

Multi-Model Ensemble (MME) prediction of rainfall using canonical variates during monsoon season in India

ASHOK KUMAR, A. K. MITRA, A. K. BOHRA, G. R. IYENGAR and V. R. DURAI*

National Centre for Medium Range Weather Forecasting (NCMRWF)

A - 50, Institute Area, Sec - 62, Noida, UP – 201 307, India

**India Meteorological Department, New Delhi – 110 003, India*

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e mails : ashok@ncmrwf.gov.in; akm@ncmrwf.gov.in; gopal@ncmrwf.gov.in; durai.imd@gmail.com

सार – एशिया क्षेत्र की ग्रीष्मकालीन मानसून वर्षा का भिन्न भिन्न दिक्ककालिक पैमानों पर पूर्वानुमान करना अभी भी एक कठिन कार्य है। अभी हाल के वर्षों में मध्य अक्षांश की तुलना में मॉनसून वर्षा का मध्य अवधि पूर्वानुमान देने की दक्षता में समानुपातिक सुधार में कमी रही है। मानसून और उष्णकटिबंधीय पूर्वानुमान में आगे और सुधार के लिए ग्लोबल मॉडलस और ऑकड़ आमेलन तकनीक का उपयोग किया जा रहा है। बहरहाल बहु निदर्श इन्सेम्बल (एम.एम.ई.) पूर्वानुमान की लोकप्रियता बढ़ रही है क्योंकि पूर्वानुमान में एकरूपता और निदर्श की अनिश्चितताओं में कमी को देखते हुए पाते हैं कि इसमें व्यावहारिक पूर्वानुमान करने के लिए अधिक सूचना कराने की संभावना है। जैसा कि प्रमुख केन्द्र वास्तविक समय के मॉडल प्रतिफलों का आपस में आदान प्रदान करते हैं इसमें एम.एम.ई. पूर्वानुमान कौशल को बढ़ाने में व्यावहारिक रूप से किफायती तरीका है। साधारण इन्सेम्बल औसत को छोड़कर एन.सी.एम.आर.डब्ल्यू.एफ./पृथ्वी विज्ञान मंत्रालय, भारत द्वारा वर्ष 2009 के मानसून के दौरान मध्य अवधि मानसून वर्षा पूर्वानुमान के लिए एम.एम.ई. पूर्वानुमान का अधिक उपयोग किया गया। इसके लिए प्रमाणिक विचार तकनीक का प्रयोग किया गया। प्राप्त किए गए प्रतिफलों की गणना करने से पता चला है कि बहु निदर्श इन्सेम्बल पूर्वानुमान की दक्षता किसी एक मॉडल पूर्वानुमानों की अपेक्षा अधिक सही है और यह आमतौर पर साधारण इन्सेम्बल औसत से भी अधिक सही है। हालाँकि ग्लोबल मॉडलस की दक्षता तीन दिन के आगे तक की होती है परन्तु एम.एम.ई. तकनीक को 5 दिनों की अवधि तक लागू करने पर इसमें महत्वपूर्ण सुधार देखा जा सकता है।

ABSTRACT. The prediction of Asian summer monsoon rainfall at various space-time scales is still a difficult task. Compared to mid-latitudes, proportional improvement in the skill in prediction of monsoon rainfall in medium range had been less in recent years. Global models and data assimilation techniques are being further improved for monsoon and tropics. However, multi-model ensemble (MME) forecasting is gaining popularity, as it has the potential to provide more information for practical forecasting in terms of making a consensus forecast and reducing the model uncertainties. As major centres are exchanging the model output in near real-time, MME is a viable inexpensive way for enhancing the forecast skill. During monsoon 2009, apart from simple ensemble mean, the MME predictions of large-scale monsoon precipitation in medium range was carried out NCMRWF/MoES, India. The canonical variates technique is used for it. The skill scores are computed, which indicate that multi-model ensemble forecast has higher skill than individual model forecasts and also higher than the simple ensemble mean in general. Although the skill of the global models falls beyond day-3, but a significant improvement could be seen by employing the MME technique up to day-5.

Key words – Monsoon-rainfall global-models, Multi-model-ensemble (MME), Canonical-variates.

1. Introduction

Asian Monsoon is one of the major components of the earth climate system. Realistic modeling, simulation and prediction of monsoon are challenging scientific tasks for the world earth system science community. For India, the monsoon rains are of enormous importance giving shape to its agriculture, economy and rhythms of life. The science pertaining to monsoon has progressed significantly in the last two decades due to an increased wealth of new data from satellite observations, understanding the processes and enhanced computing

power. Numerical models and data assimilation algorithms have further improved at all major international centers across the globe. The accuracy of the weather forecasts has improved steadily in last three decades, and the systematic errors with forecast length in medium range have reduced. However, in general the forecast skill in tropics is still lower as compared to mid-latitudes and is particularly of concern for rainfall forecast over the Indian monsoon region. The errors in the rainfall forecast are due to uncertainties in the assimilation process as well as in the physical parameterization. These uncertainties could be due to the errors in the

prescribed initial states, which may arise from observational instruments, satellite estimates and the data assimilation methods. The forecast skill is also dependent on the synoptic situation, flow regime, region and known (or unknown) tele-connections. The accuracy of a model also varies depending on the formulation, horizontal-vertical resolutions and the parameterization schemes representing the small-scale processes in the model. The process of improving forecast skill of an individual Numerical Weather Prediction (NWP) system through research and development in modeling and data assimilation is a rather slow process. For example at the European Centre for Medium Range Weather Forecasts (ECMWF), the research and development of ten years has resulted in an improvement of skills of one day. Therefore, from practical forecasting aspect one has to learn to live with these uncertainties and the current available skill of the models. The point is how to make best use of the forecasts from any (or many) centers, when each centre is having data from many deterministic models.

In the context of the availability of model data from different centers and each centre producing many ensemble members, the use of ensemble methods in short, medium range and even for short-term climate prediction have become popular in recent years. Due to the uncertainties in the modeling system, the forecast errors increase with the forecast length, until it becomes no longer useful. If one has an ensemble of forecasts (many forecasts) one can say something extra about the reliability of the forecasts to the user. Clustering (or tubing) of several similar forecasts are also useful, Atger (1999). From many ensemble forecasts one can get a clue for possible extreme/severe events. One single forecast may fail to catch the extreme event, but the ensemble might give some extra clue on the extreme (or anomalous) episode. The current practices at major centres are (i) to perturb the initial conditions (scientific based) and make many member runs from these different initial conditions (ii) make many runs by altering the model formulations, physical parameterizations, and (iii) multi-model ensemble using many different models. Multi-model ensemble (MME) is a viable option, as many centers exchange and/or provide model data in near real time. One assumption for MME is that the deterministic models do provide some signal, and the noise (and error) is less compared to signal.

Some weather/climate forecast centers perform calibration of model outputs to improve model's skills. Different statistical post-processing techniques are applied to model output parameters for the scale, region and phenomenon of interest. These post-processing methods enable the forecasters to obtain enhanced skill and value

from models. MME is another post-processing technique that enhances the skill of rainfall prediction. This paper describes the performance of the experimental MME forecast of rainfall during monsoon 2009 focusing on the large-scale aspects of monsoon rain. The difficulties in producing rainfall forecasts for smaller regions by the state of art global models are well known. Significant errors are obviously expected if one decides to come down to smaller meso-scales below the 'large scale organized convective rainfall' associated with monsoon, Chakraborty (2010). Therefore, as a first attempt, $1^\circ \times 1^\circ$ latitude/longitude grid rainfall data from four deterministic models and the associated multi-model products in the medium range are considered.

Early works by Krishnamurti *et al.* (1999) showed that it is possible to get skill improvements both in weather and climate scales by the use of the multi-model technique known as 'Super Ensemble' forecasting. Later it was extended for tropical precipitation by incorporating multi-analysis concept along with the use of multi-models, Krishnamurti *et al.*, (2000). Later Mishra and Krishnamurti (2007) applied the superensemble algorithm for Indian monsoon and showed the skill enhancement using data from seven global models. A multi-model multi-analysis ensemble system was reported to evaluate the deterministic forecasts from United Kingdom Meteorological Office (UKMO) and ECMWF ensemble data by Evans *et al.* (2000), and they showed the superiority of the multi-model system over the individual model data. Richardson (2001), used multi-model and multi-analysis data to produce both deterministic and probabilistic ensemble forecasts using four global models from UKMO, German Meteorological Service, Meteo France and National Centre for Environmental Prediction (NCEP) and showed that simple ensemble mean and simple bias correction produce useful products. The probability of precipitation and rainfall distribution by using multi-model data from seven global models for Australia region was studied by Ebert (2001). Multi-model multi-analysis data was also tried by using ECMWF and UKMO ensemble outputs for quasi-operational medium range forecasting in both probabilistic and deterministic sense (Mylne *et al.*, 2002). They noted that the MME is more beneficial than a single model Ensemble Prediction System (EPS), and the skill during winter season was higher compared to summer season. Operational consensus forecast by including several models is seen to outperform Direct Model Output (DMO) and Model Output Statistics (MOS) forecasts, (Woodcock and Engel, 2005). Multi-model products prepared by using National Centre for Environmental Prediction/Global Forecast System (NCEP/GFS) and ECMWF data also have shown improvements in week-2 forecasts, Whitaker *et al.*, (2006), improving over the MOS forecast of

individual models. Most of these studies (algorithms) used simple ensemble mean or a mean of calibrated data from deterministic models. However, by analysing the past performance of model for a region, it might be interesting to examine if model dependent weights helps further to improve the final multi-model forecast. In a very recent study, Johnson and Swinbank (2009) used ECMWF, UKMO and NCEP/GFS global model data to prepare multi-model ensemble forecasts in medium-range. These forecasts were studied for bias correction, model dependent weights, and variance adjustments. It was found that the multi-model ensemble gives an improvement in comparison to calibrated single model ensemble. They also noted that only small improvements were achieved by using the model dependent weights and variance adjustments. Recently more studies for monsoon rainfall using MME methodology were reported based upon simple linear regression approach, Roy Bhowmik and Durai (2008 and 2010) and Mitra *et al.*, (2011).

It is well known that the simple average made from many models (simple ensemble mean, giving equal weight to each deterministic model) generally produces higher skill score. Our interest here is to show that the skill of the forecast obtained by using MME methodology is better than the skill of simple ensemble mean and deterministic models forecasts. Canonical variate technique, Anderson (2003), is used for applying the MME methodology.

Section 2 describes the data and methodology. In section 3 the results and discussion are presented. Section 4 describes the conclusions.

2. Data and methodology

2.1. Data

In this study the daily medium range (day-1 to day-5) rainfall prediction data from four state of art operational global models namely NCEP/GFS, UKMO, Japan Meteorological Agency (JMA) and National Centre for Medium Range weather Forecasting (NCMRWF), for monsoon season (June, July, August, September) 2007, 2008 and 2009 are used. These model data were available up to day-7, but MME models were developed and tested only up to day-5. These models were being run at their respective centers (countries) at a higher horizontal and vertical resolution. NCEP/GFS model data was from runs made at 35 km horizontal grid and 64 vertical layers (Yang *et al.*, 2006). UKMO model data was from runs made at 40 km horizontal grid and 50 vertical layers (Rawlins *et al.*, 2007). JMA model data was from runs made at 20 km horizontal grid and 60 vertical layers, (JMA, 2007). NCMRWF/GFS model data was from runs

made at 50 km horizontal grid and 64 vertical layers, (NCMRWF, 2010). NCMRWF/GFS model is an adopted version of the NCEP/GFS system and was implemented in the year 2007.

The operational global models were run at respective centers at a higher resolution. However rainfall forecasts provided by the different centers at a coarser resolution of $1^\circ \times 1^\circ$ were used in this study to represent the large-scale aspect of the monsoon rainfall. The purpose of this study is to note the skill enhancement coming from the multi-model ensemble algorithm. The observed gridded rainfall analysis data used in model calibration (training) has to be of good quality. Otherwise, it might degrade the MME results. Hence the corresponding daily observed gridded rainfall data at $1^\circ \times 1^\circ$ resolution was prepared by merging rain-gauge values with the satellite estimates, (Mitra *et al.*, 2003). As during 2007-2009, all the participating global models did not go through any major change in their model formulation. During the mentioned period the small changes in data usage for data assimilation and changes in coefficients in physical parameterizations will have very small impact on the large-scale monsoon rainfall pattern Zapotocny (2007). Therefore, the intention of testing a MME algorithm for the large-scale rainfall pattern associated Indian monsoon may not be affected by minor model changes during the period.

2.2. MME methodology

The basic technique used is the canonical variate. The correlation between two set of variables having joint distribution is called the canonical correlation. This may be defined as the correlation between linear combination of two sets of variables and these linear combinations would be called as canonical variates. These are found in such a way that the correlation is maximum. First set of linear combinations is obtained that has the maximum correlation. Then a second set of linear combinations can be obtained which has the next maximum correlation and uncorrelated with the previous one. We can continue the procedure till then all such combinations are found.

Let be a vector of variables with covariance matrix and $E(\underline{X}) = \underline{0}$

$$\text{If } \underline{X} = \begin{bmatrix} X^{(1)} \\ X^{(2)} \end{bmatrix} \text{ where } p_1 \leq p_2; p_1 + p_2 = p$$

$$\text{and } \Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \text{ partitioned as per } \underline{X}$$

Then we have to find two linear combinations;

$$U = \alpha' X^{(1)} \text{ and } V = \gamma' X^{(2)} \text{ s.t. } \text{Var}(U) = \text{Var}(V) = 1$$

$$\text{and } E(U) = E(V) = 0$$

which has the maximum correlation and

$$\alpha' \Sigma_{11} \alpha = 1 \text{ and } \gamma' \Sigma_{22} \gamma = 1$$

$$\text{then } \text{Cor}(UV) = E(UV) = E[\alpha' X^{(1)} X^{(2)'} \gamma] = \alpha' \Sigma_{12} \gamma$$

Now maximize,

$$\phi = \alpha' \Sigma_{12} \gamma - \frac{1}{2} \lambda (\alpha' \Sigma_{11} \alpha - 1) - \frac{1}{2} \mu (\gamma' \Sigma_{22} \gamma - 1)$$

Differentiate w.r.t. α and γ

$$\Sigma_{12} \gamma - \lambda \Sigma_{11} \alpha = 0 \tag{1}$$

$$\Sigma'_{12} \alpha - \mu \Sigma_{22} \gamma = 0 \tag{2}$$

Now multiply Eqn. (1) on left by α' and Eqn. (2) on left by γ' , we get;

$$\gamma' \Sigma_{12} \alpha - \mu \gamma' \Sigma_{22} \gamma = 0$$

$$\alpha' \Sigma_{12} \gamma - \lambda \alpha' \Sigma_{11} \alpha = 0$$

$$\Rightarrow \lambda = \mu = \alpha' \Sigma_{12} \gamma \quad \because \alpha' \Sigma_{11} \alpha = 1 \text{ \& } \gamma' \Sigma_{22} \gamma = 1$$

Now from Eqns. (1) and (2)

$$-\lambda \Sigma_{11} \alpha + \Sigma_{12} \gamma = 0$$

$$\Sigma_{21} \alpha - \lambda \Sigma_{22} \gamma = 0$$

To get a non-trivial solution,

$$\begin{vmatrix} -\lambda \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & -\lambda \Sigma_{22} \end{vmatrix} = 0$$

$$\text{or } \left| \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1} \Sigma_{12} - \lambda^2 I \right| = 0$$

it is a polynomial of degree p_2

if $\lambda^2 = \nu$ and $\lambda = \sqrt{\nu}$ then

$$\left| \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1} \Sigma_{12} - \nu I \right| = 0$$

and if ν_1, \dots, ν_{p_2} be the p_2 roots of this equation

then find the maximum of

$$\sqrt{\nu_1}, \dots, \sqrt{\nu_{p_2}} \text{ say } \sqrt{\nu^{(1)}} \text{ and if we find } \gamma_{p_2 \times 1}^{(1)} \text{ s.t.}$$

$$(\Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1} \Sigma_{12} - \sqrt{\nu^{(1)}} I) \gamma' = 0$$

$$\text{and } \alpha_{p_1 \times 1}^{(1)} = \frac{R_{11}^{-1} R_{12} \gamma^{(1)}}{\sqrt{\nu^{(1)}}}$$

Then $\alpha^{(1)'} X^{(1)}$ and $\gamma^{(1)'} X^{(2)}$ will give the first set of canonical variates and the canonical correlations as $\sqrt{\nu^{(1)}}$. In this way we will get p_2 vectors of canonical weights for both $X^{(1)}$ and $X^{(2)}$ as $[\alpha^{(1)}, \dots, \alpha^{(p_2)}]$ and $[\gamma^{(1)}, \dots, \gamma^{(p_2)}]$ with canonical correlations as $\sqrt{\nu^{(1)}}, \dots, \sqrt{\nu^{(p_2)}}$.

Canonical variates are obtained between the observed and the forecasted rainfall values obtained from four different models. But before obtaining the variates the fractional powers of the rainfall values are taken starting from cube roots to one by fourth powers. fractional powers are considered for the forecasts obtained from the four models as well as for the observed rainfall values.

While doing this the rainfall plots, difference plots, skill score plots are taken and the best fractional power is arrived at. The best fractional power is 1/3.5. The canonical variate values are obtained after taking the 1/3.5th power of the forecasts from the four models and the observed rainfall values. These canonical variates are obtained by using the monsoon season data for 2007 and 2008. The evaluation of the skill is undertaken by using data for monsoon 2009.

3. Results and discussion

In this section the results for the comparative study based upon total rainfall values and skill scores for rainfall values over the Indian region for entire 2009 monsoon season of 122 days (JJAS) is presented. All deterministic global model forecast and the multi-model forecast data for the forecast length of day-1 through day-5 are used to

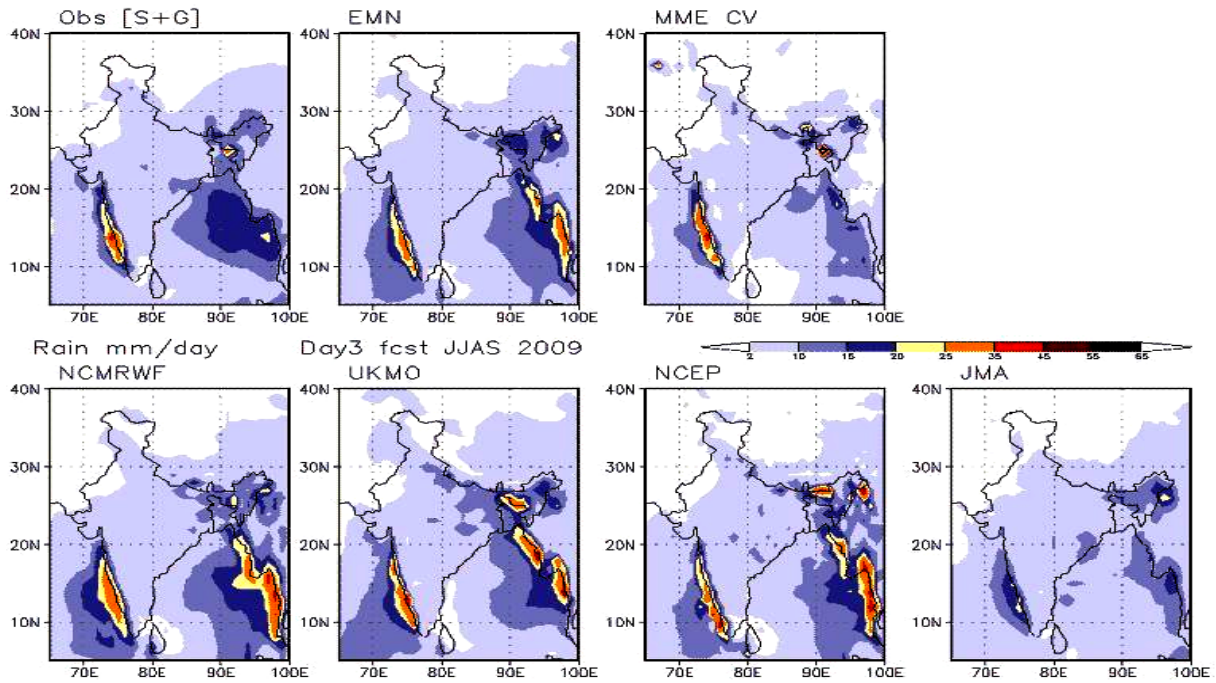


Fig. 1. Total rainfall during monsoon 2009 (JJAS) from observations, simple ensemble mean, multi-model ensemble using Canonical Variates and member models for day-3 forecast

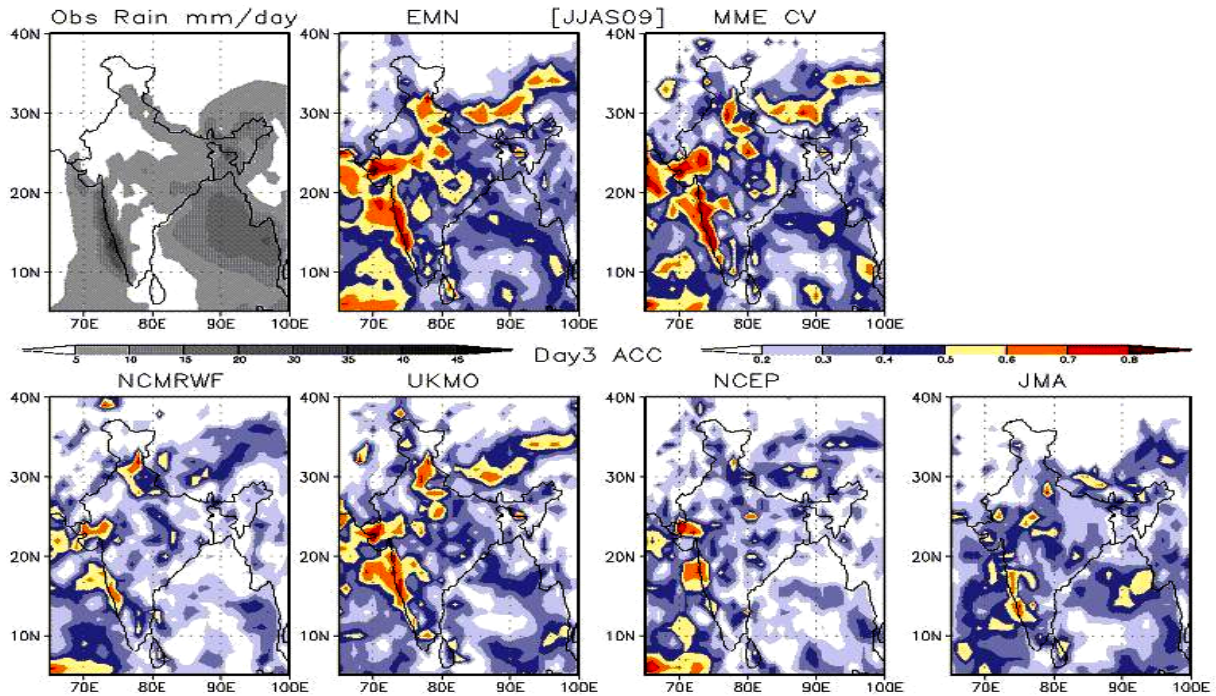


Fig. 2. Anomaly correlation coefficient (ACC) for rainfall during monsoon 2009 (JJAS) for simple ensemble mean, multi-model ensemble using Canonical Variates and member models for day-3 forecast

compute the skill of rainfall forecast during the monsoon 2009 season for the Indian region. In order to limit the number of figures the results for day-3 forecasts are shown, as the results shown are similar with a directional variations for day-1 to day-5 forecasts.

3.1. Comparative study based upon total rainfall values

Fig. 1 displays the total rainfall during the 2009 season for day-3 forecasts from the deterministic models, the simple ensemble mean and the multi-model ensemble. In each plot, the observed rainfall is shown in the top left corner in the upper row. This observed rain is produced on a daily basis by merging rain-gauge and satellite estimates from METEOSAT IR data. The rainfall of the four deterministic models are in the lower row of each diagram. Two multi-model products, namely, (i) the simple ensemble mean, (ii) the multi-model ensemble forecast using canonical variates, are shown in the two panels on the right side in upper row. A detailed comparison indicates that the member models differs from the observation in different ways and at different regions. The NCMRWF and NCEP model produces too much rain in the Arakan coast region to the east of Bay of Bengal. In NCEP model on the west coast of India the north-south rainfall band extends too much to the south and in northern plains (monsoon trough region) the model produces more rain than observations. In the UKMO model, it is seen to rain more on the west coast, Himalayan foothills and northern Bangladesh. In contrast to all the models, the JMA model produces the least rainfall. The multi-model products in the upper row when compared with observations look closer and more realistic. The MME products look superior to member models and simple ensemble mean and much closer to observations.

The anomalies of the observation and forecasts are computed from their respective seasonal means during 2009 monsoon. The anomaly correlation coefficients (ACC) for day-3 are shown in Fig. 2. During monsoon, in medium range forecasts, it is important and challenging to predict the day-to-day rainfall associated with the passing transient weather systems or the fluctuating strength of the monsoon. Therefore, the rainfall anomalies in forecasts and observations have to be examined in terms of their similarity. The anomaly correlation coefficients (ACC) are plotted in a scale of 0 to 1. The multi-model ensemble is having much higher value of ACCs as compared to individual models and simple ensemble means. Although UKMO model maintains the good skill even for day-3 and day-5. But it is worth

mentioning that the ACCs values for multi-model ensemble are much higher as compared to individual models and simple ensemble mean even for day-3 and day-5.

3.2. Comparative study based upon skill scores for rainfall values at all grid points

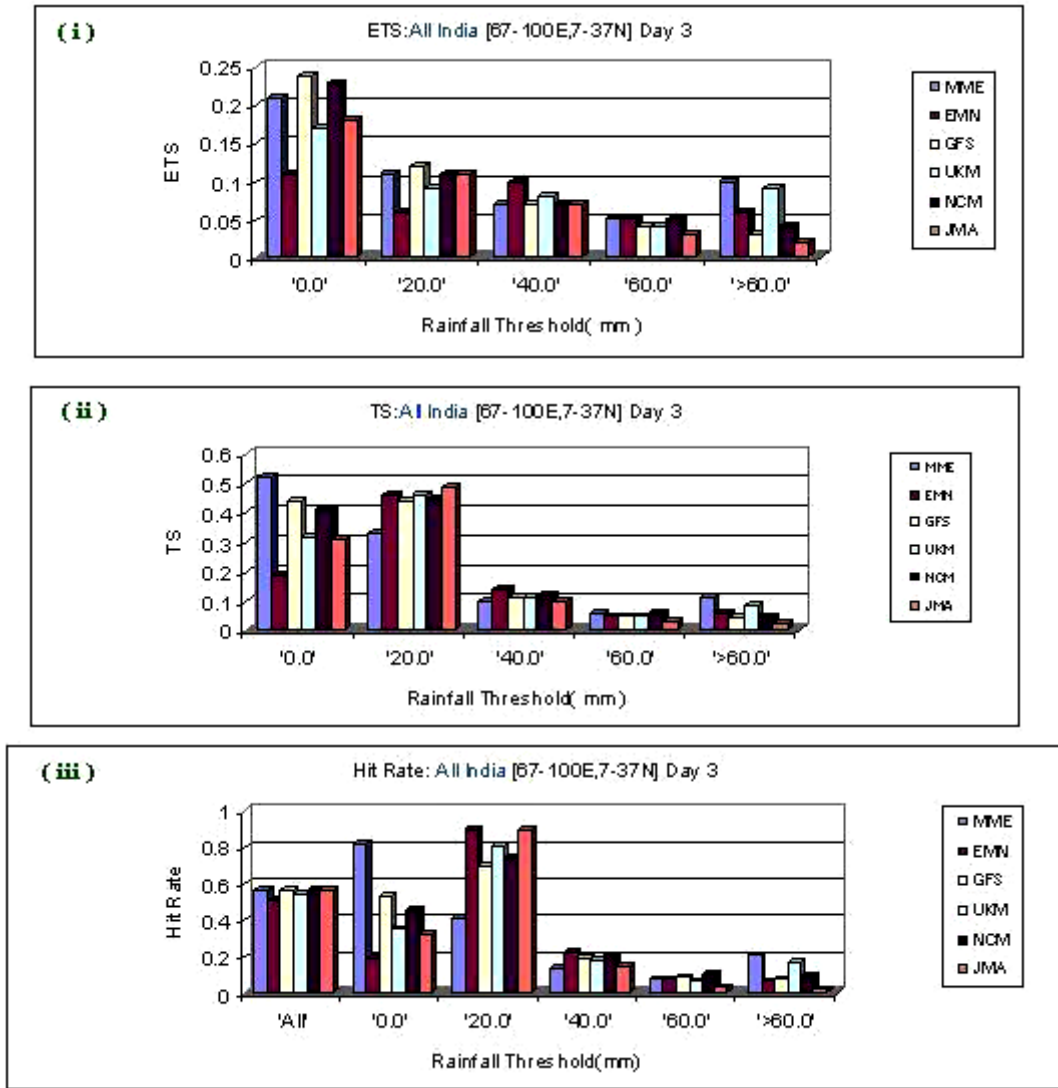
All the above results discussed gives some general idea of the quality of rainfall forecasts in terms of error statistics for monsoon for the member global models and the products from the multi-model algorithm. But we are aware of the limitations of the numerical models in simulating the final products in model that is the rainfall quantity at the right regions. Therefore, it is relevant to examine and document the skill of rainfall forecasts for rainfall amounts in different categories (different threshold amounts of rainfall) in terms of threshold statistics.

Standard statistical parameters like Equitable Threat Score (ETS), Threat Score (TS) and Hit Rate (HR) are computed for the comparisons in different categories of rainfall amounts, Ashok *et al.* (2002) and Wilks (1995). Five uniform rainfall categories are taken for this comparative study with threshold values as no rain (0.0); 20 mm ; 40 mm ; 60 mm and > 60 mm. All India domain covering all the grid points between 67° E and 100° E longitude, and 7° N and 37° N latitude is considered. The skills are computed for day-1, day-3 and day 5 forecasts, although in order to limit the number of figures only the plots for day-3 is given as Figs. 3(i-iii). With increasing length of forecast period (day-1 to day-5) for each threshold rainfall category, the skill scores fall gradually. The multi-model ensemble is giving the higher value for all the skill scores for day-1 to day-5 forecasts, as compared to individual member models and the simple ensemble mean. Although there are exceptions for TS and HR, but for ETS, which is more critical and perfect score shows that the skill of MME forecast is higher for almost all the cases.

3.3. Comparative study based upon skill scores for rainfall values at each grid point

In order to see the rainfall forecast skill scores at each grid point over the Indian region the following four skill scores are obtained and are plotted over the Indian region.

- Hanssen-Kuiper (HK) Skill score for yes/no forecast.
- Hanssen-Kuiper score for more than two classes (HKQ).



Figs. 3(i-iii). (i) Equitable threat score (ii) Threat score (iii) Hit rate for rainfall for multi-model ensemble using Canonical Variates, simple ensemble mean and member models for Day-3 forecast for JJAS 2009 for Indian region [67° - 100° E, 7° - 37° N]

A brief description of these categorical statistics is given in Ashok *et al.* (2002) and Wilks (1995).

Heavy : More than 3.5 cm to 12.5 cm

Very heavy : More than 12.5 cm.

For obtaining these scores following four classes are considered, Rashmi *et al.* (2009);

No rain : Less than threshold for rain (0.1mm)

Light to moderate rain : Threshold value to 3.5 cm.

These score are plotted for day-1 to day-5 forecast. The plots show that the values of the skill scores for each grid point over a large area, are greater for multi-model ensemble forecast as compared to that of individual models and simple ensemble mean for day-1 to day-5 forecasts, although the skill decreases as we move from day-1 to day-5. These plots are given only for day-3, (Figs. 4 & 5).

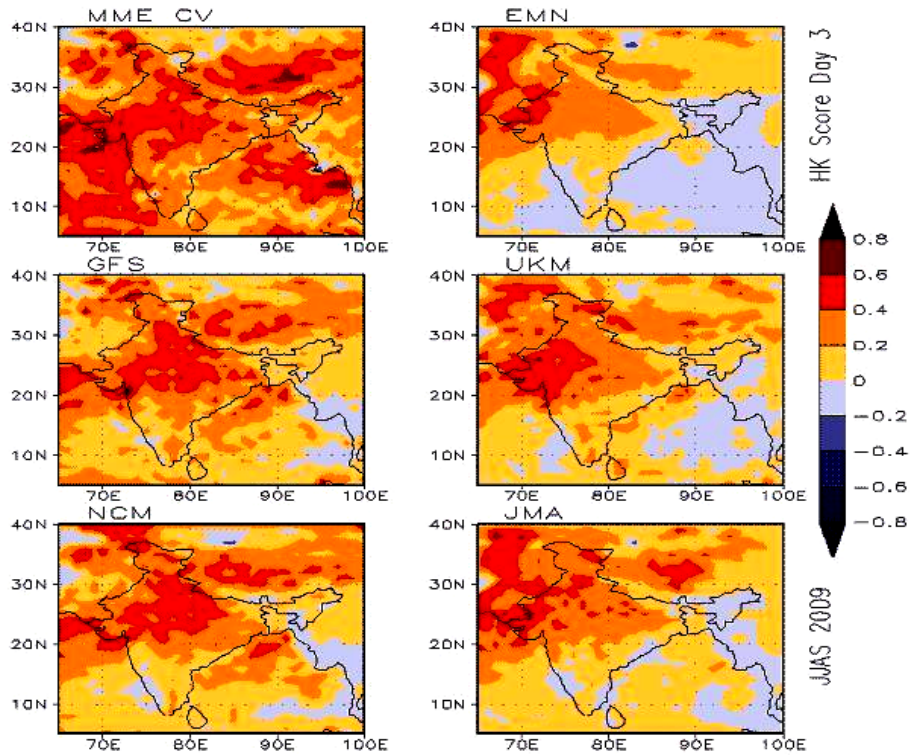


Fig. 4. Hanssen and Kuiper's (HK) score for yes/no forecast for rainfall for multi-model ensemble using Canonical Variates, simple ensemble mean and member models for day-3 forecast during monsoon 2009 (JJAS) over Indian region

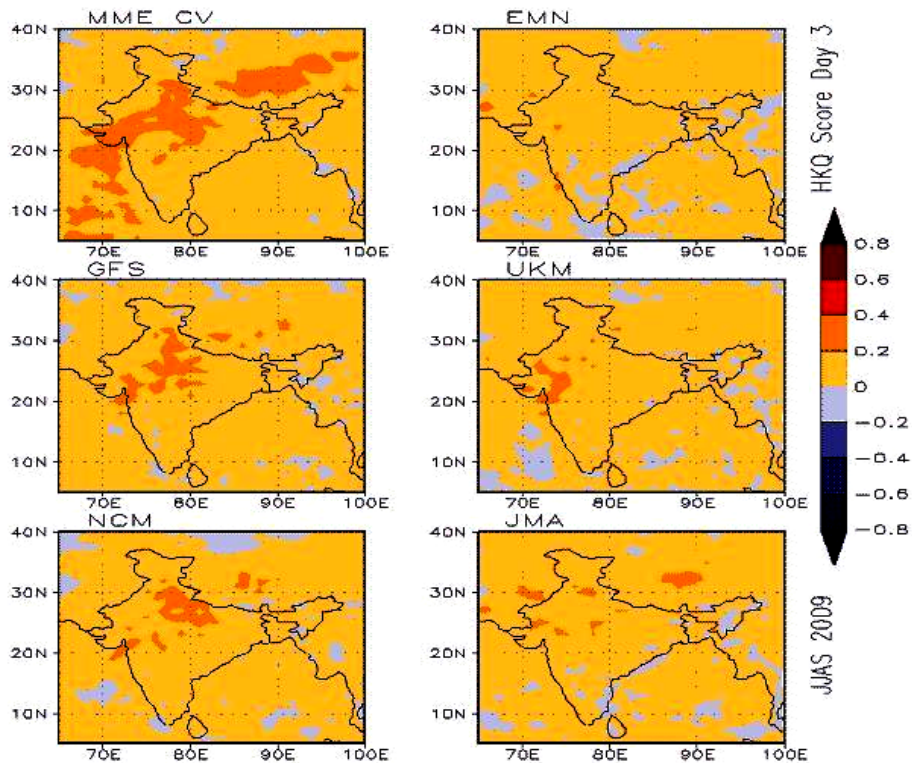


Fig. 5. Hanssen and Kuiper's (HKQ) score for more than two rainfall classes for rainfall for multi-model ensemble using Canonical Variates, simple ensemble mean and member models for day-3 forecast during monsoon 2009 (JJAS) over Indian region

4. Conclusions

During monsoon 2009 a MME forecasting of large-scale monsoon precipitation in medium range was carried out at NCMRWF/MoES, India. Apart from simple ensemble mean, canonical variates are obtained based upon forecasts from four global models in order to obtain the multi-model ensemble forecasts. In general the multi-model ensemble forecast has the better skill than individual model product and the simple ensemble mean as is indicated in the Figs. 1 to 3 and discussed in the above paragraph. The skill scores at each grid point shown in Figs. 4 & 5 over the Indian region indicate that the multi model ensemble is the best and skill of the forecast is showing the positive HK and HKQ scores for almost of the Indian region. Hence, canonical variate is one of the robust statistical techniques which can be used for deriving the multi model ensemble forecast. MME forecast so obtained is certainly a far improved forecast as compared to member models and simple ensemble mean, as in the case of different statistical techniques used for various experiments using MME technique by other authors, Roy Bhowmik and Durai (2008 and 2010), Krishnamurti *et al.* (2009) and Mitra *et al.* (2011). Moreover most of the authors had used the techniques based upon correlations and multiple linear regressions, but being the best linear unbiased estimate the technique based upon canonical variates is more robust.

It is being planned a step towards great grand MME under WMO/TIGGE from poor men's ensemble. In coming years it will be good to include other newer model data into this MME system. Data from more models could be included from the THORPEX/TIGGE setup also. However, models have to be improved for monsoon. In this study had used the standard scores to assess the usefulness and benefits of the MME forecast against member models. However, with increasing number of member models and ensemble members from each model, to be able to understand and document the full potential and usefulness of the MME products both in deterministic and probabilistic sense various skill scores have to be used, Cusack and Arribas (2008). Probabilistic ensemble forecasting has to be taken up for tropics. Bowler *et al.*, (2008) have shown the usefulness of a short-range ensemble prediction system which will be made operational at UKMO. They show that the regional ensemble is more skillful than the global ensemble and compares favorably to the ECMWF ensemble for many variables. In India also a regional ensemble system for probabilistic forecasts has to be experimented. Combination of ensembles is a promising approach for further development which will give rise to significant improvement in the predictive skill for tropics and monsoon. While looking for enhanced skill in MME, as a

by-product, the member models also get verified and we are able to keep track of the state of art model's performance. This feedback is useful for continuous model development and other modeling related research.

For operational use obtaining weights from different participating member models, past historical data are used, Roy Bhowmik and Durai (2008 & 2010). Therefore, with every update of the models, corresponding past data will be required to be used for statistical calculations. Otherwise, full benefits of the improved model might not get included in the multi-model post-processing. These data has to be obtained by running the model in hindcast mode for the region and period of interest. It will be good to explore some alternate MME algorithms to obtain weights from different models for experimenting with rainfall for the Indian monsoon. Algorithm which improves the skill in a statistical sense, and also retains the intensity and location of rainfall will be more useful.

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