

Article

# Development of Climate Data Bias Corrector (CDBC) Tool and Its Application over the Agro-Ecological Zones of India

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**Abstract:** The use of global and regional climate models has been increasing in the past few decades, in order to analyze the future of natural resources and the socio-economic aspects of climate change. However, these climate model outputs can be quite biased, which makes it challenging to use them directly for analysis purpose. Therefore, a tool named Climate Data Bias Corrector was developed to correct the bias in climatic projections of historical and future periods for three primary climatic variables—rainfall, temperature (maximum and minimum), and solar radiation. It uses the quantile mapping approach, known for its efficiency and low computational cost for bias correction. Its Graphical User Interface (GUI) was made to be feasible to take input and give output in commonly used file formats—comma and tab delimited file formats. It also generates month-wise cumulative density function (CDF) plot of a random station/grid to allow the user to investigate the effectiveness of correction statistically. The tool was verified with a case study on several agro-ecological zones of India and found to be efficient.

**Keywords:** bias correction; quantile mapping; agro-ecological zones; climate change

## 1. Introduction

The changing climate is increasingly seizing the attention of scientist communities, irrespective of their fields of interest, in the last few decades. Day-by-day, studies on climate change, and its impact on different ecological systems are becoming familiar with the increasing use of Coupled Model Inter-comparison Project (CMIP) derived future projections of global climate models (GCMs). With advancing technology and computational methods, CMIP has been continuously working on further improvement of GCM simulated outputs [1–3]. However, there are many research articles, which have explicitly mentioned that the direct use of GCM-simulated projections is still unrealistic, due to humongous uncertainty and bias present in them [4–6]. Therefore, there persists a requirement to remove bias and to reduce the uncertainty from GCM outputs before application.

Different downscaling methods have been developed to remove the bias and uncertainty from the GCM outputs. They are categorized into two major types—dynamic and statistical down-scaling. Dynamic down-scaling is a model-based downscaling method, performed under different boundary conditions, using different predictors (climatic variables) [7,8]. Whereas, statistical downscaling (like bias correction method) is a statistical approach, which develops a statistical relationship between observed and GCM outputs, in order to transform the unrealistic GCM outputs with substantial uncertainty, to somewhat realistic data with reduced uncertainty as far as possible [7–9]. There have been many studies in the last few decades, which have proposed different methods for statistical

downscaling takes less computational cost compared to dynamic downscaling [5,9,10]. Among the statistical methods, quantile mapping approach is one of the most popular, efficient, and straightforward methods with less computation cost, which is being used by a lot of researchers to remove the bias from the GCM outputs [11–14].

Most of process-based ecological and environmental simulation models require daily climatic data of precipitation, temperature, and solar radiation as the minimum requirement to simulate different biological and environmental conditions (for example, in hydrological model—SWAT, DRAINMOD, etc., generally need precipitation and temperature data; in crop model—DSSAT, RZWQM, etc., precipitation, temperature, and solar radiation data are mandatory). These days, there are different sources available (like [15,16]) which provide the downscaled bias corrected GCM future projections. However, most of the time, there persists some bias in the data which one has to remove before its use [17]. The reasons for persistent bias can be either due to the use of outdated methods of bias correction, or removing bias only at monthly scale instead of daily [18–20]. Therefore, after realizing that data is still not suitable for the application, researchers and scientists must apply the statistical bias correction methods on GCM derived projections of these climatic variables for modeling purpose. The bias correction process might sound quite simple, but when it has to be applied over a large spatial area with a large number of stations/grids, it becomes complicated. For solving the complex problem of bias correction, few packages have been developed in different languages. For example, Santander Meteorology Group developed R package (downscaleR) and Matlab toolbox (MeteoLab), which include several bias correction functions for precipitation and temperature data [21,22]. However, for the application of these packages, one must know the programming languages in which these packages are developed. Researchers might also need to remove the bias from solar radiation data, which is a very common climatic variable for crop modeling, and these packages do not include solar radiation bias correction process. Therefore, there is a need for an efficient tool that does not require any supporting software and programming languages for its installation and simulations. The tool could help the scientific community and save their precious time to bias correct GCM outputs of a large number of stations/grids for elementary climatic variables—precipitation, temperature, and solar radiation.

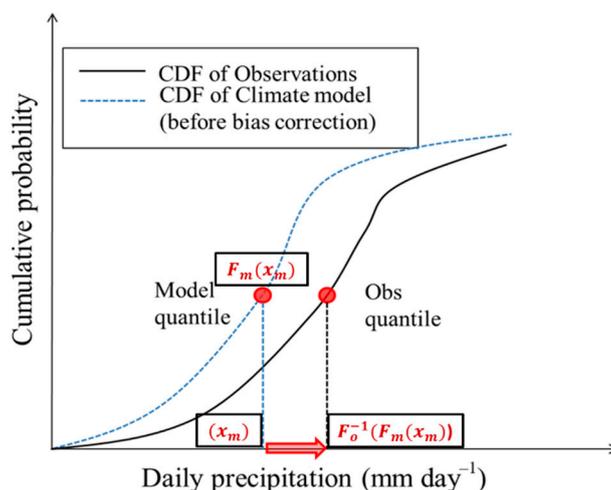
Based on the identified research gap, the objectives of this research article are

- To develop a Climate Data Bias Corrector (CDCB) tool for removing the bias for climatic model simulated outputs of precipitation, temperature, and solar radiation data, and
- To apply CDCB on the agro-ecological zones (AEZ) of India for its verification and to analyze the climate change for the mid and late century.

## 2. Methods and Tool Description

### 2.1. Bias Correction—Quantile Mapping

The quantile mapping approach has been used due to its simplicity, effectiveness, and low computational cost for development of the CDCB tool, for bias correction of climate models' outputs. A quantile mapping approach (also known as 'probability mapping' and 'distribution mapping'), is comprised of development of the statistical relationship between observed and model simulated outputs, by replacing the simulated values with observed ones at same cumulative density function (CDF) of used distribution depending on the climate variable (Figure 1). Bias correction of precipitation values (higher than 0) is performed by fitting the daily precipitation values of each month to Gamma distribution (which also only accounts for values greater than 0) (Table 1). Similarly, temperature values vary from negative to positive. Therefore normal distribution fits best for temperature data. In the same way, solar radiation data follows beta distribution as beta distribution accounts values from 0 to 1; therefore, solar radiation data at first is generally transformed into 0 to 1 range, which is again transformed back to the normal range after bias correction (Table 1).



**Figure 1.** The demonstration of quantile mapping bias correction approach (Modified from Kim et al. [26]). Please refer to Table 1 for the variable definitions.

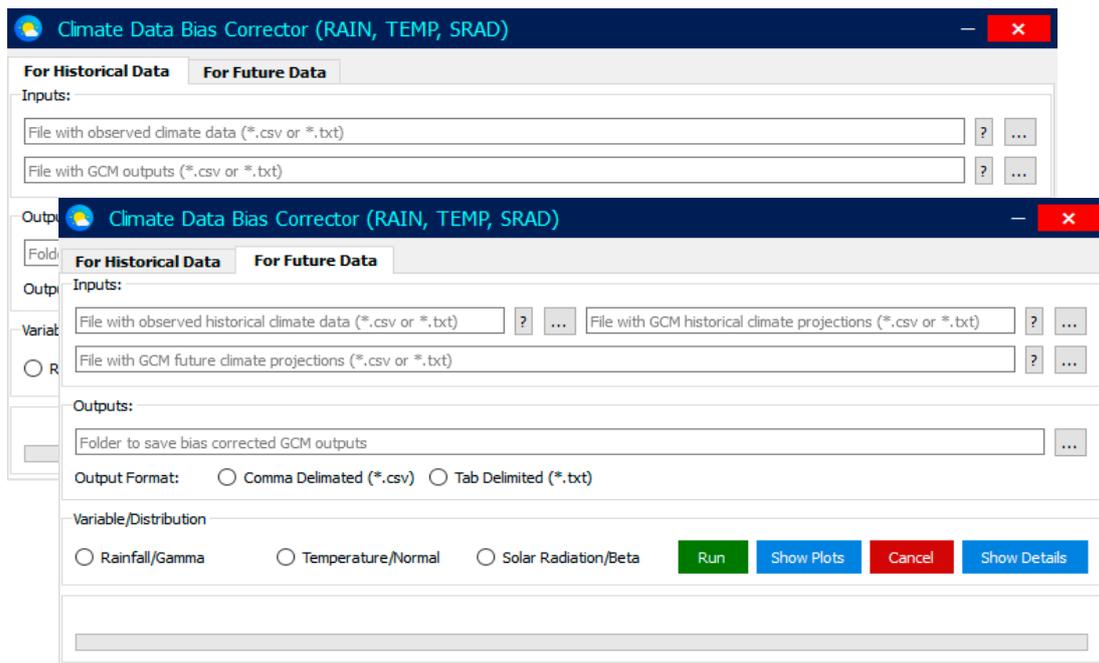
**Table 1.** Distributions and equations used for bias correction of different climatic variables.

Distributions/Climate Variables	Equations	References
Gamma/Precipitation	$\bar{x}_{ms.corr} = \begin{cases} F_{oh}^{-1}(F_{mh}(x_{ms})), & x_{ms} \geq x_{th} \\ 0, & x_{ms} < x_{th} \end{cases}$	[23]
Normal/Temperature	$\bar{x}_{ms.corr} = x_{ms} + F_{oh}^{-1}(F_{ms}(x_{ms})) - F_{mh}^{-1}(F_{ms}(x_{ms}))$	[24]
Beta/Solar Radiation	$\bar{x}_{ms.corr} = F_{oh}^{-1}(F_{mh}(x_{ms}))$	[25]

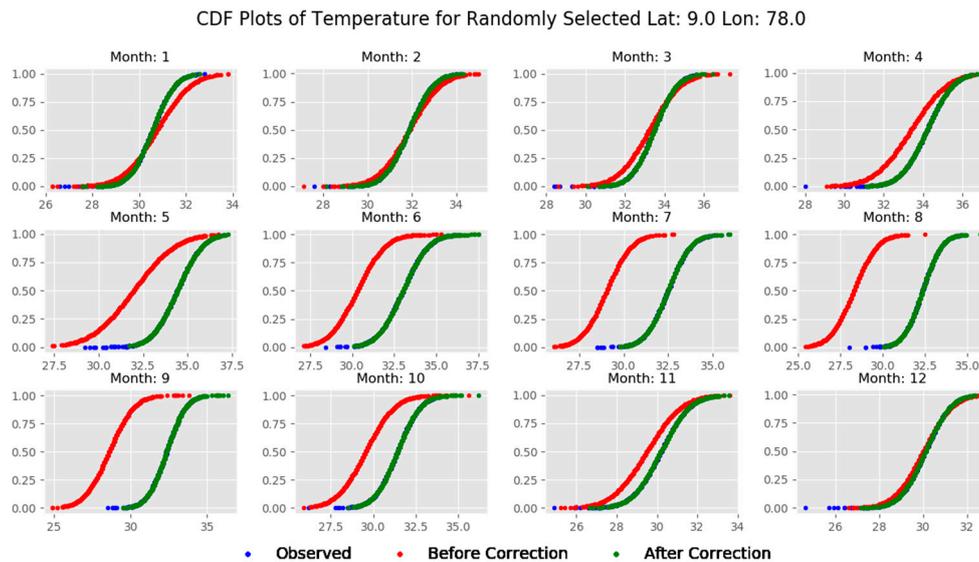
**Note:** where  $x$  is climatic variable,  $\bar{x}_{ms.corr}$  is bias corrected model simulated data; to categories between the wet and the dry day threshold value  $x_{th}$  is used (day with precipitation greater than 1 mm is assumed to be a wet day);  $F$  is CDF, whereas  $F^{-1}$  is its inverse. ( $o$  = observed,  $m$  = model,  $h$  = historical period, and  $s$  = simulation period). Here, the simulated period can either be historical or a future period.

### 2.2. CDBC Description

CDBC was developed for removing the bias from GCM and regional climate model (RCM) derived outputs of climate variables—precipitation, temperature, and solar radiation for the historical as well as the future period based on equations described in Table 1 (Figure 2a). The tool was developed using a free and open-source widget toolkit—PyQt [27] available in Python [28] (a high-level programming language getting popular in scientific areas) in such a way that it takes input and provides output in a commonly used tab and comma delimited files (\*.txt and \*.csv). There are two separate tabs developed in its graphical user interface (GUI) for bias correction of historical and future data. In the historical tab, a user has to provide two files, one with observed and other with model-simulated historical data of the same period (30 years, a general recommendation for climate change studies). The first two rows of the files must be latitude and longitude, and the first column must be the date column. Other columns will have the data of the same variable for a given latitude and longitude. Similarly, future tab takes three files for bias correction of future data—observed historical data, model-simulated historical data, and model simulated future data. Here, observed and model-simulated data must be of the same period to get accurate results. All the files must have the same order of latitude and longitude. To check the feasibility of tool, it provides an option to visualize the CDF plot, which draws for the randomly select station/grid for all the months (refer to Figure 2b for example). The tool is easy to install in all the versions of Windows and does not require any supporting software for its installation. The tool is developed in Python and the source code (available at [29,30] is distributed under Massachusetts Institute of Technology (MIT) license. This allows any user to modify/update the code in the future without any restriction [31]) for further improvement as well as the addition of new methodologies to remove the bias from GCM and RCM projections (please refer to Getting Started [32] and Technical Manual [33] to better understand the tool usage and installation procedure).



(a)



(b)

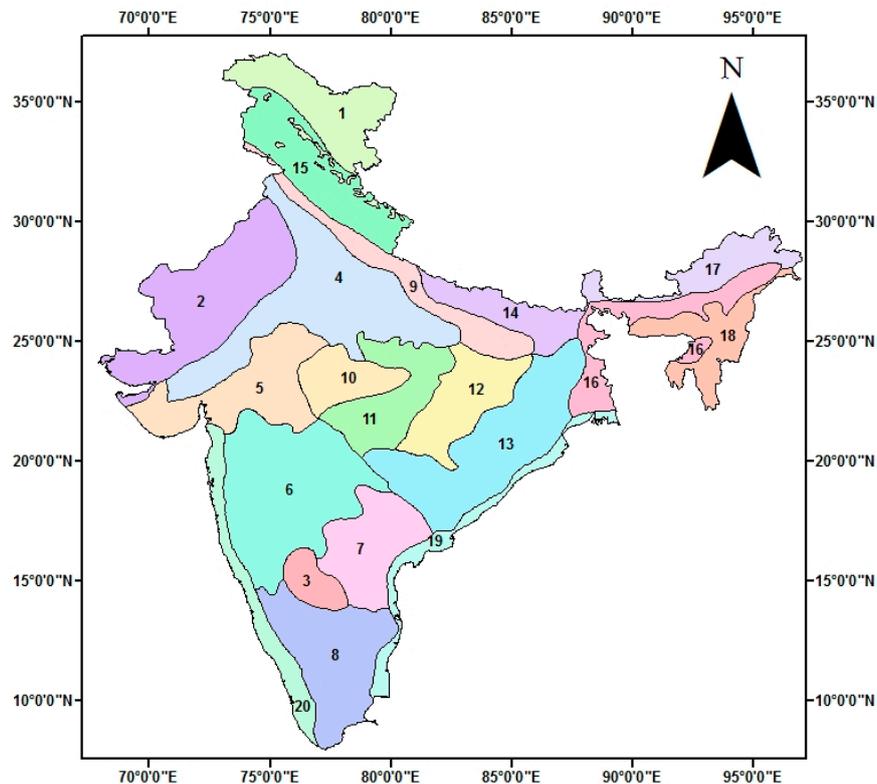
**Figure 2.** (a) Graphical user interface (GUI) of Climate Data Bias Corrector (CDBC), and (b) tool generated cumulative density function (CDF) curve of temperature on a monthly basis for a randomly selected grid for comparison of observed, before and after bias correction time series.

### 3. Application of CDBC: A Case Study

#### 3.1. Study Area

India has a total geographical area of about 3.28 Million km<sup>2</sup>, which has been classified into 20 Agro-ecological zones (AEZs) [34] (Figure 3), is being used as the study area for testing the Climate Data Bias Corrector (CDBC) tool. The reason for selecting AEZs to test CDBC, instead of any political boundary, is to ensure whether the tool is capable of removing bias from GCM simulated outputs of different climatic conditions as every AEZ has unique climatic range, soil types, physiography,

and growing period of crops. For instance, Western Himalayan zone (AEZ-1) is cold-arid eco-region, which receives annual precipitation less than 150 mm, whereas Western Plain, Kutch, and Part of Kathiawar Peninsula (AEZ-2) and Deccan Plateau (AEZ-3) are hot-arid eco-regions, which receive annual precipitation less than 500 mm. Similarly, there are semi-arid (AEZ-4 to 8), sub-humid (AEZ-9 to 15), humid-per humid (AEZ-16 to 18) and coastal (AEZ-19 and 20) eco-region, which are varied in terms of soil, climate, physiography, and length of growing period [34,35].



**Figure 3.** Map of the agro-ecological zones of India.

### 3.2. Data Preparation

India Meteorological Department (IMD) provides daily gridded climate data for precipitation and temperature (minimum and maximum), which were collected from years 1976 to 2005. As the daily observed values of solar radiation were not available, simulated daily values of solar radiation, from the National Centers for Environmental Prediction (NCEP), between 1979–2005, were used as the observed proxy dataset. Weather information for some climate variables simulated from five GCMs (Beijing Climate Center, China Meteorological Administration, China (BCC CSM1.1), Meteorological Research Institute, Japan (MRI-CGCM3), Norwegian Climate Center, Norway (NorESM1-m), Institut Pierre Simon Laplace, France (IPSL-CM5A-LR), and Atmosphere and Ocean Research Institute (University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology (MIROC5)) (selected based on the availability of all the required climate variables and high resolution) developed by CMIP Phase 5 were collected for historical (1976–2005) and future period of time (2005–2100) for four representative concentration pathways (RCPs-2.6, 4.5, 6.0 and 8.5) [36]. RCPs are the pathways depending on greenhouse gas emission and radiative forcing levels. The average radiative forcing achieved by different RCPs by the end of this century is denoted on its nomenclature like RCP 2.6 has  $2.6 \text{ Wm}^{-2}$ , RCP 4.5 has  $4.5 \text{ Wm}^{-2}$ , and so on for other RCPs. The carbon concentration is assumed to be reached about 490, 650, 850, 1370 ppm by the end of the 21st century for RCP 2.6, 4.5, 6.0, and 8.5, respectively [37]. All the collected climate data were rescaled to a spatial resolution of  $1^\circ \times 1^\circ$  using linear interpolation to maintain the uniformity and ease in explanation.

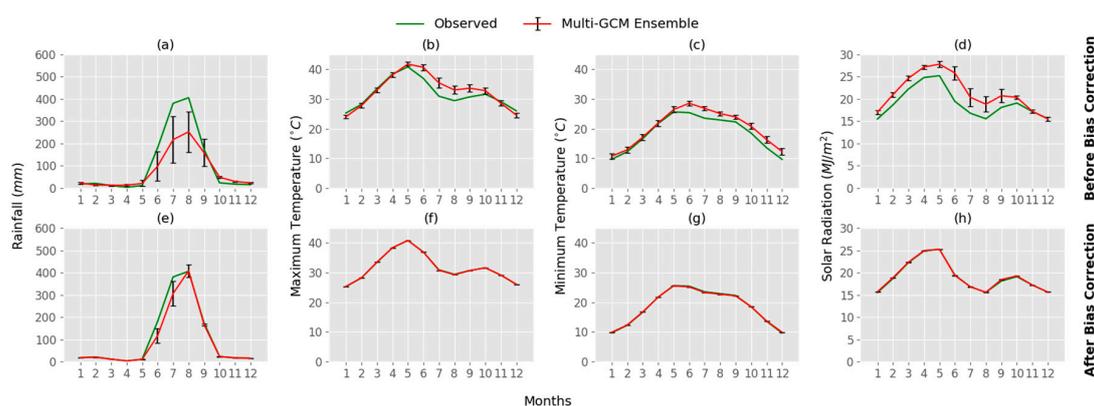
### 3.3. Bias Correction and Climate Change Estimation

After the data was prepared, the CDBC tool was used to remove the bias from the GCM data for historical (1976–2005: 1990s) as well as future period (2036–2065: 2050s and 2066–2095: 2080s) for all the climate variables, rainfall, temperature (maximum and minimum), and solar radiation at the grid scale ( $1^\circ \times 1^\circ$ ). After that, the average time series for each AEZ was prepared by aggregating the gridded data (both observed and GCM simulated data) of their respective AEZ for ease in comparison and calculations of climate change. To check the feasibility of the tool, observed and multi-ensemble of GCMs simulated historical data of the 1990s were compared at the AEZ scale, before proceeding towards the bias correction of the GCM simulated data of 2050s and 2080s. After the feasibility test and bias correction of all the GCM data, changes in climatic variables in the mid-century (2050s) and late-century (2080s) in future were analyzed at the AEZ scale.

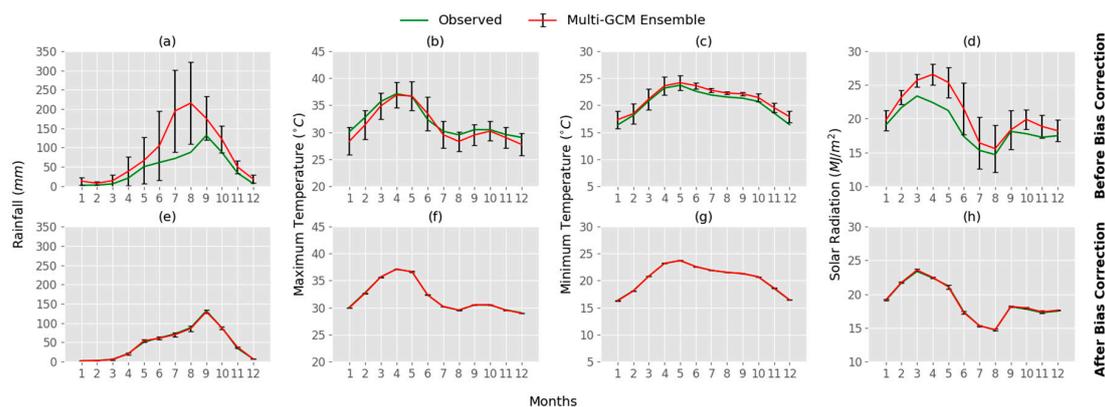
## 4. Results and Discussion

### 4.1. CDBC Performance at Grid and AEZ Scale

The monthly averaged 30-year daily time series of multi-ensemble GCMs derived rainfall, temperature, and solar radiation were compared with the observed time series of the 1990s, at a randomly selected grid at latitude  $23.0^\circ$  and longitude  $80.0^\circ$ , before and after bias correction to evaluate the bias correction performance of the tool at the grid scale (Figure 4). From Figure 4, it is clear that the tool has reduced the uncertainty among the different GCMs historical projections, which proves that the tool can be used in removing bias from the future projection of GCM outputs. However, for further cross-examination of tool performance at a large area, a similar approach has been followed for AEZ scale. The monthly average of AEZ scaled time series of rainfall, temperature, and solar radiation, aggregated from daily gridded data for the 1990s was used to evaluate the performance of bias correction for each climatic variable. Figure 5 illustrates the bias correction capability of the tool in one of the AEZs, i.e., AEZ-3. Similarly, the performance of the tool for other AEZs was also verified to ensure that the tool is capable of removing bias from the GCM data under different climatic conditions (please refer to Supplementary Materials, Figures S1–S8). There was a tremendous uncertainty, as well as bias, in all the five GCMs present in the raw multi-ensemble GCMs outputs (Figure 5a–d), which were successfully removed by using CDBC tool preserving the seasonal pattern of the climatic variables (Figure 5e–h).



**Figure 4.** Comparison of observed and multi-GCM ensemble (error bars represent variability among the five GCMs) time series of 1990s for before and after bias correction of (a) rainfall, (b) maximum temperature, (c) minimum temperature, and (d) solar radiation at a randomly selected grid (latitude  $23.0$  and longitude  $80.0$ ).



**Figure 5.** Comparison of observed and multi-GCM ensemble (error bars represent variability among the five GCMs) time series of 1990s for before and after bias correction of (a) rainfall, (b) maximum temperature, (c) minimum temperature, and (d) solar radiation in AEZ 3.

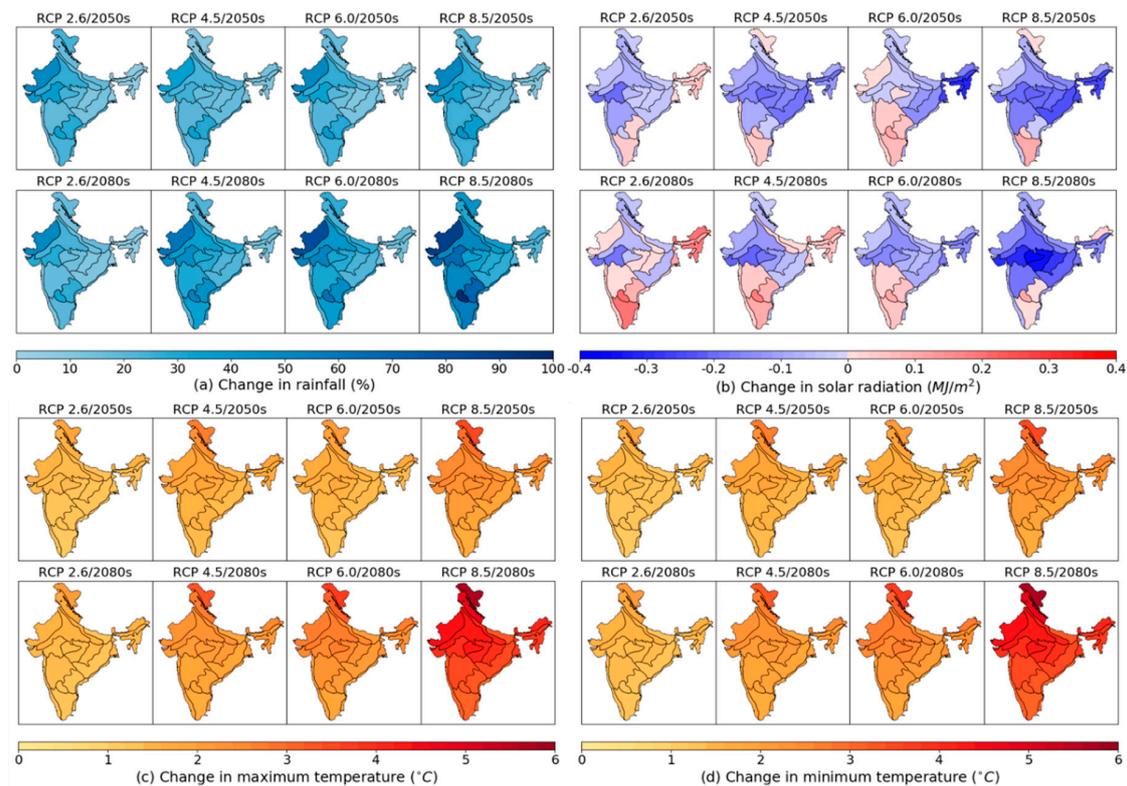
#### 4.2. Expected Changes in Climatic Variables by 2050s and 2080s

After the tool was verified at AEZ scale with the observed data for the 1990s, it was used to bias correct the future GCMs projected gridded data for two-time scenarios (2050s and 2080s) and four RCP scenarios (RCP 2.6, 4.5, 6.0, and 8.5). Like the historical data (observed and model simulated), the gridded GCM projections for the 2050s and 2080s were also aggregated to develop the time series at AEZ scale for all the five GCMs. Then, the multi-ensemble bias corrected GCM projections for the future period were compared with that for the historical period to estimate the changes in climatic variables for different RCPs scenarios and future periods. Changes in climatic variables were estimated annually as well as separately for summer (April–September) and winter seasons (October–March).

#### 4.3. Future Changes in Climate Variables on the Annual Scale

Rainfall in all the AEZs is expected to increase in the future for all RCPs (Figure 6a). The expected increase in rainfall in arid (AEZ 1–3) (2050s: 8.9–51.3%, 2080s: 16.3–100.0%) and semi-arid regions (AEZ 4–8) (2050s: 18.0–37.8%, 2080s: 16.3–71.3%) are observed to be higher than that in humid (AEZ 16–18) (2050s: 4.8–12.8%, 2080s: 4.5–23.2%) and sub-humid (AEZ 9–15) (2050s: 8.9–23.8%, 2080s: 9.2–37.3%) regions. Coastal region (AEZ 19–20) (2050s: 11.7–25.0%, 2080s: 8.5–46.8%) is also ascertained to have a significant increase in rainfall in all the RCP scenarios and periods, which is found to be higher than that in the humid region. Worse RCP scenarios resulted in higher rainfall amount in the future.

Similarly, the solar radiation time series was also analyzed to determine any significant changes in mid-century and late-century for all the plausible scenarios (Figure 6b). In all the scenarios, sub-humid AEZs are expected to experience a slight decrease in solar radiation values annually up to 0.2 MJ/m<sup>2</sup> by 2050s and 0.4 MJ/m<sup>2</sup> by 2080s. However, other regions are expected to experience a very ambiguous pattern of increase and decrease in solar radiation values for different scenarios. Though, humid AEZs and most of semi-arid AEZs could experience a significant decrease up to 0.3 MJ/m<sup>2</sup> by 2080s in last two worst scenarios (RCP 6.0 and 8.5). Similarly, there might be a small decrease in the average annual value in RCP 8.5 for both the future periods in the coastal AEZs. All the changes experienced by different agro-ecological regions in solar radiation are quite small.



**Figure 6.** Climate change analyzed based on annual mean changes in (a) rainfall, (b) solar radiation, (c) maximum, and (d) minimum temperature with respect to 1990s for two future periods—2050s and 2080s and all the representative concentration pathways (RCP) scenarios.

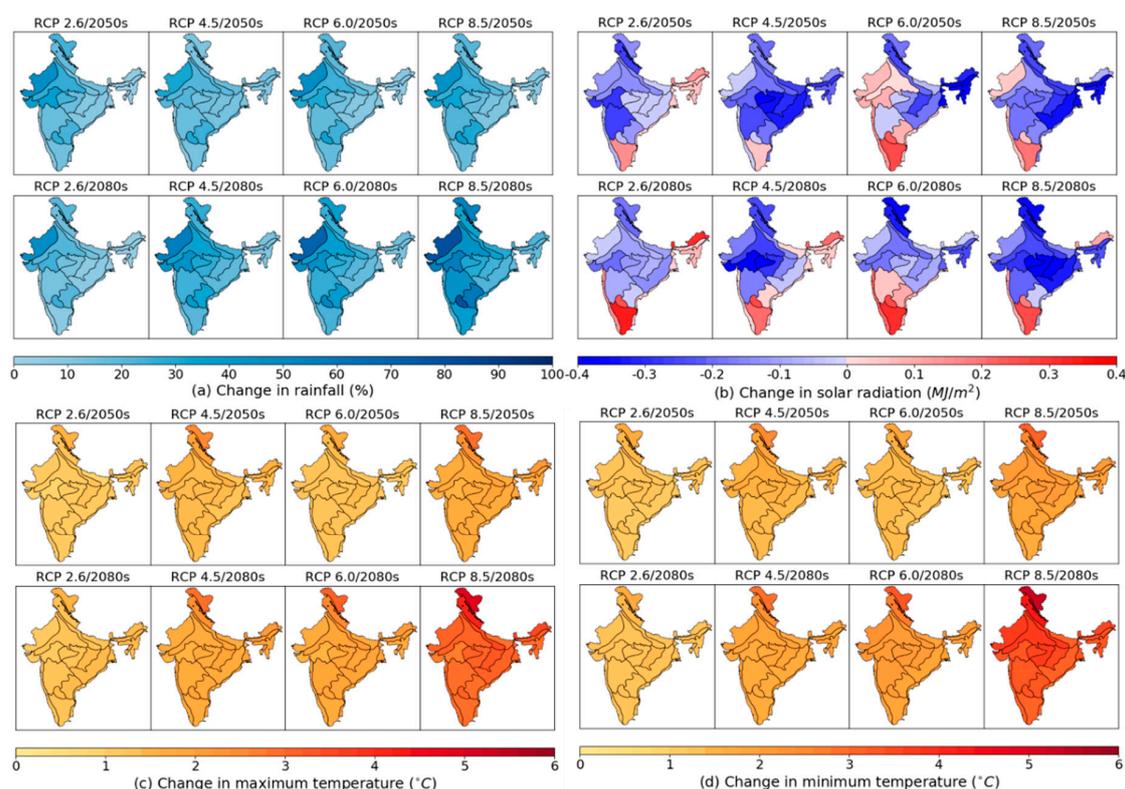
Figure 6c,d show the change in maximum and minimum temperature for different agro-ecological zones of India for various combination of future period and plausible scenarios. It is evident that, due to the increasing concentration of carbon dioxide ( $\text{CO}_2$ ) (a greenhouse gas) in the atmosphere, the temperature will rise. Therefore, with the time and moving towards the worst scenarios, higher rise in temperature is expected. The maximum rise in temperature is expected in arid and sub-humid regions, which could vary from 1.1–5.9 °C, and 1.1–4.9 °C, respectively. The least increase in temperature was found in coastal regions, varying from 1.0–3.2 °C. The remaining two regions, i.e., semi-arid and humid regions, are expected to experience an increase in a temperature varying from 1.0–4.3 °C on an average.

Mishra and Lilhare [38] reported a similar increase in rainfall and temperature using CMIP5 data on different Indian sub-continent major river basins. Kumar et al. [39] downscaled the high resolution multi-model climatic projections to quantify the changes in climatic variables, also found similar results on the country-wide scale. Similarly, other researchers also found similar changes in the climatic variables over the different part of the country [40–42]. The changes in a different climatic variable, based on annual time series analysis of a future period compared to a historical period, are interlinked with the hydrological cycle. The increase in carbon concentration is expected to trigger the increase in temperature, which is the main reason for the increase in rainfall [43,44]. The increase in temperature fastens the hydrological cycle, due to a rise in evapotranspiration. This increase would result in increasing rainfall events, along with extreme events [44]. Rainfall and solar radiation are inversely proportional to each other. Due to the fastening of the hydrological cycle, the incoming solar radiation would be intercepted by the cloud resulting in decreasing solar radiation value.

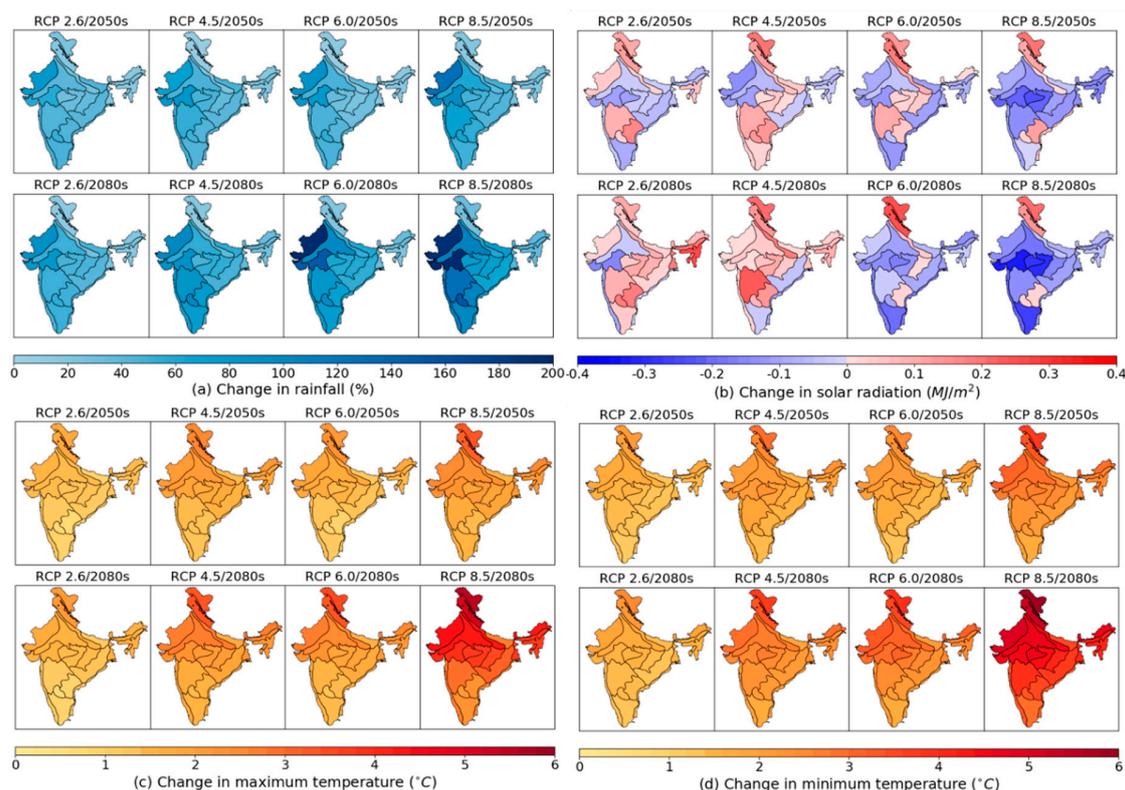
#### 4.4. Seasonal Changes in Climate Variables in Future

Like the annual analysis, changes in climatic variables have also been analyzed seasonally for two major seasons of the year—summer and winter. For summer, the analysis was performed from

April to September. Whereas, for winter, it was performed from October to March. On analysis, it was found that the percentage increase in rainfall, in the winter, is higher than that in summer in most of the AEZs except AEZ 1 (arid) and AEZ 15 (sub-humid) (Figures 7a and 8a). By the end of the 21st century, it is expected that most of arid (AEZ 2, 3), semi-arid (AEZ 4–8), and coastal regions (AEZ 20) could experience an extreme increase in winter rainfall (up to 200%). However, the increase in summer rainfall is expected to be approximately up to 80%. Similarly, solar radiation was also analyzed on a seasonal basis. Most of the AEZs of different major climatic regions are expected to experience an increase in winter solar radiation as compared to summer except AEZ 3, 8, 17, 19, and 20, where there is a significant probability of a slight decrease in winter solar radiation, ranging up to 0.6 MJ/m<sup>2</sup> (Figures 7b and 8b) by 2080s. By analyzing the temperature on a seasonal basis, a significant increase in maximum and minimum temperature was observed in most of AEZs, up to 1.4 °C. Similarly, few AEZs (AEZ 3, 7, 8, 14, 19, and 20) are projected to have an increase up to 0.8 °C in the maximum temperature during the winter than in the summer by the end of this century. There was only one AEZ (AEZ 8) where the increase in minimum temperature by 2080s was observed to lesser in winter than in summer. Overall, a very slight change in the seasonal analysis of climate change was found compared to the annual changes except for the changes in rainfall. In winter, the percentage change of rainfall is expected to be more than that in summer. However, by magnitude and distribution, the summer rainfall will still be expected to dominate during all the future periods of the whole century.



**Figure 7.** Climate change analyzed based on mean changes in summer (Apr.–Sep.) in (a) rainfall, (b) solar radiation, (c) maximum, and (d) minimum temperature with respect to 1990s for two future periods—2050s and 2080s and all the RCP scenarios.



**Figure 8.** Climate change analyzed based on mean changes during winter (October–March) in (a) rainfall, (b) solar radiation, (c) maximum, and (d) minimum temperature with respect to 1990s for two future periods—2050s and 2080s and all the RCP scenarios.

Recent pursuit and the advancement of climate change impact studies on numerous concerns have steered the use of CMIP datasets for a better understanding of the future. However, the recommendation of bias correction, before the use of these datasets, has convoluted the situation for the researchers, as the bias correction is a complicated process, which needs knowledge of mathematics, statistics, and a high-level programming language. The researchers, who are engaged with field experiments or sciences in agriculture and want to use future climatic projections in their modeling work, are generally not familiar with the statistical approach used in the bias correction. Therefore, to assist them with bias correction, the Climate Data Bias Corrector (CDBC) has been developed.

The tool has been verified in this study on AEZs of India as well as in a study on climate change impact on the hydrology of the Great Miami River watershed in Ohio, USA by Shrestha et al. [17]. After testing it on different AEZs of India which are varied in terms of climate and other crop-related parameters as well as in one of the watersheds of USA which is again possess a completely different climatic condition than India, it can be claimed that the tool is not region specific and can be used anywhere around the world.

## 5. Summary and Conclusions

An increase in the use of the global climate model (GCM) simulating future projections has triggered an idea for the introduction of a tool—the Climate Data Bias Corrector (CDBC), designed to remove the bias and reduce the uncertainty among the GCMs derived daily projections. To illustrate the capability of the CDBC tool, we conducted a case study to monitor its performance and its use on a large number of grids. In this case study, five GCMs simulated historical, and future projections along with observed gridded data were used to analyze the annual, as well as seasonal, changes in climatic variables—rainfall, temperature, and solar radiation for mid- (2050s) and late- (2080s) term of the current century. The CDBC tool was used to remove the bias from all five GCM data for historical

(1990s) and future periods (2050s and 2080s). To evaluate the performance of the tool, the observed data, and bias removed GCM simulations for the historical period, were compared at the grid, as well as the AEZ scale. From the results, it is observed that the tool has performed quite well in rectifying the GCM historical outputs. The monthly pattern and uncertainty among different GCMs have been reduced to a great extent. After that, the climate change analysis was conducted to determine the expected change in climate by 2050s and 2080s for all AEZs of India, using CDBC outputs for different GCMs. The climate change results were also found to be similar to IPCC and other researchers expectations. The change in climate was also evaluated on a seasonal basis for summer and winter separately, in order to check whether the tool is capable of preserving the intra-annual seasonality in climate change analysis. The results seem to depict an obvious pattern reported by several climatologists and scientists.

Therefore, the developed tool could help improve the future simulation and reduce uncertainty from the simulated outputs induced, due to the uncertainty and bias in future climatic projections. This could insight a better understanding of future scenarios, simulated using different agricultural and hydrological models. Hence, it is a practical tool, which can be used by diverse scientific communities analyzing the climate change impact at large, as well as small scales. The tool is designed in an open-source programming language—Python. Therefore, there is a scope of future modification or addition of new algorithms, and along with that, there is no license issue that will be advantageous for its users all over the world especially in developing nations.

**Supplementary Materials:** The following are available online at <http://www.mdpi.com/2073-4441/11/5/1102/s1>, Figure S1: Comparison of observed and multi-GCM ensemble (error bars represent variability among the five GCMs) time series of 1990s for before bias correction of rainfall for all the AEZs, Figure S2: Comparison of observed and multi-GCM ensemble (error bars represent variability among the five GCMs) time series of 1990s for after bias correction of rainfall for all the AEZs, Figure S3: Comparison of observed and multi-GCM ensemble (error bars represent variability among the five GCMs) time series of 1990s for before bias correction of maximum temperature for all the AEZs, Figure S4: Comparison of observed and multi-GCM ensemble (error bars represent variability among the five GCMs) time series of 1990s for after bias correction of maximum temperature for all the AEZs, Figure S5: Comparison of observed and multi-GCM ensemble (error bars represent variability among the five GCMs) time series of 1990s for before bias correction of minimum temperature for all the AEZs, Figure S6: Comparison of observed and multi-GCM ensemble (error bars represent variability among the five GCMs) time series of 1990s for after bias correction of minimum temperature for all the AEZs, Figure S7: Comparison of observed and multi-GCM ensemble (error bars represent variability among the five GCMs) time series of 1990s for before bias correction of solar radiation for all the AEZs, Figure S8: Comparison of observed and multi-GCM ensemble (error bars represent variability among the five GCMs) time series of 1990s for after bias correction of solar radiation for all the AEZs.

**Author Contributions:** R.G. developed the tool, conducted the presented case study, and prepared the draft manuscript. R.B. reviewed and edited the article. A.M. conceptualized the research idea, reviewed, and edited the article.

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**Conflicts of Interest:** The authors declare no conflict of interest.

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