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

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Abstract

Climate model simulations are frequently affected by biases, which makes it difficult to incorporate them directly into analyses of the impact of climate change. It is therefore essential to use bias correction methods to minimize discrepancies between real data and that generated by Regional Climate Models (RCMs). This study aims to analyze the results of three bias correction methods (LS, MQE, and MQG) applied to the processing of mean rainfall and temperature data from CORDEX-Africa's Regional Climate Models (RCMs), specifically in the north-eastern region of Lake Chad. Four statistical measures (bias, RMSE, r2, and MEA) were used to assess the effectiveness of each bias correction method. In addition, adjusted Mann-

Kendall analysis and the Sen slope estimation method were applied to study trends and their magnitude over the recent (1975-2020) and future (2021-2050) periods, using a 5% significance level. The results highlight the existence of significant biases between the uncorrected RCM outputs and the observed data. After applying the bias correction, significant reductions in bias and comparable performance between the different bias correction methods were observed, with the LS method performing slightly better in correcting biases in monthly mean precipitation and temperature. Consequently, the LS method was selectively applied to correct the biases in the RCM monthly mean precipitation and temperature projections for the 2021-2050 period under the RCP4.5 and RCP8.5 scenarios using the 1975-2004 reference period. The results of multi-model averaging of RCMs under the RCP4.5 and RCP8.5 scenarios indicate a significant increase in mean annual temperatures over the period 2021-2050. As far as annual precipitation is concerned, only an increase is forecast under the RCP4.5 scenario. Under the RCP8.5 scenario, the absence of a precipitation trend is predominant, with the exception of the south of the zone, where an increasing trend has been observed. In light of these results, it is clear that the impact of climate change will intensify in the study area in the future. It is imperative to develop strategies to adapt and reduce the impacts in order to manage the availability of water resources efficiently.

Keywords: Bias correction, MCR, climate change projections, bias correction methods, and 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 analyzing the effects of climate change on the issue of global water scarcity, 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 already being felt. These impacts are affecting key areas such as water availability, agriculture, and energy. These impacts have 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 powerful tools for predicting climate change linked to future greenhouse gas concentration scenarios, thus enabling a strategy to be implemented (Siam et al., 2013). However, Rummukainen (2016), believes that GCMs generally

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have a spatial resolution greater than 100 km × 100 km, which restricts their ability to simulate climate at local or regional scales. Previous studies have also shown that GCM simulations and forecasts of the hydrological cycle are sometimes very 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 on hydrologically relevant 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 more accurately incorporate regional features such as topography, coastlines, and islands (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. Many 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 can have an impact on water resources (IPCC, 2014), in order to manage water resources 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 the linear scaling method, the empirical quantile methods (EQM) and finally the quantile methods based on the gamma distribution (QGM), were selected in order to correct the biases in the 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 (1975-2020) and bias-corrected data for the period 2021-2050.

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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 degrees North latitude and 13 and 16 degrees 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 450 mm. July and August are characterized by heavier rainfall, with average temperatures ranging from 28°C to 36°C.

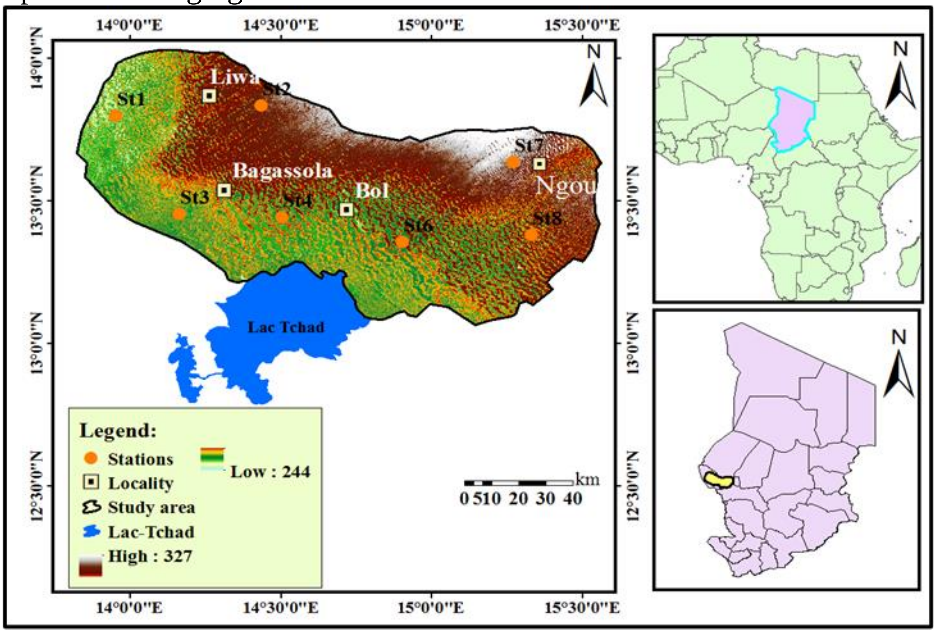

Figure 1: Location of the study area

2.2- Data

2.2.1- MCR data

In this study, daily precipitation and temperature simulated from four (04) regional climate models were used. The RCMs used are HIRHAM5, RACMO2.2T, 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). The set of simulations was performed 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 methods 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

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al., 2018a; Adeyeri et al., 2020; Mbienda et al., 2022). 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	Swedish Meteorological and Hydrological Institute, Sweden (Samuelsson et al., 2011)	MIROC-MIROC5
CanESM2	Canadian Centre for Climate Modelling and Analysis (Caya et al., 1995)	CCCma

2.2.2- Observed data

In this study, observed data from two observation stations (Ngouri and Bol), as supplied by the Chad National Meteorological Agency (ANAM), and from the Climatic Research Unit (CRU) are used to develop bias correction methods and compare them with the RCM results. Due to the lack of meteorological data, it was necessary to collect and analyse observation data from satellites. These data were obtained from the Climatic Research Unit (CRU), and 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., 2018b; Mahmood et al., 2019; Taguela et al., 2020; WB, 2020; World Bank Group, 2022).

2.3- Bias correction methods

As part of this study, three (03) bias correction methods (LS, EQM and GQM) for precipitation and temperature were chosen to correct the biases from the RCMs. Using these methods, it is possible to correct the biases in the raw outputs of the RCMs selected for this project. These techniques were selected on the basis of previous research (Lenderink et al., 2007; Maraun, 2013; Hawkins et al., 2013; Ramirez-Villegas et al., 2013; Fang et al., 2015; Holthuijzen et al., 2022) which demonstrated that each of these methods can significantly reduce the biases contained in the RCM outputs.

2.3.1- Scaling method(LS)

This approach makes it possible to establish a precise correlation between the monthly mean of the corrected values and the observed values

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(Lenderink et al., 2007). It works with monthly correction values that are 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 by Fang et al., (2015). According to these authors, precipitation is generally corrected with a multiplier factor and temperature with an additive term on a monthly basis:

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

(1)

The variables P_{cor}, m, d and Tcor,m, d refer respectively to the corrected precipitation and temperature for the dth day of the same month, while P_{raw}, m, d and T_{raw}, 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 ($P_{obs, m}$).

2.3.2- Empirical quantile methods (EQM)

One of the commonly used tools for bias correction 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 to correct the biases of these projections, hence the name of the procedure (N’tcha M’Po et al.,2016). MQE is one of the most frequently used and effective methods for bias correction(Holthuijzen et al., 2022). Several researchers (Boé et al., 2007 ; Gudmundsson et al., 2012 ; N’Tcha M'po et al.,2016; Byun & Hamlet, 2019 ; Song et al., 2021; Holthuijzen et al., 2022) have used this method to apply bias corrections to the different variables simulated by RCMs. The classical formulation is given by the following equation:

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

(2)

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Where x and y denote respectively the value to be corrected and the corrected value, while F_{obs} and F_{mod} 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., 2010). 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 remove some 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.

$$f(x) = \frac{x^{\alpha-1} \exp\left(-\frac{x}{\beta}\right)}{\Gamma(\alpha)\beta} \tag{4}$$

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 the bias correction methods (Fig. 2). The mean absolute error (MAE), the root mean square error (RMSE), the correlation coefficient (r^2), and the percentage bias (Pbiais). The criteria for evaluating bias correction techniques and climate models are selected based on various studies (Moriasi et al., 2007; Fang et al., 2015; Hamed et al., 2021; Hanchane et al., 2023) ,that have demonstrated the importance of these statistical criteria for evaluating model performance.

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$$P_{\text{BIAS}} = \frac{\sum_{i=1}^{n} \left(Y_i^{\text{obs}} - Y_i^{\text{sim}}\right)}{\sum_{i=1}^{n} \left(Y_i^{\text{obs}}\right)} \tag{5}$$

$$EAM = \frac{1}{N}\sum_{i=1}^{N} \left| X_i - Y_i \right| \tag{6}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (E_i - O_i)^2} \tag{7}$$

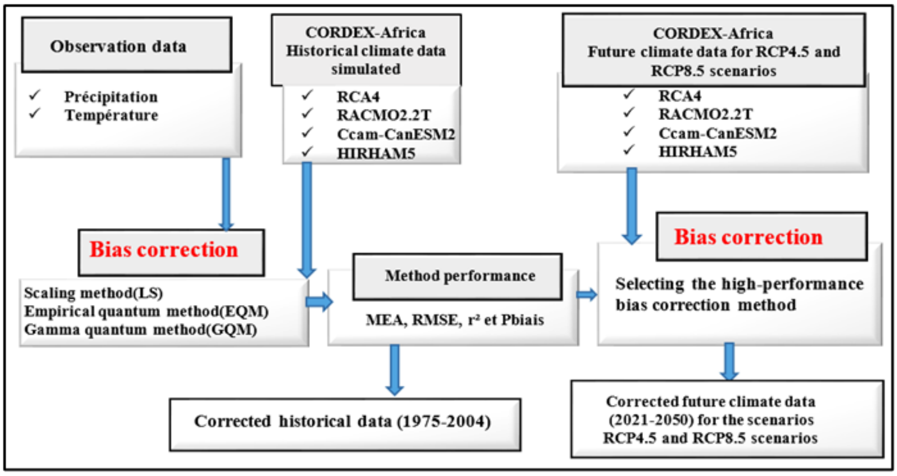

Figure 2: Framework for correcting biases in climate model data

2.5- Modified Mann-Kendall and Mann-Kendall test

2.5.1- Modified Mann-Kendall and Mann-Kendall 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). Many studies have used this test in different regions of the globe to quantify the significance 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

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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:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} Sgn(Xj - Xi) \tag{8}$$

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:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\mathrm{VAR}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\mathrm{VAR}(S)}} & \text{if } S < 0. \end{cases} \tag{9}$$

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:

$$V[S] = \frac{1}{18}[N(N-1)(2N+5)]\frac{1N}{NS*} \tag{10}$$

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

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

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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
3.1.1.1-Bias correction for average monthly rainfall simulated by RCMs

The results of the mean monthly precipitation simulated by these RCMs in the raw state and corrected state in comparison with observed data are shown in Figures 3-6. The comparison reveals both an underestimation and an overestimation of the raw monthly mean precipitation for various months across the entire study area. Nevertheless, once the three bias correction methods have been applied to adequately reduce the discrepancies between the observed and simulated raw data, the results reveal overall close agreement between the corrected and observed data, as highlighted in the graphs. Furthermore, the level of agreement between observed and corrected precipitation data varies from one locality to another, from one bias correction method to another, and also from one model to another. It is clear that these methods can be used to correct biases in future precipitation.

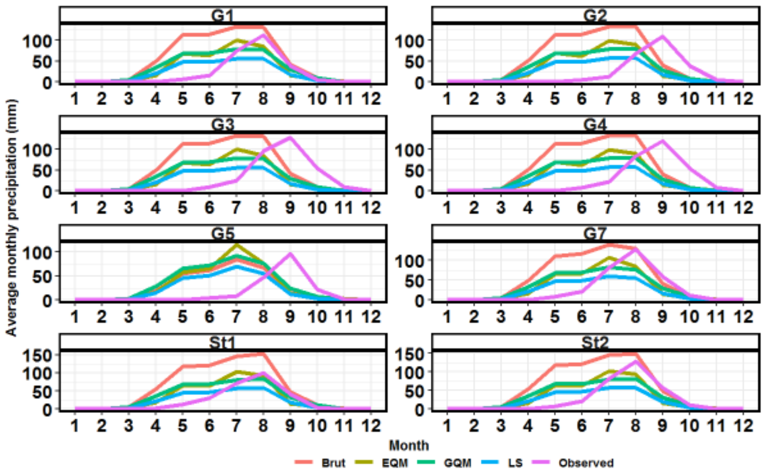

Figure 3: Comparison of average monthly precipitation observed, simulated by the CanESM2 model and corrected by the bias correction methods

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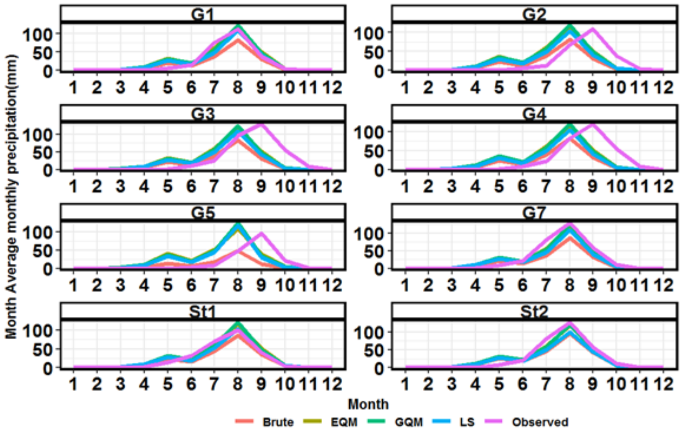

Figure 4: Comparison of average monthly precipitation observed, simulated by the HIRHAM5 model and corrected by the bias correction methods

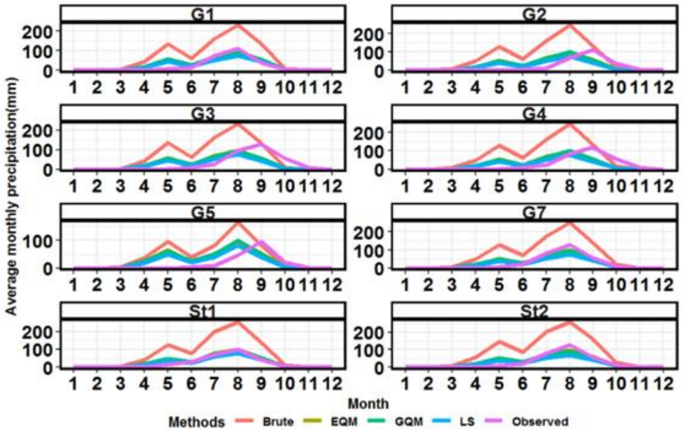

Figure 5: Comparison of average monthly precipitation observed, simulated by the RACMO2.2T model and corrected by the bias correction methods

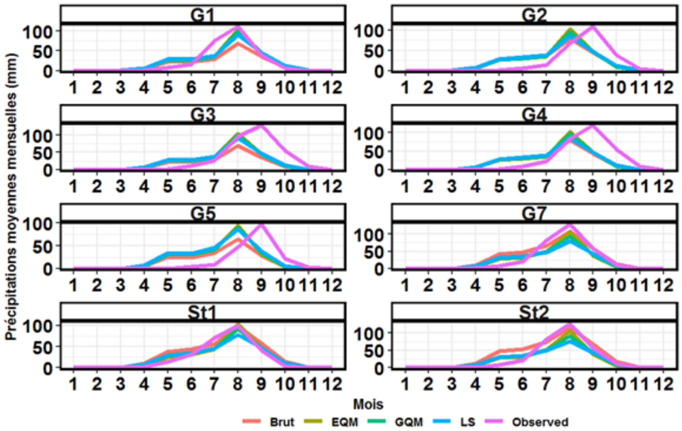

Figure 6: Comparison of average monthly precipitation observed, simulated by the RCA4 model and corrected by the bias correction methods

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3.1.1.2- Correcting for bias in mean monthly temperatures simulated by RCMs

Figures 7-10 summarize the observed, simulated, and simulated temperatures corrected by the LS method and the RMSE. Comparing the observed temperature data with the raw simulated temperature data, there is a shift in the curves, which shows an overall overestimation of temperatures. This shift is explained by an underestimation and overestimation of the temperature outputs simulated by the RCMs. This requires the biases in the temperatures simulated by the RCMs to be corrected using bias correction methods. After bias correction, the graphs showing the observed and simulated monthly mean temperature curves corrected by the bias correction methods are in agreement. The two methods used to correct the biases significantly reduced the differences between the observed and simulated data for all four RCMs used in this study. The graphs show good agreement between the curves of the two methods and the observed data.

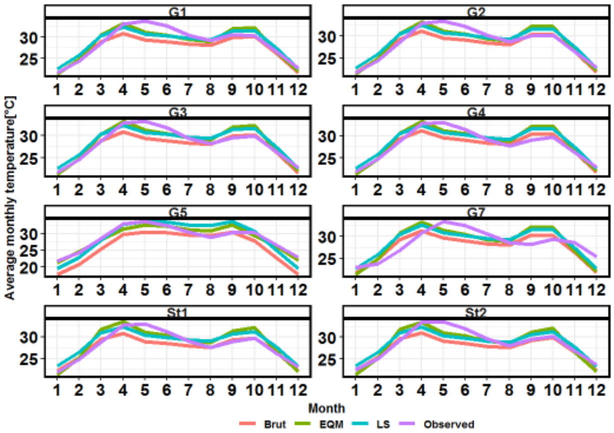

Figure 7: Comparison of average monthly temperatures observed, simulated by the CanESM2 model and corrected by bias correction methods

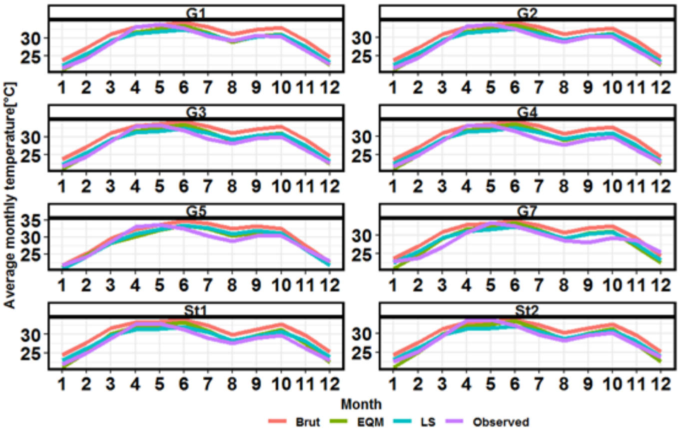

Figure 8: Comparison of average monthly temperatures observed, simulated by the HIRHAM5 model and corrected by bias correction methods.

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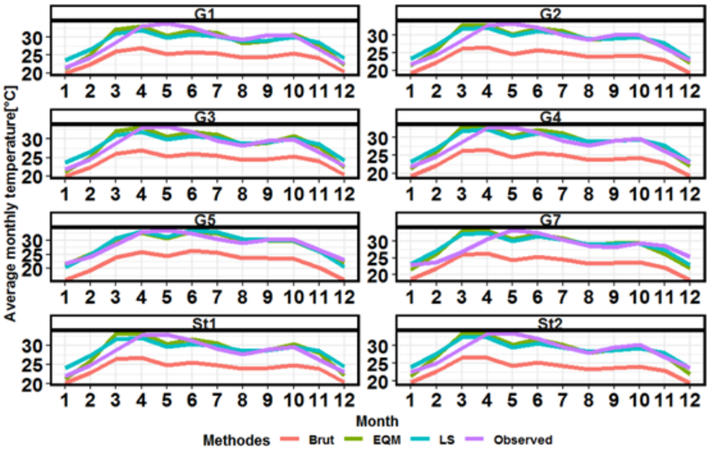

Figure 9: Comparison of average monthly temperatures observed, simulated by the RACMO2.2T model and corrected by bias correction methods

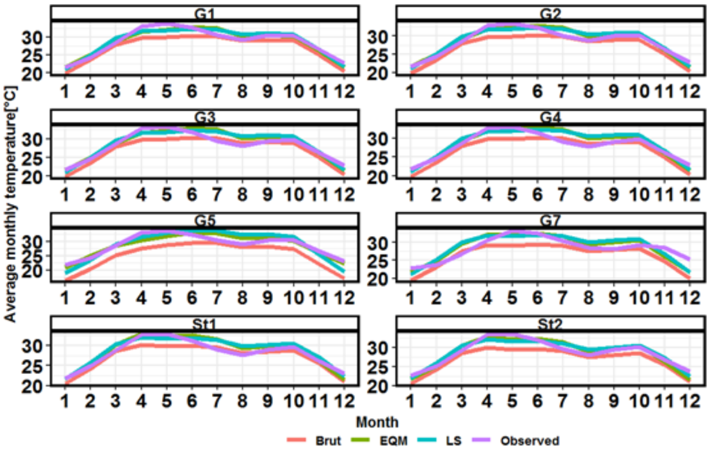

Figure 10: Comparison of average monthly temperatures observed, simulated by the RCA4 model and corrected by bias correction methods

3.1.2 Evaluation of the performance of bias correction methods.

After evaluating the performance of the three bias correction methods used to correct the biases in the RCM outputs, four statistical measures (MEA, RMSE, r2, and Pbiais) were implemented to assess their performance. A significant difference was found between the raw simulated results and the results corrected for precipitation and temperature throughout the study area. The overestimation and underestimation of precipitation and temperature simulated by the RCMs were significantly well adjusted by the three bias correction methods used. All the bias correction methods applied improved the raw precipitation and temperatures simulated by the RCMs, although disparities remained in their corrected statistics. For precipitation, the values of the statistical parameters corresponding to each method and model are

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shown in the table. The results of the study indicate that all three bias correction methods are effective in correcting the monthly mean precipitation simulated by RCMs. When comparing the values of the statistical rainfall measurements corrected by the different bias correction methods, the LS method performs better than the GQM and EQM methods. The values of the RMSE error, the MEA, and the precipitation Pbias corrected by the LS method are lower than those obtained by the GQM and EQM methods, thus demonstrating the effectiveness of this approach. In addition, the correlation coefficient values obtained from the LS method are relatively higher (greater than 0.5) than those obtained from the GQM and EQM methods. This shows a good correlation between precipitation corrected by the LS method and observed precipitation. At most of the observation sites, the LS method was found to be more effective at correcting biases than the other two methods, as shown in figures 3-10. It should be noted that the LS method was found to be more effective at correcting biases in RCM-simulated precipitation than the other two methods. Given that RMSE and MEA are two performance indicators for evaluating bias-sensitive bias correction methods (N'Tcha M'Po et al., 2016), this indicates that the linear scaling method corrects precipitation biases better than the EQM and GQM methods. Overall, the bias correction methods show acceptable performance (LS method), with the correlation coefficient (r^2) and mean absolute error (MAE) showing satisfactory values (Table II). The linear scaling and empirical quantile methods show very good correlation agreement with the observed data. However, the linear scaling method is more effective in correcting for biases in monthly mean temperatures, providing very low values for metrics such as the Pbiais, which is between 0.987 and 1%. RMSE values range from 0.987 to 1 mm and r^2 values from 0.645 to 0.746. Taking into account the calculations of Pbiais, r^2, MEA, and RMSE, it is clear that the linear scaling method offers better results for correcting biases than the empirical method, both for precipitation and corrected mean temperatures.

Table 2: Comparison of different methods for correcting bias in statistical measures of performance

		MEA	RMSE	Pbiais	r^2
		Monthly precipitation			
RCA4	Brute	18,60	36,87	-2,72	0,57
	LS	17,98	33,11	15,23	0,61
	GQM	18,39	34,99	-1,42	0,58
	EQM	17,95	36,38	-16,63	0,57
HIRHAM5	Brute	20,36	38,95	-28,91	0,57
	LS	19,53	36,99	10,41	0,71
	GQM	20,79	35,31	10,31	0,55
	EQM	21,88	37,29	-3,52	0,56
RACMO2.2T	Brute	24,04	44,32	193,86	0,50
	LS	20,64	37,11	12,14	0,63
	GQM	23,14	40,66	24,13	0,52

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	EQM	23,01	40,64	23,62	0,51
CanCM4	Brute	32,46	59,50	111,23	0,39
	LS	23,30	38,09	13 ,42	0,67
	GQM	27.32	41,40	22,08	0,40
	EQM	28,70	46,74	23,72	0,43
	Average monthly temperature				
RCA4	Brute	2,18	2,67	-6,25	0,86
	LS	1,72	2,11	0,82	0,86
	EQM	1,71	2,37	1,13	0,83
HIRHAM5	Brute	2,26	2,72	6.68	0,86
	LS	1,55	1,93	0.58	0,86
	EQM	1,72	1,935	1,12	0,82
RACMO2.2T	Brute	4,83	5,36	-16.85	0,76
	LS	1,97	2,47	0.72	0,76
	EQM	2,15	2,85	1,11	0,70
CanESM2	Brute	1,97	2,41	-3,85	0,82
	LS	1,76	2,19	0,78	0,82
	EQM	1,87	2,53	0,70	0,80

3.2- Analysis of observed and simulated precipitation and temperature trends

3.2.1- Analysis of precipitation trends

The modified Mann-Kendall test and the Sen slope estimator were applied to detect trends at the annual time step in the precipitation series of the observations and CRU data over the recent period 1975-2020 and of a multi-model ensemble of 4 RCMs of the RCP4.5 and RCP8.5 scenarios for the future period 2021-2050. The results of all the analyses carried out at the 95% confidence level ($\alpha = 0.05$) are shown 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). However, no trend was detected at the stations (St1 and St2) in the G5 grid. The magnitude (Sen slope) varies from 0.423 to 5.540. For simulated mean annual precipitation corrected by the linear scaling method, 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. The magnitudes of Sen's predicted slope estimator are in the range 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 at grid6 level (to the south), where a statistically significant upward trend in annual precipitation is observed with a magnitude ranging from 0.164 to 1.184.

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

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

3.2.2- Analysis of average annual temperature trends

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

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Discussion

Wilcke et al.(2013), defined bias as the long-term average difference between model and observation. This bias is mostly 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 al., 2012; Fang et al., 2015). For this study, three bias correction techniques (LS, EQM, and GQM) were used to correct the biases simulated by the RCMs during the monthly evaluations. After evaluating the performance of the methods mentioned, it was found that the EQM and GQM methods had difficulty in correcting the 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 Adeyeri et al.(2020), have made similar observations. This observation has been made by certain authors (Piani et al., 2010a; Gudmundsson et al., 2012; Maraun, 2013; Ezéchiel et al., 2016; N'Tcha M'Po et al., 2016). These authors argue that bias correction methods encounter obstacles due to the variability of precipitation, the assumption of bias stationarity, or the fact that this assumption is not verified in arid to semi-arid zones. Precipitation corrected by 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 LS method was more successful in correcting the biases for both precipitation and temperature, as the results show. The results of this method indicate that certain evaluation criteria are generally weak (RMSE, MEA, and Pbiais) and strong (r^2), demonstrating good performance of the LS method. By comparing seven (07) bias correction techniques in the Mekrou catchment area, it was reported that the linear scaling method performed better in reducing biases in monthly precipitation, while other methods (such as QGM) rather have a negative impact on the quality of monthly precipitation. In short, the linear scaling method was able to correct the biases simulated by the RCMs more effectively than the other two methods, even though there were some overestimates of precipitation, which seems unavoidable since, according to the authors, there is a tendency to overestimate precipitation 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 mean precipitation and temperature. These upward trends in precipitation and temperature are closely correlated with the work of Mahmood et al. (2019), in the Lake Chad basin, which revealed a trend

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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. The increase in precipitation over this period was also predicted by the RCP8.5 scenarios, although the absence of a trend dominates. These trends in future annual rainfall increase are consistent with the predictions of Adeyeri et al. (2020), who predict an increase in rainfall in the Komadugu-Yobe transboundary river (Lake Chad basin) over the period 2020-2050. The prevalence of rainfall in this study is consistent with research by Hartley et al.(2015), who estimated a 20-50% increase in rainfall between 2020 and 2049 in this region. Furthermore, these forecasts are consistent with the IPCC report (2014), which predicts significant increases in rainfall over the 21st century in the Sahelian zone. As for future mean annual temperatures, the trend analysis showed that the RCP4.5 and RCP8.5 scenarios agree in confirming strong statistically 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; GIZ, 2015; Akinsanola et al., 2015; Fotso-Nguemo et al., 2017, 2018; Nkiaka et al., 2018b; Mahmood et al., 2019; Taguela et al., 2020; Centre du climat, 2022; Fita et al., 2024). Although it is difficult to make real predictions about rainfall, 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 global approaches to encourage adaptation to climate change, which is already evident in the semi-arid study area.

Table 4: Results of the modified Mann-Kendall trend tests and Sen's slope for the time series of mean annual temperatures observed and corrected for RCM bias at the 5% significance level

		Average annual temperature(°C)				
		Z-original	P-value	Z-corrected	New-P-valu	Pente
Observed (CRU)	G1	4,450	0,006	3,663	0,003	0,032
	G2	3,825	0,001	3,490	0,000	0,026
	G3	3,591	0,000	4,275	0,000	0,020
	G4	3,739	0,000	3,213	0,001	2,941
	G5	2,313	0,002	2,214	0,007	0,018
	St1	4,351	0,003	3,611	0,003	0,291
	G6	3,270	0,001	4,373	0,000	0,023
	St2	4,506	0,000	3,688	0,000	0,028
	G1	3,425	0,006	5,861	0,000	0,038
	G2	3,354	0,007	3,354	0,007	0,033

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RCP4.5	G3	3,318	0,009	4,129	0,003	0,038
	G4	3,389	0,006	1,629	0,000	0,033
	G5	3,782	0,001	4,221	0,000	0,031
	St1	3,603	0,003	9,516	0,001	0,038
	G6	3,568	0,003	1,867	0,000	0,035
	St2	3,175	0,001	3,316	0,001	0,039
RCP8.5	G1	3,889	0,001	3,889	0,001	0,054
	G2	3,461	0,005	3,461	0,005	0,042
	G3	3,782	0,001	3,782	0,001	0,052
	G4	4,103	0,004	7,808	0,004	0,042
	G5	3,889	0,001	3,889	0,001	0,503
	St1	3,817	0,001	3,817	0,001	0,049
	G6	3,496	0,004	3,926	0,008	0,040
	St2	3,568	0,003	3,568	0,003	0,039

G1, G2,…G6 = grid; St1 and St2 = station

Conclusion

The aim of this work is to evaluate the performance of three bias correction methods in correcting the monthly mean rainfall and temperature simulated by RCMs in northeastern Lake Chad. A number of statistical measures (Pbiais, RMSE, r2, and MEA) 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 observation data and data simulated by the RCM multi-model approach under the RCP4.5 scenario showed overall upward trends in recent and future mean annual precipitation and temperature over the entire study area. On the other hand, the RCP8.5 scenarios are 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.

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