Journal of
Water & Climate Change

Journal of Water and Climate Change Vol 14 No 8, 2606 doi: 10.2166/wcc.2023.503

Comparison of bias correction methods for climate change projections in the lower Shivaliks of Punjab

Kuldeep Kaur[a] and Navneet Kaur [b,*]
[a] Department of Climate Change and Agricultural Meteorology, PAU, Ludhiana 141004, India
[b] Regional Research Station, Ballowal Saunkhri, SBS Nagar, Punjab 144521, India
*Corresponding author. E-mail: navneetkaur@pau.edu

NK, 0000-0003-2766-5638

ABSTRACT

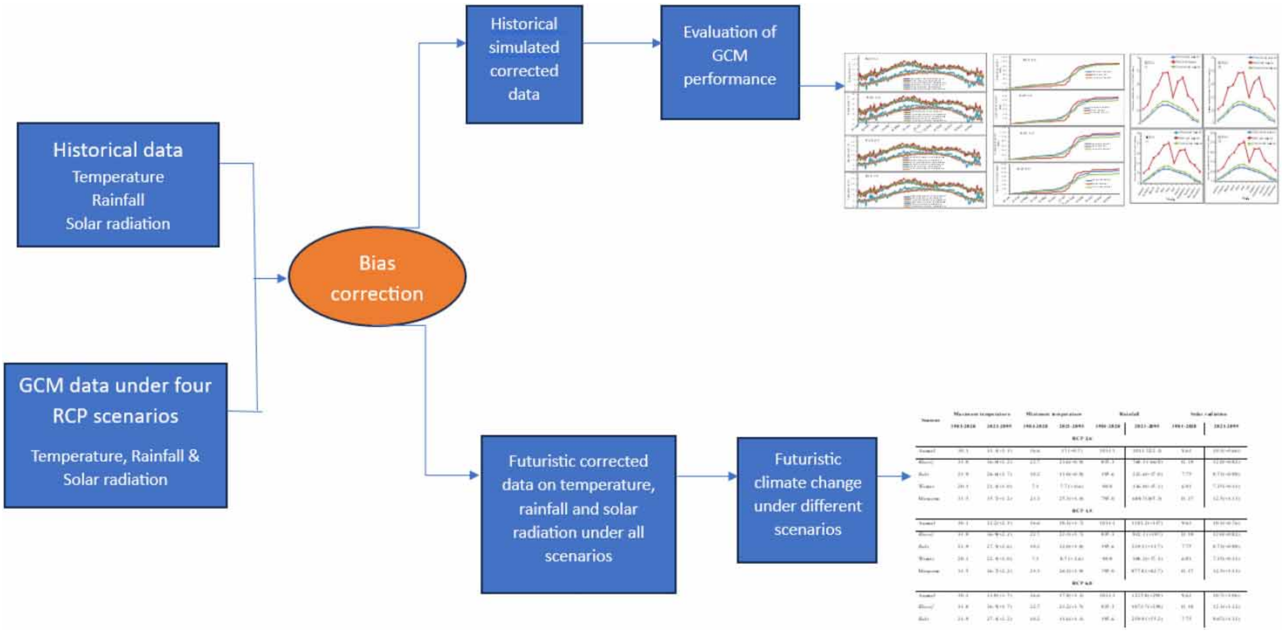
The study evaluates the performance of bias correction techniques by dividing the observed climate data period into calibration and validation sets. For this purpose, the daily data of temperature, rainfall, and solar radiation from 2010–2095 for lower Shivaliks of Punjab (Ballowal Saunkhri) were downloaded from Marksim weather generators using outputs of CSIRO-Mk3-6-0 climate model under four RCP scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5). The bias correction of model data (temperature, rainfall, and solar radiation) was done by developing correction functions (using a model and observed data from 2010 to 2015) from different bias correction methods (difference method, Leander and Buishand method, modified difference method, linear scaling, variance scaling, and quantile mapping). The corrected model data for the year 2016–2020 were validated against the observed data. The difference method was found to be best for bias correction due to low error and high efficiency. The corrected future model data (2021–2095) analysis on an annual and seasonal basis predicted a rise in maximum temperature and minimum temperature by 1.3–2.8 °C and 0.5–3.0 °C, respectively, under different scenarios. The study predicted more increase in rainfall and solar radiation under RCP 8.5 followed by RCP 6.0, RCP 4.5, and RCP 2.6 scenarios.

Key words: bias correction, climate projections, CSIRO-Mk3-6-0, Punjab, RCP scenarios

HIGHLIGHTS

- The study analyzed the implications of bias correction methods on the projection of climate change.
- The difference method of bias correction was better as compared to other methods in terms of different statistical tests.
- Validation results using the difference method showed a reduction in differences between observed and model data after correction.
- Increase in temperature is observed as compared to the historical period by the end of the 21st century.

GRAPHICAL ABSTRACT



INTRODUCTION

The world's agriculture is highly affected by rapid population growth, land use changes due to urbanization, diminishing good quality water resources, and weather extremes occurring due to changing climatic conditions resulting from global warming (Asma *et al.* 2020). The understanding of the agricultural impacts of climate change may play a pivotal role in developing adaptation and mitigation strategies for tackling the adverse effects of such changes. The historical data analysis for the lower Shivaliks of Punjab, India has shown a significantly increasing trend in temperature (Kaur *et al.* 2021a). A range of emission scenarios with climate change projections has been a key tool in assessing the impact of future climate change and exploring management strategies to adapt to climate change. Many future climate change impact assessments have been carried out using crop models and hydrological models for specific locations and agricultural regions on a global scale (Rosenweig & Parry 1994).

The futuristic climatic data are available through General Circulation Models (GCMs), at very coarse scales generally more than 200 km in resolution (Feddersen & Andersen 2005). The GCM-generated data are further downscaled using Regional Climate Model (RCM) for the generation of fine-scale data resolutions of a particular area. The RCM data are more reliable compared to GCM data, however, RCM data still require bias correction (BC) when predicted data are compared to observed data for a particular period (Buonomo *et al.* 2007; Fowler & Blenkinsop 2007). However, it becomes of utmost importance to carry out the BC of the GCM projected data prior to the impact studies, for the correction of the discrepancies between a model's climate and observed historical climate data (Amsal *et al.* 2019; James *et al.* 2019; Hawkins *et al.* 2020; Jaiswal *et al.* 2021) for fair and reliable prediction and decision-making. There are several BC methods such as the difference method (DM), linear scaling (LS) or statistical methods (Leander & Buishand 2007), quantile mapping (QM) (Boe *et al.* 2007), and probability density functions (Piani *et al.* 2010) to correct the biases in GCM–RCM outputs for various impact studies (Charles *et al.* 2019; Enayati *et al.* 2021). There is no single BC method that performs best for all regions (Fang *et al.* 2015); each of these methods has its own merits and demerits, mainly due to spatiotemporal differences in surface and rainfall properties. Various case studies are available depicting the performance of different BC methods (Table 1). Hence, the selection of methods to remove the systematic errors of climate model outputs needs to be based on a comparison of multiple BC methods. Keeping this in view, the present study was undertaken to develop BC functions through statistical comparison of different correction methods, for seasonal projections of temperature and rainfall under different scenarios.

Table 1 | Different case studies adopting different BC methods for different regions of India

Name of the case study	BC technique employed	Best bias-corrected technique	Authors of the paper
BC methods in downscaling meteorological variables in Ludhiana, Punjab	Modified difference method Linear scaling	Linear scaling	Mehraj U. Din Dar Rajan Aggarwal Samanpreet Kaur
Application of bivaraite BC approach to yield long-term attributes of Indian precipitation and temperature	Bivariate Asynchronous BC Asynchronous canonical correlation analysis	Bivariate Asynchronous BC	Chanchal Gupta Rajarshi Das Bhowmik
An improved BC method of daily rainfall data using a sliding window technique for climate change impact assessment	Distribution mapping Modified power transformation	Distribution mapping	P. S. Smitha B. Narashiman K. P. Sudheer
Comparison of BC techniques for GPCC rainfall data in semi-arid climate	Linear scaling Quantile mapping	Quantile mapping	Ashoka K. Mishra Abdul A. Khan
On the BC of general circulation model output for Indian summer monsoon	Quantile mapping method Principal Component Regression	Quantile mapping method	Nachiketa Acharaya Surajit Chattophdaya L. N. Sahoo
Evaluation of statistical BC methods for numerical weather prediction model forecasts of maximum and minimum temperatures	Difference method Variance scaling Quantile mapping	Quantile mapping	V. R. Durai Rashmi Bharadwaj

MATERIALS AND METHODS

Study area

The study was carried out for the Regional Research Station, Ballowal Saunkhri located in the lower Shivaliks sub-mountain zone of Punjab, India which is commonly known as the Kandi region. Ballowal Saunkhri has been situated at 30°07′N, 76°23′E and lies 355 m above mean sea level. The area represents a semi-arid climate with very hot and dry summers from April to June, hot and humid conditions from July to September, cold winters from November to January, and a mild climate during February and March.

Data sets

There are a series of models for which scenario-wise data are available. An earlier study by Punjab Agricultural University, Ludhiana has reported that CSIRO-Mk3-6-0 was best for the area adjacent to the current location as compared to other models (Kaur *et al.* 2021b). The daily data for the meteorological parameters like maximum and minimum temperature, rainfall, and solar radiation were downloaded from Marksim Weather Generator using the output of the CSIRO-MK3-6-0 model for the Ballowal Saunkhri location. The model-predicted data are available from 2010 to 2095 separately for four climate change scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5). The historical daily weather data (temperature, rainfall, and solar radiation) recorded at the Agrometeorological Observatory of Regional Research Station, Ballowal Saunkhri during 2010–2020 was used for BC. The correction functions were estimated by using baseline and observed data from 2010 to 2015, whereas data from 2016 to 2020 were used for validation of corrected model data.

METHODOLOGY

BC methods

BC methods are post-processing tools for numerical modeling that aim to improve the model agreement with the observations. Based on their performance in removing bias from RCMs, there are a number of BC methods that are ranked according to their tendency to adjust mean, variance, coefficient of variation, and standard deviation climate variables (Smitha *et al.* 2018; Ezechiel *et al.* 2019). The errors in the observed and predicted data on maximum temperature, minimum temperatures, rainfall, and solar radiation were minimized by using different methods of BC. Six BC methods, viz. DM, Leander and Buishand method (LB), modified difference method (MD), LS, variance scaling (VS), and QM methods were used. In the difference method of bias removal, the differences between model data (X_{model}) and observed (X_{obs}) data of the meteorological parameters (maximum temperature, minimum temperature, and rainfall) for each Julian day (365) averaged from 6 years data (2010–2015) are used as 'Correction factor'. Then these correction factors are subtracted from model uncorrected ($X_{\mathrm{modeluncorr}}$) data for another time period so that model corrected $X_{(\mathrm{modelcorr})}$ data for that period comes closer to observed data. The LB method of bias removal was given by Leander & Buishand (2007) for the temperature wherein the mean and standard deviation were added. This method is not appropriate for bias removal in precipitation since it can compute the negative values of precipitation. Modified LB was given by Leander & Buishand (2007) and it is quite similar to the difference method but used for rainfall. The LS method is the most straightforward BC technique employed in several studies. It adjusts the RCM mean value in perfect agreement with the observation data (temperature and rainfall). The VARI method was developed to correct both the mean and variance of normally distributed variables such as temperature. The QM method constructs the cumulative distribution function (CDF) of the model and observed data (temperature and rainfall) using a transform function, which in turn translates the raw model outputs into corrected output. All BC methods were applied to daily values for all methods. Therefore, strong BC methods are to be identified before using bias-corrected methods to be applied to climate models' output for future climate change impact assessment. For bias removal, the correction functions for each weather parameter under all the scenarios were developed using observed and model data from 2010 to 2015 (Tables 2–4). These correction factors were further used to correct and validate the model data for 2016–2020, i.e. the BC effect was assessed by correcting projected data and comparing results with the historical observed data under all the climate scenarios (Figure 1(a) and 1(b)).

Statistical comparison of methods used for bias removal

During the performance evaluation, different statistical parameters including coefficient of residual mass (CRM), normalized root mean square error (NRMSE), mean absolute error (MAE), mean bias error (MBE), mean absolute percentage error (MAPE), Wilmot d-index, percent bias index (PBIAS), and Nash–Sutcliffe efficiency (NSE) were used to check the performance of BC methods (Figure 1(a) and 1(b)). The CRM shows the difference in observed and predicted data relative to the observed data. Its zero, negative, and positive values indicate a perfect fit, over-, and under-prediction, respectively. NRMSE provides a measure (%) of the relative difference between predicted versus observed data. The simulation is considered excellent, good, fair, and poor if NRMSE is <10, 10–20, 20–30, and $>30\%$, respectively (Jamieson *et al.* 1991). The MAE is an absolute measure of bias that varies between 0 to $+\infty$. An MAE value close to 0 indicates an unbiased prediction, i.e. a low MAE indicates a good fit between two variables. The MBE provides information of over- and under-prediction by the model. Positive MBE indicates over-prediction, negative values indicate under-prediction, and a zero indicates equal distribution between negative and positive values (Singh *et al.* 2013). The MAPE is the mean or average of the absolute percentage errors of forecasts. Willmott (1981) proposed an index of agreement (d) as a standardized measure of the degree of model prediction error which varies between 0 and 1. The PBIAS, on the other hand, calculates the relative volume difference between modeled and observed volume. A negative value indicates under-prediction, whereas a positive value indicates over-prediction. The NSE is calculated as one minus the ratio of the error variance of the modeled time-series over the variance of the observed time-series.

RESULTS AND DISCUSSION

GCMs provide a credible picture of global climate change, yet most of the crucial phenomena are considerably misreported. For instance, some of the key processes controlling climate systems are biased along with high uncertainties in the representation of changes in these phenomena. These biases then affect the representation of regional climate conditions. The biases in the climate model simulations and observed data need to be corrected in order to predict possible changes in the future. Although the spatial resolutions and skills of GCMs/RCMs have obviously increased in recent years, it is still not enough for their direct application in impact studies at local or site scales. Under such a case, BC methods provide a solution, which combines information from the local observations and simulations leading to smaller biases and higher-resolution predictions/projections. The correction functions developed for the maximum temperature, minimum temperature, rainfall, and

Table 2 | Correction functions for maximum temperature under different RCP scenarios

	Correction functions under different BC methods				
Months	**Difference method**	**Leander and Buishand**	**Linear scaling**	**Variance scaling**	**Quantile scaling**
	RCP 2.6				
January	0.60	$T_{cor} = 17.92 + (0.65*(T_{mod} - 17.92) - 0.60)$	$T_{cor} = T_{mod} - 0.60$	$T_{cor} = T_{mod} - 18.5*(0.65 + 17.9)$	$T_{cor} = 4.10(0.51*\ T_{mod})$
February	0.85	$T_{cor} = 22.76 + (0.32*(T_{mod} - 22.76) - 0.85)$	$T_{cor} = T_{mod} - 0.85$	$T_{cor} = T_{mod} - 23.6*(0.32 + 22.8)$	$T_{cor} = 4.48(0.49*\ T_{mod})$
March	0.38	$T_{cor} = 28.47 + (0.79*(T_{mod} - 28.47) - 0.38)$	$T_{cor} = T_{mod} - 0.38$	$T_{cor} = T_{mod} - 28.9*(0.79 + 28.5)$	$T_{cor} = 6.38(0.52*\ T_{mod})$
April	0.92	$T_{cor} = 34.51 + (0.58*(T_{mod} - 34.51) - 0.92)$	$T_{cor} = T_{mod} - 0.92$	$T_{cor} = T_{mod} - 35.4*(0.58 + 34.5)$	$T_{cor} = 4.00(0.51*\ T_{mod})$
May	2.81	$T_{cor} = 39.44 + (0.77*(T_{mod} - 39.44) - 2.81)$	$T_{cor} = T_{mod} - 2.81$	$T_{cor} = T_{mod} - 42.2*(0.77 + 39.4)$	$T_{cor} = 6.94(0.51*\ T_{mod})$
June	2.76	$T_{cor} = 38.17 + (0.61*(T_{mod} - 38.17) - 2.76)$	$T_{cor} = T_{mod} - 2.76$	$T_{cor} = T_{mod} - 40.9*(0.61 + 38.2)$	$T_{cor} = 5.37(0.51*\ T_{mod})$
July	0.94	$T_{cor} = 34.05 + (0.36*(T_{mod} - 34.05) - 0.94)$	$T_{cor} = T_{mod} - 0.94$	$T_{cor} = T_{mod} - 35.0*(0.36 + 34.0)$	$T_{cor} = 4.24(0.50*\ T_{mod})$
August	1.38	$T_{cor} = 33.46 + (0.26*(T_{mod} - 33.46) - 1.38)$	$T_{cor} = T_{mod} - 1.38$	$T_{cor} = T_{mod} - 34.8*(0.26 + 33.5)$	$T_{cor} = 4.17(0.51*\ T_{mod})$
September	1.84	$T_{cor} = 33.37 + (0.36*(T_{mod} - 33.37) - 1.84)$	$T_{cor} = T_{mod} - 1.84$	$T_{cor} = T_{mod} - 35.2*(0.36 + 33.4)$	$T_{cor} = 5.07(0.49*\ T_{mod})$
October	2.35	$T_{cor} = 32.05 + (0.75*(T_{mod} - 32.05) - 2.35)$	$T_{cor} = T_{mod} - 2.35$	$T_{cor} = T_{mod} - 34.4*(0.75 + 32.0)$	$T_{cor} = 5.26(0.50*\ T_{mod})$
November	−1.22	$T_{cor} = 27.80 + (0.30*(T_{mod} - 27.80) + 1.22)$	$T_{cor} = T_{mod} - 1.22$	$T_{cor} = T_{mod} - 26.6*(0.30 + 27.8)$	$T_{cor} = 4.38(0.49*\ T_{mod})$
December	2.41	$T_{cor} = 21.78 + (0.63*(T_{mod} - 21.78) - 2.41)$	$T_{cor} = T_{mod} - 2.41$	$T_{cor} = T_{mod} - 24.2*(0.63 + 21.8)$	$T_{cor} = 3.82(0.51*\ T_{mod})$
	RCP 4.5				
January	0.33	$T_{cor} = 17.92 + (0.65*(T_{mod} - 17.92) - 0.33)$	$T_{cor} = T_{mod} - 0.33$	$T_{cor} = T_{mod} - 18.2*(0.65 + 17.9)$	$T_{cor} = 4.10(0.51*\ T_{mod})$
February	0.58	$T_{cor} = 22.76 + (0.32*(T_{mod} - 22.76) - 0.58)$	$T_{cor} = T_{mod} - 0.58$	$T_{cor} = T_{mod} - 23.3*(0.32 + 22.7)$	$T_{cor} = 4.48(0.49*\ T_{mod})$
March	0.55	$T_{cor} = 28.47 + (0.80*(T_{mod} - 28.47) - 0.55)$	$T_{cor} = T_{mod} - 0.55$	$T_{cor} = T_{mod} - 29.0*(0.80 + 28.4)$	$T_{cor} = 6.38(0.52*\ T_{mod})$
April	0.72	$T_{cor} = 34.51 + (0.59*(T_{mod} - 34.51) - 0.72)$	$T_{cor} = T_{mod} - 0.72$	$T_{cor} = T_{mod} - 35.2*(0.59 + 34.5)$	$T_{cor} = 4.00(0.51*\ T_{mod})$
May	2.79	$T_{cor} = 39.44 + (0.77*(T_{mod} - 39.44) - 2.80)$	$T_{cor} = T_{mod} - 2.80$	$T_{cor} = T_{mod} - 42.2*(0.77 + 39.4)$	$T_{cor} = 6.94(0.51*\ T_{mod})$
June	2.64	$T_{cor} = 38.17 + (0.62*(T_{mod} - 38.17) - 2.64)$	$T_{cor} = T_{mod} - 2.64$	$T_{cor} = T_{mod} - 40.8*(0.62 + 38.1)$	$T_{cor} = 5.37(0.51*\ T_{mod})$
July	0.89	$T_{cor} = 34.05 + (0.37*(T_{mod} - 34.05) - 0.89)$	$T_{cor} = T_{mod} - 0.89$	$T_{cor} = T_{mod} - 34.9*(0.37 + 34.0)$	$T_{cor} = 4.24(0.50*\ T_{mod})$
August	1.29	$T_{cor} = 33.46 + (0.26*(T_{mod} - 33.46) - 1.29)$	$T_{cor} = T_{mod} - 1.29$	$T_{cor} = T_{mod} - 34.7*(0.26 + 33.4)$	$T_{cor} = 4.17(0.50*\ T_{mod})$
September	1.48	$T_{cor} = 33.37 + (0.35*(T_{mod} - 33.37) - 1.48)$	$T_{cor} = T_{mod} - 1.48$	$T_{cor} = T_{mod} - 34.8*(0.35 + 33.3)$	$T_{cor} = 5.07(0.50*\ T_{mod})$
October	2.20	$T_{cor} = 32.05 + (0.76*(T_{mod} - 32.05) - 2.20)$	$T_{cor} = T_{mod} - 2.20$	$T_{cor} = T_{mod} - 34.2*(0.76 + 32.0)$	$T_{cor} = 5.26(0.50*\ T_{mod})$
November	−1.44	$T_{cor} = 27.80 + (0.29*(T_{mod} - 27.80) + 1.44)$	$T_{cor} = T_{mod} + 1.44$	$T_{cor} = T_{mod} - 26.3*(0.29 + 27.8)$	$T_{cor} = 4.38(0.49*\ T_{mod})$
December	2.24	$T_{cor} = 21.78 + (0.12*(T_{mod} - 21.78) - 2.24)$	$T_{cor} = T_{mod} - 2.24$	$T_{cor} = T_{mod} - 24.0*(0.62 + 21.7)$	$T_{cor} = 3.82(0.51*\ T_{mod})$
	RCP 6.0				
January	0.30	$T_{cor} = 17.9 + (0.64*(T_{mod} - 17.9) - 0.29)$	$T_{cor} = T_{mod} - 0.29$	$T_{cor} = T_{mod} - 18.2*(0.64 + 17.9)$	$T_{cor} = 4.10(0.51*\ T_{mod})$
February	0.54	$T_{cor} = 22.8 + (0.32*(T_{mod} - 22.8) - 0.54)$	$T_{cor} = T_{mod} - 0.54$	$T_{cor} = T_{mod} - 23.3*(0.32 + 22.7)$	$T_{cor} = 4.48(0.49*\ T_{mod})$
March	0.78	$T_{cor} = 28.3 + (0.89*(T_{mod} - 28.3) - 0.97)$	$T_{cor} = T_{mod} - 0.97$	$T_{cor} = T_{mod} - 29.2*(0.89 + 28.2)$	$T_{cor} = 5.81(0.52*\ T_{mod})$
April	1.37	$T_{cor} = 34.3 + (0.63*(T_{mod} - 34.3) - 1.57)$	$T_{cor} = T_{mod} - 1.57$	$T_{cor} = T_{mod} - 35.8*(0.63 + 34.3)$	$T_{cor} = 3.98(0.50*\ T_{mod})$

(*Continued.*)

Table 2 | Continued

Months	Difference method	Leander and Buishand	Linear scaling	Variance scaling	Quantile scaling
	Correction functions under different BC methods				
May	2.95	$T_{cor} = 39.3 + (0.81*(T_{mod} - 39.3) - 3.07)$	$T_{cor} = T_{mod} - 3.07$	$T_{cor} = T_{mod} - 42.3*(0.81 + 39.3)$	$T_{cor} = 6.29(0.50* T_{mod})$
June	3.00	$T_{cor} = 38.3 + (0.66*(T_{mod} - 38.3) - 2.83)$	$T_{cor} = T_{mod} - 2.83$	$T_{cor} = T_{mod} - 41.1*(0.66 + 38.3)$	$T_{cor} = 5.55(0.51* T_{mod})$
July	1.04	$T_{cor} = 34.1 + (0.40*(T_{mod} - 34.1) - 0.95)$	$T_{cor} = T_{mod} - 0.95$	$T_{cor} = T_{mod} - 35.0*(0.40 + 34.1)$	$T_{cor} = 4.22(0.50* T_{mod})$
August	1.47	$T_{cor} = 33.4 + (0.26*(T_{mod} - 33.4) - 1.50)$	$T_{cor} = T_{mod} - 1.50$	$T_{cor} = T_{mod} - 34.9*(0.26 + 33.4)$	$T_{cor} = 4.10(0.50* T_{mod})$
September	1.87	$T_{cor} = 33.4 + (0.37*(T_{mod} - 33.4) - 1.85)$	$T_{cor} = T_{mod} - 1.85$	$T_{cor} = T_{mod} - 35.2*(0.37 + 33.3)$	$T_{cor} = 4.98(0.50* T_{mod})$
October	2.24	$T_{cor} = 32.2 + (0.80*(T_{mod} - 32.2) - 2.12)$	$T_{cor} = T_{mod} - 2.12$	$T_{cor} = T_{mod} - 34.2*(0.80 + 32.1)$	$T_{cor} = 5.87(0.51* T_{mod})$
November	−1.69	$T_{cor} = 27.9 + (0.34*(T_{mod} - 27.9) + 1.82)$	$T_{cor} = T_{mod} +1.82$	$T_{cor} = T_{mod} - 26.1*(0.34 + 27.9)$	$T_{cor} = 4.49(0.50* T_{mod})$
December	2.25	$T_{cor} = 22.0 + (0.61*(T_{mod} - 22.0) - 2.00)$	$T_{cor} = T_{mod} - 2.00$	$T_{cor} = T_{mod} - 24.0*(0.61 + 22.0)$	$T_{cor} = 3.97(0.50* T_{mod})$
	RCP 8.5				
January	0.37	$T_{cor} = 17.92 + (0.64*(T_{mod} - 17.92) - 0.33)$	$T_{cor} = T_{mod} - 0.33$	$T_{cor} = T_{mod} - 18.3*(0.64 + 17.9)$	$T_{cor} = 4.10(0.51* T_{mod})$
February	0.68	$T_{cor} = 22.76 + (0.32*(T_{mod} - 22.76) - 0.68)$	$T_{cor} = T_{mod} - 0.68$	$T_{cor} = T_{mod} - 23.4*(0.32 + 22.8)$	$T_{cor} = 4.48(0.49* T_{mod})$
March	1.08	$T_{cor} = 28.19 + (0.93*(T_{mod} - 28.19) - 1.08)$	$T_{cor} = T_{mod} - 1.08$	$T_{cor} = T_{mod} - 29.3*(0.93 + 28.2)$	$T_{cor} = 6.00(0.51* T_{mod})$
April	1.42	$T_{cor} = 34.30 + (0.63*(T_{mod} - 34.30) - 1.42)$	$T_{cor} = T_{mod} - 1.42$	$T_{cor} = T_{mod} - 35.7*(0.63 + 34.3)$	$T_{cor} = 3.98(0.50* T_{mod})$
May	2.94	$T_{cor} = 39.32 + (0.81*(T_{mod} - 39.32) - 2.94)$	$T_{cor} = T_{mod} - 2.94$	$T_{cor} = T_{mod} - 42.3*(0.81 + 39.3)$	$T_{cor} = 6.30(0.50* T_{mod})$
June	2.67	$T_{cor} = 38.34 + (0.65*(T_{mod} - 38.34) - 2.67)$	$T_{cor} = T_{mod} - 2.67$	$T_{cor} = T_{mod} - 41.0*(0.65 + 38.3)$	$T_{cor} = 5.55(0.51* T_{mod})$
July	0.86	$T_{cor} = 34.14 + (0.39*(T_{mod} - 34.14) - 0.86)$	$T_{cor} = T_{mod} - 0.86$	$T_{cor} = T_{mod} - 35.0*(0.39 + 34.1)$	$T_{cor} = 4.22(0.50* T_{mod})$
August	1.49	$T_{cor} = 33.43 + (0.27*(T_{mod} - 33.43) - 1.49)$	$T_{cor} = T_{mod} - 1.49$	$T_{cor} = T_{mod} - 34.9*(0.27 + 33.4)$	$T_{cor} = 4.10(0.50* T_{mod})$
September	1.91	$T_{cor} = 33.39 + (0.37*(T_{mod} - 33.39) - 1.91)$	$T_{cor} = T_{mod} - 1.91$	$T_{cor} = T_{mod} - 35.3*(0.37 + 33.4)$	$T_{cor} = 4.97(0.50* T_{mod})$
October	2.17	$T_{cor} = 32.17 + (0.75*(T_{mod} - 32.17) - 2.17)$	$T_{cor} = T_{mod} - 2.17$	$T_{cor} = T_{mod} - 34.3*(0.75 + 32.2)$	$T_{cor} = 5.87(0.50* T_{mod})$
November	−1.82	$T_{cor} = 27.93 + (0.33*(T_{mod} - 27.93) + 1.82)$	$T_{cor} = T_{mod} +1.82$	$T_{cor} = T_{mod} - 26.1*(0.33 + 27.9)$	$T_{cor} = 4.49(0.50* T_{mod})$
December	1.78	$T_{cor} = 22.03 + (0.61*(T_{mod} - 22.03) - 1.78)$	$T_{cor} = T_{mod} - 1.78$	$T_{cor} = T_{mod} - 23.8*(0.62 + 22.0)$	$T_{cor} = 3.97(0.51* T_{mod})$

Table 3 | Correction functions for correcting the CSIRO model minimum temperature data for four RCP scenarios

	Correction functions under different BC methods				
Months	**Difference method**	**Leander and Buishand**	**Linear scaling**	**Variance scaling**	**Quantile scaling**
	RCP 2.6				
January	−0.73	$T_{cor} = 5.05 + (0.29*(T_{mod} - 5.05) + 0.73)$	$T_{cor} = T_{mod} + 0.73$	$T_{cor} = T_{mod} - 4.32*(0.29 + 5.05)$	$T_{cor} = 4.82(0.52*\ T_{mod})$
February	1.39	$T_{cor} = 8.32 + (1.00*(T_{mod} - 8.32) - 1.39)$	$T_{cor} = T_{mod} - 1.39$	$T_{cor} = T_{mod} - 9.71*(0.33 + 8.32)$	$T_{cor} = 5.19(0.50*\ T_{mod})$
March	1.25	$T_{cor} = 12.66 + (0.52*(T_{mod} - 12.66) - 1.25)$	$T_{cor} = T_{mod} - 1.25$	$T_{cor} = T_{mod} - 13.9*(0.83 + 12.6)$	$T_{cor} = 4.05(0.50*\ T_{mod})$
April	1.96	$T_{cor} = 17.32 + (0.58*(T_{mod} - 17.32) - 1.96)$	$T_{cor} = T_{mod} - 1.96$	$T_{cor} = T_{mod} - 19.2*(0.58 + 17.3)$	$T_{cor} = 4.24(0.51*\ T_{mod})$
May	5.11	$T_{cor} = 21.91 + (0.86*(T_{mod} - 21.91) - 5.11)$	$T_{cor} = T_{mod} - 5.11$	$T_{cor} = T_{mod} - 27.0*(0.86 + 21.9)$	$T_{cor} = 4.60(0.50*\ T_{mod})$
June	3.75	$T_{cor} = 24.76 + (0.76*(T_{mod} - 24.76) - 3.75)$	$T_{cor} = T_{mod} - 3.75$	$T_{cor} = T_{mod} - 28.5*(0.76 + 24.7)$	$T_{cor} = 3.96(0.52*\ T_{mod})$
July	1.80	$T_{cor} = 25.28 + (0.44*(T_{mod} - 25.28) - 1.80)$	$T_{cor} = T_{mod} - 1.80$	$T_{cor} = T_{mod} - 27.0*(0.44 + 25.2)$	$T_{cor} = 5.75(0.52*\ T_{mod})$
August	2.44	$T_{cor} = 24.50 + (0.24*(T_{mod} - 24.50) - 2.44)$	$T_{cor} = T_{mod} - 2.44$	$T_{cor} = T_{mod} - 26.9*(0.24 + 24.5)$	$T_{cor} = 5.33(0.49*\ T_{mod})$
September	2.43	$T_{cor} = 22.39 + (1.16*(T_{mod} - 22.39) - 2.43)$	$T_{cor} = T_{mod} - 2.43$	$T_{cor} = T_{mod} - 24.8*(1.16 + 22.3)$	$T_{cor} = 4.25(0.51*\ T_{mod})$
October	3.57	$T_{cor} = 16.95 + (0.91*(T_{mod} - 16.95) - 3.57)$	$T_{cor} = T_{mod} - 3.57$	$T_{cor} = T_{mod} - 50.5*(0.91 + 16.9)$	$T_{cor} = 4.39(0.48*\ T_{mod})$
November	−1.96	$T_{cor} = 10.56 + (0.31*(T_{mod} - 10.56) + 1.96)$	$T_{cor} = T_{mod} + 1.96$	$T_{cor} = T_{mod} - 8.60*(0.31 + 10.5)$	$T_{cor} = 3.54(0.50*\ T_{mod})$
December	2.85	$T_{cor} = 6.27 + (0.41*(T_{mod} - 6.27) - 2.85)$	$T_{cor} = T_{mod} - 2.85$	$T_{cor} = T_{mod} - 9.11*(0.41 + 6.27)$	$T_{cor} = 4.65(0.49*\ T_{mod})$
	RCP 4.5				
January	−0.91	$T_{cor} = 5.05 + (0.29*(T_{mod} - 5.05) + 0.91)$	$T_{cor} = T_{mod} + 0.91$	$T_{cor} = T_{mod} - 4.14*(0.29 + 5.05)$	$T_{cor} = 4.82(0.52*\ T_{mod})$
February	1.11	$T_{cor} = 8.32 + (0.32*(T_{mod} - 8.32) - 1.11)$	$T_{cor} = T_{mod} - 1.11$	$T_{cor} = T_{mod} - 9.43*(0.32 + 8.32)$	$T_{cor} = 5.19(0.50*\ T_{mod})$
March	1.03	$T_{cor} = 12.66 + (0.82*(T_{mod} - 12.66) - 1.03)$	$T_{cor} = T_{mod} - 1.03$	$T_{cor} = T_{mod} - 13.6*(0.82 + 12.6)$	$T_{cor} = 4.05(0.50*\ T_{mod})$
April	1.79	$T_{cor} = 17.32 + (0.57*(T_{mod} - 17.32) - 1.79)$	$T_{cor} = T_{mod} - 1.79$	$T_{cor} = T_{mod} - 19.1*(0.57 + 17.3)$	$T_{cor} = 4.24(0.50*\ T_{mod})$
May	5.08	$T_{cor} = 21.91 + (0.87*(T_{mod} - 21.91) - 5.08)$	$T_{cor} = T_{mod} - 5.08$	$T_{cor} = T_{mod} - 27.0*(0.87 + 21.9)$	$T_{cor} = 4.60(0.50*\ T_{mod})$
June	3.62	$T_{cor} = 24.76 + (0.76*(T_{mod} - 24.76) - 3.62)$	$T_{cor} = T_{mod} - 3.62$	$T_{cor} = T_{mod} - 28.3*(0.76 + 24.7)$	$T_{cor} = 3.96(0.52*\ T_{mod})$
July	1.73	$T_{cor} = 25.28 + (0.44*(T_{mod} - 25.28) - 1.73)$	$T_{cor} = T_{mod} - 1.73$	$T_{cor} = T_{mod} - 27.0*(0.44 + 25.2)$	$T_{cor} = 5.75(0.52*\ T_{mod})$
August	2.29	$T_{cor} = 24.50 + (0.24*(T_{mod} - 24.50) - 2.29)$	$T_{cor} = T_{mod} - 2.29$	$T_{cor} = T_{mod} - 26.7*(0.24 + 24.5)$	$T_{cor} = 5.33(0.49*\ T_{mod})$
September	2.37	$T_{cor} = 22.39 + (1.16*(T_{mod} - 22.39) - 2.37)$	$T_{cor} = T_{mod} - 2.37$	$T_{cor} = T_{mod} - 24.7*(1.16 + 22.3)$	$T_{cor} = 4.25(0.51*\ T_{mod})$
October	3.40	$T_{cor} = 16.95 + (0.90*(T_{mod} - 16.95) - 3.40)$	$T_{cor} = T_{mod} - 3.40$	$T_{cor} = T_{mod} - 20.3*(0.90 + 16.9)$	$T_{cor} = 4.39(0.48*\ T_{mod})$
November	−2.08	$T_{cor} = 10.56 + (0.31*(T_{mod} - 10.56) + 2.08)$	$T_{cor} = T_{mod} + 2.08$	$T_{cor} = T_{mod} - 8.49*(0.31 + 10.5)$	$T_{cor} = 3.54(0.50*\ T_{mod})$
December	2.65	$T_{cor} = 6.27 + (0.40*(T_{mod} - 6.27) - 2.65)$	$T_{cor} = T_{mod} - 2.65$	$T_{cor} = T_{mod} - 8.92*(0.40 + 6.27)$	$T_{cor} = 4.66(0.49*\ T_{mod})$
	RCP 6.0				
January	−0.94	$T_{cor} = 5.0 + (0.3*(T_{mod} - 5.0) + 0.9)$	$T_{cor} = T_{mod} + 0.9$	$T_{cor} = T_{mod} - 4.11*(0.29 + 5.05)$	$T_{cor} = 4.82(0.52*\ T_{mod})$
February	1.36	$T_{cor} = 8.3 + (0.3*(T_{mod} - 8.3) - 1.4)$	$T_{cor} = T_{mod} - 1.4$	$T_{cor} = T_{mod} - 9.68*(0.33 + 8.32)$	$T_{cor} = 5.19(0.50*\ T_{mod})$
March	1.27	$T_{cor} = 12.7 + (0.9*(T_{mod} - 12.7) - 1.3)$	$T_{cor} = T_{mod} - 1.3$	$T_{cor} = T_{mod}\ 13.92*(0.88 + 12.6)$	$T_{cor} = 3.63(0.50*\ T_{mod})$
April	2.25	$T_{cor} = 17.3 + (0.6*(T_{mod} - 17.3) - 2.3)$	$T_{cor} = T_{mod} - 2.3$	$T_{cor} = T_{mod} - 19.5*(0.59 + 17.3)$	$T_{cor} = 4.24(0.52*\ T_{mod})$

(*Continued*.)

Table 3 | Continued

Months	Difference method	Leander and Buishand	Linear scaling	Variance scaling	Quantile scaling
	Correction functions under different BC methods				
May	5.24	$T_{cor} = 21.9 + (1.0^*(T_{mod} - 21.9) - 5.2)$	$T_{cor} = T_{mod} - 5.2$	$T_{cor} = \mathrm{T}_{mod} - 27.1^*(0.97 + 21.9)$	$T_{cor} = 4.60(0.49^*\ T_{mod})$
June	3.72	$T_{cor} = 24.8 + (0.8^*(T_{mod} - 24.8) - 3.7)$	$T_{cor} = T_{mod} - 3.7$	$T_{cor} = T_{mod} - 28.4^*(0.77 + 24.7)$	$T_{cor} = 3.96(0.49^*\ T_{mod})$
July	1.82	$T_{cor} = 25.3 + (0.4^*(T_{mod} - 25.3) - 1.8)$	$T_{cor} = T_{mod} - 1.8$	$T_{cor} = T_{mod} - 27.1^*(0.44 + 25.2)$	$T_{cor} = 5.75(0.52^*\ T_{mod})$
August	2.24	$T_{cor} = 24.5 + (0.2^*(T_{mod} - 24.5) - 2.2)$	$\mathrm{T}_{cor} = T_{mod} - 2.2$	$T_{cor} = T_{mod} - 26.7^*(0.24 + 24.5)$	$T_{cor} = 5.33(0.49^*\ T_{mod})$
September	2.42	$T_{cor} = 22.4 + (1.2^*(T_{mod} - 22.4) - 2.4)$	$T_{cor} = T_{mod} - 2.4$	$T_{cor} = T_{mod} - 24.8^*(1.16 + 22.3)$	$T_{cor} = 4.25(0.51^*\ T_{mod})$
October	3.29	$T_{cor} = 17.0 + (0.9^*(T_{mod} - 17.0) - 3.3)$	$T_{cor} = T_{mod} - 3.3$	$\mathrm{T}_{cor} = T_{mod} - 20.2^*(0.91 + 16.9)$	$\mathrm{T}_{cor} = 4.39(0.48^*\ T_{mod})$
November	−2.31	$T_{cor} = 10.6 + (0.3^*(T_{mod} - 10.6) + 2.3)$	$T_{cor} = T_{mod} + 2.3$	$T_{cor} = T_{mod} - 8.25^*(0.33 + 10.5)$	$T_{cor} = 3.54(0.50^*\ T_{mod})$
December	2.56	$T_{cor} = 6.3 + (0.4^*(T_{mod} - 6.3) - 2.6)$	$T_{cor} = T_{mod} - 2.6$	$T_{cor} = T_{mod} - 8.83^*(0.40 + 6.27)$	$T_{cor} = 4.66(0.49^*\ T_{mod})$
	RCP 8.5				
January	−0.90	$T_{cor} = 5.05 + (0.29^*(\mathrm{T}_{mod} - 5.05) + 0.90)$	$T_{cor} = T_{mod} + 0.90$	$T_{cor} = T_{mod} - 4.15^*(0.29 + 5.05)$	$T_{cor} = 4.82(0.52^*\ T_{mod})$
February	1.35	$T_{cor} = 8.32 + (0.33^*(T_{mod} - 8.32) - 1.35)$	$T_{cor} = T_{mod} - 1.35$	$T_{cor} = T_{mod} - 9.67^*(0.32 + 8.32)$	$T_{cor} = 5.19(0.50^*\ T_{mod})$
March	1.40	$T_{cor} = 12.66 + (0.88^*(T_{mod} - 12.66) - 1.40)$	$T_{cor} = T_{mod} - 1.40$	$T_{cor} = T_{mod}\ 14.06^*(0.88 + 12.6)$	$T_{cor} = 4.05(0.51^*\ T_{mod})$
April	2.18	$T_{cor} = 17.32 + (0.60^*(T_{mod} - 17.32) - 2.18)$	$T_{cor} = \mathrm{T}_{mod} - 2.18$	$T_{cor} = T_{mod}\ 19.50^*(0.60 + 17.3)$	$T_{cor} = 4.24(0.52^*\ T_{mod})$
May	5.16	$T_{cor} = 21.91 + (0.96^*(T_{mod} - 21.91) - 5.16)$	$T_{cor} = T_{mod} - 5.16$	$T_{cor} = T_{mod}\ 27.07^*(0.96 + 21.9)$	$T_{cor} = 4.60(0.49^*\ T_{mod})$
June	3.69	$T_{cor} = 24.76 + (0.76^*(T_{mod} - 24.76) - 3.69)$	$T_{cor} = T_{mod} - 3.69$	$T_{cor} = \mathrm{T}_{mod}\ 28.45^*(0.76 + 24.7)$	$T_{cor} = 3.96(0.52^*\ T_{mod})$
July	1.89	$T_{cor} = 25.28 + (0.44^*(T_{mod} - 25.28) - 1.89)$	$T_{cor} = T_{mod} - 1.89$	$T_{cor} = T_{mod}\ 27.18^*(0.44 + 25.2)$	$T_{cor} = 5.75(0.52^*\ T_{mod})$
August	2.30	$T_{cor} = 24.50 + (0.24^*(T_{mod} - 24.50) - 2.30)$	$T_{cor} = T_{mod} - 2.30$	$T_{cor} = T_{mod}\ 26.80^*(0.24 + 24.5)$	$T_{cor} = 5.33(0.49^*\ T_{mod})$
September	2.40	$T_{cor} = 22.39 + (1.15^*(T_{mod} - 22.39) - 2.40)$	$T_{cor} = T_{mod} - 2.40$	$T_{cor} = T_{mod}\ 24.76^*(1.15 + 22.3)$	$T_{cor} = 4.25(0.51^*\ T_{mod})$
October	3.24	$T_{cor} = 16.95 + (0.92^*(T_{mod} - 16.95) - 3.24)$	$T_{cor} = T_{mod} - 3.24$	$T_{cor} = T_{mod}\ 20.19^*(0.92 + 16.9)$	$T_{cor} = 4.39(0.48^*\ T_{mod})$
November	−2.27	$T_{cor} = 10.56 + (0.33^*(T_{mod} - 10.56) + 2.27)$	$T_{cor} = T_{mod} + 2.27$	$T_{cor} = T_{mod} - 8.30^*(0.33 + 10.5)$	$T_{cor} = 3.54(0.50^*\ T_{mod})$
December	2.45	$T_{cor} = 6.27 + (0.40^*(T_{mod} - 6.27) - 2.45)$	$T_{cor} = T_{mod} - 2.45$	$T_{cor} = T_{mod} - 8.72^*(0.40 + 6.27)$	$T_{cor} = 4.66(0.49^*\ T_{mod})$

Table 4 | Correction functions for correcting the CSIRO model rainfall data for all RCP scenarios

Months	Correction functions under different BC methods			
	Difference method	Modified Leander and Buishand	Linear scaling	Quantile mapping
	RCP 2.6			
January	−12.82	$RF_{corr} = (RF_{mod} + 16.20)*0.62$	$RF_{corr} = RF_{mod} *1.63$	$RF_{corr} = 2.68(0.44* RF_{mod})$
February	−26.15	$RF_{corr} = (RF_{mod} - 26.15)*2.53$	$RF_{corr} = RF_{mod} *2.03$	$RF_{corr} = 2.61(0.44* RF_{mod})$
March	0.60	$RF_{corr} = (RF_{mod} + 0.60)*3.07$	$RF_{corr} = RF_{mod} *0.99$	$RF_{corr} = 2.59(0.45* RF_{mod})$
April	−21.90	$RF_{corr} = (RF_{mod} - 21.90)*0.62$	$RF_{corr} = RF_{mod}\ 0.00$	$RF_{corr} = 2.70(0.00* RF_{mod})$
May	3.75	$RF_{corr} = (RF_{mod} + 16.20)*0.00$	$RF_{corr} = RF_{mod} *0.85$	$RF_{corr} = 2.85(0.45* RF_{mod})$
June	−79.17	$RF_{corr} = (RF_{mod} + 3.75)*1.33$	$RF_{corr} = RF_{mod} *2.69$	$RF_{corr} = 3.08(0.44* RF_{mod})$
July	349.10	$RF_{corr} = (RF_{mod} - 79.17)*26.78$	$RF_{corr} = RF_{mod} *0.39$	$RF_{corr} = 3.24(0.47* RF_{mod})$
August	117.82	$RF_{corr} = (RF_{mod} + 349.10)*3.95$	$RF_{corr} = RF_{mod} *0.69$	$RF_{corr} = 2.98(0.45* RF_{mod})$
September	−102.95	$RF_{corr} = (RF_{mod} + 117.82)*2.12$	$RF_{corr} = RF_{mod} *6.25$	$RF_{corr} = 2.93(0.45* RF_{mod})$
October	54.77	$RF_{corr} = (RF_{mod} - 102.95)*13.52$	$RF_{corr} = RF_{mod} *0.24$	$RF_{corr} = 2.51(0.45* RF_{mod})$
November	−1.53	$RF_{corr} = (RF_{mod} - 1.53)*0.00$	$RF_{corr} = RF_{mod} *0.00$	$RF_{corr} = 2.39(0.00* RF_{mod})$
December	6.05	$RF_{corr} = (RF_{mod} + 6.05)*1.22$	$RF_{corr} = RF_{mod} *0.84$	$RF_{corr} = 2.59(0.45* RF_{mod})$
	RCP 4.5			
January	33.09	$RF_{corr} = (RF_{mod} + 33.08)*32.62$	$RF_{corr} = RF_{mod} *0.50$	$RF_{corr} = 2.68(0.44* RF_{mod})$
February	−25.52	$RF_{corr} = (RF_{mod} - 25.52)*156.74$	$RF_{corr} = RF_{mod} *1.98$	$RF_{corr} = 2.61(0.44* RF_{mod})$
March	−33.12	$RF_{corr} = (RF_{mod} - 33.10)*110.52$	$RF_{corr} = RF_{mod} *3.92$	$RF_{corr} = 2.59(0.45* RF_{mod})$
April	−21.9	$RF_{corr} = (RF_{mod} - 21.90)*0.00$	$RF_{corr} = RF_{mod}\ 0.00$	$RF_{corr} = 2.70(0.00* RF_{mod})$
May	6.89	$RF_{corr} = (RF_{mod} + 6.90)*2.91$	$RF_{corr} = RF_{mod} *0.75$	$RF_{corr} = 2.85(0.44* RF_{mod})$
June	−98.98	$RF_{corr} = (RF_{mod} - 98.97)*19.82$	$RF_{corr} = RF_{mod} *4.67$	$RF_{corr} = 3.08(0.44* RF_{mod})$
July	376.32	$RF_{corr} = (RF_{mod} + 376.32)*6.58$	$RF_{corr} = RF_{mod} *0.37$	$RF_{corr} = 3.24(0.40* RF_{mod})$
August	−49.87	$RF_{corr} = (RF_{mod} + 0.00)*1.00$	$RF_{corr} = RF_{mod} *1.23$	$RF_{corr} = 2.98(0.45* RF_{mod})$
September	−109.57	$RF_{corr} = (RF_{mod} - 109.60)*63.61$	$RF_{corr} = RF_{mod} *9.45$	$RF_{corr} = 2.93(0.44* RF_{mod})$
October	68.15	$RF_{corr} = (RF_{mod} + 68.15)*11.83$	$RF_{corr} = RF_{mod} *0.20$	$RF_{corr} = 2.51(0.45* RF_{mod})$
November	−1.53	$RF_{corr} = (RF_{mod} - 1.56)*0.00$	$RF_{corr} = RF_{mod} *0.00$	$RF_{corr} = 2.39(0.00* RF_{mod})$
December	−15.93	$RF_{corr} = (RF_{mod} + 15.93)*65.62$	$RF_{corr} = RF_{mod} *2.03$	$RF_{corr} = 2.59(0.45* RF_{mod})$
	RCP 6.0			
January	6.77	$RF_{corr} = (RF_{mod} + 6.77)*0.78$	$RF_{corr} = RF_{mod} *0.83$	$RF_{corr} = 2.68(0.44* RF_{mod})$
February	−24.72	$RF_{corr} = (RF_{mod} - 24.72)*69.87$	$RF_{corr} = RF_{mod} *1.92$	$RF_{corr} = 2.61(0.44* RF_{mod})$
March	−29.85	$RF_{corr} = (RF_{mod} - 29.85)*14.63$	$RF_{corr} = RF_{mod} *3.05$	$RF_{corr} = 2.59(0.44* RF_{mod})$
April	−21.90	$RF_{corr} = (RF_{mod} - 21.90)*0.00$	$RF_{corr} = RF_{mod}\ 0.00$	$RF_{corr} = 2.70(0.00* RF_{mod})$
May	3.93	$RF_{corr} = (RF_{mod} + 3.93)*16.03$	$RF_{corr} = RF_{mod} *0.84$	$RF_{corr} = 2.85(0.44* RF_{mod})$
June	−92.03	$RF_{corr} = (RF_{mod} - 92.03)*294.82$	$RF_{corr} = RF_{mod} *3.72$	$RF_{corr} = 3.08(0.44* RF_{mod})$
July	340.98	$RF_{corr} = (RF_{mod} + 340.98)*16.32$	$RF_{corr} = RF_{mod} *0.40$	$RF_{corr} = 3.24(0.47* RF_{mod})$
August	31.40	$RF_{corr} = (RF_{mod} + 31.40)*3,142.97$	$RF_{corr} = RF_{mod} *0.89$	$RF_{corr} = 2.98(0.44* RF_{mod})$
September	−44.77	$RF_{corr} = (RF_{mod} - 44.77)*190.15$	$RF_{corr} = RF_{mod} *1.58$	$RF_{corr} = 2.91(0.44* RF_{mod})$
October	8.40	$RF_{corr} = (RF_{mod} + 8.40)*383.47$	$RF_{corr} = RF_{mod} *0.67$	$RF_{corr} = 2.51(0.44* RF_{mod})$
November	−1.53	$RF_{corr} = (RF_{mod} - 1.53)*0.00$	$RF_{corr} = RF_{mod} *0.00$	$RF_{corr} = 2.39(0.00* RF_{mod})$
December	−3.98	$RF_{corr} = (RF_{mod} - 3.98)*1.60$	$RF_{corr} = RF_{mod} *1.14$	$RF_{corr} = 2.59(0.44* RF_{mod})$
	RCP 8.5			
January	−19.38	$RF_{corr} = (RF_{mod} - 19.38)*0.01$	$RF_{corr} = RF_{mod} *2.40$	$RF_{corr} = 2.68(0.43* RF_{mod})$

(*Continued.*)

Table 4 | Continued

Months	Correction functions under different BC methods			
	Difference method	Modified Leander and Buishand	Linear scaling	Quantile mapping
February	−27.92	$RF_{corr} = (RF_{mod} - 27.92)*0.18$	$RF_{corr} = RF_{mod}$ *2.18	$RF_{corr} = 2.61(0.44* RF_{mod})$
March	−23.50	$RF_{corr} = (RF_{mod} - 23.50)*0.01$	$RF_{corr} = RF_{mod}$ *2.12	$RF_{corr} = 2.59(0.43* RF_{mod})$
April	−21.90	$RF_{corr} = (RF_{mod} - 21.90)*0.00$	$RF_{corr} = RF_{mod}$ 0.00	$RF_{corr} = 2.70(0.00* RF_{mod})$
May	13.82	$RF_{corr} = (RF_{mod} +13.82)*0.47$	$RF_{corr} = RF_{mod}$ *0.60	$RF_{corr} = 2.85(0.45* RF_{mod})$
June	−88.28	$RF_{corr} = (RF_{mod} - 88.28)*0.04$	$RF_{corr} = RF_{mod}$ *3.35	$RF_{corr} = 3.08(0.44* RF_{mod})$
July	352.62	$RF_{corr} = (RF_{mod} +352.62)*0.21$	$RF_{corr} = RF_{mod}$ *0.39	$RF_{corr} = 3.24(0.47* RF_{mod})$
August	70.68	$RF_{corr} = (RF_{mod} +70.68)*0.33$	$RF_{corr} = RF_{mod}$ *0.79	$RF_{corr} = 2.98(0.44* RF_{mod})$
September	−50.77	$RF_{corr} = (RF_{mod} - 50.77)*0.12$	$RF_{corr} = RF_{mod}$ *1.71	$RF_{corr} = 2.93(0.44* RF_{mod})$
October	8.23	$RF_{corr} = (RF_{mod} +8.23)*0.03$	$RF_{corr} = RF_{mod}$ *0.68	$RF_{corr} = 2.51(0.45* RF_{mod})$
November	−1.53	$RF_{corr} = (RF_{mod} - 1.53)*0.00$	$RF_{corr} = RF_{mod}$ *0.00	$RF_{corr} = 2.39(0.00* RF_{mod})$
December	8.42	$RF_{corr} = (RF_{mod} +8.42)*0.29$	$RF_{corr} = RF_{mod}$ *0.79	$RF_{corr} = 2.59(0.44* RF_{mod})$

solar radiation are given in Tables 2–4. Twelve different equations have been developed for each weather parameter separately as values of these weather variables differ for every month of the year. The study area, which is located in the subtropical zone, has experienced higher monthly fluctuations in weather characteristics. This area has both hot and cold weather extremes, as well as dry and wet spells. The goal of employing the equations independently for each month in the research region was to precisely assess and adjust the model-generated forecasted data. Hence, the futuristic corrected model data were obtained by using these equations for each month. All these methods are used to fetch model and observed data closer but out of these methods the difference method gives closer values of model data relative to the observed data, so a difference method is selected.

Performance evaluation of different BC methods

BC methods are post-processing tools for numerical modeling, which aim to improve the model agreement with the observations. Overall, data bias-corrected with either of the methods exhibited substantial improvements in all the statistical parameters compared to raw model data, but improvements were more pronounced for the difference method (Table 5). In the case of maximum temperature, the uncorrected model data gave NRMSE values of 14.1, 14.0, 13.8, and 13.6% under RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5, respectively, which were reduced to 6.47, 6.48, 6.37, and 6.51%, respectively, by the difference method (Table 5). However, other methods showed NRMSE values above 8%. Likewise, the above 23% NRMSE values for uncorrected model minimum temperature under different RCP scenarios depict poor simulation results. But the BC by the difference method reduced it to 8.2, 8.1, 8.3, and 8.1% under RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5, respectively, indicating excellent simulation results by this method (Table 6). All other BC methods lagged behind the difference method due to their higher NRMSE values (more than 11%). Similar results were observed for the uncorrected model rainfall data having high NRMSE values which were reduced more by the difference method. In the case of solar radiation, the NRMSE values (115.3, 115.2, 114.5, and 115.9% under RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 scenarios, respectively) in the uncorrected model data were reduced by the difference method (16.6, 20.9, 21.9, and 21.3 under RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 scenarios, respectively) after the BC (Table 7).

Similarly, uncorrected model data for maximum temperature, minimum temperature, rainfall, and solar radiation represented higher values of MAE, MBE, MAPE, and PBIAS, but low CRM and NSE values, depicting more errors in the uncorrected model data (Tables 5–7). All these statistical parameters were improved after applying different correction techniques for all the climatic variables. However, the difference method consistently and uniquely adjusted the mean and standard deviation correctly in comparison with other methods. The difference method followed by VS and LB methods gave good fits between observed and simulated temperature as indicated by various statistical parameters (Table 5). The difference method and VS corrected the biases of simulated temperature very well, but the better statistics of the difference method over the VS encouraged us to adopt it for further correction and projections of model data beyond 2020. Hence, this method

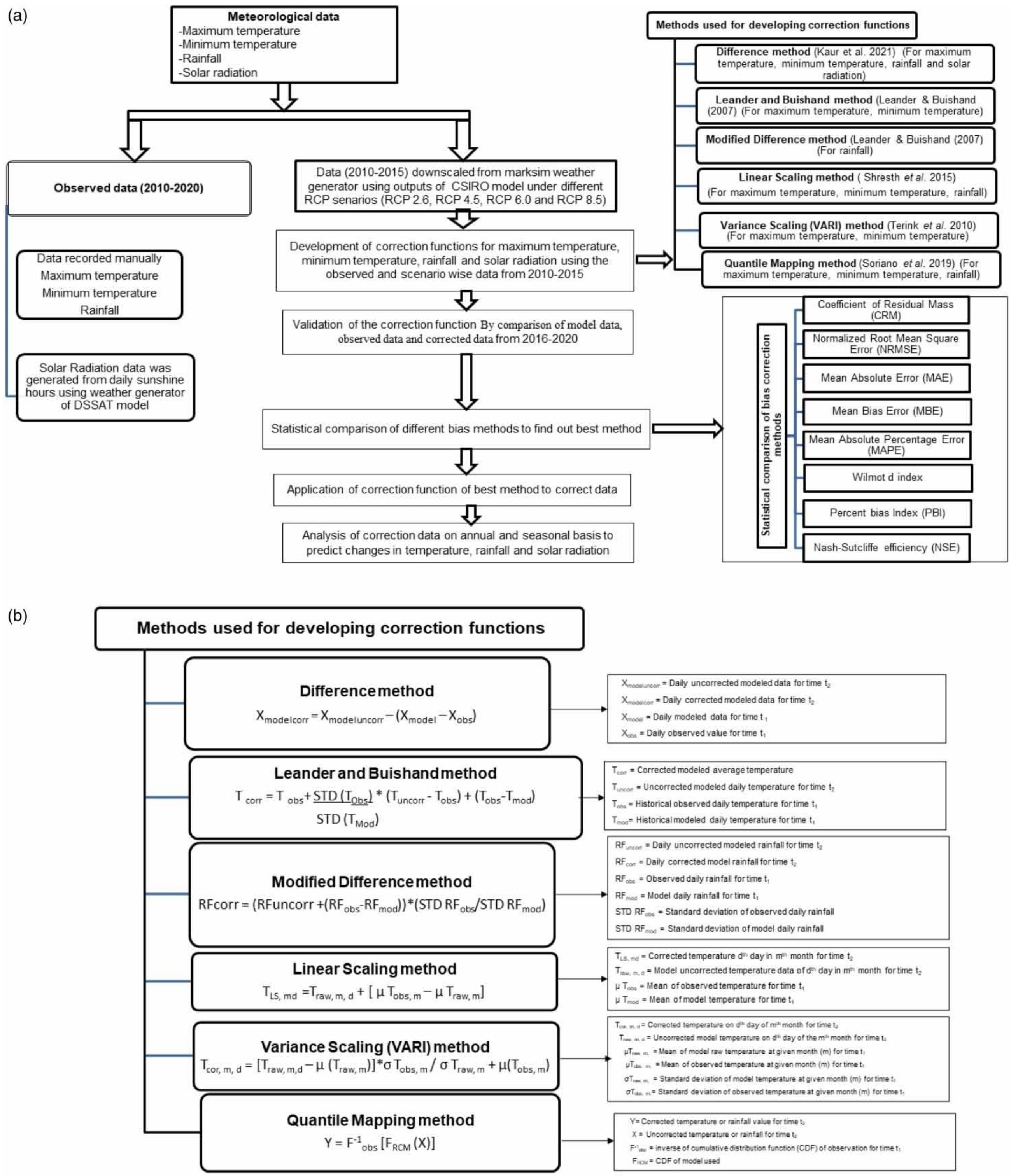


Figure 1 | Methodological framework for applying BC and correction of projected climate data (a) and mathematical expressions of different BC methods used in the study (b).

was very suitable for removing bias from GCM/RCM at this location. Furthermore, in this study, which mainly focused on the lower Shivalik region of Punjab, the difference method is the best-performing one for removing the RCM/GCM bias compared to the other methods.

Table 5 | Statistical testing of model data and data corrected by different BC methods (maximum temperature) under RCP scenarios

Statistical parameters	Model data	Difference method	Leander and Buishand	Linear scaling	Variance scaling	Quantile mapping
RCP 2.6						
PBIAS	−7.26	−2.75	−0.62	−2.75	−2.44	−169.20
NSE	0.57	0.91	0.85	0.70	0.85	−1,773.71
MBE	2.16	0.81	0.18	0.81	0.72	50.30
MAE	3.34	1.51	1.97	2.77	1.93	65.08
CRM	−0.07	−0.02	−0.006	−0.02	−0.02	−1.69
MAPE	0.12	0.05	0.07	0.10	0.07	2.18
Wilmot d-index	0.90	0.97	0.96	0.92	0.96	0.01
NRMSE	14.15	6.47	8.35	11.86	8.39	917.40
RCP 4.5						
PBIAS	−6.86	−2.90	−0.59	−2.88	−2.47	−164.22
NSE	0.58	0.91	0.86	0.69	0.85	−1,730.88
MBE	2.04	0.86	0.17	0.85	0.73	48.82
MAE	3.30	1.52	1.92	2.80	1.94	62.73
CRM	−0.06	−0.02	−0.006	−0.02	−0.02	−1.64
MAPE	0.12	0.05	0.07	0.10	0.07	2.10
Wilmot d-index	0.91	0.98	0.97	0.93	0.96	0.01
NRMSE	14.05	6.48	8.00	11.96	8.44	906.26
RCP 6.0						
PBIAS	−7.04	−2.56	−0.79	−2.56	−2.36	−141.17
NSE	0.59	0.91	0.85	0.72	0.85	−1,093.95
MBE	2.09	0.76	0.23	0.76	0.70	41.97
MAE	3.27	1.48	1.99	2.73	1.94	55.90
CRM	−0.07	−0.02	−0.008	−0.02	−0.02	−1.41
MAPE	0.12	0.05	0.07	0.10	0.07	1.86
Wilmot d-index	0.91	0.98	0.96	0.93	0.96	0.02
NRMSE	13.83	6.37	8.35	11.44	8.26	720.60
RCP 8.5						
PBIAS	−7.17	−2.81	−0.90	−2.79	−2.41	−155.57
NSE	0.60	0.90	0.85	0.73	0.86	−1,314.40
MBE	2.13	0.83	0.26	0.83	0.72	46.29
MAE	3.26	1.53	1.94	2.68	1.85	60.02
CRM	−0.07	−0.02	−0.00	−0.02	−0.02	−1.55
MAPE	0.11	0.05	0.07	0.10	0.07	1.97
Wilmot d-index	0.92	0.98	0.96	0.94	0.97	0.07
NRMSE	13.58	6.51	8.15	11.17	8.03	784.03

Comparison of the actual and corrected modeled data (2016–2020) using the difference method of BC

The distribution of the annual temperature over the lower Shivalik region indicates that considerable biases exist between uncorrected model outputs which ultimately advise against the direct application of model projections in climate change studies over this region. From the BC for weather parameters by different correction methods, the difference method has been found to be better as compared to other methods in terms of statistical results. Therefore, this method was selected as the method of correction for the future data under all the RCP scenarios. The corrected model data for 2016–2020

Table 6 | Statistical testing of model data and data corrected by different BC methods (minimum temperature) under RCP scenarios

Statistical parameters	Model data	Difference method	Leander and Buishand	Linear scaling	Variance scaling	Quantile mapping
RCP 2.6						
PBIAS	−9.85	1.96	5.28	1.95	2.51	−148.67
NSE	0.68	0.96	0.88	0.82	0.92	−161.08
MBE	1.66	−0.33	−0.89	−0.33	−0.42	25.15
MAE	3.24	1.08	1.85	2.23	1.47	32.81
CRM	−0.09	0.02	0.05	0.02	0.02	−1.48
MAPE	0.26	0.08	0.15	0.20	0.12	2.21
Wilmot d-index	0.94	0.99	0.97	0.96	0.98	0.08
NRMSE	23.63	8.21	14.37	17.80	11.44	537.33
RCP 4.5						
PBIAS	−9.08	1.85	5.12	1.50	2.44	253.24
NSE	0.69	0.96	0.90	0.82	0.92	−198.77
MBE	1.53	−0.31	−0.86	−0.25	−0.41	−42.85
MAE	3.22	1.08	1.73	2.23	1.46	42.85
CRM	−0.09	0.01	0.05	0.01	0.02	2.53
MAPE	0.26	0.08	0.13	0.20	0.12	2.77
Wilmot d-index	0.86	0.97	0.94	0.90	0.95	0.06
NRMSE	23.48	8.18	12.98	17.86	11.41	555.96
RCP 6.0						
PBIAS	−8.78	2.54	5.28	2.55	2.83	−143.09
NSE	0.70	0.96	0.90	0.82	0.92	−126.34
MBE	1.48	−0.43	−0.89	−0.43	−0.48	24.21
MAE	3.20	1.11	1.70	2.15	1.46	32.09
CRM	−0.08	0.02	0.05	0.02	0.02	−1.43
MAPE	0.26	0.08	0.13	0.20	0.12	2.11
Wilmot d-index	0.94	0.99	0.98	0.96	0.98	0.10
NRMSE	23.10	8.37	12.96	17.47	11.32	476.27
RCP 8.5						
PBIAS	−9.49	1.83	4.89	1.83	2.40	−144.71
NSE	0.69	0.96	0.90	0.83	0.92	−127.43
MBE	1.60	−0.31	−0.82	−0.31	−0.40	24.48
MAE	3.24	1.08	1.68	2.13	1.45	32.31
CRM	−0.09	0.01	0.04	0.01	0.02	−1.44
MAPE	0.26	0.08	0.13	0.19	0.12	2.14
Wilmot d-index	0.94	0.99	0.98	0.96	0.98	0.10
NRMSE	23.26	8.20	12.77	17.30	11.21	478.31

were validated by its comparison with the observed data for that period. The results of the comparison between the monthly averages of actual, model, and corrected data for maximum temperature, minimum temperature, rainfall, and solar radiation under RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 scenarios have been shown as follows.

Under RCP 2.6, the model overestimated the maximum temperature from February to December and underestimated for January. The uncorrected model data for maximum temperature were comparatively higher than that observed for February, March, and May to December, but lower for the months of January and April under the RCP 4.5 scenario. Likewise, the

Table 7 | Statistical testing of model data and data corrected by different BC methods (rainfall) under RCP scenarios

	Rainfall					Solar radiation	
Statistical parameters	**Model**	**Difference method**	**Linear scaling**	**Modified difference method**	**Quantile mapping**	**Model**	**Difference method**
RCP 2.6							
PBIAS	−1.48	2.18	29.79	−819.17	−131.97	−88.5	−10.3
NSE	−1.55	−0.31	−0.45	−654.09	−19.89	4,534.7	95.2
MBE	0.05	−0.06	−0.91	25.12	4.04	8.1	0.9
MAE	4.84	4.01	3.92	29.63	8.56	9.07	1.15
CRM	−0.01	0.02	0.29	−8.19	−1.32	−0.89	−0.05
MAPE	3.35	5.19	2.55	13.57	4.53	1.03	0.14
Wilmot d-index	0.40	0.49	0.44	0.01	0.12	0.50	0.50
NRMSE	358.8	257.8	271.2	5,748.9	1,026.7	115.3	16.6
RCP 4.5							
PBIAS	−3.25	7.10	8.57	−1,384.9	−152.8	−89.2	−9.3
NSE	−1.70	−0.01	−1.24	−1,156.3	−22.6	4,525.3	149.8
MBE	0.10	−0.21	−0.26	42.48	4.68	8.2	0.9
MAE	4.97	3.51	4.49	47.23	9.39	9.0	1.3
CRM	−0.03	0.07	0.08	−13.84	−1.52	−0.89	−0.05
MAPE	3.53	3.46	0.00	70.91	7.39	1.03	0.15
Wilmot d-index	0.39	0.58	0.41	0.02	0.12	0.34	0.86
NRMSE	369.6	226.1	336.3	7,642.3	1,093.0	115.2	20.9
RCP 6.0							
PBIAS	−5.92	8.10	11.67	−11,997.	−198.1	−89.21	−10.07
NSE	−1.98	−0.01	−1.44	−370,673.5	−40.1	4,492.9	165.56
MBE	0.18	−0.24	−0.35	368.01	6.07	8.2	0.9
MAE	4.81	3.49	4.35	372.5	10.58	9.13	1.31
CRM	−0.05	0.08	0.11	−119.9	−1.98	−0.89	−0.05
MAPE	1.56	3.53	1.62	68.7	4.43	1.04	0.15
Wilmot d-index	0.39	0.65	0.39	0.00	0.09	0.35	0.85
NRMSE	387.5	225.8	350.6	136,634.2	1,440.0	114.5	21.9
RCP 8.5							
PBIAS	−7.97	12.3	14.3	−987.4	−204.7	−89.88	−10.21
NSE	−2.06	−0.004	−1.28	−768.3	−40.6	4,585.3	155.9
MBE	0.24	−0.37	−0.44	30.2	6.28	8.2	0.9
MAE	4.85	3.48	4.31	34.90	10.74	9.21	1.27
CRM	−0.08	0.12	0.14	−9.87	−2.04	−0.90	−0.05
MAPE	1.56	3.49	1.72	11.47	4.54	1.04	0.15
Wilmot d-index	0.35	0.57	0.37	0.01	0.07	0.35	0.86
NRMSE	393.1	224.8	339.2	6,225.0	1,448.9	115.9	21.3

modeled values of maximum temperature under the RCP 6.0 scenario remained higher for February, March, and May to December, but lower for January. Under RCP 8.0, all the months had higher modeled maximum temperatures except February. These biases in the model maximum temperature data under all the scenarios were reduced after the correction as shown in Figure 2.

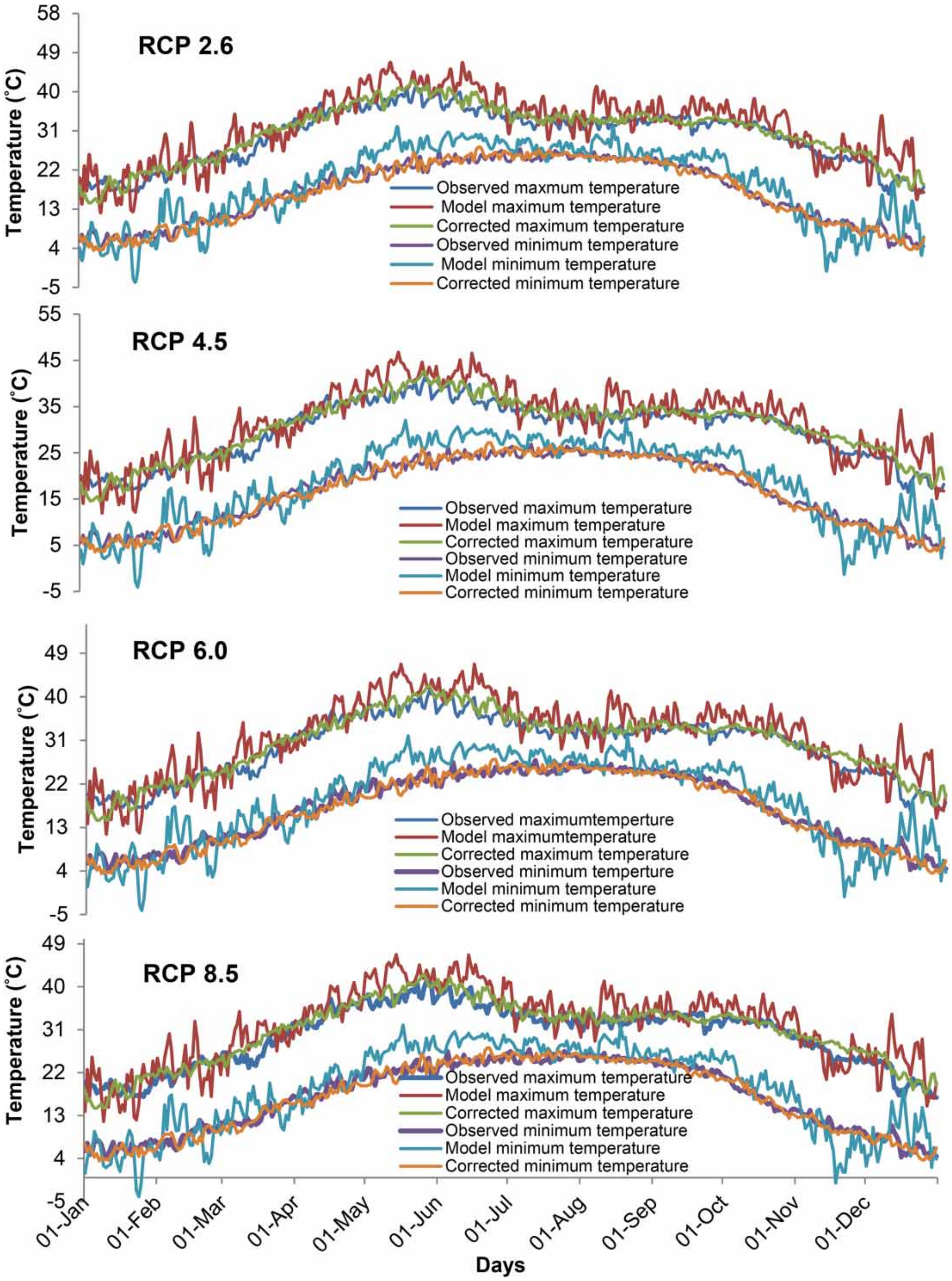


Figure 2 | Comparison of observed, model, and corrected data (2016–2020) maximum and minimum temperature under different RCP scenarios.

The model minimum temperature data were overestimated for June, July and October under RCP 2.6, for June, July and October under the RCP 4.5 scenario, for February, March, June, July, August, and October under the RCP 6.0 scenario and for February, March, June, July, and October under RCP 8.5 (Figure 2). In case of rainfall, the model estimated higher rainfall values for the months of January, February, May, July, October, and December. Under RCP 4.5, the model rainfall values were higher than those of observed values during the months of February, March, October, and December whereas it becomes lower for all other months than the observed values. The modeled rainfall values were higher for the months of February, March, October, and December but lower for all the other months as compared to observed values under RCP 6.0 and RCP 8.5 (Figure 3). On the other hand, the modeled values of solar radiation remained higher than those of

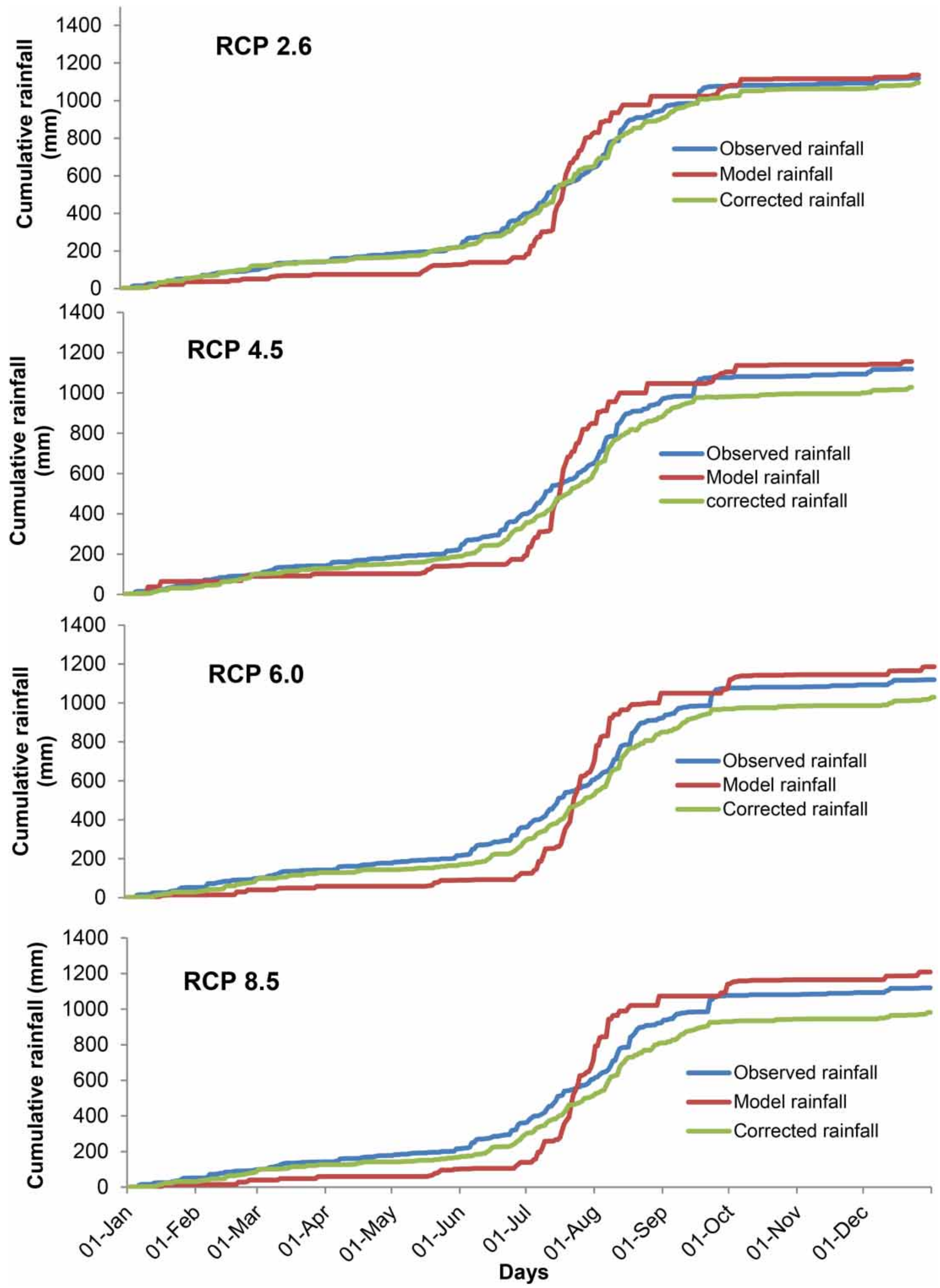


Figure 3 | Validation results (2016–2020) of BC using the difference method for rainfall under different RCP scenarios.

observed data from January to December under all four RCP scenarios which got closer to the observed data after correction (Figure 4).

Projections (2021–2095) in maximum temperature, minimum temperature, rainfall, and solar radiations under different scenarios up to 21st century

As discussed earlier, the difference method was selected for the correction of futuristic data (2021–2095) under different RCP scenarios (Table 8). The annual and seasonal perusal of projected maximum temperature, minimum temperature, rainfall, and solar radiations under different RCP scenarios for 2021–2095 showed that the maximum temperature has

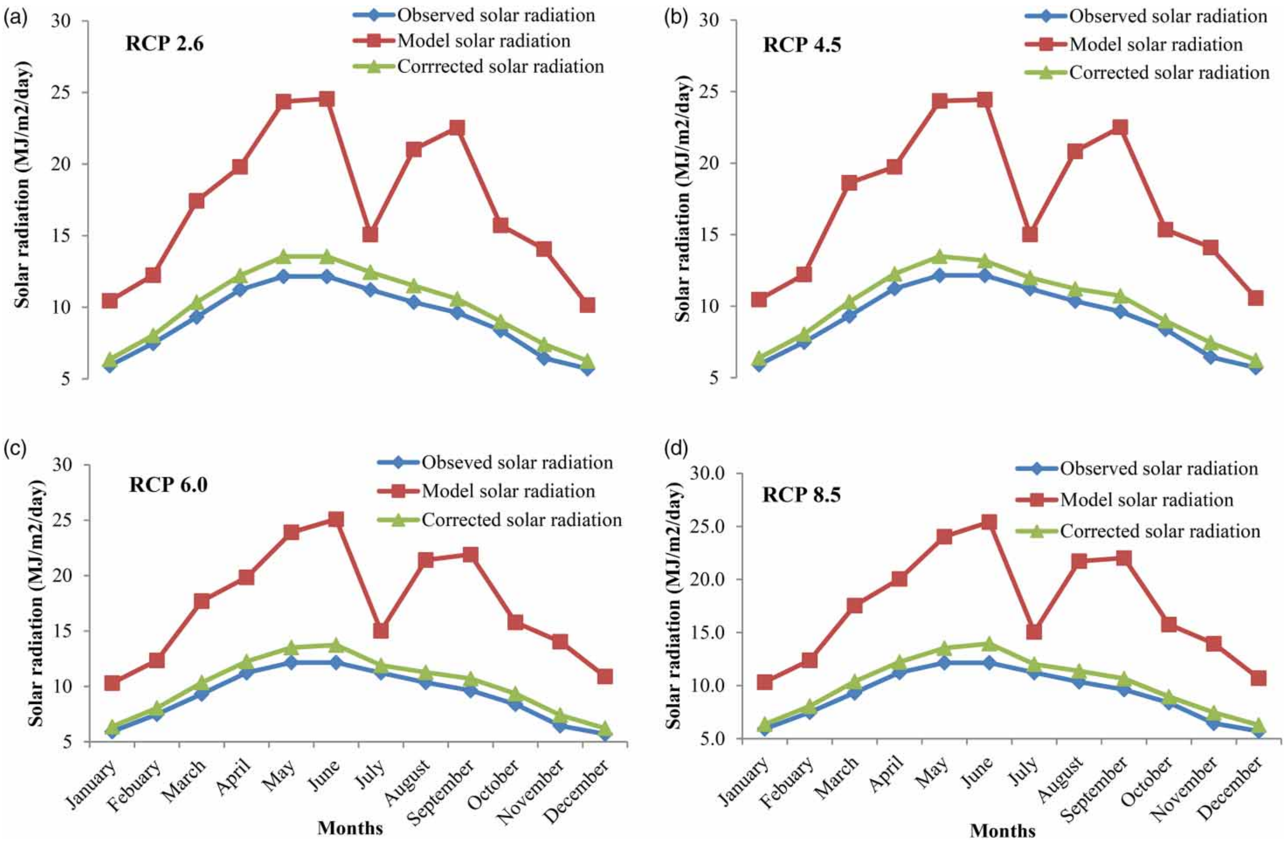


Figure 4 | Validation results (2016–2020) of BC using the difference method solar radiation under different RCP scenarios.

been expected to increase by 1.3–8.3 °C, 1.2–2.7 °C, 1.7–3.3 °C, 1.0–2.7 °C, and 1.2–2.7 °C and for the annual, *kharif*, *rabi*, winter, and monsoon seasons, respectively, during 2021–2095. The minimum temperature (2021–2095) has been expected to increase between 0.7 and 2.6 °C, 0.9 and 2.7 °C, 0.8 and 2.6 °C, 0.6 and 2.5 °C, and 1.0 and 3.0 °C for the annual, *kharif, rabi*, winter, and monsoon seasons, respectively. The difference in future temperature change for different seasons has been observed over the lower Shivalik region. The projection results denote a lower increase in the maximum and minimum temperature during kharif season as compared to rabi season, i.e. hotter months like July and August are expected to have more increment in maximum and minimum temperature as compared to the colder months such as January, February, and December. You *et al.* (2014) found a pronounced warming trend for T_{mean}, $T_{\max}$, and $T_{\min}$ in winter months with RCP8.5 in China during 2061–2090. Salman *et al.* (2018) and Almazroui *et al.* (2020) also revealed higher increases in temperature during winter months but lower in the summer months under future emission scenarios over the Arabian Peninsula. During 2021–2095 rainfall has been expected to increase by 22.4–301 mm, 107–238 mm, 43.7–66.9 mm, 17.3–45.1 mm, and 82.7–168.9 mm for the annual, *kharif, rabi*, winter, and monsoon seasons, respectively. The solar radiation for the annual, *kharif, rabi*, winter, and monsoon seasons during 2020–2095 is expected to be increased by 0.6–1.0, 0.8–3.0, 0.9–1.4, 0.4–1.2, and 0.8–1.1 MJ/m^2/day, respectively. From the data, it has been clear that more increase in maximum temperature and minimum temperature has been expected under the RCP 8.5 scenario followed by RCP 4.5, RCP 6.0, and RCP 2.6 scenarios, but rainfall and solar radiation has been expected to increase under RCP 8.5 followed by RCP 6.0, RCP 4.5, and RCP 2.6 scenarios. Abaurrea *et al.* (2018) also revealed that the temperature projections over Spain under RCP6.0 are smaller than those under RCP4.5 during 2031–2050 but a similar growth during 2051–2060. Likewise, a study conducted by Wang *et al.* (2021) also demonstrated more increase in temperature under the RCP 4.5 scenario over the coastal region of China. Similarly, an increase in the maximum temperature (under RCP 6.0 and RCP 8.5 scenarios) of 1.7–2 °C by the 2030s and 3.3–4.8 °C by the 2080s has been reported in India by Chaturvedi *et al.* (2018). These temperature changes may be yield

Table 8 | Annual and seasonal projections in maximum and minimum temperature (°C), rainfall (mm), solar radiation (MJ/m^2/day) under different scenarios and their deviation from baseline periods

	Maximum temperature		Minimum temperature		Rainfall		Solar radiation	
Seasons	1984–2020	2021–2095	1984–2020	2021–2095	1984–2020	2021–2095	1984–2020	2021–2095
RCP 2.6								
Annual	30.1	31.4(+1.3)	16.6	17.(+0.7)	1,034.1	1,011.7(22.4)	9.64	10.3(+0.66)
Kharif	34.8	36.0(+1.2)	22.7	23.6(+0.9)	835.3	768.4 (−66.9)	11.18	12.0(+0.82)
Rabi	24.9	26.6(+1.7)	10.2	11.0(+0.8)	195.6	242.6(+47.0)	7.75	8.73(+0.98)
Winter	20.4	21.4(+1.0)	7.1	7.7 (+0.6)	90.9	136.0(+45.1)	6.91	7.35(+0.44)
Monsoon	34.5	35.7(+1.2)	24.3	25.3(+1.0)	795.0	689.7(105.3)	11.37	12.5(+1.13)
RCP 4.5								
Annual	30.1	32.2(+2.1)	16.6	18.3(+1.7)	1,034.1	1,181.2(+147)	9.64	10.4(+0.76)
Kharif	34.8	36.9(+2.1)	22.7	24.4(+1.7)	835.3	942.4 (+107)	11.18	12.0(+0.82)
Rabi	24.9	27.5(+2.6)	10.2	12.0(+1.8)	195.6	239.4 (+43.7)	7.75	8.73(+0.98)
Winter	20.4	22.4(+2.0)	7.1	8.7 (+1.6)	90.9	108.2(+17.3)	6.91	7.35(+0.44)
Monsoon	34.5	36.7(+2.2)	24.3	26.2(+1.9)	795.0	877.8 (+82.7)	11.37	12.5(+1.13)
RCP 6.0								
Annual	30.1	31.8(+1.7)	16.6	17.9(+1.3)	1,034.1	1,325.8(+291)	9.64	10.7(+1.06)
Kharif	34.8	36.5(+1.7)	22.7	24.2(+1.5)	835.3	1,074.7(+239)	11.18	12.3(+1.12)
Rabi	24.9	27.1(+2.2)	10.2	11.6(+1.4)	195.6	250.9 (+55.2)	7.75	9.07(+1.32)
Winter	20.4	22.1(+1.7)	7.1	8.3 (+1.2)	90.9	105.3 (+17.8)	6.91	8.14(+1.23)
Monsoon	34.5	36.2(+1.7)	24.3	25.9(+1.6)	795.0	964.0 (+168.9)	11.37	12.5(+1.13)
RCP 8.5								
Annual	30.1	32.9(+2.8)	16.6	19.2(+2.6)	1,034.1	1,335.3(+301)	9.64	10.6(+0.96)
Kharif	34.8	37.5(+2.7)	22.7	25.4(+2.7)	835.3	1,073.8 (+238)	11.18	8.15(+3.03)
Rabi	24.9	28.2(+3.3)	10.2	12.8(+2.6)	195.6	262.6 (+66.9)	7.75	9.19(+1.44)
Winter	20.4	23.1(+2.7)	7.1	9.6 (+2.5)	90.9	118.6 (+27.6)	6.91	8.18(+1.27)
Monsoon	34.5	37.2(+2.7)	24.3	27.3(+3.0)	795.0	960.0 (+164.9)	11.37	12.2(+0.83)

limiting for the future which may increase the risk of food security in the region. Hence, different adaptation strategies pertaining to management practices may be identified to sustain the yield of crops in the future.

CONCLUSION

Six BC methods were compared and evaluated in this study on a monthly basis using different statistical parameters, with the goal of removing biases from climate models for future research. Because errors in climate models make them unsuitable for direct use in impact studies, numerous statistical BC approaches have been developed to calibrate model outputs against observations. As a result, the study was designed to investigate the consequences of BC methods on climate change projections, and it was discovered that BC approaches are extremely beneficial in enhancing the climate model simulated projected data. In terms of other statistical tests, the VS and LB approaches are likewise good in correcting the model data. However, the difference technique is more promising in eliminating biases than other methods, which is why it was chosen and recommended for correcting biases in model outputs in regional climate change impact studies. The results suggest that the use of correction functions on a monthly time-scale reduces the chances of occurrence of errors in the corrected data as the study area is characterized by more fluctuations in the weather elements, especially rainfall, throughout the year. Furthermore, all of the estimates suggested that the mean annual and seasonal minimum and maximum temperatures will likely rise in the future period of time. The study revealed more increase in maximum and minimum temperature under RCP 8.5 (2.8

and 2.6 °C) followed by RCP 4.5 (2.1 and 1.7 °C), RCP 6.0 (1.7 and 1.3 °C), and RCP 2.6 (1.3 and 0.7 °C) scenarios whereas rainfall and solar radiation are also expected to increase under RCP 8.5 (301 mm and 0.96 MJ/m^2/day), RCP 6.0 (291 mm and 1.06 MJ/m^2/day), RCP 4.5 (147 mm and 0.76 MJ/m^2/day), and RCP 2.6 (22.4 mm and 0.66 MJ/m^2/day) scenarios by end of 21st century. Due to rainfed agriculture, the lower Shivalik region is highly sensitive to changes in meteorological parameters. These are bound to have a direct effect on crop production along with their implications on water resources also. Hence, the corrected data could be helpful for the researchers in planning the impact studies related to crop planning and water reservoirs, etc. There would be more fine-scale adaptation strategies and resulting management practices. Thus, in view of the changing climatic conditions, a decrease in productivity seems forthcoming due to warming scenarios in the future. Thus, some strategies could be planned for adapting to or mitigating the effects based on the model outputs.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Abaurrea, J., Asín, J. & Cebrián, A. C. 2018 Modelling the occurrence of heat waves in maximum and minimum temperatures over Spain and projections for the period 2031-60. *Global AndPlanetary Change* **161**, 244–260. doi:10.1016/j.gloplacha.2017.11.015.

Almazroui, M., Khalid, M. S., Islam, M. N. & Saeed, S. 2020 Seasonal and regional changes in temperature projections over the Arabian Peninsula based on the cmip5 multi-model ensemble dataset. *Atmospheric Research* **239**, 104913. doi:10.1016/j.atmosres.2020.104913.

Amsal, F., Hasra, H., Linarka, U. A., Pradana, R. P. & Satyaningsih, R. 2019 Bias correction of daily precipitation from downscaled CMIP5 climate projections over the Indonesian region. *Earth and Environmental Science* **303**, 120–129.

Asma, F., Lone, B., Manzoor, N. & Andrabi, N. 2020 An overview of climate change and its impact on crop productivity. *Agricultural Research* **34**, 112–114.

Boe, J., Terray, L., Habets, F. & Martin, E. 2007 Satistical and dynamical downscaling of the Seine basin climate for hydrometeorological studies. *International Journal of Climatology* **27**, 1643–1655.

Buonomo, M. K., Luo, M., Meng, F. & Bao, A. 2007 Comparing bias correction methods used in downscaling precipitation and temperature from regional climate models: a case study from the Kaidu river basin in Western China. *Journal of Climatology* **10** (8), 156–162.

Charles, J., Brissette, F. P., Chaumont, D. & Braun, M. 2019 Performance and uncertainty evaluation of empirical downscaling methods in quantifying the Climate Change impacts on hydrology over two North American river basins. *Journal of Hydrology* **67**, 200–214.

Chaturvedi, R. K., Joshi, J. & Ravindranath, H. 2018 Muti-model climate change projections for India under representative concentration pathways. *Current Science* **7**, 791–802.

Enayati, F., Rounsevell, M. D. A., Reginster, I., Metzger, M. G. & Leemas, R. 2021 Future scenarios of European agricultural land use. 1. Estimating changes in crop productivity. *Agriculture Ecosystem and Environment* **107**, 101–116.

Ezechiel, J., Bergstrom, S., Carlsson, B., Graham, L. P. & Lindstrom, G. 2019 Hydrological change-Climate change impact simulation for Sweden. *Journal of Human Environment and Health Promotion* **33** (4), 228–234.

Fang, H. J., Blenkinsop, S. & Tebaldi, C. 2015 Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology* **27** (12), 1547–1578.

Feddersen, H. & Andersen, U. 2005 A method for statistical downscaling of seasonal ensemble predictions. *Tellus* **57**, 398–408.

Fowler, J. H. & Blenkinsop, S. 2007 Linking climate change modeling to impact studies: recent advances in downscaling techniques for hydrological modeling. *International Journal of Climatology* **27** (12), 1547–1578.

Hawkins, E., Thomas, M. O., Chun, K. H. & Andrew, J. C. 2020 Calibaration and bias correction of climate projections of crop modelling: an idealized case study over Europe. *Agricultural Forest Meteorology* **1706**, 19–31.

Jaiswal, R., Mall, R. K., Singh, N. & Dev, N. 2021 Evaluation of bias correction methods for regional climate models. *Earth and Space Science* **9** (2), 1–21.

James, J. W., Jones, D., Shin, D. K. & Mishra, A. 2019 Assessing uncertainity in crop model simulation using Bias-corrected Regional Circulation model outputs. *Climate Research* **34**, 211–222.

Jamieson, P. D., Porter, J. R. & Wilson, D. R. 1991 A test of computer simulation model ARC-WHEAT1 on wheat crops grown in New Zealand. *Field Crops Research* **27**, 337–350.

Kaur, N., Singh, M. J. & Kaur, S. 2021a Long term monthly and inter-seasonal variability analysis for the lower shivalik foothills of Punjab. *Mausam* **73** (1), 173–180.

Kaur, J., Kaur, P. & Kaur, S. 2021b Comparison of statistical procedures for bias removal in temperature, solar radiation and rainfall data predicted by CSIRO-MK3-6-0 model in Punjab. *Agricultural Research Journal* **58** (2), 200–206.

Leander, R. & Buishand, T. 2007 Resampling of regional climate model output for the simulation of extreme river flows. *Hydrology* **332**, 487–496.

Piani, S., Foster, I. & Turner, N. C. 2010 The impact of temperature variability on wheat yields. *Global Change Biology* **17** (2), 997–1012.

Rosenzweig, C. & Parry, M. L. 1994 Potential impact of climate change on world food supply. *Nature* **367**, 133–138.

Salman, S. A., Shahid, S., Ismail, T., Ahmed, K. & Wang, X. J. 2018 Selection of climate models for projection of spatiotemporal changes in temperature of Iraq with uncertainties. *Atmospheric Research* **213**, 509–522. doi:10.1016/j.atmosres.2018.07.008.

Singh, J., Mohtar, R., Braudeau, E., Heathman, G., Jesiek, J. & Singh, D. 2013 Field evaluation of the pedostructure-based model (Kamel®). *Computers and Electronics in Agriculture* **86**, 4–14.

Smitha, V., Kumar, V., Sharma, S., Sharma, R. K., Khokhar, A. & Singh, M. J. 2018 Climatic variability analysis at Ballowal Saunkhri in Submontane Punjab (India). *Climate Change and Environmental Sustainability* **5** (1), 83–91.

Wang, X., Hou, X., Piao, Y., Feng, A. & Li, Y. 2021 Climate change projections of temperature over the coastal area of China using SimCLIM. *Frontiers in Environmental Science* **9**, 1–17.

Willmott, C. J. 1981 On the validation of models. *Physical Geography* **2**, 184–194. http://doi.org10.1080/02723646.1981.10642213.

You, Q., Min, J., Fraedrich, K., Zhang, W., Kang, S. & Zhang, L. 2014 Projected trends in mean, maximum, and minimum surface temperature in China from simulations. *Global Planet Change* **112**, 53–63. doi:10.1016/j.gloplacha.2013.11.006.

First received 22 December 2022; accepted in revised form 29 June 2023. Available online 11 July 2023