Statistical Downscaling of Minimum Temperature of Raipur (C.G.) India

R.K. Jaiswal, H.L. Tiwari, A.K. Lohani and R.N. Yadava

Abstract The future projected climate parameters obtained from using generalized circulation models (GCMs) cannot be used directly on regional or basin scale because of coarse resolution. The dynamic or statistical downscaling procedures are used to convert global scale output to regional scale condition. The statistical downscaling because of its less computational skills is preferably used for generation of future climate and in the present study, minimum temperature of Raipur was forecasted for three future periods using Canadian Global Climate Model (CGCM) predictors for A1B and A2 climate forcing conditions. The statistical downscaling model (SDSM) has been used using *k-fold* validation technique for generation of multitemporal series for periods FP-1 (2020–2035), FP-2 (2046–2064), and FP-3 (2081–2100). The specific humidity at 850 hpa (ncep-s850gl), 500 hpa geopotential height (ncepp500gl), and surface airflow strength (ncep_fgl) were found to be the most appropriate parameters to generate future scenarios. The comparison of mean monthly minimum temperature of generated scenarios with base period confirmed 1.1–11.2% increase of minimum temperature under A1B climate forcing and 2.88–24.44% in summer months will have adverse effect on various demands and human health in future and adaptation measures need to be devised for the region.

Keywords Climate change · Generalized circulation model (GCM)
Regional circulation model (RCM) · Downscaling · Predictor · Predictand

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Introduction

The different reports of Intergovernmental Panel on Climate Changes (IPCC 2003, 2007) and other independent researches have confirmed that climate is changing on global and regional scale which is likely to affect availability and supplies of water (Milly et al. 2005; Gleick 1987), health, agriculture, and livestock (McCarthy et al. 2001; Ravindran et al. 2000; FAO 2001; Menzel et al. 2006; Sivakumar et al. 2012) and many more areas of human life. It can be emphasized here that changing climate has intensified probability of extreme events such as floods (Milly et al. 2002, 2005), droughts (Huntington 2006), etc. The temperature among other climatological parameters is the most important and easily detectable parameter to show impact of climate change on water availability and demands, agriculture production, human health, and many more areas of life. The prediction of future climate, its implication, and adaptation measures are keys to cope up the future challenges.

This problem of coarse grid data can be solved by downscaling GCMs to local and basin scale with the help of dynamic or statistical downscaling techniques that bridge the large-scale atmospheric conditions with local scale climatic data (Wilby and Wigley 1997; Xu 1999; Fowler et al. 2007; Tisseuil et al. 2010; etc.). The dynamic downscaling techniques use physically based model run in time slice mode and limited area (Giorgi and Mearns, 1999) having major drawback of dynamic downscaling is its complexity and high computation cost (Anandhi et al. 2008) and propagation of systematic bias from GCM to RCM (Salathe 2003). However, statistical downscaling techniques are reasonably accurate in developing relationships between GCM predictors and regional/station climatic data (Fowler et al. 2007), simple, flexible in adjustment and movement to different regions, less costly, and computationally undemanding in comparison to dynamic downscaling proved its reliability and compatibility in future projections (Hewitson and Crane 2006; Tripathi and Nanjundiah 2006; Lopes 2008; Ethan et al. 2011). In the present study, statistical downscaling model (SDSM 5.2) has been used to predict variability in minimum temperature using Canadian Global Circulation Model (CGCM) weather predictor data for A1B and A2 SRES scenarios.

Statistical Down Scaling Model (SDSM)

The SDSM is user-friendly software developed under sponsorship of A Consortium for Application of Climate Impact Assessments (ACACIA), Canadian Climate Impacts Scenarios (CCIS) Project and Environment Agency of England and Wales. The SDSM can develop multiple, low-cost scenarios of daily surface weather variables using seven key functions namely quality control and data transformation, selection of downscaling predictor variables, model calibration, weather generator, data analysis, graphical analysis, and scenarios generation for the task of daily weather downscaling and forecasting. The quality control function is used to identify the gross error, gaps, statistics, and outliers in the data which is an important step prior to calibration. The spatial and temporal variability in explanatory power of predictors makes selection of appropriate predictors difficult and screen variable operation in SDSM assists examination of seasonal variation, intercorrelation in predictors, and their correlations with predictand. The scatter diagram, correlation, partial correlation, explained variance, etc., can be used to select suitable predictors to develop statistical relationships.

After selecting the most appropriate predictors, the calibrate model tab is used to develop multiple linear regression techniques with efficient dual simplex algorithm (forced entry method) to develop a relationship between predictand and user specified set of predictors in conditional (in case of precipitation) or unconditional (in case of temperature, wind speed, etc.) process. The synthetic series for future periods can be generated using weather generator tab of SDSM software using developed relationships from calibration and CGCMs obtained predictors set from future periods. The SDSM links automatically all required predictors in a regression model developed in calibration process for a user specified period. The data analysis operation in SDSM model is carried out using summary statistics and frequency analysis operation. The frequency analysis tab is useful to compare observed and synthesized series with the help of quantile plot, PDF plot, line plot, and frequency analysis. The time series analysis tool is used to analyze observed and modeled series graphically. The scenario generation can be used to generate ensembles of synthetic daily weather series giving a treatment of percent changes in mean, occurrence or variance or linear, exponential or logistic trend in any series. The detail about the application of SDSM can be found in Goodess et al. (2003), Wilby and Dettinger (2000), Wilby et al. (2001, 2003). The graphical representation of various steps used in SDSM based downscaling can be seen in Fig. 1.

Study Area and Data Used

The study area for the present study is Raipur city, the capital of Chhattisgarh state of India. The Raipur is an important city of eastern India and has large-scale commercial and industrial development since its inception of capital of Chhattisgarh state in 2000. The river Seonath, an important tributary of river Mahanadi, passes through the city and is used to supply water for industrial and domestic demands of district. The map of the study area is presented in Fig 2. The long-term series of observed daily minimum temperature from 1971 to 2003 of Raipur city, the capital city lying in upper Mahanadi basin, has been used for calibration and validation of statistical model. The NCEP reanalyzed predictors from 1971 to 2003 and SRES A1B and B2 data of Canadian Global Circulation Model CGCM 3.1/T47 from 2001 to 2100 were used to generate future scenarios.

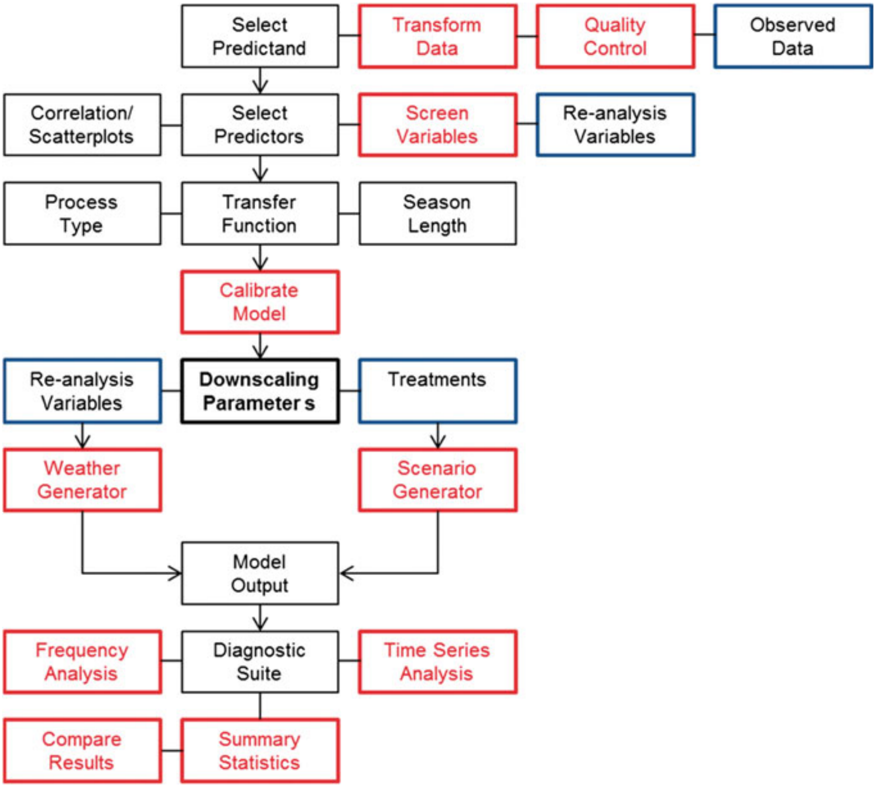

Fig. 1 Work flow in SDSM-DC (reproduced from Wilby et al. 2014)

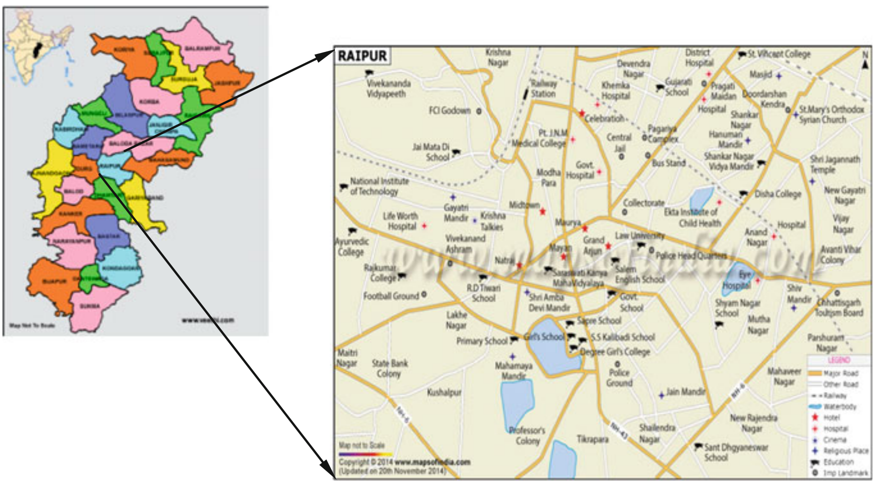

Fig. 2 Location of Raipur in Chhattisgarh state of India

Methodology

The methodology for application of SDSM for generation of minimum temperature series for future climatic scenarios consists of verification of predictand and predictors series, analysis of predictand, predictor relationship, and selection of appropriate predictors which can explain the temporal and spatial variability of predictand with reasonable degree of agreement, calibration and validation of model, generation of future time series using GCM predictors series, computation of statistics and comparison of statistics of present and future scenarios. In the present study, correlation coefficient, partial correlation coefficient, and *P*-value-based method along with scatter diagram were used. The correlation coefficients between predictand (precipitation) and predictors (26 NCEP rescaled parameters) were computed using unconditional approach for annual, monthly, and monsoon season (Mahmood and Babel 2013, 2014). The correlation coefficients were then arranged in descending order and top ten predictors were selected for further analysis. The predictors ranked first in this process can be termed as super predictor (SP) and using this super predictor, absolute correlation coefficient, absolute partial correlation, and the *P*-value were computed for remaining nine predictors with predictand. In order to avoid multicollinearity, all predictors having *P*-value more than 0.05 and other predictors having high individual correlation with super predictor (more than 0.70 for this study) were removed from consideration. The percentage reduction (PR) was then computed for remaining predictors using following equation (Pallant 2007).

$$\mathrm{PR} = \frac{\mathrm{Pr} - R}{R}, \tag{1}$$

where Pr and R are the partial and absolute correlation coefficient, respectively. At the end, a predictor having lowest PR value was considered the second super predictor. Similar approach was applied to get third, fourth, and other predictors. In general, one to three predictors are sufficient to model climatic variability (Xu 1999; Chu et al. 2010). After selecting the appropriate predictors, empirical relations between predictand and selected predictors were developed considering appropriate transformation, process (conditional for precipitation and unconditional for other climatic parameters), *k*-fold cross validation, and model types (monthly, seasonal or annual model). The whole series of predictor and selected predictands of base period is divided in two parts considering *k*-fold cross validation technique available in SDSM-DC. In this technique, the whole series can be divided into k equal size subsamples, where one sample is used for calibration while remaining for testing or validation (Bedia et al. 2013; Casanueva et al. 2014). If results of calibration and validation were found appropriate, the weather generator in SDSM can be used to generate future predictor series using predictors obtained from different GCM scenarios.

Analysis of Results

In the present study, SDSM 5.2 software has been employed to generate minimum temperature series for current and future climate forcing. For the present study, 26 NCEP rescaled predictors for the period of 1971–2003 and predictor as minimum temperature series of Raipur (Chhattisgarh) for the same period were analyzed. The scatter diagram, correlation coefficient, and partial correlation based percentage reduction were used to identify an appropriate combination of predictors which can forecast predictand with acceptable degree of error. The scatter diagram of few predictors was presented in Fig. 3. The specific humidity at 850 hpa (nceps850gl) displayed the highest correlation coefficient as 0.649 and was considered as the first super predictor. The PR values of remaining nine predictors having next highest correlation were computed and 500 hpa geopotential height (ncepp500gl) and surface airflow strength (ncep_fgl) were shortlisted as second and third super predictor for calibration. The threefold cross-validation was used which divided the whole series of data from 1971 to 2003 into two parts where first two-third parts were considered for calibration while remaining one-third part for validation.

The coefficient of determination (*R*2) and standard error for different months during calibration and validation obtained from analysis are presented in Table 1. From the analysis, it has been observed that the standard error varies from 1.01 to 3.45 in calibration and 1.20 to 3.60 in validation. The Nash–Sutcliff efficiency of minimum temperature for calibration and validation was computed as 71.55 and 73.89%, respectively, which may be considered as reasonably acceptable match. The comparison of observed versus calibrated and validated mean monthly minimum temp of Raipur has been presented in Fig. 4. The finally selected parameters in calibration were further used to synthetically generate time series of minimum temperature under CGCM supplied data of A1B and A2 forcing conditions.

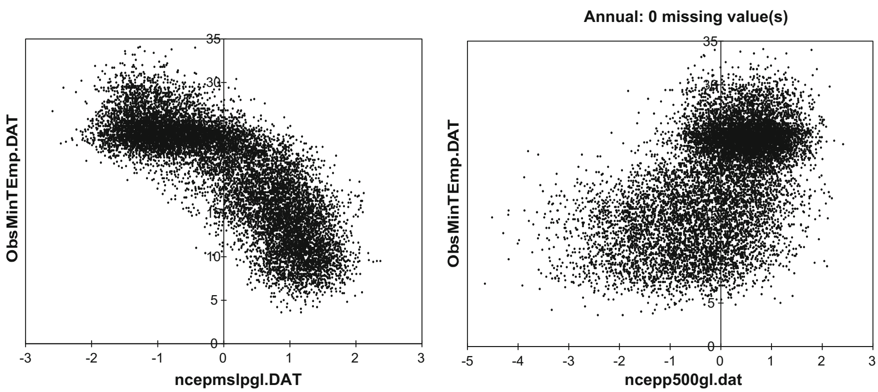

Fig. 3 Scatter diagram for few predictors used in calibration

Table 1 Coefficient of determination and standard error during calibration and validation

Month	Calibration		Validation	
	*R*2	Std. error	*R*2	Std. error
January	0.0241	3.1167	0.0025	3.1807
February	0.0042	2.9721	0.0014	3.0024
March	0.0183	2.7412	0.0021	2.7810
April	0.0682	2.6013	0.0140	2.7221
May	0.0212	2.5334	0.0020	2.6341
June	0.1180	2.3174	0.0648	2.4051
July	0.0031	1.2724	0.0749	1.3794
August	0.0199	1.1167	0.0302	1.2006
September	0.0146	1.1001	0.0487	1.1999
October	0.1072	2.5883	0.0162	2.8488
November	0.0667	3.4525	0.0190	3.5963
December	0.0462	2.7824	0.0020	2.9153
Mean	0.0426	2.3829	0.0232	2.4888

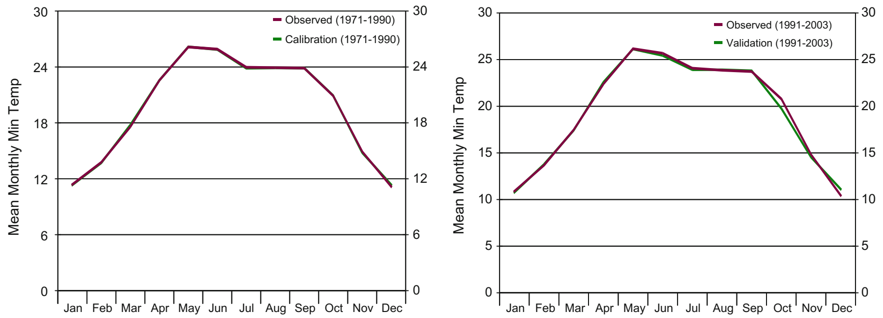

Fig. 4 Observed and calibrated/validated mean monthly minimum temperature in SDSM

CGCM A1B Forcing Condition

The finally selected combination of variables with calibrated parameters was used to synthetically generate 20 series for three future periods FP-1 (2020–2035), FP-2 (2046–2064) and FP-3 (2081–2100) using gridded predictors obtained from Canadian general circulation model (CGCM) under climatic forcing condition of A1B. The statistics including mean monthly minimum temperature, peak below threshold (PBT: number of days/year below 10 °C minimum temperature), variance, inter-quantile range, etc., were computed. The mean monthly minimum temperature and PBT of base period (1971–2003) and all three periods FP-1, FP-2, and FP-3 can be seen in Fig. 5. From the analysis, it has been observed that mean monthly minimum temperature may increase by 1.1–11.2% during summer months

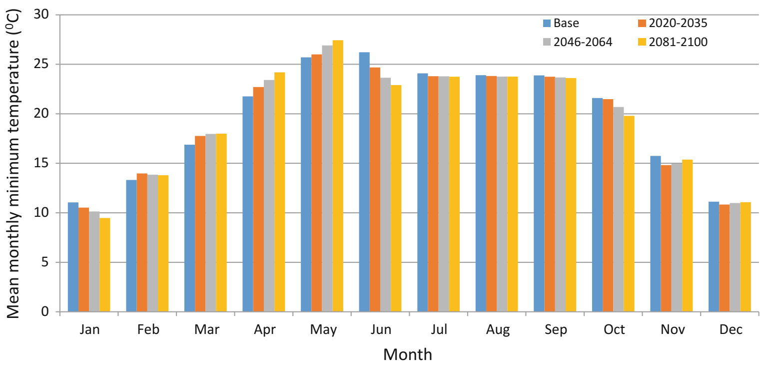

Fig. 5 Comparison of mean monthly minimum temperature for different periods of generated data with observed data under A1B climatic scenario

(February to May) in all three future predictive periods while decrease by 0.5–14.2% in remaining months (June to January) under A1B climate forcing condition. The average number of days/year below 10 °C may increase in November and January while decrease in all other months.

Generation of Series for A2 Forcing Condition

The weather generator tab of SDSM was used to generate 20 ensembles for three different periods FP-1 (2020–2035), FP-2 (2046–2064), and FP-3 (2081–2100) using CGCM gridded data under A2 forcing condition. The generated series for all the periods was used to compute statistics including mean, maximum, peak below threshold (10 °C), variance, etc., and compared with the same for the period 1973–2003. The mean monthly minimum temperature series for different periods with observed data has been presented in Fig. 6. From the analysis, it has been found that the mean monthly minimum temperature may increase by 2.88–24.61% in most of the months except June to October where there may be slight decrease of minimum temperature. The increased minimum temperature during summer and winter months may increase user demands and water requirements of crops in rabi season. The number of cold days below 10 °C may increase significantly in November and January while decrease slightly in December and February in all three future periods.

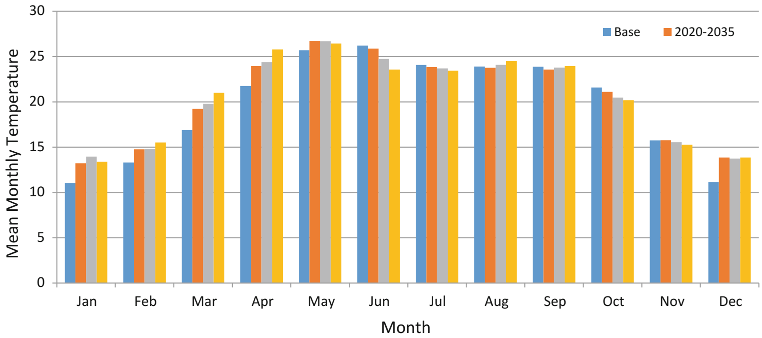

Fig. 6 Comparison of mean monthly minimum temperature for different periods of generated data with observed data under A2 climatic scenario

Conclusion

The changing climate of the world has adverse effect on different facets of life and there is need to develop adaptation strategy for water resource management, agriculture, health, and many more areas of life. The changes in minimum temperature and extreme events are now clearly visible in different parts of earth. The statistical downscaling model (SDSM) has been used to generate several future predictive series for three different periods 2020–2035 (FP-1), 2046–2064 (FP–2), and 2081–2100 (FP-3). The different goodness of fit criterions including scatter diagram, correlation coefficient, and percentage reduction confirmed specific humidity at 850 hpa (nceps850gl), 500 hpa geopotential height (ncepp500gl) and surface airflow strength (ncep_fgl) were found the most appropriate parameters to generate future scenarios. The multiple series for each three predictive periods for A1B and A2 climate forcing conditions were generated and compared statistically with base series (1971–2003). It may be concluded that mean monthly temperature may increase significantly during summer months in both A1B and A2 climate scenarios. The winter months may observe decrease of minimum temperature in A1B condition while slight increase under A2 climate condition.

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