MAUSAM, **66**, 3 (July 2015), 467-478

551.509.5 : 551.509.313.6 : 551.524.36 (540)

Temporal and spatial characteristics of systematic errors of WRF predicted location specific maximum and minimum temperature over Indian region

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सार – इस शोध पत्र में हमने वर्ष 2012 और 2013 इन दो वर्षों के आँकड़ों के आधार पर शीतऋतु (दिसम्बर और जनवरी) तथा ग्रीष्मकालीन महीनों (अप्रैल और मई) के पहले दिन, दूसरे दिन और तीसरे दिन के WRF मॉडल द्वारा पुर्वानुमानित सतही अधिकतम और न्यूनतम तापमान के माध्य त्रुटि (ME), वर्ग माध्य मूल त्रटि (RMSE) और सहसंबंध गुणांक (CC) का आकलन किया। इस कार्य के लिए हमने भारत के विभिन्न तापमानों वाले समरूपी क्षेत्रों को सही दर्शाने वाले सात स्टेशनों नामतः अमृतसर, नई दिल्ली, चेन्नै, गुवाहाटी, कोलकाता, मुम्बई और नागपुर को चुना। इस शोध पत्र का उद्देश्य सतह तापमान पूर्वानुमान के लिए भारत के अलग-अलग क्षेत्रों में WRF मॉडल के आचरण का विश्लेषण करना है। इस अध्ययन में चुने गए सात सिनॉप्टिक स्टेशनों के लिए अधिकतम और न्यूनतम तापमान के पहले दिन से लेकर तीसरे दिन तक के WRF मॉडल स्थान विशिष्ट पूर्वानुमान में क्रमबद्ध बायस को कम करने के लिए एक सांख्यिकीय बायस संशोधन एलगॉरिथ्म भी प्रस्तुत किया गया है। आगामी पूर्वानुमान के बायस को कम करने के लिए प्रयुक्त किया गया सांख्यिकीय बायस संशोधन एलगॉरिथ्म अपक्षय भारित माध्य (DWM) है और यह छोटे नमूनों के लिए उपयुक्त है। बायस संशोधित (BC) WRF के पूर्वानुमान के लिए माध्य त्रुटि (ME) और वर्ग माध्य मूल त्रुटि (RMSE) के परिमाण ग्रीष्मकालीन और शीतऋतु दोनों में प्रत्यक्ष मॉडल आउटपुट (DMO) की अपेक्षा कम है। भारत में और अधिक बेहतर स्थान का चयन करने के लिए विशिष्ट पूर्वानुमान उपलब्ध कराने के लिए प्रचालनात्मक रूप से उपयोग के लिए मौसम पूर्वानुमानकर्ताओं के लिए यह पद्धति आशानुरूप पाई गई है।

ABSTRACT. In this paper we have calculated the Mean Error (ME), Root Mean Square Error (RMSE) and Correlation Coefficient (CC) of the surface maximum and minimum temperature predicted by WRF model for day1, day2 and day3 during winter (December and January) and summer months (April and May) based on two years of data, *i.e.*, 2012 and 2013 by selecting seven stations, *viz.*, Amritsar, New Delhi, Chennai, Guwahati, Kolkata, Mumbai and Nagpur in such a manner that they are well representative of the different temperature homogeneous regions of India. The aim of the paper is to analyze the behaviour of WRF model over different regions of India in terms of surface temperature forecast. In this study, a statistical bias correction algorithm has also been introduced to reduce the systematic bias in the day1 to day3 WRF model location specific forecast of maximum and minimum temperature for 7 selected synoptic stations. 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 magnitude of Mean Error (ME) and Root Mean Squared Error (RMSE) for Bias Corrected (BC) WRF forecast is lower than Direct Model Output (DMO) during both summer and winter seasons. It is concluded from the study that the skill of WRF statistical BC forecast improves over the WRF DMO remarkably. The method is found promising for operational use by weather forecasters to provide more accurate location specific forecast over India.

Key words – Mean error, Root mean square error, Correlation coefficient, Numerical weather prediction, Maximum and minimum temperature and decaying weighted mean.

1. Introduction

Temperature forecasts are important to many sectors of the nation's economy: agriculture, transportation, energy production and healthcare. Forecasts of maximum temperature during the warm season and of minimum temperature during the cool season are used regularly by electric utility companies whose operators must decide when to commit additional generating capacity, or to purchase supplemental power from other utilities, or to

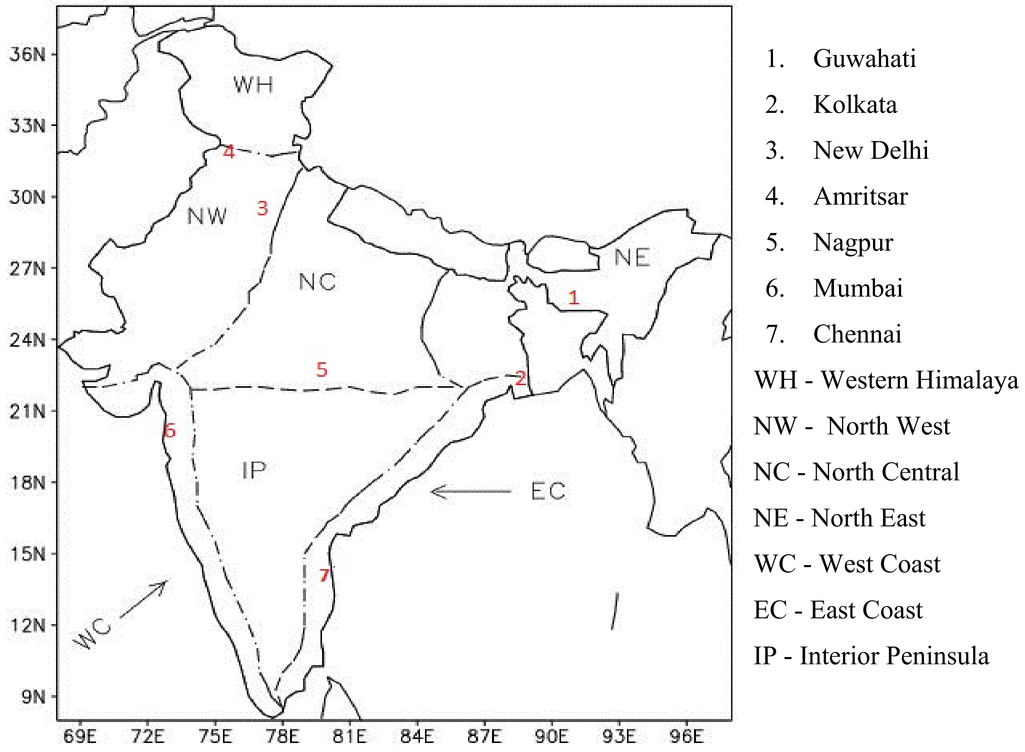


Fig. 1. Location of the selected stations on temperature homogeneous regions map of India

schedule maintenance and repairs. When used in an optimal decision procedure for power generation planning, the deterministic temperature forecasts yield substantial economic gains; the probabilistic forecasts yield even higher gains (Alexandridis and Krzysztofowicz, 1982, 1985). Minimum temperature forecasts can be of value in scheduling aircraft deicing, outdoor painting and artificial snow production (Murphy and Winkler, 1979). Extreme maximum temperatures need to be forecasted because they can be dangerous. Prediction of city specific maximum and minimum temperature has been a challenging task. Even across small distances, there can be significant variations in temperature during the course of a day. Thus, the observation point used to verify the forecast for a given place may or may not fairly represent the temperature there - or may be a good indication in some weather situations but not in others. Meteorological Service Observation sites are commonly at airports, which in general are at least some distance from the city or town they serve. The forecast maximum and minimum temperatures are for the city and suburban parts of each centre. We realize that there are variations across any such (populated) area; nevertheless, the forecast temperature is intended to be representative of it as a whole. The importance of predicted temperature towards planning and ensuring food security for the country is vital.

It is well known that NWP model forecasts contain systematic biases in the forecast of near surface parameters especially maximum and minimum temperature due to imperfect model physics, initial conditions and boundary conditions (Krishnamurti *et al*., 2004; Hart *et al*., 2004; Mass *et al*., 2002). 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 sub-grid 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 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; Chakraborti, 2006; Roy Bhowmik *et al*., 2009, etc.) to develop statistical technique of multiple linear regression analysis for predicting precipitation, maximum and minimum temperature over India using MOS techniques. 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. 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 (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. Another bias correction approach is Kalman filter, which also puts more weight on the recent data. Renata *et al.* (2008) analysed deviations between 2 m - temperature observations and forecasts provided by the European Centre for Medium Range Weather Forecasts (ECMWF) at 12 synoptic stations located in Portugal by applying Kalman Filter. They found that the Kalman Filter reduced the bias of the forecasts at each station to values close to zero.

George and Manolis (2002) proposed a one-dimensional Kalman filter for the correction of maximum and minimum near surface (2 m) temperature forecasts obtained by a Numerical Weather Prediction model. They observed that the corresponding results are rather impressive, since the systematic error of their time series almost disappears.

India Meteorological Department started providing city forecasts in short range time scale (up to 3 days) for major cities of India. In order to provide operational city forecasts, maximum and minimum temperature generated by WRF model at 9 km resolution is considered as the basic input. The Advanced Research WRF (ARW) is run for the forecast up to 3 days with double nested configuration with horizontal resolution of 27 km and 9 km and 38 Eta levels in the vertical using IMD GFS-T574L64 analysis/forecast (Durai and Roy Bhowmik, 2014) as first guess.

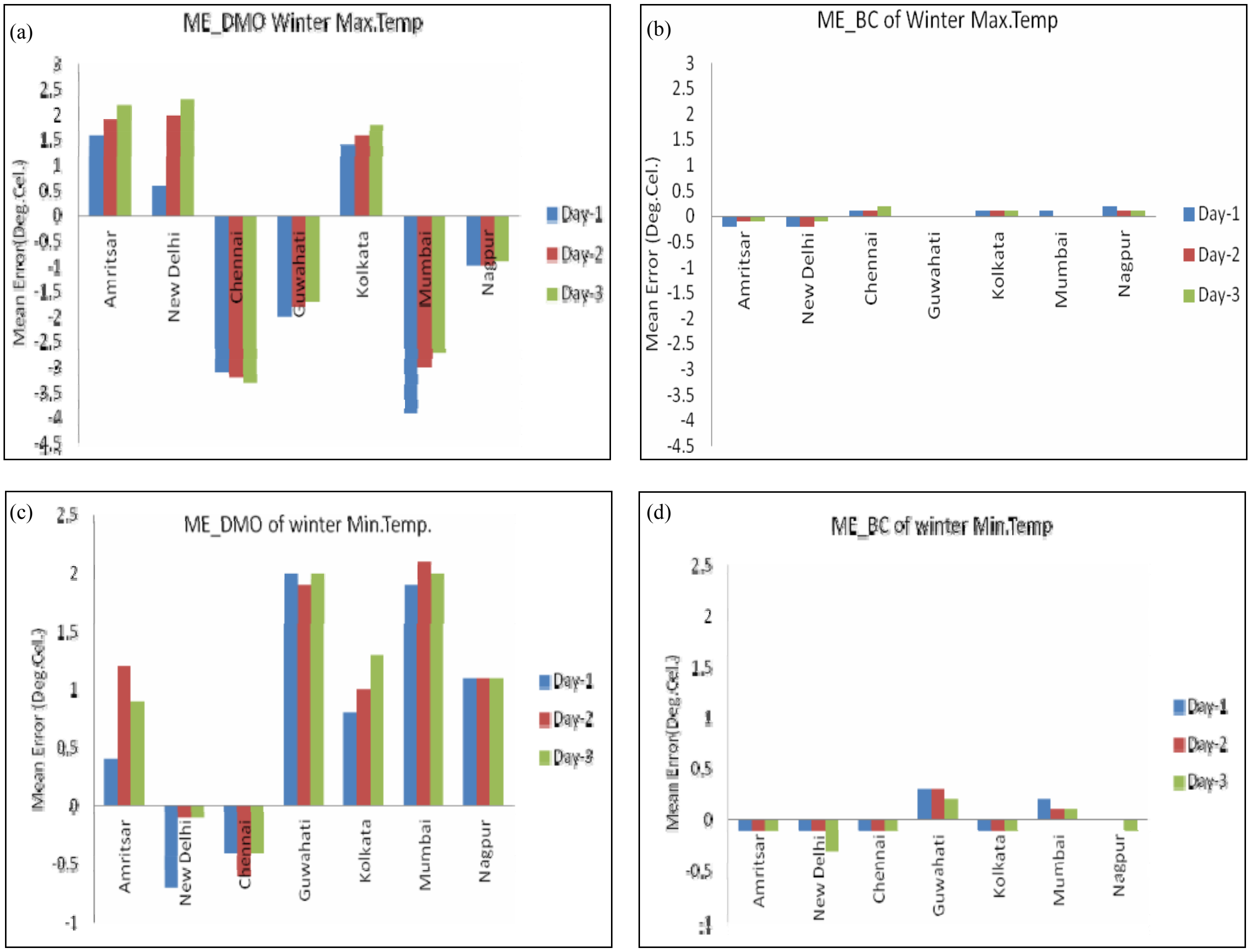
Fig. 2. Weights used in the decaying weighted mean bias correction method for computing daily model bias

In this paper an attempt is made to evaluate the performance statistics of city specific maximum and minimum temperature predicted by WRF model, which is operational at 9 km resolution at India Meteorological Department, New Delhi by selecting seven stations, *viz*., New Delhi and Amritsar , Chennai , Guwahati , Kolkata , Nagpur and Mumbai. Stations are selected in such a manner that they are well representative of the different temperature homogeneous regions of India (Fig. 1) (ftp://www.tropmet.res.in/pub/data/txtn/TEMP-REG.jpg). A statistical bias correction algorithm has also been introduced to reduce the systematic bias in the day1 to day3 WRF model location specific forecast of maximum and minimum temperature for 7 selected synoptic stations.

2. Data and methodology

The three day location specific forecast of maximum and minimum temperatures derived from Direct Model Output (DMO) of WRF model (at 9 km resolution) are collected from NWP Division at HQ of India Meteorological Department for winter (December and January) and Summer (April and May) based on two years of data, *i.e*., 2012 and 2013 and the corresponding observed maximum and minimum temperature data are collected from National Data Centre of India Meteorological Department, Pune.

To evaluate the performance statistics of city specific maximum and minimum temperature predicted by WRF model and to quantify model errors so that we can help operational forecasters understand model biases and select models for use in different conditions we have calculated the Mean Error (ME), Root Mean Square Error (RMSE) and Correlation Coefficient (CC) of the surface maximum and minimum temperature predicted by WRF model for day1, day2 and day3 during winter and Summer. In this study, the statistical algorithm used for minimizing the bias of the next forecast is the decaying weighted mean



Figs. 3(a-d). Mean error during winter for (a) Direct model output maximum temperature, (b) Bias corrected maximum temperature, (c) Direct model output minimum temperature and (d) Bias corrected minimum temperature

bias correction technique, as this is suitable for small samples. The decaying weighted mean 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 less the influence of long-term persistent errors. Here, the bias correction is done for 0000 UTC of WRF model maximum and minimum temperature forecasts (day1 to day3). The purpose of this bias correction is to identify common systematic errors that occur in the WRF DMO forecasts and then correct each forecast to eliminate these biases.

3. Bias correction

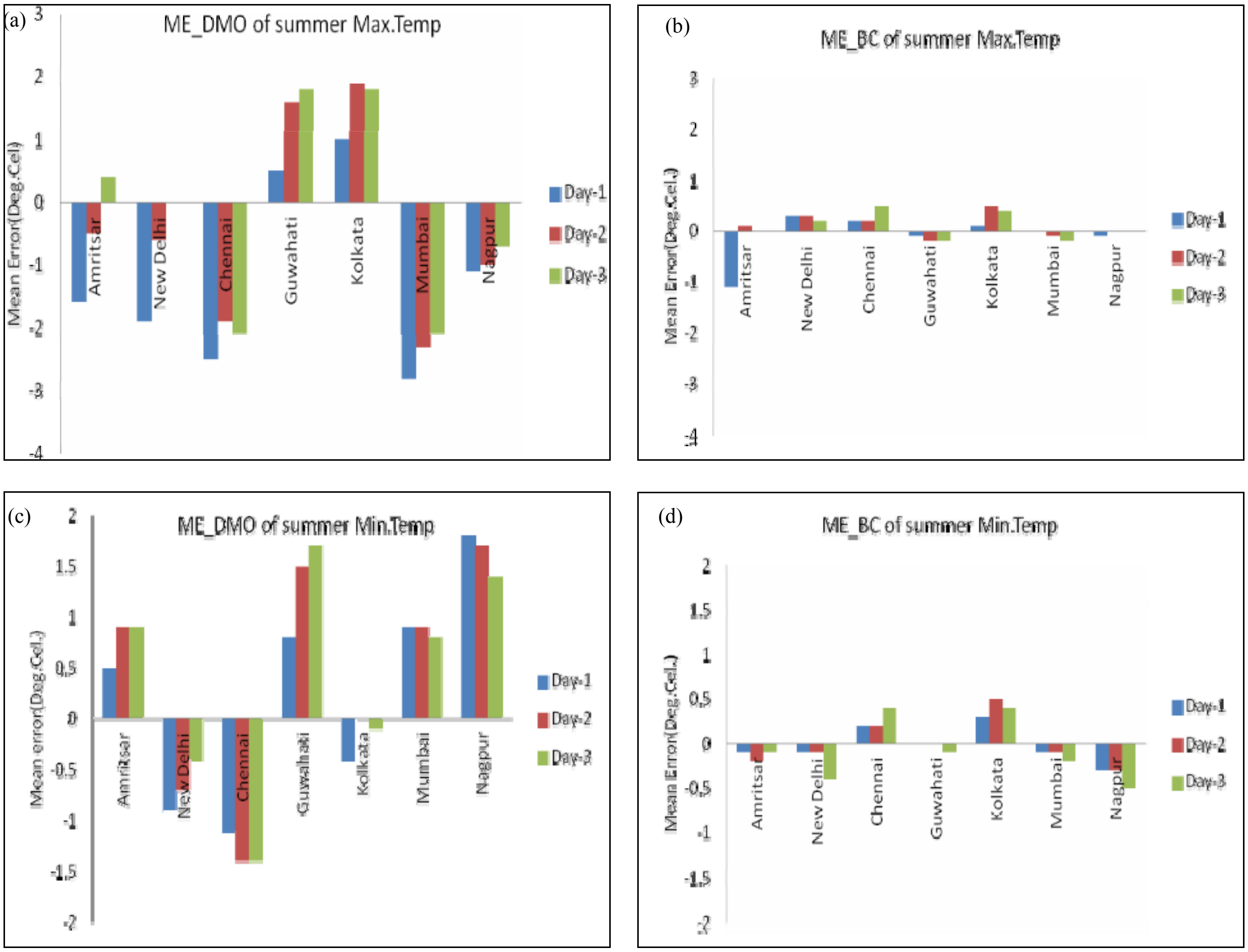
3.1. *Bias estimation*

The bias $b_k(t)$ for each station (k) and each lead-time (a day1 interval up to day3), 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 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. *Decaying weighted mean (DWM)*

This DWM bias correction method compute bias at each station (k) and at each forecast hour (t) from the previous 9 days daily bias $b_k(t)$ starting from the forecast issue day (t = 0) using decreasing weight so that nearest recent data has largest weight. The previous forecast errors are weighted averaged together using decreasing weight (Fig. 2). The 9 days period is chosen to best account for the seasonal change in model errors and the samples are large enough to eliminate noise. Fig. 2 illustrates that the weight curve decreases and reaches an asymptotic value as the number of day increases. The decrease is rapid up to 5th day and after 9th day the curve remains almost horizontal. This is the reason to



Figs. 4(a-d). Mean error during summer for (a) Direct model output maximum temperature, (b) Bias corrected maximum temperature, (c) Direct model output minimum temperature and (d) Bias corrected minimum temperature

consider 9 days period as the best correction period in this study.

The DWM with the weight coefficient is computed as (Durai and Bhardwaj, 2014),

$$wt_k(i) = \frac{w_k(i)}{\sum_{t=0}^{9} w_k(t)}$$

where, $w_k(i) = \frac{1}{(1-i)}$

and

$i = 0, -1, -2, -3, -4, -5, -6, -7, -8, -9.$

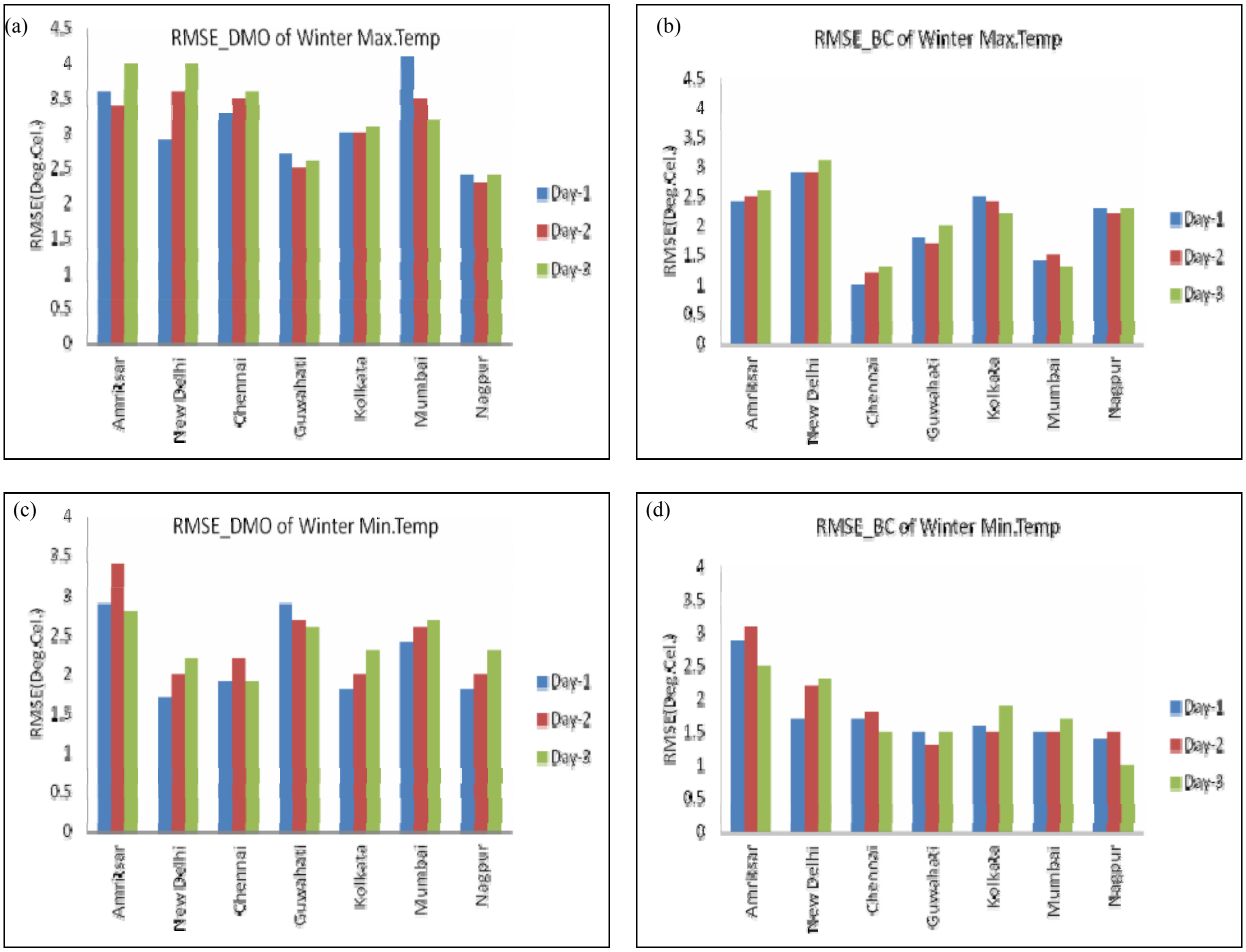
The weight $wt_k(t)$ considered for computing model bias from its past performance starting the forecast issue day (t = 0) and the previous first 9 days are 34.14, 17.07, 11.38, 8.54, 6.82, 5.69, 4.88, 4.28, 3.79, 3.41%. The weight for the forecast issue day (t = 0) is 34.14 %, followed by the previous first day $t = -1$ is 17.07%, but the weight became 3.41% for the last day ($t = -9$). 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.

3.3. *Bias corrected (BC) forecast*

The new bias corrected model forecast $F_k(t)$ has been generated by applying the bias $B_k(t)$ to current



Figs. 5(a-d). Root mean square error during winter for (a) Direct model output maximum temperature, (b) Bias corrected maximum temperature, (c) Direct model output minimum temperature and (d) Bias corrected minimum temperature

direct forecast $f_k(t)$ at each station for all day1 to day3 forecasts

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

for WRF day1 to day3 forecast at each lead time with respect to observation. This new statistical bias correction method discussed in this study use the current and previous 9 days bias to calibrate each forecast individually, at each station.

4. Results and discussion

4.1. Mean *error (ME)*

The verification of continuous variables typically provides statistics on how much the forecast values differ from the observations and, thereafter, computation of relative measures against some reference forecasting systems. The most common continuous local weather parameters to verify are : Maximum and Minimum temperature. The temperature behaves quite smoothly and follows a Gaussian distribution. The Mean Error is given by the formula

$$\mathrm{ME} = (1/N) \Sigma (T_f - T_o)$$

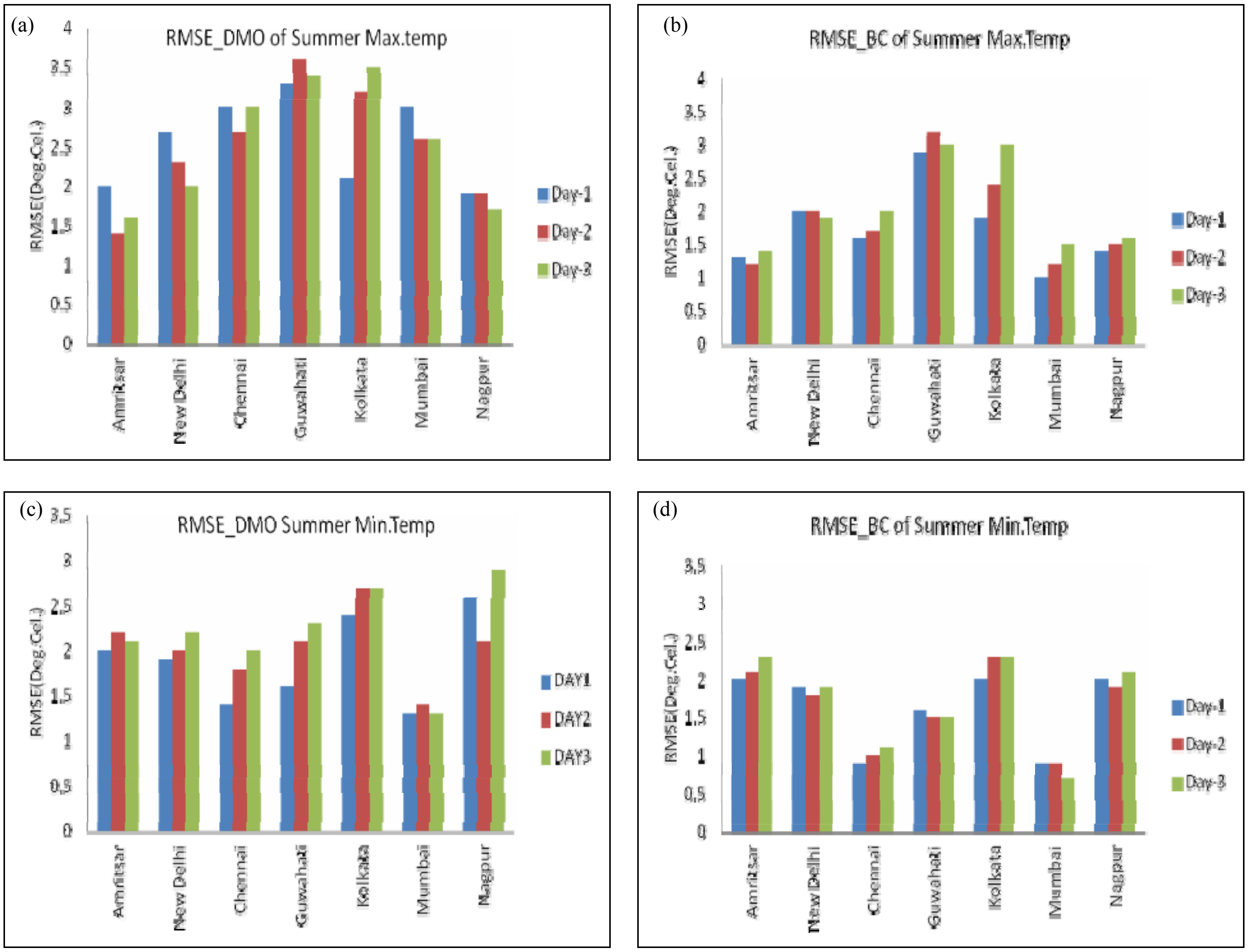
where,

N = forecast/observation pairs

T_f = forecasted temperature

T_o = observed temperature

Positive value of ME means that on an average the forecast predicted warmer temperatures than actually ended up happening and negative value indicates colder temperatures were forecasted than happened on average.



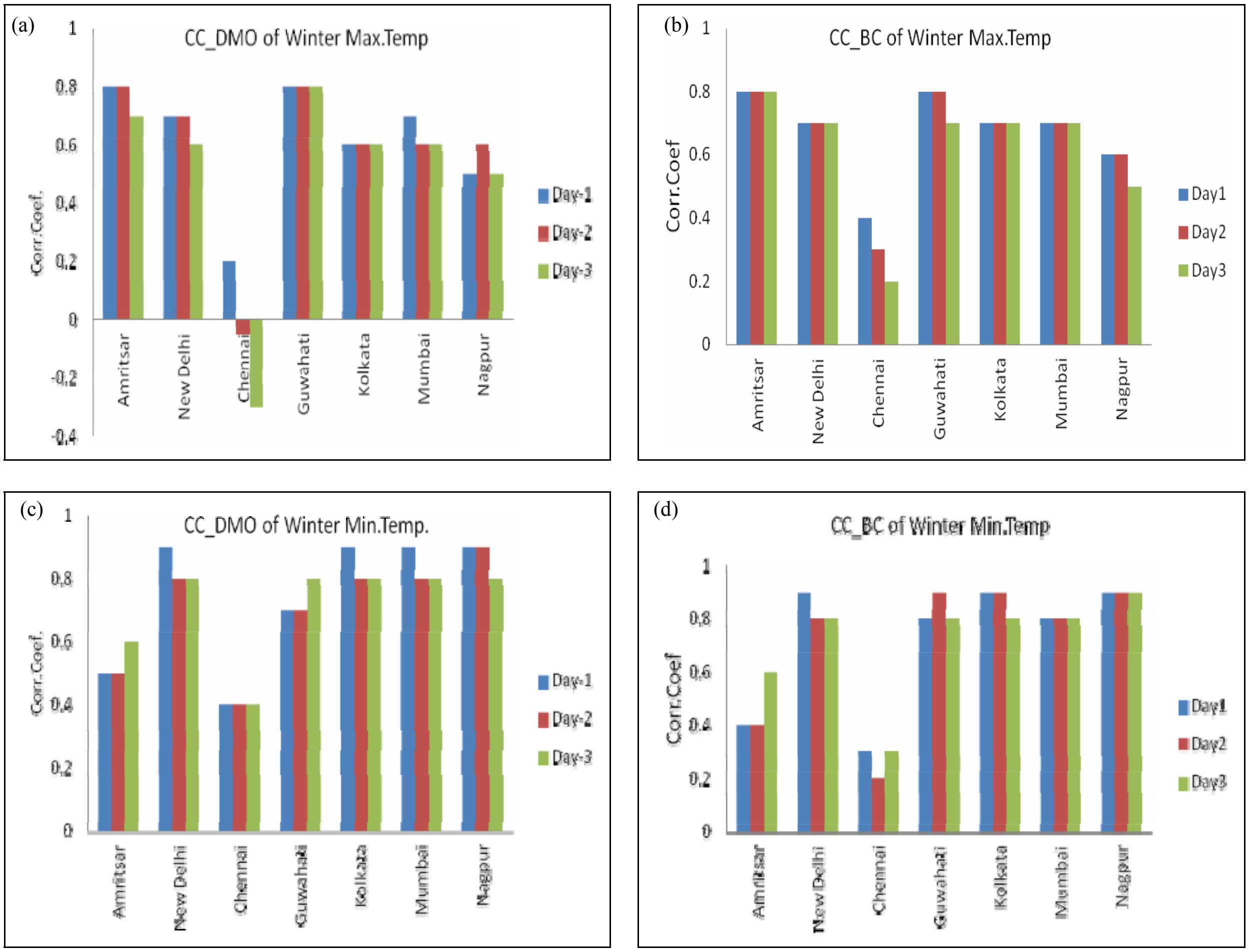
Figs. 6(a-d). Root mean square error during summer for (a) Direct model output maximum temperature, (b) Bias corrected maximum temperature, (c) Direct model output minimum temperature and (d) Bias corrected minimum temperature

The Mean Error of both the maximum and minimum temperature forecasts at each meteorological station for direct model output (ME_DMO) and bias corrected forecast (ME_BC) during winter season is shown in Figs. 3(a-d). From the Fig. 3(a) it is seen that during winter the model over estimated the maximum temperature over Amritsar, New Delhi and Kolkata where as it underestimated the same over Chennai, Guwahati and Nagpur. For the stations Amritsar, New Delhi, Chennai and Kolkata the mean error increases from day1 to day3 whereas over Guwahati and Mumbai the mean error decreases from day1 to day3 though the magnitude of the difference from day1 to day3 is very small. Over Nagpur the mean errors are smaller than the other stations and are almost equal for all the three days forecast.

From Fig. 3(c) it has been observed that during winter season the model under estimated the minimum temperature over New Delhi and Chennai but it over estimated the same for all other stations. The mean errors of minimum temperature over New Delhi and Chennai are smaller than the other stations. Except Kolkata and Nagpur no systematic trend has been observed in terms of magnitude of the error from day1 to day3.

From Figs. 3(b&d) we see that Bias Corrected forecast has very low variation of mean error and also this Bias Corrected Forecast produces Mean Error values very close to zero for most of the stations during winter season for both the maximum and minimum temperatures.

The Mean Error of both the maximum and minimum temperature forecasts at each meteorological station for direct model output and bias corrected forecast during summer season is shown in Figs. 4(a-d). Fig. 4(a) shows that the mean error of direct model output of maximum temperature during summer is positive over Guwahati and Kolkata where as it is negative elsewhere except day3



Figs. 7(a-d). Correlation coefficient during winter for (a) Direct model output maximum temperature, (b) Bias corrected maximum temperature, (c) Direct model output minimum temperature and (d) Bias corrected minimum temperature

over Amritsar where it is positive but the magnitude is very less. Over Guwahati the magnitude of mean error increases from day1 to day3 and decreases over Mumbai and Nagpur but no systematic changes in magnitude of mean errors have been observed from day1 to day3 over the remaining stations.

Similarly from Fig. 4(c) we can see that during summer season the model under estimated the minimum temperature over New Delhi and Chennai and over estimated over Amritsar, Guwahati, Mumbai and Nagpur. Over Kolkata the mean errors are either zero or negligible from day1 to day3. From the figure it has also been observed that the mean error of minimum temperature increases from day1 to day3 over Amritsar, Chennai and Guwahati where as it decreases over New Delhi, Mumbai and Nagpur.

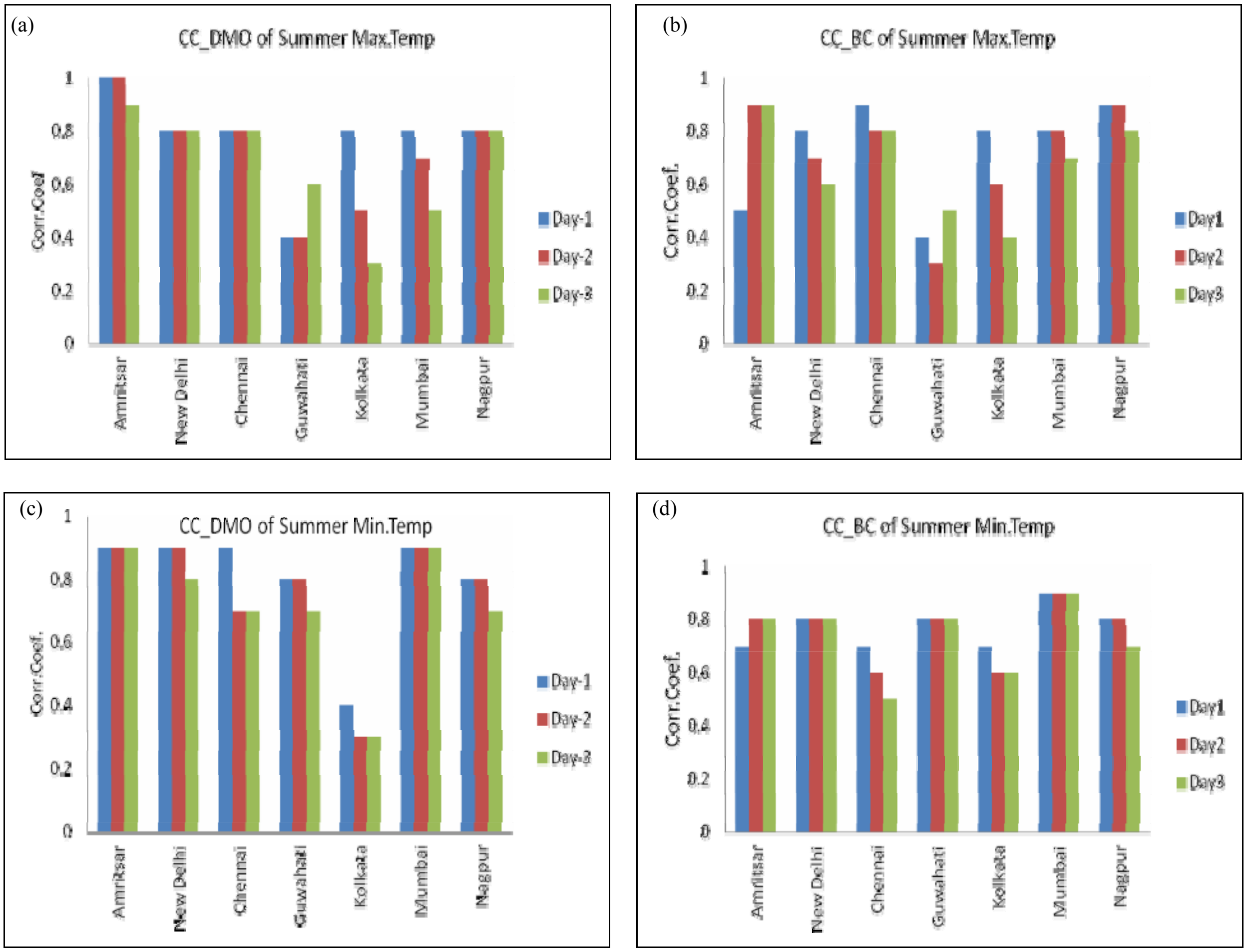
Figs. 4(b&d) show that the mean error reduces significantly after bias correction and the values are very close to zero for most of the stations during summer season for both the maximum and minimum temperatures except day1 forecast of minimum temperature over Amritsar where bias correction method did not show any improvement.

4.2. *Root mean square error (RMSE)*

The Root Mean Square Error (RMSE) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment. The RMSE of a model prediction with respect to the estimated variable T_{model} is defined as the square root of the mean squared error:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(T_{f,i} - T_{o,i}\right)^2}{n}}$$

where, T_f is modeled values and T_o is observed values *t* time/place *i*.



Figs. 8(a-d). Correlation coefficient during summer for (a) Direct model output maximum temperature, (b) Bias corrected maximum temperature, (c) Direct model output minimum temperature and (d) Bias corrected minimum temperature

The Root Mean Square Error of both the maximum and minimum temperature forecasts at each meteorological station for direct model output (RMSE_DMO) and bias corrected forecast (RMSE_BC) during winter and summer season are shown in Figs. 5 (a-d) and Figs. 6(a-d) respectively.

From the Figs. 5(a&b) it is seen that over Amritsar during winter RMSE value for maximum temperature is found to be highest for day3 forecast but for minimum temperature the RMSE value is highest for day2 forecast. During summer months the highest value of RMSE for maximum temperature is for day1 forecast whereas for minimum temperature it is highest for day2 forecast.

Over New Delhi lowest RMSE values of both the maximum and minimum temperature are found in day1 forecast except for maximum temperature during summer where it is lowest in day3 forecast.

Over Chennai during winter the values of RMSEs increases from day1 to day3 for maximum temperature forecast, for minimum temperature forecast RMSE values for day1 and day3 forecasts are equal and is slightly higher than the day2 forecast. During summer maximum temperature forecast the RMSE values for day1 and day3 forecasts are equal and slightly lower than the day2 forecast where as for minimum temperature forecast during summer the RMSE values increases from day1 to day3.

Over Guwahati during winter the RMSE for maximum temperature are almost equal for day1 to day 3 forecasts and RMSE values for winter minimum temperature decreases from day1 to day3. During summer the highest value RMSE is found for day2 forecast for maximum temperature whereas for minimum temperature forecast during summer the RMSE values increases from day1 to day3.

Over Kolkata during the winter as well as summer both maximum and minimum temperature forecasts the RMSE values increases from day1 to day3 except for maximum temperature during winter where the RMSE values for day1 and day2 forecasts are equal and are slightly lower than day3 forecast.

Over Mumbai during winter the RMSE values of maximum temperature decreases from day1 to day3 forecast whereas reverse can be seen for minimum temperature, *i.e.*, increase in RMSE values from day1 to day3. During summer the RMSE values for maximum temperature forecast for day1 and day2 are equal and are slightly higher than that of day2 forecast whereas for minimum temperature the RMSE values for day1 and day3 are equal and are slightly lower than that of day2 forecast.

Over Nagpur during winter the RMSE values for day1 and day3 are equal and are slightly higher than that of day2 forecast whereas for minimum temperature forecast the RMSE values increases from day1 to day3. For maximum temperature forecast during summer the RMSE values for day1 and day2 are equal and are slightly higher than that of day3 forecast whereas for minimum temperature the RMSE value for day3 forecast is highest and that of day2 forecast is lowest.

From Figs. 5(b&d) it is seen that the Bias Corrected RMSE value for both the maximum and minimum temperature is less than DMO RMSE in most of the stations during winter as well as summer season.

4.3. Correlation *coefficient (CC)*

The correlation coefficient measures the degree of linear association between forecasts and observations. As the strength of the relationship between the predicted values and actual values increases, the value of the correlation coefficient increases toward 1.0. A perfect fit gives a coefficient of 1.0. The Correlation Coefficient (r) is given by

$$r = \frac{\sum (T_f - \overline{T}_f)(T_o - \overline{T_o})}{\sqrt{\sum (T_f - \overline{T_f})^2} \sqrt{\sum (T_o - \overline{T_o})^2}}$$

The correlation coefficients of both the maximum and minimum temperature forecasts at each meteorological station for direct model output (RMSE_DMO) and bias corrected forecast (RMSE_BC) during winter season are shown in Figs. 7(a-d). During winter season good correlation exist between model forecast of both the maximum and minimum temperatures and observations for all the selected stations except Chennai where correlation between observed and model forecast are very poor which can be seen in the Figs. 7(a&c) .

The correlation coefficients of both the maximum and minimum temperature forecasts at each meteorological station for direct model output (RMSE_DMO) and bias corrected forecast (RMSE_BC) during summer season are shown in Figs. 8(a-d). During summer season perfect correlation exists between forecasted maximum temperature and observation over Amritsar followed by very high correlation between observation and model forecast of maximum temperatures for all the three days over New Delhi, Chennai and Nagpur and for day1 forecast for Kolkata and Mumbai followed by day3 forecast over Guwahati and day2 forecast over Kolkata. Poor correlation exists between observation and model forecast of maximum temperatures for day1 and day2 over Guwahati and day3 over Kolkata. Minimum temperature forecasts during summer season are highly correlated with the observations for all the three days except over Kolkata where observations and model forecasts of minimum temperatures are poorly correlated for all the three days.

From the figures it has been observed that the bias corrected forecast does not show any significant improvement over direct model forecast in terms of correlation coefficient

5. Conclusions

(*i*) Over Amritsar the model generally over estimated the maximum and minimum temperature during winter and summer season except maximum temperature during summer where the model underestimated in day1 and day2 forecast.

During winter season the RMSE values for both the maximum and minimum temperature are generally found to be higher than that of summer season. The observed and model forecast values of maximum and minimum temperatures are found to be highly correlated except for minimum temperature during winter season where the values of correlation coefficients are found to be relatively low.

(*ii*) Over New Delhi the model generally underestimated the maximum and minimum temperature during both the seasons except during winter where the model overestimated maximum temperature.

The RMSE values for both the maximum and minimum temperature forecasts are generally less than 3°C for all the three days and for both the seasons except day1 and day2 forecasts where it is more than 3°C. The observed and forecast values of maximum and minimum temperature are highly correlated for all the three days and for both the seasons.

(*iii*) Over Chennai the model underestimated the maximum and minimum temperature during both the seasons and for all three days.

The RMSE for maximum temperature are generally higher than that of minimum temperature.

Good correlation exists between the observed and model forecast values of maximum temperature during summer but during winter poor correlation exist between model forecast and observed values and even negative correlation have been observed for day1 and day2 forecast of winter maximum temperature.

(*iv*) Over Guwahati the WRF model overestimated maximum and minimum temperature during winter and pre monsoon season except maximum temperature during winter season where the model under estimated maximum temperature for all the three days forecast.

The RMSE values for both the maximum and minimum temperature forecasts are generally less than 3 °C for all the three days and for both the seasons except summer maximum temperature where it is more than 3 °C. The observed and forecast values of maximum and minimum temperature are highly correlated for all the three days and for both the seasons.

The observed and model forecast values of both the maximum and minimum temperature are found to be highly correlated except day1 and day2 forecast during summer where they are found to be poorly correlated.

(*v*) Over Kolkata the model generally over estimated the maximum and minimum temperature except summer minimum temperature where the model underestimated the minimum temperature but with small values of mean error.

The RMSE for maximum and minimum temperature generally increases from day1 to day3 forecast for both the season.

During winter the correlation coefficient values between model forecasted and observed temperatures are generally more than that of summer season.

(*vi*) Over Mumbai the model generally underestimated the maximum temperature and overestimated the minimum temperature during both the season for all the three days forecasts.

The RMSE values for maximum temperature during winter season are generally higher than that of other RMSE values.

The observed and model forecast values of maximum and minimum temperature are found to be highly correlated except day3 forecast of summer maximum temperature.

(*vii*) Over Nagpur the model generally over estimated the minimum temperature and underestimated the maximum temperature during both the season.

Highest RMSE values have been observed in day1 and day3 forecast of summer minimum temperature.

The observed and model forecast values of temperature are generally found to be highly correlated during both the seasons.

(*viii*) The error analysis of both the maximum and minimum temperature confirms that the bias correction method used in this study is very efficient in removing WRF DMO systematic bias for all the 7 meteorological ground stations selected in this study. The BC forecast for maximum and minimum temperatures have smaller ME and RMSE values over all the stations in Indian regions for all day1 to day3 than those produced by the DMO but no systematic improvement in bias corrected forecast has been observed in correlation coefficient

Due to growing urbanization, user specific quantitative forecast of maximum and minimum temperature in short range (three days) time scale has become an essential component of Public Weather Services for day to day activities of city dwellers. These forecasts are important to many sectors of the nation’s economy such as, transportation, tourism, power generation and distribution, healthcare etc. The information on the bias structure of location specific direct model outputs are useful inputs to a forecaster for further improvement of city forecasts by adopting a suitable value addition procedure. The bias correction method demonstrated in this paper is found promising for operational application and the bias corrected forecasts are expected to yield substantial economic gain, particularly when used in an optimal decision procedure for power generation planning. In this paper seven cities of India are considered, which represent different temperature homogeneous region of the country. Recently India Meteorological Department has started to provide quantitative city forecast for 117 cities in the country. So there is a further scope to extend the work with increased observational network and longer data period. This would be one of our future priorities of research work.

Acknowledgement

Authors are grateful to the Director General of Meteorology, India Meteorological Department for his kind support and encouragement to carry out this work. Authors like to thank the learned reviewers for his/her valuable suggestions and comments to improve the quality of the paper. Authors are also thankful to their colleagues in NWP Division of India Meteorological Department for useful discussion and other support to complete this paper.

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