Case Study

Assessing GCM Convergence for India Using the Variable Convergence Score

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Abstract: General circulation models (GCMs) use transient climate simulations to predict climate conditions in the future. Coarse-grid resolutions and process uncertainties necessitate the use of downscaling models to simulate precipitation. However, in the downscaling models, with multiple GCMs now available, selecting an atmospheric variable from a particular model which is representative of the ensemble mean becomes an important consideration. The variable convergence score (VCS) provides a simple yet meaningful approach to address this issue, providing a mechanism to evaluate variables against each other with respect to the stability they exhibit in future climate simulations. In this study, VCS methodology is applied to 10 atmospheric variables of particular interest in downscaling precipitation over India and also on a regional basis. The nested bias-correction methodology is used to remove the systematic biases in the GCMs simulations, and a single VCS curve is developed for the entire country. The generated VCS curve is expected to assist in quantifying the variable performance across different GCMs, thus reducing the uncertainty in climate impact–assessment studies. The results indicate higher consistency across GCMs for pressure and temperature, and lower consistency for precipitation and related variables. Regional assessments, while broadly consistent with the overall results, indicate low convergence in atmospheric attributes for the Northeastern parts of India.
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Introduction

General circulation models (GCMs) constitute an important tool for assessing the plausible impact of climate change on a range of human and natural systems. The GCMs perform well at continental and large regional scales, but their ability to simulate climate at finer spatial scales is still limited (Xu 1999). Simulations at these finer scales are of considerable interest to hydrologists for assessing the possible impact of climate change on water supply and related attributes. This has led to the development of a range of downscaling methods, which use the coarse-scale GCM atmospheric simulations as the basis to produce finer scale variables of interest (Fowler et al. 2007).

The Intergovernmental Panel on Climate Change (IPCC) 4th assessment report identified 23 GCMs for assessment of plausible climate-change impact on a range of human and natural systems. Different climate models have been used worldwide for climate impact–assessment studies. However, the simulations from different climate models vary at a local or regional scale and are highly uncertain (Molteni et al. 1996; Xu 1999; Kleeman 2002; Gleckler et al. 2008). These uncertainties arise due to a number of factors discussed in depth by Murphy et al. (2004), and lead to significant variability across model simulations of future climates. Model performance and model convergence have been used to evaluate GCM simulations at the regional scale. Model performance regards how well a model simulates the observed climatic record and model convergence addresses the issue as to how consistent the predictions are from a range of models in time and space (Dessai et al. 2005).

Studies related to model performance and model convergence have been performed by many researchers. Murphy et al. (2004) introduced the Climate Prediction Index (CPI)–weighted probability-distribution function (PDF), in which the CPI uses 32 model parameters that represent surface and atmospheric variables to determine the skill of the models in representing the current climate. It used each model's performance to determine an overall model weighting. Perkins et al. (2007) made a comparison between PDFs of observed data with those of model simulated by daily precipitation and maximum and minimum temperatures to evaluate the performance of 14 models across 12 regions in Australia. Tang et al. (2008) assessed model convergence by exploring several measures for quantifying potential predictability of the climate models. They concluded that if the spread of predictions from different GCMs around the ensemble mean is small, then the model convergence is good and predictions are insensitive to the choice of model. However, if the model convergence is poor, the predictions will vary markedly across GCMs. In this case, if the GCM variables are used for hydrologic impact–assessment studies, the final result is sensitive to the choice of model and is highly uncertain (Wilby and Harris 2006).

Dessai et al. (2005) suggested a skill score, which combined measures of both model performance and convergence for air temperature and precipitations in 22 regions around the world. Reliability ensemble averaging (REA), which took into account

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the criteria of model convergence and performance, was introduced by Giorgi and Mearns (2002) for calculating the average uncertainty range, and a measure of reliability of simulated climate changes at the subcontinental scale from ensembles of different atmosphere–ocean GCM simulations. Tebaldi et al. (2005) extended the REA approach further in a Bayesian framework. In their study, PDFs for temperature changes in future were based on a weighted average of nine GCMs. The weights assigned to the nine GCMs were based on a bias criterion for modeling of observed climate and a convergence criterion for good agreement in future with the weighted ensemble mean. Furrer et al. (2007) analyzed uncertainty in spatial patterns of probabilistic temperature-change projections using a multivariate Bayesian analysis. The spatial patterns of projected temperature were based on 21 different GCM outputs, in which each GCM output was given equal weightage. Johnson et al. (2011) also compared a range of GCMs with respect to their ability to simulate low-frequency variability in precipitation simulations. A set of wavelet-based skill measures was developed to compare GCM performance. They suggested that judicious selection of best performing GCMs is required for climate-impact studies.

A majority of the aforementioned studies focused on model performance with a few studies considering model convergence. However, it is very difficult to assess climate models as a whole based on an accepted metric that includes model performance as well as model convergence (Raisanen 2007; Gleckler et al. 2008; Knutti et al. 2008). Few studies (e.g., Lambert and Boer 2001; Gleckler et al. 2008; Johnson and Sharma 2009; Knutti et al. 2010; Weigel et al. 2010) have used the model outputs to compare the reliability of variables or variable performance across different GCMs rather than focusing on individual model performance. Understanding variable performance over different GCMs becomes really important, as the reliability in outputs of climate impact–assessment studies depends heavily on the GCM-simulated outputs. Lambert and Boer (2001) performed an intercomparison study for the climate simulated by 15 coupled atmospheric/oceanic models and concluded that different variables were simulated with varied success by the various models evaluated, and that no particular model was best for all variables and/or for all regions. It was also concluded that the ensemble mean of model results will have a smaller error than any of the individual models. Gleckler et al. (2008) analyzed the performance of GCMs in predicting important surface variables and observed that models vary in prediction of variables. Knutti et al. (2010) studied the reduction in bias for ensemble mean of absolute value of temperature and concluded that reduction in bias by averaging was dependent on geographical location and the initial bias present in the model outputs. Weigel et al. (2010) discussed the effect of model weighing and observed that ensemble mean for any variable on an average improved the reliability of climate projections for weather and seasonal forecasting. Johnson and Sharma (2009) extended variable assessment and developed variable convergence score (VCS), a metric that quantifies the ability with which individual variables are simulated more consistently in future settings across a range of GCMs. The metric highlights how well the models converge in projection of certain climatic variables.

Large climatic variations were observed across different regions of India due to geographical location and dominant hydroclimatic teleconnections (Kumar and Parikh 2001; Whitaker et al. 2001). Reliable prediction of hydrologic variables such as rainfall is significantly challenging and of prime importance to the socioeconomic status of India, with the country being a largely agriculture-dominated country (Maity et al. 2007). To study the hydrological consequences of climate change at basin scale in India, downscaling of climate-model outputs is required (Anandhi et al. 2008). For statistical downscaling, choice of predictors is one of the most important steps. However, the selection of predictor variables is based on the fact that they are reliably simulated by GCMs and strongly correlated with the predictand. Further, statistical downscaling methods are used to obtain the predictand (Fowler et al. 2007). Any uncertainty in the predictor variables is translated in the outputs of the hydrological response studies. Therefore, it becomes essential to quantify the variable performance across different GCMs. Unfortunately, for India where climate impact–assessment studies are extremely necessary, no records of studies related to variable performance are available, even despite the fact that in the downscaling studies performed for certain regions of India, strong evidence of uncertainty in results was found (Ghosh and Mujumdar 2006; Mujumdar and Ghosh 2008). The results of these studies were largely limited to the subset of models used and were supposed to be sensitive to any change in the predictor variables or models selected (Mujumdar and Ghosh 2008). The aforementioned VCS methodology provides a simple yet meaningful approach to examine the consistency in simulation of variables across different GCMs. Downscaling approaches relying on the predictor variables, exhibiting high consistency across GCMs, are likely to be less sensitive to the choice of GCMs used in the analysis. The VCS had been successfully applied over Australia to compare the relative performance of GCM outputs with the ensemble mean (Johnson and Sharma 2009), and is therefore adopted in this study.

Statistical correction of *GCM output* is often necessary when significant *systematic biases* exist in the observations. A common procedure is to standardize the GCM output by removing the systematic biases in the mean and variances relative to observations or reanalysis data at timescales of interest (e.g., daily; Mehrotra and Sharma 2010). This, however, often ignores the biases at other timescales, and leads to possible inaccuracies in water-resources simulations in which long-term persistence (at annual and multiannual timescales) is important. Nested bias correction (NBC; Johnson and Sharma 2011, 2012; Mehrotra and Sharma 2012) is a recently proposed method that corrects for the biases in the statistics of GCM outputs (e.g., mean, standard deviation, lag-one correlation) across a range of timescales, thus making them suitable for water-resources applications.

The aim of this study is to apply VCS in assessment of the selected atmospheric variables of relevance in downscaling of precipitation, after they have been preprocessed using the NBC. The spatial domain of interest for the study is India, with the assessment covering the entire country as well as five subregions of interest. The results from this study are expected to provide important information about the consistency of downscaling predictor variables across GCMs and reduce uncertainty in the results of the downscaling studies. This, in turn, will lead to increased reliability in climate simulations, leading to better defined plans and policies that assist in the management of water resources in the warmer climates ahead.

The remainder of this paper is organized as follows: In the "Study Area and Data Used" section, details of the study area and data used for this study are given. The "Methodology" section presents the application of the methodology followed by the "Results and Discussion" section. The conclusions drawn from the study are presented in the "Summary and Conclusions" section.

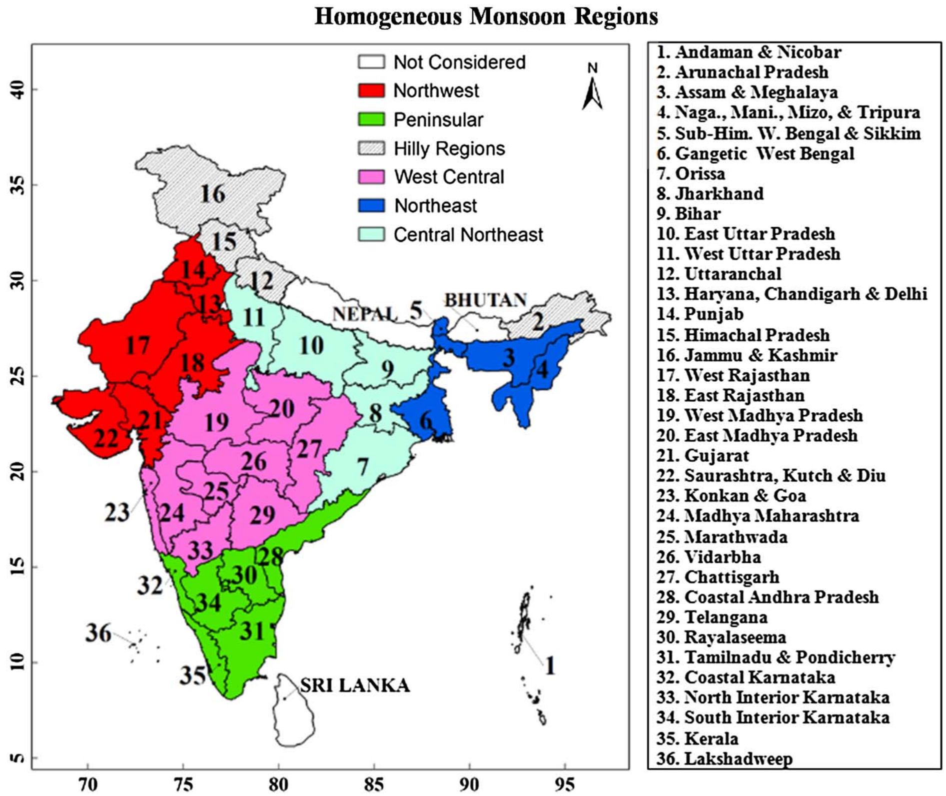

Fig. 1. Location map of the study area (based on data from the Indian Institute of Tropical Meteorology)

Study Area and Data Used

Study Area

The proposed methodology has been applied across India (latitude from 5° N to 45° N and longitude from 65° E to 95° E) covering 221 grid points using the outputs of 17 GCMs at a resolution of $2.5° \times 2.5°$. Fig. 1 shows the study region. The shape, size, location, latitudinal extent, and sharp contrasting relief features of India bring great climatic diversity across different regions of India. The Tropic of Cancer, at a latitude of 23.5° North of the equator, passes through the middle of India. The southern part of the country, being closer to the equator, experiences high temperatures throughout the year. By contrast, the northern part lies in the warm temperate zone. Distance from the sea, the northern mountain ranges, western disturbances and tropical cyclones, monsoon winds, and physical features mainly influence the air temperature, atmospheric pressure, direction of winds, and the amount of rainfall in different parts of the country (Chang 1967; O'Hare 1997)

Data Used

Atmospheric Data

The atmospheric data used as a proxy for the observed record were the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis data (Kalnay et al. 1996). The NCEP/NCAR monthly data at a grid resolution of $2.5° \times 2.5°$ for a period of 1950–1999 were used for the analysis. Although there are known uncertainties in this data set due to change in observing systems, modeling deficiencies, and human-induced errors in assimilation, the uncertainty in NCEP/NCAR data sets varies across variables (Kistler et al. 2001). Upper-level temperatures, rotational wind, and geopotential height are strongly influenced by observation and are very reliable. Moisture variables and divergent winds are influenced by both observations, and the model is comparatively less reliable. Precipitation rate is completely determined by the model. However, despite the known uncertainties in this data set, these data provide a consistent basis for assessing the multitude of atmospheric variables that are considered in this study (Kistler et al. 2001).

GCM and Variable Selection

This study considered a total of 17 GCMs for assessment of the VCS which is a subset of the 23 available GCMs, used as part of the IPCC assessment report (Meehl et al. 2007). The selection of this subset was based on the availability of the simulations for the atmospheric variables for which the VCS will be assessed. Details of the models used are provided in Table 1.

Variables of importance for hydrologic impact studies are those that are commonly used to predict rainfall and runoff in downscaling studies such as geopotential height, mean sea-level pressure, relative humidity, precipitation rate, and precipitable water, and those required for evaporation estimation, namely, temperature, wind speed, pressure, and specific humidity (Mehrotra et al. 2004). Dibike and Coulibaly (2005) performed downscaling of precipitation and temperature in Saguenay watershed, Canada, and further predicted streamflow. They identified geopotential height, mean sea-level pressure, relative humidity, specific humidity, and wind as predictors. Tripathi et al. (2006) used a similar set of predictor variables to downscale precipitation in various meteorological subdivisions of India. Benestad et al. (2007) used precipitation rate and mean sea-level pressure as predictors to downscale monthly rainfall at a site in Norway. Based on the

Table 1. Details of GCMs Used

Serial number	Model used	Organization
1	BCCR_BCM2_0	Bjerknes Centre for Climate Research, Bergen, Norway
2	CSIRO 3.5	Commonwealth Scientific and Industrial Research Organisation, Canberra, Australia
3	GFDL 2.0	Geophysical Fluid Dynamics Laboratory, Princeton, New Jersey, USA
4	GFDL 2.1	Geophysical Fluid Dynamics Laboratory, Princeton, New Jersey, USA
5	GISS	Goddard Institute for Space Studies, New York, New York, USA
6	INGV-ECHAM 4	Istituto Nazionale di Geofisica e Vulcanologia, Rome, Italy
7	INMCM 3	Institute of Numerical Mathematics, Moscow, Russia
8	IPSL_CM4	Institut Pierre Simon Laplace, Paris, France
9	MIROC3	Centre for Climate System Research, Tokyo, Japan
10	MPI-ECHAM5	Max Planck Institute for Meteorology, Hamburg, Germany
11	MRI-CGCM2	Meteorological Research Institute, Tsukuba, Japan
12	NCAR_CCSM3	Community Earth System Models, NCAR, Boulder, Colorado, USA
13	NCAR-PCMI	Parallel Climate Models, NCAR, Boulder, Colorado, USA
14	UKMO-hadcm3	U.K. Met Office, Exeter, U.K.
15	UKMO-hadgem1	U.K. Met Office, Exeter, U.K.
16	CSIRO 3.0	Commonwealth Scientific and Industrial Research Organisation, Canberra, Australia
17	CNRM_CM3	Canadian Climate Centre, Gatineau, Canada

Table 2. List of Variables Considered

Serial number	Variable	CMIP3 code
1	Mean sea-level pressure	ps
2	Precipitable water	prw
3	Precipitation rate	pr
4	Air temperature	tas
5	Geopotential height	zg
6	Relative humidity	hur
7	Vertical wind velocity	was
8	Horizontal U wind	uas
9	Horizontal V wind	vas
10	Surface-specific humidity	Huss

downscaling studies, to this end, 10 variables were obtained from each model and were used for the analysis and are listed in Table 2.

In this study, atmospheric variables at three pressure levels (500, 700, and 850 hPa) were considered. These pressure levels were considered to be of importance for downscaling of rainfall to river basin scale in India (Anandhi et al. 2008). The 850-hPa pressure height is considered to influence the regional precipitation at the basin scale. Further, temperature at 700 and 500 hPa represents the heating process of the atmosphere due to monsoonal precipitation that is maximum at mid-Troposphere at a constant pressure height (Satyanarayana and Srinivas 2008).

In a previous study performed by Johnson and Sharma (2009), it was observed that the relative difference in magnitude of VCS values across various future climate scenarios is much less. Therefore, to avoid extensive computation, only one emission scenario (for future climate), that is, Special Report on Emissions Scenarios (SRES) A2, was considered. The SRES A2 is one of the four emission scenarios developed considering possible futures of world development in the 21st century. It projects that the atmospheric CO_2 concentrations will reach 850 ppm in the year 2100 in a world characterized by high population growth, medium gross domestic product growth, high energy use, and various other factors. This scenario is the one described in Nakicenvoic et al. (2000). The approach presented for SRES A2 analysis can be used for different scenarios as well as to provide a basic understanding about how far the variables are consistent across different GCMs. The variables for coupled model intercomparison projects (CMIPs) for climate of the twentieth-century experiment 20C3M (representing past climate) for the period between 1950 and 1999, and SRES A2 (representing future climate) for the period between 2000 and 2099 were obtained from the World Climate Research Programme's CMIP Phase 3 (CMIP3) multimodel data set.

Methodology

The methodology adopted in this study involved standardization of GCM simulations and assessing the convergence of variables across GCMs for future climate. The detailed methodology is given in the following subsections (Johnson and Sharma 2009).

Data Processing

The reanalysis data sets are available at a grid resolution of $2.5° \times 2.5°$. However, outputs from different GCMs are available at varied grid points. Therefore, the data sets from different GCM grid points were interpolated to conform to the reanalysis data grid points using a weighted mean of the four nearest values, with the weights being assigned based on an inverse square distance relationship (Johnson and Sharma 2009). The interpolated GCM simulations were further transformed as the average of the nearest nine grid cells to reduce the spatial variability often observed.

NBC

Bias correction of GCM simulations is a much needed step that attempts to force the simulations to broadly conform to observations, thereby enabling an alteration of future simulations under the assumption that the bias in the past climate will remain the same in future. There are a range of innovative bias-correction alternatives, from simple correction of moments, to matching of quantiles, to the more advanced NBC rationale that attempts to address bias across multiple timescales. The performances of NBC methodology over two scaling approaches (i.e., constant scaling/delta change approach and quantile scaling) and two other bias-correction methods (i.e., monthly bias correction, quantile mapping) were studied in detail by Johnson and Sharma (2011). One of the major disadvantages in case of scaling approaches observed was the assumption inherited within it that the variability remains constant. This unchanged variability is supposed to be a problem for modeling at multiple timescales in a hydrological setting. Scaling approaches at daily scale lead to rainfall occurrence being the same for the current and future climate (Fowler et al. 2007), whereas in the future, this is expected to change in different parts of the world (Mehrotra and Sharma 2010; Trenberth et al. 2003). Of greater importance for large water-resources systems are changes in variability at low frequencies, particularly at interannual timescales. Although traditional bias-correction methods correct for daily or monthly distributions (Ines and Hansen 2006; Mehrotra and Sharma 2010), it is also possible to address biases at other timescales (Johnson 2010; Johnson and Sharma 2009). This allows the interannual variability of the future projections to evolve according to the GCM, allowing that there may be some biases in the modeling of interannual variability compared with the observations. The NBC methodology was developed by Johnson and Sharma (2009) and is aimed at representing both high-frequency variability and low-frequency variability and persistence in the GCM outputs, thereby making them useful for water-resources applications. Readers are further referred to Johnson and Sharma (2011) and Hashino et al. (2007) for reviews and comparison of the various approaches available.

The NBC approach represents a nested procedure, which addresses bias across prespecified multiple timescales. The procedure consists of the following key steps. Denoting a variable for month i in year k as $y_{i,k}$, the first step involves standardization to create $y'_{i,k}$ by subtracting the model monthly mean ($\mu_{\mathrm{mod},i}$) and dividing by the standard deviation ($\sigma_{\mathrm{mod},i}$) for that month as shown in Eq. (1)

$$y'_{i,k} = \frac{y_{i,k} - \mu_{\mathrm{mod},i}}{\sigma_{\mathrm{mod},i}} \tag{1}$$

The second step is to interpose the mean ($\mu_{\mathrm{obs},i}$) and standard deviation ($\sigma_{\mathrm{obs},i}$) of reanalysis data to create a transformed time series $y''_{i,k}$ at the monthly level

$$y''_{i,k} = y'_{i,k}\sigma_{\mathrm{obs},i} + \mu_{\mathrm{obs},i} \tag{2}$$

In the third step, the transformed monthly series ($y''_{i,k}$) are then aggregated to the annual scale and denoted as z_k. The standardization and transformation steps are repeated at the annual time step. Following the notation adopted for the monthly case, the annual time series is similarly transformed to z''_k, which exhibits the mean and standard deviation in the recorded annual data.

Subsequent to the aforementioned steps, the raw GCM simulation at the monthly time step is transformed by the NBC to

$$Y_{i,k} = y_{i,k}\left(\frac{y''_{i,k}}{y_{i,k}}\right)\left(\frac{z''_k}{z_k}\right) \tag{3}$$

where $Y_{i,k}$ represents NBC-transformed variable and the others are as described earlier. Using the transformation of Eq. (3), the corrections at monthly and annual scales can be applied to the monthly time series at the same time to create a one-step correction (Srikanthan 2009). In Eq. (3), $[(y'_{i,k}/y_{i,k})(z'_k/z_k)]$ is a weighing factor, that is, the ratio of the monthly corrected value to the raw GCM value for month i and year k, multiplied by the ratio of the yearly corrected value to the aggregated GCM rainfall for year k.

While the aforementioned equations were used to transform the GCM simulations for the current climate, their application for simulations for the future would be the same. All that is needed is to replace the monthly and annual values with future climate simulations, ensuring that the transformations adopted to ascertain $y''_{i,k}$ or z_k are based on the statistics corresponding to the current period. The end result is the series $Y_{i,k}$, which for the current period will exhibit first-order and second-order moments attributes that are similar to observed values at all the timescales considered.

It should be noted that the NBC procedure presented here is a simplified version of that presented in Johnson and Sharma (2011, 2012), with the difference being the neglect of bias in the lag-one autocorrelation statistic at the various timescales considered. This simplification has been adopted, as the NBC procedure is based on the assumption that only lag-one autocorrelation is significant. However, in this study, a wide range of variables having different distributional attributes (other correlations may become significant) are used, and incorporation of bias correction for lag-one correlation was found to create instability in the estimated moments. It should also be noted that the NBC procedure can be used across more than two timescales (as used here), the number and choice of timescales depending on the type of application the transformed variables are used for. As the purpose of this study was to assess the convergence of selected variables, the use of only monthly and annual timescales was considered adequate.

Estimation of the VCS

The VCS compares variables in time and space based on coefficient of variation (CV). The CV provides an advantage over other statistics as it is insensitive to the absolute values of the variable. Because a wide range of values are expected from different variables, a skill score based on CV is appropriate as it is the ratio of the standard deviation to the mean of the values. The CV value calculated at each grid cell for the three pressure levels from the collection of mean annual results from 17 GCMs forms the basis for VCS. The VCS is a simple comparison between CV value of one variable or one region with that of another.

The VCS is determined by calculating the cumulative distribution of the CV values for all locations, variables, pressure levels, and time. The relative position of a particular CV value compared with all other CV values can be measured in this way. Instead of fitting a theoretical distribution to the CV values, the skill score is based on an empirical cumulative distribution function (CDF) to maintain simplicity and effectiveness.

The estimation of the VCS after performing NBC transformation on GCM outputs follows the logic outlined below:

- Combine the results from all models for one ensemble for a particular variable for each grid for each 10-year window as shown in Eq. (4)

$$X_{j,t} = [x_{j,t,z,1,l}, x_{j,t,z,2,l}, x_{j,t,z,3,l}, \ldots, x_{j,t,z,n,l}] \tag{4}$$

  where $x_{j,t,z,n,l}$ = variable x at grid point j at time t, level z from model n and emission scenario l.
- Calculate CV for each cell, $\mathrm{CV}_{j,t,x}$, which is the ratio of the standard deviation to mean for the vector $X_{j,t}$.
- Pool the CV values for all grids, variables, levels, emission scenarios, and 10-year windows. In this study, 221 grid points, 10 variables (3 variables are surface variables), 3 pressure levels, 1 emission scenario, and 3 10-year windows were considered, yielding a pool of 15,912 CV values as explained below

$$\begin{aligned} &221\,(\text{grid points}) \times 7\,(\text{variables}) \times 3\,(\text{pressure levels}) \\ &\quad \times 1\,(\text{emission scenario}) \times 3\,(\text{10-year windows}) \\ &\quad + 221\,(\text{grid points}) \times 3\,(\text{surface variables}) \\ &\quad \times 1\,(\text{pressure levels}) \times 1\,(\text{emission scenario}) \\ &\quad \times 3\,(\text{10-year windows}) = 15{,}912\ \text{values} \end{aligned}$$

- Calculate the empirical CDF of CV values, assuming that the pooled CV values come from a common distribution that characterizes the variability of the climatic variables.

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$$F(\text{CV}) = \frac{r}{n} \quad (5)$$

where r = rank of the individual CV value; and n = total number of CV values.

- Calculate the VCS for a particular variable x for a particular grid cell j according to Eq. (6)

$$\text{VCS}_{x,j} = 100[1 - F(\text{CV})] \quad (6)$$

As can be seen from the aforementioned algorithm, the rationale behind the VCS is to calculate convergence based on estimates of the CV of the variable across all GCMs. It is expected that the variables that exhibit consistent values across GCMs will have a low CV and hence a high VCS, whereas the variables that exhibit significant deviation across GCMs will exhibit low VCS.

Assessments Performed

India-Wide Assessment

As mentioned in the "Introduction" section, the data from 17 GCM outputs of 10 different atmospheric variables at three different pressure levels and one emission scenario were interpolated, grid cell averaged, and bias corrected using NBC. After such a preprocessing of the data, the mean annual values for 10-year midwindows of 2030, 2050, and 2070 were calculated for each variable from each model at each level, for all grid cells. The results across 17 GCMs were combined to get values at each grid cell for each 10-year window. The 10-year time frame allowed a large enough sample size to develop reliable interperiod estimates of the mean and variance (although a longer period window would be more suitable for reliably estimating higher order moments such as skewness). It also created enough moving-window periods to observe any decadal variability or trends. Because the main interest here was estimation of mean and variance of $X_{j,t}$, a 10-year window was considered adequate for the study. Using this approach, for each grid point for one particular level and one variable, 17 values are obtained. The mean and standard deviation of the 17 values are calculated for each grid cell, followed by the estimation of the CV. Further, the CV values for 221 grid points for 10 variables, 3 pressure levels, 1 emission scenario, and 3 midwindows are pooled together, giving a set of 15,912 values. The empirical CDF was then ascertained for all the CV values. The VCS was then determined for each grid cell for each variable in the study area.

Regional Assessment

The VCS can be used to screen variables for convergence before being used as inputs in the climate-impact studies (Johnson and Sharma 2009; Mehrotra et al. 2013). The changes in local regions can be far more dramatic due to climate change compared with countrywide change. In the most recent synthesis report by IPCC it is claimed that the Indian subcontinent will adversely be affected by increased variability of climate because of rising temperature and water stress due to substantial reduction in summer rainfall in some parts (Cruz et al. 2007). Therefore, a regionwise assessment was also performed for VCS to provide insight about the variability across model simulations on a regional basis. The regional assessment was undertaken considering the broad classification of homogenous regions as adopted by the Indian Institute of Tropical Meteorology available in Parthasarathy et al. (1995) based on monsoon rainfall. These homogeneous regions are spatially coherent and have similar meteorological characteristics (Pal and Al-Tabbaa 2010). From Fig. 1, the five homogeneous regions of India can be identified. The VCS metric was developed and analyzed for the five homogeneous regions of India, namely, Northwest, Central Northeast, Northeast, West Central, and peninsular India.

Results and Discussion

VCS Assessment

Across India, the CV values varied from a minimum of 7.31×10^{-4} to a maximum of 3.64. The empirical cumulative distribution of all 15,912 CV values is shown in Fig. 2. The larger values of CVs mainly correspond to grid points over Northern India where a large part is covered by the Himalayan Range. However, GCM outputs are not considered to be reliable for the Himalayan range because of their inability to represent the complex surface and governing phenomena (Christensen et al. 2007; Solomon et al. 2009; Tabor and Williams 2010).

Table 3 provides the VCSs based on the spatially averaged values for India. The models showed best convergence for mean sea-level pressure, geopotential height, and air temperature, and the scores were lower for wind velocity, precipitable water, and precipitation rate. It may be noticed that the VCS value for specific humdity decreases at higher pressure level (500 hPa). This is in agreement with the work carried out by Paltridge et al. (2007), who stated that the specific humidity values should be considered with great caution from climate models as for heights mainly above 600 hPa, the upper-level negative trends in specific humidity are inconsistent. The meridional wind velocity at 850 hPa, which is mainly responsible for extreme weather conditions and flow of monsoon winds (Wang and Fan 1999), has low convergence compared with scores at other pressure levels. The vertical wind velocity at 500 hPa that is mainly high because of eastererly jet flows across India (Pattanaik and Satyan 2000), also has a low score. The VCS usually remained consistent for most of the variables at different pressure levels across the three time windows, except for horizontal and vertical wind velocities at 850 hPa, which are not consistent.

Ranks are also assigned to the variables based on the median scores for midyear windows of 2030, 2050, and 2070 across India. Results for 850-hPa pressure level only are shown in Table 4. For any particular variable, at 850 hPa and one midyear window (e.g., 2030), the CV values are generated at all grid points across India. Further, for the median CV value, the VCS was computed. The same step is repeated for the other variables. Based on the VCS, ranks were assigned across one midyear window. If a

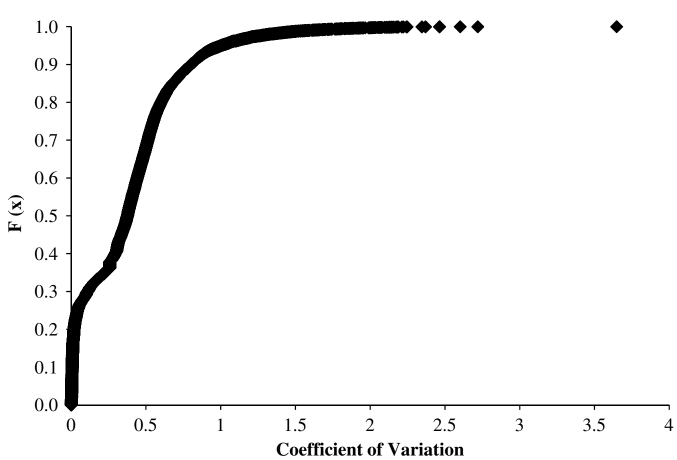

Fig. 2. Empirical cumulative distribution for all CV values

Table 3. VCS Values across India

Level	Midyear window	zg	hur	huss	uas	vas	was	tas	ps	prw	pr
Surface	2030	—	—	—	—	—	—	—	95.60	45.00	7.74
Surface	2050	—	—	—	—	—	—	—	95.32	45.00	7.56
Surface	2070	—	—	—	—	—	—	—	95.48	45.00	8.22
850 hPa	2030	87.12	61.19	47.10	35.00	15.51	40.18	79.86	—	—	—
850 hPa	2050	87.96	68.72	46.07	35.00	16.54	38.77	79.53	—	—	—
850 hPa	2070	85.13	68.72	48.10	36.83	25.67	41.35	78.97	—	—	—
700 hPa	2030	89.28	65.13	46.49	30.02	45.49	25.18	76.65	—	—	—
700 hPa	2050	89.40	64.62	37.56	31.28	45.81	24.85	76.65	—	—	—
700 hPa	2070	88.25	64.91	38.88	33.18	46.12	25.53	76.46	—	—	—
500 hPa	2030	86.66	57.93	5.62	29.42	45.81	13.65	82.58	—	—	—
500 hPa	2050	86.66	58.21	5.88	32.47	44.56	14.06	82.58	—	—	—
500 hPa	2070	86.10	58.56	5.23	32.64	46.12	14.74	82.58	—	—	—

variable, for example, temperature, has the highest VCS, Rank 1 is assigned. The ranking of variables across different time slices remains consistent in Table 4. However, the ranking of variables across different pressure levels and time windows depends on the values of VCS (as observed in Table 3) and is supposed to vary. As can be seen from Table 3, while for geopotential height VCS remains fairly constant across different pressure levels, it is not the case with specific humidity. At 500 hPa, VCS for specific humidity is low in comparison with the VCS at 850 hPa. Therefore, the ranking for specific humidity will change at 500 hPa. Overall, at 850 hPa and across the three-time windows, geopotential height and temperature have the lowest rankings followed by relative and specific humidity, as models show similar level of performance in simulating variables with low ranks. The relative rankings for wind velocities are considerably high.

The VCS value for a variable suggests how consistent the variable simulation is across different GCMs. If a particular variable has a less VCS value, it can be interpreted that the prediction from different GCMs for that variable is highly inconsistent and the usage of one particular GCM is not suitable. For example, for any study that involves preciptation rate as input (low VCS), a separate analysis is initially required to identify which particular GCM provides the best simulations of the variable. By contrast, for a variable with a high VCS, it can be ascertained that the simulation for that variable is consistent among different GCMs and use of any GCM in the downscaling study will provide similar results.

The VCS values for all the 10 variables across five different climatologically homogeneous regions, namely, (1) Central Northeast, (2) Northeast, (3) Northwest, (4) peninsular, and (5) West Central India were also calculated. Results for only one pressure level and single future time window (850 hPa and midyear window of 2030) are shown in Fig. 3. When developing the VCS for a particular region, the VCS value for the variable is calculated based on the $F(\mathrm{CV})$ value for the median CV value of that variable for that particular region. No separate empirical CDFs of CV values for different regions are constructed. The VCS for the median CV value for any particular region is determined based on the VCS curve generated for India. Overall, similar trend is observed from the regional analysis and the models show best convergence for mean sea-level pressure, geopotential height, and air temperature.

The convergence for moisture-related variables, especially precipitable water and specific humidity, is comparatively higher for peninsular, Central Northeast, and West Central regions of India, compared with VCS estimates for the other two regions. Peninsular and eastern part of the West Central region receive good amount of rainfall due to southwest monsoon. The high temperature during summer across the Northwest part of India causes low-pressure conditions across the Northwest part and the water bodies surrounding the peninsular region (Nagar and Singh 1991). The low-pressure zone attracts moisture-laden southwest monsoon winds from the Indian Ocean, which cause widespread rain over peninsular and West Central part of India (Wang 2006). The Bay of Bengal branch of southwest monsoon causes heavy and widespread rain in Central Northeast and Northeast regions of India (Wang 2006). The amount of rainfall reduces from east to west owing to the progressive decrease in humidity of these winds so that the Northwest region receives very small amount of rain. Hence, the Northwest region that mainly includes the desert zone shows very little convergence for specific humidity and precipitable water. Low convergence is observed for variables related to moisture for Northeast region, which is mostly surrounded by the Himalayan range. The GCMs have difficulty hindcasting the complex

Table 4. Variable Ranking across India for 850 hPa

	2030	2050	2070	
Variable	Rank	Rank	Rank	Overall ranking
zg	1	1	1	1
hur	3	3	3	3
huss	4	4	4	4
uas	6	6	6	6
vas	7	7	7	7
was	5	5	5	5
tas	2	2	2	2

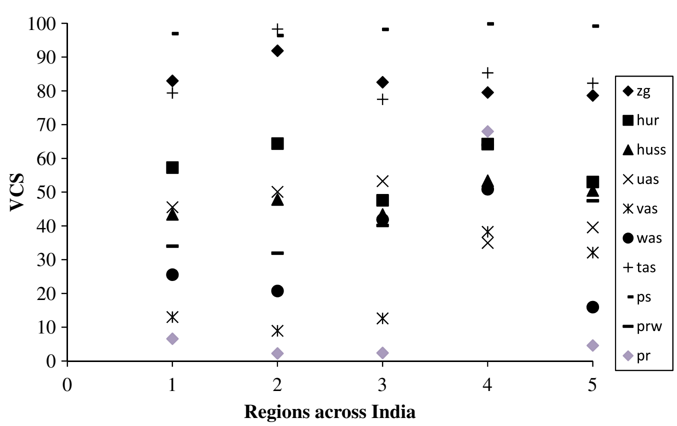

Fig. 3. VCS values for 10 variables and 5 homogeneous regions of India at 850 hPa for midyear window 2030

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Himalayan surface, and the large-scale atmospheric circulation patterns associated with southwest and Asian winter monsoon. The VCS methodology can help in prescreening variables with high convergence across the different GCMs for the Northeast region. Further, statistical and dynamical downscaling methods can be used to predict reliable climate-model outputs at a regional scale. For, Northeast region, the major limitation in using statistical downscaling methods is in terms of availability of observational records. The observational records are very sparse for the Himalayan range (Fowler and Archer 2006). Therefore, use of remote-sensing information and dynamical downscaling have been very popular to overcome the limitations of GCMs for this region. Lamadrid and MacClune (2010) stated that in the Himalayan range the high resolution of RCMs can more accurately capture the topographic influences, convective processes, and temperature differentials. However, the output of these regional climate models (RCMs) is very much dependent on the reliability of input-data information. To reduce the uncertainty, multiple RCM ensemble runs can be made using information from a suite of best performing GCMs and variables that are consistent across GCMs, to obtain reliable estimates.

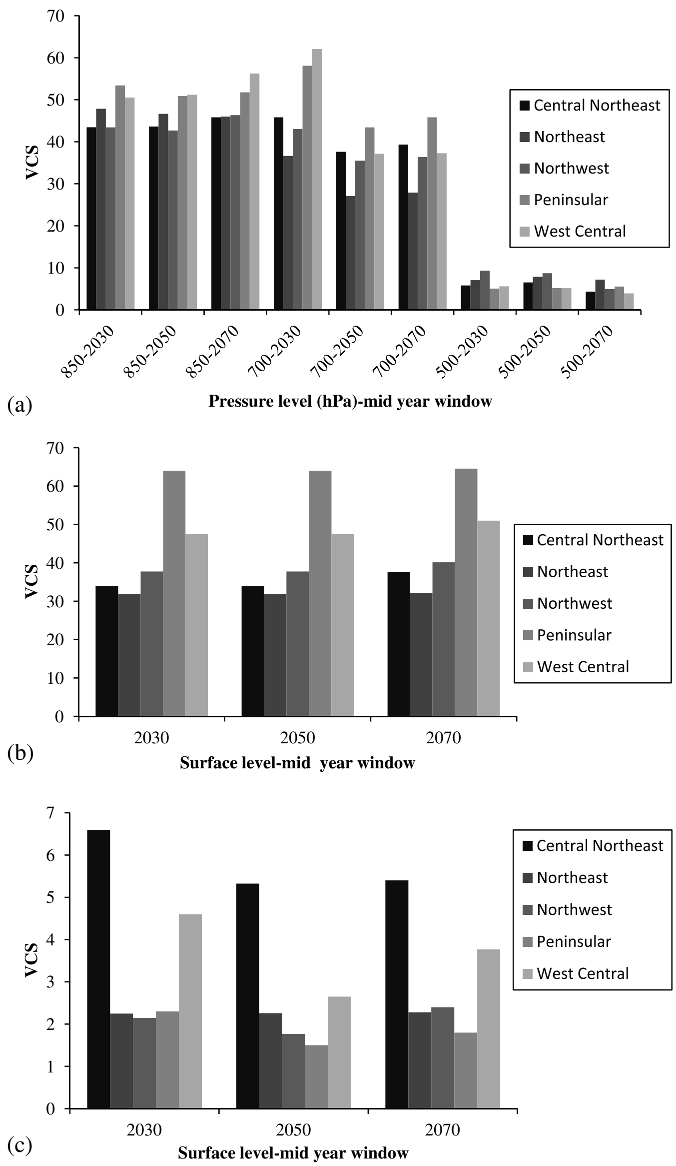

Fig. 4. VCS values for moisture-related variables across different regions of India: (a) specific humidity; (b) precipitable water; (c) precipitation rate

Table 5. Comparison of Annual CV for Current Climate after Monthly Standardization and Monthly NBC for BCCR_BCM2_0 Model at Latitude of 45° N and Longitude of 65° E for the Period between 1950 and 2000

	Annual CV values		
Variable	Observed NCEP	Poststandardization GCM simulations	Post-NBC GCM simulations
Precipitation rate	0.400	0.239	0.400
Precipitable water	0.050	0.038	0.050
Specific humidity (850 hPa)	0.052	0.043	0.052

A comparison of the VCS values of three major moisture-related variables, namely, specific humidity, precipitable water, and precipitation rate, across different pressure levels and the three midyear windows for all five regions is shown in Fig. 4.

Models show best convergence for specific humidity for peninsular and West Central regions at 850 and 700 hPa. The VCS value at 500 hPa is higher for the Northwest region. The convergence for precipitable water for peninsular and West Central regions is highest, compared with other regions for all the three midyear windows. Central Northeast region shows the maximum convergence for precipitation rate. Northeast region shows the least model convergence for all the three variables.

Impact of NBC in the Estimation of VCS

As mentioned in the "Introduction" section, this study used the NBC rationale for addressing both high- and low-frequency variability bias for assessing the VCS metric. A question not addressed yet is whether the use of NBC resulted in an improvement in the accuracy of the VCS.

This question is not easy to answer without knowledge of the true VCS for the variables being assessed. However, one can make judgments on the impact of NBC by studying the improvements noted in the key statistic that the VCS is based on. As an example, Table 5 presents a comparison of the CV for the two bias-correction approaches, one after monthly standardization and another after NBC for the current climate and for one model. As can be seen from the table, use of the NBC over standard bias-correction approach resulted in a significant reduction in bias for all three variables used. It should be noted that both bias-correction alternatives were applied to the data at a monthly timescale, whereas the results here represent an aggregate timescale and point to a better representation of variability after NBC is applied. It should also be noted that even though the VCS is subsequently estimated using monthly simulations (after postprocessing using the NBC), the assessment is for the future where no observations exist, pointing to the need for an approach that can be expected to alter raw simulations in a way that makes them closest to what they are likely to be. Use of the VCS and its ability to represent higher timescale variability is a step in that direction.

Summary and Conclusions

The VCS methodology was applied to compare the performance of outputs of 17 GCMs in simulating 10 atmospheric variables for three atmospheric levels and 3 time slices for SRES A2 scenario

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over India. The GCM outputs were first interpolated on NCEP grid points and further corrected for bias for mean, variance, and missing interannual variability using a NBC methodology. For each location, period, GCM, and each variable, the CV was calculated using the bias-corrected values. The CV values for all the locations were pooled across the study region for each variable and VCS was calculated.

It is found that GCMs show the best agreement for geopotential height, mean sea-level pressure, and temperature while the least convergence was obtained in case of precipitation rate. These results were in agreement with the earlier studies. It was noticed that grid cells falling under the Himalayan topography had a high CV value because of the inability of GCMs to represent the complex nature of the Himalayan range. Regionally across India, moisture-related variables showed the maximum convergence for peninsular region and the convergence was least for Northwest region, which is mostly a desert.

The VCS methodology applied was found to be successful in assessing the consistency among different GCMs for India. The methodology allowed easy comparison among the variables in a quantitative sense. The overall results indicate that GCMs vary in their performance for simulation of different variables, and the consistency across different GCMs in simulating different variables gets modified with change in location, pressure levels, and time windows for India. This specifies the need for similar analysis, to get reliable estimates from climate-impact studies across different regions of India.

The general results and conclusions over India and the five homogeneous regions give a broad idea about consistency of variables across different GCMs. For any new climate-impact study over any specific region (small or large watershed) the VCS curve generated for entire India can serve as a useful first step. It can be used to get region-specific simulation details. The VCS analysis will help to reduce uncertainty in the results from climate-impact studies. Overall, it can be concluded that the VCS methodology is a simple method that can be easily applied to assess the reliability of a subset of model results for different variables and different regions.

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