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Improving future temperature projections with bias correction methods in Lake of Guiers/Senegal

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Climate models are generally used to evaluate the climate change impacts. However, they have important biases at the regional or local scales. This study evaluates the future temperature projections in Lake of Guiers/Senegal. For this, the daily maximum and minimum temperature from the ensemble mean of five (5) Coordinated Regional climate Downscaling Experiment (CORDEX) regional climate models (RCMs) under the greenhouse gas scenarios RCP4.5 and RCP8.5 and three (3) bias correction methods (Linear scaling, variance scaling and quantile mapping methods) were used. The performance of raw ensemble mean of the models was first evaluated against the WFDEI data. The results show that this latter exhibits some limitations to reproduce the minimum and the maximum temperature at the Lake scale. In order to make temperature data more accurate, the three bias correction methods were used. Results show that bias correction methods improve well the simulated minimum and maximum temperature. The future temperature projections show an increase of temperature which are faster in bias-corrected data. From the results it is indicated that it is necessary to implement appropriate adaptation measures to address these climate changes.

Key words: Climate change, regional climate models, coordinated regional climate downscaling experiment (CORDEX), bias correction methods, Lake of Guiers.

INTRODUCTION

Most of the studies conducted on the West African climate show an increase in temperatures in the Sahel region (IPCC, 2013; Ly et al., 2013; Giorgi et al., 2014). These temperature increases can impact the hydrological cycle and agriculture yields (Salack et al., 2011; Gelata and Gobosho, 2018; Sarr and Camara, 2018). They can also lead to problems in the supply of fresh water to populations through the evaporation phenomena,

especially in Sahelian countries which are characterized by a short rainy season (3 to 4 months) and with variability in rainfall distribution (Tall et al., 2016; Luo et al., 2018). Therefore, climate change scenarios are needed in West Africa, particularly in Sahel to evaluate these impacts.

In West Africa climate changes have often been studied with global climate models (GCMs). However,

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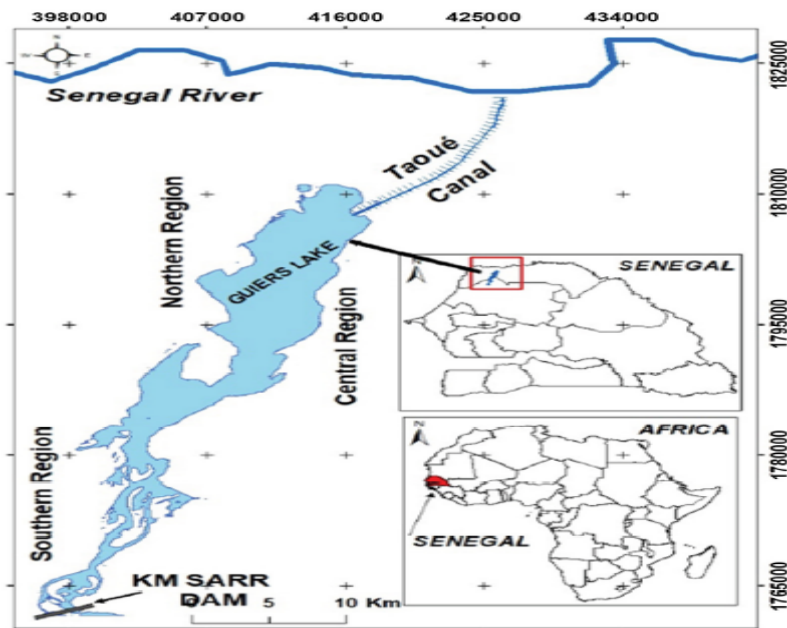


Figure 1. Study area.
Source: Diédhiou et al. (2019).

these models have large disparities in this region. In fact, GCMs have difficulty simulating certain surface heterogeneities because of their low spatial resolution (200 to 300 km). Thus, these GCMs are important only when it comes to representing global climate change. That is to say on a large scale. To address these issues, regional climate models (RCMs) are increasingly being used to dynamically disaggregate global climate models (Paeth et al., 2011). In this context, several experiments have been undertaken to produce coordinated experiments using several regional climate models (RCMs). This is the case of PRUDENCE (Baguis et al., 2010), ENSEMBLES-AMMA (Déqué et al., 2012). However, these coordinated experiments focused on limited areas. CORDEX is an international program implemented by several research centers which aim is to produce reliable climate change scenarios for impact studies. The ability of CORDEX RCMs to reproduce the present climate in West Africa has been assessed in numerous studies (Nikulin et al., 2012; Gbobaniyi et al., 2014; Klutse et al., 2015; Akinsanola and Ogunjobi, 2017). The climate change scenarios are obtained by forcing CORDEX RCMs by the Coupled Models Intercomparison Project phase 5 (CMIP5) GCMs from 1951 to 2100 (Giorgi et al., 2009). RCMs are the same basic physical principles as GCMs, but with higher horizontal resolution (~10-50 km). They are much more appropriate for impact studies because of their ability to represent the climate in complex areas such as West Africa. However, the simulated climate is not again in perfect agreement with observation. In fact, these RCMs

also have limitations when it comes to focusing at the local-scale such as at the farm or basin scales. That is why, some authors (Hawkins et al., 2012; Kum et al., 2014; Gumindoga et al., 2016; Grillakis et al., 2017) have recommended the use of bias correction methods to eliminate or reduce bias to produce reliable climate change scenarios for impact assessment purposes.

The main objective of this study is to evaluate the performance of the Coordinated Regional climate Downscaling Experiment (CORDEX) models and the three (3) bias correction methods commonly used (Linear Scaling, Variance Scaling and Distribution Mapping) to simulate present and future temperature in the Lake of Guiers.

METHODOLOGY

Study area

The study area is the Lake of Guiers (Figure 1) which is the main reserve of surface freshwater in Senegal. It is located in northern Senegal, in the upper delta of the Senegal river basin, between longitude 15°40'-16° West and between latitude 16°-16°30' North. It extends between the south of city of Richard Toll (near the border with the Mauritania) and and Louga regions (toward K M SARR) (Figure 1). The minimum and maximum daily air temperatures in this city range between 22 and 36°C, respectively, while the mean annual rainfall is about 403 mm (Niang, 2011; Diédhiou et al., 2019). The main activities carried out in the semi-desert areas surrounding the lake are breeding, fishing, rice and sugar cane cultivation. The lake water is also used as a drinking water resource for the urban centers (165,000 m³/day for a population of 5 million inhabitants) (Sambou et al., 2019).

Table 1. Description of the regional climate models.

Name	GCM forcing	Institution	References
CCLM4	CNRM-CM5	CLM-community	Baldauf et al. (2011)
RACMO22T	EC-EARTH	KNMI, The Netherlands	Meijgaard et al. (2008)
RCA4	CNRM-CM5	SMHI, Sweden	Samuelsson et al. (2011)
HIRHAM5	EC-EARTH	DMI, Denmark	Christensen et al. (2006)
REMO	EC-EARTH	MPI, Germany	Jacob et al. (2007)

Datasets

This study uses daily maximum and minimum temperature data from CORDEX RCMs. They are CCLM4, RCA4, HIRHAM, REMO and RACMO. The model institutions, the regional climate models and their reference are presented in Table 1. The spatial resolution of CORDEX RCMs is 0.44° (approximately 50 km). They cover the period 1976-2005 for the historical and 2006-2100 for future. The RCMs outputs are available from this website: <https://www.cordex.org/output.html>.

These models are described in detail by Giorgi et al. (2009). Two periods are considered in this study: the reference period (1979 - 2005) and the future period (2006 - 2100). The RCMs RACMO, HIRHAM and REMO are forced by the outputs of the GCM EC-EARTH; while models RCA4 and CCLM4 are forced by the outputs of the GCM CNRM-CM5. The climate projections are obtained by forcing the regional climate models by the outputs of the global climate models under the greenhouse gas scenarios RCP4.5 and RCP8.5 which, respectively correspond to radiative forcing of 4.5 and 8.5 W/m^2 at the horizon 2100. To evaluate the performance of bias correction methods, the Water and Global Change (WATCH) Forcing Data methodology was applied to ERA-Interim reanalysis data (WFDEI) (Weedon et al., 2014). The WFDEI data are available from 1979 to 2012. Two periods are considered in this study: the reference period (1979- 2005), which is the common period between RCMs data and WFDEI data and the future period (2006-2100).

Bias correction methods

In this study, three bias correction temperature methods commonly used namely linear scaling (LS), variance scaling (VS) and distribution mapping (DM) are considered. The period of calibration of this bias correction method is 1979-1993 and the period of validation is 1994-2005.

Linear scaling

The Linear Scaling (LS) method (Lenderink et al., 2007) corrects the outputs of the climate model by using the difference in the mean variability between the observations and climate model.

$$T_{cor,m,d} = T_{raw,m,d} + (\overline{T_{obs,m}} - \overline{T_{ref,m}}) \quad (1)$$

where $T_{cor,m,d}$ are the corrected minimum or maximum temperature on the d^{th} day of m^{th} month; $T_{raw,m,d}$ are the uncorrected minimum or maximum temperature on the d^{th} day of m^{th} month; $\overline{T_{obs,m}}$ and $\overline{T_{ref,m}}$ are the mean values of observed and simulated minimum or maximum temperature at the given

month.

Variance scaling

For the linear scaling method, the biases in variance are not corrected. That is why the Variance Scaling (VS) method was implemented to bias correct the temperature time series (Terink et al., 2010). It is given by Equation (3):

$$T_{cor,m,d} = \overline{T_{obs,m}} + [T_{raw,m,d} - \overline{T_{ref,m}}] \times \frac{\sigma(T_{obs,m})}{\sigma(T_{raw,m})} \quad (2)$$

where $\sigma(T_{raw,m})$ and $\sigma(T_{obs,m})$ represent, respectively the standards deviation of the monthly RCMs outputs and observations during the reference period.

Distribution mapping

The Distribution Mapping (DM) method was used to correct the distribution function of the raw data (Piani et al., 2010). It is used to adjust mean, standard deviation and quantiles. The Gaussian distribution (or normal distribution) with the parameters μ (mean) and σ (standard deviation) is usually considered to adjust the temperature probability distribution (Teutschbein and Seibert, 2012):

$$F_N(x|\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \times e^{-\frac{(x-\mu)^2}{2\sigma^2}}; x \in R \quad (3)$$

The corrected temperature expressed in terms of Gaussian CDF (F_N) and its inverse (F_N^{-1}) and is given by:

$$T_{cor,m,d} = F_N^{-1}(F_N(T_{raw,m,d}|\mu_{raw,m}, \sigma_{raw,m})|\mu_{obs,m}, \sigma_{obs,m}) \quad (4)$$

where F_N and F_N^{-1} represent, respectively the gamma cumulative distribution and its inverse, $T_{raw,m,d}$ is the uncorrected minimum or maximum temperature during the month m and the day d of reference period, $\mu_{raw,m}$ and $\sigma_{raw,m}$ represent, respectively the mean and standard deviation of the uncorrected temperature during the month m and $\mu_{obs,m}$ and $\sigma_{obs,m}$ are, respectively the mean and the standard deviation of the observed temperature.

Performance of statistical method

To evaluate the performance of the bias correction methods, some

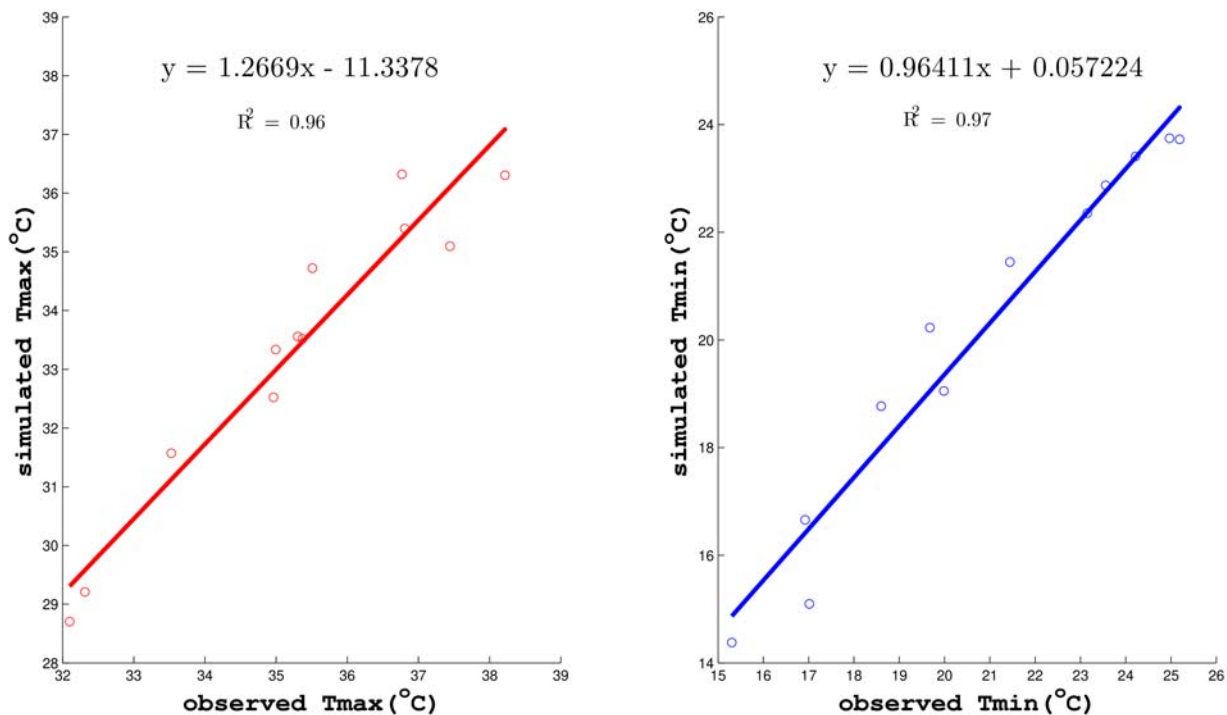


Figure 1. Scatter plots of the simulated and the WFDEI monthly maximum temperature (left panel) and monthly minimum temperature (right panel) averaged from 1979 to 2005.

statistical parameters such as the absolute bias (MB), the root mean square error (RMSE) and the Nash-Sutcliffe efficiency (NSE) were calculated.

The mean bias gives an indication of the sign of errors (underestimation or overestimation):

$$MB = \frac{\sum_{i=1}^n (T_{sim_i} - T_{obs_i})}{n} \tag{5}$$

The root mean square error (RMSE) measures the amplitude of errors committed by models.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (T_{sim_i} - T_{obs_i})^2}{n}} \tag{6}$$

The Nash-Sutcliffe efficiency (NSE) gives the relative magnitude of variance of residues compared to the observed variance. It is between $-\infty$ and 1 with 1 the optimal value. The NSE values less than 0 are considered unacceptable while those between 0 and 1 are considered acceptable.

$$NSE = 1 - \frac{\sum_{i=1}^n (T_{sim_i} - T_{obs_i})^2}{\sum_{i=1}^n (T_{obs_i} - T_{obs_i})^2} \tag{7}$$

where n is the number of time steps; T_{sim_i} and T_{obs_i} are, respectively the time series of the simulated and the observed (WFDEI) temperature.

RESULTS

Performance of the multi-model ensemble

Figure 2 shows the monthly maximum and minimum temperature simulated by the five CORDEX RCMs present in the ensemble-mean compared to WFDEI data from 1979 to 2005. The ensemble mean of the model was considered because numerous studies (Kim et al., 2014; Gbobaniyi et al., 2014) pointed that it better reproduces the spatial distribution of the surface temperature. WFDEI data show the lowest minimum and maximum temperature (around 16 and 32°C, respectively) in the Lake of Guiers between December and February. The highest minimum and maximum temperature (around 24 and 38°C, respectively) are recorded from April to June and from July to September, respectively. WFDEI data shows also a decrease of maximum temperature between the end of June and September corresponding to the rainy season in Senegal. The ensemble-mean of the models generally reproduces well the pattern of the monthly maximum and minimum temperature observed in the Lake. Also, the monthly maximum and minimum temperature simulated are closer to that observed, as shown in Figure 3 with a coefficient of determination of 0.96 and 0.97, respectively. It should also be noted that the ensemble mean of the models reproduces quite well the minimum temperature observed. This is confirmed by

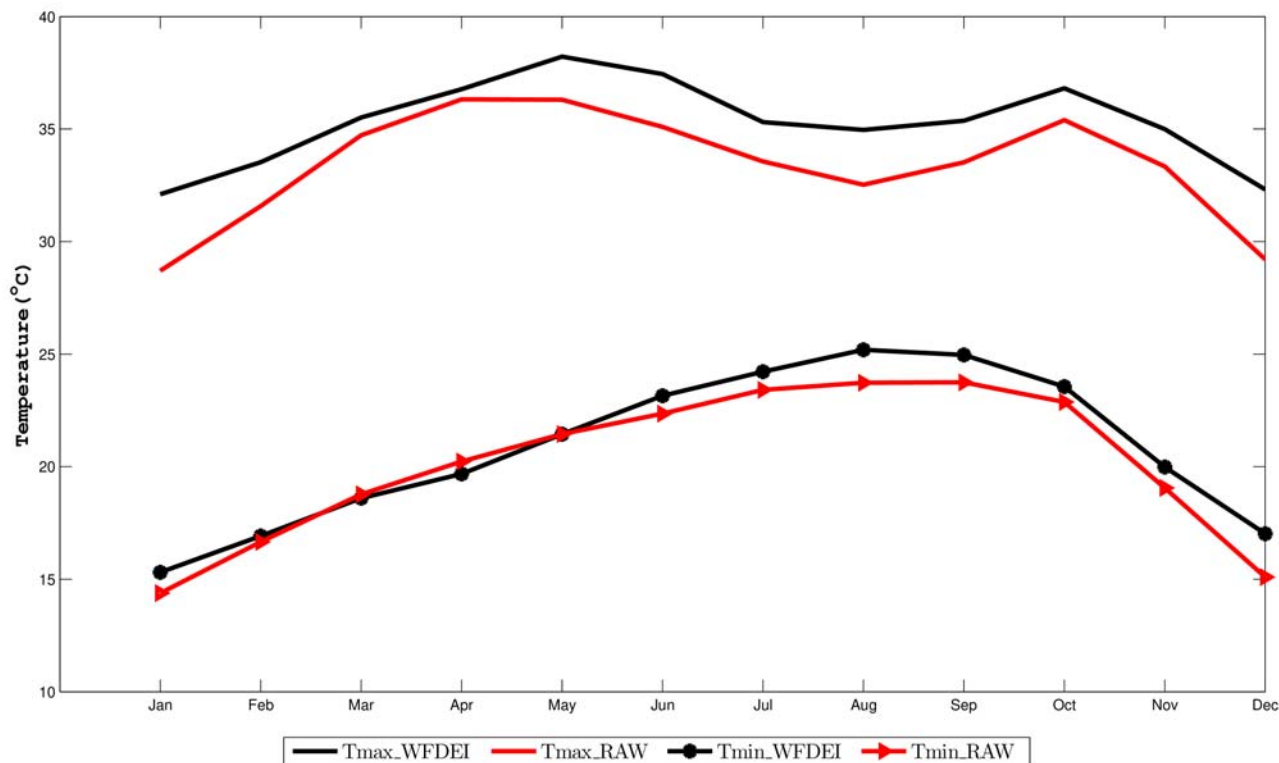


Figure 2. Monthly maximum and minimum temperature averaged from 1979 to 2005 of WFDEI data and the ensemble mean of the models. Tmax_WFDEI and Tmin_WFDEI represents respectively the maximum and the minimum temperature of WFDEI and Tmax_RAW and Tmin_RAW represent respectively the raw minimum and maximum temperature simulated by the multi-model ensemble.

Table 2. Performance measures of the raw multi-model ensemble during the period 1979-2005.

T_{max}				T_{min}			
MB	RMSE	NSE	R	MB	RMSE	NSE	R
-1.92	2.02	-0.30	0.95	-0.69	1.08	0.91	0.97

the results obtained in Table 2. Nevertheless, the simulated temperature is always biased. In fact, it presents an overestimation of the maximum temperature for all months with mean bias of -1.92. For the minimum temperature, it overestimates the observed values only between March and May. Thus, the performance of outputs of the multi-model ensemble can be increased by bias correction methods.

Figure 4 shows the comparison of the monthly maximum and minimum temperature from the WFDEI data, raw multi-model ensemble and bias-corrected respectively during the calibration period (1979-1993) and validation period (1994-2005). The results show that the bias in ensemble mean of the models temperature is remarkably reduced. All the three bias correction methods improve satisfactory the outputs of the ensemble

mean of the models. There are very slight differences between the WFDEI data and the bias-corrected multi-model ensemble compared to raw data during the calibration data. But some contrasts exist between the three bias corrected multi-model ensemble mean and their performances with respect to both parameters. In fact, results show that Linear Scaling (LS) method is closer to the observed temperature followed by Distribution mapping (DM) method. The statistical performance measures of bias-corrected temperature during the calibration and the validation periods are presented in Table 3. The statistical indicators values reflect the good performances of the three bias correction methods during the calibration and validation periods. During the calibration period the mean bias is less than 0.01 excepted VS method for the monthly maximum

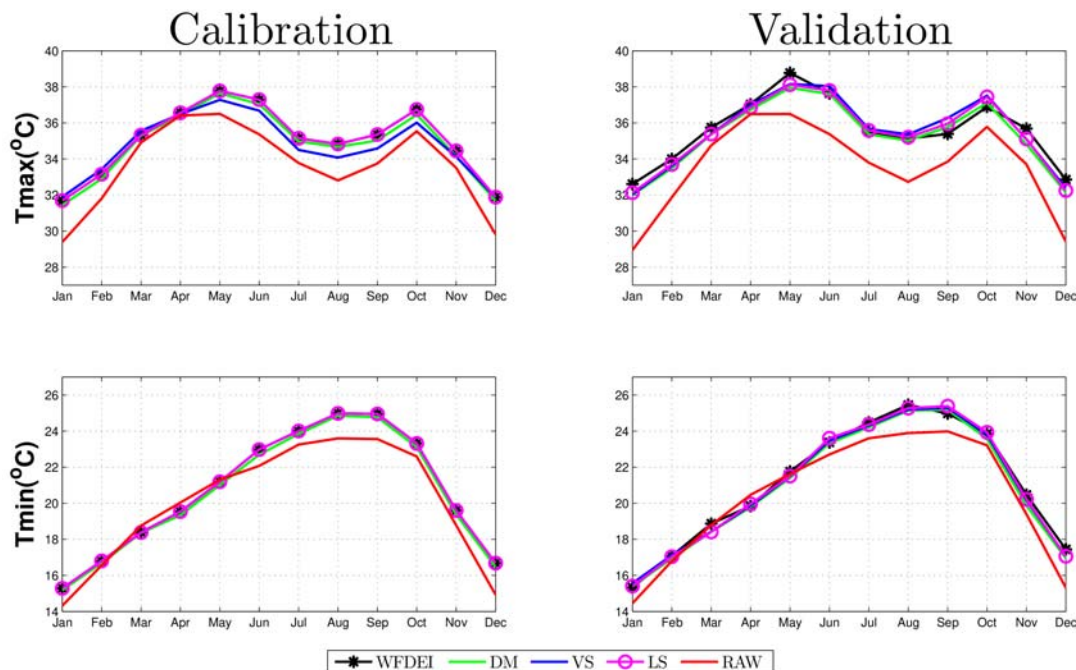


Figure 3. Monthly maximum and minimum for the calibration period (left panel) and for the validation period (right panel).

Table 3. Performance measures of the bias-corrected monthly maximum and minimum temperature during the calibration and validation periods.

Parameter	Methods	Calibration period				Validation period			
		MB	RMSE	NSE	R	MB	RMSE	NSE	R
Tmax	RAW	-1.38	1.57	0.21	0.84	-2.00	2.09	-0.48	0.83
	LS	< -0.01	0.87	0.73	0.86	-0.14	0.85	0.68	0.84
	VS	-0.30	1.02	0.65	0.85	-0.06	0.92	0.67	0.84
	DM	< 0.01	0.88	0.72	0.86	-0.10	0.88	0.67	0.84
Tmin	RAW	-0.66	1.08	0.85	0.94	-0.72	1.08	0.85	0.94
	LS	< 0.01	0.69	0.93	0.97	-0.06	0.69	0.93	0.97
	VS	< 0.01	0.66	0.94	0.97	-0.09	0.68	0.93	0.96
	DM	< 0.01	0.69	0.93	0.97	-0.05	0.70	0.93	0.97

temperature. On the other hand, VS method better corrects the mean bias of the monthly maximum temperature during the validation period. The good results obtained with the statistical parameters (RMSE < 1, NSE and R values close to 1) during both periods highlight the ability of bias correction to improve the simulated monthly maximum and minimum temperature. We also note that the ability of the three bias correction methods to better correct the minimum temperature. This might be due to fairly good capacity of the five models present in the ensemble mean to better simulate the minimum temperature. Therefore, the minimum temperature become easier to bias-corrected.

To see the performance of bias correction methods at the daily time scale, Figure 5 shows the 7-day mean of the maximum and minimum temperature from the WFDEI data, raw multi-model ensemble and bias-corrected, respectively during the calibration period (1979-1993) and validation period (1994-2005). Table 4 shows the statistical performance measures of daily maximum and minimum temperature. The results show that all bias correction methods improve also the daily maximum and minimum temperature during the calibration and the validation period. As for monthly time scale, LS and DM methods better improve the quality of daily maximum and minimum temperature simulated by multi-model

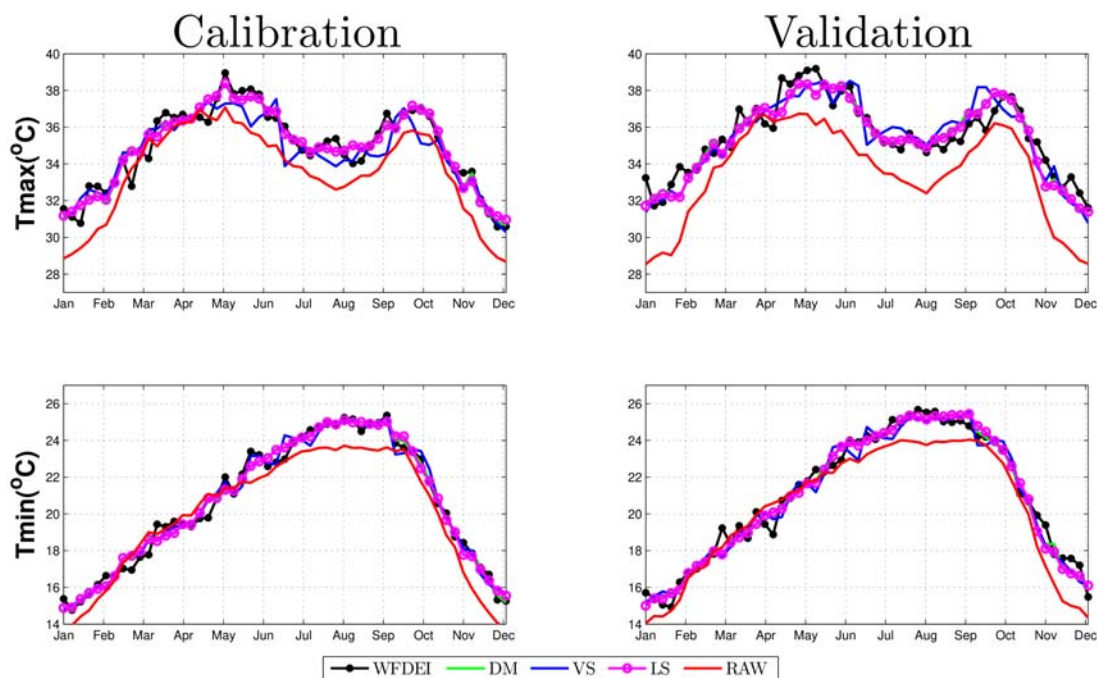


Figure 4. Daily mean maximum and minimum after smooth with the 7-day moving average method for the calibration period (left panel) and for the validation period (right panel).

Table 4. Performance measures of the bias-corrected daily maximum and minimum temperature during the calibration and validation periods.

Parameter	Methods	Calibration period				Validation period			
		MB	RMSE	NSE	R	MB	RMSE	NSE	R
Tmax	RAW	-1.38	2.78	0.02	0.50	-2.00	3.05	-0.28	0.45
	LS	< -0.01	2.44	0.21	0.57	-0.14	2.41	0.13	0.46
	VS	-0.30	2.53	0.16	0.53	-0.06	2.43	0.13	0.47
	DM	< -0.01	2.46	0.20	0.52	-0.10	2.44	0.11	0.46
Tmin	RAW	-0.66	1.89	0.61	0.80	-0.73	1.85	0.62	0.81
	LS	< -0.01	1.69	0.67	0.82	-0.06	1.63	0.68	0.83
	VS	< -0.01	1.71	0.66	0.82	-0.10	1.69	0.66	0.82
	DM	< -0.01	1.68	0.67	0.82	-0.06	1.64	0.68	0.83

ensemble. Moreover, slight differences are noted when the performance of both methods was considered. That is to say, both bias correction methods show similar performances. The results obtained in Table 4 confirm the good performances of bias correction methods. In fact, low mean bias are recorded ($MB < 0.01^{\circ}\text{C}$) for the daily temperature values except the VS method for daily maximum temperature as in monthly scale during the calibration period. However, when we compare the statistical parameters, results show that bias correction methods perform better on the monthly scale over the

daily. The results obtained during the validation period show that VS method is more suitable for daily and monthly maximum temperature. Moreover, the DM method is better suitable to bias correct the daily minimum temperature. For monthly minimum temperature, DM and LS method seem to give the best bias-correction. Globally, the three temperature bias correction methods improve the performance of the ensemble mean of the models. The ability of bias correction methods to improve the performance of the ensemble mean of the models strengthens our confidence in the future temperature

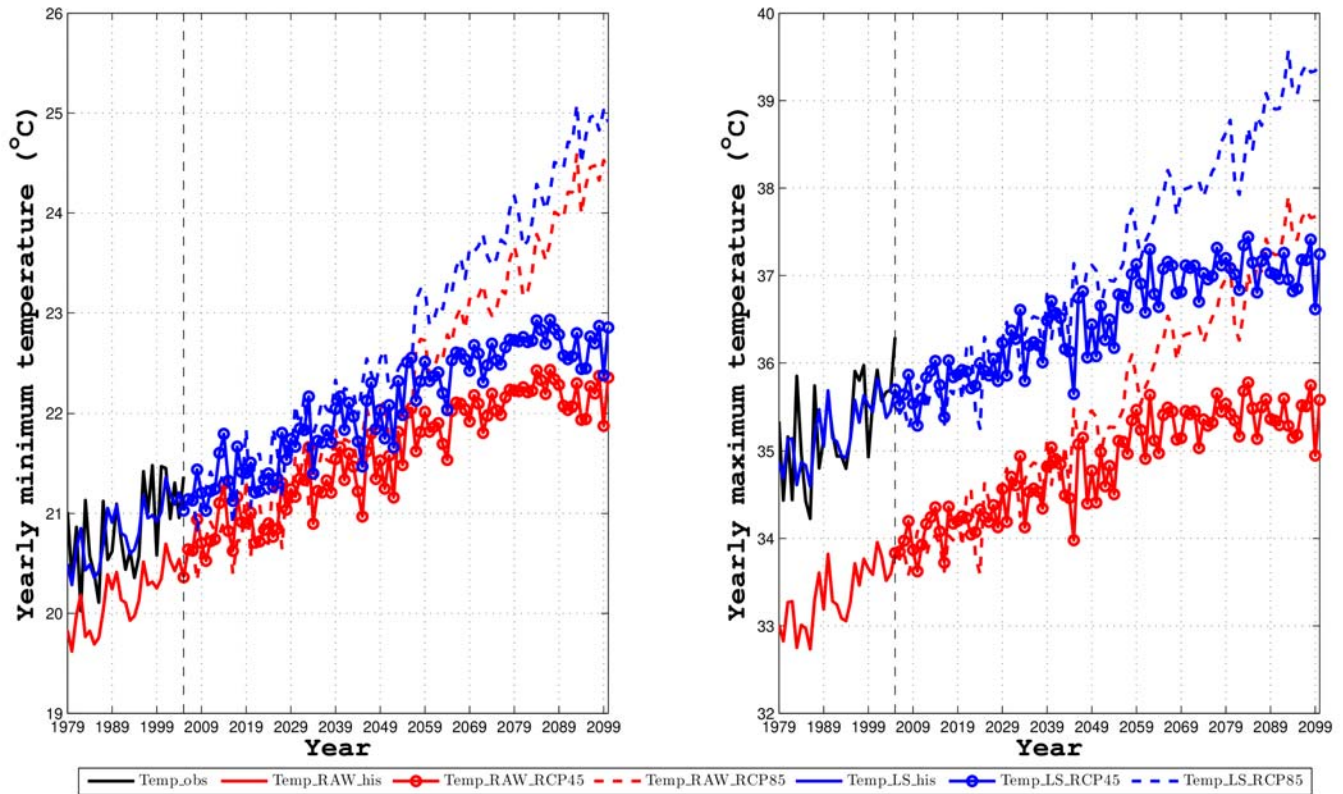


Figure 5. Impact of the LS bias correction method on projected yearly minimum and maximum temperature (left panel and right panel respectively). Temp_obs represents the observed minimum or maximum temperature, Temp_RAW_his is the raw minimum or maximum temperature during the historical period, Temp_RAW_RCP45 and Temp_RAW_RCP85 represent respectively the raw minimum or maximum temperature during the future under the scenarios RCP4.5 and RCP8.5, Temp_LS_his represents the historical minimum or maximum temperature corrected by LS method and Temp_LS_RCP4.5 and Temp_LS_RCP8.5 are respectively the future minimum or maximum temperature corrected by LS method.

projections in the Lake of Guiers.

Projection of future temperature

After evaluating the bias correction methods, the temporal evolution of annual maximum and minimum temperature from 1979 to 2100 was studied. Figures 6, 7, and 8 illustrate the impact of the LS, VS, and DM bias correction methods on the projected annual minimum and maximum temperatures, respectively. The results show that the corrected data reproduce well the WFDEI data during the reference period (1979-2005) compared to raw data. However, it was found out that the corrected data by DM method (Figure 8) shows the highest performance in simulated annual temperature (MB=0.04°C/ <0.01°C, NSE=0.39/0.36 for yearly maximum/minimum temperature, respectively) compared to VS method (Figure 8) (MB=-0.04°C/-0.01°C, NSE=0.34/0.30 for yearly maximum/minimum temperature) and LS method (Figure 7) (MB=-0.05°C/ <-0.01°C, NSE=0.39/0.30 for maximum/minimum temperature). It was also noted that

the multi-model mean corrected by the three methods considered shows an upward trend in temperatures compared to that uncorrected almost over the entire period in both scenarios (RCP4.5 and RCP8.5). This overall increase is greater in the pessimistic scenario (RCP8.5) than in the medium scenario (RCP4.5). The magnitude of the difference between the corrected and uncorrected multi-model mean is much greater when considering the maximum temperature. But the sign of the change signal in raw data is not modified in those bias-corrected. Globally, important increases are observed in future maximum and minimum temperature when the raw ensemble of the models and bias-corrected under both scenarios were considered. This is in agreement with several results obtained on the Sahel (IPCC, 2013; Ly et al., 2013; Sylla et al., 2016). This increase is greater from 2060 especially under the RCP8.5 scenario. In fact, an increase of 0.8 to 0.15°C per decade and of 0.5 to 0.53°C per decade is predicted, respectively under the RCP4.5 and RCP8.5 scenarios for the mean annual minimum temperature. For the mean annual maximum temperature, the increase range

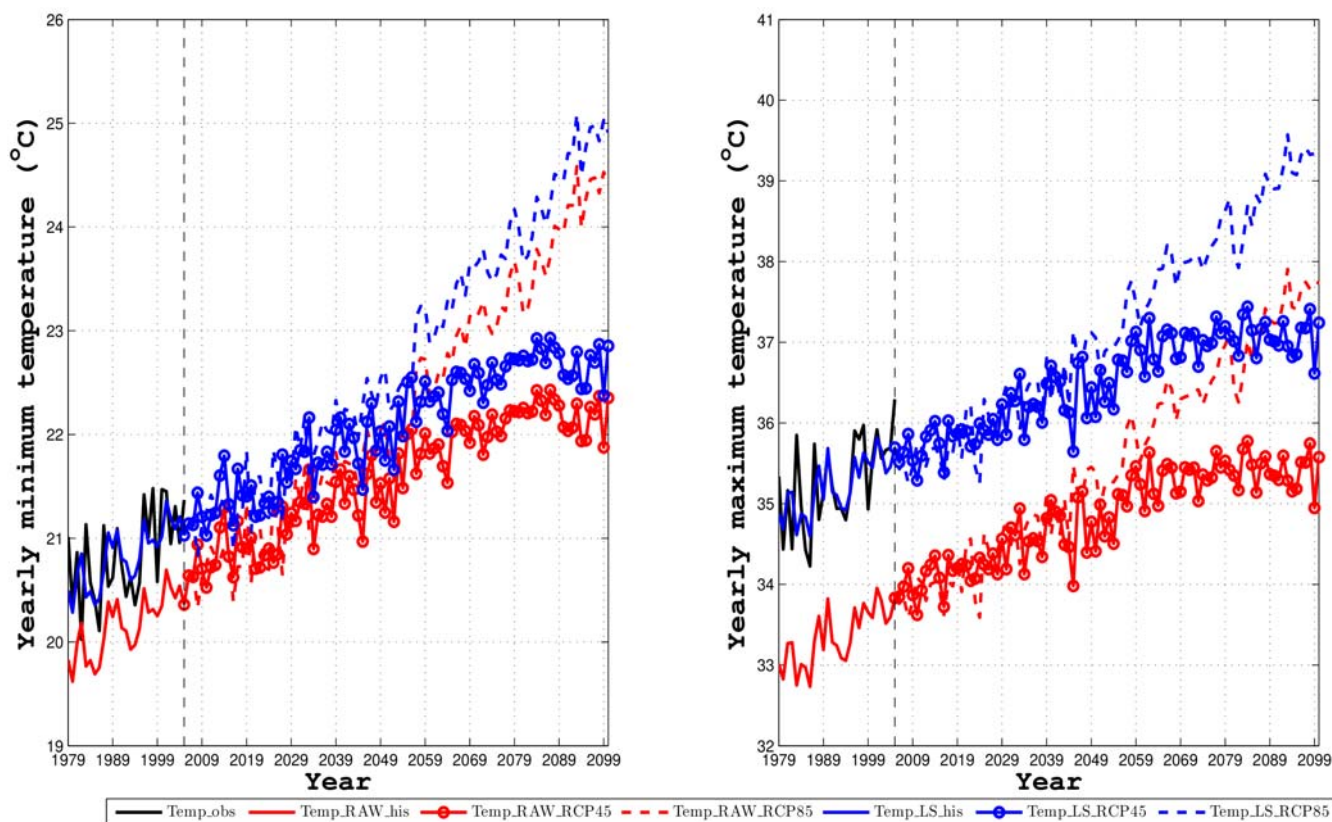


Figure 6. Impact of the VS bias correction method on projected yearly minimum and maximum temperature (left panel and right panel respectively). Temp_obs represents the observed minimum or maximum temperature, Temp_RAW_his is the raw minimum or maximum temperature during the historical period, Temp_RAW_RCP45 and Temp_RAW_RCP85 represent respectively the raw minimum or maximum temperature during the future under the scenarios RCP4.5 and RCP8.5, Temp_LS_his represents the historical minimum or maximum temperature corrected by VS method and Temp_LS_RCP4.5 and Temp_LS_RCP8.5 are respectively the future minimum or maximum temperature corrected by VS method.

between 0.08 and 0.22°C per decade and 0.55 to 0.66°C per decade, respectively under RCP4.5 and RCP8.5 scenarios. The lowest increases in minimum and maximum temperature were obtained with raw multi-model mean and the highest increases in minimum and maximum temperature were obtained with multi-model mean bias-corrected by DM (Figure 8) and VS methods (Figure 7), respectively.

DISCUSSION

This study evaluates the performance of the ensemble-mean of five (5) CORDEX regional climate models (RCMs) models and the three (3) bias correction methods commonly used (Linear Scaling, Variance Scaling and Distribution Mapping) to better simulate present and future temperature in the Lake of Guiers which plays an important role in the socio-economic development of Senegal (Sambou et al., 2019; Diedhiou et al., 2019). The results show that the ensemble-mean of model

simulates well the observed minimum and maximum temperature. However, it still contains some bias. According to Luo et al. (2018), these biases come from to the forcing of Global Climate models (GCMs) or produced by a systematic error of the model. Therefore, it is very important to bias-correct the RCMs data before studying the climate change (Chen et al., 2013; Ajaaj et al., 2015). The results show that all methods used can improve the original RCMs outputs with few differences. The simplest bias correction method is the Linear Scaling (LS) which corrects the outputs of the climate model by using the difference in the mean variability between the observations and climate model. Thus, the biases in variance are not corrected. However, it was found that for the daily and monthly minimum temperature during the validation period LS method gives the best results. Thus, the uncorrected minimum temperature might not be biased in variance. Of the three bias correction methods used, the DM method is the most advanced. It is used to adjust the mean, the standard deviation and the quantile. This method better corrects the minimum temperature at

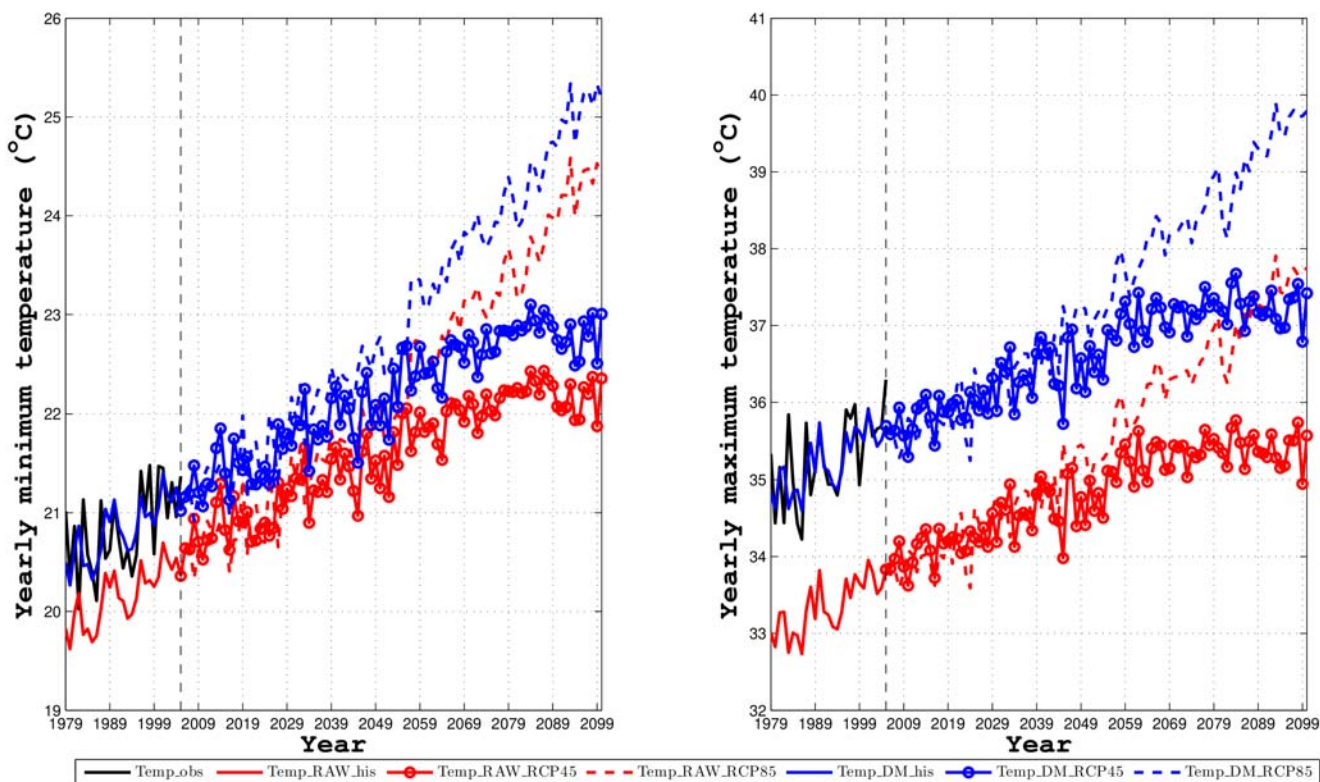


Figure 7. Impact of the DM bias correction method on projected yearly minimum and maximum temperature (left panel and right panel, respectively). Temp_obs represents the observed minimum or maximum temperature, Temp_RAW_his is the raw minimum or maximum temperature during the historical period, Temp_RAW_RCP45 and Temp_RAW_RCP85 represent respectively the raw minimum or maximum temperature during the future under the scenarios RCP4.5 and RCP8.5, Temp_DM_his represents the historical minimum or maximum temperature corrected by DM method and Temp_DM_RCP4.5 and Temp_DM_RCP8.5 are respectively the future minimum or maximum temperature corrected by DM method.

daily and monthly scale compared to others methods during the validation period. However, it seems to be more suitable when we want to bias correct the extreme events (McGinnis et al., 2015; Luo et al., 2018).

After evaluation, the evolution of the future minimum and maximum temperature corrected and uncorrected under scenarios RCP4.5 and RCP8.5 from 1979-2100 was diagnosed. The multi-model mean simulated a strong rise in minimum and maximum temperature which is more important under the RCP8.5 scenario. These results are in agreement with those obtained by Giorgi et al. (2014) and Sylla et al. (2016) in Western Sahel. After correction, the trends are not so modified but the magnitude of climate change signal is amplified in the multi-model mean bias-corrected. This is in agreement with Mbaye et al. (2015) results over Senegal river basin.

The large increase of both temperature and minimum temperature could lead to an increase in evapotranspiration phenomena in Lake of Guiers (Tall et al., 2016) and a decrease in the water content of the soil located at the edge of the lake. This could lead to problems of availability of resources because this lake is

the largest reservoir of freshwater in Senegal (Sambou et al., 2018). This situation could also be detrimental for agricultural yields. In fact, strong temperature increase can affect the grain weight and the duration of grain growth (Sarr and Camara, 2018).

Conclusion

In this work, the ensemble mean of 5 CORDEX RCMs was considered to analyze the evolution of future temperature in the Lake of Guiers. The performances of the ensemble mean of the models to reproduce the minimum and maximum temperature are first assessed. Results show that the multi-model ensemble mean reproduces globally well the observed data. However, it presents some biases which can be reduced by bias correction methods. After bias correction, the agreement between the multi-model ensemble mean and the WFDEI data has considerably increased.

Results show an increase of annual minimum and maximum temperature in the lake. Moreover, the

magnitude of this increase is more important in the multi-model ensemble mean bias-corrected compared to that raw, but the degree of frequency in raw data is not affected.

This future increase in temperature predicted by the uncorrected and corrected ensemble mean of the models can have harmful consequences for the local populations due to the increase of evapotranspiration and water demand. Therefore, it would be important to better quantify the future climate change impact on the hydrological cycle in the Lake of Guiers.

CONFLICT OF INTERESTS

The author has not declared any conflict of interests.

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