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Comparing bias correction methods in downscaling meteorological variables for climate change impact study in Ludhiana, Punjab

MEHRAJ U DIN DAR*, RAJAN AGGARWAL and SAMANPREET KAUR

Department of Soil and Water Engineering, PAU, Ludhiana

**Email:mehrajudindar24@gmail.com*

ABSTRACT

Although regional climate models (RCMs) provide more reliable results for a regional impact study of climate change,however a considerable bias still exists that needs to be corrected before they are used for climate change research. In this study two correction functions using two methods viz. modified difference approach and linear scaling method were applied for local bias correction of T_{max}. T_{min} and rainfall data at monthly scales and validated to minimize the bias between the modelled (HAD GEM2-ES-GCM) and observed climate data at Ludhiana, Punjab.Correction functions derived using linear scaling method at monthly time scale for Tmax, Tmin and rainfall were found to be better than modified difference approach for bias correction of the weather data to bring it to close to observed data.

Keywords: Bias Correction, GCM, RCM, modified difference approach, linear scaling

The raw outputs of the climatic parameters from GCM/RCM models often suffer from systematic errors which may prevent their direct application for the analysis of the behavior of the climate system, its eventual changes and their local impacts. The errors in modelled daily rainfall and temperature may afflict the monthly or annual time trends and magnitude. Downscaling approaches, either physical process based dynamic downscaling or statistically based ones, are required to remove systematic biases in models and transform simulated climate patterns at coarse grid to a finer spatial resolution of local interest (Maurer and Hidalgo 2008). The dynamic approach uses limited area models or high resolution GCMs to simulate physical processes at fine scales with boundary conditions given by the coarse resolution GCMs. The statistical approach transforms coarse scale climate projections to a finer scale through trained transfer functions that connect the climate at the two spatial resolutions. Chandniha and Kansal (2016) used regression based statistical downscaling for rainfall in Chhattisgarh, while Meena *et al.* (2016) used ANN for downscale rainfall in Madhya Pradesh. The advantages and disadvantages of both approaches have been thoroughly documented (Fowler *et al.,* 2007). The key advantage of the statistical approach is the lower computational requirement compared to the dynamical model–based alternative, and thus, statistical downscaling approaches are widely used in climate impact–related research work. Statistical downscaling approaches are generally applied to aggregate rather than daily time scales. When they are applied at a daily time scale, the perfect prognosis assumption required makes them quite susceptible to GCM biases. One approach to addressing the problem of distortion of daily variability is to aggregate GCM predictions into seasonal or sub seasonal (e.g. monthly) means, then use a stochastic weather model to disaggregate in time to produce synthetic daily weather that is conditioned on the predictions (Wilks, 2002; Hansen and Ines, 2005; Feddersen and Andersen, 2005).

MATERIALS AND METHODS

Two simple methods (1) modified difference approach and (2) linear scaling method have been used for local bias correction of temperature and rainfall. The daily data was obtained from Marksim DSSAT weather file generator under GCM(HAD GEM2-ES-GCM) for the period of 2010-2016. While the observed data were obtained from Agrometeorological observatory, Punjab Agricultural University, Ludhiana.

Modified difference approach

In the modified difference method some statistical parameters were added to improve the correction function. For example in temperature correction, mean (μ) and standard deviation were added which aimed at shifting and scaling to adjust the mean (μ) and variance (Leander and Buishand 2007). The corrected daily temperature T (cor) is obtained as:

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

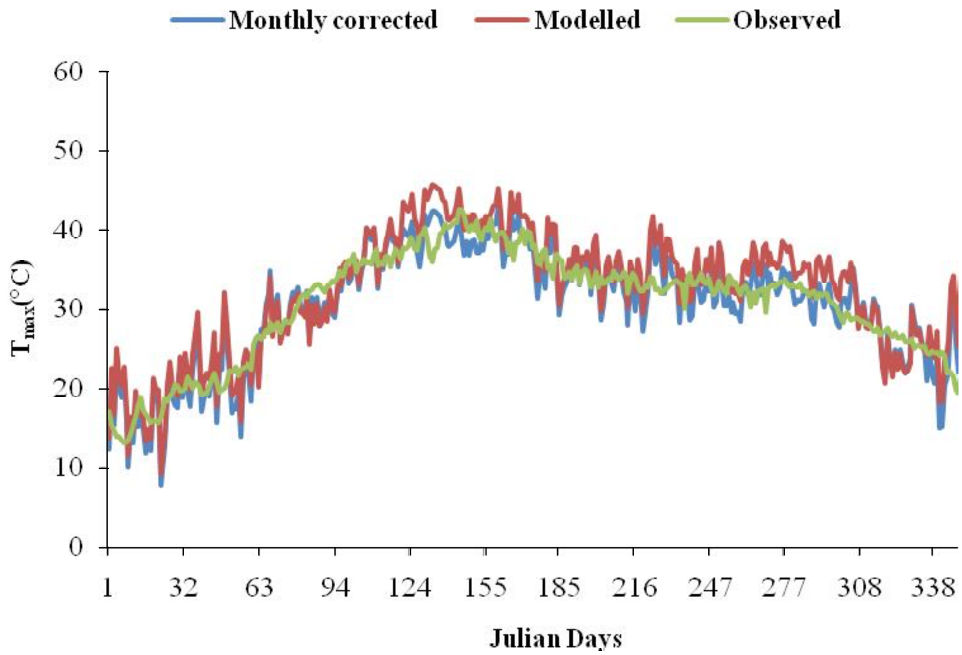

Fig 1: Observed, modelled and model corrected maximum temperature by linear scaling method

Where T (uncor) is the uncorrected daily temperature for a scenario, T (obs) and T (mod) is the observed and modelled daily temperature obtained from the baseline scenario. In this equation an over bar denotes the average over the considered period.

Similarly in case of rainfall correction, the resulting rainfall from different methods was multiplied by σRF_{obs} / σRF_{mod} as:

$$RF\ model_{cor} = (RF\ model_{unncor} + (\Delta x)) * (\sigma RF_{obs} / \sigma RF_{mod}) \quad (2)$$

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

Linear scaling method

The linear scaling method aims to perfectly match the monthly mean of corrected values with that of observed ones (Lenderink *et al* 2007). It operates with monthly correction values based on the differences between observed and raw data (raw GCM simulated data in this case). Precipitation is typically corrected with a multiplier and temperature with an additive term on a monthly basis.The multipliers and additives are based on the formulas given under linear scaling which are:

$$P_{cor,\ m,\ d} = P_{raw,\ m,\ d} \times \mu\ (P_{obs,\ m}) / \mu\ (P_{raw,\ m}) \quad (3)$$

$$T_{cor,\ m,d} = T_{raw,m,d} + \mu(T_{obs,m}) - \mu(T_{raw,m}) \quad (4)$$

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

RESULTS AND DISCUSSIONS

The seven year (2010-2016) observed, modelled and corrected by both the correction functions are presented in Table 1, while daily comparisons are mode with linear scaling methods and presented in Fig. 1 to 3 for temperature and rainfall.

Modified difference approach

Correction functions for T_{max} and T_{min} based on modified difference were developed for each of the calendar month. These correction functions were applied to 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} suggested that the differences in the mean values were comparable in corrected modelled and observed T_{max} and T_{min} at monthly time scale compared to that of modelled and observed data after correction, but differences in standard deviation and variation values in corrected and observed T_{max} and T_{min} were lesser than that of the modelled and observed data (Table 1).

Correction functions for rainfall based on modified

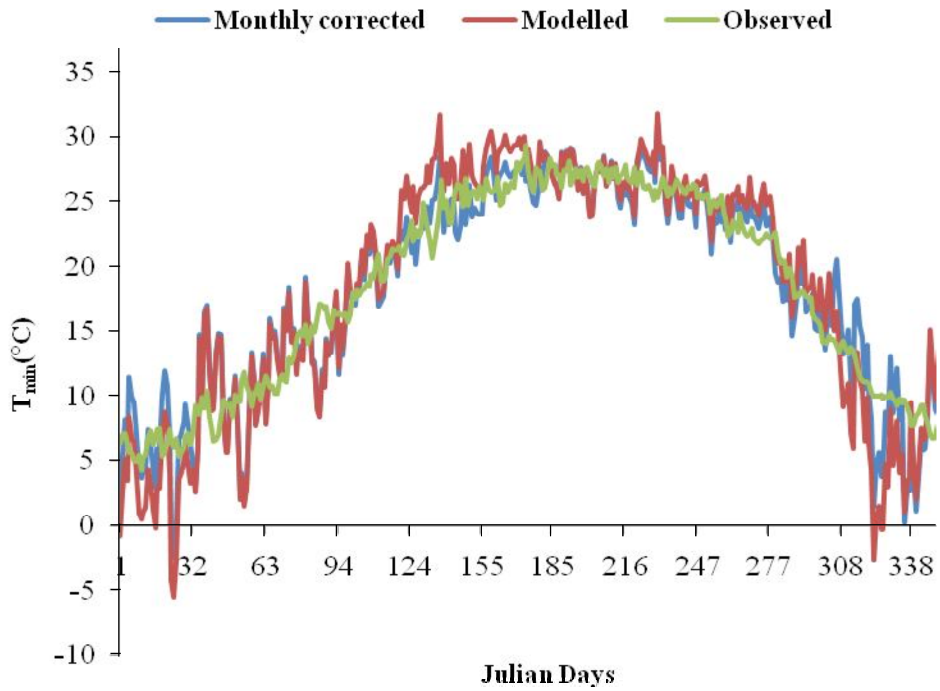

Fig 2: Observed, modelled and model corrected minimum temperature by linear scaling method

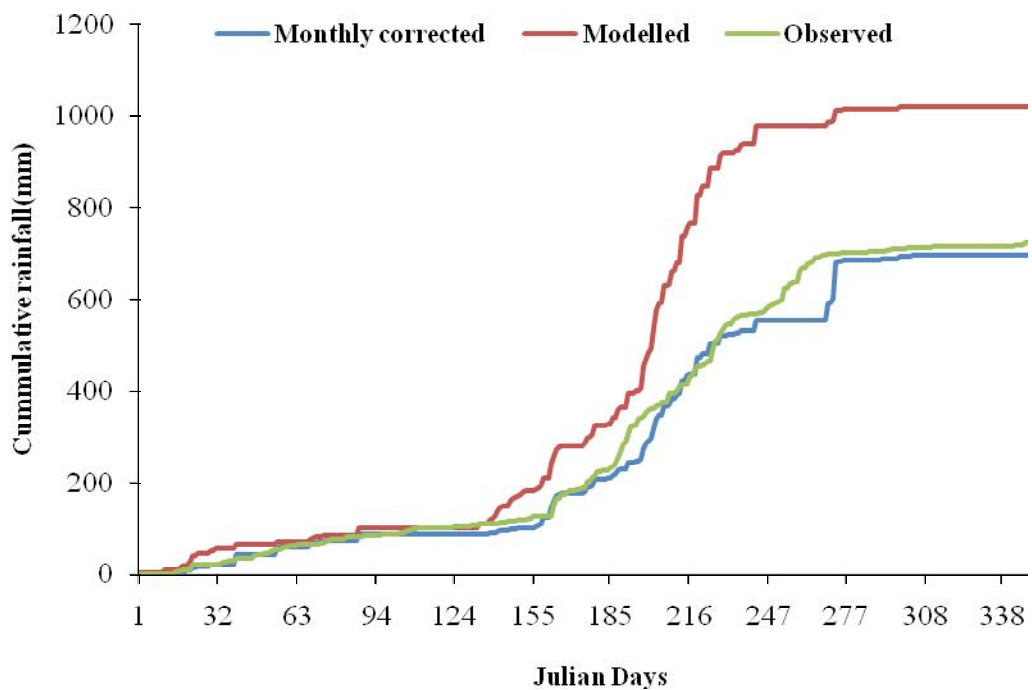

Fig 3: Observed, modelled and model corrected rainfall by linear scaling method

difference approach showed that the differences between the model corrected rainfall and the observed rainfall was more, hence it is not reliable. The variation in mean (μ), standard deviation and variance values was more in corrected modelled and observed rainfall compared to that of modelled and observed (Table 1).

Linear scaling method

Correction functions for T_{max} and T_{min} based on linear scaling method were developed based on equations 3 and 4 for each of the calendar month. These correction functions matched the time trends and magnitude of the model corrected and observed temperature for both T_{max} (Fig. 1) and T_{min}

Table 1: Statistical parameters of observed, modelled and model corrected T_{max}, T_{min} and rainfall by modified difference and linear scaling method

Parameter	Observed	Modelled	Modified difference approach (monthly)	Linear scaling method (monthly)
T_{max}(°C)				
Mean	30.05	31.71	30.1	30.1
Standard deviation	8.60	7.80	4.04	3.04
Variance	73.9	60.8	16.32	9.24
CV (RMSE),%	—	7	13	5
T_{min}(°C)				
Mean	17.65	17.78	17.69	17.69
Standard deviation	8.08	9.40	2.68	2.76
Variance	65.2	88.3	7.18	7.61
CV (RMSE),%	—	6	4	5
Rainfall (mm/day)				
Mean	2.01	2.79	4.69	2.69
Standard deviation	6.80	5.13	8.06	6.75
Variance	46.24	26.31	64.96	45.5
CV (RMSE),%	——	26	38	15

(Fig. 2) respectively. The computed statistical parameters of T_{max} and T_{min} are presented in Table 1. The differences in mean values were comparable in corrected modelled and observed T_{max} and T_{min} at monthly time scale. The differences in mean, standard deviation and variance values in corrected and observed T_{max} and T_{min} were lesser than that of the modelled and observed data.

Correction functions for rainfall based on linear scaling method showed that the variation between model corrected cumulative rainfall data and observed rainfall was less (Fig 3). The variation was of 20 mm at monthly time scale. The variation in mean (μ), standard deviation and variance values were less in corrected modelled and observed rainfall 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} and T_{min} and rainfall by different correction methods at monthly time scales (Table 1) shows that minimum coefficient of variation was observed with monthly correction function of linear scaling in both T_{max} and T_{min}. The NRMSE for the modelled T_{max} was 7 per cent, which was increased to 13 per cent by modified difference approach but was reduced to 5 per cent by linear scaling method on monthly time scale. The corresponding value for modelled T_{min} was 6 per cent, which was reduced to 4 per cent by modified difference approach on monthly time scale, 5 per cent by linear scaling method. The NRMSE for the modelled cumulative rainfall was 26 per cent. It was increased to 38 per cent by modified difference approach while as it was reduced to 15 per cent by linear scaling method. Summing all these linear scaling method performed better than modified difference approach.

CONCLUSION

Raw GCM simulations are heavily biased from observed meteorological data and this resulted in biases inthe simulated climate change results. Downscaled data showed that temperature was having more bias than precipitation data using the GCM HAD GEM2 ES Model. Correction functions derived using linear scaling method at monthly time scale for T_{max}, T_{min} and rainfall were found to be better than modified difference approach for bias correction of the weather data.

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