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A multi-model ensemble tool for predicting districts level monsoon rainfall and extreme rainfall events over India

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सार – जून से सितंबर (JJAS) तक दक्षिण-पश्चिम (SW) मानसून का मौसम भारतीय क्षेत्रों के अधिकांश हिस्सों में वर्षा की प्रमुख अवधि है। दुनिया भर में इसके असमान वितरण और पैटर्न के कारण सटीक वर्षा पूर्वानुमान संख्यात्मक मौसम पूर्वानुमान (NWP) मॉडल के सबसे महत्वपूर्ण और कम से कम अनुमानित मापदंडों में से एक है। पिछले दशक के दौरान वर्षा की घटनाओं की भविष्यवाणी करने के लिए विभिन्न NWP मॉडलों का उपयोग करते हुए कई अध्ययन किए गए हैं, और यह पाया गया है कि पूर्वानुमान कौशल में काफी सुधार हुआ है। वर्तमान अध्ययन में, पांच दिनों के लिए भारत भर में जिला स्तर पर SW मानसून वर्षा की भविष्यवाणी के लिए एक बहु-मॉडल पहनावा (MME) आधारित उपकरण विकसित किया गया है। पांच परिचालन एनडब्ल्यूपी मॉडलिंग प्रणालियों से वर्षा का पूर्वानुमान, अर्थात। (*i*) ग्लोबल फोरकास्ट सिस्टम (GFS) और (*ii*) ग्लोबल एन्सेम्बल फोरकास्टिंग सिस्टम (GEFS), भारत मौसम विज्ञान विभाग मंप चल रहा है, (*iii*) नेशनल सेंटर फॉर एनवायरनमेंट प्रेडिक्शन (NCEP) में चल रहा ग्लोबल फोरकास्ट सिस्टम मॉडल, (*iv*) यूनिफाइड मॉडल रनिंग नेशनल सेंटर फॉर मीडियम-रेंज वेदर फोरकास्टिंग (NCMRWF) और (*v*) जापान मौसम विज्ञान एजेंसी (JMA) में चल रहे ग्लोबल स्पेक्ट्रल मॉडल (GSM) का उपयोग SW मानसून 2021 के लिए MME पूर्वानुमान विकसित करने के लिए किया गया है। MME का भविष्यवाणी कौशल और व्यक्तिगत मॉडल पूर्वानुमान का मूल्यांकन जिले में देखी गई वर्षा के आधार पर किया जाता है। अलग-अलग मॉडल और एमएमई से जिला-स्तरीय भारी बारिश का पूर्वानुमान भी चेतावनी सेवाओं के लिए उपयोगी देखी गई बारिश की घटनाओं के खिलाफ मूल्यांकन किया जाता है। विभिन्न सत्यापन स्कोर जैसे सहसंबंध गुणांक (सीसी), रूट मीन स्क्वायर एरर (आरएमएसई), मीन बायस, डिटेक्शन की संभावना (पीओडी), फाल्स अलार्म अनुपात (एफएआर), इक्विटेबल ट्रीट स्कोर (ईटीएस), क्रिटिकल सक्सेस इंडेक्स (सीएसआई), आदि। की गणना सत्यापन उद्देश्य के लिए की जाती है। विभिन्न सत्यापन स्कोर से पता चलता है कि एमएमई वर्षा पूर्वानुमान ने अलग-अलग स्थानिक डोमेन और लौकिक पैमानों में अलग-अलग मॉडलों की तुलना में अच्छा प्रदर्शन किया है। देखी गई वर्षा और दिन 1 एमएमई पूर्वानुमान के बीच सीसी 0.58 है, जबकि जीएफएस, जीईएफएस, एनसीईपी, एनसीयूएम और जेएमए क्रमशः 0.43, 0.47, 0.49, 0.49 और 0.46 दिखा रहे हैं। एमएमई, जीएफएस, जीईएफएस, एनसीईपी, एनसीयूएम और जेएमए के लिए मनाया गया आरएमएसई क्रमशः 12.7, 15.2, 14.1, 14.3, 16.6 और 14.1 मिमी/दिन है जब आईएमडी की तुलना में बारिश देखी गई। मॉडल पूर्वानुमानों की अंतर-तुलना से पता चलता है कि MME विधि मानसून के मौसम के दौरान परिचालन उपयोग के लिए भारत में कुशल जिला वर्षा पूर्वानुमान उत्पन्न कर सकती है।

ABSTRACT. The southwest (SW) monsoon season from June to September (JJAS) is the major rainfall period over most parts of Indian regions. Accurate rainfall forecast is one of the most crucial and least predictable parameters of the numerical weather prediction (NWP) models because of its uneven distribution and patterns over the globe. During the last decade many studies have been carried out using different NWP models to predict rainfall incidents, and it is found that the forecast skill has been improved considerably. In the present study, a multi-model ensemble (MME) based tool has been developed for the prediction of SW monsoon rainfall at the district level over India for five days. The precipitation forecasts from five operational NWP modelling systems, *viz*., (*i*) Global Forecast System (GFS) and (*ii*) Global Ensemble Forecasting System (GEFS) running at India Meteorological Department, (*iii*) Global Forecast System model running at National Centre for Environment Prediction (NCEP), (*iv*) Unified Model running at National Centre for Medium-Range Weather Forecasting (NCMRWF) and (v) Global Spectral Model (GSM) running at Japan Meteorological Agency (JMA) have been used for developing the MME forecasts for SW monsoon 2021. The prediction skill of the MME and the individual model forecast is evaluated against observed district rainfall. The district-level heavy rainfall forecast from individual models and MME is also evaluated against the observed rainfall events useful for warning services. Different verification scores like Correlation Coefficient (CC), Root Mean Square Error (RMSE), Mean

Bias, Probability of Detection (POD), False Alarm Ratio (FAR), Equitable Treat Score (ETS), Critical Success Index (CSI), etc. are calculated for the verification purpose. The different verification score shows that MME rainfall forecast has performed well than the individual models in different spatial domains and temporal scales. The CC between observed rainfall and day 1 MME forecast is 0.58, whereas GFS, GEFS, NCEP, NCUM and JMA are showing 0.43, 0.47, 0.49, 0.49 and 0.46 respectively. The RMSE observed for MME, GFS, GEFS, NCEP, NCUM and JMA are 12.7, 15.2, 14.1, 14.3, 16.6 and 14.1 mm/day respectively when compared with IMD observed rainfall. The inter-comparison of the model forecasts reveal that the MME method can generate skillful district rainfall forecast over India for operational use during the monsoon season.

Key words – Multi-model ensemble, Southwest monsoon, District level forecast, Validation, Rainfall.

1. Introduction

Rainfall has paramount social and economic impacts on human lives compared to any other atmospheric parameter (Gadgil and Gadgil 2006; Gadgil 2003; Gadgil and Srinivasan 2010; Revadekar and Preethi 2012). Agriculture is backbone of Indian economy, thus the country is hugely dependent on the distribution and the variation of rainfall. India receives 80% of its annual rainfall from the southwest (SW) monsoon. Thus, any variation in the amount of rainfall decides the fate of natural disasters, such as flood and drought, and Indian gross domestic product (Gadgil and Gadgil 2006). The Indian summer monsoon rainfall (ISMR) exhibits a regional heterogeneous variability at different time scales, such as inter-annual, seasonal, intra-seasonal, and so on (Goswami and Ajaya Mohan 2001; Gadgil 2003; Krishnamurthy and Shukla 2007). The information about the distribution and intensity of rainfall in future will be highly helpful for the agriculture activities to increase the crop production and also for the damage control. Forecasting of rainfall over the Indian region is a challenging task due to its variability and also due to the diverse geography, with a topography that ranges from high mountain ranges to fertile plains, deltas, coasts, wetlands, rivers and deserts. Numerical weather prediction (NWP) methods have acquired greater skill and are playing an increasingly important role in the weather forecasting. However, in general, the forecast skill in the tropics is still lower compared to that of mid-latitudes and is particularly of concern for rainfall forecasts over the Indian monsoon region(Webster *et al*., 1998; Gadgil 2003; Krishnamurti, Kumar and Mitra 2006; Woods 2006). This is because of large spatial and temporal variability of rainfall and some inherent limitations of NWP models. Since these models are built on the foundation of deterministic modelling which start with some initial conditions, the inherent limitation of these NWP models is that they neglect small scale effects and they approximate complicated physical processes and interactions in time and space. The models lose skill because of the growth of the inevitable uncertainty in the initial conditions. The accuracy of a models varies depending on the assimilation process, 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 NWP system through research and development in modelling and data assimilation is going on throughout the world.

In order to address the limitations of deterministic model, a new approach known as ensemble forecasting was introduced in the 1990s (Molteni *et al*., 1996; Toth and Kalnay 1997; Zhang and Krishnamurti 1997). In this method, forecasts are made either with different models or different initial conditions or both and are combined into a single forecast to take into account the uncertainty in the model formulation and initial conditions. The idea of ensemble forecasting was first introduced in the studies of Lorenz (1963; 1965), where he examined the initial state uncertainties and the well-known butterfly effect. He noted that the atmosphere is essentially chaotic, because the processes involved in its evolution are non-linear. The study of Lorenz (1963; 1965) showed that no matter how good the observations are, or how good the forecasting techniques, there is almost certainly an insurmountable limit as to how far into the future one can forecast.

In this sense, knowledge of systematic errors occasioned by these uncertainties is of paramount importance in the realization of improvements in the forecasting system, with a view to minimizing the errors, and helping meteorologists in the preparation of weather forecasts. Multi model ensemble (MME) is the one of the techniques in which minimization of errors in the forecast is achieved by considering errors of the multiple models (Tebaldi *et al*., 2004; Weigel *et al*., 2010; Krishnamurti, Kishtawal, Shin, *et al*., 2000; Chandler 2013; Krishnamurti, Kishtawal, Zhang, *et al*., 2000). The questions that arise are those dealing with the method used to combine the forecasts. Recent research in climate modelling suggests that combination schemes with unweighted means (simple ensemble mean: giving equal weight to each deterministic model) provide better results than schemes with weighting (super ensemble model) based on the performance of each model (Christensen *et al*. 2010; Déqué and Somot 2010). And, according to Weigel (2010) and Knutti (2010), the combination of models taking into account the concept of weighting must be treated with great care, principally when applied to climate change. Past studies shows that the error of the ensemble mean is often 30% smaller than the typical error

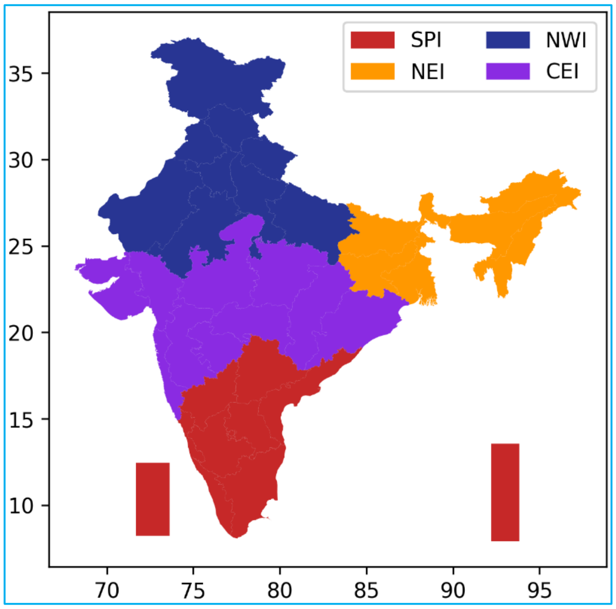

Fig. 1. Four homogeneous regions of India covering the 36 meteorological subdivisions of India

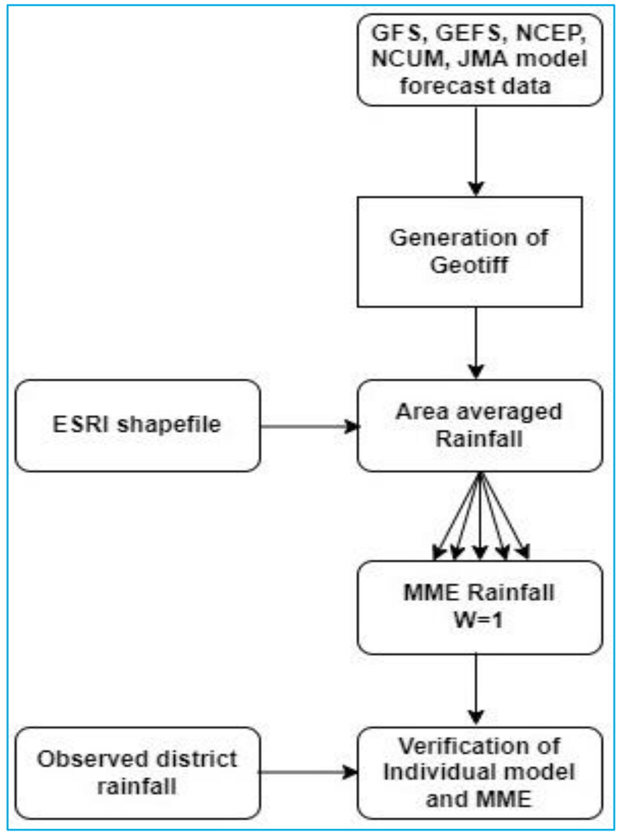

Fig. 2. Flowchart of the development and verification ofNWP model and MME rainfall forecast for 2021

of individual models, which again is the value predicted by the indistinguishable interpretation (Palmer *et al.*, 2006; Christiansen 2018; Christiansen 2019). In last two decades many studies where carried out for rainfall forecast using MME methodology during ISMR and reported significant improvement of MME over single NWP model (Roy Bhowmik and Durai 2008; Roy Bhowmik and Durai 2010; Mitra et al. 2011; Bhomia *et al.*, 2016; Kumar *et al.*, 2012).

This report describes the development and the performance of the MME district level forecast of rainfall over India from five operational NWP models available on real time basis at India Meteorological Department (IMD) New Delhi during the 2021 monsoon. Accurate prediction of district wise rainfall in medium range time scale for the country like India will be of great benefit not only for Agriculture & water sectors but also for the disaster management considering the occurrence of large-scale heavy rainfall associated flooding events over India during the southwest monsoon season. Rainfall forecast from five global NWP models are used for the development of MME forecast up to day 5 over 732 Indian districts (as shown in Fig. 1) spreading over the 4 homogeneous regions of India and this rainfall forecast is also validated with observed rainfall.

2. Data used

In the present study, rainfall forecasts from five global NWP models, *viz.*, (*i*) Global Forecasting system (GFS) runs at IMD, (*ii*) GFS model from National Centres for Environmental Prediction (NCEP), (*iii*) Global Ensemble Forecasting System (GEFS) runs at IMD, (*iv*) Unified model (NCUM) runs at National Centre for Medium Range Weather Forecasting (NCMRWF) and (*v*) operational Global Spectral Model (GSM) model of Japan Meteorological Agency (JMA) are used to generate MME forecast for Indian districts. These model forecasts are available at IMD in real-time and are routinely used by the forecasters for providing weather warnings and related decision support system. The main operational deterministic NWP model at IMD is GFS model which was adopted from NCEP (White, G and Yang, F and Tallapragda 2018). The GFS model initially implemented at IMD in 2010 with T382L64 resolution (Durai, Kotal, and Bhowmik 2011). The Current version of GFS model at IMD is 14.1.0 and it runs with spectral resolution of T1534 (~12.5 km) with 64 hybrid vertical levels (top layer around 0.27 hPa) (Johny and Prasad 2020; Prasad *et al.*, 2021). The GFS T1534 model runs daily for 10 days and the output is stored every 3 hr interval. The GFS model data from NCEP (https://www.emc.ncep.noaa.gov/emc/pages/numerical_forecast_systems/gfs.php) also

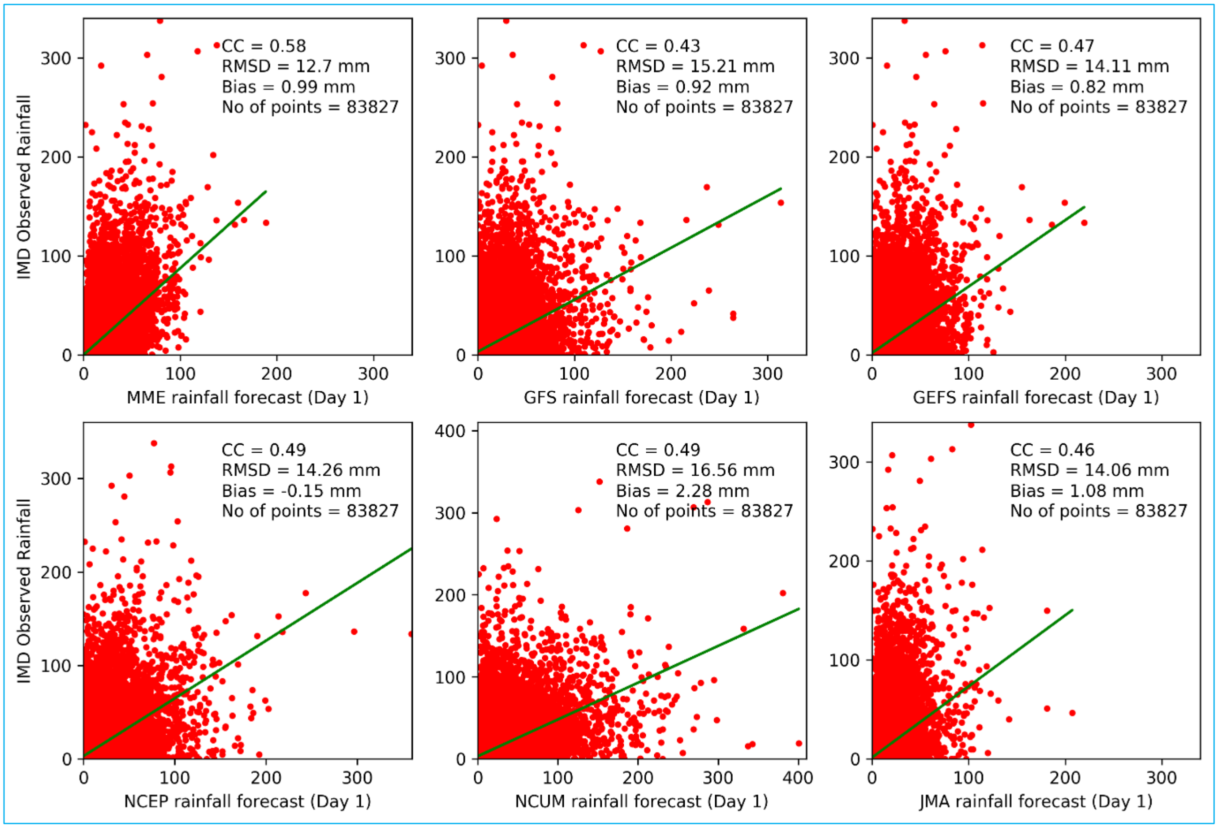

Fig. 3. Scatter plot between observed district rainfall and day 1 forecast of MME (left top), GFS (centre top), GEFS (right top), NCEP (left bottom), NCUM (centre bottom) and JMA (right bottom) for JJAS 2021. Correlation coefficient, RMSE and bias are given in each plot

available at IMD with a horizontal resolution of 0.25° × 0.25°. The forecast from NCEP-GFS is available up to 10 days at every 6 hours. Compared to the NCEP-GFS model, IMD-GFS utilizes more Indian observation during assimilation. IMD regularly receives Unified Model (UM) data which runs at NCMRWF (Rajagopal *et al*., 2012; George *et al*., 2016; Wood *et al*., 2014). The Unified model from NCMRWF (NCUM) global model's horizontal resolution is N1024 (~12 km) and has 70 levels in the vertical, reaching up to an altitude of 80 km. NCUM model forecast is available at IMD in every 3 hours for next 10 days. Another foreign NWP model data available at IMD is JMA's GSM which receives at IMD at a spatial resolution of 25 km up to day 10 (Saito *et al*., 2006). The data from above five models are used the generation of weather forecast over Indian districts.

3. Methodology

Starting from Monsoon 2021, Numerical Weather Prediction division of IMD generates district area averaged forecast (732 districts) from five models and its mean in real time as a decision support to the forecasters. Forecast of different weather parameters (rainfall, maximum temperature, minimum temperature, wind speed, wind direction, relative humidity and cloud cover) are generating for next five days and disseminating to the forecasters in real time. Mean of all grid points within the district boundary polygon is computed for each model and is represented as the weather parameter of that region. For small districts (with small spatial areas), the radius of the search was increased, so that at least three grid points were represented for each district. Then the MME forecast of each weather parameter is estimated for each district by giving equal weighs to each NWP models. The flow chart of the development of MME forecast is shown in Fig. 2. Apart from the forecast of weather parameter mentioned above, heavy rainfall warning system is also developed using the five NWP model forecast as support to the forecasters. The heavy rainfall warning system is calculated by taking the ratio of the number of grid points (from all models) with the forecasted rainfall exceeding the threshold value of rainfall (heavy ≥ 64.5 mm, very heavy ≥ 115.6 mm, extremely heavy rainfall (> 204.4 mm). All this estimation and development work is carried out in Linux environment using python scripts.

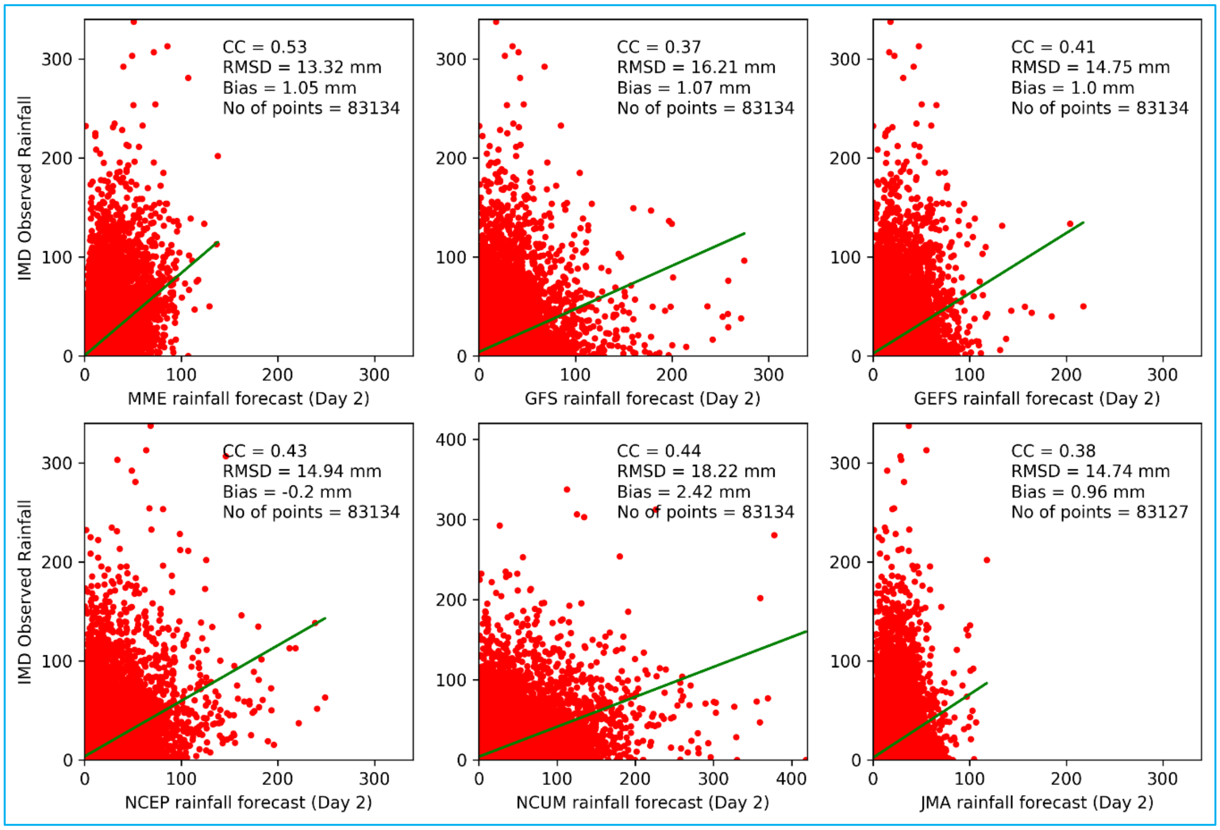

Fig. 4. Similar to Figure 3, but for day 2 forecast

In this study, the verification of district rainfall and heavy rainfall with observed rainfall is carried out during entire monsoon season of 2021 from June to September. For the verification purpose, different statistical parameters such as Pearson's correlation coefficient (R), root-mean-square deviation (RMSE) and Bias are calculated using the following equations:

$$R = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\left[\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2\right]^{1/2}} \tag{1}$$

$$\text{RMSE} = \frac{1}{N}\left[\sum_{i=1}^{N} (x_i - y_i)^2\right]^{1/2} \tag{2}$$

$$\text{Mean Bias} = \frac{1}{N}\sum_{i=1}^{N} (y_i - x_i) \tag{3}$$

where x_i and y_i are the observed and forecasted values; $\bar{x}$ and $\bar{y}$ are their respective mean, and N is the number of grids or days.

To further examine the rainfall prediction skill of different models and MME, various statistical scores are also calculated for different rainfall thresholds. The four count (a, b, c, d) events in the 2 × 2 contingency table that contains the number of hits, false alarms, misses, and correct rejections at different rainfall thresholds are used to assess the performance of rainfall forecast. Accuracy (ACC), bias score (BS), critical success index (CSI), probability of detection (POD), false alarm ratio (FAR), and equitable threat score (ETS are computed using contingency table for different rainfall thresholds. Brief descriptions of these statistical scores are given by Levine and Wilks (2000), Ashok Kumar *et al*. (2002) and Bushair *et al*. (2019).

4. Results and discussion

4.1. *Performance of model forecast during JJAS 2021*

The scatter plot between observed district rainfall and model forecasts for day 1 to day 5 are shown in Fig. 3 to Fig. 7 respectively. The quantitative comparison shows that the MME forecast performed better in terms of CC,

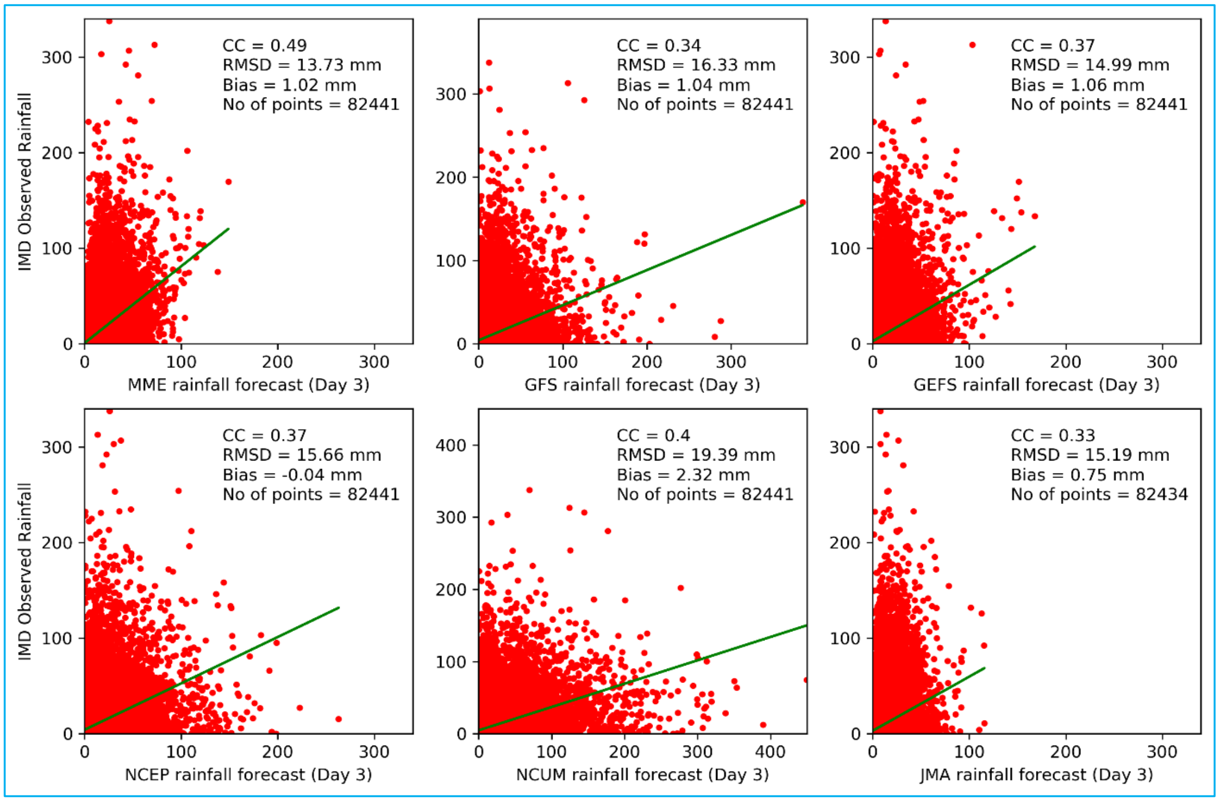

Fig. 5. Similar to Fig. 3, but for day 3 forecast

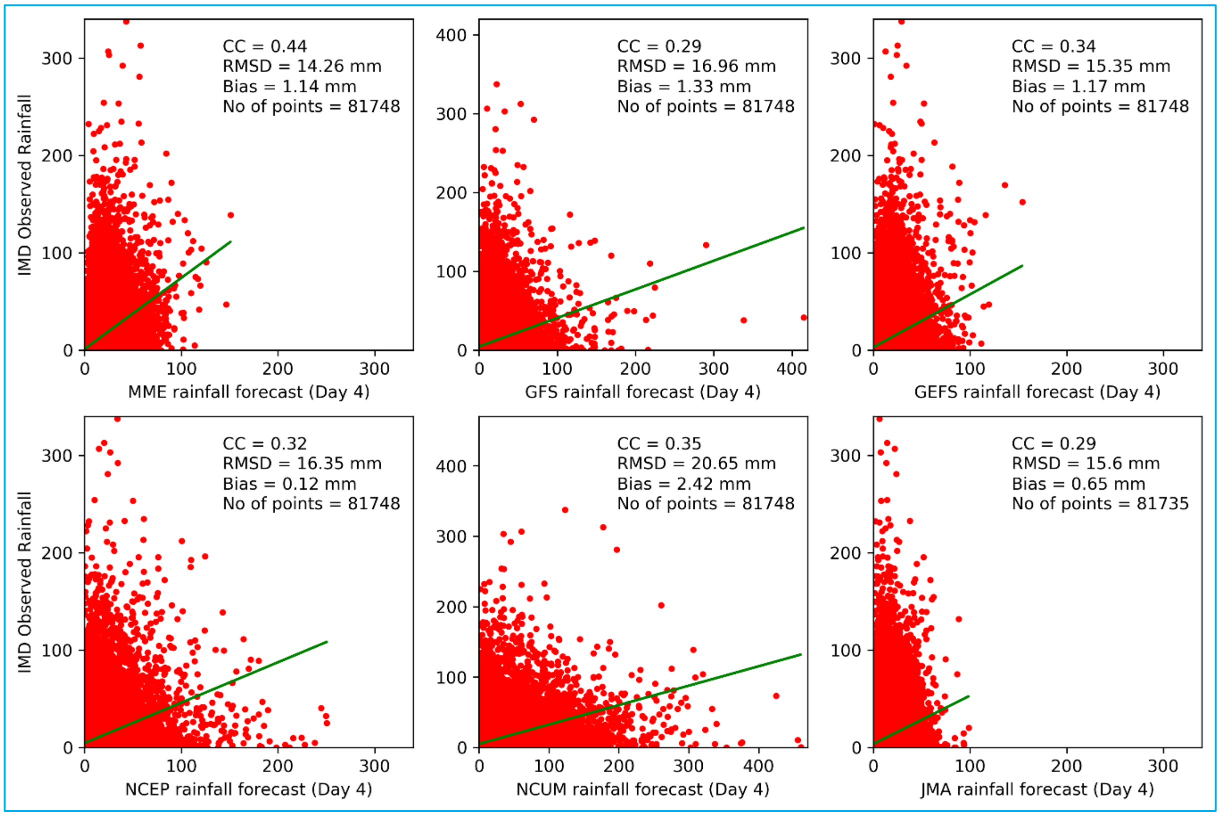

Fig. 6. Similar to Fig. 3, but for day 4 forecast

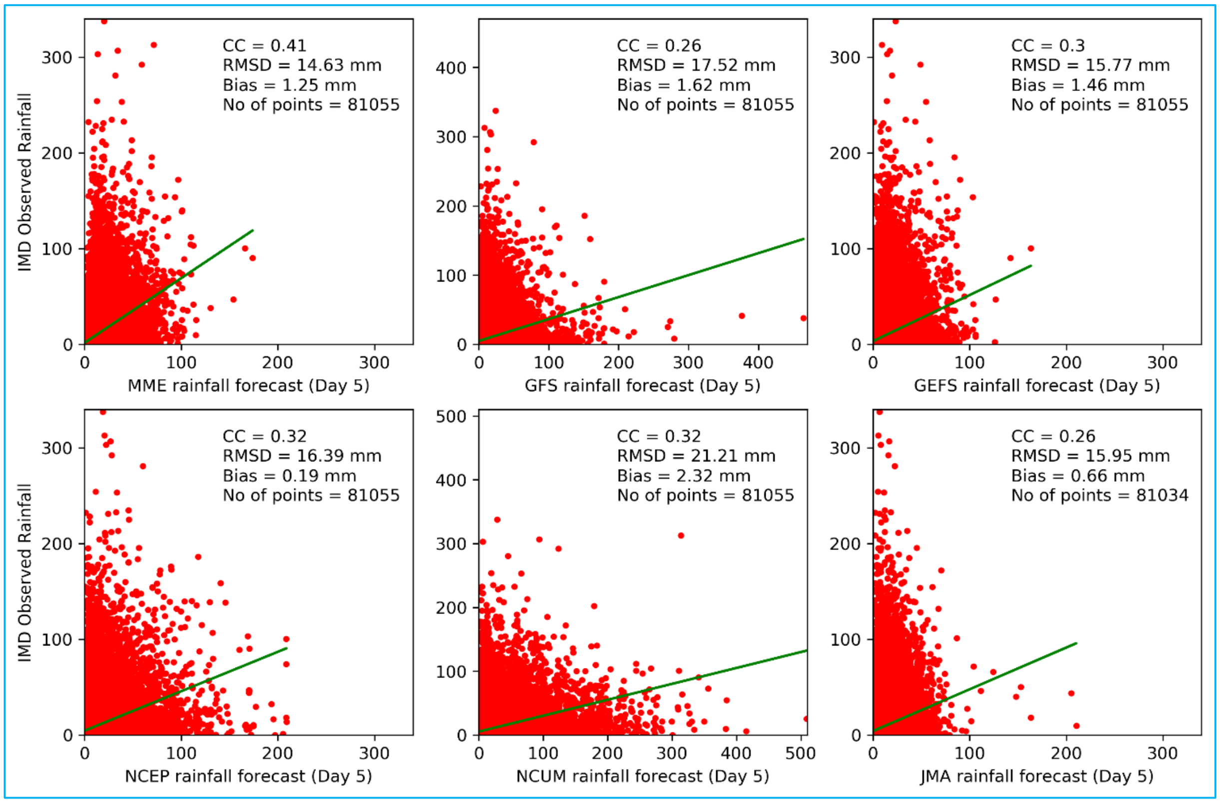

Fig. 7. Similar to Fig. 3, but for day 5 forecast

RMSE and bias for day 1 to day 5. The CC between observed rainfall and day 1 MME forecast is 0.58, whereas, the individual models like GFS, GEFS, NCEP, NCUM and JMA showed CCs of 0.43, 0.47, 0.49, 0.49 and 0.46 respectively. The RMSE observed for MME, GFS, GEFS, NCEP, NCUM and JMA are 12.7, 15.2, 14.1, 14.3, 16.6 and 14.1 mm/day respectively when compared with IMD observed rainfall. Similarly, CC of 0.53, 0.37, 0.41, 0.43, 0.44 and 0.38 is observed respectively for day 2 forecast of MME, GFS, GEFS, NCEP, NCUM and JMA (Fig. 4). The RMSE observed for day 2 forecast of MME, GFS, GEFS, NCEP, NCUM and JMA model forecast are 13.32, 16.21, 14.75, 14.94, 18.22 and 14.74 respectively. Similar trend is observed for day 3 (Fig. 5), day 4 (Fig. 6), and day 5 (Fig. 7) forecasts. While comparing the performance of individual models in terms of CC and RMSE, it is noticed that NCEP model is performed well during day 1 to day 4 forecasts and GEFS model on day 5 forecast compared to other models. It is also seen that the performance of the MME and individual model is gradually decreased when the forecast lead time increases. While comparing IMD-GFS and NCEP-GFS it is noticed that, NCEP GFS performed well during day 1 to day 5 than IMD-GFS in terms of CC, RMSE and bias. Among the individual models, NCUM model forecast has high RMSE and large wet bias compared to other four model forecasts.

To analyse the performance of model over the four homogeneous regions of India covering the 36 meteorological subdivisions over the main land of India, the observed and forecast data over Indian districts are segregated to four homogeneous regions (Fig. 1), *viz*., northwest India (NWI), east and north east India (NEI), Central India (CEI) and south peninsular India (SPI). The forecast verification scores are calculated for all the four homogeneous regions.

The CC, RMSE and bias are calculated and presented in Table 1. As shown in Table 1 the MME forecast performed much better compared to the individual model. The statistics over four regions shows that MME forecast performed very well over NWI, CEI and SPI with the best performance over the CEI region. However, the performance over NEI regions need slight improvement compared to other 3 regions. Quantitative, the CC between observed rainfall and day 1 MME forecast over CEI, SPI and NWI respectively are 0.66, 0.63 and 0.61. At the same time CC over NEI is only 0.43 which is less among the four homogeneous regions.

TABLE 1

Correlation coefficient (CC), RMSE and bias between observed district rainfall and different model and MME forecast up to day 5 over four homogenous regions of India

		Day 1			Day 2			Day 3			Day 4			Day 5		
	Model	CC	RMSE	Bias	CC	RMSE	Bias	CC	RMSE	Bias	CC	RMSE	Bias	CC	RMSE	Bias
North West India	MME	0.61	10.88	1.07	0.55	10.75	1.48	0.48	11.36	1.65	0.43	11.92	1.95	0.38	12.37	2.17
	GFS	0.47	11.86	-0.01	0.41	12.83	0.61	0.33	13.98	1.2	0.3	14.57	1.76	0.24	15.25	2.04
	GEFS	0.53	10.94	0.41	0.44	11.87	1.12	0.37	12.49	1.56	0.33	12.84	1.89	0.29	13.32	2.27
	NCEP	0.49	11.73	-0.05	0.42	12.33	0.01	0.35	12.74	0.05	0.26	14.11	0.45	0.28	13.69	0.73
	NCUM	0.53	13.33	2.16	0.48	14.41	2.29	0.4	15.39	1.9	0.33	16.7	1.84	0.29	17.77	1.98
	JMA	0.46	12.3	2.83	0.38	13.24	3.38	0.33	13.63	3.51	0.3	14.15	3.79	0.25	14.81	3.83
East and Northeast India	MME	0.43	16.05	3.31	0.37	16.49	2.9	0.34	16.67	2.67	0.29	17.19	3.05	0.27	17.53	3.39
	GFS	0.28	19.01	3.67	0.21	19.66	3.47	0.21	19.38	3.19	0.16	19.91	3.72	0.16	20.27	4.28
	GEFS	0.27	18.39	3.72	0.19	18.65	3.0	0.18	18.41	2.66	0.14	18.85	3.05	0.12	19.36	3.69
	NCEP	0.34	18.10	2.18	0.3	18.02	1.4	0.23	18.37	1.06	0.21	18.68	1.49	0.23	18.87	1.71
	NCUM	0.35	20.67	4.29	0.3	23.63	5.23	0.27	24.93	5.45	0.24	27.02	5.96	0.2	27.67	5.94
	JMA	0.34	16.92	2.65	0.25	17.29	1.4	0.21	17.62	0.97	0.18	17.9	1.05	0.17	18.16	1.31
Central India	MME	0.66	12.88	-0.04	0.6	13.83	0.25	0.54	14.56	0.27	0.48	15.31	0.02	0.44	15.76	-0.09
	GFS	0.5	15.81	0.38	0.42	17.05	0.75	0.38	17.7	0.84	0.31	18.37	0.65	0.28	19.09	0.77
	GEFS	.57	14.14	-0.03	0.49	15.28	0.67	0.45	15.77	0.98	0.4	16.16	0.76	0.36	16.63	0.84
	NCEP	0.58	14.25	-1.33	0.49	15.53	-0.88	0.42	16.81	-0.32	0.34	18.02	-0.47	0.32	18.41	-0.42
	NCUM	0.58	16.19	1.37	0.54	17.27	1.22	0.47	18.73	0.75	0.42	19.62	0.61	0.39	20.15	0.28
	JMA	0.54	14.42	-0.58	0.44	15.57	-0.53	0.36	16.39	-0.92	0.3	16.96	-1.48	0.27	17.27	-1.9
South Peninsular India	MME	0.63	10.81	-0.05	0.59	11.27	-0.18	0.58	11.42	-0.2	0.57	11.57	-0.22	0.54	11.86	-0.29
	GFS	0.49	12.96	0.17	0.42	13.84	-0.27	0.46	12.97	-0.79	0.41	13.58	-0.84	0.37	14.15	-0.65
	GEFS	0.56	11.58	-0.41	0.52	11.99	-0.54	0.51	12.07	-0.79	0.5	12.18	-0.92	0.47	12.51	-0.89
	NCEP	0.55	12.06	-1.15	0.48	13.15	-1.13	0.42	14.21	-0.75	0.46	13.56	-0.78	0.44	13.48	-1.17
	NCUM	0.53	15.61	1.63	0.49	16.69	1.48	0.48	18.29	1.94	0.45	18.94	2.13	0.44	18.76	1.84
	JMA	0.52	11.85	-0.47	0.49	12.18	-0.43	0.45	12.51	-0.59	0.42	12.77	-0.69	0.4	12.97	-0.58

Similarly, the day 1 RMSE value observed (16.15 mm/day) was also high over NE India compared to other three regions. The day 2, day 3, day 4 and day 5 comparison also showing similar trends. With regard to the bias in the forecast the individual model and MME are showing a wet bias over NEI, SPI and NWI with comparatively high values over NEI up to day 5 forecast, thus compared to the observed rainfall the model has a tendency to over predict particularly over the NEI regions. Hover, over the CEI, no significant bias is observed in day 1 to day 5 forecast of MME and individual models.

4.2. *Performance of NWP models forecast at districts level over India*

The performance of NWP models are assessed over each districts for entire southwest monsoon 2021 (122 days) by estimating CC, RMSE and bias. The spatial distribution of CC from each model for day 1, day 3 and day 5 forecasts are shown in Figs. 8(a-c). Similarly, RMSE and bias from each NWP model and MME are shown Figs. 9(a-c) and Figs. 10(a-c) respectively. The better performance of MME rainfall forecast is visible

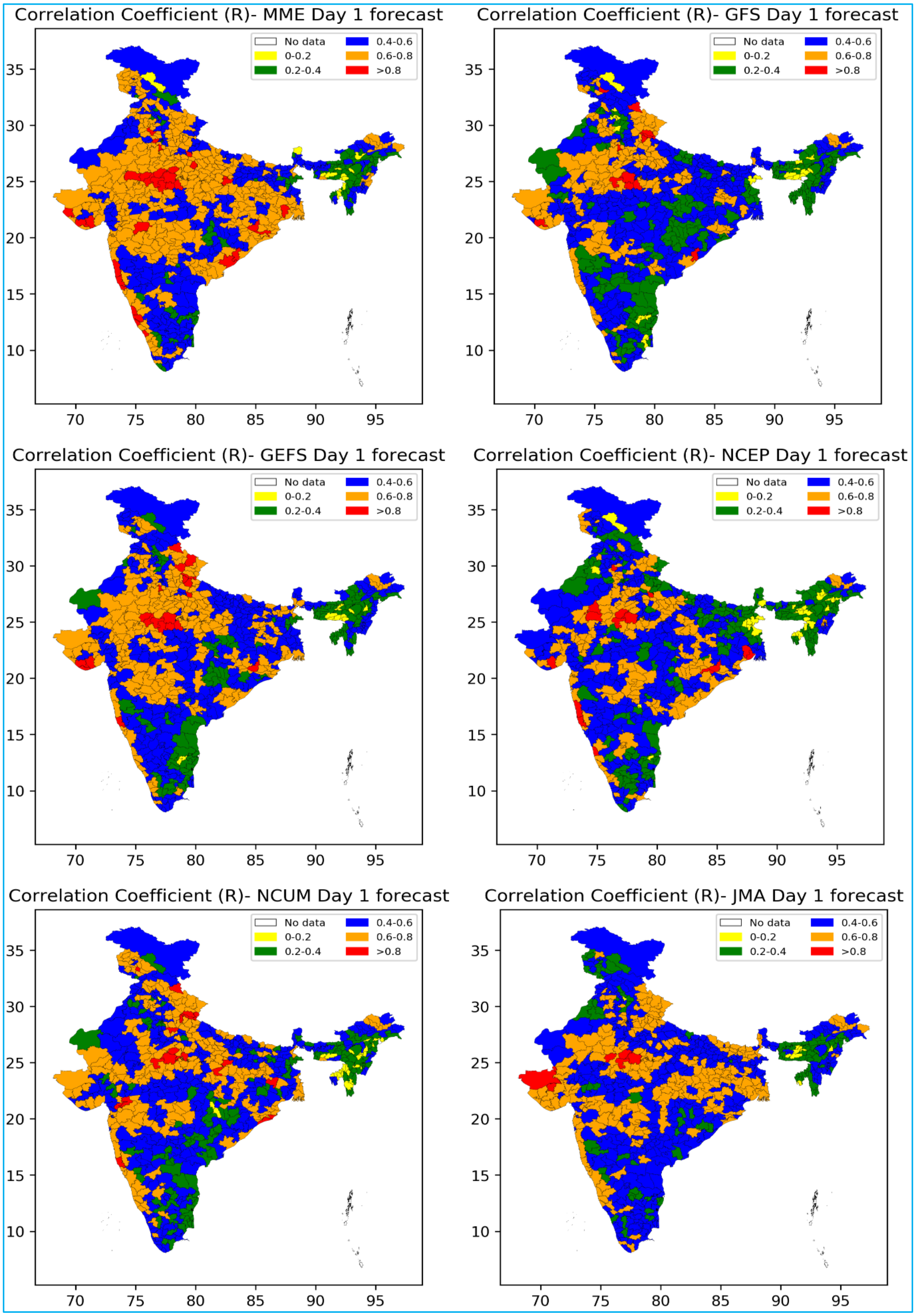

Fig. 8(a). Spatial representation of Correlation Coefficient between observed rainfall and NWP model day 1 rainfall forecast during JJAS 2021

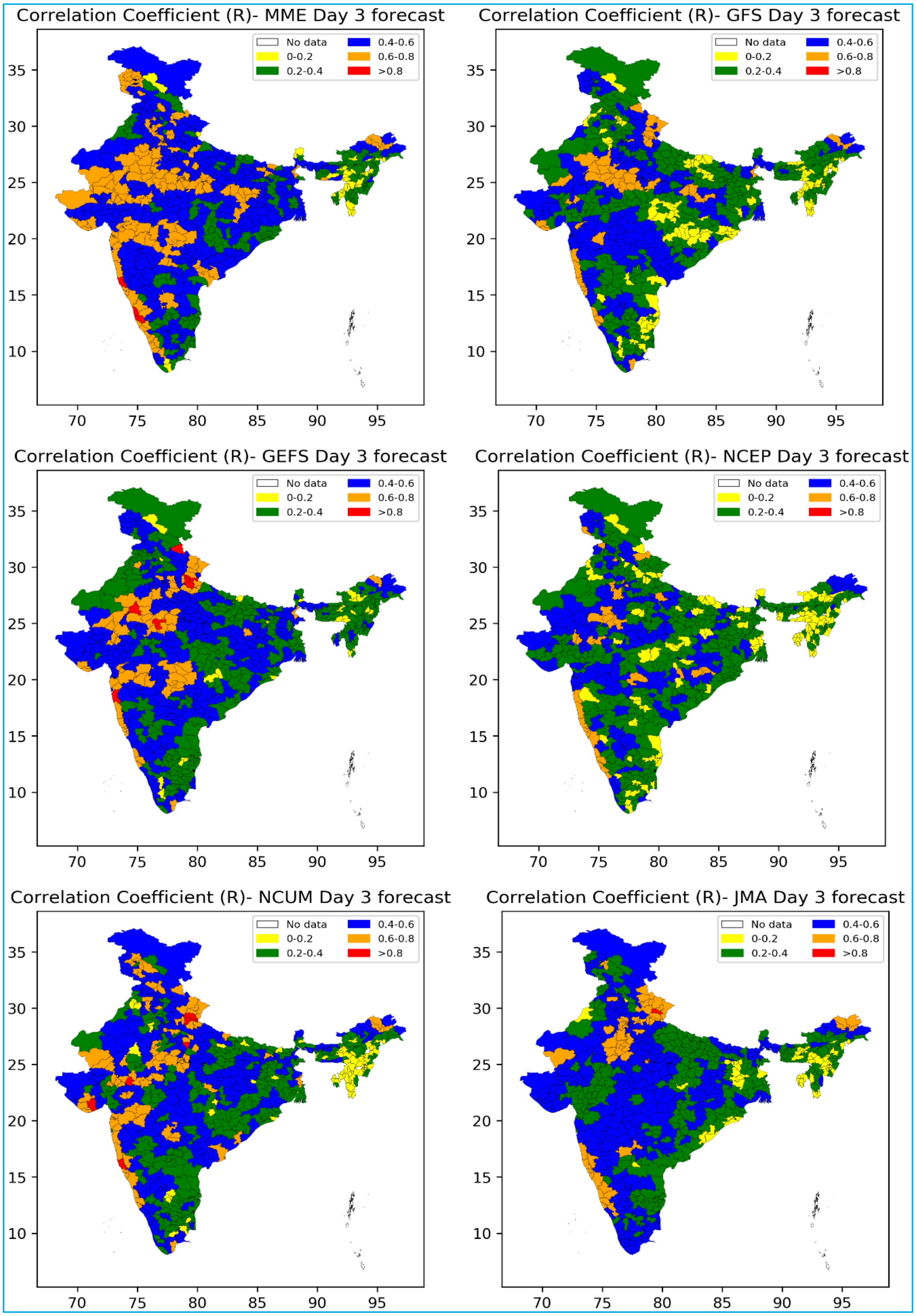

Fig. 8(b). Spatial representation of Correlation Coefficient between observed rainfall and NWP model day 3 rainfall forecast during JJAS 2021

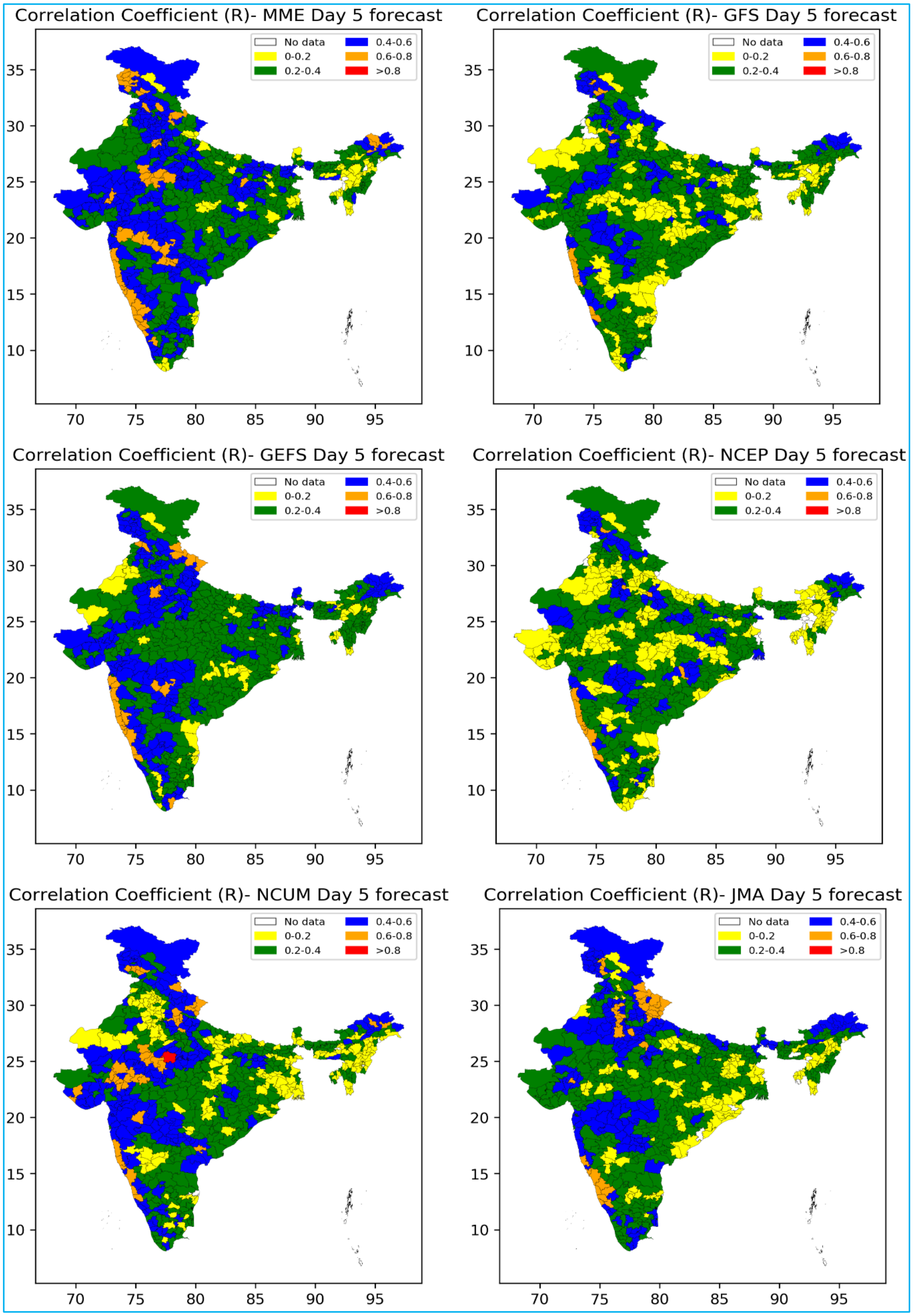

Fig. 8(c). Spatial representation of Correlation Coefficient between observed rainfall and NWP model day 5 rainfall forecast during JJAS 2021

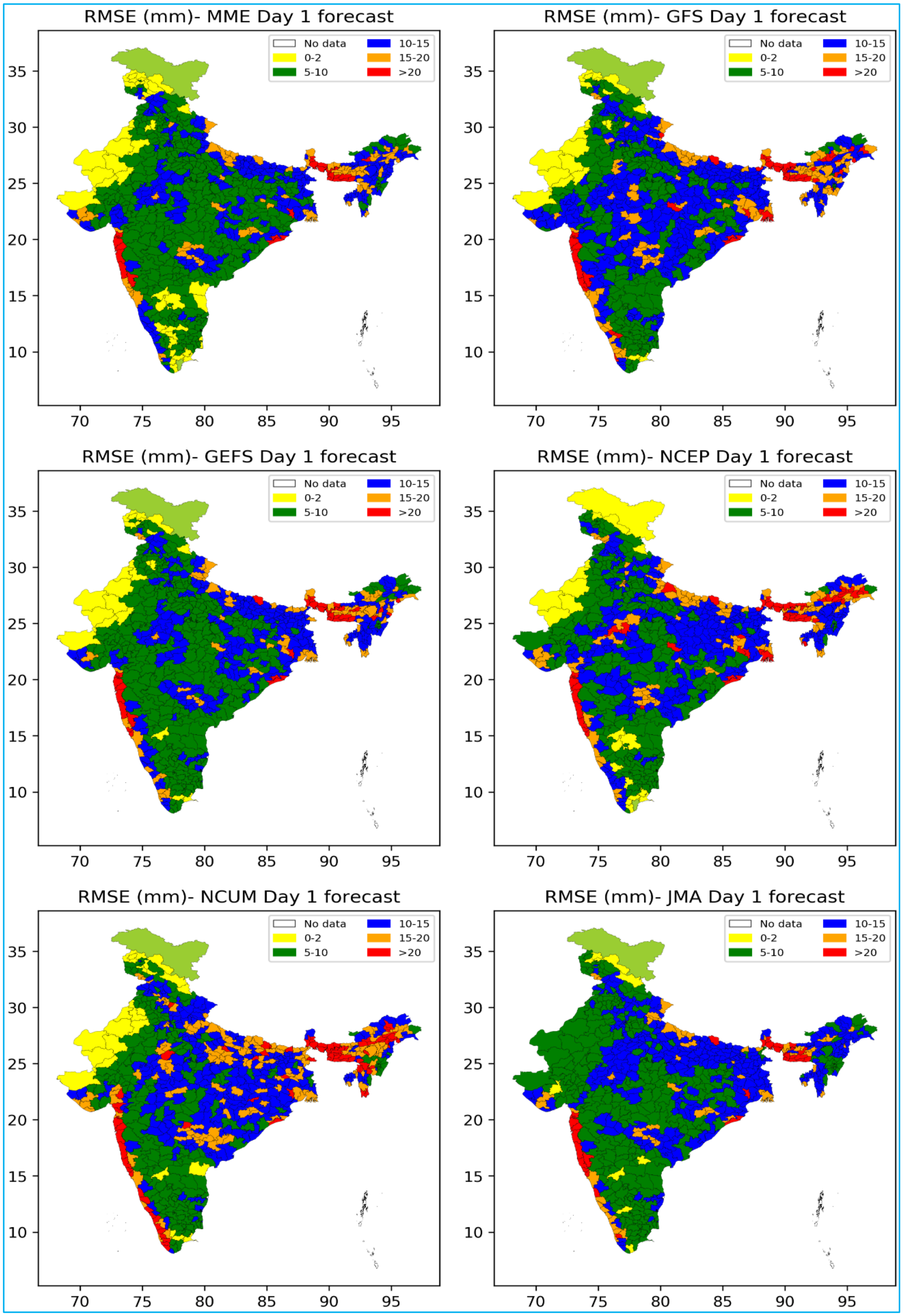

Fig. 9(a). Spatial representation of RMSE between observed rainfall and NWP model day 1 rainfall forecast during JJAS 2021

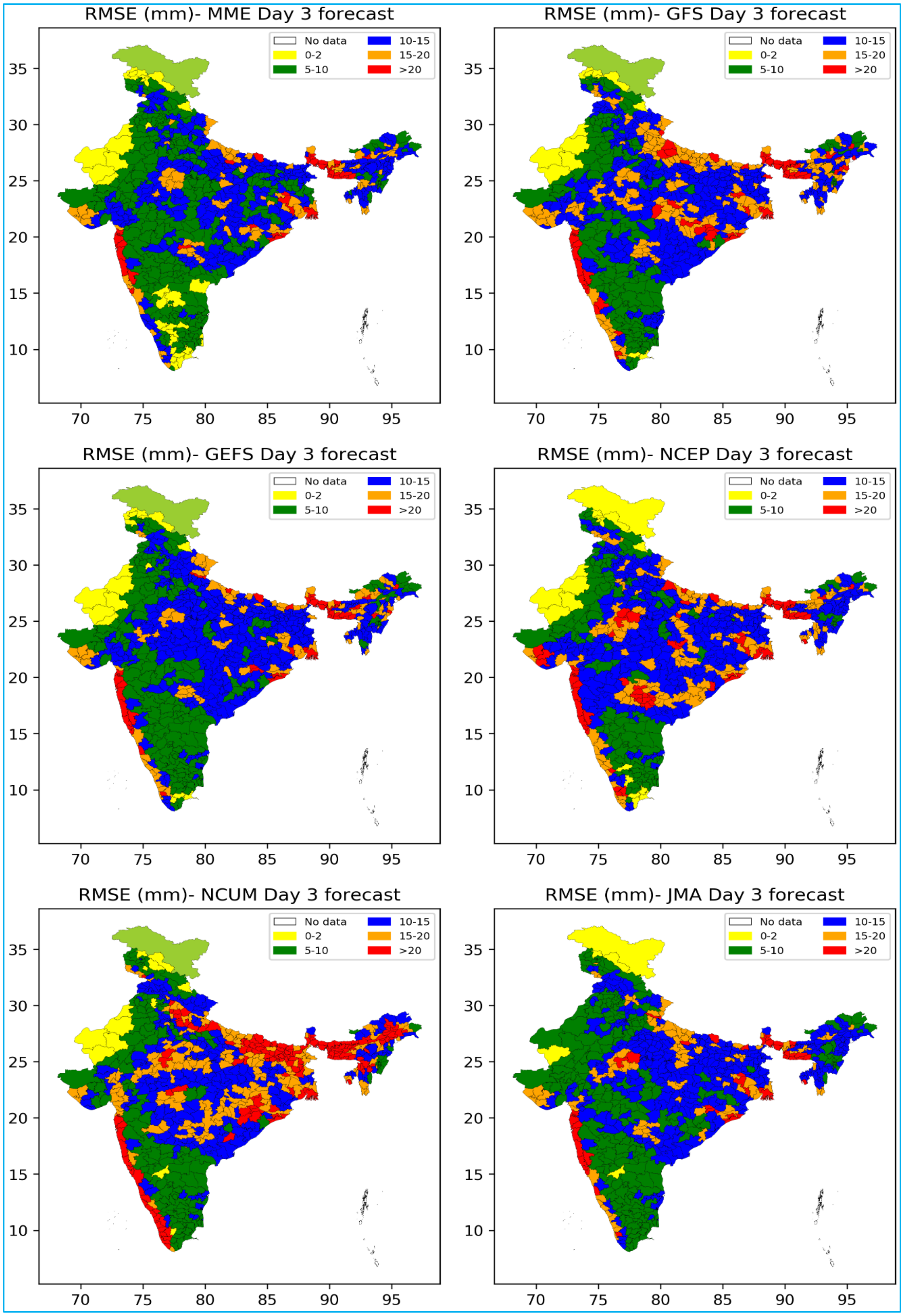

Fig. 9(b). Spatial representation of RMSE between observed rainfall and NWP model day 3 rainfall forecast during JJAS 2021

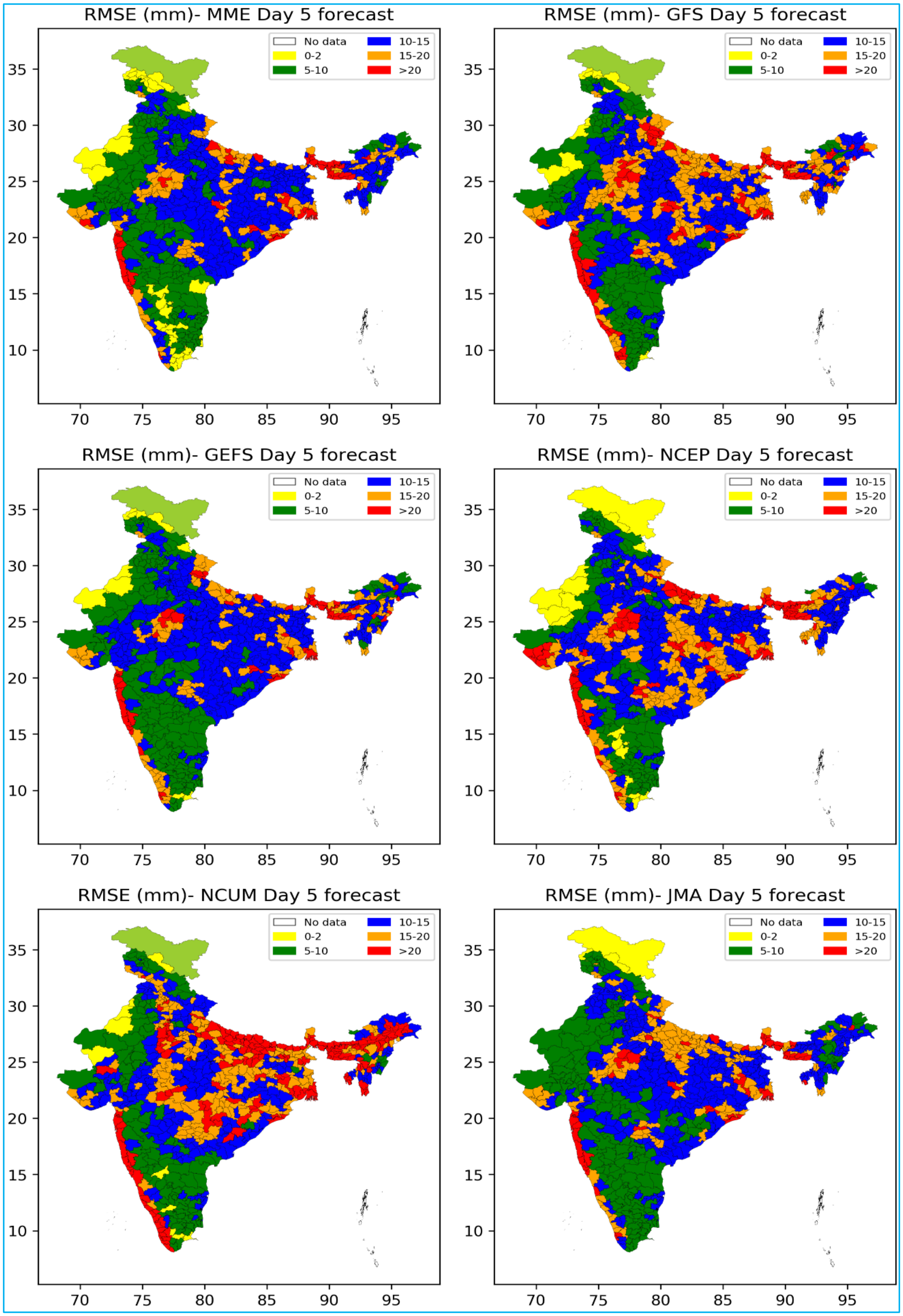

Fig. 9(c). Spatial representation of RMSE between observed rainfall and NWP model day 5 rainfall forecast during JJAS 2021

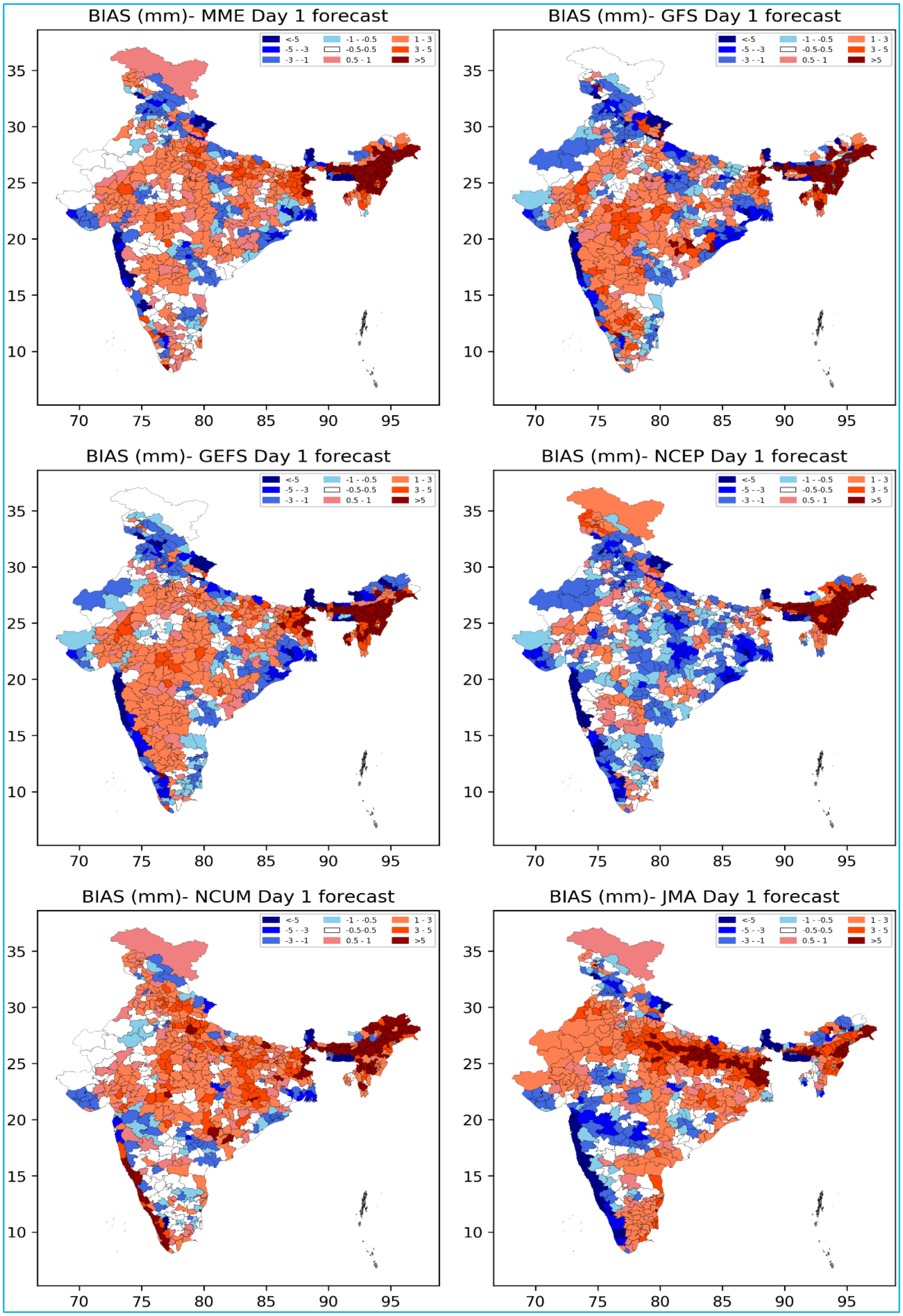

Fig. 10(a). Spatial representation of bias between observed rainfall and NWP model day 1 rainfall forecast during JJAS 2021

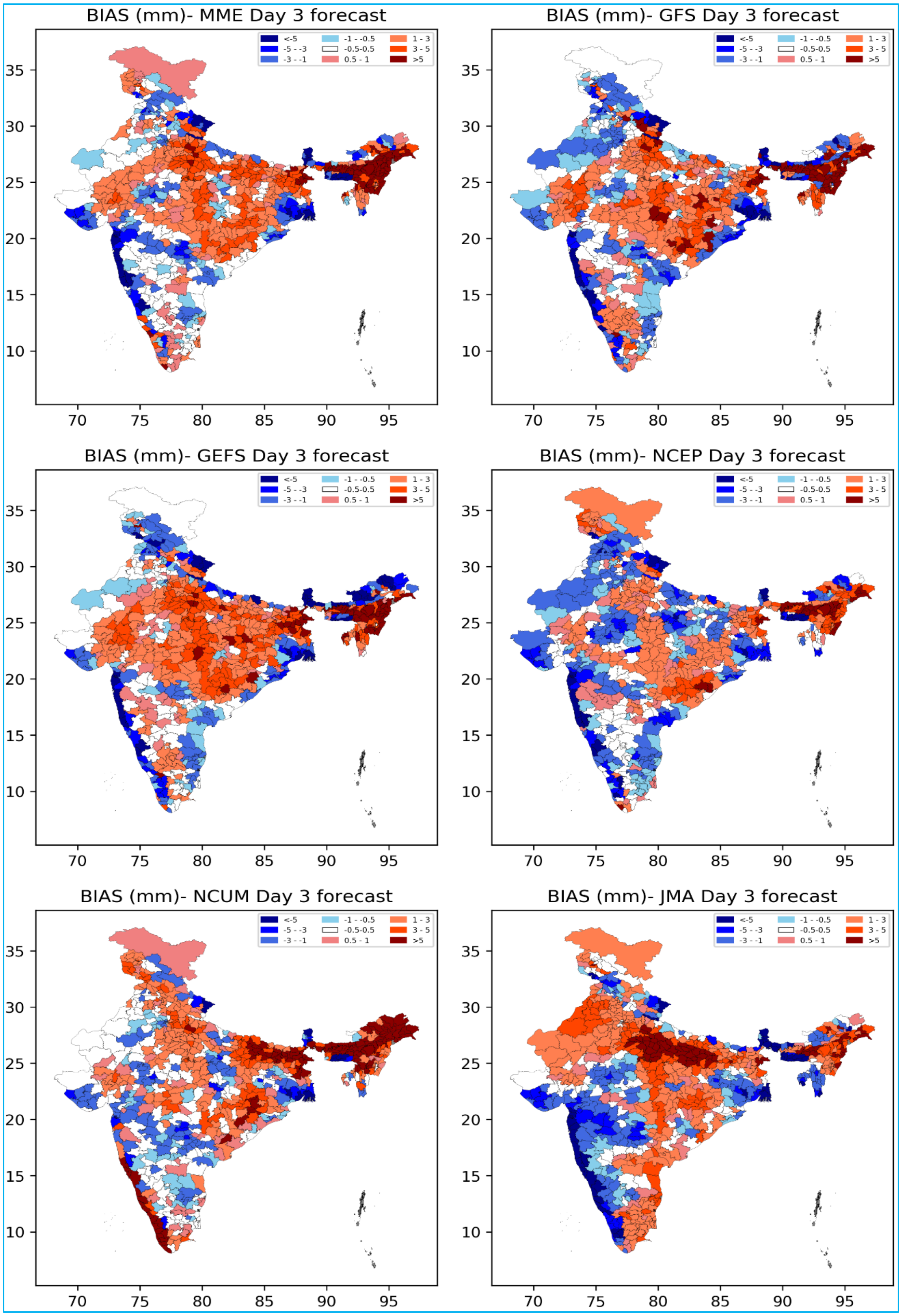

Fig. 10(b). Spatial representation of bias between observed rainfall and NWP model day 3 rainfall forecast during JJAS 2021

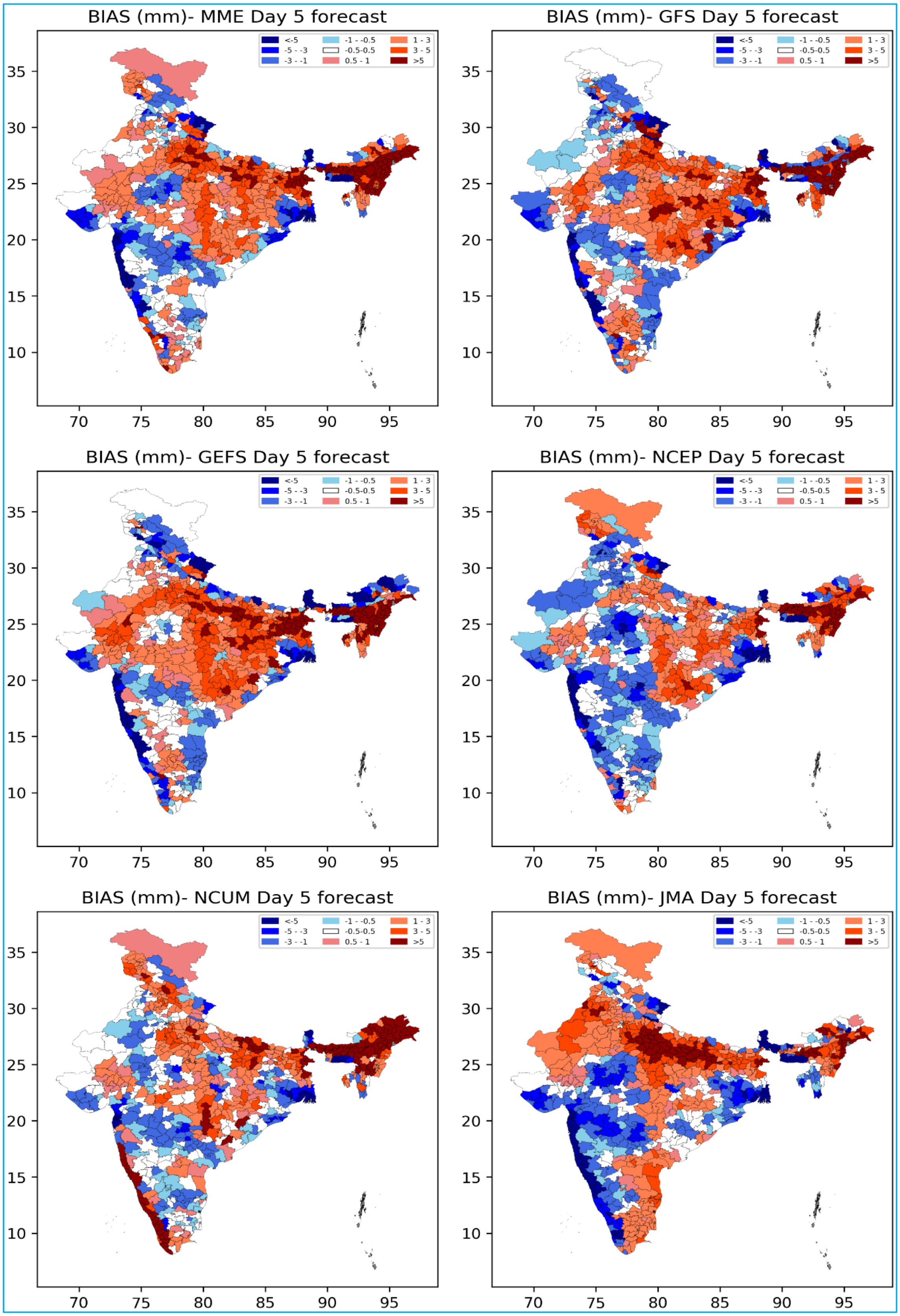

Fig. 10(c). Spatial representation of bias between observed rainfall and NWP model day 5 rainfall forecast during JJAS 2021

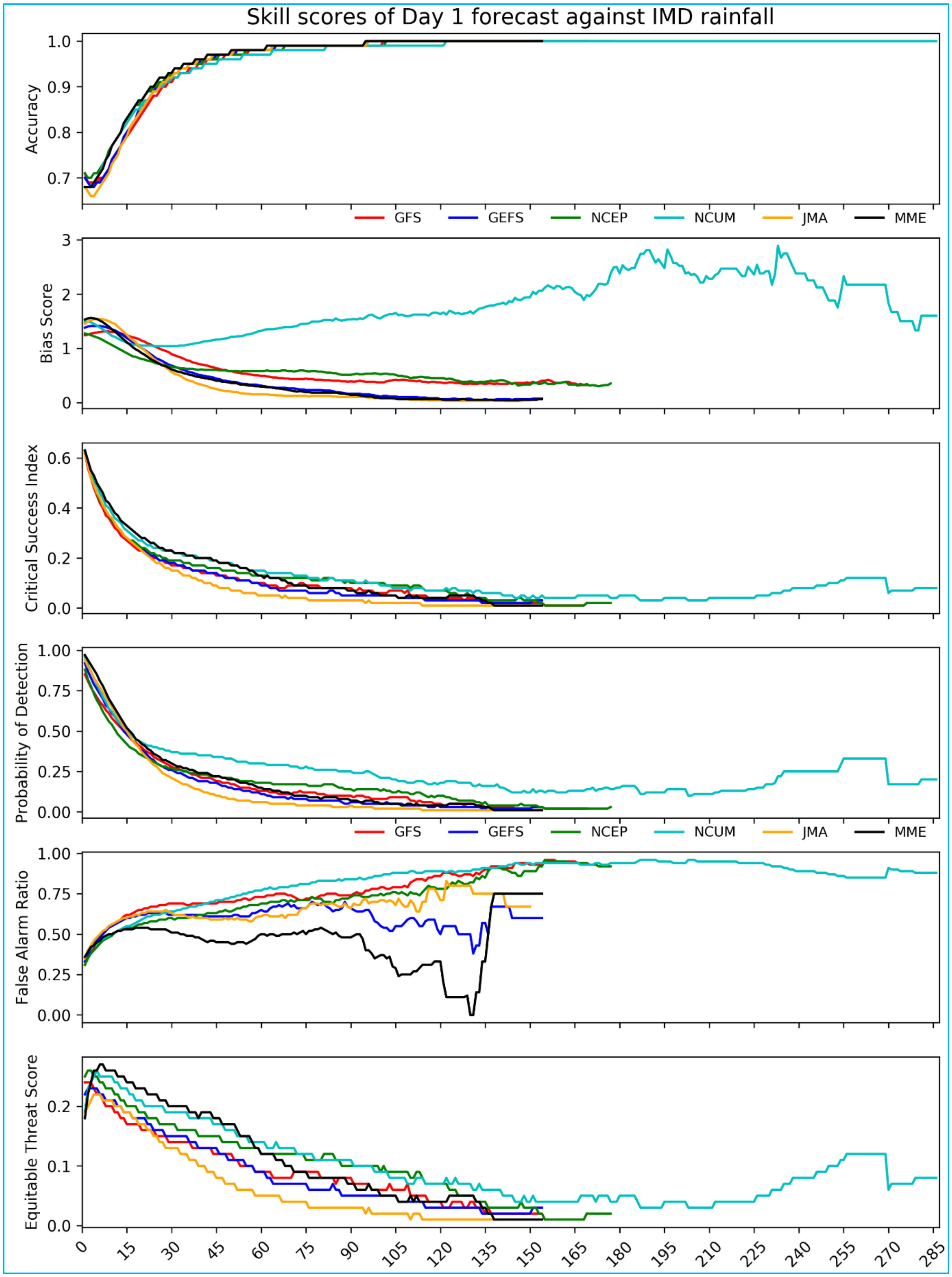

Fig. 11(a). Accuracy, bias score, critical success index, probability of detection, false alarm ratio, equitable threat score, and extreme dependency score for day 1 rainfall forecasts against IMD observations for different rainfall thresholds

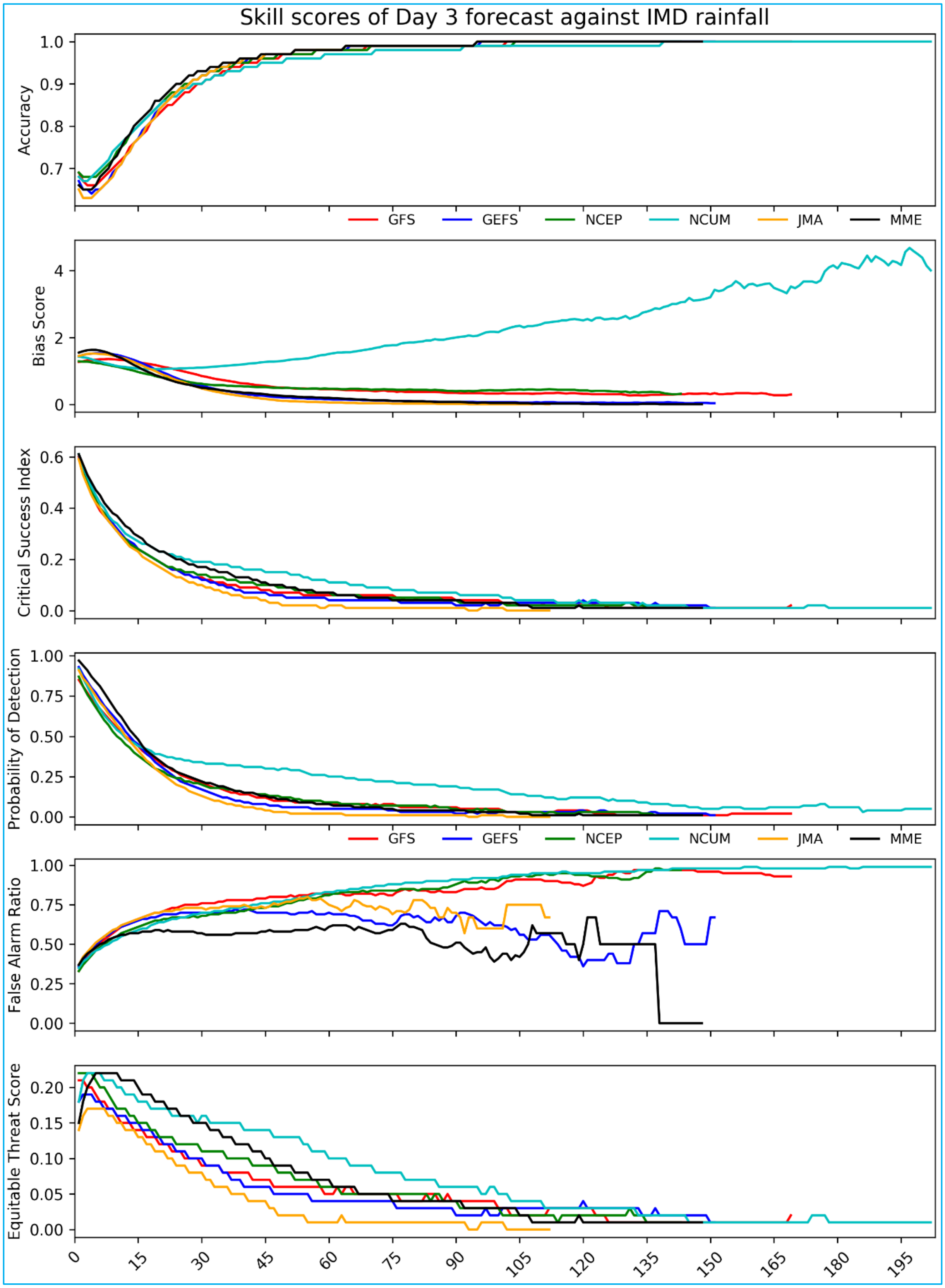

Fig. 11(b). Similar to Fig. 11(a), but for day 3 rainfall forecast

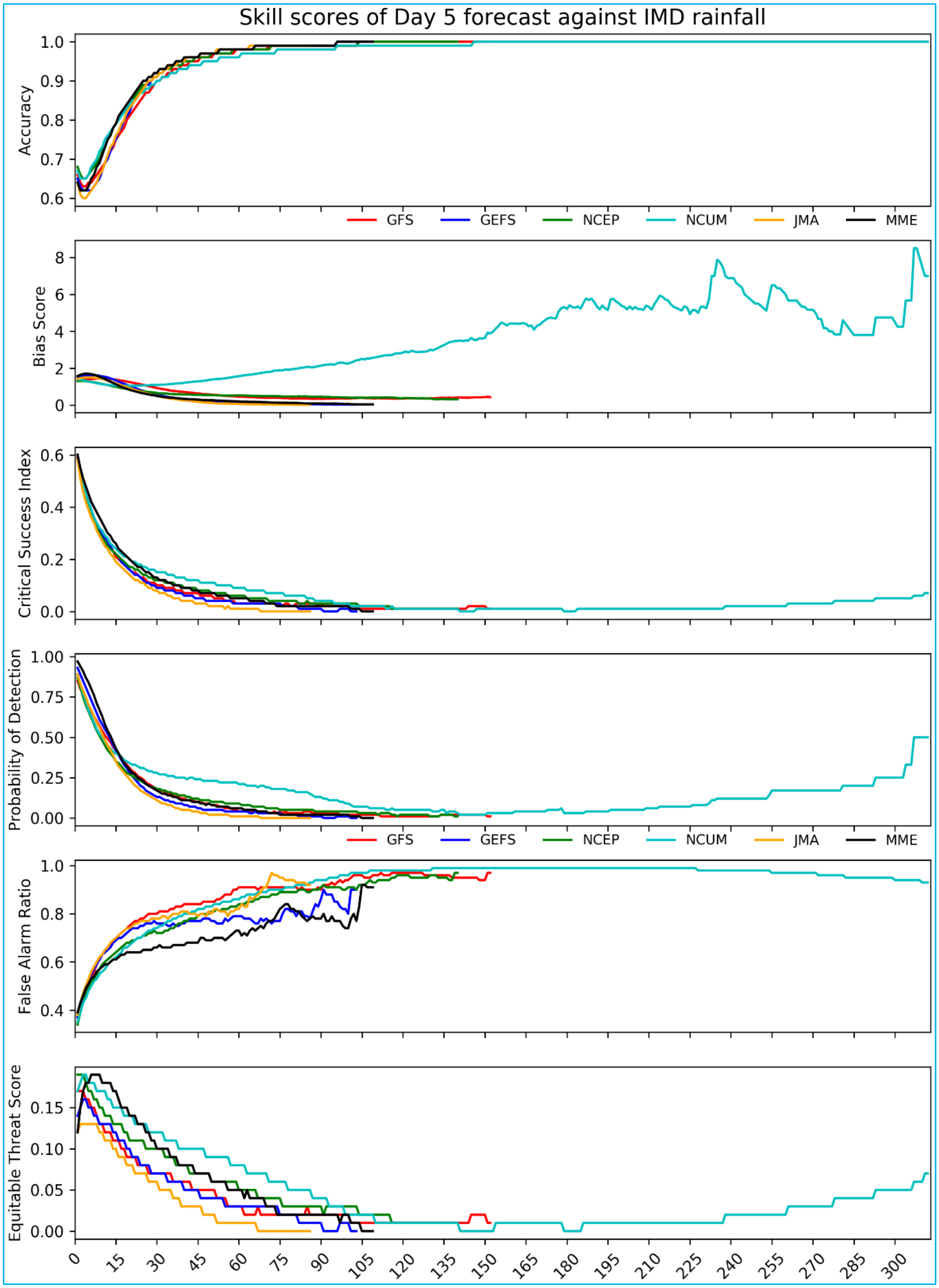

Fig. 11(c). Similar to Fig. 11(a), but for day 5 rainfall forecast also from the spatial distribution of CC, RMSE and bias. As seen from Figs. 8(a-c) the CC of MME forecast is marginally higher over most of the districts in day 1 to day 5 forecast when compared with the CC from individual model. In terms of CC and RMSE from all models, the rainfall forecast over CEI and NWI is comparatively good and over NEI the forecast is comparatively poor in day 1, day 3 and day 5. Among the individual models, GEFS model is showing good performance in terms of CC and RMSE during day 1, day 3 and day 5 forecasts. Consistent with higher CC, the RMSE of MME forecast is marginally less over most of the districts than individual model. Among individual models, NCUM forecast has large biases in day 1, day 3 and day 5 forecasts especially over east and northeastern districts. High values of RMSE are also seen in all models over the higher rainfall regions of Western Ghats and northeastern regions where high seasonal mean rainfall is recorded during southwest monsoon season [Figs. 9(a-c)]. With regard to the model bias it is seen that large dry bias over Western Ghats and large wet bias over Northeastern states are seen in day 1, day 3 and day 5 forecasts from all models except NCUM [Figs. 10(a-c)]. In NCUM model, wet bias is observed over both Western Ghats and northeastern districts. Thus, it is observed that the district level forecast skill in terms of CC, RMSE and bias from MME and individual models indicate useful skill over most parts of India except some parts of northeastern regions, where it needs some improvements.

4.3. *Other verification skill scores of NWP model forecasts over India*

To further examine the forecast skill of individual model and MME, different skill score as discussed in the section 3 such as ACC, BS, CSI, POD, FAR and ETS are estimated for different rainfall thresholds. These skill score for day 1, day 3 and day 5 forecasts from individual model and MME are shown in Figs. 11(a-c). It is clear from Figs. 11(a-c) that the accuracy of rainfall forecast is high in MME at most of the rainfall threshold during day 1, day 3 and day 5 forecasts.

With regard to the BS the forecast from individual model (except NCUM model) and MME indicate slight over prediction (BS > 1) of low rainfall regimes (Rainfall up to about 15 mm), whereas it started gradually decreasing and BS becoming < 1 particularly for the high rainfall regions (Rainfall more than 25 mm) for day 1 to day 5 forecasts. At the same time BS score in the NCUM rainfall forecast for day 1 to day 5 forecast is almost similar to that of other models and MME up to about 15 mm rainfall with BS value is slightly > 1. The only clear distinction in NCUM model compared to other model and MME is that the BS score gradually started increasing for the higher rainfall regimes (Rainfall more than 25 mm) and it gradually increases with the increase of rainfall threshold.

The Critical Success Index (CSI) of MME forecast indicate a value of about 0.6 for very low rainfall threshold for all five days forecasts. The CSI value started decreasing gradually to about 0.2 for the rainfall thresholds of about 45 mm/day in day 1 forecast, 35 mm/day in day 2 forecast, 25 mm/day in day 3 forecast, 22 mm/day in day 4 forecast and about 20 mm/day in day 5 forecast. Thus, as the lead-time increases the threshold value of rainfall gradually decreases for the same value of CSI. Comparing the CSI value of MME forecast and individual model forecast, it is seen that the CSI value is higher in case of MME forecast compared to that of individual model forecast up to 55 mm/day, 30 mm/day, 35 mm/day, 25 mm/day and 35 mm/day respectively for day 1 to day 5 forecast. In case of individual model for different rainfall thresholds, the CSI of all models becomes almost identical except the NCUM model. However, in case of NCUM model forecast the CSI values are higher even in case of higher rainfall thresholds.

The POD and FAR need to be analyzed simultaneously when forecast skills are analyzed. As NUCM has a wet bias the POD of NCUM rainfall is good at most of the rainfall thresholds in day 1, day 3 and day 5 forecasts. However, FAR and BS is also high especially for higher rainfall thresholds. So, there is a chance of over prediction of extreme rainfall from NCUM model. POD of other models are more or less similar but MME is showing slight better performance at rainfall threshold less than about 60 mm. The better skill in MME is also is also reflected with the comparatively lower value of FAR in the MME forecast at most of the rainfall thresholds during day 1 to day 5. Among the individual models, GEFS model forecast has better FAR values and GFS model forecast has poorer (higher) FAR values after NCUM model at most of the rainfall thresholds up to day 5.

The ability to predict precipitation above a certain threshold is given by ETS. ETS value of MME forecast is comparatively high at lower thresholds, whereas the ETS for NCUM model forecast is high at higher thresholds. This shows that NCUM rainfall has a skill to predict extreme rainfall events, but at the same time the possibility of false alarm is also high. Among the individual models, GFS, GEFS, JMA model forecasts have lesser values of ETS at all rainfall thresholds up to day 5. The lowest values of ETS values of JMA model indicates that, this model has skill towards the lower end compared to other models to predict extreme rain events.

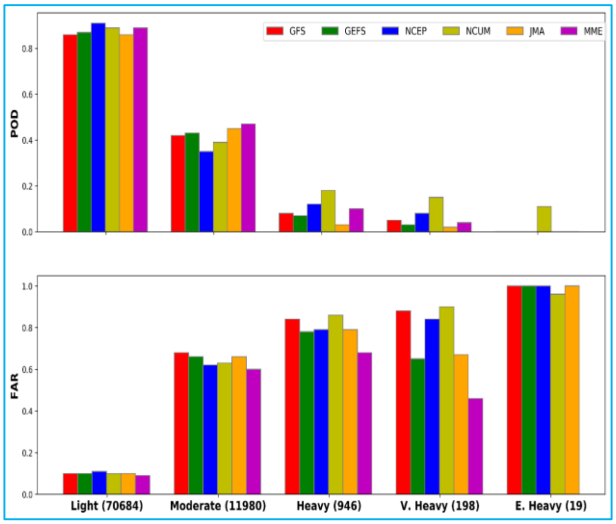

Fig. 12(a). Probability of detection and false alarm ratio for day 1 rainfall forecasts against IMD observations for different rainfall categories

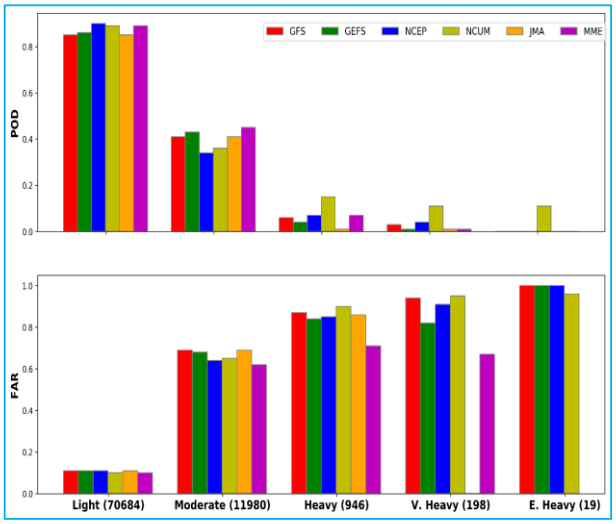

Fig. 12(b). Similar to Fig. 12(a), but for day 2 forecast

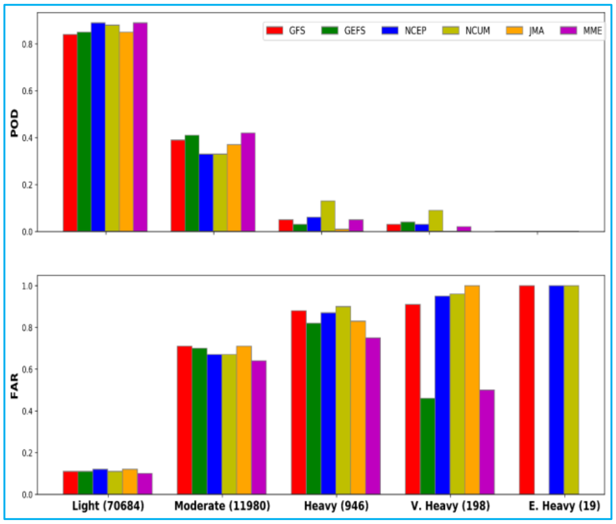

Fig. 12(c). Similar to Fig. 12(a), but for day 3 forecast

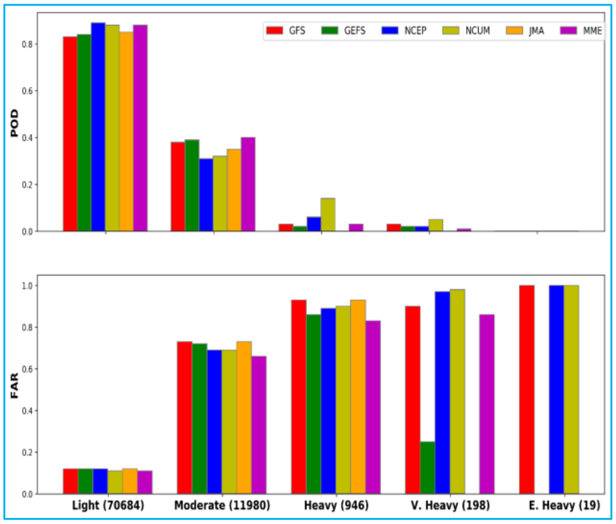

Fig. 12(d). Similar to Fig. 12(a), but for day 4 forecast

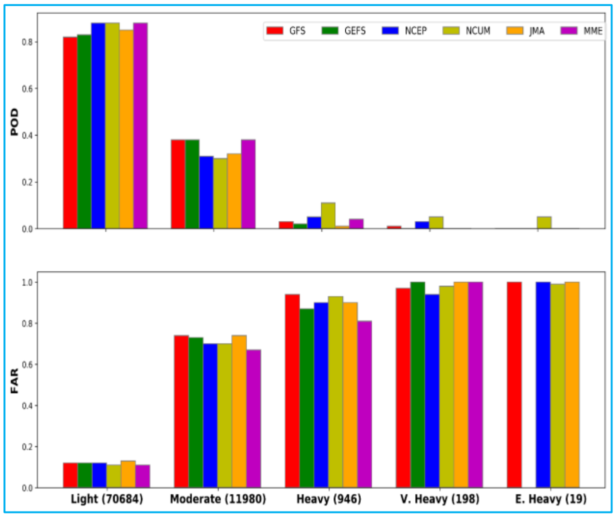

Fig. 12(e). Similar to Fig. 12(a), but for day 5 forecast

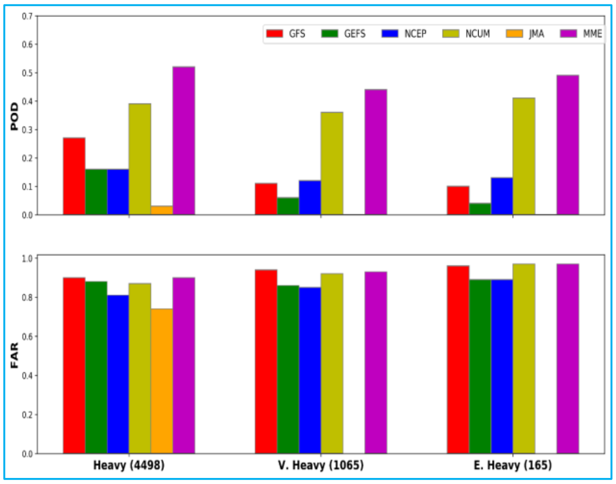

Fig. 13(a). Probability of detection and false alarm ratio for day 1 rainfall forecast against IMD observations for heavy, very heavy and extremely heavy rainfall categories. No of events in each category is given in the bracket

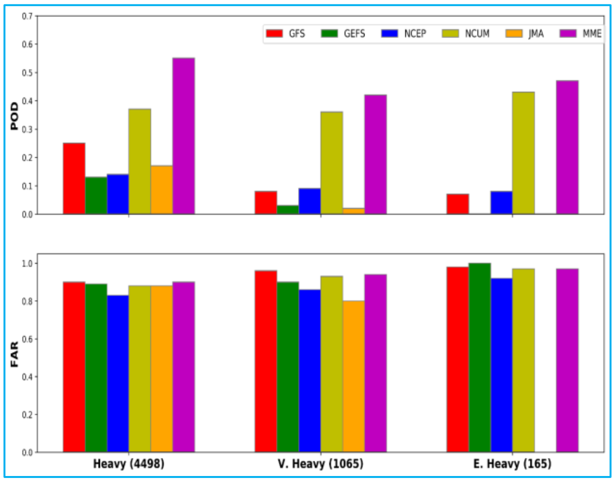

Fig. 13(b). Similar to Fig. 13(a), but for day 2 rainfall forecast

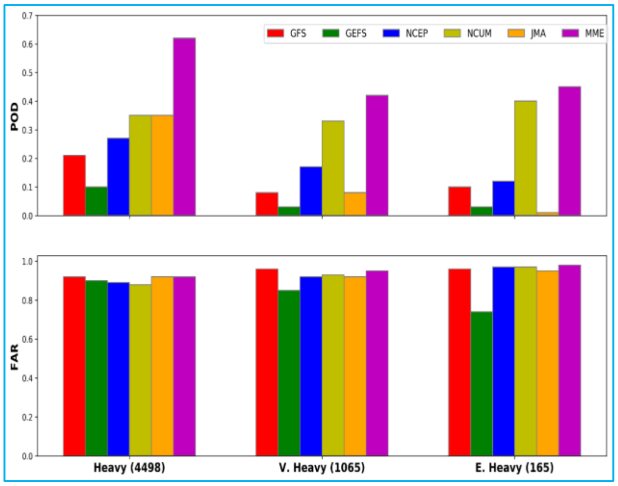

Fig. 13(c). Similar to Fig. 13(a), but for day 3 rainfall forecast

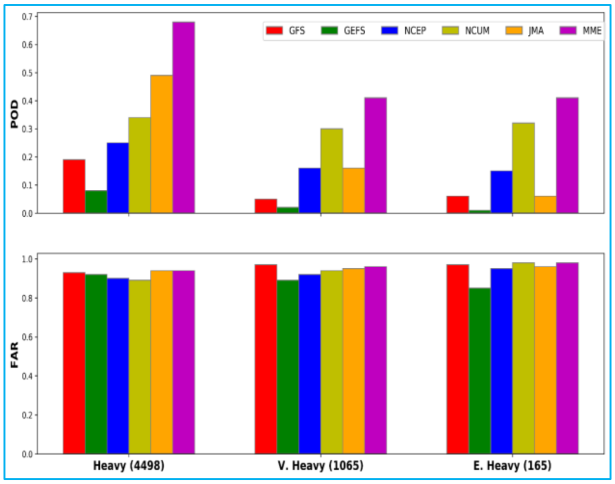

Fig. 13(d). Similar to Fig. 13(a), but for day 4 rainfall forecast

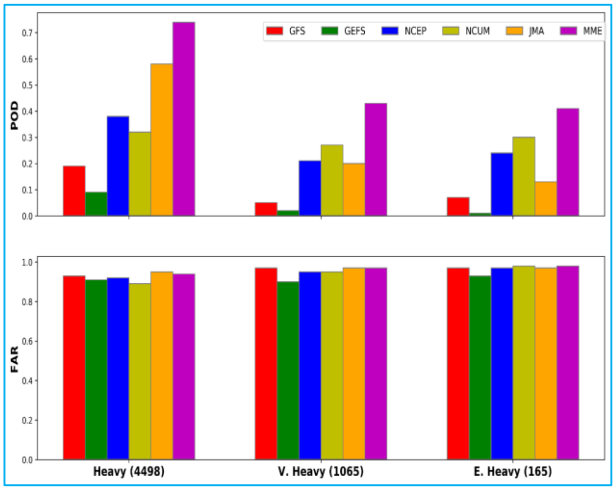

Fig. 13(e). Similar to Fig. 13(a), but for day 5 rainfall forecast

4.4. *Category-wise verification of different rainfall intensity at district level*

Further, the verification of district rainfall from each model is carried out for different category of rainfall, *viz*., light (2.5-15.5 mm), moderate (15.6-64.4 mm), heavy (64.5-115.5 mm), very heavy (115.6-204.4 mm) and extremely heavy rainfall (>204.4 mm). POD and FAR are calculated for each category up to day 5 forecasts from individual model and MME and it is presented in Figs. 12(a-e). While categorizing the observed district average rainfall during southwest monsoon 2021, there was an estimation of 70684, 11980, 946, 198 and 19 cases of light, moderate, heavy, very heavy and extremely heavy rainfall. As shown in Figs. 12(a-e) the POD of light rainfall forecast by all the models and the MME forecast are almost identical with a value exceeding 0.8 up to day 5 forecasts. Similarly, the FAR of light rainfall is less than 0.2 for all models and MME up to day 5 forecast. It is also seen that the relatively higher POD values with better skill is noticed in MME forecast for light and moderate rainfall. However, for NCUM model forecast the higher POD value is noticed for heavy, very heavy and extremely heavy rainfall up to day 5 forecast, which could be due to the wet bias in case of NCUM model. Similarly, among the individual models, only NCUM model showed the skill to predict extremely heavy rainfall during the study period. It may be noted that the high values of rainfall from models may get normalize while taking district average rainfall. This may be reason of lower skill in case of MME forecast for heavy, very heavy and extremely heavy rainfall prediction. Thus, a separate tool for heavy rainfall prediction is also need to be developed. Considering this, a separate section on this aspect is presented in section 4.6. The Figs. 12(a-e) also shows that the FAR of MME forecast is slightly less whereas, for NCUM and JMA the FAR is relatively high for all rainfall categories up to day 5. It is also clear that the POD of different rainfall category is decreasing and the FAR is increasing as the rainfall intensity increases.

4.5. *Verification of heavy, very heavy and extremely heavy rainfall forecast during monsoon season 2021*

As a decision support for the forecasters, a heavy rainfall warning system is developed at NWP/IMD using five NWP models. The distribution of heavy rainfall is calculated by taking the ratio of the number of grid points (from all models) with the forecasted rainfall exceeding the threshold value of rainfall (heavy $\geq$ 64.5 mm, very heavy $\geq$ 115.6 mm, extremely heavy rainfall (> 204.4 mm). Instead of taking average value for observed rainfall, actual observed rainfall within the district is taken for each district. During the verification period, 4498, 1065, and 165 cases of heavy, very heavy and extremely heavy rainfall is considered. POD and FAR of heavy, very heavy and extremely from all the models for day 1 to day 5 are shown in Figs. 13(a-e). From these figures, it is clear that MME have high values of POD for heavy, very heavy and extremely heavy rainfall forecast during day 1 to day 5 forecasts. MME forecast for heavy rainfall forecast have POD values of 0.52, 0.55, 0.62, 0.68 and 0.74 for day 1 to day 5 respectively. Similarly, MME forecast for very heavy rainfall forecast have POD values of 0.44, 0.42, 0.42, 0.41, and 0.43 for day 1 to day 5 respectively. Likewise, the POD values of 0.49, 0.47, 0.45, 0.41 and 0.41 respectively are observed for MME extremely heavy rainfall forecast during day 1 to day 5. Among individual models, NCUM have good skill for predicting heavy rainfall events. Among the five individual models, JMA is unable to predict most of the heavy rainfall events. FAR of all models are more or less same during day 1 to day 5 forecasts.

5. Conclusions

Based on the latest high resolutions NWP models' output an MME tool for rainfall prediction system at district scale as a decision support for the operational forecasters. Five models, *viz*., GFS, GEFS, NCEP-GFS, NCUM and JMA have been used for developing the operational MME forecasts. Rainfall forecasts for day 1 to day 5 forecasts from individual model and from simple MME technique over 732 Indian districts of India are generated and validated with observed rainfall. The prediction skill of the MME and individual model forecasts is also evaluated against observed district rainfall during Southwest monsoon season 2021. Different statistics and skill score shows that MME forecast is better than the individual models. The CC between observed rainfall and day 1 MME forecast is 0.58, whereas GFS, GEFS, NCEP, NCUM and JMA are showing 0.43, 0.47, 0.49, 0.49 and 0.46 respectively. The RMSE observed for MME, GFS, GEFS, NCEP, NCUM and JMA are 12.7, 15.2, 14.1, 14.3, 16.6 and 14.1 mm/day respectively when compared with IMD observed rainfall indicating lowest RSME in MME forecast. The superiority of MME rainfall forecast is also observed in day 2 to day 5 forecasts. The verification statistics over four homogeneous regions show that MME forecasts performed very well over NWI, CEI and SPI with the best performance over the CEI region. However, the performance over NEI regions needs slight improvement compared to other 3 regions. To see the quantitative value the CC between observed rainfall and day 1 MME forecast rainfall over CEI, SPI and NWI are 0.66, 0.63 and 0.61respectively. At the same time CC over NEI is only 0.43 which is less among the four homogeneous regions. Similarly, for the day 1 forecast the RMSE (16.05 mm/hr) was also high over NEI compared to other three regions. The day 2, day 3, day 4 and day 5 forecasts comparison also showing similar trend. A wet bias in the rainfall forecast from all models is also observed over NE India up to day 5. Thus, the statistics over four regions shows that MME forecast performed very well over NWI, CEI and SPI with the best performance over the CEI region. However, the performance over NEI regions needs slight improvement compared to other 3 regions.

While analysing different skill scores it is noticed that MME rainfall forecasts have better values of accuracy, POD, FAR, BS, CSI and ETS at most of the rainfall thresholds up to day 5. Among the individual models, NCUM rainfall have high values of BS (indicating over prediction) and FAR, however the ETS scores for NCUM model is much better, especially for high rainfall thresholds (Rainfall more than 25 mm/day) although the false alarm is also high.

Assessment of district scale heavy rainfall warning system also carried out. Better performance of MME forecast is also observed in predicting heavy rainfall events. The POD for heavy rainfall forecast with MME is found to be 0.52, 0.55, 0.62, 0.68 and 0.74 for day 1 to day 5 forecasts respectively. However, the FAR is also gradually increasing from 0.9 in day 1 forecast to 0.94 in day 5 forecast. Similarly, MME forecast for very heavy rainfall have POD values of 0.44, 0.42, 0.42, 0.41 and 0.43 for day 1 to day 5 respectively. Likewise, POD values of 0.49, 0.47, 0.45, 0.41 and 0.41 respectively are observed for MME extremely heavy rainfall forecast during day 1 to day 5. The FAR of MME forecasts for very heavy rainfall for day 1 to day 5 are found to be 0.93, 0.94, 0.95, 0.96 and 0.97 respectively whereas, for extremely heavy rainfall forecast, the FAR is 0.97, 0.97, 0.98, 0.98 and 0.98. Among individual models, NCUM have good skill for predicting heavy rainfall events and JMA model have less skill in predicting heavy rainfall events.

The inter-comparison of the model forecasts reveal that the MME method has the potential of generating skilful districts level rainfall forecast over India for operational use during the monsoon season. To further improve the MME forecast for operational use, the model output from leading centre like ECMWF will also be added for district level and extreme rainfall forecasting.

Acknowledgements

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Disclaimer : The contents and views expressed in this study are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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