

# Seasonal prediction skill of winter temperature over North India

P. R. Tiwari · S. C. Kar · U. C. Mohanty · S. Dey ·  
S. Kumari · P. Sinha

Received: 14 June 2014 / Accepted: 9 December 2014 / Published online: 15 February 2015  
© Springer-Verlag Wien 2015

**Abstract** The climatology, amplitude error, phase error, and mean square skill score (MSSS) of temperature predictions from five different state-of-the-art general circulation models (GCMs) have been examined for the winter (December–January–February) seasons over North India. In this region, temperature variability affects the phenological development processes of wheat crops and the grain yield. The GCM forecasts of temperature for a whole season issued in November from various organizations are compared with observed gridded temperature data obtained from the India Meteorological Department (IMD) for the period 1982–2009. The MSSS indicates that the models have skills of varying degrees. Predictions of maximum and minimum temperature obtained from the National Centers for Environmental Prediction (NCEP) climate forecast system model (NCEP\_CFSv2) are compared with station level observations from the Snow and Avalanche Study Establishment (SASE). It has been found that when the model temperatures are corrected to account the bias in the model and actual orography, the predictions are able to delineate the observed trend compared to the trend without orography correction.

## 1 Introduction

Seasonal temperature during the winter season (December–February, hereafter DJF) in northern India shows considerable

interannual variability. Winter crops are especially vulnerable to temperature at their reproductive stages, and it has been noticed that under different production environments, there is a differential response of temperature change (rise) to various crops (Kalra et al. 2008). Therefore, accurate prediction of temperature during the winter season is important for the agriculture of the region. In the northern and northwestern parts of India, the winters during El Niño events tend to be wet and cold, and La Niña winters tend to be warm and dry (Yadav et al. 2009, 2010; Kar and Rana 2014). The wintertime temperature variability over this region has been relatively less explored because of heterogeneity in terms of topography, surface characteristics, and variability of weather and climate conditions.

There has been a growing interest in the dynamical or statistical downscaling of the global circulation model (GCM) seasonal and climate forecasts in producing regional-scale predictions (Shukla et al. 2009; Stefanova et al. 2012). For such an approach in producing useful regional forecasts, the GCMs driving the regional predictions must have a reasonable fidelity to simulate the large-scale variability. A number of studies have shown a high predictive skill for wintertime temperatures in various dynamical models (Saha et al. 2006), but a comprehensive study documenting the inter-model comparisons of the North Indian wintertime temperature has been lacking so far. Techniques have been developed to combine the multi-model ensemble forecasts (Doblas-Reyes et al. 2000). Kar et al. (2006) have used several multi-model approaches in estimating the economic values of the forecasts and have found that the multi-model ensemble scheme improves the value of the forecasts over using a single model. In the Indian context, the GCMs have been critically analyzed for monsoon rainfall (Prasad et al. 2009; Kar et al. 2011). Tiwari et al. (2014) have examined the skill of precipitation prediction from GCMs for this region for the winter season. However, no such studies exist for the temperature prediction.

The main objectives of the present study are to examine the skill of GCMs for predicting the wintertime seasonal mean

P. R. Tiwari · S. Dey · S. Kumari · P. Sinha  
Centre for Atmospheric Sciences, Indian Institute of Technology  
Delhi, New Delhi, India

S. C. Kar (✉)  
National Centre for Medium Range Weather Forecasting,  
Noida, India  
e-mail: sckar@ncmrwf.gov.in

U. C. Mohanty  
School of Earth Ocean and Climate Sciences, Indian Institute of  
Technology Bhubaneswar, Odisha, India

temperatures over North India and to determine the skill of the National Centers for Environmental Prediction (NCEP) climate forecast system (NCEP\_CFSv2) model in predicting the maximum and minimum temperature over the western Himalayan part of northern India.

The remainder of this paper is organized as follows. The descriptions of observed data and GCMs products as well as the analysis methodologies are provided in Section 2. Discussions of the main findings of the study are presented in Sections 3 and 4. The summary and conclusions of the study are given in Section 5.

## 2 Datasets and method of analysis

### 2.1 Observed reference data

The India Meteorological Department (IMD) has developed a high-resolution ( $1^\circ \times 1^\circ$ ) daily gridded observed temperature dataset (Srivastava et al. 2009) over the Indian land area. This dataset consists of daily averages and maximum and minimum temperatures for the period 1982–2009. Srivastava et al. (2009) in their study used measurements at 395 quality-controlled stations and interpolated the station data into grids with the modified version of Shepard's angular distance-weighting algorithm (Shepard 1968). It is to be noted that DJF seasonal temperature data for a defined year is constructed by taking the average of that year's December temperature and next year's January and February temperatures. In addition to the IMD gridded temperature, the observed maximum and minimum seasonal temperature data obtained from the Snow and Avalanche Study Establishment (SASE) for 17 stations over the study region are also used to validate the model results.

### 2.2 Model data

In this study, lead one predictions of temperature from five global models are used, that is, the seasonal DJF temperature of GCMs is obtained by initializing the forecast in November. In this study, the one-tier models used are NCEP\_CFSv2, MOM3\_AC1, and MOM3\_DC2 (Table 1). The two-tier model used is ECHAM\_CFS, which is an atmosphere-only model, forced with predicted sea surface temperatures (SSTs) from the climate forecast system (CFS) (Table 1). ECHAM\_GML is a semi-coupled model with a mixed layer model for oceans except for the Pacific basin where predicted SST from CFS is used. Data of all these models except for CFSv2 are retrieved from the data library of International Research Institute for Climate and Society (IRI), Columbia University, New York. CFSv2 data are obtained from the NCEP. A brief description of these models is presented in Table 1. More details of the model forecasts used in the study are provided in Tiwari et al. (2014).

### 2.3 Analysis methods

As a first step, the temperature data obtained from the models were interpolated onto the  $1^\circ \times 1^\circ$  latitude–longitude grid resolution of the observed data. The model simulated and observed climatology for temperature have been compared over northern India from 1982 to 2009. The mean square skill score (MSSS) and its components have been calculated to estimate the amplitude and phase errors. Attempts have been made to improve the MSSS of the predictions by systematically reducing the amplitude errors and bias.

#### 2.3.1 MSSS

The MSSS is essentially the mean square error (MSE) of the forecasts (Murphy 1988) compared to the MSE of climatology for a station or grid point. This skill matrix is a part of Standardized Verification System for Long Range Forecasting (SVS-LRF) of WMO (2002) because, as opposed to the anomaly correlation, it penalizes bias in prediction models. The MSE for a forecast at a grid point (or station) is given by the following:

$$\text{MSE}_j = \frac{1}{n} \sum_{i=1}^n (f_{ij} - o_{ij})^2 \quad (1)$$

where  $o$  and  $f$  denote time series of observations and continuous deterministic forecasts.

The MSE for climatology (Murphy 1988) is given by the following:

$$\text{MSE}_{c_j} = \left( \frac{n-1}{n} \right) \text{sd}_{o_j}^2 \quad (2)$$

where

$$\text{sd}_{o_j}^2 = \frac{1}{n-1} \sum_{i=1}^n (o_{ij} - \bar{o}_j)^2 \quad (3)$$

The MSSS is therefore given as follows:

$$\text{MSSS}_j = 1 - \frac{\text{MSE}_j}{\text{MSE}_{c_j}} \quad (4)$$

Maximum value of MSSS is 1, which corresponds to the best forecast. If MSSS is negative, it shows that the forecast is worse than a climatological forecast.

MSSS<sub>j</sub> for forecasts fully cross-validated (with 1 year at a time withheld) can be expanded (Murphy 1988) as

$$\text{MSSS}_j = \left\{ 2 \frac{\text{sd}_{f_j r_{f_o j}}}{\text{sd}_{o_j}} - \left( \frac{\text{sd}_{f_j}}{\text{sd}_{o_j}} \right)^2 - \left( \frac{[\bar{f}_j - \bar{o}_j]}{\text{sd}_{o_j}} \right)^2 + \frac{2n-1}{(n-1)^2} \right\} / \left\{ 1 + \frac{2n-1}{(n-1)^2} \right\} \quad (5)$$

**Table 1** Description of GCMs/AOGCMs

| Model      | Resolution          | AGCM               | OGCM   | Ensemble member | Reference  |
|------------|---------------------|--------------------|--|-----------------|--|
| ECHAM_CFS  | (T42)<br>2.7°×2.8°  | ECHAM4p5           | CFS-predicted SST  | 24              | Roeckner et al. (1996)                                 |
| ECHAM_GML  | (T42)<br>2.7°×2.8°  | ECHAM4p5           | CFS-predicted SSTs prescribed over the tropical Pacific basin (semi-coupled) | 12              | Roeckner et al. (1996), Lee and De Witt (2009)         |
| MOM3_AC1   | (T42)<br>2.7°×2.8°  | ECHAM4p5           | MOM3 (anomaly-coupled)   | 24              | Roeckner et al. (1996), Pacanowski and Griffies (1998) |
| MOM3_DC2   | (T42)<br>2.7°×2.8°  | ECHAM4p5           | MOM3 (direct-coupled)  | 12              | Roeckner et al. (1996), Pacanowski and Griffies (1998) |
| NCEP_CFSv2 | (T126)<br>0.9°×0.9° | GFS (2009 version) | MOM4   | 24              | Saha et al. (2006)                                     |

where  $r_{foj}$  is the product moment correlation of the forecast and observation at point or station  $j$ .

$$r_{foj} = \frac{\frac{1}{n} \sum_{i=1}^n (f_{ij} - \bar{f}_j)(o_{ij} - \bar{o}_j)}{sd_{f_j}sd_{o_j}} \tag{6}$$

The first three terms (in Eq. 5) in the decomposition of  $MSSS_j$  are related to phase errors (through the correlation), amplitude errors (through the ratio of the forecast to observed variances), and overall bias error, respectively, of the forecasts. The last term takes into account the fact that the “climatology” forecasts are cross-validated as well.

### 2.3.2 Multi-model ensemble

In the present study, multi-model ensemble (MME) method assigns the same weight to all the individual member models for carrying out ensemble average. Among the model products used in this study, the maximum and minimum temperature hindcasts are available only for the NCEP\_CFSv2 model. Therefore, in order to evaluate the performance of NCEP\_CFSv2 in predicting the maximum and minimum temperature, the model output has been compared to the observations obtained from the SASE station data.

## 3 Results and discussion

The hindcasts of winter temperatures from these GCMs are analyzed individually on the basis of certain statistical measures as previously described. These are (i) long range forecast (LRF) statistics along with a simple ensemble mean of all the GCMs and (ii) correcting the model temperature data on the basis of the difference between the model and actual orography. The corrected model maximum/minimum temperature data are compared with the SASE observations.

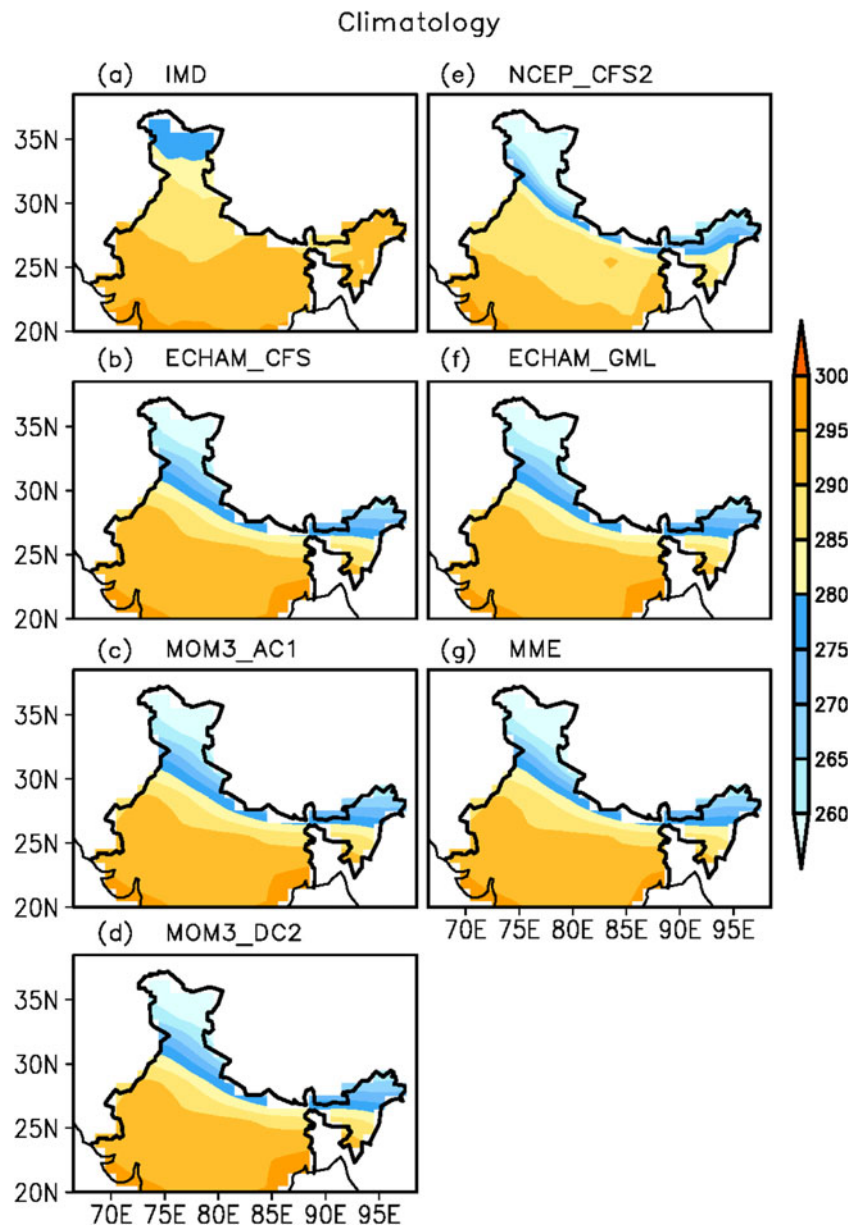
### 3.1 Observational feature

The observed climatology of temperature (Fig. 1a) depicts that the minimum temperature occurs during the winter over Northern Kashmir, which ranges from 275 to 285 K. Over the northeastern part of India, the climatology of temperature lies in the range of 290–295 K. It can be seen that the southern region has higher temperature than in the north.

### 3.2 Skill of temperature predictions

The climatology of temperature (seasonal mean) simulated by each of the five GCMs is compared with the observed climatology (Fig. 1b–f). All the models show very low temperatures over Northern Kashmir (below 260 K) and some pockets of North East India (below 265 K). Over the southern parts of India, the temperature is approximately same in all the models (295–300 K). All the models (except NCEP\_CFSv2) show almost the same pattern of seasonal temperature bias, ranging from 4° to 10° over the Jammu and Kashmir (hereafter J&K), Himachal Pradesh (hereafter HP), and Uttarakhand (hereafter UK) region (Fig. 2). On the other hand, the NCEP\_CFSv2 model (Fig. 2c) depicts a stronger bias (more than 8°) over the eastern part of J&K and few areas of northeast India. It may be noted that all the GCMs used in this study except the NCEP\_CFSv2 have almost the same atmospheric model (ECHAM model). The ECHAM model is either run using the forecasted SSTs or in a coupled ocean–atmosphere mode as described in Section 2. Therefore, the bias patterns from these models are also similar. Figure Fig. 3a–e outlines the amplitude error between the temperature from the models and those observed. This variable represents the interannual variability of temperature predictions. It can be clearly seen that the amplitude errors for most of the models over the northern parts of India are low, except in the ECHAM\_GML and ECHAM\_CFS models. Among all the models, the best one is NCEP\_CFSv2 model, which has the least amplitude error (in the range from 0.3 to 0.6) over the region of interest.

**Fig. 1 a–g** Climatology of mean winter (December to February) temperature (in K) from the models and observation for the period 1982–2009



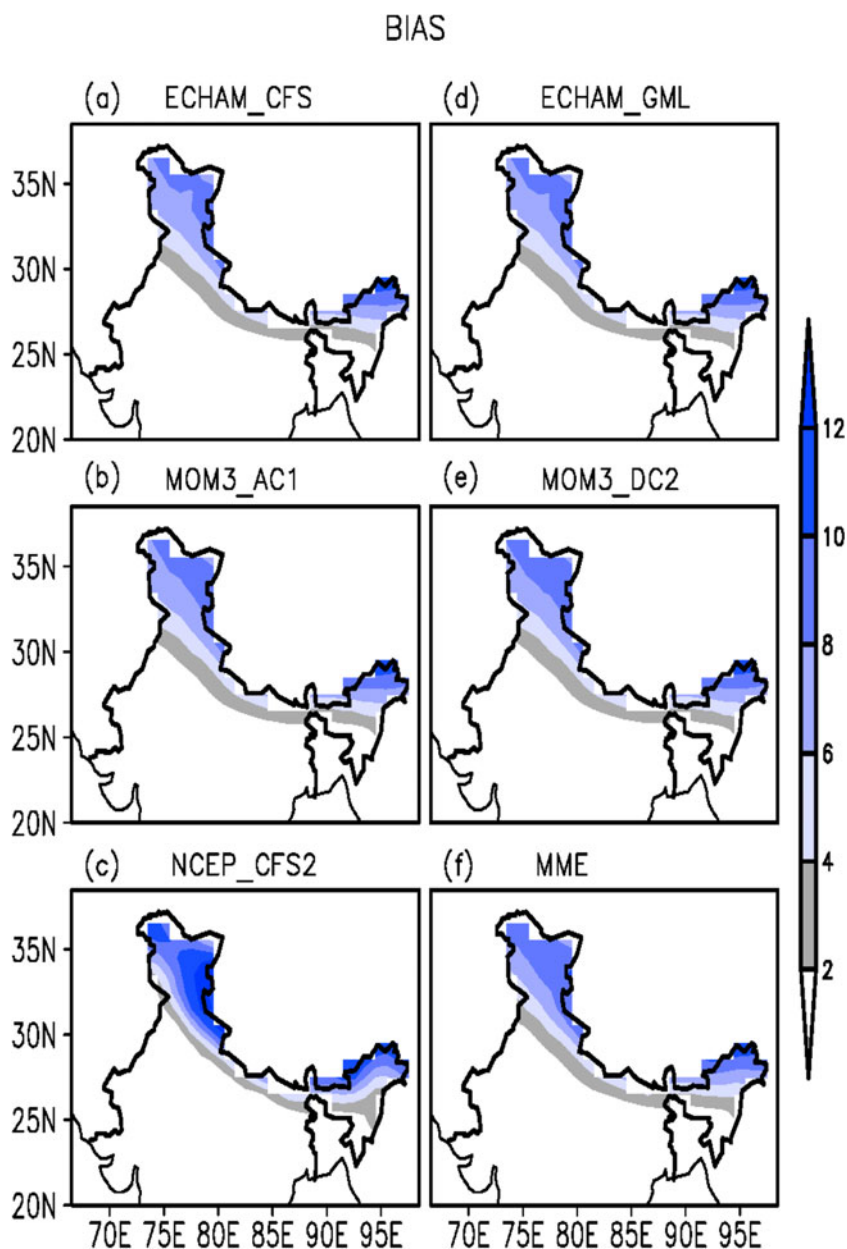
Therefore, among all the models, NCEP\_CFSv2 has better skill in predicting temperatures over the northern India during the winter season.

The phase errors of temperature between the model predictions and the observations are shown in Fig. 4a–e. Phase errors essentially represent the correlation of the model predictions with the observations. Positive and large value corresponds to better prediction skill and indicates better MSSS. The phase error values range from 0.01 to 0.3 over J&K, HP, and UK regions in most of the models. The maximum phase error ( $>0.3$ ) is seen over the eastern parts of J&K in NCEP\_CFSv2 model followed by MOM3\_AC1 and MOM3\_DC2 models. So, an analysis of phase error suggests that the skill of NCEP\_CFSv2 is better than other models in predicting temperature over the northern India.

### 3.3 MSSS analysis

In this section, an analysis of the MSSS (Murphy 1988), a measure of the MSE of the forecasts compared to the MSE of a climatological reference forecast, is carried out. Seasonal mean (DJF) temperatures from the observations and the global models have been used for the period from 1982 to 2009 (27 years). Bias of a model is an important component of the MSSS because a large bias leads to deterioration of its MSSS. A simple way to improve MSSS of a model is to remove the model bias while computing the skill. In this study, the bias of each model has been removed by replacing the model climatology of respective models with the observed climatology. So, our MSSS computations do not have a systematic bias component.

**Fig. 2 a–f** Bias (in K) for temperature between models and observation from 1982 to 2009 for December–February



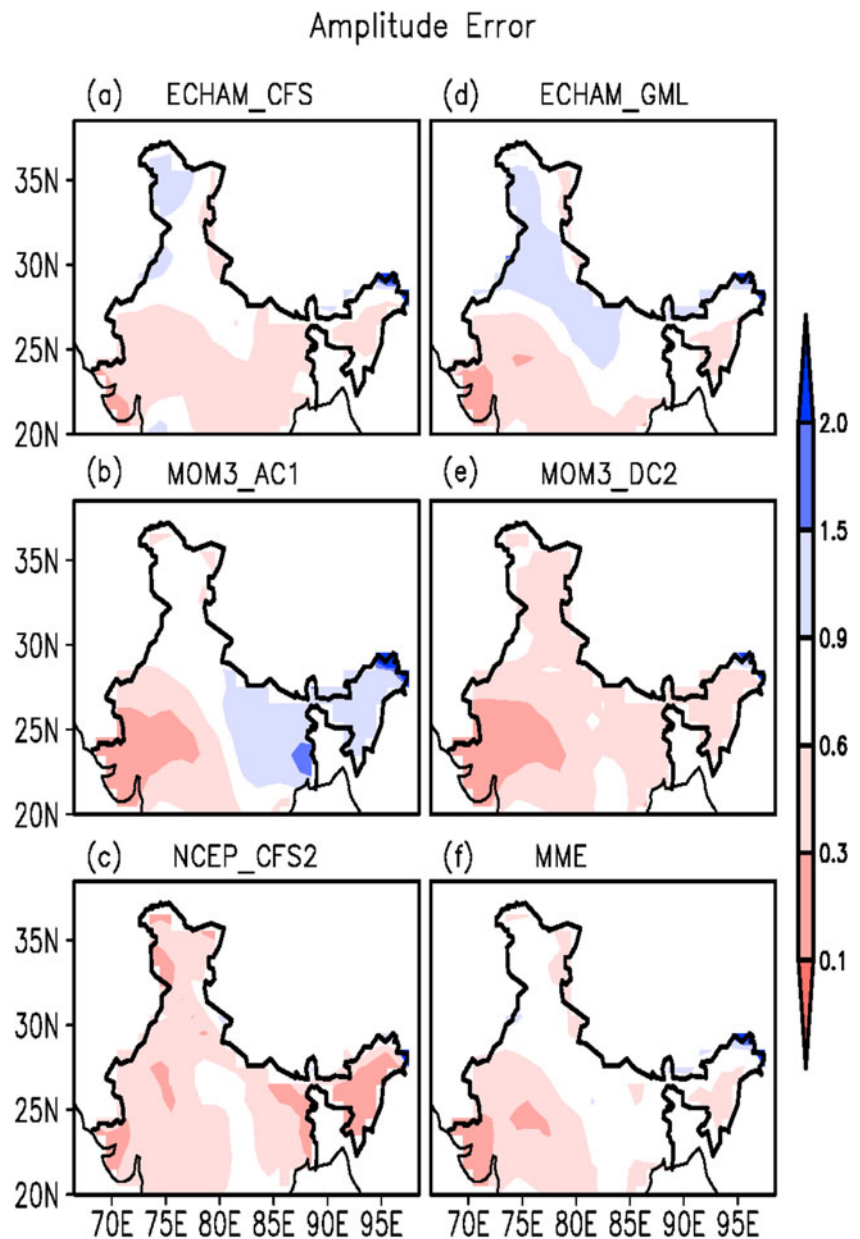
Amplitude error (observed to model variance ratio) is also an important component of the MSSS. The MSSS of a model is too small if this amplitude error is too large, i.e., the interannual variability of the seasonal mean temperatures is too large or too small compared to the observed variability. In this study, the amplitude error of each model has been removed by normalizing the model predictions with the respective model variability and multiplying the resultant with the observed variability. So, in our MSSS computation, overall bias and amplitude error have been removed.

The MSSS obtained after the removal of overall bias and amplitude errors is shown in Fig. 5. Over most parts of India, the MSSS is negative, indicating poor skill of the models compared to climatological forecasts. This negative MSSS is

due to large phase errors of the models. The major task for modeling and statistical post-processing is to reduce the phase errors from the model forecasts. A detailed analysis shows that among all the models, NCEP\_CFSv2 has the best MSSS followed by MOM3\_DC2 over the region of interest (i.e., North India). Compared to these two models, other models show less improvement in terms of MSSS after removal of the associated systematic errors.

The ability of the individual GCMs to predict winter temperature, in terms of correlation, root mean square error (RMSE), and interannual standard deviation, is shown by a Taylor diagram (Taylor 2001) presented in Fig. 6. The figure clearly indicates significant correlation with less RMSE of two coupled GCMs (NCEP\_CFSv2 and MOM3\_DC2) out

**Fig. 3** a–f Amplitude error for temperature between models and observation from 1982 to 2009 for December–February



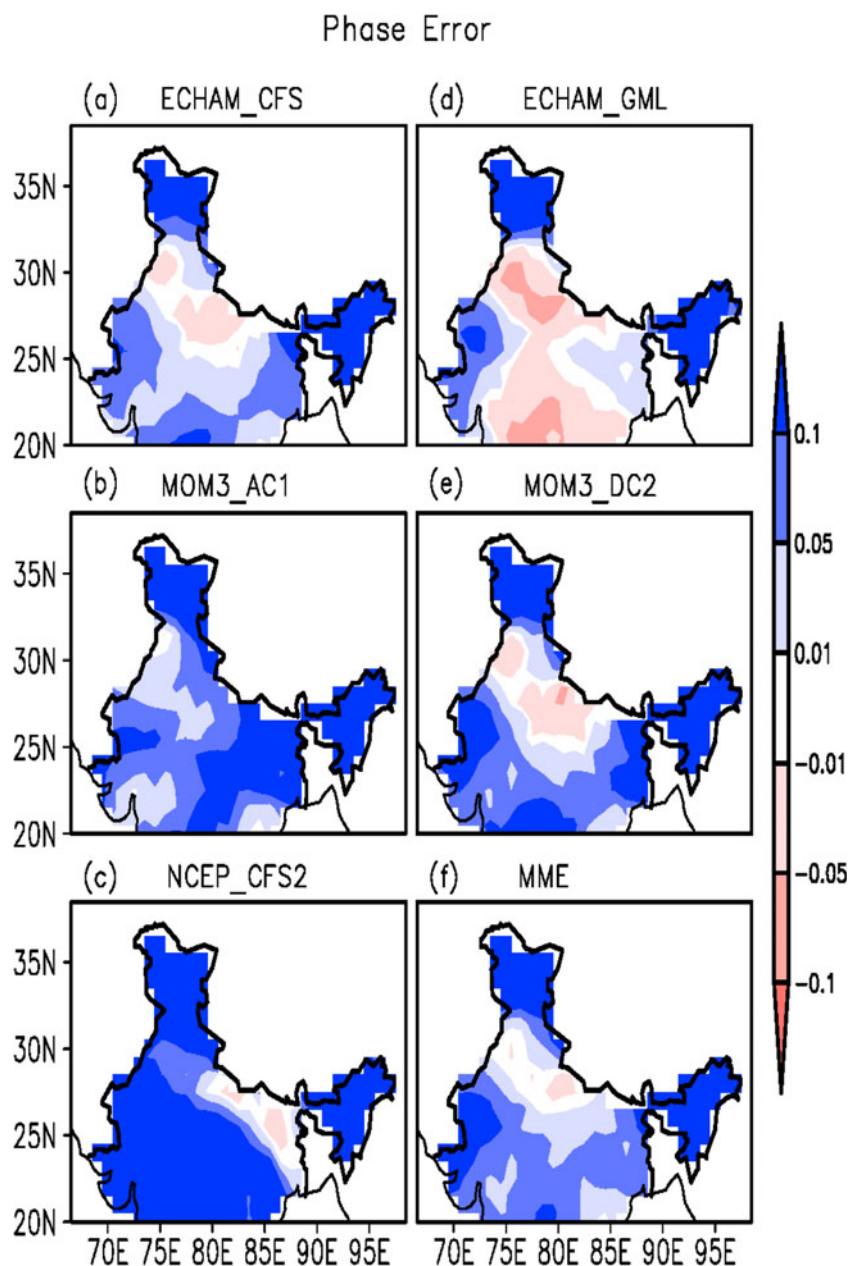
of five GCMs used in the study. Smaller correlations with higher RMSE are observed in the case of MOM3\_AC1, ECHAM\_CFS, and ECHAM\_GML.

Overall, the above analysis suggests that models are capable of replicating some aspects of the observed temperature climatology to varying degrees of accuracy over most parts of the country except some parts of North India, where almost all the models underpredict the temperature. It has been observed that out of the five models, only NCEP\_CFSv2 and MOM3\_DC2 have higher MSSS values, which is a good indicator of model performance. Furthermore, between these two models, the performance of NCEP\_CFSv2 is marginally better, having a positive MSSS over the entire J&K, HP, and UK region.

### 3.4 Skill of simple MME predictions

A simple MME method is used to investigate the improvement in temperature prediction. In this method, all the individual member models have been assigned the same weight while carrying out the multi-model ensemble (Hagedorn et al. 2005). It is seen that the MME method delineates the climatological temperature reasonably well compared to individual models over J&K and HP regions (Fig. 1g). However, it underpredicts the temperature (260–265 K) compared to the IMD observation. Over the J&K, HP, and UK regions, the bias of the MME is lesser than that of the individual models except for NCEP\_CFSv2 (Fig. 2f). The amplitude error of the MME prediction shown in Fig. 3f demonstrates that the error is

**Fig. 4** a–f Phase error for temperature between models and observation from 1982 to 2009 for December–February

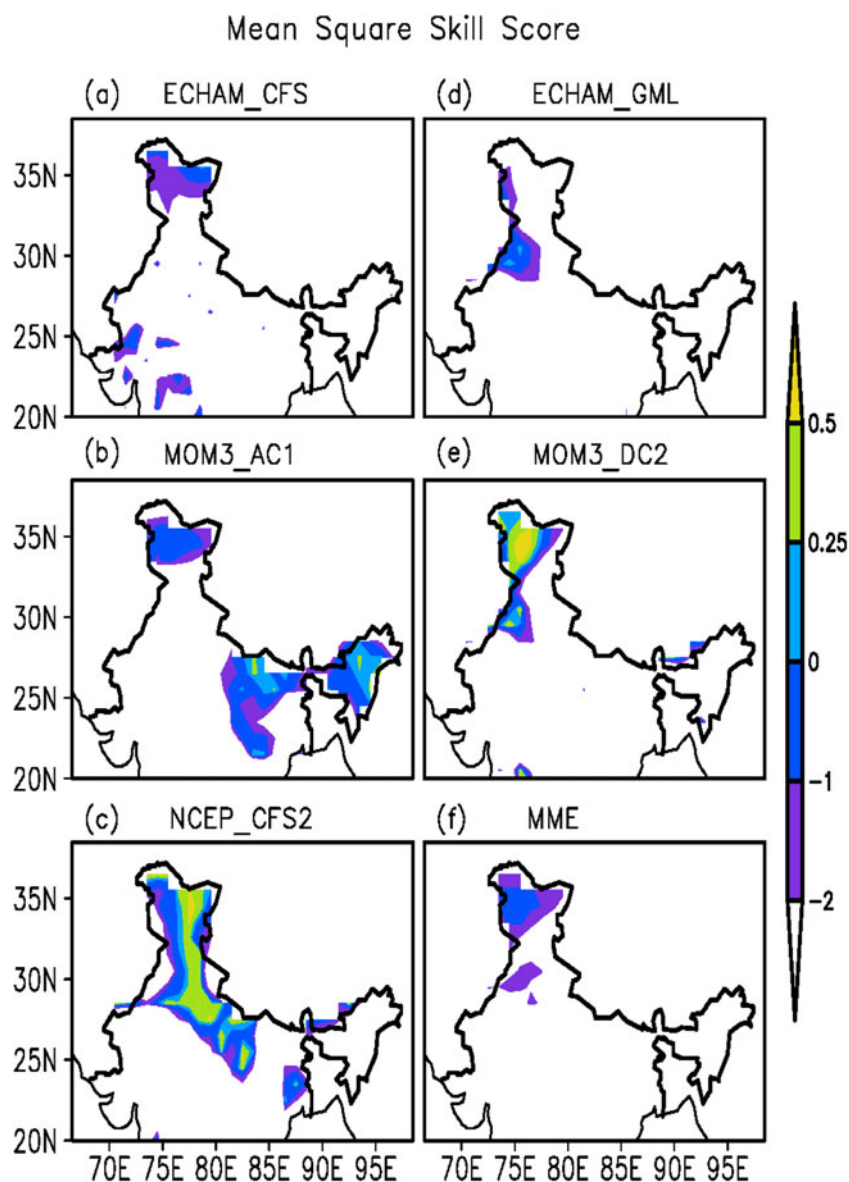


less in MME compared to that of the ECHAM\_GML and ECHAM\_CFS models over northwest and eastern parts of Kashmir. Although the MME predictions have a phase error (0.05 to 0.3) over J&K, northeastern and southern parts of India (Fig. 4f), an improvement in phase error is noticed in the MME prediction over the HP and UK regions compared to ECHAM\_GML, MOM3\_DC2, and ECHAM\_CFS. It may be noted that NCEP\_CFSv2 has a higher skill in terms of phase error over northern India compared to that of other individual models and MME. An examination of the MSSS reveals that the skill of the MME prediction (Fig. 5f) is better than ECHAM\_GML and ECHAM\_CFS, but it is lower than that of NCEP\_CFSv2. A possible reason would be that while making the multi-model ensemble, the forecasts

from other poorer models also get the same weight as the best models. Therefore, despite the scientific rationale behind the success of MME predictions by computing simple arithmetic means of all the available models, the MME predictions of temperature during the winter seasons are not very useful for the northern Indian region. The Taylor diagram (Fig. 6) indicates that the MME has the higher correlation (with magnitude 0.39) with lesser RMSE compared to individual GCM at an all-India level. However, for the region of interest, the simple MME scheme does not improve the seasonal mean predictions of temperature.

In order to further improve the forecast skill, Krishnamurti et al. (2000) have suggested the use of weighted multi-model ensemble technique in which a point-by-point multiple linear

**Fig. 5** a–f Mean square skill score for temperature between models and observation from 1982 to 2009 for December–February



regression (MLR) method is employed. The weights are computed and assigned to each model based on its performance during the training period. The calculation of weighted MME and its evaluation for temperature prediction for the region of interest are beyond the scope of the present study.

#### 4 Skill of maximum and minimum temperature predictions

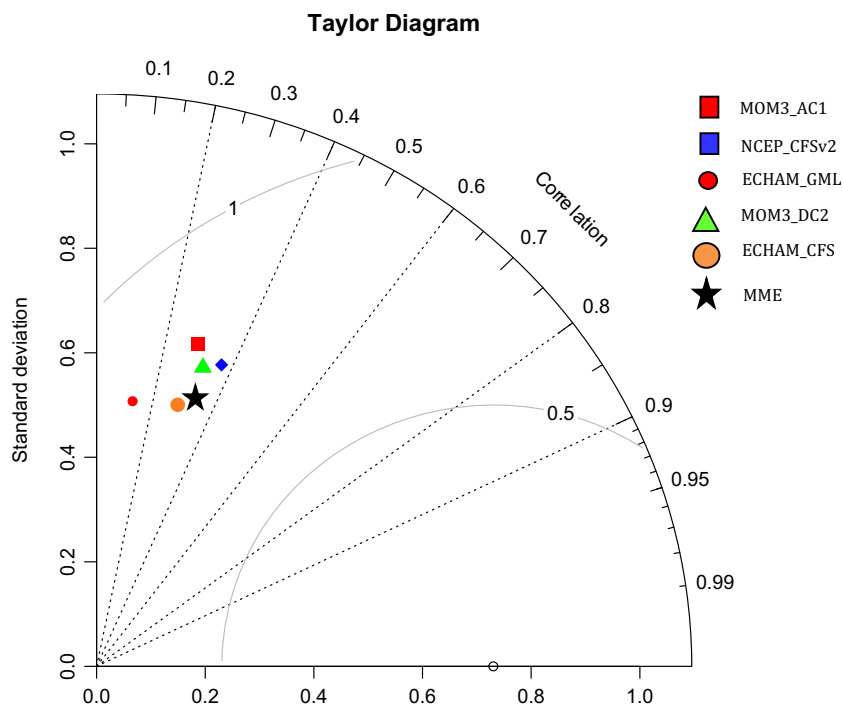
In northern parts of India, especially over the hilly regions of J&K and HP, the advanced knowledge of the maximum and minimum temperatures during winter months is very important for assessing human comfort and natural hazards as the

observed temperature reaches closer to 0 °C or below freezing levels. Various researchers (e.g., Mohanty et al. 1997) have carried out studies on predicting maximum and minimum temperatures in India, but most of these studies are based on observation datasets. No such effort has been reported so far to evaluate the skill of a GCM in predicting the wintertime maximum and minimum temperature over North India in interannual timescale. So, in this section, the performance evaluation of NCEP\_CFSv2 in predicting the maximum and minimum temperature has been carried out for the study period (1982–2009).

Observed and model simulated maximum and minimum temperatures are shown in Figs. 7 and 8, respectively. It can be seen in Fig. 7a that the observed climatological maximum temperature is lower over northern India compared to other



**Fig. 6** Taylor diagram for the prediction skills of GCMs



parts (southern, central, and north east parts) of the country, which is underestimated by the model (Fig. 7e). The observed interannual variability (IAV, shown in Fig. 7b) is higher over northern, central, and northeastern parts of India compared to the model simulated IAV (Fig. 7f). The spatial correlation (Fig. 7c) is high mainly over north (0.2–0.4) and southern parts of India (0.4–0.6).

The observed and the model simulated minimum climatological temperatures are shown in Fig. 8a, e. It can be seen that the model can delineate the minimum temperature up to a certain extent over various parts of India, except northern India where it shows a lower temperature (by 10 K) compared to the observed temperature. In the case of minimum temperature, the observed IAV (Fig. 8b) is more over the northern, central, and northeastern parts of India compared to model simulated IAV (Fig. 8f). The pattern correlation shown in Fig. 8c is also found in the range of 0.2 to 0.4 over most parts of the country, except over the northeastern parts of India where it reaches up to 0.6.

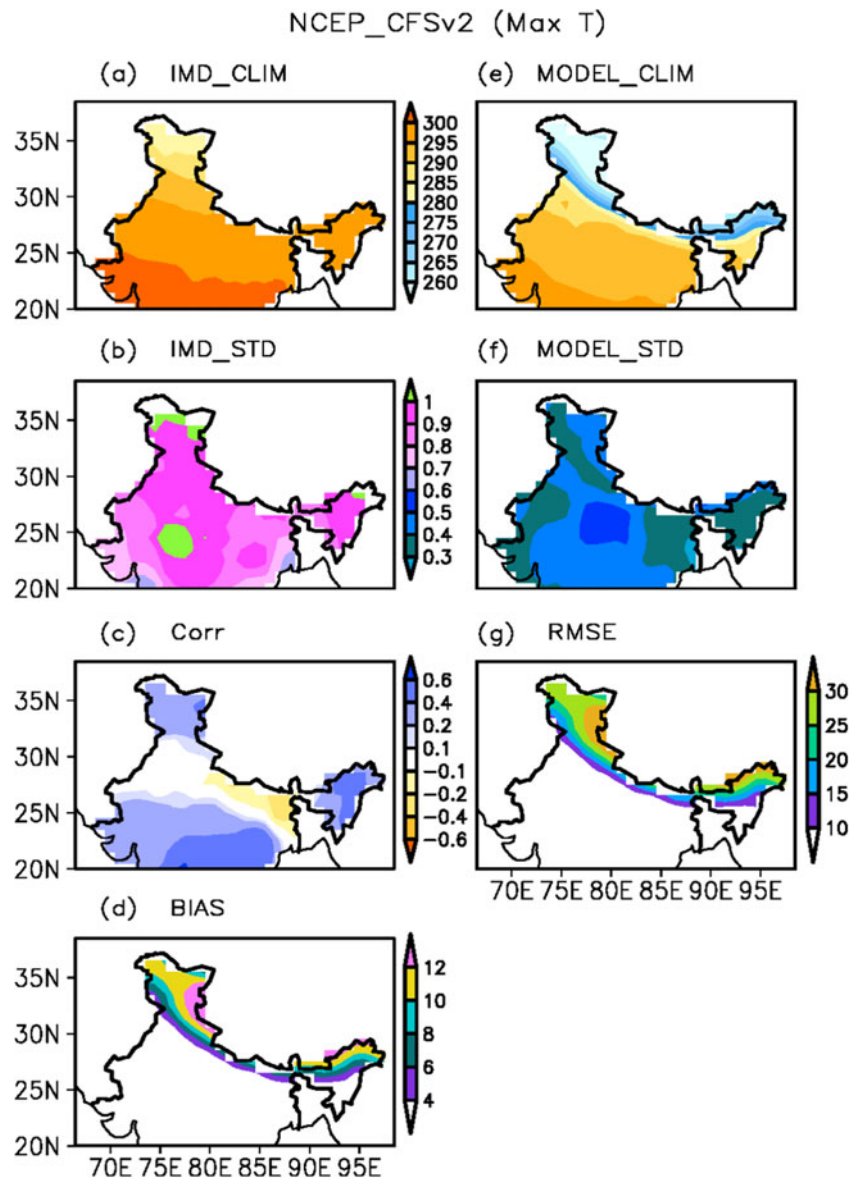
Data from 17 observation stations of the SASE are used to construct the J&K and HP maximum/minimum temperatures for 27 years (1982–2009). The observed and model predicted maximum and minimum temperatures over the stations in the J&K region are shown in Fig. 9a, b. It can be seen in Fig. 9a that there is a huge difference between the observed and model predicted maximum temperature ( $T_{\max}$ ) in terms of the range of variations in the temperature from year to year. The interannual standard deviation has been computed for the observed and model values, and it shows that the standard deviation of observed  $T_{\max}$  is 4.18 °C, whereas the model predicted

standard deviation is 0.76 °C, which is very low compared to the observed data. The standard deviation of observed minimum temperature ( $T_{\min}$ ) is 1.15 °C, whereas the model predicted standard deviation is 0.46 °C. These figures indicate a warming trend (increase in temperature with year), for both  $T_{\max}$  and  $T_{\min}$ . This increasing trend is seen in both observations and the model predictions though it is not statistically significant. However, the model shows a lesser increase compared to that in the observations. The rates of increase in  $T_{\max}$  and  $T_{\min}$  are also more rapid after 1995, both in observations and the model.

Figure 10a, b shows the observed and model predicted  $T_{\max}$  and  $T_{\min}$ , respectively, for the HP region. There is very little difference between the observed and model predicted  $T_{\max}$  in terms of the range of variation from year to year. The standard deviation of the observed maximum temperature is 0.78 °C, whereas for the model, predicted standard deviation is 0.82 °C. The standard deviation of observed  $T_{\min}$  is 0.95 °C, whereas it is 0.67 °C for the model. There is also an increasing trend in  $T_{\max}$  and  $T_{\min}$  in both observations and the model; however, the rate of increase is lesser in the model compared to the observations. The increase in  $T_{\max}$  is also rapid after 1994 both in the observation and the model.

Various studies (Chakraborty et al. 2002; Abe et al. 2003) show that the GCMs have a major problem in representing the actual orography because of their coarser resolution. As the orography representation governs the thermal and dynamical aspects in the atmosphere (Kasahara and Washington 1968; Namias 1980), it becomes imperative to correct the GCM

**Fig. 7** a–g Observe (IMD) and model (NCEP\_CFSv2) simulated climatology (K), interannual variability (K), spatial correlation, bias (K), and RMSE (K) for maximum temperature from 1982 to 2009 for December–February



products for the orography for better understanding of the temperature distribution.

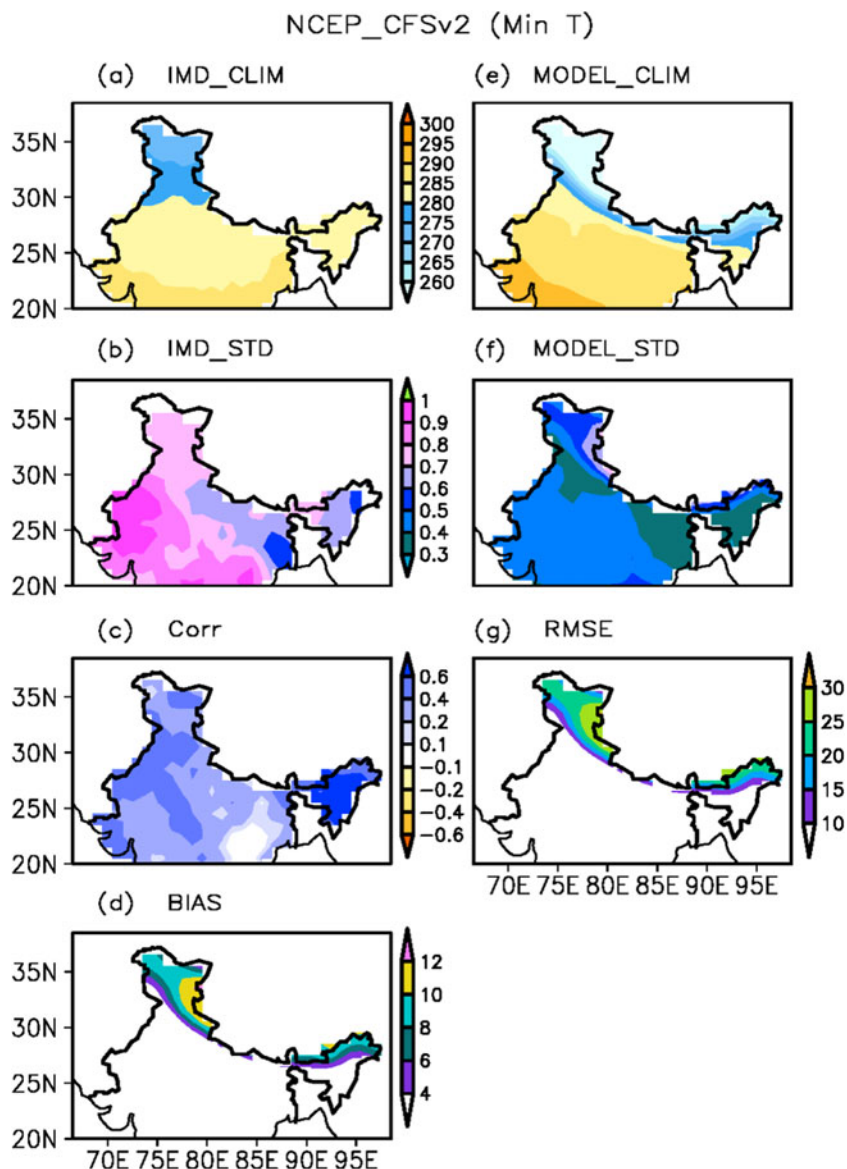
Therefore, in the present work, an orography correction has been made to see its impact in predicting  $T_{\max}$  and  $T_{\min}$  over J&K and HP. For each station location, a comparison has been made between the station height and the model orography corresponding to the same location. Surface temperature has been corrected, following dry adiabatic lapse rate based on the difference between the height of the station in the model and its actual height. It can be seen in Fig. 9a that there is a huge difference between the observed and model predicted  $T_{\max}$  in terms of the range of the temperature variability, which has been significantly reduced when the orography related correction is made to the temperature predictions. The standard deviation of  $T_{\max}$  with orography correction is 2.33 °C, whereas the standard deviation without the orography correction is

0.76 °C, which happens to be very low compared to the observations (standard deviation for observed maximum temperature is 4.18 °C).

In the case of Fig. 9b for J&K, the difference of standard deviation between the observed and orography corrected values is less, compared to the model predicted  $T_{\min}$  without orography correction. The standard deviation of  $T_{\min}$  with orography corrections is 1.73 °C, whereas without orography correction, it is 0.46 °C (standard deviation for observed  $T_{\min}$  is 1.15 °C).

Figure 10a shows the observed, orography corrected, and without the orography corrected models' standard deviation for  $T_{\max}$  for HP. The standard deviation of  $T_{\max}$  with orography correction is 0.69 °C, whereas without the orography correction, the standard deviation is 0.82 °C, which happens to be greater compared to the observations (standard deviation for observed maximum temperature is 0.78 °C).

**Fig. 8** a–g Observe (IMD) and model (NCEP\_CFSv2) simulated climatology (K), interannual variability (K), spatial correlation, bias (K), and RMSE (K) for minimum temperature from 1982 to 2009 for December–February



In Fig. 10b for HP, it can be noticed that the difference of standard deviation between the observed and orography corrected temperature is less compared to that of the model predicted minimum temperature without an orography correction. The standard deviation of minimum temperature from the orography corrected temperature is 0.72 °C, whereas without orography correction, the standard deviation is 0.67 °C, which is lower than the observations (standard deviation for observed minimum temperature is 0.96 °C).

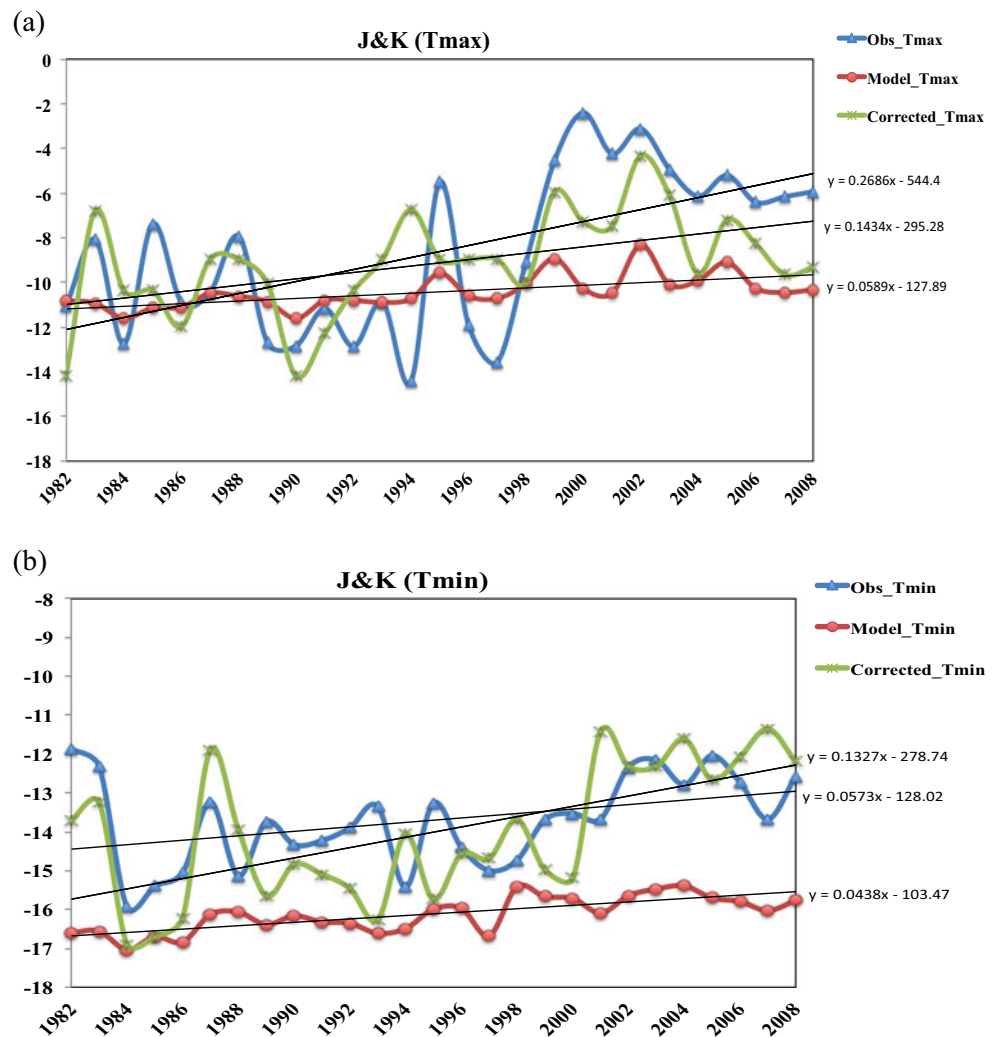
In addition to differences between actual orography and model orography that leads to surface temperature difference, surface temperature in a model is predicted using surface energy balance. Maximum and minimum temperature depends on the surface condition such as vegetation cover, soil moisture, snow cover, etc. For correctly separating sensible, latent, and ground heat fluxes as well as incoming and outgoing

radiative fluxes at the surface in a model, sophisticated land surface process parameterization schemes are used. Any error or any simplification in the surface parameterization scheme would lead to error in surface temperature predictions. From this study, it is seen that land surface schemes used in the models do not adequately represent the surface processes in the northern as well as central parts of India. This might be responsible for the differences in the interannual standard deviation between the model products and IMD observations.

#### 4.1 Willmott’s index of agreement

Willmott (1982) stated that although the relative difference measures such as the ratio between RMSE and observed climatology frequently appear in the literature, they have the limitation that they are not bounded and are unstable for very

**Fig. 9** a, b Maximum and minimum temperature over J&K region for 27 years (1982–2009) obtained from observations and model with and without orography-related correction



small (near zero) climatology of observation. As a remedy, Willmott (1982) proposed new skill metrics called “index of agreement ( $D$ ),” as follows:

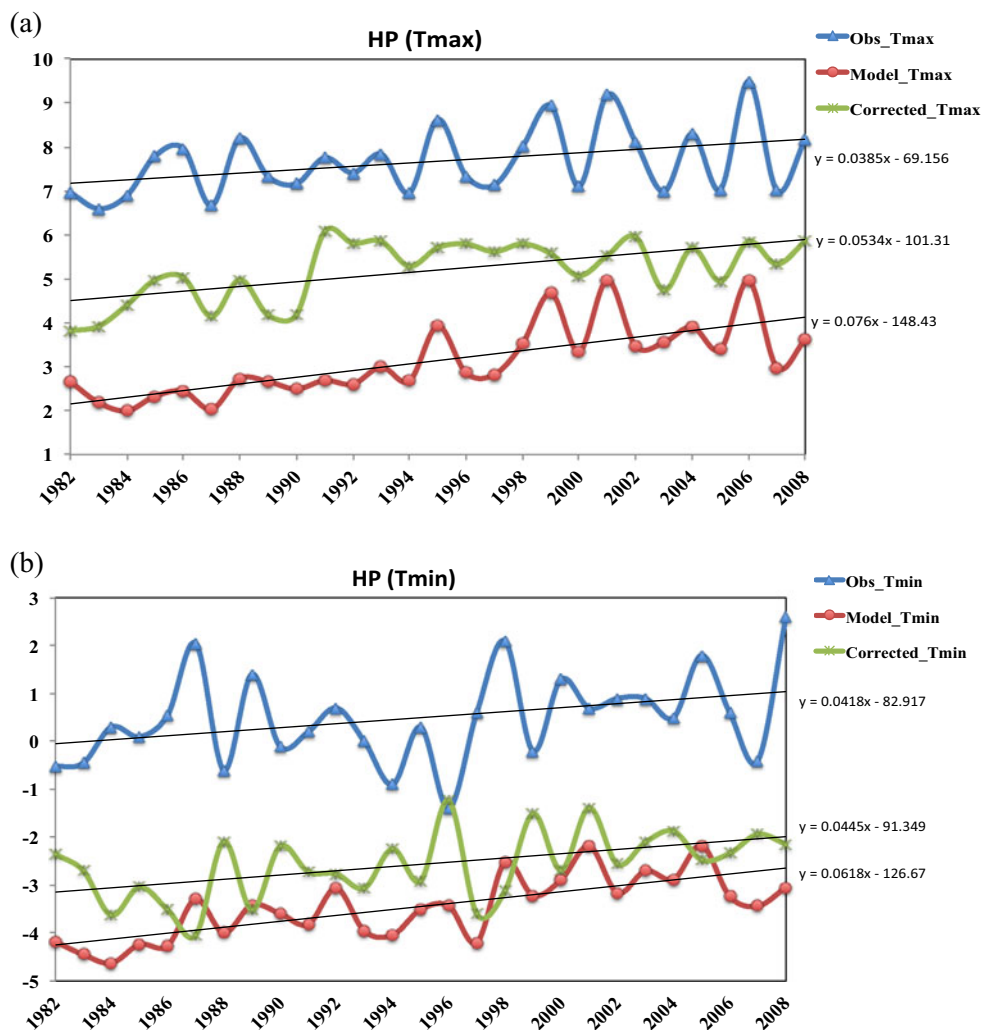
$$D = 1 - \left[ \frac{\sum_i (M_i - O_i)^2}{\sum_i (|M_i - \bar{O}| + |O_i - \bar{O}|)^2} \right]$$

where  $M_i$  and  $O_i$  are the  $i$ th year forecast and observation, respectively, and  $O$  is the observed climatology. This skill metric is relative and is bounded between 0 and 1 ( $0 \leq D \leq 1$ ). The closeness of this index to 1 indicates the efficiency of the model in producing a good forecast. In the present work, this skill metric, calculated for the maximum/minimum temperature of J&K and HP by using and not using orography correction of the model products, is provided in Table 2. It is seen that in case of J&K, the index of agreement for the maximum (minimum) temperature is 0.62 (0.72) with

orography correction and 0.49 (0.68) without orography correction. On the other hand, the index of agreement for maximum (minimum) temperature for HP is 0.57 (0.48) with orography correction and 0.51 (0.43) without orography correction. It is clear from the discussion above that orography correction has made significant improvement to the value of the index of agreement.

Therefore, in most of the cases, the model is capable of predicting these interannual variations of maximum and minimum temperatures, while there are only few years when the model predictions are closer to the actual observations. This could be due to coarse resolution of the model and incorrect predictions of the synoptic weather systems such as the western disturbances (WDs). The WDs remain for a short duration of time (having a huge influence on maximum/minimum temperature) and are difficult to be captured properly by the GCMs, leading to incorrect maximum/minimum temperature predictions. Another reason for poor skill of the model is that it predicts its own excess, deficit, and normal years, which do not match with observed excess, deficit, and normal

**Fig. 10 a, b** Maximum and minimum temperature over HP region for 27 years (1982–2009) obtained from observations and model with and without orography-related correction



precipitation years. Finally, the close examination of the prediction of maximum and minimum temperature with NCEP-CFSv2 indicates that there is further scope for improvement of the forecast skill through incorporation of statistical corrections. These post-processing techniques such as orography correction will reduce the forecast errors of maximum/minimum temperature prediction over the mountain region.

### 5 Conclusions

The skill of state-of-the-art five GCMs is examined for the period 1982–2009 in predicting wintertime (DJF) temperature over North India, which is very important for the winter crops. For this, the seasonal hindcast temperature data from these GCMs have been used at 1-month lead. In order to improve the temperature prediction during the winter season, the MME mean is also used. The key findings of the present study are as follows:

- The GCM, in general, underestimates the observed climatology of temperature especially over the northern and northeastern parts of India. It has been also seen that most of the GCMs are capable of predicting the observed IAV magnitude to some extent, but none of the models are able to depict the observed IAV correctly.
- The amplitude error and phase error between observation and models have been computed, and it is found that the NCEP\_CFSv2 model has better skill compared to that of

**Table 2** Willmott’s index of agreement for NCEP\_CFSv2 predicted maximum/minimum temperature

|     | $T_{max}$                    |                           | $T_{min}$                    |                           |
|-----|------------------------------|---------------------------|------------------------------|---------------------------|
|     | Without orography correction | With orography correction | Without orography correction | With orography correction |
| J&K | 0.49                         | 0.62                      | 0.68                         | 0.72                      |
| HP  | 0.51                         | 0.57                      | 0.43                         | 0.48                      |

the other models. The MSSS (after removing the overall bias and amplitude errors) shows that the NCEP\_CFSv2 has a better skill score.

- A simple MME approach has been also employed. It is found that the MME predictions do not have very useful skill in predicting winter season temperature over the northern Indian region.
- Furthermore, to document the prediction skill of NCEP\_CFSv2 for maximum/minimum temperature over J&K and HP, station level data for 27 stations (12 over J&K and 5 over HP) obtained from the SASE is analyzed. It is found that the model temperatures, when corrected to take into account the difference between the actual and model orography, show the increasing trend.

This study is essentially meant for estimating the prediction skill of large-scale seasonal mean temperature variability in interannual timescale over the region using GCM products. Most of the models used in this study have rather coarse resolution. If a similar study is undertaken with high-resolution models instead of these low-resolution models, then it is expected that high-resolution models will bring out more detailed features of temperature variability over the region. The IAV will also get modified as the representation of sub-grid scale processes would be better in high-resolution models, which may further lead to improved model skill.

**Acknowledgments** This research has been conducted as part of the project entitled “Precipitation and temperature variability and extended range seasonal prediction during winter over Western Himalayas” at IIT, Delhi, sponsored by the Snow Avalanche Study Establishment (SASE), Chandigarh. We gratefully acknowledge the International Research Institute for Climate and Society (IRI), Data Library group for making five of their GCM-based seasonal forecasting systems available to this study. Also, the authors sincerely thank the India Meteorological Department (IMD) for providing the gridded temperature data for this study. The authors are thankful to Bianca C. for editing/correcting the English grammar of the manuscript. The authors also acknowledge the comments by the anonymous reviewers, which helped in improving the earlier version of the manuscript.

## References

- Abe M, Kitoh A, Yasunari T (2003) An evolution of the Asian summer monsoon associated with mountain uplift—simulation with the MRI atmosphere–ocean coupled GCM. *J Meteorol Soc Jpn* 81:909–933
- Chakraborty A, Nanjundiah RS, Srinivasan J (2002) Role of Asian and African orography in Indian summer monsoon. *Geophys Res Lett* 29(20):2002. doi:10.1029/2002GL015522
- Doblas-Reyes, Deque FJM, Piedelievre JP (2000) Multi-model spread and probabilistic seasonal forecasts in PROVOST. *Q J R Meteorol Soc* 126:2069–2088
- Hagedorn R, Doblas-Reyes FJ, Palmer TN (2005) The rationale behind the success of multi-model ensembles in seasonal forecasting—I. Basic concept. *Tellus* 57:219–233
- Kalra N, Chakraborty D, Sharma A, Rai HK, Jolly M, Chander S, Kumar PR, Bhadraray S, Barman D, Mittal RB, Lal M, Sehgal M (2008) Effect of increasing temperature on yield of some winter crops in northwest India. *Curr Sci* 94(1):82–88
- Kar SC, Rana S (2014) Interannual variability of winter precipitation over northwest India and adjoining region: impact of global forcings. *Theor Appl Climatol* 116(3–4):609–623. doi:10.1007/s00704-013-0968-z
- Kar SC, Hovsepyan A, Park CK (2006) Economic values of the APCN multi-model ensemble categorical seasonal predictions. *Meteorol Appl* 13(3):267–277
- Kar SC, Acharya N, Mohanty UC, Kulkarni MA (2011) Skill of monthly rainfall forecasts over India using multi-model ensemble schemes. *Int J Climatol* 32:1271–1286
- Kasahara A, Washington WM (1968) Thermal and dynamical effects of orography on the general circulation of the atmosphere. NCAR manuscript, No. 68–208
- Krishnamurti TN, Kishtawal CM, Shin DW, Williford CE (2000) Multi-model superensemble forecasts for weather and seasonal climate. *J Clim* 13:4196–4216
- Lee DE, De Witt DGA (2009) New hybrid coupled forecast system utilizing the CFSST, 2009 forecasts [http://portal.iri.columbia.edu/portal/server.pt/gateway/PTARGS\_0\_4972\_5734\_0\_0\_18/NOAAabstract2009]
- Mohanty UC, Ravi N, Madan OP, Paliwal RK (1997) Forecasting minimum temperature during winter and maximum temperature during summer at Delhi. *Meteorol Appl* 4:37–48
- Murphy AH (1988) Skill scores based on the mean square error and their relationships to the correlation coefficient. *Mon Weather Rev* 16: 2417–2424
- Namias J (1980) The art and science of long-range forecasting. *Eos Trans AGU* 61:449–450
- Pacanowski RC, Griffies SM (1998) MOM 3.0 manual. NOAA/Geophysical fluid dynamics laboratory, Princeton, 608 pp
- Prasad K, Dash SK, Mohanty UC (2009) A logistic regression approach for monthly rainfall forecasts in meteorological subdivisions of India based on DEMETER retrospective forecasts. *Int J Climatol* 30:1577–1588
- Roeckner E and Coauthors (1996) The atmospheric general circulation model ECHAM4: model description and simulation of present-day climate. Max-Planck-Institut für Meteorologie Rep. 218, Hamburg, 90 pp
- Saha S, Nadiga S, Thiaw C, Wang J, Wang W, Zhang Q, van den Dool HM, Pan H-L, Moorthi S, Behringer D, Stokes D, Peña M, Lord S, White G, Ebisuzaki W, Peng P, Xie P (2006) The NCEP climate forecast system. *J Clim* 19:3483–3517
- Shepard D (1968) A two-dimensional interpolation function for irregularly spaced data. *Proc. 23rd National Conf., New York, NY, Association for Computing Machinery* 517–524
- Shukla J, Hagedorn R, Hoskins B, Kinter J, Marotzke J, Miller M, Palmer T, Slingo J (2009) Revolution in climate prediction is both possible and necessary. A declaration at the world modelling summit for climate prediction. *Bull Am Meteorol Soc*. doi: 10.1175/2008BAMS 2759.1
- Srivastava AK, Rajeevan M, Kshirsagar SR (2009) Development of a high resolution daily gridded temperature data set (1969–2005) for the Indian region. NCC research report 8/2008. National Climate Centre, India Meteorological Department
- Stefanova L, Misra V, Chan S, Griffin M, O'Brien JJ, Smith III TJ (2012) A proxy for high-resolution regional reanalysis for the southeast United States: assessment of precipitation variability in dynamically downscaled reanalyses. *Clim Dyn* 38: 2449–2466
- Taylor KE (2001) Summarizing multiple aspects of model performance in a single diagram. *J Geophys Res* 106:7183–7192

- Tiwari PR, Kar SC, Mohanty UC, Kumari S, Sinha P, Nair A, Dey S (2014) Skill of precipitation prediction with GCMs over north India during winter seasons. *Int J Climatol* 34:3440–3455
- Willmott CJ (1982) Some comments on the evaluation of model performance. *Bull Am Meteorol Soc* 63:1309–1313
- WMO (2002) Standardised verification system (SVS) for long-range forecasts (LRF). New attachment II-9 to the manual on the GDPS (WMO-No.485), volume 1, WMO, Geneva, 21pp
- Yadav RK, Rupa Kumar K, Rajeevan M (2009) Increasing influence of ENSO and decreasing influence of AO/NAO in the recent decades over northwest India winter precipitation. *J Geophys Res* 114: D12112, doi:[10.1029/2008JD011318](https://doi.org/10.1029/2008JD011318), 1–12
- Yadav RK, Yoo JH, Kucharski F, Abid MA (2010) Why is ENSO influencing Northwest India winter precipitation in recent decades? *J Clim* 23:1979–1993