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Multiscale assessments of hydroclimatic modelling uncertainties under a changing climate

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ABSTRACT

Since the 1970s, climate change has led to decreasing water resources in the Sahel. To cope with climate change, reliable modelling of future hydroclimatic evolutions is required. This study uses multiclimate and hydrological modelling approaches to access past and future (1951–2100) hydroclimatic trends on nine headwater catchments of the Niger River Basin. Eight global climate models (GCMs) dynamically downscaled under the CORDEX CMIP5 project were used. The GCM data were bias-corrected with quantile–quantile mapping. Three rainfall–runoff models (IHACRES-CMD, IHACRES-CWI and Sacramento) were calibrated and validated with observed data and used to simulate runoff. The projected future runoff trend from 2061 to 2090 was compared across the three hydrological models to assess uncertainties from hydrological models. Results show that the bias correction positively enhanced the quality of eight GCMs across the nine catchments. An average Nash–Sutcliffe Efficiency (*NSE*) across the nine catchments was improved from 0.53 to 0.68 and the Kling–Gupta Efficiency (*KGE*) was enhanced from 0.65 to 0.83. The three hydrological models were calibrated and validated appropriately on the nine catchments. Despite this, high hydrological modelling uncertainties were witnessed with contrasting projected future runoff patterns by the three models. We recommended the use of ensembles of both climate and hydrological models to provide reliable hydroclimatic modelling.

Key words: climate change, ensembles, hydrology, runoff, uncertainty

HIGHLIGHTS

- CMIP5 hydroclimatic projections are accrued with biases on the Niger Basin.
- Quantile mapping corrected biases in the climate projections.
- IHACRES-CWI, IHACRES-CMD and Sacramento hydrological models simulate runoff with high accuracies.
- Future runoff patterns on the Niger Basin are highly uncertain.
- Ensembles of both climate and hydrological models were recommended for future hydroclimatic projections.

INTRODUCTION

Severe impacts due to climate change have been predominant in the Niger Basin and West Africa. In recent decades, there has been a decline in food security as a result of an increase in temperature, a change in rainfall patterns and an increase in extreme climatic conditions (Intergovernmental Panel on Climate Change (IPCC) 2019). Climate change has aggravated a decrease in river discharge and an increase in Sahel drought since 1970, with 1984 being the driest year on record (Biasutti 2019). Furthermore, future projections have indicated that there will be an increase in the intensity of rainfall and flood magnitudes (Sylla *et al.* 2015a). Topsoil losses due to an increase in the rainfall–runoff erosivity are projected in the 21st century (Amanambu *et al.* 2019). Despite water being important in different sectors such as agriculture and hydropower, Sylla *et al.* (2018) have shown that high temperature and evapotranspiration will reduce the potential to sustain dams and irrigation in West Africa.

Effective design and planning of sustainable adaptation mechanisms to climate change requires an efficient prediction of future climate and hydrological patterns. Past changes in climate are not properly documented owing to an insufficient and deteriorating number of dependable observation stations ever since the 1980s (Ali & Lebel 2009). Satellite-based records of rainfall have also shown inherent biases due to insufficient observed data for model assessments (calibration and validation) (Sylla *et al.* 2013). Future hydrological and meteorological predictions from CMIP3 and CMIP5 regional climate model (RCM)/global climate model (GCM) ensembles were ascribed with large uncertainties (Druyan 2011; Oyerinde & Diekkrüger 2017). Therefore, there is an urgent need to improve hydro-meteorological modelling methodologies in West Africa.

Several studies have attempted to determine contributions of climate and hydrological models to climate change uncertainties (Lespinas *et al.* 2014; Her *et al.* 2016, 2019; Hattermann *et al.* 2018; Zhang *et al.* 2019; Gangrade *et al.* 2020). Lespinas *et al.* (2014) assessed uncertainties associated with RCMs with one hydrological model at a monthly temporal scale on multiple catchments with all being located in France. The authors found uncertainties stemming from the GR2M hydrological models used in the study. Hattermann *et al.* (2018) concluded in their article that hydrological models are very sensitive to little changes in temperature from GCMs which have coarse resolution and are not good for hydrological impact studies. Zhang *et al.* (2019) evaluated the impacts of parameterization of a hydrological model on uncertainties. The authors showcased that the parameter uncertainty could drive variability up to 10% annually and 26% monthly for future climate change scenarios. The study by Gangrade *et al.* (2020) shows that the selection of climate models is more important than the choice of the hydrologic model at the United States. They recommended site-specific insights into hydroclimate response and associated uncertainties to enhance informed decisions. A limited number of studies have assessed the combined role of climate and hydrological models' uncertainties in West Africa. In view of this, our study assessed the contribution of the RCM/GCM and hydrological models to future runoff projections on nine Niger Basin catchments in West Africa. The objectives of the study are to:

- assess uncertainties of climate (rainfall and potential evapotranspiration (PET)) projections from eight RCMs/GCMs on the Niger River Basin,
- evaluate runoff projections from the combination of three rainfall–runoff models forced with eight RCMs/GCMs and
- determine uncertainties ascribed with hydroclimatic projections on multiple catchment scales.

Study area

The Niger River Basin has a total area of 2.27 million km^2 with a 50% active drainage area (Ogilvie *et al.* 2010). The basin is the ninth largest in the world and third in Africa with a length of 4,200 km. The basin cut across 10 countries: Guinea (source), Mali, Cote d'Ivoire, Niger, Burkina Faso, Algeria, Benin, Nigeria, Chad and Cameroon (Odunuga *et al.* 2015). The source of the river basin is at the Fouta Djallon Mountains of Southern Guinea. Table 1 and Figure 1 present characteristics and geographical location of the selected nine Niger Basin catchments for this study. Flow patterns on the Niger are highly seasonal and show high inter-annual variability with a clear decreasing trend since the 1970s (Thompson *et al.* 2017). The average annual river discharge varies depending on the location on the basin. The discharge ranges from

Table 1 | Characteristics of the nine selected catchments on the Niger Basin

S.No.	Catchment name	Gauging station	Average discharge (m^3/s) from 1997 to2010	Catchment area (km^2)
1	Banakoro	Banakoro	668	70,057
2	Sota	Couberi	28	13,410
3	Bani	Douna	257	101,600
4	Sirba	Garbey kourou	80	39,000
5	Dagol	Kakassi	28	7,109
6	Mekrou	Kompongou	22	5,670
7	Koulikoro	Koulikoro	1,136	120,000
8	Niger	Lokoja	6,310	2,061,866
9	Benue	Makurdi	3,613	301,685

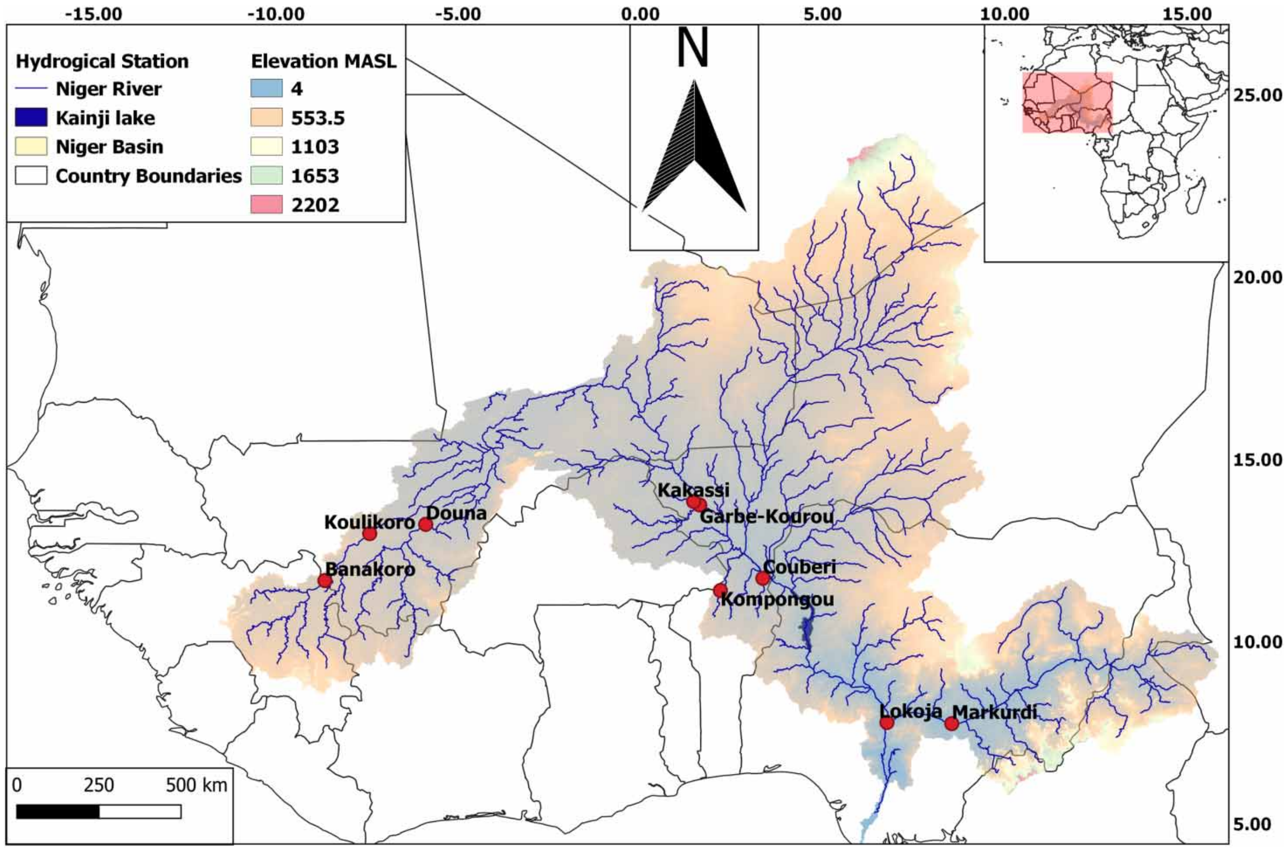

Figure 1 | Map of the Niger Basin showing the distribution of evaluated catchments.

22 m^3/s at Kompongou in Benin Republic to 6,310 m^3/s at Lokoja in Nigeria (Table 1). The population density in the Niger River Basin varies from <1 person per km² at the desert parts of the north to >1,000 at Nigeria (Aich *et al.* 2016).

Data

Observations

The three hydrological models use daily precipitation and PET to simulate river discharge. Daily precipitation was obtained from the Global Precipitation Climatology Project (GPCP) (Huffman *et al.* 1997), and PET was calculated from 2 meter temperature of the Modern Era Retrospective analysis for Research and Applications (MERRA) (Rienecker *et al.* 2011). The Hamon model that provides good estimations of PET was used (Oudin *et al.* 2005; Oyerinde *et al.* 2017a). River basin boundary for the Niger basin was obtained from Hydrosheds (Lehner *et al.* 2008). Catchment area and boundaries of hydrological stations (Figure 1) were delineated with the Hortonian drainage network analysis (Jasiewicz & Metz 2011). We used the latitudinal-weighted modelling approach of Oyerinde *et al.* (2016) to get over the challenge of a large temperature and rainfall gradient. The gradient arises as a result of the back and forth movement of the Inter-Tropical Discontinuity (ITD) (Lucio *et al.* 2012).

Future projections

Precipitation data of eight GCMs (Table 2) from CORDEX CMIP5 experiments, which have two emission scenarios (RCP4.5 and RCP8.5), were utilized. The GCMs were dynamically downscaled with the Sveriges Meteorologiska och Hydrologiska Institute (SMHI-RCA) RCM to 0.44°×0.44° resolution within the CORDEX-Africa regional downscaling experiments. CORDEX data are popularly used for hydrological studies in the region (Mounkaila *et al.* 2014; Tall *et al.* 2016; Oyerinde *et al.* 2017a). Basin projection data were extracted as stated for the observation data. Future PET was calculated from extracted temperature using the Hamon model. Simulated runoff from the three models was aggregated into a future time period of 2061–2090 and was matched to a historical period (1951–2005).

Table 2 | List of CMIP5 global climate models used in the study

Modelling centre (or group)	Model name	Institute ID
Canadian Centre for Climate Modelling and Analysis	CanESM2	CCCMA
Centre National de Recherches Météorologiques/Centre Européen de Recherche et Formation Avancée en Calcul Scientifique	CNRM-CM5	CNRM-CERFACS
NOAA Geophysical Fluid Dynamics Laboratory	GFDL-ESM2M	NOAA GFDL
Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)	HadGEM2-ES	MOHC
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC5	MIROC
Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)	MPI-ESM-LR	MPI-M
Norwegian Climate Centre	NorESM1-M	NCC
EC-EARTH consortium	EC-EARTH	ICHEC

METHODS

Modelling framework

Hydrological models

Selected hydrological models are components of the 'Hydromad' R package (Andrews *et al.* 2011). The three models estimate river discharge at the outlet of the catchment with inputs of daily rainfall and PET. The three models were selected because of their common usage and acceptance in hydrological studies over the study area (Gosset & Viarre 2013; Oyerinde *et al.* 2017b).

IHACRES-CMD

This model utilizes the identification of hydrographs and flow component purely from evapotranspiration, rainfall and river discharge data (Croke & Jakeman 2004). It has a non-linear loss module, where rainfall is converted to effective rainfall (rainfall excess), and a linear discharge routing module. The two-store loss module simulates at time step k, quickflow, $x_k^{(q)}$ and slow-flow, $x_k^{(s)}$, which combines additively to yield streamflow (discharge), q_k:

$$q_k = x_k^{(q)} + x_k^{(s)} \tag{1}$$

$$x_k^{(q)} = \alpha_q x_{k-1}^{(q)} + \beta_q U_k \tag{2}$$

$$x_k^{(s)} = \alpha_s x_{k-1}^{(s)} + \beta_s U_k \tag{3}$$

where U_k is the effective rainfall. The parameters α_q and α_s can be expressed as time constants for the quick- and slow-flow stores, respectively.

IHACRES-CWI

The second model is the IHACRES-CWI, which has a one-store loss module that converts rainfall to effective rainfall (Jakeman *et al.* 1990; Ye *et al.* 1997; Andrews 2011; Oyerinde *et al.* 2017c). Effective rainfall (rainfall excess) u_k is calculated from rainfall r_k, PET E_k, drying rate tw_k and storage or soil moisture index s_k as described by Oyerinde *et al.* (2016) and Ye *et al.* (1997).

$$u_k = c \times (s_k - l)^p \times r_k \tag{4}$$

$$s_k = \left(1 \frac{1}{tw_k}\right) \times s_{k-1} + r_k \tag{5}$$

$$tw_k = tw \times \exp\left(-0.062 \times f \times E_k\right) \tag{6}$$

Sacramento

The third model is the Sacramento model (Andrews *et al.* 2011; Burnash 2012; Kunnath-Poovakka & Eldho 2019). Of the three models, it is the most complex. Two soil zones, upper and lower, are defined. The interception storage is contained in the upper zone, while the lower zone indicates soil moisture and longer groundwater storage. In each soil zone, two moisture storages are represented: tension water and free water. A special aspect of the model lies in the representation process of the percolation from the upper zone to the lower zone. Evapotranspiration is computed using each part of the model according to a hierarchy of priorities. A mass balance approach is used to calculate the effective rainfall from lateral drainage that is contributed from each of the soil zones (Kumar & Marcy 2017).

Model calibration

The models were automatically calibrated using the 'fitByOptim' algorithm on R (Andrews *et al.* 2011). The function derives best parameters that give the best Nash–Sutcliffe Efficiency (*NSE*). The observed and simulated river discharges were compared with the following four efficiency criteria. The selected efficiency criteria have been used widely in the region with good acceptability: Nash–Sutcliffe Efficiency ($\infty < NSE \leq 1$) (Nash & Sutcliffe 1970), Kling–Gupta Efficiency ($0 \leq KGE \leq 1$) (Kling *et al.* 2012), root mean square error (*RMSE*) and coefficient of determination ($0 \leq R^2 \leq 1$) (Legates & McCabe 1999).

NSE can be defined as:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{7}$$

where O represents the observed river discharge and S is the simulated river discharge value at day i. The *NSE* of 1 indicates a perfect match between simulated and observed river discharges. The *KGE* was designed to create an exciting decomposition of the *NSE* (Kling *et al.* 2012). This will enhance the analysis of the relative significance of its different components related to hydrological modelling (Kling *et al.* 2012).

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \tag{8}$$

$$\beta = \frac{\mu_s}{\mu_o} \tag{9}$$

$$\gamma = \frac{CV_s}{CV_o} \tag{10}$$

where r is a dimensionless correlation coefficient between S and O, β is the dimensionless bias ratio, γ is the dimensionless variability ratio, μ is the average river discharge in m^3/s and CV is the dimensionless coefficient of variation. The *KGE* is optimum at the value of 1 (Kling *et al.* 2012).

The coefficient of determination (R^2) is the proportion of the variance in the dependent variable that is predictable from the independent variable(s).

$$R^2 = 1 - \frac{\sum_i (O_i - \bar{O})^2}{\sum_i (O_i - S_i)^2} \tag{11}$$

where O and S are the observed and simulated runoffs, respectively.

RMSE indicates a perfect match between O and S values when it equals 0 (zero), with increasing *RMSE* values indicating an increasingly poor match.

Uncertainty and sensitivity analysis

We used the Generalized Likelihood Uncertainty Estimation (GLUE) method to assess the three hydrological models' parameter sensitivities and uncertainties (Beven & Binley 1992; Chaibou Begou *et al.* 2016; Oyerinde & Diekkrüger 2017). The

GLUE is the Monte Carlo method for the hydrological models' sensitivity and uncertainty analysis. The method uses large numbers of model runs with different combinations of parameter values chosen randomly and independently from the prior distribution in the parameter space. We used 10,000 model runs with different parameter sets in the study. The total sample of simulations was divided into 'behavioural' and 'non-behavioural' based on a threshold value of $NSE \geq 0.5$ (Chaibou Begou *et al.* 2016), a 90% coverage of the observed values and a GLUE quantile range of 0.05–0.95. GLUE prediction uncertainty was assessed with the *P*-factor and the *R*-factor (Abbaspour *et al.* 2004; Chaibou Begou *et al.* 2016). The *P*-factor represents the percentage of observed data bracketed by the 90% predictive uncertainty band of the model calculated at the 5 and 95% levels of the cumulative distribution of an output variable obtained through random sampling. The *R*-factor is the ratio of the average width of the 90% predictive uncertainty band and the standard deviation of the measured variable. For uncertainty assessment, a value of *P*-factor >0.5 (i.e., more than half of the observed data should be enclosed within the 90% predictive uncertainty band) and *R*-factor <1 (i.e., the average width of the 90% predictive uncertainty band should be less than the standard deviation of the measured data) should be adequate for this study, especially considering limited data availability.

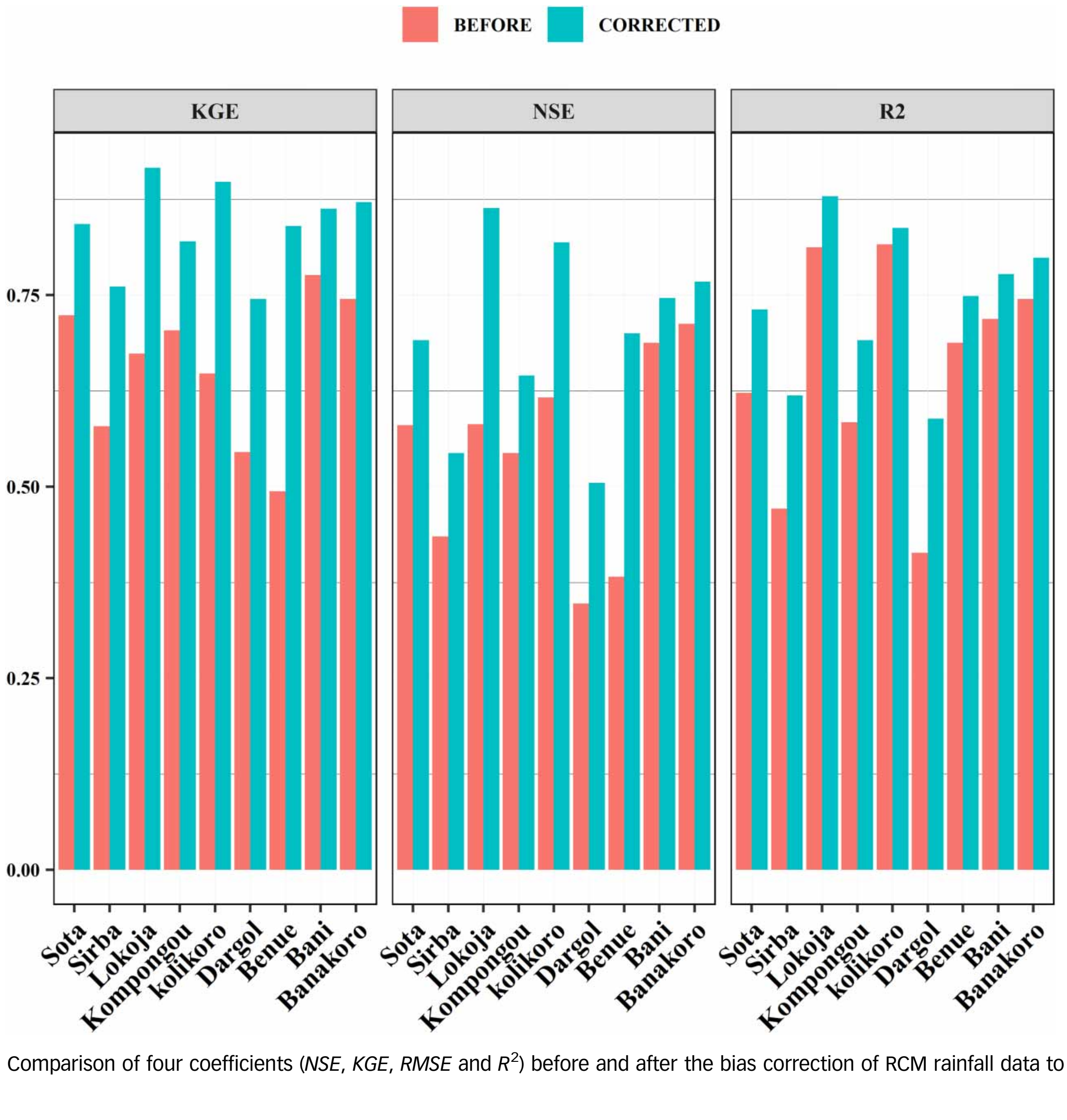

Figure 2 | Comparison of four coefficients (*NSE*, *KGE*, *RMSE* and R^2) before and after the bias correction of RCM rainfall data to the GPCP.

Bias correction of RCMs/GCMs and evaluation

Bias adjustments reduce the margin of errors from climate models when compared with historical observations (Kling *et al.* 2012). It depends on differences between the RCM/GCM and observed data. In this study, we used MERRA and GPCP datasets from 1997 to 2010 to correct biases in RCM/GCM datasets. The quantile mapping bias correction (Gudmundsson *et al.* 2012; Ravazzani *et al.* 2016; Enayati *et al.* 2021) was used to improve the CMIP5 temperature and rainfall data. It corrects moments of the probability distribution function (PDF) of input variable by deriving both cumulative distribution functions (CDFs) and transfer function from the PDFs of the observed data and the RCM. Here, a quantile–quantile parametric transformation shown in the following equation was used:

$$P_o = bP_m^c \tag{12}$$

where P_o is the observed data, P_m is the RCM empirical CDF and b and c are the free parameters.

Mapping was done on a monthly scale. The original daily RCM/GCM and bias-adjusted rainfall data were compared with the observed data using the four efficiency criteria described earlier above. In this study, the quantile mapping bias correction was implemented on the R Statistical Software Package 'qmap'.

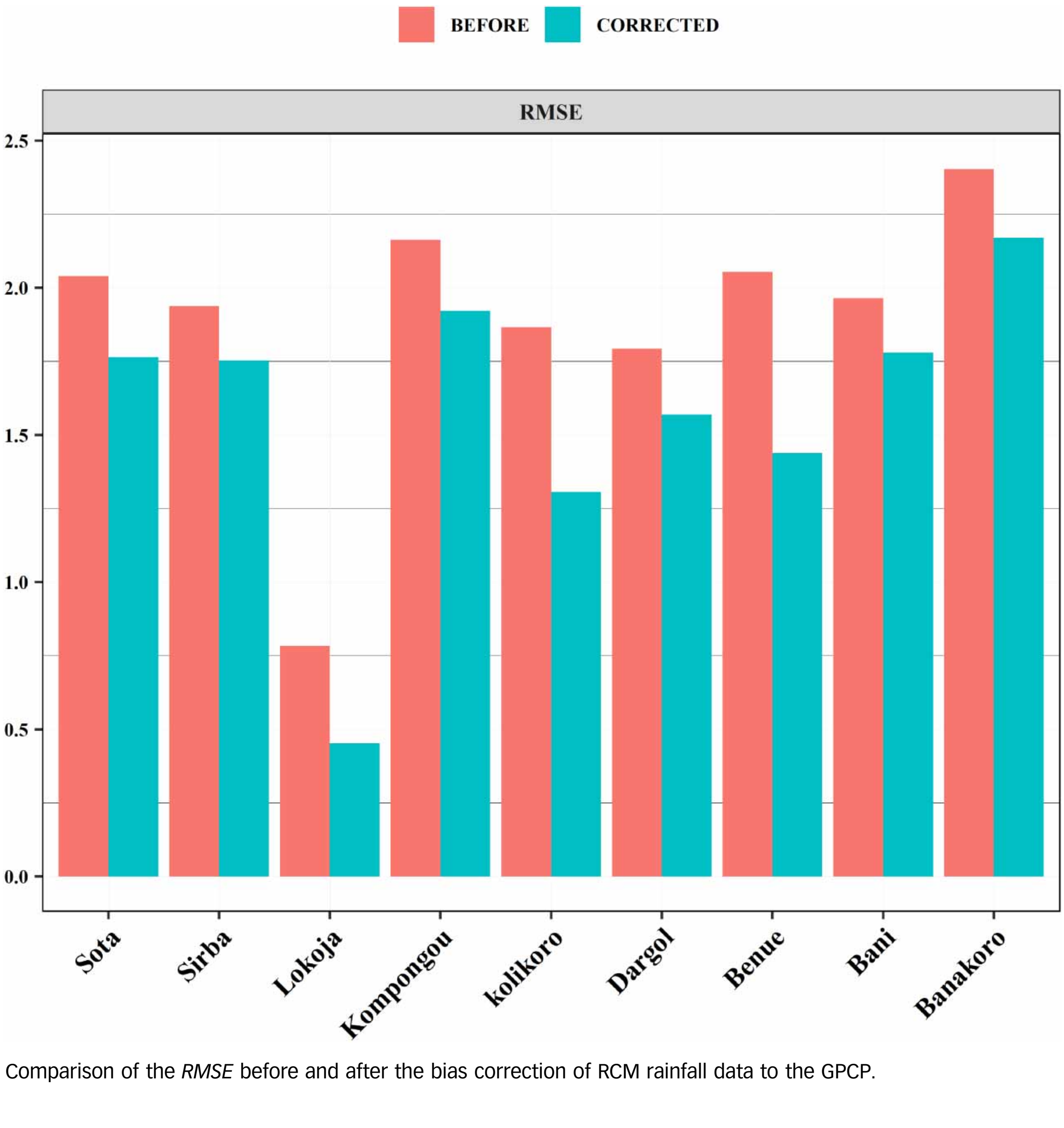

Figure 3 | Comparison of the *RMSE* before and after the bias correction of RCM rainfall data to the GPCP.

RESULTS

Bias adjustments and future climate trends

The efficiency coefficients used in comparing rainfall quantile–quantile mapping bias correction are presented in Figures 2 and 3. All the four coefficients (*NSE*, *KGE*, *RMSE* and R^2) were improved by bias correction in the nine catchments. Bias

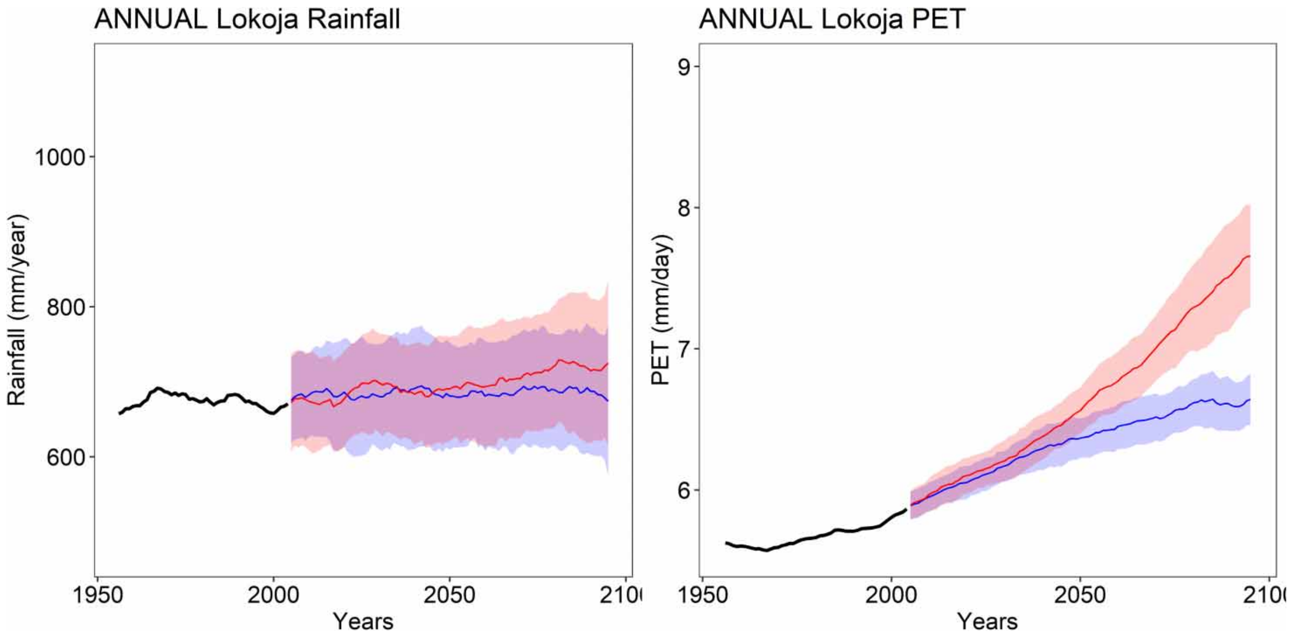

Figure 4 | CMIP5 historical and future trends of rainfall and PET under RCP4.5 (blue) and RCP8.5 (red) scenarios on the Niger Basin (Lokoja Station).

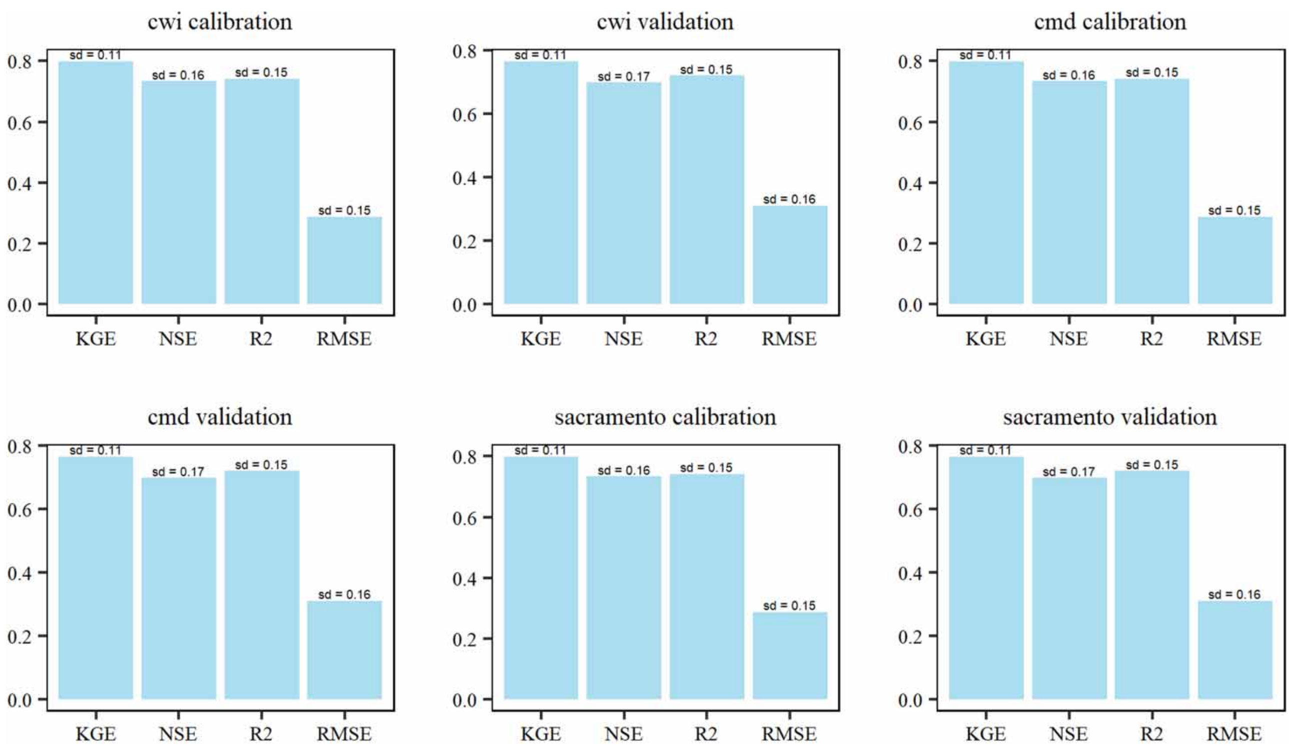

Figure 5 | Mean and standard deviation (SD) of efficiency coefficients from nine catchments during the hydrological model calibration and validation.

correction improved the *NSE* and the *KGE* more than the value of R^2. In Figure 3, the error derived from *RMSE* values was reduced after bias correction.

Figure 4 presents eight downscaled RCM/GCM annual ensemble median rainfall and PET trends with uncertainty bands on the Niger Basin at the Lokoja Station. The high emission scenario (RCP8.5) will lead to an increase in rainfall above the historical normal, while there will be no change in rainfall under the Business-as-Usual emission scenario (RCP4.5). PET will increase under the two emission scenarios.

Hydrological model evaluation

Figure 5 shows mean and standard deviation of *NSE*, *KGE*, *RMSE* and R^2 across the nine catchments during hydrological model calibration and validation. The three hydrological models performed very well across the nine catchments by having good efficiency coefficients.

Hydrological model uncertainty analysis

Table 3 presents the results of 10,000 model runs using different parameter sets. The three evaluated models show different *P* and *R* factors across the catchments. The CWI hydrological model has an acceptable *P*-factor (>0.5) at four catchments (Banakoro, Benue, Dargol and Koulikoro), while the remaining catchments had *P*-factors that are <0.5. The CMD hydrological model has a good *P*-factor at two catchments (Benue and Kompongou), while the Scaramento model witnessed a good *P*-factor on three catchments (Banakoro, Benue and Sota). An *R*-factor shows different responses for the three hydrological models across catchments. CWI models have a good *R*-factor at Benue and Dargol catchments, while CMD and Scaramento hydrological models displayed a poor *R*-factor on all catchments.

Future runoff trends and uncertainties

Figure 6 shows ensemble median (eight RC M/GCM combinations) future runoff trends on nine catchments of the Niger Basin from three hydrological models under the RCP4.5 and RCP8.5 scenarios. The three hydrological models have a similar runoff trend across the nine catchments in the RCP4.5 scenario (Figure 6). Under the RCP8.5 scenario, IHACRES-CWI and Sacramento gave an increasing runoff pattern toward the end of the century on the Niger Basin (Lokoja Station), while IHACRES-CMD gave a decreasing trend. At Banakoro, while IHACRES-CWI gave no trend, the remaining two hydrological models showed an increasing trend. At the Bani catchment, IHACRES-CWI progresses from no trend to a mild decrease toward the end of the century, and the remaining two models progress to about a 20% increase.

On the Benue catchment, all the three models unanimously agree on a decreasing runoff trend with varying margins. Similar model agreements were observed on the Dargol catchment where the models projected an increasing trend. At Koulikoro, IHACRES-CWI gave clear decreasing runoff of up to about 20%, while 10% increases were projected by IHACRES-CMD and Sacramento models. On the Mekrou (Kompongou) and Sota catchments, IHACRES-CWI gave a decreasing trend up to end of the century, while IHACRES-CMD and Sacramento gave a decreasing trend to 2080 where mild increases were observed.

Table 3 | *P* and *R* factors for evaluated catchments on the Niger Basin

	CWI				CMD				Sacramento			
	Calibration		Validation		Calibration		Validation		Calibration		Validation	
Catchments	P	R	P	R	P	R	P	R	P	R	P	R
Banakoro	0.64	0.70	0.61	0.60	**0.35**	0.39	**0.28**	0.34	0.61	0.48	0.61	0.44
Bani	**0.14**	0.18	**0.17**	0.18	**0.16**	0.27	**0.16**	0.28	**0.25**	0.16	**0.23**	0.17
Benue	0.55	**1.07**	0.53	**1.10**	0.54	0.60	0.54	0.61	0.64	0.52	0.65	0.53
Dargol	0.59	**4.78**	0.61	**4.77**	**0.32**	0.81	**0.32**	0.82	**0.41**	0.66	**0.48**	0.67
Kolikoro	0.51	0.44	0.52	0.44	**0.48**	0.45	**0.43**	0.45	**0.44**	0.28	**0.43**	0.28
Kompongou	**0.26**	0.98	**0.27**	0.96	0.63	0.51	0.68	0.49	0.26	0.60	0.28	0.51
Lokoja	**0.20**	0.26	**0.21**	0.26	**0.35**	0.47	**0.34**	0.46	**0.31**	0.66	**0.31**	0.61
Sota	**0.25**	0.47	**0.27**	0.48	**0.18**	0.59	**0.17**	0.53	0.58	0.42	0.55	0.39

Bold values indicates P and R Factors values that are below or above acceptable limits.

At Sirba, both IHACRES models moved from no trend to increasing trend at the end of the century, but the Sacramento model showed a high percentage decrease in runoff from beginning to the end of the 21st century.

Figure 7 presents uncertainties in runoff projections on multiple catchments. The three hydrological models show different far future (2061–2090) runoff deviations from the historical period (1951–2005) under the RCP4.5 and RCP8.5 scenarios. On the whole Niger Basin, IHACRES-CWI and Sacramento models gave increasing runoff trends under both RCP4.5 and RCP8.5 scenarios, while the IHACRES-CMD gave an opposite trend of decrease in runoff (Figure 6). On Banakoro and Bani catchments, IHACRES-CWI gave no trend, while IHACRES-CMD and Scaramento unanimously gave an increasing trend. At the River Benue, all models agree on a decreasing trend with different magnitudes. The IHACRES-CWI model gave a negative projection on Koulikoro, while other models show no trend in the RCP4.5 scenario and a mild increase in the RCP8.5 scenario. There were good model agreements on Sirba, Mekrou and Sota. Across all the nine catchments,

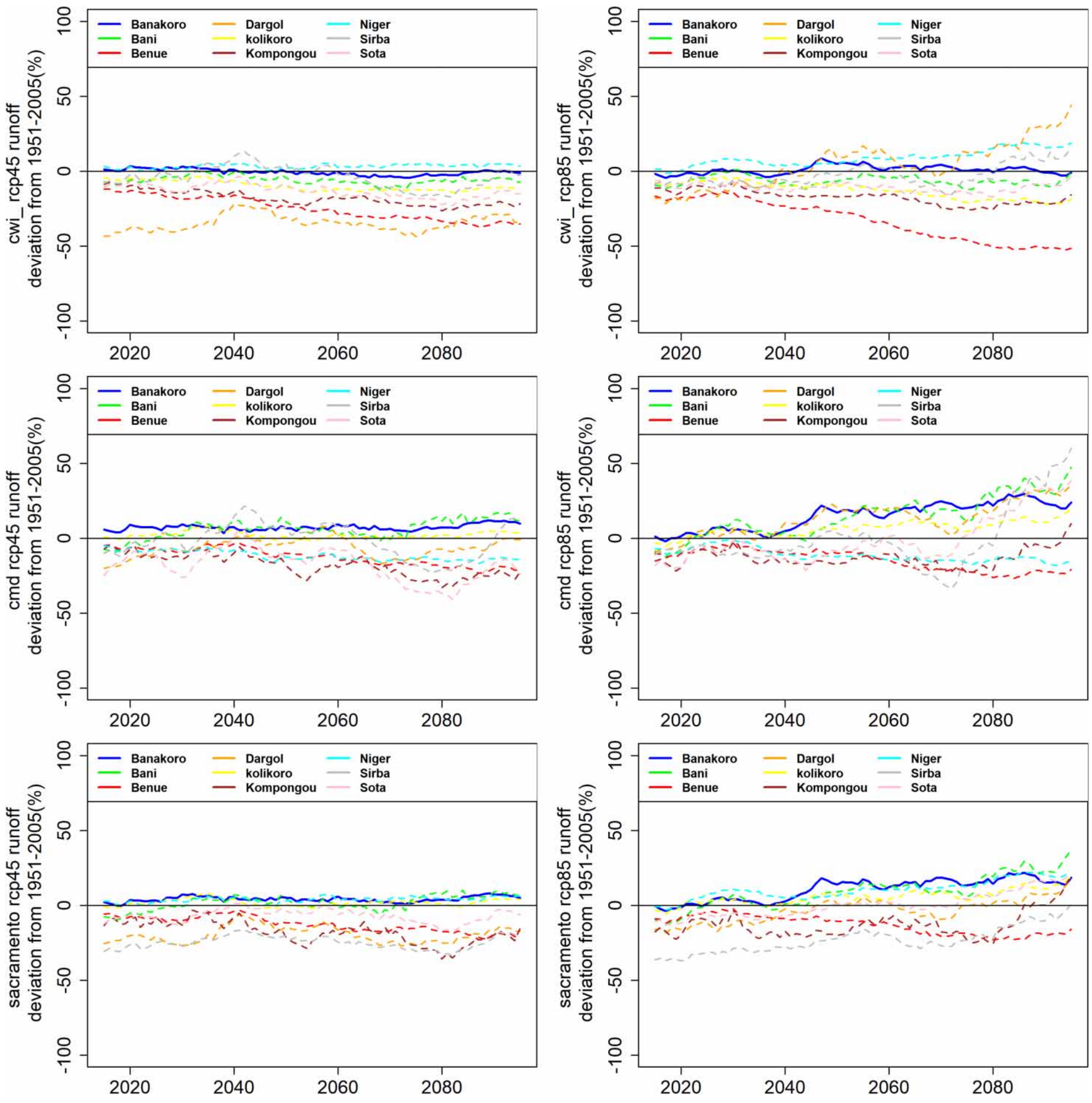

Figure 6 | Multihydrological models' future ensemble median runoff trends on the nine Niger Basin catchments.

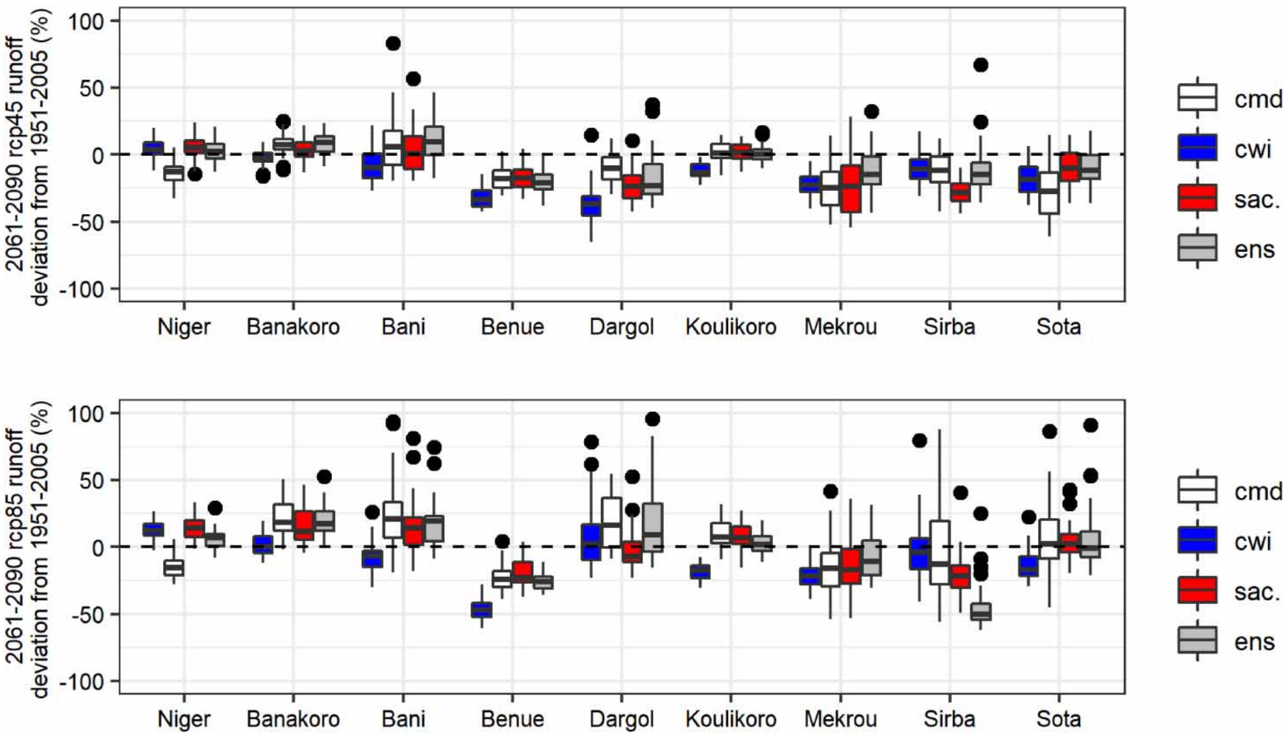

Figure 7 | Multihydrological models' 2061–2090 runoff trends on the nine Niger Basin catchments.

the ensemble of the three hydrological models gave an average prediction that filtered out the hydrological model uncertainties.

DISCUSSION

We improved the accuracy of the CORDEX CMIP5 RCM outputs using the quantile–quantile mapping bias correction. Precipitation data from climate models often have weak accuracy when compared to observations. Climate models overrate the 'drizzle' amount (Sun *et al.* 2006; Perkins *et al.* 2007) thereby generating biased data when compared to observations (Lenderink *et al.* 2007). CMIP5 models also have been characterized with such biases in the region (Biasutti 2013; Klutse *et al.* 2015). This is in line with previous studies done on similar subject in West Africa (MPo *et al.* 2016; Oyerinde *et al.* 2017a). MPo *et al.* (2016) found out that the RCM generally overestimates precipitation and quantile–quantile adjustments were able to correct the biases. Another set of West African authors used quantile mapping to improve discharge simulations from a rainfall–runoff model (Oyerinde *et al.* 2017a). They were also able to significantly decrease the biases adhered with RCM outputs (Oyerinde *et al.* 2017a).

Bias-corrected rainfall projections show that climate change will drive an increase in rainfall at the Niger Basin in line with previous studies. Wetter Sahel have been projected in the 21st century by CMIP5 models (Biasutti 2013; Badou *et al.* 2018). Comparison of climate variables between historical and future periods suggests that rainfall will increase in the region (Badou *et al.* 2018). Sylla *et al.* (2015b) have projected increases in the intensity of very wet rainfall events in the Sahel by the end of the 21st century.

The performances of three rainfall–runoff models were assessed across nine catchments with different scales. All the three models had excellent performance which shows that the models are adapted to the Niger Basin. Similar studies on the Niger Basin have found that the models are appropriate for the region (Oyerinde *et al.* 2016, 2017a). Disparities shown by the three hydrological models in projecting future runoff trends across the nine catchments are due to structural uncertainties and differences in the structures of the three hydrological models. Structural uncertainties come from simplified assumptions made in approximating the actual environmental system with mathematical functions (Renard *et al.* 2010; Cornelissen *et al.* 2013; Oyerinde & Diekkrüger 2017). We assessed the structural uncertainties with the GLUE and found out that the CWI hydrological model performed better than the CMD and Sacramento models with better *P*-factor and *R*-factor on a greater number of catchments. This is in line with previous studies where the CWI model was recommended to give a better prediction than the CMD on ephemeral catchments (Ye *et al.* 1997).

We used ensembles of climate and hydrological models to get a clearer representation and decrease the climate and hydrological modelling uncertainties. The hydrological model ensemble was reported to give a more accurate representation of catchment water balance (Thapa *et al.* 2017). It compensates for the effects of model uncertainties, and the ensemble result is a more reliable estimation of future runoff characteristics (Oyerinde & Diekkrüger 2017). Gyamfi *et al.* (2021) further corroborate our findings by recommending that for climate impact assessment and hydrologic modelling studies, multi-model ensembles should be used.

CONCLUSIONS

Climate and hydrological modelling have been ascribed with uncertainties. Most previous studies have focused on climate models as a major source of uncertainty in hydroclimatic prediction. In this study, we were able to showcase the influence of structural uncertainties of three hydrological models in hydroclimatic predictions on nine catchments. The CWI, CMD and Sacramento hydrological models were used for our study. The hydrological models were forced with temperature and rainfall data from eight dynamically downscaled GCMs from 1951 to 2100. The climate models' data were bias-corrected with quantile mapping to reduce uncertainties from climate models. We assessed structural uncertainties of the three hydrological models with GLUE using observed rainfall, temperature and river discharge data. Results of uncertainty assessments showed that different hydrological models responded differently to varying climate and hydrological conditions on nine different catchments. This greatly affected the projected trends by different models on nine Niger Basin catchments. We recommend the consideration of hydrological modelling uncertainties as a major factor in hydroclimatic modelling.

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AUTHOR CONTRIBUTIONS

Data collection, running of hydrological models, graphics and tables were done by G.T.O. and A.E.L.. The post-doctoral study is supervised by A.E.L. All authors contributed to the writing of the manuscript.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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