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Bias correction of CORDEX-Africa regional climate model simulations for trend analysis in northeastern Lake Chad: Comparison of three bias correction methods

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[Doi: 10.19044/esipreprint.7.2024.p549](https://doi.org/10.19044/esipreprint.7.2024.p549)

Approved: 25 July 2024
Posted: 29 July 2024

Cite As:
Dingamadji M., Adounkpe J., Abderamane H. & Abdallah M.N. (2024). *Bias correction of CORDEX-Africa regional climate model simulations for trend analysis in northeastern Lake Chad: Comparison of three bias correction methods.* ESI Preprints.
https://doi.org/10.19044/esipreprint.7.2024.p549

Abstract

In order to better adapt to the consequences of climate change, regional climate models (RCMs) have been set up for simulations. However, these simulations are often subject to biases, making it difficult to use them directly in studies of the impact of climate change. It is therefore necessary to use bias correction methods to reduce discrepancies between observed data and the data simulated by RCMs. The aim of this study is to analyse the results of three bias correction techniques (scaling, EQM and GQM) applied to rainfall data and mean minimum and maximum temperatures from CORDEX-Africa Regional Climate Models (RCMs), specifically in the north-eastern region of Lake Chad. Various statistical measures such as Pbiais, RMSE, R2 and EAM were used to assess the performance of each bias correction method in this study. In addition, the adjusted Mann-Kendall test and the Sen slope estimator were used to examine trends and their magnitude over the recent (1975-2004) and future (2021-2050) periods with a significance level of 5%. Overall, based on the statistical measures evaluating the effectiveness of the bias correction techniques, this study shows that all the methods tested were able to reduce the biases of the RCM outputs satisfactorily. In particular, the linear scaling approach proved to be more effective in correcting biases than the EQM and GQM methods. Therefore, an analysis of future trends in mean annual precipitation and temperature (minimum and maximum) was carried out for the RCP4.5 and RCP8.5 scenarios using the linear scaling method to correct for data biases. An increase in precipitation and temperature was observed in the study area over the recent period. The results of multi-model averaging of regional climate change for the RCP4.5 and RCP8.5 scenarios indicate a significant increase in mean annual temperatures (minimum and maximum) in the future. As far as annual precipitation is concerned, only an increase is forecast under the RCP4.5 scenarios. Under the RCP8.5 scenarios, a trend towards stable precipitation is predominant, with the exception of the south of the zone, where an increase has been observed. In the light of these results, it is clear that the impact of climate change will intensify in the region studied in the future.

Keywords: Bias correction, regional climate models, modified Mann-Kendall test, trend analysis, northeastern Lake Chad

1. Introduction

The management of water resources in the context of climate change represents a major challenge for the scientific community over the coming decades. By examining the impact of climate change on the problem of water scarcity on a global scale, Gosling & Arnell (2016), noted that climate change is likely to lead to significant changes in the global hydrological cycle due to variations in climatic parameters. In sub-Saharan Africa, particularly in the Sahel region, the effects of climate change are perceptible. These impacts affect key areas such as water availability, agriculture and energy. These impacts are having repercussions on key sectors such as water supply, agriculture and energy(N'Tcha M'Po et *al*., 2016). In its fourth report, the IPCC(2007), indicated that climate change has begun to have an impact on the frequency, intensity and duration of extreme events, such as high temperatures and large fluctuations in precipitation. General circulation models (GCMs) are the most effective tools for predicting climate change linked to future greenhouse gas concentration scenarios, making it possible to implement a strategy to reduce greenhouse gas emissions(Siam et *al*., 2013). However, Rummukainen (2016), believes that GCMs generally have a spatial resolution of more than 100 km × 100 km, which limits their ability to simulate climate on a local or regional scale. Previous studies have also shown that GCM simulations and forecasts of the hydrological cycle are sometimes highly uncertain, and that the processes governing local precipitation are difficult to resolve(Siam et *al*., 2013; Lafon et *al*., 2013; N'Tcha M'Po et *al*., 2016; Rummukainen, 2016; Pastén-Zapata et *al*., 2020). It therefore appears necessary to reduce the scale in order to obtain a simulation at relevant hydrological spatial and temporal scales. Downscaling is an increasingly common technique in hydrology for assessing the effects of climate change. According to Fowler et al. (2007), it aims to reduce the difference between low spatial resolution hydrological models and regional, catchment or point scale hydrological models. Regional climate models (RCMs) are used. RCMs offer a physically more realistic approach to downscaling GCMs than statistical downscaling, as they allow explicit representation of the mesoscale atmospheric processes that drive heavy precipitation(Lafon et *al*., 2013). These models focus on specific sub-regional areas and incorporate regional features such as topography, coastlines and islands more accurately (Pastén-Zapata et *al*., 2020). Today, they have a resolution ranging from 50 km to around 1 to 5 km(Rummukainen, 2016). However, RCMs do not always accurately reproduce precipitation and temperature at all times of day. Numerous previous studies have highlighted the fact that the data simulated by RCMs cannot be used directly as input data without being protected against systematic errors(Christensen et *al*., 2007; Piani et *al*., 2010; Hagemann et *al*., 2011; Gudmundsson et *al*., 2012; Kaboré et *al*., 2015). These errors are generally caused by sources such as errors transferred from GCMs to RCMs(Ibrahim, 2012). A number of methods have been developed to minimize these errors. These are known as bias correction methods. These methods help to reduce biases in the mean, variance or overall distribution of the simulated climate variables(Teutschbein & Seibert, 2012; Lafon et *al*., 2013; Maraun, 2013). In addition, given that climate change may have an impact on water resources (*Giec*, 2014), to manage the latter in a region, it is essential to carry out an in-depth study that examines long-term climate trends in order to improve the results of these actions. For the present study, the most frequently used bias correction methods, such as linear scaling, empirical quantile methods (EQM) and gamma quantile methods (GQM), were selected to correct biases in RCM simulations. The primary objective of this work is to evaluate the performance of three (03) bias correction methods for monthly mean precipitation and temperature. The second objective of this work is to analyze trends in precipitation and temperature based on observed data (1975-2020) and corrected for bias over the period 2021-2050.

2. Materials and Methods

2.1. Description of the study area

The study area, the north-east of Lake Chad, is located in the sedimentary basin of Lake Chad, in the Lake Chad Province of Chad. Geographically, it lies between 12° and 14° north latitude and 13° and 16° east longitude (Fig. 1). It covers an area of 1,2187 km2. The climate in this area is semi-arid, with two distinct seasons: the dry season lasting around 7 months, from October to April, and the rainy season covering 5 months, from May to September. Annual rainfall can reach up to 450mm. July and August are characterised by heavier rainfall, with average monthly temperatures ranging from 28°C to 36°C.

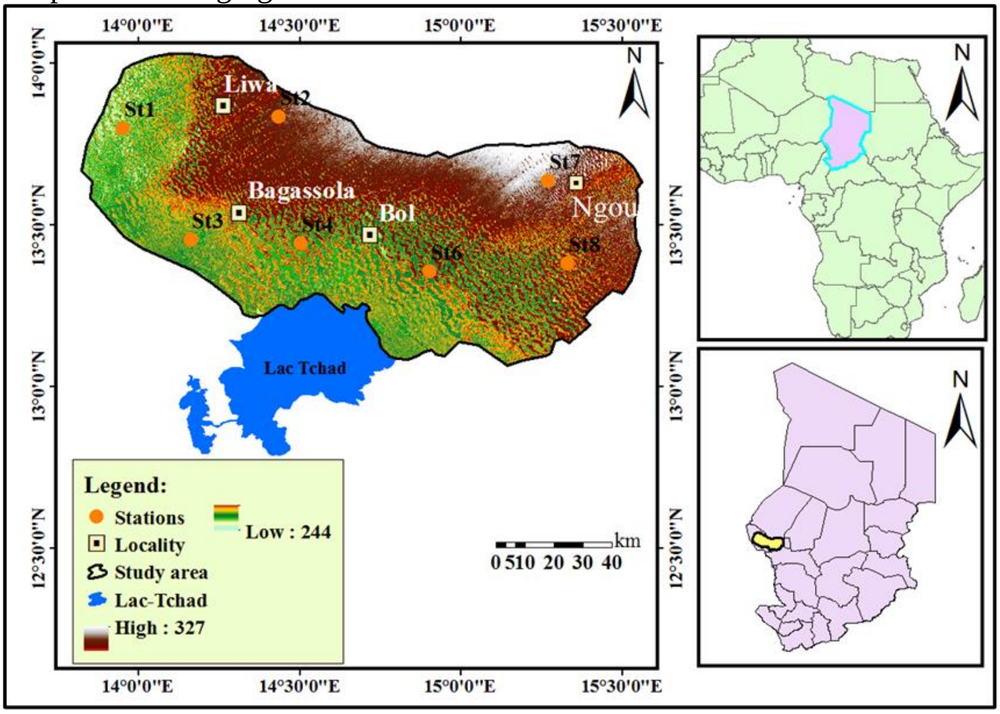

Figure 1: Location of the study area

2.2. Data

2.2.1. MCR data

In this study, daily precipitation and temperature (maximum and minimum) simulated from four (04) regional climate models were used. The RCMs used are HIRHAM5, RACMO22 T, RCA4 and CCCma-CanESM2 (Table 1). These models are available as part of the Coordinated Regional Climate Scale Experiment (CORDEX) over Africa, based on CMIP5(Taylor et *al*., 2012). All the simulations were carried out with a resolution of 0.44° for the period 1950 to 2100, in the same CORDEX-Africa domain. Several previous studies have made extensive use of these techniques in Central

Africa, particularly in the Lake Chad basin, and the results have demonstrated reasonable performance.(Akinsanola et *al*., 2015; Fotso-Nguemo et *al*., 2018; Nkiaka et *al*., 2018a; Adeyeri et *al*., 2020; Mbienda et *al*., 2022; Taguela et *al*., 2020). The RCM forecast scenarios used for this work are those of RCP8.5 and RCP4.5, which are available for the period 2006-2100.

Table 1: Summary of regional climate models

MCRs	**Institutions/ Reference**	**MCGs**
HIRHAM5	Darmarks Meteorologiske Instut (DMI)(Christensen et *al*., 2007)	ICHEC-EC-EARTH
RACMO22T	Koninklijk Nederlands Meteorologisch Instituut (KNMI), Netherlands (Meijgaard et *al*., 2008)	ICHEC-EC-EARTH
RCA4	Institut suédois de météorologie et d'hydrologie, Suède (Samuelsson et *al*., 2011)	MIROC-MIROC5
CCCma-CanCM4	Canadian Centre for Climate Modelling and Analysis (Caya et *al*., 1995)	CCCma-CanESM2

2.2.2. Observed data

In this study, observed data and Climatic Research Unit (CRU) data are used to develop bias correction techniques and compare them with the results of Regional Climate Models (RCMs). Due to the lack of meteorological data, it was necessary to collect and analyze observation data from satellites. These data were obtained from the Climatic Research Unit (CRU), more specifically from the latest version of CRU TS4.7 (Climatic Research Unit gridded Time Series) developed by Harris et *al*.(2020). These data, with a grid resolution of 0.05° (~5 km), have been used as a reference for observing precipitation and temperature. Various previous studies have used these data to assess the effectiveness of CMIP5 models(Rowell, 2013; GIZ, 2015; Nkiaka et *al*., 2018; Taguela et *al*., 2020). Six grids were selected and supplemented with data from two observation stations located in the study area, as supplied by the Chad National Meteorological Agency.

2.3. Bias correction methods

Three (03) bias correction methods (Scaling, EQM and GQM) were selected as part of this study to correct biases in precipitation and temperature data from Regional Climate Models (RCMs). These methods are used to correct the distortions present in the uncorrected outputs of the RCMs used in this project, and their choice was based on previous studies(Lenderink et *al*., 2007; Hawkins et *al*., 2013; Ramirez-Villegas et *al*., 2013; Maraun, 2013; Fang et *al*., 2015; N'Tcha M'po et *al*.,2016; Holthuijzen et *al*., 2021) which have demonstrated that each of these methods can significantly reduce the deviations of the RCMs.

2.3.1. Scaling method

This method makes it possible to establish a precise correlation between the monthly average of the adjusted values and the observed values(Lenderink et *al*., 2007). It works with monthly correction values based on the differences between observed data and raw data simulated by climate models(Fang et *al*., 2015). There are several formulations for this linear scaling method(Lenderink et *al*., 2007; Fang et *al*., 2015). The formulation used in this work is from Fang et *al*.(2015). According to these authors, precipitation is generally corrected with a multiplication factor and temperature with an additive term on a monthly basis:

$$P_{\mathrm{cor,m,d}} = P_{\mathrm{raw,m,d}} \times \frac{\mu\left(P_{\mathrm{obs,m}}\right)}{\mu\left(P_{\mathrm{raw,m}}\right)}, \qquad (1)$$
$$T_{\mathrm{cor,m,d}} = T_{\mathrm{raw,m,d}} + \mu\left(T_{\mathrm{obs,m}}\right) - \mu\left(T_{\mathrm{raw,m}}\right)$$

The variables *Pcor*, m, d and *Tcor*, m, d refer respectively to the corrected precipitation and temperature for the dth day of the same month, while *Praw*, m, d and *Traw*, m, d refer to the raw precipitation and temperature for the same day of the same month. The expectation operator, denoted µ(.), is used to represent the average rainfall observed in a given month m, for example µ (Pobs, m).

2.3.2. Empirical quantile methods (EQM)

One of the commonly used tools to correct the bias of RCM simulations is empirical quantile mapping (EQM), which maps simulated to observed cumulative distribution functions (CDFs), which are empirically constructed based on data from a historical period(Byun & Hamlet, 2019). According to Déqué et *al*.(2007), the quantile-quantile bias correction method involves comparing the observed quantiles with the simulated quantiles during the reference period in order to establish equality. It uses the empirical distributions of the data series (precipitation and temperature) observed and simulated by the RCMs in order to correct the biases of these projections, hence the name of the procedure (N'tcha M'Po et *al*.,2016). EQM is one of the most frequently used and effective methods for correcting bias. (Holthuijzen et *al*., 2022). Several researchers (Boé et *al*., 2007 ; Gudmundsson et *al*., 2012 ; Byun & Hamlet, 2019 ; Holthuijzen et *al*., 2022; N'Tcha M'po et *al*.,2016; Song et *al*., 2021) have used this method to apply bias corrections to the various variables simulated by RCMs. The classical formulation is given by the following equation:

$$y = F_{obs}^{-1}\left(F_{\mathrm{mod}}\left(x\right)\right) \qquad (2)$$

Where x and y denote respectively the value to be corrected and the corrected value, while Fobs and Fsim represent respectively the distributions of the values observed and simulated by the climate model.

2.3.3. Gamma distribution quantile method (GQM)

This method is only applicable to precipitation(Piani et *al*., 2010a). In general, the non-parametric bias correction method is used for all possible precipitation distributions, without making any assumptions about the actual precipitation distribution (Fang et *al*., 2015). It is known that this method can improve the bias correction simulated by RCMs. The theoretical distribution is used rather than the empirical distribution. The two-parameter gamma distribution is used to describe daily precipitation(Vlček & Huth, 2009). The theoretical distribution is used rather than the empirical distribution. It also has the ability to suppress certain extreme values caused by errors, while preserving the limiting value. The equation that gives its probability density function f(x) is as follows:

$$f(x) = \frac{x^{\alpha-1}\exp\left(-\frac{x}{\beta}\right)}{\Gamma(\alpha)\beta} \tag{3}$$

Where α and β are shape and scale parameters, respectively, and Γ(γ) is the Gamma function. Several authors (Vlček & Huth, 2009; Piani et al., 2010a; Wilcke et al., 2013) have had to revisit this approach in their work.

2.4. Evaluation of the performance of bias correction methods

For this study, four criteria were used to evaluate the performance of bias correction methods. The mean absolute error (EAM), the root mean square error (RMSE), the coefficient of determination (R2) and the percentage bias (Pbiais). The criteria for evaluating bias correction techniques and climate models are selected on the basis of various studies(Moriasi et *al*., 2007; Li et *al*., 2010; Fang et *al*., 2015 ; Hamed et *al*., 2021; Hanchane et *al*., 2023) that have demonstrated the value of these statistical criteria for evaluating model performance.

$$P_{\text{BIAS}} = \frac{\sum_{i=1}^{n}\left(Y_i^{\text{obs}} - Y_i^{\text{sim}}\right)}{\sum_{i=1}^{n}\left(Y_i^{\text{obs}}\right)} \tag{4}$$

$$EAM = \frac{1}{N}\sum_{i=1}^{N}\left|X_i - Y_i\right| \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E_i - O_i)^2} \tag{6}$$

2.5. Analysis of precipitation and temperature trends

Observed and bias-corrected data for mean annual precipitation and temperature (minimum and maximum) were analyzed using the modified Mann-Kendall test and Sen's slope estimation.

2.5.1. Mann-kendall and Mann-Kendall modified test

The Mann-Kendall test is a rank-based statistical test frequently used to analyse trends in climate data(Mavromatis & Stathis, 2011). The aim of this test is to statistically evaluate whether or not there is a monotonic trend towards an increase or decrease in the variable studied over time(Souleymane et *al*., 2019). Not only does it have the advantage of being less sensitive to outliers and missing values, but it also does not require a normally distributed data set, which is common in hydroclimatic data(Ahmad et *al*., 2015; Yazid & Humphries, 2015). Numerous studies have used this test in different parts of the world to quantify the importance of trends in hydrometeorological time series(Bayazit & Önöz, 2007; Gocic & Trajkovic, 2013 ; Nkiaka et *al*., 2017) and have shown that the non-parametric Mann-Kendall test is more powerful than some parametric tests, especially when dealing with asymmetric data. The Mann-Kendal test is based on two assumptions. The assumption (H0) is that there is no trend in the data, while the alternative assumption (H1) suggests that there has been a monotonically increasing or decreasing (rising or falling) trend over time(Agbo et *al*., 2021). The Mann-Kendall S statistic is calculated from the following equation:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} Sgn(Xj - Xi) \qquad (7)$$

Where the function Sgn is defined by Sgn(X) = 1 for X > 0; Sgn (X) = 0 for X = 0 and Sgn(X) = -1 for X < 0. Xj and Xk are sequential data values for the time series data of length n.

The Z statistic is calculated as follows:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{\mathrm{VAR}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \dfrac{S+1}{\sqrt{\mathrm{VAR}(S)}} & \text{if } S < 0. \end{cases} \qquad (8)$$

According to Neha(2012), time series analysis first requires trends to be tested by taking into account autocorrelation or serial correlation, which is the correlation of a variable with itself over successive time intervals. According to the same author, autocorrelation increases the chances of detecting significant trends, even if they are neglected, and vice versa. It is from this point of view that Hamed & Rao(1998), proposed a modified Mann-Kendall test that calculates the autocorrelation between ranks after removing the apparent trend. Unlike the original Mann-Kendall test, the modified Mann-Kendall test offers the advantage of reducing the impact of correlation between series by taking into account the dependence between series by including a covariance term in the calculation of the variance of the MK test. The adjusted variance is determined by the following equation

$$V[S] = \frac{1}{18}[N(N-1)(2N+5)]\frac{1N}{NS*} \quad (9)$$

where $\frac{1N}{NS*} = 1 + \frac{2}{N(N-1)(N-2)}\sum_{i=1}^{\rho} (N-i)(N-i-1)(N-i-2)\rho s(i) \quad (10)$

With N representing the observation size of the sample, NS* represents the effective number of observations to take into account the autocorrelation in the data, ρs(i) represents the autocorrelation between the ranks of the observations for lag i, and ρ represents the maximum lag considered(Sinha & Cherkauer, 2008). For the present work, the "mkmodified" package developed in the R language was downloaded free of charge and used to determine trends in precipitation and temperature (minimum and maximum) at annual and seasonal time steps for the recent (1975-2020) and future (2021-2099) periods.

3. Results and Discussion

3.1. Results

3.1.1. Evaluation of bias correction methods

Three (03) bias correction methods were applied to the precipitation and temperatures simulated by the four (04) RCMs selected for this work. The results show that the correction methods used were more successful in correcting the biases of the raw precipitation simulated by the RCMs. There were no significant differences between the different bias correction methods. However, the linear scaling method was able to better adjust the mean precipitation values simulated by the RCMs. There is good agreement between the observed data and those corrected for bias by this method. The gamma quantile and empirical methods give more or less varied results, especially in terms of precipitation. They tend to overestimate the precipitation outputs simulated by the RCMs (Fig.).

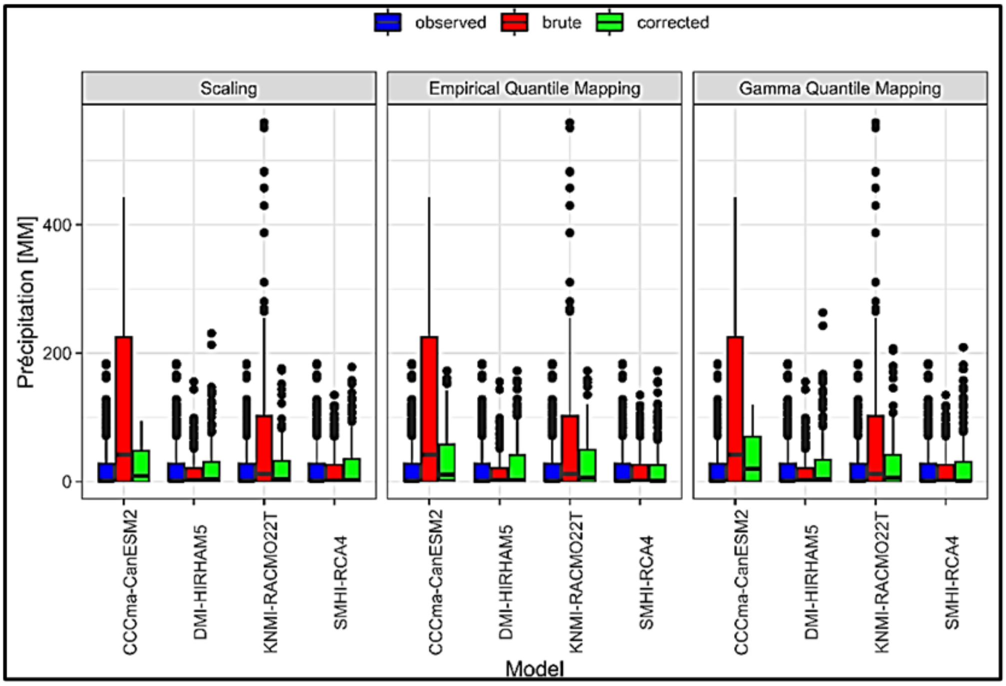

Figure 2: Boxplots of observed, raw and bias-corrected precipitation from RCMs using bias correction methods

As with precipitation, both the linear scaling method and the empirical method were effective in correcting the biases in mean maximum and minimum temperatures. Both approaches significantly corrected the biases in the raw temperatures. After applying these correction methods, a substantial reduction in bias was observed. However, the linear scaling method was found to slightly improve the overall RCM-simulated minimum and maximum temperatures more accurately than the quantile-based empirical method, as shown in the quantile-quantile diagram (Fig4). The latter illustrates explicitly that the minimum and maximum temperature data corrected by the linear scaling method are in perfect agreement with the observed data. On the other hand, the empirical quantile estimation approach does not reveal any significant difference compared with the untreated minimum and maximum temperature data.

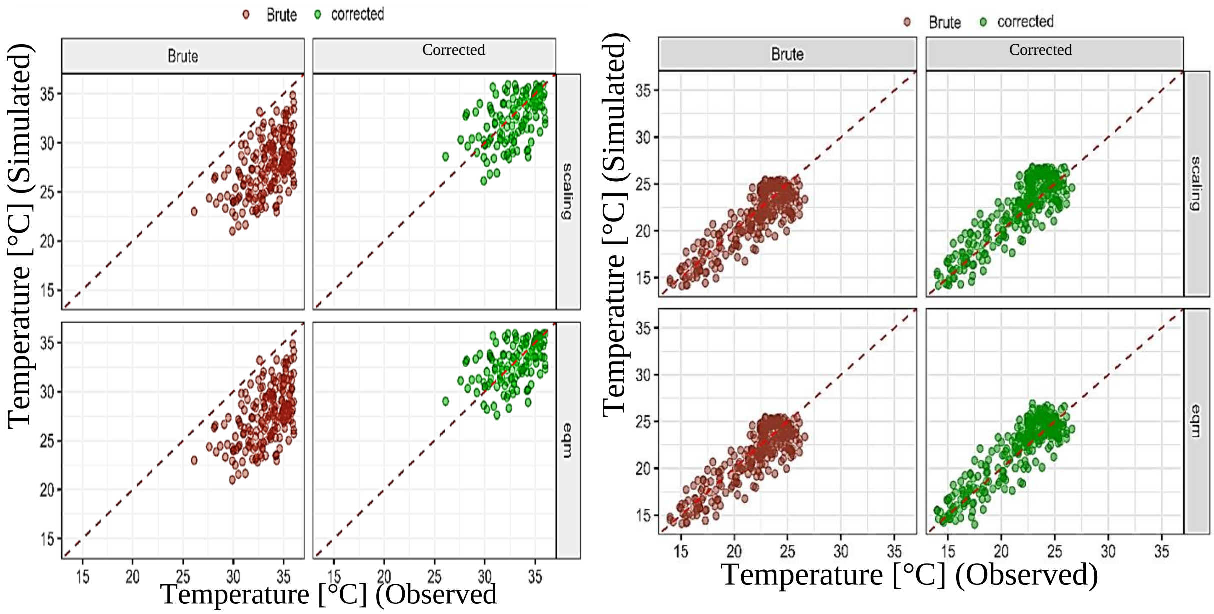

Figure 4: Quantile-quantile diagram of raw and bias-corrected RCM temperatures a = minimum temperature et and b = maximum temperature

3.1.2. Evaluation of the performance of bias correction methods.

Table 2 presents a summary of monthly precipitation and temperature data (minimum and maximum) after bias correction of the statistical indices used to evaluate the performance of bias correction methods. Based on the bias, R2, RMSE and EAM values, it is clear that there is a clear improvement in bias reduction for monthly precipitation compared with the raw data. For most of the monthly mean precipitation simulated by the RCMs, the linear scaling method shows a bias value ranging from -3.573% to 31.92%. The CCCma-CanCM4 model shows biases ranging from an underestimate (Pbiais of RCA4: -3.712%) to an overestimate (Pbiais=37.111%) of mean monthly precipitation compared with the empirical quantile method. The GQM shows bias values ranging from -5.500% to 40%. Within RMSE, the linear scaling method showed relatively moderate deviations (between 28.80 and 32.2) compared to the other methods. RMSE and EAM values for the linear scaling method are relatively lower than those obtained by GQM and GQM. Given that RMSE and EAM are two performance indicators for evaluating bias-sensitive bias correction methods (N'Tcha M'Po, 2016), this indicates that the linear scaling method corrects precipitation bias better than the GQM and GQM methods. Overall, the bias correction methods show acceptable performance (linear scaling method), with the correlation coefficient (R2) and mean absolute error (EAM) showing satisfactory values (Table 2). The linear scaling and empirical quantile methods show very good correlation agreement with observed data. However, the linear scaling method is more effective in correcting for minimum and maximum temperature bias, providing very low values for metrics such as Pbiais, which ranges from 0.987 to 1%. RMSE values range from 0.987 to 1 mm and R2 values from 0.645 to 0.746. Taking into account the Pbiais, R2, EAM and RMSE calculations, it is clear that the linear scaling method offers better bias-correction results than the empirical method, for both precipitation and corrected minimum and maximum temperatures.

Table 2: Comparison of different bias correction methods using statistical performance evaluation measures

Methods	Statistical indices	Precipitation			
		HIRHAM5	RCA4	RACMO22T	CCCma-CanESM2
EQM	R^2	0,527	0,485	0,472	0,385
	EAM	16,583	16,000	18,191	22,475
	Pbia	7,750	-3,712	18,22	37,111
	RSMSE	30,095	31,203	32,675	34 ,400
GQM	R^2	0.49	0,495	0,445	0,398
	EAM	17.225	15,811	19,127	22,085
	Pbia	8.0375	-5,500	17,885	40,000
	RSMSE	32.23625	30,798	34,641	35,445
LS	R^2	0,505	0,523	0,433	0,401
	EAM	15,920	15,260	17,595	19,393
	Pbiais	-6,537	-6,050	-6 ,537	-6,537
	RSMSE	30,501	28,805	31,922	32,000
		Temperatures			
EQM	R^2	0,738	0,745	0,645	0 ,726
	EAM	1,691	1,635	1,893	1,602
	Pbia	1,000	1,000	1,000	0,987
	RSMSE	2,085	2,055	2,437	1,952
LS	R^2	0,746	0,747	0,626	0,726
	EAM	1,535	1,635	1,791	1,710
	Pbia	0,987	0,987	0,978	1,000
	RSMSE	1,880	2,036	2,261	2,141

3.1.2. Analysis of observed and simulated precipitation and temperature trends

3.1.2.1. Analysis of precipitation trends

The modified Mann-Kendall test and Sen's slope estimator were applied to detect trends at annual time step in precipitation series from observations and CRU data over the recent period 1975-2020 and from a 4 RCM multi-model ensemble of RCP4.5 and RCP8.5 scenarios for the future period 2021-2050. The results of all analyses performed at the 95%

confidence level (α = 0.05) are reported in Table 3. The results of the analyses revealed statistically significant upward trends in annual precipitation observed at the level of the CRU grids (G1, G2, G3, G4 and G6). In contrast, no trend was detected at the stations (St1and St2) at grid G5. The magnitude (Sen's slope) ranges from 0.423 to 5.540. For simulated mean annual precipitation corrected by the linear scaling method (Scaling), the multi-model mean analysis of the RCP4.5 scenario predicts a statistically significant upward trend in simulated annual precipitation over the entire study area. Sen's predicted slope estimator amplitudes range from 1.472 to 2.252. Under the pessimistic RCP8.5 scenarios, the absence of a trend is observed in almost the entire study area, except in grid6 (to the south), where a statically significant upward trend in annual precipitation is observed, with a magnitude ranging from 0.164 to 1.184.

Table 3: Results of modified Mann-Kendall trend tests and Sen's slope for observed and BCA bias-corrected annual precipitation time series at 5% significance level

Grid /station		Z-original	P-valu	Sen's slope	New-P-valu	Z-corrected	Sen's slope
	G1	3,484	0,000	3,142	0,001	2,694	3,484
	G2	3,294	0,000	2,992	0,002	5,540	3,294
	G3	3,427	0,000	4,175	0,000	1,194	3,427
	G4	2,859	0,001	3,219	0,001	2,941	2,859
CRU	G5	2,745	0,062	2,745	0,050	0,423	2,745
	St1	0,662	0,507	0,765	0,444	0,742	0,662
	G6	3,313	0,000	3,313	0,000	2 ,941	3,313
	St2	0,795	0,426	0,795	0,426	0,781	0,795
	G1	2,854	0,004	2,252	2,854	0,004	2,252
	G2	2,176	0,029	1,535	2,176	0,029	1,535
	G3	1,998	0,045	1,712	1,998	0,045	1,712
RCP4.5	G4	1,926	0,054	1,736	2,872	0,054	1,736
	G5	1,748	0,004	1,624	2,105	0,004	1,624
	St1	2,105	0,003	1,472	4,507	0,035	1,472
	G6	1,926	0,054	1,725	3,905	0,000	1,725
	St2	2,176	0,029	1,759	1,759	0.000	1,759
	G1	0,214	0,830	-0,141	0,214	0,830	0,758
	G2	0,499	0,483	0,293	0,483	0,628	0,293
	G3	0,249	0,802	-0,164	-0,249	0,802	0,164
RCP8.5	G4	0,606	0,544	0,322	0,606	0,544	0,322
	G5	0,142	0,886	0,448	0,142	0,886	0,448
	St1	0,677	0,497	-1,184	-0,677	0,497	1,184
	G6	0,285	0,775	0,453	0,285	0,775	0,453
	St2	0,249	0,802	-0,344	-0,279	0,779	0,930

3.1.2.2. Temperature trend analysis (minimum and maximum)

Observational temperature data (minimum and maximum) and the multi-model mean of the Regional Climate Models (RCM) under the RCP4.5 and RCP8.5 scenarios were subjected to an analysis similar to that of precipitation, using the modified Mann-Kendall test with a 95% confidence level to identify trends and assess Sen's slopes. Examination of observational and Climatic Research Unit (CRU) data reveals, at a 5% significance level, an upward trend in minimum and maximum temperatures, as presented in Table 4**.** The magnitudes of significant upward trends range from 0.018°C/year to 2.941°C/year for maximum temperatures, and from 0.016°C/year to 0.021°C/year for minimum temperatures. In contrast to simulated annual precipitation, RCP4.5 and RCP8.5 mean RCMs show statistically significant upward trends in mean annual temperatures (minimum and maximum) over the entire study area. The amplitudes of the trends predicted under the RCP4.5 scenario range from 0.031°C/year to 0.039°C/year for maximum temperatures, and from 0.034°C/year to 0.037°C/year for annual minimum temperatures. Under the RCP8.5scenario, variations in maximum temperature amplitudes range from 0.03°C/year to 0.503°C/year, while those for minimum temperatures vary from 0.044°C/year to 0.04°C/year.

Table IV: Results of modified Mann-Kendall trend tests and Sen's slope for observed and bias-corrected annual minimum and maximum temperature time series at 5% significance level

		Maximum temperature (°C)					Minimum temperature(°C)				
		Z-original	P-value	Z-corrigé	New-P-valu	Sen's slope	Z-original	P-valu	Z-corrigé	New-P-valu	Sen's slope
Observed (CRU)	G1	4,450	0,006	3,663	0,003	0,032	4,203	0,000	7,894	0,000	0,019
	G2	3,825	0,001	3,490	0,000	0,026	3,351	0,008	3,479	0,005	0,016
	G3	3,591	0,000	4,275	0,000	0,020	3,796	0,001	3,796	0,001	0,018
	G4	3,739	0,000	3,213	0,001	2,941	4,611	0,000	5,106	0,000	0,021
		2,313	0,002	2,214	0,007	0,018	4,847	0,003	9,158	0,002	0,021
	St1	4,351	0,003	3,611	0,003	0,291	4,478	0,000	7,828	0,000	0,019
	G6	3,270	0,001	4,373	0,000	0,023	4,857	0,001	4,857	0,001	0,021
	St2	4,506	0,000	3,688	0,000	0,028	4,582	0,004	4,948	0,007	0,020
RCP4.5	G1	3,425	0,006	5,861	0,000	0,038	4,674	0,002	4,674	0,002	0,034
	G2	3,354	0,007	3,354	0,007	0,033	4,852	0,000	4,852	0,000	0,035
	G3	3,318	0,009	4,129	0,003	0,038	4,745	0,001	4,745	0,001	0,036
		3,389	0,006	1,629	0,000	0,033	5,066	0,004	5,066	0,004	0,035
	G5	3,782	0,001	4,221	0,000	0,031	5,245	0,000	5,245	0,000	0,035
	St1	3,603	0,003	9,516	0,001	0,038	4,888	0,001	4,888	0,000	0,037
	G6	3,568	0,003	1,867	0,000	0,035	5,102	0,003	5,102	0,003	0,035
	St2	3,175	0,001	3,316	0,001	0,039	4,924	0,008	4,924	0,008	0,035
RCP8.5	G1	3,889	0,001	3,889	0,001	0,054	5,066	0,004	5,066	0,000	0,044
	G2	3,461	0,005	3,461	0,005	0,042	5,066	0,000	1,942	0,000	0,044
	G3	3,782	0,001	3,782	0,001	0,052	5,031	0,004	5,031	0,000	0,045
		4,103	0,004	7,808	0,004	0,042	5,138	0,002	5,135	0,002	0,044
	G5	3,889	0,001	3,889	0,001	0,503	5,459	0,004	5,459	0,002	0,049
	St1	3,817	0,001	3,817	0,001	0,049	5,280	0,001	5,208	0,001	0,045
	G6	3,496	0,004	3,926	0,008	0,040	5,352	0,008	5,352	0,008	0,046
	St2	3,568	0,003	3,568	0,003	0,039	5,352	0,000	5,352	0,000	0,047

3.2. Discussion

Wilcke et *al*.(2013), have defined bias as the long-term mean difference between model and observation. This bias, for the most part, is caused by sources such as errors transmitted by GCMs to RCMs, internal climate variations and downscaling tools and methods(Fowler et *al*., 2007; Ibrahim, 2012; Phuong et *al*., 2020). Several bias correction methods have been developed by a number of scientists(Piani et *al*., 2010a; Piani et *al*., 2010b ; Themeßl et a*l*., 2012 ; Fang et *al*., 2015). For this study, three bias correction techniques (scaling, EQM and GQM) were used to rectify the biases simulated by the MCRs during the monthly valuations. After evaluating the performance of these methods, we found that the EQM and GQM methods had difficulty in correcting biases more effectively than the linear scaling method. It is possible that these problems are linked to the distribution of climatic variables (precipitation and temperature), but also to the weather. Using these methods to correct biases in the transboundary Komadugu-Yobe river basin, Adeyeri et *al*.(2020), have made a similar observation. This observation was made by some authors(Piani et *al*., 2010a; Gudmundsson et *al*., 2012; Maraun, 2013a; Ezéchiel et *al*., 2016; N'tcha M'po et *al*., 2016). These authors argue that bias correction methods are hampered by rainfall variability, the assumption of bias stationarity, or the fact that this assumption is not verified in arid to semi-arid zones. Precipitation obtained using the EQM and GQM methods shows a large discrepancy with observed precipitation. This discrepancy is attributable to the inability of these methods to successfully correct for variations in precipitation as a function of monthly time. The linear scaling method (Scaling) managed to better bias both precipitation and temperature (minimum and maximum), as shown in the results. The results of this method indicate that some evaluation criteria are generally weak (RMSE, EAM and Pbiais) and strong (R2), demonstrating good performance of the linear scaling method. Comparing seven (07) bias correction techniques in the Mékrou watershed, Ezéchiel et *al*. (2016), indicated that the linear scaling method performed better than the other two in reducing the biases in monthly precipitation, whereas the other methods (such as the GQM) tended to have a negative impact on the quality of monthly precipitation. In short, the linear scaling method succeeded in correcting the biases simulated by the RCMs more effectively than the other two, even if there were some overestimates concerning precipitation, which seems unavoidable, because according to Pastén-Zapata et *al*.(2020), no bias correction method can totally eliminate bias. According to Nguyen et *al*. (2017), the choice of bias correction methods depends on the specific needs of each study. Trend analysis using the modified Mann-Kendall test for both observational and CRU data showed overall positive upward trends in annual precipitation and temperature (maximum and minimum). These upward trends in precipitation and temperature (minimum and maximum) are closely correlated with the work of Mahmood et *al*. (2019), in the Lake Chad Basin, which revealed a trend towards a gradual increase in rainfall after the 1980s and high temperatures since the drought periods (1973 and 1985). The multi-model approach under the RCP4.5 scenario predicts a statistically significant increase in annual rainfall over the 2021-2050 period in almost the entire study area. Precipitation increases over this period were also predicted by the RCP8.5 scenario, although the absence of a trend dominates. These trends in future annual precipitation increases corroborate the predictions of Adeyeri et *al*. (2020), which forecast an increase in rainfall in the transboundary Komadugu-Yobe River (Lake Chad Basin) over the period 2020-2050. The prevalence of precipitation in this study is in line with research carried out by Hartley et *al*. (2015), which estimated a 20-50% increase in rainfall between 2020 and 2049 in this region. Moreover, these forecasts are consistent with the IPCC report (2014), which predicts significant increases in precipitation over the 21st century in the Sahelian zone. As for future mean (minimum and maximum) annual temperatures, the trend analysis showed that the RCP4.5 and RCP8.5 scenarios agree in confirming strong statically significant trends over the entire study area. Strong upward trends in future temperatures have also been confirmed by several studies carried out in Central Africa, particularly in the Lake Chad basin(Taylor et *al*., 2012; Akinsanola et *al*., 2015; GIZ, 2015; Fotso-Nguemo et *al*., 2017, 2018; Mahmood et *al*., 2019; Nkiaka et *al*., 2018; Taguela et *al*., 2020). While it is difficult to make actual precipitation forecasts, as indicated by the IPCC (2014), the high temperatures and slight increases in precipitation predicted are already being felt in the study area through disasters such as floods and droughts. These phenomena could lead to poor agricultural yields, poor water quality, the disappearance of certain animal species (kouri cattle), the increasing advance of the desert and the disappearance of arable land. It is therefore suggested that decision-makers and programs adopt comprehensive approaches to help adapt to climate change, which is already evident in the semi-arid study area.

Conclusion

The aim of the present work is to evaluate the performance of three bias correction methods in correcting RCM-simulated monthly mean rainfall and temperature in northeastern Lake Chad. A number of statistical measures (Pbiais, RMSE, R2 and EAM) were used to evaluate the performance of the bias correction methods. The results showed that the linear scaling method outperformed the other bias correction methods. Trend analysis using the modified Mann-Kendall test for CRU observed data and those simulated by the RCM multi-model approach under the RCP4.5 scenario showed overall upward trends in recent and future annual precipitation and temperature over the entire study area. In contrast, the RCP8.5 scenario is dominated by a lack of trend in recent and future precipitation on the one hand, and an increase in recent and future annual temperature (2021-2050) on the other.

Acknowledgement

The authors express their gratitude to the Government of Benin, the World Bank and the Agence Française de Développement (AFD) for their financial support for the project of the Centre d'Excellence d'Afrique pour l'eau et l'assainissement (C2EA) of the Institut National de l'Eau (INE), which enabled this study to be carried out. In addition, thanks are extended to the Agence Nationale de la Météorologie du Tchad for providing the meteorological data used in this work, and to the anonymous reviewers.

Conflict of Interest: The authors reported no conflict of interest.

Data Availability: All data are included in the content of the paper.

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