Towards a climate modeling system for West Africa: Sensitivity studies and input bias correction for WRF

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1. Introduction

The credibility of regional climate simulations over West Africa depends on the ability to reproduce its key climatic feature, the West African Summer Monsoon. This seasonal shift in large-scale wind patterns plays a pivotal role in every day's life, and any modification induced by climate change and changes in land use will greatly impact the future of this region.

To assess the impact of climate change on West Africa, ensembles of latest global circulation models (GCMs), for example those within CMIP5 (Covey et al. 2003), are often used for analysis and for further statistical or dynamical downscaling. Large-scale international collaborations such as CORDEX (Giorgi et al. 2009) demonstrate the added value of regional climate simulations, in particular its ensemble information.

Yet, despite the continuous increase in spatial and temporal resolution, regional climate simulations are still struggling to simulate the onset, duration and geographical displacement of the monsoon rain band. Severe biases are introduced not only by the regional climate model itself, but also by the driving global circulation model data (Sylla et al. 2010). A large uncertainty in observational data from sparse and often insufficiently-maintained observation networks further complicates the validation of the models. Here, we present results of two studies which are important steps towards establishing a regional climate modeling system for West Africa.

In Sect. 2, we report on an extensive study of model configurations, specifically targeted to improve the West African Monsoon representation in WRF, while in Sect. 3 we present a comparison of two bias correction methods of global model data prior to ingesting it into WRF. Our conclusions and a brief outlook are given in Section 4.

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2. West African Monsoon representation in WRF

WRF provides a huge number of model configurations through the combination of parameterization schemes for the land surface, planetary boundary layer etc. The choice of the model physics has a strong impact on the simulation results and has been studied extensively over continental US, Europe and other regions of primary interest. With respect to West Africa, only few such investigations have been carried out (for a review, see Paeth et al. 2011), focusing on short- to mid-term forecasting (Noble et al. 2014) or considering a small number of parameterisations only (Flaounas et al. 2011). We aim to extend this work by incorporating a large number of model physics combinations and by taking the analysis to seasonal scales. Accurate mid-term and long-term forecasts are very important for decision makers and stakeholders, for example in the context of forecasting the onset and duration of the rainy season and its projected future under the impact of climate change. In our work, we focused on two years as examples for extreme conditions, with 1999 being considerably wetter than the climatological average and 2002 being considerably drier. In the following, we discuss the results for 1999 only.

In a first step, we focused on parameterisation schemes which influence the moisture distribution in the atmosphere (CU, PBL, MP) using the ERA-Interim re-analysis (Dee et al. 2011) as forcing data. In a second step, we investigated the applicability of promising configurations for long-term climate simulations using MPI-ESM GCM data (Stevens et al. 2013). In total, 53 different configurations were considered (see Table 3 in Appendix A1).

Our results confirm that the choice of model physics strongly influences small-scale and large-scale dynamics: While all simulations are able to represent the governing dynamic features of the West African Monsoon (Saharan Heat Low SHL, Tropical Easterly Jet TEJ, African Easterly Jet AEJ, westerly winds), the intensity and position of the monsoon rains differ significantly. We identified the AEJ in August as a good indicator for these: In 1999

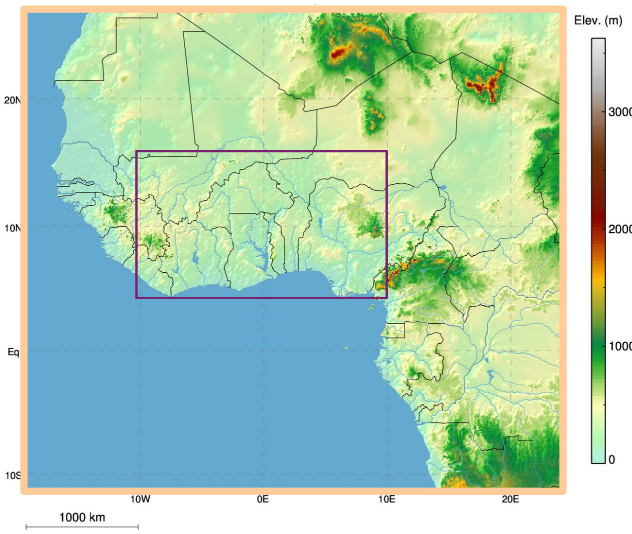

FIG. 1. Geographical extend of the WRF domain at 24km resolution for the WRF sensitivity studies. The black box marks the area used to assess the model performance.

(wet), the AEJ is located at approximately 14.2°N in ERA-Interim, while in 2002, it is shifted southwards to 11.2°N.

(i) First selection using re-analysis forcing data

The WRF domain used in this study is depicted in Fig. 1. For the wet year 1999, we found that the AEJ position ranges from 11.5°N to 15°N depending on the model physics (ERA-Interim: 14.2°N), spanning a range from very dry to very wet conditions (Fig. 2). We were able to classify the parameterizations according to their favoured monsoon regime (dry to wet), where the "extreme" schemes tend to dictate the regime and the moderate schemes can be pushed to either side:

- **CU:** BMJ < KF < GF
- **MP:** WSM3 < LIN < TH
- **PBL:** ACM2 < YSU < MYJ

We found that on seasonal scales, the choice of the PBL scheme is the determining factor for the movement of the rain band. This is due to its impact on the lower-level temperature gradient, which influences the position of the AEJ. Meanwhile, the choice of the MP scheme affects the overall precipitation amount, i. e., it shows the same tendency in the South and in the North. The choice of the CU scheme plays a secondary role on seasonal time scales, but is probably important for the frequency of the rain events and on diurnal time scales.

The model configurations were evaluated against observational data from CRU (Jones and Harris 2013), TRMM

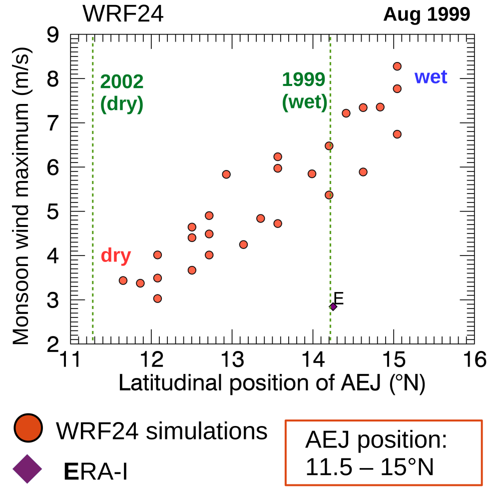

FIG. 2. Latitudinal position of the AEJ and monsoon (westerly) wind maximum for different model configurations for August 1999. The over-prediction of the westerly winds compared to the forcing data ERA-Interim is correlated with a positive bias of the 2m temperature over the Sahara in all simulations.

(Huffman et al. 2007) and surface station data, obtained directly from the corresponding meteorological services. We assessed statistical measures (MAE, BIAS, PCC, STD) for precipitation, onset and duration of the monsoon, AEJ position and 2m temperature to rank the configurations accordingly (see Tab. 1).

(ii) Extension towards long-term climate simulations

Promising configurations were taken to further evaluation in the second step, using ERA-Interim re-analysis and the MPI-ESM GCM as forcing data (Table 3, configurations 30–55). To be considered for a West African climate modeling system, a model must be able to perform well for both forcing data sets[1].

The Dudhia SW and RRTM LW schemes used in step *(i)* do not contain any information about the evolution of green house gas concentrations and aerosols, an important aspect of climate studies. In this second step, we replaced the SW/LW schemes with CAM and RRTMG. As before, model runs were conducted for 1999 and 2002, but only results for 1999 are shown here.

Figure 3 displays the precipitation bias for the monsoon season 1999 for the model runs 31, 34, 44, 47 in Table 3. These configurations were chosen based on their good performance in the first step (runs 2, 28). The best-performing configuration in step *(i)*, BMJ-LIN-MYJ-DUDHIA-RRTM, now using RRMTG SW/LW, strongly overestimates the

[1] The MPI-ESM is close to the CMIP5 multi model mean and thus a suitable representative for GCM data sets (e. g., Jones et al. 2012).

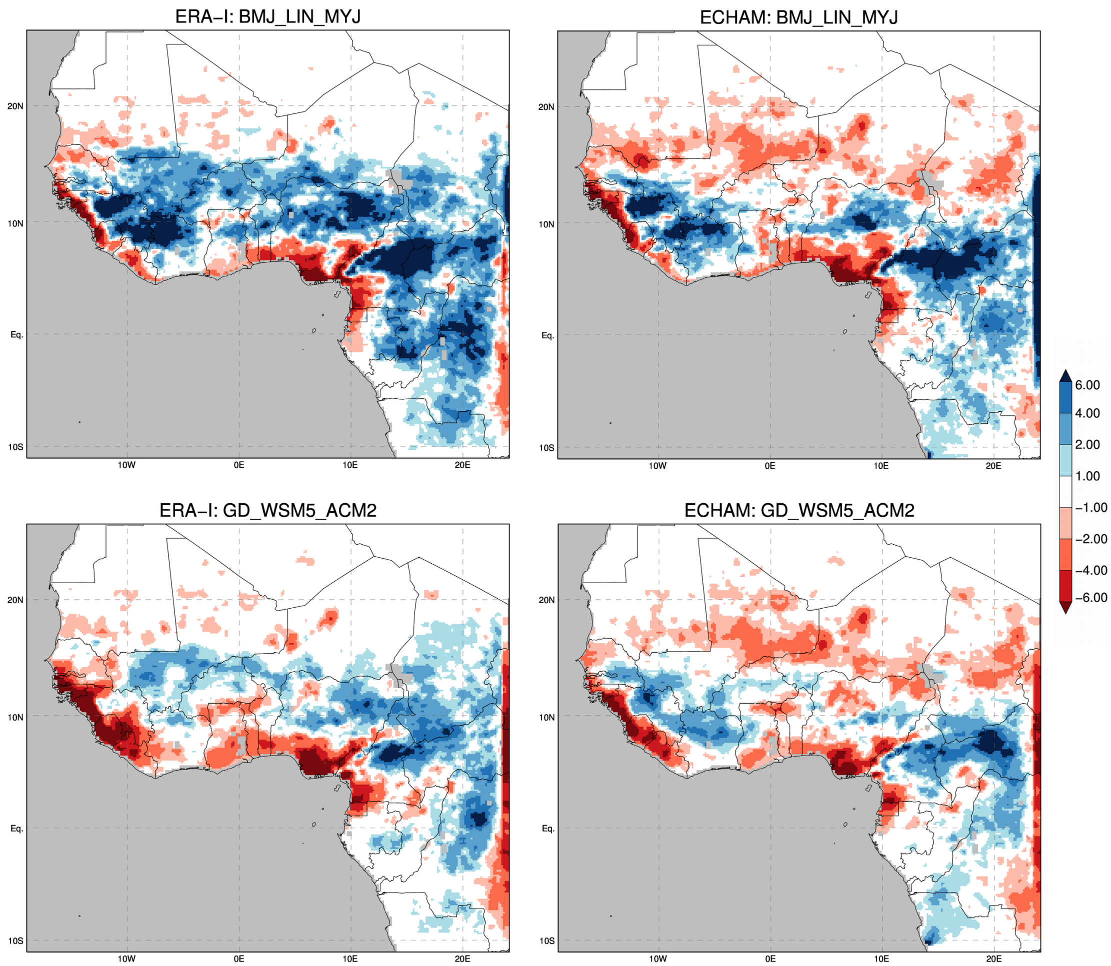

Fig. 3. Precipitation bias [mm/day] averaged over the monsoon season (July–September) 1999 for two of the best-performing configurations (#31/44 and #34/47 in Table 3), using ERA-Interim (ERA-I) and MPI-ESM (ECHAM) as forcing data. Radiation schemes are RRMTG for LW and SW.

Table 1. Ranking of model configurations based on runs forced with ERA-Interim for 1999 and 2002. The default NCAR configuration (except LW/SW radiation) ranks 17th out of the 29 initial configurations, while the Noble et al. (2014) setup ranks 3rd.

CU	**MP**	**PBL**	**SW**	**LW**	**Rank**
BMJ	LIN	MYJ	DUDHIA	RRTM	1
BMJ	TH	YSU	DUDHIA	RRTM	2
BMJ	TH	MYJ	DUDHIA	RRTM	2
GD	WSM5	ACM2	DUDHIA	RRTM	3
KF	WSM3	MYJ	DUDHIA	RRTM	3
KF	TH	ACM2	DUDHIA	RRTM	4
...	...	...	...	...	...
KF	WSM6	YSU	DUDHIA	RRTM	17

precipitation over land when forced with ERA-Interim, and produces too much (too little) rain around 10°N (15°N) with MPI-ESM: The monsoon rain band is not moving far enough to the North, but rather remains stationary around 10°N. A similar pattern, but with a smaller signal, is found for GD-WSM5-ACM2-RRTMG-RRTMG. In Noble et al. (2014), this configuration (with RUC instead of NOAH LSM) was found to give the best overall performance for short-term to mid-term forecasting purposes. Likewise, we found that it is the best compromise when both ERA-Interim and MPI-ESM forcing is considered.

3. Bias correction of global circulation model data

In the previous section, we used ERA-Interim data as well as MPI-ESM data as lateral boundary conditions for WRF to identify an optimal WRF model configuration for West Africa. Albeit some limitations, ERA-Interim is supposed to represent a "perfect atmosphere", which allows one to estimate the bias introduced by WRF. On the other hand, it is well known that global circulation models often have large biases (in temperature, wind, etc.) that can impose serious limitations on the validity of the results and may sometimes render them useless (Done et al. 2012; Rocheta et al. 2014). The combination of the bias inherent to the GCM and that inherent to WRF will almost certainly have non-linear effects on the outcome, making it difficult to assess the accuracy of the model.

To address this issue, we implemented bias correction techniques for the input global model data based on two methods currently favoured by the climate modeling community (David Gochis, priv. comm.):

i. In the Colorado Headwaters project, Rasmussen et al. (2010) use a so-called pseudo-global warming or delta-change approach. They calculate the difference between a ten-year period at present and a ten-year period in the future from a GCM for each month for temperature, humidity, geopotential height and wind. These differences (deltas) are then added to a current climate re-analysis to obtain a warming signal. This approach allows one to see how "current weather" would look like in a future climate. *(Pseudo-Global Warming method, PGW)*

ii. In a climatological study of tropical cyclones, Done et al. (2012) estimate the bias based on the average annual cycle of a current climate simulation comparison with re-analysis data and subtract out the bias fields from the future simulated climate. This method attempts to allow one to look at changes in circulation and storm frequency patterns and changes in thermodynamic variables by imposing a mean bias correction. *(Perturbed Average Climate method, PAC)*

Both methods rely on re-analysis data as truth field (here: ERA-Interim), which is compared to a GCM (here: MPI-ESM). The sheer amount of data require an efficient implementation of the algorithms, which was realized by combining Python with the NoSQL database Redis[2]. The bias correction is performed on the output of `real.exe`, i. e., on `wrfbdy_d01`, `wrflowinp_d01` and `wrflowinp_d02` using a calibration period from 1990 to 2000, and a validation/reference period from 2000 to 2010.

A total of six WRF runs were conducted with one of the top model configurations from the previous section (#33 in Table 3). Figure 4 displays the nested WRF domain over the West African continent at 18 km resolution. The six runs are (1) ERA-Interim 1990–2000, (2) ERA-Interim 2000–2010, (3) MPI-ESM 1990–2000, (4) MPI-ESM 2000–2010, (5) Pseudo-Global Warming PGW 2000–2010, and (6) Perturbed Average Climate PAC 2000–2010.

[2]`http://redis.io`

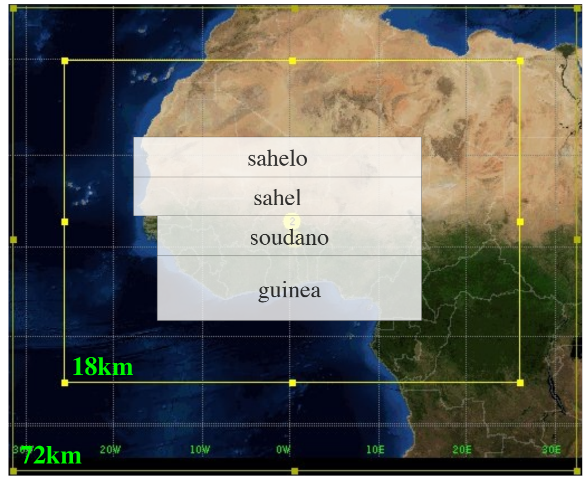

Fig. 4. 72 km and nested 18 km WRF domain used in the bias correction study. Also shown is the usual classification of West Africa into four agro-climatical zones, following a south-north gradient in precipitation.

Table 2. 10-year mean sea surface temperature and bias relative to ERA 2000–2009.

Model		**SST [K]**	**Bias [K]**
ERA	1990–1999	298.94	-0.09
ERA	2000–2009	299.03	0.00
MPI	1990–1999	299.33	0.30
MPI	2000–2009	299.53	0.50
PGW	2000–2009	299.16	0.13
PAC	2000–2009	299.15	0.12
NCDC	2000–2009	299.06	0.03

Figure 5 displays the effect of the bias correction on the input data for the 10-year mean of the sea surface temperature field SST, while Fig. 6 shows the 9-year mean of the model output 2m temperature field T2M (to account for the model spinup, the first year of each model run is neglected).

Table 2 compares the bias for the input SST for the inner domain d02 of the six model runs. The ERA 2000–2009 data is used as reference, since it does not enter the bias correction methods and can be considered as the truth field for the validation period. The NCDC[3] 2000–2009 mean SST is included to allow for a further comparison with an observational data set.

Both bias correction methods succeed in reducing the bias of the GCM from 0.5 K to 0.13 K (PGW) and 0.12 K (PAC), respectively. This bias is a result of an overestimation of the SST change of the GCM, which increases

[3]NOAA National Climatic Data Center / Group for High Resolution Sea Surface Temperature GHRSST, `http://www.ghrsst.org`

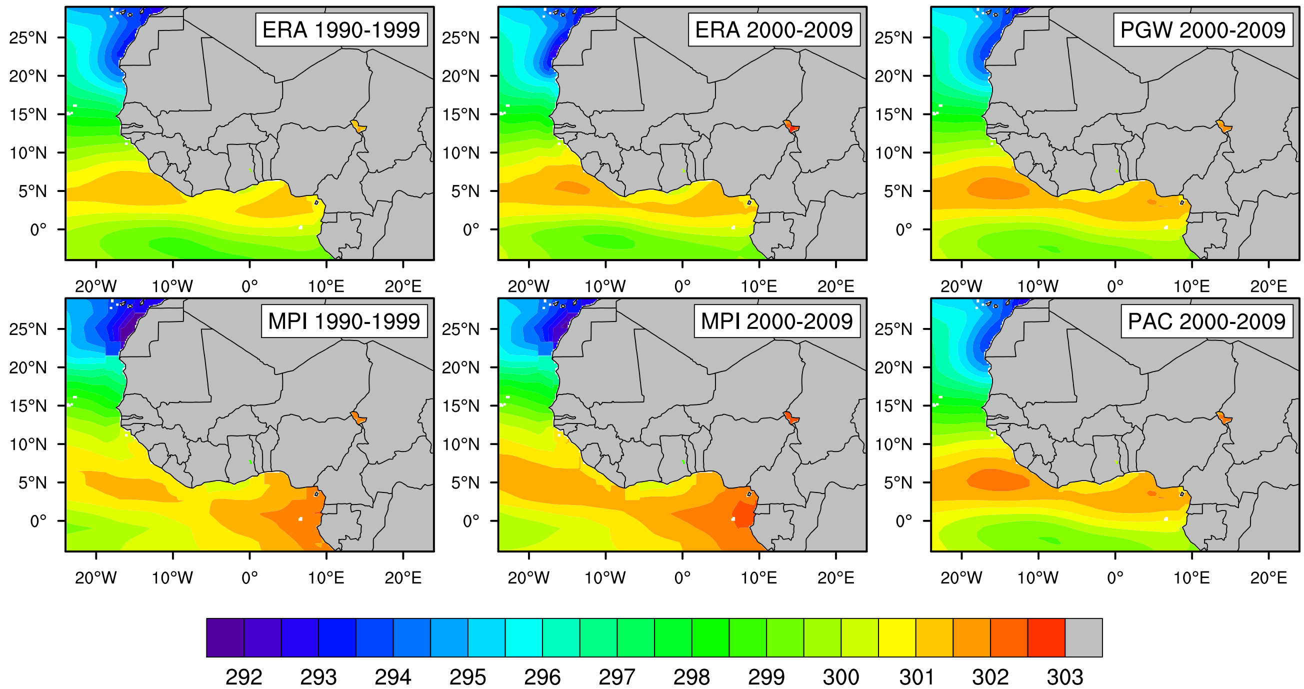

FIG. 5. *Input* mean sea surface temperature [K] for the 10-year calibration/validation period for all six forcing data sets.

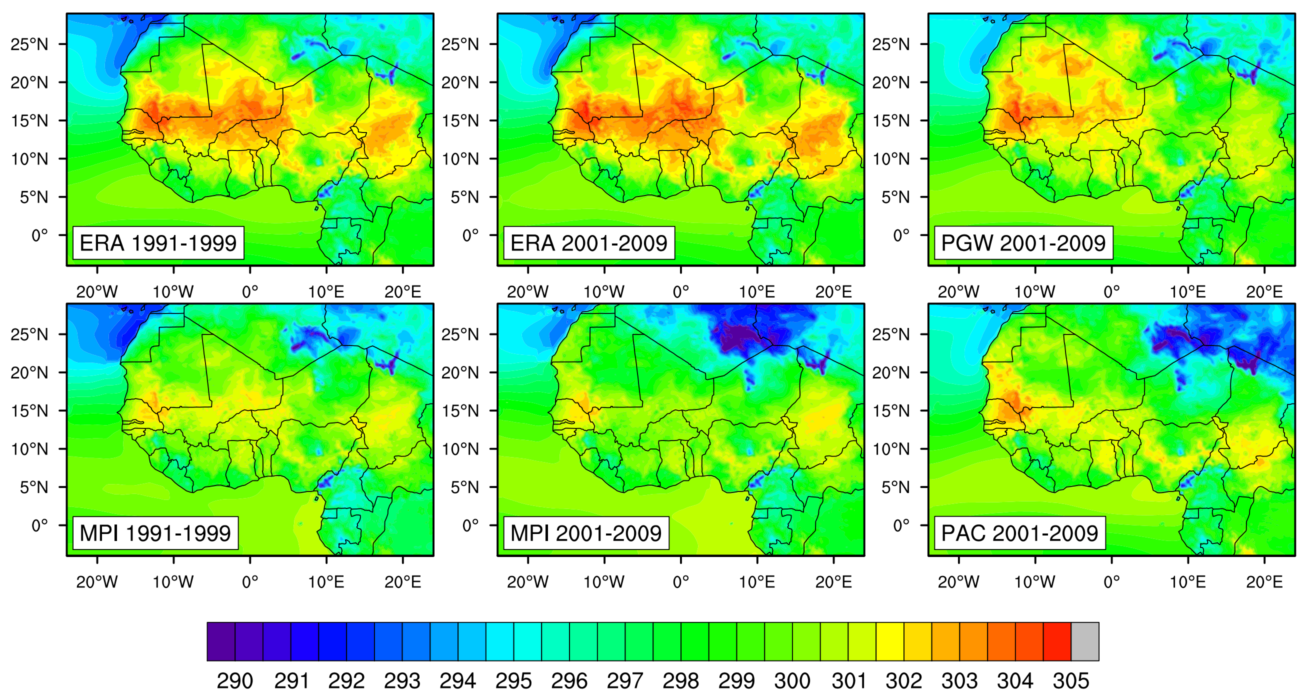

FIG. 6. *Output* mean surface temperature [K] for the 9-year calibration/validation period for all six forcing data sets.

by 0.2 K between the calibration and validation period, as opposed to a 0.09 K increase in the ERA-Interim dataset. This stronger climate change signal is added to the ERA 1990–1999 data. Since the SST field is slowly varying, the difference between the two bias correction methods is small.

Table 4 in Appendix A2 summarizes the statistics for the output T2M field for the inner domain d02 and for the usual agro-climatical subregions (c. f., Fig. 4). Again, the ERA 2001–2009 data is used as reference and the CRU and CPC (Fan and van den Dool 2008) observational data sets are added for further comparison. In general, all model runs underestimate the 2m temperatures over land with respect to the observational data sets, with the reference data ERA 2001–2009 being closest, and with the uncorrected MPI 2001–2009 having the largest negative bias. Interestingly, the MPI 1991–1999 model run is close to the ERA 2000–2009 model run, while the MPI 2001–2009 model run is consistently cooler over land.

Comparing the two ERA-Interim model runs, this cooling signal between the two decades is missing and thus reflects itself in the statistics for the PGW/PAC runs. However, both bias correction methods improve over the raw MPI 2001–2009 model run. The PGW (PAC) model run is closer to the ERA-Interim (MPI-ESM) model run, which is expected from the design of the bias correction methods.

The Pearson Correlation Coefficient is very high for ERA 1991–1999 and MPI 1991–1999, and lowest for MPI 2001–2009 and the CRU/CPC observations. Both bias correction methods consistently improve the correlation with ERA 2001–2009, compared to the raw MPI 2001–2009 model run. It is worth noting the differences in mean, bias and PCC between the two observational data sets CRU and CPC, highlighting the great uncertainty of the observations in the data-sparse region of West Africa.

4. Conclusions and outlook

In the first part, we investigated how different WRF model configurations influence the representation of the West African Monsoon and the total precipitation. In principal, all configurations were able to reproduce the seasonal movement of the rain band. However, we found large differences in how far it moves to the North and consequently in the total precipitation over the West African continent. We identified a number of model configurations suitable for both control runs (using re-analysis data) and climate projections (using GCM data). We also found that on seasonal time scales, the choice of the cumulus scheme is less important than the choice of the planetary boundary layer and microphysics schemes. In a next step, we will investigate how the cumulus scheme influences the diurnal cycle and the short-term frequency of precipitation events.

In the second part, we applied two different bias correction methods to the MPI-ESM global circulation model, using ERA-Interim re-analysis data for calibration. We applied the bias correction, derived from the period 1990-1999, to the following decade 2000–2009. For the input sea surface temperature and the output 2m temperature, both methods led to a consistent improvement over the raw GCM data, with differences between them as expected. In the future, we will discuss the results on precipitation and other climate key variables and focus on the comparison with observational data sets in addition to re-analysis data.

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APPENDIX

A1. WRF sensitivity study – model physics configurations

Table 3. Model physics configurations tested in the WRF sensitivity study. All configurations use Noah LSM.

#	CU	MP	PBL	SW	SW	Forcing	Notes
	First 27+2 experiments in step *(i)*						
1	BMJ	LIN	ACM2	DUDHIA	RRTM	ERA-Interim	
2	BMJ	LIN	MYJ	DUDHIA	RRTM	ERA-Interim	
3	BMJ	LIN	YSU	DUDHIA	RRTM	ERA-Interim	
4	BMJ	TH	ACM2	DUDHIA	RRTM	ERA-Interim	
5	BMJ	TH	MYJ	DUDHIA	RRTM	ERA-Interim	
6	BMJ	TH	YSU	DUDHIA	RRTM	ERA-Interim	
7	BMJ	WSM3	ACM2	DUDHIA	RRTM	ERA-Interim	
8	BMJ	WSM3	MYJ	DUDHIA	RRTM	ERA-Interim	
9	BMJ	WSM3	YSU	DUDHIA	RRTM	ERA-Interim	
10	GF	LIN	ACM2	DUDHIA	RRTM	ERA-Interim	
11	GF	LIN	MYJ	DUDHIA	RRTM	ERA-Interim	
12	GF	LIN	YSU	DUDHIA	RRTM	ERA-Interim	
13	GF	TH	ACM2	DUDHIA	RRTM	ERA-Interim	
14	GF	TH	MYJ	DUDHIA	RRTM	ERA-Interim	
15	GF	TH	YSU	DUDHIA	RRTM	ERA-Interim	
16	GF	WSM3	ACM2	DUDHIA	RRTM	ERA-Interim	
17	GF	WSM3	MYJ	DUDHIA	RRTM	ERA-Interim	
18	GF	WSM3	YSU	DUDHIA	RRTM	ERA-Interim	
19	KF	LIN	ACM2	DUDHIA	RRTM	ERA-Interim	
20	KF	LIN	MYJ	DUDHIA	RRTM	ERA-Interim	
21	KF	LIN	YSU	DUDHIA	RRTM	ERA-Interim	
22	KF	TH	ACM2	DUDHIA	RRTM	ERA-Interim	
23	KF	TH	MYJ	DUDHIA	RRTM	ERA-Interim	
24	KF	TH	YSU	DUDHIA	RRTM	ERA-Interim	
25	KF	WSM3	ACM2	DUDHIA	RRTM	ERA-Interim	
26	KF	WSM3	MYJ	DUDHIA	RRTM	ERA-Interim	
27	KF	WSM3	YSU	DUDHIA	RRTM	ERA-Interim	
28	GD	WSM5	ACM2	DUDHIA	RRTM	ERA-Interim	Noble et al. (2013) (except LW/SW/LSM)
29	KF	WSM6	YSU	DUDHIA	RRTM	ERA-Interim	WRF User's Guide (except LW/SW)
	Testing CAM and RRTMG radiation schemes						
30	BMJ	LIN	MYJ	CAM	CAM	ERA-Interim	
31	BMJ	LIN	MYJ	RRTMG	RRTMG	ERA-Interim	
32	BMJ	TH	ACM2	CAM	CAM	ERA-Interim	
33	BMJ	TH	ACM2	RRTMG	RRTMG	ERA-Interim	
34	GD	WSM5	ACM2	RRTMG	RRTMG	ERA-Interim	Noble et al. (2013) (except LSM)
35	GF	TH	MYJ	CAM	CAM	ERA-Interim	
36	GF	WSM6	MYJ	CAM	CAM	ERA-Interim	
37	KF	TH	MYJ	CAM	CAM	ERA-Interim	
38	KF	TH	YSU	CAM	CAM	ERA-Interim	
39	KF	WSM6	MYJ	CAM	CAM	ERA-Interim	
40	KF	WSM6	YSU	CAM	CAM	ERA-Interim	WRF User's Guide
41	BMJ	LIN	MYJ	RRTMG	RRTM	ERA-Interim	Change of SW only
	Testing GCM forcing data for promising configurations						
43	BMJ	LIN	MYJ	DUDHIA	RRTM	MPI-ESM	
44	BMJ	LIN	MYJ	RRTMG	RRTMG	MPI-ESM	
45	BMJ	LIN	YSU	DUDHIA	RRTM	MPI-ESM	
46	BMJ	TH	ACM2	RRTMG	RRTMG	MPI-ESM	
47	GD	WSM5	ACM2	RRTMG	RRTMG	MPI-ESM	
48	GF	WSM5	ACM2	DUDHIA	RRTM	MPI-ESM	
49	GF	WSM5	ACM2	RRTMG	RRTMG	MPI-ESM	
50	KF	LIN	YSU	DUDHIA	RRTM	MPI-ESM	
51	KF	TH	ACM2	DUDHIA	RRTM	MPI-ESM	
52	KF	WSM5	MYJ	RRTMG	RRTMG	MPI-ESM	
53	KF	WSM6	YSU	CAM	CAM	MPI-ESM	WRF User's Guide

TABLE 4. 9-year mean 2m near surface temperature, bias and correlation with respect to ERA 2000–2009 over land, sea, and the four agro-climatical subregions of West Africa. Two observational datasets are added for comparison.

			land	**sea**	**sahelo**	**sahel**	**soudano**	**guinea**
ERA	1990-1999	MEAN	299.64	298.24	301.23	302.36	300.73	298.17
		BIAS	−0.21	−0.14	−0.15	−0.13	−0.23	−0.14
		PCC	0.99	0.99	0.99	0.99	0.99	0.99
ERA	2000-2009	MEAN	299.85	298.38	301.39	302.49	300.97	298.31
		BIAS	0.00	0.00	0.00	0.00	0.00	0.00
		PCC	1.00	1.00	1.00	1.00	1.00	1.00
MPI	1990-1999	MEAN	298.43	298.55	299.58	300.69	299.60	297.43
		BIAS	−1.43	0.18	−1.81	−1.79	−1.36	−0.88
		PCC	0.98	0.95	0.96	0.95	0.97	0.98
MPI	2000-2009	MEAN	297.84	299.01	298.20	300.03	299.46	297.85
		BIAS	−2.01	0.63	−3.19	−2.46	−1.50	−0.46
		PCC	0.77	0.94	0.71	0.72	0.86	0.98
PGW	2000-2009	MEAN	299.36	298.54	300.62	301.33	300.13	298.27
		BIAS	−0.49	0.17	−0.77	−1.16	−0.84	−0.04
		PCC	0.90	0.99	0.87	0.91	0.94	0.99
PAC	2000-2009	MEAN	298.14	298.56	298.37	300.15	299.87	298.10
		BIAS	−1.72	0.19	−3.03	−2.34	−1.09	−0.21
		PCC	0.79	0.99	0.71	0.78	0.93	0.98
CRU	2000-2009	MEAN	300.00	−	301.93	302.30	300.34	298.87
		BIAS	0.15	−	0.53	−0.19	−0.63	0.56
		PCC	0.91	−	0.74	0.79	0.87	0.78
CPC	2000-2009	MEAN	300.21	−	302.14	302.50	300.29	298.79
		BIAS	0.36	−	0.75	0.02	−0.68	0.48
		PCC	0.81	−	0.59	0.71	0.49	0.65