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INHERENT BIAS CORRECTION IS NECESSARY FOR WEATHER DATA OF GLOBAL AND REGIONAL CIRCULATION MODELS

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ABSTRACT

The predicted outputs of global and regional circulation models are afflicted with biases. So to assess this biasness, 17 GCMs data available at *gisweb.ciat.cgiar.org/MarkSimGCM/* was downscaled for Ludhiana. The observed annual mean Tmax was 30.35°C and the GCMs overestimated it within the range 32.11 (MIROC-ESM) to 33.08°C (IPSL-CM5A-LR), i.e. the overestimation range lied between 1.76 to 2.73°C. The observed annual mean Tmin of 18.28°C was both underestimated (17.71-18.20°C) and overestimated (18.29-18.49°C) by the GCMs. The annual mean observed RF was 542 mm and it was overestimated within the range 635 mm (GFDL-ESM2M) to 997 mm (MICROC-ESM). The annual mean observed SR was 15.29 Wm^{-2} its overestimation ranged between 17.29 (MIROC5) to 18.45 Wm^{-2} (GFDL-ESM2M). The validation results of the study showed that amongst 17 GCMs, four GCMs (CSIRO-Mk3-6-0, FIO-ESM, IPSL-CM5A-MR) and one Ensemble model predicted Tmax, Tmin, RF and SR satisfactorily. Hence, bias correction in projected data is necessary before its usage in impact assessment studies.

Keywords: Bias removal, GCMs, Ludhiana, Meteorological parameters, RCPs

Climate change which has occurred in past is well documented but an insight into the projected changes of climate is provided by general circulation models (GCMs). These models are primary source of data for constructing climate scenarios, and they provide the basic input data required for climate change impacts assessments at all scales, i.e. from local to regional to global (Tabor and Williams, 2010). The primary elements of climate like temperature, rainfall, etc. GCMs are mathematical representations of physical processes in the atmosphere, ocean and land surface, which generate meteorological variables such as precipitation, temperature, wind speed, relative humidity and solar radiation among others (Campbell *et al.,* 2011) and typically run with horizontal scales of 300 km, while the regional climate models (RCMs) can resolve features down to 50 km or less (IPCC, 2014). In these GCMs, the meteorological variables are generated by solving the primitive equations of thermodynamics, mass and momentum (Teixeira *et al.,* 2014). However, GCMs outputs remain relatively coarse in terms of their spatial and temporal resolutions (Chen *et al.,* 2013). Systematic biases caused by imperfect conceptualization, spatial averaging and non-inclusion of local features make the direct use of GCMs outputs unreliable so as to force fine-scale impact assessment models (Ghimire *et al,.* 2019).

These GCMs simulate climate data under four Representative Concentration Pathways (RCPs) which include time series of emissions, concentrations of all the greenhouse gases (GHGs), aerosols and chemically active gases as well as land use / land cover (Moss *et al.,* 2008). Sometimes sub grid scale features like clouds, topography cannot be properly modeled by the GCMs due to their coarse spatial resolution and so the predicted climate parameters have an inherent bias. Hence it is not appropriate to use the uncorrected temperature and rainfall data for evaluating its impact on the hydrological cycle and crop productivity (Christensen *et al.,* 2008; Haerter *et al.,* 2011).

The projected climate data can be corrected by either dynamic or statistical corrective strategies (Ramirez-Villegas *et al*., 2013) based on the assumption that large-scale weather exhibits a strong influence on local-scale weather but, in general, disregards any reverse effects from local scales upon global scales. In these techniques, statistical relationship between observed and model output are developed so that the unrealistic GCM output is transformed to somewhat realistic data with reduced uncertainty (Sharma *et al.,* 2007; Hansen *et al.,* 2005; Feddersen and Andersen, 2005). The bias corrected datasets can be used for evaluating the impact of climate change on agricultural crops, water resources; land use practices (Xu *et al.,* 2021). Punjab state is an agriculture dependent region of India and it contributes significantly to the rice and wheat reserve food pool of the country. The assessment of climate change on crop productivity of rice-wheat cropping system has been attempted by Jalota *et al.* (2012) which has shown that adaptation strategies will be needed to combat the adverse effect of changes in

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climate system on the crops.

As reported by earlier studies (Christensen *et al.,* 2008; Hagemann *et al.,* 2011; Haerter *et al.,* 2011) the simulated data on temperature, rainfall, etc. by the GCMs as well as RCMs needs corrective treatment for their inherent biasness. So, the current study has been planned with an objective to evaluate whether there actually exists a need for bias correction in climate datasets for the Punjab region.

MATERIALS AND METHODS

The daily data for maximum (Tmax) and minimum (Tmin) temperature, solar radiation (SR) and rainfall (RF) were downscaled under RCP 2.6 scenario for 17 GCMs and one ensemble models from weather generator available at the site *http://gismap.ciat.cgiar.org/MarkSimGCM/* using BCC-CSM1-1, BCC-CSM1-1-M, CSIRO-Mk3-6-0, FIO-ESM, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, GISS-E2-H, GISS-E2-R, HadGEM2-ES, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC5, MIROC-ESM, MIROC-ESM-CHEM, MRI-CGCM3, NorESM1-M and Ensemble models. The data was evaluated for the site Ludhiana (30°-54'-33"N, 75°-48'-22"E, 247 m above the m.s.l.) located in the central irrigated plains of Punjab in Trans-Gangetic agro-climatic zones of India. The daily weather data on Tmax, Tmin, SR and RF (2010-2017) recorded at the agro meteorological observatory was used for developing correction factors on daily and monthly time scales using the 2010-2015 years data which were later validated using 2016-2017 years of the baseline data by using the observed and the modeled data.

The bias correction was done using the difference method in which first daily difference between model data (X_{model}) and observed data (X_{obs}) of meteorological parameters for each Julian day (365 days) averaged from 6 years data (2010-15) used from which past records were calculated. These were taken as a "Daily Correction Factor". Then these correction factors were subtracted from the modeled uncorrected ($X_{modeluncorr}$) data so that the model corrected ($X_{modelcorr}$) data comes closer to the actual data. In an earlier study, Kaur *et al.* (2021) used three methods i.e. Difference method, Leander and Buish and method and Modified difference method at daily and monthly scale to correct the biasness in data which were then analyzed statistically. The analysis of the corrected data showed that amongst the different techniques, the Difference method of bias removal performed best for maximum temperature (Tmax) and rainfall (RF) on monthly time scale but for solar radiation at daily time scale. There was no need for bias removal in the minimum temperature (Tmin) because model data gave the best estimate w.r.t. to the observed Tmin. In case of Tmax, the RMSE value of 4.57% in the model data was reduced by difference method to 2.70, 3.70 and 3.82% respectively, whereas in case of Tmin, the RMSE value of 3.71% in the model data was reduced/increased by 2.00, 3.28 and 3.75% at daily, monthly and annual time scale respectively. The formula for difference method of bias removal is given as under:

$X_{modelcorr} = X_{modeluncorr} – (X_{model} - X_{obs})$

$X_{modeluncorr}$ = Daily modelled average of 6 years

$X_{modelcorr}$ = Daily corrected modelled average of 6 years

X_{model} = Daily modeled value X_{obs} = Daily observed value

The corrected data was verified by computing statistical parameters like Mean (μ), Standard Deviation (σ), Variance (σ²), residual mean square error (RMSE), normalized residual mean square error (NRMSE)

$$\text{RMSE}=\sqrt{\sum_{i=1}^{n}\frac{(Mi-Oi)^2}{n}}*100$$

$$\text{NRMSE}=\sqrt{\sum_{i=1}^{n}\frac{(Mi-Oi)^2}{n}}*100\ /\text{M}$$

Where M_i = modeled value O_i = Observed value

I = Number of observations ranging from 1 to n M = mean of observed variables.

In the present study the Tmax, Tmin and RF were corrected at monthly scale while the SR was corrected at daily time scale. Jamieson et al. (1991) reported that, the simulation is considered excellent, good, fair and poor if NRMSE is <10, 10-20, 20-30 and >30%, respectively. When the value becomes equal to the zero for a model then it will show best fit between observed and model data.

RESULTS AND DISCUSSION

Change in the pattern of maximum temperature (Tmax) with bias removal

The comparison of the monthly averages of the data showed that all the seventeen GCMs overestimated the Tmax at Ludhiana from the observed during all the months (Fig. 1) especially during summer season (May to September). The observed annual mean Tmax was 30.35°C while all the GCMs simulated within the range of 32.11 (MIROC-ESM model) to 33.08°C (IPSL-CM5A-LR model), i.e. there was overestimation within the range of +1.76 to 2.73°C and after bias removal it was reduced within -0.89 to -0.06°C (Table 1). The statistical evaluation of corrected Tmax data the standard deviation (SD) in the model simulated values ranges from 7.50 (IPSL-CM5A-MR) to 7.78°C (MIROC5), RMSE varied from by 3.65 (MIROC-ESM-CHEM) to 3.92 (MIROC5) % and NRMSE varied from by 12.00 (MIROC-ESM-CHEM) to 12.90 (MIROC5) % at monthly scale (Table 2a).

Change in the pattern of minimum temperature (Tmin) with bias removal

The simulated Tmin compared to the observed at Ludhiana was underestimated during January and November, overestimated during May to July and predicted fairly close during the remaining months (Fig. 2). The annual mean observed Tmin was 18.28^{o}C and all the seventeen GCMs simulated within the range of 17.71 (MRI-CGCM3) to 18.49^{o}C (IPSL-CM5A-MR) some GCMs underestimated and overestimated within the range of -0.57 to -0.04^{o}C and after bias removal it becomes -0.54 to -0.27^{o}C (Table 1). The statistical evaluation of corrected Tmin data the standard deviation (SD) in the model simulated values ranges from 8.04 (IPSL-CM5A-LR) to 8.28^{o}C (IPSL-CM5A-MR), RMSE varied from by 3.30 (GISS-E2-H) to3.45 (GFDL-ESM2M) % and NRMSE varied from by 17.92 (CSIRO-Mk3-6-0) to 18.85 (GFDL-ESM2M) % at monthly scale (Table 2a).

Change in the pattern of rainfall (RF) with bias removal

The cumulative total of the RF showed that the modeled rainfall was underestimated from January to June and the trend was reversed up to December (Fig. 3). The observed annual mean RF was 542 mm while all the seventeen GCMs simulated within the range of 635 mm (GFDL-ESM2M) to 997 mm (MICROC-ESM) and GCMs overestimated within the range of +93 to +455 mm and after bias removal it becomes -155 to +104 mm (Table 1). The statistical evaluation of corrected RF data showed that the standard deviation (SD) in the model simulated values ranges from 4.89 (Ensemble) to 7.20 mm (MIROC-ESM), RMSE varied from by 6.31 (NorESM1-M) to 7.95% (CSIRO-Mk3-6-0) and NRMSE varied from by 1.16 (NorESM1-M and Ensemble) to 1.54% (MIROC-ESM) at monthly scale (Table 2b).

Change in the pattern of solar radiation (SR) with bias removal

The SR predicted by all the GCMs was very close to actual during February to May but was overestimated from June to December (Fig. 4). The observed annual mean SR (15.29 Wm^{-2}) and SR simulated by the seventeen GCMs within the range of 17.29 Wm^{-2} (MIROC5) to 18.45 Wm^{-2} (GFDL-ESM2M). All GCMs overestimated within the range of 2.00 to 3.16 Wm^{-2} and after bias removal it was reduced -0.22 to +0.08 Wm^{-2} (Table 1). The statistical evaluation of corrected SR data showed that the standard deviation (SD) in the model simulated values ranges from 4.98 (GISS-E2-R) to 6.84 Wm^{-2} (GFDL-CM3), RMSE varied from by 3.55 (GFDL-ESM2M) to 5.88 (GFDL-CM3) % and NRMSE varied from by 23.17 (CSIRO-Mk3-6-0) to 29.79 (MIROC-ESM-CHEM) % at monthly scale (Table 2b).

Selection of GCM's on the basis of statistical parameters after bias removal

The meteorological parameters (Tmax, Tmin, RF and SR) simulated by the GCMs were corrected with appropriate bias removal and the results were compared with the actual observed data. So, finally amongst the seventeen GCMs, three GCM's i.e. CSIRO-Mk3-6-0, FIO-ESM, IPSL-CM5A-MR and one ensemble model on the basis of statistical properties of Tmax, Tmin, RF and SR were selected after bias removal. These selected models gave the simulated data values closest to the observed data values after bias removal which provides more reliable results for futuristic climate projections. The observed and modeled corrected data by Difference method after bias removal for Tmax, Tmin, RF and SR for 17 GCM's and one ensemble model are given in the tables 1 and their statistical verification results in Tables 2a and 2b.

The models CSIRO-Mk3-6-0, FIO-ESM, IPSL-CM5A-MR and ensemble predicted mean annual Tmax of 29.90, 29.86, 30.29 and 29.86^{o}C, respectively as compared to observed Tmax of 30.37^{o}C; Tmin of 17.88, 17.82, 18.01 and 17.87^{o}C, respectively as compared to observed Tmin of 18.33^{o}C, SR of 15.26, 15.25, 15.25 and 15.22 Wm^{-2}, respectively as compared to observed SR of 15.28 W m^{-2} and RF of 1.60, 1.51, 1.50 and 1.28 mm, respectively as compared to observed RF of 1.50 mm. The Standard deviation (SD) of the models CSIRO-Mk3-6-0, FIO-ESM, IPSLCM5A-MR and ensemble predicted mean annual Tmax was 7.56, 7.59, 7.50 and 7.56^{o}C, respectively as compared to observed Tmax SD of 7.10^{o}C; Tmin was 8.18, 8.19, 8.28 and 8.18^{o}C, respectively as compared to observed Tmin SD of 7.88^{o}C, SR was 4.99, 5.04, 5.04 and 5.00 Wm^{-2}, respectively as compared to observed SR SD of 5.97 Wm^{-2} and RF was 6.41, 5.87, 5.22 and 4.89 mm, respectively as compared to observed RF SD of 4.81 mm.

The simple reason for the biasness in the GCM simulated data is that assumptions are made in development of a GCM in terms of parameterizations and empirical formulae due to incomplete knowledge about the geophysical processes. So due to these assumptions, a GCM may not simulate climate variables accurately and there is a difference between the observed and simulated climate variable for almost all the GCMs. This difference is known as "bias". So, it becomes important to remove the bias from the GCM output for projecting the future hydrologic and climatic scenario correctly. Thus, in several studies (Wood *et al.,* 2004; Boé *et al.,* 2007; Ashfaq *et al.,* 2010; Piani *et al.,* 2010; Yang *et al.,* 2010; Hagemann *et al.,* 2011) bias correction has been used to post process the climate

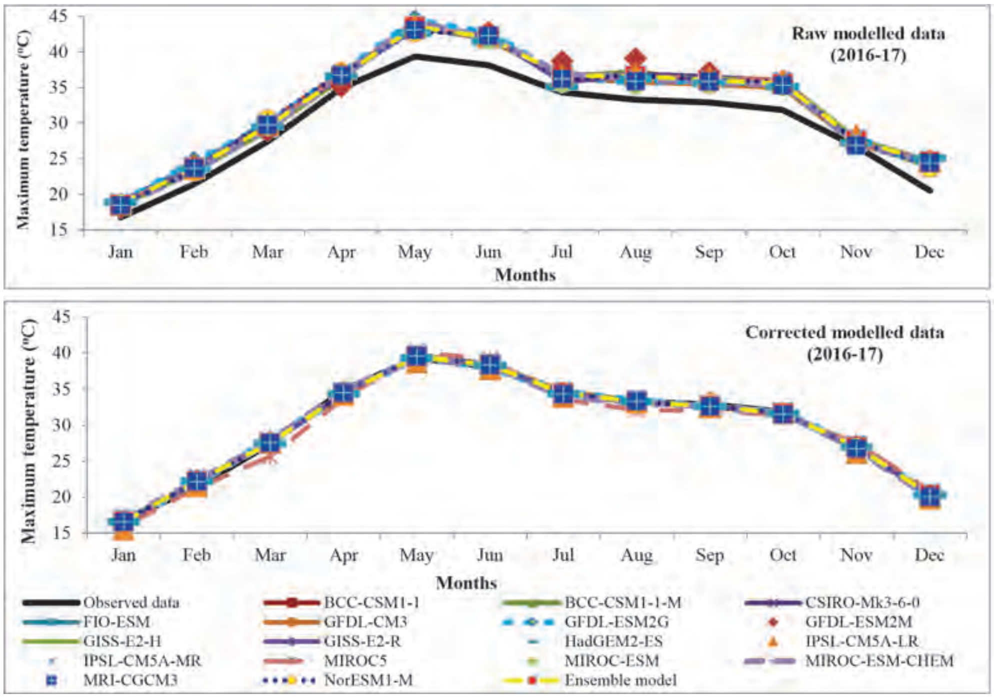

Fig. 1. Comparison of raw and corrected modeled data of monthly maximum temperature at Ludhiana

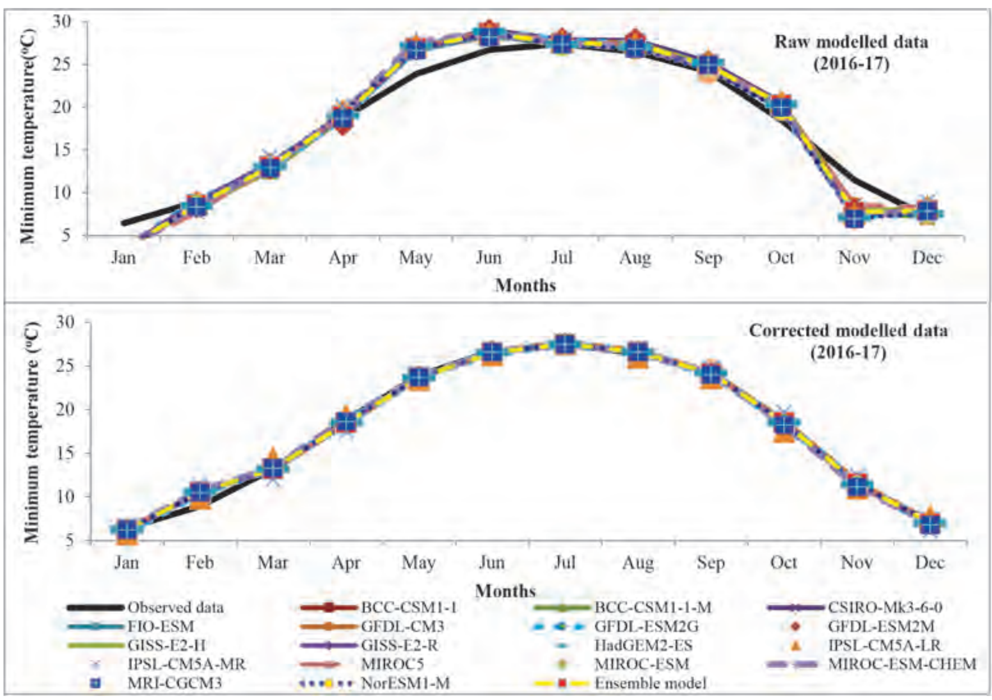

Fig. 2. Comparison of raw and corrected modeled data of monthly minimum temperature at Ludhiana

model output prior to application for impact studies. Xu *et al.* (2021) has reported that the bias-corrected data are of better quality than the individual CMIP6 models in terms of the climatological mean, inter-annual variance and extreme events. In another study by Ines and Hansen (2006) an improvement in the daily rainfall forecast by ECHAM4p5 model was reported after correcting it with a quantile based methodology. The same technique was used by Li *et al.* (2010) for preparing the Intergovernmental Panel on Climate Change AR4 reports.

Hence the results of the analysis of the projected

Table 1. Range of variability in GCMs simulated temperature, rainfall and solar radiation with and without bias removal in comparison to actual observed for the years 2016-2017 at Ludhiana

Observed data	Meteorological parameters and their variability	General Circulation models (gisweb.ciat.cgiar.org/MarkSimGCM/)																	
		BCC-CSM1-1	BCC-CSM1-1-M	CSIRO-Mk3-6-0	FIO-ESM	GFDL-CM3	GFDL-ESM2G	GFDL-ESM2M	GISS-E2-H	GISS-E2-R	HadGEM2-ES	IPSL-CM5A-LR	IPSL-CM5A-MR	MIROC5	MIROC-ESM	MIROC-ESM-CHEM	MRI-CGCM3	NorESM 1-M	Ensemble model
		Maximum Temperature (°C)																	
30.35	Raw modelled data	32.80	32.49	32.90	32.72	32.52	32.82	33.02	32.73	32.59	32.29	32.65	33.08	32.44	32.11	32.51	32.45	32.62	32.66
	Range of variability from observed (°C)										+1.76 to +2.73°C								
	Corrected modeled data	29.84	29.90	29.90	29.86	29.96	29.85	29.85	29.89	29.85	29.83	29.46	30.29	29.82	29.83	29.48	29.81	29.86	29.86
	Range of variability from observed (°C)										-0.89 to -0.06°C								
		Minimum Temperature (°C)																	
18.28	Raw modelled data	17.91	17.80	18.32	17.86	18.20	17.94	18.06	18.12	17.99	17.93	18.29	18.49	18.17	17.73	18.00	17.71	17.82	18.02
	Range of variability from observed (°C)										-0.57 to -0.04°C								
	Corrected modeled data	17.85	17.88	17.88	17.82	17.95	17.83	17.86	17.86	17.84	17.86	17.74	18.01	17.86	17.88	17.92	17.81	17.87	17.87
	Range of variability from observed (°C)										-0.54 to -0.27°C								
		Rainfall (mm)																	
542	Raw modelled data	817	801	773	753	919	839	635	712	730	841	796	789	764	997	816	809	815	726
	Range of variability from observed (mm)										+93 to +455mm								
	Corrected modeled data	577	511	496	475	603	499	387	444	473	532	488	521	484	646	528	550	575	451
	Range of variability from observed (mm)										-155 to +104mm								
		Solar Radiation (Wm^{-2})																	
15.29	Raw modelled data	18.27	18.30	18.19	18.25	17.56	18.18	18.45	18.03	18.06	17.93	18.03	18.11	17.29	17.53	18.21	18.04	18.13	18.18
	Range of variability from observed (Wm^{-2})										2.00 to +3.16 Wm^{-2}								
	Corrected modeled data	15.07	15.20	15.26	15.25	15.37	15.20	15.29	15.34	15.22	15.25	15.14	15.25	15.06	15.29	15.25	15.25	15.19	15.22
	Range of variability from observed (Wm^{-2})										-0.22 to +0.08 Wm^{-2}								

Table 2a. Statistical verification results of the modeled temperature data after bias removal for 2016-17

Model's Name	Maximum Temperature (^{o}C) at monthly scale					Minimum Temperature (^{o}C) at monthly scale				
	Mean	SD	C.V. (%)	RMSE (%)	NRMSE (%)	Mean	SD	C.V. (%)	RMSE (%)	NRMSE (%)
Observed data	30.37	7.10	50.48	-	-	18.33	7.88	62.17	-	-
BCC-CSM1-1	29.84	7.57	57.28	3.74	12.32	17.85	8.19	67.09	3.34	18.20
BCC-CSM1-1-M	29.90	7.60	57.75	3.76	12.39	17.88	8.18	66.91	3.35	18.30
CSIRO-Mk3-6-0	29.90	7.56	57.09	3.70	12.17	17.88	8.18	66.92	3.28	17.92
FIO-ESM	29.86	7.59	57.65	3.76	12.39	17.82	8.19	67.08	3.33	18.18
GFDL-CM3	29.96	7.56	57.18	3.78	12.44	17.95	8.23	67.67	3.32	18.13
GFDL-ESM2G	29.85	7.53	56.74	3.73	12.28	17.83	8.17	66.82	3.33	18.18
GFDL-ESM2M	29.85	7.58	57.50	3.76	12.39	17.86	8.24	67.89	3.45	18.85
GISS-E2-H	29.89	7.55	56.98	3.73	12.27	17.86	8.16	66.52	3.30	18.00
GISS-E2-R	29.85	7.56	57.13	3.72	12.25	17.84	8.17	66.72	3.31	18.06
HadGEM2-ES	29.83	7.52	56.49	3.72	12.23	17.86	8.16	66.63	3.34	18.21
IPSL-CM5A-LR	29.46	7.65	58.57	3.78	12.44	17.74	8.04	64.67	3.33	18.14
IPSL-CM5A-MR	30.29	7.50	56.27	3.74	12.31	18.01	8.28	68.58	3.44	18.76
MIROC-ESM	29.82	7.54	56.92	3.78	12.45	17.86	8.16	66.65	3.34	18.25
MIROC-ESM-CHEM	29.83	7.51	56.44	3.65	12.00	17.88	8.15	66.34	3.34	18.20
MIROC5	29.48	7.78	60.49	3.92	12.90	17.92	8.18	66.9	3.38	18.46
MRI-CGCM3	29.81	7.58	57.5	3.72	12.25	17.81	8.20	67.24	3.35	18.25
NorESM1-M	29.86	7.55	56.96	3.68	12.11	17.87	8.14	66.27	3.33	18.16
Ensemble	29.86	7.56	57.17	3.72	12.26	17.87	8.18	66.92	3.32	18.17

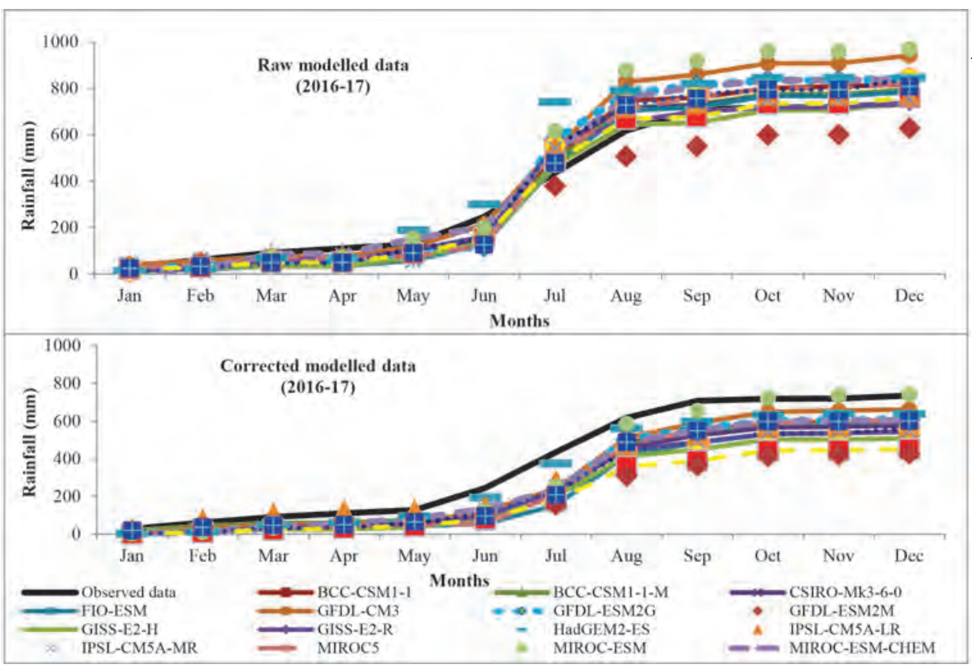

Fig. 3. Comparison of raw and corrected modeled data of cumulative monthly rainfall at Ludhiana

Table 2b. Statistical verification results of the modeled solar radiation and rainfall data after bias removal for 2016-17

Model's Name	Rainfall (mm/day) at monthly scale					Solar Radiation (Wm^{-2}) at daily scale				
	Mean	SD	C.V. (%)	RMSE (%)	NRMSE (%)	Mean	SD	C.V. (%)	RMSE (%)	NRMSE (%)
Observed data	542	4.81	23.13	-	-	15.28	5.97	35.61	-	-
BCC-CSM1-1	577	6.30	39.63	7.46	1.37	15.07	5.03	25.29	3.87	25.35
BCC-CSM1-1-M	511	6.16	37.98	7.39	1.35	15.20	4.99	24.91	3.57	23.35
CSIRO-Mk3-6-0	496	6.41	41.10	7.95	1.46	15.26	4.99	24.92	3.54	23.17
FIO-ESM	475	5.87	34.42	7.15	1.31	15.25	5.04	25.38	3.60	23.58
GFDL-CM3	603	6.32	39.97	7.59	1.39	15.37	6.84	46.79	5.88	38.44
GFDL-ESM2G	499	6.21	38.55	7.62	1.40	15.20	5.09	25.95	3.70	24.22
GFDL-ESM2M	387	4.45	19.77	6.48	1.19	15.29	5.01	25.06	3.55	23.22
GISS-E2-H	444	5.56	30.91	6.83	1.25	15.34	5.03	25.33	3.60	23.58
GISS-E2-R	473	5.80	33.67	7.30	1.34	15.22	4.98	24.76	3.56	23.28
HadGEM2-ES	532	6.00	35.97	7.50	1.37	15.25	5.04	25.38	3.60	23.58
IPSL-CM5A-LR	488	5.43	29.53	6.92	1.27	15.14	5.19	26.97	3.67	23.98
IPSL-CM5A-MR	521	5.22	27.26	6.54	1.20	15.25	5.04	25.38	3.60	23.58
MIROC-ESM	484	7.20	51.84	6.41	1.54	15.06	5.16	26.58	3.70	24.22
MIROC-ESM-CHEM	646	5.90	34.77	6.87	1.26	15.29	5.14	66.32	3.61	29.79
MIROC5	528	6.12	37.40	6.87	1.26	15.25	5.04	25.38	3.60	23.58
MRI-CGCM3	550	6.27	39.36	7.66	1.40	15.25	5.04	25.38	3.60	23.58
NorESM1-M	575	5.41	29.29	6.31	1.16	15.19	5.02	25.18	3.56	23.29
Ensemble	451	4.89	23.90	6.35	1.16	15.22	5.00	25.04	3.58	23.44

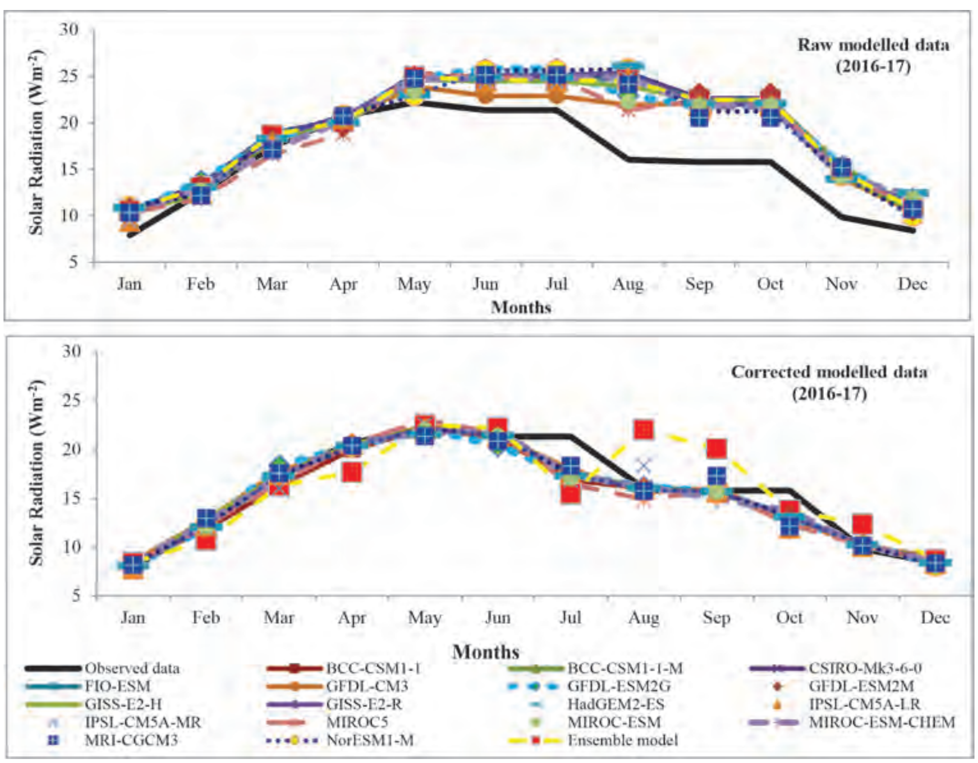

Fig. 4. Comparison of raw and corrected modeled data of monthly solar radiation at Ludhiana

meteorological data by 17 GCMs in the present study clearly bring out that :

1. Bias correction of the data is necessary before it can be used in impact assessment studied.
2. The models CSIRO-Mk3-6-0, FIO-ESM, IPSL-CM5A-MR and ensemble model predicted mean annual Tmax of 29.90, 29.86, 30.29 and 29.86^{o}C, respectively as 30.37^{o}C compared to observed Tmax of; Tmin of 17.88, 17.82, 18.01 and 17.87^{o}C, respectively as compared to observed Tmin of 18.33^{o}C, SR of 15.26, 15.25, 15.25 and 15.22 Wm^{-2}, respectively as compared to observed SR of 15.28 Wm^{-2} and RF of 1.60, 1.51, 1.50 and 1.28 mm, respectively as compared to observed RF of 1.50 mm.

Generally systematic biases of climate model simulations relative to observations widely exist due to various reasons. It can be very difficult and sometimes even not possible to use model outputs directly in impact assessment studies, e.g., as forcing for hydrological and agricultural models. The correction in predicted weather data is very important for a local region as it helps in preventing the adverse effects of local weather conditions. The continuous climate change threatens to cause major food losses all over the world and Punjab being the major food producer in India requires thorough study of its predicted weather for obtaining efficient solutions for the same. The accurate impact of weather conditions could be known through usage of corrected weather parameters thus bias removal should be considered as a very important step in climate change studies.

General circulation models (GCMs) are proved to be an efficient scientific tool for predicting climate change in the future. Studies show the presence of large biases in the GCMs that affect its performance. This study concludes that biases remain in the data of Tmax, Tmin, RF and SR derived from the RCP climate model for Ludhiana district. The projected climate data of rainfall, solar radiation and temperature with minimum bias is useful for estimation of flood and droughts in future and their efficient management strategies. Thus bias-corrected data set provides high-quality large-scale forcing for simulations and will improve the reliability of future projections of the regional climate and environment.

Authors' contribution

Conceptualization of research work and designing of experiments (JK, PK); Execution of field/lab experiments and data collection (JK, PK); Analysis of data and interpretation (JK, PK, SS, SK); Preparation of manuscript (JK, PK, SS, SK).

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