OUT-PERFORMING BIAS-CORRECTED GCM MODELS AND CMIP6-BASED PRECIPITATION AND TEMPERATURE PROJECTIONS FOR THE BAGMATI IRRIGATION AREA

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Abstract

The selection of General circulation models (GCMs) and suitable bias correction methods for any particular study area in very crucial for the projection of precipitation and temperature using climate models which can be used for estimating the future crop water requirement. The results of a General Circulation Model (GCM) are being downscaled and compared to a baseline climatology for two IPCC scenarios (ssp245 and ssp585) based on Coupled Model Inter-comparison Project Phase 6 (CMIP6) climate model. We choose four GCMs models out of ten by evaluating their performance to observe historical data. Performance indicators (NSE, PBAIS, and RSR) are computed by comparing bias-corrected historical data with observed historical data. We found that GCM models EC-Earth3, NorESM2-MM, GDFL-ESM4, and IPSL-CM6A-LR showed a higher rating for maximum and minimum temperature, and GCM models EC-Earth3, NorESM2-MM, GDFL-ESM4, and MPI-ESM2-MM showed a higher rating for precipitation. Among the different bias correction functions power X_o transformation and Power transformed functions, Bernoulli's Weibull showed the best performance for minimum temperature), maximum temperature, and precipitation, respectively. These models and bias correction could be used to project the climate variables of the surrounding basins.

Keywords*: GCMs, CMIP6, NSE, PBIAS, RSR, ssp245, ssp585.*

1. Introduction

Climate change is a major environmental problem around the world. About two-thirds of Nepalese agriculture is strongly reliant on the monsoon, resulting in an excess of food production imbalance. Climate change has emerged as a significant worldwide issue that has sparked widespread concern at both the national and international levels [1]. According to several studies, Climate change has been linked to a drop in crop yield [2,3].

The main objective of this project is to evaluate the impact of climate change on future crop water. The specific objectives are as follows:

To select the best performing CMIP-6 models along with the best bias correction method for the Bagmati Irrigation Project area.

To generate a multi-model ensemble from biased corrected data of best-performing GCM models and generate a monthly historic plot of observed, raw, and bias-corrected data.

2. Problem Statement

Climate change is a major concern in today's modern world, influencing all human activities. Climate change has an impact on agricultural practices, particularly in countries that rely on rain-fed agricultural systems. Changes in hydrologic cycles and water availability for irrigation are predicted to be a major influence on climate change.

The Koshi, Gandaki/Narayani, and Karnali are Nepal's three largest river basins. The Koshi River Basin has been the subject of some future climate projection research [4, 5, 6] and on the Bagmati river basin [7]. However, limited research on future climate projections for the Bagmati River Basin has been conducted using the CMIP3 climate model [8].

To full fill this research gap, the goal of this work is to project the future temperature and precipitation of the BIP using the latest CMIP6 model output and evaluate the future crop water requirement. Climate models' systematic biases obstruct their use in regional hydrological climate change effects assessments and lead to inaccuracies.

The performance of available bias correction methods for climatic parameters forecasts is compared in this work, and the best bias correction approach for BIP is identified. This type of bias correction strategy could be valuable for future academics that want to widen their research on this irrigation project.

STUDY AREA

The project area lies between longitudes $85^{0}17'$ to $85^{0}36'$ east and latitude $26^{0}46'$ to $27^{0}6'$ North and Comprises land in the Sarlahi district of Janakpur Zone and Rauthat district of Narayani Zone of the Central Development Region. The command area of the project lies in the south of the East-West highway and north is the Churia hills. It is a flat plain with ground elevations varying typically, between 60m above mean sea level on the southern border with India to 130m at the boundary of Siwalik.

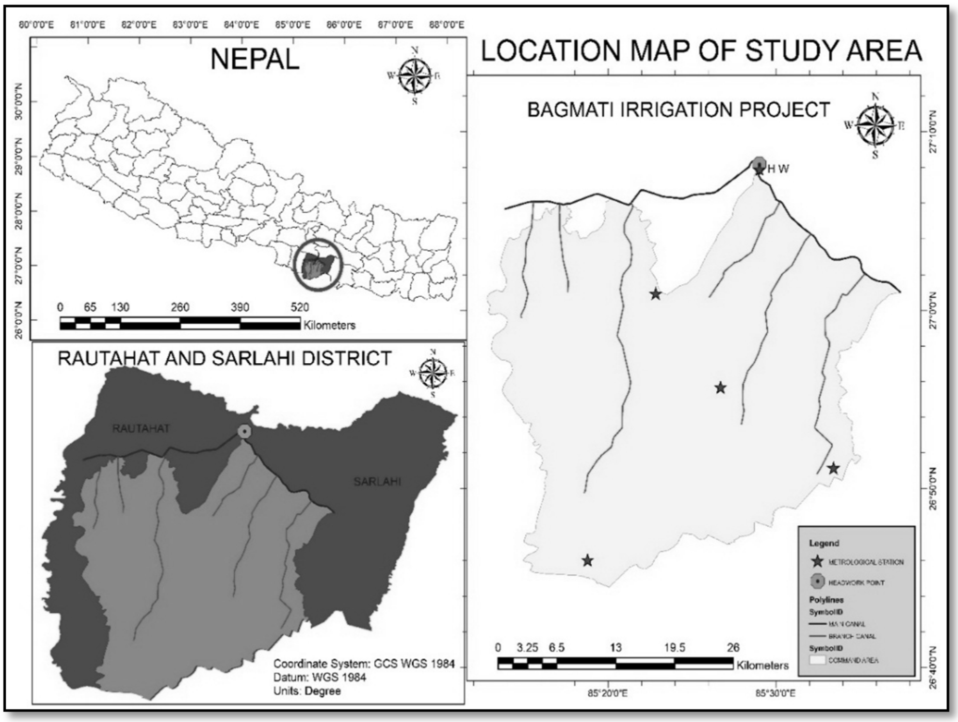

Figure 1 Location Map of Study Area

3. Methodology

For the study of climate change in BIP using CMIP6 GCM models, we selected 10 GCM models that participated in Coupled Model Intercomparison Project Phase 6 (CMIP6) for the pool of raw GCMs. These models are selected based on the previous research performed on south Asian countries [9, 10, 11] The historical (1985 - 2014) precipitation, maximum, and minimum temperature data of each GCM model are downloaded from the CMIP6 database website (https://esgf-node.ilnl.gov/search/cmip6). The downloaded data were in netCDF format and on a global scale. We merged the data from the year (1985 - 2014) into a single netCDF file format for each GCM model and each variable i.e. tmax, tmin, and pr. We clipped the data for our study area from the merged file by providing a limit of latitude and longitude. The merge and clip operation is performed using the climate data operator tool (CDO) available in the Linux operating system Ubuntu. Then we extracted the gridded data to point data from netCDF file format to comma delimited text (CSV) format for five stations of the study area for all variables using the python codes.

The gap in daily observed data obtained from the department of hydrology and meteorology (DHM) was filled using the missing data filling approach of linear interpolation from the nearby stations [12]. Using performance evaluation metrics Root Mean Square Error (RSR), Percentage Bias (PBIAS), and Nash-Sutcliff Efficiency (NSE) the performance metrics of historical raw GCMs were evaluated for each station and each variable compared with the observed historical data (1985-2014). Concerning the value of each performance metrics, the rating is provided as mentioned in table 1. From all stations average rating is calculated for each GCM and four GCMs with the highest rating are selected to prepare the multi-model ensemble for each precipitation, maximum and minimum temperature.

Table 1: Performance Evaluation Criteria of Historical Raw GCMs [13]

Performance Rating	NSE	RSR	PBIAS	Rating
Very Good	0.75<NSE<=1.00	0.00<RSR<=0.50	PBIAS< 10	**5**
Good	0.55<NSE<=0.75	0.50<RSR<=0.6	10 <= PBIAS	**4**
Satisfactory	0.40<NSE<=0.55	0.60<RSR<=0.70	15 <= PBIAS <25	**3**
Unsatisfactory	0.25<NSE<=0.40	0.70<RSR<=0.80	25 <= PBIAS	**2**
Poor	NSE<=0.25	RSR>0.80	PBIAS>=35	**1**

The bias correction method Quantile mapping (QM) with 13 statistical transformation functions available in the Qmap package in R for bias correction is used. The transformation functions are as follows:

• Bernoulli Exponential
• Bernoulli Gamma
• Bernoulli Weibull
• Bernoulli Log-normal
• Exponential Asymptote
• Exponential Asymptote x0
• Linear Transformation
• Power Transformation
• Power x0 Transformation
• Scale Transformation
• Non-parametric Quantile Mapping
• Non-parametric Robust Quantile Mapping
• Smoothing Spline

The bias-corrected daily precipitation and maximum and minimum temperature for the baseline period (1985-2014) from the selected GCMs are compared with the observed data obtained from the department of hydrology and meteorology (DHM) to evaluate the performance metrics RSR, PBIAS, and NSE. The bias correction methods are rated based on the criteria as shown in table 2. The bias correction method with the highest rating is selected for each variable.

Table 2 : Performance Evaluation Criteria of Bias Correction Methods

Performance Rating	**NSE**	**RSR**	**PBIAS**	**Rating**
Very Good	0.85<R2<=1.00 0.75<R2<=0.85	0.00<RSR<=0.25 0.25<RSR<=0.50	PBIAS< 5 5 <= PBIAS<10	**8** **7**
Good	0.70<R2<=0.75 0.65<R2<=0.70	0.55<RSR<=0.60 0.50<RSR<=0.55	10 <= PBIAS <12.5 12.5 <= PBIAS <15	**6** **5**
Satisfactory	0.57<NSE<=0.65 0.50<NSE<=0.57	0.65<RSR<=0.70 0.60<RSR<=0.65	15 <= PBIAS<20 20 <= PBIAS <25	**4** **3**
Unsatisfactory	0.4<NSE<=0.5	0.70<RSR<=0.80	25 <= PBIAS <35	**2**
Poor	NSE<=0.4	RSR>0.80	PBIAS>=35	**1**

Data of the best bias correction method for each best-performing GCM model and each variable are taken which are averaged to obtain the multi-model ensemble (MME). Include all the models/ensembles with available data and simply take an average of all the predicted outcomes [14].

The future data in our study are analyzed and interpreted by dividing the future time series into the following classification presented in Table 3. We calculated the monthly data for each variable from observed historical and for the bias-corrected GCM model future data (ssp245 and ssp585) for all best performing GCM models and multi-model ensemble (MME) diving future time-series to NF, MF, and FF.

Table 3: Future Periods considered in the study and their duration in the year

S.N.	**Start Year**	**End Year**	**Future Period**	**Abbreviation**
1.	2022	2046	Near Future	**NF**
2.	2047	2073	Mid Future	**MF**
3.	2074	2100	Far Future	**FF**

1. Results

1.1. Selection of best performing GCMs for Multi-model Ensemble from the pool of raw GCMs.

The performance metrics (i.e. RSR, PBIAS, and NSE) are used to calculate the average rating of the individual GCMs for each station and each variable. The rank is assigned for all 10 models based on the average of all stations for Tmax, Tmin , and Pr. A summary of the obtained average rating is shown in table 4. We found that GCM models EC-Earth3, NorESM2-MM, GDFL-ESM4, and IPSL-CM6A-LR showed a higher rating for maximum and minimum temperature, and GCM models EC-Earth3, NorESM2-MM, GDFL-ESM4, and MPI-ESM2-MM showed a higher rating for precipitation.

The above-mentioned GCMs are selected for a multi-model ensemble of each variable (Tmax, Tmin, and Pr) and for further bias correction. Preciously performed study on this area shows Precipitation outputs from the Hadley Centre Coupled Model, version 3 (HadCM3), and the Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS) performed well. [15] The impact of climate change on flood damage in the agricultural sector using MRI-AGCM3.2s precipitation outputs was analyzed.[16]

Table 4: Average rating of the 10 GCMs for the selection of 4 GCMs for Multi-model Ensemble

S.N.	GCMs	pr	tmax	tmin
1	EC-Earth3	**2.45**	**3.50**	**4.17**
2	FGOALS-f3-L	1.60	2.08	4.00
3	GFDL_ESM4	**2.55**	**2.50**	**4.00**
4	INM-CM4-8	1.15	1.75	3.33
5	INM-CM5-0	1.60	1.83	2.58
6	IPSL-CM6A-LR	1.15	**3.83**	**4.75**
7	MIROC6	1.20	2.00	2.17
8	MPI-ESM1-2-LR	**1.70**	1.83	2.00
9	MRI-ESM2-0	1.45	2.33	2.83
10	NorESM2-MM	**1.75**	**3.92**	**5.00**

1.2. Selection and Performance Evaluation of Bias Correction Methods

Historical temperature and precipitation data of selected GCMs with the help of three performance matrices (i.e PBIAS, RSR, NSE) are bias-corrected for nine different and thirteen different bias correction functions for temperature and precipitation respectively. The bias correction functions rank is assigned based on the average rating of all stations rating. For maximum temperature among nine functions, PTFmodprecip_01_pow showed the best performance. Similarly, for minimum temperature, PTFmodprecip_01_expasym showed the best performance and for Precipitation, DISTmodprecip_01bernweibull showed the best. so, the future precipitation and temperature data are corrected accordingly above mentioned, biased correction function.

Table 5: Average rating of the 10 GCMs for the selection of 4 GCMs for Multi-model Ensemble

S.N	Correction Method	Pr	Tmin	Tmax
1	Bernoulli Exponential	1.463	0.000	0.000
2	Bernoulli Gamma	2.475	0.000	0.000
3	**Bernoulli Weibull**	**2.538**	0.000	0.000
4	Bernoulli Log-normal	1.788	0.000	0.000
5	Exponential Asymptote	2.188	2.375	2.896
6	Exponential Asymptote x0	2.225	2.625	2.979
7	**Power x0 Transformation**	1.700	**4.983**	3.813
8	Linear Transformation	2.163	4.958	3.813
9	**Power Transformation**	2.325	4.708	**3.938**
10	Scale Transformation	1.500	4.729	3.792
11	Non-parametric Quantile Mapping	2.275	2.646	2.938
12	Non-parametric Robust Quantile Mapping	2.263	2.917	3.042
13	Smoothing Spline	2.225	4.146	3.271

1.3. GCM Maximum Temperature Bias Correction Performance Evaluation

From the historical maximum temperature plot for all stations, it is observed all the bias-corrected GCM's maximum temperatures are nearly close to the observed historical plot but for the month's April and May the maximum bias-corrected plot is exceeding the observed maximum temperature plot. All raw GCMs data for all stations are very close to the observed plot.

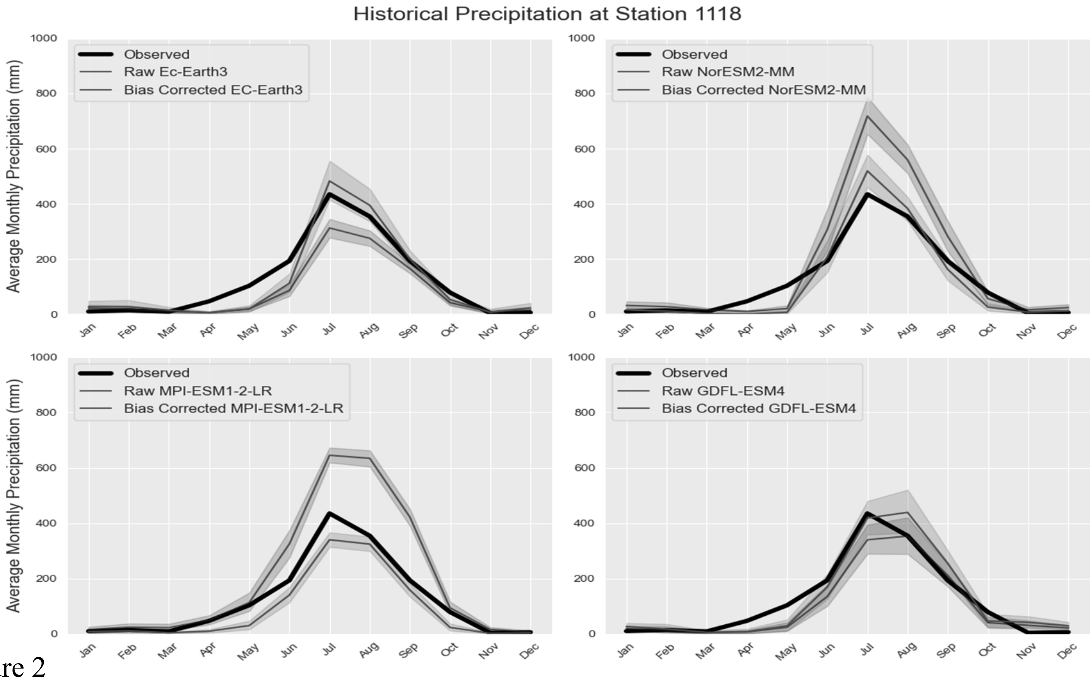

Figure 2

Monthly average observed, raw GCMs, and bias-corrected Precipitation for 1118 Stations from 1985 to 2014.

1.4. Time Series of Maximum and Minimum Temperatures

Precipitation

The projections are accessible for the past (1985-2014) as well as the future (2015-2100). Precipitation is projected for four GCMs and one multi-model ensemble under two scenarios, ssp245 and ssp585. The annual precipitation series of the projected precipitation doesn't show any significant change in the annual precipitation. The annual projected precipitation is in the range of 1000mm to 2000mm under both ssp245 and ssp585 scenarios. The annual projected precipitation under the ssp585 scenario is found to be slightly greater than that of the ssp245 scenario.

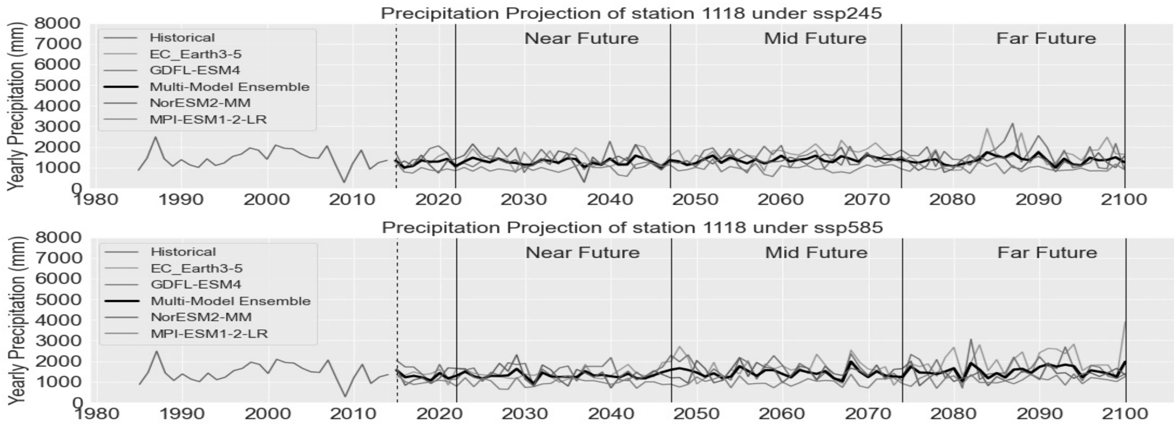

Figure 3 Baseline (1985-2014) annual average precipitation and projected future (Near Future (2022-2046), Mid Future (2047-2073), and Far Future (2074-2100)) average annual precipitation at station 1118 (Manusmara) under two scenarios (ssp245 & ssp585).

Maximum Temperature

The ssp245 scenario anticipated a smaller temperature rise, but the ssp585 scenario predicted a slightly steep rise in temperature for all three GCMs. The figures below show a maximum temperature estimate based on three GCMs and two SSP scenarios. It also shows that maximum temperature is expected to increase in the future. Based on linear transformation bias-corrected data, the projected range of the Multi-Model Ensemble for the maximum temperature under the (ssp245) is between 30°C and 35°C, whereas under the ssp585 scenario is between 30°C and 38°C.

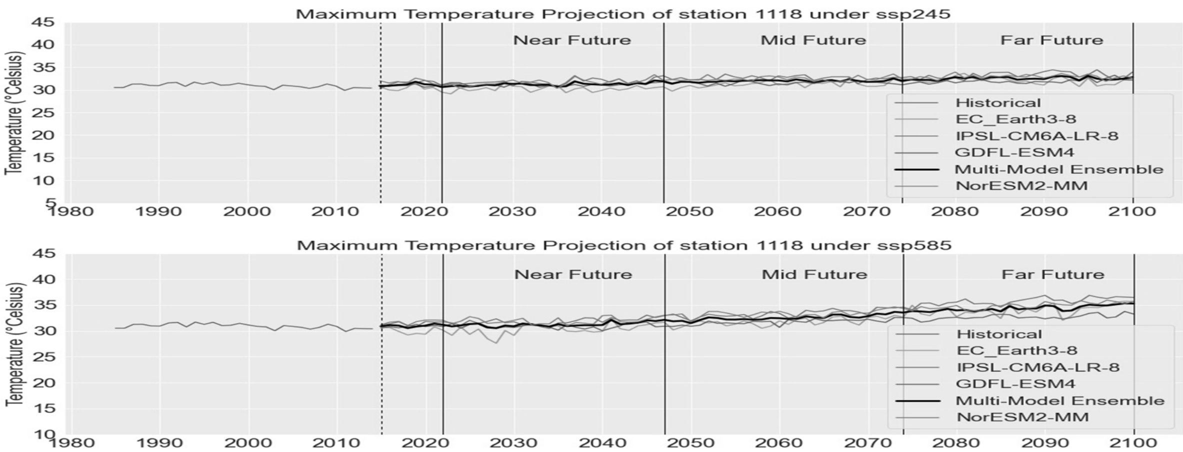

Figure 4 Baseline (1985-2014) annual average Maximum temperature and projected future (Near Future (2022-2046), Mid Future (2047-2073) and Far Future (2074-2100)) average annual Maximum temperature at station 118(Manusmara) under two scenarios (ssp245 & ssp585).

Minimum Temperature

Under both scenarios, the expected minimum temperature for the future time shows a rise in minimum temperature. In terms of minimum temperature, the ssp245 scenario anticipated a lower rise in temperature, but the ssp585 scenario suggested a steeper rise in temperature for all three GCMs. Based on linear transformation bias-corrected data, the estimated range of the Multi-Model Ensemble for the minimum temperature under (ssp245) is between 20° C and 24 ° C, whereas under the ssp585 scenario is between 20° C and 27 ° C

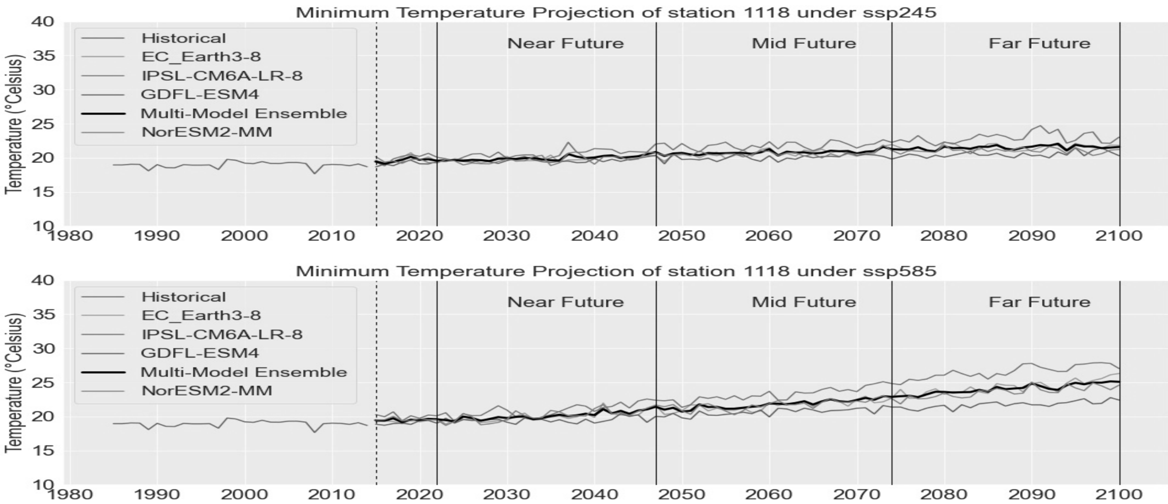

Figure 5 Baseline (1985-2014) annual average Minimum temperature and projected future (Near Future (2022-2046), Mid Future (2047-2073), and Far Future (2074-2100)) average annual Minimum temperature at station 118 (Manusmara)

4. Conclusion

The following is a summary of the key findings.

1) The precipitation and temperature projections of the Bagmati irrigation project area using the latest model CMIP6 are projected with bias-corrected monthly and annually (2015-2100) for two scenarios ssp585 and ssp245. This trend analysis was done for the near (2022-2046), mid (2047-2073), and far (2074-2100) future.
2) According to the findings, GCM models EC-Earth3, NorESM2-MM, GDFL-ESM4, and IPSL-CM6A-LR showed a higher rating for maximum and minimum temperature. These are the models useful for assessing future maximum and minimum temperature of BIP and EC-Earth3, NorESM2-MM, GDFL-ESM4, and MPI-ESM2-MM showed a higher rating for precipitation.
3) Based on the average of combined ratings of all metrics at all selected stations using 13 bias correction methods, the best performing bias correction method for precipitation was as Bernoulli Weibull method. Likewise, the maximum temperature and minimum temperature were bias-corrected by nine methods, and the selection of the best bias correction method was done by using the performance rating of past data. Based on the average of combined ratings of all metrics at all selected stations using 9 bias correction methods, the best performing bias correction method for

maximum temperature was Power transformation and for minimum temperature was Power x_o transformation.

4) The magnitude of the mean annual trend is 0.011°C per year in NF, 0.021°C per year per MF, and 0.025°C per year in FF for maximum temperature under ssp245. Similarly, 0.0127°C per year in NF, 0.072°C per year in MF, and 0.049°C per year in FF are obtained under ssp585 for maximum temperature. Also, the magnitude of the mean annual trend is 0.045°C per year in NF, 0.04°C per year in MF, and 0.039°C per year in FF for minimum temperature under ssp245. Similarly, 0.0588°C per year in NF, 0.076°C per year in MF, and 0.05°C per year-1 in FF are obtained under ssp585 for minimum temperature. Similarly for precipitation, the %change of mean annual trend and monthly percentage change was done under ssp245 and ssp585 scenarios. The analysis above result obtained mean annual data of temperature (maximum and minimum indicated that there is a significant increasing trend for a future period.
5) According to the scenarios ssp245 and ssp585, the analysis revealed that both maximum and minimum temperatures will rise significantly in the future. The rise in future temperature with ssp585 was substantially bigger than with ssp245, in both the maximum and minimum temperature cases. According to the findings, both ssp585 and ssp245 are expected to increase both seasonal and annual precipitation. The projected increase for ssp585 is higher than for ssp245. Overall ssp585 is giving results higher side compared to ssp245.
6) Based on the findings and analysis, it is predicted that precipitation will increase in the study area for a certain period and then decrease, while mean minimum and maximum temperatures will rise in the future. As a result, the requirement for crop water and irrigation water is expected to rise in the future.

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