Original Research Article

Bias correction of climate model outputs using IMD Srinagar datafor climate change impact assessment

ABSTRACT

Regional climate models (RCMs) give more credible findings for a regional climate change impact assessment, but they still have a bias that must be rectified. Two correction functions using two methods, the modified difference approach and linear scaling method, were utilized for local bias correction of T_{max}, $T_{min,}$ and precipitation data at monthly scales and validated to minimize the bias between modelled (HAD GEM2-ES-GCM) and observed climate data at IMD Srinagar Station, J&K. Linear scaling technique at monthly time scale for T_{max}, T_{min}, and precipitation was superior to modified difference approach for bias correction of modelleddata to close it to observed data.

Keywords: Bias Correction, Central Kashmir,GCM, RCM, modified difference approach, linear scaling method.

1. INTRODUCTION

The raw outputs of GCM/RCM models climatic parameters typically include systematic flaws that impede their direct use for analyzing the climate system's behaviour, changes, and local repercussions. Daily rainfall and temperature errors may affect monthly or yearly trends and magnitude. Physical process-based dynamic downscaling or statistical downscaling is necessary to reduce model biases and adapt simulated climatic patterns at a coarse grid to a smaller geographical resolution of local relevance [1]. The dynamic method employs restricted area models or high-resolution GCMs to simulate fine-scale physical processes with coarse-resolution GCM boundary conditions. Statistical methods use trained transfer functions to link climate projections at different geographical resolutions. Chandniha and Kansal (2016) [2] downscaled rainfall in Chhattisgarh using regression, whereas Meena et al. (2016) utilized ANN [3]. Both techniques have benefits and downsides [4]. Statistical downscaling methodologies are extensively employed in climate impact research because they need less computing than dynamical model-based alternatives. Statistical downscaling is often used on aggregate, rather than daily, time periods. When used everyday, the perfect prediction assumption renders GCMs biassed. One way to reduce daily variability distortion is to aggregate GCM predictions into seasonal or subseasonal (e.g., monthly) averages, then use a stochastic weather model to disaggregate in time to generate synthetic daily weather [5, 6, 7]. In separate studies in Central Kashmir and Ludhiana linear scaling method performed better than other methods while comparing the model corrected data with uncorrected data [8, 9].

2. MATERIALS AND METHODS

The present study focuses on Central Kashmir of the Indian western Himalayas which lies on latitude 34°03'01" N, longitude 74°48'15" E and altitude of 1588 ams (Fig. 1).The station data used for the analysis is IMD Srinagar station. Modified difference technique and Linear scaling approaches were employed to address temperature and precipitation biases in this study. There is often a clear bias from observations in the statistics of variables produced by GCMs such as temperature and precipitation due to limitations in, among others, due to the incorporation of local topography and non-stationary phenomena within the GCMs. A weather file generator (HAD GEM2-ES-GCM) obtained from the Marksim DSSAT weather file generator was used to generate the daily data for 2010-2019.While the observed data was obtained from the IMD Srinagar station.

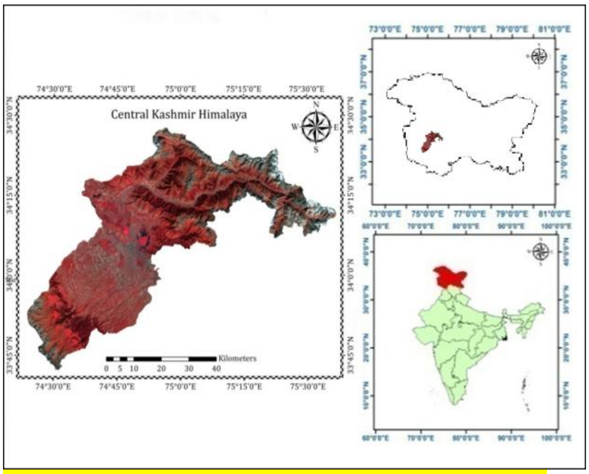

Fig.1. Location map of the Central Kashmir

2.1 Modified difference approach

Statistical parameters were introduced to the modified difference approach to enhance the correction function. Mean (μ) and standard deviation was included as part of the temperature adjustment process to shift and scale the mean (μ) and variance [10].The corrected daily temperature T (cor) is obtained as:

$$\overline{T(cor)} = \overline{T(obs)} + \frac{\sigma(obs)}{\sigma(mod)} \times (T(uncor) - \overline{T(obs)} + (\overline{T(obs)} - \overline{T(mod)}) \quad \textbf{(1)}$$

T (obs) and T (mod) are the daily observed and modelled temperatures from the baseline scenario. T (uncor) is the scenario's uncorrected daily temperature. The overbar in this equation represents the average across the time period being studied.

Several techniques of precipitation correction resulted in a different amount of precipitation being multiplied by σRF_{obs} / σRF_{mod} as:

$$RFmodel_{cor} = (RFmodel_{uncor} + (dx)) \times \left(\frac{\sigma RF_{obs}}{\sigma RF_{mod}}\right) \quad \textbf{(2)}$$

Where (dx) is the averaged daily difference of observed and modelled values.

2.2 Linear scaling method

The Linear scaling (LS) approach ensures that the monthly mean of corrected values is precisely the same as observed values [11]. Correction functions are calculated based on observed and raw data disparities (raw GCM simulated data in this case). On a monthly basis, precipitation and temperature are rectified using a multiplier and an additional term.

The linear scaling multipliers and additives are derived from the following formulas:

$$T_{cor,m,d} = T_{raw,m,d} + \mu(T_{obs,m}) - \mu(T_{raw,m}) \quad \textbf{(3)}$$

$$P_{cor,m,d} = P_{raw,m,d} \times \frac{\mu(P_{obs,m})}{\mu(P_{raw,m})} \quad \textbf{(4)}$$

Where P_{cor}, *m, d* and T_{cor}, *m, d* are corrected precipitation and temperature on the *d*th day of *m*th month, andP_{raw}, *m, d* andT_{raw}, *m, d* are the raw precipitation and temperature on the*d*th day of *m*th month. *μ*(...) represents the expectation operator (e.g. $\mu(P_{obs}, m)$ represents the mean value of observed precipitation at given month *(m)*.

3. RESULTS AND DISCUSSIONS

The ten year (2010-2019) observed,modelled and corrected climate variables by both the correction functions are presented in Table 1.

3.1 Modified difference approach

3.1.1 Temperature

Correction functions based on the modified difference [10] were developed (equation 1) for each of the calendar months and are presented in (Table 1). The use of these correction functions to correct the modelled data to make it close to observed data for both T_{max} and T_{min}. The computed statistical parameters of T_{max} and T_{min} are presented in Table 3. The differences in μ values were comparable in corrected modelled and observed T_{max} and T_{min} at a monthly time scale compared to that of modelled and observed data after correction, but differences in σ, σ^2 values in corrected and observed T_{max} and T_{min} were lesser than that of the modelled and observed data.

3.1.2 Precipitation

Correction functions were developed using a modified difference approach (equation 2), for monthly basis and these functions for each calendar month are presented in Table 1.With modified difference approach (equation 2), the variation in cumulative model corrected to that of the observed precipitation was increased, which is unreliable. The variation in μ, σ, and σ^2 values was more in corrected modelled and observed precipitationthan that ofmodelled and observed (Table 3).

3.2 Linear scaling method

3.2.1 Temperature

Correction functions based on the linear scaling method were developed based on equation 3 for each calendar month and are presented in Table 2. These correction functions matched the time trends and magnitude of the model corrected and observed temperature for both $T_{max}$and T_{min}respectively. The computed statistical parameters of T_{max} and T_{min} are presented in Table 3. The differences in μ values were comparable in corrected modelled and observed T_{max} and T_{min} at monthly time scale. The differences in σ, σ^2 values in corrected andobserved T_{max} and T_{min} were lesser than that of the modelled and observed data.

3.2.2 Precipitation

Correction functions based on linear scaling method of bias correction were developed based on (equation 4) for monthly basis and these functions for each calendar month are presented in Table 2.With linear scaling method, variation in the cumulative model corrected to that of the observed precipitation was decreased. The variation in μ, σ and σ^2 values was less in corrected modelled and observed precipitation than that ofmodelled and observed (Table 3).

3.3 Best estimate

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 3) shows that minimum coefficient of variation was observed with monthly correction function of linear scaling in both T_{max} and T_{min}. On a monthly time scale, the RMSE for the modelledT_{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 for IMD Srinagar station. RMSE for modelledT_{min} was 5.37 %, which was modified to 6.17 % using the modified difference approach on a monthly time scale, and 4.59 % using the linear scaling method (Table 3) for IMD Srinagar station.The RMSE for the modelledcumulative precipitation was 9.13 per cent. It was increased to 10.93per cent by modified difference approach while as itwas reduced to 9.64 per cent by linear scaling method.Summing all these linear scaling method performed betterthan modified difference approach.

It can be seen from Table 3 that using a monthly correction function of linear scaling results in the lowest coefficient of variation for T_{max} and T_{min}, as well as the μ, σ, σ2, and coefficient of variance of root mean squared error (RMSE). For IMD Srinagar station linear scaling technique reduced the modelledT_{max} RMSE by 5.34 percent on a monthly time scale compared with the modified difference approach, which raised it to 6.49 percent (Table 3). When utilising the modified difference approach on a monthly time scale and the linear scaling method for the IMD Srinagar station, the model's RMSE for T_{min} was 6.17 percent and 5.37 percent, respectively. The root mean square error was 9.13% for the modeled total precipitation. While linear scaling lowered it to 9.63 percent, the modified difference approach increased it to 10.93 percent. The modified difference technique was outperformed while comparing with linear scaling method.

Table 1: Correction functions derived using modified difference approach for modeled 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 2: Correction functions derived using linear scaling for modelled 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 3: Statistical parameters of IMD Srinagar Station 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} (^oC)				
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} (^oC)				
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

4. CONCLUSION

In Central Kashmir in the Great Himalayas, this article analyses the performance of RCM correction approaches for (precipitation and temperature bias). It is impossible to directly employ RCM results in climate change analysis since they are highly biased. The region and seasonality significantly impact how the RCM simulations appear. Although the bias correction approach greatly determines their outcomes, all bias correction methods can increase the accuracy of precipitation and temperature. In the GCM HAD GEM2 ES Model, downscaled data indicated that temperature data had a more significant bias than precipitation data. Bias correction of climate data was more effective using linear scaling methods at monthly time scales for T_{max}, T_{min}, and precipitation than modified difference approaches.

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