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REVIEW ARTICLE

Evaluating a finer resolution global hydrological model's simulation of discharge in four West-African river basins

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Abstract

Performance evaluation of hydrological models enables their consolidation, thereby allowing for the evaluation of water resource conservation approaches. This research aims to evaluate the performance of a finer resolution version (5 arcmin) of the PCRaster Global Water Balance (PCR-GLOBWB) for discharge estimation, in four basins in data-scarce West Africa; the Niger, Komadugu-Yobe, Jama'are, and Ogun. At the Ogun, discharge simulation was validated in a proxy basin, Ouémé, which is hydrologically comparable. The model performance was evaluated using Nash–Sutcliffe efficiency (NSE), coefficient of determination (r^2), Kling–Gupta efficiency (KGE), RMSE—observations standard deviation ratio (RSR), percent bias (PBIAS) and visual plots. PCR-GLOBWB was found to be suitable in all four basins but yielded better performance at three of the basins; the Niger, Jama'are, and Komadugu-Yobe (NSE, KGE, and r^2 above 0.7) compared to the Ogun basin where a proxy validation approach was followed. Results at the Ogun underlined the importance of measured data in hydrological studies. Still, model performance was satisfactory in the Ogun. PCR-GLOBWB performances across the four basins, in the area, validate its reliability as a tool applicable for water resources management strategies and further investigation of impacts of climate variations on river dynamics.

Keywords PCR-GLOBWB · Validation · Performance evaluation · Proxy · Hydrological models

Introduction

Nigeria's population is the eighth largest in the world, and the country is susceptible to multiple hazards, including floods and droughts. The rising sea level, recent flooding in the country's coastline, prolonged droughts, and growing desertification in the North, gulley-erosion devastating the South-East region of the country, contributing to deprivation among residents is evidence of this vulnerability (Ebele and Emodi 2016; Elisha et al. 2017). More so, climate change impacts are more catastrophic due to the susceptibility and inadequate response mechanisms (Femi Monday 2019). Water is an essential resource that has become a challenge in the country. Hence, to improve water resources, management strategies are crucial for the viable development of human society (Vilaysane et al. 2015).

Hydrological models (HMs) are valuable tools for studying hydrological processes (Jiang and Wang 2019; Khaki et al. 2019; Zhang et al. 2019). They are veritable tools for possible forecasting of changes in the hydrological system, thereby bolstering decisions in water resource management (Zhao et al. 2018). Various global hydrological models (GHMs) and regional (basin) hydrological models (RHMs) have been developed for impact studies. Examples of RHMs, amongst others, include; Soil and Water Assessment Tool, SWAT (Arnold et al. 1998); Hydrologiska Byrans Vattenavdelning, HBV (Lindström et al. 1997); Soil and Water Integrated Model, SWIM (Krysanova et al. 1998); the Hydrological Simulation Program-Fortran, HSPF (Bicknell et al. 1996); Systeme Hydrologique Europeen, SHE (Refsgaard et al. 2010) and LISFLOOD (van der Knijff

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et al. 2010). Examples of GHMs include; the H08 model (Hanasaki et al. 2008a, b); Water And Snow balance MODeling system, WASMOD-M; (Widén-Nilsson et al. 2007), Water–Global Analysis and Prognosis, WaterGAP, (Alcamo et al. 2003; Döll et al. 2003), the PCRaster GLOBal Water Balance model PCR-GLOBWB (Van Beek and Bierkens 2009; Sutanudjaja et al. 2018; Wada et al. 2014), and Global Water Availability Assessment method, GWAVA, (Haddeland et al. 2011). One main distinguishing feature between the RHMs and GHMs is that GHMs are most times not calibrated, while RHMs hydrological models are usually calibrated. In previous research on Nigerian rivers, major hydrological modelling efforts have been on a basin-scale with the use of RHMs. Some modelling efforts include; the application PITMAN rainfall-runoff model to evaluate variations to the water resources in southern Nigeria (Ayeni et al. 2015); calibration and validation of the SWAT model with remotely-sensed datasets of actual evapotranspiration (AET) for the Ogun catchment located southwest of Nigeria (Odusanya et al. 2019); the prediction of water yield and balance using the SWAT model at the Jebba lake in North Central Nigeria (Adeogun et al. 2014); employing an integrated SWAT-WEAP model to propose a water resource allocation system for simulation of hydrology and prediction of sustainable prognostic scenarios (Abdulmalik et al. 2020). Abdulmalik et al. (2019) employed the SWAT model to determine the climate change effects resulting from changing rainfall patterns in the Lower Benue river watershed, North-central, Nigeria. They proposed different adaptation scenarios for the present and potential distribution of water allocation in the region; Daramola et al. (2019) predicted hydrological processes, the sediment transport mechanism and sediment yield in Kaduna watershed northern Nigeria from 1990 to 2018 with the SWAT model.

Over the last few decades, research efforts have increasingly parameterized the interactions between terrestrial water systems, climate change, human activities, and environment management in GHMs (Wada et al. 2017). Furthermore, the water cycle is a universal occurrence, and understanding anthropogenic influence on the hydrological cycle and climate goes beyond the regional scale (Bierkens 2015). Various GHMs have been employed widely for both global and regional studies; for different purposes, including flood risk assessment (Towner et al. 2019), irrigation area planning (Kaune et al. 2020) drought event identification and assessment (Strohmeier et al. 2020; Trambauer et al. 2014), climate change impact studies (Hattermann et al. 2017; Wang et al. 2019), groundwater storage simulation (Koirala et al. 2019; Li et al. 2019). Few GHM studies have been carried in Nigeria. Todd and Agumagu (2015) used GHMs from the EU WATCH to project climate change effects on hydrology in the Niger Delta region. Extended research making use of global hydrological models are needed in more detail in this region as Sub-Sahara Africa is recognized as highly susceptible to impacts of climate change.

PCR-GLOBWB 2.0 (hereafter PCR-GLOBWB) is a hyper resolution GHM that has evolved from its previous version PCR-GLOBWB 1.0 (Van Beek et al. 2011) over more than 10 years. Its applications globally have indicated the model to be a valuable scientific tool for research and policymaking (van Beek et al. 2011; Veldkamp et al. 2018; Wada et al. 2014, 2017). PCR-GLOBWB has been used in several studies to evaluate water resource dynamics, groundwater issues, human impacts on the hydrological system and forecast (Bosmans et al. 2017; Lee et al. 2018; Li et al. 2019; Masaki et al. 2017; Strohmeier et al. 2020; Tangdamrongsub et al. 2017, 2018; Towner et al. 2019; Trambauer et al. 2014; Wanders et al. 2019; van der Wiel et al. 2019).

This study's objective is to assess the performance of the finer resolution (5 arcmin) GHM; PCR-GLOBWB in simulating the discharge of four river basins in different parts of Nigeria through validation of their observed monthly flow. The selected basins are found in different parts of the country, characterized by varying physio-graphic conditions and climates, thereby allowing for a detailed comparison of the model performance over different areas (Gupta et al. 2014). We are unaware of any modelling study that has employed PCR-GLOBWB or other GHMs to compare the simulation results achieved with a similar validation method at different river basin in the country.

Our interest in this study is to explore the future possibilities offered by the fast-growing advances in GHMs for applications in developing countries like Nigeria. By joining the global modelling community, researchers from Nigeria and other developing countries would benefit from the open-access code, consistency with new input datasets, developing model structure, and collaborative support through practice chains. The use of GHMs allows for examination in contrast with other such models, replicability, and possible applications in the majority of the country's ungauged basins. More so, this study is distinctive in that it validates a GHM over catchments that were previously modelled by regional hydrological models. In the method section, we first describe the study area, secondly the PCR-GLOBWB model, and after that, forcing data and the performance metrics for validating the results.

Study area

We selected four basins, with a minimum of 3-year consecutive hydrological records, across 1958–2015 (the temporal span of simulated discharge data). The rivers are from the available set of West African basins of the Global Runoff Data Centre (GRDC) (Bierkens 2015). The selected rivers (Niger, Komadugu-Yobe, Jama'are, and Ogun) have their gauges located and distributed over Nigeria, in the Southwest, North-central, and the North-east (Fig. 1). In addition, the gauges' location covers the extensive tropical savannah climate, which dominates the major part of Nigeria (western to central) and the Arid climate located towards the North (Beck et al. 2018). This range in climatic characteristics is sufficient to ascertain the PCR-GLOBWB model's performance in simulating responses to hydrology. A fifth river basin, the Ouémé, was selected as a proxy to validate the hydrological model for the Ogun, a poorly gauged catchment in the southwestern part of Nigeria (KlemeŠ 1986). Table 1 gives brief information about the selected basins.

The Niger catchment is the longest river in West-Africa. The Guinean highland is the river source, from which it flows in a northern arc course through the dry Sahelian zone, and the re-enters the wetter tropical region north of the Gulf of Guinea. The Niger catchment extends over the territory of ten west African countries, covering approximately 2,270,000 km^2. The wetter climate of upstream parts of the basin and the Benue tributary influences the river regime at the selected gauge station (Aich et al. 2014). In our study, the chosen gauge is at the Lokoja gauge station.

The Komadugu-Yobe basin is approximately 62,150 km^2 in size and lies between latitudes 12.12° and 12.86° N and longitudes 11.2° and 11.04° E. Two rivers drain the Yobe

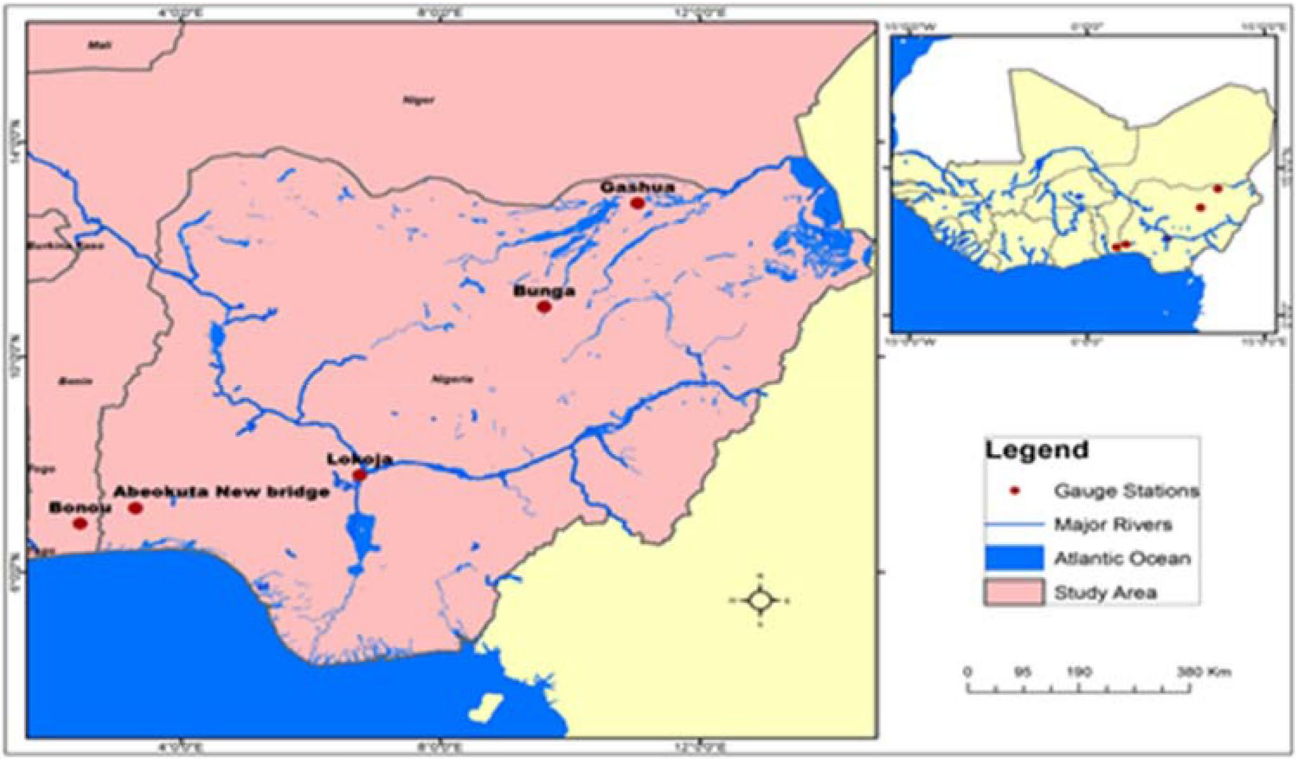

Fig. 1 Study area map

Table 1 Overview of selected GRDC stations and basins

	Niger	Ogun	Jama'are	Kamodugu-Yobe	Ouémé
Area (km^2)	2,270,000	23,700	7977	62,150	46,990
Gauging station	Lokoja	Abeokuta	Bunga	Gashua	Bonou
GRDC number	1,834,101	–	1,837,255	1,837,107	1,733,600
Annual precipitation (1971–2000) (mm)	1403	1230	909	414	
Mean temperature (1971–2000) (°C)	26.7	27.1	25.7	27.9	
Koppen-Geiger climate classification	Tropical Savannah (Aw)	Tropical Savannah (Aw)	Tropical Savannah (Aw)	Arid Steppe hot (Bsh)	Tropical Savannah (Aw)

river basin; Hadejia and Jama'are (Adeyeri et al. 2019). The study site on this river is at the Gashua gauging station, located in North-Eastern Nigeria. The Arid Steppe hot (Bsh), according to the Koppen Climate Classification system (Beck et al. 2018), characterizes the climate in this region. The Jama'are river is one of the tributaries of the Komadugu Yobe river basin. It has a catchment size of 7977 km^2. The climate in this region is characterized as Tropical Savannah (Aw) (Beck et al. 2018). The Jama'are river is located in North-Eastern Nigeria. The rainy season in this area is short, lasting only a few months, while the rest of the year is dry and hot. Ouémé catchment is located in the Republic of Benin; it is bordered to the east by Nigeria. The Bonou outlet is the selected gauging station for this study. It has a catchment size of about 46,990 km^2 with 8% of this lying in Nigeria. This catchment was selected for this study due to its similar spatial characteristics to the Ogun river basin.

Methods

Model description: PCR-GLOBWB

Figure 2 shows a schematic sketch of the PCR-GLOBWB used in this study to simulate discharge. Although the GHM simulates river discharge globally, we focus, specifically, on the four West African basins. PCR-GLOBWB is a grid-based, leaky bucket type global hydrology and water resources model that integrates human activities into

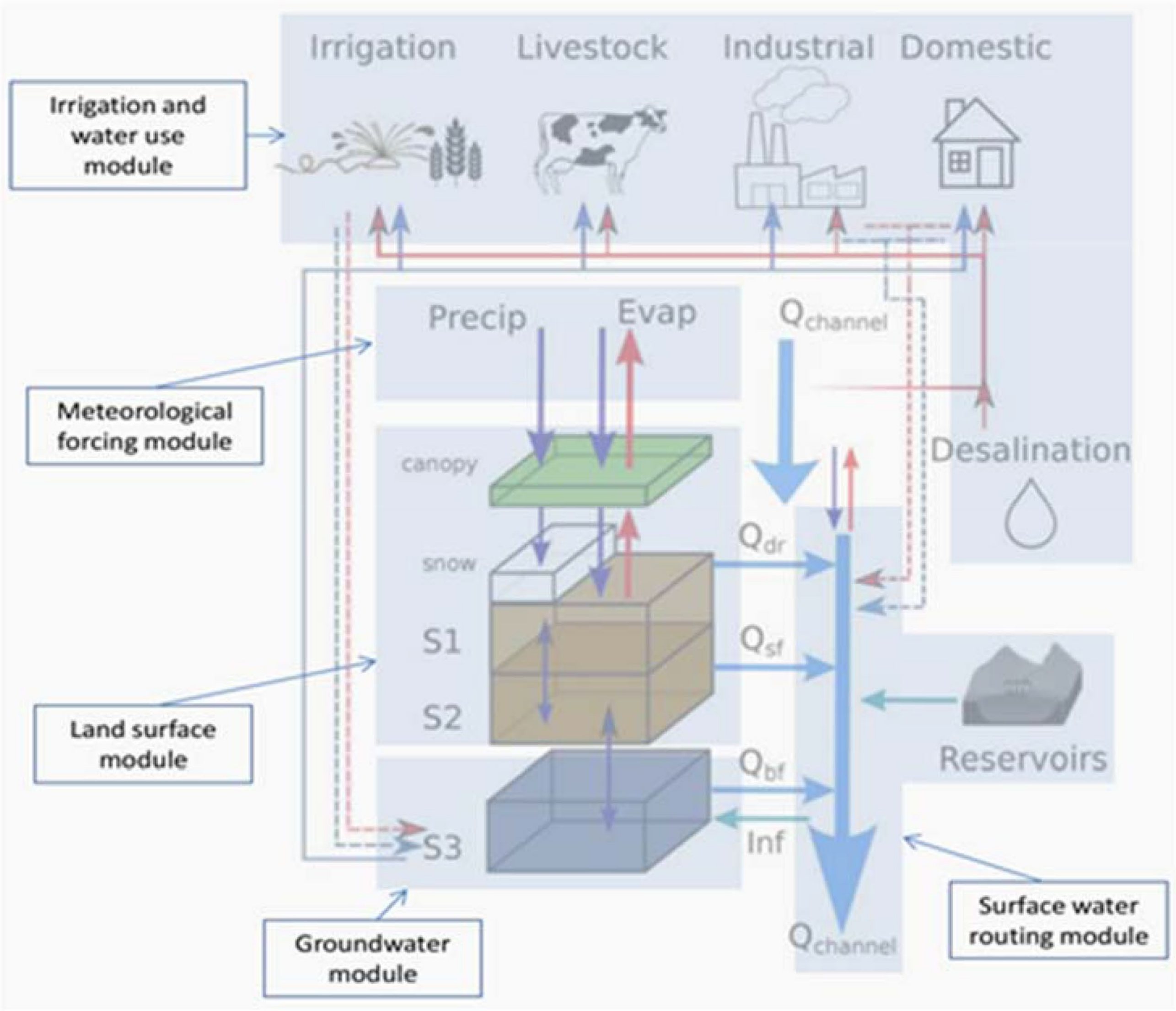

Fig. 2 Overview of PCR-GLOBWB hydrological model [Adapted from Sutanudjaja et al. (2018)]

hydrology. The model is employed at a spatial resolution of 5 arcmin 10×10 km^2, at a daily time step. For every grid cell and time step, PCR-GLOBWB computes the components of water balance. These components include water storage in two vertical upper soil layers S_1 and S_2; one underlying groundwater reservoir S_3. Furthermore, the model simulates water exchange among the soil (percolation, infiltration, capillary rise), between the atmosphere and topsoil layer (precipitation, evaporation, transpiration, and snowmelt) and in between the soil and the active groundwater layer are also computed. The model also calculates canopy interception and snow storage. Subgrid variability is accounted for in the model by considering different land cover types, soil types, and elevation.

Total runoff from each cell is made up of excess surface runoff (Q_{dr}), second soil reservoir (interflow) runoff (Q_{sf}), and groundwater (baseflow) runoff (Q_{bf}). Specific runoff from each cell is accumulated and gathered from all grid cells and routed along the drainage network to obtain the river discharge ($Q_{channel}$). The routing method is the travel-time solution (Karssenberg et al. 2007). The model simulates at each time step (i) water demands from irrigation, households, livestock, and industry, (ii) water withdrawals from surface water, desalinization, and groundwater resources (Sutanudjaja et al. 2018; Wada et al. 2014, 2016).

Selection of river basins and gauging station

We considered the following criteria when selecting the river basins for this study:

1) A continuous discharge record length of at least 3 years (≥ 3 years) during the simulation period of 1958–2015. Kuchment and Gelfan (2009) showed in a detailed work that 3–4 years of streamflow observation data are sufficient to test the robustness of hydrological models. Vrugt et al. (2006) presented that 2–3 years of observed discharge data are enough for stable parameter assessment for the SAC-SMA model.
2) Proximity to the catchment area of interest (proxy basin approach: Daggupati et al. 2015; KlemeŠ 1986). Following Hrachowitz et al. (2013), when considering predictions in ungauged basins (PUB), streamflow observations from sparsely-gauged regions can provide useful information on hydrological dynamics and projections in adjacent ungauged catchments. Dinicola (1992) employed the proxy basin approach to validate the HSPF rainfall-runoff model over Puget Sound in Washington, and Parajuli et al. (2009) also calibrated and validated the AnnAGNPS and SWAT models in south-central Kansas using this approach. The two basins used for this approach in this study have similar physiography (Table 2) characteristics.
3) River basins are located in different regions of the country to ensure local representation of the area.

Data

Forcing datasets

Precipitation, temperature, and reference potential evapotranspiration are the meteorological data needed to drive the PCR-GLOBWB model. The datasets of CRU TS 3.2 (Harris et al. 2014) were used. CRU TS 3.2 datasets were prepared by interpolating observed past time-series of stations to a global grid resolution of 0.5°. Because of the daily resolution of PCR-GLOBWB, the CRU TS 3.2 monthly datasets were downscaled to daily resolution with ERA 40 (1958–1978, Uppala et al. 2005) and ERA-Interim (1979–2015, Dee et al. 2011). ERA 40 and ERA-I had been spatially downscaled from their initial spatial resolutions of 1.2° and 0.7°–0.5° in the resampling scheme of the European Centre for Medium-Range Weather Forecasts (ECMWF). This downscaling was done by first allotting the larger values ERA40 and ERA-I to the middle of the cells and then interpolating spatially to the higher resolution of 0.5°. Downscaling of precipitation was done, first, by temporarily assigning a threshold of 0.1 mm day^{-1} to the daily time series of ERA, thereby estimating the number of days with rain and eliminating the drizzle effect. The rainfall quantity below this threshold was proportionally allocated to the rainy days. Thereafter, CRU monthly precipitation was reproduced by multiplicative scaling of the daily rainfall totals. In addition, monthly reference potential evaporation, estimated from the CRU dataset with

Table 2 Ogun river basin and Proxy Ouémé river basin characteristics

Description	Ogun	Ouémé
Area, km^2	23,700	46,920
Geology	Precambrian basement	Precambrian basement
Dominant soil type	Ferric luvisols	Ferric luvisols
Mean annual rainfall range, mm/year	1260	1100
Mean temperature, °C	27 °C	27.7 °C
Koppen-Geiger classification	Tropical climate (Aw)	Tropical climate (Aw)

Penman–Monteith, was scaled using multiplicative scaling and downscaled to daily data using a daily temperature-based ET product, derived from daily ERA temperatures. An additive scaling method was used for air temperature (see Sutanudjaja et al. 2018 and for more details). In this study, we followed the guideline of standard parameterization given in Sutanudjaja et al. (2018). We used globally available datasets, including vegetation, geological information, and soil properties for model parameterization, and simulate the selected river basins discharge at daily time steps over the 1958–2015 simulation period. Monthly averages were used to report the output from the model.

Discharge data

Monthly observed discharge data were obtained from the Global Runoff Data Centre (GRDC) (Bierkens 2015).

Validation of PCR-GLOBWB model

The performance of the PCR-GLOBWB model in estimating the discharge at the river basins was evaluated by examining the simulated results with observed data at each river's gauging stations. Following López et al. (2017), Kouchi et al. (2017), and Moriasi et al. (2007, 2015), seven performance evaluation metrics were used to assess the monthly discharge simulated by PCR-GLOBWB. Five of these criteria were quantitative measures that evaluated the agreement between simulated and observed values. These statistics are the percent bias (PBIAS), Nash–Sutcliffe efficiency criteria (NSE), the ratio of RMSE-observations standard deviation (RSR), the coefficient of determination (r^2) and Kling–Gupta efficiency (KGE). The remaining two criteria are visual plots: flow duration curves (FDC) and hydrographs.

A brief overview of each evaluation metric is given below;

The Nash–Sutcliffe efficiency criteria (Nash and Sutcliffe 1970): it is a normalized metric used to determine how well the plot of simulated versus observed value fits the 1:1 line. It is given as:

$$\mathrm{NSE} = 1 - \left[\frac{\sum_{i=1}^{n} \left(O - P_i \right)^2}{\sum_{i=1}^{n} \left(O_i - \overline{O} \right)^2} \right], \tag{1}$$

where P_i and O_i represent the simulated and observed variables at a monthly time step, $\overline{O}$ is the mean of observed data and n is the total number of observations. NSE is widely applied for the validation of the hydrological model for streamflow. NSE varies from $-\infty$ to 1. NSE = 1 implies a perfect match of simulated and observed discharge, NSE = 0 implies that simulated values perform accurately as the mean of observed and NSE < 0 suggest that simulated values perform worse than the observation mean.

The percent bias (PBIAS) an error-index, measures the mean tendency of the simulated variables to be higher or smaller than the observed variables (Gupta et al. 1999):

$$\mathrm{PBIAS} = \frac{\sum_{i=1}^{n} O_i - P_i}{\sum_{i=1}^{n} O_i} \times 100, \tag{2}$$

where O_i and P_i represent the monthly mean observed and simulated variables, n is the total number of months in the discharge series. PBIAS of zero is the optimal value. Positive values indicate underestimating model bias; negative values suggest overestimating model bias and lower values, suggesting correct model simulations.

The RSR is the ratio of RMSE-observations standard deviation (Moriasi et al. 2007). This statistic standardizes RMSE using the observation's standard deviation. The following equation calculates it:

$$\mathrm{RSR} = \frac{\mathrm{RMSE}}{\mathrm{STDEV_{obs}}} \frac{\sqrt{\sum_{i=1}^{n} \left(O_i - P_i \right)^2}}{\sqrt{\sum_{i=1}^{n} \left(O_i - \overline{P} \right)^2}}. \tag{3}$$

RSR values vary from zero (the best value) to large positive values, and the lower the RSR, the better the model simulation performance.

The coefficient of determination (r^2) shows the degree of a linear relationship between observed and simulated data. The r^2 value close to one signifies a good performance. Nonetheless, it is sensitive to very high values. The following equation calculates it:

$$r^2 = \left[\frac{\sum_{i=1}^{n} \left(O_i - \overline{O} \right) \left(P_i - \overline{P} \right)}{\sqrt{\sum_{i=1}^{n} O_i - \overline{O}} \sqrt{\sum_{i=1}^{n} P_i - \overline{P}}} \right]^2. \tag{4}$$

Kling–Gupta efficiency: Gupta et al. (2009) suggested an alternative performance evaluation metric to NSE to avoid problems that could arise from using the NSE criterion. KGE is given by:

$$\mathrm{KGE} = 1 - \sqrt{(r-1)^2 + (\alpha - 1) + (\beta - 1)^2}, \tag{5}$$

where α is the ratio between the variance of the simulated variable and the variance of the observed variable, r is Pearson's correlation coefficient, and β is the ratio between the mean of the simulated variable and the mean of the observed variable, i.e. β, represents the bias. KGE varies between $-\infty$ and 1, and the ideal value is 1. KGE measures bias, variability, and correlation simultaneously.

The performance ratings for quantitative statistics based on Kouchi et al. (2017) are presented in Table 3.

Results and discussion

Evaluation results of PCR-GLOBWB

Validation of the PCR-GLOBWB model against observed GRDC discharge data was done at the gauging stations of each of the watershed. Figure 3a–d show hydrograph and Fig. 4a–d show the FDC plots, comparing observed and simulated discharge for validation periods (Table 4).

The results for all evaluation measures; of KGE, RSR, NSE, r^2, and PBIAS for PCR-GLOBWB are provided in Table 5. With these values, the PCR-GLOBWB performance for the validation periods of each station, can be rated as ranging from satisfactory to very good, based on the evaluation statistics ratings provided in Table 4.

On the Niger river basin, the PCR-GLOBWB performance provided a "very good" NSE, RSR, and r^2 values, and a "satisfactory" KGE and PBIAS values for the validation period, respectively (Fig. 3a; Table 5). These ratings indicate the PCR-GLOBWB ability to capture both the monthly variation and pattern of discharge. The flow pattern of monthly observed hydrograph was reproduced (Fig. 4a), but at a moderate overestimation, which is also reflected in the PBIAS statistic value (−24%).

Looking into the hydrograph and FDC for the Kamodugu-Yobe (Figs. 3b, 4b), the model reproduces well the pattern of monthly discharge. PCR-GLOBWB performance measures indicate an excellent agreement between the simulated and observed discharge data, also deduced from the high r^2, PBIAS, and NSE values (Table 5).

The PCRGLOBWB simulated series on the Jama'are river also presents (Fig. 3c), a relatively good agreement with the observed flows, which indicates the model's robustness for predicting flow (Table 5). PCR-GLOBWB correctly simulated the range of magnitude of flows, as shown in Fig. 4c, a close agreement for the high flows and base-flow

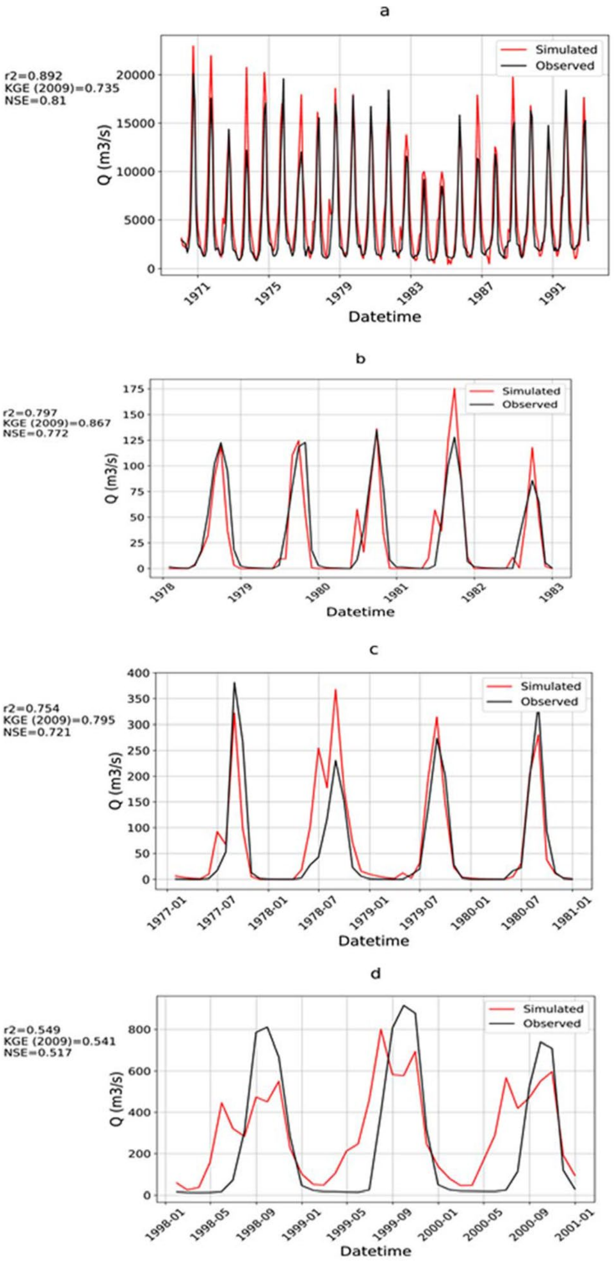

Fig. 3 Hydrographs for the different validation period of the four basins **a** Niger, **b** Yobe, **c** Jamaare, **d** Ogun rivers

Table 3 General performance ratings for a monthly time step (Kouchi et al. 2017)

Performance ratings	r^2	NSE	RSR	PBIAS	KGE
Very good	$0.75 < r^2 \leq 1$	$0.75 < \mathrm{NSE} \leq$	$0 \leq \mathrm{RSR} \leq 0.5$	$\mathrm{PBIAS} < \pm 10$	$0.9 \leq \mathrm{KGE} \leq 1$
Good	$0.65 < r^2 \leq 0.75$	$0.65 < \mathrm{NSE} \leq 0.75$	$0.5 < \mathrm{RSR} \leq 0.6$	$\pm 10 \leq \mathrm{PBIAS} < \pm 15$	$0.75 \leq \mathrm{KGE} < 0.9$
Satisfactory	$0.5 < r^2 \leq 0.65$	$0.5 < \mathrm{NSE} \leq 0.65$	$0.6 < \mathrm{RSR} \leq 0.7$	$\pm 15 \leq \mathrm{PBIAS} < \pm 25$	$0.5 \leq \mathrm{KGE} < 0.75$
Unsatisfactory	$r^2 \leq 0.5$	$\mathrm{NSE} \leq 0.5$	$\mathrm{RSR} > 0.7$	$\mathrm{PBIAS} \geq \pm 25$	$\mathrm{KGE} < 0.5$

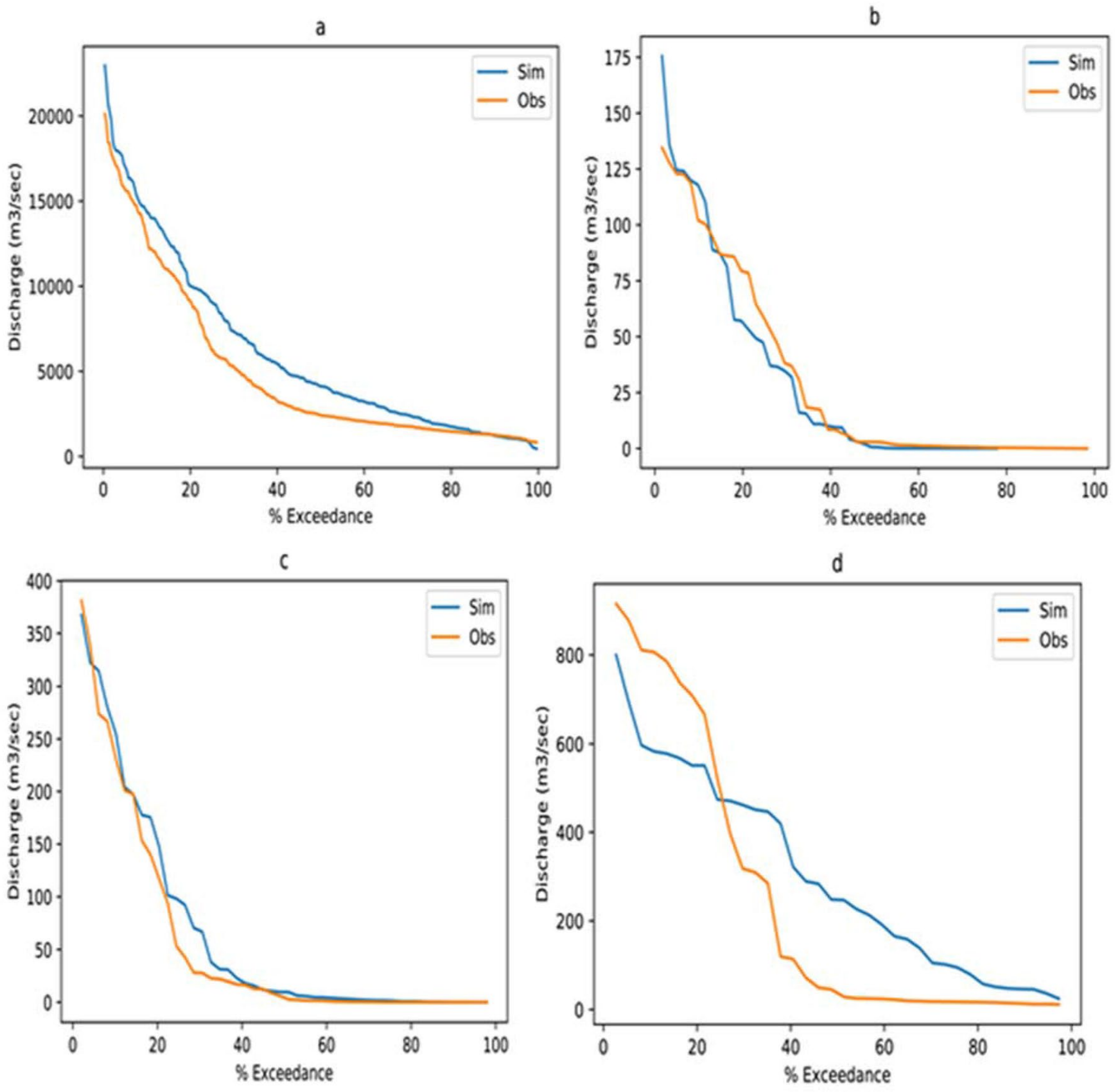

Fig. 4 Flow duration curves for the different validation period of the four basins **a** Niger, **b** Yobe, **c** Jamaare, **d** Ogun rivers

Table 4 Validation period for each basin

River	Gauge station	Validation period
Niger	Lokoja	1998–2001
Kamodugu-Yobe	Gashua	1970–1992
Jama'are	Bunga	1977–1981
Ogun	Abeokuta	1978–1983

components is seen in this figure. The high NSE (above 0.7) and r^2 and moderately low RSR (below 0.5) indicate good correlation and consistency between simulated and measured discharge.

PCR-GLOBWB shows a moderate overestimation of discharge during the validation periods of Niger and Jama'are (PBIAS value in Table 5). Still, uncertainty in the observed

Table 5 The results of PCRGLOB-WB average monthly discharge model output, for all the stations, considered

Rivers	Gauge station	RSR	KGE	NSE	PBIAS %	r^2
Niger	Lokoja	0.43	0.73	0.81	−24	0.89
Kamodugu-Yobe	Gashua	0.47	0.86	0.77	6.72	0.79
Jama'are	Bunga	0.5	0.79	0.72	−15	0.75
Ogun	Abeokuta	0.68	0.54	0.51	−21	0.54

datasets profoundly affects PBIAS estimates (Moriasi et al. 2007). Precipitation in the CRU TS 3.2 forcing datasets across Africa is of limited quality because of sparse CRU stations and limited data available at the time of re-analysis of ERA-40 (van Beek et al. 2011). The datasets are, therefore, inclined to uncertainties due to spatial and temporal differences in station density (van Beek et al. 2011). This uncertainty explains the overestimation of discharge simulations at the stations. Nevertheless, CRU is a preferred dataset as it matches other past climate datasets well (van Beek et al. 2011). Nonetheless, the magnitude of PBIAS at the Niger and Jamaare corresponds to a satisfactory performance rating (Table 3).

For the Niger river basin, the PCRGLOB-WB simulation performance is comparable to the results of Poméon et al. (2018), which modelled the catchment with the SWAT model. The study reported calibration values of $r^2 = 0.87$ and KGE = 0.60 and validation values $r^2 = 0.88$ and KGE = 0.66. Although the SWAT model was calibrated for the Niger basin in that study, PCR-GLOBWB model performance ($r^2 = 0.89$ and KGE = 0.73) is much better. Xie et al. (2010) also calibrated the SWAT model for the Niger river and achieved an NSE value of 0.54, where the PCR-GLOBWB had a value of 0.81. Oyerinde and Diekkrüger (2017) assessed how well three runoff models (IHACRES-CMD, GR4J, Sacramento) estimated the streamflow in the Upper Niger basin. Their study reported, the IHACRES-CMD model had the highest NSE values of 0.92 (calibration) and 0.86 (validation). The NSE (0.81) results of the PCR-GLOBWB is also comparable with this study. Compared with a previous study on the Jama'are river basin, the PCR-GLOBWB simulation is a little better (NSE = 0.72 and $r^2 = 0.75$) than the performances reported by Ejieji et al. (2016) for calibration (NSE = 0.51 and $r^2 = 0.57$) and validation (NSE = 0.65 and $r^2 = 0.71$) of the SWAT model for this river basin.

Figures 3d and 4d show the FDC and hydrograph plots of the simulated discharge for the Ogun river against the proxy river observation of the Ouémé basin. At this basin, the performance of the model was lower compared with other stations' results. The flow pattern of monthly observed hydrograph was reproduced, but significant variations were observed between the simulated and observed peak and base flows. Underestimation of peak flows, and overestimation of base flows are seen from the FDC (Fig. 4d). The shape of the model FDC simulation curve is less steep than the observation curve; the variability of the observed FDC was not well captured. The model performance at this basin is attributed to the lack of observed data. There are no GRDC observation data for the Ogun river or any river in the southwestern part of Nigeria. The model simulation was, therefore, validated with the observation from the Ouémé river (Proxy river). The results at this station emphasize the importance of using measured observation data within and around a study area of interest. However, the (NSE = 0.51, RSR = 0.68, $r^2 = 0.54$, KGE = 0.54, PBIAS = −21%) performances all indicate a "satisfactory" agreement between the observed and the estimated discharge for this basin. More so, our results are comparable to those obtained by (Odusanya et al. 2018), which used the SWAT model to validate simulated streamflow from the Ogun river against observed streamflow from the Oueme river with the validation results of ($r^2 = 0.6$, NSE = 0.56, PBIAS = 20.6%).

In general, the simulated discharge from the model at the four stations showed good agreements with the observed. However, PBIAS magnitude indicates the tendency of PCR-GLOBWB to overestimate the observed data, attributed to the uncertainty in forcing datasets, as explained above. Though these performances could become better with calibration, this may cover up the uncertainty in forcing datasets (Biemans et al. 2009). The following localization will disturb the dynamics over catchments not gauged and hinder the physical basis of the model. Lopez et al. (2017) calibrated the PCRGLOB-WB using satellite-based products and concluded that the impacts of precipitation on streamflow estimates were more critical than model parameter calibration. Overall, based on the KGE, NSE, r^2, RSR, and PBIAS values at each station, the PCR-GLOBWB was able to simulate the monthly discharge at this river realistically well during the entire period considered. According to these results, the model can reproduce the monthly discharge with sufficient accuracy without calibration.

Conclusion

This study evaluated the performance of the hyper resolution GHM PCR-GLOBWB in stimulating the discharge of four river basins, namely: the Niger, the Kamodugu-Yobe, the Jama'are, and the Ogun. The gauges of the selected river basins are distributed over Nigeria, in the southwest, North-central, and the Northeast and cover the extensive tropical savannah climate dominating the major part of the country and the Arid climate located towards the North. Precipitation and air temperature are obtained directly from CRU datasets, while the reference potential evapotranspiration is obtained following the guidelines provided by the FAO of Allen et al. (1998). PCR-GLOBWB was validated at different periods for each basin, depending on the availability of at least 3 years of continuous observation data. At one of the basins, the Ogun being a poorly gauged river, the model simulations were validated in a proxy Oueme river basin.

According to performance evaluation statistics and hydrographical fit, PCR-GLOBWB performed well at three basins; Niger, Kamodugu-Yobe, and Jama'are. The PCR-GLOBWB was capable of simulating the monthly discharge, with adequate accuracy, ranging from good to very good NSE and

RSR (NSE, from 0.71 to 0.81 and RSR from 0.52 to 0.43), very good r^2 (from 0.75 to 0.89), satisfactory to very good PBIAS (from − 24 to 6.72%), and good KGE (0.73 to 0.86). However, it is noted that the model under-performed at the Ogun compared with the rest of the stations (NSE = 0.51, KGE = 0.54, r^2 = 0.54, PBIAS = − 21%, RSR = 0.68). There were no reliable-measured discharge data for this basin, and the proxy validation approach was used. The results provided at this basin underline the importance of the availability of stations measured discharge data, as this greatly affects the applicability of a given model. However, it is noted that the PCR-GLOBWB had a "satisfactory" model performance for all statistics at this basin. Overall, the PCR-GLOBWB is suitable to support water resources management and planning in data-scarce areas such as Nigeria. Especially, where measured data for catchment/river basin scale, hydrological models are not always available or reliable to calibrate and validate such models.

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Data availability the dataset's availability is as acknowledged in the references.

Code availability The version of PCR-GLOBW used in this study is available as open-source codes on https://github.com/UU-Hydro/PCR-GLOBWB_model.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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