

Bias-free rainfall forecast and temperature trend-based temperature forecast using T-170 model output during the monsoon season

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ABSTRACT: An objective forecasting system for medium-range location-specific forecasting of surface weather elements has been evolved at the National Centre for Medium Range Weather Forecasting, India (NCMRWF). The basic information used for this is the output from the T-170 general circulation model (GCM). The direct model output (DMO) forecast is briefly explained along with the T-170 model. The two important weather parameters considered in detail are rainfall and temperature. Both the parameters have biases. Techniques used for obtaining bias-free rainfall forecasts and temperature trend-based forecasts are explained in detail. These forecasts are obtained for all of the 602 districts of India. Finally, an evaluation of the accuracy of rainfall and temperature forecasts for selected districts for which the observed data could be obtained during the 2006 monsoon is presented. Copyright © 2007 Royal Meteorological Society

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1. Introduction

Historically, a weather forecast in India was mainly issued in qualitative terms with the use of conventional methods assisted by satellite data and synoptic information for the location of interest. These forecasts were subjective and could not be used for risk assessment in quantitative terms. Hence, work was initiated to develop an objective medium-range local weather forecasting system in India in 1988 at the National Centre for Medium Range Weather Forecasting (NCMRWF). An R-40 general circulation model with a resolution of $2.8^\circ \times 1.8^\circ$ was installed for this purpose in 1989 and a T-80 general circulation model with a higher resolution of $1.5^\circ \times 1.5^\circ$ was made operational in 1993. In 2002, a T-170 general circulation model with a still higher resolution $0.7^\circ \times 0.7^\circ$ was made experimentally operational.

An objective forecast is a forecast that does not depend on the subjective judgement of the person issuing it. Strictly speaking, an objective forecasting system is one that can produce one and only one forecast from a specific set of data. The objective forecast for the above surface parameters is directly obtained from the general circulation model operational at NCMRWF and is called the *direct model output* (DMO) forecast, as this forecast has the biases and systematic errors of the general circulation model. The work for removing biases and systematic errors from the most important weather

parameters has been undertaken. These forecasts are used operationally at NCMRWF for providing the final local weather forecast for these parameters at different locations. In the present paper, the bias-free DMO forecast using T-170 model output is explained in detail.

In Section 2, the T-170 model and the forecast for the important surface weather elements, which are directly obtained from the numerical weather prediction (NWP) model, are explained. In Section 3, the bias-free rainfall forecast is presented. Section 4 discusses the temperature forecast based on temperature trends in detail. Section 5 describes the evaluation of the forecast skill for the bias-free rainfall forecast and trend-based temperature forecast.

2. T-170 model and direct model output (DMO) forecast

2.1. T-170 model

The NCMRWF T-170/L28 global spectral model was developed in-house (Kar, 2002). It was based on the NCEP T80/L18 model (Kanamitsu, 1989; Kalnay *et al.*, 1990; Kanamitsu *et al.*, 1991) and subsequent changes were made to the T80/L18 model at NCMRWF. Atmospheric dynamics were based on primitive equations with vorticity, divergence, logarithm of surface pressure, specific humidity and virtual temperature as dependent variables.

In this model, horizontal representation is spectral (spherical harmonic basis functions) with transformation

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Table I. Brief description of T-170/L28 global spectral model.

Model elements	Components	Specifications
Grid	Horizontal	Global spectral-T-170 (512×256)
	Vertical	28 Sigma layers [$F = 0.995, 0.982, 0.964, 0.942, 0.915, 0.883, 0.845, 0.801, 0.750, 0.693, 0.632, 0.568, 0.501, 0.435, 0.372, 0.312, 0.258, 0.210, 0.168, 0.132, 0.102, 0.078, 0.058, 0.041, 0.028, 0.017, 0.009, 0.002$]
Dynamics	Topography	MEAN
	Prognostic variables	Relative vorticity, divergence, virtual temp., log of surface pressure, water vapour mixing ratio
	Horizontal transform	Orszag's technique
	Vertical differencing	Arakawa's energy-conserving scheme
Physics	Time differencing	Semi-implicit with 450 s of time step
	Time filtering	Robert's method
	Horizontal diffusion	Second order over quasi-pressure surfaces, scale selective
	Surface fluxes	Monin–Obukhov similarity
	Turbulent diffusion	Non-local closure
	Radiation	Short-wave: Harshvardhan <i>et al.</i> (NASA/Goddard) Long-wave- Fels and Schwarzkopf
	Deep convection	Kuo scheme modified
	Shallow convection	Tiedtke method
	Large-scale condensation	Manabe-modified scheme based on saturation
	Cloud generation	Slingo scheme
	Rainfall evaporation	Kessler's scheme
	Land surface processes	Pan scheme having a three-layer soil model for soil temperature and bucket hydrology of Manabe for soil moisture prediction
	Air–sea interaction	Roughness length over sea computed by Charnock's relation. Climatological SST*, bulk formulae for sensible and latent heat fluxes
Gravity wave drag	Lindzen and Pierrehumbert scheme	

to a Gaussian grid for calculation of non-linear quantities and physics. The horizontal resolution is spectral triangular truncation with 170 waves (T-170). In physical space, the horizontal resolution is of 512×256 grid size. This is roughly equivalent to $0.7^\circ \times 0.7^\circ$ latitude/longitude grid spacing. The vertical domain is from the surface to about 2.0 hPa, which is divided into 28 unequally spaced sigma layers (Kar, 2002). For a surface pressure of 1000 hPa, the lowest atmospheric level is at a pressure of about 995 hPa. The sigma layers in the model are represented as P/P_s , where P is the pressure at height at which the layer is defined and P_s is surface pressure. The layers are located in such a way that near the surface and near the tropopause the layers are closely spaced compared to the layers at other heights. This has been done to represent the turbulence near the Earth's surface and the temperature gradient near the tropopause realistically.

The model has a comprehensive physics package, which includes parameterization schemes for cumulus convection, shallow convection, radiation, planetary boundary layer, surface processes and gravity wave drag due to mountains.

The time integration scheme is semi-implicit. The time step is 7.5 min for computation of the dynamics and physics terms. However, full calculation of radiation (short-wave and long-wave) is done once every 6 h. This is to reduce computationally expensive full radiation computations. However, care has been taken to represent the diurnal cycle realistically by suitably interpolating

radiative heating and cooling to each time step. A complete description of the T-170 model is given in Tables I and II (Kar, 2002).

2.2. Model output

From the 512×256 Gaussian grid points of the T-170 model, an Indian window of size 50×50 grid (total number of 2500 grid points) covering India is considered,

Table II. Specifications of initial surface boundary fields and cloud parameters.

Fields	Land	Ocean
Surface temperature	Forecast	Observed
Soil moisture	Forecast	NA
Albedo	Climatology (S)	Climatology (S)
Snow cover	Forecast	Forecast
Roughness length	Climatology (S)	Forecast
Plant resistance	Climatology (S)	NA
Soil temperature	Forecast	NA
Deep soil temperature	Climatology (A)	NA
Convective cloud cover	Forecast	Forecast
Convective cloud bottom	Forecast	Forecast
Convective cloud top	Forecast	Forecast
Sea ice	NA	Observed

(S) Seasonal.

(A) Annual.

NA Not Available.

starting at 38.9°N latitude and 65.39°E longitude to 4.6°N latitude and 100.55°E longitude. For a particular day, 192 forecast values are obtained and the model is run for 5 days starting from 0000 UTC initial conditions.

The model output is obtained at each time step at 2500 grid points for the following six surface weather elements.

- Surface pressure (hPa)
- Rainfall rate (mm s^{-1})
- Zonal wind component at 3.048 m (ms^{-1})
- Meridional wind component at 3.048 m (ms^{-1})
- Temperature at 1.3716 m ($^{\circ}\text{C}$)
- Specific humidity at 1.3716 m (g g^{-1})

The cloud amount (%) is obtained from the model at 0000 UTC and 1200 UTC for each forecast day.

2.3. Interpolated forecast values

As the forecasts are obtained on the Gaussian grids and not at a particular location, the simplest way to obtain a forecast at a specific location is to use the interpolated value from the four grid points surrounding it. As the distances between any two grid points of a $0.7^{\circ} \times 0.7^{\circ}$ grid window are not very large, the simple formulation of the Bessel interpolation formula is used for obtaining the forecast values of a particular station location (Figure 1)

2.4. Direct model output (DMO) forecast

DMO forecast values (interpolated) for each location of interest are obtained. A 4-day forecast for the following parameters is obtained by using forecast values at each time step of 7.5 min.

- Average mean sea level pressure (hPa)
- Cloud amount (morning and evening) (okta)
- Rainfall (24 h accumulated) (mm)
- Maximum temperature ($^{\circ}\text{C}$)
- Minimum temperature ($^{\circ}\text{C}$)
- Average wind speed (ms^{-1})
- Predominant wind direction ($^{\circ}$)
- Maximum relative humidity (g g^{-1})
- Minimum relative humidity (g g^{-1})

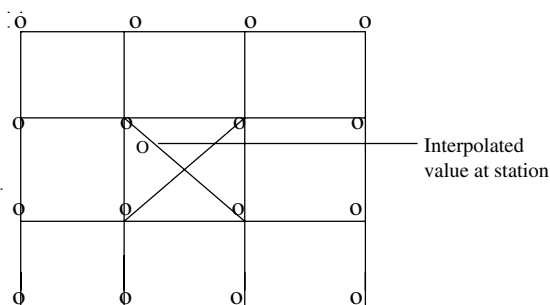


Figure 1. Area considered around a station for getting interpolated DMO forecast values.

Table III. State-specific HK scores attained and threshold values for T-170 model forecast.

SN	States/UT	Order of the HK scores attained	Threshold rainfall values (mm)
1	Andhra Pradesh	0.06–0.20	5.0
2	Assam	0.10–0.25	2.0
3	Arunachal Pradesh	0.08–0.26	2.0
4	Bihar	0.11–0.31	2.0
5	Chhattisgarh	0.20–0.43	2.0
6	Gujarat	0.25–0.46	0.5
7	Haryana	0.15–0.34	0.1
8	Himachal Pradesh	0.12–0.25	0.5
9	Jammu and Kashmir	0.10–0.20	0.5
10	Jharkhand	0.16–0.26	2.0
11	Karnataka	0.06–0.22	7.0
12	Kerala	0.08–0.15	7.0
13	Madhya Pradesh	0.24–0.49	1.0
14	Maharashtra	0.22–0.43	2.0
15	Manipur	0.10–0.23	2.0
16	Meghalaya	0.06–0.15	2.0
17	Mizoram	0.07–0.11	2.0
18	Nagaland	0.08–0.17	2.0
19	Orissa	0.15–0.34	2.0
20	Punjab	0.12–0.26	0.1
21	Rajasthan	0.21–0.39	0.1
22	Sikkim	0.09–0.16	2.0
23	Tamilnadu	0.05–0.26	5.0
24	Tripura	0.13–0.23	2.0
25	Uttaranchal	0.18–0.35	0.5
26	Uttar Pradesh	0.16–0.32	0.5
27	West Bengal	0.20–0.25	2.0
28	Delhi	0.40	0.1
29	Goa	0.26	2.0
30	Pondicherry	0.23	2.0
31	Lakshadweep	0.22	7.0
32	Daman and Diu	0.16	2.0
33	Dadra and Nagar	0.18	2.0
34	Chandigarh	0.29	0.1
35	Andaman and Nicobar	0.24	7.0

Here, the validity of the forecast values for a particular day is for the subsequent 24 h starting from 0300 UTC (0830 local time) of that day. As at the NCMRWF, the T-170 model is run only for 5 days based on 0000UTC analysis, hence only the 24-, 48-, 72- and 96-h forecasts can be obtained.

2.5. Bias-free DMO forecast

To obtain a bias-free DMO forecast during any season, the forecast and observed values of the prediction during the recent one or two seasons are considered and correction factors are obtained by a trial and error method so that the skill of the forecast is maximized. The same correction factors are used while obtaining the bias-free DMO forecast during the current season. During the present study, correction factors are calculated on the basis of monsoon seasons (June, July, August and September) of 2001, 2002 and 2003.

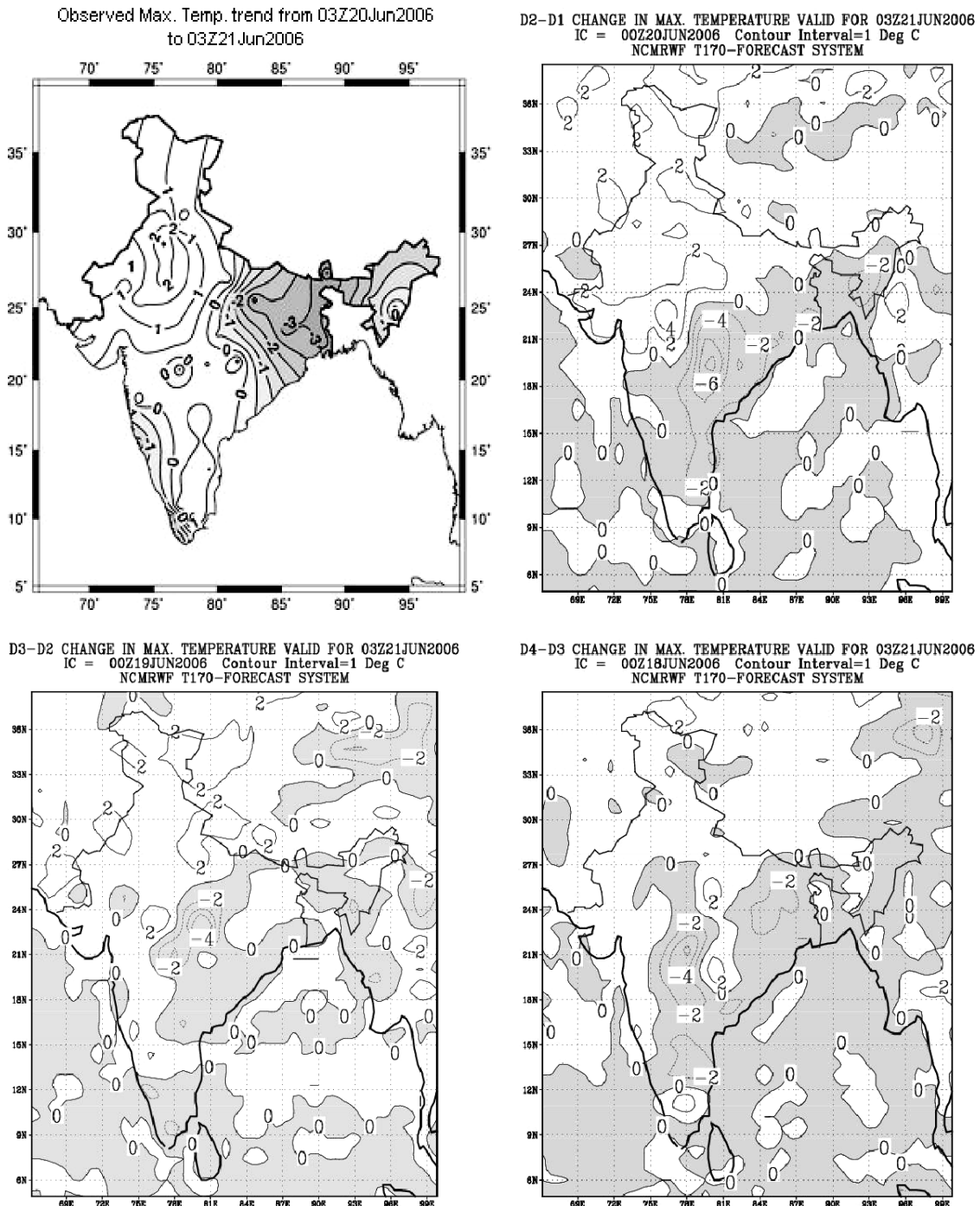


Figure 2. Observed and forecasted maximum temperature trends from 0300 UTC 20 June 2006 to 0300 UTC 21 June 2006.

3. Bias-free rainfall forecast

An optimal rainfall threshold value is set to maximize the skill score. The optimal threshold value means that if the forecasted rainfall amount is less than the threshold then the forecasted value is taken as a zero, otherwise it is taken as the forecasted rainfall amount. The optimal threshold is calculated as follows. Let the forecasted rainfall series during the seasons considered be denoted as R_{fi} , $i = 1, 2, \dots, n$, and Th be the threshold up to which the rainfall is taken as zero. Beyond the Th value, rainfall is taken as the actual value. Using the Th

value forecasted, yes/no rainfall series is derived from the forecasted rainfall series as follows:

- if $R_{fi} \leq Th$ then no rain case i.e. 0 (or N) case, and,
- if $R_{fi} > Th$ then rainfall case i.e. 1 (or Y) case.

Similarly, if the observed rainfall series during the seasons under consideration is denoted by R_{oi} , $i = 1, 2, \dots, n$, and the threshold value is 0.1 mm, the observed Yes/No rainfall series is derived from the observed rainfall series using similar logic.

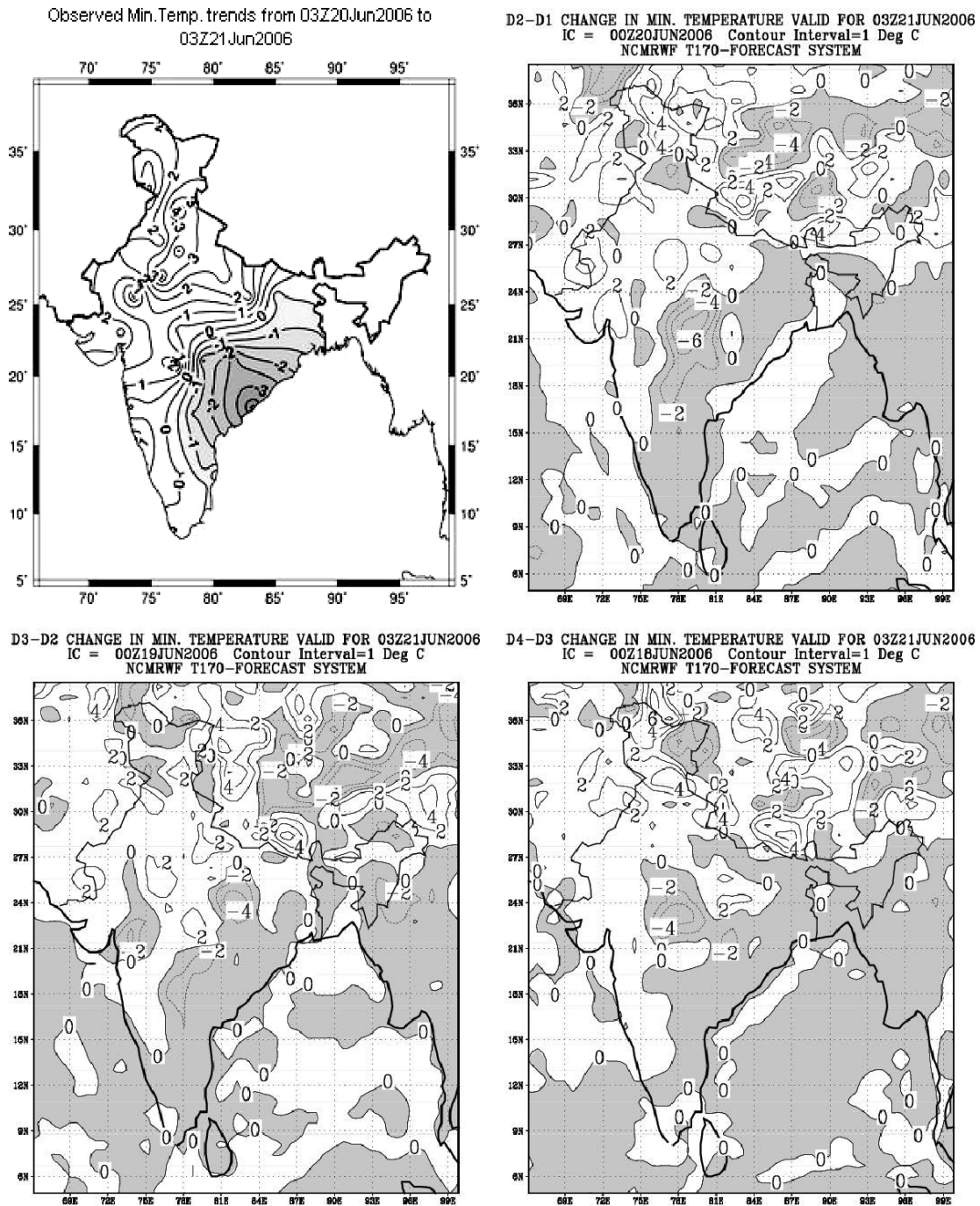


Figure 3. Observed and forecasted minimum temperature trends from 0300 UTC 20 June 2006 to 0300 UTC 21 June 2006.

As scores used for verification of the rainfall forecast are the ratio score and Hanssen and Kuipers (HK) skill score (Kumar *et al.*, 2000), the ratio score measures the percentage of correct forecasts out of the total forecasts issued. The HK skill score is the ratio of economic saving over climatology. Hence, the HK skill score is calculated by using the observed and forecasted yes/no rainfall series based on the data from the previous two to three seasons. The HK skill score is then maximized by varying the threshold (Th) value used for deriving forecasted yes/no rainfall series and the threshold value which maximizes the HK Skill Score during previous seasons is applied for deriving the yes/no rainfall forecast from the DMO

rainfall forecast during the current season. The maximum HK Skill Scores attained are given in Table III, and can be explained by the following contingency table.

Forecasted	Observed	
	Rain	No Rain
Rain	YY	YN
No rain	NY	NN

Ratio Score = $(YY + NN)/N$

HK skill score = $(YY*NN - YN*NY)/(YY + YN)*(NY + NN)$

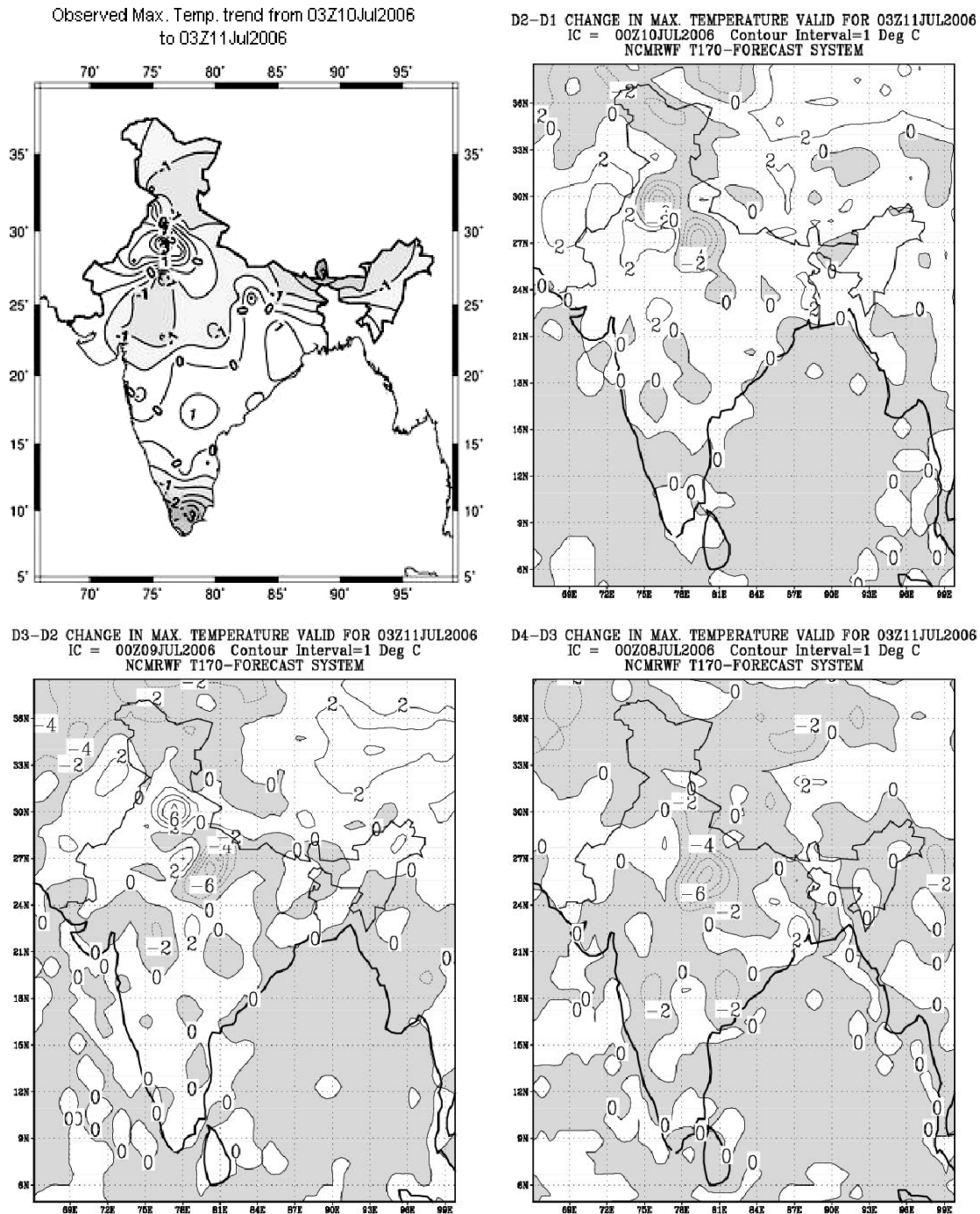


Figure 4. Observed and forecasted maximum temperature trends from 0300 UTC 10 July 2006 to 0300 UTC 11 July 2006.

If the HK skill score is closer to 1, the forecasts are better, and when the HK Score is near or less than 0 the forecasts are poorer.

In the present study, the rainfall threshold values are calculated, and representative values are derived for the stations of each state of India. These values are given in Table III.

4. Temperature trend-based temperature forecast

Let $T_f(I)$ and $T_o(I)$ be the forecasted and observed temperatures ($^{\circ}\text{C}$) respectively on day 1 ($I = 1, \dots, n$),

where n is the number of observations considered during the season. Forecasted temperature values are for 24, 48, 72 and 96 h forecasts from the T-170 model.

If $Td_f(I)$ and $Td_o(I)$ are the forecasted and observed temperature trends respectively on day 1 ($I = 1, \dots, n$), then

$$Td_f(I) = T_f(I) - T_f(I - 1) \tag{1}$$

$$Td_o(I) = T_o(I) - T_o(I - 1) \tag{2}$$

Let Tb_f and Tb_o be the minimum value of the forecasted and observed temperatures considered respectively

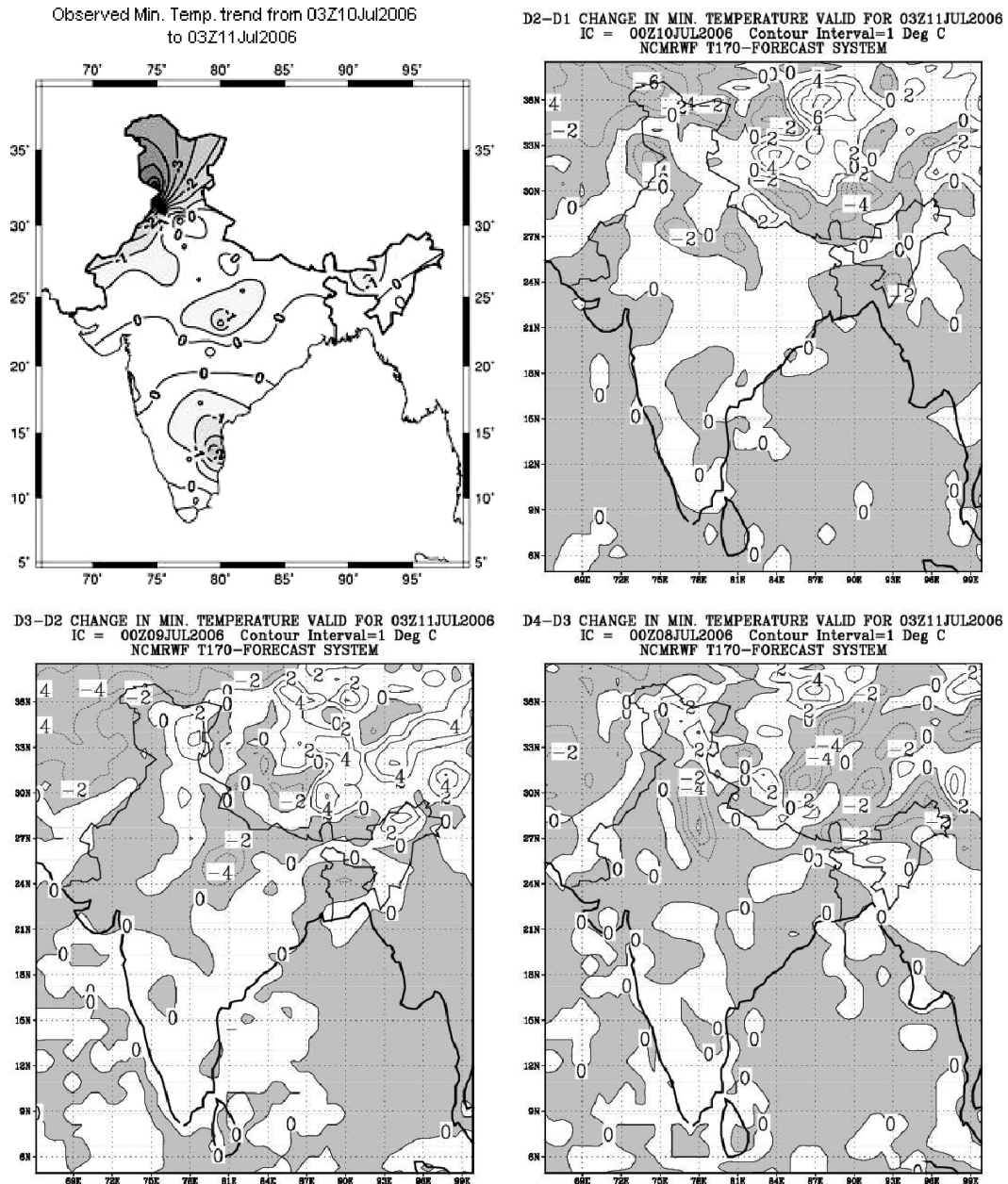


Figure 5. Observed and forecasted minimum temperature trends from 0300 UTC 10 July 2006 to 0300 UTC 11 July 2006.

and T_b the minimum of T_{b_f} and T_{b_o} . By considering T_b as the base value, the forecasted and observed temperatures can be represented in terms of the new series of positive values as follows:

$$T_f(I) = T_b + c(I) \tag{3}$$

$$T_o(I) = T_b + d(I) \tag{4}$$

where $c(I)$ and $d(I)$ are positive for all $I, I = 1, \dots, n$. Then, as

$$\sum_{I=2}^n (T_{d_f}(I) - T_{d_o}(I))^2 = \sum_{I=2}^n (((T_f(I) - T_f(I-1)) - (T_o(I) - T_o(I-1)))^2 \text{ (from Equation 1 and 2)}$$

$$\begin{aligned} &= \sum_{I=2}^n (((c(I) - c(I-1)) - (d(I) - d(I-1)))^2 \text{ (from Equation 3 and 4)} \\ &\leq \sum_{I=2}^n ((c(I) - d(I))^2 \text{ as } c(I) \text{ and } d(I) \text{ are positive for } I = 1, \dots, n \\ &\leq \sum_{I=1}^n ((c(I) - d(I))^2 \\ &= \sum_{I=1}^n ((c(I) + T_b) - (d(I) + T_b))^2 \\ &= \sum_{I=1}^n (T_f(I) - T_o(I))^2 \text{ (5) (from 3 and 4)} \end{aligned}$$

Table IV. Skill score for 24-h rainfall, maximum/minimum temp. during the June–September 2006 monsoon.

SN	Station	Rain		Max. temp.		Min. temp.	
		Ratio (%)	HK	RMSE	Corr	RMSE	Corr
1	Agartala	59	0.17	0.94	0.93	0.68	0.81
2	Ahmedabad	66	0.32	1.14	0.96	0.64	0.93
3	Akola	58	0.17	1.29	0.95	0.86	0.87
4	Allahabad	64	0.28	1.75	0.94	1.05	0.89
5	Ambala	64	0.17	1.99	0.88	1.13	0.93
6	Amritsar	61	0.10	1.98	0.92	1.56	0.90
7	Bhopal	74	0.49	1.28	0.97	0.99	0.90
8	Bikaner	52	0.14	1.65	0.90	1.42	0.92
9	Bangalore	60	0.06	0.87	0.84	0.62	0.87
10	Chennai	58	0.11	0.81	0.93	0.44	0.96
11	Coimbatore	65	0.21	0.93	0.84	0.54	0.78
12	Dehradun	58	0.23	1.66	0.88	0.96	0.86
13	Delhi	64	0.40	1.97	0.88	1.66	0.84
14	Gwalior	67	0.27	1.81	0.92	1.38	0.91
15	Hissar	57	0.31	2.06	0.89	1.72	0.85
16	Hyderabad	61	0.27	1.16	0.93	0.77	0.88
17	Imphal	68	0.18	0.62	0.95	0.87	0.72
18	Indore	66	0.36	1.56	0.95	1.19	0.90
19	Jabalpur	73	0.48	1.39	0.97	1.26	0.83
20	Jodhpur	68	0.42	1.47	0.95	1.19	0.90
21	Jaipur	52	0.10	1.74	0.91	1.27	0.88
22	Jammu	65	0.18	2.05	0.93	1.33	0.91
23	Kolkata	58	0.21	1.23	0.94	0.61	0.89
24	Lucknow	59	0.20	1.64	0.90	1.33	0.75
25	Ludhiana	72	0.34	1.89	0.93	1.24	0.93
26	Madurai	60	0.17	1.11	0.88	0.58	0.93
27	Mumbai	69	0.49	0.59	0.96	0.50	0.92
28	Nagpur	58	0.19	1.36	0.95	1.17	0.81
29	Patiala	62	0.18	2.00	0.90	1.23	0.93
30	Patna	57	0.15	1.62	0.89	1.09	0.79
31	Pune	72	0.34	0.97	0.95	0.60	0.84
32	Raipur	60	0.19	1.30	0.96	1.11	0.81
33	Ranchi	73	0.45	1.70	0.94	0.88	0.88
34	Shimla	59	0.21	1.81	0.85	0.99	0.88
35	Srinagar	68	0.46	1.46	0.96	1.20	0.96
36	Udaipur	64	0.36	1.15	0.97	0.80	0.92
37	Varanasi	57	0.17	1.64	0.94	1.13	0.71
38	Vishakhapatnam	56	0.10	0.81	0.92	0.52	0.94

Hence, from Equation (5) it is clear that the root mean square error (RMSE) for the observed and forecasted temperature trends is less than the RMSE for the observed and forecasted temperatures. This simple relation is due to the NWP model's bias (i.e. the tendency of the model to always over predict or under predict the temperatures). Hence, if the temperature trends are used, such biases are removed and do not contribute to the RMSE. Moreover, the accuracy of forecast trends is strengthened further by observing the marked resemblance between the observed temperature trends and the forecasted temperature trends for the 24, 48 and 72 forecasting hours between any two particular days, as given in Figures 2–5.

The temperature trend forecast is obtained for maximum and minimum temperature for all the 602 districts of India. The user can add the present-day temperature

to the trends in order to get the temperature forecasts for the future days.

5. Evaluation of the accuracy of the forecast

For evaluation of the accuracy of the forecast, the bias-free rainfall forecasts and temperature trend-based temperature forecasts based on the T-170 model are obtained for the selected districts from the 602 districts of India. These selected districts are the stations for which the observed data are easily available through the global telecommunication system (GTS). The verification study is conducted by using the forecasted and observed data during the monsoon of 2006. Ratio scores and the HK skill score are calculated for the rainfall forecast. Correlations and RMSEs are calculated for the maximum and minimum temperature forecasts.

Table V. Skill score for 48-h rainfall, maximum/minimum temperature during the June–September 2006 monsoon.

SN	Station	Rain		Max. temp.		Min. temp.	
		Ratio (%)	HK	RMSE	Corr	RMSE	Corr
1	Agartala	57	0.12	1.07	0.47	0.83	0.25
2	Ahmedabad	68	0.36	1.27	0.80	0.74	0.35
3	Akola	62	0.24	2.06	0.63	0.89	0.20
4	Allahabad	62	0.28	1.99	0.73	1.26	0.30
5	Ambala	66	0.22	2.42	0.51	1.42	0.15
6	Amritsar	65	0.17	2.62	0.48	1.78	0.21
7	Bhopal	72	0.47	2.58	0.46	1.14	0.19
8	Bikaner	52	0.19	1.99	0.59	1.64	0.32
9	Bangalore	59	0.05	0.94	0.54	0.68	0.12
10	Chennai	57	0.11	0.86	0.67	0.87	0.30
11	Coimbatore	65	0.13	1.14	0.39	0.71	0.20
12	Dehradun	59	0.26	2.10	0.54	1.25	0.23
13	Delhi	63	0.38	2.56	0.50	1.89	0.10
14	Gwalior	66	0.27	2.20	0.68	1.61	0.24
15	Hissar	56	0.23	2.58	0.46	2.00	0.19
16	Hyderabad	56	0.16	1.29	0.62	0.90	0.25
17	Imphal	66	0.15	0.80	0.49	1.04	0.25
18	Indore	68	0.38	1.60	0.83	1.06	0.21
19	Jabalpur	72	0.42	1.64	0.82	1.41	0.39
20	Jodhpur	64	0.31	1.83	0.64	1.42	0.29
21	Jaipur	52	0.15	2.10	0.67	1.56	0.19
22	Jammu	67	0.18	2.62	0.56	1.49	0.28
23	Kolkata	61	0.24	1.55	0.59	0.62	0.20
24	Lucknow	61	0.23	2.12	0.55	1.65	0.11
25	Ludhiana	72	0.34	2.44	0.52	1.53	0.22
26	Madurai	63	0.20	1.30	0.66	0.72	0.26
27	Mumbai	67	0.50	0.67	0.70	0.60	0.27
28	Nagpur	62	0.25	1.46	0.81	1.36	0.35
29	Patiala	66	0.23	2.46	0.49	1.52	0.20
30	Patna	56	0.14	2.01	0.60	1.43	0.15
31	Pune	73	0.39	1.06	0.74	0.66	0.14
32	Raipur	61	0.21	1.54	0.76	1.26	0.41
33	Ranchi	70	0.37	1.97	0.59	1.07	0.22
34	Shimla	62	0.27	2.25	0.39	1.29	0.08
35	Srinagar	68	0.44	1.91	0.52	1.29	0.46
36	Udaipur	64	0.34	1.38	0.78	0.95	0.31
37	Varanasi	57	0.18	1.98	0.64	1.37	0.24
38	Vishakhapatnam	54	0.05	0.86	0.49	0.61	0.43

These scores are shown in Tables IV–VI. In Table IV for the 24-h forecast, rainfall forecasts show the ratio scores up to 74% and HK skill score up to 0.48. Maximum temperatures show the RMSE varying from 0.52 to 2.05 and correlation from 0.84 to 0.96. Similarly, minimum temperatures show the RMSE varying from 0.44 to 1.66 and correlations from 0.71 to 0.96. For 48- and 72-h forecasts, similar scores are shown in Tables V and VI, but with slight variations.

The evaluation of accuracy scores has shown quite encouraging results and has proved that the bias-free rainfall forecasts and temperature trend-based temperature forecasts from the T-170 model are usable forecasts with high accuracy scores. The skill of the absolute surface temperature and rainfall forecasts directly obtained from the NWP model is not very high, as these two

weather parameters are highly dependent on local orography. However, the above study has shown that it is possible to forecast the temperature trend-based temperatures and bias-free rainfall forecast for yes/no cases with high accuracy by using the direct model output. Hence, it could easily be inferred that the variations in the day-to-day surface temperatures and rainfall and no-rainfall cases at a particular place could be forecasted well by an NWP model of moderately high resolution, say the T-170. The installation of a still higher resolution model, i.e. the T-254, at the NCMRWF in order to obtain forecasts of higher accuracy, is currently being planned.

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Table VI. Skill score for 72-h rainfall, maximum/minimum temperature during the June–September 2006 monsoon.

SN	Station	Rain		Max. temp.		Min. temp.	
		Ratio (%)	HK	RMSE	Corr	RMSE	Corr
1	Agartala	56	0.07	1.22	0.28	0.89	0.55
2	Ahmedabad	67	0.34	1.42	0.74	0.89	0.51
3	Akola	64	0.28	2.64	0.62	0.99	0.37
4	Allahabad	60	0.27	2.15	0.65	1.39	0.44
5	Ambala	66	0.25	2.75	0.37	1.56	0.34
6	Amritsar	62	0.11	2.98	0.33	1.99	0.33
7	Bhopal	70	0.42	2.57	0.50	1.34	0.19
8	Bikaner	59	0.18	2.19	0.45	1.80	0.48
9	Bangalore	57	0.02	0.98	0.36	0.75	0.47
10	Chennai	55	0.06	0.93	0.36	1.03	0.49
11	Coimbatore	63	0.03	1.19	0.27	0.81	0.50
12	Dehradun	59	0.25	2.43	0.42	1.41	0.29
13	Delhi	60	0.31	2.90	0.39	2.01	0.27
14	Gwalior	65	0.24	2.46	0.62	1.79	0.38
15	Hissar	56	0.19	2.90	0.31	2.18	0.36
16	Hyderabad	55	0.15	1.33	0.49	0.94	0.50
17	Imphal	63	0.10	0.85	0.34	1.07	0.51
18	Indore	68	0.39	1.72	0.78	1.15	0.44
19	Jabalpur	72	0.43	1.83	0.76	1.50	0.48
20	Jodhpur	67	0.29	2.01	0.54	1.61	0.51
21	Jaipur	52	0.16	2.32	0.58	1.74	0.42
22	Jammu	68	0.21	2.95	0.43	1.70	0.36
23	Kolkata	61	0.20	1.70	0.44	0.76	0.43
24	Lucknow	60	0.23	2.41	0.45	1.80	0.36
25	Ludhiana	69	0.28	2.78	0.38	1.75	0.33
26	Madurai	64	0.20	1.53	0.51	0.84	0.53
27	Mumbai	65	0.41	0.71	0.60	0.65	0.49
28	Nagpur	64	0.29	1.51	0.76	1.41	0.50
29	Patiala	64	0.19	2.78	0.34	1.72	0.34
30	Patna	57	0.16	2.23	0.42	1.63	0.38
31	Pune	72	0.35	1.17	0.67	0.70	0.44
32	Raipur	60	0.20	1.61	0.70	1.36	0.51
33	Ranchi	69	0.35	2.10	0.45	1.18	0.41
34	Shimla	62	0.27	2.55	0.25	1.49	0.28
35	Srinagar	66	0.39	2.12	0.35	1.52	0.54
36	Udaipur	64	0.33	1.55	0.71	1.19	0.50
37	Varanasi	55	0.17	2.15	0.53	1.43	0.39
38	Vishakhapatnam	54	0.05	0.94	0.34	0.67	0.61

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