

## Verification of quantitative precipitation forecasts from operational ensemble prediction systems over India

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**सार** – इस शोध पत्र में भारत में अल्पावधि से मध्यावधि समय मान पर “प्रेक्षित प्रणाली अनुसंधान और पूर्वानुमानित परीक्षण” (THORPEX) अन्वयोन्यक्रिया मुख्य भूमंडलीय समुच्चय (TIGGE) डाटाबेस से प्राप्त किए गए यूरोपीय मध्यावधि मौसम पूर्वानुमान केंद्र (ECMWE), ब्रिटेन मौसम कार्यालय (UK MO) संयुक्त राज्य राष्ट्रीय पर्यावरण पूर्वानुमान केंद्र (NCEP) और जापान मौसम विज्ञान एजेंसी (JMA) के चार प्रचालनात्मक समुच्चय पूर्वानुमान प्रणाली (EPS) के निष्पादन का अध्ययन किया गया है। निर्धारणात्मक और प्रायिकतात्मक दोनों संवेदकों में EPS के इन वर्षा पूर्वानुमान निपुणता का परीक्षण किया गया। इनसे प्राप्त परिणामों से यह पता चला है कि इन चारों (EPS) के समुच्चय माध्य पूर्वानुमान से उत्तर पूर्वी और मध्य भारत सहित पश्चिमी तट की पट्टियों पर मौसमी माध्य भारी वर्षा फिर से हो सकती है। सक्रिय वर्षा (सकारात्मक विसंगति) और वर्षा की कमजोर अथवा अशक्त स्थिति (नकारात्मक विसंगति) सभी EPS समुच्चय माध्य पूर्वानुमानों के दायरे में हैं। ECMWF EPS से प्राप्त समुच्चय माध्य वर्षा पूर्वानुमान में सामान्यतः सबसे अधिक निपुणता है। ECMWF EPS से प्राप्त समुच्चय माध्य वर्षा पूर्वानुमान में सामान्यतः सबसे अधिक निपुणता है। उसके बाद UKMO, NCEP और JMA EPS में है। प्रायिकता पूर्वानुमान के लिए मध्यावधि में भारत के BSS, RPSS और ROC का उपयोग करते हुए इसे मापने पर NCEP और UK MO EPS में लगभग एक जैसी निपुणता पाई गई है।

**ABSTRACT.** In this paper the performance of four operational Ensemble Prediction System (EPS) of the European Centre for Medium-Range Weather Forecasts (ECMWF), the UK Met Office (UKMO), the US National Centers for Environmental Prediction (NCEP) and the Japan Meteorological Agency (JMA) available from “The Observing System Research and Predictability Experiment” (THORPEX) Interactive Grand Global Ensemble (TIGGE) database are studied over India in short to medium range time scale. The rainfall prediction skill of these EPS is examined in both deterministic and probabilistic senses. Results suggest that the ensemble mean forecast of all four EPS could reproduce the seasonal mean heavy rainfall belts along the west coast, over north east and central India reasonably well. The active rainfall (positive anomaly) and weak or break condition of rainfall (negative anomaly) activity is well captured by all EPS ensemble mean forecasts. The ensemble mean rainfall forecast from ECMWF EPS generally has the highest skill, followed by UKMO, NCEP and JMA EPS. For the probability forecast, the NCEP and UKMO EPS appeared to have more or less similar skill when measured using BSS, RPSS and ROC over India in the medium range.

**Key words** – THORPEX, TIGGE, EPS, Indian monsoon, Ensemble prediction system, Comparison, Rainfall prediction skill.

### 1. Introduction

For day to day weather forecasts, one has to depend on Numerical weather prediction (NWP) model. These model forecasts have become increasingly accurate as physical understanding of the behavior of the atmosphere, observational data resources, data assimilation methodologies, model grid resolution, and computational resources have improved. However, the chaotic nature of the atmosphere, first described in the 1960's by Lorenz (1963), prevents perfect weather forecasting. NWP models lose skill due to forecast errors arise as a result of errors both in the initial conditions and in the forecast model itself. In order to overcome these two sources of

uncertainty in the single deterministic forecast, a new approach known as Ensemble prediction systems (EPS) have been used. Significant advancements in computational resources made ensemble forecasting practical in the 1990's. Initially the ensemble approach was made operational at the U. S. National Centers for Environmental Prediction (NCEP) (Tracton and Kalnay, 1993) and the European Centre for Medium-Range Weather Forecasts (ECMWF) (Buizza and Palmer, 1995), with different initial perturbation generation methods. Thereafter, a lot of countries, established their own EPS and put them into operation in different ways, including different initial perturbation generations, multiple forecast models, varied model resolutions, a variety of model

physics perturbations, changed number of ensemble members and so on (Park *et al.*, 2008).

The operational weather forecasting community all over the world has started experimenting with the performance skill of operational global EPS using dataset available from “The Observing System Research and Predictability Experiment” (THORPEX) Interactive Grand Global Ensemble (TIGGE) database. Buizza *et al.* (2008) summarized two of the main advantages of ensemble-based probabilistic forecasts as the ability of an EPS to predict the most likely scenario; and the ability of an EPS to predict the probability of occurrence of any event, and provide more consistent successive forecasts. Bougeault *et al.* (2010) performed case studies with the EPS and gave a comprehensive description about TIGGE dataset. Park *et al.* (2008) compared eight EPSs and found that the best and worst control and ensemble mean forecasts had large differences of about 2 days of predictability for 5-day forecasts. Tittley *et al.* (2008) compared the ECMWF and UKMO EPSs and found that the ECMWF EPS has higher skill than the UKMO EPS. Evans *et al.* (2000) used multi-model multi-analysis ensemble approach to evaluate the deterministic forecasts from UKMO and ECMWF EPS and showed that the superiority of the multi-model system over the individual EPS data.

Multi-Model Ensemble (MME) forecasting studies have been carried out over Indian monsoon regions using deterministic NWP models by Roy Bhowmik and Durai (2008, 2010, 2012), Durai and Bhardwaj (2013, 2014), Mitra *et al.* (2011); Krishnamurti *et al.* (2009) and Kumar *et al.* (2012) to provide precipitation forecast and found that the MME shows a major improvement in the short range over India. Kar *et al.* (2011) studied the NCEP based global EPS with 8 members over India for a monsoon season and found that the ensemble mean rainfall is good in short range time scale. Most of the EPS performance studies over India were limited in assessment of one EPS's capability or in comparison between the deterministic forecast. The geographic regions of India represent the transition region between better performance of initial perturbation based ensembles toward mid latitudes and predominant skill of model perturbation based ensembles toward the tropics. To date, there have been no systematic comparisons of ensemble mean and probabilistic forecasts generated from operational EPS available at TIGGE database verified to assess the relative strengths and weaknesses of these EPS ensemble members over India in the short to medium range time scale.

The main aim of this study is to evaluate the rainfall prediction skill of four operational EPS of ECMWF, UKMO, NCEP and JMA over India in short to medium range time scale over India during monsoon 2012. The

24-hr accumulated ensemble mean and probabilistic forecasts of rainfall were generated and then examined in terms of different statistical skill scores to recognize the advantages and shortcomings of these four operational EPSs over India during summer monsoon seasons. The data used in this study are described in Section 2, followed by a description of the verification analysis methods in Section 3. As the main part, the skills of ensemble mean forecasts and probabilistic forecasts are discussed in Sections 4. Section 5 presents the summery and conclusions.

## 2. Data source

### 2.1. Numerical models

In this study, the day-1 to day-7 rainfall forecast data from four operational EPS namely European Centre for Medium-Range Weather Forecasts (ECMWF), the U.S. National Centers for Environmental Prediction (NCEP)'s Global Forecasting System (GFS), U. K. Met. Office (UKMO) and Japan Meteorological Agency (JMA) is used. The ensemble forecast data from ECMWF, UKMO and NCEP are based on 0000 UTC and JMA is 1200 UTC run for the period from 1 June to 30 September, 2012. These models were being run at their respective centers (countries) at high horizontal and vertical resolutions. For size consistency and to facilitate skill comparisons, only the first 20 perturbed ensemble members forecast of 24-hr accumulated precipitation from the ECMWF, UKMO, NCEP, and JMA EPS archived in the TIGGE database at ECMWF were used in this study. Buizza *et al.* (2005) used only the first 10 ensemble members for comparing the performance of ECMWF, NCEP and Meteorological Service of Canada (MSC) EPS. Hamill (2012) verified the probabilistic quantitative precipitation forecast over the continuous United States (CONUS) using only the first 20 member forecasts of 24-hr accumulated precipitation data from the UKMO, MSC, NCEP and ECMWF ensemble systems archived in the TIGGE database at ECMWF. When considering the quantitative results of this study, the reader should be aware that the ensemble size has an impact on ensemble skill. For example, the ECMWF EPS operates with 51 members, but Buizza and Palmer (1998) show that most of the skill score improvement is gained by going from two to eight members. It appears that 8-10 members are sufficient to realize most of the benefits obtainable through ensemble averaging (Leith, 1974; Toth and Kalnay, 1997).

Ensemble mean and Probabilities were calculated directly from the ensemble members of the EPS. Daily ensemble mean forecasts of 24-hr accumulated precipitation were examined from day-1 to day-7 during the monsoon periods. Regardless of the original model resolution, all centers' forecasts were bi-linearly

**TABLE 1**  
**Characteristics of the ECMF, UKMO, NCEP and JMA EPS**

Operation center	ECMF	UKMO	NCEP	JMA
Initial perturbation method	SV	ETKF	ETR	SV
Model error simulation	YES	YES	YES	YES
Horizontal resolution	T639 T319	0.83 × 0.55 deg	T190	T319
Vertical level	62 62	85	42	60
Forecast length (days)	0-10 10-15	0-15	0-16	0-11
Perturbation members	50	23	20	50
Runs per day (UTC)	2(00/12)	2(00/12)	4(00/06/12/18)	1(12)
Members per day	102	48	84	51
Initial date of TIGGE operational mode	1 Oct 2006	1 Oct 2006	5 Mar 2007	1 Oct 2006

interpolated to a  $1 \times 1$  deg latitude-longitude grid covering India  $0-40^\circ$  N and  $60^\circ-100^\circ$  E using ECMWF's TIGGE portal software. ECMWF's interpolation procedure set the amount to zero if there was no precipitation at the nearest neighboring point and the interpolated value was less than 0.05 mm. The main characteristics of the EPS currently operational at ECMWF, UKMO, NCEP, and JMA are presented in Table 1. For the initial perturbation methods, the ECMWF and JMA EPS uses singular vectors (SVs), the NCEP EPS use Ensemble Transform with Rescaling (ETR), while the UKMO EPS uses Ensemble Transform Kalman Filter (ETKF). The ECMWF EPS run at T639L62 ( $\sim 20$  km) horizontal resolution for the first 10 days then the model resolution became T319L62 (40 km) from 10-15 days. The changes to the ensemble stochastic treatments are described in Palmer *et al.* (2009).

The ensemble was initialized with a combination of initial-time and evolved total-energy singular vectors (Buizza and Palmer, 1995; Barkmeijer *et al.*, 1999; Leutbecher, 2005) and utilized stochastic perturbations to physical tendencies. NCEP used the Global Forecast System (GFS) model in their ensemble system at T190L28 (70 km) resolution (Hamill *et al.*, 2011). Perturbed initial conditions were generated from grid point statistical interpolation (GSI) analysis (Kleist *et al.*, 2009) with the ensemble transform with the rescaling

technique of Wei *et al.* (2008). Stochastic perturbations were included, following Hou *et al.* (2008). The UKMO EPS was run at a resolution of  $0.838 \times 0.558$  degree on regular latitude - longitude grid with 70 vertical levels. Initial condition perturbations were generated from an implementation of the ensemble transform Kalman filter (Hunt *et al.*, 2006; Bowler *et al.*, 2008). The model included a parameterization of one type of model uncertainty via its stochastic kinetic-energy backscatter scheme, following Shutts (2005) and Tennant *et al.* (2011). JMA has been operating a one-week EPS since 2001. The current JMA EPS version is TL319L60 ( $\sim 40$  km) global spectral model operated with 51 members (Saito *et al.*, 2010) with applies stochastic perturbation of physics tendency to the numerical model.

## 2.2. Observational data

The daily observed (Rain Gauge) rainfall data from the India Meteorological Department (IMD) are quality controlled and objectively analysed at  $1^\circ \times 1^\circ$  latitude - longitude grid (Rajeevan *et al.*, 2005). The objective technique used for this rainfall analysis is based on the Cressman interpolation method (Cressman, 1959). The Cressman weight function used in the objective rainfall analysis is defined by :

$$W(r_{i,m}) = \begin{cases} \frac{R^2 - r_{i,m}^2}{R^2 + r_{i,m}^2} \end{cases}^2, \text{ for } r_{i,m} < R \\ = 0, \text{ for } r_{i,m} \geq R$$

where,  $R$  is the radius of rainfall influence ( $R = 200$  km) and  $r_{i,m}$  is the distance of the synoptic station from the grid point in km.

The analysed observed rainfall (rain gauge) used for the study is accumulated rainfall in the 24 hours ending 0830 hrs IST (0300 UTC). The final daily rainfall analysis data at the resolutions of  $1^\circ \times 1^\circ$  is prepared by merging rain-gauge observations data for the land areas and Tropical Rainfall Measuring Mission (TRMM) 3B42V6 data for the Sea areas (Durai *et al.*, 2010). In India, the synoptic observation of rainfall is performed over a 24-hour period ending at 0300 UTC. Hence, we have verified the model forecast valid at 0000 UTC against the observed rainfall analysis (rain gauge) ending at 0300 UTC. The error caused by the timing mismatch is usually negligible compared to model forecast errors.

## 3. Verification methodology

EPS rainfall forecast is evaluated for day-1 to day-7 forecasts of 24-hr accumulated ensemble mean as well as

probabilistic forecast over India. An excellent review of forecast verification methods have been carried out by Wilks (1995). The ensemble mean deterministic forecast is evaluated by calculating simple point by point comparisons like root mean square error (RMSE), correlation coefficient (CC) and anomaly correlation coefficient (ACC) between forecast and analysis. RMSE of the ensemble mean measure the distance between forecasts and analyses.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (F_i - O_i)^2},$$

where,  $N$  is the total number of ensemble members,  $F_i$  is the ensemble forecast and  $O_i$  is the observed rainfall analysis at the grid. Ensemble spread (SPRD) is calculated by measuring the deviation of ensemble forecasts from their mean (Zhu, 2005). Usually, SPRD is defined as,

$$\text{SPRD} = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (\bar{F}_i - F_i)^2},$$

where  $\bar{F} = \frac{1}{N} \sum_{i=1}^N F_i$  is for the ensemble mean.

For computation of ACC, observed daily climatology of gridded rainfall dataset (Rajeevan *et al.*, 2005) based on rain gauge measurements from 1803 stations over Indian land for the period 1951-2003 from IMD is used.

$$\text{ACC} = \frac{\sum_{i=1}^N (F_i - \bar{F})(O_i - \bar{O}_i)}{\sqrt{\sum_{i=1}^N (F_i - \bar{F})^2} \sqrt{\sum_{i=1}^N (O_i - \bar{O}_i)^2}}$$

The most common measure of the quality of probability forecasts is the Brier Score (BS). The BS (Brier, 1950) is a scalar measure corresponding to the mean-squared error in terms of the probabilities. It is defined as,

$$\text{BS} = \frac{1}{N} \sum_{i=1}^N (p_i - o_i)^2$$

where, index  $i$  denotes the numbering of observation-forecast pairs,  $p_i$  are the forecast probabilities of the given

event and  $o_i$  the corresponding observed values, having integer values 1 or 0, if the event occurred or did not, respectively. Analogous to earlier definitions, it is customary to generate a skill score, where a reference forecast system is required. The Brier Skill Score (BSS) is defined as (Wilks, 1995),

$$\text{BSS} = \frac{\text{BS}_{\text{cli}} - \text{BS}}{\text{BS}_{\text{cli}}},$$

where,  $\text{BS}_{\text{cli}}$  is BS reference observed climatology.

A vector generalization of the BSS to multi-event or multi-category situations is defined by the Ranked Probability Score (RPS). It is defined as,

$$\text{RPS} = \frac{1}{k-1} \sum \left\{ \left( \sum p_i \right) - \left( \sum o_i \right) \right\}^2,$$

where,  $k$  is the number of probability categories.

It measures the sums of squared differences in cumulative probability space for a multi-event probability forecast. It penalizes forecasts more severely when their probabilities are further from the actual observed distributions. In this study, the Ranked Probability Skill Score (RPSS) is defined as,

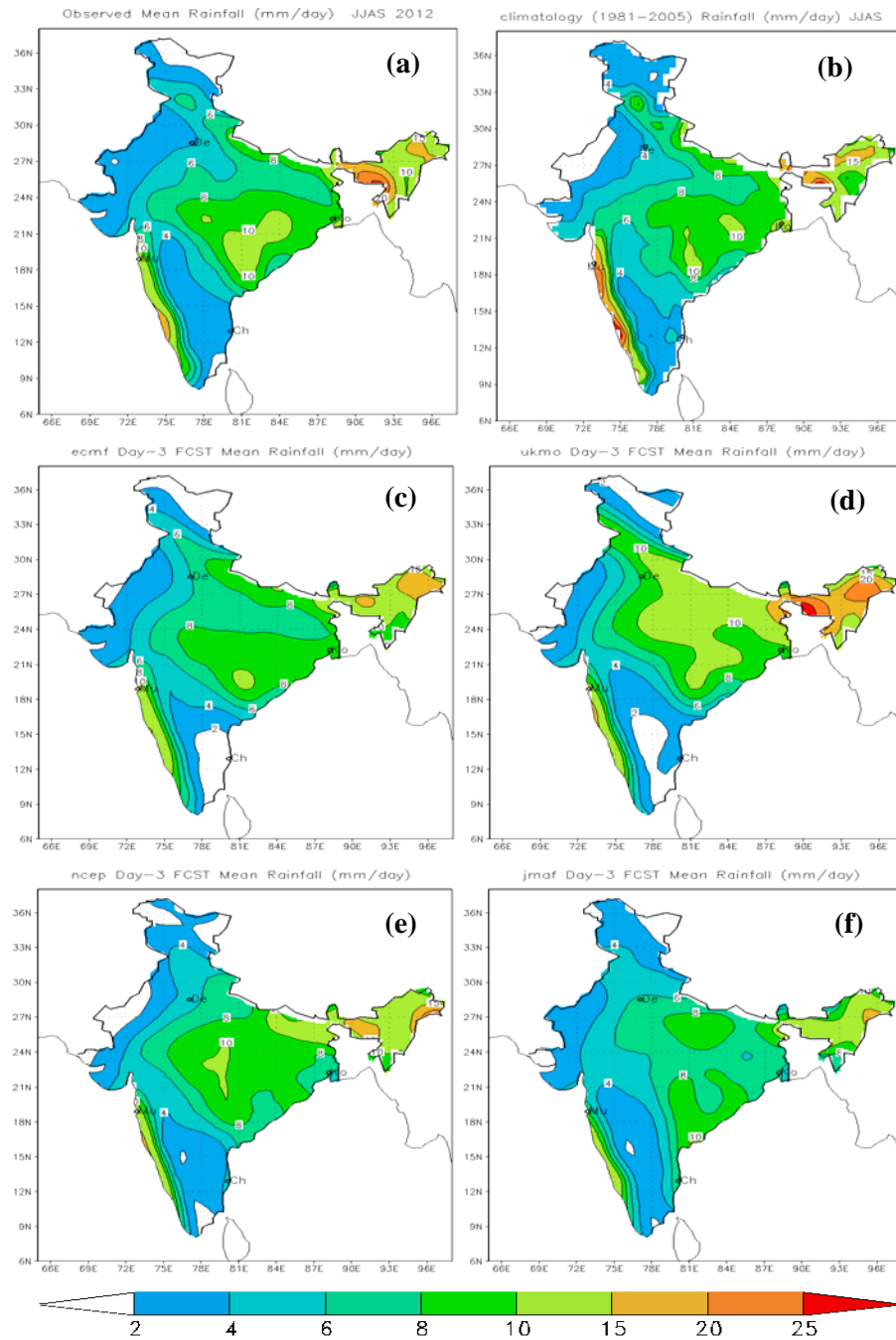
$$\text{RPSS} = \frac{\text{RPS}_{\text{cli}} - \text{RPS}}{\text{RPS}_{\text{cli}}},$$

where,  $\text{RPS}_{\text{cli}}$  is RPS reference observed climatology.

To assess the skill of categorical forecast, a categorical forecast verification method is used here. The rainfall thresholds considered to define the transition between a rain-event versus no-rain-events are based on rainfall threshold used by the operational forecasters of IMD. 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 ( $H$ ). The relative operating characteristic (ROC) is a plot of the hit rate (HR) against the false alarm rate (FAR) for categorical forecasts based on probability thresholds varying between 0 and 1.

The Hit rate (HR) is defined as  $\text{HR} = \frac{H}{H+M}$ .

While the false alarm rate (FAR) can be generated easily by defining  $\text{FAR} = \frac{F}{Z+F}$ .

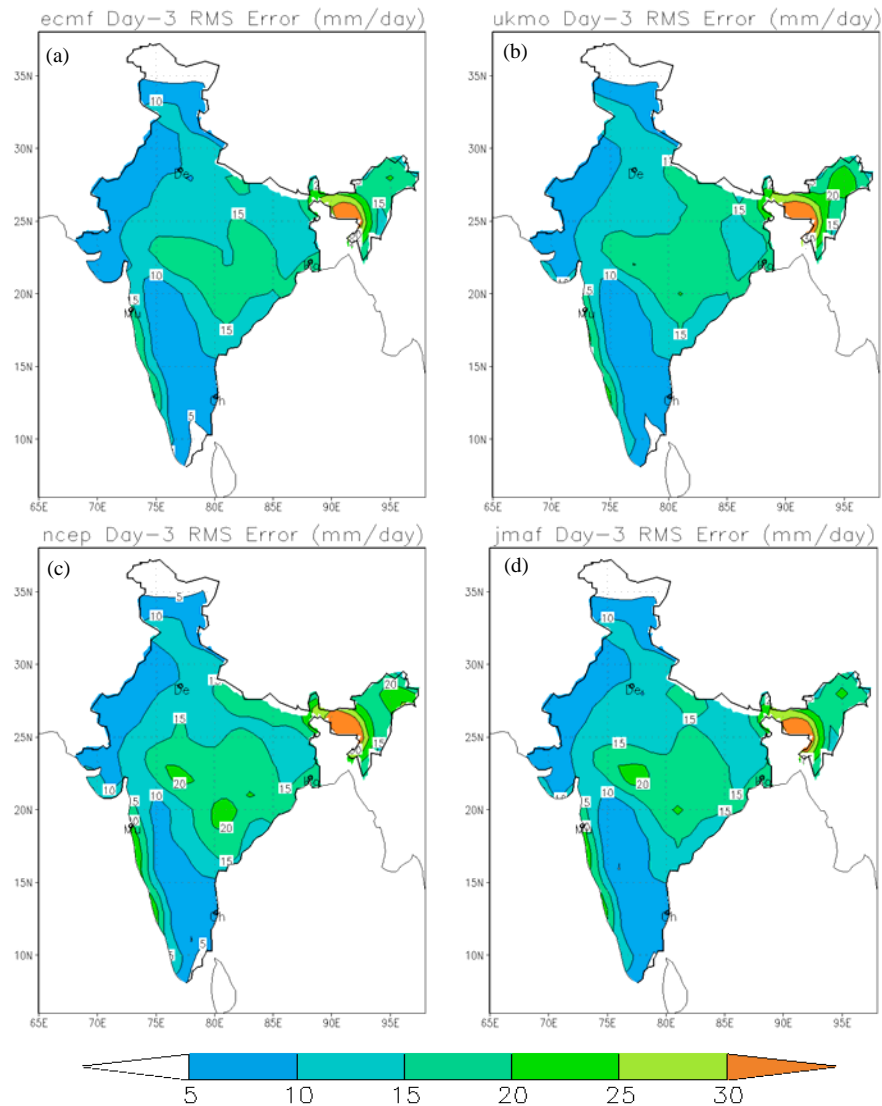


**Figs. 1(a-f).** Spatial distribution of seasonal mean (a) observed, (b) climatology rainfall (mm/day) and day-3 ensemble mean rainfall (mm/day) forecast from (c) ECMWF, (d) UKMO, (e) NCEP and (f) JMA EPS for the period from 1 June to 30 September 2012

#### 4. Results and discussion

The performance of all the four EPS currently operational at ECMWF, UKMO, NCEP, and JMA is discussed in the following three sub-sections for summer monsoon 2012. A first approach for comparison of the quality of EPS member forecasts with the quality of

deterministic forecasts is to use the ensemble mean or the ensemble median as a deterministic representative for the ensemble forecast and apply standard verification scores. The verification of the deterministic forecast is relatively simple. It is the measure of the difference between forecasts and observations. Calculations of the ACC and RMSE, as the standard methods for quantitative forecast



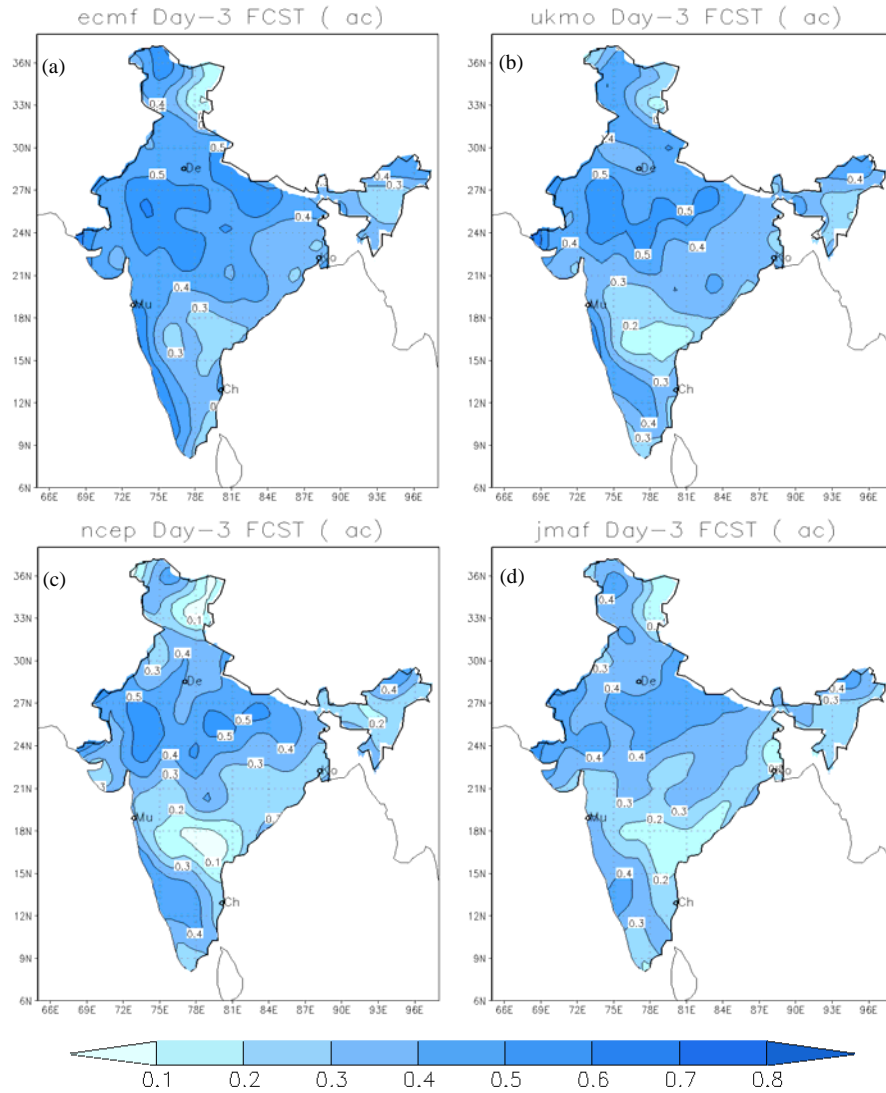
**Figs. 2(a-d).** Spatial distribution of seasonal root mean square error (rmse) rainfall (mm/day) based on day-3 forecast of (a) ECMWF, (b) UKMO, (c) NCEP and (d) JMA global Ensemble Mean for the period from 1 June to 30 September 2012

verification recommended by the World Meteorological Organization (WMO, 1992) are used here. The probabilistic forecast verification is more complicated as compared to deterministic forecast. The categorical rainfall thresholds used for probabilistic forecast are 0.1, 2.5, 7.0, 35, 64 mm/day. The quality of probability forecasts is verified using BSS, RPSS and ROC. All the verifications statistical skill score are averaged over all the verified grid points over Indian land areas.

#### 4.1. Skill of EPS deterministic forecasts

The skill of ensemble mean forecasts of ECMWF, UKMO, NCEP and JMA EPS in terms of spatial and

domain mean values of rainfall, RMSE and ACC has been compared and discussed in this section. First, the spatial distribution of seasonal mean observed, climatology rainfall and ensemble mean rainfall (mm/day) in the day-3 forecast of ECMWF, NCEP, UKMO and JMA EPS for the period from 1 June to 30 September, 2012 is shown in Figs. 1(a-f). The observed seasonal mean rainfall distribution during monsoon 2012 shows a north-south oriented belt of heavy rainfall along the west coast of India with a peak of ~ 15 mm/day over Konkan coast. The sharp gradient of rainfall between the west coast heavy rainfall and the rain shadow region to the east, which is normally expected from the climatology field [Fig. 1(b)], is noticed in the observed field [Fig. 1(a)]. Another



**Figs. 3(a-d).** Spatial distribution of anomaly correlation coefficient between the observed and the model ensemble mean rainfall in the day-3 forecast of (a) ECMWF, (b) UKMO, (c) NCEP and (d) JMA global ensemble models for the period from 1 June to 30 September, 2012

heavy rainfall belt ( $\sim 20$  mm/day) is observed over the North East (NE) India, extending from Cherrapunji of Meghalaya to southern part of Assam. A rainfall belt of order 10-15 mm/day is noticed over the eastern central parts of the country over adjoining Gangetic West Bengal (GWB) regions. Rainfall of more than 10 mm/day is also observed over NE India with a peak over Meghalaya. The region of scanty precipitation over the desert to the west of the country and over south east peninsular India (southern part of Tamilnadu) are also noticed with the seasonal accumulated precipitation of less than 4 mm/day. The day-3 ensemble mean forecast of ECMWF [Fig. 1(c)] and NCEP [Fig. 1(e)] EPS, show 8 to 10 mm/day rainfall

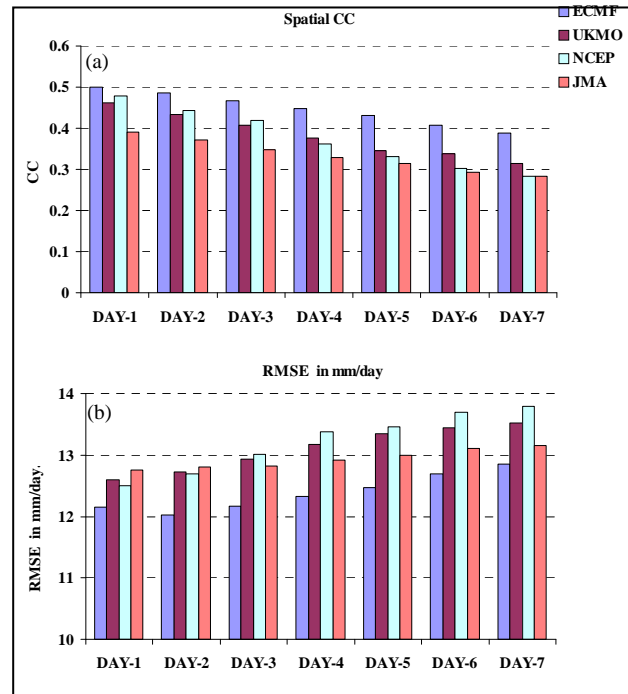
in the eastern part of the country particularly over Coastal Orissa and adjoining Gangetic West Bengal (GWB). The location and magnitude of seasonal mean rainfall estimated by the day-3 ensemble mean forecast of both ECMWF and NCEP is matching with the observed rainfall. UKMO [Fig. 1(d)] EPS shows rainfall of more than 10 mm/day over the entire GWB and along the foot hills of the Himalaya regions, which is higher than the observed rainfall. The day-3 rainfall produced by JMA [Fig. 1(f)] EPS is less than the observed rainfall over these heavy rainfall regions. The large seasonal mean rainfall over the eastern part of the country (IMD, 1981) particularly over GWB regions is due to dynamical



forcing produced by the generation of cyclonic circulations near the eastern end of the monsoon trough dipping into the Bay of Bengal (Rao, 1976). The ensemble mean rainfall from all four EPS [Figs. 1(c-f)] could reproduce the seasonal heavy rainfall belts along the west coast, over the north east India and over east central India reasonably well.

Broadly similar pattern of RMSE in day-3 ECMWF, UKMO, NCEP and JMA ensemble mean rainfall forecast is observed over Indian land areas. The RMSE range between 10-15 mm over most parts of India [Figs. 2(a-d)] and it is relatively higher (25-30 mm) over parts of NE India and along the west coast of India in all four EPS ensemble mean forecast. The magnitude of RMSE over parts of NE India is in the order of 25-30 mm in day-3 forecast. ECMWF has relatively smaller RMSE, while other three EPS ensemble mean has higher RMSE values in all the regions over India. RMSE of the ECMWF EPS is always the lowest, followed by UKMO, NCEP, and JMA EPSs successively. The value of ACC over a large part of central India is higher in all the EPS. All the EPS show higher values of ACC along the monsoon trough region and smaller values over North West (NW) and Southern Peninsular (SP) India in day-3 forecasts. ECMWF EPS has higher scores of ACC values in day-3 forecast compared to the other EPS over most of the country during monsoon 2012 [Figs. 3(a-d)]. The magnitude of ACC values decreases from west coast of India to east coast of India in all the EPS forecast. ECMWF EPS has higher skill than other three EPS over most parts of the country. It has also been observed that among all the EPS, the ACC value for JMA is very low in day-3. Thus for monsoon rainfall forecasts, the current EPS models have some skill for day to day forecast in the short range time scale. For a sample size of 122 (monsoon days), the ACC is statistically significant at the 99% confidence level for ACC values exceeding 0.239. Hence, the ACC exceeding 0.239 is considered to be good for precipitation forecast. The comparison of ACCs of the four EPSs during monsoon season shows that the ACC of ECMWF EPS is higher and JMA is smaller during the period of study over India.

Fig. 4(a) presents an inter-comparison of country mean spatial CC of ensemble mean rainfall forecasts by ECMWF, UKMO, NCEP and JMA global ensemble models for day-1 to day-7 forecast. For the ECMWF, CC ranges from 0.4 to 0.5 for day 1 to day 7 forecasts, for UKMO it ranges between 0.31 to 0.45, for NCEP between 0.29 and 0.48, and for JMA between 0.29 and 0.40. The inter comparison of spatial CC show that ECMWF EPS ensemble mean forecast is superior to other three EPS ensemble mean model in all day-1 to day-7 the forecasts. All India seasonal mean RMSE of ensemble mean rainfall

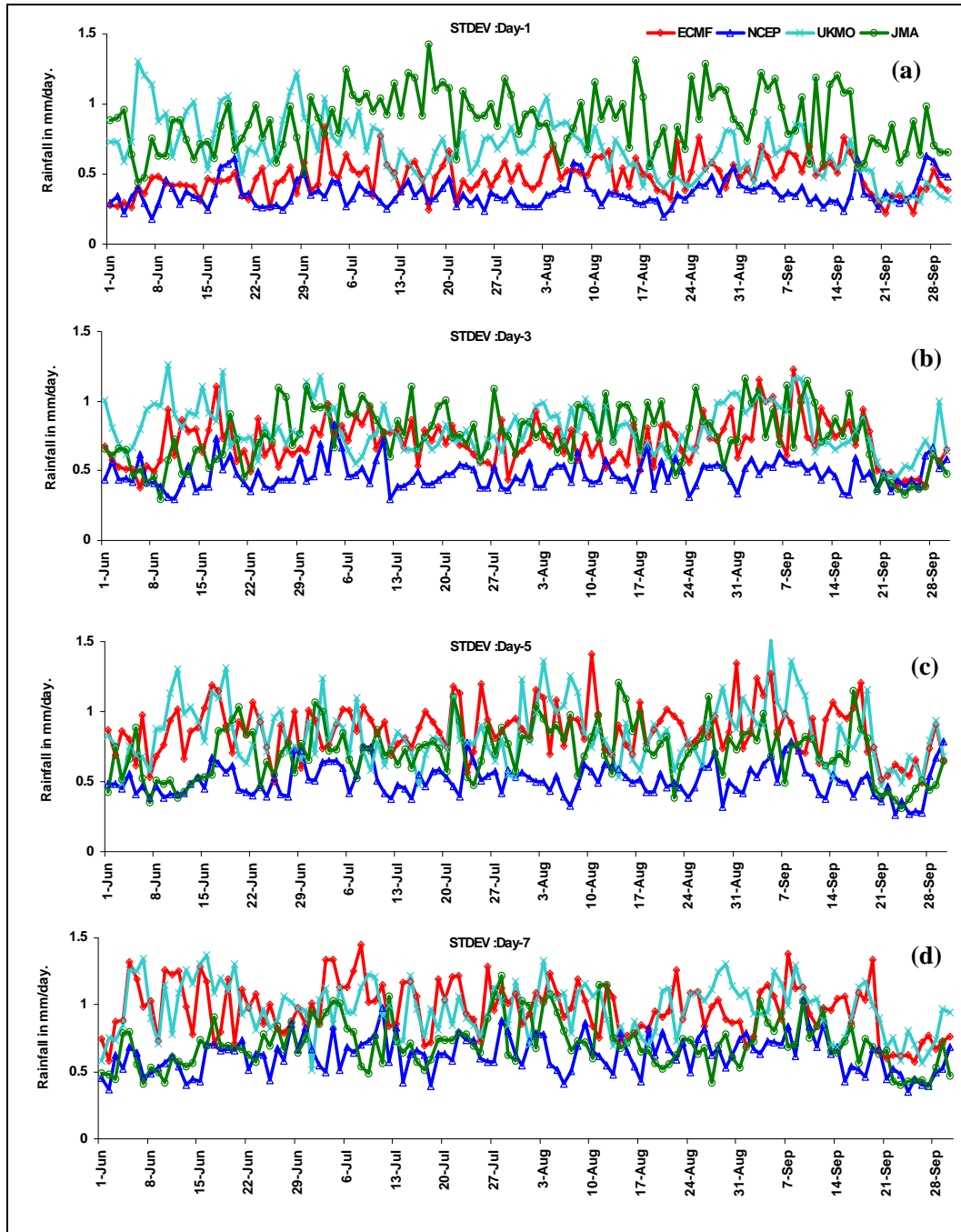


**Figs. 4(a&b).** An inter-comparison of country mean (a) spatial CC and (b) RMSE of ensemble mean rainfall forecasts by ECMWF, UKMO, NCEP and JMA global ensemble models for the period from 1 June to 30 September, 2012

forecasts by ECMWF, UKMO, NCEP and JMA EPS for day-1 to day-7 forecast during the period from 1 June to 30 September, 2012 is given in Fig. 4(b). RMSE is influenced more strongly by large errors than by small errors. Squaring forces RMSE to weight both positive and negative errors equally. Thus RMSE is a measure of both the random and systematic components of the model forecast error. The inter-comparison very clearly shows that the RMSE has been lowest in the ECMWF ensemble mean in all days of forecast. For 24 hour forecast, among four EPS, JMA has higher RMSE values. The seasonal allIndia mean RMSE for ECMWF is smaller than other three EPS in all days (day-1 to day-7) of forecast. In day-3, the RMSE values for all EPSs are higher as compared to day-1. The errors grow gradually from day-1 to day-7. It is observed from Fig. 4(b) that the value of RMSE increases with forecast lead time in all four EPS ensemble mean forecast. For all days of forecast, the RMSE for all four EPS is of the order 13-14 mm/day. Among the individual EPS model, ECMWF is found to be the best in terms minimum RMSE.

The standard deviation (STDEV) of all India daily mean rainfall (mm/day) among individual ensemble

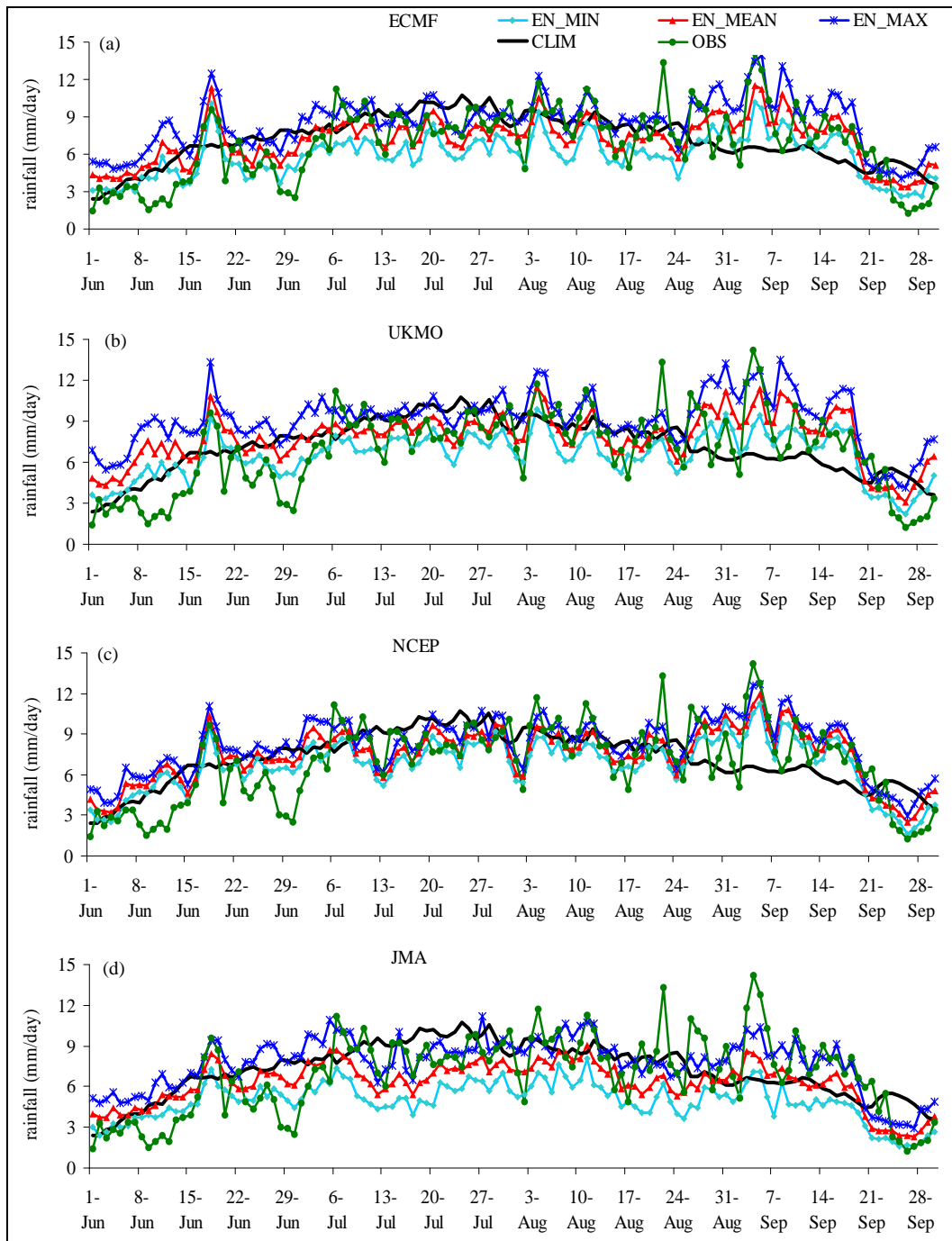




**Figs. 5(a-d).** All India domain mean daily standard deviation (STDEV) of rainfall (mm/day) among individual (20) ensemble members of ECMWF, NCEP, UKMO and JMA EPS for (a) day-1, (b) day-3, (c) day-5 and (d) day-7 forecast during 1 June -30 September, 2012

members of ECMWF, NCEP, UKMO and JMA EPS for day-1, day-3, day-5, and day-7 forecasts during 1 June to 30 September, 2012 is depicted in Figs. 5(a-d). In the day-1 forecast, UKMO and JMA show higher STDEV of daily mean rainfall (mm/day), while NCEP shows lower STDEV throughout the monsoon periods. The spread of

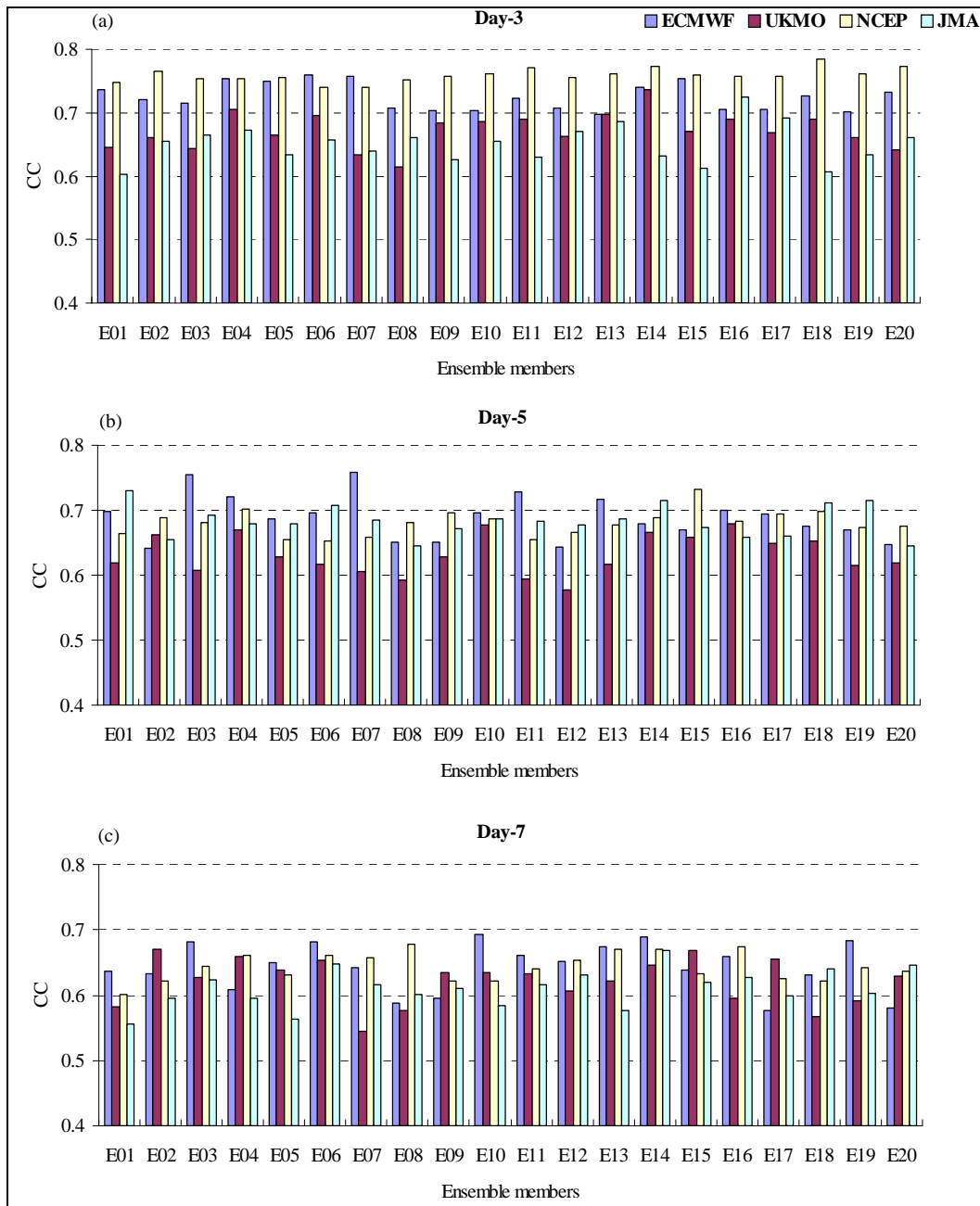
all India mean rainfall from ensemble members of each EPS increases marginally with forecast lead time. The increase of spread with lead time may be due to increase of uncertainties in the prediction of all India mean rainfall in the ensemble members of EPS. In general, all the EPS models underestimate the all India mean rainfall with



**Figs. 6(a-d).** Time series of all India mean observed, climatology and day-3 rainfall forecast from ensemble members having minimum (EN\_MIN), maximum (EN\_MAX) values and its mean (EN\_MEAN) values for (a) ECMWF, (b) UKMO, (c) NCEP and (d) JMA EPS during monsoon 2012

forecast lead time. If these deviations are due to uncertainties in the diabetics processes in the EPS, uncertainties shall be large when there is a large amount of rainfall. NCEP EPS continuously have lower deviation of rainfall from ensemble mean in all day-1 to day-7 as

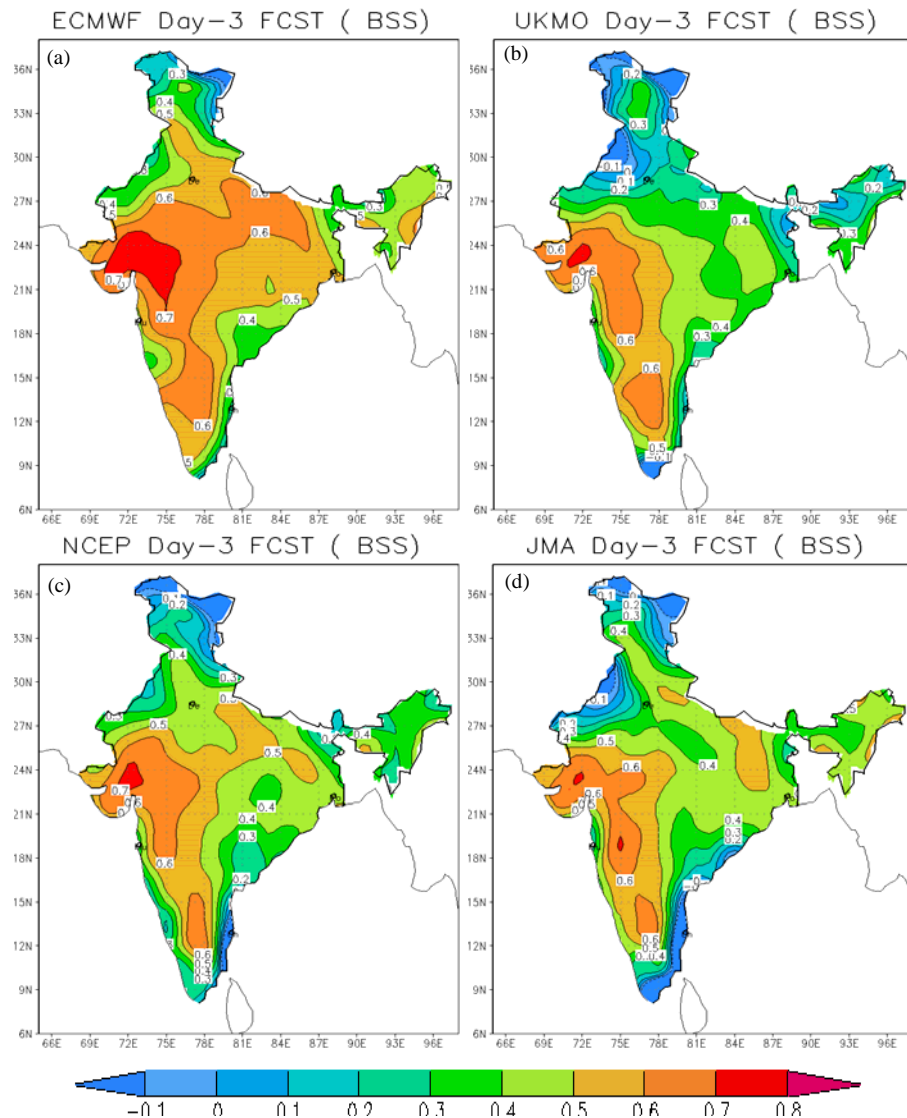
compared to other three EPS. In general, an ideal ensemble forecast will be expected to have the same size of ensemble deviation as their RMS error at the same lead time in order to represent full forecast uncertainty (Zhu, 2005; Buzza *et al.*, 2005).



**Figs. 7(a-c).** The temporal CC between all India mean observed rainfall and predicted rainfall from individual ensemble members of ECMWF, UKMO, NCEP and JMA EPS for (a) day-3, (b) day-5 and (c) day-7 forecast

Time series of daily all India mean observed rainfall, climatology and day-3 rainfall forecast from ensemble members having minimum (EN\_MIN), maximum (EN\_MAX) values and its ensemble mean (EN\_MEAN) values for ECMWF, NCEP, UKMO and JMA EPS is presented in Figs. 6(a-d). The active and weak spell of rainfall activity is well reflected in the daily all India mean rainfall in all the four EPS EN\_MEAN forecast. It is seen from Figs. 6(a-d) that the UKMO EPS have higher

variation of EN\_MEAN as compared to the observed mean value. Though, the EN\_MEAN value of UKMO is higher among all the EPS, the difference between the EN\_MEAN and EN\_MAX is small and its EN\_MEAN value is higher than observation. Most of the days during monsoon periods, the EN\_MIN and EN\_MEAN values of JMA EPS are lower than the observed all India mean rainfall. The EN\_MEAN value of JMA underestimates the all India means rainfall, although it has less spread among

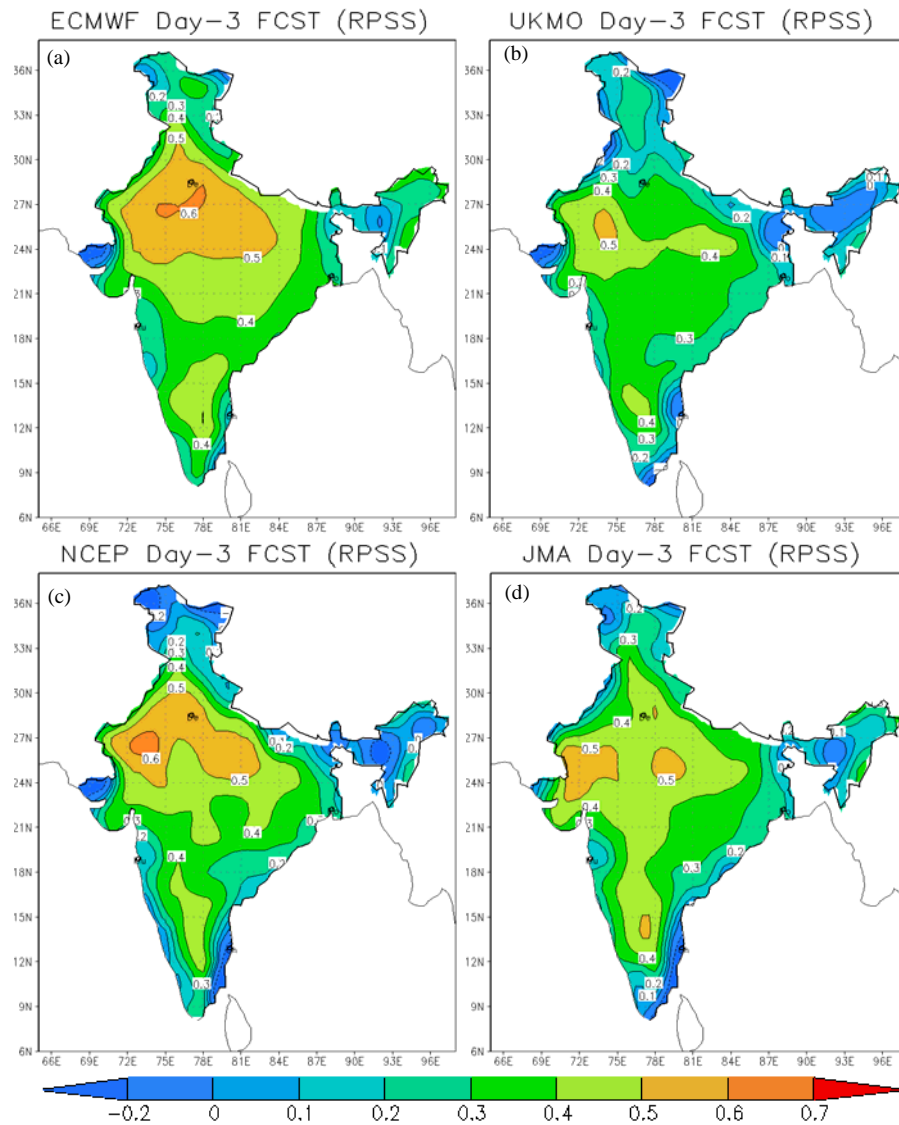


**Figs. 8(a-d).** Spatial distribution of Brier Skill Score (BSS) for rainfall threshold of >10 mm/day for day-3 forecast of (a) ECMWF, (b) UKMO, (c) NCEP and (d) JMA global Ensemble members for the period from 1 June to 30 September, 2012

members. The magnitude of difference between the EN\_MAX and EN\_MIN value of NCEP EPS is small and its EN\_MEAN value is slightly higher than the daily observed all India mean rainfall. The EN\_MEAN value of ECMWF EPS is more or less matching with the observed rainfall. It is also noticed from Figs. 6(a-d) that the deviation of both EN\_MIN and EN\_MAX from observed mean rainfall is lower for ECMWF EPS as compared to other EPS. The domain mean rainfall forecast of all four EPS are in phase (active/weak spell of rainfall) with the corresponding observed rainfall, indicating the predictability of all India mean rainfall in short to medium

range time scale. In general, the active rainfall activity (positive anomaly) during the last week of September and weak or break condition of rainfall activity (negative anomaly) during the middle of June month is well captured by all EPS ensemble mean forecasts.

The temporal correlation coefficient (CC) between the all India area averaged observed rainfall and forecast rainfall is computed individually for all 20 ensemble members of ECMWF, NCEP, UKMO and JMA EPS during monsoon 2012. This temporal CC is a statistical measure of the degree to which changes to the value of



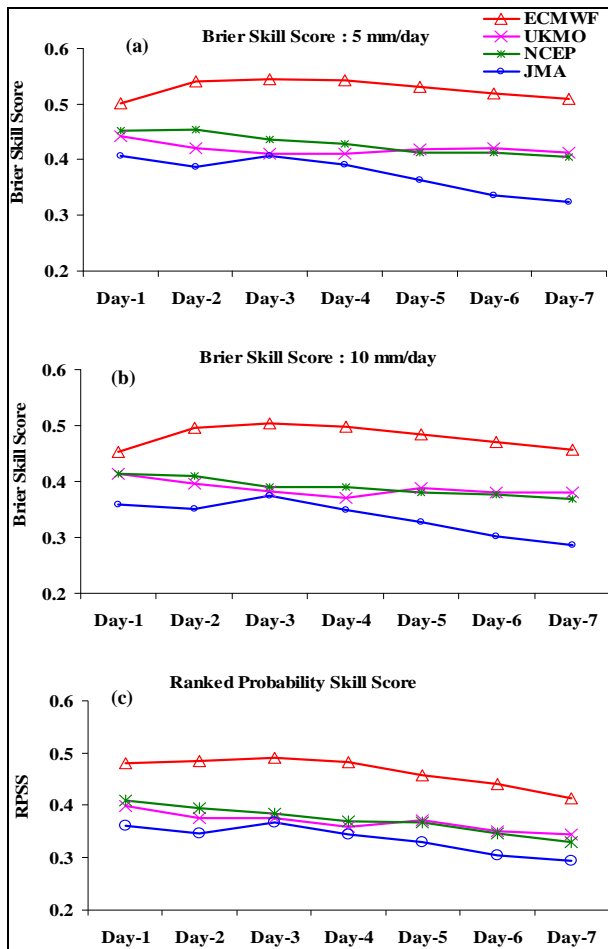
**Figs. 9(a-d).** Spatial distribution of Ranked probability skill score (RPSS) for day-3 forecast of (a) ECMWF, (b) UKMO, (c) NCEP and (d) JMA global Ensemble members for the period from 1 June to 30 September, 2012

one variable predict change to the value of another. An inter-comparison of domain mean temporal CC between all India domain mean rainfall day-3, day-5 and day-7 forecast from ECMWF, NCEP, UKMO and JMA EPS individual members (20 members) during monsoon (1 June - 30 September) 2012 is shown in Figs. 7(a-c). It is noticed from Figs. 7(a-c) that the magnitude of temporal CC in the day-1 forecast is higher for all EPS members (figure not shown), but NCEP and ECMWF members have higher scores of temporal CC as compared to other two EPS members. In the day-3 forecast, CC lies between 0.6 and 0.7 for ECMWF and NCEP EPS members, while it is less than 0.7 for UKMO and JMA EPS members. The values of CC decrease with the forecast lead time and by

day-7 (168 hour forecast) the CC values lie between 0.6 and 0.7. In general, NCEP and ECMWF EPS members have higher CC than UKMO and JMA members for all day-1 to day-7 forecasts. Among the individual EPS, JMA is found to be less skillful in terms of lower temporal CC. It is also noticed that the day-3 and day-5 CC is higher than the day-1 CC for JMA EPS members over India during monsoon periods.

#### 4.2. Skill of EPS probabilistic forecast

The probabilistic forecast verification is much more complicated. For users of the forecasts, the failure to forecast a serious synoptic event that has occurred will



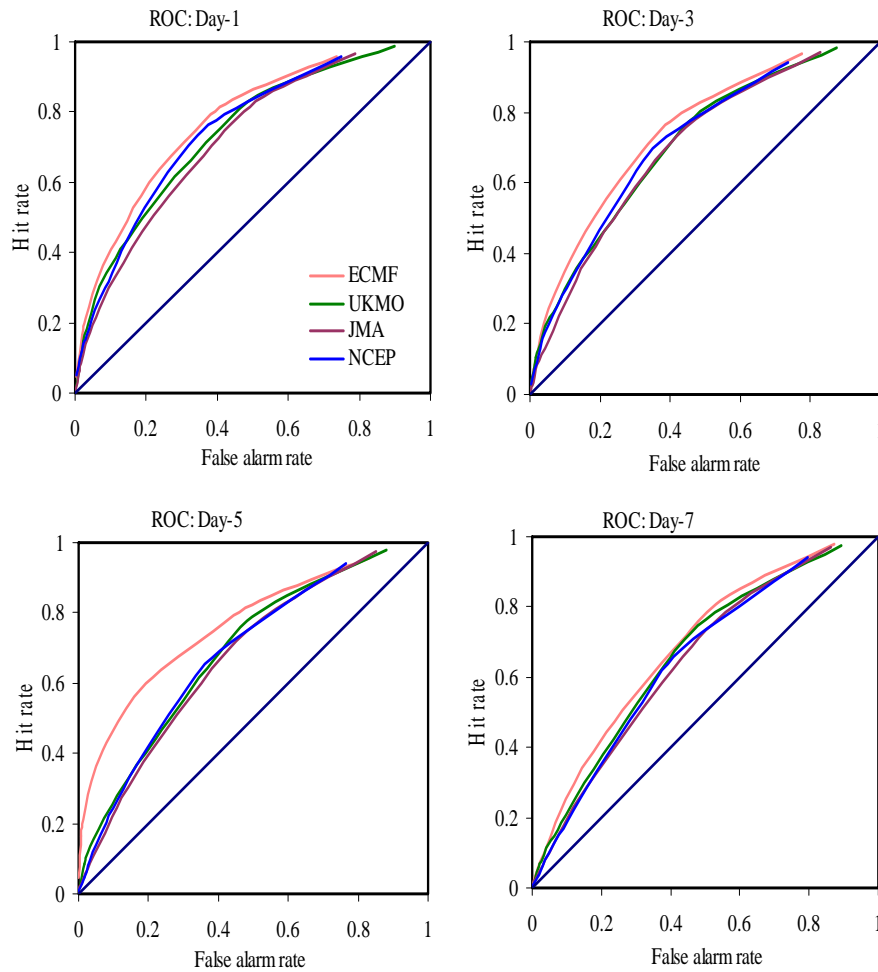
**Figs. 10(a-c).** BSSs of ECMWF, NCEP, UKMO and JMA for rainfall threshold of (a) >5 mm/day, (b) >10 mm/day and (c) Ranked Probability Skill Score (RPSS) as a function of forecast lead time for the period from 1 June to 30 September 2012. Heavy (left panel) and Very Heavy (right panel) Rainfall from ECMF, NCEP, UKMO and JMAF model on 06September 2012

have much more dramatic consequences than forecasting an event that does not occur. To assess the forecast skill under these conditions, categorical forecast verification methods should be used. For the probabilistic forecast, if a threshold is given, a forecast can be transformed into a yes/no categorical forecast easily. The quality of probability forecasts is verified using BSS and RPSS. Figs. 8(a-d) shows the spatial distribution of BSS for rainfall threshold of >10 mm/day for day-3 forecast of ECMWF, NCEP, UKMO and JMA global Ensemble members for the period from 1 June to 30 September, 2012. The BSS measures the mean squared difference between forecasts and observations in probability space and is the equivalent of MSE of categorical forecasts. Likewise, it is negatively oriented, with perfect forecasts having  $BS = 0$ . The JMA and UKMO forecasts have negative BSS skill and GFS has less skill over the

extremely dry regions of India, *i.e.*, over NW India. ECMWF generally produced the most skillful forecast over all the regions of India. JMA produce negative skill over coastal Tamilnadu and adjoining regions, but all other EPS have positive skill over these regions. Spatial distribution of RPSS for day-3 forecast of ECMWF, NCEP, UKMO and JMA global ensemble members for the period from 1 June to 30 September, 2012 is shown in Figs. 9(a-d). The spatial distribution of RPSS values in all four EPS is almost very similar with maximum value over the wet regions and minimum over the dry regions of India during monsoon periods. The higher values of RPSS are noticed over the regions of monsoon trough and central India in all four EPS in the day-3 forecast. ECMWF EPS has comparatively higher magnitude of RPSS in the day-3 forecast. The magnitude of RPSS values over India for all four EPS is in the range between 0.3 and 0.6 during monsoon 2012. The RPSS value for UKMO is generally smaller than the other three EPS in the day-3 forecast. The conventionally calculated RPSS is dominated by the performance of the forecasts in the climatologically wet areas (Hamill and Juras, 2006). There is inherently greater climatological variance of precipitation for the wet regions, and associated with this there are generally much larger RPSS values than in dry regions.

Fig. 10(a) shows the BSS calculated for rainfall threshold of >5 mm/day as a function of forecast lead time for the period from 1 June to 30 September, 2012. BSS values greater than zero indicates better skill than observed climatology based forecast. The BSS values for all the ECMWF, NCEP, UKMO and JMA EPS are greater than zero indicating a performance better than the climatology forecast. The EPS of ECMWF shows higher BSS values for all the forecast lead time over Indian land areas. The BSS skill for NCEP and UKMO seems to be similar and generally higher than JMA. The BSS for rainfall threshold of 10 mm/day [Fig. 10(b)] is smaller than the same for 5 mm/day in all the four EPS. The ECMWF EPS is consistently the most skillful for all the forecast lead time and rainfall thresholds among the four EPS. RPSS as a function of forecast lead time for the EPS of ECMWF, NCEP, UKMO and JMA is presented in Fig. 10(c). The RPSS skill score shows that the ECMWF EPS forecasts generally appeared to be more skillful than all other EPS forecasts. The better system behaviors benefit from the better combination of the following: data assimilation system, numerical models, initial perturbations, and stochastic model perturbations. The RPSS methods equally weight the RPSS at all grid points, irrespective of whether the climatological event probability was extremely high or extremely low. The RPSS skill for NCEP and UKMO seems to be more or less similar in all forecast days. The RPSS values for





**Fig. 11.** ROC curves for categorical probabilistic rainfall forecast by ECMWF, UKMO, JMA and NCEP global ensemble models for day-1, day-3, day-5 and day-7 forecast for the period from 1 June to 30 September 2012

NCEP and UKMO is 0.4 in day-1 and became 0.3 in day-7. The RPSS value for JMA is generally smaller among the four EPS in all forecast lead time. The conventionally calculated RPSS is dominated by the performance of the forecasts in the climatologically wet areas.

The ROC curves for categorical probabilistic rainfall forecast by ECMWF, UKMO, JMA and NCEP global ensemble models for the period from 1 June to 30 September, 2012 is shown in Fig. 11. As shown in Fig. 11, the ROC curve demonstrates the hit rate and the false alarm rate of the probabilistic prediction on different probabilistic thresholds. The probabilistic forecasts can be converted into deterministic forecasts given that the probability exceeds a certain threshold. Every point on the curve from lower left to upper right corresponds to the threshold from 0% to 100%, respectively. The closer the

curve is to the upper left corner, the higher the hit rate and the lower the false alarm correspond, and the better forecasts are obtained. All the four EPS have roughly equal resolutions in all forecast lead time over India during monsoon season. ECMWF has the highest resolution, while the JMA system has the lowest resolution in all day-1 to day-7 forecast. As the forecast lead time goes longer, the curve is closer to the diagonal, which means that there is a decline of the forecast skill. At the same time, the difference of the four systems is reduced. In the day-5 forecast, the differences in the resolution of the ECMWF EPS and the other three EPS seem large. The larger area corresponds to the higher hit rate and the lower false alarm rate, *i.e.*, the better forecast skill. From Fig. 11, it is seen that the ROC area of the ECMWF system is always the biggest and the same for NCEP and UKMO EPSs are comparative. For all the forecast lead times, the area of the JMA EPS is the



smallest. In general, the resolution of ECMWF is always the highest, the JMA EPS is the lowest, and the other two are in the middle. The skill of the NCEP EPS is slightly better than the JMA EPS in all forecast days over India.

## 5. Summery and conclusions

This paper assesses the performance skill of four operational EPSs of the ECMWF, UKMO, NCEP and JMA available from TIGGE database over Indian region in spatial and temporal scales during summer monsoon season of 2012. The rainfall prediction skill of the EPS is examined in both deterministic and probabilistic senses using the observed rainfall analysis. Ensemble forecasting has gained substantial ground in NWP in the past decade. In a chaotic system like the atmosphere, probabilistic information is recognized as the optimum format for weather forecasts both from a scientific and a user perspective. Ensemble forecasts are well suited to support the provision of such probabilistic information. Since NCEP generates only 20 perturbed forecasts from each initial time, for ease of comparison and interpretation, the performance studies has been limited to 20-member ensembles. The verification statistics for EPS focus on the ensemble mean and probabilistic forecasts. A number of statistical methods, such as Ensemble Spread, ACC, RMSE, ROC, BSS and RPSS analysis, are used for the comparison of EPS ensemble mean and probability forecast over Indian monsoon regions.

The ensemble mean forecast from all four EPS could reproduce the seasonal mean heavy rainfall belts along the west coast of India, over north east and central India reasonably well. UKMO and JMA show higher standard deviation of daily mean rainfall, while NCEP shows lower standard deviation throughout the monsoon periods. The daily domain mean rainfall forecasts of all four EPS members are in phase (active/weak) with the corresponding observed rainfall indicating the predictability of rainfall in short to medium range time scale. The active rainfall activity (positive anomaly) during the last week of September and weak condition of rainfall activity (negative anomaly) during the middle of June is well captured by all EPS ensemble mean forecasts. The BSS values for JMA and UKMO EPS forecasts are negative, while it is very low for NCEP EPS over the extremely dry regions of India. The RPSS score shows that the ECMWF EPS forecast generally appeared to be more skillful than the other three EPS forecasts. NCEP and UKMO seem to have more or less similar RPSS values in all day-1 to day-7 forecasts. The RPSS value for JMA is generally smaller as compared to other three EPS in all forecast lead time. Results suggest that the probability forecast of ECMWF EPS exhibits the most skillful performance when measured using BSS, RPSS

and ROC measures over India during monsoon 2012. The probability forecast skill of all four EPS is higher for light and moderate rainfall in the short range. It is also observed in this study that the ensemble mean forecasts along with the probabilistic rain forecasts that give more useful information for heavy rainfall forecast. It has been further found from the case studies of heavy rainfall that the probabilistic rainfall prediction skill of ECMWF and NCEP are higher and more reliable than UKMO and JMA EPS. The improvement was larger for heavier precipitation events in the short range time scale.

All verification measures indicate that the ECMWF EPS has the best overall performance, with the NCEP and UKMO system being competitive during the first few days of the 7-day forecast period over India. However, the difference in the performance skill of NCEP and UKMO in the medium-range time scale is smaller. The inter comparison of the four EPS reported in this study can be considered as a first step towards the development of a multimodel ensemble (MME) based quantitative and probability forecast system using ensemble members from multiple operational EPS data available at TIGGE database over India in the short and medium range time scale. The ensemble mean and probabilistic approach in EPS will continue to gain in importance among operational forecasters in the next decade for the short to medium-range weather forecasts. This preliminary comparison helps to further recognize the rainfall prediction skill of the operational EPSs and provides important references for wide applications of the TIGGE dataset, and supplies useful information for improving the skill of EPS over Indian monsoon region.

## Acknowledgments

Authors are thankful to the Director General of Meteorology and Deputy Director General of Meteorology (NWP Division), India Meteorological Department for their encouragements and supports to complete research work. Authors are grateful to Guru Gobind Singh Indraprastha University for providing research facilities. The authors would like to acknowledge THORPEX for providing interactive grand global ensemble model forecast data for this study.

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