Scientific African 13 (2021) e00921

Contents lists available at ScienceDirect

Scientific African

journal homepage: www.elsevier.com/locate/sciaf

Assessing the skills of inter-sectoral impact model intercomparison project climate models for precipitation simulation in the Gongola Basin of Nigeria

AbdulRazaq Salaudeen[a,b,*], Abubakar Ismail[a], Babatunde K. Adeogun[a], Morufu A. Ajibike[a], Shamsuddin Shahid[c]

[a] Department of Water Resources and Environmental Engineering, Ahmadu Bello University Zaria, Nigeria
[b] Department of Civil Engineering, Abubakar Tafawa Balewa University, Bauchi, Nigeria
[c] School of Civil Engineering, Faculty of Engineering, Universiti Teknologi Malaysia (UTM), Johor Bahru, Malaysia

ARTICLE INFO

Article history:
Received 31 March 2021
Revised 21 July 2021
Accepted 29 July 2021

Editor: Dr. B. Gyampoh

Keywords:
Model performance assessment
Climatology
ISI-MIP
GCM
Gongola basin
GPCC
Precipitation

ABSTRACT

The study quantitatively assesses the ability of five Global Circulation Models (GCMs) in the fast track of Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) to reproduce the observed precipitation climatology over the Gongola river basin of Nigeria for the period 1982–2004. The recent occurrences of recurrent flooding episodes in the basin is alarming. Hence, the models' present-day precipitation is evaluated relative to Global Precipitation Climatology Centre (GPCC) observational datasets based on spatial analysis, statistical measures and climate indices at annual, monthly and daily cycles to identify the most appropriate GCM for impact model in the basin. The results show that climate models replicate the annual precipitation pattern well, both spatially and in magnitude with varying margins. Moreover, the GCMs captured the orographic pattern in the Jos plateau and the general decreasing precipitation trend towards the basin's northeast. amongst the GCMs, IPSL-CM5A-LR better captured the rainy season in the basin extents from April to October and May to October respectively over the Jos plateau and other regions, with maximum rainfall occurring in August, exhibiting a unimodal pattern. The HADGEM2-ES however, better represented the most occurring rainfall intensity in the basin (5 to 50 mm hr^{-1}) in most regions. The degree of pattern correspondence was found highest for IPSL-CM5A-LR with a correlation coefficient of 0.73. Only HADGEM2-ES was able to capture the spatial variability of maximum consecutive dry days over the study domain, increasing from 150 days around the Jos plateau to 200 days over Uba plain. In any case, the HADGEM2-ES appeared to be the most promising model for simulating the extreme conditions over the Gongola basin and can therefore be selected for the application of hydrological impact model for adaption strategy.

* Corresponding author.
E-mail address: asalaudeen@atbu.edu.ng (A. Salaudeen).

https://doi.org/10.1016/j.sciaf.2021.e00921

Introduction

The role of precipitation on Earth's hydrological cycle is vital, hence well documented in the literature. It constitutes one of the most commonly used climate variables in hydrological impact assessments [7,12]. In the timeline of African Union's Agenda 2063, the need to develop strategies to mitigate risks and threats arising from both natural and human disturbances were emphatically stressed, particularly the climate change impacts. By the way, improved understanding on the current and future hydrological conditions of the region can help realise the set goals. Climate scientists rely mainly on GCM outputs to estimate present/future precipitation globally [2,9]. However, the GCMs are well known for their coarse spatial scales with attendant uncertainties [28], which must be downscaled to suit local scale hydrological impact studies. Dynamical and statistical downscaling techniques are used to transfer coarse GCM simulations to finer resolution for impact assessments [14,16].

Statistical downscaling has some limitations [10], which include; temporal stationarity of the models' correction functions for future periods, alteration of the physical consistency of climate models and, notably inability of the downscaling methods to account for uncertainties in the reference observation datasets [23]. Therefore, dynamical downscaling is often suggested for reliable downscaling of climate projections. However, the dynamical downscaling approach is known for its high computational cost. Moreover, the RCMs take inputs from the GCMs which remained the driving model. Thus, a poorly performed GCM can significantly affect the performances of the RCM [1]. As a consequence, many researchers have to recourse to the use of statistical downscaling methods as effective alternatives to dynamical downscaling.

Statistical downscaling (i.e. disaggregation method) uses bias correction (BC) approach to correct model output, resulting in lesser systematic errors. A quite number of BC methods have evolved and had been used by different authors including, quantile mapping [5,20], histogram matching [27], mean monthly factor [11], local intensity scaling [30], gamma-gamma transformation [33] and delta change method [14–16]. Statistical downscaling has several advantages, including low computational cost, flexibility and ease of use [16,23]. Recently, trend preserving bias correction methods have been developed to keep the original climate change signal of GCMs in future projections. Therefore, it can provide reliable projections of climate like dynamical downscaling models [16].

In recent years, there have been accelerated research efforts amongst climate scientists to improve the spatial resolutions of GCMs through downscaling to suit studies at a regional scale. For example, the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) and Coordinated Regional-climate Downscaling Experiment (CORDEX). ISI-MIP is an international project founded to provide easy access to information necessary to better assess global climate change impacts and enhance regional climates' understanding ([13,19]). The ISI-MIP provides statistically downscaled projections of five CMIP5 GCMs at a global scale. Outputs of the models are available in high resolution, as they have been downscaled to 0.5° x 0.5° spatial resolutions with a temporal scale of a standard Gregorian calendar [16]. The ISI-MIP approach premised on a trend-preserving statistical bias correction method, which uses a constant offset for air temperature or multiplicative correction factor in the case of precipitation to correct the observed and simulated anomalies datasets in the historical period irrespective of the timescale. For these advantages, ISI-MIP models have been widely used for impact assessment studies in different regions of the globe. Though the performance of ISI-MIP GCM simulations has been found good globally, it does not guarantee their performance in every region as different regions of the world have a particular climate [22]. This indicates the need for performance assessment of bias-corrected GCMs at a local scale before their use in impact assessment.

Different researchers have used various metrics in different regions of the world to evaluate GCMs. For instance, in a comparative analysis of 14 GCMs of CMIP3 and CIMP5 over China for ten years, Sun et al. [35] found that the GCMs from the two projects captured the observed patterns of the probability density functions (PDFs) well in all regions. Although models from both projects showed improvements in simulating mean daily temperatures than precipitation, CMIP5 showed better results, consistent with the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) [18]. However, there are no improvements whatsoever in CMIP5 mean daily precipitation simulations over its counterpart. Also, Zebaze et al. [39] assessed Africa's historical climate in the multimodel mean (MMM) of 28 CMIP5 GCMs for the period 1975–2005. They showed the highest correlation coefficients with respect to CRU data. Although the RMSE were minimal, the MMM showed weak warming over most regions, and they lack the skills to capture the sign and magnitude of the observed precipitation trends. Akinsanola et al. [4] compared outputs of nine dynamically downscaled CMIP5 models over west Africa with Global Precipitation Climatology Project (GPCP) datasets for 25 years period (1980 to 2005). They used various statistical measures for the evaluations and demonstrated that all the GCM simulations agree to a large extent with GPCP spatial patterns over the study domain. They, however, noted weak performance over the Guinea coast. Shiru et al. [34] assessed the similarities in 20 CMIP5 models with reference to GPCC precipitation observations and CRU temperature datasets during 1961–2005. They selected the best four performing models for future drought projections over the region. Furthermore, Hassan et al. [14] evaluated the performances of 26 CMIP5 models for the common period 1980–2005 with CRU observational daily precipitation and temperatures using symmetrical uncertainty (an entropy-based) method over the Niger Delta region of Nigeria. They also selected the four best performing models for future climate projections.

The focus of most evaluations in previous studies had been on annual, seasonal, monthly and even interannual time scales, with only a few assessments on a daily scale [35]. In this regard, several researchers (e.g. [26,35]) argued that biases inherent in a daily dataset might be concealed if aggregated to monthly, seasonal or longer averages. They further opined that mean and standard deviations do not allow thorough assessments of the entire data distribution. To overcome this shortcoming, some researchers have emphasised the need to use continuous distribution functions (CDFs) and some ex-

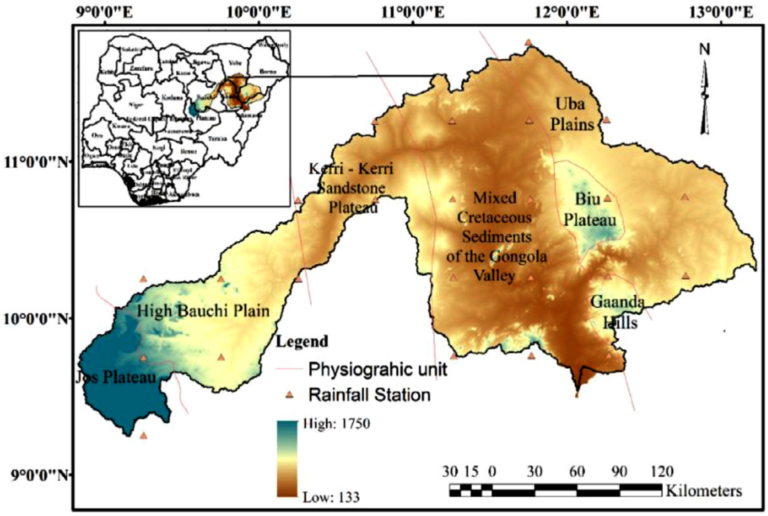

Fig. 1. The topography and physiographic units of the study area.

treme climate indices to explore the capability of GCMs in simulating the features of daily precipitation and extreme events ([36,32]).

In this study, the authors seek to assess the Coupled Model Intercomparison Project Phase 5 (CMIP5) outputs in ISI-MIP in replicating historical precipitation indices in the Gongola basin, northeast Nigeria. Different climatological descriptions, statistical indices, including CDFs and few selected climate indices with emphasis on a daily time scale, were used to select the most appropriate model for hydro-climatological impact assessments over the region. The Gongola basin provides water resource to several communities in the northeast of Nigeria, spreading across the Jos Plateau, Bauchi, Gombe, Borno and Adamawa States. The basin is well known for its major contribution to the annual runoff volume of river Benue (to the tune of 60 billion m^3) [21], owing to its large size, estimated to be approximately 56,000 km^2. The basin is vulnerable to extreme weather conditions due to large seasonal and spatial variabilities, with attendant natural and human-induced disasters. Despite these tendencies, evaluation of the General Circulation Model (GCM) precipitation outputs necessary to drive hydrologic models in the basin for mitigating negative impacts are non-existence, which leaves a wide research vacuum that should be filled. The present study is perhaps the first of its kind in the basin as far as literature search is concerned. It is therefore obvious that studies to extensively evaluate these much-needed climate variables as basis for vulnerability assessments in the basin and perhaps provide the possible outlook of future changes in climate is lacking. Consequently, the detail evaluation on a daily timescale in this study provides useful information on GCMs simulations' capability to replicate rainfall extremes and their skills in capturing convective storm in the Gongola basin. Besides, the spatial analysis allows thorough assessments of the GCMs in replicating rainfall variability due to geographical variation and topographical heterogeneity in the basin. The output from this study is useful for selecting most appropriate GCM for future precipitation projections and can serve as input data for impact modelling especially in hydrology and environmental management. Lastly, the evaluation procedure proposed can be adopted for better assessment of GCM performance for various tailored hydro-climatic studies in any region.

Study area and dataset

The study area

The topography and major physiographic units of the Gongola basin are shown in Fig. 1. The Gongola river emerges from the Jos Plateau (western region) at an elevation of approximately 1750 m above mean sea level (amsl), which later flow passed the high Bauchi plains over basement complex formations where the elevation drops to about 600 m amsl. Incidentally, there exist isolated inselbergs that rise abruptly about 300 m above the surrounding plains. Consequently, the river flows northeast to Dindima, where it plunges to a highly porous Kerri-Kerri sandstone plateau, consisting of less relief than the Bauchi plains. The river became perennial after Nafada and advanced eastward towards Dadin Kowa. The physiography at this region consists of mixed cretaceous sediments comprising of plains of clays, shales and limestones and ranges of sandstone hills. Biu plateau and high ground exist to the south of the river, consisting of undulating plains of approximately 900 m amsl, which formed the major left bank tributary – the Hawal. The middle and lower reaches of Hawal lie over basement complex rocks as well, consisting of several inselbergs. The combined flows of the Gongola and the left bank tributary finally debauches into River Benue at Numan, Adamawa state at 130 m amsl.

The Gongola is particularly a large river basin in the northeast of Nigeria that covers a drainage area of about 56,000 km^2 with the main river length of approximately 570 km. It is the largest flow contributor to Benue at the right arm, with an estimated annual runoff volume of 60 billion m^3 [21]. The basin lies in two climatic zones: The Northern Guinea zone and the Sudan zone. The difference in climate between the zones is significant and therefore controls the micro-climate of the basin. For instance, the mean annual rainfall varies from 1200 mm around the Jos plateau to about 700 mm somewhere at the northern boundary of the mixed cretaceous sediment zone. The rainfall distribution premise in the five summer months, May to September inclusive. The basin's annual temperature is 26 °C [21] though to be lower on the plateaux.

The basin is blessed with abundant water resources and vast arable lands for both irrigated and rain-fed agriculture. It thus has the potential to boost the local and national economies. Sylla et al. [36] has projected the likely occurrences of more frequent and high-intensity precipitation events over West Africa and Sahel, particularly over the Guinea Highlands and Cameroun Mountains, including the Jos plateau, during May and June. The effects of these extreme conditions are evident in the basin in recent years. Consequently, the Gongola river overflowed its bank in summer 2019, leaving one person dead. Over 100 houses were destroyed, including several farmlands in Dindima and several other communities along its banks in Bauchi state, rendering many homeless [8]. Despite these adverse conditions, studies to assess the capability of CMIP5 models in the basin are still minimal, and a clear picture of possible future incidence is lacking, which remained a challenge.

Present-day observed climatology

Like most other regions of Africa, one of the key challenges in evaluating the performances of GCM simulations over Nigeria, including the Gongola basin, dwells in paucity of high-quality ground-based observations at appropriate spatiotemporal scales. Consequently, this study chooses the GPCC v.2018 precipitation dataset as reference data due to its acceptable performance in previous studies and quantitative accuracy [22]. Studies in recent literature where GPCC dataset had been used for climate model evaluations include Ahmed et al. [2] over the sub-Himalayan region of Pakistan, Agyekum et al. [1] over the Volta basin in west Africa, Homsi et al. [17] over Syria, Nikulin et al. [24] over Africa domain, and Shiru et al. [34] over Nigeria. The data is gauge-based precipitation product freely available at 0.5° grids over the entire global land surface for the period 1982−2016. The GPCC receives data from over 35,000 weather stations per month worldwide [40]. In addition, the GPCC dataset undergoes rigorous quality control checks, which include visual and semi-automatic processes. The GPCC utilises the SHEREMAP interpolation method and concentrates on anomalies interpolation over the global surface rather than interpolating absolute values, leading to improved accuracy of the datasets [31]. This accounts for why the GPCC can accurately reproduce precipitation pattern and amount over rough terrain [3,31].

Climate models

Five CMIP5 GCMs were selected in the fast track of Inter-Sectoral Impact Model Inter-comparison Project (ISI-MIP; https://www.isimip.org): GFDL-ENSM2M, HADGEM2-ES, MIROC-ESM-CHEM, IPSL-CM5A-LR and NoerENS1-M for this study (Table SM1 gives the overview of the models). The features and limitations of CMIP5 models are well documented and extensively studied as compared to CMIP6 in many literatures. The motivation for the selection of a given sets of climate models are guided by the type of study and the purpose of the research. Moreover, the ultimate choice of GCMs for a particular application lies in identifying the best models from the pools of available GCMs [6,28]. Also, Anandhi et al. [6] debated that the selection of GCM models are primarily based on three general approaches including; the use of all available climate models, multimodel ensemble mean selected from a particular set of GCMs and selecting a subset of climate models which are considered most appropriate for specific impact models. Based on these facts, five GCM outputs are selected from CMIP5 database in this study as contained in the fast track of ISI-MIP for evaluation. A detailed description of the method is given in Hempel et al. [16]. The fidelity of the CMIP5 climate models to simulate the present-day climatology was investigated for a common period of 1982–2004.

Methodology

The capability of the GCMs to replicate the observed climatology over the six physiographic units and the whole Gongola basin are analysed relative to observational data. The climate models were directly compared with the GPCC datasets for the annual, monthly and daily timescales since both data have been the same horizontal spectral resolution of 0.5° lon/lat. Fig. 1 presents the location map of the Gongola basin, including the six physiographic units. The annual scale analysis considers the climatological description using the spatial description of the study's rainfall pattern. The area-averages of the annual cycle for the six physiographic units and the whole Gongola basin were computed to examine the models' skills in replicating the precipitation patterns.

Because of the importance of model performance in daily timescale in hydrological impact assessment, more detailed statistical analyses were carried out to select models having better skills according to Cumulative Distribution Function (CDF), Taylor diagrams, and some other statistical indices along with few climate indices generally used for characterisation of daily rainfall and extreme events. The use of CDFs for performance evaluation of climate models has become popular in recent literature (e.g. [4]) due to its ability to assess the datasets' entire distribution thoroughly. The Taylor diagram, on the

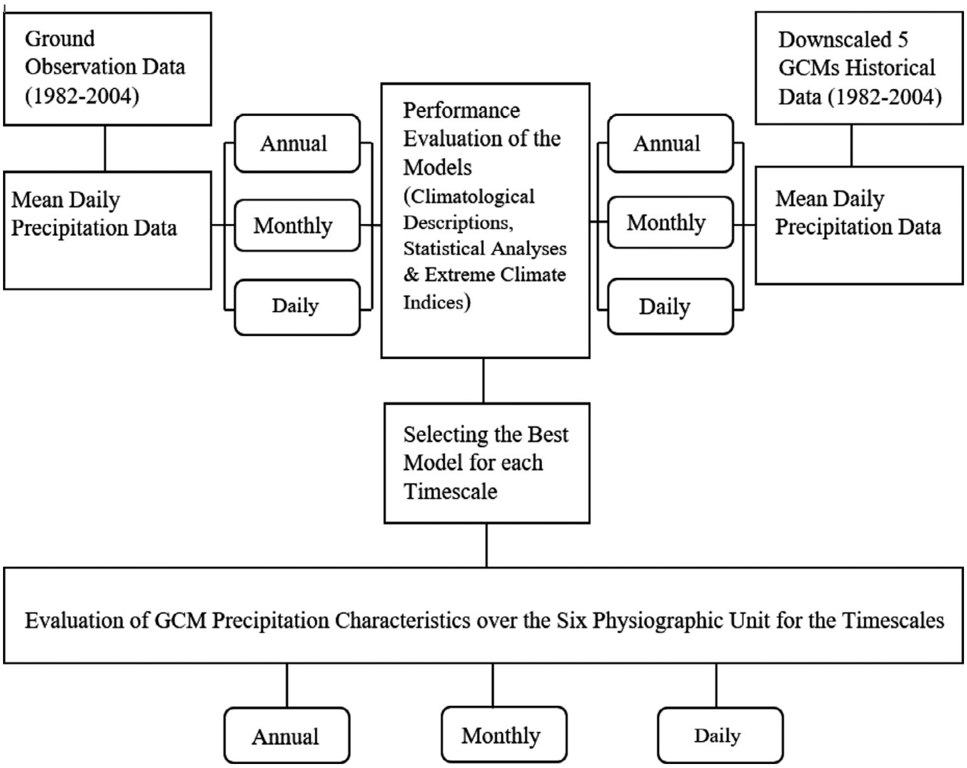

Fig. 2. Flowchart of the methodology adopted for this study.

one hand, presents the basic statistics such as; the correlation (r), root mean square difference (RMSD), and the deviations (σ), which measures the temporal patterns, errors and variabilities, that summarise the relative importance of assemblage of various models [38], while the statistical indices, on the other hand, considers the refined index of agreement (d_{ref}) [25], mean bias error (MBE), and mean absolute error (MAE) to further assess consistency in simulations [2]. Table SM2 summarises the few selected climate indices.

The extreme climate dataset quality was checked using R ClimDex (1.0) – a source code in R software packages, as contained in Zhang and Feng (2004). Also, the climate indices' evaluations considered the use of the same software package as utilised by Zhang et al. (2012; 2019). This detects outliers and excludes them from the dataset before analysis. The CDD, CWD and the PRCPTOT were analysed using the same software package.

Results and discussions

The CMIP5 climate models' skills in replicating the observed precipitation in annual, monthly and daily timescales over the study domain are hereby presented and discussed.

Mean annual climatology

The spatial distribution of the climatological mean of annual total wet-day precipitation (PRCPTOT) over the Gongola basin is shown in Fig. 2 for GPCC, the GCMs and their ensemble mean. On a general note, the GCMs rainfall climatology is consistent with the GPCC dataset, though with varying levels of accuracies. Nonetheless, the highest amount of precipitation was noted over the Jos Plateau. The rainfall maximum observed over this region has a value of 1200 mm/a, which persistently decreases towards the northeast, where the value is about 575 mm/a around Uba plain in the Sudan Savannah region. The high annual rainfall recorded over the Jos plateau was due to orgraphic effects which is known to play an important role in the West Africa precipitation patterns consistent with Akinsanola et al. [4]. All the models well replicate the general north to south gradient of precipitation. Interestingly, all the GCMs replicate the Jos plateau's orographic pattern well but generally overestimated the observed rainfall amounts over most parts of the study domain. GFDL-ESM2M has the best replica of the observed precipitation, followed by IPSL-CM5A-LR, with HADGEM2-ES being the least.

It was observed that no single model consistently outperforms individual models in the subregions and over the whole study domain, except the ENSMEAN, which recorded the lowest bias in all ramifications. However, GFDL-ESM2M and HADGEM2-ES showed better performance in most cases and are found to outperform ENSMEAN over Uba plain.

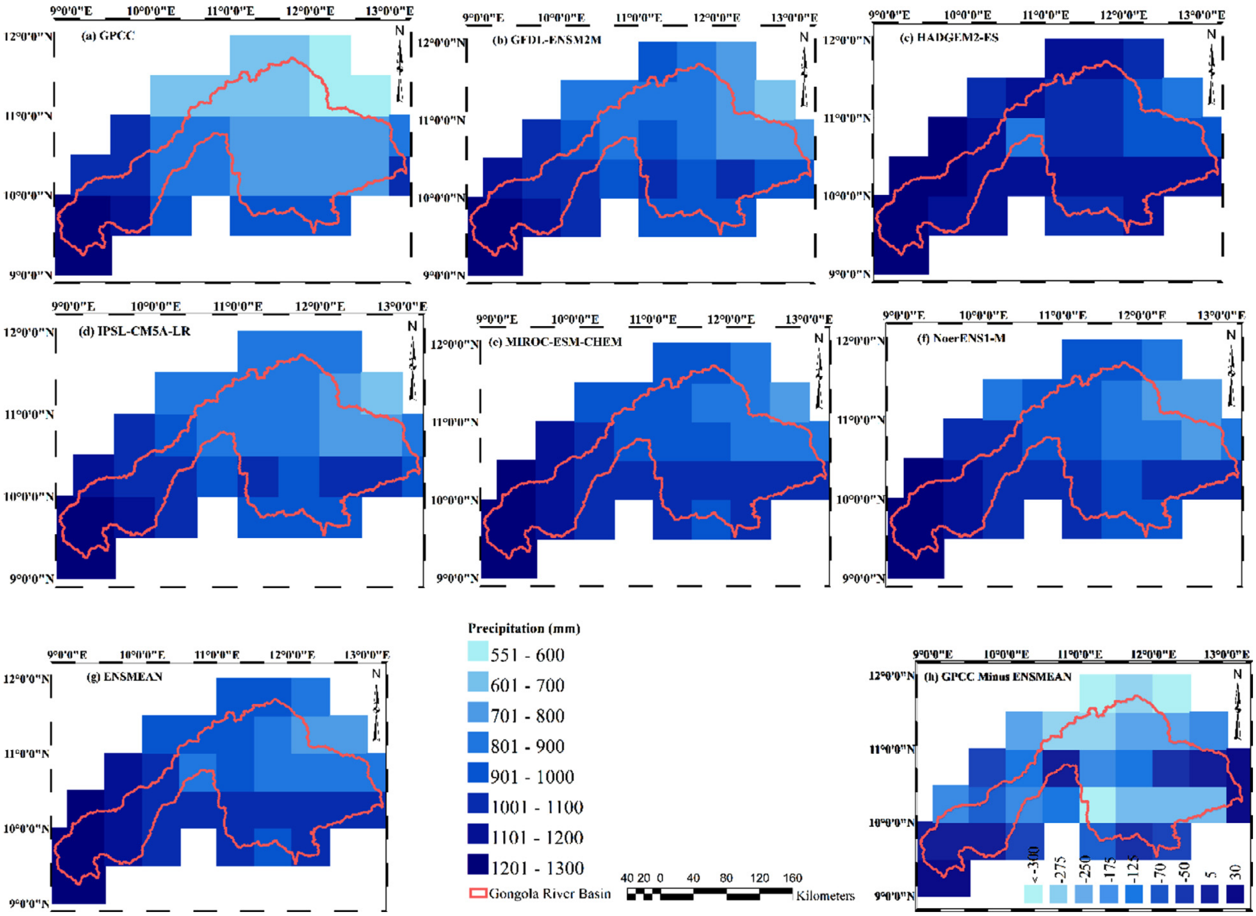

Fig. 3. Spatial distribution of mean annual rainfall over the Gongola River Basin for the period 1982–2004 for (a) GPCC, (b) GFDL-ENSM2M, (c) HADGEM2-ES, (d) IPSL-CM5A-LR, (e) MIROC-ESM-CHEM, (f) NoerENS1-M, and (g) ENSMEAN (h) GPCC minus Models.

Annual cycle of monthly climatology

The ability of CMIP5 GCMs and their multimodel ensemble mean to reproduce the annual precipitation cycle relative to GPCC over the subregions and the entire Gongola basin is investigated as shown in Fig. 3(a-h). Over the Jos plateau, the rainy season's length spreads across six summer months, usually from April to October, with peak rainfall of 245 mm in August, having a distinctive unimodal peak. The tendencies of the models to accurately simulate precipitation patterns depend largely on their ability to effectively simulate the meridional movement of the intertropical convergent zone (ITCZ) [1], which controls spatial distribution of rainfall over Africa [39]. The models replicated this trend. However, they overestimated the peak rainfall amount in all cases. The Bauchi high plain exhibits similar characteristics to the Jos Plateau but with a relatively less peak rainfall of 235 mm. Here, the models have a better match during the onset and retreat than over the Jos plateau.

Furthermore, the GPCC observation indicates the length of the rainy season to stretch between May and October in other subregions, having its peak rainfall amount in August. These features are well captured by all the models, except that they all overestimated the highest rainfall amounts as noted in Jos and Bauchi, though with varying magnitudes. The northward propagation and gradual retreat of rainfall in the basin concur with West African Monsoon's identifiable feature [4]. Despite the overestimation, the IPSL-CM5A-LR outperformed the individual models, including the ENSMEAN, to replicate the annual precipitation cycle.

The Guinea mountains, Cameroun highlands and the Jos plateau are three orographic regions of the West Africa (WA) with identifiable precipitation maxima and temperature minima which greatly influence the micro-climate of the region. On the whole, the rainfall variability over West Africa (WA) are particularly influenced by the major climatological feature known as the West African Monsoon (WAM). Consequently, the monsoon variability itself is controlled by a number of factors such as the continental landsurface conditions, sea surface temperatures (SSTs) and atmospheric circulations. The rainfall producing systems are themselves encompassed in the region's atmospheric circulation schemes consisting of African Easterly Jets (AEJ), Africa Easterly Waves (AEWs), ITCZ and Tropical Easterly Jets (TEJs). In any case, the amount as well as the variability of rainfall over the region are modulated by the position and the intensity of these atmospheric features signifying the importance of the interactions between these elements on the WAM [36]. Apart from the well established orographic rainfall over the Jos plateau, convective storms prevails over other regions particularly as one moves towards the northern fringes of the basin. Convective storms are characterised with high intensity and short duration which often combine with the high orographic rainfall in the basin to cause recurrent floodings. Thus, accurate representations of the complex interactions between the WAM over the basin requires modelling for improved knowledge on the region's climate to global warming has remained a haculian task. Nonetheless, the computational requirements of GCMs to accurately represent these complex features over a long period often affect their skills. In any case, the systematic bias generated by the RCMs along with those inherited from the parent GCMs are identified as the major sources of errors, which are due to difficulties in predicting natural variability, imperfection of model physical parameterizations, spatial scale mismatch and perhaps observational uncertainties. However, the skills of the bias corrected GCMs in the study to replicate the precipitation maxima over the Jos plateau due to orography and the convective storm at the northern fringes of the basin along with mutual agreement of the models in terms of mean annual cycle demonstrate the skills of the models to reproduce the precipitation of the Gongola basin and the larger WAM features such as AEWs, AEJs and TEJs.

Evaluation of daily precipitation

Assessing the fidelity of daily rainfall climatology becomes necessary owing to its relevance in hydrologic impact studies. This account for the sole reason why more attention was being paid to the assessment in this research. The CDFs of daily rainfall between the observational data and the models, including their ENSMEAN are presented in Figure SM1 (a)-(g) to show the relative frequency of rainfall occurrence. The majority of the rainfall in the basin occurs at the rate 5 mm hr^{-1} to 50 mm hr^{-1} (hereinafter referred to as 'most occurring rainfall"). This places the rainfall into light-moderate (5 to 10 mm hr^{-1}), low heavy (10 to 20 mm hr^{-1}) and high heavy rainfall (20 to 50 mm hr^{-1}). This is the interval where the rainfall is noted to either be under- or overestimated. There is an almost perfect match for rainfall less than 5 mm in all the subregions and the whole basin. However, the region of extreme rainfall ($>$ 50 mm hr^{-1}) differs considerably from region to region and are particularly difficult to interpret.

Over the Jos Plateau, the probability of having 20 $mmhr^{-1}$ rainfall intensity and below in HADGEM2-ES and ENSMEAN was measured to be 0.90 indicating a close match with the observed probability which recorded 0.86. Thus, these two models measured the observed frequency closely and captured the most occurring rainfall amount reasonably well, though with slight underestimations. Other models either under- or overestimate the rainfall amount. The discrepancies are more in Bauchi plains between the models and the observational data. Although the datasets exhibit similar trends, even the best performing model (HADGEM2-ES) substantially overestimate the observed frequency of the most occurring rainfall. An improved representation of the observed rainfall by MIROC-ESM-CHEM over Kerri-Kerri sandstone plateau and Biu plateau were noted with probability of 0.80 for the model and the observed CDFs for the rainfall intensity of 20 mm. However, all the climate models underestimate the observed pattern of the rainfall distribution in these regions. The rainfall distribution of ENSMEAN showed strong performance over the whole Gongola basin along with GFDL-ENSM2M. They have probability of 0.96 for rainfall intensity less or equal to 20 mm placing them as the most closely matched dataset to the observed CDF with probability of 0.92. However, the performances of MIROC-ESM-CHEM, HADGEM2-ES and NoerESM1-M appear to be relatively weak over most regions. Overall, the ENSMEAN provide the best fit over the entire study domain with encouraging results.

Further evaluations of the daily precipitation dataset consider the use of Taylor diagrams to assess the models' skills and their ENSMEAN since the acceptable performance of GCMs at annual, seasonal and monthly timescales may not imply good performance on a daily timescale. The Taylor diagram provides statistical outputs of the degree of correspondence between the models, and the reference observed data in terms of temporal pattern, error and variability [38] as shown in Fig. 4. On a general note, the models' overall performances in the subregions and the whole Gongola basin are similar. However, some models perform better than others in replicating the observed patterns with differing margins. Over the Jos plateau, the models capture the reference observation with some degree of accuracy, with correlation coefficient varying between 0.60 and 0.68, deviations of 4.20 to 7.41 mm and RMSD of 6.64 to 8.86 mm. MIROC-ESM-CHEM has the smallest r value. The highest error and deviations turnout to be the worst model in reproducing the observed precipitation pattern, while ENSMEAN is rated the best of all. Like the Jos plateau, the ENSMEAN consistently outperformed the individual models in all other subregions and the entire study domain with r values ranged between 0.65 and 0.73. IPSL-CM5A-LR exhibited better performance over the individual models in most subregions, placing it next to the ENSMEAN. In contrast, GFDL-ENSM2M and MIROC-ESM-CHEM are weak due to their consistent least performances everywhere in the study area. Over the mixed cretaceous sediment of the Gongola valley, the models' performances are generally weak in capturing the GPCC observation, with relatively low r values (0.44 to 0.52). However, IPSL-CM5A-LR and ENSMEAN recorded r values, 0.50 and 0.52, which further reveal these models' strengths.

Statistical performance

In furtherance to the CDFs and Taylor diagrams used for assessing the daily precipitation datasets in this study, additional three statistical indices including Wilmott refined index of agreement (d_{ref}), mean bias error (MBE) and mean absolute error

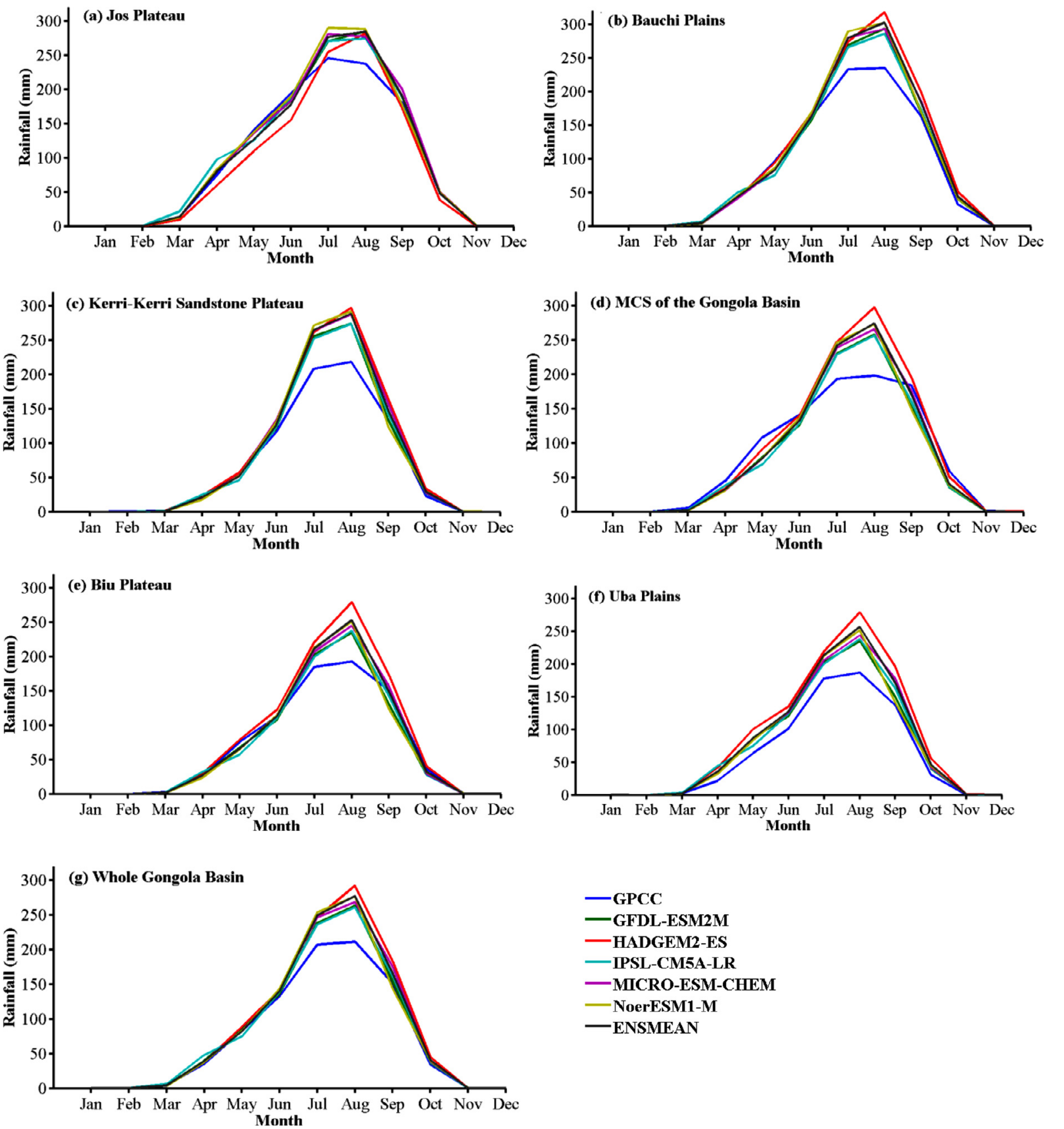

Fig. 4. Annual cycle of monthly total precipitation for the common period, 1982–2004.

(MAE) were considered. The results are shown in Table 1, where the boldened values and those with asterisk signify the most suitable models. The d_{ref} provides the degree of pattern correspondence between two independent datasets, similar to the correlation coefficient. Its choice in this study was guided by the fact that d_{ref} weights errors and differences, which prevents exaggeration of squared values as it is the case in r, thereby producing outputs that are less sensitive to outliers. The d_{ref} generally varies between 0.50 and 0.63. The IPSL-CM5A-LR consistently outperformed individual models in the subregions including the ENSMEAN by recording the highest d_{ref} and having the lowest errors, though with little margins.

The ENSMEAN turnout to be the best performing model over the larger Gongola basin. The MBE of the models varies from −0.01 to 0.88 mm. The positive and negative values indicate over- and underrepresentation of the models. Based on this, it is clear that most of the GCMs, including the ENSMEAN systematically overrepresented the observed rainfall amounts throughout the study site. While the IPSL-CM5A-LR was remarkable compared to the other models in this mea-

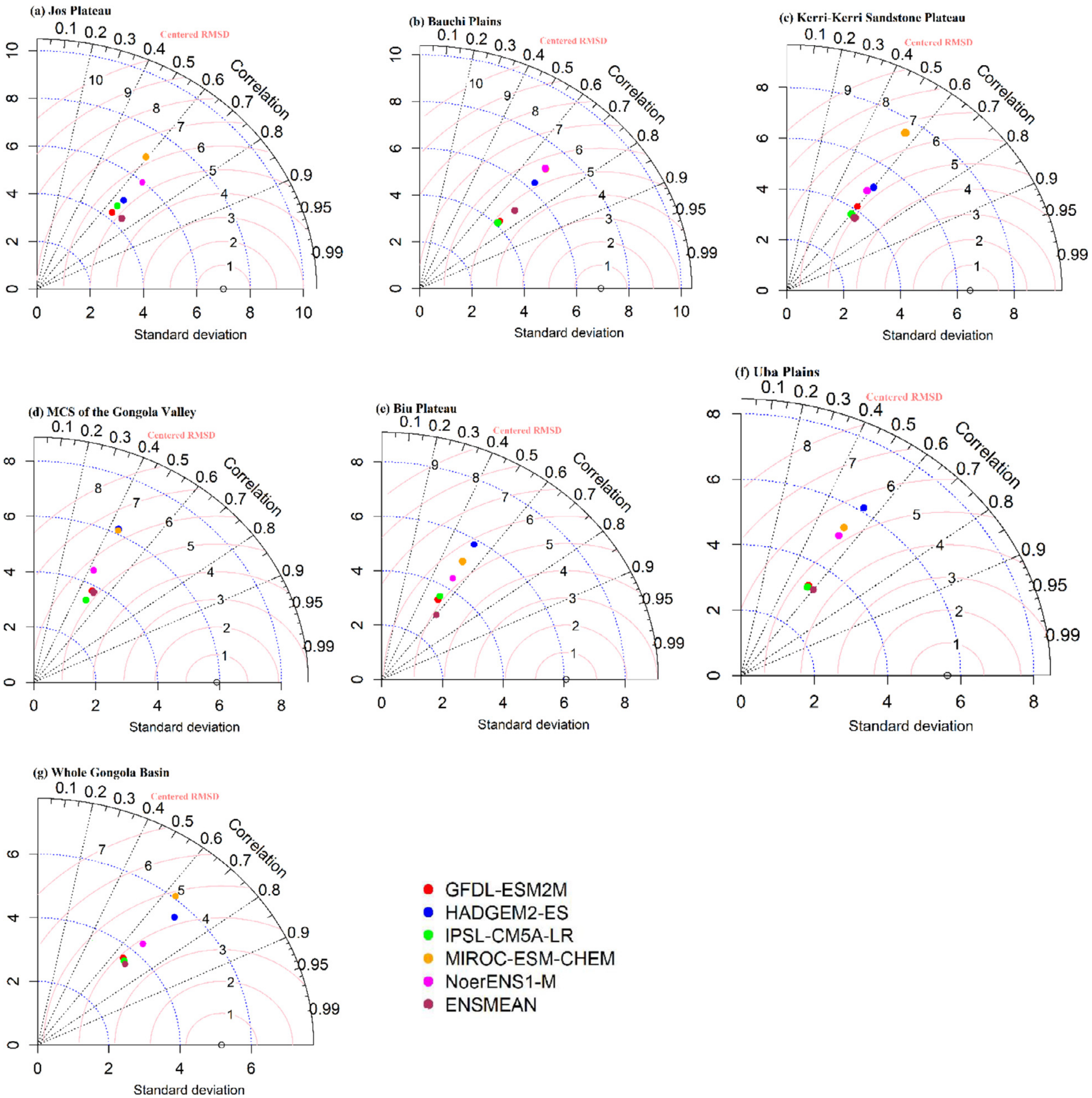

Fig. 5. Taylor diagrams for mean daily precipitation.

sure, HADGEM2-ES appeared to be the weakest in capturing the observed rainfall pattern over the subregions and the entire basin. The performance of the GCMs in terms of error and level of correspondence with the ground reference observations concur to a large extent with previous reports over the West Africa domain by Akinsanola et al., [4]; Agyekum et al., [1]; and Zebaze et al., [39].

Evaluation based on extreme precipitation

The results of the four selected indices from the Expert Team on Climate Change Detection and Indices (ETCCDI) are presented in Figs. 2, SM2, SM3 and SM4 to test the efficacy of the CMIP5 GCMs in replicating extreme precipitation events over the study domain. The indices include PRCPTOT, CDD, CWD and Rx1day. While the first three indices emphasised the frequency of precipitation, the last index premised on evaluating the precipitation intensity between the observational data and the models. PRCPTOT has been extensively discussed in section 4.1. The maximum annual consecutive dry days (CDD)

Table 1
Performance Evaluations of GCMs using Statistical Metrics.

Model	Jos Plateau			High Bauchi Plains			Kerri-Kerri Sandstone Plateau		
	MAE	MBE	d_{ref}	MAE	MBE	d_{ref}	MAE	MBE	d_{ref}
GFDL-ENSM2M	3.63	0.13	0.60*	3.27	0.17	0.59*	2.90	0.24	0.58*
HADGEM2-ES	3.57	−0.13	0.60*	3.66	0.54	0.54*	3.07	0.55	0.55*
IPSL-CM5A-LR	3.54	0.13	0.61*	3.18	0.16	**0.60**	2.83	0.24	**0.59**
MIROC-ESM-CHEM	4.12	0.25	0.54*	3.75	0.34	0.53*	3.28	0.46	0.52*
NoerENS1-M	3.81	0.22	0.58*	3.75	0.34	0.53*	3.00	0.35	0.56*
ENSMEAN	3.49	0.12	**0.61**	3.27	0.31	0.59*	2.82	0.37	0.59*
Model	Mixed Cretaceous Sediment of the Gongola Valley			Biu Plateau			Uba Plains		
	MAE	MBE	d_{ref}	MAE	MBE	d_{ref}	MAE	MBE	d_{ref}
GFDL-ENSM2M	3.63	−0.11	0.58*	2.74	−0.01	0.59*	2.72	0.36	0.56*
HADGEM2-ES	4.08	0.37	0.52*	3.25	0.47	0.52*	3.24	0.88	0.48*
IPSL-CM5A-LR	3.59	−0.11	**0.58**	2.72	0.00	**0.60**	2.69	0.39	**0.57**
MIROC-ESM-CHEM	3.89	0.08	0.55*	3.01	0.17	0.55*	3.01	0.53	0.52*
NoerENS1-M	3.73	0.03	0.56*	2.93	0.08	0.57*	2.94	0.45	0.53*
ENSMEAN	3.65	0.05	0.57*	2.72	0.14	0.60*	2.76	0.55	0.56*

Model	Whole Gongola Basin		
	MAE	MBE	d_{ref}
GFDL-ENSM2M	2.58	0.21	0.61*
HADGEM2-ES	2.91	0.52	0.56*
IPSL-CM5A-LR	2.50	0.21	0.62*
MIROC-ESM-CHEM	3.04	0.38	0.54*
NoerENS1-M	2.67	0.30	0.60*
ENSMEAN	2.49	0.33	**0.63**

Bold *– most suitable; *suitable*

in GPCC dataset is 150 days around the Jos plateau, as shown in Figure SM4 (a), which continue to increase exponentially as one move towards the northeast region of the basin until it reaches a maximum of 200 days around Uba plain. This area is known for its least rainfall amount owing to its geographical location, which lies in the Sudan Savannah region. This trend was reasonably captured by the models, including their ensemble median (ENSMEDIAN) over the entire Gongola study domain, though with varying magnitudes. However, the HADGEM2-ES was observed to be skilful in replicating the observed features both spatially and in magnitude, and was therefore found to be most suitable in replicating the observed CDD patterns over the subregions and the entire basin, as shown in Figure SM4 (c).

The CWD of GPCC, the CMIP5 GCMs and their multimodel ensemble median are shown in Figure SM2(a)-(g). The CWD generally varies between 6 and 9 days, with maximum value observed over Jos Plateau, and the minimum around Uba plain. The GCMs in their entirety are, however, noted to be dubious in capturing the observed pattern of the CWD, but rather grossly overestimate the number of wet days. For instance, the IPSL-CM5A-LR recorded a maximum CWD of 160 days over Jos Plateau, GFDL-ENSM2M recorded 99 days, while NeorENSI-M, HADGEM2-ES, MICRO-ENS-CHEM indicate a maximum value of 73, 60 and 24 days, respectively. These values are impracticable anywhere in the catchment, as they are unrealistically high. Moreover, the ENSMEDIAN aligned with the individual models to provide high CWD values over the entire basin.

GCM's ability to replicate rainfall intensity is also evaluated owing to the influence of rainfall intensity on floods over the Gongola basin. The Jos Plateau witnessed a median maximum rainfall of 85 mm over the period, which increase progressively until it reaches 120 mm at the most northern axis of the basin (Figure SM3 (a)). Other regions with less annual rainfall total exhibit higher rainfall intensity than the Jos plateau. This feature can be attributed to convective storm, which according to Sylla et al. [37], dominates over the West African monsoon region. This type of precipitation often attains higher intensity within a period than frontal and orographic storms [29], resulting from local or mesoscale convective systems. Nevertheless, the Jos plateau is characterised by exceptional precipitation maximum in the region due to orographic effects. Consequently, the individual GCMs, including the ENSMEDIAN failed to capture the observed pattern. They either overestimate or underestimate the precipitation occurrences everywhere in the basin, except HADGEM2-ES, which, to some extent, replicate reasonably well the observed pattern, as shown in Figure SM3 (b).

Conclusions

This study evaluates the performance of five CMIP5 GCMs in the fast track of ISI-MIP in reproducing the mean precipitation climatology over the Gongola basin for the common period of 1982–2004 relative to GPCC observations based on insight from literatures. Climatological descriptions, statistical analyses and few selected climate indices were used to test the models' efficacy in replicating present-day observed climatology, considering annual, monthly and daily timescales. The geographical distribution of mean annual climatology of the total wet-days showed that the individual models, including their ENSMEAN replicated reasonably well the observed precipitation pattern over the six subregions and the entire study area. Based on our findings, the following conclusions are drawn:

(1) The GFDL-ESM2M and IPSL-CM5A-LR were noted to be the most outstanding in capturing the observed pattern of the annual total wet days.
(2) The ENSMEAN and HADGEM2-ES performed remarkably well in capturing the observed daily distribution in CDF curves.
(3) Good relationships between the models and the reference observed data were found, with pattern correlation varying between 0.5 and 0.73 at daily timescale, suggesting a good match.
(4) Ultimately, the ENSMEAN and IPSL-CM5A-LR have less variability, errors and bias with the highest correspondence pattern. This shows that the two GCMs measure the precipitation estimates closely, with overall better performances.
(5) Furthermore, the spatial representation of the models and their ENSMEDIAN revealed HADGEM2-ES to be the only model with an accurate representation of the measured extreme rainfall over the entire Gongola study domain.
(6) Considering the individual models, IPSL-CM5A-LR is the most outstanding model for daily simulations along with ENSMEAN, while HADGEM2-ES is the best model for modelling extreme conditions.
(7) Adaptation strategies to climate risk and natural disasters remained one of the focal points of Agenda 2063 of the African Union, thus this study provides useful information to a large extent on the level of accuracy and dependability of the climate models in the region which are the most powerful tools available to experts and policy makers for decisions on current and future hydrological conditions.

On the whole, the ENSMEAN provide an improved representation of precipitation over the entire basin except for extreme conditions. In essence, the precipitation field evaluated in this study can be used for impact modelling in hydrology and environmental management at both regional and local scales. Future work that will consider dynamical downscaling approach with much higher resolution for better assessments of the present-day and future precipitation conditions in the Gongola basin is warranted for improved adaptation strategies.

Funding

The financial support to the first author by the Federal Government of Nigeria through Tertiary Education Trust Fund for Academic Staff Training and Development is greatly acknowledged.

Consent for publication

The authors give their consents that this work be published in Scientific African.

Research data

The CMIP5 climate datasets analysed during this study are available in the fast track of Inter-Sectoral Impact Model Inter-comparison Project (ISI-MIP; https://www.isimip.org). The GPCC dataset is also freely available and downloadable from http://gpcc.dwd.de.

Code availability

The code used for the analysis of extreme climate indices is a Source R code available at: http://cccma.seos.uvic.ca/ETCCDMI/RClimDex/rclimdex.r.

Declaration of Competing Interest

The authors declare no conflict of interest.

CRediT authorship contribution statement

AbdulRazaq Salaudeen: Conceptualization, Methodology, Writing – original draft. **Abubakar Ismail:** Supervision, Writing – review & editing. **Babatunde K. Adeogun:** Visualization, Methodology, Writing – review & editing. **Morufu A. Ajibike:** Investigation, Data curation, Writing – review & editing. **Shamsuddin Shahid:** Methodology, Software, Validation, Writing – review & editing.

Acknowledgment

The authors are grateful to the services that have operated the climate models used in this study and the GPCC.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sciaf.2021.e00921.

References

[1] J. Agyekum, T. Annor, B. Lamptey, E. Quansah, R.Y.K. Agyeman, Evaluation of CMIP5 global climate models over the volta basin: precipitation, *Adv. Meteorol.* 2018 (2018) 1–24, doi:10.1155/2018/4853681.

[2] K. Ahmed, Z. Iqbal, N. Khan, B. Rasheed, N. Nawaz, I. Malik, M. Noor, Quantitative assessment of precipitation changes under CMIP5 RCP Scenarios over the Northern Sub-Himalayan Region of Pakistan, *Environ. Dev. Sustain.* (2019), doi:10.1007/s10668-019-00548-5.

[3] K. Ahmed, S. Shahid, X. Wang, N. Nawaz, K. Najeebullah, Evaluation of gridded precipitation datasets over arid regions of Pakistan, *Water (Basel)* 11 (2) (2019) 210, doi:10.3390/w11020210.

[4] A.A. Akinsanola, V.O. Ajayi, A.T. Adejare, O.E. Adeyeri, I.E. Gbode, K.O. Ogunjobi, G. Nikulin, A.T. Abolude, Evaluation of rainfall simulations over West Africa in dynamically downscaled CMIP5 global circulation models, *Theor. Appl. Climatol.* 132 (1–2) (2017) 437–450, doi:10.1007/s00704-017-2087-8.

[5] N.R. Aloysius, J. Sheffield, J.E. Saiers, H. Li, E.F. Wood, Evaluation of historical and future simulations of precipitation and temperature in Central Africa from CMIP5 climate models, *J. Geophys. Res. Atmos.* 121 (2016) 130–152, doi:10.1002/2015JD023656.

[6] A. Anandhi, A. Frei, S.M. Pradhanang, M.S. Zion, D.C. Pierson, E.M. Schneiderman, AR4 Climate model performance in simulating snow water equivalent over catskill mountain Watersheds, New York, USA, Hydrol. Process. 25 (21) (2011) 3302–3311, doi:10.1002/hyp.8230.

[7] S. Arai, K. Urayama, T. Tebakari, B. Archvarahuprok, Characteristics of gridded rainfall data for Thailand from 1981 to 2017, Eng. J. 23 (6) (2019) 461–468, doi:10.4186/ej.2019.23.6.461.

[8] A. Bakam, Flood kills one, destroys houses, Bridge in Bauchi Villages, Nigerian Punch Newspaper (2019).

[9] S. Doulabian, S. Golian, A.S. Toosi, C. Murphy, Evaluating the effects of climate change on precipitation and temperature for Iran using RCP scenarios, *J. Water Clim. Change* (2020), doi:10.2166/wcc.2020.114.

[10] U. Ehret, E. Zehe, V. Wulfmeyer, K. Warrach-Sagi, J. Liebert, HESS opinions "should we apply bias correction to global and regional climate model data? Hydrol. Earth Syst. Sci. 16 (9) (2012) 3391–3404, doi:10.5194/hess-16-3391-2012.

[11] H.J. Fowler, C.G. Kilsby, Using regional climate model data to simulate historical and future river flows in Northwest England, Climatic Change 80 (3–4) (2007) 337–367, doi:10.1007/s10584-006-9117-3.

[12] A. Ghozat, A. Sharafati, S.A. Hosseini, Long-term spatiotemporal evaluation of CHIRPS satellite precipitation product over different climatic regions of Iran, *Theor. Appl. Climatol.* 143 (1–2) (2020) 211–225, doi:10.1007/s00704-020-03428-5.

[13] T.S.M. Hosseini, S.A. Hosseini, B. Ghermezcheshmeh, A. Sharafati, Drought hazard depending on elevation and precipitation in Lorestan, Iran, *Theor. Appl. Climatol.* 142 (3–4) (2020) 1369–1377, doi:10.1007/s00704-020-03386-y.

[14] I. Hassan, R.M. Kalin, C.J. White, J.A. Aladejana, Selection of CMIP5 GCM ensemble for the projection of spatio-temporal changes in precipitation and temperature over the Niger Delta, Nigeria, *Water (Basel)* 12 (385) (2020) 1–19, doi:10.3390/w12020385.

[15] L.E. Hay, R.L. Wilby, G.H. Leavesley, A comparison of delta change and downscaled GCM scenarios for three mountainous basins in the United States, J. American Water Resour. Assoc. 36 (2) (2000) 387–397, doi:10.1007/s00704-020-03386-y.

[16] S. Hempel, K. Frieler, L. Warszawski, J. Schewe, F. Piontek, A Trend-preserving bias correction – the ISI-MIP approach, Earth Syst. Dynam. 4 (2013) 219–236, doi:10.5194/esd-4-219-2013.

[17] R. Homsi, M.S. Shiru, S. Shahid, T. Ismail, S.B. Harun, N. Al-Ansari, K.-.W. Chau, Z.M. Yaseen, Precipitation projection using a CMIP5 GCM ensemble model: a regional investigation of Syria, Eng. Appl. Comput. Fluid Mech. 14 (1) (2020) 90–106, doi:10.1080/19942060.2019.1683076.

[18] IPCC, Climate change impact 2014: impacts, adaptation, and vulnerability. Part B: regional aspects, in: V.R. Barros, C.B. Field, D.J. Dokken, M.D. Mastrandrea, K.J. Mach, T.E. Bilir (Eds.), Contribution of Working Group II to the Fifth Assessement Report of the Intergovernmental Panel On Climate Change, Cambidge University Press, Cambridge, United Kingdom and New York, NY, USA, 2014, p. 668.

[19] R. Ito, H. Shiogama, T. Nakaegawa, I. Takayabu, Uncertainties in climate change projections covered by the ISIMIP and CORDEX model subsets from CMIP5, Geosci. Model Dev. 13 (2020) 859–872, doi:10.5194/gmd-13-859-2020.

[20] M. Jakob Themeßl, A. Gobiet, A Leuprecht, Empirical-statistical downscaling and error correction of daily precipitation from regional climate models, Int. J. Climatol. 31 (10) (2011) 1530–1544, doi:10.1002/joc.2168.

[21] Japan International Cooperation Agency (JICA), National water resources master plan 2013Federal Ministry of Water Resources, Federal Government of Nigeria, Abuja, 2014 *Volume 4.*.

[22] S. Kamworapan, C. Surussavadee, Evaluation of CMIP5 global climate models for simulating climatological temperature and precipitation for Southeast Asia, *Adv. Meteorol.* 2019 (2019) 1–19, doi:10.1155/2019/1067365.

[23] D. Li, J. Feng, Z. Xu, B. Yin, H. Shi, J. Qi, Statistical bias correction for simulated wind speeds over CORDEX-East Asia, *Earth Space Sci.* 6 (2) (2019) 200–211, doi:10.1029/2018ea000493.

[24] G. Nikulin, C. Jones, F. Giorgi, G. Asrar, M.B. Chner, R. Cerezo-Mota, O.B. Christensen, M. DéQué, J. Fernandez, A.H. Nsler, E. Vanmeijgaard, P. Samuelsson, M.B. Sylla, L. Sushama, Precipitation climatology in an ensemble of CORDEX-Africa regional climate simulations, J. Clim. 25 (2012) 6057–6077, doi:10.1175/JCLI-D-11-00375.1.

[25] H.R. Pereira, M.C. Meschiatti, R.C.D.M. Pires, G.C. Blain, On the performance of three indices of agreement: an easy-to-use r-code for calculating the Willmott indices, Bragantia 77 (2) (2018) 394–403, doi:10.1590/1678-4499.2017054.

[26] S.E. Perkins, A.J. Pitman, N.J. Holbrook, J. Mcaneney, Evaluation of the AR4 climate models' simulated daily maximum temperature, minimum temperature, and precipitation over australia using probability density functions, J. Clim. 20 (2007) 4356–4376, doi:10.1175/JCLI4253.1.

[27] C. Piani, G.P. Weedon, M. Best, S.M. Gomes, P. Viterbo, S. Hagemann, J.O. Haerter, Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models, J. Hydrol. 395 (3–4) (2010) 199–215 doi:10.1016/j.jhydrol.2010.10.024.

[28] K.S. Raju, D.N. Kumar, Ranking general circulation models for India using TOPSIS, J. Water Clim. Change. 06 (2) (2015) 288–299, doi:10.2166/wcc.2014.074.

[29] M. Sangiorgio, S. Barindelli, Spatio-temporal analysis of intense convective storms tracks in a densely urbanised Italian Basin, Int. J. Geoinf. 9 (183) (2020) 1–14 doi:10.3390/ijgi9030183.

[30] J. Schmidli, C. Frei, P.L. Vidale, Downscaling from GCM precipitation: a benchmark for dynamical and statistical downscaling methods, Int. J. Climatol. 26 (5) (2006) 679–689, doi:10.1002/joc.1287.

[31] U. Schneider, A. Becker, P. Finger, A. Meyer-Christoffer, M. Ziese, B. Rudolf, GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle, *Theor. Appl. Climatol.* 115 (1–2) (2013) 15–40 doi:10.1007/s00704-013-0860-x.

[32] A. Sharafati, E. Pezeshki, A strategy to assess the uncertainty of a climate change impact on extreme hydrological events in the semi-arid dehbar catchment in Iran, *Theor. Appl. Climatol.* 139 (1–2) (2019) 389–402, doi:10.1007/s00704-019-02979-6.

[33] D. Sharma, A.D. Gupta, M.S. Babel, Spatial disaggregation of bias-corrected GCM precipitation for improved hydrologic simulation: ping river basin, Thailand, Hydrol. Earth Syst. Sci. 11 (2007) 1373–1390.

[34] M.S. Shiru, S. Shahid, A. Dewan, E.-.S. Chung, N. Alias, K. Ahmed, Q.K. Hassan, Projection of meteorological droughts in Nigeria during growing seasons under climate change scenarios, Sci. Rep. 10 (10107) (2020) 1–18 doi:10.1038/s41598-020-67146-8.

[35] Q. Sun, C. Miao, Q. Duan, Comparative analysis of CMIP3 and CMIP5 global climate models for simulating the daily mean, maximum, and minimum temperatures and daily precipitation over China, J. Geophys. Res. Atmos. 120 (2015) 4806–4824, doi:10.1002/2017RG000574.

[36] M.B. Sylla, A.T. Gaye, G.S. Jenkins, On the fine-scale topography regulating changes in atmospheric hydrological cycle and extreme rainfall over West Africa in a regional climate model projections, Int. J. Geophys. 2012 (2012) 1–15, doi:10.1155/2012/981649.
[37] M.B. Sylla, F. Giorgi, P.M. Ruti, S. Calmanti, A. Dell'aquila, The impact of deep convection on thewest African summer monsoon climate: a regional climatemodel sensitivity study, Q. J. R. Meteorol. Soc. 137 (2011) 1417–1430, doi:10.1002/qj.853.
[38] K.E. Taylor, Summarising multiple aspects of model performance in a single diagram, J. Geophys. Res. Atmos. 106 (D7) (2001) 7183–7192 doi:10.1029/2000jd900719.
[39] S. Zebaze, S. Jain, P. Salunke, S. Shafiq, S.K. Mishra, Assessment of CMIP5 multimodel mean for the historical climate of Africa, Atmos. Sci. Lett. (2019) 1–12, doi:10.1002/asl.926.
[40] M. Ziese, A. Rauthe-Schoch, A. Becker, P. Finger, A. Meyer-Christoffer, U. Schneider, GPCC Ful data daily version.2018 at 1.0°: daily land-surface precipitation from rain-gauges build on GTS-based and historic data, in: G.P.C. Centre (Ed.), The Full Data Daily Product V.2018 (V.2), 2018 Germany.