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Improving precipitation forecasts skill over India using a multi-model ensemble technique

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In this paper a Multi-Model Ensemble (MME) technique is experimented for improving day to day rainfall forecast over India in short to medium range time scale during summer monsoon of 2010. Four operational global Numerical Weather Prediction (NWP) models namely, ECMWF, JMA, NCEP GFS and UKMO available on real time basis at India Meteorological Department (IMD), New Delhi are used simultaneously with appropriate weights to obtain the MME Technique. In this technique, weights for each NWP model at each grid point is assigned on the basis of the correlation coefficient (CC) between model forecasts and observed daily rainfall time series of south west monsoon (JJAS) season. Apart from MME, a simple ensemble mean (ENSM) forecast are also generated and experimented. The rainfall prediction skill of the weighted MME is examined against ENSM and member models. The inter-comparison reveals that the weighted MME is able to provide more accurate forecast of rainfall over Indian monsoon region by taking the strength of each constituent member model. It has been further found that the rainfall prediction skill of MME is higher as compared to ENSM and member models in the short range time scale. The rainfall prediction skill of weighted MME technique improved significantly over India.

Keywords: numerical weather prediction, multi-model ensemble (MME) forecasting, rainfall prediction skill, global model

1. Introduction

For the generation of day to day operational quantitative rainfall forecasts, one has to depend on Numerical Weather Prediction (NWP) model outputs. The current deterministic NWP models have acquired greater skill in forecasting upper atmospheric weather parameters in short to medium range time scale. But the prediction skill of NWP model for surface variables is lower as compared to upper atmospheric weather parameters. The foundation of these NWP models are deterministic model based on some initial conditions, which neglect small scale effects and also approximate complicated physical processes and interactions. The models lose skill due to the growth of the inevitable uncertainty in the initial conditions and modeling system. These uncertainties in the data assimilation system could be due to the errors in the prescribed initial conditions, which may arise from observational instruments, satellite estimates and the data assimilation techniques. Due to said uncertainties in the data assimilation and modeling system, the forecast error increase as the forecast length increases.

In order to overcome these shortcomings in the NWP modeling system, a new approach known as ensemble forecasting was introduced in the 1990s (Toth and Kalnay, 1997; Molteni et al., 1996). In this method, forecasts are made either with different models or different initial conditions or both and are combined into a single forecast. If we have an ensemble of forecasts we can say something extra about the reliability of the forecasts to the user community. Clustering of several NWP model forecasts is also useful. The ensemble forecast might give some extra clue on the extreme episode compared to one single model forecast. In ensemble forecasting, the main issue relates to the removal of the collective errors of multi-models. The major drawback of the straight average approach of assigning an equal weight of 1.0 to each model is that it may include several poor models. The average of these poor models degrades the overall results.

To address this problem of ensemble forecasting, Krishnamurti et al. (1999; 2000) introduced a Multimodel super ensemble technique that shows a major improvement in the prediction skill. In the super ensemble approach, weight is assigned to each model based on spatial and temporal performance of respective models. The strategy for the Multimodel super ensemble involves two phases: training period and forecast phase. In the first phase, one utilizes the multi-model and observed fields to derive statistics and in the second phase, one utilizes the multi-model forecast and aforementioned statistics to obtain the final super ensemble forecast. Roy Bhowmik and Durai (2010; 2012) used the Correlation Coefficient (CC) method to find weights for member model and then make a MME forecast. However, the benefit of giving weights to member models over a simple ensemble mean was not documented there. In another recent study, the Multimodel super Ensemble precipitation forecast for Indian monsoon was reported by Krishnamurti et al. (2009), Mitra et al. (2011) and Kumar et al. (2012). The authors claimed that the super ensemble is able to produce the lowest root mean square error (RMSE) and skill improvement over the best model.

In the present study, a weighted MME technique similar to that of Roy Bhowmik and Durai (2010; 2012) is used to prepare MME forecasts daily using four operational global NWP (deterministic) models available on near real time at IMD New Delhi. The MME forecasts prepared daily are made available in the IMD web site (http://www.imd.gov.in/section/nhac/distforecast/dist_fcst.htm). The main purpose of this study is to evaluate the MME precipitation forecast skill improvement over India in short to medium range time scale (up to 120 hours) during summer monsoon 2010. Apart from MME, a simple ensemble mean (ENSM) forecast are also generated and experimented. The prediction skill of the member model, ENSM and MME technique is examined and discussed in terms of different statistical skill scores at 1°×1° latitude / longitude resolution.

2. Methodology and data sources

In this study, the day-1 (24 hour) to day-5 (120 hour) rainfall forecast data from four state of art operational global NWP models namely European Centre for Medium-Range Weather Forecasts (ECMWF), the U.S. National Centers for Environmental Prediction (NCEP)'s Global Forecasting System (GFS), UK Met Office (UKMO) and Japan Meteorological Agency (JMA) is used. These NWP global models were being run at their respective centers (countries) at a higher horizontal and vertical resolution. ECMWF global model (Persson and Grazzini, 2007) runs at 20 km horizontal grid resolution 91 vertical layers. NCEP/GFS (Kanamitsu, 1989) runs at 27 km horizontal grid and 64 vertical layers. UKMO model runs at 40 km horizontal grid and 50 vertical layers (Davies et al., 2005). JMA (Saito et al., 2006) model runs at 20 km horizontal grid and 60 vertical layers. Thus, simulation is done at higher spatial scales than the MME which have been analyzed at 1°×1° resolution.

In order to develop the method, in the first step, model outputs of constituent models are interpolated at the uniform grid resolution of 1°×1° Lat/Lon for the domain from lat. 0 °N to 40 °N and long. 60 °E to 100 °E. In the second step, the weight for each model and for each grid is determined objectively by computing the correlation co-efficient between the predicted rainfall and observed rainfall. Daily rainfall analysis (Durai et al., 2010) at the same resolution (1°×1°) based on rain gauge observations and satellite estimates (KALPANA-1) is considered as the observed rainfall. The Ensemble Mean (ENSM) Forecast is computed as

$$ENSM = \frac{1}{N}\sum_{k=1}^{k=M}\left[F_k\right]$$

where F_k is the model (k) forecast and M is the total number of models used in the Ensemble forecast.

The MME forecast is generated from the model dependent weight and model forecasts using the equation

$$MME = \frac{1}{N}\sum_{k=1}^{k=4} W_{i,j,k}\, F_{i,j,k}$$

where $i = 1, 2, \ldots, 41$; $j = 1, 2, \ldots, 41$.

The weights $W_{i,j,k}$ for each grid (i, j) of each model (k) are obtained from the following quation:

$$W_{i,j,k} = \frac{C_{i,j,k}}{\sum_{k=1}^{4} C_{i,j,k}}$$

where $i = 1, 2, \ldots, 41$; $j = 1, 2, \ldots, 41$ and $C_{i,j,k}$ is the correlation coefficient between rainfall analysis and forecast rainfall for the grid (i, j) of model (k). For the computational consistency, $C_{i,j,k}$ is taken as 0.0001 in case $C_{i,j,k}$ is less than or equal to 0.

This method is applied to day-1 -to day-5 forecasts of daily rainfall during the summer monsoon (1 June to 30 September) 2010 using the rainfall prediction

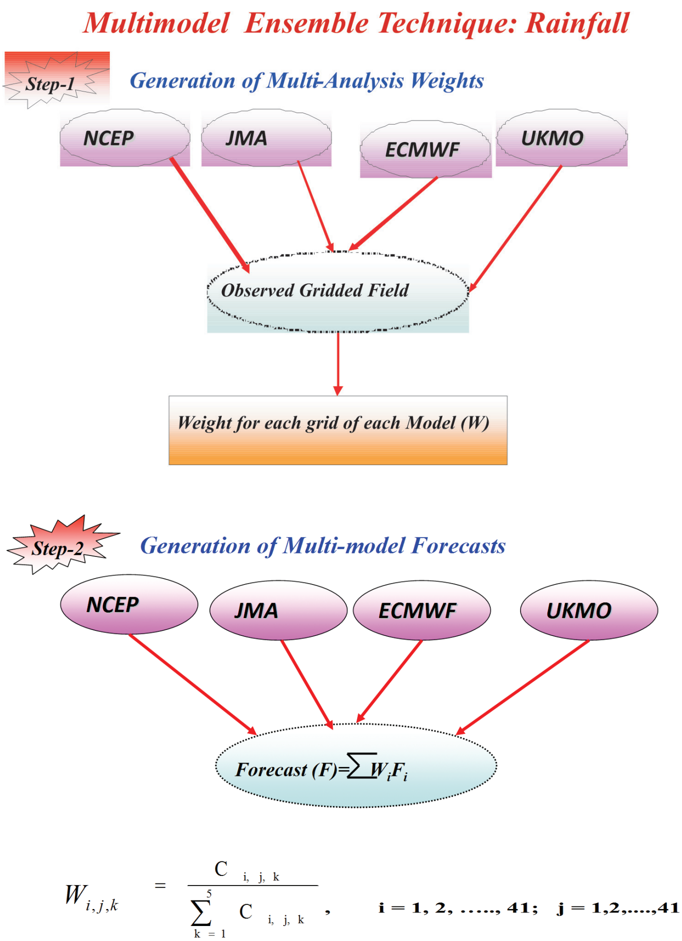


Figure 1. A schematic diagram showing the MME approach.

of constituent models with the pre-assigned grid point weights. The MME method is illustrated as a schematic diagram in Fig. 1. The pre-assigned grid point weights are determined for each model using time series of 122 days daily data of south west monsoon 2009.

In this study performance skill are carried out for MME, ENSM and member model against daily rainfall analysis at the resolution of 100 km. Direct comparison is made of accumulated values of seasonal rainfall, seasonal mean errors and root mean square errors. In addition to these simple measures, a number of categorical statistics are applied. The term categorical refers to the yes/no nature of the forecast verification at each grid point. Some threshold (i.e., 0.1, 1, 2, 5, 10, 15, 20 and 25 mm/day) is considered to define the transition between a rain event versus no-rain event at a particular rainfall threshold. Then at each grid point, each verification time is scored as falling under one of the four categories of correct no-rain forecasts (Z), false alarms (F), misses (M), or hits (H).

A number of categorical statistics skill measures are used, computed from the elements of this rain/no-rain contingency table. The threat score (TS) measures the fraction of observed and/or forecast events that were correctly predicted. Threat score (critical success index)

$$Threat\,Score(TS) = \frac{H}{H + M + F}$$

In additional to above threat score, probability of detection (POD) could be generated easily by defining, probability of detection (POD)

$$POD \text{ or } Hit\,Rate = \frac{H}{H + M}$$

The probability of detection (POD) is equal to the number of hits divided by the total number of rain observations; thus it gives a simple measure of the proportion of rain events successfully forecast by the model. It is also called hit rate (HR). An excellent review of forecast verification methods have been carried out by Fuller (2004) and Wilks (1995).

3. Evaluation of MME prediction skill

The standard procedure for the NWP model rainfall forecast verification (WMO, 1992) is to compute RMSE and anomaly correlation coefficient (ACC) between forecast and analyzed fields valid for the same verification time. For the evaluation of this technique, we have computed the spatial distribution of RMSE, ACC and domain mean area weighted (equator to 40° N and 60° to 100° E) error statistics among member models and the MME forecast. Rainfall is a different type of weather parameter and has to be dealt differently in statistical evaluation (Hamill et al., 2008). It is highly variable in space and time. A quantitative inter-

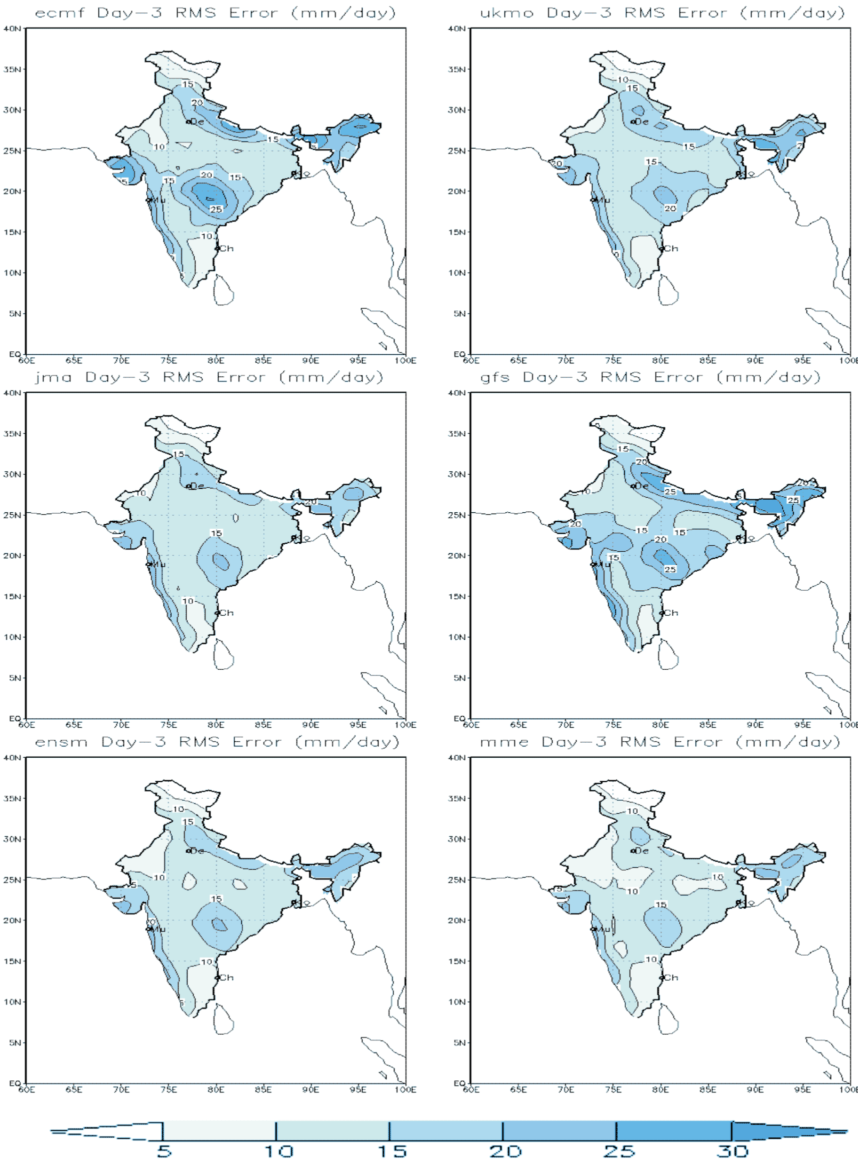


Figure 2. Spatial distribution of seasonal (JJAS) Root Mean Square Error (RMSE) in mm day^{-1} of member models, ENSM and MME for day-3 forecasts.

comparison of the error statistics (absolute mean error, RMSE), CC and threshold skill score for day-1 -to day-5 forecasts of ENSM, member models and MME is discussed below.

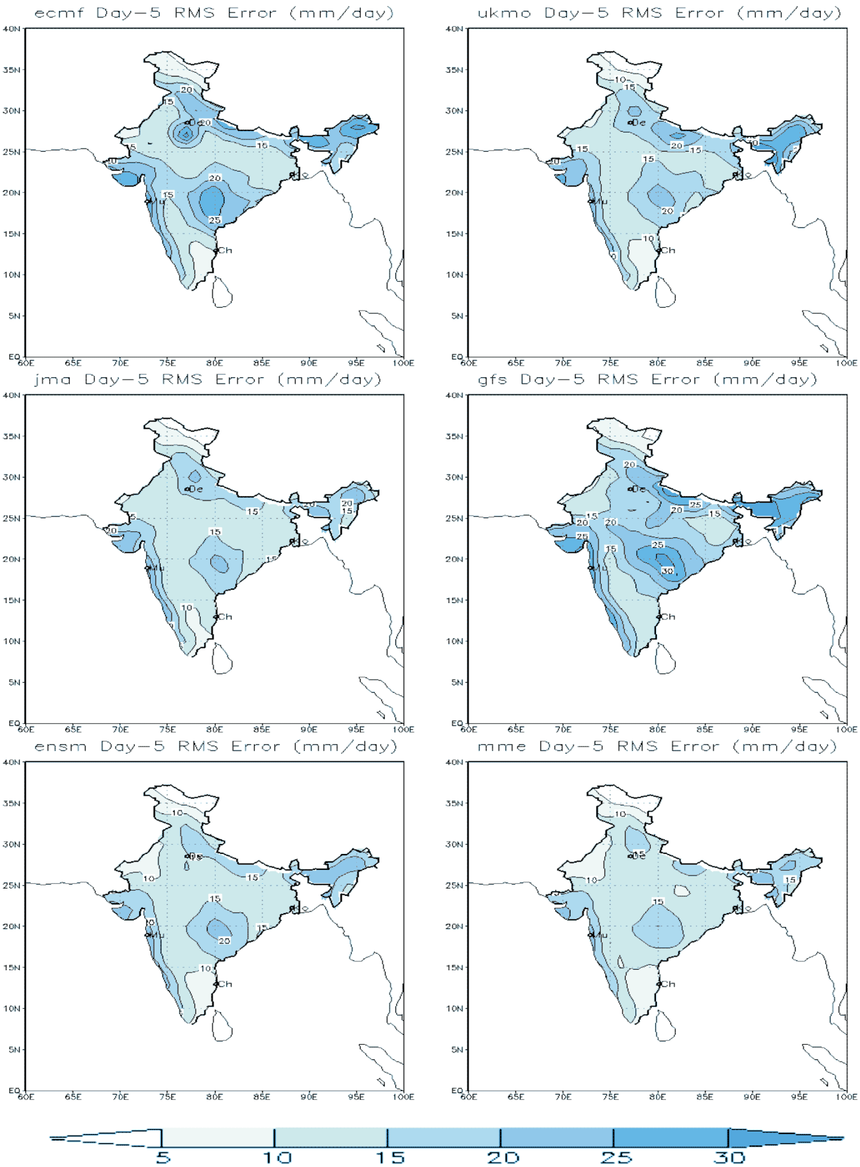


Figure 3. As in Fig. 2, but for day-5 forecasts.

3.1. Root mean square error (RMSE)

The spatial pattern of RMSE for the entire 2010 monsoon season is shown in Fig. 2 for day-3 forecast and Fig. 3 for day-5 forecast. For ECMWF, UKMO and JMA, the RMSE ranges between 20-25 mm along the west coast in day-3 forecast. The magnitude of RMSE over parts of North East India and Central India is in the order of 15–20 mm in day-3 forecast. GFS has higher RMSE values among member models in all the regions over India. RMSE also shows that the errors are more in models where rainfall amounts are also more. The higher RMSE values are seen over the west coast of India and monsoon trough region. RMSE for MME in day-3 is smaller than member models and ENSM. In day-5, the RMSE values for all member models are larger as compared to day-3. The errors grow gradually from day-3 to day5. MME again have smaller RMSE as compared to respective member models in the day-5 forecast. For both day-3 and day-5 forecasts, the RMSE is of the order 10–15 mm for MME over most parts of the country. Broadly similar pattern is observed for ENSM in day-3 and day-5 forecast. MME have smaller RMSE compared to ENSM and member models in both day-3 and day-5 forecasts.

3.2. Anomaly correlation coefficient (ACC)

Anomaly correlation coefficient of the observation and forecasts are computed from their respective seasonal mean during 2010 monsoon for day-3 (Fig. 4) and day-5 (Fig. 5) forecasts. The magnitude of day-3 ACC is higher for all models, but MME and ENSM have higher scores of ACC compared to member models over most of the country. The ACC lies between 0.5 and 0.7 over a large part of central and East India in all the models except NCEP GFS. The magnitude of ACC decreases with the forecast lead time, and by day 5 ACC values over most parts of India are between 0.2 and 0.4, except in pockets near the east coast and south peninsular India where the ACC values are below 0.2.

For a sample size of 122 (monsoon days), the ACC is statistically significant at the 99% confidence level for ACC values exceeding 0.239. Inter-comparison reveals that MME has relatively higher ACC than ensemble mean and member models in both day-3 and day-5 forecast. Hence, the ACC exceeding 0.3 is considered to be good for precipitation forecast. For day-3 forecasts, the ACC are higher for all member models, but MME has higher scores of ACC compared to ENSM and member models. MME, ENSM and member models show higher values of ACC along the monsoon trough region and smaller values over NW and SP India in both day-3 and day-5 forecasts. The magnitude of ACC decreases with the forecast lead time and by day-5 ACC values over most of India lies between 0.3 and 0.5, except MME and ENSM forecast. MME has higher skill than ENSM and member models in day-5 also. It has been observed that all the member model, ENSM and MME skills are very low in day-5, and may not be having any forecast value. Thus for monsoon rainfall forecasts, the current state of art global models have some skill till day-3, which is enhanced by the MME technique

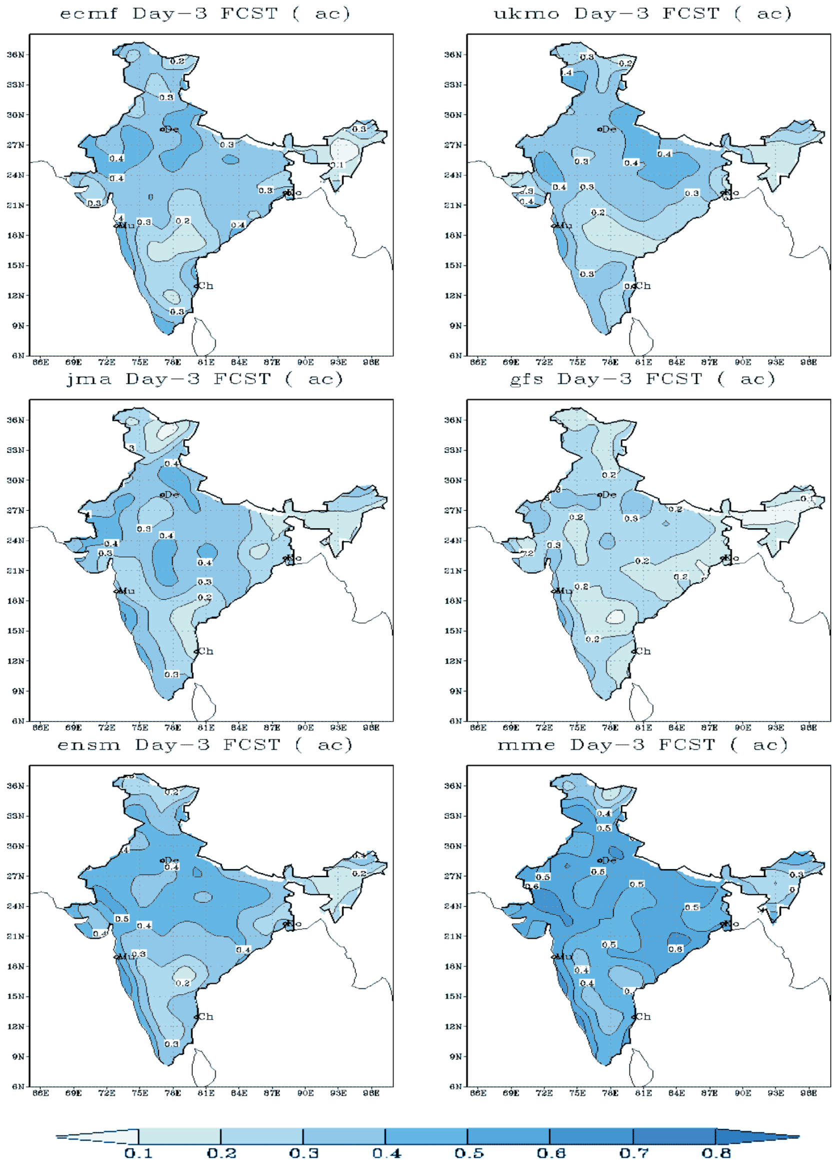


Figure 4. Spatial distribution of season's (1 June to 30 September 2010) Anomaly Correlation Coefficient (ACC) of member models and MME products for *(a)* day-1 and *(b)* day-3 forecasts.

3.3. Skill score

The Mean Absolute Error (MAE) is the arithmetic average of the absolute values of the differences between forecast and observation. It is a scalar measure

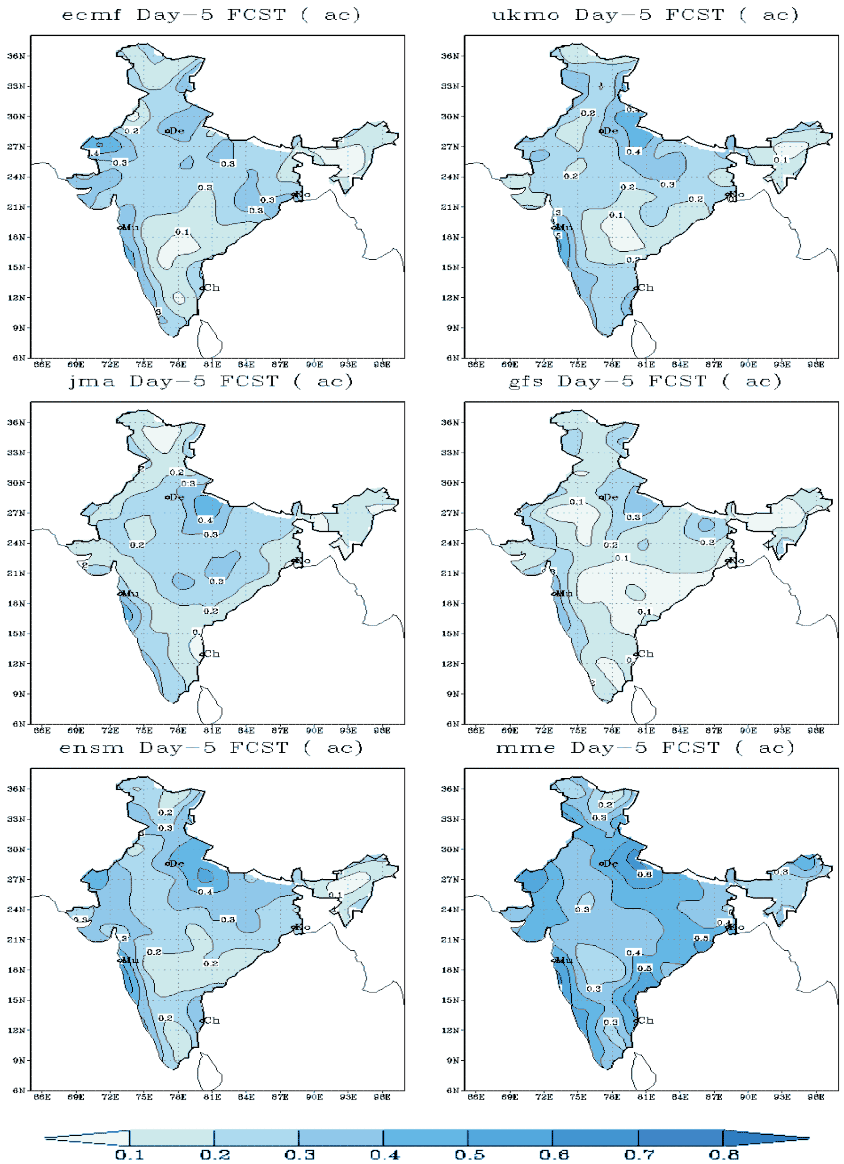


Figure 5. As in Fig. 3, but for day-5 forecasts.

of forecast accuracy. Clearly the MAE is zero if the forecasts are perfect, and increases as discrepancies between the forecasts and observations become larger. The seasonal MAE (mm/day) over Indian monsoon region during summer monsoon 2010 for MME and member models forecast based on day-1, day-3 and day-5 forecasts is shown in Fig.6a. In all days (24 to 120 hr) of forecast, among member models, ECMWF has smaller MAE values. The MAE of MME and Ensemble forecast show minimum error for all days (24 to 120 hour) as compared to member models. A clear trend of forecast improvement through MME is also evident, as the MAE for MME is comparatively smaller than the member models used in this study. The substantial reduction in error between MME and member model is a clear indication of improved forecast skill using MME technique as compared to member model.

RMSE is a measure of the random component of the forecast error.All India mean RMSE of the member model and MME forecast in comparison to the observations are given in Fig. 6b for day-1, day-3 and day-5 forecast. It shows similar trend as MAE for MME and member models. The inter-comparison very clearly shows that the RMSE has been lowest in the MME and ensemble mean in all days of forecast. For 24 hour forecast, among member models, JMA has higher RMSE values. RMSE for ECMWF is smaller than all member models in all days. RMSE also shows that the errors are higher in models for larger rainfall amounts. ENSM and MME have smaller RMSE compared to member models. In day-3 the RMSE values for all member models are higher compared to day-1. The errors grow gradually from day-1 to day5. ENSM and MME again have smaller RMSE compared to respective member models in 72 hr and 120 hr forecast. For all days of forecast, the RMSE for all member models and MME is of the order 1.5–2.5 mm/day. Among the individual model, ECMWF is found to be the best in terms minimum RMSE.

The temporal correlation coefficient (CC) between trends in the forecast and observation is a measure of the phase relationship between them. The CC between daily domain mean observed and forecasted precipitation of 24, 72 and 120 hour forecast for all-India during monsoon (1 June–30 September) 2010 is shown in Fig. 7a. The magnitude of 24 hr temporal CC is higher for all models, but MME and ENSM have higher scores of temporal CC compared to member models. The CC lies between 0.8 and 0.95 for MME and all member models in 24 hour forecast and its values decreases with the forecast lead time and by day-5 (120 hr forecast) the CC values lies between 0.7 and 0.8, except MME and ENSM forecast. ENSM and MME have higher skills than member models for all 24 to 120 hr forecasts. Among the individual model, ECMWF is found to be the best in terms higher temporal CC.

Figure 7b presents an inter-comparison of country mean spatial CC of rainfall forecasts by MME, mean ensemble and individual models. For the NCEP, CC ranges from 0.31 to 0.21 for day 1 to day 5 forecasts, for ECMWF it ranges between 0.35 to 0.28, for JMA between 0.40 and 0.28, and for UKMO between 0.40 and 0.27. For the MME, CC lies between 0.41 and 0.34. The results show that MME is superior to each member model at all the forecasts (day 1 to day 5). The result of mean ensemble is found to be closed to the MME results. The spatial CC for JMA is slightly better in days 1–3, but slightly worse days 4 and 5.

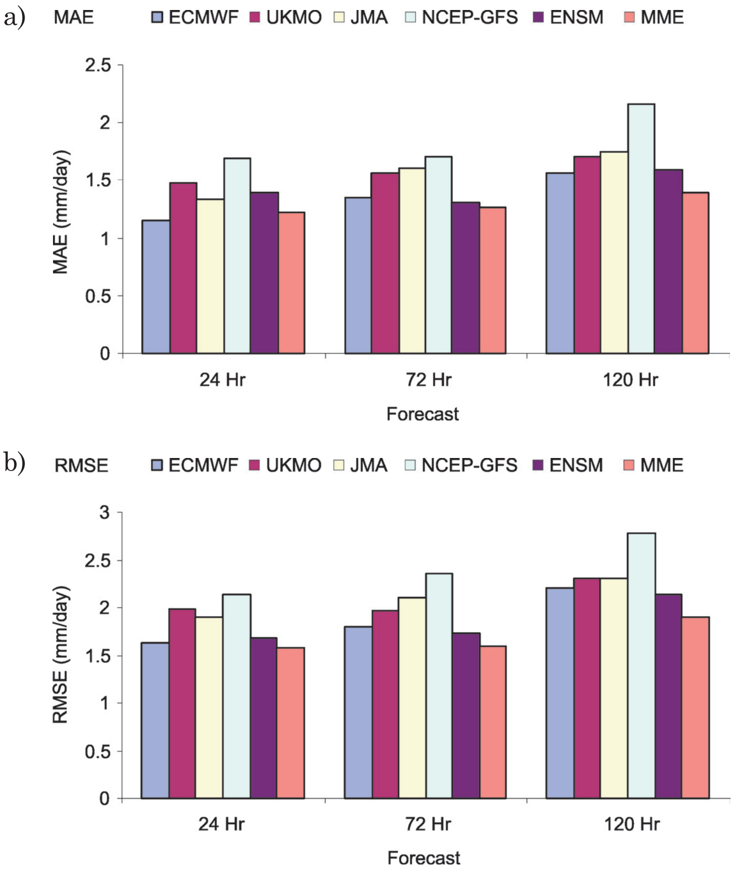


Figure 6. *(a)* Mean Absolute Error (MAE). *(b)* Root Mean Squared Error (RMSE) for member models, ENSM and MME during monsoon 2010 over All India.

ECMWF and UKMO have similar spatial CC. GFS has lower spatial CC in all day-1 to day-5 forecasts.

3.4. Threshold statistics

All the above results give some general idea of the quality of rainfall forecasts in terms of error statistics. The statistical parameters based on the frequency of occurrences in various classes are more suitable for determining the skill of a model in predicting precipitation. Therefore, it is relevant to examine the skill of rainfall forecasts in terms of rainfall amounts in different thresholds. Standard statistical parameters like Threat Score (TS) also called the critical success index, (CSI, e.g., Schaefer, 1990) and Probability of Detection (POD) or Hit Rate (HR) are computed for the comparisons in different categories of rainfall amounts. A

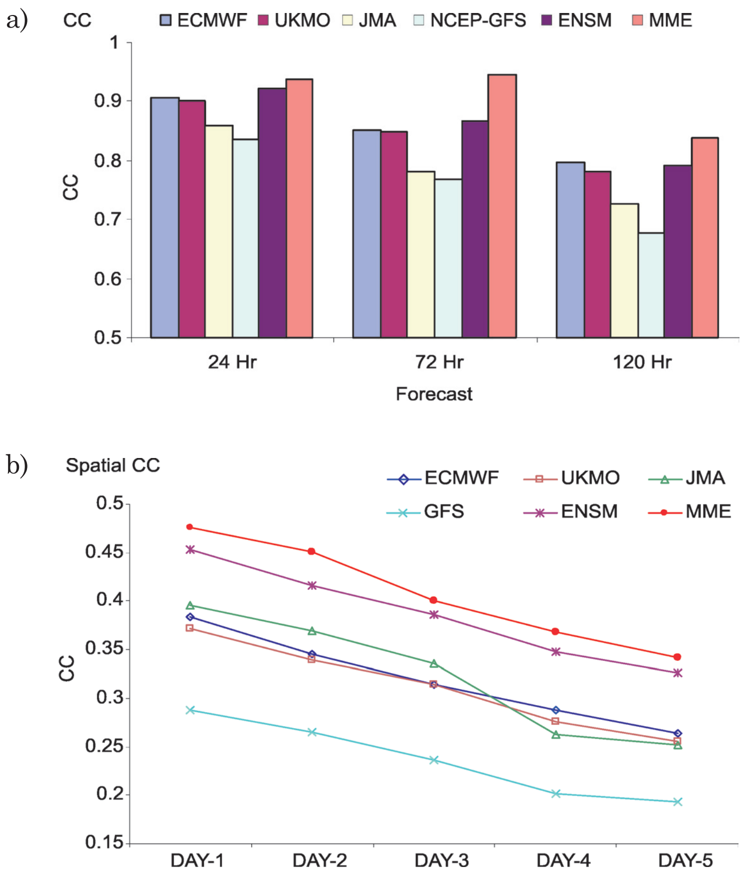


Figure 7. *(a)* Temporal Correlation Coefficient (CC) and *(b)* spatial CC for member models, ENSM and MME during monsoon 2010 over All India

brief description of these categorical statistics is given in Ebert et al. (2007). TS is the ratio of the number of correct model prediction of an event to the number of all such events in both observed and predicted data. POD or HR is the ratio of the number of correctly forecast points above a threshold to that of the number of forecast points above the corresponding threshold. These scores are obtained from the data covering the daily values for the entire 2010 monsoon season of 122 days. The rainfall forecast in terms of rainfall amounts in thresholds from 0.1 to 25 mm per day is considered for the study.

POD for Rainfall threshold of 0.1, 2.5, 5, 10, 15, 20 and 25 mm/day, for member models, ENSM and MME products over all India during monsoon 2010 is shown in Fig. 8a for day-3 and Fig. 8b for day-5 forecast. It is observed that the POD is more than 60% for class marks below 10 mm/day for day-3 forecast, while it is

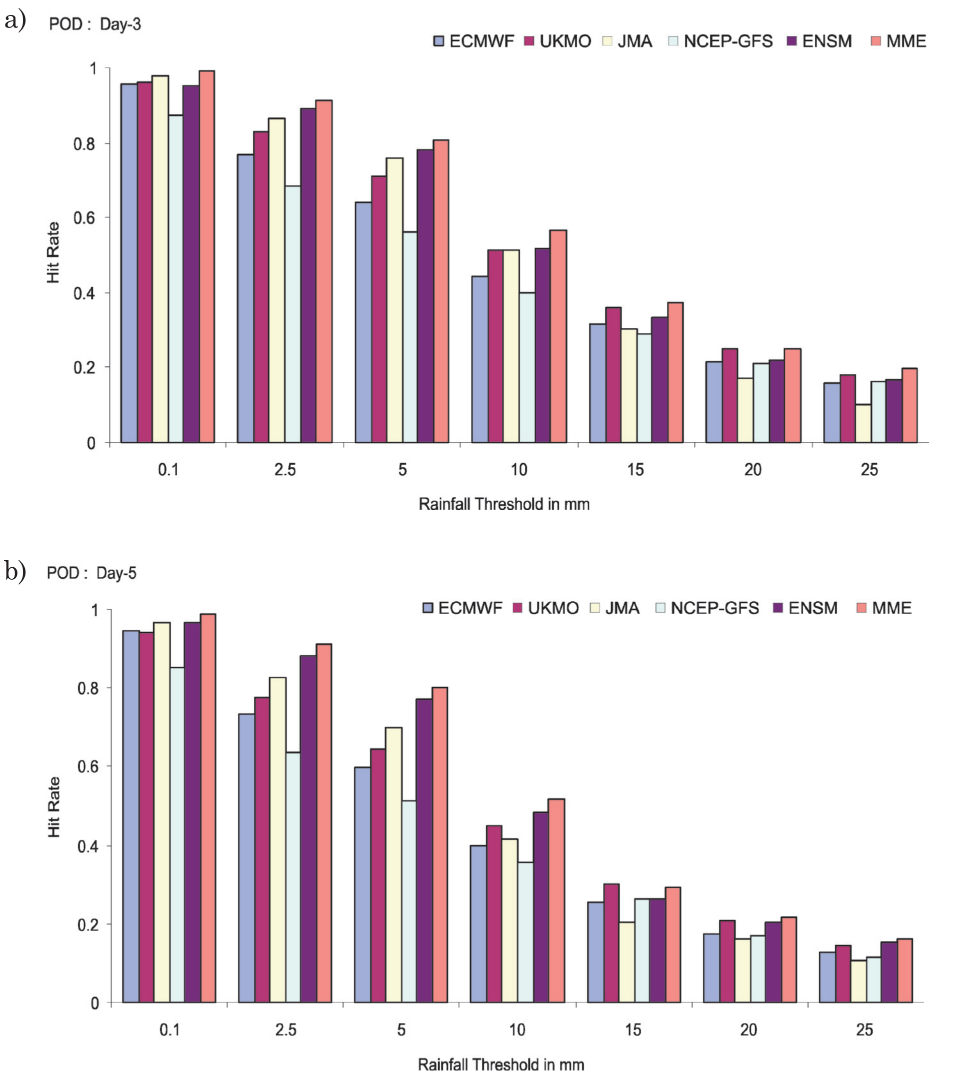


Figure 8. Hit Rate (HR) or Probability of Detection (POD) for rainfall threshold of 0.1, 2.5, 5, 10, 15, 20 and 25 for *(a)* day-3 and *(b)* day-5 forecast of member models, ENSM and MME during monsoon 2010 over All India.

further below for day-5 forecast for all the models. Also, it is shown that skill is a strong function of threshold as well as forecast lead time (day-1 to day-5), with POD decreasing from about 80-90% for rain/no rain (> 0.1 mm/day) to about 20% or 30% for rain amounts around 25 mm/day. For POD, the ENSM and MME products are mostly seen to perform much better than the member models. For all

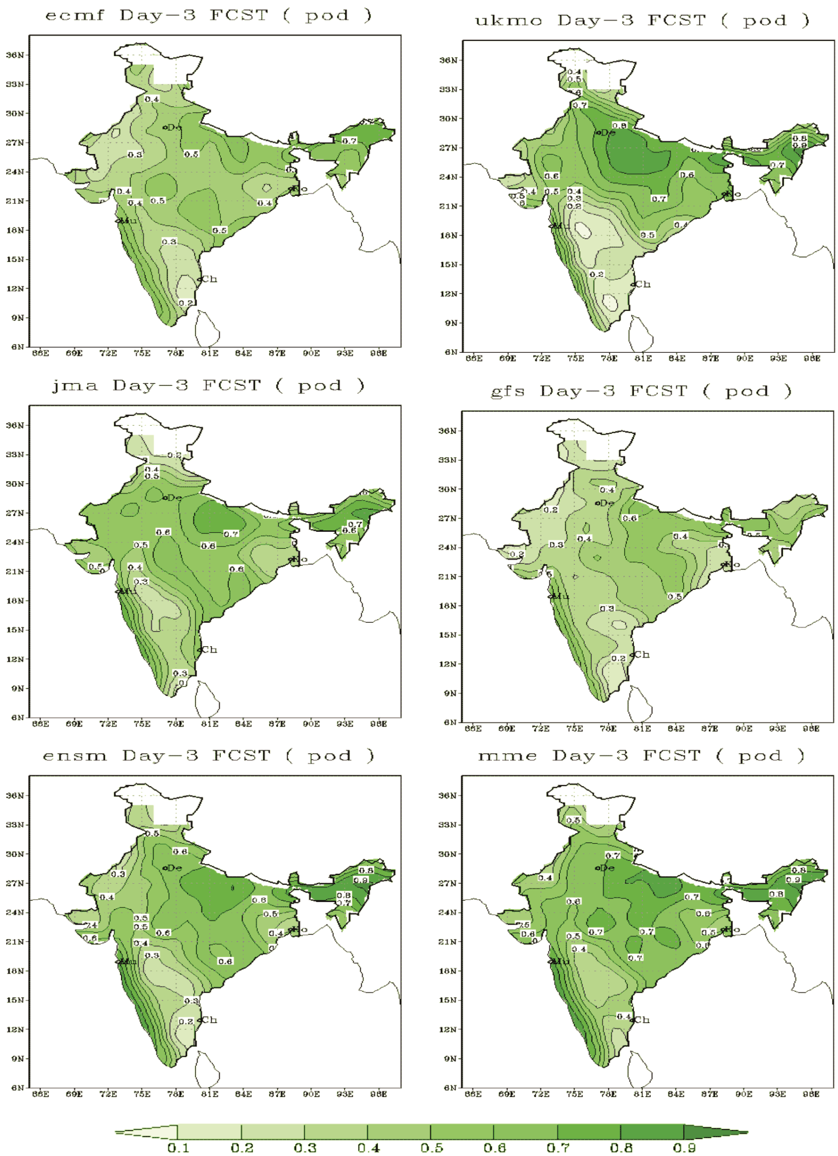


Figure 9. Spatial distribution of Hit Rate (HR) score for rainfall threshold of 15 mm/day, for day-3 forecast of member models, ENSM and MME products during monsoon 2010.

days, POD from MME and ENSM are superior to the member models in all thresholds range. MME shows slightly higher values of POD skill than ENSM and other member models for all days and for all thresholds over all India regions.

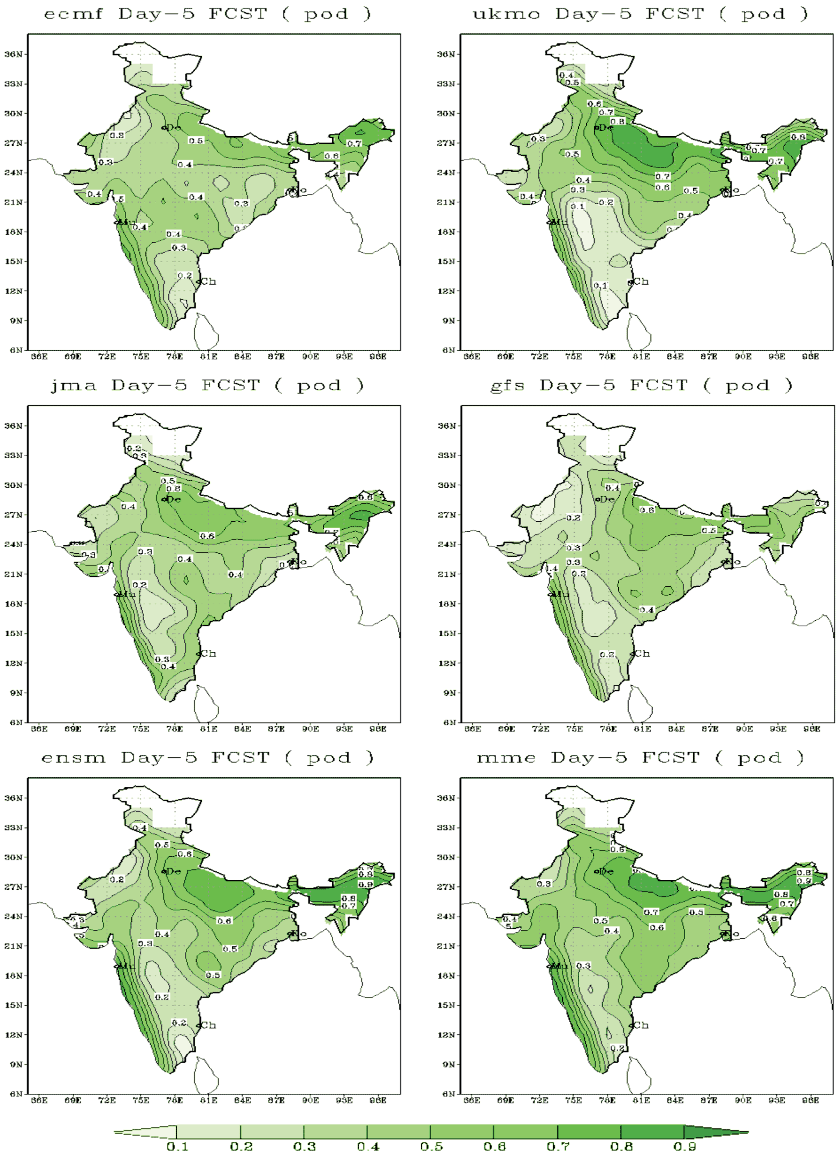
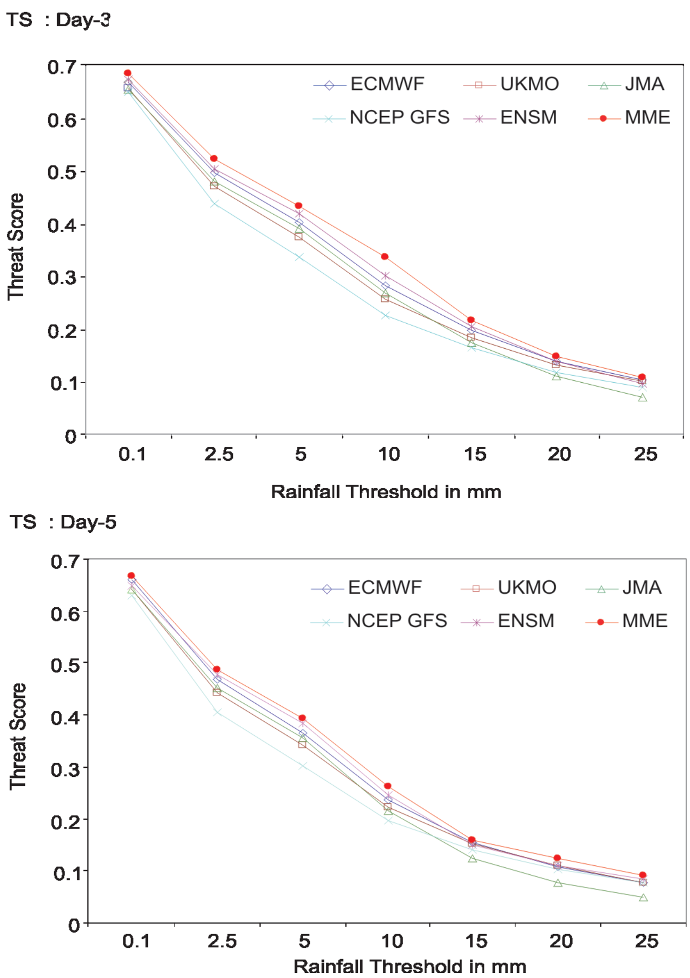


Figure 10. As in Fig. 9, but for day-5 forecasts.

The spatial distribution of POD skill score for rainfall threshold of *15 mm/day* of member models, ENSM and MME during monsoon 2010 is shown in Fig. 9 for day-3 and Fig. 10 for day-5 forecast. From Fig. 9, it is seen that the POD values of day-3 UKMO and JMA over Central India, East India, North East India and a)



b)

Figure 11. Threat Score for *(a)* day-3 and *(b)* day-5 forecast of member models, ENSM and MME during monsoon 2010 over All India. MME and member models.

west coast of India have values greater than 0.70 and decrease to 0.5 to 0.6 in day-5 forecast Among member models, NCEP GFS has very low values of POD and UKMO has higher values of POD score, followed by JMA over all the regions of study in both day-3 and day-5 forecast. All the member models including MME and ENSM have lower POD over NW and SP India. In general, the values of POD for day-3 and day-5 forecasts of MME has higher scores (POD greater than 0.7) compared to ENSM and member models in all the regions.

For accuracy, correct negatives have been removed from consideration, i.e., TS is only concerned with forecasts that count. It does not distinguish the source

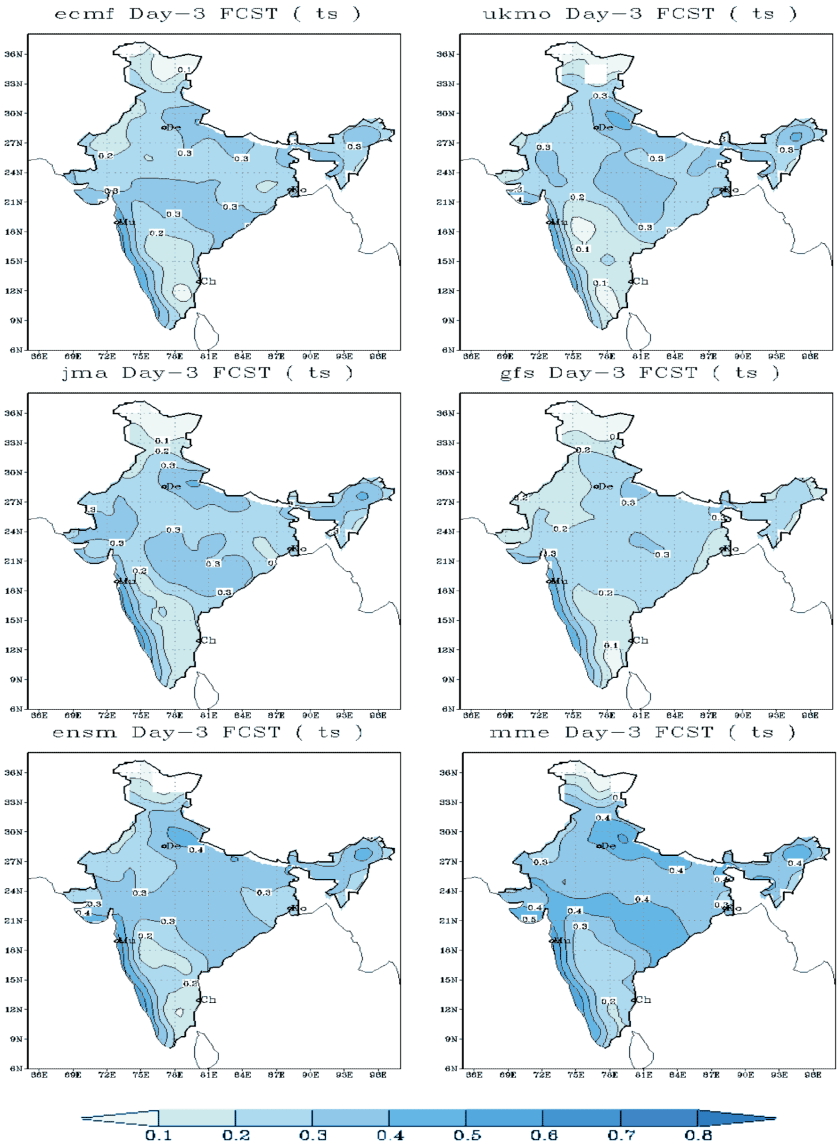


Figure 12. Spatial distribution of Threat Score (TS) for rainfall threshold of 15 mm/day, for day-3 forecast of member models, ENSM and MME during monsoon 2010.

of forecast error and just depends on climatological frequency of events (poorer scores for rarer events) since some hits can occur purely due to random chance. The higher value of a threat score indicates better prediction with a theoretical

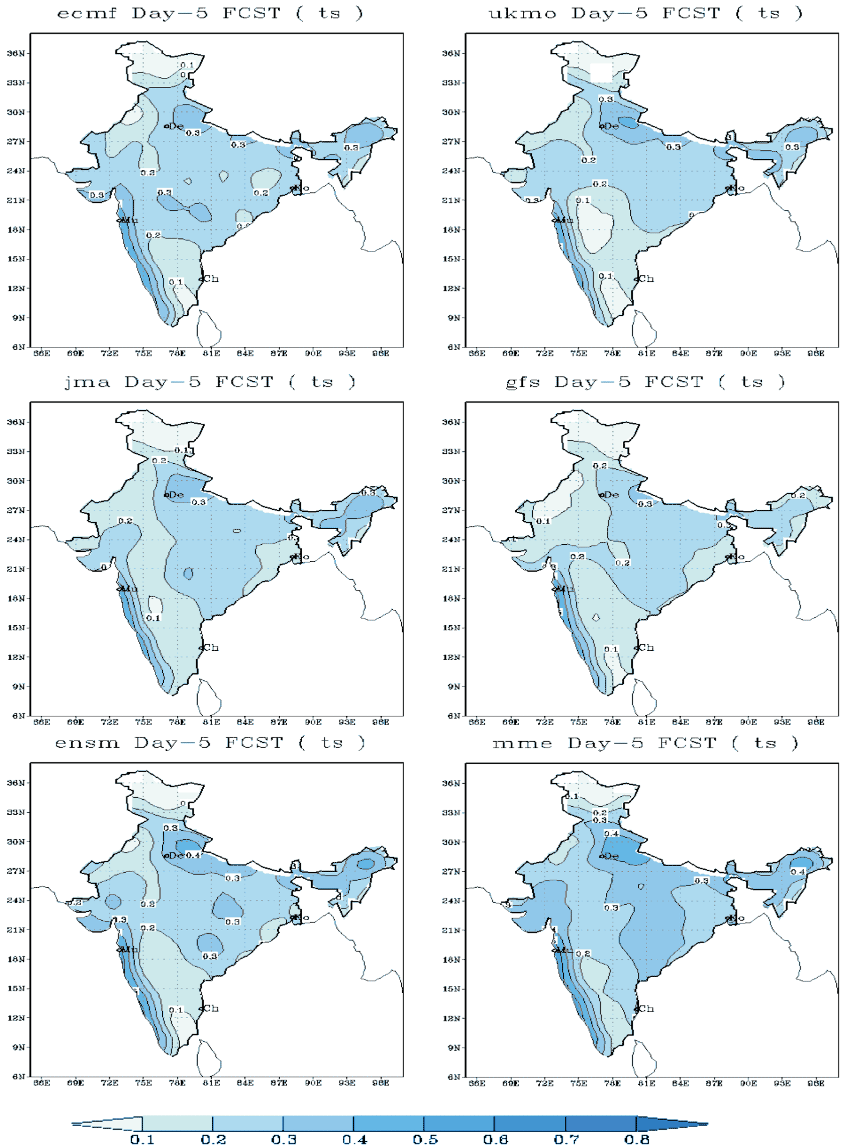


Figure 13. As in Fig. 12, but for day-5 forecasts.

limit of 1.0 for a perfect model. In the day-3 (Fig. 11a) forecast, the score for MME and member models starts close to 0.7 and then becomes 0.5 at the 2.5 rain threshold, 0.4 at 5 mm rain threshold, 0.3 at 10 mm rain threshold and becomes 0.25 at 15 mm rain threshold. In the day-5 forecast, the score begins from 0.65 and then decreases to 0.51, 0.40, 0.25 and 0.2 at the threshold values of 0.1 mm, 2.5 mm, 5 mm, 10 mm and 15 mm respectively. Similar to day-3 forecast, the TS skill score for day-5 (Fig. 11b) forecast begins from 0.65 for the threshold values of 0.1 mm and then decreases to 0.15 for the threshold values of 15 mm. The inter comparison clearly shows that MME has the highest skill at all the thresholds for both day-3 and day-5 forecasts. TS skill gradually decreases with increase in threshold. Also, with increase in length of forecast period from day-3 to day-5 for each threshold rainfall category, TS skill score falls gradually. TS for all member models look similar for all forecast length and thresholds. However, in general TS of MME is slightly higher than ENSM and other member models for all thresholds even with increase in forecast lengths. A multi-model product for rainfall in terms of TS skill concludes that the use of multi-model has some benefits compared to using single independent models for rainfall forecasts.

The spatial distribution of TS for rainfall threshold of *15 mm/day* for the member model, ENSM and MME forecast are given in Fig. 12 for day-3 and Fig. 13 for day-5 forecast. The spatial pattern of TS skill score for all member models looks similar in both day-3 and day-5 forecasts. The TS skill score is more than 0.4 over a large part of central and East India in all the member models except NCEP GFS, but the same for MME is slightly higher in day-3 forecast (Fig. 12). The magnitude of TS value for MME forecast is slightly higher in all the regions over India as compared to ENSM and member models in day-3 forecast. Similar to day-3 forecasts, the magnitude of TS in the day-5 forecasts (Fig. 13) of MME is also high as compared to ENSM and member models. The TS skill score distribution pattern of day-5 forecast looks almost similar to day-3 forecast with larger TS skill score value over west coast of India, NE India and East India and smaller over NW and SP India. The magnitude of TS skill score is smaller in day-5 forecast as compared to day-3 forecast in all the models. In general, the TS skill score of MME remains relatively higher than ENSM and other member models in all the regions of study.

4. Conclusions

The study provides a concise and synthesized documentation of the current level of skill of the Multi-Model Ensemble (MME) Technique for forecasting rainfall over India in the short to medium range time scale during summer monsoon of 2010. Four global Numerical Weather Prediction (NWP) models namely, ECMWF, JMA, NCEP GFS and UKMO are used simultaneously with adequate weights to obtain the MME Technique. The weight for each of the model at each grid is assigned on the basis of their past performance. Weights for each NWP model at each grid points is determined by computing the correlation coefficient (CC) between model forecasts and observed daily rainfall time series of south west monsoon (JJAS) season. Apart from MME, a simple ensemble mean (ENSM) forecast are also generated and experimented. The inter-comparison of rainfall prediction skill of the MME forecast against the constituent models reveals that the MME is able to provide more accurate forecast of rainfall over Indian monsoon region by taking the strength of each constituent model. The MAE, RMSE and CC clearly indicate that MME forecast is superior to the forecast of constituent models and ENSM. RMSE is found to be lowest in MME forecasts. The fluctuations of day to day MAE and RMSE errors are relatively less in case of MME forecast. The rainfall forecasts in terms of error statistics show that MME has higher skill than member models and ENSM. The skill of rainfall forecasts in terms of rainfall amounts in different thresholds over India indicates that MME produce better skill compare to ENSM and member models. Statistical combination of NWP model output is a promising approach for further development which will give rise to significant improvement in the predictive skill. It is demonstrated that the weighted MME technique have higher skill in predicting daily rainfall compared to ENSM and individual models. Through the MME methods, skill of rainfall predictions improved significantly over India. In general, the MME method is found to give a significant increase in forecast skill for rainfall over the Indian monsoon region. However, the skill for the higher rainfall thresholds (>10 mm) is small and MME does not increase it by much.

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SAŽETAK

Poboljšanje uspješnosti prognoze oborine nad Indijom primjenom metode višemodelskog ansambla

V. R. Durai i Rashmi Bhardwaj

U ovom radu primijenjena je metoda višemodelskog ansambla (MME) s ciljem poboljšanja kratkoročnih do srednjoročnih dnevnih prognoza količine oborine nad Indijom tijekom ljetnog monsuna 2010. godine. Pri tome su istovremeno te s odgovarajućim težinama korištena četiri operativna globalna modela za numeričku prognozu vremena (NWP): ECMWF, JMA, NCEP GFS i UKMO, a koji su na raspolaganju u realnom vremenu pri Indijskom meteorološkom odsjeku (IMD) u New Delhiju. Težine za svaki NWP model u svakoj točki mreže pridijeljene su na temelju koeficijenta korelacije (CC) između modelskih prognoza i mjerenog niza dnevne količine oborine za sezonu jugozapadnog monsuna (od lipnja do rujna). Pored MME, generirane su i ispitane jednostavne prognoze dobivene srednjakom ansambla (ENSM). Uspješnost prognoze količine oborine dobivene MME metodom procijenjena je usporedbom rezultata dobivenih tom metodom i onih na temelju ENSM te sa svakim pojedinačnim modelom. Međusobna usporedba pokazuje da metoda MME točnije prognozira količinu oborine u području indijskog monsuna ponderiranjem doprinosa svakog pojedinog modela u ansamblu. Nadalje, utvrđena je veća uspješnost kratkoročnih prognoza količine oborine pomoću metode MME u odnosu na rezultate metode ENSM te u odnosu na prognoze pojedinačnih modela ansambla. Primjena ponderirane metode MME značajno poboljšava uspješnost prognoze količine oborine nad Indijom.

Ključne riječi: numerička prognoza vremena, višemodelska ansambl prognoza (MME), uspješnost prognoze količine oborine, globalni model

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