

# Comparison of statistical and dynamical downscaling methods for seasonal scale winter precipitation predictions over North India

P.R. Tiwari<sup>1</sup>, S.C. Kar<sup>2\*</sup>, U.C. Mohanty<sup>3</sup>, S. Dey<sup>4</sup>, P. Sinha<sup>5</sup>, M.S. Shekhar<sup>6</sup> and R. S. Sokhi<sup>1</sup>

<sup>1</sup>Centre for Atmospheric and Climate Physics Research, Hatfield, United Kingdom

<sup>2</sup>National Centre for Medium Range Weather Forecasting, Noida, India

<sup>3</sup>School of Earth Ocean and Climate Sciences, IIT Bhubaneswar, India

<sup>4</sup>Centre for Atmospheric Sciences, IIT Delhi, India

<sup>5</sup>Indiana State Climate Office, Purdue University, USA

<sup>6</sup>Snow and Avalanche Study Establishment, Chandigarh, India

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\*Correspondence

Dr. S.C. Kar

National Centre for Medium Range Weather Forecasting (NCMRWF),

A-50, Sector-62, Noida, India

Email: [sckar@ncmrwf.gov.in](mailto:sckar@ncmrwf.gov.in)

## Abstract

The main aim of the present study is to analyze the capabilities of two downscaling approaches (statistical and dynamical) in predicting wintertime seasonal precipitation over North India. For this purpose, a Canonical Correlation Analysis (CCA) based statistical downscaling approach and dynamical downscaling (at 30 km) with an optimized configuration of the Regional Climate Model (RegCM) nested in coarse resolution global spectral model have been used for a period of 28 years (1982–2009). For CCA, nine predictors (precipitation, zonal and meridional winds at 850 and 200hPa, temperature at 200hPa and sea surface temperatures) over 3 different domains were

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selected. The predictors were chosen based on the statistically significant teleconnection maps and physically based relationships between precipitation over the study region and meteorological variables. The validation revealed that both the downscaling approaches provided improved precipitation forecasts compared to the global model. Reasons for improved prediction by downscaling techniques have been examined. The improvement mainly comes due to better representation of orography, westerly moisture transport and vertical pressure velocity in the regional climate model. Further, two bias correction methods namely Quantile Mapping (QM) and Mean Bias-remove (MBR) have been applied on downscaled RegCM, statistically downscaled CCA as well as the global model products. It was found that when the QM based bias correction is applied on dynamically downscaled RegCM products, it has better skill in predicting wintertime precipitation over the study region compared to the CCA based statistical downscaling. Overall, the results indicate that the QM based bias corrected downscaled RegCM model is a useful tool for wintertime seasonal scale precipitation prediction over North India.

Key words: North India, winter precipitation, downscaling, CCA, RegCM, bias correction.

## 1. Introduction

Precipitation during winter seasons in north India (NI) is very important for Rabi crops, particularly for wheat as it supplements the moisture and maintains low temperature for the development of the crops. This NI region (comprising of the Indian states of Punjab, Haryana in the plains and Jammu and Kashmir, Himachal Pradesh, Uttarakhand in the Himalayas) receives about 25% to 30% of the annual precipitation during winter seasons (Tiwari *et al.* 2016a). Most of the precipitation during winter over the mountainous regions of NI (western Himalayas) is in the form of snow which helps in maintenance of glaciers throughout the year. Snow and ice melt

(during spring and summer seasons) in the Himalayas influences the water availability downstream in the major river basins of south Asia (Tiwari *et al.* 2016b). Thus, advance information of winter precipitation (in terms of seasonal mean or anomaly) is useful for agriculture, water management sectors and various other sectors. Moreover, there is a demand of skillful seasonal prediction of winter precipitation from the resource managers as well as the farming community in north India (Mohanty *et al.* 2018).

Seasonal prediction skill in the tropical region is driven by slowly varying boundary conditions such as sea surface temperatures, snow cover and soil wetness etc, therefore, should have higher skill than sub-seasonal or monthly prediction (Shukla *et al.* 2000). Although there has been considerable advancement in computing resources and representation of physical processes in General Circulation Model (GCM), the skill of GCMs is still not satisfactory in simulating the spatial and temporal variability of seasonal mean temperatures and precipitation over India (Kumar *et al.* 2005; Wang *et al.* 2005; Barnston *et al.* 2010; Tiwari *et al.* 2014 and Tiwari *et al.* 2016a). A contributing factor is the coarse spatial resolutions (average spatial resolution is  $\sim 1.3^\circ$ ; Taylor *et al.* 2012) of these GCMs that are insufficient to correctly represent the regional processes, land surface distribution and topography (Tiwari *et al.* 2017). Moreover, there are inadequacies on how well the large-scale teleconnection patterns linking global forcing such as El Nino Southern Oscillation (ENSO) or North Atlantic/Arctic Oscillations (NAO/AO) with the regional climate are represented in global climate models. As a result, direct use of the GCMs products may not be useful in predicting seasonal precipitation distribution at a regional scale..

In order to overcome the spatial scale issue, two approaches namely statistical and dynamical downscaling techniques are mainly used to downscale the coarse resolution GCM products to get regional information at finer scale. Christensen *et al.* (2007), in the Fourth

Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, AR4) have assessed the performance of several downscaling techniques and suggested that downscaling techniques are also capable of improving the skill of the predictions at local-scale. Similar conclusions on the use of downscaling techniques are reported by Flato *et al.* (2012) in the IPCC AR5 assessment. Dynamical downscaling is based on nesting of high-resolution regional climate models (RCMs) to simulate finer scale physical processes consistent with large scale weather simulated by a GCM (Giorgi *et al.* 2001). Statistical downscaling approach uses statistical relationships between the regional climate and statistical characteristics of the GCM data (Wilby *et al.* 2004; Marun *et al.* 2010; Goodess *et al.* 2012; Sachindra *et al.* 2014a; 2014b; Ayar *et al.* 2015) and are grouped into three different categories namely perfect prognosis, model output statistics (MOS) and weather generators. Sachindra *et al.* (2012) have reported that while dynamic downscaling approach is based on the use of complex physics of atmospheric processes and involves high computational costs, statistical downscaling is computationally less expensive. These reports further encourage to use the downscaling approaches for prediction of local/regional scale climate, however, both the techniques have some advantages and limitations. The canonical correlation analysis (CCA) technique is very popular amongst the MOS techniques due to its ease in implementation and interpretation. However, this linear technique does not represent the non-linearity in the relationship between predictors and predictands. A comparison of linear and non-linear artificial neural network (ANN) models by (Trigo and Palutikof, 2001) for downscaling of monthly precipitation over Iberia had shown that the linear ANNs had better skill. Moreover, Ramirez *et al.* (2006) have reported that when the predictor-predictand relationship is nonlinear, or when the predictand is non-Gaussian (e.g daily precipitation) ANNs have an advantage over standard parametric approaches. Therefore, superiority of any non-linear statistical downscaling

method over the canonical correlation analysis method has not yet been established for downscaling monthly mean precipitation.

In last few years, many efforts (Sinha *et al.* 2013a; Sachindra *et al.* 2014b; Ayar *et al.* 2015) have been made using statistical downscaling techniques to predict regional precipitation at monthly as well as seasonal timescale. In all the studies, a clear improvement in precipitation prediction compared to parent GCM was obtained. On the other hand, studies using dynamical downscaling approaches (Sinha *et al.* 2013b, Tiwari *et al.* 2016b; Sorland *et al.* 2018) have also emphasized that the dynamical downscaling approach has potential to reproduce finer scale information with higher skill than the parent GCMs. A recent study conducted by Sorland *et al.* (2018) has shown that the regional climate models have systematically reduced the bias over the Alps and other regions of Europe. Further, these models are able to modify the climate change signals obtained from the driving GCMs, even on the scales that are considered well resolved by the driving GCMs.

Further studies (e.g. by Schmidli *et al.* 2007; Su *et al.* 2017; Grigory *et al.* 2018) have been carried out to compare dynamical and statistical downscaling methods over different regions worldwide. Schmidli *et al.* (2007) have used statistical and dynamical methods over European Alps region and stated that performance of these methods varies significantly from region to region and season to season. Su *et al.* (2017) have compared the monthly rainfall generated from statistical and dynamical methods over Heihe River Basin in China and reported that the skill of these two methods of downscaling varied from month to month. Recently Grigory *et al.* (2018) have applied statistical and dynamical downscaling methods and assessed their utility to provide seasonal forecast (June–September) for impact modelling in eastern Africa. The study reports that where dynamical downscaling method is able to reproduce the predictive signal evident in the

driving GCM in hindcast, statistical downscaling, in general, loses a part of the GCM signal at grid box scale. Furthermore the study also states that there are no clear evidences that the dynamical and statistical downscaling provide added value compared to the driving GCM over the eastern Africa.

In view of the above discussion and absence of any systematic effort to analyze the usefulness of either of these downscaling methods in predicting wintertime (seasonal mean) precipitation over northern India (NI), here we have attempted to downscale the GCM outputs so that these forecasts become useful to the user community at regional scale. Further an attempt has been also made to evaluate the skill of different bias correction techniques for wintertime precipitation over NI. Therefore, the main objectives of the present study are to:

- develop a canonical correlation analysis (CCA) based statistical downscaling technique for wintertime precipitation forecasts over NI; and
- compare the CCA based statistical downscaling against bias corrected dynamically downscaled RCM and bias corrected CCA model.

The description of model, data used and methodology are provided in Section 2. Discussions of the main findings of the study are presented in Sections 3. The summary and conclusions of the study are given in Section 4.

## **2. Model description and experimental framework, data used and methodology**

### ***2.1 The Model and Experimental framework***

In this study, products from the National Centre for Medium Range Weather Forecasting (NCMRWF) global spectral model (hereafter referred as T80 model) have been used. This model

has 80 waves in Triangular truncation equivalent to  $1.4^\circ \times 1.4^\circ$  (~150 km) horizontal grid resolution. Further details about the model are provided in Kar (2007) and Kar et al. (2011). The model is initialized in November and integrated until the end of February for each year over the period 1982 to 2009. The 10 member ensembles are generated using the initial conditions from 1-10 November (total 10 different days) of each year, and for each initial date. The NCEP Climate Forecast System version 2 (CFSv2; 126 waves in Triangular truncation equivalent to  $0.9^\circ \times 0.9^\circ$ , ~100 km horizontal grid resolution) forecasted SST (Saha *et al.* 2014) is provided to the model as boundary condition. The regional climate model used in the present study is the International Centre for Theoretical Physics (ICTP) Regional Climate Model (RegCM4, version 4.1.1). More details of the model can be found in Elguindi *et al.* (2011) and Giorgi *et al.* (2012). The configuration of the RegCM used in the present study has been optimized for the domain of interest in a previous study by Tiwari *et al.* (2016b). For dynamical downscaling, the T80 model products at 12 hourly intervals are provided as the input to RegCM.

## 2.2 Data used

In this study ensemble mean of 10 members of the T80 model outputs for the period 1982-2009 are considered for statistical downscaling approaches. The observed SST (Smith *et al.* 2008) and ERA-Interim reanalysis (Dee *et al.* 2011) for the period 1982-2009 are used to examine observed teleconnection patterns. Observed daily rainfall data at  $0.25^\circ \times 0.25^\circ$  resolution (Pai *et al.* 2014) obtained from India Meteorological Department (IMD) and station data sets from Snow Avalanche Establishment (SASE) has been used for validation purpose.

## 2.3 Technique

As mentioned earlier, so far, no statistical downscaling approaches using CCA have been developed for predicting wintertime precipitation over northern India. In the present study, the

model output statistics approach is the CCA based on Wilks (1995). This CCA technique considers two multivariate datasets and selects a sequence of pairs of patterns. The original data are then projected onto these patterns and sets of transferred variables are constructed. The technique is elaborated further in the next paragraph.

In the CCA technique, the original data  $P$  (independent) and  $Q$  (dependent) are transformed into a new set of variables  $X_m$  and  $Y_m$  respectively, called canonical variables (Wilks, 1995). Here,  $P$ 's are the predictor variables from the global model and  $Q$  is the predictant (observed precipitation data).

The canonical variables are defined as:

$$X_m = A \times P \quad \dots(1)$$

$$Y_m = B \times Q \quad \dots(2)$$

The calculation of canonical vectors ( $A$  and  $B$ ) is similar to that of Principal Component Analysis (PCA). The linear regression between the canonical variables can be written as:

$$Y_m = a \times X_m \quad \dots(3)$$

It can be easily proved that  $a = T_c$ , where  $T_c$  is the diagonal matrix of the canonical correlations. The original data  $Y$  can be easily estimated using the relation  $Q = B^{-1} Y_m B$ . Further details of the CCA methodology can be found in Singh *et al.* (2012) and Sinha *et al.* (2013).

Observations as well as model output data for the period from 1982–2009 are averaged from December to February for each month to get monthly values. From these monthly values, seasonal mean (DJF) values are also computed. Model precipitation fields were bi-linearly interpolated to the observed grid. Application of any other interpolation method (such as spline) did not provide any different output. The model precipitation outside the Indian region are not considered in the present study.



Two bias correction methods (i) quantile mapping (QM) and (ii) mean bias correction (MBR) described in Tiwari et al (2016b) have been used in the present study. The bias corrections have been applied to monthly mean precipitation predictions from the T80 model, the RegCM model and the CCA model before making seasonal mean. Based on the observed data few wet years (1991-92, 1994-95, 1995-96, 1997-98) and dry years (1984-85, 1996-97, 2000-01, 2008-09) were selected for more detailed analysis. For evaluation of the results, several skill metrics such as mean squared error, multiplicative bias, Kendall rank correlation coefficient, Willmott's index of agreement (WIOA), percent error of prediction have been used. The Student *t*-test is used for statistical significance test of correlation and the critical value is 0.33 at 95% confidence level. The above mentioned skill metrics are briefly discussed below:

*Mean squared error:* It measures the mean squared difference between the forecasts (F) and observations (O). The perfect score for this metric is 0.

$$MSE = \frac{1}{N} \sum_{i=1}^N (F_i - O_i)^2$$

*Multiplicative bias:* This skill metric mainly represent the model's ability to simulate the observed climatology and it is defined as ratio of the climatology of predicted and observed climatology. The perfect score for this metric is 1.

*Kendall rank correlation coefficient:* It is commonly referred as Kendall's tau and measures the association with the presumption that the predictor–predicted relationship may not be linear (Wilks 2006). This skill metric is considered more general and alternative to Pearson's correlation.

*Willmott's index of agreement:* Willmott (1982) proposed a skill metrics which is called 'Willmott's index of agreement (WIOA)' and it is defined as:

$$WIOA = 1 - \left[ \frac{\sum_i (F_i - O_i)^2}{\sum_i (|F_i - \bar{O}| + |O_i - \bar{O}|)^2} \right]$$

where  $F_i$  and  $O_i$  are the  $i$ th year forecast and observation respectively and  $\bar{O}$  is the observed climatology. WIOA is bounded between 0 and 1 ( $0 \leq WIOA \leq 1$ ) and the perfect score for this index is 1.

*Percent error of prediction (PE)*: Perez and Reyes (2001) suggested that a predictive model will be termed as good one if the PE is close to 0. It is computed as:

$$PE = \frac{\langle |F_i - O_i| \rangle}{\langle O_i \rangle} \times 100$$

where  $O_i$  and  $F_i$  denotes the observed and predicted values in the  $i$ th case and  $\langle \rangle$  implies the average over the whole test set.

### 3. Application

The techniques described in section 2.3 have been applied here and presented into three segments namely i) the NCMRWF global model diagnosis, ii) model output statistics (MOS) approach for predicting wintertime (DJF) precipitation and, iii) comparison of dynamical (bias corrected downscaled RCM) and statistical downscaling. Before presenting the results related to the prediction of wintertime precipitation using statistical downscaling, the results of a brief diagnostic study of the NCMRWF (T80) model output are described.

#### 3.1 Global model diagnosis

As the global T80 model simulated precipitation is provided as input to the statistical downscaling model, as a first step, salient features of the model simulated precipitation have been

examined. As mentioned earlier, western disturbances (WD) propagating from west to east contribute to major part of precipitation during winter over the NI region. In order to study the precipitation characteristics, the longitudinal mean of precipitation (Hovmoller diagram) of available 26 years (1982-2007) from the observation and the T80 model are plotted in Figure 1 (a) and (b) respectively. It can be seen from Fig. 1 (a) that the maximum precipitation lies between the latitudinal belt of  $32^{\circ}$  N to  $36^{\circ}$  N for each year. The northern part of Kashmir receives maximum precipitation (2-7 mm/day) during winter and the precipitation amount reduces gradually southward. Figure 1 (b) indicates that the precipitation distribution is represented well in the model simulations, however the maximum precipitation belt is shifted towards south. Further, the model simulated precipitation amount is lower (by about 2 mm/day) than observed values in some years. Fig. 1 (C) has the bias between the model and observed precipitation. It is seen that the T80 model has dry bias mainly between  $33^{\circ}$ N to  $36^{\circ}$ N. Interannual precipitation variability (standard deviation) at each grid point has been calculated from the observed and model simulated precipitation for the period of study (figure not shown). It is noticed that the interannual standard deviation is high over NI region and some pockets of North East India. The values of interannual standard deviation (ISD) over these regions range from 15 to 35 mm. The highest ISD is found over the areas experiencing large amount of precipitation during winter that is the northern part of India in observation. The T80 global model is able to show the total variance of precipitation as in observation up to certain extent and the ISD values are less than 30 mm over NI region.

The spatial averages (NI region) of seasonal mean precipitation anomalies (based on baseline period 1982-2007) from the observed gridded data and the ensemble mean along with individual members of the T80 model forecasts are shown in Figure 2. It is seen from the figure that over the region of interest, maximum observed precipitation was in 1994 and minimum

precipitation occurred in 2000 (~1 mm/day). The T80 model generally produces less precipitation over NI region as compared to observed precipitation as discussed below. In 1994, observed precipitation during the season was more than 4 mm/day. However, the precipitation value from the T80 model is within 2 mm/day, indicating large bias in the model precipitation. Moreover, it is seen from the figure that interannual variability of the model-simulated precipitation does not agree with that of observed precipitation. Further it can be also noted that the model precipitation anomaly shows opposite sign compared with observations during the few extreme years such as 1996, 2000.

Figure 3 (a) and (b) show the correlation coefficient (CC) and normalized mean squared error (NMSE) between the model precipitation and observations respectively. It can be seen that the values of correlation coefficients for the T80 model over Northern parts of India are low and range from 0.3 to as low as -0.1. For the number of years used this computations, correlation values greater than 0.33 are statistically significant at 95% confidence level. Therefore, the T80 model does not have statistically significant correlation skill for precipitation over the NI region during winter season. The NMSE values lies in between 0.5 to 2 mm/day over Jammu and Kashmir (J&K) region of NI. Further the maximum value of NMSE can be see over the northwest Kashmir where it is about 2 mm/day.

This study reveals that the T80 model has a number of deficiencies in its predictions of the precipitation in terms of intensity and variability. Interannual variation as well as the flow pattern for extreme years in the model exhibit differences with that of the observations. Interannual variability of the model ensemble-mean precipitation depends on how the model responds to local and remote SST forcing prescribed in the model. The analysis of precipitation variability of the model presented so far indicates that the model may be incorrectly responding to prescribed SSTs.

It also appears that the model precipitation over NI region is linked to the sea surface temperature over the Pacific and the Indian Ocean. This aspect is further examined in the next section while developing the CCA model. In the following, the potential for statistical downscaling of model output using CCA is explored to improve seasonal forecasts of wintertime precipitation over NI region.

### **3.2 Wintertime precipitation prediction using MOS approach**

As mentioned earlier, Model Output Statistics (MOS) approach using the CCA technique has been used in this study. As a first step towards this, teleconnection maps have been prepared to find suitable predictors as well as domains and, then predictions of wintertime (DJF) precipitation over NI region have been made using MOS. Monthly values from observation as well as the T80 model have been used to build the CCA model. Seasonal mean precipitation for each year has been computed from these monthly mean downscaled values.

#### ***3.2.1 Teleconnection maps***

Precipitation over NI is largely influenced by several global forcing such as the ENSO, NAO and AO (Kar and Rana, 2013). Teleconnection maps are generated using the correlation between wintertime precipitation over NI and different meteorological parameters (surface as well as upper air) obtained from observations and the T80 model output separately for the period 1982–2007. For this, correlation maps between NI precipitation and global variables (meteorological parameters of surface and upper air) are produced at 95% confidence level. The analysis is performed separately using observed and model hindcast data respectively, and the correlation maps are drawn. Based on the teleconnection maps and physically based relationships between NI precipitation and meteorological variables, nine predictors out of which two are precipitation and

meridional wind at 200hPa over the domain-1, four predictors (zonal wind at 850 and 200hPa, meridional wind at 850hPa and temperature at 200hPa) over the domain-2 and three predictors (zonal wind at 850 and 200hPa and SST) over domain-3 are considered for statistical downscaling from the T80 model using CCA. The anomaly correlation between wintertime precipitation over NI and different meteorological parameters (surface as well as upper air) obtained from observations and the T80 model output for the period 1982–2007 is shown in in Figure 4. Furthermore, the exact domains with their corresponding dimensions in latitude/longitude directions are shown in Figure 5. Since the length of the data period is moderate (26 years), only nine predictors have been chosen for the present study. The domain-1 covers the Indian region. Precipitation is the first automatic choice for the CCA model to predict precipitation. The meridional winds at 200hPa indicate the amplitude and zone of the westerly troughs over the study area which has strong relationship with precipitation variability in the region (Kar and Rana, 2014). The domain-2 covers the north Indian Ocean along with central and west Asia. Interannual variation of precipitation over north India is due to passage of western disturbances that originate in the Mediterranean Sea and Caspian Sea regions. Zonal and meridional winds at 850hPa and 200hPa and upper air temperature at 200hPa adequately represent the passage of these western disturbances. Moreover, the impact of the North Atlantic Oscillation and Arctic Oscillation are noticed in these variables. So there parameters get chosen for the CCA model. The domain-3 is the eastern and central Pacific region and indicates the ENSO through the seas surface temperature and zonal winds at 850hPa and 200hPa. The relationship between precipitations over NI with that of ENSO has been described by Kar and rana (2014). Therefore, these 3 parameters have also been chosen for the CCA model

### ***3.2.2 Prediction of DJF precipitation***

In this study, while developing the CCA model, data for 26 years (1982–2007) have been considered for training period to compute canonical variables and correlations for the regression equations. Various studies (Ayar *et al.* 2015; Tiwari *et al.* 2014; Sinha *et al.* 2013a) have suggested that when the data length is limited, cross validation approach is very useful. Therefore, in the present study, leave-three-out (one forecasted year and another two years randomly selected) cross-validation technique has been used for calculation of the canonical coefficients. The omission of the two random years in addition to the forecasted year was found to make the CCA model more robust and reduces the cross-validation bias (Mason and Tippet 2004, Sinha *et al.* 2013a). The anomaly correlation has been plotted in Figure 6 to understand the performance of the CCA model. It is seen that all predictors have reasonable skill in prediction of wintertime (DJF) precipitation over most parts of NI. However, reasonable skill of forecast using composite techniques is obtained over larger area than individual predictors. The number of grid points with skill more than 0.33 CC is 62 for composite forecast which is the highest as compared to any individual predictor forecast (47 grid points is the maximum among individual predictor forecasts) or mean forecast (31 grid points exhibit more than 0.33 CC). Figure 6 also indicates that among all the predictor fields, the model precipitation over NI region has less potential than large-scale flow patterns in predicting wintertime (DJF) precipitation. This may be due to poor performance of the T80 model in predicting year-to-year precipitation variation as well as intensity over NI. It may be noted here that the correlation of the model precipitation (direct model output interpolated over observation grid) with observed precipitation is poor (statistically not significant) over NI region (Figure 3a) while, an improvement in skill is noticed with the use of CCA based statistical downscaling approach.

### 3.3 Comparison of Statistical and dynamical downscaling approaches

Evaluation of performance of both the statistical and dynamical downscaling approaches (forecast mode) has been made in predicting wintertime (DJF) precipitation over the NI region. For this purpose, model precipitation has been interpolated over IMD grid point and areas outside the Indian landmass are not considered. For dynamical downscaling, high-resolution (at 30 km) simulations of RegCM4 (along with two bias corrected methods namely MBR and QM) have been considered. The bias correction methods are explained in Tiwari et al (2016b). In the case of statistical downscaling, composite forecast of wintertime (DJF) precipitation have been considered to compare both the dynamical and statistical downscaling approaches. Firstly a comparison for a period of 26 years (1982-2007) is made. A number of statistical skill metrics such as multiplicative bias, Kendall rank correlation coefficient, Wilmort's index of agreement (WIOA) and percentage error and prediction yield have been calculated and discussed below. Further, for better representation, the magnitude of all above stated skill metrics have been presented in Table 1 for the T80, CCA, RegCM and two bias corrected methods (MBR and QM) applied on T80 model (hereafter referred as T80\_MBR and T80\_QM), statistical downscaling based CCA model (hereafter referred as CCA\_MBR and CCA\_QM) and dynamical downscaled RCM (hereafter referred as RegCM\_MBR and RegCM\_QM) respectively.

### 3.3.1 *Multiplicative bias*

To compare the climatology of the forecast with the climatology of observed precipitation, multiplicative bias has been computed and shown in Table 1. Essentially it represents the model's ability to simulate the climatology of observations and is defined as the ratio of the climatology of predicted and observed climatology. Efficiency of the prediction is considered to be maximum when this index is close to 1. The Multiplicative bias of the T80, T80\_MBR, T80\_QM, CCA, CCA\_MBR, CCA\_QM, RegCM, RegCM\_MBR and RegCM\_QM is 0.49, 0.51, 0.54, 0.67, 0.69,



0.76, 0.58, 0.72 and 0.81 respectively.. The results clearly indicate that the QM based bias corrected downscaled RCM (i.e. RegCM\_QM) is more efficient than CCA based statistical downscaling, bias corrected CCA (CCA\_MBR and CCA\_QM) and other methods to reproduce the observed precipitation climatology.

### 3.3.2 Kendall rank correlation coefficient

While the Pearson's correlation coefficient is a measure of linear association (i.e. it considers only linear relationship between the predicted and actual observation), the Kendall rank correlation coefficient (Kendall's tau), measures the association with a presumption that the predictor–predicted relationship may not be necessarily linear (Wilks 2006). This skill metric is considered to be more robust and in general an alternative to Pearson's correlation coefficient. The Kendall rank correlation coefficient (Kendall's tau) for the T80, T80\_MBR, T80\_QM, CCA, CCA\_MBR, CCA\_QM, RegCM, RegCM\_MBR and RegCM\_QM is computed (Table 1) and which are 0.21, 0.24, 0.29, 0.33, 0.36, 0.41, 0.30, 0.37 and 0.45 respectively. A two tailed Student t-test has been performed and it shows that the Kendall's tau for bias corrected dynamically downscaled RCM has significant skill (significant at 95% confidence level). Moreover, the advantages of QM based bias corrected downscaled RCM is also established in terms of Kendall's tau.

### 3.3.3 Wilmott's index of agreement (WIOA)

The above stated skill metrics have certain limitations as they are not bounded and are not suitable for very small (near zero) climatology of observation (Willmott 1982). Willmott index of agreement (WIOA) is bounded between 0 and 1 ( $0 \leq \text{WIOA} \leq 1$ ). The closeness of this index to 1 indicates the efficiency of the model in producing a good forecast. The usefulness of such a metric in judging the precipitation predictions has been discussed in many studies (Chattopadhyay *et al.*

2010; Acharya *et al.* 2013; Tiwari *et al.* 2014). In this study, the WIOA for the T80, T80\_MBR, T80\_QM, CCA, CCA\_MBR, CCA\_QM, RegCM, RegCM\_MBR and RegCM\_QM has been computed and shown in Table 1. The WIOA for the T80, T80\_MBR, T80\_QM, CCA, CCA\_MBR, CCA\_QM, RegCM, RegCM\_MBR and RegCM\_QM is 0.36, 0.39, 0.44, 0.55, 0.57, 0.63, 0.51, 0.64 and 0.76 respectively. The result clearly indicates that bias corrected downscaled RCM has an edge over the RegCM and CCA based statistical downscaling in predicting wintertime precipitation over NI region.

### 3.3.4 Percentage error and prediction yield

We have calculated percentage error for the T80, T80\_MBR, T80\_QM, CCA, CCA\_MBR, CCA\_QM, RegCM, RegCM\_MBR and RegCM\_QM. The average percentage error (averaged over 26 years) is 23.9, 23.7, 23.6, 22.4, 22.3, 22.2, 23.5, 22.1 and 21.7 respectively.. This further shows that the bias corrected downscaled RCM has an edge over the bias corrected CCA based statistical downscaling in predicting wintertime precipitation over NI region. The predicted yield for different error categories (5, 10, 15 and 20 % error) as followed by Chattopadhyay *et al.* (2010) were also computed for the T80, T80\_MBR, T80\_QM, CCA, CCA\_MBR, CCA\_QM, RegCM, RegCM\_MBR and RegCM\_QM respectively as well. It is found that if we allow an error as small as 5 %, the predicted yields of the T80, T80\_MBR, T80\_QM, CCA, CCA\_MBR, CCA\_QM, RegCM, RegCM\_MBR and RegCM\_QM turns out to be 0.06, 0.073, 0.08, 0.12, 0.121, 0.136, 0.10, 0.14 and 0.18 respectively.. Further, if 10, 15, and 20 % errors of prediction are allowed, then the prediction yields are 0.24, 0.31 and 0.51 respectively for RegCM\_QM method. Furthermore, it can be noticed that the prediction yields by the T80, T80\_MBR, T80\_QM, CCA, CCA\_MBR, CCA\_QM, RegCM and RegCM\_MBR methods for 10, 15, and 20 % are less than the corresponding values in the case of RegCM\_QM. For better understanding, the values of the

prediction yields for different percentage error categories is presented in Fig. 7. The result clearly indicates that the QM based bias corrected downscaled RCM (RegCM\_QM) has an edge over the bias corrected CCA model (CCA\_QM) in predicting wintertime precipitation over the NI region.

Finally, the role of both downscaling approaches (CCA based statistical downscaling and two bias correction based dynamical downscaling methods) in prediction of magnitudes of precipitation anomalies for individual years (extreme years) has been examined. Forecasts for the NI region has been prepared independently for the year 2008 and 2009. In Figure 8, different bars (black, grey, cyan, sky-blue, dark-blue chocolate, green and gold) represents observed and predicted percentage departure of precipitation respectively. It can be noticed from the diagram that over the NI region for year 2008 the observed departure is -17.2% while the predicted precipitation departure is -8.9%, -9.1%, -10.4%, -13.7%, -12.9% and -15.7% for the T80, T80\_QM, CCA, CCA\_QM, RegCM and RegCM\_QM respectively. Similarly, in 2009, the predicted percentage departures are of the same sign but the magnitude is 23.8%, 9.5%, 10.1%, 15.6%, 18.7%, 18.1% and 21.4% respectively for observation, T80, T80\_QM, CCA, CCA\_QM, RegCM and RegCM\_QM. In conclusion, the QM based bias corrected downscaled RCM (i.e. RegCM\_QM) is able to capture most of the observed features in the years 2008 and 2009 and has maximum skill followed by the CCA\_QM based predictions.

From the above discussions, it is evident that the QM based bias corrected downscaled RCM (i.e. RegCM\_QM) consistently outperforms other downscaling or bias correction methods. However, it may be noted that the quantile mapping procedure corrects the statistical moments and some statistical attributes of the cumulative distribution function (CDF) but it disrupts the temporal sequence Sachindra et al. 2014b. Improved time series data could be generated by employing monthly data for bias correction in the study of Sachindra et al. 2014b. Therefore, in

this study, bias correction has been carried out using monthly data (of global model, RegCM and statistically downscaled). The quantile mapping bias correction has also been applied to the raw model data before downscaling. It is found that the seasonal mean precipitation time series data obtained after following this procedure has better skill as compared to other methods. Sachindra et al. 2014b have suggested the use of nested bias correction (NBC) method to overcome the disruption of time sequence when quantile mapping bias correction is applied. However, in this study, the NBC method has not been used and will be attempted in future studies.

### **3.4 Comparison and validation of downscaled precipitation with station observations**

In the present section, both the downscaling approaches (CCA based statistical downscaling and QM based bias corrected dynamically downscaled RCM) along with the T80 global model are validated against the Snow and Avalanche Study Establishment (SASE), observations over seventeen stations located over the North Indian part of the Western Himalayas (IWH) region. The station-wise seasonal mean precipitation obtained from SASE observation, both the downscaling approaches and the T80 model is presented in Table 2. The italic shaded values indicate the closest ones to the SASE observations. Further, for a better insight, the Phase synchronizing events (PSE) have been computed based on Table 2 results. More details of PSE computation can be found in Tiwari *et al.* (2016b). It is noticed from Table 2 that the PSE value is maximum (with 94%) for composite (i.e., model output matches the sign of with observations 94% times) of wet minus dry years for QM method followed by CCA based statistical downscaling method (with 88%), T80\_RegCM (with 70%) and T80 model (with 58%). Therefore, it can be concluded that the QM based bias corrected dynamically downscaled RCM is able to represent the precipitation well compared to CCA based statistical downscaling, T80 driven RegCM and the T80 model.

## **4. Conclusion**

Two downscaling approaches (CCA based statistical downscaling and dynamical downscaling using RegCM4 model) have been evaluated for wintertime (DJF) precipitation prediction over North India (NI) region. The NCMRWF global spectral model (T80) outputs have been used as input for both downscaling approaches. The major findings of this study are enumerated as follows:

- The global T80 model has a dry bias over North India during winter seasons. The simulated mean climatological precipitation amount as well as its interannual variation are less than that of observations.
- A CCA based model has been developed to statistically downscale the wintertime precipitation in seasonal timescale using the T80 model products. Based on the teleconnection maps and physically based relationships between NI winter precipitation and meteorological variables, nine predictors are considered for the CCA. The CCA method improves the forecast skill over some parts of NI. Further, the domain with higher correlations is more in case of composite forecast than the forecasts from individual predictors.
- A detailed comparison of CCA and bias corrected CCA model is made against bias corrected dynamical downscaled RCM for a period of 26 years (1982-2007). All the skill metrics clearly indicate that the CCA based statistical downscaling has higher skill compared to the RCM based dynamical downscaling and the T80 model. Further analysis suggests that the QM based bias corrected downscaled RCM has an edge over the CCA based statistical downscaling and bias corrected CCA model in predicting wintertime precipitation over the NI region.

- The performance of both downscaling approaches in prediction of precipitation anomaly magnitudes for two extreme winter seasons has been examined. The result clearly indicates that the performances of both the downscaling techniques in representing the seasonal mean precipitation over the NI region are better than the GCM. Further, the QM based bias corrected downscaled RCM has maximum skill over the NI region.

This study has shown that both the downscaling techniques have the efficiency to improve the skill in predicting wintertime seasonal precipitation over the NI region. Both the techniques are able to correct the GCM forecasts of precipitation over the NI region. Finally, QM based bias corrected downscaled RCM has statistically better performance over RegCM and CCA based statistical downscaling and can be used as a seasonal prediction system in predicting wintertime precipitation over the NI region.

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## List of Figures

Figure 1. Hovmoller diagram (longitudinal mean) of precipitation (in mm/day) of each year form (a) observation (b) T80 model simulations and (c) bias.

Figure 2. Spatial average of DJF precipitation anomaly over NI for observed (black line) and model simulations (red line denotes ensemble mean, red closed diamonds denote individual ensemble members respectively).

Figure 3. Statistical analysis between observed and T80 model DJF precipitation (model precipitation is interpolated in observed grid) for the period 1982-2007 shown (a) for Correlation Coefficient and (b) for normalized mean squared error (mm/day).

Figure 4. Anomaly correlation between wintertime (DJF) precipitation over NI and different meteorological parameters (surface as well as upper air) obtained from the observation vs T80 model output for the period 1982–2007. Only values significant at the 95% level are plotted.

Figure 5. Spatial domains of various predictors used in MOS approaches.

Figure 6. Anomaly correlation coefficient skill of Model Output Statistics (MOS)-corrected hindcasts (1982–2006) using various T80 model predictors over the three domains in Fig. 5: (a) precipitation, domain 1; (b) meridional wind at 200 hPa, domain 1; (c) zonal wind at 850 hPa, domain 2; (d) meridional wind at 850 hPa, domain 2 (e) zonal wind at 200 hPa, domain 2 (f) temperature at 200 hPa, domain 2; (g) zonal wind at 850 hPa, domain 3; (h) zonal wind at 200 hPa, domain 3; (i) composite of all predictors forecast.

Figure 7. Prediction yields for T80, bias corrected T80 (T80\_MBR & T80\_QM), CCA, bias corrected CCA (CCA\_MBR & CCA\_QM), RegCM and bias corrected RegCM (RegCM\_MBR & RegCM\_QM) for different categories of percentage error.

Figure 8. Area average precipitation percentage departure (%) for T80 (in grey bars), QM based bias correction method applied on T80 (T80\_QM, in cyan bar), CCA based statistical downscaling (in coral bars), QM based bias correction method applied on CCA (CCA\_QM, in dark orchid bar), dynamical downscaling based RegCM (RCM, in sky-blue bar), QM based bias corrected method for downscaled RCM (in green bars) and the observed departure (in black bars) for years (a) 2008 and (b) 2009 respectively.



## List of Tables

Table 1. Skill scores of the T80, bias corrected T80 (T80\_MBR & T80\_QM), CCA, bias corrected CCA (CCA\_MBR & CCA\_QM), RegCM and bias corrected RegCM (RegCM\_MBR & RegCM\_QM) during 1982-2007.

Table 2. Seasonal mean precipitation over seventeen (17) stations obtained from SASE observation, T80, CCA based statistical downscaling, T80 driven RegCM (RCM) and bias corrected RegCM (QM) for composite wet minus dry years. The shaded values are closer to the observations. The model data is bi-linearly interpolated to the station locations.

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<b>Skill Metrics</b>	<b>T80</b>	<b>T80_MBR</b>	<b>T80_QM</b>	<b>CCA</b>	<b>CCA_MBR</b>	<b>CCA_QM</b>	<b>RegCM</b>	<b>RegCM_MBR</b>	<b>RegCM_QM</b>
<b>Multiplicative Bias</b>	0.49	0.51	0.54	0.67	0.69	0.76	0.58	0.72	0.81
<b>Kendall's tau</b>	0.21	0.24	0.29	0.33	0.36	0.41	0.30	0.37	0.45
<b>WIOA</b>	0.36	0.39	0.44	0.55	0.57	0.63	0.51	0.64	0.76

Table 2. Seasonal mean precipitation over seventeen (17) stations obtained from SASE observation, T80, CCA based statistical downscaling, T80 driven RegCM (RegCM) and bias corrected RegCM (QM) for composite wet minus dry years. The shaded values are closer to the observations. The model data is bi-linearly interpolated to the station locations.

Station	Composite (wet minus dry)				
	SASE	T80	CCA	RegCM	RegCM_QM
1. Bahadur	<b>1.41</b>	1.76	1.32	-0.33	1.35
2. Banihal	<b>4.70</b>	3.11	3.58	4.42	2.31
3. Bhang	<b>2.08</b>	-0.51	1.91	3.62	0.97
4. Dhundi	<b>2.53</b>	-0.23	2.96	4.05	2.91
5. Dras	<b>5.06</b>	2.21	4.63	5.30	5.81
6. Gulmarg	<b>3.14</b>	-0.33	2.81	3.23	3.19
7. H-Taj	<b>5.61</b>	3.05	5.92	6.37	5.63
8. Kanzalwan	<b>6.05</b>	2.91	6.25	4.12	6.16
9. Kumar	<b>1.46</b>	1.41	4.75	2.73	2.18
10. Neeru	<b>2.32</b>	1.84	2.26	-1.38	2.25
11. Patsio	<b>1.58</b>	-0.07	1.45	-0.41	1.47
12. Pharki	<b>4.32</b>	1.41	3.83	4.73	4.24
13. Solang	<b>5.31</b>	3.31	5.27	4.29	3.91
14. Stg-II	<b>6.83</b>	3.61	4.58	3.52	6.54
15. Z-Gali	<b>3.31</b>	-0.23	3.85	4.63	3.27
16. Gugaldhar	<b>3.52</b>	-0.16	-0.50	-0.49	-0.48
17. Dawar	<b>1.71</b>	-0.17	-0.06	-0.32	1.74

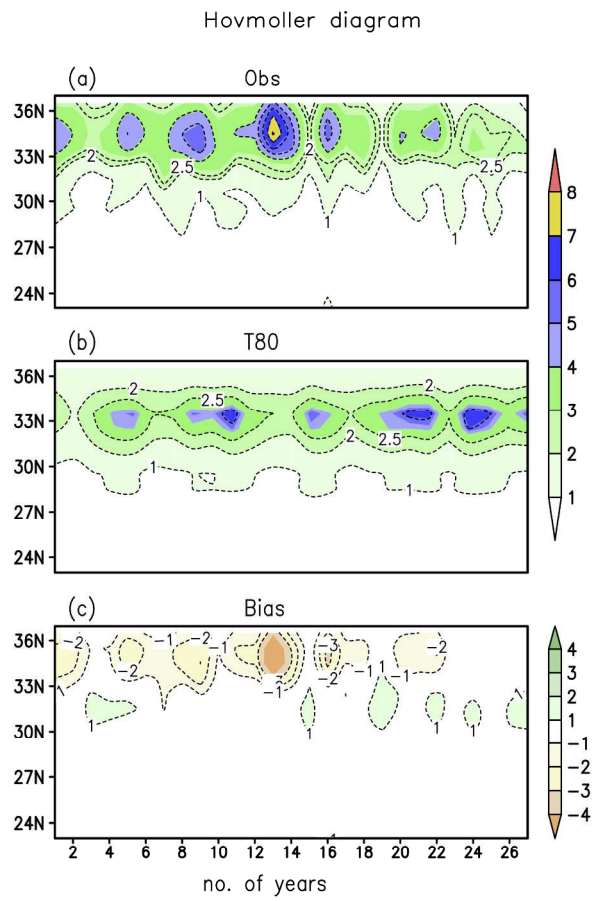


Figure 1. Hovmoller diagram (longitudinal mean) of precipitation (mm/day) of each year from (a) observation (b) T80 model simulations and (c) bias.

215x279mm (300 x 300 DPI)

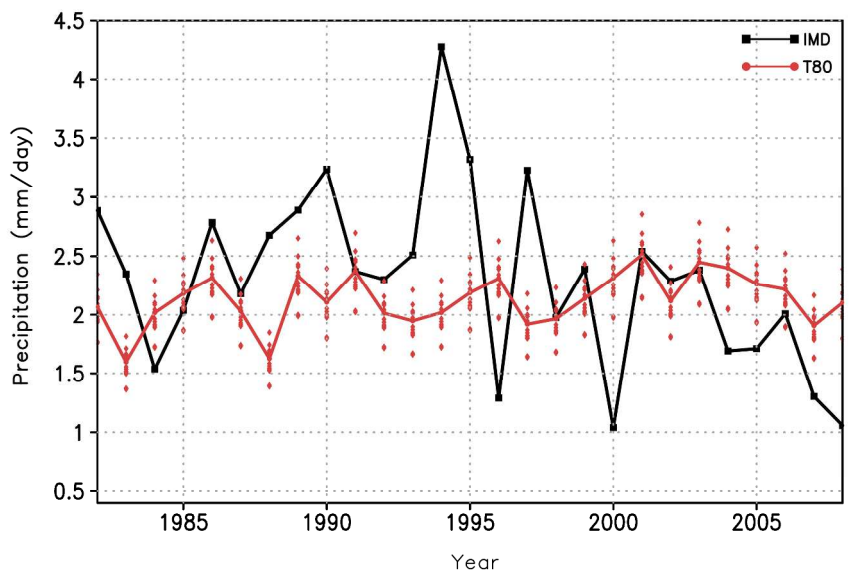


Figure 2. Spatial average of DJF precipitation anomaly over NI for observed (black line) and model simulations (red line denotes ensemble mean, red closed diamonds denote individual ensemble members respectively).

279x215mm (300 x 300 DPI)

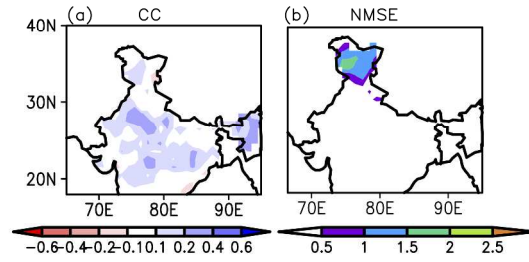


Figure 3. Statistical analysis between observed and T80 model DJF precipitation (model precipitation is interpolated in observed grid) for the period 1982-2007 shown (a) for Correlation Coefficient and (b) for normalized mean squared error (mm/day).

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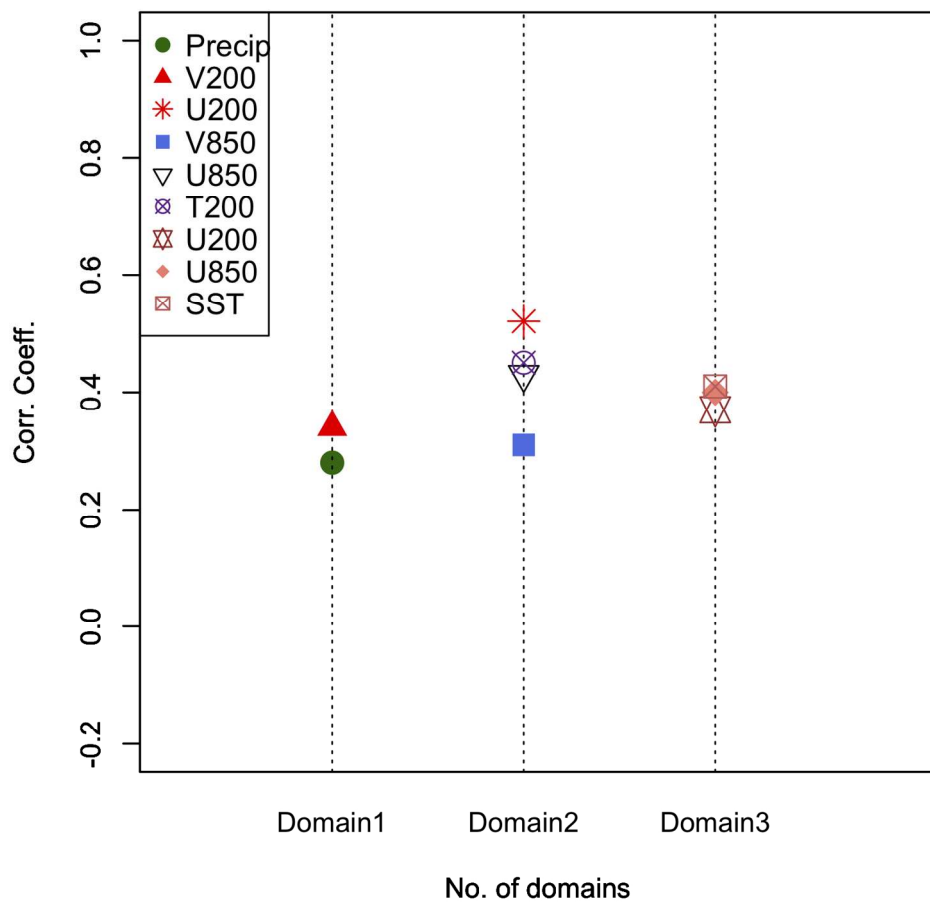


Figure 4. Anomaly correlation between wintertime (DJF) precipitation over NI and different meteorological parameters (surface as well as upper air) obtained from the observation vs T80 model output for the period 1982–2007. Only values significant at 95% level are plotted.

153x163mm (300 x 300 DPI)

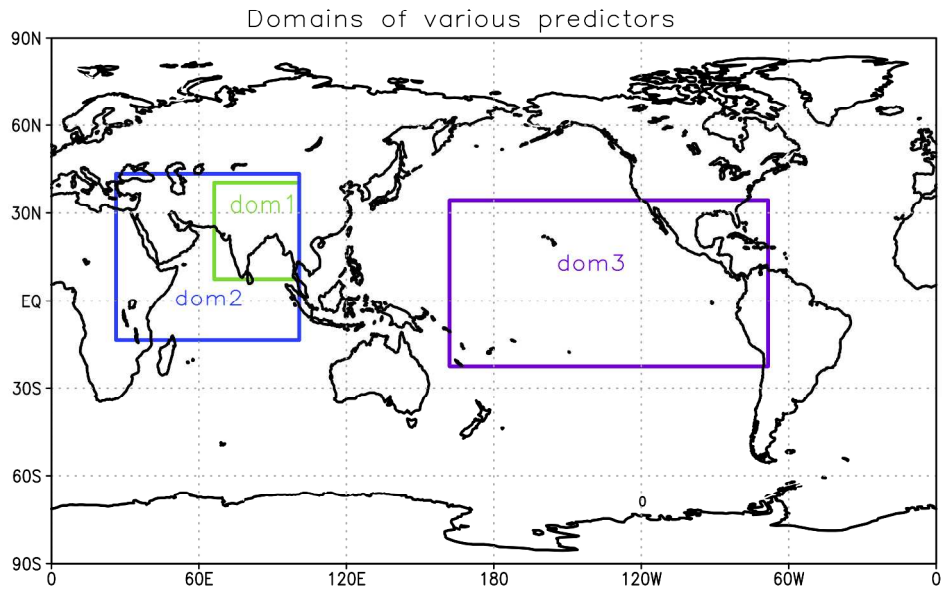


Figure 5. Spatial domains of various predictors used in the MOS approach.

279x215mm (300 x 300 DPI)



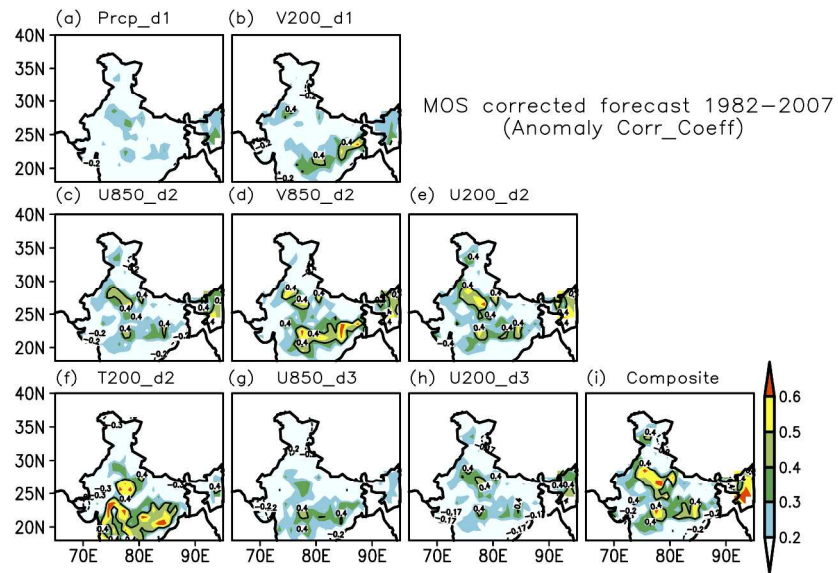


Figure 6. Anomaly correlation coefficient skill of Model Output Statistics (MOS)-corrected hindcasts (1982–2006) using various T80 model predictors over the three domains in Fig. 5: (a) precipitation, domain 1; (b) meridional wind at 200 hPa, domain 1; (c) zonal wind at 850 hPa, domain 2; (d) meridional wind at 850 hPa, domain 2 (e) zonal wind at 200 hPa, domain 2 (f) temperature at 200 hPa, domain 2; (g) zonal wind at 850 hPa, domain 3; (h) zonal wind at 200 hPa, domain 3; (i) composite of all predictors forecast.

279x215mm (300 x 300 DPI)

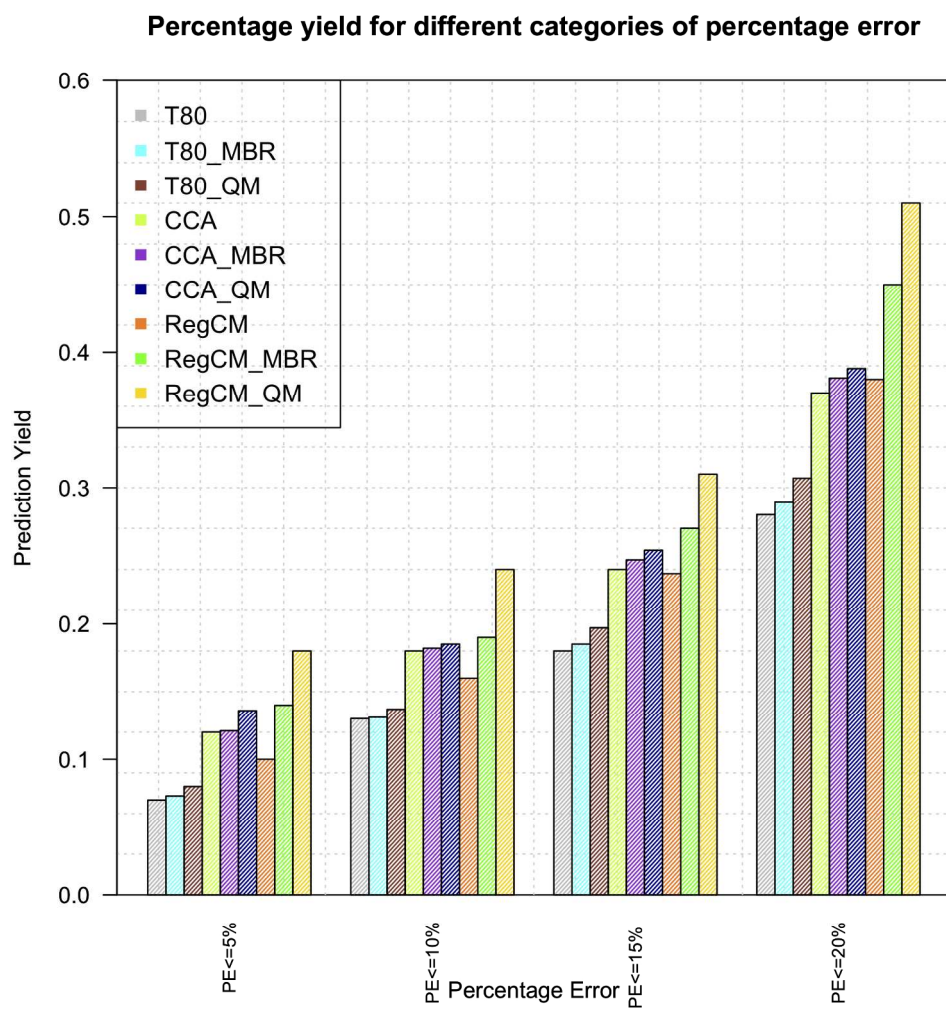


Figure 7. Prediction yields for T80, bias corrected T80 (T80\_MBR & T80\_QM), CCA, bias corrected CCA (CCA\_MBR & CCA\_QM), RegCM and bias corrected RegCM (RegCM\_MBR & RegCM\_QM) for different categories of percentage error.

187x199mm (300 x 300 DPI)

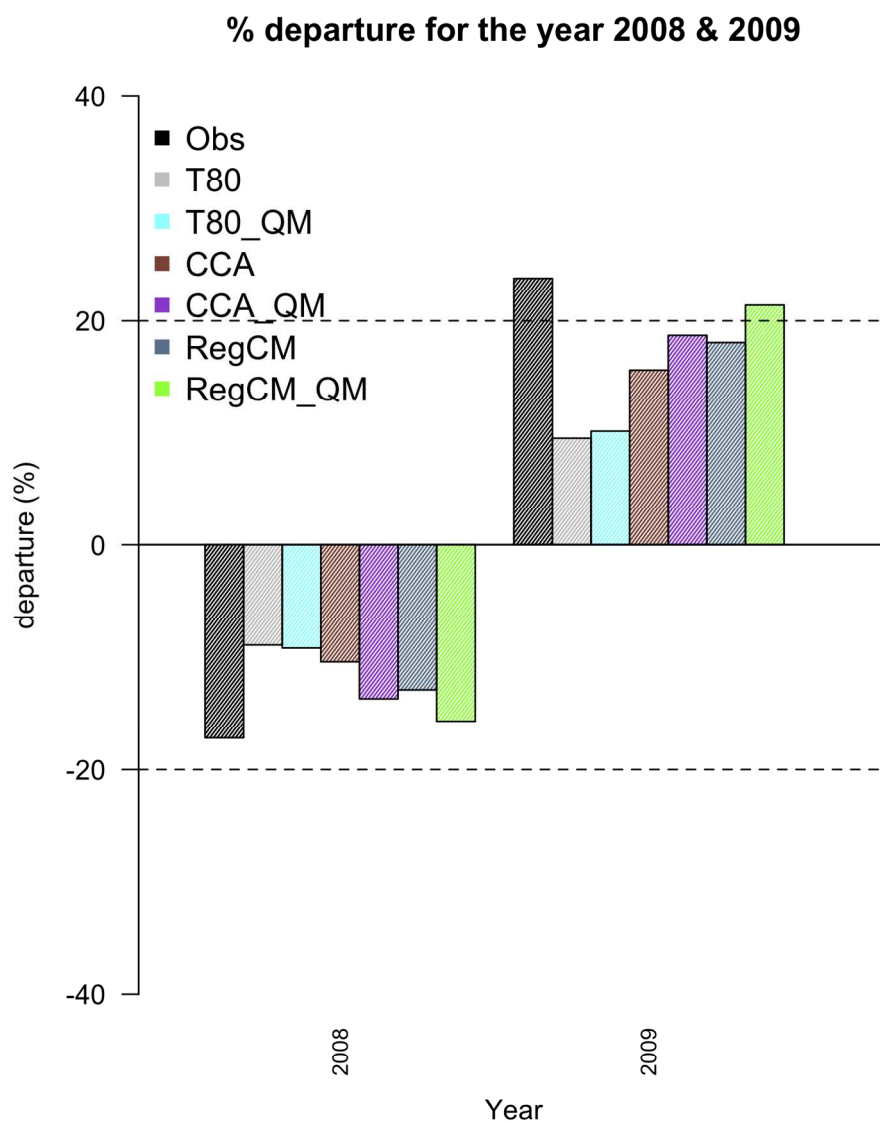


Figure 8. Area average precipitation percentage departure (%) for T80 (in grey bars), QM based bias correction method applied on T80 (T80\_QM, in cyan bar), CCA based statistical downscaling (in coral bars), QM based bias correction method applied on CCA (CCA\_QM, in dark orchid bar), dynamical downscaling based RegCM (RCM, in sky blue bar), QM based bias corrected method for downscaled RCM (in green bars) and the observed departure (in black bars) for years (a) 2008 and (b) 2009 respectively.

147x185mm (300 x 300 DPI)