Location specific forecasting of maximum and minimum temperatures over India by using the statistical bias corrected output of global forecasting system

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The output from Global Forecasting System (GFS) T574L64 operational at India Meteorological Department (IMD), New Delhi is used for obtaining location specific quantitative forecast of maximum and minimum temperatures over India in the medium range time scale. In this study, a statistical bias correction algorithm has been introduced to reduce the systematic bias in the 24–120 hour GFS model location specific forecast of maximum and minimum temperatures for 98 selected synoptic stations, representing different geographical regions of India. The statistical bias correction algorithm used for minimizing the bias of the next forecast is Decaying Weighted Mean (DWM), as it is suitable for small samples. The main objective of this study is to evaluate the skill of Direct Model Output (DMO) and Bias Corrected (BC) GFS for location specific forecast of maximum and minimum temperatures over India. The performance skill of 24–120 hour DMO and BC forecast of GFS model is evaluated for all the 98 synoptic stations during summer (May–August 2012) and winter (November 2012–February 2013) seasons using different statistical evaluation skill measures. The magnitude of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for BC GFS forecast is lower than DMO during both summer and winter seasons. The BC GFS forecasts have higher skill score as compared to GFS DMO over most of the stations in all day-1 to day-5 forecasts during both summer and winter seasons. It is concluded from the study that the skill of GFS statistical BC forecast improves over the GFS DMO remarkably and hence can be used as an operational weather forecasting system for location specific forecast over India.

1. Introduction

There is a growing operational demand to provide quantitative location specific accurate forecasts of maximum and minimum temperatures in short to medium range time scale. Numerical Weather Prediction (NWP) is the only state-of-the-art tool currently available in the operational forecaster to provide quantitative weather forecast in real time. One very specific requirement for the Integrated

Agro-Advisory Service (AAS) of the India Meteorological Department (IMD) is to provide district level quantitative weather forecasts for surface parameters like rainfall, maximum and minimum temperatures, etc., in the short to medium range time scale to the farming community to minimize any adverse impact due to extreme temperature events. But, accurate forecasting of surface parameters, particularly maximum and minimum temperatures over India, is a difficult task due to

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its complex terrain having different altitudes and orientations. Over the years, NWP models are playing an increasingly important role in delivering operational real time weather forecasts. Significant improvement in accuracy and reliability of NWP products has been driven by computational power, sophisticated numerical techniques, and by the phenomenal increase in meteorological satellite-based observations. The global NWP models, though able to provide reasonably good short- to medium-range weather forecasts, have comparatively less skill in forecasting surface parameters. It is well known that NWP model forecasts contain systematic biases in the forecast of near surface parameters especially maximum and minimum temperatures due to imperfect model physics, initial conditions, and boundary conditions (Mass *et al.* 2002; Hart *et al.* 2004; Krishnamurti *et al.* 2004).

The systematic bias in the NWP model is a result not only of the shortcoming in the physical parameterization, but also of the inability of these NWP models to handle subgrid scale phenomena correctly. The NWP models necessarily simplify and homogenize the orographic and land surface characteristics, by representing the world as an array of grid points. Due to this, small-scale effects important to local weather may be represented weakly or may not be included in the model. DMO of NWP models are available at the model grid point, but operational forecasters and end users are interested in location specific district/city level forecast. However, there is no perfect method for downscaling model grid point data to specific locations, i.e., district, block, and village, etc., especially when the model elevation differs from that of the observing site. Even when the model resolution is increased, it does not necessarily improve model performance (Mass *et al.* 2002). For these reasons, the Model Output Statistics (MOS) approach (Glahn and Lowry 1972) has been successfully used to improve upon model output through bias removal and statistical correction and provide location-specific forecasts from model guidance. MOS uses multiple linear regressions and it remains a useful post-processing tool. Efforts are made by several researchers (Singh and Jaipal 1983; Raj 1989; Attri *et al.* 1995; Dimri *et al.* 2002; Chakraborty 2006; Bhardwaj *et al.* 2007, etc.) to develop statistical technique of multiple linear regression analysis for predicting precipitation, maximum and minimum temperatures over India using MOS techniques.

One major drawback of MOS is that it requires a long training period of archived model data from an unchanged or static model. Today, modelling centers around the world make frequent changes to numerical procedures, physics, and resolution of

NWP models (Landberg 1994; Joensen *et al.* 1999). To overcome this ever-changing model base, other techniques more dynamic in nature are being investigated. To adapt model changes, an updateable MOS system has been developed by Wilson and Vallée (2002) and used over Canada. Mao *et al.* (1999) developed a similar technique that updated bias daily and relied on only the most recent 2–4 weeks of model and observational data. Maini *et al.* (2003) developed a perfect prognostic method (PPM) using multiple linear regressions for generating forecasts of maximum and minimum temperatures for 12 locations over India during the monsoon season. Mohanty and Dimri (2004) and Dimri and Mohanty (2007) have presented the performance of statistical downscaling on NWP model outputs of various models and shown enhanced skills by implementing statistical techniques for probability of precipitation (PoP) forecasting and quantitative precipitation forecasting (QPF) over the complex Himalayan region. Dimri *et al.* (2008) developed a k-nearest neighbour statistical technique based on past observational data to forecast PoP occurrence/non-occurrence and its quantity over western Himalayan region. There are, however, other post-processing methods that do not require a long training dataset such as the Kalman filter, and running-mean bias removal techniques are available to the operational forecaster to use NWP model output effectively. Kalman (1960) introduced the concept of the Kalman filter (KF) that described a recursive solution to a discretized linear filtering problem. The KF combines a model with observations to provide a better estimate of a state variable than either the model or observations can provide alone.

Bhardwaj *et al.* (2007) evaluated the KF approach for location specific temperature forecast over India in the short- to medium-range time scale and found that Kalman filtered temperature forecasts have better skills as compared to DMO forecasts. Stensrud and Skindlov (1996) showed that a simple bias correction method using the previous 7-day running mean (RM) bias correction improved the direct model forecasts of maximum temperature. The lagged Linear Regression (LR) method has been used in the past (e.g., Stensrud and Yussouf 2005), and it uses a least-squares line to model the trend in the bias of the forecasts over the training period at each location. Woodcock and Engel (2005) evaluated the usefulness of the best easy systematic mean statistics (BES) bias correction methodology for the bias correction of 2-m maximum and minimum temperature forecasts over Australia. Steed and Mass (2004) experimented with several different spatial techniques of applying bias removal to temperature forecasts from a mesoscale model. Their study

showed that a bias removal method using a 2-week running bias had the least amount of error compared to periods of 1, 3, 4, and 6 weeks. In the present study, output from the general circulation model GFS T574L64 operational at IMD is used for obtaining location specific forecast of surface weather elements, i.e., maximum and minimum temperatures in the medium range time scale. However, it is well known that in spite of higher resolution, the global models are unable to account for the small-scale effects (e.g., of topography, local environmental features) important in predicting surface weather parameters like rainfall, temperature, etc. This necessitates the use of statistical bias corrections to the surface weather elements. Maximum and minimum temperature forecasts are subsequently obtained from statistical BC GFS T574 model output.

In this study, a statistical bias correction algorithm has been introduced to reduce the systematic bias in the 24–120 hr GFS model location specific forecast of maximum and minimum temperatures for 98 selected synoptic stations, representing different geographical regions of India, i.e., northwest (NW), east and northeast (NE), central India (CI) and southern peninsular (SP) India. The statistical bias correction algorithm used for minimizing the bias of the next forecast is Decaying Weighted Mean (DWM), as it is suitable for small samples. IMD requires an assessment of the accuracy of this location specific forecast generated from Direct Model Output (DMO) and bias corrected (BC) GFS, before making this forecast operational. The main objective of this study is to evaluate the performance skill of DMO and BC GFS T574L64 model forecast for location specific forecast of maximum and minimum temperatures for these 98 selected synoptic stations over India during summer (May–August 2012) and winter (November 2012–February 2013) seasons using different statistical measures. This paper comprises of five sections. Section 2 gives a brief description of NCEP global forecast system. The data and statistical bias correction methodology, including evaluation measures used in this work are described in section 3. The prediction skill and verification results of maximum and minimum temperatures during summer and winter seasons are discussed in section 4. Finally, the summary and concluding remarks are given in section 5.

2. The NCEP GFS

The NCEP GFS run at IMD is a primitive equation spectral global model with state-of-the-art dynamics and physics (Kanamitsu 1989; Kalnay *et al.* 1990; Kanamitsu *et al.* 1991; Moorthi *et al.*

2001). This GFS model conforms to a dynamical framework known as the Earth System Modeling Framework (ESMF) and its code was restructured to have many options for updated dynamics and physics. Details about the NCEP GFS are available at <http://www.emc.ncep.noaa.gov/GFS/doc.php>. The details about model physics and dynamics are discussed in the recent study by Durai and Roy Bhowmik (2013). The model physics changes from its previous version to current version at T574 are mainly in radiation, gravity wave drag, planetary boundary layer processes, shallow and deep convection schemes and an introduction of tracer transport scheme in the vertical (Saha *et al.* 2010).

The assimilation system (for GFS T574) is a global 3-dimensional variational technique, based on NCEP Grid Point Statistical Interpolation (GSI 3.0.0; Kleist *et al.* 2009) scheme, which is the next generation of Spectral Statistical Interpolation (SSI; David *et al.* 1992). The T574 Global Data Assimilation System (GDAS) uses variational quality control, flow dependent re-weighting of background error statistics, use of the new version of Community Radiative Transfer Model (CRTM 2.0.2), and improved tropical cyclone relocation algorithm. In the operational mode at IMD, the GDAS cycle runs 4 times a day (00, 06, 12 and 18 UTC) and GFS model runs 2 times a day (00 and 12 UTC). The analysis and forecast for 7 days are performed using the High Power Computing System (HPCS) installed in IMD Delhi. One GDAS cycle and 7 days (day-1 to day-7) GFS forecast at T382L64 (~35 km in horizontal over the tropics) takes about 30 minutes on IBM Power 6 (P6) machine using 20 nodes with seven tasks (seven processors) per node, while the same for GFS T574 (~22 km in horizontal over the tropics) is approximately 1 hour 40 minutes.

3. Data and methodology

3.1 Data source

In this study, the day-1 to day-5 maximum and minimum temperature forecast data from the state-of-the-art GFS model run at 00 UTC is used for generating 5 days location-specific forecast in real time experimental basis during January 2012–February 2013. The GFS model data used for generating the location specific station level forecast is at $0.25^\circ \times 0.25^\circ$ uniform latitude/longitude (~22 km over tropics) resolution. The daily observed maximum and minimum temperature data from Global Telecommunication System (GTS) available at IMD are quality controlled and used for computing daily bias at all model forecast hours. These station level datasets are used to perform bias removal

using statistical bias correction methods on each day's model forecast, and the resulting corrected forecasts are archived for later comparison with the uncorrected DMO forecast and with each other with respect to observation. For computation of ACC, observed daily climatology of maximum and minimum temperatures computed from 1981 to 2005 is used. Validation is carried out using daily observed and bias corrected maximum and minimum temperature forecast for some selected 98 metrological stations (table 1) over different homogeneous regions of India (figure 1a and b), i.e., northwest India, east and northeast India, central India and southern peninsular India during summer (May–August 2012) and winter (November 2012–February 2013) seasons.

3.2 Methodology

Bias correction removes only the portion of error that can be estimated through calculating the average of past errors. Random errors cannot be corrected. If the systematic bias error is higher than the random error (RMSE), then the improvement

to the bias corrected forecast is greater. In this study, the statistical algorithm used for minimizing the bias of the next forecast is the decaying weighted mean bias correction technique, as this is suitable for small samples. The decaying weighted mean average bias gives more weight to recent error data and less to older error data. The higher the decaying average weight for the current day error, the faster the bias-correction responds to day-to-day changes in forecast bias, and the lesser the influence of long-term persistent errors. Here, the bias correction is done for 00 UTC of GFS model maximum and minimum temperature forecasts (day-1 to day-5). The purpose of this bias correction is to identify common systematic errors that occur in the GFS DMO forecasts and then correct each forecast to eliminate these biases.

3.2.1 Bias estimation

The bias $b_k(t)$ for each station (k) and each lead-time (a 24-hr interval up to 120 hr), is defined as the difference between the observation $O_k(t)$ and forecast $f_k(t)$ at the same valid time t , on the latest

Table 1. *Meteorological stations selected for the location-specific study.*

Northwest India (NW)	Code	East and northeast India (ENE)	Code	Central India (CI)	Code	Southern peninsular India (SP)	Code
Srinagar	SRN	Pasighat	PSG	Gwalior	GWL	Ramagundam	RMD
Jammu	JMU	Gangtok	GTK	Guna	GNA	Hyderabad	HYD
Dharmasala	DRM	N-Lakhimpur	LKR	Satna	STN	Vishakhapatnam	VSK
Amritsar	AMR	Mohanbari	DBH	Bhuj	BHJ	Vijayawada	VJW
Shimla	SML	Jalpaiguri	JPG	Ahmadabad	AHM	Machilipatnam	MPT
Patiala	PTL	Gauhati	GHT	Bhopal	BHP	Kakinada	KND
Ambala	AMB	Tezpur	TZP	Jabalpur	JBP	Belgaum	BLG
Chandigarh	CHD	Patna	PTN	Rajkot	RJK	Gadag	GDG
Dehradun	DDN	Bhagalpur	BGP	Baroda	BRD	Kurnool	KRN
Ganganagar	GGN	Purnea	PRN	Indore	IND	Chitradurga	CHT
Hissar	HSR	Malda	MLD	Pendra	PND	Anantapur	ANT
Bikaner	BKN	Shillong	SHL	Surat	SRT	Madras	MDS
Delhi	SFD	Kohima	KHM	Nagpur	NGP	Mangalore	MNG
Bareilly	BRL	Gaya	GYA	Raipur	RPR	Panambur	PNB
Agra	AGR	Imphal	IMP	Jharsuguda	JRG	Madikeri	MDK
Jaisalmer	JSM	Ranchi	RNC	Balasore	BLS	Bangalore	BNG
Jodhpur	JDP	Panagarh	PNG	Akola west	AKL	Amini	AMN
Jaipur	JPR	Agartala	AGT	Bhubaneswar	BBS	Kozhikode	KZK
Lucknow	LKN	Jamshedpur	JSD	Bombay	SCZ	Coimbatore	CMB
Kota	KTA	Calcutta	ALP	Ahmadnagar	AMN	Salem	SLM
Allahabad	ALB			Aurangabad	AGD	Cuddalore	CDL
Udaipur	UDP			Jagdalpur	JGD	Pondicherry	PDC
				Gopalpur	GPL	Tiruchchirapalli	TRP
				Poona	PNE	Karaikal	KRL
				Ratnagiri	RTN	Nagappattinam	NPT
				Sholapur	SLP	Cochin(in-Navy)	CHN
				Goa(Panjim)	PJM	Madurai	MDU
						Palayamkottai	PLM
						Thiruvananthapuram	TRV

Figure 1. (a) Topography and distribution of synoptic stations and (b) meteorological subdivision of India.

available observation. The bias at each station and for each forecast hour is computed daily as:

$$b_k(t) = f_k(t) - O_k(t).$$

3.2.2 Decaying weighted mean (DWM)

This DWM bias correction method computes bias at each station (k) and at each forecast hour (t)

from the previous 14 days daily bias $b_k(t)$ starting from the forecast issue day ($t = 0$) using decreasing weight so that the nearest recent data has the largest weight. The previous forecast errors are weighted averaged together using decreasing weight (figure 2). The 14-day period is chosen to best account for the seasonal change in model errors and the samples are large enough to eliminate noise.

The DWM with the weight coefficient $wt_k(t)$ is computed as:

$$wt_k(i) = \frac{w_k(i)}{\sum_{t=0}^{14} w_k(t)}$$

where $w_k(i) = \frac{1}{(1-i)}$; and $i = 0, -1, 2, -3, \dots, -14$.

The weight $wt_k(t)$ is considered for computing model bias from its past performance starting the forecast issue day ($t = 0$) and the previous first

Figure 2. Weights used in the decaying weighted mean bias correction method for computing daily model bias.

14 days are 30.14, 15.07, 10.05, 7.53, 6.03, 5.02, 4.31, 3.77, 3.35, 3.01, 2.74, 2.51, 2.32, 2.15, 2%. The weight for the forecast issue day ($t = 0$) is 30.14 %, followed by the previous first day $t = -1$ is 15.07%, but the weight became 2% for the last day ($t = -14$). The systematic bias $B_k(t)$ at each station is computed daily by applying the weight coefficient $wt_k(t)$ at each forecast hour as:

$$B_k(t) = Wt_k(t) * b_k(t).$$

This is the final bias field which is subtracted from the raw forecasts to produce the bias-corrected forecast.

3.2.3 Bias corrected (BC) forecast

The new bias-corrected model forecast $F_k(t)$ is generated by applying the bias $B_k(t)$ to current direct forecasts $f_k(t)$ at each station for all day-1 to day-5 forecasts.

$$F_k(t) = f_k(t) - B_k(t).$$

This new statistical bias correction is applied to GFS day-1 to day-5 forecast at each lead time with respect to observation. This new statistical bias correction method discussed in this study uses the current and previous 14 days bias to calibrate each forecast individually, at each station.

3.3 Evaluation parameters

For an objective comparison of the forecasts, we consider a number of evaluation parameters

Figure 3. DMO (ME_DMO) and BC (ME_BC) mean error of minimum temperature day-3 forecasts at each meteorological station during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

described below. To compare the DMO and bias corrected forecast, mean error (ME), mean absolute error (MAE), and root-mean-square error (RMSE), anomaly correlation coefficient (ACC) and mean squared skill score (MSSS) are used.

The mean error (ME) in daily forecasts is defined as:

$$\text{BIAS} = \frac{1}{N} \sum_{i=1}^N (F_i - O_i);$$

Figure 4. Day-1 to day-5 DMO (MAE_DMO) and BC (MAE_BC) MAE of minimum temperature forecasts at each meteorological station over NW, ENE, CE, and SP India during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

where F_i and O_i are the i th forecast and observation; and $N = 123$ days for summer and $N = 120$ for winter seasons.

The mean absolute error (MAE) in daily forecasts is defined as:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |(F_i - O_i)|$$

Then RMSE is defined as:

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

RMSE indicates total amount of difference between forecast and observation map. The score is always ≥ 0.0 . If the forecast is perfect, the score of RMSE equals to 0.0.

ACC is pattern correlation between predicted and observed anomalies defined as:

$$\text{ACC} = \frac{\sum_{i=1}^N (F_i - \bar{F}) (O_i - \bar{O})}{\sqrt{\sum_{i=1}^N (F_i - \bar{F})^2} \sqrt{\sum_{i=1}^N (O_i - \bar{O})^2}}$$

where overbar is time average. The ACC score always ranges from -1.0 to 1.0 . If the forecast is perfect, the score of ACC equals to 1.0.

In addition to daily and seasonal average errors, we consider a skill score (SS) defined in terms of mean-square error (MSE). A detailed description of mean squared skill score (SS) is provided by WMO (2002). The standard mean squared skill score (SS), defined with respect to the mean

square error of a reference forecast can be written as:

$$\text{SS} = 1 - \frac{\text{MSE}_f}{\text{MSE}_c}$$

where the MSE_f is the MSE of model forecast

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

Correspondingly, the MSE_c is defined such that

$$\text{MSE}_c = \frac{1}{N} \sum_{i=1}^N (\bar{O}_i - O_i)^2$$

where the overbar denotes the observation mean. The SS is 1.0 for perfect forecasts and 0.0 (negative) for forecasts that are only as accurate as (less accurate than) the climatology reference forecast.

The percentage of improvement skill by the bias-corrected forecasts over the DMO as measured in terms of the MAE is given by:

$$\text{SKILL}(\%) = \frac{(\text{MAE}_{\text{DMO}} - \text{MAE}_{\text{BC}})}{\text{MAE}_{\text{DMO}}} \times 100$$

where MAE is the MAE for the direct or raw model output and MAE represents the bias-corrected values.

4. Result and discussions

A quantitative intercomparison of error statistics between DMO and BC forecast for all the 98

Figure 5. DMO (ME_{DMO}) and BC (ME_{BC}) MAE of day-3 minimum temperature forecasts at each meteorological station during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013).

station over India are discussed in this section. Forecast accuracy refers to the association between individual pairs of forecasts and observations over

the period of verification. Some of the common measures of accuracy are MAE, MSE, and RMSE. Bias is the difference between the forecast and its

Figure 6. Day-1 to day-5 DMO (RMSE_DMO) and BC (RMSE_BC) RMSE of minimum temperature forecasts at each meteorological station over NW, ENE, CE, and SP India during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

observation. MAE uses the mean absolute value of the bias, and RMSE is the mean of square root of the sum of the squared bias. The error statistics (ME, MAE, RMSE, ACC and skill score) based on the daily observed maximum and minimum temperatures and corresponding day-1 to day-5 BC and DMO forecasts have been computed during summer (May–August 2012) and winter (November 2012–February 2013) seasons. Stationwise distribution of MAE, RMSE and skill score for minimum and maximum temperatures are also discussed for in this section.

4.1 Minimum temperature forecasts

The DMO (ME_DMO) and BC (ME_BC) mean error (systematic bias) of minimum temperature day-3 forecasts at each meteorological station during summer (May–August 2012) and winter (November 2012–February 2013) seasons is shown in the scatter diagram figure 3(a and b), respectively. The systematic bias has very marked variations from one station to another and is in the order of -0.2 to $+0.2^\circ\text{C}$ for BC while it is in the order of -4 to $+4^\circ\text{C}$ for DMO in both summer and winter seasons for most of the stations. The comparison of systematic bias of BC and

DMO of minimum temperature for day-3 forecast for each station also shows that this BC forecast produces bias values almost close to zero for most of the stations in summer as well as winter. We observe that only a few stations have a DMO mean bias as low as that using the BC forecast.

Figure 4 shows the MAE for day-1 to day-5 DMO and BC minimum temperature forecasts at each meteorological stations averaged over NW, ENE, CE, and SP India during summer (figure 4a) and winter (figure 4b) seasons. We notice a significant reduction of mean absolute errors in the BC forecast as compared to DMO in all subdivisions and in all the forecast hours. Figure 5 compares the MAE of BC and DMO for each station for summer (figure 5a) and winter (figure 5b). The MAE of minimum temperature day-3 forecasts ranged from 1° to 4.0°C for DMO and from 1° to 1.5°C for BC in most of the stations during both summer and winter. We also notice that the BC forecast shows an MAE below 1.5°C during summer and below 2°C during winter season for most of the stations, while DMO frequently gives a MAE between 1° and 4°C . It is also seen that the DMO MAE is below 2.5°C in summer and below 3°C in winter for most of the stations. We observe also that only a few stations have a DMO MAE as low as that using the BC forecast.

Figure 7. RMSE ($^\circ\text{C}$) in day-3 minimum temperature forecast for the 98 stations during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

The BC RMSE value for minimum temperature is less than DMO RMSE in all the subdivision of India in summer (figure 6a) and winter (figure 6b)

Figure 8. The improvement of error in % for the statistical bias corrected (BC) minimum temperature forecast over DMO during (a) summer (May–August 2012) and (b) winter November 2012–February 2013) seasons.

seasons. The DMO RMSE value varies between 3° and 3.5°C while the BC RMSE values ranges between 1.5° and 2.0°C . The DMO shows higher RMSE over SP India and the lower RMSE over NW and ENE India in both summer and winter seasons. The seasonal variation of mean error, MAE and RMSE in minimum temperature is lower for both DMO and BC forecast in summer season. The day-3 RMSE in minimum temperature forecast for all 98 stations during summer (figure 7a) and winter seasons (figure 7b) indicates that the DMO RMSE is higher than BC RMSE in all the stations and also in both the seasons. The higher DMO RMSE is observed in most of the stations over SP India in both summer and winter seasons. The BC RMSE of minimum temperature is always less than the DMO in all the stations and in all the forecast hours during both summer and winter.

The improvement of MAE skill in % for the statistical bias corrected (BC) minimum temperature forecast over DMO during summer and winter seasons is shown in figure 8. The MAE skill score ranges from 0 to 100 with value of zero indicating no improvement skill and a value of 100 is for perfect forecasting skill. We observed a significant reduction of MAE in BC compared to DMO in all subdivision for all forecast days (day-1 to day-5)

Figure 9. The improvement of error in % for the statistical bias corrected (BC) minimum temperature forecast over GFS DMO for the 98 stations during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

during both summer and winter seasons. The improvement of MAE skill score in day-3 forecast for each individual station is given in figure 9. Figures 8 and 9 clearly indicate that the BC forecast has positive skill and perform better than the DMO in all the seasons. As is seen in figures 8

and 9, the BC forecast has significant improvement in forecasting minimum temperature from 40–50% over the DMO forecasts. More improvement ($> 60\%$) is noticed in MAE over SP India regions in all day-1 to day-5 forecasts in both summer and winter seasons.

Figure 10. Day-1 to day-5 DMO (ACC_DMO) and BC (ACC_BC) ACC of minimum temperature forecasts at each meteorological station over NW, ENE, CE, and SP India during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

The ACC between the observed and the model forecast of minimum temperature for day-1 to day-5 of BC and DMO at each meteorological station averaged over NW, ENE, CE, and SP India during summer and winter seasons are plotted in a

scale of 0–1 in figure 10. The ACC between trends in the forecast and observation is a measure of the phase relationship between them. The ACC is statistically significant at the 99.9% confidence level for a value of 0.3 and above. The ACCs for

Figure 11. Day-1 to day-5 DMO (SS_DMO) and BC (SS_BC) skill score of minimum temperature forecasts at each meteorological stations averaged over NW, ENE, CE, and SP India during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

BC day-1 to day-5 minimum temperature forecasts over all the subdivisions are higher than DMO in both summer (figure 10a) and winter (figure 10b) seasons. It is also noticed that the ACC value for BC forecast varies between 0.8 and 0.9 while the same for DMO forecast varies between 0.7 and 0.8 in both the seasons. The lower DMO ACC is observed over SP India and the higher over NW and ENE India in both summer and winter seasons. In general, the ACC for minimum temperature is higher in summer than in winter season over all the subdivisions of India for both BC and DMO forecast in all days of forecasts.

The forecast skill score is the accuracy of the forecasts of interest relative to the accuracy of forecasts produced by a standard of reference such as climatology or persistence. The day-1 to day-5 DMO and BC MSE skill score (SS) of minimum temperature forecasts at each meteorological station averaged over NW, ENE, CE, and SP India is

shown in figure 11(a) for summer and figure 11(b) for winter seasons. In all the subdivisions, the MSE skill scores for BC forecast are better than both DMO and climatology reference forecast and its skill score values are more than 0.7. The DMO skill scores are slightly better than the climatology forecast over NW, ENE and central India while it is worse than the reference forecast over SP India in summer (figure 11a) season. A very similar pattern of BC and DMO skill score for summer is seen in winter (figure 11b) for all the subdivisions of India except the DMO forecast skill which is equal to reference climatology forecast over CE and SP India subdivisions.

The MSE skill score in day-3 minimum temperature forecast at each individual meteorological stations during summer (figure 12a) and winter (figure 12b) seasons indicate that the BC skill score is higher than DMO score in all the 98 stations in both the seasons. A positive value of skill score indicates a better performance of the model

Figure 12. The MSE skill score (SS) for the statistical bias corrected (BC) day-3 minimum temperature forecast for all the 98 stations during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

over climatology, while a negative value of skill score indicates that the model does not have the skill even to match the climatology. The DMO skill score value of less than or equal to zero is observed in some of the stations, mostly over central and SP India in both summer and winter seasons. The BC skill score of minimum temperature is higher in summer than winter season. Figure 13 compares the day-3 MSE skill score of BC and DMO for each station for summer (figure 13a) and winter (figure 13b). The minimum temperature forecasts

skill score for BC varied from 0.7 to 0.9 and for DMO varied from 0.4° to 0.6°C at each individual station in both summer and winter. The MSE skill scores for BC forecast are better than both DMO and climatology reference forecast and its skill score values are greater than 0.7 for most of the stations during both summer and winter. It is seen that the BC forecast skill scores for minimum temperatures are reasonably high for all day-1 to day-5 forecasts in all the stations in both the seasons.

Figure 13. DMO (SS_DMO) and BC (SS_BC) skill score of day-3 minimum temperature forecasts at each meteorological station during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

Figure 14. DMO (ME_DMO) and BC (ME_BC) mean error of maximum temperature day-3 forecasts at each meteorological station during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

4.2 Maximum temperature forecasts

Figure 14 shows the maximum temperature day-3 forecasts bias (mean error) of BC and DMO of all the 98 stations during summer (May–August 2012) and winter (November 2012–February 2013) seasons. Compared with the corresponding minimum temperature in figure 3, we see that the DMO has a bias of very marked variations from one station

to another. The DMO maximum temperature bias is between -6.0°C and $+4.0^{\circ}\text{C}$ in summer while it is between -4.0°C and $+2.0^{\circ}\text{C}$ in winter season. It is also seen that this BC forecast produces bias values close to zero for most of the stations in both summer and winter seasons. We also observed that only a few stations have a DMO mean bias as low as that using the BC maximum temperature forecast.

Figure 15. (a) DMO (MAE_DMO) and BC (MAE_BC) MAE of maximum temperature day-3 forecasts at each meteorological station during summer (May–August 2012) season. (b) As in (a) but for winter season (November 2012–February 2013).

Figure 15 shows the MAE for day-1 to day-5 DMO and BC maximum temperature forecasts over the subdivisions of India during summer (figure 15a) and winter (figure 15b) seasons. We notice a significant reduction of mean errors in the BC compared to DMO in all subdivisions and in all the forecast hours. The scatter diagram of MAE of BC and DMO at each meteorological station for summer (figure 16a) and winter (figure 16b) shows that the maximum temperature MAE ranged from 1.5° to 4°C for DMO and from 1° to 2°C for BC at most of the stations in both summer and winter. The BC forecast shows an MAE below 2.5°C during summer and below 2°C during winter season for most of the stations. Though, the DMO maximum temperature forecast gives an MAE between 1° and 4°C in both summer and winter, the MAE in winter season is lesser than in summer season.

The BC RMSE of maximum temperature is less than DMO RMSE in all the subdivisions of India in both summer (figure 17a) and winter (figure 17b) seasons. The DMO RMSE value varies between 3° and 4°C while the BC RMSE values ranges between 1.5° and 2.5°C . The higher DMO RMSE is observed over SP India and the lower RMSE over NW and ENE India in both summer and winter seasons. Both the DMO and BC RMSE of maximum temperature in winter are generally less than the same in summer season. The RMSE in day-3 maximum temperature

forecast for all the 98 stations during summer (figure 18a) and winter (figure 18b) seasons indicates that the DMO RMSE is higher than the BC RMSE in all the stations and also in both the seasons. The higher DMO RMSE is observed in some of the stations over central and SP India in summer and mostly over SP India in winter seasons. The BC RMSE of maximum temperature is always less than the DMO in all the stations and in all the forecast days. The smallest RMSE errors in maximum temperature for DMO and BC forecast occur in winter season and the greatest RMSE errors in summer.

The improvement of MAE skill score in % for the statistical bias corrected maximum temperature forecast over DMO during summer and winter seasons is shown in figure 19. A significant reduction of mean absolute errors in BC maximum temperature forecast as compared to DMO is noticed in all the subdivisions of India during both summer and winter seasons. The improvement of MAE score over subdivision (figure 19) and at each individual station (figure 20) for both summer and winter seasons clearly indicates that the BC forecast has positive skill and performs better than the DMO. As it is seen in figure 19, the bias corrected forecast has significant improvement in forecasting maximum temperature from 20 to 30% over the DMO forecasts. More improvement (more than 50%) is noticed in maximum temperature over SP India regions in all day-1 to day-5 forecasts in both

Figure 16. DMO (ME_DMO) and BC (ME_BC) MAE of day-3 maximum temperature forecasts at each meteorological station during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

summer and winter seasons. The seasonal variation of MAE skill improvement in maximum temperature occurs in winter season for both DMO and BC forecast.

The ACC between the observed and the model forecast of maximum temperature for day-1 to

day-5 of BC and DMO at each meteorological station averaged over NW, ENE, CE, and SP India during summer and winter seasons is shown in figure 21. The ACC values for BC and DMO maximum temperature is almost very similar to minimum temperature forecast discussed earlier in

Figure 17. Day-1 to day-5 DMO (RMSE_DMO) and BC (RMSE_BC) MAE of maximum temperature forecasts at each meteorological station over NW, ENE, CE, and SP India during summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

Figure 18. RMSE ($^{\circ}\text{C}$) in day-3 maximum temperature forecast for the 100 stations during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

Figure 19. The improvement of error in % for the statistical bias corrected (BC) maximum temperature forecast over DMO for the 98 stations during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

section 4.1. Here also, the ACC score for BC forecast is higher than DMO over all the subdivisions of India in both summer (figure 21a) and winter

(figure 21b) seasons. The ACC is statistically significant at the 99.9% confidence level for a value of 0.3 and above. The ACC for BC varies between

Figure 20. The improvement of error in % for the statistical bias corrected (BC) maximum temperature forecast over GFS DMO for the 100 stations during (a) summer (May–August 2012) (b) winter (November 2012–February 2013) seasons.

0.8 and 0.95 while the same for DMO varies between 0.7 and 0.8 for maximum temperature in day-1 to day-5 forecasts over all the subdivisions of India in both summer and winter. The ACC values for both BC and DMO forecast are higher over NW, ENE and CI subdivisions of India in both summer and winter seasons. However, a lower value of ACC for DMO is observed over SP India in both summer and winter seasons.

Figure 22 shows day-1 to day-5 DMO and BC forecast MSE skill score for maximum temperature over NW, ENE, CE, and SP India during summer and winter seasons. In all the subdivisions, the MSE skill scores for BC forecast are better than both DMO and climatology reference forecast and skill score values varied from 0.6 to 0.8 in both summer and winter. The DMO skill scores for maximum temperature are slightly better than the climatology forecast over NW, ENE and central India while it is worse than the reference forecast and skill score values varied from 0.2 to 0.6 over NW, ENE and central India and varied from 0 to 0.2 over SP India in summer (figure 22a) season. A very similar pattern of BC and DMO skill scores for all the subdivisions is seen in winter (figure 22b) season except that the DMO forecast skill is worse than the reference climatology forecast skill over SP India subdivision.

The MSE skill scores in day-3 maximum temperature forecast at each individual meteorological stations indicate that the BC forecast score is higher than DMO score in all the stations during both summer (figure 23a) and winter (figure 23b) seasons. The DMO skill score value of less than or equal to zero is observed in some of the stations over central and SP India in both summer and winter seasons. The BC forecast skill score of maximum temperature is higher in summer than in winter season. Figure 24 compares the day-3 maximum temperature skill scores of BC and DMO for each station for summer and winter seasons. The maximum temperature forecasts skill score for most of the stations varied from 0.7 to 0.9 for BC and from -0.4 to 0.8 for DMO in summer (figure 24a), while it varied from 0.5 to 0.8 for BC and from -0.4 to 0.8 in winter (figure 24b). The skill scores for BC forecasts are better than both DMO and climatology reference forecast, while the skill score for DMO is better than climatology for most of the stations in NW, ENE and CI subdivisions of India in both summer and winter seasons. The DMO forecast skill is worse than the climatology (reference) forecast skill over SP India subdivision. In general, it is seen that the MSE skill scores for BC maximum temperature forecast are reasonably high for all day-1 to day-5 in all the subdivisions of India in both the seasons.

Figure 21. Day-1 to day-5 DMO (ACC_DMO) and BC (ACC_BC) ACC of maximum temperature forecasts at each meteorological station over NW, ENE, CE, and SP India during summer (May–August 2012) season.

5. Conclusions

The performance of GFS DMO and BC forecasts is evaluated for improving both maximum and minimum temperatures for the 98 meteorological stations over India during summer (May–August

2012) and winter (November 2012–February 2013) seasons. This study shows that the raw model forecast for both maximum and minimum temperatures has either warm or cold bias. The error analysis for both minimum (figure 3) and maximum (figure 14) temperatures confirms that the bias

Figure 22. Day-1 to day-5 DMO (SS_DMO) and BC (SS_BC) skill score of maximum temperature forecasts at each meteorological station over NW, ENE, CE, and SP India during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

correction method used in this study is very efficient in removing GFS DMO systematic bias for all the 98 meteorological ground stations selected in this study. The BC forecast for maximum and minimum temperatures have smaller ME, MAE, and RMSE values over all the stations in Indian regions for all day-1 to day-5 than those produced by the DMO. However, the BC minimum temperature forecast shows slightly lower error (ME, MAE, and RMSE) than the corresponding BC maximum temperature forecast for most of the stations in all day-1 to day-5 forecast hours during summer. The magnitude of the bias at each station

depends upon geographical location and seasons. The BC forecast shows better performances in cases of extreme events, because the estimated correction is easily adapted to the new meteorological conditions.

The BC forecast shows significant reduction (35–50%) of MAE (figures 8 and 19) in minimum and maximum temperatures as compared to the DMO forecasts over all the subdivisions of India in all day-1 to day-5 forecasts during both summer and winter seasons. More improvement (more than 50%) is noticed over SP India in all day-1 to day-5 forecasts in both summer and winter seasons.

Figure 23. The MSE skill score (SS) for the statistical bias corrected (BC) day-3 maximum temperature forecast for 100 stations during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

Figure 24. DMO (SS_DMO) and BC (SS_BC) skill score of day-3 maximum temperature forecasts at each meteorological station during (a) summer (May–August 2012) and (b) winter (November 2012–February 2013) seasons.

The statistical bias correction method used in this study increases the GFS raw forecast skill as shown by the skill score. The skill score for BC forecasts of both minimum and maximum temperatures are better than both DMO and climatology (reference) forecasts (figures 11 and 22) in all the subdivisions of India. The DMO skill score are slightly better than the climatology forecast over NW, ENE and central India while it is worse than the climatology forecast over SP India in both the seasons. However, the study points out the feasibility of this bias removal method to improve the GFS model raw forecast skill of maximum and minimum temperatures over India.

This bias correction at the station level can be effective in improving forecast skill up to 5 days in a satisfactory way. This study also shows that the DWM statistical bias correction method can be applied to GFS DMO forecast with better skill up to lead time of 5 days. The daily bias corrected location specific forecast is found persistently closer to the observations. Results also suggest that the BC GFS forecast shows considerable skill at station level small scales. In general, the statistical BC GFS forecast is more accurate (less error) as compared to GFS DMO over most of the stations in all day-1 to day-5 forecasts during both summer and winter seasons. This comparative study indicated that the statistical BC GFS forecast improves over the GFS DMO remarkably and hence can be used as an operational weather forecasting system. It is concluded that for operational applications, this builds confidence in the use of this bias correction method for location specific forecasts in real time.

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