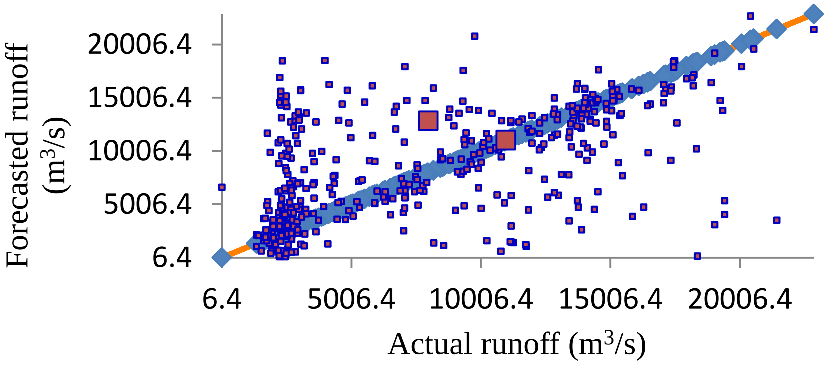

Figure 10: Scatter plot of forecasted against actual runoff for Idah

2.3.6 ANN Model Prediction

The trained and tested ANN model was used to predict the monthly runoff for the stations. Ten years runoff was forecasted for Lokoja and Kainji (2011 – 2020), while twenty years runoff was forecasted for Baro and Idah (2001 – 2020). The statistical summary of the predicted runoff is presented in Table 3 to 6 for Lokoja, Kainji, Baro and Idah respectively.

Table 3: Statistics of the mean monthly predicted runoff (m^3/s) for Lokoja (2011 – 2020)

Statistics	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean	1642.	1979.9	2166.69	2360.40	2450.41	2628.13	2394.79	2746.70	3123.35	3827.26	2348.59	1804.94
Stdev	356.52	419.00	443.34	347.77	489.88	280.28	413.80	419.55	798.98	652.00	184.16	696.50
CV	0.22	0.21	0.20	0.15	0.20	0.11	0.17	0.15	0.26	0.17	0.08	0.39
Skew	-0.78	-0.73	-0.51	-0.44	-1.38	0.12	-1.02	0.43	2.68	-0.14	0.07	0.63
Max	2144.	2445.9	2823.9	2878.9	3017.0	2993.0	2833.8	3343.6	5305.7	4766.5	2621.9	3155.2
Min	914.8	1144.6	1275.7	1807.6	1343.6	2224.4	1499.4	2211.3	2421.8	2848.1	2049.7	921.82

Table 4: Statistics of the mean monthly predicted runoff (m^3/s) for Kainji (2011 – 2020)

Statistics	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean	368.52	486.57	519.74	528.87	555.82	582.44	628.32	648.56	684.16	846.43	601.76	457.09
Stdev	110.15	94.77	58.58	139.94	96.75	43.37	43.06	45.40	91.35	119.16	110.58	156.54
CV	0.30	0.19	0.11	0.26	0.17	0.07	0.07	0.07	0.13	0.14	0.18	0.34
Skew	-0.45	-1.22	0.99	-0.61	-1.05	0.60	0.10	-0.62	-1.26	0.91	-0.03	-1.23
Max	512.20	585.41	648.13	710.99	668.65	650.10	702.87	705.06	776.04	1091.5	800.18	595.55
Min	192.60	276.87	435.97	282.01	345.88	531.75	553.77	574.95	490.26	695.80	415.38	136.64

Table 5: Statistics of the mean monthly predicted runoff (m^3/s) for Baro (2001 – 2020)

Statistics	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean	946.85	1090.33	1178.27	1190.77	1213.40	1279.37	1242.52	1305.59	1370.64	1579.35	1190.57	1074.83
Stdev	207.40	121.54	90.76	117.62	103.04	213.43	122.43	151.10	155.15	342.84	172.49	161.92
CV	0.22	0.11	0.08	0.10	0.08	0.17	0.10	0.12	0.11	0.22	0.14	0.15
Skew	0.15	1.68	0.54	1.44	1.06	2.74	0.90	1.05	0.36	2.45	0.74	0.93
Max	1491.35	1510.27	1360.52	1544.55	1536.87	2096.74	1521.42	1750.28	1679.86	2797.65	1580.82	1582.58
Min	560.17	918.52	1012.32	1022.24	1036.56	1115.45	1025.57	1039.47	1102.39	1288.01	936.39	796.50

Table 6: Statistics of the mean monthly predicted runoff (m^3/s) for Idah (2001 – 2020)

Statistics	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean	1290.00	1542.86	1852.95	2806.40	2222.88	2650.66	3777.53	4128.46	5713.28	7064.28	2716.74	1797.98
Stdev	1030.43	534.82	402.61	3775.52	518.64	596.66	4086.23	2184.48	3671.90	3697.12	1261.56	462.23
CV	0.80	0.35	0.22	1.35	0.23	0.23	1.08	0.53	0.64	0.52	0.46	0.26
Skew	4.27	0.88	0.38	4.90	0.45	0.22	4.65	2.07	1.62	0.83	2.21	-0.28
Max	6005.67	2964.53	2723.92	20814.44	3610.99	3603.81	22967.95	10941.00	16615.73	14842.26	7295.82	2553.17
Min	453.20	477.81	1102.74	1376.07	1136.84	1705.31	982.23	2249.12	513.08	2183.87	1161.61	923.11

2.3.7 Variation in Predicted Runoff

The predicted runoff was subjected to trend analysis to determine percentages variation by plotting the mean annual predicted runoff against the year. Figures 11 - 14 depict the runoff variations. The percentage variation was also determined as follow; -9.75%, +4.58%, -12.07% and - 6.48% for Lokoja, Kainji, Idah and Baro respectively.

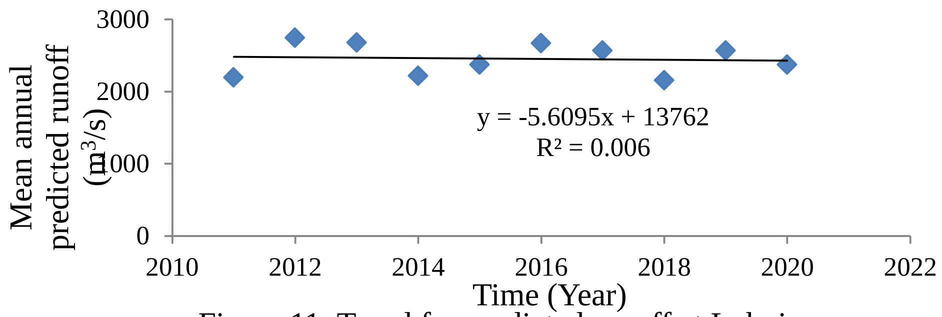

Figure 11: Trend for predicted runoff at Lokoja

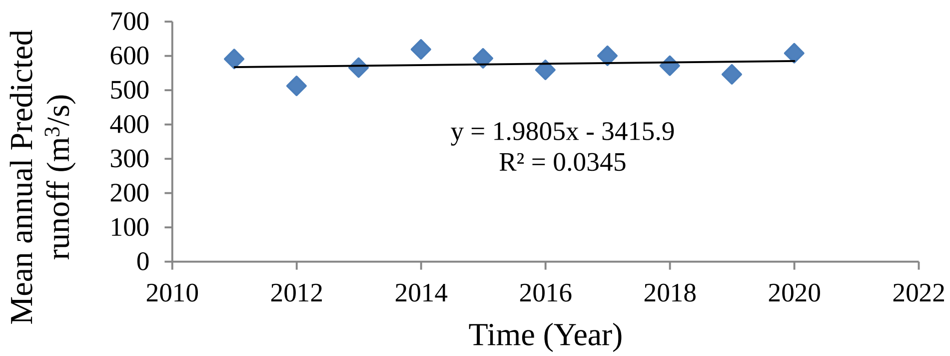

Figure 12: Trend for predicted runoff at Kainji

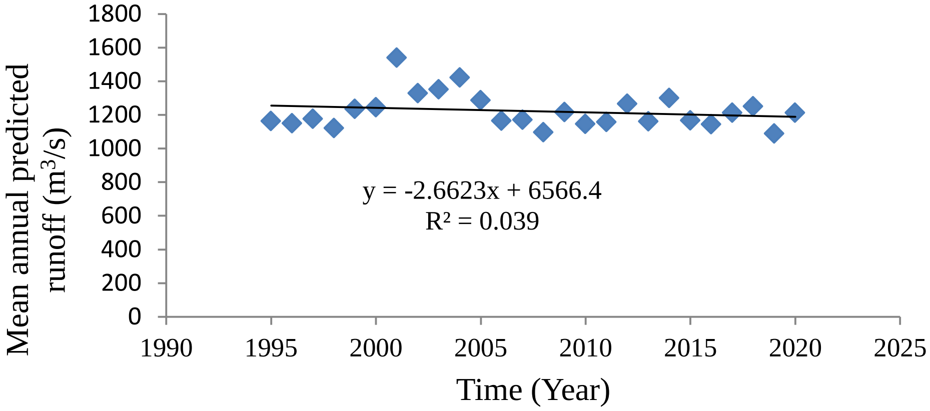

Figure 13: Trend for predicted runoff at Baro

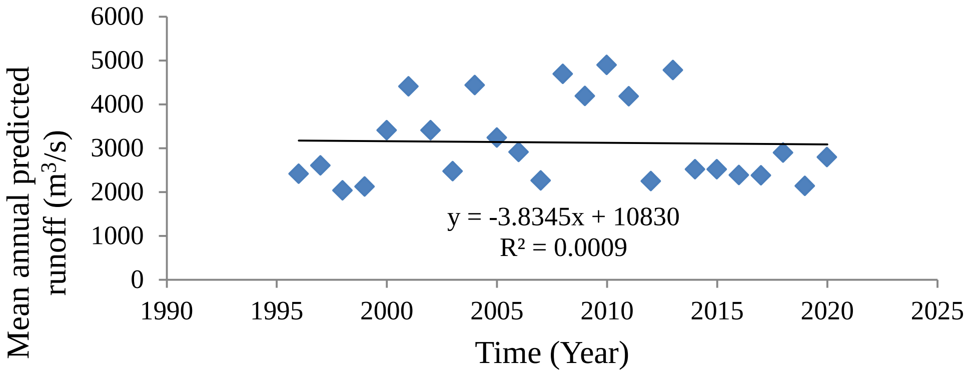

Figure 14: Trend for predicted runoff at Idah

3.0 Results and Discussion

The characteristic of Kainji reservoir is presented in Table 1, while the geographical location of gauging station with year of records is presented in Table 2. The statistics summary of the predicted runoff is presented in Table 3 to 6 for Lokoja, Kainji, Baro and Idah respectively. Figure 1 presents the River Niger Basin and the countries within the basin, while map of republic of Nigeria showing Kainji dam on River Niger is presented in Figure 2. The relationship between the actual and forecasted runoff is depicted in Figure 3 to 6 for Lokoja, Kainji, Baro and Idah respectively, while Figure 7 to 10 presents the scatter plot of forecasted and actual runoff for Lokoja, Kainji, Baro and Idah respectively. The variation of the mean annual predicted runoff with time is presented in Figure 11 – 14, this depicts the trend of the runoff for Lokoja, Kainji, Baro and Idah respectively.

The ANN model results for the selected locations in the study show the percentage of data used for model calibration, validation and testing, sum of square error (SSE) and relative error (RE). At Lokoja gauging station, it was found that about 69%, 19% and 11% of the data are used for ANN calibration, validation and testing respectively, while the SSE for the training data is 10.219 and its RE was 0.873. The validation had SSE of 2.579 and RE of 0.714 and the testing had RE of 0.886. The coefficient of determination (R^2) and correlation(r) were 0.29 and 0.62 respectively which shows a positive relationship between the actual and the forecasted runoff. At Kainji gauging station, the SSE for the training data was 4.014 and its RE was 0.642 while its validation had SSE of 1.967 and RE of 0.839 and the testing had RE of 0.842. R^2 and r were 0.19 and 0.57 respectively which show a positive relationship between the actual and the forecast runoff. At Baro gauging station, the SSE for the training data was 5.814 and its RE was 0.858 while its validation has SSE of 0.730 and RE of 0.720 and the testing has RE of 0.754. R^2 and r were 0.12 and 0.55 respectively showing a positive relationship between the actual and the forecasted runoff. At the Idah gauging station, the SSE for the training data was 7.390 and its RE was 0.945 while its validation had SSE of 2.41 and RE of 0.882, the testing had RE of 0.928. R^2 and r were 0.12 and 0.55 respectively which show a positive relationship between the actual and the forecasted runoff.

The predicted mean annual runoff indicates negative trend at Lokoja, Baro and Idah, while it has positive trend at Kainji. The percentage variation for the predicted runoff indicates a decrease of 9.57%, 6.48% and 12.07% for Lokoja, Baro and Idah respectively, while runoff at Kainji is expected to increase by 4.58%.

4.0 Conclusion

The ANN model results reveal a decreasing trend in runoff at Lokoja, Baro and Idah while an increasing trend at Kainji Lake. A decrease in runoff has been estimated at 9.57%, 6.48% and 12.07% at Lokoja, Baro and Idah stations respectively while an increase of 4.58% has been estimated for Kainji. Also the hydropower generation at Kainji station is expected to increasedue to availability of more water. However, the risk of flooding at Kainji station may be envisaged while Lokoja, Baro and Idah stations are prone to reduction in available water for domestic and irrigation purposes. It is suggested that optimization model should be developed for optimal water management within the Kainji Lake Basin.

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