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Verification of WRF forecasts with TRMM rainfall over India during monsoon 2010: CRA method

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सार – इस शोध पत्र में वर्ष 2010 के मॉनसून ऋतु के दौरान WRF (डब्ल्यू आर एफ) मॉडल पूर्वानुमान का सत्यापन 0.25° स्थानिक विभेदन पर दैनिक रूप से प्रेक्षित TRMM (टी आर एम एम) वर्षा के साथ किया गया है। औसत त्रुटियाँ तथा वर्गमूल औसत त्रुटियाँ जैसे सर्वमान्य स्कोर्स की गणना करने के लिए परंपरागत ग्रिड प्वांइट सत्यापन तकनीक को लगाया गया है। व्यापक रूप से इस्तेमाल किए जाने वाले सुनिश्चित कौशल स्कोर्स का भी प्रयोग सात भिन्न भिन्न वर्षा अवसीमाओं की गणना करने के लिए किया गया है। यह स्कोर्स केवल 7.5 मि.मी. अवसीमा में मॉडल के निष्पादन की सामान्य प्रकृति की जानकारी दे सकता है जो सामान्य श्रेणी की वर्षा से अधिक का पूर्वानुमान सटीकता में अपकर्ष को दर्शाता है। वर्षा पूर्वानुमान सत्यापन के लिए उद्देश्य अभिमुख निकटस्थ वर्षा क्षेत्र (CRA) विधि पर विचार किया गया है। इस विधि से यह भी संपुष्टि हुई है कि वर्षा की मात्रा में वृद्धि होने से मॉडल के कार्य निष्पादन में कमी आई है। ठीक इसी प्रकार निकटस्थ वर्षा क्षेत्र विधि में औसत वर्ग त्रुटि वियोजन स्पष्ट रूप से देखी गयी है। प्रेक्षण की तुलना में मॉडल पूर्वानुमान में बड़ी त्रुटि वर्षा की स्थिति अथवा घटना में विस्थापन के कारण हुई है। आमतौर पर इस मॉडल से दिन के 1 पूर्वानुमान में पैटर्न त्रुटिकी तुलना में मात्रात्मक त्रुटि का कम योगदान रहा है जबकि यह दिन के 2 पूर्वानुमानों के तुल्य रहा है। महत्वपूर्ण श्रेणी के ऑकड़ों का प्रयोग करके दिए गए निकटस्थ वर्षा क्षेत्रों के पूर्वानुमान 35.5 मि.मी. की अवसीमा में प्रेक्षित स्थितियों से 80 प्रतिशत से अधिक बार अच्छी तरह मेल खाते हैं और 64.5 मि.मी. की अवसीमाओं में पूरे मॉनसून के दौरान 50 प्रतिशत मेल खाते हैं। जब ऋतु के दौरान 10 भिन्न भिन्न तेज बौछारों वाली घटनाओं पर अलग से अध्ययन किया जाए तो पूर्वानुमान के मेल खाने की प्रतिशतता में और वृद्धि हो सकती है।

ABSTRACT. WRF model forecast during monsoon season 2010 have been verified with daily observed TRMM rainfall at 0.25° spatial resolution. Conventional grid-point verification technique has been deployed to calculate common scores like mean errors and root mean square errors. Widely used categorical skill scores have also been computed for seven different rainfall thresholds. The scores only could find the general nature of the model performance depicting the degradation of forecast accuracy exceeding moderate rainfall category with 7.5 mm threshold. Subsequently the object oriented contiguous rain area (CRA) method has been considered for rainfall forecast verification. The method also confirmed that the performance of the model deteriorates along with the increase in rainfall amount. At the same time, within CRA method, the decomposition of mean square error has clearly found out that the major error has been occurred due to displacement of rain object or event in the model forecast compared to observation. In general, volume error contributes less as compared to pattern error in day-1 forecasts of the model whereas they are comparable in day-2 forecasts. Applying statistically significant best-fit criteria, the forecast CRAs have been successfully matched to observed events more than 80% of the time for 35.5 mm threshold and 50% for 64.5 mm thresholds respectively during whole monsoon season. The percentage of match further increases when 10 different active spells of the season has been considered separately.

Key words – Contiguous rain area, WRF forecast, Forecast verification, TRMM rainfall.

1. Introduction

Forecasting of rainfall over India during summer monsoon season is the most challenging task for numerical weather prediction models. As the rain bearing systems of monsoon embedded in large scale flow portray non-linear scale interactions and variety of physical processes, their observed nature in terms of rainfall is still the subject of continual study. The rainfall forecasts of numerical weather prediction (NWP) model over the region are associated with the monsoon systems are being constantly verified for further improvement in the model. Many studies by several authors (Basu, 2005; Roy Bhowmik *et al*., 2006; Mandal *et al*., 2007; Roy Bhowmik and Durai, 2009) on rainfall verification over Indian peninsular region and its sub-regions during monsoon

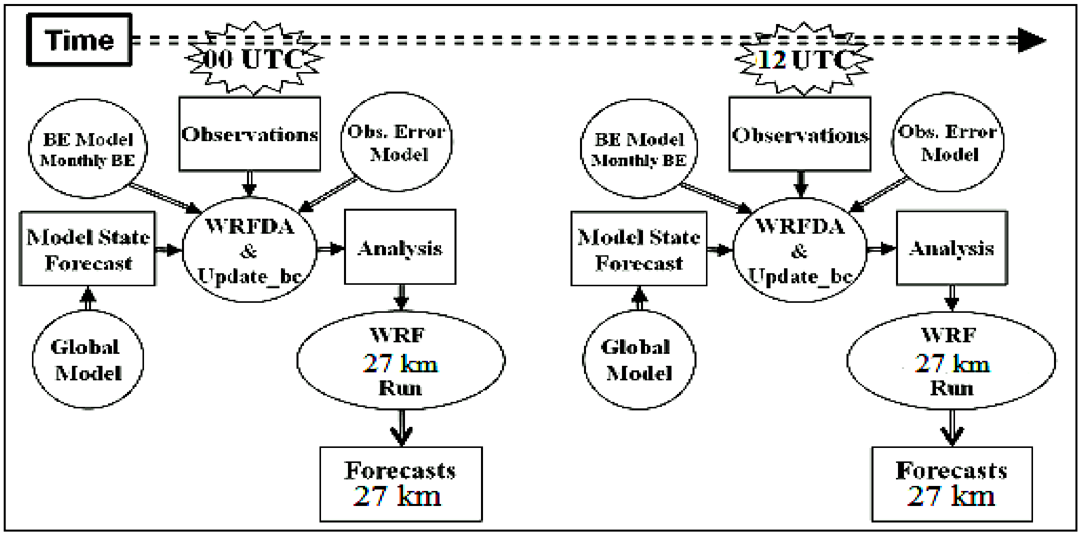


Fig. 1. The schematic diagram of the assimilation procedure of WRFDA-WRF-ARW system

season have been carried out considering different time and horizontal scales during monsoon for different kinds of models. Quantitative verification studies (Das *et al*., 2008; Ashrit and Mohandas, 2010) using categorical and continuous skill scores collectively portray inadequate picture for mesoscale forecasts. Categorical scores also could not bring reasonable picture for observed rainfall events with changing amount, *i.e*., the equitability of the score depends on the sample size of the verification dataset (Hogan *et al*., 2010).

WWRP/WGNE (World Weather Research Programme/Working Group of Numerical Experimentation (WMO, 2008) recommended about standardize verification of short range prediction of rainfall by NWP model. Accordingly, the verification of rainfall forecasts can be sought to improve forecast quality through better understanding of forecasts errors. There are various methods of verification alternative to point-wise comparison between forecast and observation. Applying three such different verification techniques for wind components (*e.g*., anomaly correlation, object-based verification and variance anomalies), Riffe and Davis (2005) illustrated the benefit of high-resolution over coarse grid structure of the model in terms of temporal error variance and realistic nature of error growth. Newly modified neighborhood verification approach (Ebert, 2008, fractions skill scores; Roberts and Lean, 2008) have advantages over the traditional metrics (*e.g*., root mean square error, mean error, correlation coefficient, skill scores and etc. Theis *et al*., 2005) but give credit only to the close forecasts. As mentioned in the recommendations (WMO, 2008), diagnostic methods give more in-depth information about the model performance. Simple methods using maps; time series; scatter plots; quantile-quantile or exceedance probability produce handy graphical results. But advance diagnostic methods have proven to be very much useful in evaluating deterministic models both in research and operational settings. Some examples include multi-scale spatial statistics, scale decomposition methods, field verification methods and object oriented methods. Harris *et al*. (2001) employed three methods of multiscale statistical analysis to assess model forecasts at high resolution for a convective storm using radar observations. Scale decomposition methods for precipitation forecasts define the intensity and scale of the errors, *e.g*., intensity based scale separation (Casati *et al*., 2004). For objective evaluation of a regional ensemble forecasting system Kiel and Craig (2007) proposed a technique based on pyramidal matching algorithm. Object oriented verification methods, *e.g*., Contiguous Rain Area (CRA) method (Ebert and McBride, 2000; Grams *et al*., 2006), Method for Object-based Diagnostic Evaluation (MODE) by Davis *et al*. (2006) and Structure-Amplitude-Location (SAL) method (Wernli *et al*., 2008) are feature based model evaluation and address the skill of forecasts for episodic and localized phenomena. In addition, the object oriented verification methods are basically designed for rainfall verification at high resolution and thus applicable for the performance evaluation of mesoscale models during monsoon season. Dube *et al*. (2014) compared the performances of two global models using CRA method while taking the rain objects associated with the heavy rainfall over Himalayan region.

In this paper, the quantitative verification of WRF-ARW model (operational in India Meteorological

Department - IMD) forecasts over Indian region for a whole monsoon season has been completed. The study is based on object-oriented CRA method described by Ebert and Gallus (2009). The method has employed using Tropical Rainfall Measuring Mission 3B42 Version 6 (TRMM 3B42V6) rainfall observations along with model forecasts with matching resolutions (temporal and spatial). The inference has been drawn on the basis of the results obtained during one monsoon season.

2. Data and methodology

2.1. *Model and data*

The regional mesoscale analysis and forecasting system WRFDA + WRF is installed for real-time use in IMD, Delhi with its different components (*i.e*., preprocessing program - WPS and REAL, assimilation program - WRFDA, boundary condition update - update_bc and forecasting model - WRF-ARW). The processed observational data from different sources are assimilated in WRFDA system to improve the first guess (Global Forecasting System analysis. Assimilation is done in a domain (23.2° S to 46.2° N; 39.6° E to 120.5° E) with 27 km horizontal resolution and 38 vertical eta levels up to 50 hPa pressure level at the top. The cold-start mode of assimilation is presently adopted for WRFDA system the schematic diagram of the same procedure is shown in Fig. 1. The above mentioned modeling system has been utilized to generate forecasts during whole monsoon season of 2010. The WRF model has then been integrated up to 51 hours twice a day at 0000 and 1200 UTC. The WRF model has been configured with full physics (including cloud microphysics, cumulus, planetary boundary layer and surface layer parameterization) as well. In the present study, only 0000 UTC model forecasts have been considered.

The verification experiments make use of available three hourly TRMM (3B42 V6) rainfall analyses and the forecasts operationally generated every day in IMD during monsoon 2010. The TRMM rainfall at horizontal resolution (0.25°) within a box (Latitude: from 6.5° N to 38.5° N and Longitude : from 66.5° E to 100.5° E) covering Indian region have been utilized in this study. Following the conventional practice in the region, the accumulation period of observed rainfall for a day is considered from 0300 UTC of a day to next day 0300 UTC. Over same specified region, the WRF-ARW forecast rainfall has been interpolated to 0.25° from its native 27 km resolution using bilinear interpolation. The accumulation period also has been matched with the observation.

TABLE 1

Classification of daily rainfall based on intensity

Descriptive term used	Category	Rainfall amount in mm
No Rain	I	0.0
Very light Rain	II	0.1- 2.4
Light Rain	III	2.5 – 7.5
Moderate Rain	IV	7.6 – 35.5
Rather Heavy	V	35.6 – 64.4
Heavy Rain	VI	64.5 – 124.4
Very Heavy Rain	VII	124.5 – 244.4
Extremely Heavy Rain	_	≥ 244.5
Exceptionally Heavy Rain		When the amount is a value near about the highest recorded rainfall at or near the station for the month or season.

2.2. *Verification*

The verifications using neighborhood technique with two different approaches have been completed with the grid-point analyses and up scaled forecast rainfall for whole India region. In first approach, the scores like mean error (ME), mean square error (MSE) and root mean square error (RMSE) have been computed along with two widely used two categorical skill scores (threat score - TS and equitable threat score - ETS) for seven rainfall thresholds. In next approach, objected oriented CRA method has been employed for verification over whole India region.

The CRA method utilized in this study has been developed following the technique described in a study by Ebert and Gallus (2009) but the realization of the steps of working algorithm are formulated according to the distinct features and characteristics of observed and forecast rainfall over the region during whole monsoon season. The rainfall threshold defined for CRA method have been selected on the basis of the nature and size the rainfall objects over the region. At the same time, the analysis through computed categorical scores has shown that the comparison of model performance between different thresholds could not bring out distinct differences and provided required information for the selection of threshold at the time of CRA verification.

The rain categories used in India Meteorological Department (described in Table 1) are used for the computation of categorical skill scores. The last two categories above very heavy rain class in the Table 1 are not considered for the verification purpose as their occurrences are limited over a region with comparatively

TABLE 2

Average sizes of CRA for different rain thresholds converted to equivalent square

Rainfall Thresholds in mm per day	Average no of adjacent points from 0.25° × 0.25° gridded data	Average size of CRA approximated to equivalent square area
2.4	1974	11° × 11°
7.5	876	7.5° × 7.5°
21.5	184	4° × 4°
35.5	68	2° × 2°
50	46	1.5° × 1.5°
64.5	38	1° × 1°

small spatial coverage throughout monsoon season 2010. At the same time, the previous studies (Ashrit and Mohandas, 2008; Das *et al*., 2008; Durai *et al*., 2010) also depicted that the NWP models always underestimated heavy rainfall events. The widespread rainfall over Indian region during the monsoon season showed few discontinuities, making it difficult to apply the CRA analysis at low thresholds. As a result, the computed spatial extent of the object (CRA) were too big for the rainfall categories 2.4 mm and 7.5 mm and therefore have not been considered in CRA method. The average sizes of the CRAs for different rainfall thresholds are given in Table 2.

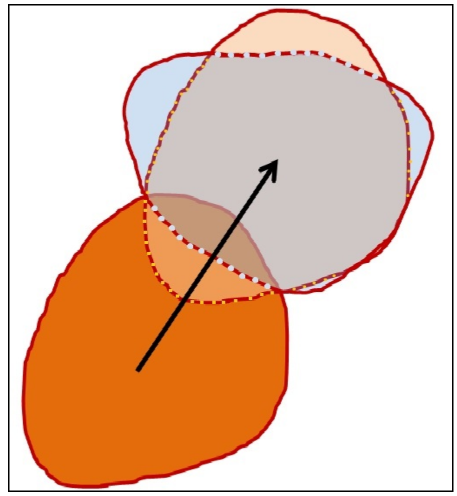


Fig. 2. CRA formed by the overlap of the forecast and observed rain areas. The area shaded in solid orange color shows the position of forecast template and final best fit position is shown in light orange shaded region. The observed template is shown in blue shade and the arrow is showing the direction of translation of the forecast CRA. The red outline surrounding the whole area shows the region for which verification statistics have been computed

Fig. 2 shows the schematic view of CRA formation which has been adopted from the work by Ebert and Gallus (2009). The figure is self-explanatory with the representation of forecast, observed field and merged fields. The working implementation of the CRA method for the present study has been formulated in the following steps.

(*i*) Both observed and forecast rainfall fields are merged by retaining greater value of rainfall at certain grid point.

(*ii*) Extract the grids points with rain value greater than or equal to a given threshold based on considered rainfall categories.

(*iii*) Flood fill (seed fill) algorithm has been employed to find contiguous rain area (a collection of grid points exceeding threshold adjacent to each other) from extracted grid points in previous step (*ii*).

(*iv*) For a certain rain threshold, the minimum size restriction (in terms of number of grid points) has been applied to select a CRA for further computation.

(*v*) The rectangular template from observed field according to horizontal span of the CRA zone (maximum and minimum value of latitude and longitude) has been defined for further procedural steps.

(*vi*) Sufficiently large search domain from forecast field has been created by extending the boundaries of the previously selected rectangular template in all the four sides. In present study, 1.5 times of observed template length and breadth have been enlarged to set the search domain. The maximum horizontal extension is limited to 5 degrees or less on each side.

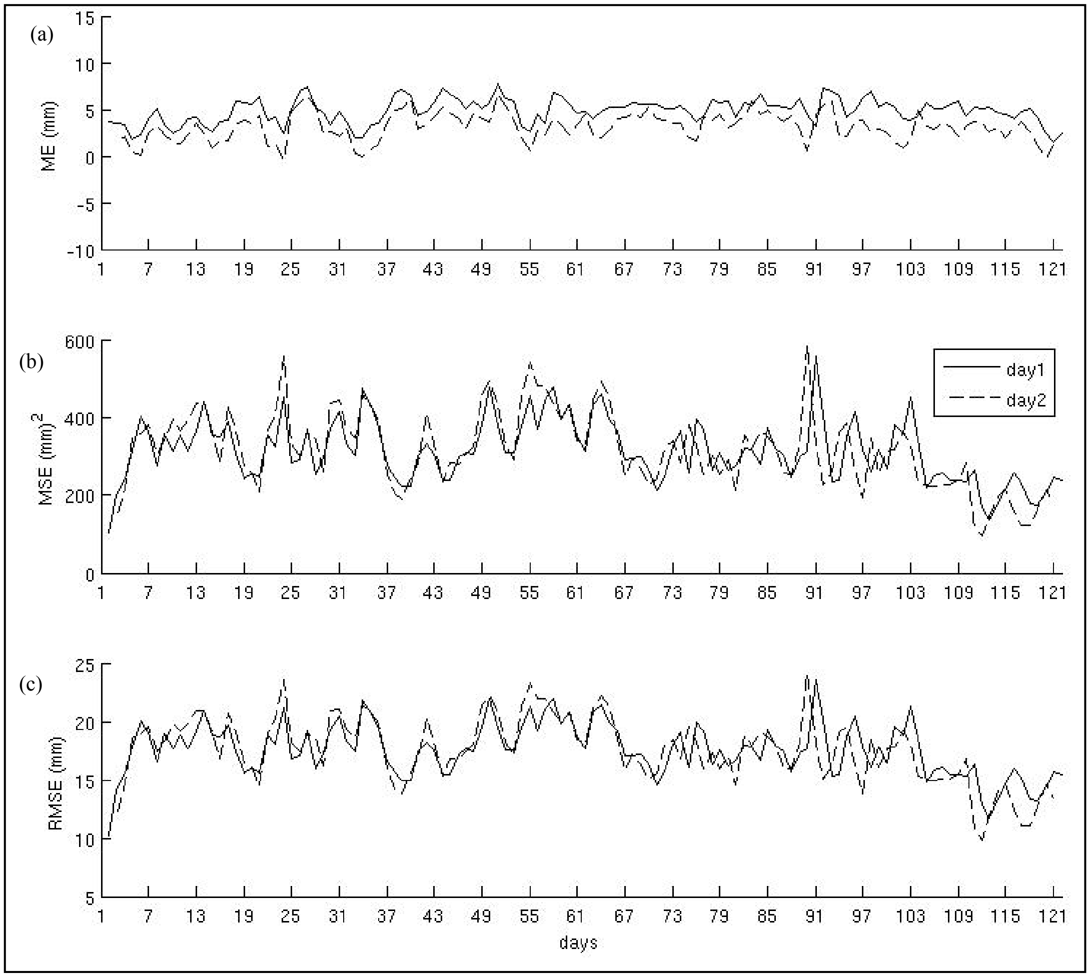
(*vii*) Consequently, observed template has been displaced over search domain of forecast field till best match criterion has been fulfilled, *i.e*., maximum spatial correlation coefficient has been reached.

(*viii*) Only those rain grid point information has been retained for which simultaneously both defined criteria (spatial correlation coefficient $\geq$ 0.3 and Mean Squared Error <1600 mm^2) has been satisfied.

(*ix*) Finally according to Ebert and McBride (2000), total mean square error in terms of percentage displacement, volume and pattern has been decomposed as

$$MSE_{total} = MSE_{displacement} + MSE_{volume} + MSE_{pattern.}$$

The decomposition procedure computes the displacement component as the difference in the mean



Figs. 3(a-c). Errors in rainfall forecasts averaged over whole India region (a) Mean error, (b) Mean square error and (c) Root mean square error (mm)

squared error before and after shifting the forecast, the volume error as the bias in mean intensity and the pattern error as a residual.

$MSE_{displacement} = MSE_{total} - MSE_{shifted}$,

$MSE_{volume} = \left(\overline{F} - \overline{X}\right)^2$ and

$MSE_{pattern} = MSE_{shifted} - MSE_{volume}$, where $\overline{F}$ and $\overline{X}$ are the mean forecast and observed values after the shift.

(*x*) But for the cases where MSE total< MSE shift, *i.e.*, %MSE displacement is negative the modified formula from Murphy (1995) have been utilized.

$$MSE_{total} = \left(\overline{F} - \overline{X}\right)^2 + \left(s_x - rs_F\right)^2 + \left(1 - r^2\right)s_F^2$$

where, s_F and s_x are the standard deviations for forecast and observed values respectively; and r is the original spatial correlation between the forecast and observed rain. Shifting the forecast template location improves its correlation with the observations to r_{opt}. The decomposition formula now become

$MSE_{displacement} = 2\, s_F\, s_x\, (r_{opt} - r)$

$MSE_{volume} = \left(\overline{F'} - \overline{X'}\right)^2$ and

$MSE_{pattern} = 2\, s_F\, s_x\, (1 - r_{opt}) + (s_F - s_x)^2$

Independently for each day of the season, all CRAs have been defined and then selected following the algorithm stated above for four selected thresholds (*i.e.*, 21.5, 35.5, 50.0 and 64.5 mm daily rainfall). The CRAs are stenciled separately for four different thresholds in a day and every individual CRA has been considered to make a match between observed and forecast fields. The forecast error for each CRA has been computed with three

TABLE 3

Selected spells during summer monsoon 2010

Spell No	Duration during 2010
1	7 - 9 June
2	5 - 7 July
3	19 - 22 July
4	24 - 27 July
5	30 July - 1 August
6	5 - 8 August
7	19 - 22 August
8	25 - 27 August
9	7 - 9 September
10	16 - 20 September

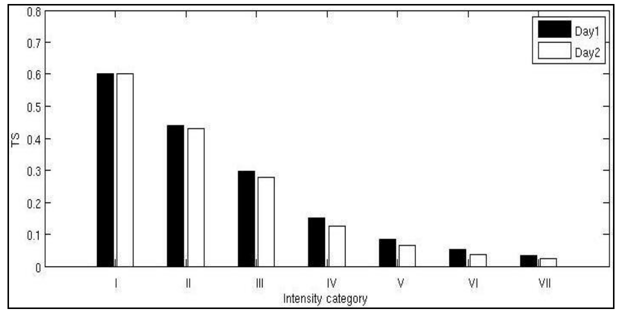


Fig. 4. Threat scores at different rainfall categories in rainfall forecasts averaged over whole India region

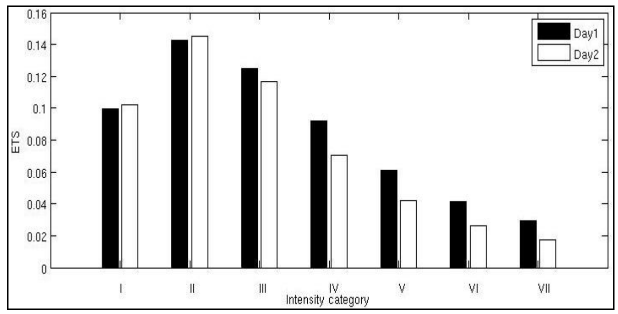


Fig. 5. Equitable threat scores at different rainfall categories in rainfall forecasts averaged over whole India region

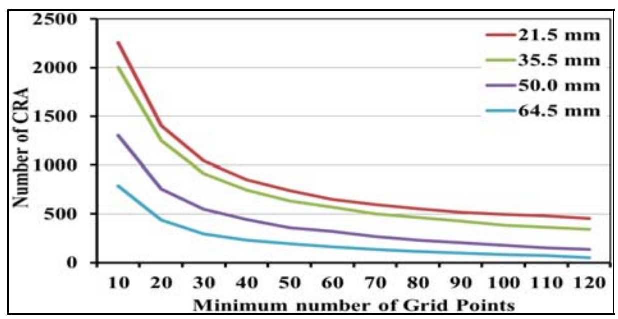


Fig. 6. Variation in numbers of CRA at day-1 forecasts over whole India domain during the season with varying thresholds in rainfall amount and minimum number of grid points in a CRA. for 21.5, 35.5, 50 and 64.4 mm rainfall thresholds

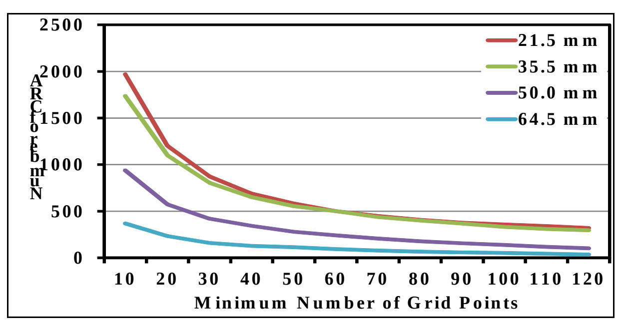


Fig. 7. Same as figure 6 but for day 2 forecasts

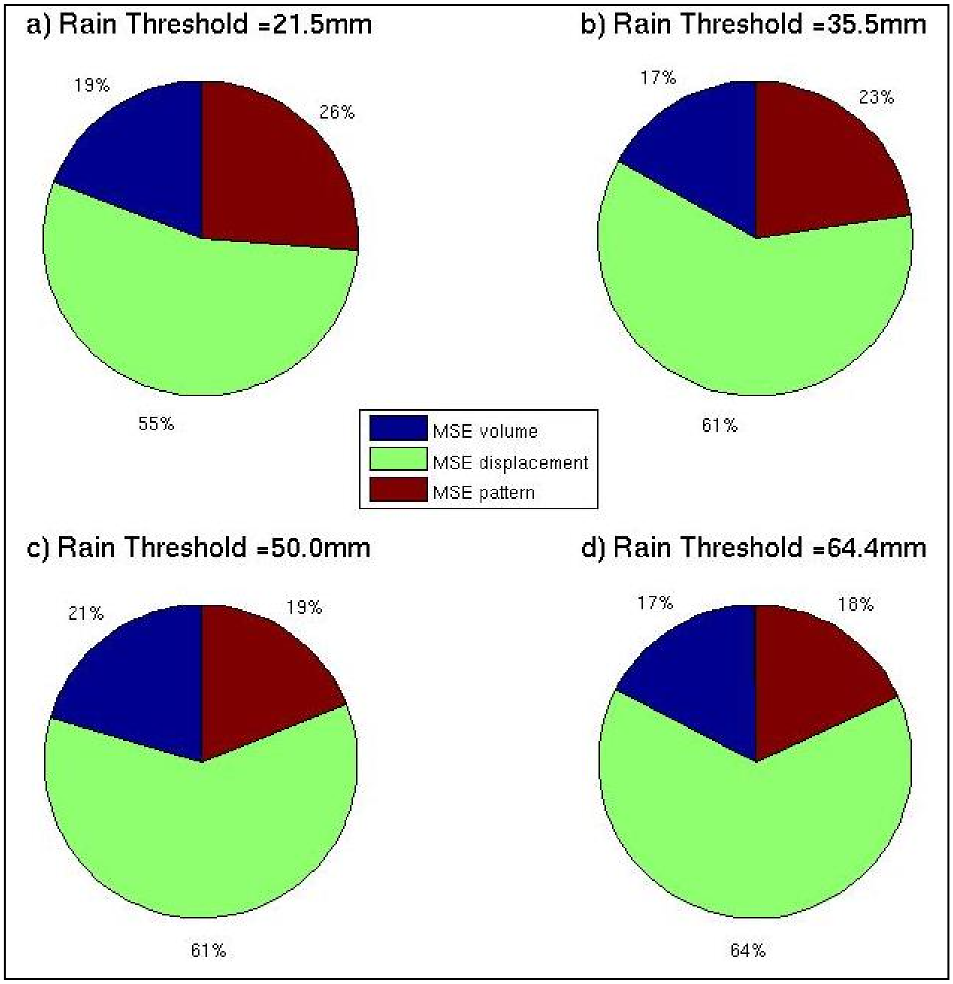
partitions, *i.e.*, displacement, pattern and volume errors. The mean value has been computed considering all CRAs for a certain threshold happened during the season irrespective of their locations and the days of occurrence. The CRA method has been employed separately for day-1 and day-2 forecasts. The average statistics of CRA for all days during whole monsoon season has been computed from each day CRA scores.

Ten different spells of monsoon season have been when the monsoon was active over Indian region and the all India total rainfall exceeded climatological normal of the same. The specific durations have been mentioned in Table 3. The CRA method has been employed to find the matches between observation and model forecasts for each rain object separately putting the matching criteria described above. A rain object found in observation has been searched in the forecast, and the match or HIT case for the model forecast has been considered when the forecast CRA after shifting produce optimal spatial correlation with respective observed CRA. On the contrary, it is a MIS. The reverse search has not been considered, *i.e.*, a rain object found in forecast has not been searched in the observation. For the days in all different 10 spells, the number of HITs and MISes has been counted separately for four different thresholds.

3. Results and discussion

3.1. *Verification scores for rainfall*

Verification of forecast rainfall with observed analysis has been done for Indian region considering whole monsoon period JJAS 2010 on the basis of standard scores such as RMSE, ME, MSE which has been computed and summarized for day-1 (27 hour) and day-2 (51 hour) forecasts. The scores mentioned above are computed daily taking average over the region to show

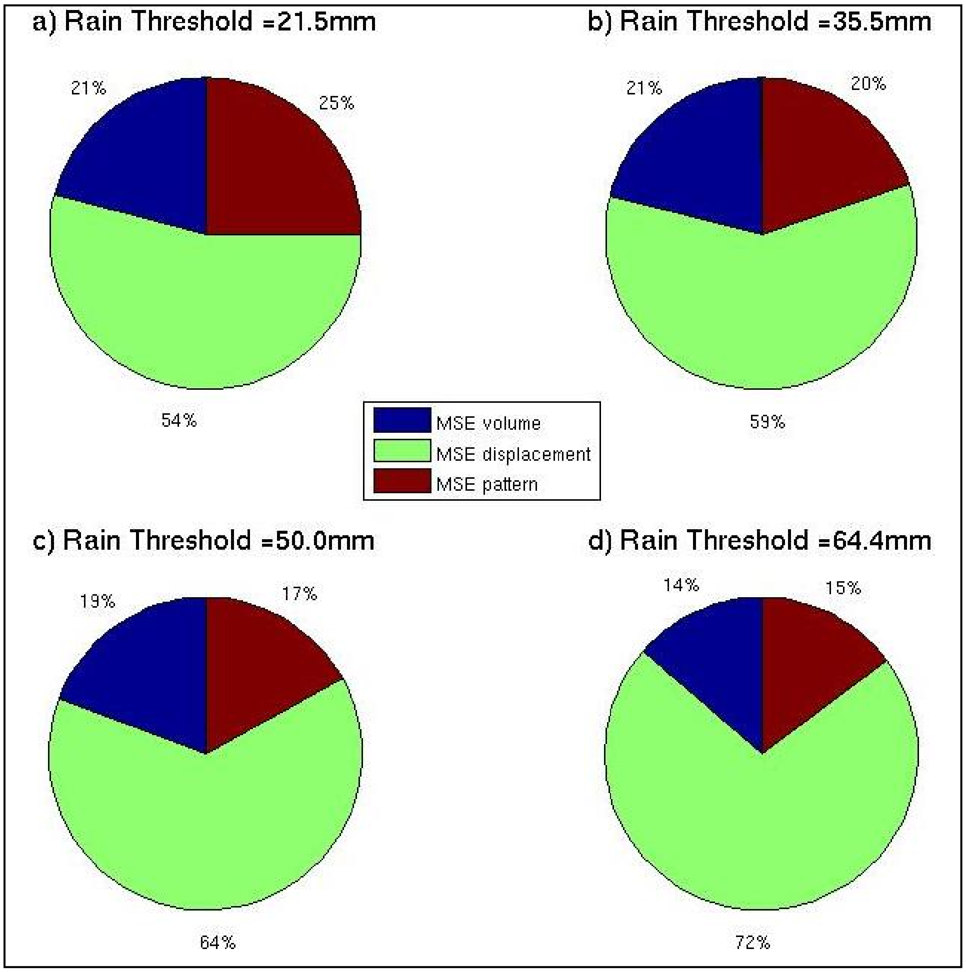


Figs. 8(a-d). Pie chart of volume, displacement and pattern mean square errors in day-1 forecasts for different rainfall thresholds for (a) 21.5 mm (b) 35.5 mm (c) 50.0 mm and (d) 64.4 mm

time series of the errors in Figs. 3(a-c). The time series graphs of model performance for day-1 and day-2 forecasts do not show any specific feature during whole monsoon season rather the systematic error is less than its random error. Fig. 3(a) shows that the rainfall is overestimated by the model in day-1 (~ 5 mm) which is reduced in day-2 forecast (~2.0 mm). But, there is no significant improvement in RMSE with forecast hours. The model errors (MSE and RMSE) vary in day to day forecasts and the systematic contribution in the error is less compared to its randomness.

Although, model produce positively biased rainfall over every region throughout the season, the small values of mean error compared to MAE and RMSE depict the randomness of the error. The errors also enhances over the region of higher rainfall, *e.g.*, west-coast and north-eastern states. The order of errors does not portray any significant differences between different forecast lengths and specifically, day-2 have little higher values compared to day-1.

In our study, the description has been limited to two specific categorical skill scores Threat Score (TS) and Equitable Threat Score (ETS) also known as critical success index and Gilbert skill score respectively. The domain average scores have been computed daily considering all grid points over the region. The finally seasonal mean values of the scores have been derived separately for each threshold. The TS for seven threshold valued of rainfall masked over whole Indian domain shown in Fig. 4 depicted well-known characteristics of the score. The TS score degraded with an increase in rainfall intensity. The model performed poorly for the rain thresholds above 35.5 mm as the TS value approach to zero (no skill value). The ETS score has also been plotted in a similar manner in Fig. 5 and it approaches to zero (no skill value) as rainfall amount rises above 35.5 mm and



Figs. 9(a-d). Same as figure 8 but for day-2 forecasts

the values of the score far below 1.0 associated with correct forecast. The ETS score is portraying inadequate picture about the model performance. In their study, Bousquet *et al*. (2006) indicated that these scores at higher resolution could not give necessary picture for verification and ability of phase correction and filtering over scales are necessary. As usual, model provides best performance in predicting rain and no-rain events (considering threshold of 0.1 mm). These two scores over whole India region signify that the model performed poorly above moderate (7.5 mm) rainfall amount (with TS below 0.1 and ETS below 0.05) which is also in agreement with other previous verification studies with models over the region (Ashrit and Mohandas, 2010; Mandal *et al*., 2007).

The mean error, root mean square error gives performance measure of the model in absolute sense and do not ensure the specific nature of the model forecasts over the region. Categorical skill scores have treated the model forecasts with double penalty as the model could not forecast rainfall events location (grid coverage) with absolute accuracy. Therefore, the displacement of the rain event in the model forecast from the observed location leads to the fact that the grid points with observed rainfalldo not show rainfall in the model forecast and vice versa. Then, the total error in model forecasts is primarily the displacement error added with the errors in pattern and intensity of rainfall. In the next section, the results of verification with an object oriented method have been discussed.

3.2. *Verification with CRA method*

The experiments have been conducted for the model forecasts with different thresholds to determine the minimum size of the CRA for certain rainfall category. The variation in the number of CRA detected within the forecast and observed rainfall distribution during the season have been noticed as the required minimum number of grid point changes. Figs. 6 and 7 show that the

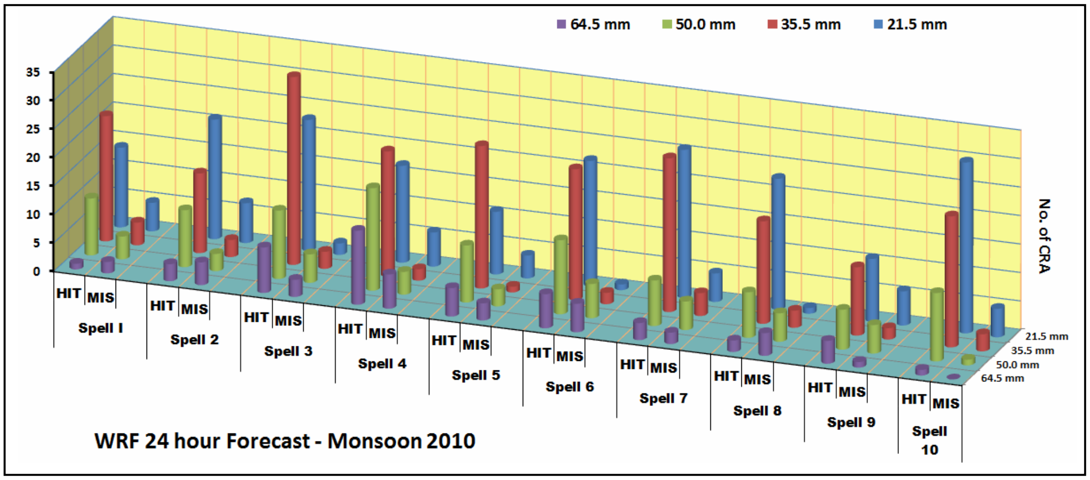


Fig. 10. Number of observed CRA and number matches found (HIT) or no matches found (MISS) in the day-1 forecasts for different thresholds of rainfall

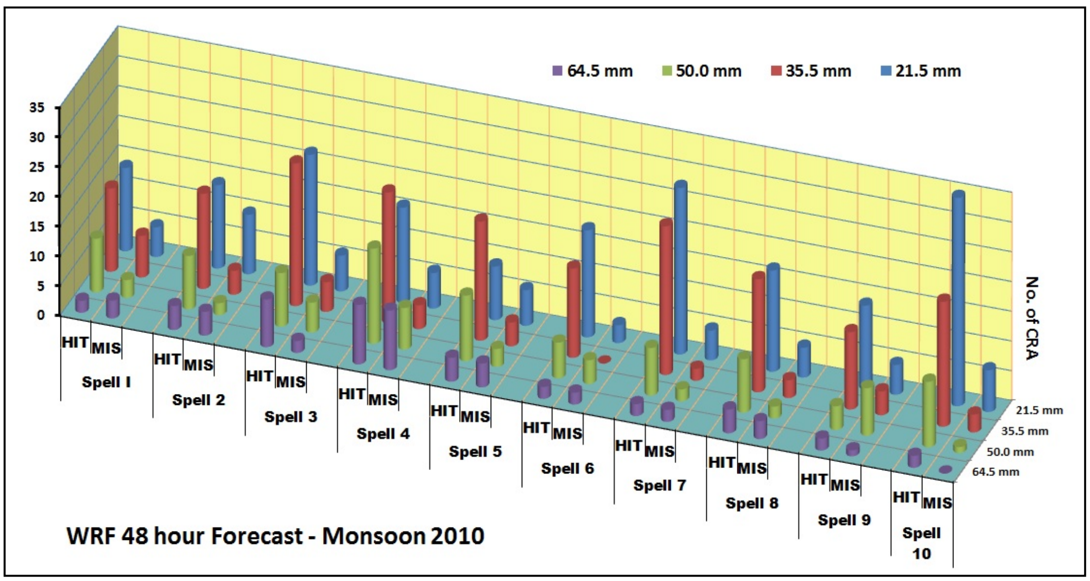


Fig. 11. Same as figure 10 but for day-2 forecast

number of CRA for all thresholds decreases steadily with an increase in grid points for both day-1 and day-2 forecasts respectively. As we restrict the size of CRA, the increase in intensity threshold focuses more on the peak rain areas rather than the broad rain areas. Alongside, for small CRA over the specific region the selection of best match between observation and forecast is also difficult. The larger size also restricts to put best-fit criteria in a rather stringent manner. Although, the slope and number of CRA are not same for day-1 and day-2, but their overall nature is same for each threshold. The number of CRA increases rapidly as the number grid points drops below 20 for all thresholds. When the minimum size of CRA is set above 20 number of grid points, the number of CRA decreases slowly for all categories. Therefore, for all rain thresholds, a common optimal size has been selected based on the curves in Figs. 6 and 7. The computation has been completed with a minimum size of CRA consisting at least 20 grid points for all days of the season.

The Figs. 8 and 9 depicted the decomposition of MSE in day-1 and day-2 rainfall forecasts respectively for different thresholds during whole monsoon season of 2010. The Fig. 8 represents the seasonal day-1 error partitions for four rain thresholds. From the pie charts it is clear that the maximum error is due to

TABLE 4

Percentage of matches between observed CRA and forecasts and average absolute linear displacement of CRAs for different thresholds of rainfall

Rainfall threshold category (mm)	Match (HIT) in forecasts (%)				Average linear displacement in forecasts (degree)			
	Day-1		Day-2		Day-1		Day-2	
	Spell	Season	Spell	Season	Spell	Season	Spell	Season
21.5	82.5	80.9	76.3	76.5	2.7	2.6	2.8	2.7
35.5	89.5	87.4	84.0	84.7	2.8	2.7	3.0	2.9
50.0	72.9	77.0	71.3	68.8	2.4	2.6	3.1	2.9
64.4	60.5	54.9	56.3	51.7	2.7	2.6	2.5	2.9

displacement irrespective of rainfall amount. More than half of the forecast error arises due to the displacement of the rainfall objects in the forecast from their observed positions. The day-2 has also found to follow similar characteristics in Fig. 10. In day-1 forecasts, the error contribution of pattern mismatch is always found to be greater than volume error for all rain thresholds. In other words, the day-1 forecasts of the model maintain consistent relations among the components of MSE for all rain thresholds. The least error occurred due to rain intensity estimation, highest error values because of displacement and pattern mismatch errors were in between them. But the similar behavior has not been portrayed by day-2 forecasts. The volume and pattern errors have nearly similar significance within total forecast error for two rain thresholds (35.5 and 50 mm) but they are irregular for other two. This typifies the fact that the model forecasts lose coherence between structure and intensity for certain CRAs in day-2 forecasts. Thorough inspections yield that the volume error shows a little increasing trend with rainfall amount. Although, the displacement plays the major role in model performance but portrays different characteristics for different thresholds (also not homogeneous over the spatial extent of the region). This implies that the model has comparatively poor skill for higher rainfall amount but does not provide any obvious information about forecast bias (systematic error) towards rainfall amount. The major share of displacement error also shows an increase from 21.5 mm to 35.5 mm threshold but decreases thereafter in both forecasts hours (day-1 and day-2).

The results of match between observed and forecast CRAs for ten spells are displayed in Figs. 10 and 11 for day-1 and day-2 forecasts respectively. Different colors correspond to various rain thresholds. Two series of bar graphs side by side are representing total HIT and MIS numbers for a certain spell. Both figures show that the number of HIT reduces along with the increase in rainfall threshold. The figures also show that the match percentage is higher at 35.5 mm category compared 21.5 mm although total number of observed CRA decreases considerably. The poor match percentage at higher rainfall is very much clearly seen for both forecast hours. For a few spells, the MIS number exceeds HIT although total numbers of CRA are very less at higher thresholds. The comparison between forecast hours while carried out spell by spell, shows the percentage HIT is more in day-1 compared to day-2 up to rainfall threshold of 50 mm whereas MIS exceeds HIT numbers for several spells.

The Table 4 also summarizes the percentage of matches (HIT) found in case spells and whole season for day-1 and day-2 forecasts considering four different thresholds. It is also obvious that during whole season, the day-1 forecast of the model shows the superiority over day-2 for each category. The percentage HIT increases during active spells of monsoon compared with whole season. The average percentage match for rain objects between observation and forecast is found to above 50% for 64.4 mm rain threshold which increases towards lower rainfall amount for both day-1 and day-2 forecasts. The HIT percentages are above 80% for 35.5 mm.

The average linear displacements of the center of mass of forecast CRAs from their corresponding matches in observation has been computed for each 4 rain thresholds (right most 4 columns shown in Table 4). It is found that the order of average linear shift does not change drastically with rain intensity but a marginal increase has been found from day-1 to day-2. The significant difference also not has been found between the values for spells and season. Because, the computation of mean have considered comparatively large number of CRA for lower thresholds (number of CRA falls with an increase in rain intensity shown in Figs. 6 and 7). The average size of rain objects also shrinks for higher amount which in turn produce less error in locating the center of mass of each CRA compared to lower threshold.

4. Conclusion

The present study attempted to utilize the strength of the object oriented CRA method for rainfall verification to get an insight of the forecast error in terms of displacement, pattern and volume. The common verification scores like ME and RMSE along with categorical skill scores could bring out a few facts regarding model performance such as :

(*i*) The errors in rainfall forecasts are random in nature but overall overestimation has been found during the whole season which is marginally reduced in day-2 forecast from day-1.

(*ii*) Categorical skill scores show that the model performance declines and shows poor performance exceeding moderate rainfall category (with TS below 0.1 and ETS below 0.05).

(*iii*) Model performed poorly for heavy rainfall categories which have also been found in previous studies.

But, an insight in the model performance has been achieved applying CRA method and decomposed MSE have explained the comparative error contribution amongst displacement, pattern and volume. The following facts have been brought out after using the specific object oriented verification.

(*i*) The model performance has shown evident decline in model performance with time and also with increasing rainfall intensity.

(*ii*) Still, the match between observed and forecast CRAs is above 70 per cent when best-fit criteria have been deployed up to 50 mm rainfall threshold throughout the season and during active spells over whole India.

(*iii*) The displacement error has the major share within total MSE irrespective of forecast duration or rainfall threshold.

(*iv*) The day-1 forecasts of the model are more consistent in terms of the relative amplitudes of three different partitions of total MSE with varying threshold, but the regularity diminishes in day-2 forecasts.

(*v*) The mean displacement (shifting) of forecast CRA from the respecting match in observed field does not vary significantly with rain intensity but a certain increase have been noticed from day-1 to day-2 forecast.

The study only shows the beneficial use of CRA method for the verification of mesoscale forecasts. The CRA verification using rainfall analyses with higher horizontal and temporal resolution is expected to be more critical about model performance. Ten different active spells have been considered in the study to find out existing variation of CRA nature during the specified duration compared to seasonal average. But, performance of the model does not differ very much from average picture.

Furthermore, in continuation, future studies will consider the dependency of model performance over spatial heterogeneity over different geographical regions. Different spells (active or subdued) of several monsoon seasons may also be studied to bring out specific nature of the model forecasts over temporal scales.

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