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Bias correction of maximum temperature forecasts over India during March–May 2017

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In recent times, instances of intense heat waves have increased over the Indian subcontinent. This increase in temperature has an adverse effect on human health and the economy. Over India, such high temperatures are usually seen during the months of March–May (summer). For weather forecasters, it is a challenging job to accurately predict the timing and intensity of this anomalous high temperature. The difficulty in the accurate prediction of weather is increased because of the presence of systematic biases in the models. These biases are present because of improper parameterizations or model physics. For increasing the reliability or accuracy of a forecast it is essential to remove these biases by using a process called post-processing. In this study the biases in the surface temperature maximum are corrected using two methods, namely, the moving average and the decaying average. One of the main advantages of both the methods is that they do not require a large amount of past data for calibration and they take into account the most recent behaviour of the forecasting system. Verification, for maximum surface temperature during March–May 2017, was carried out in order to decide upon the method giving the best temperature forecast. It was found that both the bias correction methods lead to a decrease in the mean error in maximum surface temperature ($T_{\max}$). However, the decaying average method showed a higher decrease in the mean error. Scores obtained from a contingency table like POD, FAR and PSS, showed that for $T_{\max}$, the decaying average method outperforms the forecasts, i.e., raw and moving average in terms of having high POD and PSS and a low FAR.

Keywords. Surface temperature; bias correction; decaying average; POD; FAR; PSS.

1. Introduction

Tropical weather is difficult to forecast. In the mid-latitudes, weather is dominated by synoptic systems moving in the westerlies and the baroclinic instability results from air masses with contrasting temperature and density. However, in the tropics, there is a relatively homogeneous air mass and fairly uniform distribution of surface temperature and pressure. Therefore, local and mesoscale effects are more dominant than synoptic influences. For example, surface temperature and pressure can change quickly with convective processes. This makes the prediction of weather in the tropical regions, like India, relatively challenging. It is the day to day changes of weather elements such as rainfall, surface temperature, wind speed and humidity which are important and need to be monitored on a continuous basis. An accurate forecast of these elements has become a necessity in order to avoid losses due to natural catastrophies like extreme precipitation, resulting floods,

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excessive increase in temperature, resulting heat waves. Extreme weather conditions, more particularly, higher daily peak temperatures and longer, more intense heat waves are becoming increasingly frequent globally due to climate change. India too, is experiencing the effect of climate change in terms of increased instances of heat waves which are intensifying with each passing year. These anomalous high temperatures may have devastating impacts especially on human health, can cause casualties, wild fires, destruction of crops and adversely affect the economy.

A heat wave is defined as a period of abnormally high temperatures, more than the normal maximum temperature that occurs during the summer season over north-western parts of India. Heat waves typically occur between March–April–May (hereafter MAM) over the Indian land mass. However, in rare cases, they can extend over to June and July. The criteria for a heat wave as given by the India Meteorological Department (IMD) are:

- The maximum surface temperature (hereafter $T_{\max}$) should be at least 40°C for plains and 30°C for hilly regions.
- If $T_{\max}$ is more than 40°C, then heat wave occurs if the departure from normal is 4.5°C to 6.4°C and a severe heat wave occurs when the departure 6.4°C or more.
- When actual $T_{\max}$ remains 45°C (47°C) or more, irrespective of normal $T_{\max}$, heat waves (severe heat waves) occur.

Over the Indian subcontinent, instances of heat waves have increased in the past few decades. During MAM, some parts of the Indian land mass experience very high temperatures (Shah *et al.* 2016). In 2016, the average surface temperature over India was +1.36°C than normal. There were approximately 2000 deaths due to heat waves in 2015 and more than 1000 in 2016. There were several heat wave cases reported during MAM of 2017. On 15th May 2017, temperatures in the plains of northwest, west and central India were about 4–6°C above normal (figure 1). Mostly, during the summer months over the Indian plains, maximum 2 m temperature forecasts show a warm bias. On the other hand, over the mountains, there is a cold bias observed in the temperature forecasts. This warm and cold bias over the plains and mountains of India is also clearly seen from figure 2, which shows the mean error in $T_{\max}$ between the Day-1, 3, 5 and 7 forecasts and observations for MAM 2017. This figure shows that parts of eastern, western and peninsular India have a warm bias, whereas, northern parts of India shows a cold bias during MAM 2017. Removal of these biases is essential for a timely and accurate prediction of these high temperatures.

With increase in the computational capabilities and the usage of numerical weather prediction (NWP), it has now become possible to obtain fairly reliable forecasts for $T_{\max}$ over tropical regions. In India, India Meteorological Department (hereafter IMD) provides surface temperature forecasts up to 10 days at 12 km using the Global Forecast System (GFS; T1534) adopted from NCEP. At the National Centre for Medium Range Weather Forecasting (hereafter NCMRWF) the Unified Model (hereafter NCUM; N768L70) is used for the prediction of surface temperature up to 10 days at 17 km resolution. More details about NCUM are presented in section 2. Although the deterministic NWP models have become very refined and have state-of-the-art techniques for parameterizations along with a high resolution for predicting small scale processes like convection, they are still affected by the systematic biases. For preparing a more reliable forecast using the NWP models these biases need to be removed by using post-processing techniques. There are many statistical methods and studies available for correcting the systematic biases in NWP model forecasts (Yusuf and Stensrud 2006; Cheng and Steenburgh 2007; Hacker and Rife 2007; Gel 2007; Piani *et al.* 2010; Amengual *et al.* 2012; Wetterhall *et al.* 2012; Gutjahr and Heinemann 2013; Hempel *et al.* 2013; White and Toumi 2013; Maraun 2013).

In the current study, an attempt has been made to correct the bias in the forecast of the 2 m temperature ($T_{\max}$) over Indian region for MAM 2017. Bias correction is done by the following study performed by Cui *et al.* (2012) and they have corrected the bias in different variables using two different methods: (a) moving average bias estimation and correction, and (b) decaying average method. More details about the method of bias correction are given in section 2. Further, the raw and bias corrected forecasts are compared by using some standard verification scores like probability of detection (POD), false alarm rate (FAR) and Hanssen and Kuipers score or Peirce's skill score (PSS).

This manuscript is divided into following sections: in section 1 introduction, section 2 deals with the detailed description of the observed data and the forecasts along with the modelling system used in the current analysis and also gives details about the bias correction and verification methodology followed.

Section 3 deals with the results and discussions and finally section 4 lists out some salient conclusions based on the current study.

2. Observation, model description, and verification methodology

2.1 *Observed maximum temperature*

For correcting the biases in the forecast issued by an NWP model, a reliable set of analysis/observations are required. For surface temperature, IMD has recently developed a high resolution daily gridded dataset with 0.5° resolution. Data processing procedure adopted by IMD in preparing this dataset is available in many research papers (Srivastava *et al.* 2009). The final compiled, digitized, quality controlled and archived dataset is obtained from the National Data Centre (NDC). In this study, we have used IMD's real-time daily gridded (Rajeevan *et al.* 2005; Srivastava *et al.* 2009) $T_{\max}$ data to correct the bias in the deterministic 2 m maximum temperature forecasts from NCUM for a period of MAM 2017 over the Indian land area.

2.2 *NCMRWF Unified Model (NCUM) and T_{max} forecasts*

The Unified Model (Rajagopal *et al.* 2012; John *et al.* 2016; Rakhi *et al.* 2016), operational at NCMRWF (NCUM) consists of an observation processing system (OPS 30.1), four-dimensional variational data assimilation (VAR 30.1) and Unified Model (UM 10.5). This analysis system makes use of various conventional and satellite observations. The analysis produced by this data assimilation system is being used as initial condition for the daily operational high resolution (N768L70) global NCUM 10-day forecast since January 2016. The horizontal resolution of NCUM system is 17 km and has 70 vertical levels extending from surface up to 80 km height. The NCUM model forecast temperature ($T_{\max}$) data have been interpolated to the 0.5°×0.5° resolution using bilinear interpolation method to match the resolution and grids of the observed data.

2.3 *Bias correction of NCUM T_{max} forecasts*

In spite of many significant improvements in NWP models including major improvements in the model physics and resolution, these models still suffer from systematic biases. There are several methods available to remove these systematic errors from a model, for example, by applying statistical post-processing algorithms. In the current paper, we have made an attempt to correct the bias in $T_{\max}$ forecasts obtained from NCUM for MAM 2017 by applying two different techniques described below:

1) *Moving average bias correction*: In this method, the bias (*f-o*) is estimated as weighted average of the biases (*f-o*) in each of the previous 3 days. This bias is computed for each lead time and on each day based on forecasts from previous three days.

$$\mathrm{Bias}(t) = 0.5 \times \mathrm{b}_1 + 0.3 \times \mathrm{b}_2 + 0.2 \times \mathrm{b}_3 \qquad (1)$$

where b_1 b_2 *and* b_3 are the biases in recent 3-day forecasts respectively.

The bias correction is then done by subtracting the estimated bias from today's forecast $T_{\max}$.

$$F_{bc}(t) = F(t) - \mathrm{Bias}(t) \qquad (2)$$

where $F_{bc}(t)$ represents the bias corrected forecast and $F(t)$ is NCUM raw forecasts and *Bias(t)* is the bias calculated in equation (1).

2) *Decaying average bias correction*: This statistical post-processing method applies an adaptive [Kalman filter type (KF)] algorithm to accumulate the decaying averaging bias (Kalman 1960; Cui *et al.* 2012; Glahn 2012).

At a particular time '*t*', the bias is updated by using the bias calculated at a previous time '*t* −1' by using a weight called the 'decaying average' (Cui *et al.* 2012), i.e.,

$$\mathrm{Bias}(t) = (1 - w) \times b(t - 1) + wB \qquad (3)$$

where w is the weight, b$(t-1)$ is day 1 bias ($[F_1 - O_1]$) and $B = \frac{1}{N}\sum_1^{30}(F_i - O_i)$ mean bias for last month.

This method allows the incorporation of the most recent behaviour of the system into the estimation of the bias. Sensitivity experiments have been performed with different values of the decaying weight (0.02, 0.05, 0.1, 0.2 and 0.3) and an optimal value of 30% has been adopted for the current study. After the bias estimation has been done for the current time the bias correction of the output is performed as per equation (2).

In this study, we have considered the moving average bias correction technique as a sort of a benchmark and the improvement of the decaying average method will be decided by comparing the different scores obtained during verification of the bias corrected forecasts from both the methods. The verification methods that are used in this study are described in the next section.

2.4 *Verification methodology*

There are several scores available for the categorical verification of forecasts which are based on the formation of a contingency table. However, in the current study, we have used the POD, FAR, and PSS. A brief description of these scores is presented here:

The probability of detection (POD) or hit rate (H): The POD tries to answer the question, "What fractions of the observed 'yes' events were correctly forecast?" It is very much sensitive to hits but ignores false alarms. It is also very sensitive to the climatological frequency of the event. It is good for rare events and can be artificially improved by issuing more 'yes' forecasts to increase the number of hits. Its value varies from 0 to 1 and for perfectly forecasted events POD=1 and it is computed by equation (4).

$$\mathrm{POD} = \frac{\mathrm{Hits}}{\mathrm{Hits} + \mathrm{Misses}}. \tag{4}$$

False alarm rate (FAR): FAR answers the question, "What fraction of the predicted 'yes' events actually did not occur"? FAR is sensitive to false alarms, but ignores misses and is very sensitive to the climatological frequency of the event. FAR should be used in conjunction with the POD and it is computed by equation (5).

$$\mathrm{FAR} = \frac{\text{False Alarms}}{\text{Hits} + \text{False Alarms}}. \tag{5}$$

Peirce's skill score (PSS): The PSS answers the question: "How well did the forecast separate the 'yes' events from the 'no' events"? Also known as true skill statistic or Hanssen and Kuipers discriminant (HK) and computed by equation (6).

$$HK = \left[\frac{\text{hits}}{\text{hits } + \text{misses}}\right] - \left[\frac{\text{false alarms}}{\text{false alarms } + \text{correct negatives}}\right] \tag{6}$$

The score ranges from –1 to 1, 0 indicates no skill and the perfect score is 1. PSS uses all elements in contingency table and does not depend on climatological event frequency. However, this score can also be interpreted as (accuracy for events) + (accuracy for non-events) − 1. For rare events, HK is unduly weighted towards the first term (same as POD), so this score may be more useful for more frequent events.

3. Results and discussions

Bias correction method followed in this study is similar to the method described in Cui *et al*. (2012). For $T_{\max}$ forecasts from NCUM, the bias estimation and correction is started from December 2016 onwards using both the moving and decaying average bias correction methods. In the decaying average method, for a cold start, the mean bias for the previous t-82 was considered. Finally, the verification was carried out for $T_{\max}$ for MAM 2017 against the observed temperature for this duration. The results of this verification using POD, FAR and PSS are presented below:

3.1 *T_{max} verification*

Figure 3(a and b) shows the mean error between the Day-1, 3, 5 and 7 bias corrected forecasts and observed $T_{\max}$ over India during MAM 2017 using the moving and decaying average methods respectively. Both the figures show a considerable reduction in the mean error when compared with the mean error seen with respect to the raw NCUM forecasts (figure 1a). On comparing figure 2(a) and (b), it is seen that figure 2(b) which corresponds to the decaying average bias correction method shows lower error. In the Day-1 forecast the moving average method shows higher bias over the northern parts of India (Jammu and Kashmir), this bias is almost negligible in the case of decaying average method. In the Day-3 forecasts, the moving average method shows high bias over entire northern India including parts of central India. However, this bias is considerably smaller in the case of decaying average. Similarly, in the Day-5 and 7 forecasts also decaying average method leads to a higher correction in the bias as compared to the moving average method.

3.2 *Categorical verification of T_{max}*

The events considered for constructing a contingency table for performing a categorical verification are: $T_{\max}$ lying within the following ranges: 30–32, 32–34, 34–36, 36–38, 38–40 and 40–42°C. Figure 4 shows the POD for $T_{\max}$ lying within these temperature ranges for Day-1, 3, 5 and 7 forecasts. From all the figures, it is seen that the

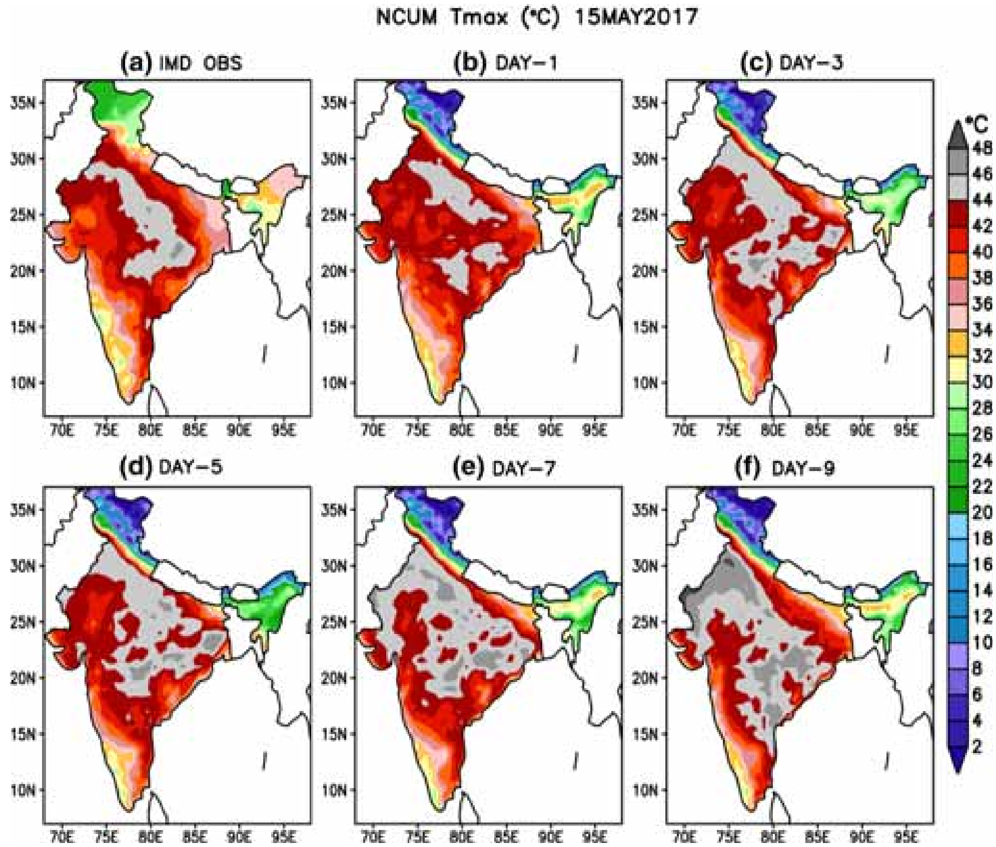

Figure 1. Observed and Day-1, 3, 5, 7 and 9 NCUM forecast for $T_{\max}$ valid for 15th May 2017 (heat wave case).

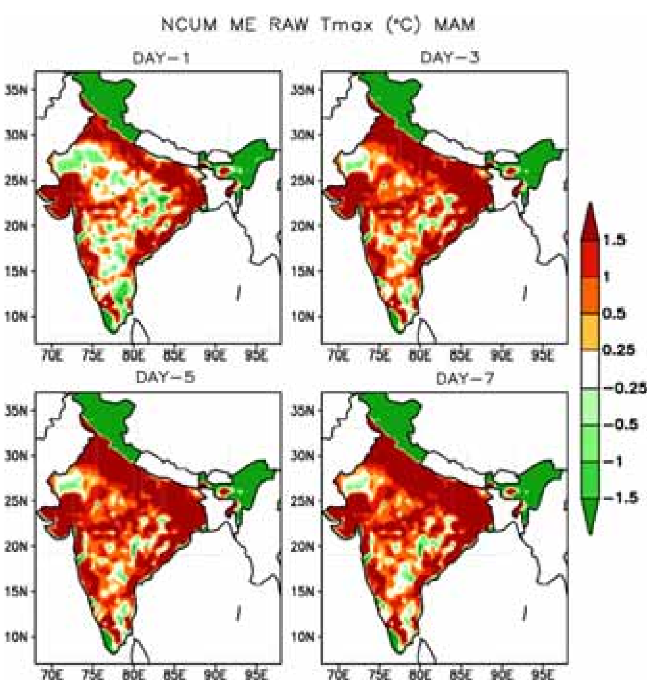

Figure 2. Mean error in the NCUM $T_{\max}$ direct model output forecasts for lead times 1, 3, 5 and 7 days.

bias correction shows a higher POD for all the ranges and all lead times as compared to the raw forecasts. However, for temperature within 40–42°C, the raw forecasts are seen to have a higher POD. An intercomparison of the two bias correction methods shows that the decaying average performs better than the moving average method in terms of having a higher POD for all ranges and lead times.

Figure 5 shows the FAR for $T_{\max}$ lying within the above-mentioned ranges and Day-1, 3, 5 and 7 forecasts. In the Day-1 and 3 forecasts, it is seen that both the bias correction methods show lower FAR for all ranges. The decaying average is seen to have a lower FAR as compared to moving average for all temperature ranges. For the Day-5 and 7 forecasts, it is seen that FAR for raw forecasts is comparable with the bias corrected forecasts from both the methods especially for lower temperature ranges (30–34°C). However, for temperatures exceeding 34°C, it is seen that decaying average method shows a lower FAR than both the raw and moving average method.

In the PSS (figure 6) shows $T_{\max}$ within the above ranges and Day-1, 3, 5 and 7 forecasts from NCUM and the two bias correction methods. The PSS from both the bias correction methods is seen to be higher as compared to the raw forecasts in all the days' forecasts. Decaying average as in the previous cases is seen to be better than the moving

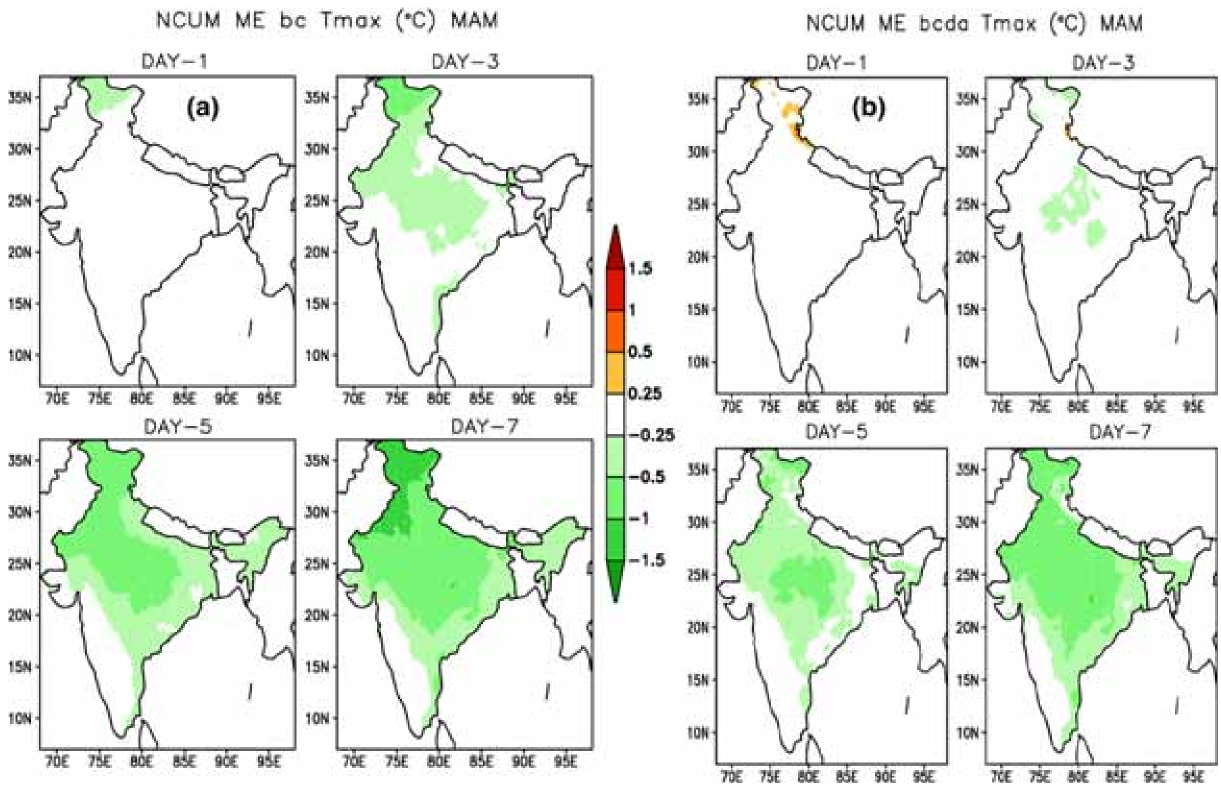

Figure 3. Mean error in the NCUM $T_{\max}$ forecasts during MAM using the **(a)** moving average bias correction method, **(b)** using the decaying average bias correction method.

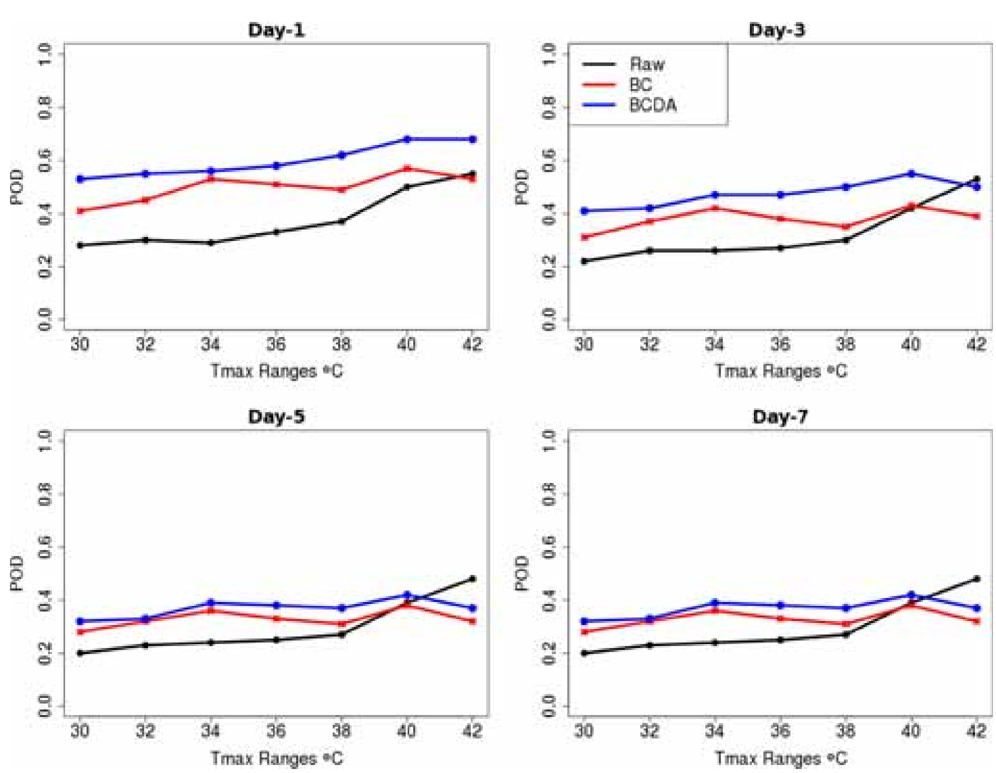

Figure 4. POD for verification of $T_{\max}$ from raw NCUM, moving and decaying average bias correction methods for Day-1, 3,5 and 7 forecasts for $T_{\max}$ within 30–32, 32–34, 34–36, 36–38, 38–40 and 40–42°C.

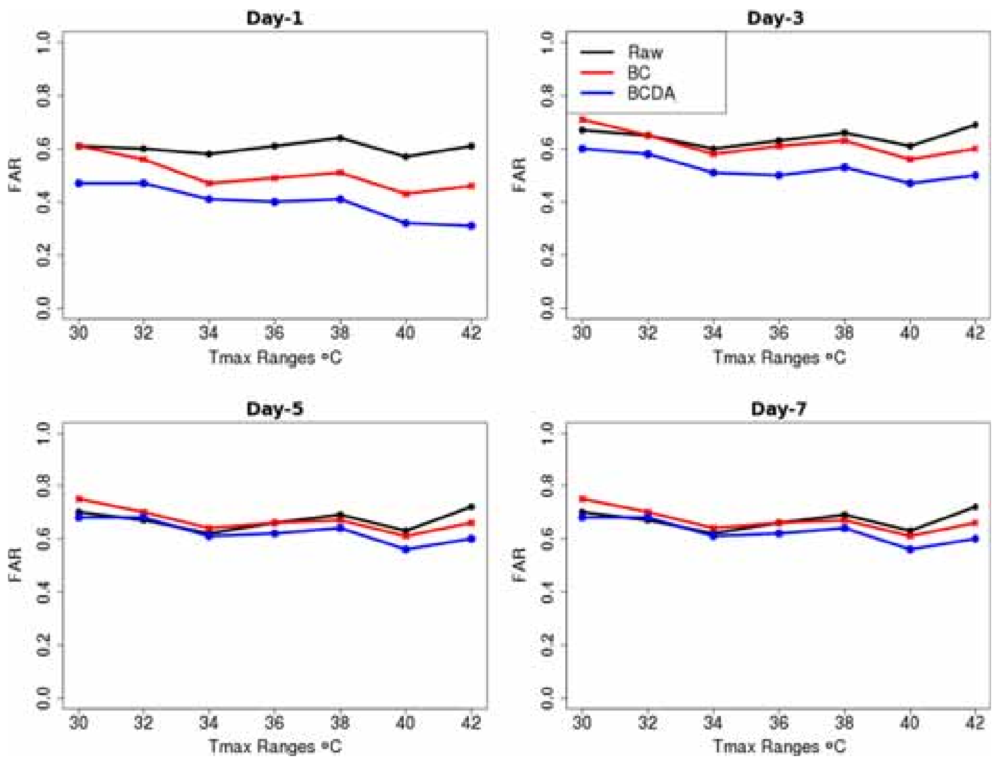

Figure 5. FAR for verification of $T_{\max}$ from raw NCUM, moving and decaying average bias correction methods for Day-1, 3,5 and 7 forecasts for $T_{\max}$ within 30–32, 32–34, 34–36, 36–38, 38–40 and 40–42°C.

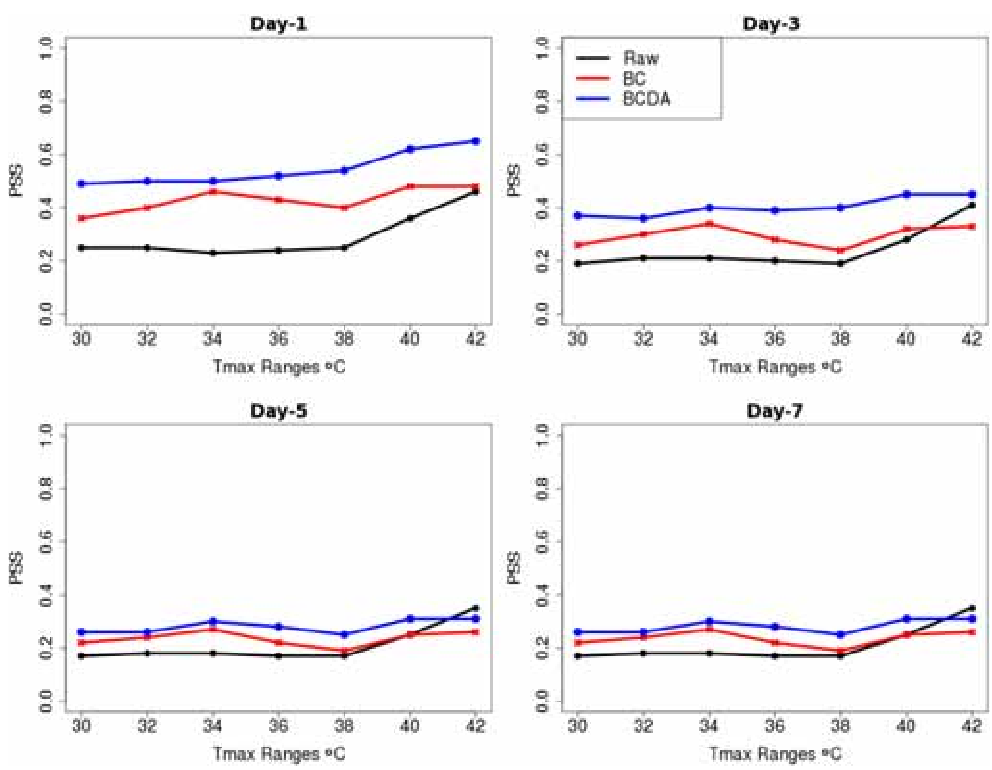

Figure 6. PSS for verification of $T_{\max}$ from raw NCUM, moving and decaying average bias correction methods for Day-1, 3, 5 and 7 forecasts for $T_{\max}$ within 30–32, 32–34, 34–36, 36–38, 38–40 and 40–42°C.

average method for all temperature ranges and lead times. In the Day-3 forecast verification, it is seen that the PSS for the raw forecasts is higher than the moving average method for $T_{\max}$ lying in the range 40–42°C. For Day-5 and 7 forecasts, the PSS is seen to be higher than the moving average method for

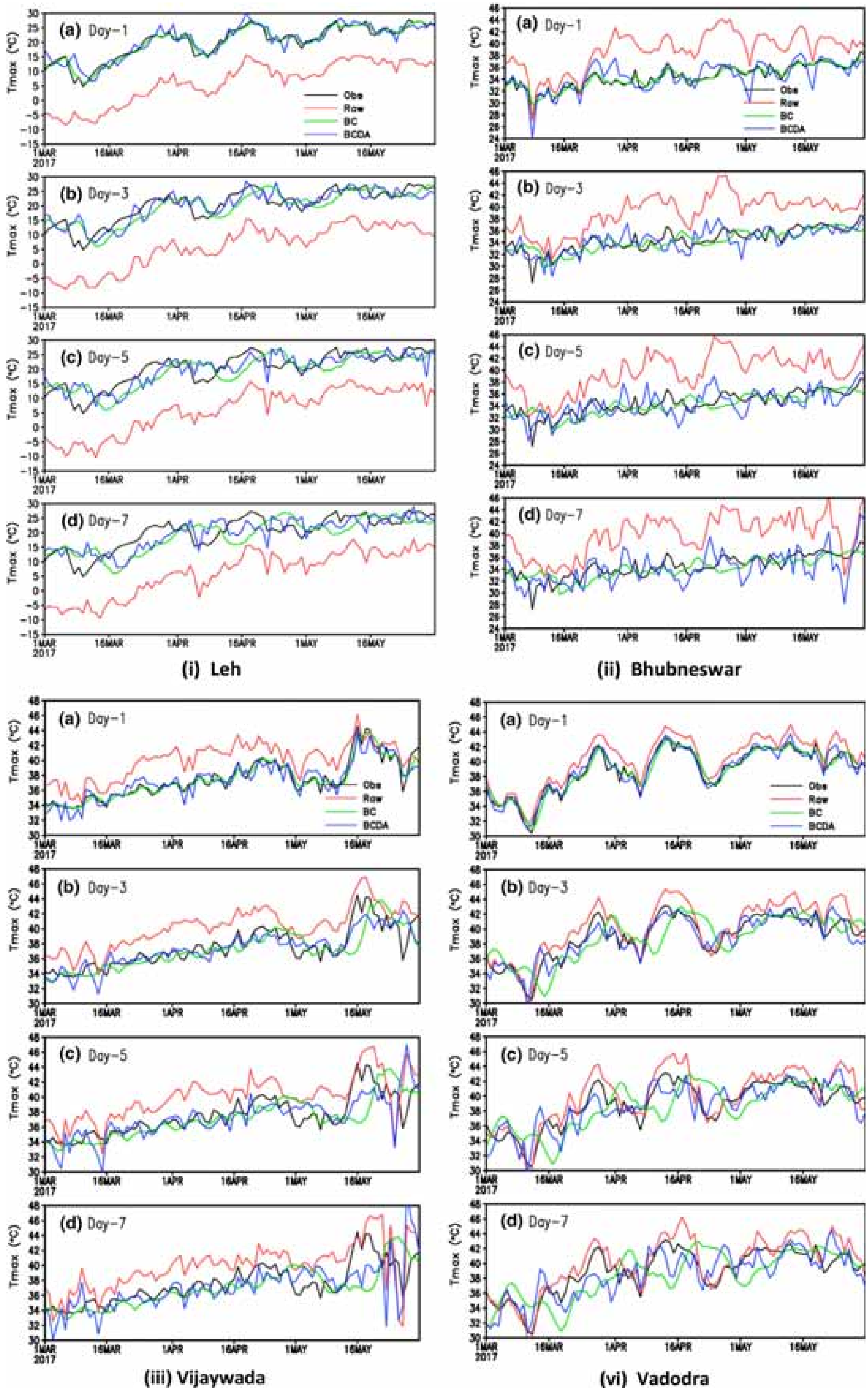

Figure 7. Time series of observed and Day-1, 3, 5 and 7 raw and bias corrected $T_{\max}$ forecasts for (i) Leh, (ii) Bhubaneswar, (iii) Vijaywada, and (iv) Vadodara.

40–42°C temperature range. For the same lead times, the PSS for raw forecasts is also seen to be higher as compared to the decaying average method for the 40–42°C temperature range.

Figure 7(i and ii), shows a time series plot of observed $T_{\max}$ as well as raw forecasts and the bias corrected forecasts (Day-1, 3, 5 and 7) from moving average (BC) and decaying average (BCDA) methods for two locations of Leh, Jammu and Kashmir in north and for Bhubaneswar, Odisha in east. Bhubaneswar being in the plains shows a warm bias in the raw NCUM forecasts. Leh in Jammu and Kashmir on the other hand shows a cold bias in the raw NCUM forecasts for $T_{\max}$ being much lower than the observed temperatures. It is clearly seen from the figures that both the bias correction methods lead to considerable improvement in the predicted $T_{\max}$ at these two locations and the bias corrected forecasts lie much closer to the observation curve for all lead times. This is also reflected in figure 7(iii and iv) where panels show time series plot of observed, row and bias corrected forecast of $T_{\max}$ for cities of Vijayawada in Andhra Pradesh in east and Vadodara in Gujarat in west. Hence we can conclude that bias correction has lead to an overall improvement in the predicted maximum 2 m temperature during the Indian summer months of 2017.

4. Conclusions

In the current study, an attempt has been made to correct the biases in the $T_{\max}$ forecasts obtained from the NCUM forecasts starting from December 2016. For the purpose of correcting the bias, two different approaches were considered: A moving average method and the decaying average method. One of the main advantages of both the methods is that they do not require a large amount of past data for calibration. They take into account the most recent behaviour of the forecasting system and not the climatology as most of the statistical bias correcting algorithms require. The verification of the raw and bias corrected forecasts for temperature maximum was carried out using the gridded observations obtained from IMD for a period of March to May 2017.

- Both the bias correction methods lead to a decrease in the mean error in maximum surface temperature during MAM 2017 over India. However, the decaying average method showed a higher decrease in the mean error as compared with the moving average method.
- Categorical verification of $T_{\max}$ forecasts clearly indicate increased POD and PSS values as well as decreased FAR (at all lead times) after bias correction. Further, the decaying average method of bias correction is seen to be superior to both the methods in terms of having higher POD and PSS and a lower FAR at all threshold and lead times.

It can be concluded from the above study that, even a very simple method of bias correction like moving average can lead to a significant improvement in the forecasts of maximum surface temperatures. Decaying average method of bias correction has now been implemented to run operationally for the correction of bias in the maximum surface temperature.

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