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Evaluation of CMIP5 and CMIP6 Performance in Simulating West African Precipitation

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Abstract

An analysis of spatial distributions of West African rainfall during monsoon period (JJAS) of six ensemble members from Coupled Intercomparison Model Project Phase 5 and 6 (CMIP5 and CMIP6) and compared to two observational datasets of Global Precipitation Climatologic Center and Climate Hazard Group InfraRed Precipitation with Station (GPCC and CHIRPS) using six extremes precipitation indices from Expert Team on Climate Change Detection and Indices (ETCCDI). The annual cycle of indices based on daily rainfall such as consecutive dry (CDD) and wet (CWD) days, was used over the Sahelian, Savannah and Guinean regions with satellite daily precipitation estimates. The root mean square error (RSME) and standard deviation were compared using a Taylor diagram for each subregion over West Africa. A higher positive correlation is found between CMIP6 and the reference dataset. Despite the high uncertainties, a strong correlation was found over the Savannah region between the GPCC and model simulations with extreme precipitation events (EPEs). This indicates that CMIP6 reproduces the rainfall pattern over the areas better than its CMIP5 counterpart.

Keywords: West Africa; rainfall; CMIP5 and CMIP6 models; climate change

Introduction

Rainfall is essential in West Africa and people in this area are highly linked to rainfall activities. West Africa is a highly populated area with approximately 427,311,326 inhabitants: 52.3% of the population is rural and the total land area is 6,064,060 km2 based on the latest United Nations estimates in 2022. Most people live in agriculture that is adapted to climatic conditions. The Guinean region is favorable for agriculture, the savanna is characterized by rainfed agriculture and livestock while in the Sahel area livestock is the dominant practice [1]. Agriculture is a dominant economic factor in the region; it is particularly dependent on atmospheric moisture supply by precipitation, where the annual cycle of the West African monsoon precipitation is a primary feature of the West African climate [2]. The rainfall mainly starts from April to October, with major differences between the wetter Guinean region where precipitation displays two annual peaks (in June and in September), the semi-arid Savannah, which shows a rainfall period from May to September and the more arid Sahelian region, which displays a single peak centered on August [2].

However, rainfall is increasingly affected by climate change. Increasing dry and wet days have led to extremes, drought and flood years in recent decades, causing a change in the annual cycle of monsoon precipitation [3-5]. In particular, the western Sahel seems to be the most sensitive region to anthropogenic climate change [6]. The studies revealed substantial increases in both, dry day length and extreme precipitation intensity. Between 1981 and 2014, the Gulf of Guinea also experienced more intense precipitation events [7]. In the entire region, an increasing trend of extreme heavy precipitation has been observed over the last decades [8]. This implies that West African countries are already facing important adaptation challenges [2]. Recently, [9] found a positive trend in consecutive dry days (CDD), simple day indices (SDII) and extreme heavy precipitation (R30 mm), and a negative trend in consecutive wet days.

Furthermore, projections of climate change point to further changes in rainfall in a future climate. For instance [10] showed that an increase in global warming will enhance the onset of late rains over the entire West African region under the RCP4.5 scenario, but reported the opposite behavior under RCP8.5.

While the findings point to increasing problems in rainfall supply, several studies [2] found strong uncertainties in the simulation of several important parameters, such as the CWD and the CDD over the Sahel and the Guinean areas. Several studies based on CMIP6 HighResMIP scenarios on West African precipitation found that the annual peak of precipitation in August appears to be underestimated by some of the models and the ensemble mean in all of West Africa [11]. Some previous studies [5] evaluated extreme precipitation indices over West Africa in CMIP6 models. They found that CMIP6 models reasonably reproduce the spatial patterns of the extreme precipitation indices over the entire region, although their performance is quite different between the Sahel and Guinea subregions. A main problem of uncertainties in the studies is that only two climatic zones are investigated by most studies. However, West Africa has at least three major climatic zones: the Sahel, savanna and Guinean regions [12]. Each region has its specific agroclimatic characteristics and thus might be affected by climate change in a different way, so it is essential to characterize the strength response of each climatic zone during recent decades. Only a few studies have investigated the three subregions of West Africa like [10]. However, they only focus on the seasonal aspect of rainfall in West Africa. The annual cycle of rainfall was investigated by a few studies, using two subregions (Sahel and Guinean region) and did not investigate the three seasonal regions including Savannah.

Thus, to date, there is hardly any information on the future development, particularly of changes in the intensity and duration of extreme events (strong rains, droughts), and the quality to reproduce them by climate model scenarios (CMIP5/CMIP6). Consequently, we examined the rainfall characteristics of six extreme precipitation indices over all of West Africa, and the (CDD) and CWD) annual cycles were used over the three subregions. We need to understand the response of each climatic zone to climate change. This is why this study focuses on how West African feature rain-fall is influenced by climate change. Furthermore, it will also evaluate the performance of CMIP5 and CMIP6 to capture the West African climate and help improve future models. Therefore, the present study intends to provide more information on the savanna because most of the last floods happened in this area according to [13-14].

The study is structured as follows: After an introduction, section 2 describes the data and methods used in this study, section 3 presents and discusses the results and section 4 provides the conclusion.

Data and Methodology

For consistency analysis, the observation data from the Global Precipitation Climatology Centre (GPCC), Climate Hazard Group Infrared Precipitation with Station data (CHIRPS) and Coupled Model Intercomparison Project (cmip5/cmip6) presented herein were carried out by considering a common period of simulation (1983 - 2012) due to the processing and availability of data. All the daily data were regridded to a common 1°×1° (lon/lat), and all the calculations and analyses are for June, July, August and September (JJAS). We calculated the mean bias error (MBE), root mean square error (RMSE) and standard deviation (STD). The CMIP data are downloaded from [15]. We used six models from the CMIP6 output and six corresponding models from the CMIP5 output represented in Table 1.

The formula is expressed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \| y(i) - \hat{y}(i) \|^2}{N}} \qquad (1)$$

$$MBE = \frac{1}{N} \sum_{i=1}^{N} (Pi - Oi) \qquad (2)$$

$$STD = \sqrt{\frac{\sum_{i=1}^{n} (Xi - \bar{X})^2}{N-1}} \qquad (3)$$

S/No	***Model***	***Institute***	***Resolution (^{0}lon× ^{0}lat)***
1.	CanESM5	Canadian Earth System Model and Analysis	2.81×2.81
2.	CMCC-CM2	Centro Euro-Mediterraneo per I Cambiamenti Climatici	0.748 × 0.75
3.	CNRM-CM6-1	Centre National de Recherches Météorologiques	1.41×1.41
4.	FGOALS-g3	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University	2.81 ×2.81
5.	IPSL-CM6A-LR	Institute Pierre-Simon Laplace	2.50 ×1.26
6.	MIROC6	Japan Agency for Marine-Earth Science	1.40 ×1
1.	CanESM2	Canadian Earth System Model and Analysis	2.81 ×2.81
2.	CMCC-CESM	Centro Euro-Mediterraneo per I Cambiamenti Climatici	3.443 × 3.75
3.	CNRM-CM5	Centre National de Recherches Météorologiques	1.40 ×1.40
4.	FGOALS-g2	LASG–Center for Earth System Science (CESS)	2.81 ×2.81
5.	IPSL-CM5A2	Institute Pierre-Simon Laplace	1.80 ×3.75
6.	MIROC5	Atmosphere and Ocean Research Institute (University of Tokyo), National Institute for Environmental Studies, and Japan Agency	1.40 ×1.40

Table 1: Information on the six CMIP6 and CMIP5 climate models used in this study.

Six extreme precipitation indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) calculated in this study are summarized in Table 2; we used daily precipitation data.

S/No	*Extreme indices*	*Name*	*Definition*	*Units*
1.	SDII	Simple daily intensity	Let PRwj be the daily precipitation amount on wet days, PR ≥1 mm in period *j*. If *W* represents number of wet days in *j*, then: SDIIj= $(\sum W\, w{=}1\, PRwj)/W$	mm/day
2.	CDD	Consecutive dry days	Let PRij be the daily precipitation amount on day *i* in period *j*. Count the largest number of consecutive days where Prij < 1 mm	days
3.	CWD	Consecutive wet days	Let Prij be the daily precipitation amount on day *i* in period *j*. Count the largest number of consecutive days where Prij > 1 mm	days
4.	R10 mm	Heavy precipitation days	Let Prij be the daily precipitation amount on day *i* in period *j*. Count the number of days where Prij> 10 mm	days
5.	R20 mm	Very heavy precipitation days	Let Prij be the daily precipitation amount on day *i* in period *j*. Count the number of days where Prij> 20 mm	days
6.	Rx5day	Maximum 5 days precipitation	Let PRkj be the precipitation amount for the 5-day interval ending *k*, period *j*. Then maximum 5 day values for period *j* are: RX5dayj = max (PRkj)	mm

Table 2: List of precipitation indices used in this study.

Study area: West Africa (20oW, 20oE, 0oN, 30oN).

The sub region designated the Sahel, Savannah and Guinea region in the study is due to the data blending and processing procedure. Guinea region (4oN: 8oN); Savannah (8oN: 12oN) and Sahel (12oN: 16oN).

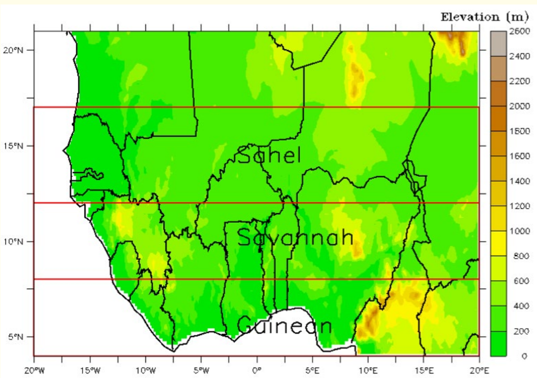

Figure 1: Topographic map of West Africa with subregions shows as red lines.

Results and Discussion

We used the spatial representation of extreme precipitation indices over West Africa. All the models and observed data showed a moderate dry day over the southern part of West Africa. However, some models such as CanESM, CNRM-CM, FGOALS, and MIROC from both CMIP5/CMIP6 underestimate the width of consecutive dry days in the northern part of West Africa compared to the observed data while, CMCC and IPSL from CMIP5/CMIP6 extend the width and length of crucial dry days. Their Ensmean underestimated the

CDD event with a negative bias.

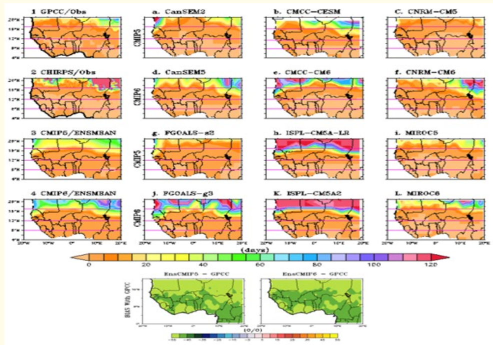

Figure 2: Consecutive dry days (CDD) with observed dataset GPCC, CHIRPS (1, 2); Ensmean CMIP5/CMIP6 (3, 4); CMIP5 (a, b, c, g, h and i) CMIP6 (d, e, f, j, k and L) from 1983 to 2012 and bias with GPCC dataset in the bottom.

All the models and observed data showed moderate dry days over the southern part of West Africa. However, some models such as CanESM, CNRM-CM, FGOALS, and MIROC from both CMIP5/CMIP6 underestimate the width of consecutive dry days in the northern part of West Africa compared to the observed data while, CMCC and IPSL from CMIP5/CMIP6 extend the width and length of crucial dry days. Their Ensmean underestimated the CDD event with a negative bias.

In contrast with the dry spell, the wet days (CWD) showed a significant wet period increasing from the Sahel to the Guinea region during this last thirty years. This wet period is more highlighted by observation data (GPCC) than some models such as FGOALS and IPSL from CMIP5/CMIP6. The CMIP5 and CMIP6 ensemble mean showed a negative bias with GPCC consecutive wet days, which means that they underestimated the CWD activities over West Africa.

The (SDII) extreme event of precipitation is well captured by observations data and all the models; the highest values of Simple Daily Intensity (SDII) are found over the Guinea region and Savannah. However, the FGOALS-s2 from CMIP5 underestimated the spatial distribution of SDII events in comparison with GPCC over central-southern West Africa and the northern area up to 12oN across West Africa. In contrast, the SDII events are overestimate under the CanESM5, MIROC6 from CMIP6 and MIROC5 from CMIP5 simulations, which display the greater intensities between 14 mm and 16 mm over the central area of the Guinea and Savannah regions. The SDII ensemble mean bias is much higher in CMIP5 than in CMIP6 over most West African areas. F.3

Similarly, with the CWD, the most activity with the highest 5 day precipitation is collected in the Guinea coast and Savannah region over West Africa. The lowest value of (Rx5day) is represented beyond 15°N over West Africa for all the calculated and GPCC datasets except for CMCC-CESM, FGOALS-s2 and ISPL-CM5A-LR from CMIP5 and ISPL-CM5A2 from CMIP6, which underestimate the width of Rx5day and show a crucial decrease over the central area of the Guinea region and Savannah region. We obtained a negative bias with both the Ensmean and GPCC except for the southern area in the Guinean region.

Only the southern region over West Africa is affected by heavy precipitation from 0°N to 15°N. All six models from CMIP6 match well with the observed data compared to their correspondents in CMIP5. All the models with observations showed heavy precipitation activity across the eastern and western areas of the Guinea region and Savannah region. However, MIROC5/MIROC6 from CMIP5/CMIP6 respectively and CanESM5 from CMIP6 extend the R10 mm activity over the central region of the Guinea and Savannah in West Africa. The northern region of West Africa showed a positive bias with the CMIP5 ensemble mean while it showed a negative bias with the GPCC R10 mm event with the CMIP6 ensemble mean.

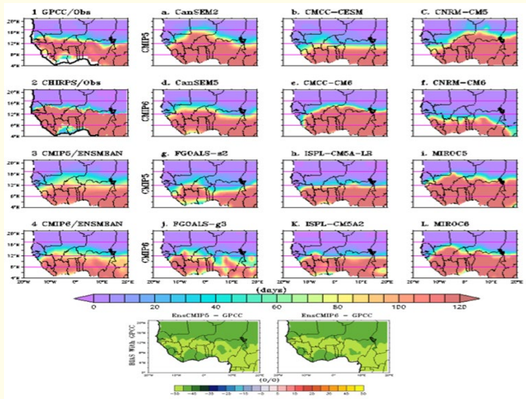

Figure 3: Same as Figure 2, but for consecutive wet days (CWD).

The temporary trend of the annual cycle with consecutive dry and wet days (CDD and CWD) over each subregion in West Africa will highlight with accuracy the response of different regions to climate influence. The dry and wet climatologic period is identified by the process of these precipitations events, and the length of rainfall is also mainly linked to these precipitations indices due to the process of onset and secession period. In this study we focus on the availability of each model to capture the diurnal processes of CDD and CWD over the Guinea, Savannah and Sahel regions to determine the specificity of each climatic zone in West Africa. Previous studies have well emphasized that rainfall features over West Africa especially the Guinea and Sahel regions have been most relevant, noting that a very large area and uncertainties are observed between the Sahel and Guinea regions, this region is called Savannah. In this study, in addition to the Sahel and Guinea we investigated the rainfall pattern over the Savannah region. Over each region, we observed a very high uncertainty in the CMIP5 and CMIP6 models (fig 4).

The length of the dry period is relatively higher in the CMIP6 model than in CMIP5 and shrinks from the Sahel (north of W.A) to Guinea regions (south of W.A), this shrinkage is mainly linked to monsoon activity over West Africa. The length of consecutive dry days (CDD) in the Guinea region spread from November to February in CMIP5 while in the CMIP6 model most of the simulated data are strongly correlated to the observed data and show a dry length from November to March. However, the FGOALS-s2 in CMIP5 overestimates the dry days over the Guinea region extending from November to the end of May. A significant increase in the length of the CDD event is observed over the Savannah region spreading from October to the end of April in the CMIP5 model and from October to early June in the CMIP6 model, while the satellite dataset GPCC records the length of the dry period from October to May. The most significant enlargement of consecutive dry days (CDD) is represented over the Sahel region, and there are no significant rainfall activities. We observed a simple peak in August during the wet period (CWD) (fig 5) for all the CMIP6 output models and their Ensmean in agreement with the observed data. However, these wet days are highly overestimated by CMCC-CM6 in the CMIP6 model while, they are overestimated by FGOALS-s2 in the CMIP5 model over the Sahelian region. The annual cycle of wet days over the Guinea region is longer and shows two peaks (June and September) which is similar to a previous study [2]. The intensity of wet days is strongly overestimated by CMCC-CESM and FGOALS-s2 in both CMIP5 models while it is overestimated by MIROC6 in the CMIP6 model. The Savannah region brings great uncertainties between models for representing feature rainfall due to the presence of many climatic drivers (monsoon, ZCIT), and the Savannah area located between the Guinea and Sahel regions is subject to climate disasters (flood, drought). The succession of these two disasters over West Africa is mostly common in the Savannah region because of the delay of the wet period and the sudden onset of the dry period which affect many activities, such as agriculture, fishing and energy generation.

We used a Taylor diagram to facilitate the comparative assessment of different models and to quantify the degree of correspondence between the modeled and observed behavior in terms of three statistics: the Pearson correlation coefficient, the root mean square error and the standard deviation. We used three statistics plots for six output models represented by a different letter on the diagram and the distance between each model and the point labeled "observed" in a measure of how realistically the model reproduces observations. The Pearson correlation coefficient is related to the azimuthal angle (black straight line), the root mean square error (RMSE) is proportional to the distance from the point on the x-axis identified as "observed" (green contours) and the standard deviation is proportional to the radial distance from the origin (black contours). We summarized the results from these diagrams in Table 3 for consecutive dry days (CDD) and Table 4 for consecutive wet days (CWD).

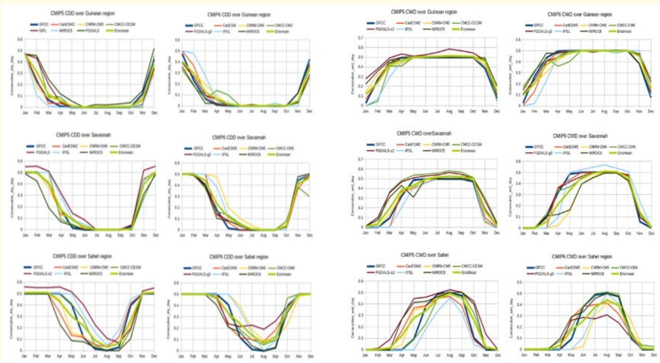

Figure 4: Annual cycle of consecutive dry days (CDD) (left panel) and, consecutive wet days (CWD) (right panel) in each subregion over West Africa with CMIP5 (left) and CMIP6 (right) and their ensmean simulation with the observational dataset (GPCC) from the period 1983 to 2012.

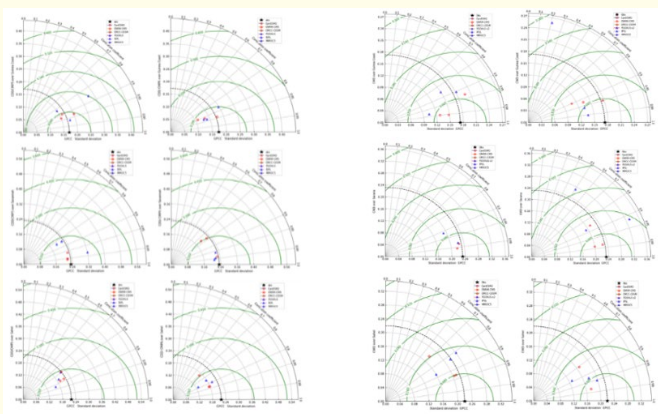

Figure 5: Taylor diagram with consecutive dry days (CDD) (left panel) and, consecutive wet day (CWD) (right panel) with CMIP5 (left), and CMIP6 (right) simulations of six models estimated with (GPCC) observed data over each subregion in West Africa, Guinea region on (top), Savan-nah, (middle) and Sahel, (bottom).

CDD		CMIP5						CMIP6					
		CanESM2	CNRM-CM5	CMCC-CESM	FGOALS-s2	ISPL	MIROC5	CanESM5	CNRM-CM6	CMCC-CM6	FGOALS-g3	ISPL	MIROC6
GUI	STdev	0.162	0.149	0.201	0.382	0.184	0.15	*0.177*	*0.13*	*0.108*	*0.13*	*0.199*	*0.14*
	RMSE	0.097	0.086	0.077	0.159	0.091	0.148	*0.061*	*0.06*	*0.064*	*0.067*	*0.106*	*0.06*
	Cor. Coef	0.892	0.93	0.93	0.858	<u>0.963</u>	0.826	*0.939*	*0.91*	*0.898*	*0.924*	*0.867*	*0.934*
	MBE (%)	- 0.07	- 0.09	0.169	0.138	- 0.29	1.39	*0.023*	*0.04*	*- 0.15*	*- 0.12*	*0.29*	*-0.15*
SAV	STdev	0.216	0.217	0.223	0.32	0.221	0.183	*0.225*	*0.22*	*0.191*	*0.212*	*0.224*	*0.217*
	RMSE	0.031	0.027	0.063	0.189	0.126	0.140	*0.041*	*0.17*	*0.151*	*0.027*	*0.074*	*0.033*
	Cor. Coef	<u>0.989</u>	<u>0.992</u>	<u>0.961</u>	<u>0.980</u>	0.838	0.839	*<u>0.982</u>*	*0.77*	*0.754*	*<u>0.993</u>*	*<u>0.996</u>*	*<u>0.989</u>*
	MBE (%)	- 0.026	- 0.01	- 0.11	1.28	0.203	- 0.39	*-0.003*	*0.71*	*-0.26*	*0.009*	*0.29*	*0.03*
SAH	STdev	0.192	0.210	0.218	0.189	0.16	0.217	*0.174*	*0.16*	*0.178*	*0.129*	*0.177*	*0.197*
	RMSE	0.103	0.116	0.141	0.211	0.083	0.167	*0.07*	*0.14*	*0.068*	*0.1*	*0.105*	*0.098*
	Cor. Coef	0.877	0.878	0.786	0.854	0.924	0.787	*0.932*	*0.7*	*0.932*	*0.884*	*0.849*	*0.898*
	MBE (%)	- 0.20	- 0.31	- 0.04	1.30	0.50	- 0.57	*0.074*	*0.42*	*0.16*	*0.36*	*0.40*	*- 0.19*

Table 3: Statistical results between the calculated models CMIP5/CMIP6 and GPCC for consecutive dry days (CDD). All correlations higher than 0.95 are underlined.

CWD		CMIP5						CMIP6					
		CanESM2	CNRM-CM5	CMCC-CESM	FGOALS-s2	ISPL	MIROC5	CanESM5	CNRM-CM6	CMCC-CM6	FGOALS-g3	ISPL	MIROC6
GUI	STdev	0.148	0.12	0.197	0.15	0.182	0.104	*0.177*	*0.134*	*0.109*	*0.132*	*0.258*	*0.137*
	RMSE	0.029	0.054	0.078	0.15	0.08	0.084	*0.055*	*0.066*	*0.084*	*0.055*	*0.257*	*0.039*
	Cor. Coef	<u>0.991</u>	<u>0.989</u>	0.93	0.856	0.903	<u>0.979</u>	*0.949*	*0.923*	*0.9*	*<u>0.96</u>*	*0.206*	*<u>0.99</u>*
	MBE (%)	0.089	0.165	-0.19	1.03	-0.16	0.424	*- 0.03*	*- 0.05*	*0.15*	*0.12*	*- 0.29*	*0.15*
SAV	STdev	0.225	0.217	2.710	0.444	0.223	0.191	*0.225*	*0.213*	*0.2*	*0.272*	*0.331*	*0.194*
	RMSE	0.041	0.027	3.694	0.614	0.051	0.097	*0.041*	*0.137*	*0.044*	*0.259*	*0.178*	*0.117*
	Cor. Coef	<u>0.982</u>	<u>0.992</u>	0.899	0.691	<u>0.979</u>	0.914	*<u>0.982</u>*	*0.857*	*<u>0.984</u>*	*0.502*	*0.919*	*0.878*
	MBE (%)	-0.04	0.009	2.33	1.71	-0.2	0.28	*0.002*	*- 0.60*	*- 0.08*	*- 0.008*	*0.74*	*- 0.42*
SAH	STdev	0.179	0.211	0.205	0.242	0.161	0.217	*0.174*	*0.168*	*1.303*	*0.129*	*0.177*	*0.198*
	RMSE	0.159	0.087	0.078	0.208	0.127	0.148	*0.061*	*0.135*	*1.4*	*0.121*	*0.094*	*0.068*
	Cor. Coef	0.675	0.931	0.931	0.812	0.875	0.828	*<u>0.979</u>*	*0.803*	*0.947*	*0.886*	*0.926*	*<u>0.952</u>*
	MBE (%)	0.18	0.31	0.04	1.20	-0.49	0.65	*- 0.07*	*- 0.42*	*0.78*	*- 0.37*	*- 0.41*	*0.193*

Table 4: Statistical results between the calculated models CMIP5/CMIP6 and GPCC for consecutive wet days (CWD). All correlations higher than 0.95 are underlined.

Summary and conclusion

We observe that most of the higher correlations in the model and GPCC are over Savannah in the both tables (Table 3 and Table 4). With CDD the CMIP6 model displays all the highest correlations greater than 0.95 and four higher correlations in CMIP5 over the Savannah region. This study has highlighted the complexity of the representation of daily rainfall characteristics in climate models over three subregional areas especially in the Savannah region, which is likely linked to monsoon dynamics. We found that from one precipitation index to another, and according to the area, the uncertainties change dramatically. In the Sahel region the CMIP6 model fit better than CMIP5 with wet spell representation. However, during the wet spell over the Guinea and Savannah, CNRM-CM5 and ISPL in CMIP5 gave a better fit with the GPCC observed data than their corresponding data in CMIP6.

Finally, we argue that further studies are necessary, to understand whether and how these extreme precipitation indices are translated into future projections with climate models over West Africa, particularly shifts in the monsoon season, and changes in mean and extreme precipitation amounts.

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