



Verification of Pre-Monsoon Temperature Forecasts over India during 2016 with focus on Heat Wave Prediction

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Abstract. The operational medium-range weather forecasting based on Numerical Weather Prediction (NWP) models are complemented by the forecast products based on Ensemble Prediction Systems (EPS). This change has been recognized as an essentially useful tool for the medium range forecasting and is now finding its place in forecasting the extreme events. Here we investigate the extreme events (Heat waves) using a high-resolution numerical weather prediction and its ensemble forecast in union with the classical statistical scores to serve the verification purposes.

10 With the advent of climate change related studies in the recent past, the rising extreme events and their plausible socio-economic effects have encouraged the need for forecasting and verification of extremes. Applying the traditional verification scores and the associated methods on both, deterministic and the ensemble forecast, we attempted to examine the performance of the ensemble based approach as compared to the traditional deterministic method. The results indicate towards an appreciable competence of the ensemble forecasting detecting extreme events (Heat waves) as compared to deterministic forecast. Locations of the events are also better captured by the ensemble model. Further, it is found that the EPS smoothes down the unexpectedly soaring signals, which thereby reduce the false alarms and thus prove to be more reliable than the deterministic forecast.

1. Introduction

20 Reliable weather forecasting plays a pivotal role in our everyday activities. Over the years NWP systems have been employed to serve the purpose. While the NWP models have demonstrated an improved forecasting capability in general, they still have a challenge in the accurate prediction the extreme events. Extreme weather events comprehend non-linear interactions usually between the small scale natural processes (Legg and Mylne, 2014). These small-scale interactions are difficult to predict accurately (Meehl et al., 2001) and a small deviation in these could lead to completely different results, as a result of the forecast evolution process (Lorenz, 1969). The inherent uncertainty in the weather and climate forecasts can be well handled by employing ensemble based forecasting (Buizza et al., 2005). The EPS (Mureau et al., 1993, Toth and Kalnay, 1997, Molteni et al., 1996) were first introduced in the 1990s in an effort to quantify the uncertainty caused by the synoptic scale baroclinic instabilities in the medium range weather forecasting (Legg and Mylne, 2014). Ensemble forecasting has emerged as the practical way of estimating the forecast uncertainty and making probabilistic forecasts. Based on multiple perturbed initial conditions, ensemble approach samples the errors in the initial conditions to estimate the forecast uncertainty (spread in member forecasts). The skill of the ensemble forecast shows marked improvement over the deterministic forecast when comparing the ensemble mean to deterministic forecast after a short lead time



The new EPS at the NCMRWF is now running for operational purposes (Sarkar et al., 2016). This global medium-range weather forecasting system has been adopted from the UK Met office (Sarkar et al., 2016). Generally, the model and the ensemble forecast applications in addition to their verifications are used for prevalent events with a limited focus on the rare extreme weather events. It would be for the first time that the EPS technique has been employed from this model output for the extreme events over India to study the heat wave events. The heat wave is considered if maximum temperature of a station reaches at least 40°C or more for Plains and at least 30°C or more for Hilly regions. Based on departure from normal, a station is declared to have heat wave conditions if departure from normal is 4.5°C to 6.4°C and severe heat wave if the departure from normal is >6.4°C. In terms of the actual maximum temperature, a station is under heat wave when actual maximum temperature $\geq 45^\circ\text{C}$ and severe heat wave when the maximum temperature is $>47^\circ\text{C}$. There has been increasing interest in predicting such extremes, the heat wave and cold wave events in India due to the associated loss of life. An increasing number of extreme temperature events over India were documented by a few recent studies (Qin et al., 2013). A study conducted over the Indian sub-continent between 1969 and 1999 indicated more frequent cold and heat wave events over the Indo-Gangetic plains of India. 5-6 heat wave events and 2-3 cold wave events are reported to occur every year in the Northern parts of the country. The global temperatures have exhibited a warming trend of about 0.85 °C due to anthropogenic activities between 1880 and 2012 (Molteni et al., 1996). Similar trends were also observed in India with the annual air surface temperature rise between 1901 and 2014.

The annual mean temperature has been shown to increase by 0.42°C per 100 years while the maximum land temperature over the India has shown an overall increase of 0.92°C per 100 years (Arora et al., 2009). Minimum temperature, on the other hand, does also show a warming trend over the Indian sub-continent but with a smaller magnitude of about 0.09°C (per 100 years) (Arora et al., 2009).

Another study reported a significant rising trend of 0.05°C in the mean surface temperature of India between 1901 and 2003 has documented a warming by about 0.22°C per decade (Arora et al., 2009). This period also includes the monsoon months which additionally represent unprecedented warming, unusual according to the author's experience (Kothawale, 2005). On the other hand, a recently reiterated IPCC report (2013) notified an "unequivocal" proof of the increasing warming trend, globally which could be associated with the variations in the climate system. This indicates a need to comprehend the heat wave events on weather and climatic scales. While there is an extensive literature discussing the heat wave events and their trends on the climatic scales, however, the literature is rather limited (especially over India) focusing such events on monthly sales. This paper thus tries to fill in the gap and attempt to demonstrate the capability and strength of predicting such events using ensemble forecast forecasts both, deterministic and ensemble forecasting. This research investigates the most recent heat wave events during the summer months March, April & May (MAM) 2016 in India. This investigation considers two case studies to demonstrate the strength and weaknesses of the EPS approach in predicting such extreme events.

With these factors in mind, we can say that temperature (Minimum and Maximum both), forms a vital component of weather and climatic studies which are becoming increasingly important and challenging. Reliable projections of such changes in



our weather and climate are critical for adaption and mitigation planning by the agencies involved. The knowledge would undoubtedly be useful for a layman and the society. Testing for the reliability of the NWP model results is efficiently done by the forecast verification methods. Forecast verification plays an important role in addressing two main questions: How good is a forecast? And how much confidence can we have in it?

5 Verification by employing statistical scores is a well-established method adopted in this study. However, not all score lead to the same conclusion. This is the challenging situation when one needs to decide how much confidence can be placed in a model. Depending upon the statistical characteristics of the variable addressed, the score type is chosen and is employed for the verification. Not all scores are equally efficient in describing a variable. This fact offers a choice and challenge to adopt and the most compatible score type. The set of verification scores used here are listed and briefly discussed in the next
10 section.

In this paper, we investigate the utility of the ensemble prediction system over the deterministic forecast in studying extreme events like heat waves. This forms the first documented study of the recent heat wave events over India which was verified using the deterministic and the ensemble forecasts ensemble forecasts. This paper talks about what an EPS can and can't do. This also provides some important insights into the use of ensemble forecast over the deterministic forecast in predicting
15 extreme events like a heat wave and a cold wave. However, this study is unable to encompass an entire discussion on the efficiency of the EPS in general as the work examines a narrow range of phenomena over a not so wider region.

The paper begins with a brief explanation of the observed temperature (*Tmax* & *Tmin*) data sets, model description and the methodology used. It will then go on to the results' section which encompasses two case studies from the recent heat wave events in India, followed by the verification results and finally ending with the discussions and conclusions.

20

2 Observation, Model description and verification methodology

2.1 Observed Temperature (Maximum and Minimum)

Recently, IMD has developed a high resolution daily gridded temperature dataset at $0.5^\circ \times 0.5^\circ$ resolution, which was $1^\circ \times 1^\circ$ resolution a few years earlier over Indian land area. Data processing procedure has been well documented (Srivastava et al.,
25 2009). IMD has compiled, digitized, quality controlled and archived these data at the National Data Centre (NDC). In this study, we have used IMD's real-time daily gridded (Srivastava et al., 2009, Caesar et al., 2006, Kiktev et al., 2003, New et al., 2000, Piper and Stewart, 1996, Rajeevan et al., 2005 and Shepard, 1968) temperature (maximum and minimum) data to verify the deterministic and ensemble mean forecast temperatures from NCUM and NEPS respectively. The verification is carried out for the entire period from March 2016 to May 2016 at $0.5^\circ \times 0.5^\circ$ resolution over Indian land area.

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2.2 NCMRWF Unified Model (NCUM)

The Unified Model (John et al., 2016), operational NCMRWF at consists of an Observation processing system (OPS 30.1), four-dimensional variational data assimilation (VAR 30.1) and Unified Model (UM 8.5). 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 levels in the vertical extends from surface to 80 km height. The NCUM model forecast temperature (T_{max} & T_{min}) data have been interpolated to the $0.5^{\circ} \times 0.5^{\circ}$ resolution using bilinear interpolation method to match the resolution and grids of the observed data.

2.3 NCMRWF Ensemble Prediction System (NEPS)

NEPS is a global medium-range ensemble forecasting system (Sarkar et al., 2016) adapted from the UK MET Office. The configuration consists of four cycles of assimilation corresponding to 00Z, 06Z, 12Z 18Z and 10-day forecasts are made using the 00Z initial condition. The N400L70 forecast model consists of 800x600 grid points on the horizontal surface and has 70 vertical levels. Horizontal resolution of the model is approximately 33 km in the mid-latitudes. The 10-day control forecast run starts with the operational NCUM (N768L70) analysis and 44 ensemble members start from different perturbed initial conditions consistent with the uncertainty in initial conditions. The initial perturbations are generated using Ensemble Transform Kalman Filter (ETKF) method (Bishop et al., 2001). Uncertainty in forecasting model is taken into account by making small random variations to the model and using a stochastic kinetic energy backscatter scheme, (Tennant et al., 2010). In this study, the forecast data is interpolated to match the grid and resolution of observations i.e. $0.5^{\circ} \times 0.5^{\circ}$ for verification.

2.4 Verification Metrics

There are several scores available for the categorical verification of ensemble forecasts. However, in the current study, we have used the POD, FAR, ETS, HK, and SEDI. A brief description of these scores is presented here.

POD Score or the Hit Rate(H): POD tries to answer the question, “*What fraction of the observed “yes” events were correctly forecast?*” It is very much sensitive to hits, but ignores false alarms and 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, for perfectly forecasted events $POD=1$.

$$POD = \frac{hits}{hits+misses} \quad \text{Eq. 1}$$

FAR (F): *What fraction of the predicted “yes” events actually did not occur?* FAR is sensitive to false alarms, but ignores misses, very sensitive to the climatological frequency of the event and should be used in conjunction with the probability of detection.

$$FAR = \frac{hits}{hits+false\ alarms} \quad \text{Eq. 2}$$

HK: It reveals the true skill statistic and focuses on how well the forecast separates the “Yes” events from the “No” events. HK uses all elements in the contingency table, does not depend on climatological event frequency. The expression is



identical to $HK = POD - POFD$, but the Hanssen and Kuipers score can also be interpreted as (*accuracy for events*) + (*accuracy for non-events*) - 1. The score ranges between -1 to 1, both inclusive along with 0, which indicates no skill and 1 denotes a perfect skill.

$$HK = \left[\frac{hits}{hits+misses} \right] - \left[\frac{false\ alarms}{false\ alarms+correct\ negatives} \right] \quad \text{Eq. 3}$$

5 This score is efficient at verifying the most frequent events. Temperature possesses continuous values just like precipitation amount and a few other NWP variables. In such cases mean error, MSE, RMSE, correlation and anomaly correlation are best suitable (4th international verification methods workshop, Helsinki, June 2009). Categorical values for instance precipitation occurrences are well suited for the verification analysis using POD, FAR, Heidke skill score, equitable threat score and H-K Statistics. However, in order to take advantage of these scores, for our continuous variable, temperature (Maximum and
 10 Minimum), we categorize it using the temperature ranges, 30-32, 32-34, 34-36, 36-38, 38-40, and 40-42 °C.

ETS: It is also known as, the Gilbert skill score describe how well the forecasted “yes” events agree with the observed “Yes” events and thus exploring the hits by chance. This score ranges between -1/3 to 1. '0' shows no skill and 1 denotes the perfect skill. The score express the fraction of observed or the forecasted events projected accurately.

$$15 \quad ETS = \frac{hits - hits_{random}}{hits + misses + false\ alarm - hits_{random}} \quad \text{Eq.4}$$

Where $hits_{random} = \frac{(hits+miss)(hits+false\ alarms)}{total}$

SEDI: It expresses the association between a forecast and the observed rare events. It ranges between -1 and 1 where the perfect score is 1. This score converges to (2X -1) as the event frequency advance towards 0, where "X" denotes the variable
 20 that specifies the hit rate's convergence to 0 for the rarer events. SEDI is not influenced by the base rate SEDI score approaches 1.

$$SEDI = \frac{\ln F - \ln H + \ln(1-H) - \ln(1-F)}{\ln F + \ln H + \ln(1-H) + \ln(1-F)} \quad \text{Eq.5}$$

3 Results and Discussions:

25 Traditionally, the performance of a forecast model is determined by a variety of statistical measures and scores which offer an effective way to quantify a model's efficiency. Before moving over to such methods, we begin with looking at the ensemble based and deterministic forecasts (on a daily basis) over a period of three hot summer months in India, March, April and May, and also compare it with the observations The models are running operationally and are providing the forecasts out to 10 days every day. The verification is confined to MAM 2016, over six different threshold temperatures. For
 30 T_{max} , the temperature thresholds are 32, 34, 36, 38, 40 & 42°C and for the T_{min} , however, it is 22, 24, 26, 28, 30 & 32°C.



T_{max} & T_{min} forecasts from deterministic and ensemble-based approach are averaged over 3 months (MAM) and are illustrated in the Figs.-1(a) and 1(b).

The y-axis in each of the Figs represents the number of forecasts points possessing the temperature value above a threshold. The values on the Y-axis are divided by 2686 to present it in an easy to read format, which is then multiplied with 100 to express the values as percentages.

As can be seen in the Figs-1(a & b), both, deterministic and ensemble-based approaches predict better temperature during the warm days, especially for the temperature exceeding 38°C. NEPS performs better than the NCUM forecast (Fig 1a), indicating better performance of the ensemble forecast over the deterministic one. This feature has also been highlighted in the figures (Fig. 5) and (Fig. 4). Both, NCUM and NEPS forecasts converge to the observations at higher temperatures for both, T_{max} and T_{min} .

Deterministic forecast hardly shows any variation in either of the considered days and illustrates quasi-stationary characteristics of the deterministic forecast from Day-1 through Day-10 forecast. In the case of T_{min} forecast, both the models underperform in terms of the temperature prediction and vary in not so distinctive fashion. Both the forecasts tend to converge to the observations at higher temperatures.

From the spatial map Fig. (2.), the frequency of the observed maximum temperature (T_{max}) $T_{max} \geq 40^\circ\text{C}$ in the Maharashtra and adjoining regions shown maximum (more than 70 counts) over the entire period of MAM 2016, which is picked up by both deterministic and ensemble models. However, deterministic model is showing more frequency spread over MP, UP and Bihar, Orissa, AP and adjoining states from day-1 to day-9. As forecast lead time increases from day-1 to day-9 the heat wave frequency increases from central India to north and east India. Consequently, higher number of heat wave extremes was predicted by deterministic model NCUM over east UP, Bihar, West-Bengal, Orissa, Jharkhand, Chhattisgarh and AP. On the other hand, NEPS (Fig.3) prediction for the day -1 to day -9 is much subdued than in the NCUM forecasts. However, both models, NCUM and NEPS are, predicting more frequently the heat waves above said regions. Comparatively, *the ensemble based model NEPS is performing better (spatially) for the extremes of heat-wave events than the deterministic model NCUM over most of the Indian states up to day-9.*

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4. Case Studies for Extreme Heat waves

4.1 Weather conditions during MAM-2016

Heat wave conditions prevailed at some places over the central and adjoining western parts of the country during last week of March-2016 (Climate Diagnostics Bulletin of India, March 2016) and over parts of central and northwest India (Climate Diagnostics Bulletin of India, April 2016) during the first week of April. These conditions prevailed over most parts of east India all through the second week. The severity and extent of heating increased during the next week resulting in the establishment of severe heat wave conditions over parts of north and eastern India. These conditions continued to prevail over east India and also spread over parts of south India during the fourth week, however, its intensity and areal extent



reduced towards the end of the week. During the last few days of the April month, heat wave conditions prevailed over parts of Odisha, Bihar, Gangetic West Bengal and Kerala.

During the month of May-2016 at isolated places on some occasions over Parts of Rajasthan, Punjab, Odisha, Gangetic West Bengal and Kerala during the first fortnight of the month (Climate Diagnostics Bulletin of India, May 2016). Severe heatwave / heatwave conditions developed and intensified over parts of northwest India from 15th May, spread and persisted over parts of central and north peninsular India till 22nd of the month. Jammu & Kashmir, west & east Rajasthan, west & east Madhya Pradesh and Vidarbha were especially affected during this period. Some stations of West Rajasthan viz. Barmer, Bikaner, Ganganagar, Jaisalmer, and Jodhpur observed severe heat wave conditions for 4 to 5 days in succession from 17 to 21 May and temperature observed $\geq 50^{\circ}\text{C}$. Heat wave conditions gradually abated from most parts of the country after 23rd and prevailed only at isolated places over parts of Coastal AP and Telangana during last few days of the month.

4.2 Casualties reported during MAM-2016

Prevailing heat wave over India took a toll more than 500 loss of lives. Heatwave claimed one life each (Climate Diagnostics Bulletin of India, March 2016) in Maharashtra (Nanded, 13 March) & Kerala (Palakkad, 5 March). It took a toll of over 200 lives (Climate Diagnostics Bulletin of India, April 2016) from central and peninsular India during the April month. Of these, 88 lives were reported from Odisha, 79 from Telangana, 40 from AP, 9 from Maharashtra and one each from Karnataka and Tamil Nadu. In the month of May heat wave claimed over 275 lives from central and peninsular parts of the country. Of these, over 200 lives (Climate Diagnostics Bulletin of India, April 2016) were reported from Telangana alone. 39 lives were reported from Gujarat and 34 from Maharashtra.

4.3.1 Case-I Heat Waves on 11th April 2016

As per the IMD reports (Climate Diagnostics Bulletin of India, April 2016), the heat wave conditions prevailed over parts of central peninsular and east India during the second week of the April. It took a toll of over 200 lives (Table-1) from central and peninsular India during the April month. The spatial distributions and NCUM & NEPS forecast T_{max} with of observed IMD T_{max} prevailing heat-waves over Odisha, AP, Telangana, and some parts of Maharashtra on 11th April 2016 is shown in Fig. 6 & 7. The NEPS is better predicting the extremes of Heat Waves up to day -9 then the NCUM.

4.3.2 Case-II Heat Waves on 21st May 2016

The severe heat wave conditions developed and intensified over parts of northwest India entire third week of May-2016 and persisted over parts of central and north peninsular India. Some stations of West Rajasthan temperature observed $\geq 50^{\circ}\text{C}$ viz. Barmer, Bikaner, Ganganagar, Jaisalmer & Jodhpur and observed severe heat wave conditions for 4 to 5 days in succession from 17th to 21st May-2016. The spatial distributions of NCUM & NEPS forecast T_{max} with of observed IMD T_{max} prevailing heat-waves over Rajasthan, MP, UP, Delhi, Haryana, Punjab and some parts of Maharashtra on 21st May 2016 is shown in Fig. 8 & 9. Both the models deterministic and ensemble able to predict the extreme temperature ($T_{max} > 48^{\circ}\text{C}$)



over west Rajasthan up day-3 only. However, the NCUM is predicting more wide-spreading $T_{max} > 46^{\circ}\text{C}$, over Rajasthan, MP, UP, Delhi, Haryana, Punjab and parts of Maharashtra all days forecast.

H-K scores of the maximum temperature (T_{max}) between the range 30-42 °C, constructed as box and whiskers for both NCUM and NEPS, indicate towards better performance of the ensemble based forecast as compared to the deterministic one.

5 Interestingly, the forecast score does not fade away with the lead time contrary to the expectation. This depicts that the NEPS performs better and its prediction skill remains quasi-constant throughout the lead time of 10 days (Fig 11).

Similar observations can be made from the ETS plots (Fig 10). The most obvious finding to emerge from the box and whiskers plots of the ETS scores is the better performance of the ensemble based forecast (NEPS) than that of the deterministic forecast (NCUM). This result is consistent with the earlier documented findings. At all the T_{max} thresholds
10 (between 30 and 42°C), NEPS mean stands above the NCUM mean. The same observation holds during all the illustrated forecasts (Day1, 3, 5, 7, and 9). The scores falling under the 25% in the case of ensemble based forecast are either similar or lie little above the deterministic forecast unlike the values underlying 75% which in the NEPS case are markedly higher than that of the NCUM's.

This finding raises an intriguing question regarding the difference in the characteristic distribution of both NEPS and NCUM
15 forecasts. This result also advocates better performance of the ensemble based forecast over the deterministic forecast.

Importantly, the ensemble-based forecast predicts low false alarm than its counterpart, NCUM, especially in the high-temperature range. In the low-temperature range, between 30 and 32, NEPS has low FAR score (where 0 denotes the perfect score) for Day-1 and Day-3 forecast. Similarly, a comparatively higher score on Day-5, 9 and Day-7 respectively (Fig. 9).

POD: Probability of detection of ensemble based forecast is higher than the deterministic forecast during all the lead times
20 and at all the temperature thresholds except for the Day-1 forecast score for the NEPS in the range between 40-42°C where NCUM shows better performance (Fig. 8).

SEDI: At higher temperature ranges, representing rare events, the performance of NEPS and NCUM can be clearly seen from the SEDI score plot (fig). We can notice a considerable difference between the performance of the two techniques for extreme events lying between 40 and 42 C, on all the days.

25 Apparently, NEPS demonstrates higher skill than that of NCUM in predicting the heat wave events. The heat wave event prediction skill is best seen on the Day-5 forecast with NEPS's SEDI score encompassing the score value of 0.7.

A consistent result attained from the NEPS and NCUM verification demonstrates the better skill of the ensemble forecasts compared to the deterministic forecast for the considered cases.

5. Summary and Conclusions:

30 Unless the atmosphere is in a highly predictable state, we should not expect an ensemble to forecast extreme events with a high probability (Legg and Mylne, 2014). This is due to the small scale non-linear interactions involved in a model (NWP). One of the several predicted interactions could be climatologically extreme and are hence more difficult to predict. A small variation in the intensity, timing, and position of such anomalies could lead to a large difference in their prediction growth in



time. Thus, despite the efficiency of the EPS over the deterministic forecast in detecting extreme events, we should be extremely careful in declaring it locally as explained above. The ensemble mean is relatively better in predicting the extremes of heat-wave events than the deterministic model over all Indian states up to day-9.

- 1) The ensemble forecast provides appreciable forecasts on all the days and is most reliable after the Day-2 forecast. This characteristic is more pronounced for extreme events than for the less extreme events where the ensemble forecast after Day-2 is less reliable as can be seen from the FAR and POD scores at the lower thresholds. This suggests that the performance of EPS on different thresholds is different that is, if it performs well at higher thresholds, it does not necessarily mean that it would perform equally well at the lower thresholds too. Thus, we need to understand the model performance at all the concerned ranges and based upon those verification results, employ the ensemble forecast accordingly for operational purposes.
- 2) Our forecasts were obtained for the current summer season in India, MAM and since, the severe events are rare in nature it limits the sample size for the ensemble forecast and thus pose a challenge for the efficient forecasting verification. Despite the caveats involved, the ensemble forecast has shown to predict the heat waves several days ahead of the event, as discussed in the results. The severe heat waves ($>40^{\circ}\text{C}$) can reliably be predicted for Day-2 onwards with less false alarms as compared to the deterministic forecast as observed here. This could be explained by the inherent smoothing characteristic of the ensemble based prediction contrary to the deterministic one which in our case shows warm bias.
- 3) Comparatively, low efficiency of the ensemble based prediction on a shorter time scales ($< \text{Day-2}$) propose that the ensemble prediction may need a longer duration of time for the perturbation growth. This observation would prove to be an important aspect to consider for the future evolution of the ensemble based forecasting. If this hypothesis is true, for the short-range forecasts, ensemble based prediction could fall at the back of other methods like moist SV's optimization (Coutinho et al., 2004), the ETKF (12, 13). However, over a medium range forecast and for the extreme events like heat waves, the ensemble-based approach proves to be one of the most economic and effective tools.

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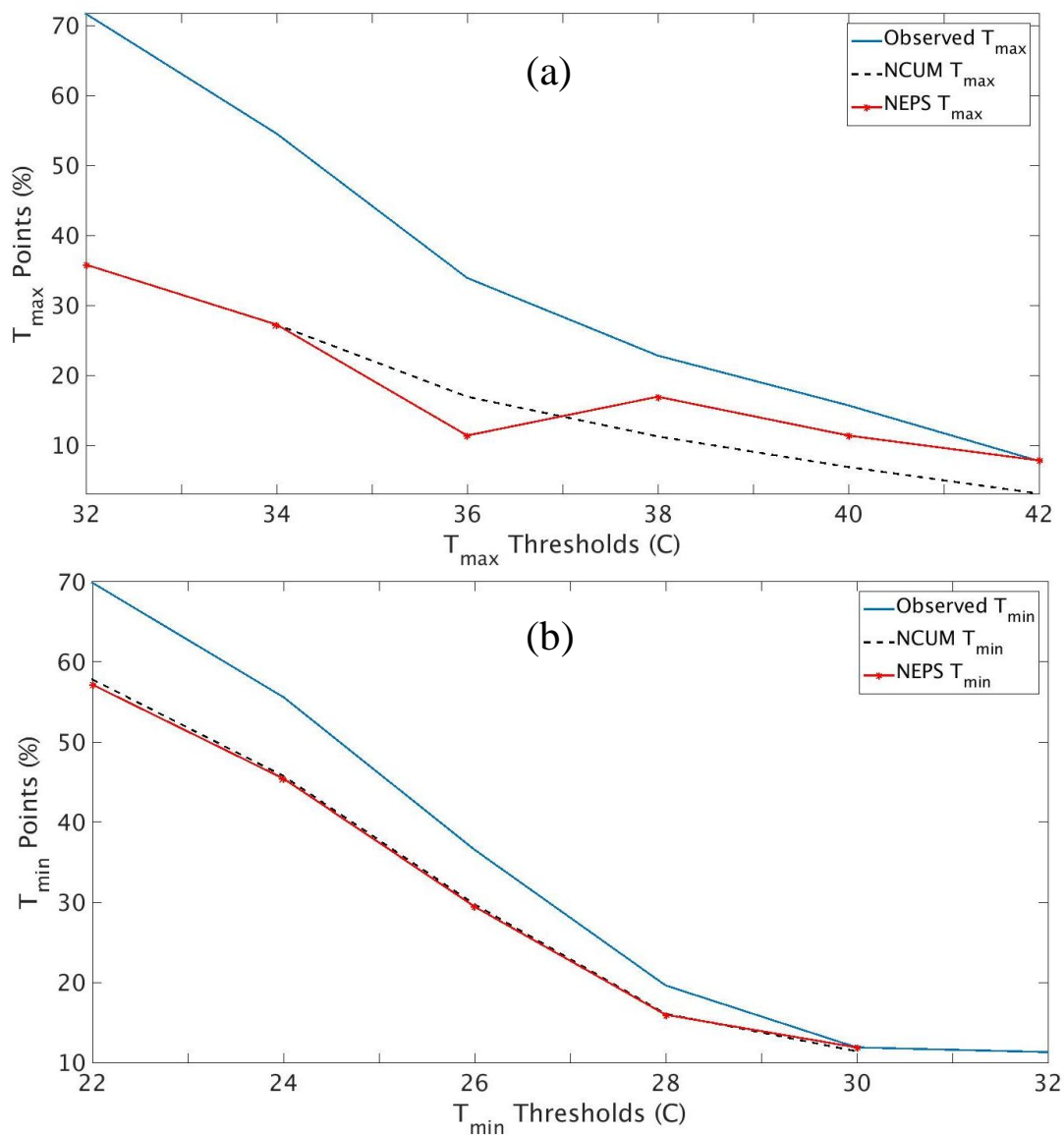


Figure 1. Frequency distribution of observed, and forecast (NCUM and NEPS) (a) T_{max} (°C) and (b) T_{min} (°C) over India during March-May 2016.

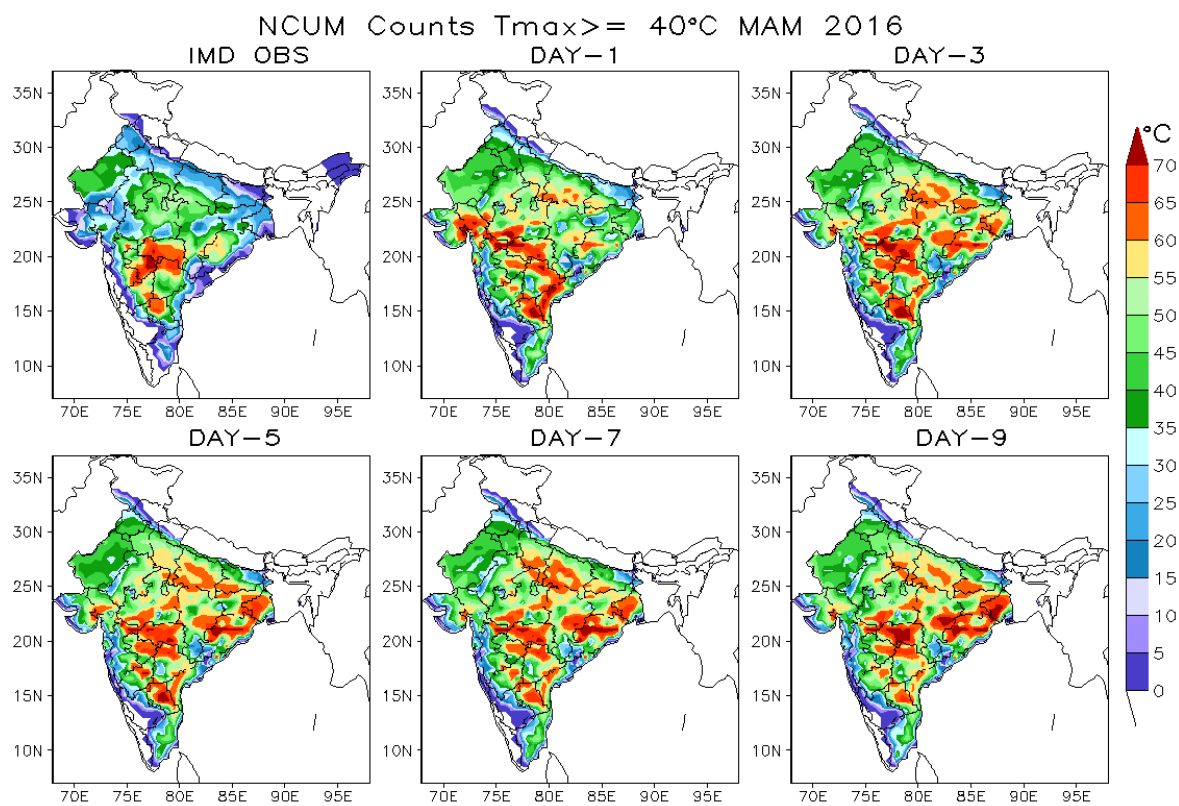


Figure 2. Spatial distribution of observed and NCUM forecasts number of days with $T_{max} \geq 40^{\circ}\text{C}$ during the period of March to May 2016

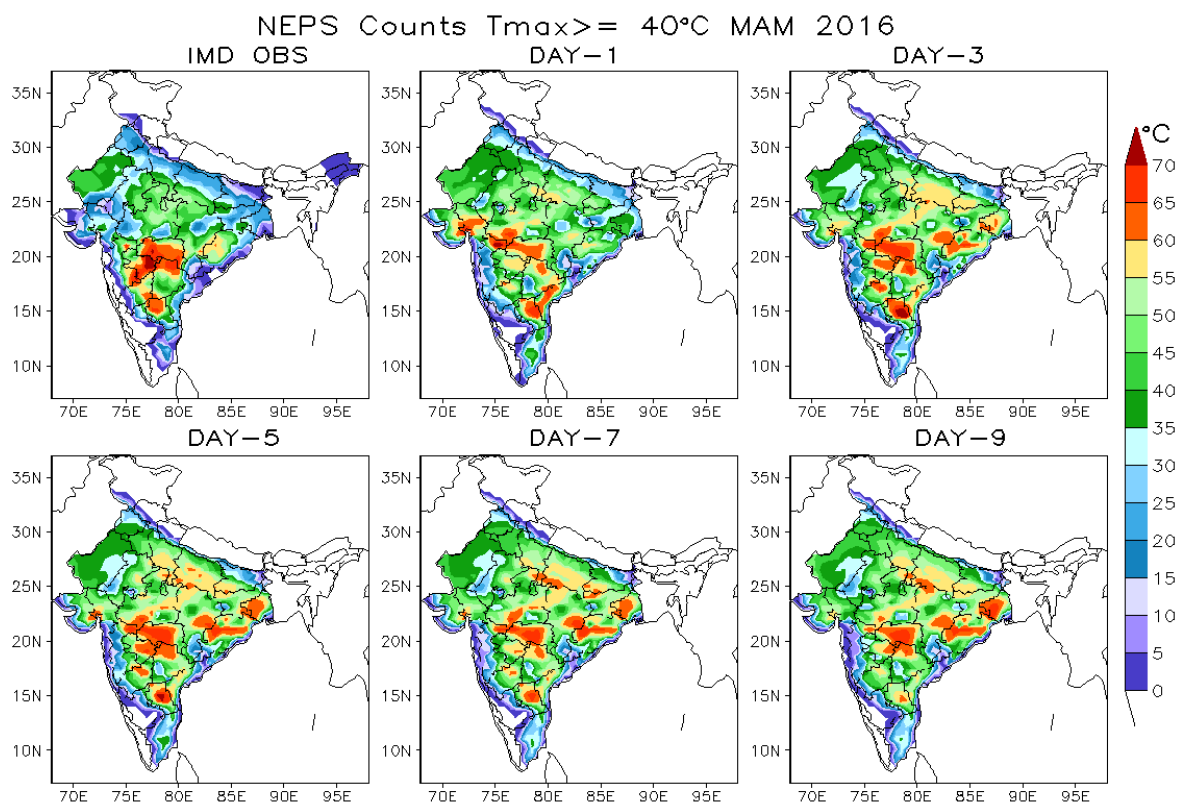


Figure 3. Spatial distribution of observed and NEPS forecasts number of days with $T_{max} \geq 40^{\circ}\text{C}$ during the period of March to May 2016

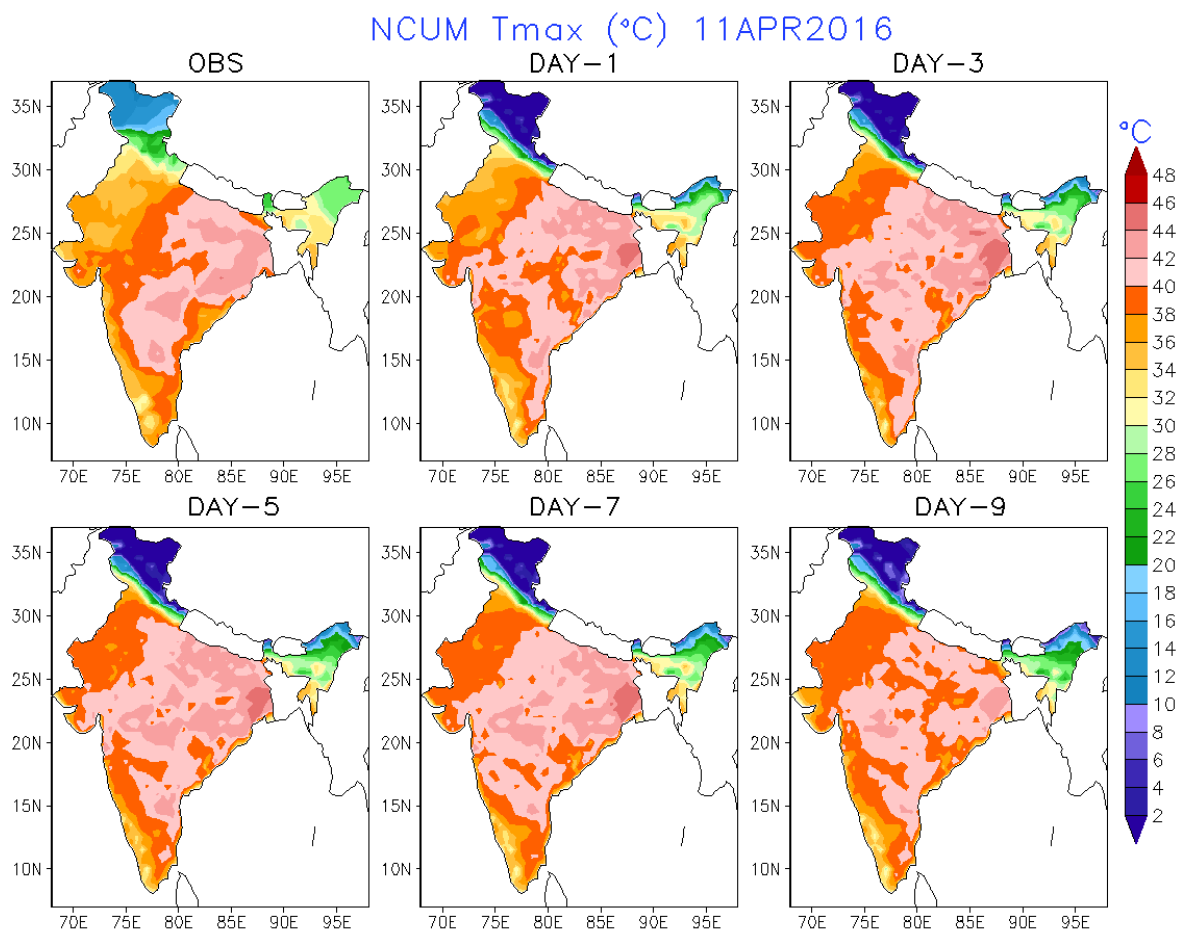


Figure 4. Spatial distributions of Observed T_{max} and NCUM forecast T_{max} prevailing heat-waves over, MP, Odisha, AP, Telangana and some parts of Maharashtra on 11th April 2016

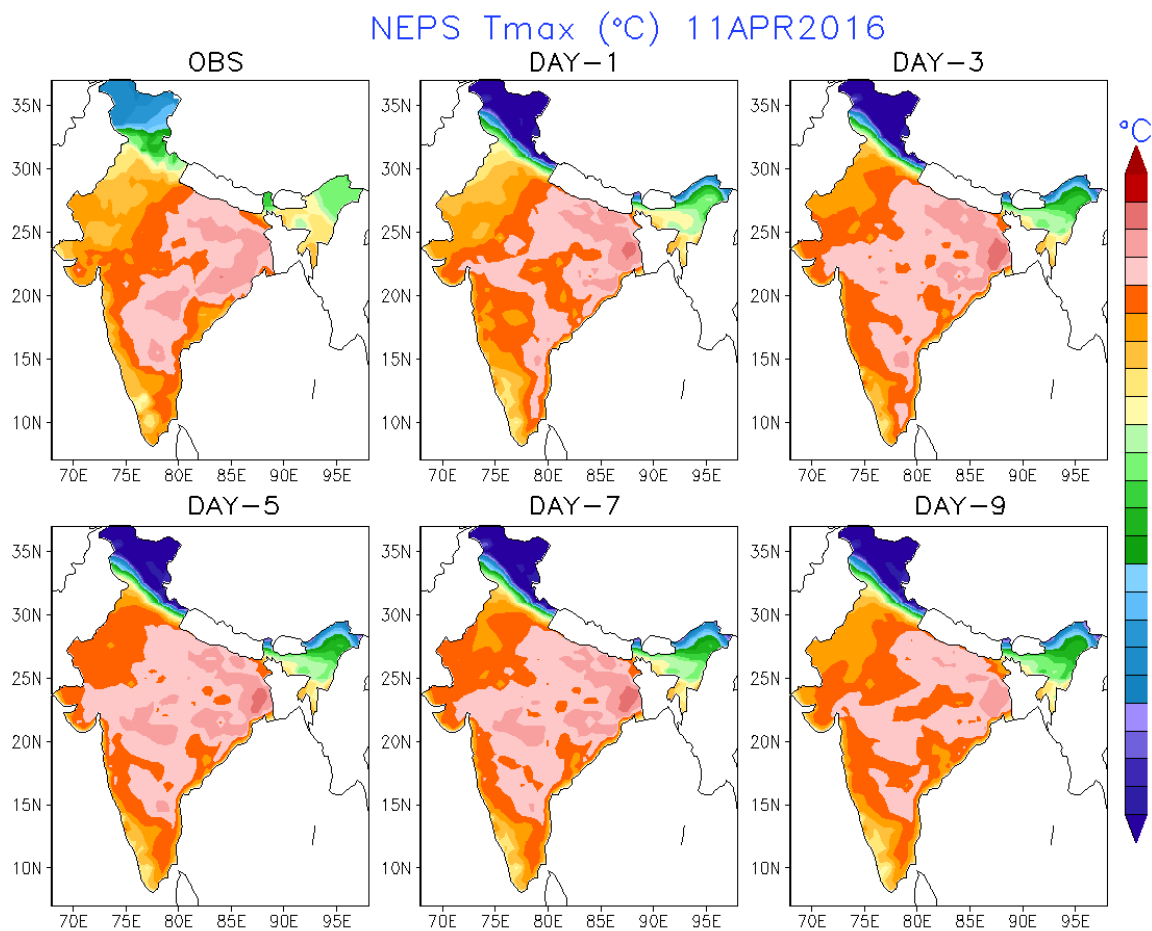


Figure 5. Spatial distributions of Observed T_{max} and NEPS forecast T_{max} prevailing heat-waves over, MP, Odisha, AP, Telangana and some parts of Maharashtra on 11th April 2016

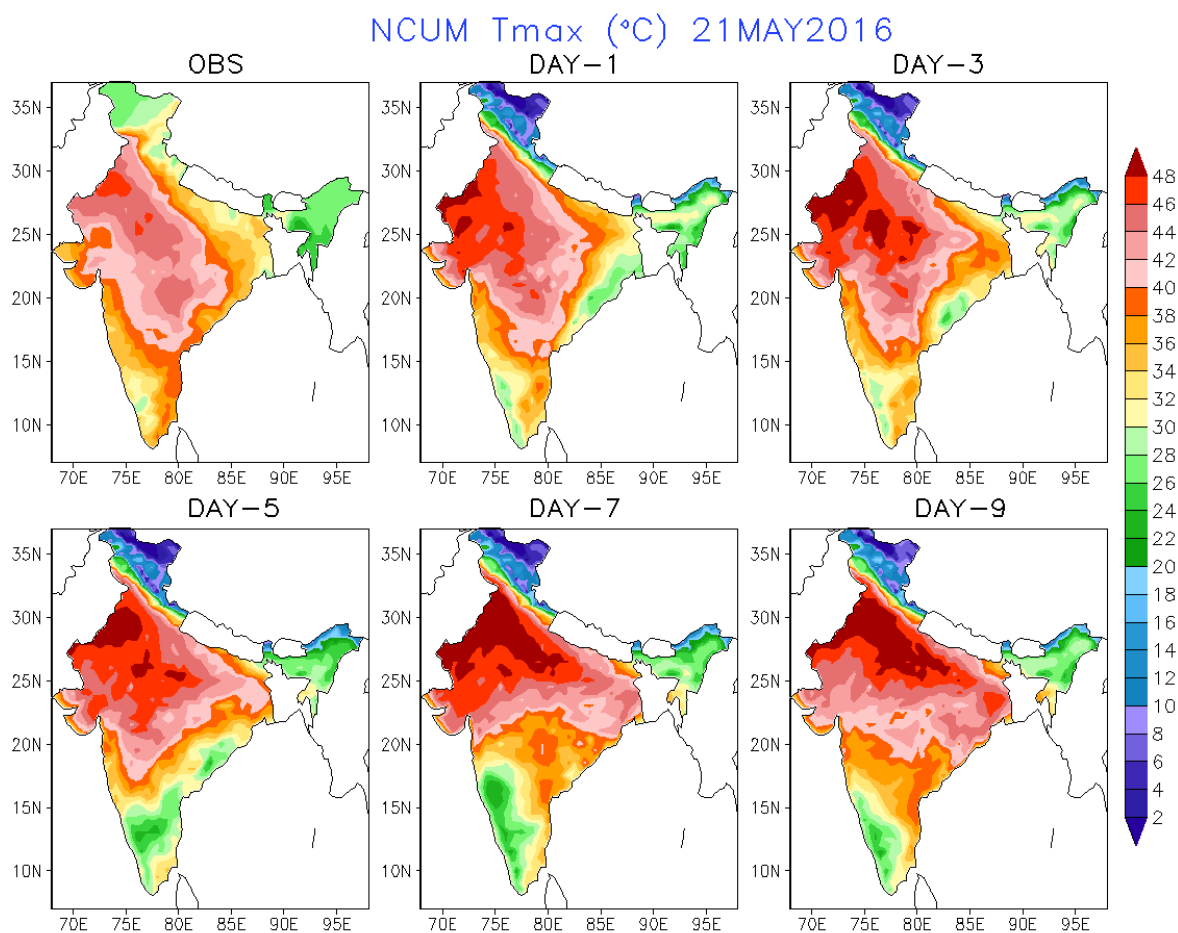


Figure 6. Spatial distributions of Observed T_{max} and NCUM forecast T_{max} prevailing heat-waves over Rajasthan, MP, UP, Delhi, Haryana, Punjab and some parts of Maharashtra on 21st May 2016

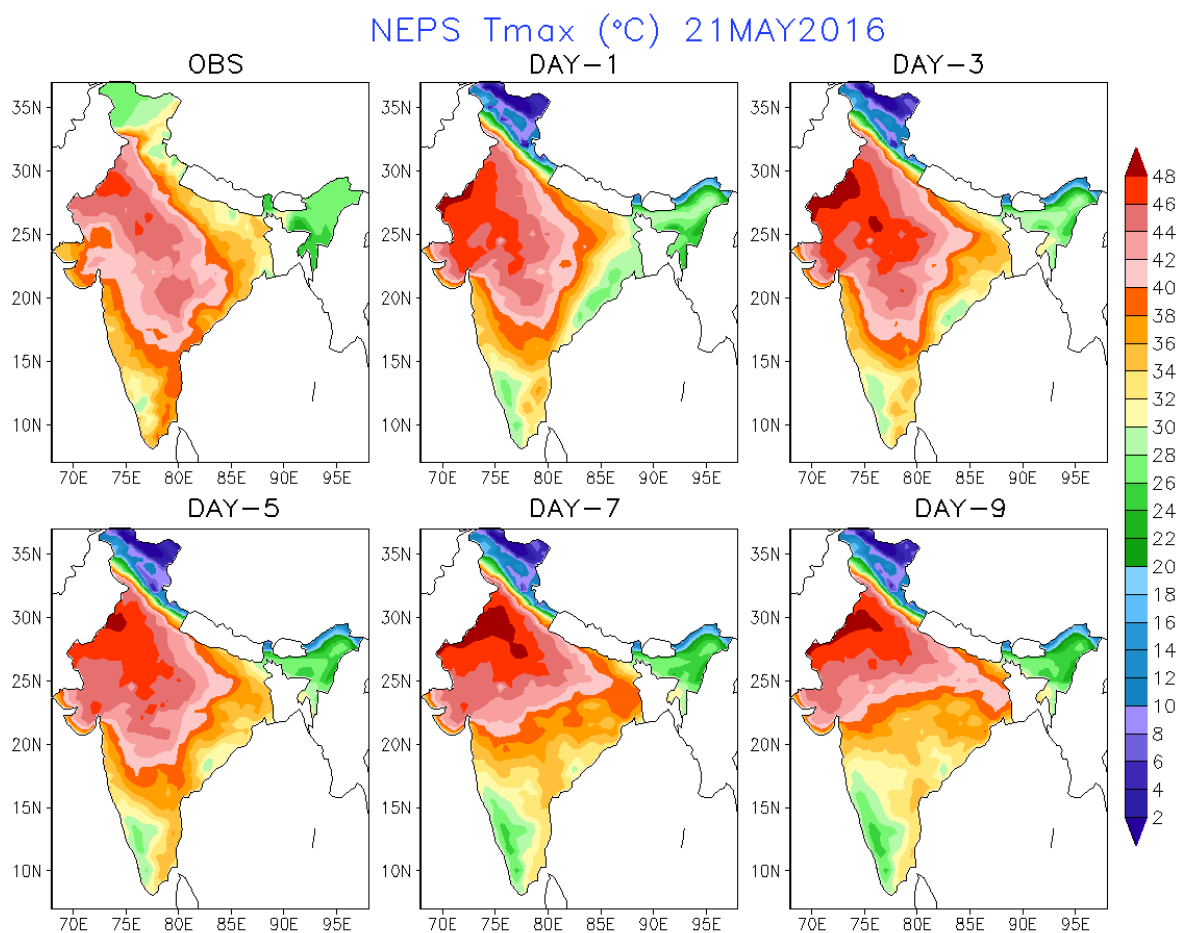


Figure 7. Spatial distributions of Observed T_{max} and NEPS forecast T_{max} prevailing heat-waves over Rajasthan, MP, UP, Delhi, Haryana, Punjab and some parts of Maharashtra on 21st May 2016

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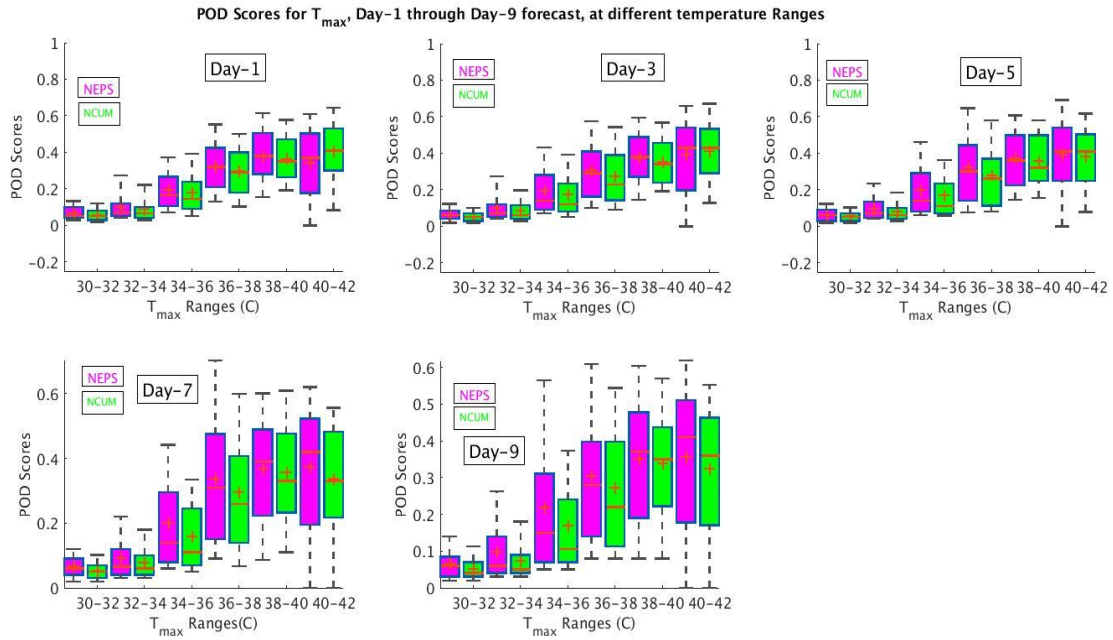
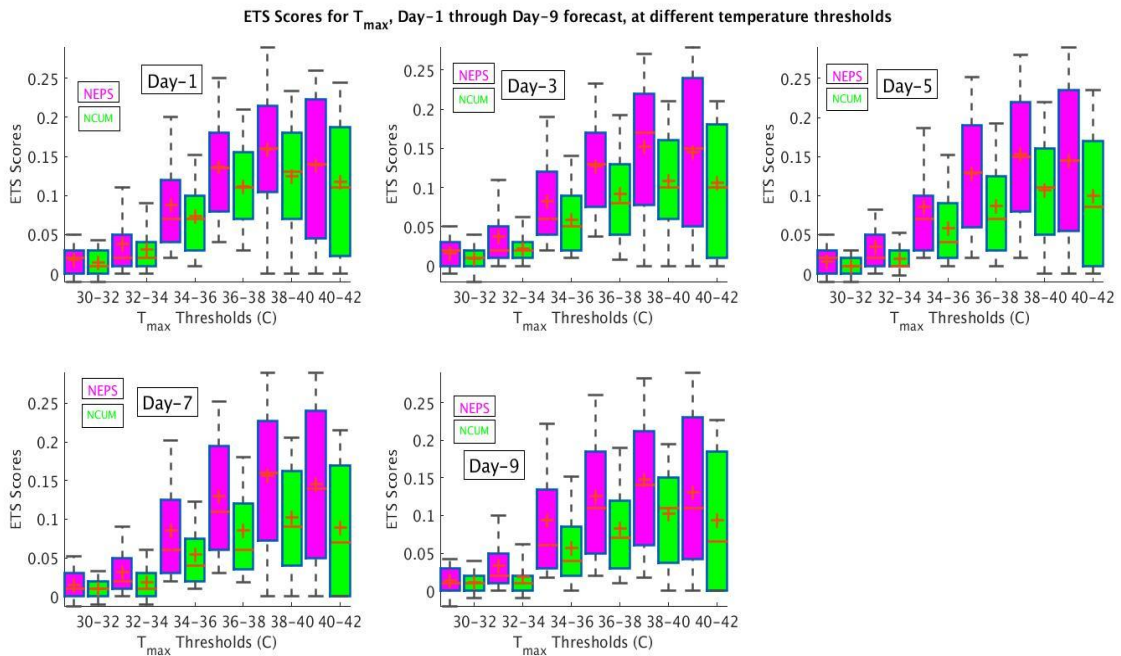


Figure 8. Box plots for Probability of Detection (POD) for NCU and NEPS form March to May 2016



5 Figure 9. Box plots for Equitable Threat Score (ETS) for NCU and NEPS form March to May 2016

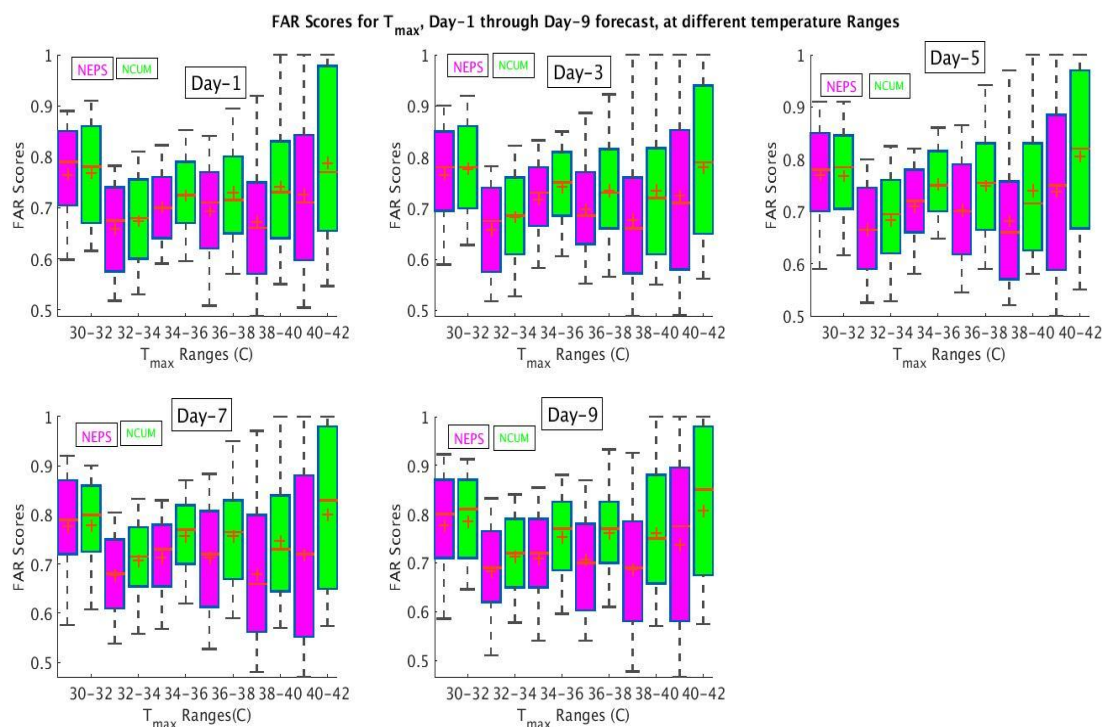


Figure 10. Box plots for False Alarm Ratio (FAR) for NCUM and NEPS form March to May 2016

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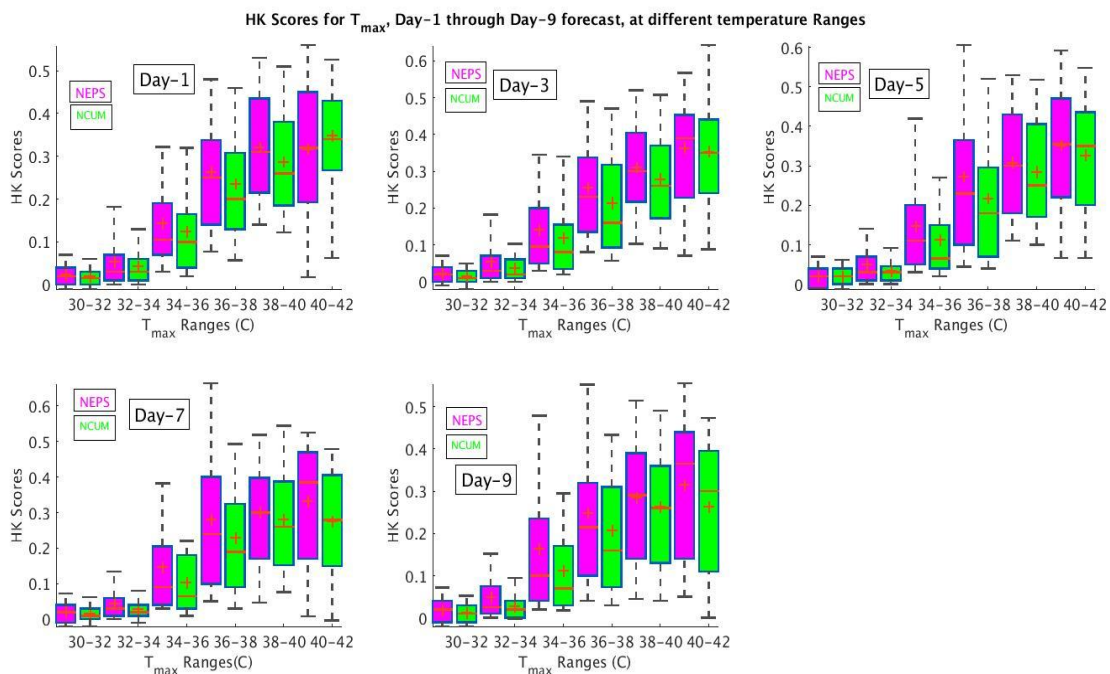


Figure 11. Box plots for HK scores for different temperature ranges (T_{max}) NCLM and NEPS form March to May 2016

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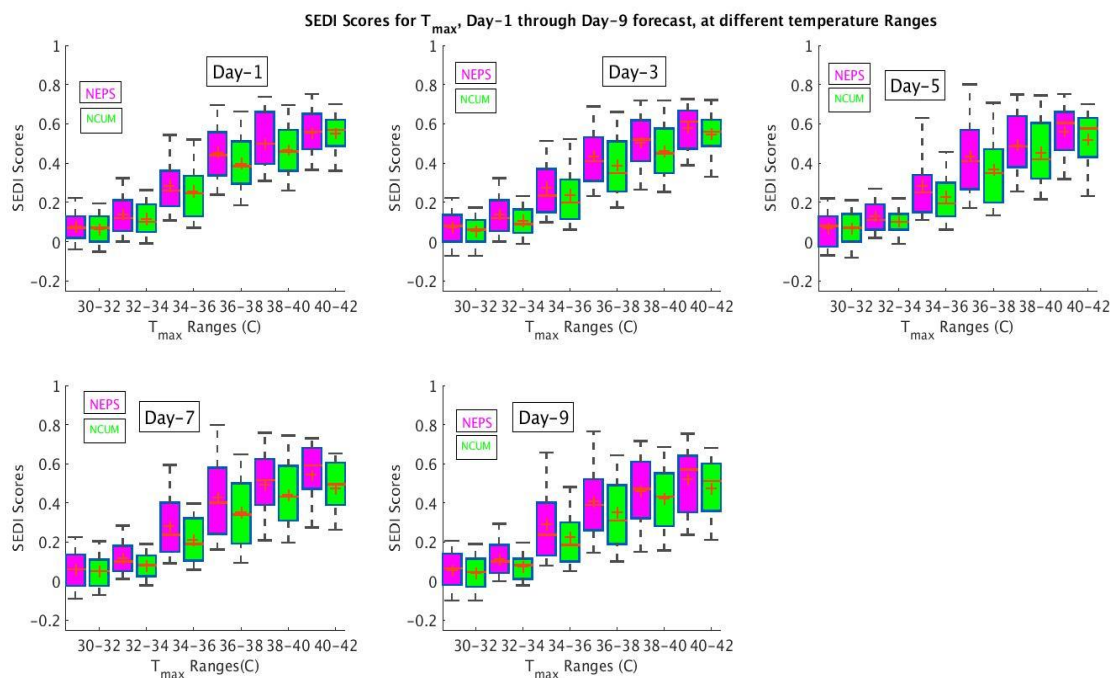


Figure 12. Box plots for Symmetric Extremal Dependence Index (SEDI) for NCUM and NEPS form March to May 2016



Table 1. List of Abbreviations

EPS	Ensemble Prediction Systems
NCMRWF	National Centre for Medium Range Weather Forecasting
NEPS	NCMRWF Ensemble Prediction System
NCUM	NCMRWF Unified Model
NWP	Numerical Weather Prediction
MAM	March, April and May
<i>T_{max}</i>	Maximum Temperature
<i>T_{min}</i>	Minimum Temperature
IMD	Indian Meteorological Department
NDC	National Data Centre
ETKF	Ensemble Transform Kalman Filter
POD	Probability Of Detection
FAR	False alarm ratio
<u>HK</u>	<u>Hanssen and Kuipers</u>
ETS	Equitable Threat Score
SEDI	Symmetric Extremal Dependence Index
MP	Madhya Pradesh
UP	Uttar Pradesh
AP	Andhra Pradesh
SV	Singular Vector



Table 2. Causalities reported during MAM-2016 due to prevailing heat waves over India

Month	State/ Region	No. of loss of lives	Total
March	Maharashtra	1	2
	Kerala	1	
April	Odisha	88	220
	Telangana	79	
	AP	40	
	Maharashtra	9	
	Karnataka	1	
	Tamil Nadu	1	
May	Telangana	200	273
	Gujrat	39	
	Maharashtra	34	

Table 3. Monthly $T_{max} > 40^{\circ}\text{C}$ scores for NCUM and NEPS forecast with IMD observed temperature

Month	Score	NCUM					NEPS				
		Day 1	Day 3	Day 5	Day 7	Day 9	Day 1	Day 3	Day 5	Day 7	Day 9
MAR	POD	0.25	0.23	0.27	0.30	0.28	0.23	0.20	0.22	0.24	0.22
	FAR	0.81	0.71	0.75	0.75	0.79	0.49	0.54	0.53	0.53	0.43
	ETS	0.09	0.09	0.09	0.08	0.08	0.10	0.09	0.10	0.11	0.11
	HK	0.22	0.21	0.24	0.27	0.25	0.21	0.18	0.21	0.23	0.21
	SEDI	0.33	0.32	0.36	0.38	0.36	0.31	0.30	0.34	0.34	0.33
APR	POD	0.39	0.39	0.38	0.36	0.36	0.43	0.43	0.41	0.42	-
	FAR	0.66	0.65	0.66	0.66	0.66	0.62	0.61	0.62	0.61	0.62
	ETS	0.16	0.16	0.15	0.15	0.15	0.19	0.19	0.19	0.19	0.19
	HK	0.30	0.29	0.28	0.27	0.26	0.34	0.34	0.34	0.33	0.33
	SEDI	0.46	0.45	0.45	0.43	0.42	0.51	0.51	0.52	0.51	0.50
MAY	POD	0.30	0.30	0.28	0.26	0.24	0.32	0.34	0.31	0.31	0.27
	FAR	0.70	0.71	0.72	0.74	0.75	0.67	0.69	0.70	0.71	0.75
	ETS	0.12	0.11	0.11	0.10	0.09	0.14	0.14	0.13	0.12	0.10
	HK	0.22	0.22	0.21	0.19	0.17	0.25	0.26	0.24	0.23	0.19
	SEDI	0.39	0.38	0.36	0.33	0.30	0.43	0.43	0.40	0.39	0.33