The evaluation of weekly extended range river basin rainfall forecasts and a new bias correction mechanism for flood management in India

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Abstract

Operational extended range forecasts are being disseminated once every week by the India Meteorological Department (IMD) for several sectorial applications. These forecasts show a reduction in amplitude and variance as a function of lead-time. Such reductions in variance can be due to several physical factors: inherent forecast model bias, a problem relating to initial conditions, lead-dependent statistical biases, etc. A week-by-week analysis shows that such biases are not systematic. Rainfall forecasts are underestimated in some regions, while others overestimate rainfall amplitude. To correct the bias in the extended range weekly averaged forecast, a statistical post-processing method (normal ratio correction) is proposed to make the outlook more valuable at a longer lead-time. The correction method is based on the World Meteorological Organization (WMO) technical guidance on rainfall estimation and is also shown to be useful for rainfall forecasts. In this analysis, we evaluate the extended range forecast skill at the river sub-basin-scale and show that there are several river sub-basins over the central Indian region where the correction has improved the model forecast in the one to two-week range. Although this analysis was tailored toward making the river basins and sub-basins of India more readily realizable for flood forecasters, it can be used for any administrative boundaries such as block, district, or state-level requirements.

Keywords

Extended range prediction, rainfall bias correction, flood management.

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1. Introduction

One of the major purposes of the extended range forecast is to provide a high-resolution spatial-temporal forecast on a weekly scale, with up to 2-3 weeks lead time. The weekly outlooks can provide important input to the decision-making process of various stakeholders (Pattanaik, Das 2015; Chattopadhyay et al. 2018; Pattanaik et al. 2019; Sahai et al. 2019a-b). The extended range forecasts of the India Meteorological Department (IMD) are being generated at a spatial resolution of 1°X1° Grid. Forecasts of rainfall in different river basins have several important hydrometeorological applications, especially in flood forecasting based on rainfall variables (Ming et al. 2020; Webster, Hoyos 2004; Webster et al. 2010; Gilewski, Nawalany 2018; Sayama et al. 2020; Gilewski 2021). In this regard, the most critical application is the forecast of heavy rainfall (daily rainfall of 7 cm or more) in the river basins. This can lead to flooding and inundations, and a considerable loss of life and property. Hence, for flood forecasting and other hydrometeorological requirements, the precipitation forecast must be as quantitative as possible. However, it is occasionally found that there is a significant bias in amplitude and variance in the forecasted rainfall. This often leads to a severe underestimation of rainfall outlook, thereby adding additional input errors to hydrological models that use these quantitative rainfall forecasts.

The Ministry of Earth Sciences, the Government of India, and the IMD have the mandate to provide rainfall forecast and long-range outlooks in the S2S (seasonal to sub-seasonal) scale[1]. Such predictions are required to be as accurate as possible. Bias in rainfall forecasts is a common problem in raw model forecast data, which can be problematic for quantitative precipitation forecast. Such amplitude biases in rainfall in longer lead times arise due to inefficient representation of model physics and dynamics, or due to systematic errors in the large-scale forcing. To make the forecast more useful, these biases should be reduced as much as possible. One crucial error in rainfall forecasts is the underrepresentation of rainfall amplitude after a forecast lead-time of a few days. The forecast often shows that the variance is severely underrepresented in the forecasted rainfall, as lead-time increases. Several statistical post-processing methods, using complex to simple approaches to correct the rainfall bias, exist to improve the rainfall forecast under such circumstances (Boé et al. 2007; Leander, Buishand 2007; Ghimire et al. 2019). These bias corrections are shown to improve hydrological forecasts (Teutschbein, Seibert 2012). The results show that a bias in rainfall arising due to improper amplitude attenuations as a function of lead-time, could be corrected under many circumstances – provided climatological or observed rainfall amplitude is known for any lead day. This shows promise for correcting amplitude bias arising in operational dynamical models (Singh et al. 2017; Jabbari, Bae 2020).

The presented study aimed to provide better basin-wise weekly rainfall forecasts for the river sub-basins of India, using a novel method to correct the forecast bias in the extended range weekly forecast. The forecast ability of extended range weekly rainfall forecasts, as well as bias-corrected extended range weekly rainfall forecasts, were satisfactory in both 1-week and 2-weeks lead time. These forecasts can thus be used as model inputs for flood forecasting. Although this study focused on basin-wise rainfall forecast, the method is general and can be applied to the average rainfall of any administrative boundaries or geographical locations like districts or states.

2. Data and methodology

2.1. Data

The current study uses the daily observed rainfall data from the IMD 0.25 Deg × 0.25 Deg gridded data (Pai et al. 2014) and daily 1Deg × 1Deg rainfall forecast data received from the IMD_IITM extended range forecast system [*ERF*]. Daily observed gridded rainfall data of 0.25 Deg × 0.25 Deg has been generated by the IMD from the quality controlled daily rainfall data of rain gauge stations[2]. The dataset covers a geographical domain of 6.5°-38.5°N and 66.5°-100.0°E and contains only values from land regions. The extended range forecast models generate precipitation forecast data up to four weeks in advance, based on the conditions observed at any given time (Chattopadhyay et al. 2019; Pattanaik et al. 2019, Sahai et al. 2019b). Currently, an operationally extended range forecast is disseminated once every week. For every week's operational forecast, there is corresponding "on the fly" hindcasts for the same set of recorded

[1] https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1706073

[2] https://imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html

conditions since 2003. The data is generated for the global domain. In this analysis we have used the data for the river basins of India. The Central Water Commission divides the country into 25 major river basins and 101 river sub-basins (Fig. 1 and Table 1). River sub-basins shapefiles were obtained from the Central Water Commission. Using the shapefile, the gridded data (both observation and forecast data) was masked and basin averaged data was prepared for each of the 101 river basins.

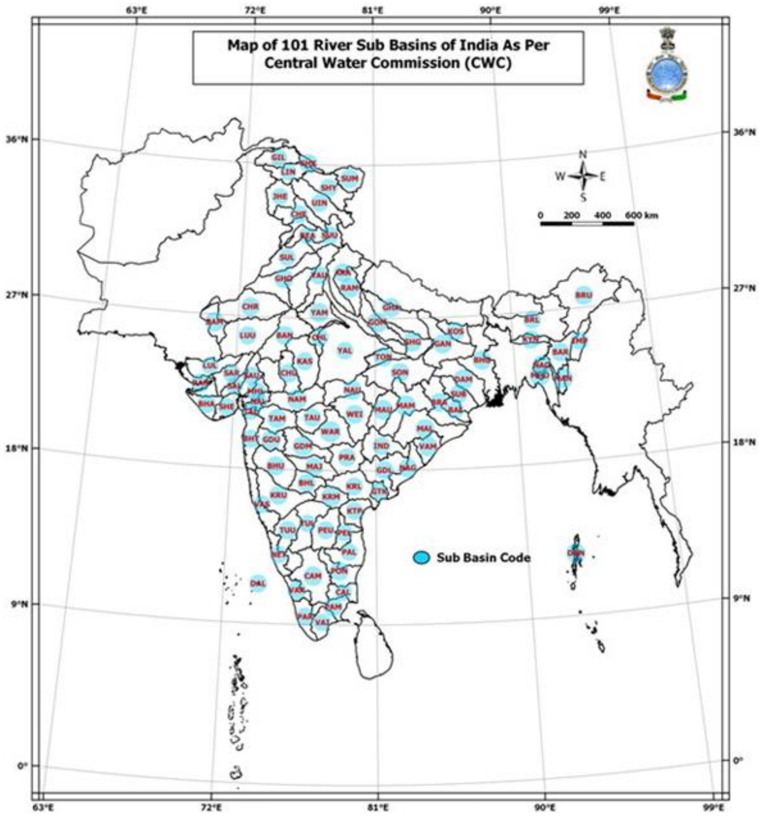


Fig. 1. Locations of the 101 river sub-basins of India.

Table 1. List of the 101 river sub-basins of India and their codes.

Sub Basin No.	SBCODE	Major Basin	SUB_BASIN
1	ARA	Ganga Basin	Above Ramganga Confluence
2	BAI	Brahmani and Baitarni Basin	Baitarni
3	BAM	Indus (Up to border) Basin	Barmer
4	BAN	Ganga Basin	Banas
5	BAR	Barak and others Basin	Barak
6	BEA	Indus (Up to border) Basin	Beas
7	BHA	West flowing rivers of Kutch and Saurashtra includ-ing Luni Basin	Bhadar and other west flowing rivers
8	BHG	Ganga Basin	Bhagirathi and others (Ganga Lower)
9	BHL	Krishna Basin	Bhima Lower
10	BHT	West flowing rivers South of Tapi Basin	Bhatsol and others
11	BHU	Krishna Basin	Bhima Upper
12	BRA	Brahmani and Baitarni Basin	Brahmani
13	BRL	Brahmaputra Basin	Brahmaputra Lower

14	BRU	Brahmaputra Basin	Brahmaputra Upper
15	CAL	Cauvery Basin	Cauvery Lower
16	CAM	Cauvery Basin	Cauvery Middle
17	CAU	Cauvery Basin	Cauvery Upper
18	CHA	Indus (Up to border) Basin	Chautang and others
19	CHE	Indus (Up to border) Basin	Chenab
20	CHL	Ganga Basin	Chambal Lower
21	CHR	Indus (Up to border) Basin	Churu
22	CHU	Ganga Basin	Chambal Upper
23	DAL	Drainage Area of Lakshadweep Islands Basin	Drainage Area of Lakshadweep Islands
24	DAM	Ganga Basin	Damodar
25	DAN	Drainage Area of Andaman and Nicobar Islands Basin	Drainage Area of Andaman and Nicobar Islands
26	GAN	Ganga Basin	Gandak and others
27	GDL	Godavari Basin	Godavari Lower
28	GDM	Godavari Basin	Godavari Middle
29	GDU	Godavari Basin	Godavari Upper
30	GHA	Ganga Basin	Ghaghara
31	GHG	Ganga Basin	Ghaghara Confluence to Gomti confluence
32	GHO	Indus (Up to border) Basin	Ghaghar and others
33	GIL	Indus (Up to border) Basin	Gilgit
34	GOM	Ganga Basin	Gomti
35	GTK	East flowing rivers between Godavari and Krishna Basin	East flowing rivers between Godavari and Krishna
36	IMP	Minor rivers draining into Myanmar Basin	Imphal and others
37	IND	Godavari Basin	Indravati
38	JHE	Indus (Up to border) Basin	Jhelum
39	KAS	Ganga Basin	Kali Sindh and others up to Confluence with Parbati
40	KOS	Ganga Basin	Kosi
41	KPO	Minor rivers draining into Bangladesh Basin	Karnaphuli and others
42	KRL	Krishna Basin	Krishna Lower
43	KRM	Krishna Basin	Krishna Middle
44	KRU	Krishna Basin	Krishna Upper
45	KTP	East flowing rivers between Krishna and Pennar Basin	East flowing rivers between Krishna and Pennar
46	KYN	Barak and others Basin	Kynchiang and other south flowing rivers
47	LIN	Indus (Up to border) Basin	Lower Indus
48	LUL	West flowing rivers of Kutch and Saurashtra including Luni Basin	Luni Lower
49	LUU	West flowing rivers of Kutch and Saurashtra including Luni Basin	Luni Upper
50	MAJ	Godavari Basin	Manjra
51	MAL	Mahanadi Basin	Mahanadi Lower
52	MAM	Mahanadi Basin	Mahanadi Middle
53	MAN	Minor rivers draining into Myanmar Basin	Mangpui Lui and others
54	MAU	Mahanadi Basin	Mahanadi Upper
55	MHO	Minor rivers draining into Bangladesh Basin	Muhury and others

56	MHU	Mahi Basin	Mahi Upper
57	NAG	East flowing rivers between Mahanadi and Godavari Basin	Nagvati and other
58	NAM	Narmada Basin	Narmada Middle
59	NAO	Barak and others Basin	Naoch chara and others
60	NAU	Narmada Basin	Narmada Upper
61	NET	West flowing rivers South of Tapi Basin	Netravati and others
62	PAL	East flowing rivers between Pennar and Cauvery Basin	Palar and other
63	PAM	East flowing rivers South of Cauvery Basin	Pamba and others
64	PAR	West flowing rivers South of Tapi Basin	Periyar and others
65	PEL	Pennar Basin	Pennar Lower
66	PEU	Pennar Basin	Pennar Upper
67	PON	East flowing rivers between Pennar and Cauvery Basin	Ponnaiyar and other
68	PRA	Godavari Basin	Pranhita and others
69	RAM	Ganga Basin	Ramganga
70	RAN	West flowing rivers of Kutch and Saurashtra including Luni Basin	Drainage of Rann
71	RAV	Indus (Up to border) Basin	Ravi
72	SAL	Sabarmati Basin	Sabarmati Lower
73	SAR	West flowing rivers of Kutch and Saurashtra including Luni Basin	Saraswati
74	SAU	Sabarmati Basin	Sabarmati Upper
75	SHE	West flowing rivers of Kutch and Saurashtra including Luni Basin	Shetranjuli and other east flowing rivers
76	SHK	Area of North Ladakha not draining into Indus Basin	Shaksgam
77	SHY	Indus (Up to border) Basin	Shyok
78	SON	Ganga Basin	Sone
79	SUB	Subernarekha Basin	Subernarekha
80	SUL	Indus (Up to border) Basin	Sutlaj Lower
81	SUM	Area of North Ladakha not draining into Indus Basin	Sulmar
82	SUU	Indus (Up to border) Basin	Sutlaj Upper
83	TAM	Tapi Basin	Tapi Middle
84	TAU	Tapi Basin	Tapi Upper
85	TON	Ganga Basin	Tons
86	TUL	Krishna Basin	Tungabhadra Lower
87	TUU	Krishna Basin	Tungabhadra Upper
88	UGO	Ganga Basin	Upstream of Gomti confluence to Muzaffarnagar
89	UIN	Indus (Up to border) Basin	Upper Indus
90	VAI	East flowing rivers South of Cauvery Basin	Vaippar and others
91	VAM	East flowing rivers between Mahanadi and Godavari Basin	Vamsadhara and other
92	VAR	West flowing rivers South of Tapi Basin	Varrar and others
93	VAS	West flowing rivers South of Tapi Basin	Vasishti and others
94	WAR	Godavari Basin	Wardha
95	WEI	Godavari Basin	Weinganga
96	YAL	Ganga Basin	Yamuna Lower

97	YAM	Ganga Basin	Yamuna Middle
98	YAU	Ganga Basin	Yamuna Upper
99	MHL	Mahi Basin	Mahi Lower
100	NAL	Narmada Basin	Narmada Lower
101	TAL	Tapi Basin	Tapi Lower

2.2. Methodology

Weekly grid point cumulative rainfall data for the years 2003-2019 were used. Average cumulative rainfall (in mm) in each sub-basin for every week was calculated using the Raster Statistics Method in the QGIS Software. More details on the operational extended-range forecast can be seen in a study by Sahai et al. (2019b). A diagram illustrating how the operational forecast is generated currently, is shown in Figure 2. The operational extended-range forecast is an ensembled mean of four dynamical models. Two of them are high resolution (denoted by suffix T382 or ~38 km), and two are low resolution models (indicated by suffix T126 or ~110 km). Two of the models have coupled models (CFS), and two are atmospheric models (GFS). Each model shares the same dynamic core but slightly different physics and resolutions. Each model has 4-member ensemble runs. Thus, we have a total of $4 \times 4 = 16$ ensemble members from the CFST126, CFST382, GFST126, and GFST382 models for runs from each set of condition. Atmospheric and oceanic initial conditions were generated by NCMRWF and INCOIS, respectively. The sea surface temperature boundary conditions for the GFS were derived from the CFS runs. Since the CFS sea surface temperature has a bias, a simple bias correction using observed climatology was applied to generate the final input boundary conditions for the GFS.

There are various metrices for evaluating rainfall forecasts (e.g., Barnston 1992; Huang, Zhao 2022). Several papers have used root mean square errors and correlation coefficients as a first order measure to evaluate the deterministic forecast ability of rainfall in the extended range (e.g., Joseph et al. 2019). Similarly, there are several methods to evaluate hydrological forecasts (e.g., Hoshin et al. 2009; Gilewski, Nawalany 2018). In this study, we computed and compared the "normalized root mean square error" (*NRMSE*) and "correlation coefficient" of raw extended range weekly forecast data (hereafter *ERF*) and bias-corrected forecast data (hereafter *BERF*). For basin averaged extended range forecast, it would be shown that the bias-corrected forecast improves the model performance.

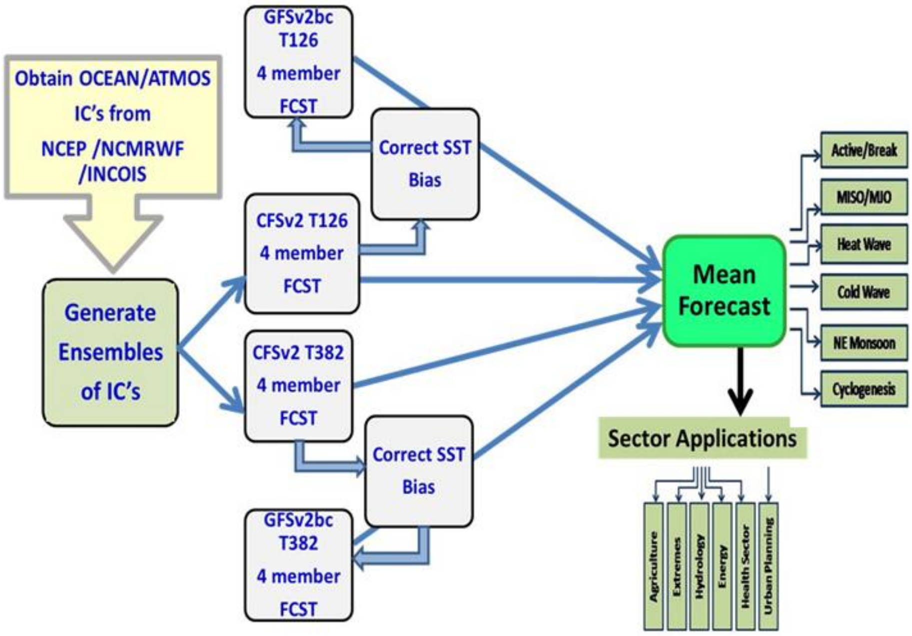


Fig. 2. Schematics of the end-to-end forecast and dissemination system implemented for Extended Range Prediction in India. Abbreviations: CFSv2: Coupled forecasting system version2; GFSv2: Global forecasting system; T382 and T126 suffixes specify the CFS and the GFS model horizontal spatial resolutions and different spectral truncations. T382 implies models CFS or GFS model run at ~38 km resolution. In comparison, T126 indicates the model to run at ~110 km spatial resolution. The suffix "bc" suggests that the GFS runs with bias-corrected sea surface temperature (SST) as boundary conditions. "FCST" indicates forecast runs, and ICs indicate initial conditions from which the model is run. INCOIS (Indian National Center for Ocean Information services) and NCMRWF (National Centre for Medium-Range Weather Forecasting) generate the ICs (i.e., initial conditions) for the operational forecasts. Models are an adapted version of models developed at the National Centre for Environmental Predictions (NCEP), USA, which also generates the ICs. MISO or MJO is the intra-seasonal monsoon oscillations and the Madden Julian Oscillations.

2.3. Bias correction with Normal Ratio Method

For the estimation of missing or unknown rainfall values, a normal ratio method is suggested by WMO (2018). We have adopted a similar approach to perform bias correction of the raw extended rainfall forecast (*ERF*) by multiplying the Bias correction ratio with the raw *ERF* rainfall. The normal ratio method is generally used for rainfall estimation, whereas difference correction is advised for temperature and other parameters.

According to the normal ratio method, the missing precipitation is given as:

$$P_x = \frac{1}{n}\sum_{i=1}^{n}\frac{N_x}{N_i}P_i \quad (1)$$

Where P_x is the missing precipitation for any storm at the interpolation station 'x', P_i is the precipitation for the same period for the same storm at the "ith" station of a group of index stations, N_x is the normal precipitation value for the 'x' station and N_i the normal precipitation value for 'ith' station. In our bias correction method, P_i is the precipitation from raw *ERF*, N_i is the climatology of P_i, N_x is the observed climatology, and P_x is the bias corrected *ERF*.

Figure 3 shows the climatological differences between raw *ERF* rainfall and realized rainfall of 101 sub-basins of India for each of the 18 weeks of southwest monsoon. The first week of this period was from 30th May to 5th June and the last week was from 26th Sept to 2nd Oct (as 18th week). It can be seen that *ERF* has no systematic bias, as it is overestimating in some areas and underestimating in others. These differences also changed as the monsoon progresses. During the initial onset phase of the monsoon in June, the *ERF* climatology was higher than the observed climatology in most sub-basins. Still, during the peak monsoon period from July to August, *ERF* underestimated the rainfall for most sub-basins. Particularly during week number 8 (18th Jul to 25th July), *ERF* climatology was less significant for all the sub-basins of India – except one sub-basin in the extreme eastern parts of India. Another important finding in *ERF* was overestimation throughout the season, except one or two weeks for the sub-basins over Bihar, east UP, and adjacent areas. Thus, bias correction based on the normal ratio method has to be applied for all the weeks separately. This overcomes both the underestimating and overestimating of the raw *ERF* rainfall forecast and makes the prediction closer to the realized one. Thus, the bias correction ratio was different for each basin, as well as for each week during the monsoon onset, progress, and retreat phases.

The bias correction ratio for each of the 101 sub-basins and all the 18 weeks during the southwest monsoon season was estimated by the ratio of Actual Rainfall Climatology (for the same week in the period 2003-2019) and *ERF* Climatology (for the same week in the period 2003-2019). Here we have used the normal ratio in equation (1) for the estimation of missing rainfall, as the bias correction ratio in our bias correction method. This assists in improving the forecast value by giving weight to observed climatology.

Therefore, to improve the accuracy of the sub-basin rainfall forecast, we have adopted a new bias correction method given as follows:

The Bias Corrected Rainfall Forecast for each week and each basin = *ERF* (Rainfall) for that week X Bias correction ratio for the corresponding week of the same basin.

The correlation coefficient is one of the possible choices for forecast verification (Barnston 1992) and is given as:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{2}$$

where: r – correlation coefficient; x_i – values of the x-variable in a sample; $\bar{x}$ – mean of the values of the x-variable; y_i – values of the y-variable in a sample; $\bar{y}$ – mean of the values of the y-variable.

In statistical modeling, another way of measuring the quality of the fit of the model, is the *RMSE* (also called Root Mean Square Deviation) (Barnston 1992) given by:

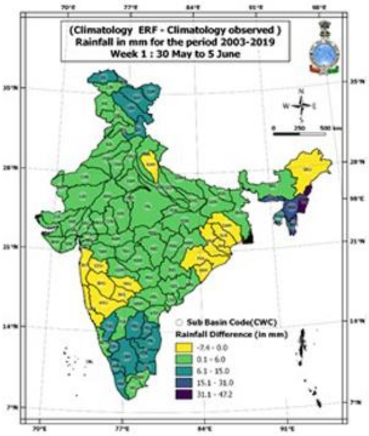
$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{3}$$

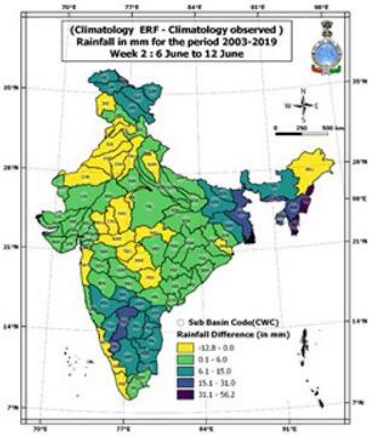
where y_i is the i[th] observation of y and $\hat{y}_i$ the predicted y value given the model. If the predicted responses are very close to the correct responses, the *RMSE* will be small. If the predicted and true responses differ substantially – at least for some observations – the *RMSE* will be large.

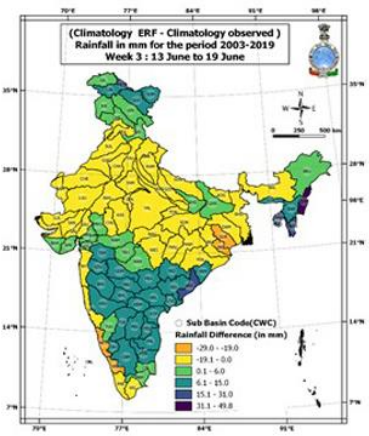
To compare *RMSE* of rainfall forecast of the different river basins with different mean rainfall patterns, we have used Normalized Root Mean Square Error (*NRMSE*) as:

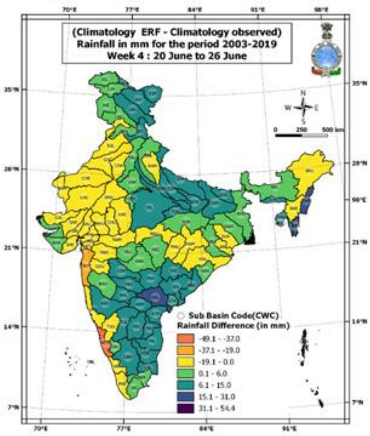
$$NRMSE = RMSE/\text{Mean (observed values)} \tag{4}$$

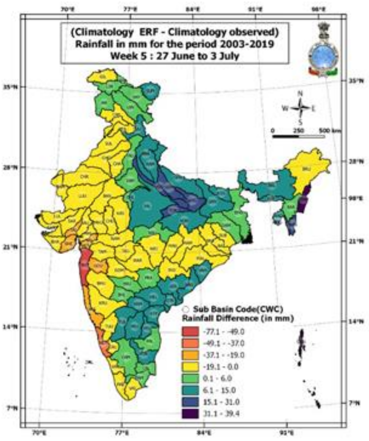
In the next sections, the *NRMSE* and the correlation coefficient will be used as the standard skill score measures to evaluate the improvement in the rainfall forecast.

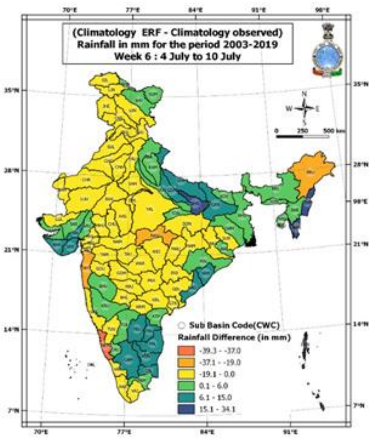

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 1 : 30 May to 5 June
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-7.4 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 47.2

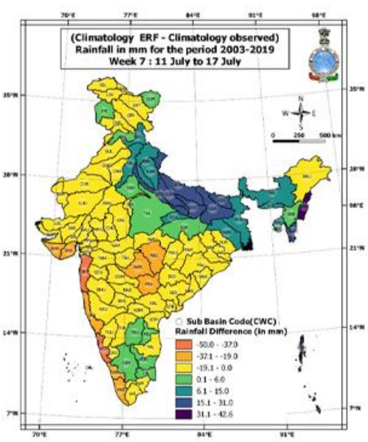

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 2 : 6 June to 12 June
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-12.8 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 56.2

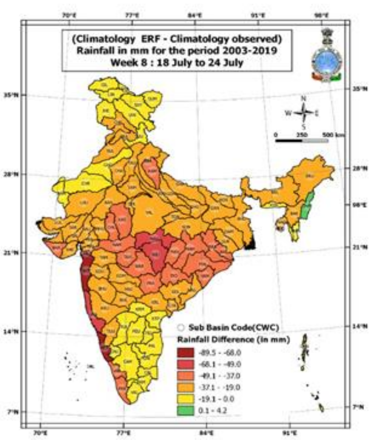

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 3 : 13 June to 19 June
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-29.0 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 49.8

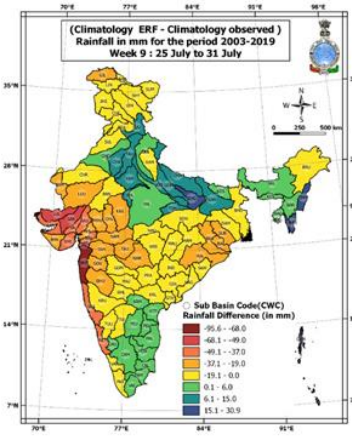

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 4 : 20 June to 26 June
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-49.1 - -37.0
-37.1 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 54.4

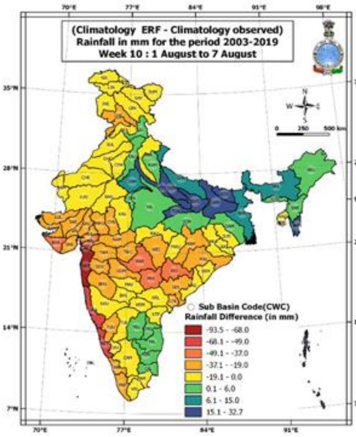

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 5 : 27 June to 3 July
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-77.1 - -49.0
-49.1 - -37.0
-37.1 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 39.4

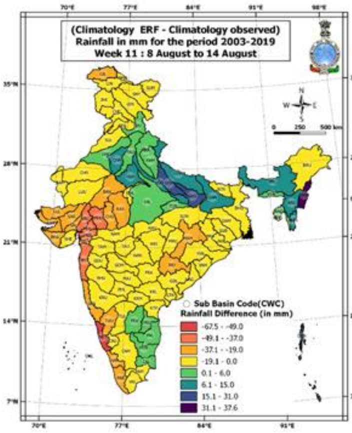

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 6 : 4 July to 10 July
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-39.3 - -37.0
-37.1 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 34.1

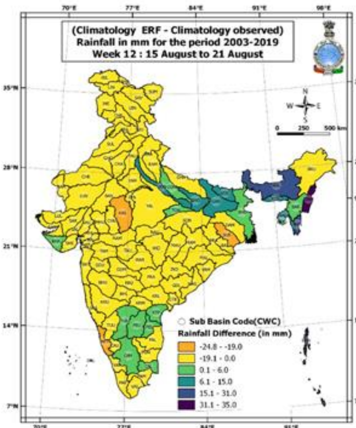

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 7 : 11 July to 17 July
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-50.0 - -37.0
-37.1 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 42.6

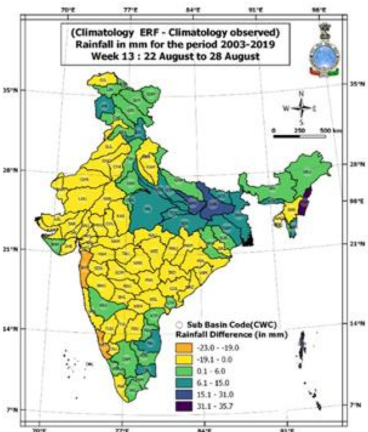

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 8 : 18 July to 24 July
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-89.5 - -68.0
-68.1 - -49.0
-49.1 - -37.0
-37.1 - -19.0
-19.1 - 0.0
0.1 - 4.2

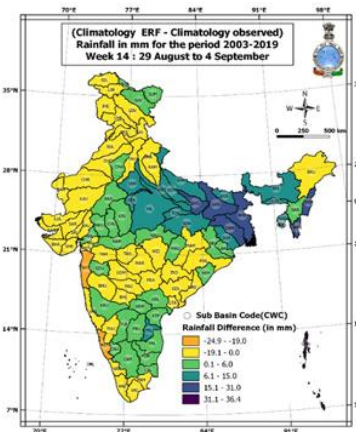

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 9 : 25 July to 31 July
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-95.6 - -68.0
-68.1 - -49.0
-49.1 - -37.0
-37.1 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 30.9

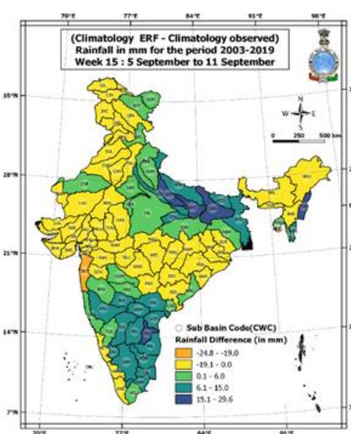

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 10 : 1 August to 7 August
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-93.5 - -68.0
-68.1 - -49.0
-49.1 - -37.0
-37.1 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 32.7

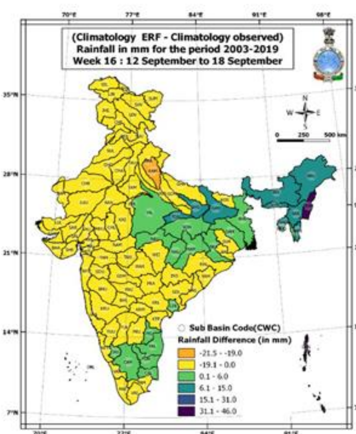

(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 11 : 8 August to 14 August
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-67.5 - -49.0
-49.1 - -37.0
-37.1 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 37.6


(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 12 : 15 August to 21 August
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-24.8 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 35.0


(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 13 : 22 August to 28 August
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-23.0 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 35.7


(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 14 : 29 August to 4 September
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-24.9 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 36.4


(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 15 : 5 September to 11 September
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-24.8 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 29.6


(Climatology ERF - Climatology observed)
Rainfall in mm for the period 2003-2019
Week 16 : 12 September to 18 September
Sub Basin Code(CWC)
Rainfall Difference (in mm)
-21.5 - -19.0
-19.1 - 0.0
0.1 - 6.0
6.1 - 15.0
15.1 - 31.0
31.1 - 46.0

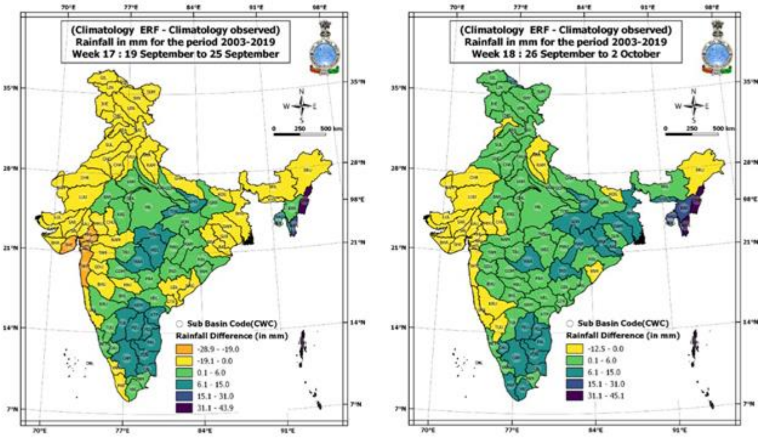


Fig. 3. Differences in climatology of raw *ERF* with realized rainfall climatology for the 18 weeks of the SW monsoon season (2003-2019).

3. Results and discussion

3.1. Performances of forecast

From a hydrological forecast perspective, the monsoon onset phase is perhaps the most important phenomenon. Every year, the onset over Kerala, and its subsequent propagation over the Indian Landmass, is monitored for agrometeorological predictions. The onset phase is often associated with a northward propagating rainfall pulse, providing rain over large regions of India and several river basins.

Rainfall during the onset phase of the monsoon is crucial for agricultural planning. Additionally, most flood events occur during July and August, when the monsoon is active. Week-by-week performances of the week 1 extended-range forecast, as well as the bias-corrected forecast, are shown for June (Fig. 4a), July (Fig. 4b), August (Fig. 4c), and September (Fig. 4d) of 2003-2019.

For all the weeks, the Normalized *RMSE* of bias-corrected *ERF* was less than 1 in most cases and for most sub-basins. In week 1 (Fig. 4a), due to bias correction, *NRMSE* of *ERF* has been reduced from 2.4 to 0.5 for the Drainage Area of Andaman and Nicobar Islands sub-basin, from 1.6 to 0.4 for the Drainage Area of Lakshadweep Islands sub-basin, from 1.7 to 1.4 for the Sulmar sub-basin, 1.0 to 0.7 for the Kynchiang sub-basin, and other south-flowing rivers of Barak basin during onset phases of the SW monsoon. For all four weeks of June (Fig. 4a), *NRMSE* of these sub-basins were high (more than 1.5) for raw *ERF*, whereas due to bias correction, *NRMSE* has come down by around 0.5. Furthermore, for all four weeks of June, *NRMSE* of bias-corrected *ERF* was less than the *NRMSE* of raw *ERF*. This was within 0.2 to 0.9 for all the sub-basins, except a few sub-basins in the first week and one sub-basin in the second and third weeks.

In the first week of July (27th Jun to 3rd July) (Fig. 4b), the bias corrections of several sub-basins have helped to improve the *NRMSE* by keeping it less than 0.8. In the following two weeks, though the *NRMSE* of bias-corrected *ERF* was less than the raw *ERF* for all the sub-basins, there was no significant improvement. However, in the last two weeks of July, significant improvement of the ability of bias-corrected *ERF* was seen for most of the sub-basins.

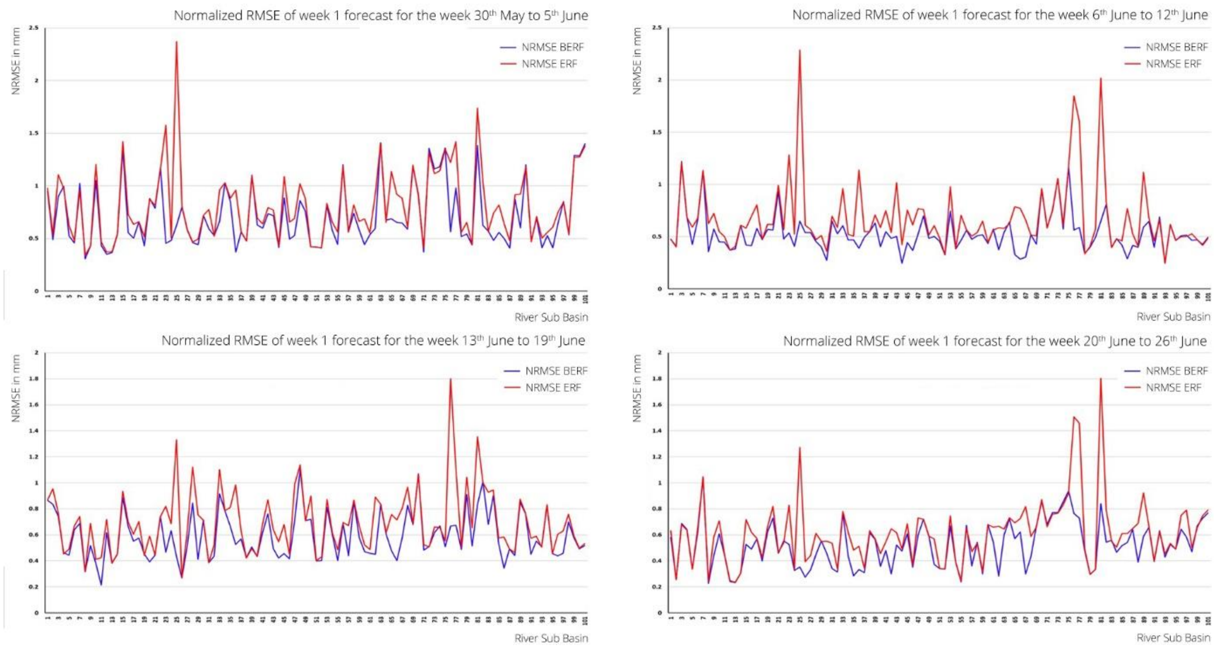


Fig. 4a. Normalized *RMSE* of Bias corrected *ERF* (*BERF*) and raw *ERF* of Week 1 rainfall during June.

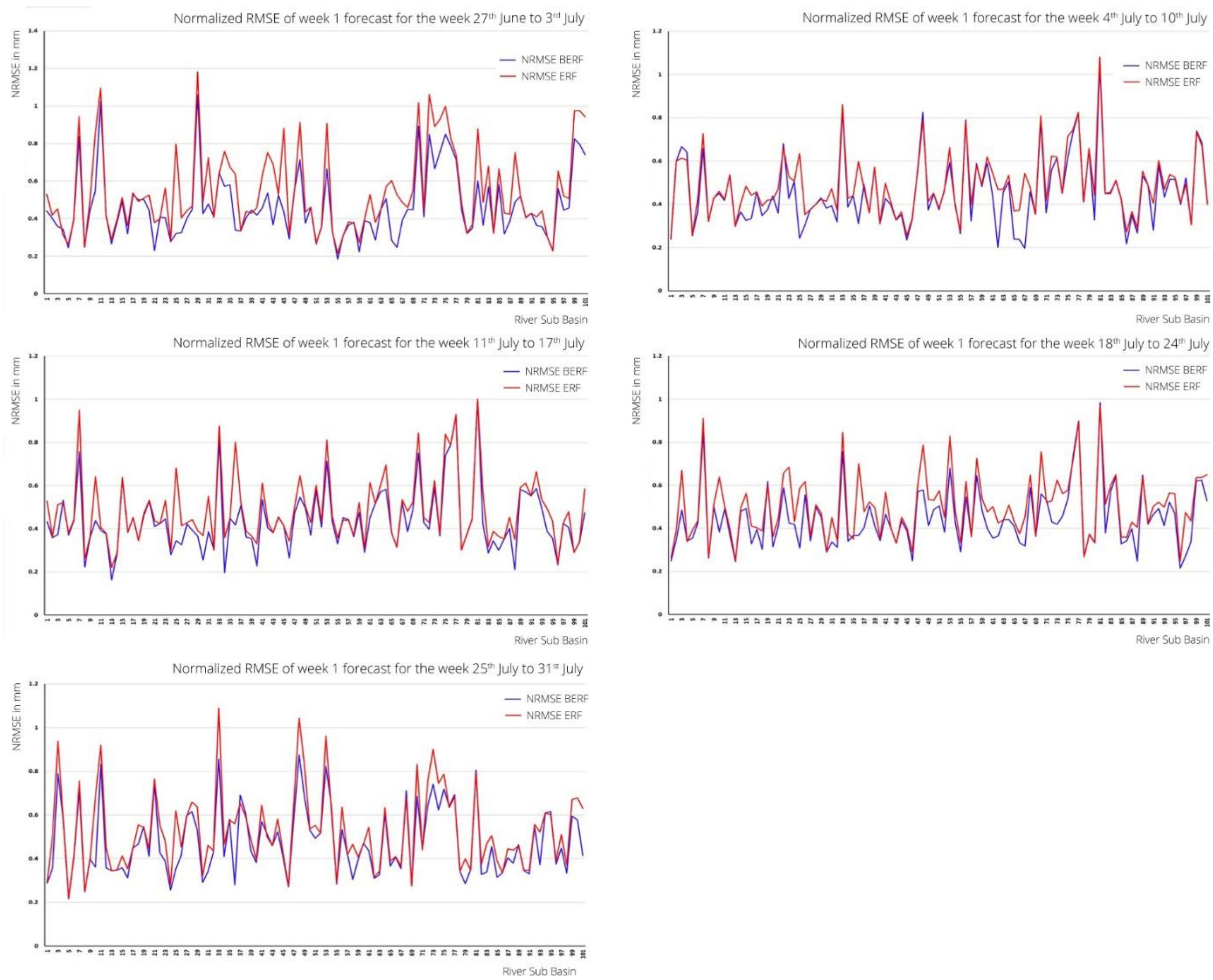


Fig. 4b. Normalized *RMSE* (*NRMSE*) of Bias corrected *ERF* (*BERF*) and raw *ERF* of Week 1 rainfall during July.

There is a remarkable improvement in the skill of bias-corrected *ERF* for the first two weeks of August (Fig. 4c), as *NRMSE* of bias-corrected *ERF* was between 0.2 to 0.6 in most of the sub-basins. Since most of the floods in India occur during July and August, bias correction can help improve flood forecasts and better flood management.

Even during all the weeks of September (Fig. 4d), bias correction reduced the *NRMSE* value to well below 1.0 of the *NRMSE* value and greater than 1 of raw *ERF*.

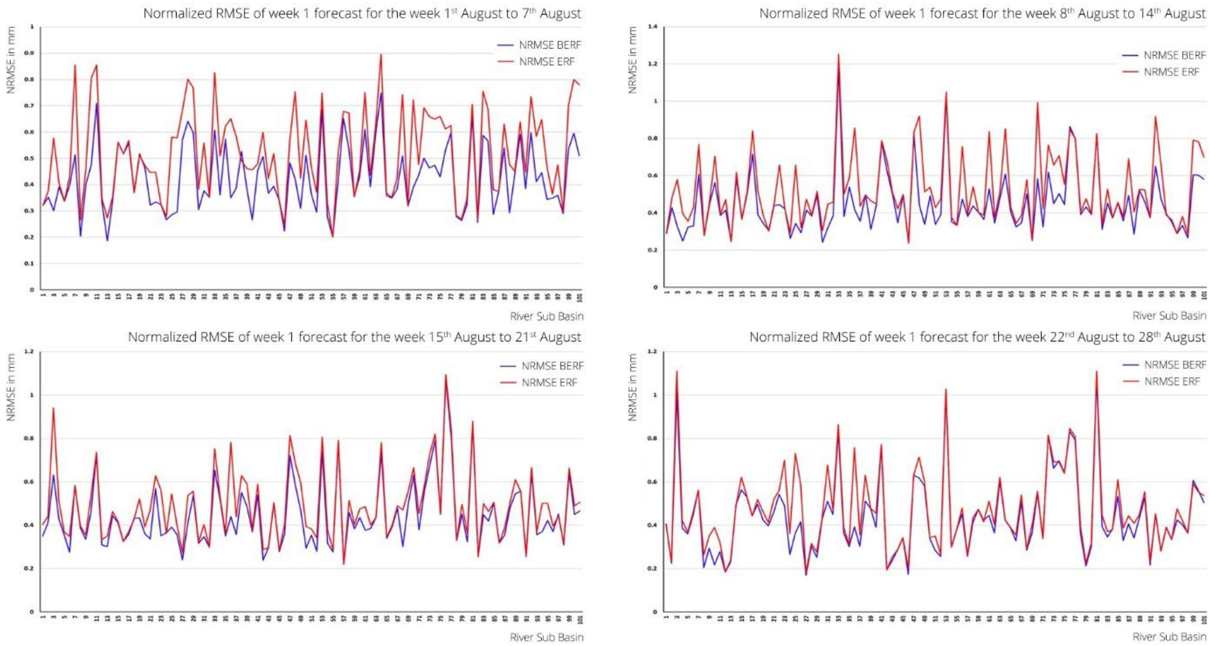


Fig. 4c. Normalized *RMSE* of Bias corrected *ERF* (*BERF*) and raw *ERF* of Week 1 rainfall during August.

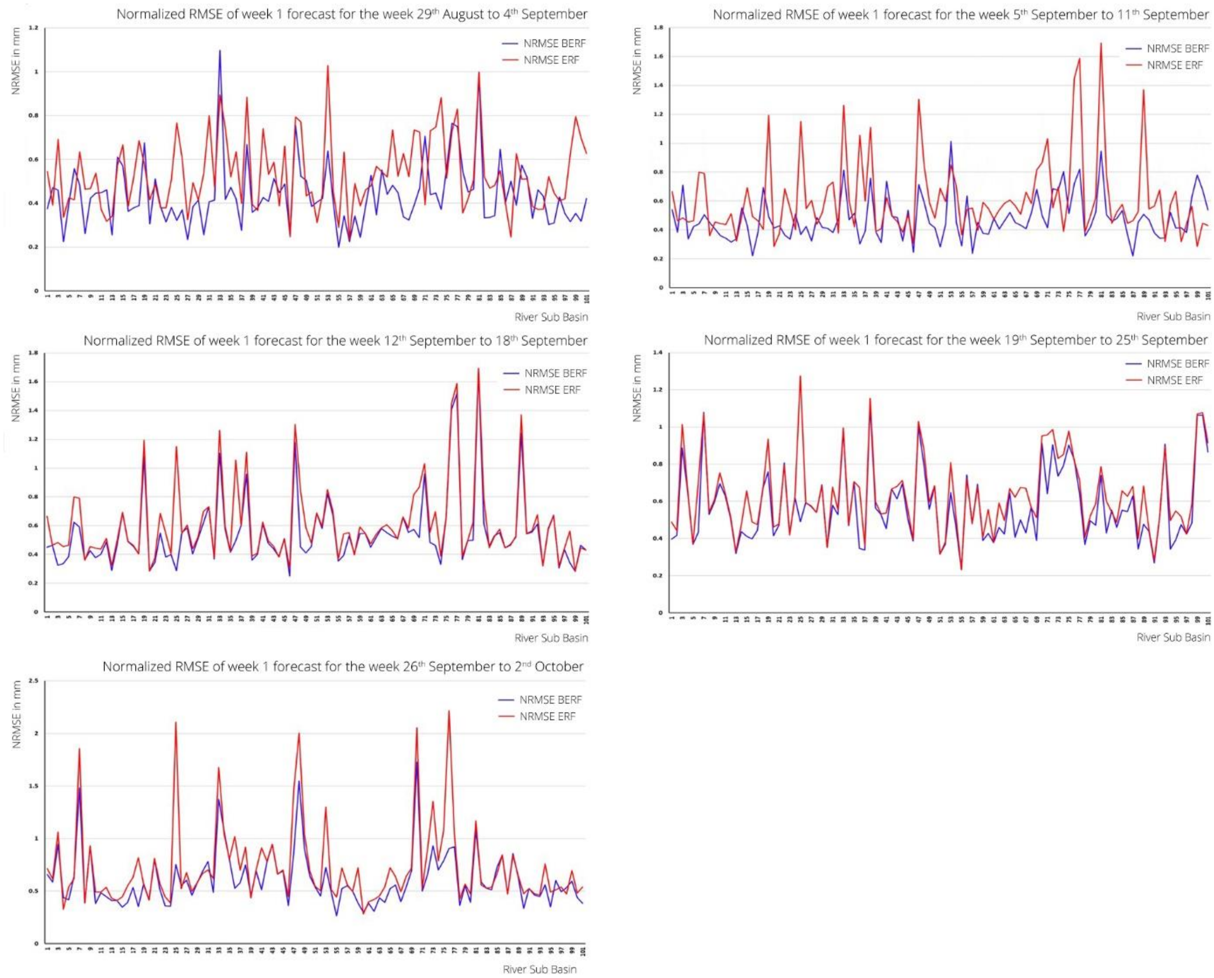


Fig. 4d. Normalized *RMSE* of Bias corrected *ERF* (*BERF*) and raw *ERF* of Week 1 rainfall during September.

3.2. The spatial pattern of Extended Range onset forecast skill for the period 2003-2019

To demonstrate the skill of the extended range forecast for the 1-week and 2-weeks lead-time during the monsoon season, we have computed the correlation coefficient and the normalized root mean square error (*NRMSE*) map between the *ERF* and observed rainfall for the years 2003-2019. The samples consisted of 18 weeks and 17 years (18×17 = 306 samples) for each of the 101 sub-basins for the monsoon season. Figures 5a-b shows the basin-wise map of the correlation coefficients and normalized root mean square error for the raw *ERF* (left panels), respectively. The plot indicates relatively high correlations in the central and northern Indian basins and relatively low correlations in the southern peninsular basins. Furthermore, there were low correlations and higher *NRMSE* in the Jammu, Kashmir, and Ladakh regions. The root mean square error in Figure 5b shows that the model had the lowest error in central and northern India.

Similarly, Figures 5c-d show the same skill metrics for the bias-corrected forecast. The bias-corrected forecast shows some improvement in correlation skills in the Maharashtra sub-basins and some basins of peninsular India. There was also a significant decrease in *RMSE* over the basins of central to southern peninsular India.

Figure 6 shows the same skill plots but for the 2-week forecast.

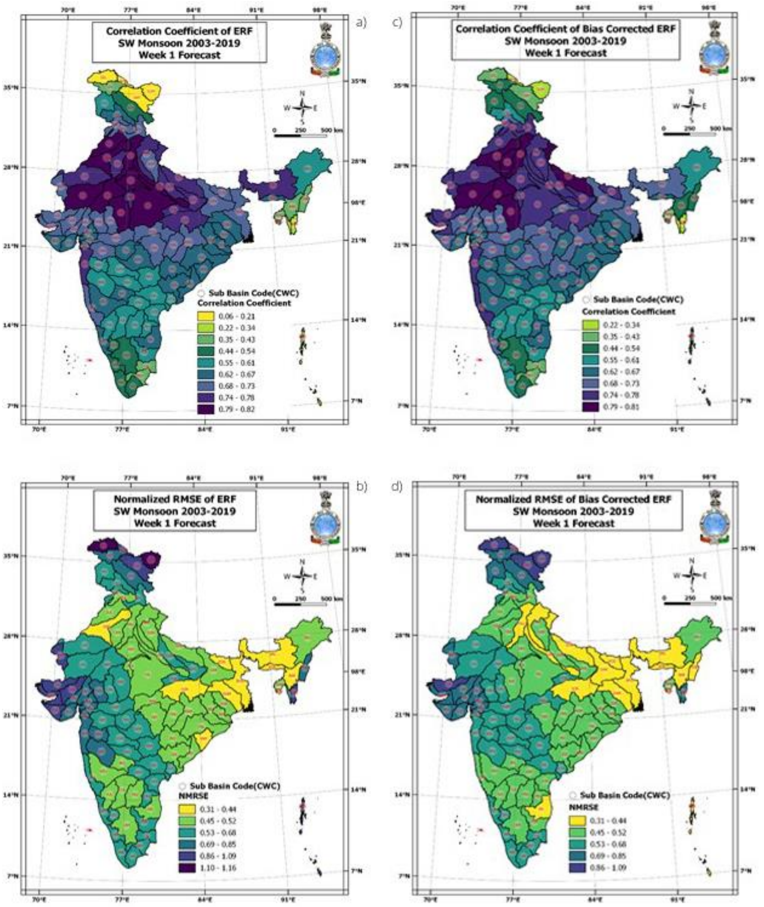


Fig. 5. (a) Correlation map of 1-week actual forecast, (b) RMSE of the actual forecast, (c) same as (a) but showing the cc map for bias-corrected forecast, (d) same as (b) but showing RMSE of bias-corrected forecast.

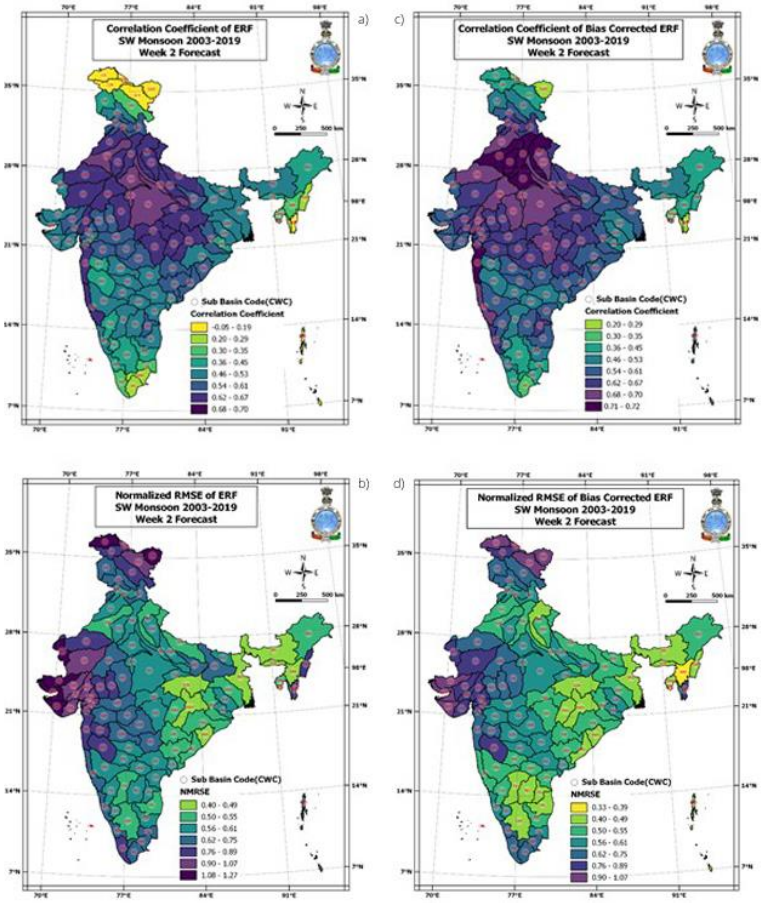


Fig. 6. Same as (5) but for the 2-week forecast.

3.4. Floods in Maharashtra and Bihar during 2019 and the evaluation of skill forecast for the year 2019

In 2019, several parts of the country had experienced severe floods affecting lakhs of people (Shagun 2019; Kambli 2020). During July and August 2019, heavy flooding occurred in Maharashtra due to intense rainfall. The Sangli and Kolhapur district in the Krishna sub-basin experienced severe floods of long durations. Substantial losses of life, property and crops were reported. At the beginning of the flood period, i.e., from 27th Jul to 3rd Aug, heavy rainfall events were localized in the northern part of the Konkan and adjoining North Madhya Maharashtra. Many stations in the Pune and Nasik districts recorded rainfall of more than 150 mm/day from 3rd to 5th August. Towards the latter part of the week, the rainfall belt shifted towards southern Madhya Maharashtra. Mahabaleshwar recorded the highest rainfall of 380 mm on 5th Aug 2019. It is also observed that the Kolhapur district continuously experienced heavy rain throughout this period, with the highest rainfall amounts on 6th Aug 2019. Gaganbawda recorded its highest rainfall of 340 mm on 6th Aug 2019. It is also seen that, though heavy rainfall occurred in the western part of the districts in Madhya Maharashtra, their eastern parts were devoid of rainfall. Furthermore, during the heavy rain spell of Aug 2019, many stations in the Kolhapur district and western parts of the Satara district have surpassed their previous record of 7 days rainfall. Compared to 2018, rainfall over the region was widespread and remained very intense for an extended period from 27th Jul to 13th Aug 2019

(Government of Maharashtra 2020). The expert committee of the Government of Maharashtra recommended that IMD 1-week and 2-week river sub-basin rainfall forecasts should be used in flood forecasting to improve the accuracy of the forecast. Another major affected state was Bihar, where around 306 lives were lost due to floods and heavy rain.

We have analyzed the 1-week forecasted rainfall of raw *ERF* compared to the actual rainfall for all the sub-basins of these two states, and showed how the bias-corrected forecast could have helped the flood management. The losses could have been minimized by using the bias-corrected forecast for these regions.

Figure 7 shows the realized, bias-corrected *ERF* and *ERF* rainfall for 18 weeks of SW Monsoon season of 2019. This includes the sub-basins viz. Godavari Upper, Godavari Middle, Wardha, Wainganga, Tapi Middle, Bhima Upper, Krishna Upper, Bhatsol and others, and Vasishti and other Flood-affected Maharashtra states. In the 9th and 10th weeks (25th Jul to 31st Jul and 1st Aug to 7th Aug), all nine of these sub-basins reported a significant increase in rainfall compared to previous weeks, which raw *ERF* was not able to predict in most of the cases. The sub-basins Weinganga, Vasishti, and others also reported increased rainfall activity in 11-weeks. The raw *ERF* underestimated the rainfall for all these basins. Applying the bias correction forecast to rainfall from these basins was almost comparable to that of the realized rainfall, indicating the usefulness of the bias-corrected Week 1 rainfall in improving flood management.

Fig. 7. Realized, Bias corrected *ERF* (*BERF*) and *ERF* rainfall for 18 weeks of the 2019 SW Monsoon season in 9 sub basins of the flood affected Maharashtra state.

For the Bihar flood, we have selected four sub-basins viz. Ghaghara, Ghaghara Confluence to Gomti confluence, Gandak and others, and Koshi. Figure 8 shows the realized, bias-corrected *ERF* and ERF rainfall for 18 weeks of the 2019 SW Monsoon season for sub-basins of Flood-affected Bihar. In the 6th and 7th weeks, all four sub-basins have reported increased rainfall activities causing devastating flooding over this region. The week 1 raw *ERF* rainfall has been overestimated in all these cases. The bias correction could help to minimize the differences between observed rainfall and forecast rainfall.

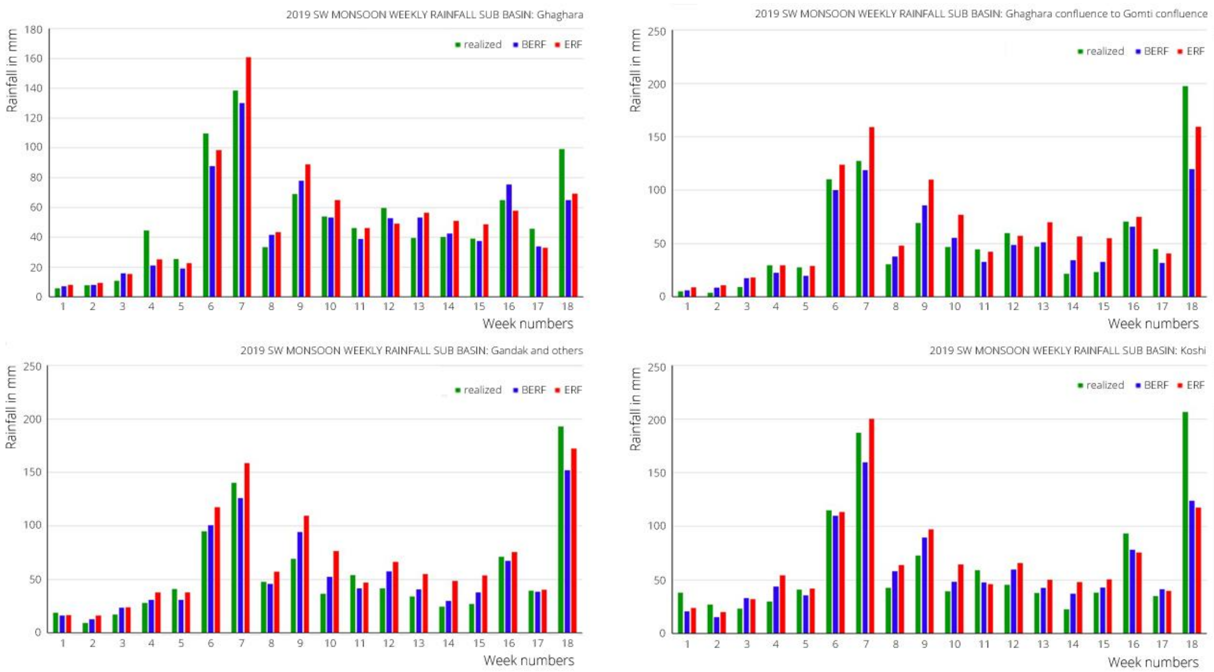


Fig. 8. Realized, Bias corrected *ERF* (*BERF*) and *ERF* rainfall for 18 weeks of SW Monsoon season 2019 of sub basins of flood-affected districts of the Bihar state.

To see the performance of raw *ERF* and bias-corrected *ERF* for the year 2019, the correlation coefficient between observed and forecast rainfall and normalized *RMSE* was calculated using 18 samples (all eighteen weeks of SW monsoon 2019) for both the 1-week and 2-week lead forecasts. Figure 9 shows the (a) correlation and (b) *RMSE* of the raw extended range forecast, calculated using the weekly data for the year 2019. (c) same as (a) but after using bias correction. (d) same as (b) but after using bias correction for the 1-week lead forecast.

The left column shows the raw extended range forecast, and the right column shows the corresponding bias-corrected forecast. There was a significant improvement in the correlation coefficient for most sub-basins, mainly over the northern and central parts of India. The normalized root means square error shows that there was a considerable improvement in the bias-corrected forecast, especially in the east and central parts of India, as normalized *RMSE* has been reduced to less than 0.3 due to bias correction over these parts. Additionally, in the western parts of Maharashtra, *NRMSE* has been reduced from near 1 in raw *ERF* to less than 0.5.

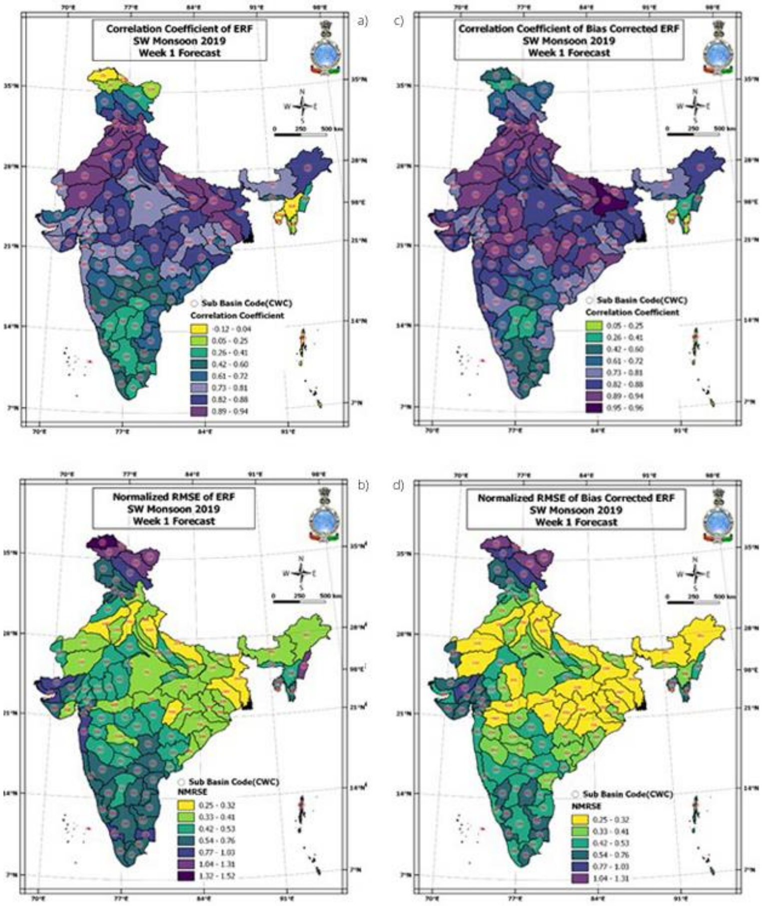


Fig. 9. (a) Correlation and (b) *RMSE* of the raw extended range forecast calculated using the weekly data for the year 2019 of 1-week forecast. (c) same as (a) but after using bias correction. (d) same as (b) but after using bias correction.

Figure 10 shows the (a) correlation and (b) *RMSE* of raw extended range forecast calculated using the weekly data for the year 2019. (c) same as (a) but after using bias correction. (d) same as (b) but after using bias correction for the 2-week lead forecast.

The left column shows the actual extended range forecast, and the right column shows the corresponding bias-corrected forecast. In the 2-week forecast, the correlation coefficient for the sub-basins of Maharashtra has been increased from around 0.7-0.8 in raw *ERF* to 0.93-0.97. The correlation coefficient is between 0.7-0.8 in most of the sub-basins of central India in the bias-corrected forecast. Normalized *RMSE* is also less than 0.5 in the bias-corrected forecast for most of the sub-basins of India, with central India being less than 0.3.

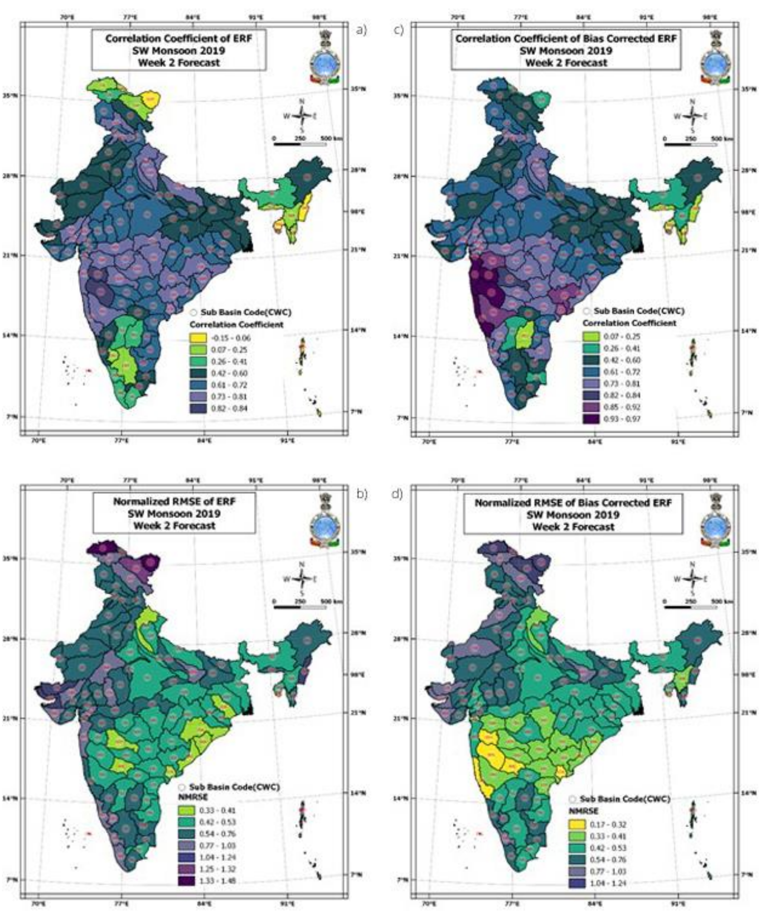


Fig. 10. (a) Correlation Coefficient and (b) *RMSE* of raw extended range forecast calculated using the weekly data for the year 2019 of the 2-week forecast (c) same as (a) but after using bias correction (d) same as (b) but after using bias correction.

4. Conclusions

For efficient flood and disaster management, an accurate rainfall forecast is essential to provide a quantitative prediction of precipitation during the June to September (monsoon) season over river basins of the Indian subcontinent. The weekly averaged extended range rainfall forecast of up to 2-weeks lead-time is important, as it provides a valuable input for generating flood forecast models in a time-scale that is crucial for water and dam management. A proper rainfall forecast with a longer lead time is always desirable to manage floods and their impact on disaster risk reduction. India's present operational flood forecasting models are primarily dependent on 1-3 days quantitative rainfall forecast and a forecast of up to 5 days generated by India Meteorological Department. In the extended range (i.e., 2-weeks lead time) the rainfall forecast is often not accurate, owing to the decrease in rainfall amplitude. In the current study, we have provided a comprehensive basin averaged rainfall skill analysis over different sub-basins of India, using the extended range retrospective forecast and proposing a bias correction method to improve the rainfall forecast in the extended range. We have found that the extended forecast has an unsystematic bias (i.e., overestimation and underestimation) for weekly averaged rainfall. The bias in precipitation is not systematic, and different sub-basins show the bias of different amplitude. Such amplitude biases would likely impact forecast ability. Our bias corrected forecast has shown significant skill in predicting sub basin rainfall of 1-week as well as 2-weeks lead time.

We hypothesized that a part of the amplitude bias might be associated with systematic forecast model bias. Due to rainfall forecast error associated with model physics, dynamics, and several other factors, such biases can arise. Using an amplitude correction method based on the "Normal Ratio" correction method from the WMO manual, we devised an approach to see if the normal ratio correction would improve the first-order skill scores (root mean square error and correlation) for weekly extended range forecast over the Indian land region. The results show an encouraging improvement in statistical skill scores for several river basins over India. The long-term (2003-2019) skill analysis shows enough improvement in the weekly mean forecast. Similarly, case studies over the Maharashtra and Bihar river basins for 2019 show significant improvement in the weekly mean rainfall estimates. We also verified the week-by-week forecast from the onset to the withdrawal phase. The onset phase rainfall forecast over different sub-basins shows sufficient improvement. We propose that the analysis could be used as a background for operational forecast bias correction using the normal ratio method. This can be implemented for products based on extended range forecast and all forecast products in the sub-seasonal to seasonal (s2s) time-scale. Thus, these extended range basin rainfall forecasts of 1-week and 2-week lead times have shown good skill during the 2003-2019 period. In addition to existing flood forecasting systems of the central water commission of India, these findings can be used for generating flood forecasts with longer lead times to reduce disaster impacts.

Acknowledgment

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