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Evaluation of CORDEX Africa multi-model precipitation simulations over the Pra River Basin, Ghana

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ABSTRACT

Study region: Pra River Basin (PRB) located in Ghana
Study focus: Now, hydrological and climate change impact studies are shifting towards reliance on openly accessible databases particularly for regions with limited observed datasets. There is therefore the need to evaluate the reliability of such datasets in order to reduce modelling uncertainties and boost confidence in modelling results. We present an evaluation of the performance of nine CORDEX RCA4 Regional Climate Model simulations in replicating the observed precipitation for a 31-year period (1975–2005).
New hydrological insights for the region: On the annual timescale, CanESM2, IPSL, CNRM-CM5 and HadGEM2-ES reproduced minimal annual mean biases (0.8–18.4 %) and thus selected for the seasonal and monthly timescale analysis. Generally, with the exception of spring (March, April and May), all the selected models were able to simulate quite well the seasonal climatology of the Pra River Basin (PRB) with noticeable distinctions in the reproducibility of the spatial patterns, variability and magnitude of the observed data. The multi-model ensemble means indicated strong correlation with observations ($r > 0.75$) but with weak spatial variability ($\sigma < 0.25$). It is recommended that for climate impact assessment and hydrologic modelling studies, multi-model ensembles of CanESM2, IPSL, CNRM-CM5 and HadGEM2-ES be used. However, on singular basis, the CanESM2 and HadGEM2-ES RCA4 simulation outputs present better representation of the climate of the basin.

1. Introduction

Globally, concerns on cutting down greenhouse gas (GHGs) emissions have gained strides in the past decade owing to the devastating contributory role to climate change (O'Neill et al., 2017; Pittock, 2017; Prather and Holmes, 2017; Urry, 2015). The exploit to reduce GHGs is further necessitated by increases in human induced causative factors such as population growth, agricultural exploitation, urbanization and technological advancement which aggravate the climate change phenomenon by altering the atmosphere-biospheric system (Griggs and Noguer, 2002; Liu and Bae, 2018; Morris et al., 2017; O'Neill et al., 2017; Paul et al., 2018; Valentini et al., 2014; Van Vuuren et al., 2017). Based on the medium variant population projection scenario proposed by the UN

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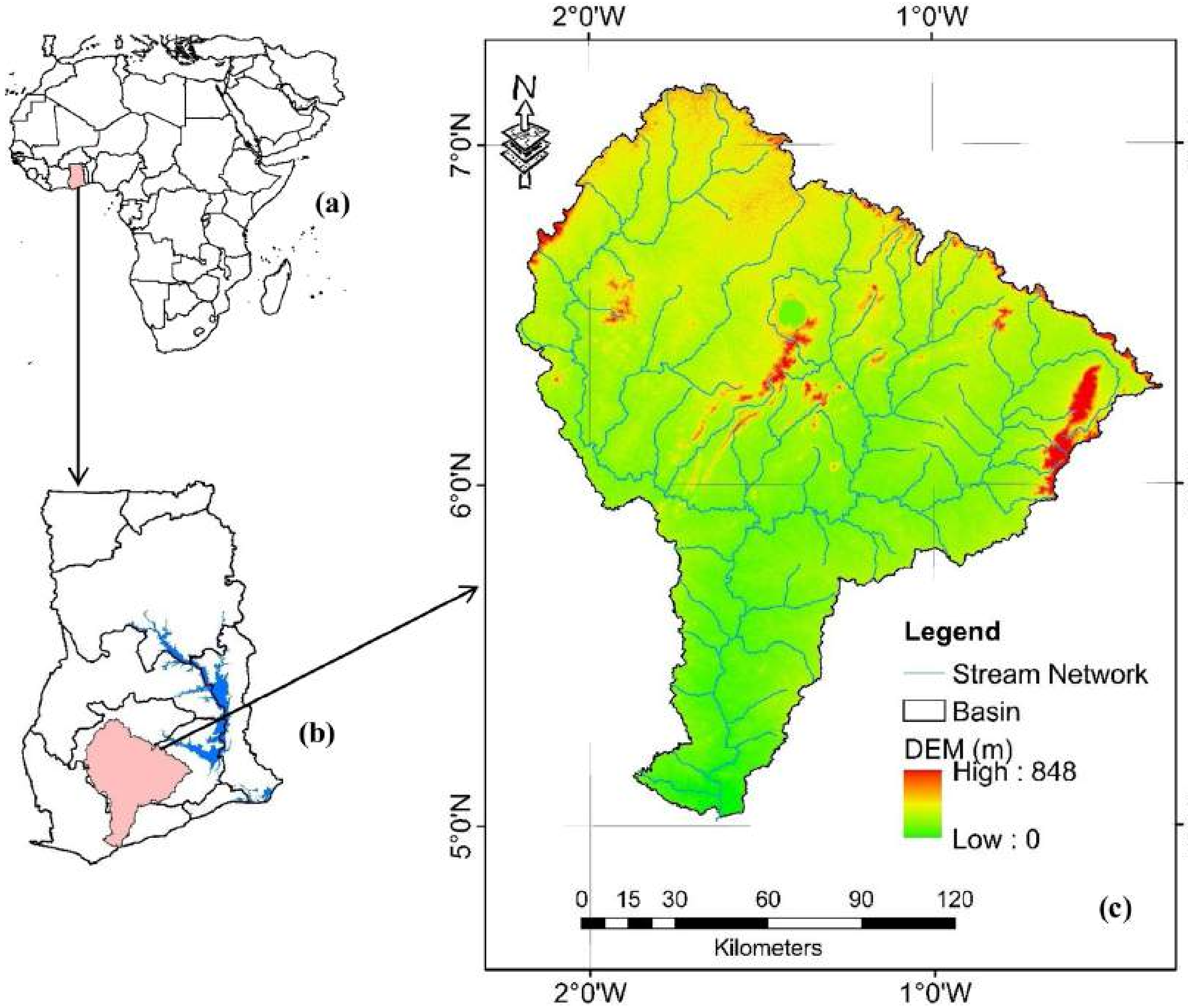

Fig. 1. Location of the study area; (a) African context, (b) National context and (c) Pra River Basin.

Department of Economics and Social Affairs (UNDESA), world population is expected to rise from 7.6 billion in 2018 to a total of 11.2 billion by the year 2100 (UNDESA, 2017). Though the change is not so astronomical compared to the lapse time (79 years from now), it is expedient to however acknowledge that these changes will correspondingly trigger surges in socio-economic development, agriculture diversity and industrialization culminating into major shifts in land uses and climatic patterns. Inevitably, these developmental trajectories will result in alterations of the atmosphere-biosphere system with the hydrological cycle being the most affected (Duan et al., 2017; Tan et al., 2017).

In a bid to minimize the impact of such changes in the future, hydrologic and climate scientist have foster joint research initiatives of predicting future hydrological dynamics as a result of climate change and land use alterations (Osei et al., 2018). This approach is deemed one of the most reliable means of evaluating water resources availability of the future under climate change (Xu, 1999). Ultimately, the broader agenda is to inform policy action through empirically based scientific evidence. Some of the renowned approaches in this arena of science are the use of General Circulation Models (GCMs) or Regional Climate Models (RCMs) in generating forcing variables as inputs into hydrologic models (Muthuwatta et al., 2018; Roth et al., 2018; Sharma et al., 2019; Tan et al., 2017). An added advantage in the use of RCMs and GCMs is the ability to make predictive studies for even ungauged basins. Owing to this advantage, many researchers have employed RCMs and GCMs in their quest to comprehending the biosphere-hydrologic cycle-climate change nexus (Chilkoti et al., 2017; Trang et al., 2017; Akinsanola et al., 2018; Oyerinde et al., 2017).

In West Africa, Sylla et al. (2016) evaluated the shift in climate zones as a result of anthropogenic activities using ensembles of CMIP5 GCM, CORDEX RCM and HIRES RegCM4. Their results indicate the relevance of the application of RCMs and GCMs simulation outputs in unraveling the anthropogenic consequences to climate alterations. Yira et al. (2017) also assessed the impact of climate change on hydrological processes of a tropical West African Catchment using ensemble of RCMs under two RCP scenarios. Notwithstanding, Oyerinde et al. (2017) affirms the inconsistencies found in GCMs application and how this translates into difficulties in modeling the perturbations in hydro-climatic conditions of regions. In view of this, the ability of RCMs and GCMs in replicating precipitation as an essential climatic input for a given climatic region for hydrologic modelling cannot be overstated. It is worth noting that the inconsistencies noted in RCMs and GCMs can in part be attributed to the physical discrepancies in geographic locations of particular climatic regions which are very much sensitive to land surface scheme components of global circulation models. Natural climate variability and imperfect characterization of tropical precipitation systems have also been noted to contribute to the divergence found in model simulation outputs (Cook and Vizy, 2006; Foley, 2010). The performance evaluation of RCMs and GCMs also ensures the selection of an appropriate global or regional model for evaluating the dynamics of climate change on water resources. Pertinent to the call of climate modeling and it impact assessment on diverse related fields, are the roles played by precipitation and temperature. In fact, changes in these two climatological variables gives indication of the changes occurring in global climate and thus their frequent assessment remains imperative to understanding the perturbations therein.

In its entirety, the application of RCMs and GCMs in espousing future climate changes in semi-arid Ghana has not been well articulated with the few works (Agyekum et al., 2018; Annor et al., 2018; Jin et al., 2018; Darko et al., 2019; Okafor et al., 2019) focusing primarily on the Volta Basin. It is imperious to admit that though these studies have contributed significantly to understanding the climatology of Ghana, its application has been skewed towards the Volta Basin. Harnessing water resources of Ghana in a sustainable manner in the near future and ensuring the continual survival of ecosystem services calls for pragmatic measures in the wake of climate change and thus scaling out climate change studies into other equally important basins become crucial.

In this study, we focused our attention on the Pra River Basin (PRB) primarily because of two major reasons; (i) the PRB has the highest density of settlements in Ghana (both rural and urban) (Bessah et al., 2018) and thus the impact of future climate change resulting in floods, droughts and other related events will be dire and (ii) the PRB is home to some rare and endangered ecosystem species (UICN/PACO, 2010) most of which are water reliant and thus ensuring their continual survival and provision of their essential ecosystem services remain fundamental. To this end, resilient climate change adaptation strategies backed by apt scientific evidence need to be deployed along the divergent hierarchy of the decision-making process to inform policy makers, engineers and planners.

The current study evaluates the performance of nine RCMs in replicating the observed precipitation, a key determinant of the hydrologic cycle of the Pra River Basin with the aim of providing a firm understanding for the selection of appropriate RCMs for future impact assessment of climate change on hydrological dynamics of the Basin. In section 2, the observational and model datasets, their sources and the analysis performed are presented. Section 3 discusses the results with study limitations given in section 4. The study is summarized and concluded in section 5.

2. Study area and data availability

2.1. Study area

The Pra River Basin (PRB) is a key river system in south-central part of Ghana. It is located between geographic latitudes 05° 00’ 00” N - 7° 11’ 24” N and longitudes 00° 26’ 30” W - 02° 14’ 40” W (Fig. 1). The Pra River is drained mainly by the Anum, Birim, Offin and the Oda river tributaries. With a drainage area of about 23, 200 km^2 (Water Resources Commission (WRC, 2012), the PRB spans four regions namely Ashanti, Eastern, Central and Western with corresponding coverage areas of 55 %, 23 %, 15 % and 7 % respectively (Water Resources Commission (WRC, 2012). Originating from the eastern and north-western fringes of Ghana, the Pra River traverses a distance of 240 km before finally emptying into the Gulf of Guinea. Generally, topography of the basin is flat with some isolated cases of higher altitudes in the mid and northern portions (Fig. 1).

The basin is found within the forest ecological zone of Ghana with a wet sub-equatorial climatic condition characterized by two rainy seasons; major and minor occurring in May-July and September-November respectively. The mean annual precipitation for 1981–2010 is about 1,446 mm (Bessah et al., 2020) with noted spatio-temporal variations in the westwards and south-westwards directions. Mean annual potential evapotranspiration is estimated to be 1650 mm (Kankam-Yeboah et al., 2013). The average minimum and maximum air temperatures are 23 °C and 33 °C (Awotwi et al., 2019). The PRB is home to about 4.2 million people most of whom are engaged in agriculture. Subsistence farming remains the major farming option where farm crops such as maize, cassava and plantain are cultivated to cater for the needs of the family. Large commercial farms focus on the production of only cocoa. Farming activities in the PRB are mainly rain-fed as irrigation technologies are pervasive and as a result understanding the precipitation patterns with its seasonal and interannual variations will provide a resourceful tool for farmers in farm planning and scheduling.

Surface water resources of the basin originate from precipitation and are thus very useful for domestic, industrial and agricultural purposes. There exist a number of dams constructed on different tributaries of the Pra River to provide water for economic development. Reduction in precipitation amount due to drought will hamper water supply for domestic, agricultural and industrial uses translating into stunted economic growth. The study area is renowned for its high gold deposits especially in the Tarkwaian and Birimian rock series (Smith et al., 2016; Tetteh and Effisah-Otoo, 2017) with active mining companies such as AngloGold Ashanti, Resolute Amansie limited, Chirano Gold mines among others operating from here. These companies rely on surface water or ground water sources for their operational activities and thus any changes in the precipitation and temperature patterns within the basin will adversely affect operations of these companies.

2.2. Data sources and methods

2.2.1. Observational data

The difficulties encountered in the acquisition of ground observed climatological variables resulting from lack of well distributed gauging networks and policy directives on data usage is driving the frontiers of hydro-climatological studies into relying on open

Table 1
Details of forcing GCMs and RCMs used in this study.

Driving GCM	RCM	Short name	Spatial resolution (Lon x Lat)
CCCma-CanESM2	RCA4	CanESM2	0.44° x 0.44°
MOHC-HadGEM2-ES	RCA4	HadGEM2-ES	0.44° x 0.44°
MPI-M-MPI-ESM-LR	RCA4	MPI-LR	0.44° x 0.44°
CNRM-CERFACS-CNRM-CM5	RCA4	CNRM-CM5	0.44° x 0.44°
CSIRO-QCCCE-CSIRO-MK3-6-0	RCA4	CSIRO-Mk3	0.44° x 0.44°
ICHEC-EC-Earth	RCA4	EC-Earth	0.44° x 0.44°
IPSL-IPSL-CM5A-MR	RCA4	IPSL	0.44° x 0.44°
MIROC-MIROC5	RCA4	MIROC5	0.44° x 0.44°
NCC-NorESM1-M	RCA4	NorESM-1	0.44° x 0.44°

source gridded datasets (Annor et al., 2018; Pinto et al., 2016). Open source datasets provide an avenue where huge climatic datasets are freely acquired for hydrological and climate impact assessment without limitation to local or regional scale tendencies. One such open source data is the gridded precipitation data based on gauge-satellite products. The accuracy of various types of open source gridded data is thoroughly examined in the literature (Nerini et al., 2015), with successful applications with hydrologic models for hydrological assessment at the basin scale (Skoulikaris et al., 2020). In this study, version 7 (v7) of the Global Precipitation Climatology Centre (GPCC) precipitation time series dataset was used as reference data in validating precipitation outputs from the models (available at ftp://ftp.dwd.de/pub/data/gpcc/html/fulldata-monthly_v2018_doi_download.html). The GPCC was chosen over other available open source gridded precipitation datasets such as the Global Precipitation Climatology Project (GPCP), Tropical Precipitation Measuring Mission (TRMM) and Climate Prediction Center Morphing Technique (CMORPH) because of its ability to capture the high variability observed in West African climate (Agyekum et al., 2018; Annor et al., 2018; Okafor et al., 2019). It is also the case that GPCC has been extensively used in the evaluation of Africa Climate zones with proven track record of robustness (Asfaw et al., 2018; Agyeman et al., 2017; Nikulin et al., 2012; Nicholson et al., 2003). Moreover, the development of GPCC saw the incorporation of quite a substantial number of gauge records from the West African Sub-region (Annor et al., 2018). The GPCC version 7 consists of gridded daily time-step precipitation data with spatial resolution of 0.5° × 0.5° covering the entire globe and spanning 1901-2013.

2.2.2. Model data

The Regional Climate Model (RCM) simulation outputs analyzed in this work are that from the Swedish Meteorological and Hydrological Institute Rossby Centre; Regional Climate Model (RCA4) driven by nine (9) Global Circulation Models (GCMs). The simulation outputs were all from the same ensemble members (i.e realization, initialization and perturbation 1; r1i1p1). These datasets forms part of the CORDEX Africa project which features in the fifth phase of the Coupled Model Intercomparison Project (CMIP 5). The choice of RCM-RCA4 was premise on the extensive use of RCA4 model output simulations and data availability for the RCP scenarios (Okafor et al., 2019; Wilcke and Bärring, 2016) which provide relevant sources of information for climate change impacts assessment as well as for hydrologic modelling of the basin. Table 1 presents the nine forcing GCMs, their acronyms and their spatial resolution. For the purposes of analysis, daily time step outputs of model simulations were acquired for precipitation for a 31-year period (1975–2005). For ease of comparison, all the model datasets were bilinearly interpolated into a 0.5° × 0.5° grid resolution conforming to that of the observed. Bias adjustments were not executed, as the aim of this study was to evaluate the performance of the raw climate simulation outputs to the observed. However, it is imperative that bias corrections be carried out when outputs of model simulations are being used for impact assessment.

2.2.3. Methods

The performance of the models in replicating the observed precipitation over the PRB was carried out at the annual, seasonal and monthly timescales during 1975–2005. This time period was chosen to maximize observational data availability in the PRB domain. Spatial relative biases of the models were generated based on the annual mean and annual totals for precipitation. At the seasonal scale, analysis was grouped based on the standard seasons; winter (DJF), spring (MAM), summer (JJA) and fall (SON) to discriminate how well the models predict the observed with respect to seasons. The temporal patterns, variability and errors inherent in the models were assessed using the pattern correlation, standardized deviation and root mean square difference respectively. These metrics were summarized using the Taylor diagram (Gleckler et al., 2008; Pincus et al., 2008; Taylor, 2001). Trends in seasonal precipitation were analyzed with the Mann-Kendall (MK) test (Kendall, 1948; Mann, 1945) and change point detection with the non- parametric Pettitt test (Pettitt, 1979). The Mann-Kendall and Pettitt test were computed at the 95 % significance level.

3. Results and discussion

3.1. Annual mean climatology

First, the annual performance of the selected downscaled RCA4 CORDEX Africa multi-model simulations in comparison with the GPCC precipitation data (i.e observed) were examined (Fig. 2). CanESM2, CNRM-CM5, CSIRO-Mk3, HadGEM2-ES and IPSL underestimated the observed mean annual precipitation of 1331.3 mm/yr with corresponding values of 1040.2 mm/yr, 1224.6 mm/yr, 608 mm/yr, 1307.8 mm/yr and 1328.4 mm/yr respectively. CSIRO is an outlier when it comes to simulating the long-term mean annual

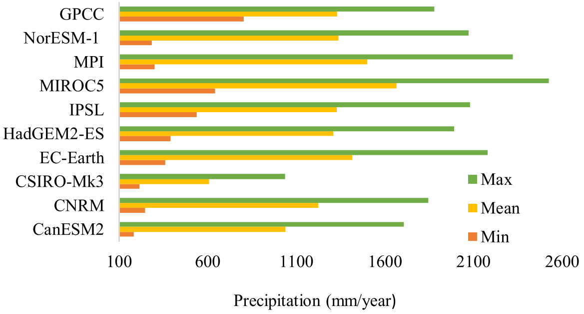

Fig. 2. Annual precipitation for the observed and nine RCA4 models for the period, 1975-2005.

precipitation. HadGEM2-ES and IPSL closely predicted the observed mean annual precipitation. Models that overestimated the observed were EC-Earth, MIROC5, MPI and NorESM-1 with corresponding values of 1416.3 mm/yr, 1664.4 mm/yr, 1499.3 mm/yr and 1338.8 mm/yr respectively. The maximum observed precipitation (1877.8 mm/yr) though underestimated was closely simulated by CanESM2 (1707.7 mm/yr), CNRM-CM5 (1846.1 mm/yr) and slightly overestimated by HadGEM2-ES (1991.6 mm/yr). Spatial mean relative bias plots of the RCA 4 models and the observed are shown in Fig. 3. Except CSIRO-Mk3, all the remaining models consistently overestimated the long-term annual mean precipitation with mean bias ranges of 0.8 % to 45.6 %. For a greater portion of the PRB, CanESM2, IPSL, CNRM-CM5 and HadGEM2-ES captured fairly the observed precipitation with mean biases of 0.8 %, 16.7 %, 18.1 % and 18.4 % respectively. CanESM2 estimates very well the observed precipitation over the middle belt of the PRB with overestimations and underestimations recorded in the northern and southern sections of the basin respectively (Fig. 3a)

Bessah et al. (2018) also found CanESM2 and IPSL to be performing well for the PRB, however their analysis focused on temperature. Generally, for all the models analysed in this study except CSIRO-Mk3, the observed precipitation in the northern parts of the PRB were greatly overestimated with narrowing trends towards the southern direction. The overestimations of the observed were high with descending pattern in the order for MIROC5 (Max: 63.1 %, Avg: 45.6 %, Min: 13.5 %), MPI-LR (Max: 57.2 %, Avg: 39.5 %, Min: -4.5 %) and NorESM-1 (Max: 51.6 %, Avg: 27.0 %, Min: -23.1 %). MIROC5 and CSIRO-Mk3 were the two RCA4 models found to be on the extremes with MIROC5 overestimating the observed over the entire PRB whiles CSIRO-Mk3 underestimated the observed for the whole basin. For CSIRO-Mk3, the under estimations were higher in the southern part of the basin with bias of -60 % improving through the middle belt (bias of -43 %) and the northern section (-25 %). Unlike CSIRO-Mk3, MIROC5 rather showed increasing deviation in the mean observed precipitation in the south to north direction of the basin. Based on the annual mean climatology, it seems to suggest that CanESM2, IPSL, CNRM-CM5 and HadGEM2-ES are predicting relatively well the observed annual mean precipitation. Considering the predictive power of the four RCA4 CORDEX Africa models, further analysis at the seasonal and monthly timescales is limited to only these models and their ensemble mean.

3.2. Climatological mean for seasonal totals

The climatological mean for seasonal totals is presented for the standard seasons; winter (December, January, February-DJF), spring (March, April, May-MAM), summer (June, July, August-JJA) and fall (September, October, November-SON) for CanESM2, IPSL, CNRM-CM5, HadGEM2-ES and Ensemble mean (Figs. 4–7). Winter and summer observed precipitation were respectively underestimated and overestimated by all the models. In winter minimal precipitation is recorded with heavy precipitation in the summer season. The nonperformance of these models in simulating the characteristics of winter and summer precipitation could be attributed to the model's inability to capture the inherent characteristics of the atmospheric and physiologic conditions (eg, convective clouds, vegetation, orography) that dictates precipitation patterns at a shorter time scale (Wilby and Wigley, 1997). It is also the case that in summer, precipitation varies substantially in space as a result of differing convective activities which may militate against the performance of the models at the mesoscale (Nicholson and Grist, 2003; Laing and Fritsch, 1993).

Over the PRB, the magnitude of the underestimations was higher in the northern part and decreases down south for the winter period (Fig. 4) whilst for summer a range of spatial variability in bias magnitude was observed (Fig. 6). In summer, IPSL exhibited a stronger positive mean bias magnitude in the south of the basin contradicting that from CNRM-CM5 which rather showed a stronger magnitude in the north of the basin. These disparities suggest that depending on the governing boundary conditions upon which these models were built, sharp contrast could be detected owing to how the models translate scale-related sensitivities of cloud feedback effects, water vapour and other geographic physiognomies into its system. For both spring and fall, CNRM-CM5 and the Ensemble mean revealed the least deviations from the observed precipitation (Figs. 5 and 7). In both seasons, CNRM-CM5 overestimates the observed (mean bias of 3.8 % for spring and 2.5 % for fall). The Ensemble mean indicated good model performance however with underestimations to the tune of -9.9 % and -2.2 % respectively for spring and fall. Findings show that there is not a particular model that does well for all the seasons and thus leveraging on the respective seasonal strength of each of the models could improve the

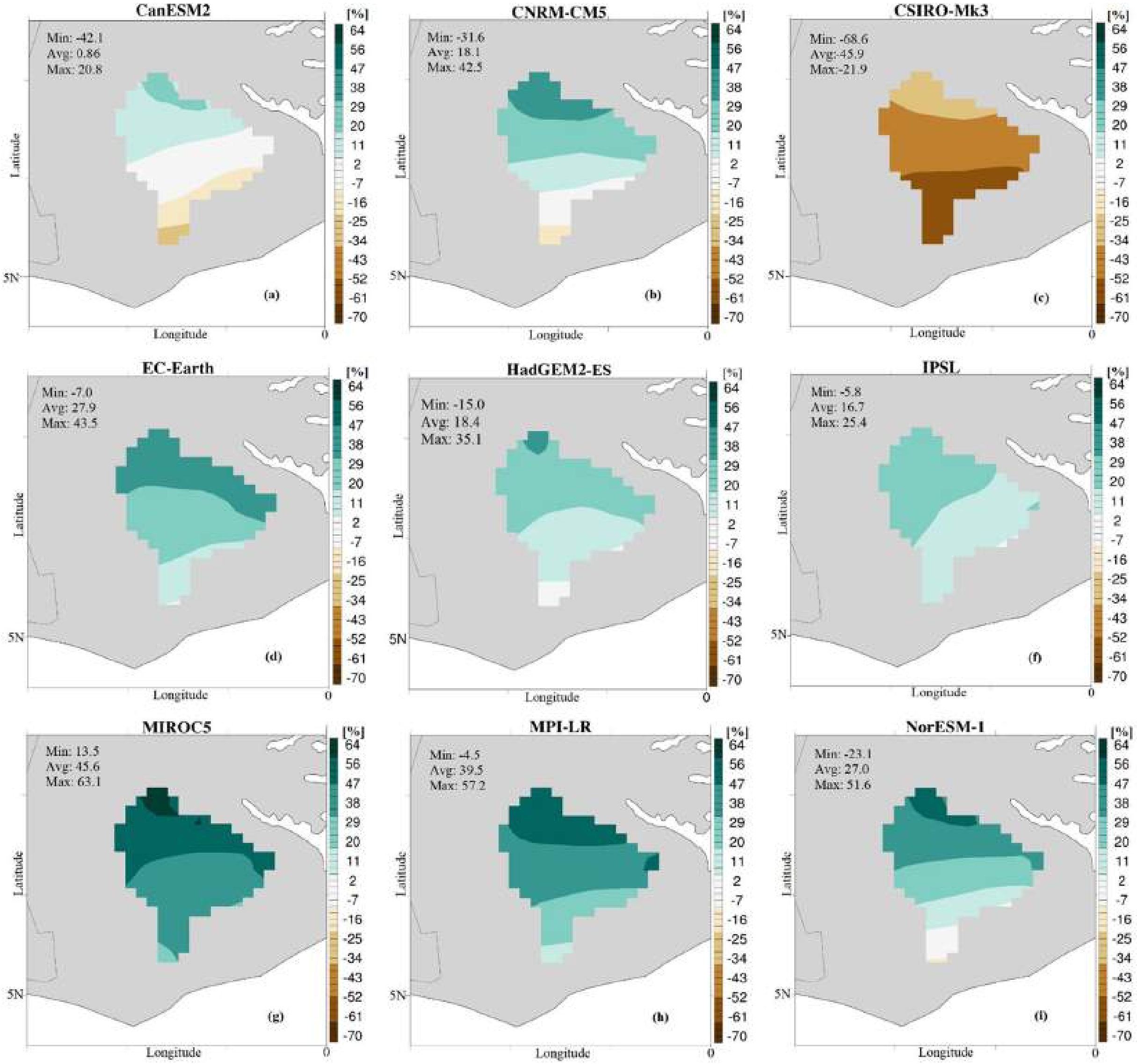

Fig. 3. Bias maps (1975-2005) for climatological mean of annual precipitation for models: (a) CanESM2, (b)CNRM-CM5, (c) CSIRO-Mk3, (d) EC-Earth, (e) HadGEM2-ES, (f) IPSL, (g) MIROC5, (h) MPI-LR and (i) NorESM-1 in comparison with GPCC precipitation data.

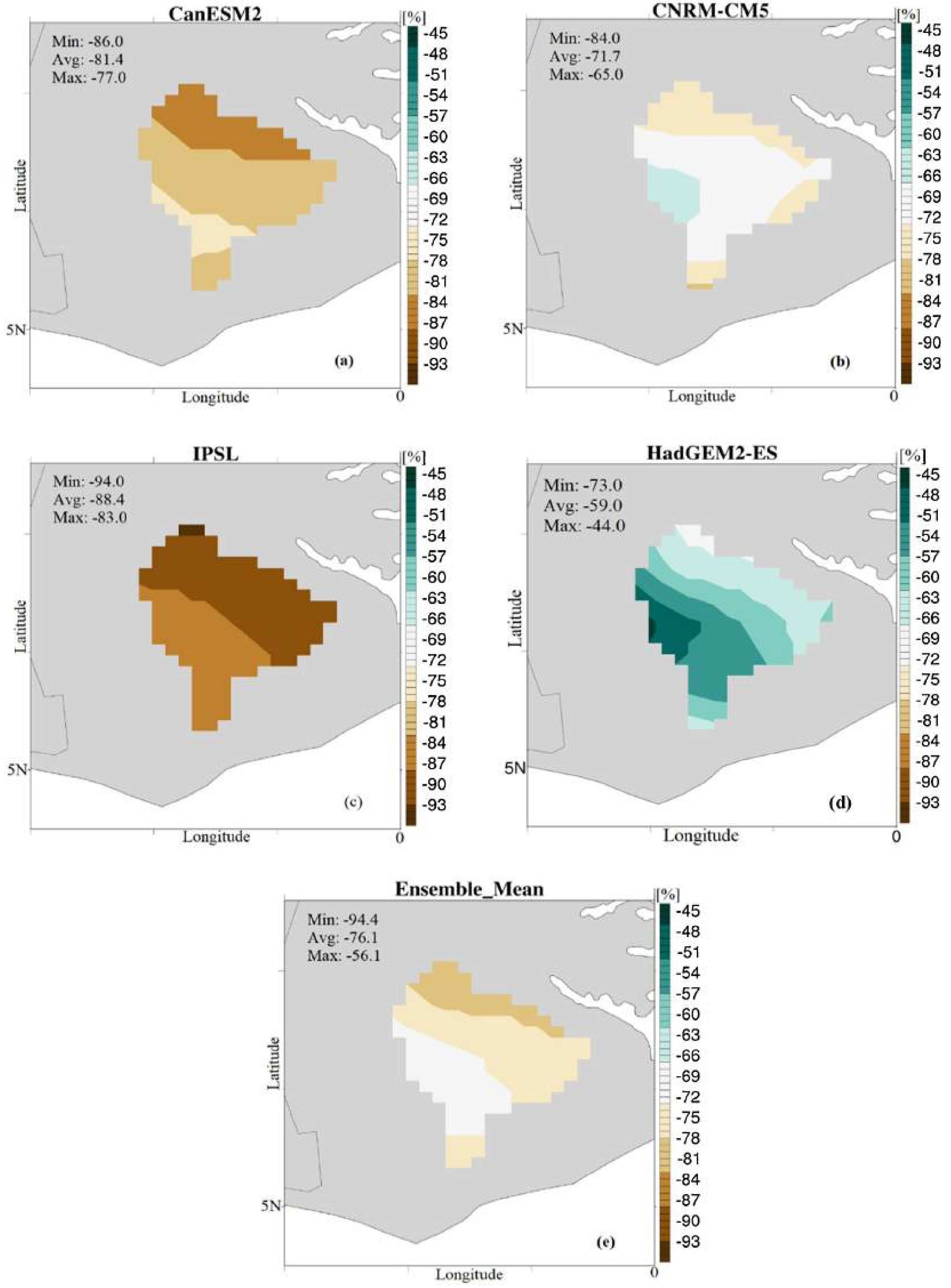

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Fig. 4. Bias maps (1975-2005) for climatological mean of winter (DJF) seasonal precipitation for models: (a) CanESM2, (b) CNRM-CM5, (c) IPSL, (d) HadGEM2-ES and (e) Ensemble Mean in comparison with GPCC precipitation data.

credence of climate change impact assessment. Overestimations of the observed precipitation predominantly occurred in the northern part of the basin during spring and fall periods.

3.3. *Annual cycles of monthly climatology*

For climate impact analysis where seasonality and sensitivity of precipitation as a variable is essential for forecasting, it is imperative that climate models are able to predict the migration pattern of precipitation onset through till its cessation in the northwardly direction (Laux et al., 2008). The long-term monthly climatology averaged over the PRB was examined with results presented in Fig. 8.

Model simulations indicate the presence of bimodal precipitation patterns peaking in June and October over the PRB in accordance with that detected by the observed dataset. The first peak (228.55 mm) in the observed data (GPCC) occurs in June with HadGEM2-ES (236.25 mm) closely capturing this peak although overestimated. The remaining models including the Ensemble mean (CanESM2,165.30 mm; CNRM-CM5, 151.90 mm; IPSL, 187.98 mm; Ensemble mean, 156.66 mm) underestimated the peak precipitation for the period. The second peak in the observed data occurred in October (159.52 mm) and was underestimated by all the models. A general observation is that, HadGEM2-ES reproduce well the long-term monthly variations over the PRB in comparison with the observed GPCC. The precipitation pattern decreases from June to a minimum (76.67 mm) in August, indicating the occurrence of a mild dry season. All the models failed to capture this mild dry season observed in the summer period with HadGEM2-ES relatively mimicking this characteristic of the annual cycle.

The general precipitation pattern with respect to onset, mild dry season and cessation is similar to that reported for the Volta Basin by Okafor et al. (2019). It is instructive to note that although the PRB is not part of the Volta Basin, these two basins share a boundary and thus similar characteristics in bimodal precipitation patterns is not out of the ordinary. In fact, the Volta Basin and the PRB all recorded their bimodal precipitation peaks in the same months of June and October (Okafor et al., 2019). The models were unable to capture exactly the mild dry season which occurred in the summer period, although they followed the general pattern observed in the GPCC dataset with the exception of IPSL. Variations in magnitude of the model simulations for August viz-a-viz those of the observed GPCC dataset were noticeable. Earlier studies by Laux et al. (2008) and Agyekum et al. (2018) indicate that the Guinea coast in which the PRB is located exhibits similar precipitation patterns with major and minor peaks in June and September. Mainly, the onset of precipitation for the PRB is in February with all the models capturing the time extent however with differing magnitude. Similar observation is true for the cessation of precipitation in November.

3.4. *Interannual variability*

The deviations of annual mean precipitation from the long-term mean for the period 1975–2005 was examined for all the four models and the multi-model Ensemble mean (Fig. 9). The interannual variability provides information on the consistency of the models compared to the observed GPCC. From Fig. 9, the models captured to a large extent the interannual variability that characterized the precipitation patterns within the PRB however with some disparities in the magnitude and timing. Akinsanola et al. (2015) and Okafor et al. (2019) reported similar features of the CORDEX Africa Models in capturing the interannual variability of observed data. The performance of the models was also assessed using their predictive power in identifying wet and dry years during 1975–2005. The wet and dry years were identified based upon whether the annual mean precipitation for a particular year was greater or lesser than the long-term mean for the period 1975–2005. For the period in question, thirteen dry years and eighteen wet years were identified based on the observed GPCC (Fig. 10). The Ensemble mean and HadGEM2-ES simulated similar occurrence of dry and wet years but not necessarily for corresponding years as recorded by the GPCC (Fig. 10).

The remaining models (CanESM2, CNRM-CM5 and IPSL) overestimated the occurrence of dry and wet years. Deviation ranges for all the models were 0.56–32.28 % and 2.41–32.62 % for dry and wet years respectively in comparison with the long-term mean of the observed. Considering wet years, 1979 was found to be the wettest (1731 mm) with precipitation amount in excess of 30 % from the long-term mean (1331.4 mm) for 1975–2005. The multi-model Ensemble mean of the RCA4 simulations predicted fairly well the 1979 wet year (1242 mm) with 28 % variation from that observed by GPCC (1731 mm). The driest year (936 mm) coincided with 1983 with 29.7 % deviation from the long-term mean (1331.4 mm) for the GPCC data. Similarly, the multi-model Ensemble mean simulated quite well the 1983 dry conditions (1215 mm) with a margin of error of about 8.7 % from the long-term mean of the observed GPCC dataset.

3.5. *Taylor diagrams*

In order to assess the various model’s ability to reproduce the spatio-temporal patterns and variability inherent in the GPCC

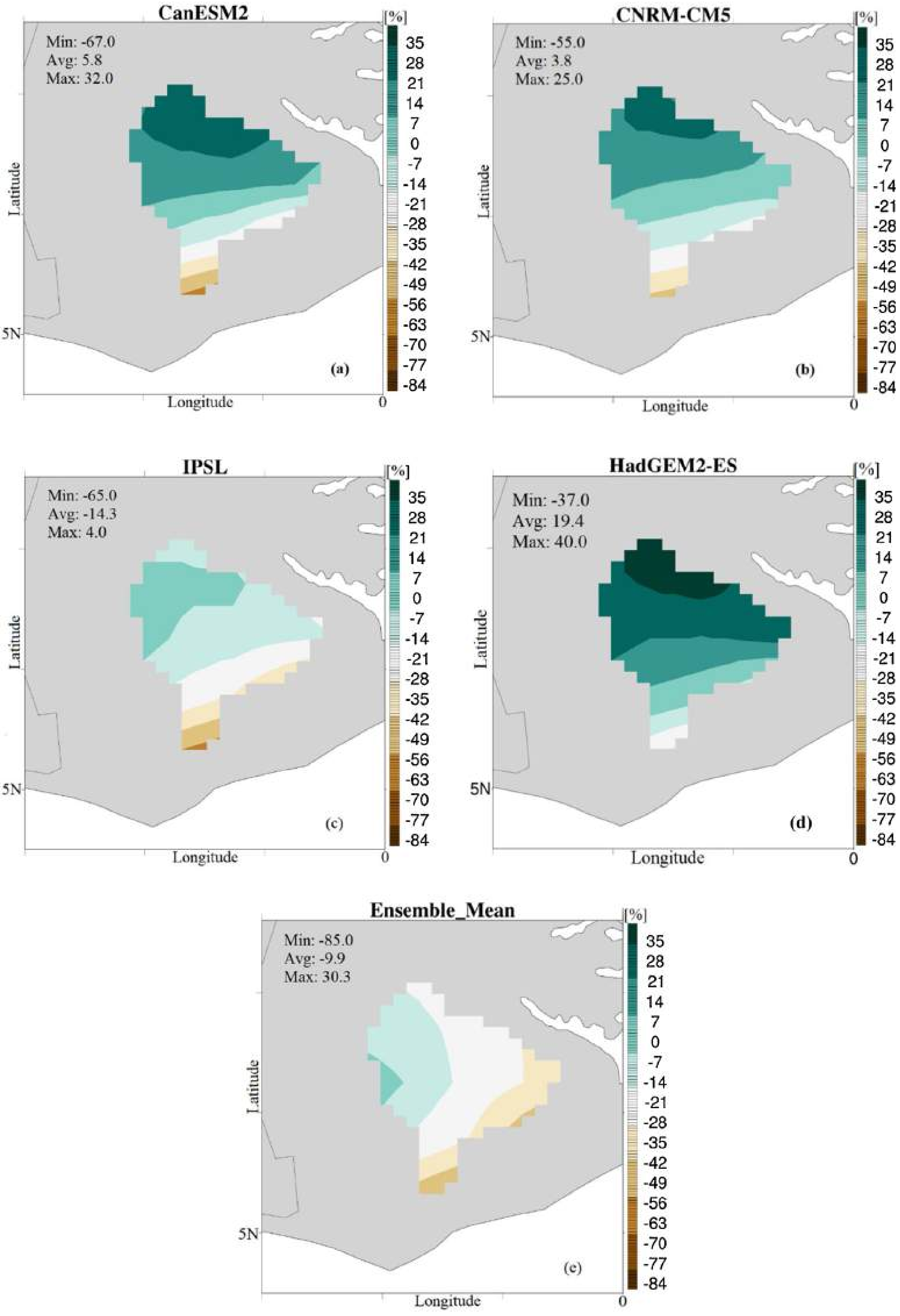

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Fig. 5. Bias maps (1975-2005) for climatological mean of spring (MAM) seasonal precipitation for models: (a) CanESM2, (b) CNRM-CM5, (c) IPSL, (d) HadGEM2-ES and (e) Ensemble Mean in comparison with GPCC precipitation data.

observed precipitation data, Taylor diagrams (Taylor, 2001) were plotted for the PRB (Fig. 11). The Taylor diagram presents a statistical summary of model's predictive power of variability, pattern and errors in comparison with GPCC data using the normalized standardized deviation (σ), correlation coefficient (r) and root mean square difference. The vertical (or horizontal axis), the main arc and inner arcs indicate respectively the normalized standard deviation, correlation and root mean square difference. All the models showed differences in variability and pattern at the seasonal scale. In winter, IPSL and CanESM2 showed a positive correlation with the GPCC data however reproducing weakly the temporal variability ($\sigma < 0.25$) inherent in the observed. In spring, all the models presented a negative correlation (no points shown on the taylor diagram) indicating the inability of the models in predicting the characteristics of precipitation in this season. In summer, IPSL ($r = 0.40$), CanESM2($r = 0.20$) and HadGEM2-ES ($r = 0.25$) correlated positively with the observed indicating the capability of the models in simulating the spatial pattern of precipitation although low. Low temporal variability was captured by IPSL and CanESM2 with σ ranging 0.25−0.50. Contrary to the variability performance of IPSL and CanESM2, HadGEM2-ES showed high variability ($\sigma = 1.40$) in summer. For fall, HadGEM2-ES and CNRM-CM5 simulates similar spatio-temporal variability ($\sigma = 0.60$) but with dissimilarities in pattern recognition; HadGEM2-ES ($r = 0.10$) and CNRM-CM5 ($r = 0.20$).

The Ensemble mean of the RCA4 simulations correlated negatively for winter and spring but positively for summer and fall. The positive correlation for the summer and fall season is attributed to the maximum precipitation patterns occurring mostly during these seasons. For summer and fall, the Ensemble means captured well the spatial patterns of the observed GPCC data ($r > 0.75$) but poorly simulated the variability ($\sigma < 0.25$) of the observed. In general, the HadGEM2-ES RCA4 model performed well both in terms of simulating the spatio-temporal patterns and variability of the observed GPCC data. Although, the Ensemble mean performed creditably well with respect to the spatial patterns of the observed precipitation, it fell short in capturing the observed spatial variability.

3.6. *Trend analysis*

Further assessment of the RCA4 simulation models was carried out using the Mann-Kendall test to analyze the trends inherent in the models in the observed precipitation. The trend analyses were performed at the 95 % confidence level with corresponding threshold value (Z) of ±1.96. The null hypothesis of no trend in the time series data is rejected should $|Z_s| \geq Z_{\alpha/2}$. The Pettitt test was used in identifying the change point within the time series data of the observed and model simulations with the significance of the change point being detected at the 95 % confidence level. The trend test results for the four standard seasons (winter-DJF, spring-MAM, summer-JJA and fall-SON) are presented in Table 2.

A snapshot of the trend statistics indicates a general decline in observed and simulated precipitation for all the seasons except fall although these declines are not significant. During winter observed precipitation reduced by 0.17 mm per season, however this reduction is not significant ($p > 0.05$). CanESM2, CNRM-CM5 and HadGEM2-ES were able to capture the declining pattern of precipitation in winter, nonetheless with differing magnitudes. CanESM2 and CNRM-CM5 depicted relatively well the decline in observed precipitation by 0.12 mm and 0.16 mm per season respectively. Predicted increases in precipitation were recorded by IPSL (0.09 mm per season) and the ensemble mean (0.03 mm per season) during the winter season contrary to that detected in the observed.

Similar observation is made in spring for the declining trend in observed precipitation (0.72 mm per season) which is fairly captured by CanESM2 (-1.19 mm per season) and CNRM-CM5 (-0.17 mm per season). In summer, CanESM2 and HadGEM2-ES detected the decreasing patterns of precipitation with magnitudes exceeding that of the observed data. The Ensemble mean for winter, spring and summer gave contradictory performance of the observed with most indicating precipitation increases over 0.1 mm per season.

None of the models were able to simulate adequately the change points noticed in the observed dataset. This goes to suggest that although some of the models have capabilities of capturing the trends, they are unable to detect the point of transition in the observed precipitation.

It could generally be inferred from the trend analysis that precipitation occurring over the PRB is declining although the rate of decline may seem to be insignificant. The uncertainty of 'lack of significance' in precipitation within climate models for this region is commonly known from previous studies (Okafor et a., 2019; Agyekum et al., 2018), and also translates to future climate projections. The decline in precipitation over the PRB could have detrimental implications on water resources availability, ecosystem services and functions as well as on socio-eco-hydrological characteristics of the basin.

4. Study limitations

The study presents useful information for the climate and hydrologic modeling community and in particular for the study region. However, the study comes along with some limitations. Only one RCM driven by multiple GCMs was considered. Although this

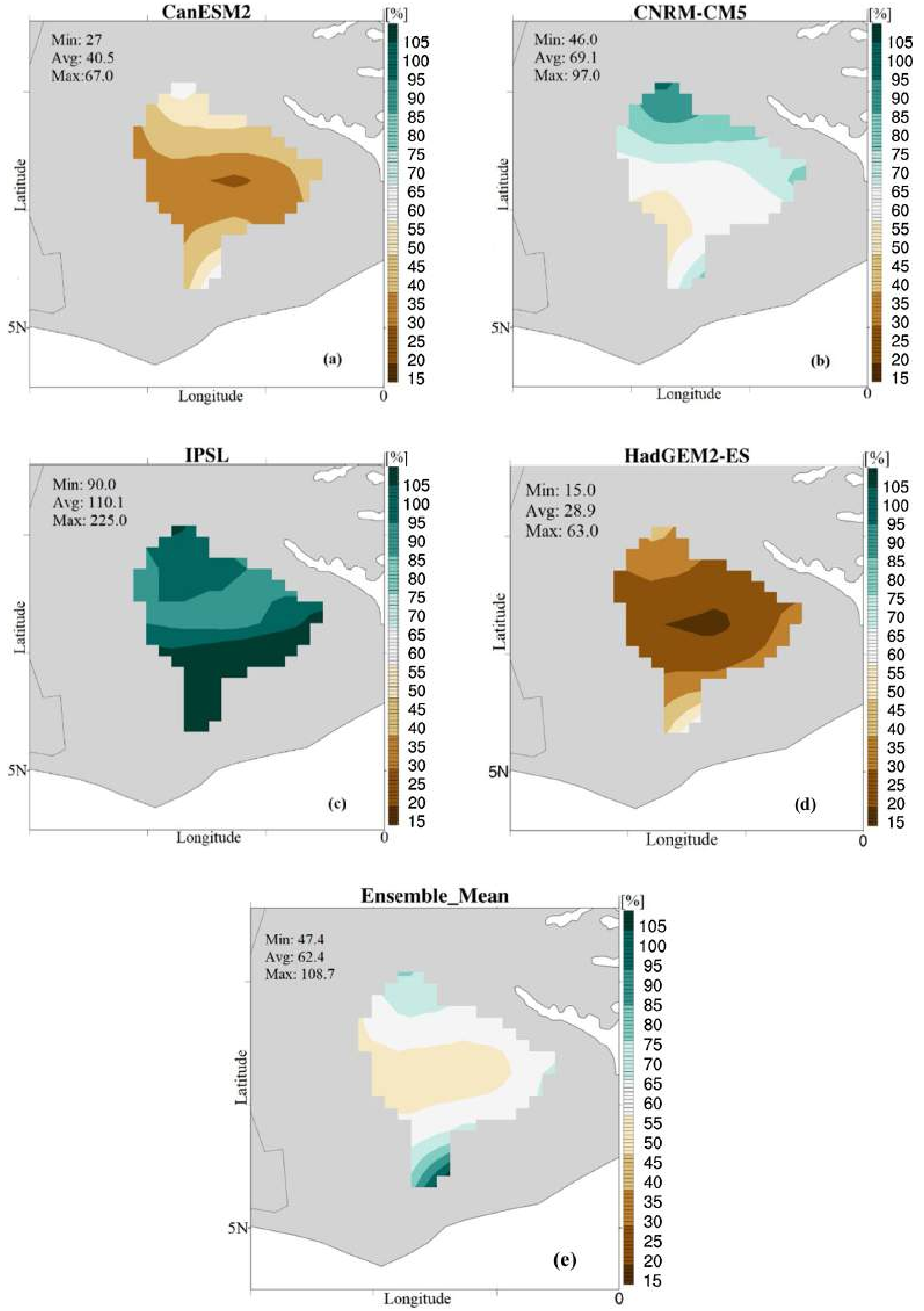

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Fig. 6. Bias maps (1975-2005) for climatological mean of summer (JJA) seasonal precipitation for models: (a) CanESM2, (b) CNRM-CM5, (c) IPSL, (d) HadGEM2-ES and (e) Ensemble Mean in comparison with GPCC precipitation data.

approach eliminates modeling uncertainty associated with the use of multiple RCMs driven by GCMs, it also presents the challenge of not capturing the full range of uncertainties that could have been observed had variant RCMs been used. In order to project future changes in precipitation over the PRB, a process-based evaluation is needed to ascertain the validity and ability of the models to represent key processes and dynamic features that control precipitation.

5. Summary and conclusions

Nine RCA4 CORDEX Africa multi-model simulations together with their Ensemble mean have been analyzed to evaluate their performance in reproducing the observed precipitation over the PRB. This assessment comes on the backdrop that climate change and hydrologic studies are shifting from the over reliance on ground station observed data to the use of climate models/ satellite-based information and thus the reliability of such datasets need to be affirmed to boost confidence in modelling exercises that rely on such types of datasets. Performance metrics were computed on the annual, monthly and seasonal scales. The findings of the study are summarized as follows;

- Based on the timescale, the nine RCA4 models exhibited varying degree of reproducibility of the observed precipitation in the PRB with CanESM2, IPSL, CNRM-CM5 and HadGEM2-ES predicting relatively fairly the observed across all timescales. On the annual scale, CanESM2 and IPSL gave good prediction of the observed with mean biases of 0.8 % and 16.7 % respectively. On the monthly timescale, simulation outputs from HadGEM2-ES indicated relatively good performance metrics in comparison with the observed.
- The spatio-temporal pattern and variability characterizing the precipitation of the PRB was captured relatively well by the simulation outputs of the HadGEM2-ES model. CanESM2 model equally detected the trends that were inherent in the observed GPCC data.
- There is a general decline in precipitation over the PRB. For the summer season where a greater proportion of the precipitation is recorded, a declining rate of 0.05 mm per season was noted in the observed although this decline was insignificant. The basin is also noted to be going drier at a rate of 0.17 mm per season in the winter period which happens to be the driest period in the year.

In conclusion, for hydro-climatological studies relying on RCM model simulations, it is recommended that the timescale at which the assessment is carried out be factored in the selection of the appropriate model. Overall, CanESM2 and HadGEM2-ES performed creditably well irrespective of the timescale and thus could be employed for detailed impact assessment. The discrepancies that exist in the models as compared to the observed maybe related to the convective parameterizations used in the models and thus remain a critical area for future investigations by the CORDEX community.

Authorship contribution

Charles Gyamfi: Conceptualization, data analysis and write up
Jacob Zora-Oni Tindan: Data curation and data analysis
Gislar Edgar Kifanyi: Structuring, data analysis and review

Declaration of Competing Interest

The authors report no declarations of interest.

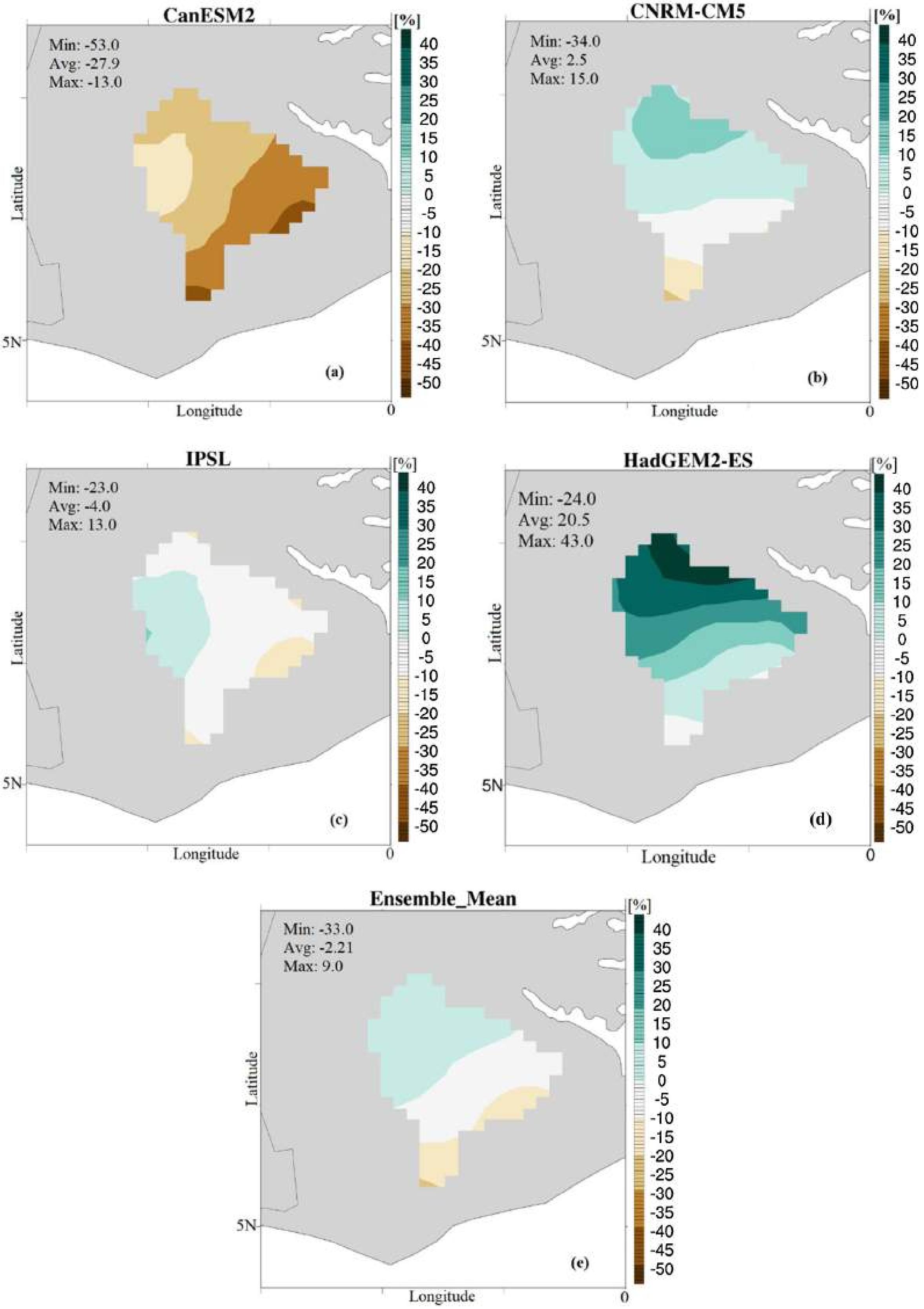

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Fig. 7. Bias maps (1975-2005) for climatological mean of fall (SON) seasonal precipitation for models: (a) CanESM2, (b) CNRM-CM5, (c) IPSL, (d) HadGEM2-ES and (e) Ensemble Mean in comparison with GPCC precipitation data.

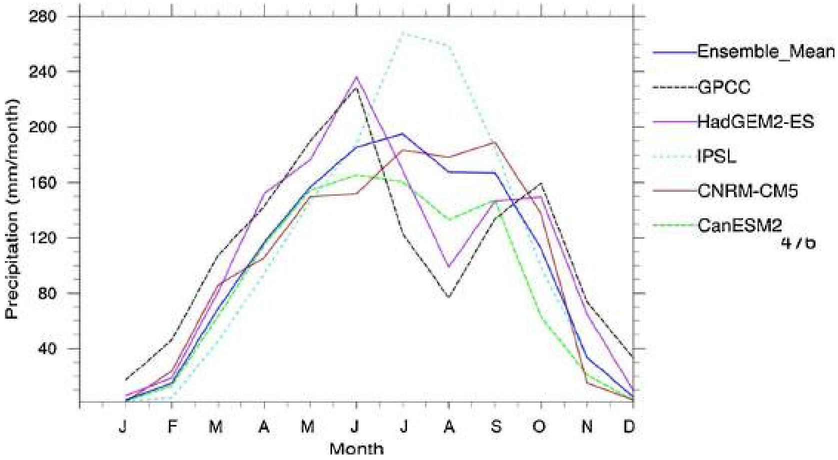

Fig. 8. Annual cycle of monthly total precipitation of the period mean averaged over the PRB.

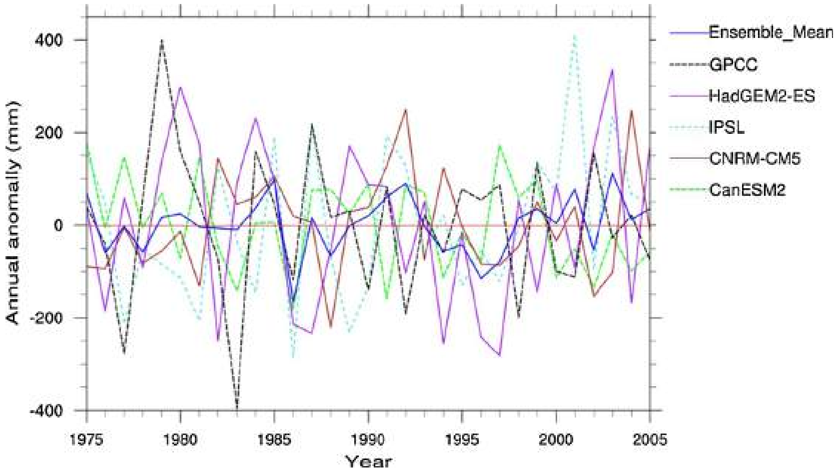

Fig. 9. Interannual variability over the Pra Basin for the period 1975-2005.

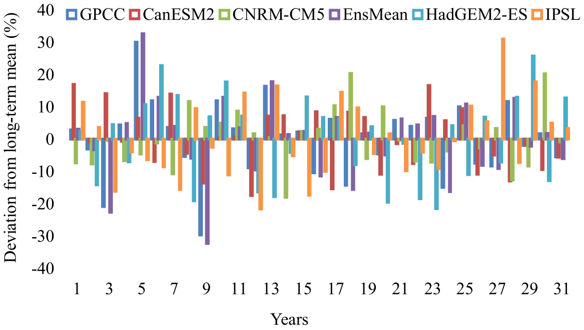

Fig. 10. Occurrence of dry and wet periods during 1975-2005.

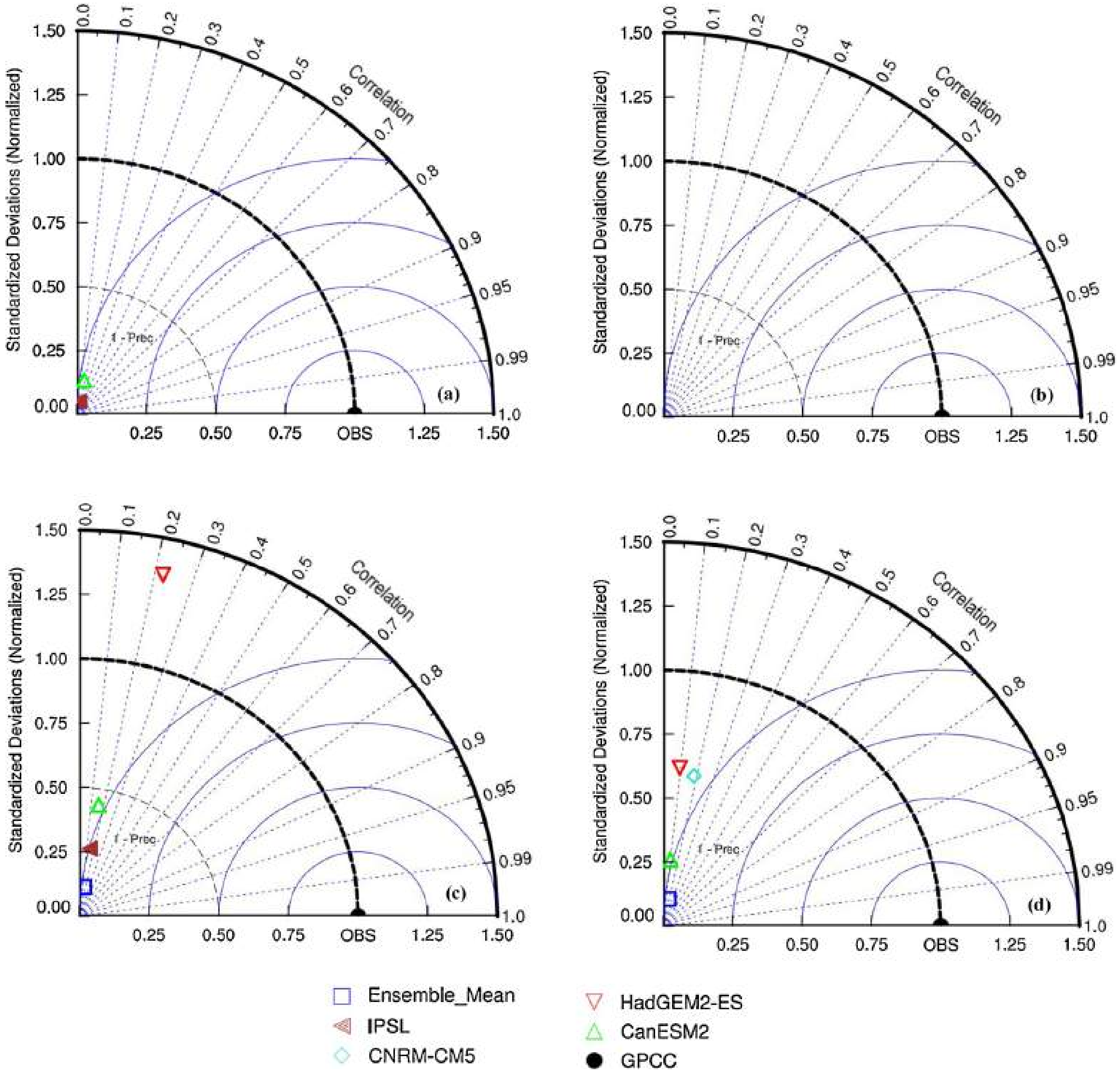

Fig. 11. Taylor diagrams for seasonal total precipitation with GPCC as reference dataset: (a) winter-DJF, (b) spring-MAM, (c) summer-JJA and (d) fall-SON.

Table 2
Trend analysis for precipitation over the Pra River Basin.

Models	Z	p-value	Slope	p-value (change point)	Change point year
Winter (DJF)					
GPCC (observed)	−0.2	0.811	−0.17	0.768	1981
CanESM2	−0.4	0.658	−0.12	1.085	1996
CNRM-CM5	−0.4	0.658	−0.16	1.276	1995
HadGEM2-ES	−0.6	0.496	−0.34	1.418	1984
IPSL	0.6	0.540	0.09	0.648	1995
Ensemble_Mean	0.3	0.759	0.03	1.037	1980
Spring (MAM)					
GPCC (observed)	−0.6	0.496	−0.72	0.573	1982
CanESM2	−0.8	0.414	−1.19	0.573	1997
CNRM-CM5	−0.1	0.918	−0.17	0.768	1992
HadGEM2-ES	0.3	0.708	0.95	0.899	2001
IPSL	1.0	0.307	1.34	0.573	1993
Ensemble_Mean	0.9	0.358	0.77	0.990	2000
Summer (JJA)					
GPCC (observed)	−0.1	0.945	−0.05	1.132	1978
CanESM2	−0.5	0.586	−1.27	0.768	1999
CNRM-CM5	1.1	0.276	1.37	0.411	1989
HadGEM2-ES	−0.5	0.563	−2.16	0.768	1984
IPSL	1.5	0.117	3.44	0.411	1989
Ensemble_Mean	0.1	0.945	0.15	1.228	1988
Fall (SON)					
GPCC (observed)	0.2	0.838	0.40	0.990	1994
CanESM2	−1.6	0.095	−1.51	0.099	1988
CNRM-CM5	0.03	0.972	0.03	1.085	1981
HadGEM2-ES	0.2	0.811	0.66	1.228	1997
IPSL	0.7	0.454	1.32	0.538	1998
Ensemble_Mean	0.1	0.918	0.11	1.085	1997

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ejrh.2021.100815.

References

Agyekum, J., Annor, T., Lamptey, B., Quansah, E., Agyeman, R.Y.K., 2018. Evaluation of CMIP5 global climate models over the Volta Basin: precipitation. Adv Meteorol.

Agyeman, R.Y.K., Annor, T., Lamptey, B., Quansah, E., Agyekum, J., Tieku, S.A., 2017. Optimal physics parameterization scheme combination of the weather research and forecasting model for seasonal precipitation simulation over Ghana. Adv Meteorol.

Akinsanola, A.A., Ogunjobi, K.O., Gbode, I.E., Ajayi, V.O., 2015. Assessing the capabilities of three regional climate models over CORDEX Africa in simulating west African summer monsoon precipitation. Adv. Meteorol. 2015, ID935431.

Akinsanola, A., et al., 2018. Evaluation of rainfall simulations over West Africa in dynamically downscaled CMIP5 global circulation models. Theor. Appl. Climatol. 132, 437–450.

Annor, T., Lamptey, B., Wagner, S., Oguntunde, P., Arnault, J., Heinzeller, D., Kunstmann, H., 2018. High-resolution long-term WRF climate simulations over Volta Basin. Part 1: validation analysis for temperature and precipitation. Theor. Appl. Climatol. 133, 829–849.

Asfaw, A., Simane, B., Hassen, A., Bantider, A., 2018. Variability and time series trend analysis of rainfall and temperature in northcentral Ethiopia: a case study in Woleka sub-basin. Weather Clim. Extrem. 19, 29–41.

Awotwi, A., Anornu, G.K., Quaye-Ballard, J.A., Annor, T., Forkuo, E.K., Harris, E., Agyekum, J., Terlabie, J.L., 2019. Water balance responses to land-use/land-cover changes in the Pra River Basin of Ghana, 1986–2025. Catena. 182, 104129.

Bessah, E., Raji, A.O., Taiwo, O.J., Agodzo, S.K., Ololade, O.O., 2018. Variable resolution modeling of near future mean temperature changes in the dry sub-humid region of Ghana. Model. Earth Syst. Environ. 4 (3), 919–933.

Bessah, E., Raji, A.O., Taiwo, O.J., Agodzo, S.K., Ololade, O.O., 2020. The impact of varying spatial resolution of climate models on future rainfall simulations in the Pra River Basin (Ghana). J. Water Clim. Change. 11 (4), 1263–1283.

Chilkoti, V., Bolisetti, T., Balachandar, R., 2017. Climate change impact assessment on hydropower generation using multi-model climate ensemble. Renew. Energy 109, 510–517.
Cook, K.H., Vizy, E.K., 2006. Coupled model simulations of the West African monsoon system: twentieth-and twenty-first-century simulations. J. Clim. 19, 3681–3703.
Darko, D., Adjei, K.A., Appiah-Adjei, E.K., Odai, S.N., Obuobie, E., Asmah, R., 2019. Simulation of climate characteristics and extremes of the Volta Basin using CCLM and RCA regional climate models. Theor. Appl. Climatol. 135, 741–763.
Duan, K., et al., 2017. Impact of air pollution induced climate change on water availability and ecosystem productivity in the conterminous United States. Clim. Change 140, 259–272.
Foley, A., 2010. Uncertainty in regional climate modelling: a review. Prog Phys Geog. 34, 647–670.
Gleckler, P.J., Taylor, K.E., Doutriaux, C., 2008. Performance metrics for climate models. J. Geophys Res-Atmos. 113 (D6).
Griggs, D.J., Noguer, M., 2002. Climate change 2001: the scientific basis. Contribution of working group I to the third assessment report of the intergovernmental panel on climate change. Weather 57, 267–269.
Jin, L., Whitehead, P.G., Addo, K.A., Amisigo, B., Macadam, I., Janes, T., Crossman, J., Nicholls, R.J., McCartney, M., Rodda, H.J., 2018. Modeling future flows of the Volta River system: impacts of climate change and socio-economic changes. Sci. Total Environ. 637, 1069–1080.
Kankam-Yeboah, K., Obuobie, E., Amisigo, B., Opoku-Ankomah, Y., 2013. Impact of climate change on streamflow in selected river basins in Ghana. Hydrolog. Sci. J. 58 (4), 773–788.
Kendall, M.G., 1948. Rank Correlation Methods.
Laing, A., Fritsch, J.M., 1993. Mesoscale convective complexes in Africa. Mon. Wea. Rev. 121, 2254–2263.
Laux, P., Kunstmann, H., Bárdossy, A., 2008. Predicting the regional onset of the rainy season in West Africa. Int. J. Climatol. 28, 329–342.
Liu, X., Bae, J., 2018. Urbanization and industrialization impact of CO_2 emissions in China. J. Clean. Prod. 172, 178–186.
Mann, H.B., 1945. Nonparametric tests against trend Econometrica. Journal of the Econometric Society 245–259.
Morris, K.I., et al., 2017. Urbanisation and urban climate of a tropical conurbation, Klang Valley, Malaysia. Urban Clim. 19, 54–71.
Muthuwatta, L., Sood, A., McCartney, M., Silva, N.S., Opere, A., 2018. Understanding the impacts of climate change in the Tana River Basin, Kenya. Proc. Int. Assoc. Hydrol. Sci. 379, 37–42.
Nerini, D., Zulkafli, Z., Wang, L., Onof, C., Buytaert, W., Lavado-Casimiro, W., Guyot, J.A., 2015. Comparative analysis of TRMM-Rain gauge data merging techniques at the daily time scale for distributed rainfall-runoff modeling applications. J. Hydrometeorol. 16, 2153–2168.
Nicholson, S.E., Grist, J.P., 2003. The seasonal evolution of the atmospheric circulation over West Africa and Equatorial Africa. J. Climate 16, 1013–1030.
Nicholson, S.E., Some, B., McCollum, J., Nelkin, E., Klotter, D., Berte, Y., Diallo, B.M., Gaye, I., Kpabeba, G., Ndiaye, O., Noukpozounkou, J.N., 2003. Validation of TRMM and other rainfall estimates with a high-density gauge dataset for West Africa. Part I: validation of GPCC rainfall product and pre-TRMM satellite and blended products. J. Appl. Meteorol. Climatol. 42, 1337–1354.
Nikulin, G., Jones, C., Giorgi, F., Asrar, G., Büchner, M., Cerezo-Mota, R., Christensen, O.B., Déqué, M., Fernandez, J., Hänsler, A., van Meijgaard, E., 2012. Precipitation climatology in an ensemble of CORDEX-Africa regional climate simulations. J. Climate 25, 6057–6078.
O'Neill, B.C., et al., 2017. IPCC reasons for concern regarding climate change risks. Nat. Clim. Chang. 7, 28.
Okafor, G., Annor, T., Odai, S., Agyekum, J., 2019. Volta basin precipitation and temperature climatology: evaluation of CORDEX-Africa regional climate model simulations. Theor. Appl. Climatol. 137 (3), 2803–2827.
Osei, M.A., Amekudzi, L.K., Wemegah, D.D., Preko, K., Gyawu, E.S., Obiri-Danso, K., 2018. Hydro-Climatic Modelling of an Ungauged Basin in Kumasi, Ghana. Hydrol. Earth Syst. Sci. 1–21.
Oyerinde, G.T., Hountondji, F.C., Lawin, A.E., Odofin, A.J., Afouda, A., Diekkrüger, B., 2017. Improving hydro-climatic projections with bias-correction in Sahelian Niger Basin, West Africa. Climate 5, 8.
Paul, B., et al., 2018. Agricultural intensification scenarios, household food availability and greenhouse gas emissions in Rwanda: ex-ante impacts and trade-offs. Agr. Syst. 163, 16–26.
Pettitt, A., 1979. A non-parametric approach to the change-point problem. Appl. Stat. 126–135.
Pincus, R., Batstone, C.P., Hofmann, R.J.P., Taylor, K.E., Glecker, P.J., 2008. Evaluating the present-day simulation of clouds, precipitation, and radiation in climate models. J Geophys Res-Atmos. 113 (D14).
Pinto, I., Lennard, C., Tadross, M., Hewitson, B., Dosio, A., Nikulin, G., Panitz, H.J., Shongwe, M.E., 2016. Evaluation and projections of extreme precipitation over southern Africa from two CORDEX models. Clim. Change 135, 655–668.
Pittock, A.B., 2017. Climate Change: Turning up the Heat. Routledge.
Prather, M.J., Holmes, C.D., 2017. Overexplaining or underexplaining methane's role in climate change. Proc. Natl. Acad. Sci. 114, 5324–5326.
Roth, V., Lemann, T., Zeleke, G., Subhatu, A.T., Nigussie, T.K., Hurni, H., 2018. Effects of climate change on water resources in the upper Blue Nile Basin of Ethiopia. Heliyon 4, e00771.
Sharma, T., Gusain, A., Karmakar, S., 2019. Future hydrologic scenarios in India under climate change. Climate Change Signals and Response. Springer, pp. 39–59.
Skoulikaris, C., Anagnostopoulou, C., Lazoglou, G., 2020. Hydrological modeling response to climate model spatial analysis of a South Eastern Europe International Basin. Climate. 8, 1.
Smith, A.J., Henry, G., Frost-Killian, S., 2016. A review of the Birimian Supergroup-and Tarkwaian Group-hosted gold deposits of Ghana. Episodes 39, 177–197.
Sylla, M.B., Elguindi, N., Giorgi, F., Wisser, D., 2016. Projected robust shift of climate zones over West Africa in response to anthropogenic climate change for the late 21st century. Clim. Change 134, 241–253.
Tan, M.L., Yusop, Z., Chua, V.P., Chan, N.W., 2017. Climate change impacts under CMIP5 RCP scenarios on water resources of the Kelantan River Basin, Malaysia. Atmos. Res. 189, 1–10.
Taylor, K.E., 2001. Summarizing multiple aspects of model performance in a single diagram. J Geophys Res-Atmos. 106 (D7), 7183–7192.
Tetteh, G.M., Effisah-Otoo, E., 2017. Petrography and Geochemistry of some Granitoids associated with Gold Mineralisation at Mpohor area in southeastern Ashanti Belt of the Birimian, Ghana. Ghana Min. J. 17, 31–42.
Trang, N.T.T., Shrestha, S., Shrestha, M., Datta, A., Kawasaki, A., 2017. Evaluating the impacts of climate and land-use change on the hydrology and nutrient yield in a transboundary river basin: a case study in the 3S River Basin (Sekong, Sesan, and Srepok). Sci. Total Environ. 576, 586–598.
UICN/PACO, 2010. Parks and Reserves of Ghana: Management Effectiveness Assessment of Protected Areas. UICN/PACO, Ouagadougou.
United Nations, Department of Economic and Social Affairs (UNDESA), Population Division, 2017. World Population Prospects: The 2017 Revision, Key Findings and Advance Tables. Working Paper No. ESA/P/WP/248. Available at https://esa.un.org/unpd/wpp/Publications/Files/WPP2017_KeyFindings.pdf. Accessed: 02 April, 2019.
Urry, J., 2015. Climate change and society. Why the Social Sciences Matter. Springer, pp. 45–59.
Valentini, R., Arneth, A., Bombelli, A., Castaldi, S., Cazzolla Gatti, R., Chevallier, F., Ciais, P., Grieco, E., Hartmann, J., Henry, M., Houghton, R.A., 2014. A full greenhouse gases budget of Africa: synthesis, uncertainties, and vulnerabilities. Biogeosciences 11, 381–407.
Van Vuuren, D.P., et al., 2017. Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm. Glob. Environ. Chang. 42, 237–250.
Water Resources Commission (WRC), 2012. Pra River Basin - Integrated Water Resources Management Plan. Available at http://www.wrc-gh.org/dmsdocument/15. Accessed: 15 February, 2019.
Wilby, R.L., Wigley, T., 1997. Downscaling general circulation model output: a review of methods and limitations. Prog. Phys. Geog. 21, 530–548.
Wilcke, R.A., Bärring, L., 2016. Selecting regional climate scenarios for impact modelling studies. Environ. Model. Softw. 78, 191–201.
Xu, C.Y., 1999. Climate change and hydrologic models: a review of existing gaps and recent research developments. Water Resour. Manag. 13, 369–382.
Yira, Y., Diekkrüger, B., Steup, G., Bossa, A.Y., 2017. Impact of climate change on hydrological conditions in a tropical West African catchment using an ensemble of climate simulations. Hydrol. Earth Syst. Sci. 21, 2143–2161.