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21st Century climate change projections of temperature and precipitation in Central Kashmir Valley under RCP 4.5 and RCP 8.5

SYED ROUHULLAH ALI*, JUNAID N. KHAN, ROHITASHW KUMAR, FAROOQ AHMAD LONE, SHAKEEL AHMAD MIR and IMRAN KHAN

Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir – 190 025, India

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***e mail : agarooh@skuastkashmir.ac.in**

सार — **क्षेत्रीय जलवायु मॉडल** (RCMs) **जलवायु परिवर्तन के क्षेत्रीय प्रभाव अध्ययन के लिए अधिक विश्वसनीय परिणाम देते हैं लेकिन उनमें अभी भी एक महत्वपूर्ण पूर्वाग्रह है जिसे जलवायु परिवर्तन अनुसंधान में उपयोग किए जाने से पहले ठीक किया जाना चाहिए। इस अध्ययन में, मासिक पैमाने पर अधिकतम तापमान, न्यूनतम तापमान और वर्षा डेटा के स्थानीय पूर्वाग्रह सुधार के लिए दो तरीकों, अर्थात् संशोधितअंतर दृष्टिकोण** (MDA) **और रैखिक स्केलिंग** (LS) **विधि को लागू किया गया और मॉडल के बीच पूर्वाग्रह को कम करने के लिए मॉडल** (HAD GEM2-ES-GCM) **और मध्य कश्मीर घाटी में प्रेक्षितजलवायु डेटा से वैधीकृत किया गया। मासिक समय पैमाने पर** LS **पद्धति का उपयोग करके प्राप्त किए गए अधिकतम तापमान, न्यूनतम तापमान और वर्षा के संशोधन फलन को मौसम डेटा के पूर्वाग्रह सुधार के लिए** MDA **की तुलना में उत्कृष्ट दिखाया गया ताकि इसे दोनों परिदृश्यों** (RCP4.5 **और** 8.5) **में प्रेक्षित डेटा के करीब बनाया जा सके।** LS **पद्धति का उपयोग करके मध्य कश्मीर घाटी में जलवायु परिवर्तन की सीमा निर्धारित करने के लिए दो परिदृश्यों के बीच तुलना की गई। पिछले** 30 **वर्षों में औसत तापमान और वर्षा क्रमशः** 14.17 **डिग्री सेल्सियस और** 734.06 **मिमी थी, जिसे तुलनात्मक उद्देश्य के लिए आधार रेखा माना गया।** 4.5 **और** 8.5 **के तहत वार्षिक औसत तापमान** (°C) **में सभी तीन समय खंडों में वृद्धि और सुदूर भविष्य** (FF) (2071-2095) **के दौरान क्रमशः** 3.09 **और** 5.72 °C **की अधिकतम वृद्धि देखी गई। जबकि, वार्षिक औसत वर्षा के परिणामों में भी भविष्य के परिदृश्य में वृद्धि देखी गई और** 4.5 **और** 8.5 **के तहत भविष्य के मध्य** (2046-2070) **के दौरान** 29.25 **मिमी** (3.98%) **और भविष्य के अंतिम** (2071-2095) **चरण में** 215.98 **मिमी** (29.42%) **की क्रमशः अधिकतम वृद्धि देखी गई। यह निष्कर्ष निकाला गया कि** RCP 4.5 **की तुलना में** RCP 8.5 **परिदृश्य के तहत जलवायु परिवर्तन काफी महत्वपूर्ण था।**

ABSTRACT. Regional climate models (RCMs) give more reliable results for a regional impact study of climate change, but they still have a significant bias that has to be corrected before they can be utilised in climate change research. In this study, two methods for local bias correction of T_{max}, T_{min} and precipitation data at monthly scales, namely the modified difference approach (MDA) and the linear scaling (LS) method, were applied and validated to minimize the bias between the modelled (HAD GEM2-ES-GCM) and observed climate data in Central Kashmir Valley. T_{max}, T_{min} and precipitation correction functions generated using the LS method on a monthly time scale were shown to be excellent than MDA for bias correction of weather data to make it close to observed data in both scenarios (RCP 4.5 & 8.5). Comparison between two scenarios was done to determine the climate change extent in Central Kashmir Valley using LS method. The past 30 years observed average temperature and precipitation was 14.17 °C and 734.06 mm, respectively considered as a baseline for comparison purpose. Annual $T_{average}$ (°C) showed increase in all the three time slices and maximum increase by 3.09 and 5.72 °C during far future (FF) (2071-2095) under RCP 4.5 & 8.5, respectively. Whereas, the results of average annual precipitation also showed increase in future scenario and maximum increase by 29.25 mm (3.98%) during mid future (2046-2070) and 215.98 mm (29.42%) during end future (2071-2095), under RCP 4.5 & 8.5 respectively. It was concluded that under RCP 8.5 scenario climate change was quite significant than RCP 4.5.

Key words – Climate change, Central Kashmir Valley, Temperature, Precipitation, Representative concentration pathways.

1. Introduction

Systematic errors in the raw outputs of climatic variables from GCM/RCM models might impede their direct use for studying the dynamics of the climate system, it's inevitable changes and their local implications. The yearly and monthly temporal patterns and magnitudes may be affected by errors in predicted

TABLE 1

Details of climate models with resolution and scenarios used in present study [Ogata *et al.* (2014)]

Model	Modelling centre (or group)	Resolution (Lat)- deg	Resolution (Long)- deg	Scenario Involved
BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration	2.812	2.812	4.5 and 8.5
CSIRO-Mk3-0	Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence, Australia	1.895	1.875	4.5 and 8.5
GFDL-ESM -2M	NOAA Geophysical Fluid Dynamics Laboratory	2.000	2.500	4.5 and 8.5
GISS-E2-R	GISS-E2-R NASA Goddard Institute for Space Studies, USA	2.022	2.517	4.5 and 8.5
Had GEM 2-ES	Met Office Hadley Centre, UK	1.250	1.875	4.5 and 8.5

daily climatic variables. Downscaling approaches, either physical process based dynamic downscaling or statistically based downscaling, are essential to minimise systematic biases in models and adapt simulated climatic patterns at coarse grid to a finer geographical resolution of local significance (Maurer and Hidalgo, 2008). Using limited area models or high resolution GCMs, the dynamic method simulates physical processes at fine scales with boundary conditions specified by coarse resolution GCMs. The statistical approach converts coarse scale climate forecasts to a finer scale by training transfer functions that relate the climate at the two geographical resolutions. Chandniha and Kansal (2016) utilised regression-based statistical downscaling in Chhattisgarh, whereas Meena *et al*. (2016) used ANN to downscale rainfall in Madhya Pradesh. Both techniques have been fully documented in terms of their benefits and drawbacks (Fowler *et al*., 2007). The main benefit of the statistical approach is that it requires less computing power than the dynamical model-based alternative; as a result, statistical downscaling techniques are frequently utilized in climate impact research. Statistical downscaling methods are often used on aggregate time scales rather than daily time periods. When used on a daily time period, the perfect analysis assumption that is necessary leaves them vulnerable to GCM biases. Aggregating GCM predictions into seasonal or sub-seasonal (*e.g*., monthly) means, then disaggregating in time using a stochastic weather model to produce synthetic daily weather based on the predictions, is one technique to deal with the problem of daily variability discrepancy (Wilks, 2002; Hansen and Ines, 2005; Feddersen and Andersen, 2005).

Climate change has been one of the most contentious issues in recent years. Climate models are the most common tools used to produce climate change projections.

TABLE 2

RMSE and NRMSE values of models used in present study

Model	RMSE	NRMSE
BCC-CSM1-1	4.71	0.283
CSIRO-Mk3-0	4.89	0.295
GFDL-ESM -2M	5.16	0.314
GISS-E2-R	4.89	0.298
HAD GEM2-ES	4.49	0.272

Climate change is being attributed for changes in temperature and precipitation patterns in the Himalayan area, as well as their effects on natural resources such as water, glaciers, ecology, and agriculture (Dimri and Dash 2012; Shekhar *et al*., 2010). Various researches on climate change in the Himalayas have produced conflicting conclusions on the influence of natural resources. According to Bhutiyani *et al*. (2007), the Northwest Himalayan area has experienced a considerable increase in air temperature of roughly 1.6 °C over the previous century, with winters warming at a quicker pace. Dash *et al*. (2007) reported that the air surface temperature in India increased by around 1 and 1.1 degrees Celsius during the winter and post-monsoon months, respectively, based on observed data and model reanalyzed fields. According to Yadav *et al*. (2004), the cooling trend in mean pre-monsoon temperature is due to a significant drop in minimum temperatures at a pace approximately

TABLE 3

Correction functions derived using modified difference approach for modelled daily temperature and precipitation for IMD Srinagar station under RCP 4.5

Month	T_{max} (°C)	T_{min} (°C)	Precipitation (mm)
Jan	$T_{cor}=8.18+0.797*(T_{mod}-13.59)$	$T_{cor}=-2.35+0.827*(T_{mod}+1.56)$	$P_{cor}=(P_{mod}-0.10)*(0.94)$
Feb	$T_{cor}=10.91+0.803*(T_{mod}-12.24)$	$T_{cor}=0.8+0.827*(T_{mod}-1.58)$	$P_{cor}=(P_{mod}+1.74)*(2.30)$
Mar	$T_{cor}=16.16+0.801*(T_{mod}-17.63)$	$T_{cor}=4.83+0.829*(T_{mod}-5.26)$	$P_{cor}=(P_{mod}+2.33)*(2.51)$
Apr	$T_{cor}=20.11+0.803*(T_{mod}-20.39)$	$T_{cor}=8.56+0.828*(T_{mod}-9.42)$	$P_{cor}=(P_{mod}+2.85)*(3.41)$
May	$T_{cor}=24.81+0.802*(T_{mod}-21.01)$	$T_{cor}=11.52+0.826*(T_{mod}-6.69)$	$P_{cor}=(P_{mod}-1.31)*(0.61)$
Jun	$T_{cor}=28.25+0.804*(T_{mod}-25.68)$	$T_{cor}=15.27+0.827*(T_{mod}-12.97)$	$P_{cor}=(P_{mod}+0.78)*(2.06)$
Jul	$T_{cor}=29.9+0.806*(T_{mod}-29.07)$	$T_{cor}=18.65+0.831*(T_{mod}-17.59)$	$P_{cor}=(P_{mod}-2.23)*(0.48)$
Aug	$T_{cor}=29.61+0.805*(T_{mod}-25.59)$	$T_{cor}=18.16+0.830*(T_{mod}-15.37)$	$P_{cor}=(P_{mod}-0.07)*(0.97)$
Sep	$T_{cor}=27.26+0.808*(T_{mod}-25.31)$	$T_{cor}=13.38+0.829*(T_{mod}-12.57)$	$P_{cor}=(P_{mod}+1.55)*(7.07)$
Oct	$T_{cor}=23.24+0.807*(T_{mod}-20.40)$	$T_{cor}=7.16+0.828*(T_{mod}-3.44)$	$P_{cor}=(P_{mod}-0.79)*(0.48)$
Nov	$T_{cor}=15.84+0.807*(T_{mod}-16.49)$	$T_{cor}=1.74+0.825*(T_{mod}-3.96)$	$P_{cor}=(P_{mod}+0.26)*(1.47)$
Dec	$T_{cor}=10.51+0.813*(T_{mod}-8.96)$	$T_{cor}=-2.2+0.834*(T_{mod}+4.53)$	$P_{cor}=(P_{mod}-0.17)*(0.79)$

TABLE 4

Correction functions derive using modified difference approach for modelled daily temperature and precipitation for IMD Srinagar Station under RCP 8.5

Month	T_{max} (°C)	T_{min} (°C)	Precipitation (mm)
Jan	$T_{cor}=8.18+0.805*(T_{mod}-13.96)$	$T_{cor}=-2.35+0.831*(T_{mod}+1.04)$	$P_{cor}=(P_{mod}-0.18)*(0.90)$
Feb	$T_{cor}=10.91+0.812*(T_{mod}-11.92)$	$T_{cor}=0.8+0.833*(T_{mod}-0.99)$	$P_{cor}=(P_{mod}+2.06)*(3.04)$
Mar	$T_{cor}=16.16+0.809*(T_{mod}17.57)$	$T_{cor}=4.83+0.835*(T_{mod}-4.83)$	$P_{cor}=(P_{mod}+1.33)*(1.52)$
Apr	$T_{cor}=20.11+0.811*(T_{mod}-19.81)$	$T_{cor}=8.56+0.833*(T_{mod}-9.18)$	$P_{cor}=(P_{mod}+3.80)*(17.13)$
May	$T_{cor}=24.81+0.810*(T_{mod}-20.86)$	$T_{cor}=11.52+0.831*(T_{mod}-6.52)$	$P_{cor}=(P_{mod}-1.59)*(0.56)$
Jun	$T_{cor}=28.25+0.813*(T_{mod}-25.82)$	$T_{cor}=15.27+0.833*(T_{mod}-12.93)$	$P_{cor}=(P_{mod}+0.69)*(1.85)$
Jul	$T_{cor}=29.9+0.815*(T_{mod}-29.05)$	$T_{cor}=18.65+0.836*(T_{mod}-17.66)$	$P_{cor}=(P_{mod}-2.08)*(0.49)$
Aug	$T_{cor}=29.61+0.815*(T_{mod}-25.99)$	$T_{cor}=18.16+0.835*(T_{mod}-15.44)$	$P_{cor}=(P_{mod}+0.00)*(1)$
Sep	$T_{cor}=27.26+0.817*(T_{mod}-25.78)$	$T_{cor}=13.38+0.835*(T_{mod}-12.73)$	$P_{cor}=(P_{mod}+1.56)*(7.30)$
Oct	$T_{cor}=23.24+0.816*(T_{mod}-20.82)$	$T_{cor}=7.16+0.833*(T_{mod}-3.56)$	$P_{cor}=(P_{mod}-1.50)*(0.32)$
Nov	$T_{cor}=15.84+0.816*(T_{mod}-16.82)$	$T_{cor}=1.74+0.830*(T_{mod}-4.15)$	$P_{cor}=(P_{mod}+0.20)*(1.33)$
Dec	$T_{cor}=10.51+0.822*(T_{mod}-8.78)$	$T_{cor}=-2.2+0.839*(T_{mod}+4.57)$	$P_{cor}=(P_{mod}-0.01)*(0.98)$

TABLE 5

Correction functions derived using linear scaling for modelled daily temperature and precipitation for IMD Srinagar Station under RCP 4.5

Month	T_{max} (°C)	T_{min} (°C)	Precipitation (mm)
Jan	5.41	0.79	0.94
Feb	1.33	0.78	2.30
Mar	1.47	0.43	2.51
Apr	0.28	0.86	3.41
May	-3.8	-4.83	0.61
Jun	-2.57	-2.3	2.06
Jul	-0.83	-1.06	0.48
Aug	-4.02	-2.79	0.97
Sep	-1.95	-0.81	7.07
Oct	-2.84	-3.72	0.48
Nov	0.65	2.22	1.47
Dec	-1.55	-2.33	0.79

TABLE 6

Correction functions derived using linear scaling for modelled daily temperature and precipitation for IMD Srinagar Station under RCP 8.5

Month	T_{max} (°C)	T_{min} (°C)	Precipitation (mm)
Jan	5.78	1.31	0.90
Feb	1.01	0.19	3.04
Mar	1.41	0	1.52
Apr	-0.3	0.62	17.13
May	-3.95	-5	0.56
Jun	-2.43	-2.34	1.85
Jul	-0.85	-0.99	0.49
Aug	-3.62	-2.72	1.00
Sep	-1.48	-0.65	7.30
Oct	-2.42	-3.6	0.32
Nov	0.98	2.41	1.33
Dec	-1.73	-2.37	0.98

three times larger than the rate of increase in maximum temperatures recorded in local climatic records. Dimri and Dash (2012) reported winter temperature trends, as did Archer and Fowler (2004). Temperatures rose throughout the monsoon and post-monsoon seasons, according to Jhajharia and Singh (2011). The Himalayas, however, cover such a huge area that its sub-regions respond to climate change in a number of ways. India's yearly mean and maximum temperatures have risen by roughly 0.7 and 0.8 degrees Celsius, respectively (Dash *et al*., 2007). Climate change has been seen in several parts of India, including the west coast, central India, the interior peninsula, and the north-east (Dash *et al*., 2007).

2. Data methodology

The present study focuses on the Central Kashmir Valley of Great Himalayas which lies on latitude 34° 3' 2" N, longitude 74° 48' 14" E and altitude of 1590 amsl. Long-term observed maximum temperature (T_{max}), minimum temperature (T_{min}) and precipitation data from IMD Srinagar Station (1989-2019) were collected and used as a baseline. Site specific past and future T_{max}, T_{min} and precipitation were generated from five GCMs, namely, Hadley Center Global Environment Model 2 - Earth System (HADGEM2-ES), GFDLESM-2M, CISRO MK 3-0, BCC-CSM 1-1 and GISS-E2R (Table 1) under the RCP 4.5 (representative concentration pathways) and RCP 8.5, using MarkSim DSSAT weather generator. Geographic coordinates are required by MarkSim GCM. After statistically evaluating for RMSE and NRMSE (Table 2), HAD GEM2-ES was one of the best performer, with the least error followed by BCC-CSM 1-1 and was utilized further for climate projections for the research area.

For local bias correction of T_{max}, T_{min} and precipitation, two basic methods were used: modified difference approach method (equations 1 & 2) and linear scaling method (equations 3 & 4). Modelled climate data from MarkSim DSSAT was available from 2010-2095 and for derivation of correction functions time slice of 2010-2019 was used both observed and modeled (Tables 3, 4, 5 & 6).

Modified Difference Approach (Leander and Buishland 2007):

$$\overline{T(\mathrm{cor})} = \overline{T(\mathrm{obs})} + \frac{\sigma(\mathrm{obs})}{\sigma(\mathrm{mod})} \times \left\{ T(\mathrm{mod}) - \overline{T(\mathrm{obs})} + \left[\overline{T(\mathrm{obs})} - \overline{T(\mathrm{mod})} \right] \right\} \tag{1}$$

$$P_{cor} = \left[P_{mod} + (\mathrm{d}x) \times \left(\frac{\sigma P_{obs}}{\sigma P_{mod}} \right) \right] \tag{2}$$

TABLE 7

Statistical parameters of AFMU SKUAST observed, modelled and model corrected T_{max}, T_{min} and precipitation by modified difference and linear scaling method

Parameter	Observed	Modelled	Modified difference approach	Linear scaling method
T_{max} (°C)				
Mean	20.21	20.93	21.87	20.25
Standard deviation	8.89	10.67	11.71	8.89
Variance	79.03	113.84	137.45	78.23
CV (RMSE)	-	5.11	6.49	5.34
T_{min} (°C)				
Mean	6.63	8.73	9.98	6.71
Standard deviation	7.41	9.74	10.21	8.19
Variance	54.91	94.86	104.38	66.49
CV (RMSE)	-	5.37	6.17	4.59
Precipitation (mm)				
Mean	2.17	1.69	3.12	2.01
Standard deviation	8.57	5.94	8.32	7.32
Variance	73.52	36.03	68.13	52.91
CV (RMSE)	-	9.13	10.93	9.64

where, (μ) mean, (σ) standard deviation, $T_{(cor)}$ corrected temperature, P_{cor} corrected precipitation, $T_{(mod)}$ and P_{mod} modelled/uncorrected daily temperature and precipitation for a scenario, $T_{(obs)}$ and $P_{(obs)}$ observed temperature and precipitation obtained from the baseline scenario. Over bar represents the average over the time period under analysis. The averaged daily difference between observed and modelled values is represented by (d*x*).

Linear Scaling Method (Lenderink *et al.*, 2007):

$$T_{cor,m,d} = T_{mod,m,d} + \mu\left(T_{obs,m}\right) - \mu\left(T_{mod,m}\right) \qquad (3)$$

$$T_{cor,m,d} = P_{mod,m,d} \times \frac{\mu\left(P_{obs,m}\right)}{\mu\left(P_{mod,m}\right)} \qquad (4)$$

where, $P_{cor,m,d}$ and $T_{cor,m,d}$ are corrected precipitation and temperature on the d^{th} day of m^{th} month. $P_{mod,m,d}$ and $T_{mod,m,d}$ are the modelled/uncorrected precipitation and temperature on the d^{th} day of m^{th} month. μ(...) is the expectation operator; for example, ($P_{obs,m}$) is the mean value of observed precipitation for a particular month (*m*).

Model corrected data was divided into three time slices near future (NF) climate change projection (2021-2045), mid future (MF) projection (2046-2070) and far future (FF) projection (2071-2095) and climate change extent was compared with baseline (1989-2019).

3. Results and discussion

Correction functions for T_{max} and T_{min} under RCP 4.5 and 8.5 using modified difference approach were developed using equations 1 & 2 for each calendar month (Tables 3 & 4). For both T_{max} and T_{min} these correction functions were used to the modelled data to get it closer to observed data. The computed statistical parameters of T_{max}

TABLE 8

Average annual based climate predictions for IMD Srinagar station using LS corrected modeled data

	Observed/ Baseline (1989-2019)	4.5			8.5		
		NF (2021-2045)	MF (2046-2070)	FF (2071-2095)	NF (2021-2045)	MF (2046-2070)	FF (2071-2095)
Annual T_{max} (°C)	20.39	21.07	22.37	22.35	21.36	22.99	24.96
Annual T_{min} (°C)	7.96	10.88	11.75	12.16	11.09	12.78	14.83
Annual $T_{average}$ (°C)	14.17	15.96	17.06	17.26	16.23	17.88	19.89
Average Annual Precipitation (mm)	734.06	709.5	763.31	756.24	724.11	828.98	950.04

and T_{min} indicated that differences in mean values were comparable in corrected modelled and observed T_{max} and T_{min} at monthly time scale compared to modelled and observed data after correction, but differences in standard deviation and variation values were higher in corrected and observed T_{max} and T_{min} than in modelled and observed data after correction (Table 7). Correction functions for precipitation based on modified difference approach showed that the differences between the model corrected precipitation and the observed precipitation was more, hence it is not reliable. The variation in mean (μ), standard deviation and variance values was more in model corrected and observed precipitation compared to that of modelled and observed (Table 7).

Under RCP 4.5 and 8.5, correction functions for T_{max} and T_{min} using linear scaling method were developed based on equations 3 and 4 for each calendar month (Tables 5 & 6). For both T_{max} and T_{min} these correction functions complemented the time trends and magnitude of the model corrected and observed temperature. The computed statistical parameters of T_{max} and T_{min} are presented in Table 7. At a monthly time scale, the discrepancies in mean values were comparable in model corrected and observed T_{max} and T_{min}. The corrected and observed T_{max} and T_{min} data had less discrepancies in mean, standard deviation, and variance than the modelled and observed data. The variation between model corrected cumulative precipitation data and observed precipitation was less when correction functions for precipitation based on linear scaling method were used. The variation in mean (μ), standard deviation and variance values were less in model corrected and observed precipitation compared to that of modelled and observed.

The mean, standard deviation, variance and coefficient of variance of root mean squared error (RMSE) for T_{max}, T_{min} and precipitation by different correction methods at monthly time scales (Table 7) shows that minimum coefficient of variation was observed with monthly correction function of linear scaling in both T_{max} and T_{min} in both the RCPs under consideration. On a monthly time scale, the RMSE for the modelled T_{max} was 5.11 %, which was increased to 6.49 % by the modified difference approach but decreased to 5.34 % by the linear scaling method. Modelled T_{min} was 5.37 %, which was improved to 6.17 % using the modified difference approach on a monthly time scale, and 4.59 % using the linear scaling method (Table 7). The modelled cumulative precipitation had an RMSE of 9.13 %. It was enhanced to 10.93 % using the modified difference approach, but was dropped to 9.64% using the linear scaling method (Table 7). Analysing the results linear scaling method accomplished better results than modified difference approach. Further analysis was done using the model corrected data using linear scaling method and corrected scenarios were divided into three time slices to predict the climate change extent while comparing with the baseline.

Analysis under RCP 4.5 & 8.5 scenario from Table 8 average annual T_{max} and T_{min} showed an increasing trend in near future (NF) under both the scenarios. The T_{max} and T_{min} were found increasing at the rate of 3.33% and 36.68% and 4.76% and 39.32% under RCP 4.5 & 8.5 scenario, respectively. The average annual precipitation was found a decreasing trend for the same period under both the scenarios at the rate of -3.35% and -1.35%, respectively (Table 8).

Average T_{max} and T_{min} showed an increasing trend in the mid future (MF) under both the scenarios. T_{max} and T_{min} were also recorded increasing rate of 9.71% and 12.75%, and 41.61% and 60.56%, for RCP 4.5 and 8.5 scenario from baseline, respectively. For both scenarios, the average annual precipitation indicated an increasing trend over the mid future (MF) at a rate of 3.98% and 12.93%, respectively (Table 8).

Average T_{max} and T_{min} showed an increasing trend in the far future (FF) while comparing with baseline under both the scenarios. T_{max} and T_{min} were also recorded increasing rate of 9.61% and 22.41% and 52.76% and 86.31%, for RCP 4.5 and 8.5 scenario from baseline, respectively. The average annual precipitation showed an increasing trend for the end future (EF) under both scenarios at the rate of 3.02% and 29.42%, respectively (Table 8).

Many prior research (Aggarwal and Mall 2002; Mall *et al*., 2006) predicted future climate using modelled climate data from the baseline period (1961-1990) without taking into account observed data. While the current analysis takes into account both observed and station data. Under both RCP 4.5 and 8.5 scenarios, future trends revealed a rise in T_{max}, T_{min} and precipitation. As mentioned in the results, mean temperature and precipitation would increase significantly in all time slices. These findings are in accordance with those of Kumar *et al*. (2011), who used PRECIS under the A1B scenario to show significant warming and increasing rainfall over India by the end of the century, and with Chaturvedi *et al*. (2012), who used multi model outputs for climate projections to show northern India will experience higher levels of warming than the rest of the country. According to the PRECIS climate model, the Indo-Gangetic plains are projected to see a 0.5-1 °C rise in average temperatures in the mid-century and a 3.5-4.5 °C rise at the end-of-century, as well as an increase in the frequency of severely wet rainy seasons. Another research of climate predictions for Ludhiana, Punjab, found that temperatures and rainfall will rise in the mid- and end-century under both RCP 4.5 and 8.5 scenarios (Dar *et al*., 2019).

4. Conclusion

For bias correction of climate data, correction functions derived using the linear scaling method on a monthly time scale for T_{max}, T_{min} and precipitation were found to be better than the modified difference approach. For both scenarios of RCP 4.5 and 8.5, the average annual T_{max}, T_{min} and precipitation observed and model corrected results were very close when applying the linear scaling technique compared to the modified approach. The climate projections for 21st century under the scenario RCP 8.5 showed a significant increase in average annual temperature and precipitation for all the time slices whereas annual climate projections under the scenario RCP 4.5 showed less rise compared to RCP 8.5 scenario.

Disclaimer : The contents and views expressed in this study are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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