

Statistical Downscaling and Bias Correction for Projections of Indian Rainfall and Temperature in Climate Change Studies

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Abstract. Climate change impacts are assessed by the General Circulation Models (GCMs), which simulate large scale climate variables globally incorporating the green house emissions. However, the scale on which, GCMs work are coarser than, that required for impacts assessment and regional planning, adaptation. Furthermore, GCM simulations have systematic errors called bias, which need to be corrected. In the present work, a quartile based mapping method is used for bias correction of interpolated Indian temperature. As the GCMs are not good in simulating rainfall, a statistical downscaling method is used to project rainfall from the large scale variables, which are well simulated by a GCM. The results show, the efficiency of the model, and these methods may be used for next century projection of Indian rainfall and temperature, which are essential for hydrologic modeling.

Keywords: Climate Change, GCM, Bias, Statistical Downscaling

1. Introduction

Climate change refers to any systematic change in the long-term statistics of climate elements (such as temperature, pressure, or winds) sustained over several decades or longer time periods. Climate change describes changes in the global temperature over time (i.e., increase in global temperature or global warming) and its consequences on other climatic variables, such as pressure, humidity, wind etc. Observations that delineate how global temperature has increased in the past, show that the global average surface temperature has increased by $0.74^{\circ}\text{C}/\text{Century}$. General Circulation Models (GCMs) are tools designed to simulate time series of climate variables globally, accounting for effects of greenhouse gases in the atmosphere. They attempt to represent the physical processes in the atmosphere, ocean, cryosphere and land surface. They are currently the most credible tools available for simulating the response of the global climate system to increasing greenhouse gas concentrations, and to provide estimates of climate variables (e.g. air temperature, precipitation, wind speed, pressure etc.) on a global scale. GCMs demonstrate a significant skill at the continental and hemispheric spatial scales and incorporate a large proportion of the complexity of the global system; they are, however, inherently unable to represent local sub-grid scale features and dynamics. The spatial scale on which a GCM can operate (e.g., 3.75° longitude X 3.75° latitude for Coupled Global Climate Model, CGCM2) is very coarse compared to that of a hydrologic process (e.g., precipitation in a region, streamflow in a river etc.) of interest in the climate change impact assessment studies. Moreover, accuracy of GCMs, in general, decreases from climate related variables, such as wind, temperature, humidity and air pressure to hydrologic variables such as precipitation, evapo-transpiration, runoff and soil moisture, which are also simulated by GCMs. These limitations of the GCMs restrict the direct use of their output in

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hydrology. Downscaling in the context of hydrology, is a method to project local scale finer resolution hydrologic data from large scale climatological data.

GCMs are good in simulating temperature; however there is a systematic error, known as bias, in those simulations. Bias correction methods include mean correction, standardization (Wilby et al., 2004) or quartile based mapping (Li et al., 2010). The present study uses quartile based mapping for bias correction in projecting temperature of entire India AT 1⁰ resolution.

2. Bias Correction and Modelling Temperature

Due to incomplete knowledge about the geophysical processes, assumptions are made in development of a GCM in terms of parameterizations and empirical formulae. Because of these assumptions, a GCM may not simulate climate variables accurately and there is a difference between the observed and simulated climate variable for almost all the GCMs. This difference is known as bias. It is important to remove the bias from the GCM output for projecting the future hydrologic and climatic scenario correctly. Standardization (Wilby et al., 2004) is used to reduce systematic biases in the mean and variances of GCM predictors relative to the observations or NCEP/NCAR data. The procedure typically involves subtraction of mean and division by standard deviation of the predictor variable for a pre defined baseline period for both NCEP/NCAR and GCM output.

The other methodology by Li et al. (2010) is quartile based mapping method on cumulative distribution functions of observed, training and testing data (Fig. 1). The methodology includes the following steps:

1. Cumulative Distribution Functions (CDFs) are first fitted to the observed (X_O) as well as GCM (X_{GCM}) simulated data.
2. For a given value of GCM simulations (x_{GCM}) compute the CDF ($F_{GCM}(x_{GCM})$) and corresponding to the computed CDF, obtain the value from observed CDF. This is the corrected value for training/ baseline.
3. For future/ testing, corresponding to a CDF value, the change is computed from GCM simulations of future and observed period. The change is then applied to the corrected CDF obtained for training/ base-line.

The methodology is applied to Canadian GCM, CGCM3, with 1969-1984 as training data and 1985-2000 as testing data. All the plots are presented for testing data. The gridded observed temperature data is obtained from India Meteorological Department (IMD).

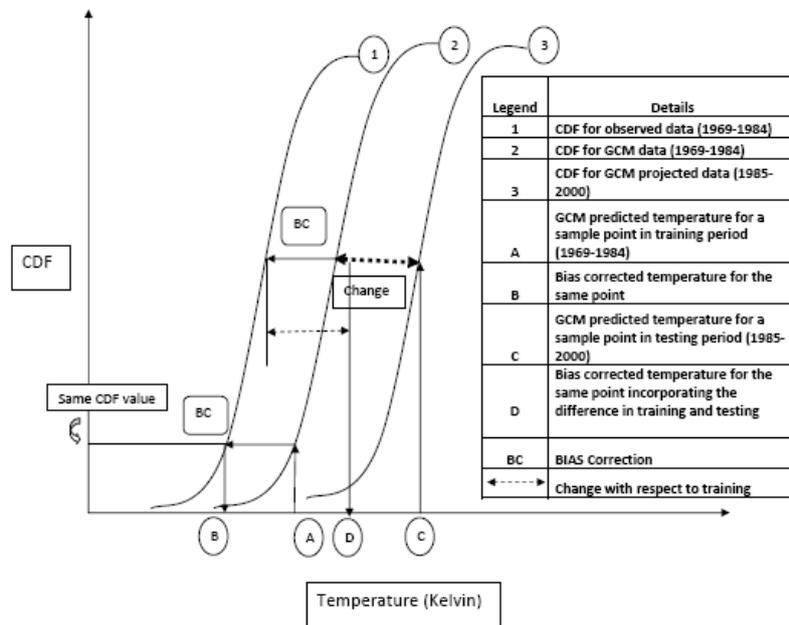


Fig. 1: Bias Correction Method

The results for Indian temperature, observed and simulated are presented in Fig. 2. They show a very good match, which reflects the efficiency of the model and hence, it may be used for future projections with A1B, A2 or B1 scenarios (2000-2100)

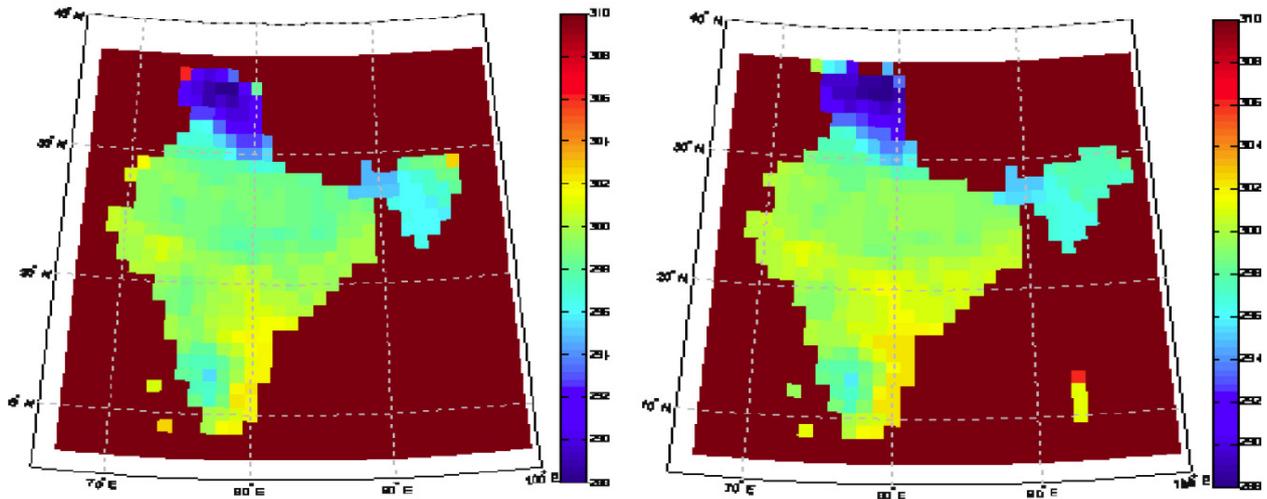


Fig.2 (a) Mean Temperature from Observed Data (b) Mean Temperature from Bias Corrected GCM Simulated Data

3. Statistical Downscaling and Modelling Rainfall

Statistical downscaling methods first develop statistical relationship between large scale climate variables and local scale rainfall, and then further use this relationship to the project future outputs. The regional climate models cannot meet the needs of spatially explicit models of ecosystems or hydrological systems, and there will remain the need to downscale the results from such models to individual sites or localities for impact studies (Wilby and Wigley, 1997). There are three implicit assumptions involved in statistical downscaling (Hewitson and Crane, 1992): Firstly, the predictors are variables of relevance and are realistically modelled by the host GCM. Secondly, the empirical relationship is valid also under altered climatic conditions. Thirdly, the predictors employed fully represent the climate change signal. In absence of observed data, NCEP/NCAR reanalysis data is used for developing relationship. The relationship between predictors and predictands can be established in many ways. Crane and Hewitson (1998) used ANN in an empirical down-scaling procedure to derive daily subgrid-scale precipitation from GCM output of geo potential height and specific humidity. Cortereal et al. (1995) developed Multivariate Adaptive Regression Splines (MARS) model to capture the observed relationships between sea level pressure (SLP) anomalies over the Euro-Atlantic sector and the winter time (December-February) monthly rainfall at eight sites in Portugal. In a more recent study Tripathi et al. (2006) used Least Square Support Vector Machine (LS-SVM) for statistical downscaling to project rainfall at Meteorological Sub-Divisions (MSDs) in India. One of the major challenges in multi-site statistical downscaling is that, the cross correlations between different sites are difficult to preserve. To overcome this limitation of statistical downscaling, an innovative approach is applied, where first the rainfall state of region is obtained with Classification and Regression Tree (CART) and then conditional on the state rainfall amounts at different sites are computed. The flowchart is presented in Fig. 3.

The advantage of the methodology is that the rainfall state of the region captures the spatial distribution of rainfall amounts and hence the cross-correlation is preserved. Kernel regression is used as a regression model for this purpose. The results for testing period are presented in Figs. 4 and 5.

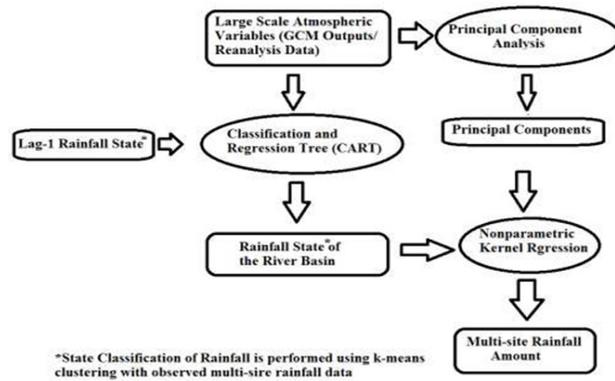


Fig. 3 Flowchart of Multi-site Downscaling Model

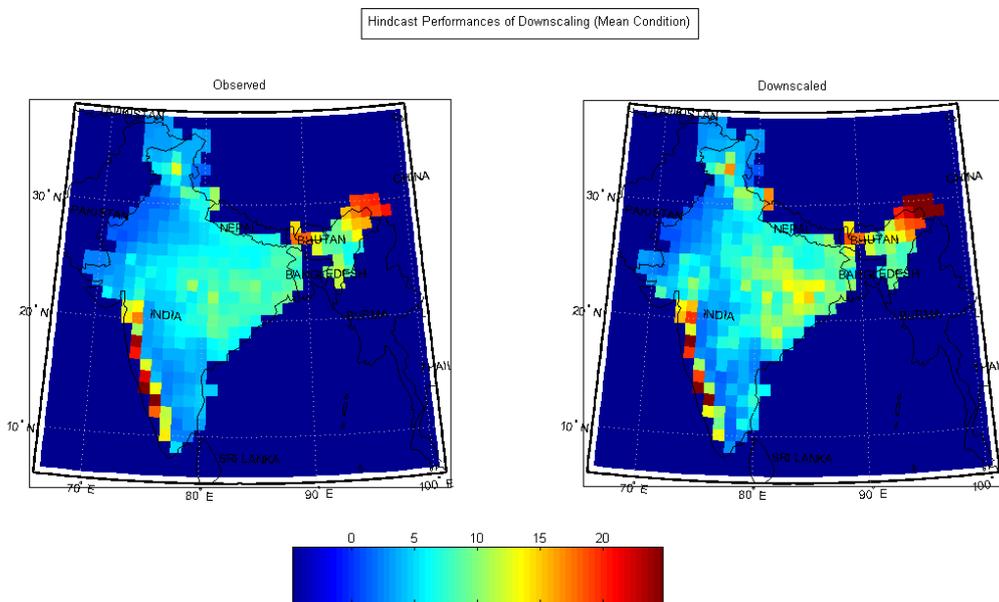


Fig. 5 Observed (a) and Simulated (b) mean Rainfall of India

The results show a good match. Similarly for standard deviation of rainfall also, a good match is observed. It is also observed that the spatial distribution is also preserved well.

4. Concluding Remarks

‘Bias correction’ is the most important step in statistical downscaling as the success of downscaling is dependent on the accuracy of the results projected by GCM. It is evident from the results that the physics behind the variations in temperature is well understood by the GCMs and hence able to project the same. Also the matching values of predicted data and observed data at each grid point show that the statistical downscaling for temperature is not required. Interpolation at desired grid size followed by bias correction will give accurate results. The quartile based mapping method on cumulative distribution functions is working fine in removing bias. This gives an indication of the robustness of the method and highlights regions of high confidence or large uncertainty. Although statistical downscaling approaches do not provide a physical explanation for biases, they have a computational advantage to dynamic downscaling and have skill comparable to limited area climate models. The statistical downscaling with prior projections of rainfall state able to capture spatial pattern and hence the present model able to capture the rainfall pattern. These models may now be used for future projections.

5. References

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