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Predicting the impact of climate change and the hydrological response within the Gurara reservoir catchment, Nigeria

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Abstract: The 2150 km^2 transboundary Gurara Reservoir Catchment in Nigeria was modelled using the Water Evaluation and Planning tool to assess the hydro-climatic variability resulting from climate change and human-induced activities from 1989 to 2019 and projected to the future till 2050. Specifically, the model simulated the historic dataset and predicted the future runoff. The initial results revealed that monthly calibration/validation of the model yielded acceptable results with Nash–Sutcliff efficiency (*NSE*), percent bias (*PBIAS*), and coefficient of determination (R^2) values of 0.72/0.69, 0.72/0.67 and 4.0%/1.0% respectively. Uncertainty was moderately adequate as the model enveloped about 70% of the observed runoff. Future predicted runoffs were modelled for climate ensembles under three different representative concentration pathways (RCP4.5, RCP6.5 and RCP8.5). The RCP projections for all the climate change scenarios showed increasing runoff trends. The model proved efficient in determining the hydrological response of the catchment to potential impacts from climate change and human-induced activities. The model has the potential to be used for further analysis to aid effective water resources planning and management at catchment scale.

Keywords: climate change, Gurara reservoir catchment, hydrology, modelling, water availability

INTRODUCTION

Hydrology of large rivers in the world has been experiencing changes in their hydrological characteristics and morphological processes due to variations and impacts from changing climate [Pekel *et al.* 2016]. These changes in the hydrological characteristic have majorly been attributed to impacts from climate change [Ma *et al.* 2010; Wang *et al.* 2009], resulting in the occurrence of extreme weather and variability in precipitation and temperature patterns [Awotwi *et al.* 2017; Lehmann *et al.* 2017], and caused increase in runoff [Huo *et al.* 2008]. Climate change in itself is the average change in weather [2013]. Climate and weather are closely intertwined and greatly related but still there are important distinctions [Lehmann *et al.* 2017]. A common distinction is the difficulty encountered by scientists in predicting the weather in few weeks while confidently predicting the climate for a 50 year period [Agunbiade, Jimoh 2013; Awotwi *et al.* 2015].

The human-induced activities [Eduvie, Oseke 2021; Yang, Tian 2009] such as afforestation, construction of reservoirs, water diversion systems, deforestation, alternate land cover, agriculture, domestic and industrial water demands influenced catchments hydrology especially runoff. In this regards, changes in climate in region like the Gurara reservoir catchment (GRC) is envisaged to occur in the future [Eduvie *et al.* 2019]. This is because the GRC is a region best described as semi-arid which is prone to extreme water stress, since the hydrological characteristics of a semi-arid environment are exceptionally vulnerable to impacts from climate change [Awotwi *et al.* 2017]. Meanwhile, the implications of climate change can go well beyond the water sector, as most of the serious effects of climate change on non-water areas are mediated via water [Rogers 2010; Syvitski *et al.* 2005]. In the GRC, authorities have been taking measures to protect the catchments ecosystem by estimating the impact of climate variability and human-induced activities on the runoff using a data-driven approach. Predicting the long-term variability using quality data in a hydrologic time series has scientific and practical importance to policy makers [Kundzewicz 2004].

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A data-driven approach in assessing the impact of climate change requires specific consideration through hydrological research [Awotwi *et al.* 2017]. In the application of hydrologic research, the daily, monthly and annual variability in precipitation and temperature from climate change can be simulated using scenarios to predict the hydrological response [Jin *et al.* 2018]. For the prediction of the hydrological responses, future projections in climate parameters are required as inputs which are derivatives of global climate models (GCMs).

Although there is global acceptance in the application of (GCMs) in assessing the behavior of projected climate change dynamics on catchments hydrology, the limitations in their ability to make grid-point predictions make GCMs very difficult to adapt to the regional analysis [Awotwi *et al.* 2017]. This is because, though the impact of climate change is a global phenomenon, the consequence is mostly felt on a regional scale [Eduvie, Oseke 2021]. Not until recently, there is a need for higher resolution climate models for better prediction of climate change analysis. This has resulted in several studies propagating the use of regional climate models (RCMs) [Awotwi *et al.* 2017]. RCMs safeguard the physical coherence between atmospheric and land surface factors [Awotwi *et al.* 2018] and dynamically downscale GCMs to make grid-point predictions for a limited study area of interest. According to Annor *et al.* [2017], the use of RCMs in assessing the impact of climate change on water resources at regional scale have demonstrated higher correction outcome in predicting future hydrological characteristics responses than GCMs. Although RCMs data are regarded as being biased [Fowler, Kilsby 2007], it is required that RCMs be corrected before utilisation, particularly within the GRC, a semi-arid regions where evidence suggests, the catchments hydrology have been greatly influenced by changes in the climatic conditions [Agunbiade, Jimoh 2013].

The GRC is Nigeria's pioneer and the only catchment performing a water diversion operation from the Gurara reservoir to Lower Usuma reservoir in Abuja. The city of Abuja is Nigeria's administrative capital serving over 2.7 mln people [Oseke *et al.* 2020]. According to Oseke *et. al.* [2020], upsurge in human-induced activities in recent years such as expanded irrigation activities, increased water demand for domestic and industrial demand consumption are major factors affecting the runoff within the GRC. Agunbiade and Jimoh [2013] reported the response from human-induced activities and climate change using a computer-based Remote Sensing and Geospatial Streamflow Model, the report shows that an increase in temperature will result in a decrease in runoff. Furthermore, the report reveals a decrease in rainfall will reduce runoff from the watershed. Similar observations on human-induced activities were made by Dalil *et al.* [2015], suggesting that obstructing natural stream flow by constructing reservoirs will result in reduced runoff downstream especially during the dry season. Investigations on the impact of land-cover changes and climate variability on water balance components, using SWAT model in the White Volta Basin, West Africa [Awotwi *et al.* 2015a], reveals an increase in precipitation and temperature resulted in increase in surface runoff including base flow and evapotranspiration. Accordingly, Zhang and Tian [2009] report that human-induced activities contribute to increase in runoff by approximately 80% during dry season.

In this regard, this study aims is to predict the impact of climate change and hydrological response within the GRC by quantifying the contribution from variations in precipitation and temperature. This is pursued through multiple climate change scenarios while considering plausible socio-economic developments. Accordingly, the decisions support system Water Evaluation and Planning (WEAP) model was utilised. The WEAP model, a computer-based analytical framework developed for evaluating climate change impact by water resources managers in response to commonly encounter challenges using different scenarios [Yates *et al.* 2005]. Likewise, the WEAP model coupled with RCMs from CORDEX-Africa can be used as a database for climate change predictions depending on the focus of the study. Due to prevailing heterogeneous conditions of global water bodies similar to GRC, findings from this study can be used as a baseline for other related research aimed at understanding the changes in water resources availability for efficient planning and management at catchment scale.

MATERIALS AND METHODS

THE STUDY AREA

The Gurara Reservoir Catchment (GRC) lies between latitude 8° 15' and 10°05' N and longitude 6°30' and 8°30' E on the Gurara River, north central Nigeria (Fig. 1). The catchments river system has an estimated area of 8,600 km^2 with its middle and lower sections in Abuja. The river system originates from the high plateaus of Jos, and began flowing southwest covering a distance approximately 250 km downstream to join the Niger River at Dere upstream of Lokoja (a confluence town between the Niger River and the Benue River). Major rivers within the GRC include the Gurara, Kaduna, Tapa, Dinya, Usuma and the Jatau.

Climatically, the GRC falls with the semi-arid to humid zone characterised by high temperature and mono-modal rainfall distribution. The annual rainfall within the GRC ranges between 749 and 1464 mm with a duration spanning between four to six months, from May to October. The average annual temperature is between 30.6 and 36.5°C with the hottest period occurring in the months of March and April. The highest mean monthly temperature is observed in April with 36.5°C, while the lowest mean monthly temperature is in December with 14.7°C. The catchment mean temperature is 33.85°C while the annual mean evaporation is 83.3 mm.

DESCRIPTION OF WEAP MODEL

The WEAP model is an integrated water resources management system designed to simulate water supplies generated through watershed-scale hydrologic models, driven by water demands and environmental requirements [Abdullahi *et al.* 2014]. According to Abdullahi *et al.* [2014], WEAP analyses a wide range of issues concerning water resources using a scenario-based approach. The application of scenarios in water resources cover areas such as climate change and variability, ecosystem functioning, project water demand, policy formation, watershed conditions, operational dynamics as well as sustainability concerns of water infrastructures [Yates *et al.* 2005], assessment of climate change and its impact on hydrology and adaptation scenarios on water resources [Yates *et al.* 2005].

According to Awotwi *et al.* [2017], the integration of WEAP model with is useful in assessing and dealing with extensive data

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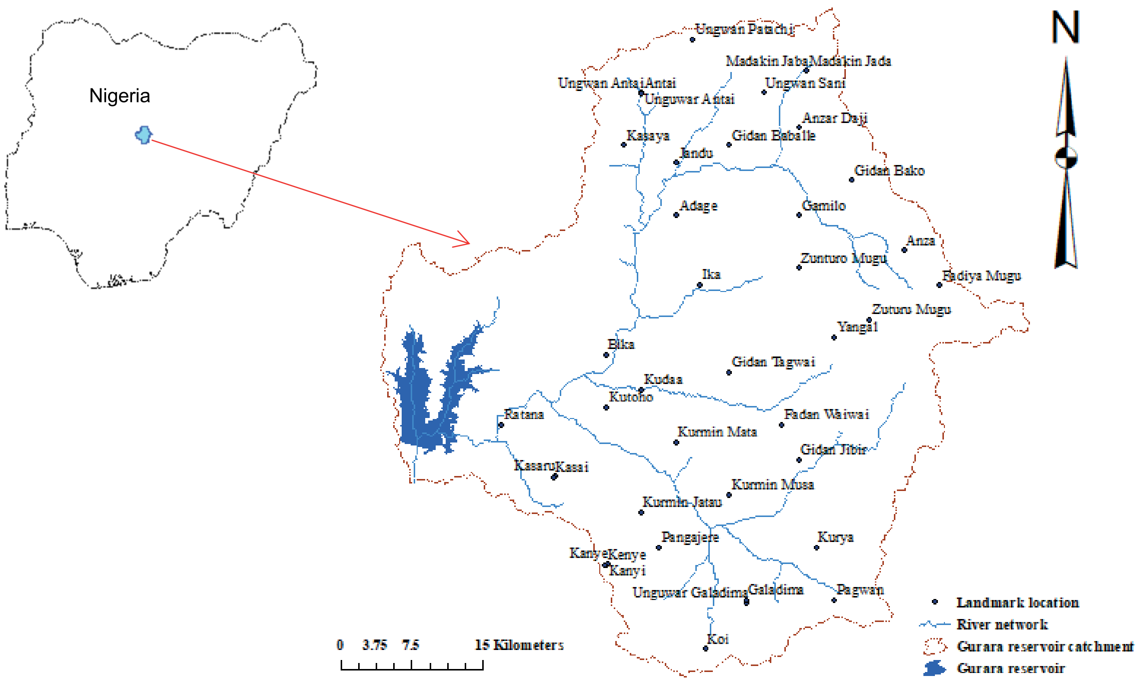

Fig. 1. Map showing Gurara reservoir catchment boundaries and country location; source: own elaboration

sets on a different geographical scale in the assessment of changing climate. Besides, WEAP model also performs a mass balance of flow sequentially down a river system [Yates *et al.* 2005], making allowance for abstractions and inflows [Awotwi *et al.* 2017].

The working dynamics of WEAP involves configuring the model to simulate a recent baseline year for which water availability and demands can be determined confidently [Abdullahi *et al.* 2014]. Subsequently, WEAP model also has a flexible user interface that ensures ease in applying the model for useful dialogue on water resources planning and management among relevant stakeholders [Levite *et al.* 2003]. The generalised form of WEAP model in simulating inflow and outflow scenarios is expressed using Equation (1) as reported by Abdullahi *et al.* [2014].

$$Rd_j \frac{dz_{i,j}}{dt} = P_e(t) - PET(t)K_{cj}(t)\frac{5z_{i,j} - 2z_{1,j}^2}{dx} - \\ + P_e(t)Z_{1,j}^{\mathrm{RRF_j}} - f_j K_{S,J}\, z_{1,j}^2 - (1 - f_j)K_{Z,J}\, Z_{1,j}^2 \quad (1)$$

where: $Z_{1,j}$ = (1,0) is the relative storage given as a fraction of the total effective storage of the root zone, Rd_j = measured in mm for land cover fraction j, P_e = the effective precipitation (mm), excluding the snowmelt since snow is not experienced within the Gurara reservoir catchment.

HYDRO-METEOROLOGICAL DATA PREPROCESSING

The processing of hydro-meteorological data using a linear model in its simplest form is for trend detection using the Student's *t*-test [Hameed, Rao 2008]. The Student's *t*-test requires that the series of data under testing be normally distributed [Hameed, Rao 2008]. Unfortunately, most researchers ignore this important check. If normality is violated of the measured dataset available, thus not following a normal distribution, then the nonparametric test such as the Mann–Kendall test is applied to assess the statistical significance of trends [Turgay, Ercan 2006; Xu *et al.* 2003].

The dataset collected were processed and used on monthly and annually basis for analytical convenience. Preprocessing of the data was carried to determine stationary status as quality control using Shapiro–Wilk (W) in agreement with Shapiro *et al.* [1965] and Hipel and McLeod [2005]. The result is presented at confidence α = 0.005. The recommendation of the normality test for climatic dataset behaviour has been suggested by Cribbie *et al.* [2011], with the rationale to assess the monotonic pattern of time series dataset by testing its normality. The Shapiro statistical method of testing is given as:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (2)$$

where: $x_{(i)}$ = the i^{th} order statistic, i.e., the i^{th} = smallest number in the sample; $\bar{x}$ = $(x_1 + \ldots + x_n)/n$ = the sample mean. The coefficient a_i is given by:

$$a_i = \frac{m^T V^{-1}}{C} \quad (3)$$

where C is a vector expressed using Eq. (4)

$$C = \left(m^T V^{-1} V^{-1} m\right)^{1/2} \quad (4)$$

And the vector V is the covariance matrix of those normal order statistics, while m is made of the expected values of the order statistics of independent and identically distributed random variables sampled from the standard normal distribution; and is obtained using Eq. (5):

$$m = (m_1 \ldots m_n)^T \quad (5)$$

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MODEL INPUT DATA

Digital elevation model (DEM)

A 90 m resolution digital elevation model (DEM) from the Shuttle Radar Topography Mission (SRTM) was used for this study (Fig 2). The DEM was used to delineate the catchment watershed and analyse the drainage patterns of the terrain. Other parameters of the catchment such as stream network characteristics: channels slope, length, and width were also obtained from the DEM.

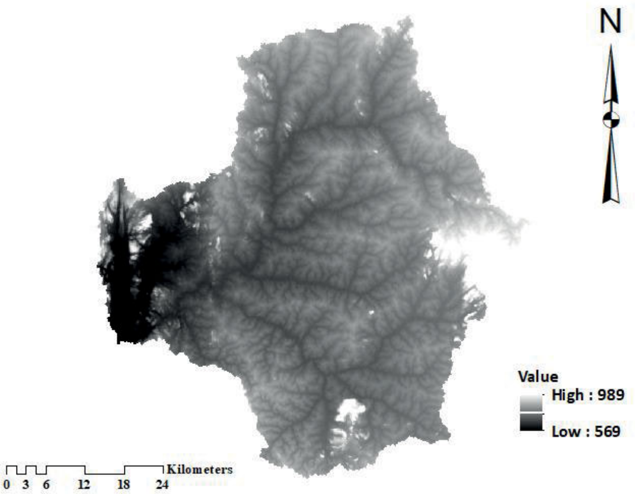

Fig. 2. Digital elevation model of Gurara reservoir catchment; source: own study

Land cover types

The land cover map was obtained from hybrid classification of 2019 Enhanced Thematic Mapper (ETM+) Landsat image. The relevant land cover information extracted was used for analysing the water resources, especially the hydrological processes. Agricultural, forest land, woodland and water body are the main land-cover in the catchment (Fig. 3).

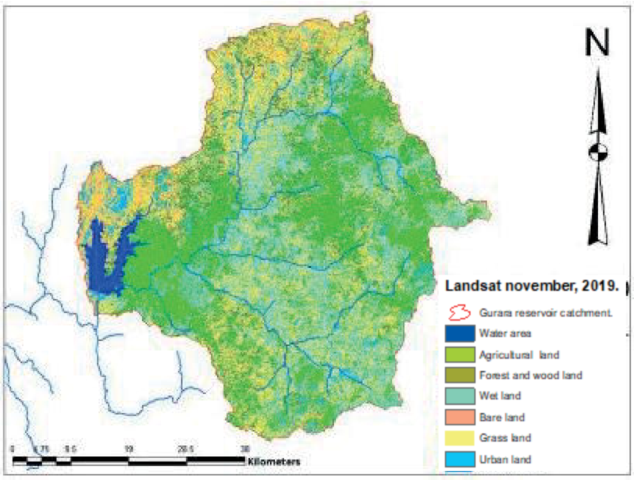

Fig. 3. Land use land cover categorisation map within the Gurara reservoir catchment; source: own study

Elevation volume curve

The elevation volume curve (Fig. 4) is derived from previous bathymetry survey conducted in the Gurara reservoir. The curve is important for planning and operation purposes in the reservoir's management, reflecting the storage capacity relationship to determine reservoir water volume changes. The elevation curve is an input in the WEAP model.

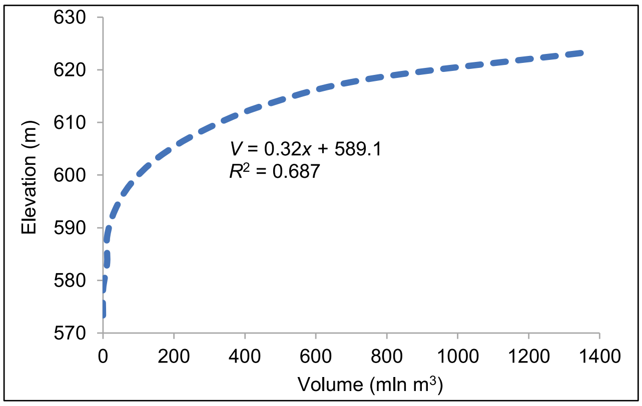

Fig. 4. Elevation–volume relationship of Gurara reservoir based on bathymetric exploration; source: own study

Climate data

Weather parameters used for deriving the hydrological balance are monthly mean precipitation and the mean monthly temperature dataset from the Jere gauging station (Fig. 5) for the period of 1989–2019 and were used as the baseline year. The yearly average of the climatic dataset used were obtained from the Nigerian Meteorological Agency.

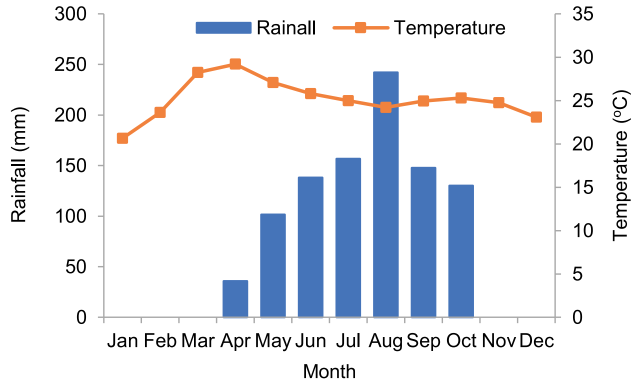

Fig. 5. Mean monthly rainfall and temperature relationship in Gurara reservoir catchment; source: own elaboration

PROJECTED CLIMATIC CHANGE SCENARIOS

This study relied on the IPCC Representative Concentration Pathway (RCP) 4.5, 6.5 and 8.5 scenarios to assess the impacts of climatic change on runoff within the GRC. The RCP8.5 is regarded as the strongest climate signal with the highest emission of greenhouse gases. RCP4.5 is presumed to be the state of maintaining the current emission with the prospect of reduced emission in the future and RCP6.5 is intermediate and rated

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among well-performing climate models. Here, historical simulated data from 1989–2005 was utilised as the reference period and 2005–2050 representing future projected period. The RCPs and their descriptions are represented in Table 1, while Table 2 presents the overview of climate models used in this study.

Table 1. Representative concentration pathway (RCP) classified based on the process description

RCP	Description	IA model
8.5	rising radiative forcing pathway leading to 8.5 W·m^{-2} in 2100	MESSAGE
6.5	stabilisation without overshoot pathway to 6 W·m^{-2} at stabilisation after 2100	AIM
4.5	stabilisation without overshoot pathway to 4.5 W·m^{-2} at stabilisation after 2100	GCAM
2.6	peak in radiative forcing at ~3 W·m^{-2} before 2100 and then decline	IMAGE

Explanation: IA = integrated assessment.
Source: van Vuuren *et al.* [2011].

Table 2. Model institutions, regional climate models (RCMs) and general circulation models (GCMs) considered and code

Model institution	RCM	GCMs	Model code
Swedish Meteorological and Hydrological Institute (SMHI)	RCA4	NOAA-GFDL-GFDL-ESM2M	RCAS
Max Planck Institute for Meteorology, Germany	REMO	ESM-LR	MPI-M-MPI-ESM-LR
Climate Limited-Area Modeling community (CLMcom)	CCLM4-8-17	MOHC-Had-GEM2-ES	CCL2
Royal Netherlands Meteorological Institute (KNMI)	RACMO22T	ICHEC-EC-EARTH	RACI
Climate Limited-Area Modeling community (CLMcom)	CCLM4-8-17	CNRM-CM5	CCL1
Swedish Meteorological and Hydrological Institute (SMHI)	RCA4	CCCma_Ca-nESM2	RCA1
Swedish Meteorological and Hydrological Institute (SMHI)	RCA4	CNRM-CER-FACE-CNRM-CM5	RCA2
Danish Meteorological Institute (DMI)	HIRHAMS	NCC-Nor-ESM-M	HIR

Source: own study.

BIAS CORRECTION

The use of a model with biases can cause unreliable outcomes in hydrological modelling [Awotwi *et al.* 2017], thus, there is the need to improve the exactness of the modelled hydrological components. In this regard, the relative bias method was adopted and expressed as:

$$RB = \frac{Md - Ob}{Ob} 100 \qquad (6)$$

where: RB = relative bias, Md = model data, Ob = observed data respectively.

The rationale behind this is to normalise the modelled data by the average of the observed which is regarded as the deviation. According to Awotwi *et al.* [2017], this method of bias correction yields a very good result in hydrological modelling.

RANKING OF REGIONAL CLIMATE MODEL

In selecting the best RCM for climate model ranking, it important to note that the model must depict the physical collaborations between the atmospheres, the oceans, land surfaces, and sea ice regarding a multitude of processes functioning on various space and time scales [Climate data guide 2013]. The first step in ranking of RCMs is through a Taylor diagram for four seasons (Spring – March, April, May: Fall – September, October, and November: Winter – December, January, and February: Summer – June, July, and August) corresponding to the wet and dry season. The Taylor diagram is a statistical summary that provides how well the models match each other in terms of their correlation, their root-mean-square difference and the ratio of their variances [Climate data guide 2013]. Taylor diagram provides a series of points on a polar plot. Consequently, all these three statistical factors should be considered at the same time with equal weight in selecting the best model. The best performing RCMs was used as input data for the WEAP model in this study.

RUNOFF COMPUTATION

Several hydrologic methods have global applications in the computation of catchments runoff. Popular amongst these methods includes SCS-CN (Soil Conservation Service curve number) [NEH 1985; USDA 1972], HEC-1 (model developed by the Hydrologic Engineering Center, U.S. Army Corps of Engineers), HEC-HMS (Hydrologic Modeling System) [HEC 1990; 2001], SWAT (soil & water assessment tool) [Shadeed, Almasri 2010] and water balance model [Kabede *et al.* 2006]. In this study, the SCS-CN method for computing runoff was adopted. Adopting this method is due to the absence of long time series hydrological data and the availability of a curve number (CN) within the study area.

The SCS–CN method has been established since 1954 by the USDA SCS, and defined as the Soil Conservation Service (SCS) by the National Engineering Handbook (NEH-4) Section of Hydrology [Ponce, Hawkins 1996]. The soil conversation service curve number approach is based on the water balance computation [Lingcheng *et al.* 2015]. Accordingly, the SCS-CN runoff prediction method links rainfall response to soils, land use and

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antecedent moisture condition [NEH 1985]. The soil conservation service curve number approach is frequently used empirical methods to estimate the direct runoff from a catchment [FMWR 2013], with its classification descriptions shown Table 3.

According to DOMFEH *et al.* [2015], the main challenge associated with applying the SCS-CN method lies in the lack of monitoring rainfall and runoff data, with both data being primary input in any hydrological model. The need for reliable monitoring flow data can lead to dependable calibration and validation of catchment parameters [DOMFEH *et al.* 2015], and best in predicting event-based runoff volume in an ungauged catchment. The general form of SCS-CN equation given as follows:

$$Q = \frac{(P - l_a)^2}{(P - l_a) + S} \tag{7}$$

where: Q = the gathered runoff (mm), P = the rainfall amount (mm), l_a = the initial abstraction (mm) and surface storage, interception, and infiltration prior to runoff in the catchment and empirical relation was developed for the term l_a and it is given by. The empirical relationship is:

$$l_a = 0.2S \tag{8}$$

For the Nigeria's condition, the form S in the potential maximum retention and it is given by:

$$S = \frac{1000}{CN} - 10 \tag{9}$$

where: CN = the curve number which can be taken from SCS handbook of hydrology (NEH-4), section-4 [USDA 1972].

A CN of 75% utilised in previous study by FMWR [2013] was adopted. This was due to the development level in the catchment and bearing in mind that the catchment is also highly forested [FMWR 2013]. Thus Equations (7), (8) and (9) will become.

$$Q = \frac{(P - 0.6667)^2}{(P + 2.6666\ )} \tag{10}$$

The curve number is based on the ability of soils to allow infiltration of water with respect to land use/land cover and antecedent soil moisture condition [AMUTHA, PORCHELVAN 2009]. Based on Soil Conservation Service (SCS), soils are distributed into four hydrologic soil groups such as group A, B, C and D with respect to rate of runoff probable and final infiltration.

CALIBRATION, VALIDATION AND MODEL PERFORMANCE EVALUATION

In the simulation of hydrological models, some input parameters used cannot be directly measured in the field hence the need for certain adjustments to enhance the correlation between observed and predicted datasets (Fig. 6). In this regard, the mean monthly discharge dataset (1st January 1978 – 31st December 1986) obtained from Kaduna state water cooperation were used for calibration, while the remaining dataset (1st January 1986 – 31st December 1991) were used for validation indicating the period data was last collected from the Gurara gauge station, the inlet to the GRC.

Table 3. Soil Conservation Service classification

Hydrologic soil group (HSG)	Soil textures	Runoff potential	Water transmission	Final infiltration
A	deep, well drained sands and gravels	low	low rate	>7.5
B	moderately deep, well drained with moderate	moderate	moderate rate	3.8–7.5
C	clay loams, shallow sandy loam, soils with moderate to fine textures	moderate	moderate rate	1.3–3.8
D	clay soils that swell significantly when wet	low	low rate	<1.3

Source: own elaboration based on USDA [1974].

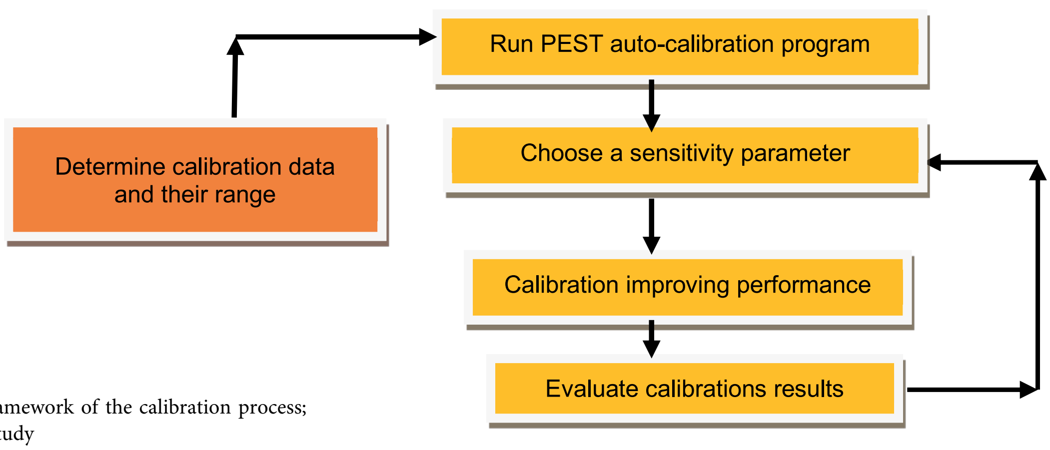

Fig. 6. The framework of the calibration process; source: own study

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To obtain a certain degree of best fit, a manual method of calibration was applied, thus, the model parameters were manually adjusted till the model predict the runoff to an acceptable performance range. The calibration process was done according to the framework as shown in Figure 6 and a direct comparison of measured versus predicted monthly hydrographs was obtained. The reliability of the simulation was assessed by three statistical indices, namely the Nash–Sutcliff efficiency (*NSE*), percent bias (*PBIAS*), and coefficient of determination (R^2), and expressed by the following equations:

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}\left(Q_i^{\text{obs}} - Q_i^{\text{sim}}\right)^2}{\sum_{i=1}^{n}\left(Q_i^{\text{obs}} - Q_{\text{mean}}^{\text{obs}}\right)^2}\right] \tag{11}$$

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Q_i^{\text{obs}} - Q_i^{\text{sim}}\right)}{\sum_{i=1}^{n}\left(Q_i^{\text{obs}}\right)}100 \tag{12}$$

$$R^2 = \left\{\frac{\sum_{i=1}^{n}\left(Q_i^{\text{obs}} - Q_{\text{mean}}^{\text{obs}}\right)\left(Q_i^{\text{sim}} - Q_{\text{mean}}^{\text{sim}}\right)}{\sqrt{\sum_{i=1}^{n}\left(Q_i^{\text{obs}} - Q_{\text{mean}}^{\text{obs}}\right)}\sqrt{\sum_{i=1}^{n}\left(Q_i^{\text{sim}} - Q_{\text{mean}}^{\text{sim}}\right)}}\right\} \tag{13}$$

where: Q_i^{obs} and $Q_{\text{mean}}^{\text{obs}}$ = the observed and mean observed values respectively, while Q_i^{sim} and $Q_{\text{mean}}^{\text{sim}}$ = the simulated and mean simulated values respectively.

The rating performance according to the statistical parameters *NSE*, *PBIAS* and R^2 for the hydrological model proposed by Moriasi *et al.* [2007] is shown in Table 4.

months was reclassified into three categories: those with "moderate concentration" of rainfall (coefficient of 1.0–1.9), "high concentration" of rainfall (coefficient of 2.0–2.9), and "very high concentration" of rainfall (coefficient of 3.0 and above). This technique is used to determine the spatial pattern seasonality of rainfall by analysing mean monthly rainfall data. Listed in Table 5 is the classification scheme of monthly rainfall values.

ANALYSIS OF CLIMATE CHANGE IMPACT ON HYDROLOGY

The analysis to capture the impact of climate change on the seasonal variability of water availability and demand in a monthly time scale expressed in Equation (14) was adopted.

$$PI = \frac{ALSWA}{ALAWA}100 \tag{14}$$

where: *PI* = percentage impact, *ALSWA* = available simulated water in a given scenario, while *ALAWA* = the actual available water from the observed dataset.

The quantity of water available is based on the different projected climate scenarios. The difference between the respective incoming and outgoing flow rates for each scenario was used to estimate the average flow volumes. Thus, the available water within each scenario is the sum of the scenarios contributed and the inflow from the surrounding catchment. The relationship between water availability was addressed by water balance accounting and order of priority.

Table 4. Statistical rating indicators recommended for model analysis

Performance rating	*NSE*	R^2	*PBIAS*
Very good	0.75 < *NSE* < 1.00	R^2 > 0.70	*PBIAS* < ±10
Good	0.65 < *NSE* < 0.75	0.60 < R^2 < 0.70	±10 < *PBIAS* < ±15
Satisfactory	0.50 < *NSE* < 0.65	0.50 < R^2 < 0.60	±15 < *PBIAS* < ±25
Unsatisfactory	*NSE* < 0.50	0.00 < R^2 < 0.50	*PBIAS* > ±25

Explanations: *NSE* = Nash–Sutcliffe efficiency, *PBIAS* = percent bias, R^2 = coefficient of determination, *PBIAS* = percent bias.
Source: own elaboration based on Oseke *et al.* [2020].

CLASSIFICATION OF RAINFALL VALUES

The classification technique for rainfall values modified by Gamachu [1977] was adopted. The technique involves estimating a coefficient called the rainfall coefficient for each month from the observed data. This coefficient is the ratio between the mean monthly rainfall and one-twelfth of the annual mean rainfall [Ufoegbune *et al.* 2011]. Subsequently according to Ufoegbune *et al.* [2011], a month is designated as "rainy" if the rainfall coefficient is 0.6 or over. In like manner, "small rains" is used to describe the rainfall coefficients ranging between 0.6 and 0.9, while "big rains" designated rainfall coefficient of 1.0 and above. Due to the peculiarity of the study area, the "big" rainy

Table 5. Classification scheme of monthly rainfall values

Designation	Rainfall coefficient
Dry month	<0.6
Rainy month	≥0.6
Small rains	0.6–0.9
Big rains	≥1
Moderate concentration	1.0–1.9
High concentration	2.0–2.9
Very high concentration	≥3.0

Source: Gamachu [1977].

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RESULTS AND DISCUSSION

NORMALITY TEST

The trend of the precipitation from the Gurara reservoir catchment (GRC) presented in Figure 7 demonstrated a normal distribution. Similar results were observed in the *Q–Q* plot indicating a normality trend in the rainfall dataset at 0.05 level of significance. In this regard, the null hypothesis is accepted as the rainfall is normally distributed. The Shapiro–Wilk (W) output for the observed rainfall dataset to detect normality is $W = 0.95818$, p-value = 0.2782. Thus, the observed rainfall dataset can be used for further study with RCMs owing to their stochastic nature.

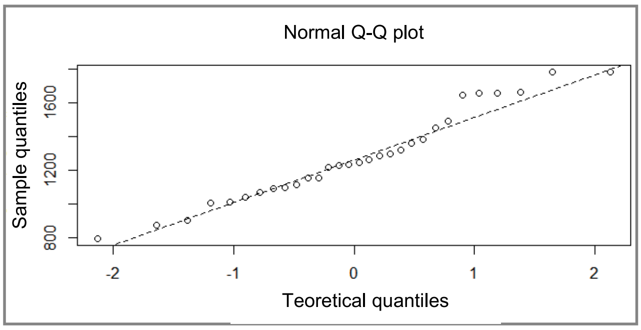

Fig. 7. *Q–Q* plot of annual rainfall (mm) in Gurara reservoir catchment; source: own study

WATER RESOURCES ASSESSMENT

The use of efficient and robust techniques in ensuring optimal distribution of water resources is important in setting up an evaluation tool helps in creating an integrated mechanism [Dessu *et al.* 2014]. In addition to the quantity and distribution of available water, assessment procedures need to address the relationship between available water and impact of climate change to ensure sustainability and ecosystem functioning [Awotwi *et al.* 2017; Dessu *et al.* 2014; Eduvie, Oseke 2021]. The findings from this study when analysed presented an easy to understand method by relevant stakeholders with an opportunity to negotiate and address priority of water use. The method of predicting available water using different projected climate change scenarios has been applied in Ghana by Awotwi *et al.* [2017], in the United Kingdom by Fowler and Kilsby [2007] and in Nigeria by Gloria and Ogbu [2018]. Thus, the study exploited the rank of relationship between climate change and water availability in a semi-arid catchment to predict water resource status and impact of climate change in the GRC.

RUNOFF CALIBRATION AND VALIDATION

The comparison of observed and predicted hydrographs for the calibration and validation epochs is illustrated in Figure 8. The graph revealed a decent agreement between the observed and predicted mean monthly runoff producing a correlation.

The calibrated and validated estimated runoff dataset using the SCS-CN method is listed in Table 6. The coefficient of determination (R^2); calibration 0.72; validation 0.69, obtained describes the degree of colinearity between observed and the predicted runoff. The correlation coefficient, which ranges from −1 to 1, is an index of the degree of linear relationship between observed and predicted dataset. If $R^2 = 0$, no linear relationship exists; if $r = 1$ or $r = -1$, a perfect positive or negative linear relationship exist. Here, R^2 ranges from 0 to 1, with higher values demonstrating less error variance, and typically values greater than 0.5 are considered unacceptable according to van Liew *et al.* [2003].

Table 6. Calibration and validation performance of the SCS-CN model method

Stage	Statistics indicators		
	NSE	*PBIAS*	R^2
Calibration	0.72	−0.04	0.70
Validation	0.69	−0.01	0.72

Source: own study.

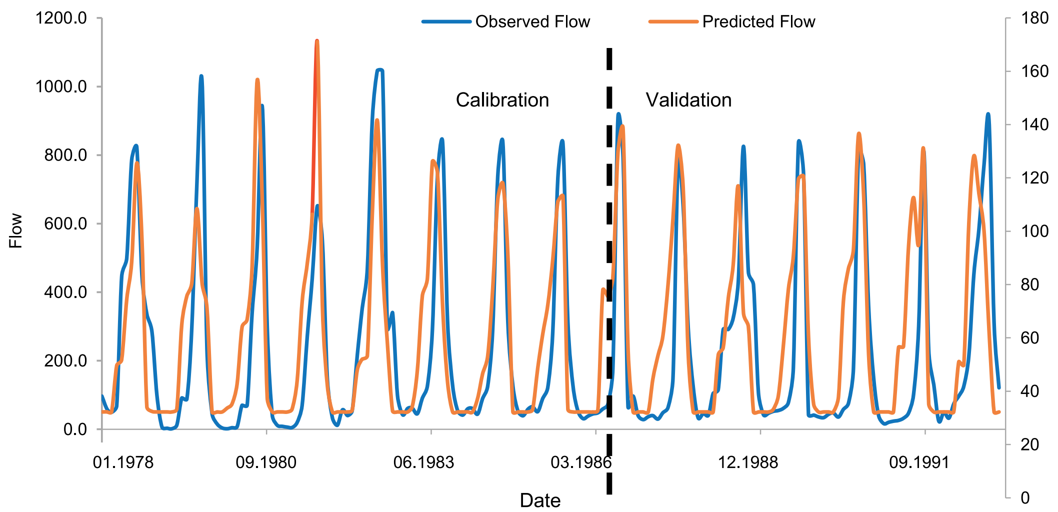

Fig. 8. Model flow fit on the predicted flow for the period of 1978–1991; source: own study

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Although coefficient of determination (R^2) has been widely used for model performance evaluation especially in hydrology, these statistical indices are oversensitive to high extreme values (outliers) and insensitive to additive and proportional differences between model predictions and observational datasets [Moriasi *et al.* 2005].

The dependability of the model developed from the SCS-CN method to predict runoff was additionally affirmed by percent bias (*PBIAS*) values within the range of ±10% which demonstrates very good performance of the model. The percent bias measures the average tendency of the predicted data to be larger or smaller than their observed counterparts [Moriasi *et al.* 2005]. The Nash–Sutcliffe efficiency (*NSE*) value of more than 0.72 is adequate for further hydrological analysis and is a normalised statistic that determines the relative magnitude of the residual variance compared to the measured data variance [Moriasi *et al.* 2005]. It is worth knowing that the runoff model developed using SCS-CN method is not a physical model, as such, it should not be expected to yield usable results outside the range of runoff for which it was calibrated.

Despite the suitability of the SCS-CN model for further hydrological analysis, the predicted model overestimated the observed runoff of 0.06% and 0.025% in the calibration and validation process respectively. The overestimation is portrayed by the negative *PBIAS* value (Tab. 5). A similar calibration concern was faced by Hjelmfelt *et al.* [2001], when the SCS-CN based model was used to predict surface runoff in the forested Coweeta catchment. This may be attributed to the general assumption that the predicted flow in catchment using SCS-CN method is all overland flow. This is because the hypothesis behind SCS-CN method is based on the empirical prediction of how much of the rainfall contributes to the surface runoff [Hjelmfelt *et al.* 2001]. Furthermore, the overestimation of the runoff may be due to the curve number, as the land-cover might have changed over time which could result in increased or decreased contribution from direct precipitation in the catchment. This is a condition which is synonymous models developed using SCS-CN method [Hjelmfelt *et al.* 2001].

SELECTION OF RCMS USING RANKING OF CLIMATE MODEL

The eight selected models represented in Taylor diagrams for projected temperature and precipitation climate models dataset are shown in Figures 9 and 10 respectively.

THE MODELS FOR FUTURE CLIMATE PROJECTIONS

The analysed projected temperature (Tab. 7) represented in Taylor diagram (RCP4.5, RCP6.5 and RCP8.5) is based on the annual mean and the monthly mean. This is because these

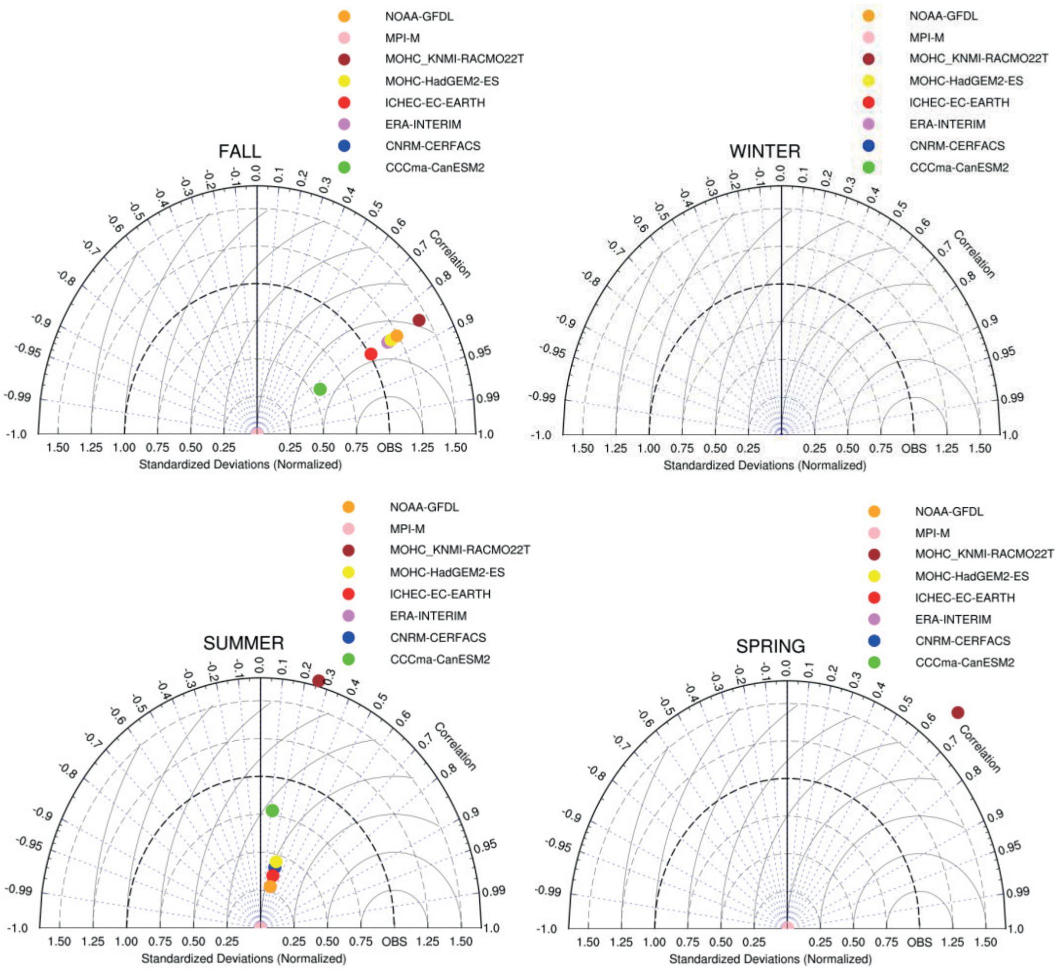

Fig. 9. Taylor diagram for the selected climate regional climate models (RCMs) modelled against the observed depicting the normalised standard deviation, the correlation, and the root mean square error (*RMSE*) within the precipitation models in the Gurara reservoir catchment; source: own study

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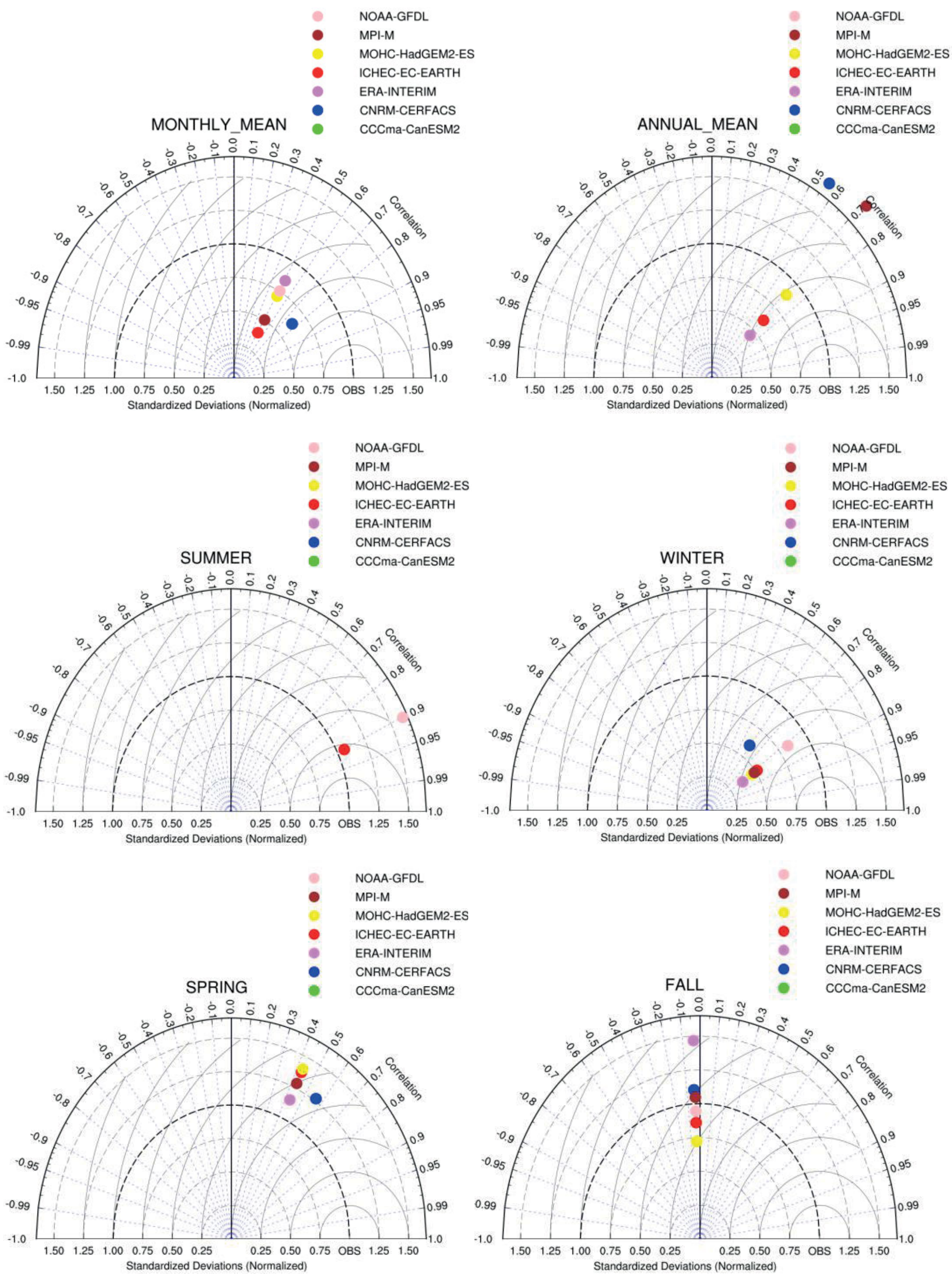

Fig. 10. Taylor diagram for the selected climate regional climate models (RCMs) modelled against the observe depicting the normalised standard deviation, the correlation, and the root mean square error (*RMSE*) within the mean temperature models in the Gurara reservoir catchment; source: own study

seasons have a dataset from RCMs with describable tendencies. The RCM MOHC-HadGEM2-ES model performs best by optimally predicting the variability of the observed dataset. According to IPCC [2017], the annual mean temperature globally is predicted to show an increase from the currently experienced, hence, there will be more emission of greenhouse gases into the atmosphere. Consequently, the scenario represented as RCP8.5 projected higher temperatures than RCP4.5 and RCP6.5 even with the same climate models. The projected higher temperatures for both RCP6.5 and RCP8.5 reveal a possible warmer period in future climate. These projections are in agreements with Abdullahi *et al.* [2014] in the Sokoto Rima River Basin and Morán-Tejeda *et al.* [2014] in Aragón, where increase in temperature are envisage in the near future and end of the 21st century.

Presented in Table 8 is the ranked climate model of precipitation within the GRC, showing the percentage mean annual for climate scenarios RCP4.5, RCP6.5 and RCP8.5. The analysis revealed CNRM-CERFACE-CNRM-CM5 model predicted the observed better and subsequently adopted for the

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Table 7. Weighted and ranked climate model of team temperature

Global climate model	Model code	Correlation	Standard deviation
Annual mean			
NOAA-GFDL-GFDL-ESM2M	RCAS	out of range	out of range
ESM-LR	MPI-M-MPI-ESM-LR	0.70	1.75
MOHC-HadGEM2-ES	CCL2	0.71	0.88
ICHEC-EC-EARTH	RACI	0.73	0.63
CNRM-CM5	CCL1	0.55	1.25
CCCma_CanESM2	RCA1	out of range	out of range
CNRM-CERFACE-CNRM-CM5	RCA2	out of range	out of range
NCC-NorESM-M	HIR	0.70	0.625
Monthly mean			
NOAA-GFDL-GFDL-ESM2M	RCAS	out of range	out of range
ESM-LR	MPI-M-MPI-ESM-LR	0.50	0.75
MOHC-HadGEM2-ES	CCL2	0.50	0.69
ICHEC-EC-EARTH	RACI	0.50	0.38
CNRM-CM5	CCL1	0.80	0.63
CCCma_CanESM2	RCA1	out of range	out of range
CNRM-CERFACE-CNRM-CM5	RCA2	out of range	out of range
NCC-NorESM-M	HIR	0.50	0.38

Source: own study.

climate change impact assessment. For all scenarios, CNRM-CERFACE-CNRM-CM5 predicted more precipitation with an average increase of approximately 3% for RCP6.5 and 5% for RCP8.5. The upsurge in predicted mean monthly precipitation in all scenarios measuring up to 2% reveals some level of uncertainty in the near future and thus, Tall *et al.* [2016] suggest more rainfall. Unlike variations in temperature, precipitation variations indicate much uncertainty under different RCMs and climate change scenarios. These results are consistent with studies carried out by Tall *et al.* [2016] in Lake of Guiers, Awotwi *et al.* [2017] in the Pra Basin and Domfeh *et al.* [2015] in the Berekese reservoir catchment, where climate models have predicted different trends of annual precipitation increase under different emissions scenarios. The uncertainties resulting from the use of climate models might be associated with the assumptions and results surrounding models construction [Awotwi *et al.* 2017].

STATISTICAL CLASSIFICATION OF RAINFALL COEFFICIENT

The coefficient of rainfall value classification is listed in Table 9 describing the increasing pattern from moderate to high rainfall within the catchment area. The statistical classification reveals the GRC is highly prone to the risk of flooding suggesting more rain

Table 8. Weighted and ranked climate model of precipitation

Global climate model	Model code	Correlation	Standard deviation
Summer			
NOAA-GFDL-GFDL-ESM2M	RCAS	0.76	0.27
ESM-LR	MPI-M-MPI-ESM-LR	0	0
MOHC-HadGEM2-ES	CCL2	0.25	1.63
ICHEC-EC-EARTH	RACI	0.75	0.38
CNRM-CM5	CCL1	0.10	0.75
CCCma_CanESM2	RCA1	0.25	0.44
CNRM-CERFACE-CNRM-CM5	RCA2	0.25	0.44
NCC-NorESM-M	HIR	0.75	0
Fall			
NOAA-GFDL-GFDL-ESM2M	RCAS	out of range	out of range
ESM-LR	MPI-M-MPI-ESM-LR	0.85	1.25
MOHC-HadGEM2-ES	CCL2	1.19	0.19
ICHEC-EC-EARTH	RACI	0.85	1.00
CNRM-CM5	CCL1	0.85	1.13
CCCma_CanESM2	RCA1	out of range	out of range
CNRM-CERFACE-CNRM-CM5	RCA2	0.85	0.56
NCC-NorESM-M	HIR	0.85	1.13

Source: own study.

Table 9. Rainfall coefficient and aerial pattern in Gurara reservoir catchment

Month	Rainfall coefficient value	Season	Classifi-cation	Further classification
Jan	0.0	dry		
Feb	0.0	dry		
Mar	0.0	dry		
Apr	0.4	dry		
May	0.9	raining	small rains	
Jun	1.6	raining	big rains	moderate rains
Jul	2.0	raining	big rains	high rains
Aug	2.4	raining	big rains	high rains
Sep	1.7	raining	big rains	moderate rains
Oct	0.8	raining	small rains	
Nov	0.0	dry		
Dec	0.0	dry		

Source: own study.

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in the future. The rainfall classification shows the coefficients agrees with the predictions based on RCPs projections in the near future.

The projected climate data following the statistical output was assumed to be reliable for predicting the impact of climate change. The projected dataset up to 2050 climate pattern run from 1989–2005 representing the present (baseline data).

CLIMATE CHANGE IMPACT ON HYDROLOGICAL PROCESSES

The result of climate change impact on hydrological processes reveals increase in surface runoff which is in agreement with the study carried out by Agunbiade and Jimoh [2013], within the GRC. The increasing rainfall from moderate to high subsequently experienced within the GRC (Tab. 8) corresponds to increase in monthly peak runoff. The monthly runoff increased from 311 to 326 $m^3 \cdot s^{-1}$ which represents 23%, in response to an incremental rainfall of 8.3% and 4.3% in temperature respectively. The future runoff scenario and pattern in the catchment is the same as the present, but differs in magnitude with the rainfall being the deciding factor (Fig. 8).

WATER BALANCE AND AVAILABILITY

The water balance illustrating the demand reliability on inflow and outflow under current and projected climate change scenarios is shown in Figure 11. Similarly, Figure 12 illustrates the consumption, inflow, outflow and precipitation for the climate change scenario. Listed in Table 10, is the projected water availability which substantially increases up to 3.5% and 4.3% for RCP6.5 and RCP8.5 climate scenarios respectively. The shows increased runoff depths with the highest under RCP8.5 emission scenario and lowest under RCP6.5. This result agrees with the findings from research in the Pra Basin where RCP8.5 emissions regarded as the worst case scenario predicting increasing changes in runoff [Awotwi *et al.* 2018].

The variation from the predicted runoff in the future may have significant concern for the resident of Abuja and by extension Abuja water board management authority, as Abuja is already faced with water availability problems [Agunbiade, Jimoh 2013] from Lower Usuma reservoir during the dry season.

The city of Abuja is rapidly expanding, as such, the occurrence of an extreme event such as late onset of rainfall

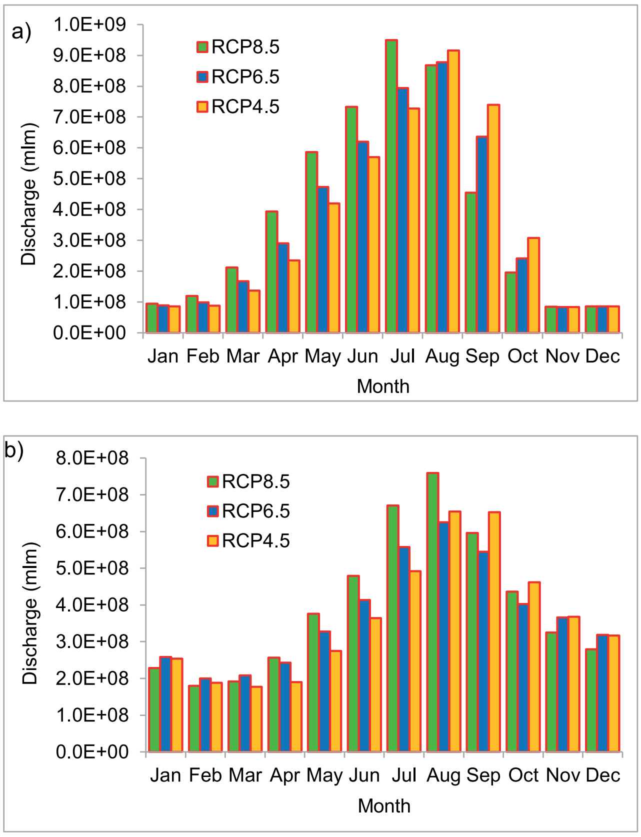

Fig. 11. Mean monthly simulated inflow (a) and outflow (b) under current and projected climate change for all scenarios; source: own study

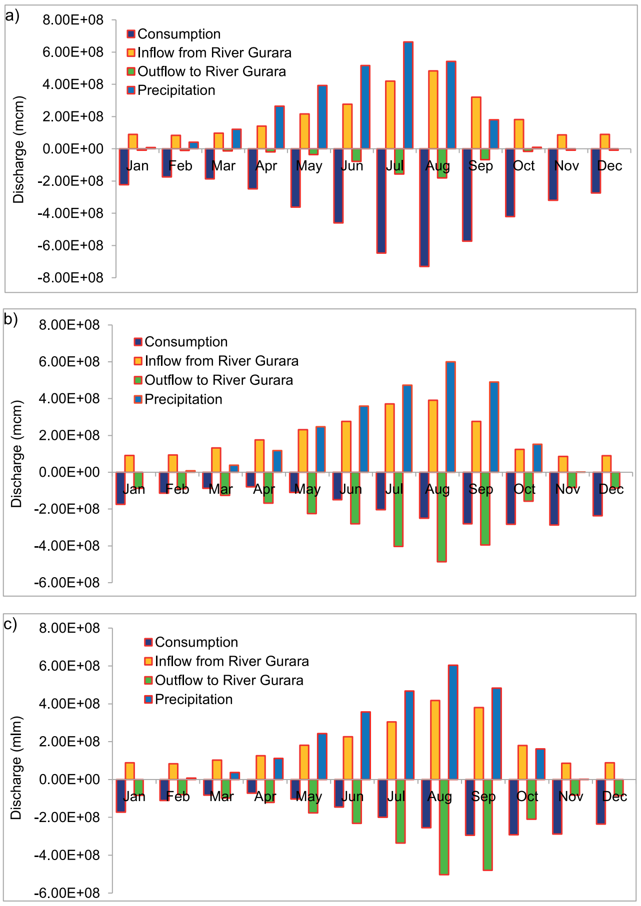

Fig. 12. Mean monthly water balance on inflow and outflow under current and projected climate change scenarios (RCPs): a) RCP4.5, b) RCP6.5, c) RCP8.5; source: own study

Table 10. Water availability based on simulation of projected climate change scenarios (RCPs)

Specification	Amount of water available (mln m^3)		
	RCP4.5	RCP6.5	RCP8.5
Available water (mln m^3)	4.38	4.46	4.78
Difference (mln m^3)	NA	319	398
% of increase	NA	3.5	4.3

Source: own study.

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and reduction in the length of wet season as a result of variability in future climate will result in changes in the magnitude of rainfall. Subsequently, these changes in the magnitude of rainfall combined with occurrence of higher temperatures may affect operations of the Abuja water treatment plant and the water diversion, which are primary beneficiaries of the GRC. Consequently, higher temperatures in water at catchment level will have an unfavorable effect on the water environment [Awotwi *et al.* 2015], leading to increase in blue-green algae populations. In this regard, there should be an advocacy campaigns to sensitise relevant stakeholders concerning the risk associated with climate change, coupled with a robust water supply and management mechanism. This is to increase awareness while attempting to alleviate impending water stress in catchments. This must be carried out without undermining the need for infrastructural development within the catchment [Domfeh *et al.* 2015].

The realisation from the result illustrating an increase in the runoff within the GRC strengthens the need for authorities to put in place appropriate investments in the planning and management of the water resources, like the expansion of the irrigation to accommodate multiple planting season and expansion of the Abuja water treatment plant that can effectively and efficiently utilise the expected increase in runoff.

Abuja will continue expanding in its infrastructural development due to urbanisation and growth in population. Hence, to achieve the objective of utilising the excess water, there is the proposed project of further transferring water from the Gurara reservoir to a new destination, namely: the Shiroro catchment for hydropower generation [Katashaya 1986]. Besides, to supply water to support the Izom irrigation farm [Katashaya 1986] with the view that more water will be put into productive use like agriculture to ensure food security. However, it is regrettable to note the current practice and designs of the water infrastructures within the catchment area are being carried out without assessing the impacts of climate change. It is the position of this study that during design stage, the components of climate change impact is factored in, using RCMs which depict an alternative climate scenario for robust assessment. This will usually result in a logical conclusion, as logical conclusions are important for wide acceptance of research findings, especially for integrated water resource management.

In line with sustainability, authorities within the catchments management ranks should ensure that existing infrastructures and yet to be initiated water infrastructures must count the plausible climate change impact on catchments hydrology and take mitigating measures which are to be accommodated in the planning and design.

CONCLUSIONS

The vulnerability of GRC to climate change was simulated while improving management options using relatively bias-corrected CORDEX-Africa and RCP based climate model. The technique was customised to illustrate the delicate balance of water utilisation by human settlement through water diversion operation. The model outcomes predicted greater climate variability such as higher temperature. Similarly there observed uncertainties over the trend of the variations for both precipitation and runoff during the period of 1978–2019.

The climate scenarios RCP6.5 and RCP8.5 evidently reveals the impact of climate change, thereby recommending appropriate authorities within the catchment to invest in cost-effective water management techniques like constructing of water infrastructures such as treatment plants, irrigation system to utilise more of the available water during the wet season, and reservoirs to store for gradual release during the dry season. This is necessary because optimal use of the catchments water resources is geared towards sustainable development and food security. A projected change in climate within the catchment supposes that future development within the catchment should incorporate in it, the probable effects of climate change on the future hydrological characteristics, and ensure adequate measures for mitigation.

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