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Assessment of Stream Hydrological Response Using Artificial Neural Network: A Case Study of River Kaduna, Nigeria

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Abstract

Hydrological alterations may result either from changes in average condition or from changes in the distribution and timing of extreme events. In view of this, the study attempted an evaluation of the hydrological response of River Kaduna at Shiroro Dam site, Nigeria to hypothetical climate change scenarios using the Artificial Neural Network (ANN) paradigm. For the deployment of the ANN, monthly historichydrometeorological data (i.e., evaporation, rainfall, streamflow and temperature) spanning 33 years were obtained. To this end, four climate change scenarios: +10% rainfall, 2×coefficient of variation in rainfall, -10% rainfall and +3^{0}C average temperature were considered. The historical data were used as input to the ANN and selected monthly synthetic streamflow hydrographs in the seasons (i.e., dry and wet) were generated with an average high value of the goodness-of-fit (R^2=0.96). The response pattern indicated a variability index for the River to be in the range of 0.85-1.25 while for the recession pattern it is 0.75-0.81. It is imperative to note that the ANN enhanced the generalization of the flow dynamics of the extreme events (peak and low flow regime) with relative predictability capacity values of 103% (R_{max}) and 96.35% (R_{min}), respectively. However considering the fact that the upgraded temperature and coefficient of variation in rainfall might impact negatively on the average runoff, flow variability, flood frequency and predictability, there is the need for the use of an extensive hydrometeorological data base coupled withthe application of associated risk value for effective flood forecasting in real-time.

Keywords: Stream hydrological response, climate change scenario, artificial neural network, Shiroro River, dynamics

1. Introduction

In line with Alexi et al., (2007), any critical evaluation of hydrological impact of climate change find relevance against the backdrop of the need to plan for effective water resources management. Because of the importance of this subject, different methods have been employed to assess the severity of the impact of climate change. Thus, regardless of uncertainty in future climate, there are manifestations/features that there would be significant result on the water cycle and its environs (Merritt, *et al*., 2006). Water cycle rises when there is increasing evaporation which in turn causes excessive rainfall (Zhang *et al*., 2007a and Ahn, *et al*., 2011). Rainfall intensity and amount vary with time and space and these changes have either positive or negative significance on the water resource management (Ahn *et al*., 2011) thereby causing hydrological response. In this context therefore, hydrological response of a stream is simply by the production of runoff against a given rainfall, which in turn is characterized by basin morphometric properties, soil characteristics and land use pattern (Ajibade*et al*.,2010).

There are basic methods for the assessment of hydrological response which are downward and upward approaches. Downward approach gives best fitness between observations and simulations while the upward approach represents all the hydrological processes in the river system (Hulme and Brown, 1998; Merritt *et al*., 2006). Climate impacts on runoff and stream response are assessed and accomplished by coupling General Circulation Model (GCM) outputs and hydrological models. Andersson *et al*., (2006) employed four GCMs and Pitman stochastic and physical based model to measure the impact of varied development and climate change scenarios about river system within Okavango river basin. Merritt *et al.* (2006) appraised the response of the river to scenarios of climate change in Okanagan basin accompanied with three GCMs. Zhang*et al*., (2007b) forecasted the consequence of possible climate change on streamflow quantity in Luohe river basin using two GCMs and Soil and Water Assessment Tool (SWAT) model (Ahn *et al*., 2011). Regardless of this, prediction of climate change is still challenging (ASCE Task Committee, 2000; Merritt *et al*., 2006). But available information lacks adequate real-time planning especially during the incidences of flood situation and its mitigation. Therefore the study aimed to assess stream hydrological response using ANN

2. Materials and Methods

(i) Hydrology of the study

The Shiroro is located on latitude 9° 58’ 00” N and latitude 6° 51’ 00” E. River Kaduna is the only riverfeeding Shiroro dam. Shiroro River has fifteen drainage tributaries among its watershed and these tributaries are rivers Dinya, Sarkin Pawa, Guni, Erena, and Muyi as shown in Figure 1 below;the tributaries flow in the North-South direction and then meander in the Northwest to Southeast direction. This river has a low base flow problem and the volume of the rivers swell in volume with ranging torrent while in the dry season they dry up.

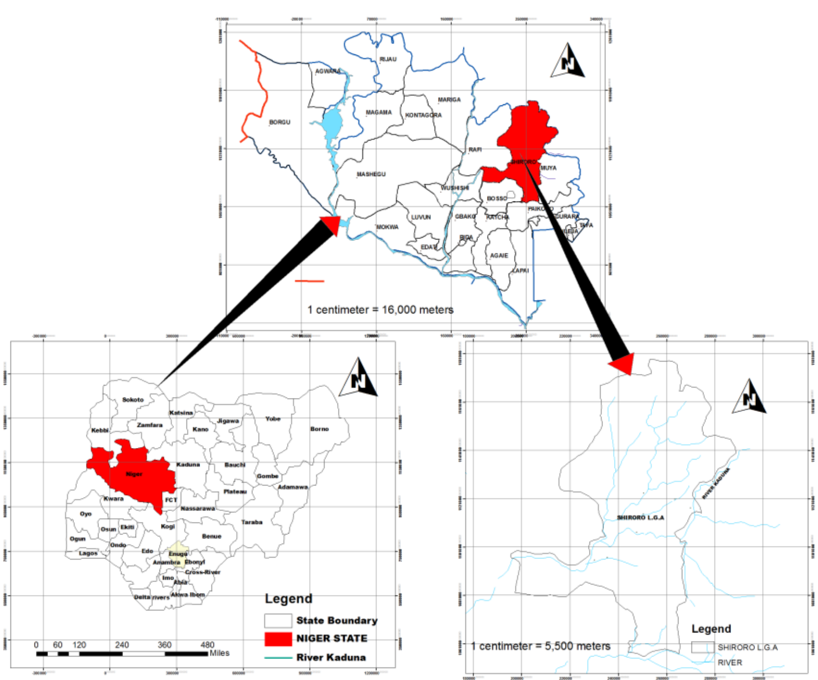


Fig. 1: Map of Nigeria Showing the Location of Niger State with the projected extracts (top and right) of Niger State with Shiroro dam inset and the River Kaduna drainage basin, respectively
Source: Shiroro Local Government Secretariat (2005)

(ii) Data collection/assembly

Monthly discharge (streamflow), rainfall, temperature and evaporation records were obtained for a period of thirty three (33) years (1980 -2012) from the Shiroro Hydroelectric Plc.(2013). These variables were used to examine the hydrological response of the area.

(iii) Establishment of Climate Change Scenarios

This study utilized incremental scenarios to determine the climate change scenario of the river. The establishment of the climate change scenarios was hypothetical, premised on the recommendations of Shaka (2008).The thirty-three (33) years streamflow, rainfall and temperature data were subjected to climate change scenario and these scenarios according as:

Scenario I: rainfall data increases by 10%; this was predicated on the seasonal variation of the rainfall; 1.13 seasonal variation index. This implies that on the average, the river experiences about 10% increase at the commencement of the raining seasons.

Scenario II: rainfall data decreases by 10%

Scenario III: rainfall's Coefficient of Variation was doubled

Scenario IV: temperature data was increased by 3^0C.

The study used hydrological statistics such as mean flow, high flow and low flow of the river; in this case, the mean flow estimates the average flow in the river channel. The percentage coefficient of variation of the monthly hydro-climatic data was estimated as the division of the standard deviation by the mean times 100. In the same context, flood frequency and Baseflow were also considered. Based on the submissions of Poff *et al*. (1996)flood predictability was estimated as the degree or magnitude to which all bank full events occur over the entire period of the record. Itwas computed as the ratio of the number of flood occurrence to the entire event distribution or size while Baseflow on the other hand as the ratio of the minimum average flow to the mean flow.

(iii) Development of the ANN

Artificial Network structure consists of input and output dimensions; the Network architecture is as shown in Figure 2. The input include monthly discharge (Q), rainfall (±10%, R), coefficient of variation (2CV), temperature (+3^0C (T) and evaporation (E) for time steps of t-1. while the output dimension is streamflow at time t. The ANN has a total 15nodes in the hidden layer for both training and validation based on sequential network optimization.

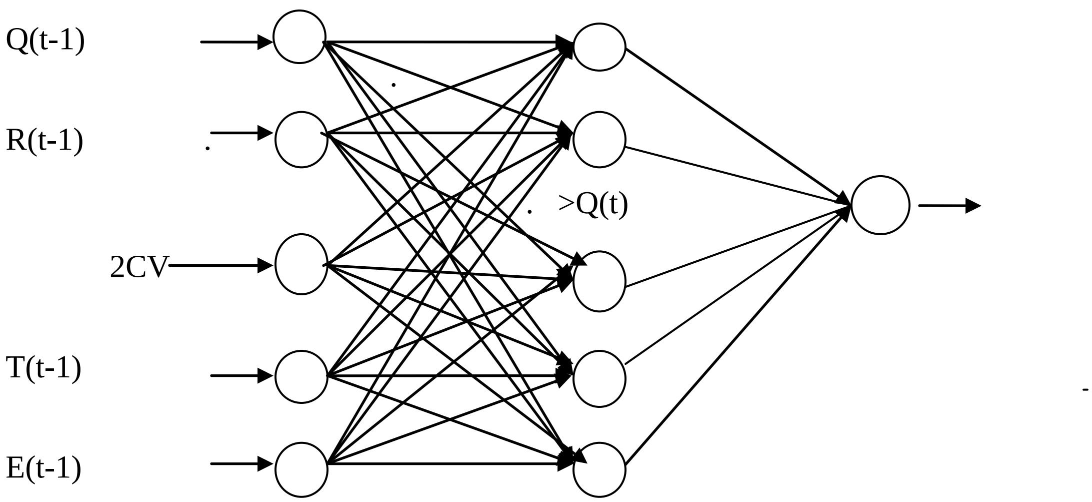


Fig. 2:Structure of the feed-forward Artificial Neural Network Architecture

(a) Modelling Strategy

The ANN model is written as shown below:

$y = f\,(uj)$ (1)

where

$uj = \Sigma w_i x_i - \theta_j$

and,

x_i= inputs to flow, w_i= weight of $x_i$and θ_j= critical value. The output of node j, y_j, was calculated to determine the response of a node to the total input signal it received.

The forecast function used for this study as stated in equation 2.

$$\bar{Q}_{i,j} = \gamma_1 + \alpha_{1,1}б\,(-\beta + \omega_i{}^{(i)} Q_{\boldsymbol{i,j-1}} + \omega_1{}^{(\mathbf{2})}\eta_{i,j-1} + \omega_1{}^{3}\eta_{i,j-2} \quad (2)$$

Where:

i= year,

γ, α, **β,** and $\boldsymbol{\omega}$ are parameter sets,

$\bar{Q}_{i,j}$ = predicted streamflow

$\eta_{i,j}$ = applicable hydro-climatic variables as a function of season and elements of climate change scenario.

$Q_{i,j-1}$ =previousmonthly streamflow

(b) Database Management

The entire time series of length of 198 monthly values was partitioned into two sets of 138 and 60 data point corresponding to training and validation, respectively. The outcome of the training procedure relies on the power of the optimization method utilized to search the response surface for the best parameters estimates; training was executed using the Bayesian regularization training algorithm so as overcome generalization problems that do results from over fitting (Otache*et al*., 2012). The entire input and output data were pre-processed and standardized using the long term mean and standard deviation for the training and validation data sets. The network training was implemented using Matlab routine.

(vi) Performance Criteria

The performance of the ANN model was evaluated by using both global and distribution statistics; these statistics were correlation coefficient (R^2), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) as in equation 3-5:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_{i-}x_i)^2}{N}} \quad (3)$$

$$R^2 = \frac{\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2\sum_{i=1}^{N}(y_i-\bar{y})^{\ 2}}} \quad (4)$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{n}\frac{(x_i-y_i)}{x_i} \quad (5)$$

where:

$x_i$are the observed values at the *i*th time step

$y_i$are the simulated values

$N$is the number of data points

$\bar{x}$and $\bar{y}$are the mean value of observations and simulations

The measures of forecast accuracy were computed with respect to high and low extreme values(Otache*et al.,* 2012):

$$R_{max}(\%) = \frac{\hat{y}_t}{\hat{j}_t} \quad (6a)$$

$$R_{min}(\%) = \frac{\bar{y}_t}{\bar{\imath}_t} \quad (6b)$$

Where:

$\hat{y}_t$ = forecasted maximum

$\hat{j}_t$ = observed maximum

$\bar{y}_t$ = forecasted minimum

$\bar{\imath}_t$ = observed minimum

3. Results and Discussion

(i)Flow Simulation

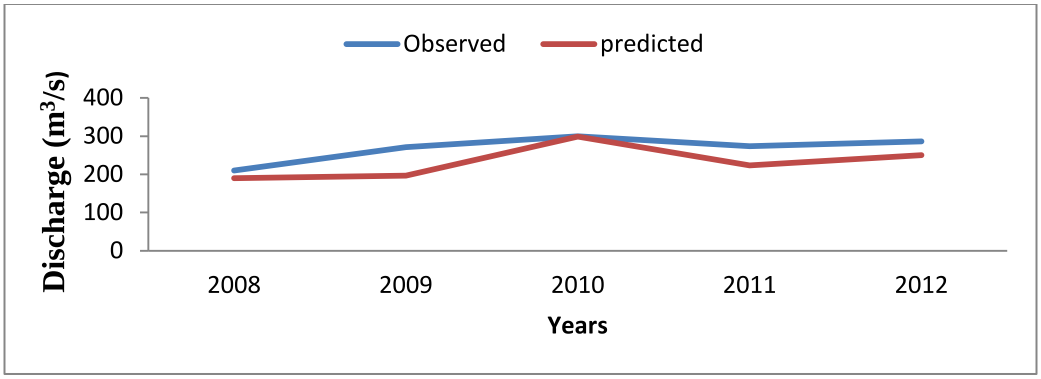
The results of the convergence patterns as a function of RMSE and R^2 were shown in the Table.1 below.

Table 1: Convergence patterns as a function of RMSE and R^2

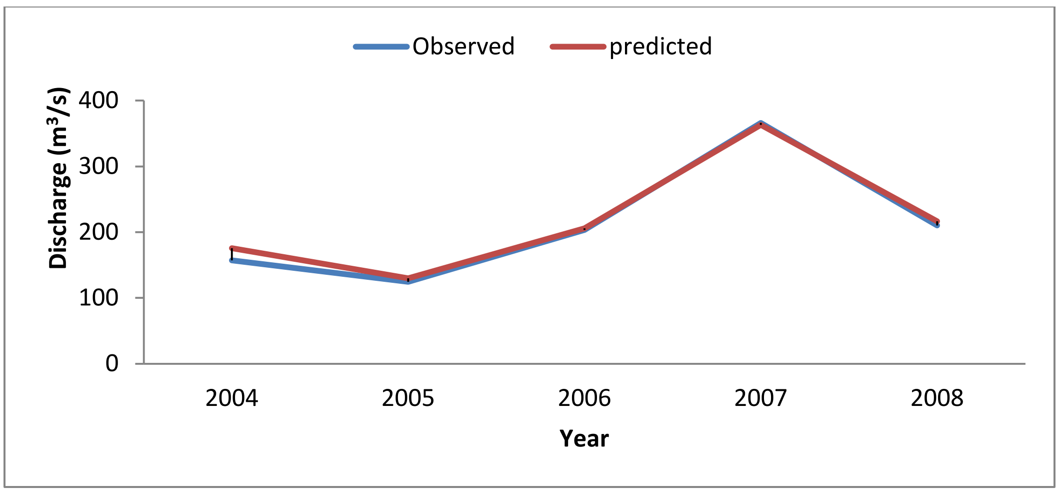
	Training		Validation	
Month	**RMSE**	**R^2**	**RMSE**	**R^2**
Jan	6.55E-04	0.97	6.58E-04	0.96
Feb	1.04E-03	0.79	6.40E-04	0.97
Mar	5.96E-04	0.92	5.92E-04	0.93
Sept	6.20E-04	0.87	3.25E-04	0.83
Oct	6.42E-04	0.86	4.81E-04	0.87
Nov	4.69E-04	0.92	6.28E-04	0.88

Table.1 above shows the RMSE and Correlation Coefficient computed for training and validation data sets. Generally, RMSE values ranged between 1.04E-03 and 6.55E-04 for training set while that of validation set ranges from 3.25E-04 to 6.58E-04, respectively. The ANN model shows varying predictive capability for both seasons in terms of R^2. As shown in Table. 1, the ANN model, on the average performed much better in the dry season period for the training and validation periods. The situation in the wet season though good relatively perhaps considering the test statistics in the overall could be explained as a direct consequence of the seeming variable runoff accretion dynamics. On the other hand, Figure 3(a-f) shows that the comparative simulation hydrograph for the different months considered and the variations in the simulation regime. It is obvious from the figure that the ANN was able to capture the flow dynamics well; this lends credence to the adequacy of the model architecture and effectiveness of the optimization algorithm employed. But while it is obvious from Figure 3 (a-c) that the results of the estimation between observed and predicted have relative good agreement, Figures 3 (d-f) is to the contrary; there is a seeming under-prediction between 2004 and 2008 year periods. The only conjecture for this is sheer debilitating climate change effects.

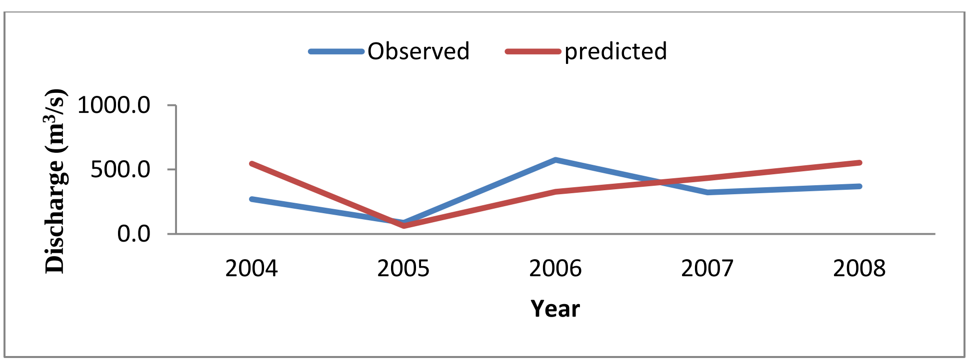
(a) January



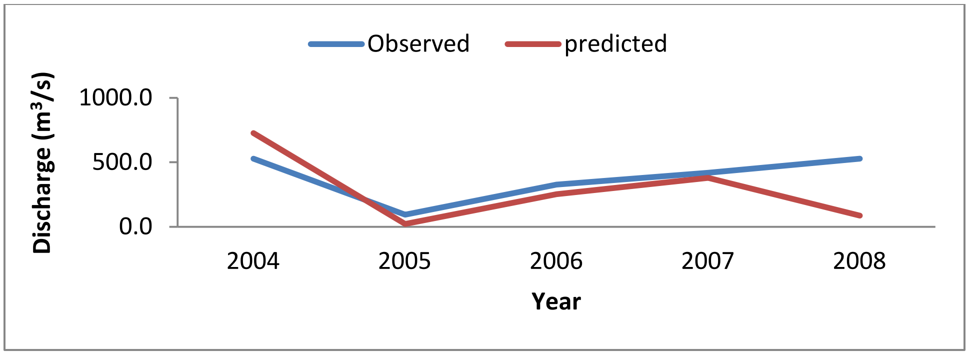
(b) February



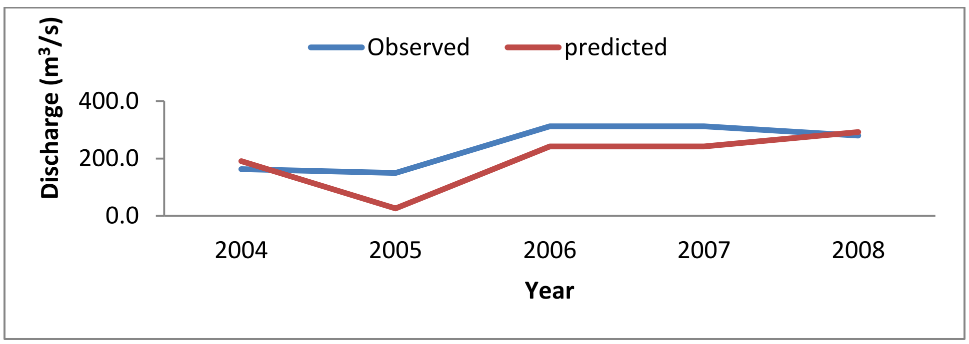
(c) March



(d) September



(e) October



(f) November

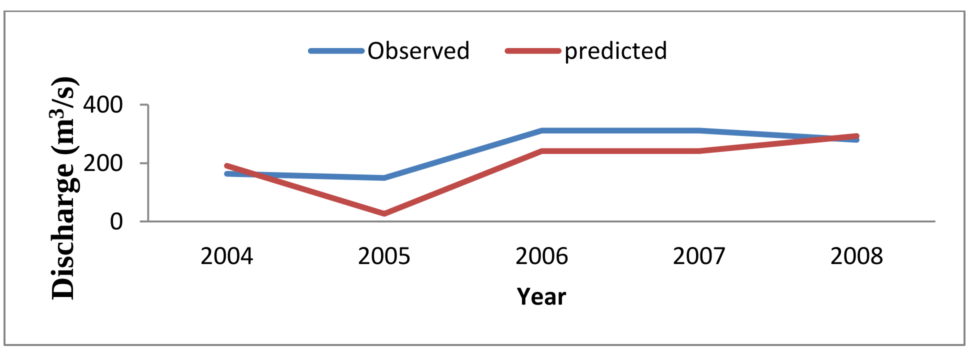


Fig. 3: Simulation hydrographs of the seasons in Shiroro hydrological Station

Table 2: Summary of measured and simulated hydrological Characteristics

Variables	Observed	Predicted
Average flow	6.6	6.2
Monthly CV (%)	20.1	16.7
Predictability of monthly flow (%)	30	70
Flood Frequency(1/yr)	0.9	1.1
Flood free period(Fraction of year)	0.3	0.7
Baseflow (Min/Mean)	0.8	0.3

The monthly predictability, flood frequency, flood free period show greater deviation than observed values as shown in Table2 above. Also, the average flow, CV flow, and base flow exhibited greater deviation than simulated values. It is interesting to note that the findings here are relatively in accord with similar works, e.g., Poff *et al*. (1996), though values of climate change scenarios on incremental basis differ slightly and too, there is a seeming variation in hydro-climatic regime. Precisely, the simulated values had greater deviation than the actual values whereas monthly predictability, flood frequency and flood free period exhibited greater deviation than the observed streamflow in this study. This can be attributable to the erratic inflow regime or accretion in the upstream and probably the definition of climate change scenarios adopted.

Table 3: ANN Model Performance in terms of extreme events

Months	R_{max} (%)	R_{min} (%)
Jan	99.6	90
Feb	91.2	104
Mar	101	99
Sept	137	129
Oct	96.2	71.4
Nov	94	84.7
Average	103	96.35

Table.3 above shows the performance of the Artificial Neural Network model in terms of flow variability. The extreme flow indices: R_{max} and R_{min}indicate that the ANN model, on the average, reproduced the variability of the flow pattern adequately. The Artificial Neural Networkmodel over predicted maximum and minimum flow situation; the inability of the Artificial Neural Network model to adequately produce flood situation and low flow situation could be attributed to variability in rainfall-runoff formation regime.

(ii) Hydrological Response to Climate Change Scenarios

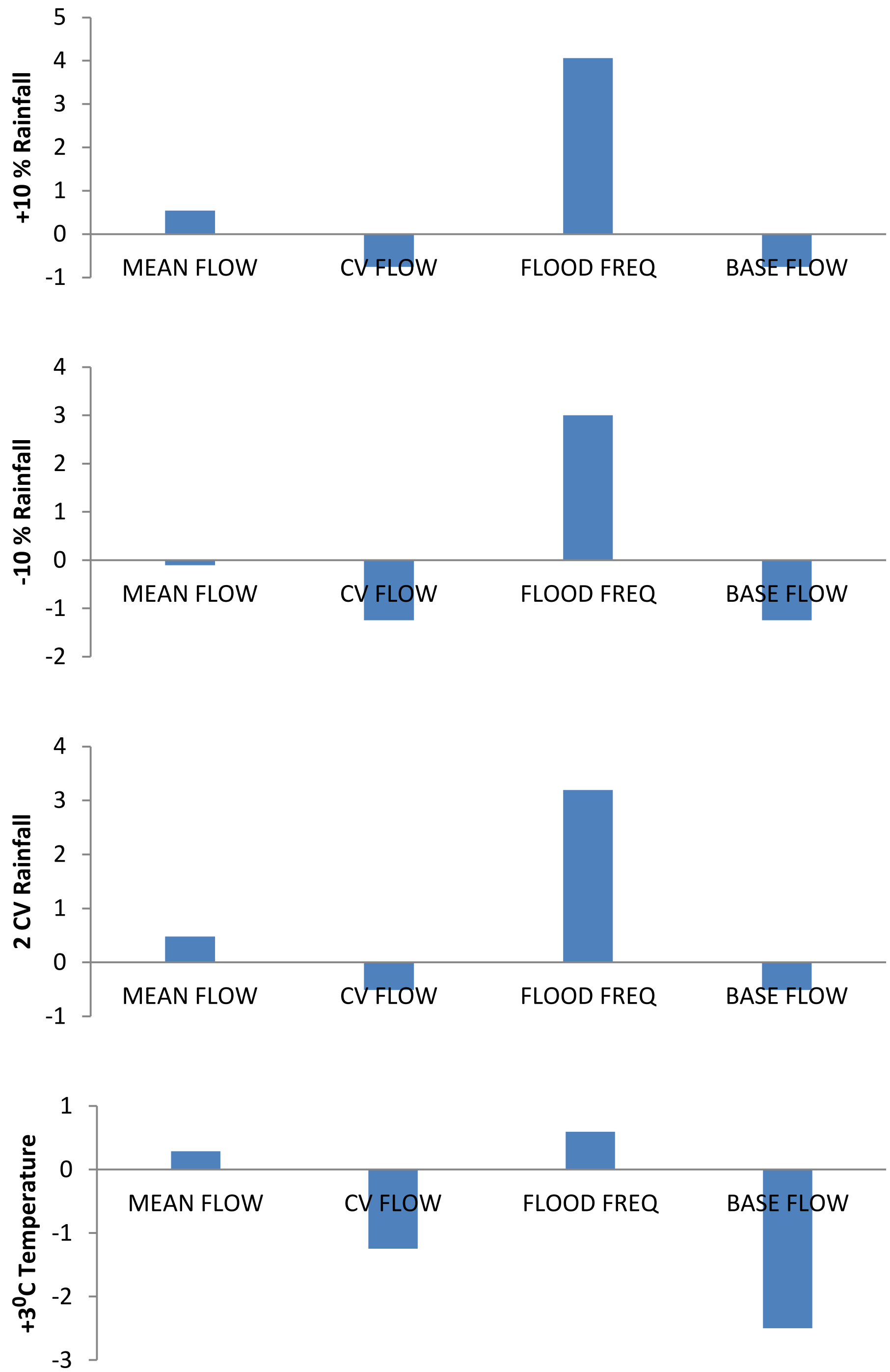


Fig. 4: Responses of hydrological variables in the flow system

Figure 4 shows the hydrological response of the flow system to climate change scenarios adopted for the study. The results of the 10% increase in rainfall yielded excess runoff in the area. When compared with the normalmean rainfall pattern, the riverexperienced about9.5 % increase in rainfall which in turn produced increased hydrological variability whereas 10% decrease in rainfall resulted in less runoff in the area culminating in 18.5% reduction in flow volume of the river. By and large, this scenario led to reduction of flood frequency, mean flow, flow coefficient of variation and Baseflow. The results of double CV increased flood frequency, mean flow and reduced coefficient of variation flow and base flow. Lastly, the results of increase temperature by 3^0Cled to low mean flow, flood frequency; the river experienced additional 11.1 % increase in temperature and thus reduced coefficient of variation and Baseflow which in turn increased the surface water evaporation of the drainage basin. In summary, against the backdrop of the findings here, it suffices to note that the application of climate change scenarios particularly by ±10% in rainfall and doubled coefficient of variation producedstaggering high flood during the wet season and low flow availability in the drying season period. On the other hand, increase in temperature led inadvertently to high evaporation. Considering the overall scenario, the definition of the hypothetical climate change situation should as a matter of principle derive directly from a holistic analysis of the long term trend pattern of the historic data. It is important because anything to the contrary might fail to capture appropriately the variations in hydro-climatic dynamics of the basin. This is so because of the nonlinear nature of the rainfall-runoff relationship against the unusual assumption of linearity.

4. Conclusions

Globally, climate variability has resulted in fluctuations and increasing rainfall which in turn cause river/stream to rise and fall. In view of this, the study assessed the stream hydrological response of the basin. From the results, monthly predictability, flood frequency, and flood free period deviated strongly from normality; this could be as a result of seeming volatility in hydro-climatic processes. It is evidently clear however that the ANN forecasting approach is robust and effective in view of its high generalization ability. The ANN could simulate stream hydrological responsehydrograph with staggering vagaries. The ANN model predicted high flow much better than low flow regime; basically because of erratic inflow regime in the upstream of the river culminating in unstable dry season regime. The maximum prediction coefficient of correlation (R^2) between the observed and predicted value for the long term monthly streamflow was found to be 0.97 (February) while the least was found to be 0.83 (November) which is in concord with the variability in wet and dry seasons' inflow dynamics with respect to the basin drainage density. However, based on the findings it is imperative to stress the need for mobilization of sufficient hydrological and climatic data for effective and efficient flood forecasting based on flood frequency analysis. Similarly, the use of risk value, resilience and reliability relationship with respect to flood adaptation and mitigation in the general context of varying hydro-climatic change scenarios is not just expedient but a viable complement to the overall general assessment protocol.

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