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Seasonal Prediction Skill of Winter Temperature over North India

P.R. Tiwari[1], S.C. Kar[2], U.C. Mohanty[3], S. Dey[1], S. Kumari[1], and P. Sinha[1]

[1]Centre for Atmospheric Sciences, IIT Delhi, India

[2]National Centre for Medium Range Weather Forecasting, Noida, India

[3]School of Earth Ocean and Climate Sciences, IIT Bhubaneswar, India

Correspondence

Dr. S. C. Kar

National Centre for Medium Range Weather Forecasting (NCMRWF),

A-50, Sector-62, Noida, India

Email: sckar@ncmrwf.gov.in

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 the 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 NCEP climate forecast system model (NCEP_CFSv2) is 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 that which doesn't have orography correction.

Keywords: North India, Wintertime temperature, Predictability, General Circulation Models.

1. Introduction

Seasonal temperature during the winter season (Dec-Feb, 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 2013). 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. 2012a). 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 aim of this study is to examine the existing seasonal prediction skill—or lack thereof—of the state-of-the-art GCMs for wintertime temperatures over the northern India.

The main objectives of the present study are to examine the skill of GCMs for predicting the wintertime seasonal mean 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. Data Sets and Method of Analysis

2.1 Observed Reference data

The India Meteorological Department (IMD) has developed a high-resolution (1° × 1°) daily gridded observed temperature dataset (Srivastava et al. 2009) over the Indian land area. This dataset consists of daily averages, 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 seventeen stations over the study region are also used to validate the model results.

2.2 Model products

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 SSTs from the 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. Predictions of all these models are collected from the International Research Institute for Climate and Society (IRI), Columbia University, New York, data library except for CFSv2, which 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 $1^{o} \times 1^{o}$ 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 Mean Square Skill Score (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:

$$MSE_j = \frac{1}{n}\sum_{i=1}^{n}\left(f_{ij} - o_{ij}\right)^2 \qquad \text{………………….(i)}$$

Where, o and f denotes time series of observations and continuous deterministic forecasts.

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

$$MSE_{cj} = \left(\frac{n-1}{n}\right) sd_{oj}^2 \qquad \text{….......……………(ii)}$$

where $$sd_{oj}^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(o_{ij} - \overline{o}_j\right)^2 \qquad \text{…………………..(iii)}$$

The MSSS is therefore given as:

$$MSSS_j = 1 - \frac{MSE_j}{MSE_{cj}} \qquad \text{…………………..(iv)}$$

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.

$MSSS_j$ for forecasts fully cross-validated (with one year at a time withheld) can be expanded (Murphy 1988) as

$$MSSS_j = \left\{ 2\frac{sd_{fj}}{sd_{oj}} r_{foj} - \left(\frac{sd_{fj}}{sd_{oj}}\right)^2 - \left(\frac{\left[\bar{f}_j - \bar{o}_j\right]}{sd_{oj}}\right)^2 + \frac{2n-1}{(n-1)^2} \right\} \Big/ \left\{ 1 + \frac{2n-1}{(n-1)^2} \right\} \quad \text{……..(v)}$$

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

$$r_{foj} = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(f_{ij} - \bar{f}_j\right)\left(o_{ij} - \bar{o}_j\right)}{sd_{fj} sd_{oj}} \quad \text{…………………(vi)}$$

The first three terms (in equation v) 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.

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, (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 (Figure 1(a)) depicts that the minimum temperature occurs during the winter over Northern Kashmir, which ranges from 275 to 285 ^{o}K. Over the northeastern part of India, the climatology of temperature lies in the range of 290-295 ^{o}K. It can be seen that the temperature has gradually increased towards the south.

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 and are shown in Figure 1b-f. All the models show very low temperatures compared to the observations over Northern Kashmir (below 260 ^{o}K) and some pockets of North East India (below 265 ^{o}K). Over the southern parts of India, the temperature is approximately same in all the models (295-300 ^{o}K) and comparable to the observations. So, overall the models are capable of replicating the observed climatological temperature up to a certain extent over the most parts of India, except for the northeastern parts. All the models (except NCEP_CFSv2) show almost the same pattern of seasonal temperature bias, ranging from 4 to 10 ^{o}K over the Jammu and Kashmir (hereafter J&K), Himachal Pradesh (hereafter HP) and

Uttarakhand (hereafter UK) region (Figure 2). On the other hand, the NCEP_CFSv2 model (Figure 2(c)) depicts a stronger bias (more than 8 ^{o}K) 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. The figure 3 (a - 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 from the diagram that the values of amplitude error 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 followed by MOM3_DC2 and MOM3_AC1 models. Therefore, among all the models, NCEP_CFSv2 is better in predicting temperatures over the northern India during the winter season in an interannual timescale.

The phase error of temperature between the model predictions and the observations is shown in Figure 4 (a-e). Phase errors essentially represent the correlation of the model predictions with the observations. In this case, positive and large phase error corresponds to better prediction and indicates to 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 in interannual timescale.

3.3 MSSS Analysis

In this section, an analysis of the mean square skill score (Murphy 1988), which is essentially 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. 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. By removing this amplitude error, the MSSS of a model can be improved. In this study, the amplitude error of each model has been removed by normalizing the model predictions which is done 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 systematic removal of overall bias and amplitude errors is shown in Figure 5. Over the most parts of India, the MSSS is negative, indicating poor skill of the models compared to a climatological forecast. 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 higher 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), and presented in Figure 6. The figure clearly indicates significant correlation with less RMSE of two coupled GCMs (NCEP_CFSv2 and MOM3_DC2) out of five GCMs used in the study. Smaller correlations with more 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 under-predict the temperature. It has been observed that out of the five models; only two models (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 multi-model ensemble (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 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 region (Figure 1 (g)). However, it under-predicts the temperature (260-265 ^{0}K) against 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 (Figure 2 (f)). The amplitude error of the MME prediction is shown in Figure 3 (f), which demonstrates that the error is lesser in MME compared to that of the ECHAM_GML and ECHAM_CFS models over northwest and eastern parts of Kashmir. However, the amplitude error of MME is more compared to other models. Although, the MME predictions have a phase error (0.05 to 0.3) over J&K, northeastern and southern parts of India (Figure 4 (f)), an improvement in phase error is noticed in the MME prediction over some parts of the northern India (especially over the HP and UK region) compared to the individual models (ECHAM_GML, MOM3_DC2 and ECHAM_CFS). In fact, with the use of MME, the phase error has improved but remains insignificant over most parts of India. 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. On the other hand examination of the MSSS reveals that the skill of the MME prediction (Figure 5 (f)) is improved compared to that of the individual member models (here ECHAM_GML and ECHAM_CFS), but it is lower in MME than the best model (here NCEP_CFSv2). A possible reason would be that while making the multi-model ensemble, the forecasts from other poorer models also gets 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 (Figure 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.

Further to improve the forecast skill against simple MME, Krishnamurti et al (2000) have suggested the use of weighted multi-model ensemble (WMME) technique in which a point-by-point multiple linear regression (MLR) method is employed. The weights are computed and assigned to each model based on its performance, which leads to an improvement in forecast skill. The calculation of weighted MME is beyond the scope of the present study and will we taken up separately in our next work.

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 ^{o}C or below freezing levels. This information also plays a vital role in many organizational aspects where men and machines are employed to operate in the open, viz. for agriculture, defense force, tourism, transport, etc. So, it is very important to predict the future state of maximum and minimum temperatures over this region. 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.

The performance of NCEP_CFSv2 in its ability to predict maximum and minimum temperature is evaluated for the study period (1982-2009). Observed and model simulated maximum and minimum temperatures are shown in fig. 7 and 8**,** respectively. It can be seen in fig. 7 (a) that the observed climatological maximum temperature is lower over northern India compared to other 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 temperature are shown in Fig. 8 (a) and (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 ^{o}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. 8(c) 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 seventeen observation stations of the SASE are used to construct the J&K and HP maximum/minimum temperatures for the 27 years (1982-2009). Out of these seventeen stations, twelve stations fall over J&K region, while five stations fall over HP region. The observed and model predicted maximum and minimum temperatures over the stations in the J&K region are shown in Figure 9 (a, b). It can be seen in Fig. 9 (a) 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 ^{o}C whereas the model predicted standard deviation is 0.76 ^{o}C, which is very low compared to the observed data. The standard deviation of observed minimum temperature (T_{min}) is 1.15 ^{o}C, whereas the model predicted standard deviation is 0.46 ^{o}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 10 (a & b) shows the observed and model predicted T_{max} and T_{min} respectively for the HP region. It can be seen that 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 ^{o}C whereas for the model, predicted standard deviation is 0.82 ^{o}C. The standard deviation of observed T_{min} is 0.95 ^{o}C whereas it is 0.67 ^{o}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 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 the Fig. 9 (a) 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 ^{o}C, whereas the standard deviation without the orography correction is 0.76 ^{o}C, which happens to be very low compared to the observations (standard deviation for observed maximum temperature is 4.18 ^{o}C).

In the case of Fig. 9 (b) 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 ^{o}C, whereas without orography correction, it is 0.46 ^{o}C (standard deviation for observed T_{min} is 1.15 ^{o}C).

Figure 10 (a) 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 ^{o}C, whereas, without the orography correction, the standard deviation is 0.82 ^{o}C, which happens to be greater compared to the observations (standard deviation for observed maximum temperature is 0.78 ^{0}C).

In Fig. 10 (b) 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 ^{o}C, whereas, without orography correction, the standard deviation is 0.67 ^{o}C, which is lower than the observations (standard deviation for observed minimum temperature is 0.96 ^{o}C).

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

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

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, 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 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 one-month lead. In order to improve the temperatures prediction during the winter season, the ensemble mean (EM) is also used. The key findings of the present study are as following:

- The GCM, in general, underestimate 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 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 multi-model ensemble (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 seventeen stations (twelve over J&K and five 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, shows the increasing trend.

Finally if a similar study is undertaken with high-resolution models instead of low-resolution models, then the IAV will get modified as the representation of sub grid scale processes would be better in high resolution models, which will further lead to improved model skill.

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Table 1: Description of GCMs/AOGCMs

Model	**Resolution**	**AGCM**	**OGCM**	**Ensemble Member**	**Reference**
ECHAM_CFS	(T42) $2.7^0 \times 2.8^0$	ECHAM4p5	CFS-predicted SST	24	Roeckner.et al.1996
ECHAM_GML	(T42) $2.7^0 \times 2.8^0$	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) $2.7^0 \times 2.\ 8^0$	ECHAM4p5	MOM3 (anomaly -coupled)	24	Roeckner.et al.1996 , Pacanowski.et al 1998
MOM3_DC2	(T42) $2.7^0 \times 2.\ 8^0$	ECHAM4p5	MOM3 (direct -coupled)	12	Roeckner.et al.1996 , Pacanowski.et al 1998
NCEP_CFSv2	(T126) $0.9^0 \times 0.9^0$	GFS (2009 version)	MOM4	24	Saha et al. 2006

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

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 Japan 81: 909-933

Agnihotri CL, Singh MS (1982) Satellite study of western disturbances. Mausam 33: 249–254

Chakraborty A, Nanjundiah RS, Srinivasan J (2002) Role of Asian and African orography in Indian summer monsoon. Geophys Res Lett 29(20). doi:10.1029/2002GL015522, 2002

Doblas-Reyes, Deque FJM, Piedelievre JP (2000) Multi-model spread and probabilistic seasonal forecasts in PROVOST. Quart J Roy Meteor 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. Current Sci 94 (1): 82–88

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

Kar SC, Rana S (2013) Interannual variability of winter precipitation over northwest India and adjoining region: impact of global forcings. Theor. Appl. Climatol., doi: 10.1007/s00704-013-0968-z

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. Climate 13: 4196–4216.

Lee DE, De Witt DGA (2009) New Hybrid Coupled Forecast System Utilizing the CFSSST, 2009 Forecasts[http://portal.iri.columbia.edu/portal/server.pt/gateway/PTARGS_0_49 72_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

Mooley DA (1957) The role of western disturbances in the pro- duction of weather over India during different seasons. Indian J Meteor Geophys 8: 253–260

Murphy AH (1988) Skill scores based on the mean square error and their relationships to the correlation coefficient. Mon Wea 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

Pisharoty PR, Desai BN (1956) Western disturbances and Indian weather. Indian J Meteor Geophys 8: 333–338

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-Institutitute fur 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 Climate 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:10.1175/2008BAMS2759.1

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, SmithIII TJ (2012a) A proxy for high-resolution regional reanalysis for the southeast United States: assessment of precipitation variability in dynamically downscaled reanalyses. Climate Dynamics 38: 2449–2446

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

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, 1-12

Yadav RK, Yoo JH, Kucharski F, Abid MA (2010) Why Is ENSO Influencing Northwest India Winter Precipitation in Recent Decades? J Climate 23: 1979-1993

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

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