A review on the monthly and seasonal forecast of the Indian summer monsoon

U. C. MOHANTY, P. SINHA, M. R. MOHANTY, R. K. S. MAURYA,

M. M. NAGESWARA RAO and D. R. PATTANAIK*

School of Earth Ocean and Climate Sciences, IIT Bhubaneswar, Odisha – 752 050, India

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

email : ucmohanty@gmail.com

सार – भारत जैसी कृषि पर निर्भर अर्थव्यवस्था के लिए भारतीय ग्रीष्मकालीन मॉनसून से जुड़ी महत्वपूर्ण ऋतुनिष्ठ वर्षा बहुत महत्वपूर्ण है। ऋतुनिष्ठ वर्षा में असंतुलन के कारण सूखे या बाढ़ के रूप में तबाही हो सकती है। कृषि क्षेत्र के अलावा, विभिन्न अन्य क्षेत्र भी व्यापक रूप से मॉनसून की वर्षा से जुड़े हैं और इसका भारत की अर्थव्यवस्था पर सीधा प्रभाव पड़ सकता है। मॉनसून की वर्षा के कारण बड़े क्षेत्रों के प्रभावित होने की वजह से भारतीय ग्रीष्मकालीन मॉनसून वर्षा के कुशल पूर्वानुमान की मांग लगातार बढ़ रही है।

यह समीक्षा लेख भारतीय ग्रीष्मकालीन मॉनसून वर्षा के पूर्वानुमान के लिए सांख्यिकीय और गतिकीय पद्धति की हाल की घटनाओं और सफलता पर केंद्रित है। 20वीं शताब्दी के उत्तरार्ध में सांख्यिकीय विधियों का व्यापक रूप से उपयोग किया गया था, जब कम्प्यूटेशनल शक्ति की उपलब्धता सीमित थी। लेकिन, कम्प्यूटेशनल प्रौद्योगिकियों में प्रगति के साथ गतिकीय पद्धतियां विकसित की गईं और उनका समुचित सफलता के साथ उपयोग किया गया। इस समीक्षा ने भारत मौसम विज्ञान विभाग (IMD) की प्रचालनात्मक पूर्वानुमान प्रणाली के लंबे इतिहास की एक झलक प्रदान की है, जिसमें हाल के प्रयासों और उन्नत वैश्विक जलवायु मॉडल और बहुसांख्यिकीय - दृष्टिकोणों का उपयोग करके भारतीय वैज्ञानिक समुदाय की सफलता भी शामिल है। हाल ही के वैज्ञानिक अध्ययनों में एक हाइब्रिड - गतिकीय - सांख्यिकीय - मॉडल के निर्माण की भी चर्चा की गई है जहां गतिकीय रूप से डाउनस्केल उत्पादों के परिणामों को सांख्यिकीय रूप से विभिन्न सांख्यिकीय विधियों का उपयोग करके ठीक किया जाता है, जिससे एक कुशल पूर्वानुमान प्रणाली के लिए एक दृढ़ पद्धति बनाई जा सकती है।

ABSTRACT. The importance seasonal rainfall associated with the Indian summer monsoon is very significant for an agricultural-dependent economy like India. An imbalance in the seasonal rainfall can create havocs in the form of droughts or flood. Other than agricultural sector, various other sectors are also widely associated with the monsoon rainfall and can have a direct impact on the economy of India. With large sectors at stake due to monsoon rainfall, the demand for a skillful prediction of Indian summer monsoon rainfall has been ever increasing.

This review article focuses on the recent developments and success of the statistical and dynamical methods for the prediction of Indian summer monsoon rainfall. Statistical methods were widely used in the late 20th century, when the availability of computational power was limited. But, with advancements in computational technologies dynamical methods were developed and used with reasonable success. This review has provided a glimpse of the long history of India Meteorological Department (IMD) operational forecast system, including the recent efforts and the success by the Indian scientific community using advanced global climate models and multi-statistical approaches. Recent scientific studies have also been discussed for the creation of a hybrid-dynamical-statistical model where the results of dynamically downscaled products are statistically corrected using various statistical methods, thereby creating a robust method for a skillful prediction system.

Key words – Indian summer monsoon, GCMs, Statistical techniques, Dynamical downscaling, Forecast.

1. Introduction

Monsoon systems around the world have been known to have a significant impact on the area associated with respective monsoon systems (Webster *et al.*, 1998). Monsoon is the word derived from the Arabic word 'Mausim' meaning seasonal reversal of wind associated with rainfall over a larger region. Apart from reversal of wind, monsoon systems have been characterized by rainy and dry seasons. Broad monsoon systems around the globe have been classified as the East Asian monsoon, South Asian monsoon, the Australian monsoon, North

African & South African monsoon, Mexican & Southwest U.S. monsoon and the South American monsoon. Modern definitions to the monsoon are not confined to the seasonal reversal of winds only, rather, the monsoon systems are treated as complex processes that have a significant impact on various sectors of the region associated.

Focusing on the South Asian monsoon, which is also well known as the Indian summer monsoon (ISM), is the most prominent monsoon systems across the globe. The significance comes with the net rainfall received during the summer monsoon period, which is about 80% of the annual rainfall over the months June through September (JJAS). With $1/3^{rd}$ of the agricultural land rain-fed, the agricultural activities have been strictly tied to the seasonality of the monsoon over the Indian mainland region. The agricultural sector employees about 49% of total employments directly or indirectly and adds up to 14% of total GDP of India (Ministry of Finance, 2018). Besides agricultural sector, improvement of other sectors such as the hydro-power, water management, husbandry, farming, mining, textile industries are also associated with the net seasonal rainfall. Also, fluctuations in mean seasonal rainfall can cause havocs and natural calamities in the form of floods and droughts causing loss of life and property (Kumar et al., 2013). Droughts and floods also have an adverse impact on the economy, for example the 2002 drought brought down the GDP of India by 1% (Gadgil et al., 2003); this infers that monsoon seasons having excessive or scantier monsoon rainfall has an adverse impact on the economy as well as social lives in the Indian sub-continent. With such large-scale dependencies and high socio-economic impact, the prediction of the Indian summer monsoon rainfall (ISMR) at a certain lead time has been a challenge for the scientific as well as the planning communities.

The Indian summer monsoon is not only dependent on some certain selected atmospheric variables. Various atmospheric conditions such as the high pressure over the Tibetan region, the Tropical Easterly Jet stream at 200 hpa, the low-level jet stream near the Somalia coast at 850 hpa, the prolonged presence of the monsoon trough from North West India to the head bay of Bengal, the Mascarene high play an important role in the effectiveness of the monsoon (Mohanty et al., 2012). Besides these large-scale features, complex terrain over the Indian land (such as the Himalayas, Western Ghats, Deccan plateau), small-scale convective systems arising because of land atmosphere feedback, monsoon depressions, rainfall variability in the form of active and break spells etc. tend to induce rainfall variability over space and time. Thus, the summer monsoon is a complex and highly heterogeneous system. The monsoon rainfall is not only a resultant of the seasonal reversal of winds rather various other factors such as land surface processes, ocean-atmosphere feedback, aerosols in the atmosphere, ice over land and sea etc., leading to making a complex climatic system. Although compilation of all these complexities stated above sums up the difficulty in the operational and research communities, however the risk associated with monsoon rainfall aberrations can be minimized through a skillful and timely forecast.

The past few decades have witnessed immense efforts to meet the demand of the people as well as the planning communities for a skillful forecast of the ISM. Several methods have been proposed by different scientists across the world to understand the complexities involved with monsoon systems and use them in an efficient manner for preparing operational forecasts. Large-scale atmospheric teleconnection [for e.g., relating the monsoon with the Eurasian snow cover, El Nino Southern Oscillation (ENSO), Indian Ocean dipole (IOD) etc.] have led to the development of statistical methods such as regression models which showcased certain skill in predicting the mean features and rainfall during the monsoon seasons (Banerjee, 1978; Verma et al., 1985; Bhalme et al., 1987). In the late 90s, Numerical Weather Prediction (NWP) models were developed and used for seasonal prediction of the ISM. Subsequently, Atmospheric Global Climate Models (AGCMs) and Atmosphere Ocean Coupled Global Models (AOGCM) were used with comparative success rate (Saha et al., 2006, 2014). Several model developmental activities by intense research helped in making the AOGCMs a robust platform for a skillful prediction of the mean seasonal rainfall, onset dates and active/break phases during the monsoon season (Chattopadhyay et al., 2016). The application of statistical methods such as bias-correction, multi-model ensemble (Mitra et al., 2011), weighted mean on the GCMs products (Mohanty et al., 2013) were able to improve the prediction skills that helped the end-users in getting a better forecast for implementing as per their respective needs. Further, researchers showed that downscaling (statistical and dynamical) approaches applied on GCMs predictions have the potential to uplift the forecast skill. In the recent years, the tenacity of hybrid statistical-dynamical models, the dynamical-downscaling and then statistical corrections is seen in reducing the forecasts errors significantly.

This paper addresses the recent significant developments and future scope on the monthly and seasonal prediction of the Indian summer monsoon.

2. A brief history of the operational forecast of ISM

Scientific studies on Indian monsoon during initial periods can be dated as back as to the year 1875 with the

	1886	1909	1924	1988	2003
Period	Seasonal (JJAS)	Seasonal (JJAS)	Seasonal (JJAS)	Seasonal (JJAS)	Seasonal (JJAS)
Domain	India (Single Unit)	India (Single Unit)	2- Homogeneous Regions (HRs)	3-HRs and India (Single Unit)	3-HRs and India (Single Unit)
Method	Statistical (Empirical)	Statistical (Linear regression)	Statistical (Linear regression)	Statistical (Linear regression)	Statistical (Power regression)
Parameter	Rainfall	Rainfall	Rainfall	Rainfall	Rainfall
Type	Subjective & Qualitative	Quantitative	Quantitative	Quantitative	Quantitative

Fig. 1. Historical chronology of statistical prediction of ISM at IMD

establishment of India Meteorological Department (IMD). The first forecast on the Indian monsoon was empirical made by Blanford (1884) using the snow cover of the Himalayan region and relating it to the Indian monsoon, he concluded that excessive snow cover led to a deficit monsoon season and less snow cover resulted in an excessive monsoon season. Later, statistical relations of the Indian monsoon with chosen predictors led to the development of a regression model by Walker (1910) who used correlation techniques to prepare linear regression equations. The southern oscillation in the mean Sea Level Pressure (SLP) which was proposed by Walker led to the discovery of the Walker circulation by Bjerknes (1969). Banerjee (1978) also found the linkage of ISM with the mean latitudinal location of the 500 hPa ridge along the 750E longitude in the month of April. Joseph (1981) saw the relationship of the upper tropospheric wind at 200 hPa with ISM. Major studies linking the ISM with the cross equatorial flow near Somali coast were addressed, which led to the strengthening of the regression model by adding the important predictors for ISM. These important studies were used by IMD in preparing the forecast by using regression models involving 8, 10 predictors. By the year 1988, IMD used linear regression models which involved 16 predictors for the forecast of ISM. Further studies led to the development of power regression models which were operational by the year 2003. The chronology of the history of statistical forecast of the ISM (major breakthrough) shown in Fig. 1.

Extensive research on the relationship of the Indian monsoon with various predictors were carried out in the subsequent years and their application in formulating statistical models is being undertaken till date (Kar *et al.*, 2012; Singh *et al.*, 2012a; Nair *et al.*, 2013). Though forecast by NWP models using computers started in 1950s, systematic research on the application of NWP began in the early 1970s at IMD as well as Indian Institute of Tropical Meteorology (IITM). Since 1992, medium range monsoon prediction model was used for operational purposes at National Center for Medium Range Weather Forecast (NCMRWF). The past few decades have witnessed immense efforts for making a skillful forecast (Webster *et al.*, 1998; Gadgil and Gadgil, 2006).

Modern day forecast is mainly based on both dynamical and statistical methods. The dynamical models used in these organizations are highly sophisticated, fully coupled ocean-atmosphere general circulation models and the integrations are carried out for several months to generate the dynamical outputs which are ultimately used to prepare monthly and seasonal forecasts. The key to a robust and useful seasonal forecast thus lies in the following components:

(*i*)   A good observational network.

(*ii*) A model (dynamical/statistical) that can use the observations to yield the forecast of atmospheric variables.

(*iii*) Post-processing and Evaluation of the output generated by the models.

(*iv*) Usability of the forecast by decision makers.

(*v*)   Dissemination of the forecast to the end-users.

3.   Performance of GCMs in predicting ISMR

A dynamical model can be considered as a set of mathematical equations which are based on the

fundamental primitive equations which govern the atmospheric motions. Fundamental parameters of the atmosphere are represented by a set of seven fundamental equations. Thus, a dynamical approach of prediction can be defined as a set of mathematical equations which represent the state of the atmosphere and these equations are supplemented with the parameterizations of turbulence, radiation, moist processes, heat exchange, soil, vegetation, surface waters, kinematic effects of terrain, convection and many other atmospheric processes.

The Geophysical Fluid Dynamics Laboratory (GFDL), European Centre for Medium-Range Weather Forecasts (ECMWF), National Centers for Environmental Prediction (NCEP), the Center for Ocean-Land Atmosphere Studies (COLA) have developed AOGCMs which are quite successful in representing the mean monsoon features in hindcast mode (Mohanty *et al*., 2013; 2019). Though the mean features were comparatively well simulated, the variability in monsoon rainfall was poorly depicted by these GCMs (Gadgil and Sajani, 1998). The lacunas of the models were specifically found with the correlations of the observed local SST and precipitation anomalies were negative over the West-north Pacific (Wang *et al*., 2005) and the poor simulation of monsoon-Equatorial Indian Ocean Oscillation (EQUINOO) link (Gadgil *et al*., 2005). These lacunas led to the development of fully coupled Ocean-Atmosphere models so that the feedback and response of the Ocean, which is a quite important parameter in the monsoon process can be well represented in the model, thereby improving the skill of monsoon prediction.

The IMD used the Indian version of Climate Forecast System version 2 (CFSv2) (Saha *et al*., 2014) which is specifically optimized for forecasting of the atmospheric state for the Indian region. The IMD-CFSv2 is a fully coupled ocean-atmosphere spectral model. Since the Indian monsoon is a complex coupled system, a fully coupled GCM can help to get a credible forecast (Chaudhari *et al*., 2013). The IMD-CFSv2 has been configured by numerous sensitive experiments aimed at skillful prediction of the ISM (Chaudhari *et al*., 2013; Saha *et al*., 2014). Major challenges with the GCMs were found to be the model's inability to realistically simulate the large-scale features driving the monsoon, namely the land and ocean heat contrast, seasonal fluctuation of inter-tropical convergence zone (ITCZ) and tropospheric temperature gradient (TTG). Along with these, hosts of global climate mode, *viz*., ENSO, Indian Ocean Dipole (IOD), EQUINOO and extratropical SSTs, also have an effect on the potential predictability of ISMR.

Alongwith the proper representation of the atmospheric processes, computational capabilities were a major hindrance in the path of dynamical models. GCMs are integrated over the entire globe and with the minimum possible time step of computation. But the mathematical integrations require ample time. Due to the computational constraint, GCMs are run at coarse resolution. The local-scale features such as deep convection, land surface fluxes are not quite well represented in the GCMs. With the introduction of Nano technology and parallel computing, there has been a significant transition in the grid spacing of the dynamical model. The IMD-CFSv2 model is run at comparatively higher spectral resolution of T382 (38 km near the equator) for the seasonal forecast of monsoon. The model is run with 44 ensembles and the ensemble mean is considered as the forecast for the corresponding season.

The comparison of the hindcast output of the IMD-CFSv2 with high resolution rainfall data over Indian main land region (Rajeevan *et al*., 2007; Pai *et al*., 2014). The IMD-CFSv2 model has the potential skill in simulating the large-scale circulations. The SST over the Indian Ocean is also well captured by the IMD-CFSv2 model in seasonal as well as free runs. Though the rainfall amount was quite varying in the free run, other large-scale meteorological parameters are satisfactorily simulated and seasonality of the ISM well represented. However, there are certain patches over the Indian land mass where the meteorological parameters have a significant bias. For rainfall, the model underestimates the rainfall when simulated with different resolutions (Chattopadhyay *et al*., 2016) [Figs. 2(a-e)]. The IMD-CFSv2 model has a dry bias over most of the Indian mainland region (Sahai *et al*., 2013). The biases in SST, especially over the Tropical Pacific and Indian Ocean tend to create anomalies in wind circulation over the Tropical Oceans, thereby creating anomalous monsoon circulations (Sabeerali *et al*., 2014). Dry bias can be observed over the West Indian Ocean whereas there is a very large region of wet bias over the North East India as well as the Eastern Indian Ocean. Chaudhari *et al*. (2013) concluded that the IMD-CFSv2 model simulated warm bias over the West Indian Ocean and cold bias over East Indian Ocean can be associated with the processes governing the Indian Ocean dynamics. These warm and cold SST biases co-occur with the wet and dry rainfall biases. The sustained SST biases might be the reason for the persistent biases in rainfall over Eastern India during the monsoon season. The SST biases also drive anomalous easterly winds which further drives cold biases over the Oceanic regions and dry bias over the land region. Despite all these limitations in preparing a skillful prediction, the IMD-CFSv2 model has evolved over time and the skill has increased with every modification done to the model by the sensitivity studies. Customization of the model has been carried out based on the cumulus convection schemes, land surface physics, ocean
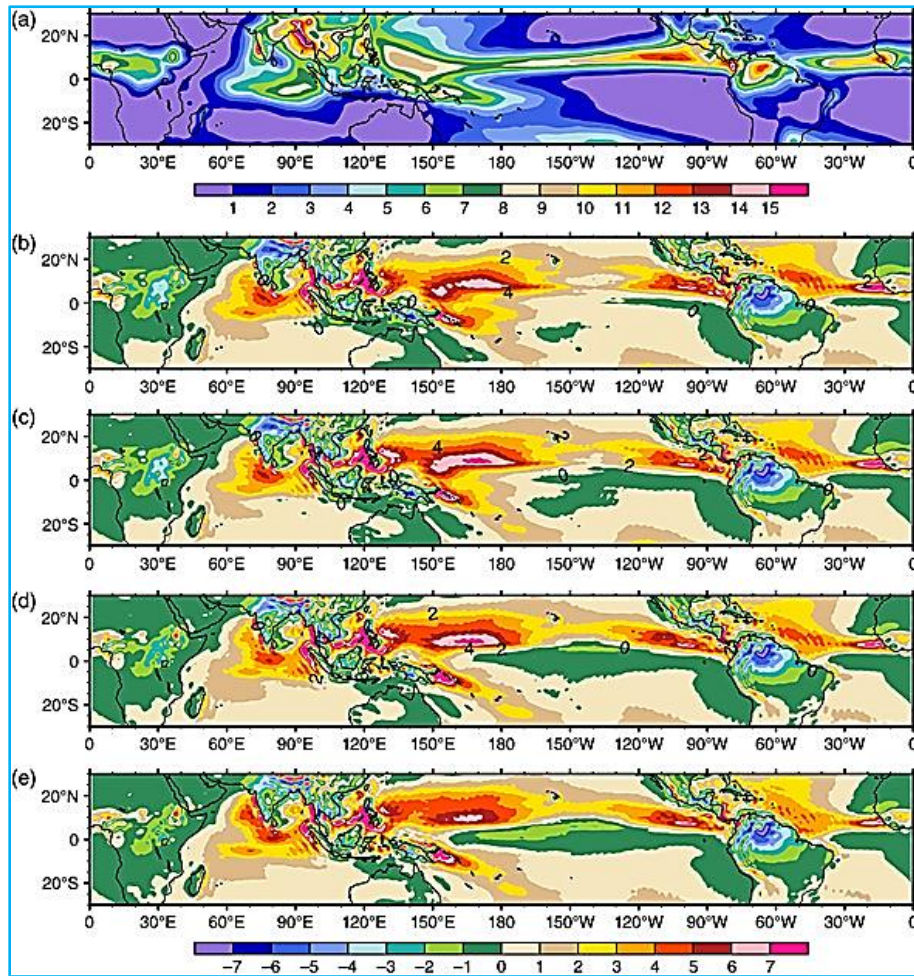
Figs. 2(a-e). (a) Mean JJAS rainfall (mm/day) as simulated by CFSv2. Panels (b-e) represent the mean rainfall bias (mm/day) in CFSv2 with respect to GPCP with February, March, April and May initial conditions respectively [Chattopadhyay *et al.* (2016)]

atmosphere coupling, autoconversion rates, cloud water accretion and many other sensitivity studies.

The NCMRWF uses a coupled model for medium range forecast during monsoon season known as the NCMRWF Unified Model (NCUM) (Mitra *et al.*, 2013) at convection permitting scales and concluded that the rainfall was simulated quite realistic in the 2-week simulations. The NCUM also had various lacunas in the simulation of MJO activities. Accurate medium range prediction during the monsoon period is essential since the variability associated with monsoon can create a massive impact. The NCUM has been upgraded in the subsequent years by reducing the grid spacing, applying NEMOvar, an ocean data assimilation technique to provide the best possible real-time observational data.

In the early 21st century, many institutes across the world started disseminating operational forecast particularly on the ISM. The validation of the forecast by various models was necessary to figure out the best available model that captures the rainfall better than the other models. Numerous studies were conducted to verify the skill of the models in predicting the rainfall during ISM and they found that most of the GCMs could able to replicate the mean pattern of JJAS rainfall, however, the intensity is underestimated by the all (Acharya *et al.*, 2011, 2012, 2013a,b,c, 2014a,b; Singh *et al.*, 2012a). It is also proven by several studies including the above that inter-annual variability in the GCMs are lesser than the observations. During this review, the climatology and standard deviation of six global models along with the observations have been plotted for 36 years period (1982-2017) and shown in Figs. 3&4 respectively. It is clearly depicted from the figures that although the spatial pattern is well represented, most of the models are underestimating the intensity in the all-India scale. The model efficacy is quite less for the high-rainfall area such
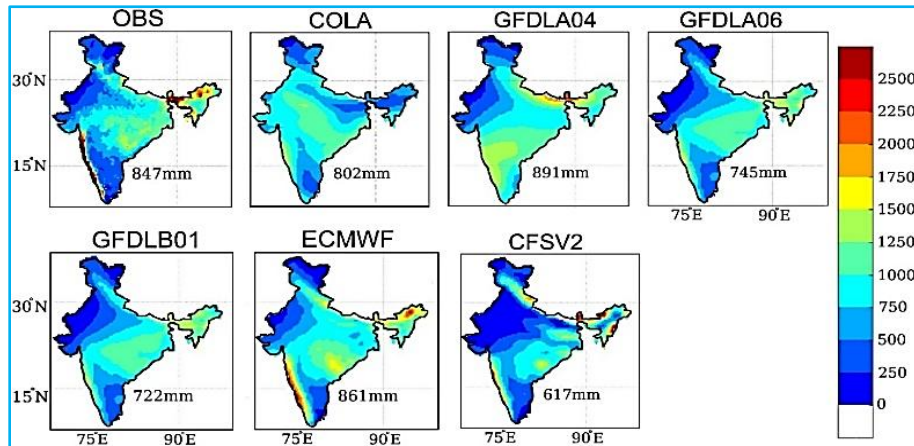
Fig. 3. Climatological mean of mean simulated rainfall (mm) during ISM by CFSv2, COLA, GFDL with 3 different ocean models, ECMWF and as observed by the IMD dataset
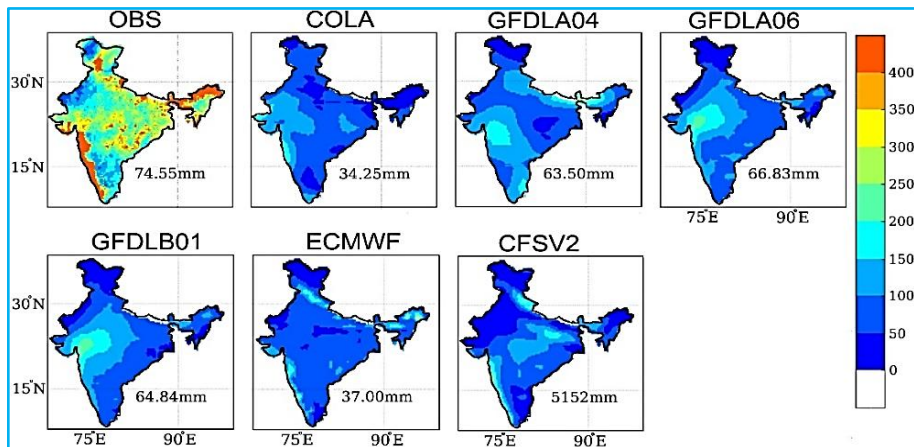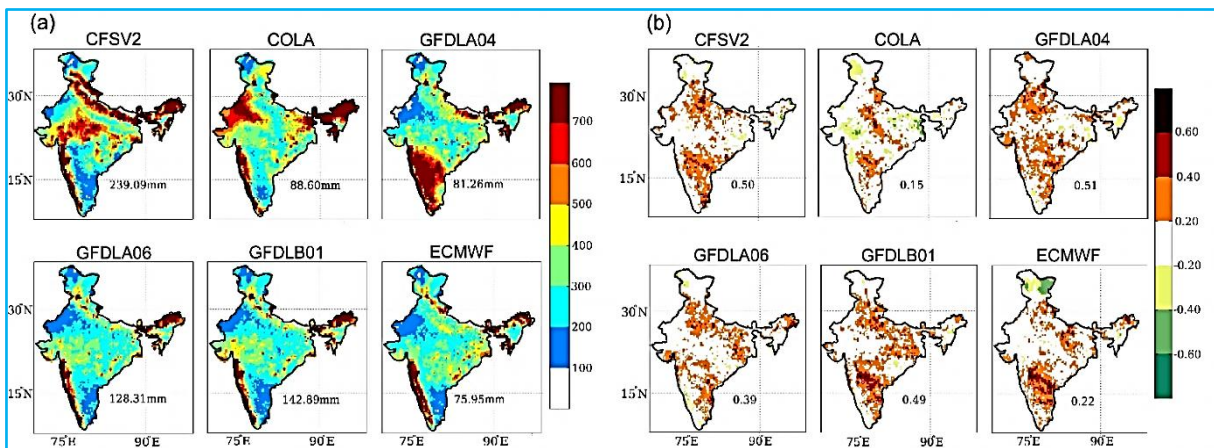

Fig. 4. Mean intra-annual variability of mean simulated rainfall (mm) during ISM by CFSv2, COLA, GFDL with 3 different ocean models, ECMWF and as observed by the IMD dataset

Figs. 5(a&b). (a) Root Mean Squared Error (mm) of CFSv2, COLA, GFDL and ECMWF model in predicting the JJAS mean seasonal rainfall and (b) Same as of (a) but represents the correlation coefficients with respect to the IMD observed rainfall dataset

as the Western Ghat and North East India. The standard deviation of the June-September (JJAS) rainfall is poorly represented by all the models and the root mean square error (RMSE) is notably high [Fig. 5(a)]. Interestingly, the
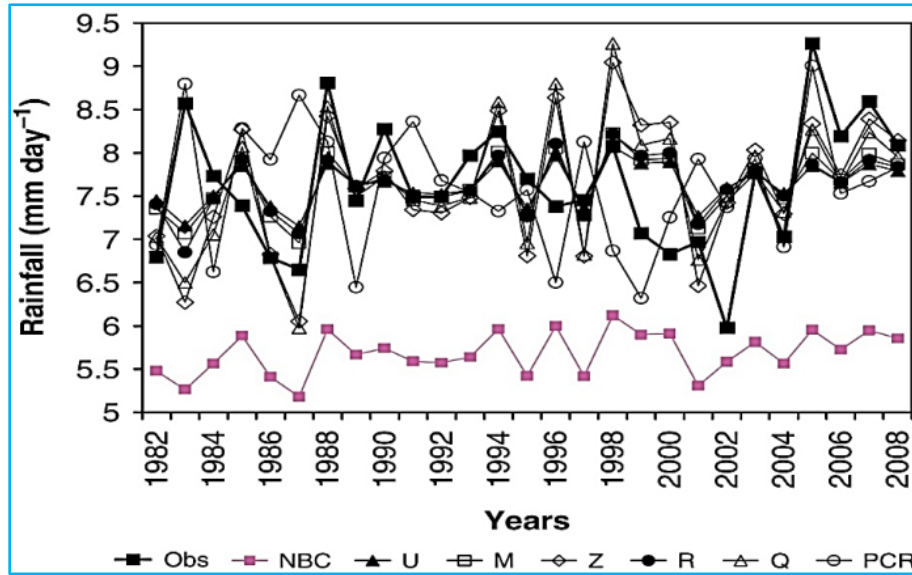
Fig. 6. Time series of JJAS rainfall (mm/day) from observation, raw model and six bias correction methods from 1982 to 2008 [Acharya *et al.* (2013a)]

models have some skill when temporal correlation is computed, however the skill varies region-to-region [Fig. 5(b)]. Although the GCMs show encouraging prediction skill during June-September, a considerable bias is evident mainly over the Indian region and the same has been documented over the Indian land mass by Singh *et al.* (2013). Fig. 6 represents the bias corrected GCM products and compared with the observations along with the 'No bias Corrected (NBC)'. It is clearly indicating that all the bias correction method could able to adjust the model mean and standard deviation close to observations, however, the performance of the bias correction varies method-to-method.

The investigation on the bias corrected GCMs to understand the usefulness of the methods and use several standard skill metrics are presented in Table 1. They have found that the Standardized-reconstruction technique (Z) and Quantile Mapping Method (Q) are more skilful than the others and both are equally skilful in simulating ISMR and recommended that the simple standardized-reconstruction technique is good enough for bias correction for ISMR. The newer generation models are achieving the correlation between observation and prediction of seasonal mean precipitation over India to better than 0.30 (Rajeevan *et al.*, 2010). However, the skill of prediction of the south Asian monsoon rainfall by all models currently remains significantly below the potential limit of predictability. Several reasons are likely to contribute to this problem.

El Nino-Southern Oscillation has a major influence on the Asian monsoon and the errors in the model may

contribute to the poor skill of monsoon prediction. Finally, almost all models have serious systematic biases in simulating the observed climate over the Asian monsoon region (Sabeerali *et al.*, 2014). These systematic biases are likely to contribute to the poor skill of monsoon forecasts.

GCMs, despite their limitations have been quite successful in the mean seasonal forecast of the Indian summer monsoon; a major limitation arises from the coarser resolution at which GCMs are integrated. Due to this, the local-scale features such as land surface complexities, local scale convective activities are not well represented in the model. Therefore, direct application of GCMs output has been often inadequate because of their limited representation of mesoscale atmospheric processes, topography and land sea distribution in GCMs. Also, some regions which can be of particular interest forrainfall variability can be completely missed in the GCMs. One of the most prominent methods for improving the skill can be by the method of downscaling. Downscaling can be defined as a process where information at a larger scale is used to reduce the scale and make predictions at local-scale. Any information that is presented at spatial scales finer than 50 km × 50 km and temporal scales finer than monthly values has undergone a process called downscaling. While it produces climatic information at scales finer than the initial projections, this process involves additional information, data and assumptions, leading to further uncertainties and limitations of the results, a consequence that is often not made explicit to end-users. Since the research community is still developing downscaling methods, users often need to read highly technical and specialized explanations in

TABLE 1

Skill scores for not bias corrected model (NBC) and all bias correction techniques : mean bias-remove technique (U), multiplicative shift technique (M), standardized reconstruction technique (Z), regression technique (R), quantile mapping method (Q) and principal component regression (PCR) along with observation (Obs) [Acharya *et al*. (2013a)]

Statistic	Obs	Raw	U	M	Z	R	Q	PCR
Mean (mm/day)	7.63	5.68	7.63	7.63	7.63	7.63	7.61	7.61
SD (mm/day)	0.75	0.25	0.25	0.34	0.78	0.34	0.76	0.72
RMSE (mm/day)	-	2.06	0.69	0.44	0.83	0.72	0.80	0.83
Index of agreement (d)	-	0.37	0.45	0.58	0.65	0.48	0.66	0.60

order to understand and adequately apply the results for impact studies, planning or decision-making.

4.   Research and developments on downscaling approaches for prediction of ISM

The concept of downscaling arose from the fact that the regional climate is largely conditioned by the large-scale climate. The process in which the information is cascaded down from larger to smaller scales is known as downscaling. In climate studies downscaling can be largely helpful by the detailing of specifics such as the atmospheric or oceanic circulation, topography, land-sea distribution and land-use. Two types of downscaling which are primarily and widely used are the statistical and dynamical downscaling.

4.1. *Statistical downscaling*

Despite continuous efforts for more than a century, the predictability of ISMR is always questionable as there is always some uncertainty associated with it. Plethora of studies is in favor that the phenomena is very chaotic in nature and is attributable to the internal process in addition to the slowly varying boundary conditions. Statistical downscaling follows the principle of establishing a statistical/empirical relationship between large-scale atmospheric variables (predictors) such as precipitation, specific humidity, temperature, geopotential height, etc., with station (local) scale meteorological variables (predictands) such as temperature and precipitation.

Prasad *et al*. (2010) developed logistic regression to predict rainfall on monthly timescale in three study regions namely, India as a whole and two homogeneous regions of India by using DEMETER retrospective forecasts for the period of 1959-2001. With the availability of large number of GCMs several multi-model/statistical approaches were introduced and applied for prediction of precipitation (Sahai *et al*., 2000, Kar *et al*., 2012; Kulkarni *et al*., 2012; Acharya *et al*., 2013c;

Nair *et al*., 2013; Singh *et al*., 2012b; Sinha *et al*., 2013a). Kar *et al*. (2012) used multi-model ensemble (MME) technique based on super-ensemble approach for prediction of July rainfall. In a similar context, monthly rainfall prediction was attempted by Nair *et al*. (2013) using supervised principal component regression and it was reported that the model is able to capture observed rainfall in the month of June, August and September. Some studies documented an improvement in the skill of seasonal rainfall prediction but a deprivation in skill is noticed while attempting monthly-scale prediction (Singh *et al*., 2012b; Mohanty *et al*., 2013; Nair *et al*., 2013).

The strategy involving statistical method of prediction involves regression techniques. The regression coefficients are determined by using a long-term analysis of observational and GCMs outputs. Other than regression techniques modern day innovative statistical and dynamical methods such as neuro-computing approach using SST anomaly as a predictor (Acharya *et al*., 2012), supervised Principal Component Regression (Nair *et al*., 2013), Artificial Neural Network technique (Nair *et al*., 2018), multi-model Canonical Correlation Analysis (Singh *et al*., 2013; Sinha *et al*., 2013a), Weighted multi-model ensemble (Acharya *et al*., 2014a) etc., were developed and each method was found to have an significant impact while using the statistical techniques for predicting rainfall. Development of these methods led to the development of a framework under the Extended Range Forecast System (ERFS) which used the techniques efficiently to prepare experimental forecast at met-subdivisional level (Acharya *et al*., 2013a,c,b; Mohanty *et al*., 2013, 2019; Singh *et al*., 2012b, 2014; Sinha *et al*., 2013a). Sinha *et al*. (2013a) have identified potential predictor fields (such as zonal and meridional wind at 850 hPa and 200 hPa, specific humidity at 850 hPa) for three different domains (d1, d2 and d3) and used those predictor fields in the CCA method for downscaling of JJAS precipitation in India. They have applied the CCA methods on the NCMRWF global model outputs. Their study concluded that statistical downscaling approach is reasonably well for prediction of precipitation over

TABLE 2

Observational and reanalysis data used in the study (SD = Statistical downscaling products using CCA) [Sinha *et al*., 2013a]

Area	2006		2007		2008		2009	
	NCMRWF	SD	NCMRWF	SD	NCMRWF	SD	NCMRWF	SD
INDIA	0.55	0.7	0.59	0.8	0.49	0.66	0.55	0.85
NWI	0.37	0.42	0.68	0.79	0.66	0.79	0.78	0.88
WCI	0.66	0.76	0.67	0.87	0.49	0.8	0.58	0.89
SPI	0.74	0.89	0.73	0.85	0.8	0.8	0.72	0.95
CNEI	0.49	0.07	0.44	0.36	0.04	0.12	0.31	0.52
NEI	0.03	0.31	0.03	0.76	−0.09	0.25	−0.01	0.52

different homogeneous regions in India. They have also shown that the method has significantly improve the prediction skill over the host GCM of NCMRWF (Table 2). However, the skill of this method is not uniform over space. In another study by Sahai *et al*. (2003), they reported that SST can be a good predictor for the prediction of the ISMR.

4.2. *Dynamical downscaling*

Dynamical downscaling techniques, involve the extraction of regional scale information from large-scale GCM data based by the modeling of regional climate dynamical processes using a Regional Climate Model (RCM). An improvement in the forecast by GCMs can be achieved by the dynamical downscaling of the GCM outputs using a RCM (Giorgi *et al*., 2012). RCMs are simulated for a particular region of interest at a higher resolution using the initial and boundary conditions derived from the GCMs. The dynamical downscaling is based on the scientific reason that the lower bound are forcing by the oceans in the form of SST, sea-ice cover and by land surface moisture, temperature, albedo, vegetation cover evolve on a slower time scale as compared to the weather systems. These parameters can give rise to significant predictability which might be missing in the GCMs.

The RCMs are of increasing interest owing to not only to its satisfactory skill in seasonal scale simulations but also capable of representing the small-scale processes better than its host GCMs (Sinha *et al*., 2013b). Finer representations of the land surface can have a significant impact on the radiative forcing. Secondly, by the use of non-hydrostatic formulations, the RCM can be the prospect of permitting instead of parameterizing the convection. At convection permitting resolutions, the structural evolution of convective systems can be well captured as well as cold air intrusion in the mountainous

regions and the land-sea breeze can be simulated better. However, they also possess certain limitations in the form of accuracy and intervals of Initial and Boundary Conditions (ICBC), choice of physical parameterizations (Sinha *et al*., 2019) and land surface physics (Singh *et al*., 2007; Maurya*et al*., 2017). Some of the key atmospheric features are parameterized in the GCMs due to lack of physics as well as computational capabilities. Whereas these processes can be represented in the RCMs. Thus, there is a need to optimize RCM for dynamical downscaling of the GCMs for improvement in the forecast skill of the Indian summer monsoon.

The regional climate model RegCM has been widely used by the research community to improve the skill of GCM outputs by the method of dynamical downscaling. Several studies have been conducted to customize the model by various sensitivity studies (Sinha *et al*., 2013b, 2014, 2019; Maurya *et al*., 2017, 2018; Mohanty *et al*., 2019). Customizing the model based on orography, cumulus parameterization, land surface model, horizontal resolution, domain size, moisture flux adjustment, auto conversion coefficients etc. have led to improvement in the skill of the RCM in simulating the Indian summer monsoon rainfall. Sinha *et al*. (2014) have shown that the RegCM is quite sensitive to the Himalayan orography. Minor changes in the height of the Himalayan orography led to significant changes in the mean summer monsoon seasonal rainfall. Similarly, Maurya *et al*. (2017) concluded that the Community Land Model (CLM4.5) performed better over the previous version of CLM (3.5) and the BATS land surface scheme. A significant finding was established in the paper by Maurya *et al*. (2018) where the RegCM was found to be quite sensitive to the domain size and optimum model resolution for simulation of ISM. The RegCM was found to improve the skill of rainfall forecast up to a certain grid spacing. Decreasing the grid spacing to very high resolutions led to further deterioration of model skill. A regional climate model,
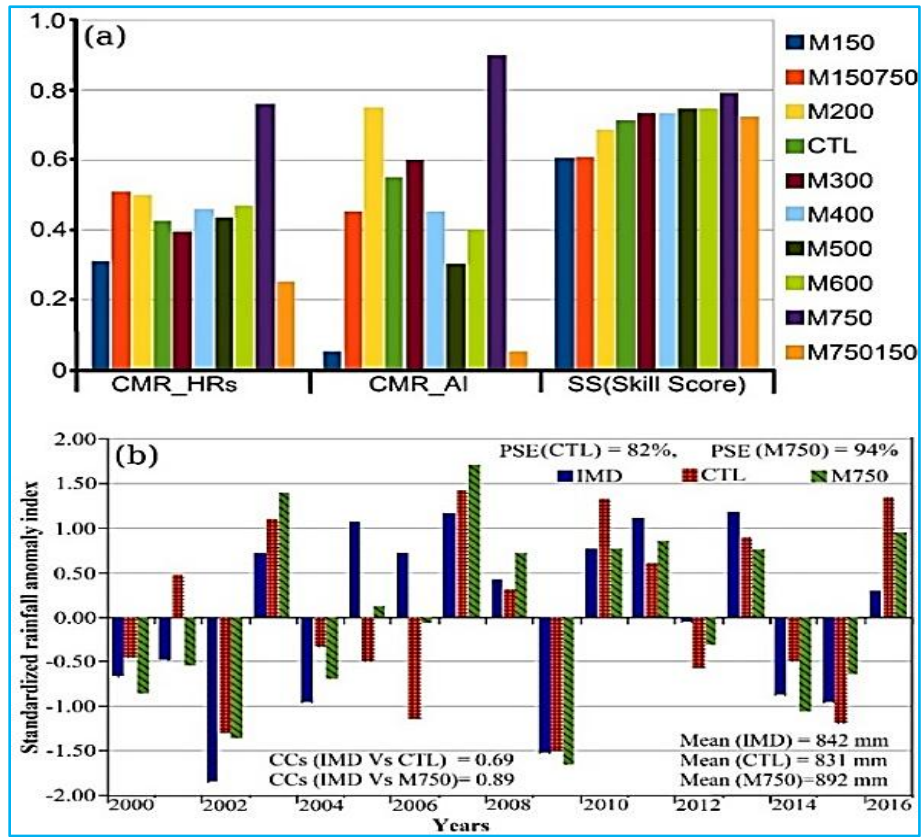
Figs. 7(a&b). Comprehensive Rating Matrices (CRM) in (a) over homogeneous regions of India (CRM HRs) and India as a whole (CRM AI) and Skill Score (SS) of RegCM4-R with different autoconversion experiments computed for the Indian domain. Standardized rainfall anomaly index as observed (IMD) and as simulated by the control (CTL) and M750 simulations for the JJAS, 2000-2016 in (b) [Mohanty *et al*. (2019)]
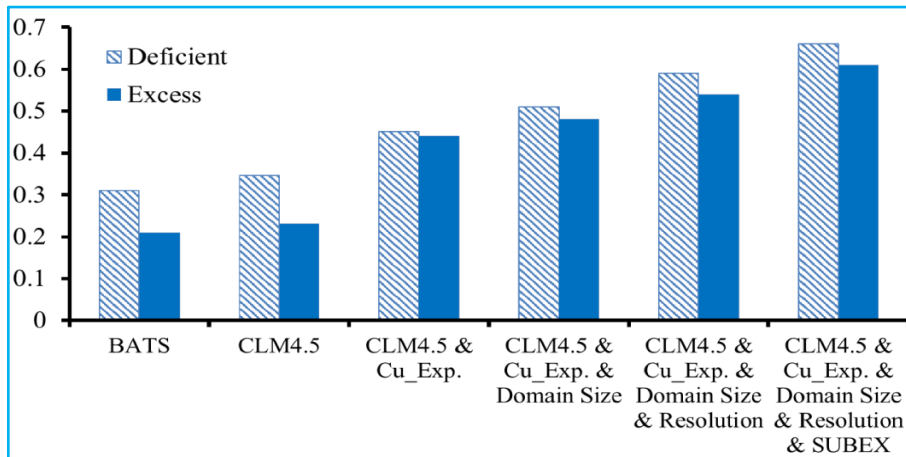

Fig. 8. Correlation coefficients of three composite excess (1983, 1988 and 1994) and deficit monsoon seasons (1982, 1986 and 1987) with default (BATS), addition of CLM4.5, CLM4.5 with customized Cumulus scheme, with domain customized, with resolution customized and with autoconversion coefficient customized respectively

when used for downscaling should only be used a certain resolution to get the best outcome of the downscaled product. The comprehensive rating matrices and the skill scores supports the fact that a regional climate model can

perform well/poor based on the domain of choice and the resolution used for downscaling.

Significant discrepancies were observed when the model was simulated with different cumulus parameterization schemes (Sinha *et al.*, 2013b, 2019). Different cumulus schemes yielded varying rainfall amount and pattern over core regions of the monsoon over Indian main land region. Microphysical schemes were also found to have a major impact on the net simulated seasonal rainfall which was studied by Mohanty *et al.* (2019). Minor changes to the autoconversion coefficient, which is responsible for the conversion of cloud water to rainfall, led to major improvement in the rainfall skill by RegCM [Figs. 7(a&b)]. The above studies have inferred that the customization of a RCM by sensitivity studies to various physical parameters for a specific region of interest is quite important. The mean seasonal rainfall pattern and intensities were found to have significant discrepancies with different cumulus schemes and different auto-conversion rates.

The impact of the approximations can be summarized by the finding that a RCM needs to be customized before using it for a particular region of interest. Fig. 8 represents the gradual correlation coefficients of three composite excess and three composite deficit years with the customization of the RCM based on the different physics and coefficients of approximation. The correlation coefficients can be clearly seen to be improving over the default model configuration. With the addition of CLM and choosing a better performing cumulus scheme, the model is found to be improving. Similarly the choice of the domain and finding a suitable resolution adds to the improving skill of the model. With the addition of the customized auto conversion coefficient the model possess some potential skill to be used a RCM for dynamical downscaling of Indian summer monsoon rainfall.

5. Multi-statistical approach on GCM for single forecast

It is well established that present day advanced General Circulation Models (GCMs) have the ability to simulate the seasonal climate with higher skill. Continuous efforts are being made for the robust combination of the output of the GCMs in order to develop seasonal forecast systems based on multiple GCM outputs all over the globe. Min *et al.* (2014) evaluated the performance of APCC prediction using multi-model ensemble products for seasonal climate over the globe for all seasons on real-time mode (2008-2013) and they found a reduction in forecast errors of seasonal climate prediction that resulted

in an improved forecast skill. Goddard *et al.* (2003) also evaluated the multi-model ensemble forecast of seasonal climate over the globe by IRI from 1997 to 2001 and they found a larger area of positive skill in the net assessment forecasts compared to any single prediction model.

The need for seasonal scale precipitation prediction at met-subdivision level threw an urgent requirement for developing methodologies for providing advance weather and climate information in extended range (monthly to seasonal scale) which motivated the scientists of the meteorological and agricultural fields to undertake a determined research effort, *via* a multi-institutional approach, for development and application of extended range forecast of rainfall for climate risk management in agriculture that led to the multi-institutional research project "Development and Application of Extended Range Forecast System for Climate Risk Management in Agriculture (ERFS)" sponsored by Department of Agriculture Cooperation & Farmers Welfare, Ministry of Agriculture & Farmers Welfare, Government of India. In the ERFS, a number of scientists at various stages from different national and international institutions have significantly contributed to improve the prediction skill of ISM by using existing methodologies or developing new methods. The results obtained in the ERFS have been extensively evaluated.

The ERFS forecast is based on the statistical downscaling of a number of dynamical models obtained from various national and international organizations. Mohanty *et al.* (2013, 2019) have applied three statistical downscaling approaches, namely, a multivariate regression technique based on singular value decomposition (SVDMR) method, supervised principal component regression (SPCR) and canonical correlation analysis (CCA) on the bias corrected GCMs for the ISM rainfall prediction at meteorological subdivision level. They developed a monthly and seasonal scale forecast system ERFS (they kept the name same as the project abbreviation) to integrate the outputs from three downscaling approaches (SVDMR, SPCR and CCA) for generating a single prediction system of summer monsoon rainfall and assessed the skill of the ERFS forecasts. Mohanty *et al.* (2013, 2019) showed an improvement in the prediction skill of summer monsoon rainfall using ERFS.

Although, Mohanty *et al.* (2013, 2019) have shown that the robustness of the single consensus forecast using multi-statistical techniques applied on the bias corrected GCM outputs and its useful application in the agricultural model, in this review work, the authors have further evaluated the real-time ERFS summer monsoon products

TABLE 3

A brief details of the GCMs

S. No.	Model	Resolution	Ensemble members	Type
1.	CCCM3v6	(T42) 2.7° × 2.8°	24	2-Tier
2.	ECHAM4p5 CA SST	(T42) 2.7° × 2.8°	24	2-Tier
3.	ECHAM4p5 CFS SST	(T42) 2.7° × 2.8°	24	Semi-Coupled
4.	CFSv2 (NCEP)	(T26) 0.9° × 0.9°	24	Fully Coupled
5.	COLA-RSMAS-CCSM3	T106	6	Anomaly Coupled
6.	GFDL	T42	10	Fully Coupled
7.	GFDL-CM2p5-FLOR-A06(GFDLA06)	T42	12	Fully Coupled
8.	GFDL-CM2p5-FLOR-B01(GFDLB01)	T42	12	Fully Coupled
9.	ECMWF	0.75° × 0.75°	15	Fully Coupled
10.	IMD-SFM	T42	10	2-Tier

TABLE 4

The climatology and standard deviation of GCMs, MME BC and ERFS along with IMD observation for all seasonal precipitation (mm/day) for hindcast period of 1982-2008

GCMs	JJAS Rainfall	
	Climatology (mm/day)	Standard Deviation (mm/day)
Obs	7.47	0.65
CCM3v6	6.36	0.3
CASST	7.48	0.3
CFSSST	7.36	0.52
CFSv2	5.36	0.39
COLA	6.58	0.25
GFDL	7.32	0.53
GFDLA06	6.03	0.53
GFDLB01	5.86	0.47
SFM	3	0.63
ECMWF	6.15	0.29
MME_Raw	6.25	0.27
MME_BC	7.46	0.48
ERFS	7.49	0.56

by considering additional three forecast years (2015-2017) along with the six forecast years (2009-2014) considered in Mohanty *et al*. (2019). The success of the ERFS products in real-time has motivated to carry out an extensive evaluation to examine the quality and reliability of the ERFS products at various meteorological subdivisions for nine forecasted years.

A total ten GCMs products are used in the present study and a glimpse of each model is presented in Table 3. Among the ten GCMs, seven are made available from IRI, USA. The remaining three GCMs namely, NCEP Climate Forecast System version 2 (CFSv2), European Centre for Medium-Range Weather Forecasts (ECMWF) and atmospheric GCM Seasonal Forecast Model by India Meteorological Department (IMD-SFM) are made available from the corresponding organization/source of the GCMs products. Lead 1 prediction (one month in advance) of above-stated GCMs is extracted for each season from 1982 to 2017 and further the mean of all ensemble members corresponding to each GCM is considered for statistical bias corrections. The developed forecast products are verified against the observational reference at 1° × 1°gridded data set generated by IMD (Rajeevan *et al*., 2006).

The methodology of the ERFS has been nicely described in Mohanty *et al*. (2013, 2019), still, a brief on the methodology is presented here as a quick reference for the readers. A two-stage procedure of post-processing is carried out on the GCMs predicted precipitation. First, the GCM output is re-gridded at observational grid (1° × 1°) points by using the bilinear interpolation technique. Secondly, the systematic bias is removed from the GCM predicted precipitation using the standardized reconstruction technique which is found to exhibit significant skill over the Indian domain (Acharya *et al*., 2013a, 2014a). In the training data sets of 27 years (1982-2008), leave-one-out cross validation method is used to understand the efficiency of the bias correction method. In the leave-one-out method, forecasted year is not considered in the training dataset and the remaining 26 years data are used to calculate model and observed climatological mean and standard deviation (Acharya *et al*., 2011). The same procedure was implemented for real-time forecasts (2009-2017). To enhance the quality of seasonal prediction, after removing the systematic bias of all individual GCMs for the ensemble mean forecasts, statistical approaches such as the Singular Value Decomposition based multivariate regression (SVDMR) (Kar *et al*., 2012; Acharya *et al*., 2013a,c; Mohanty *et al*., 2013, 2019), Supervised principal component regression (SPCR) (Nair *et al*., 2014; Mohanty *et al*., 2013, 2019), Canonical correlation analysis (CCA) (Singh *et al*., 2012b; Sinha *et al*., 2013b) have been used. The outputs from the above three
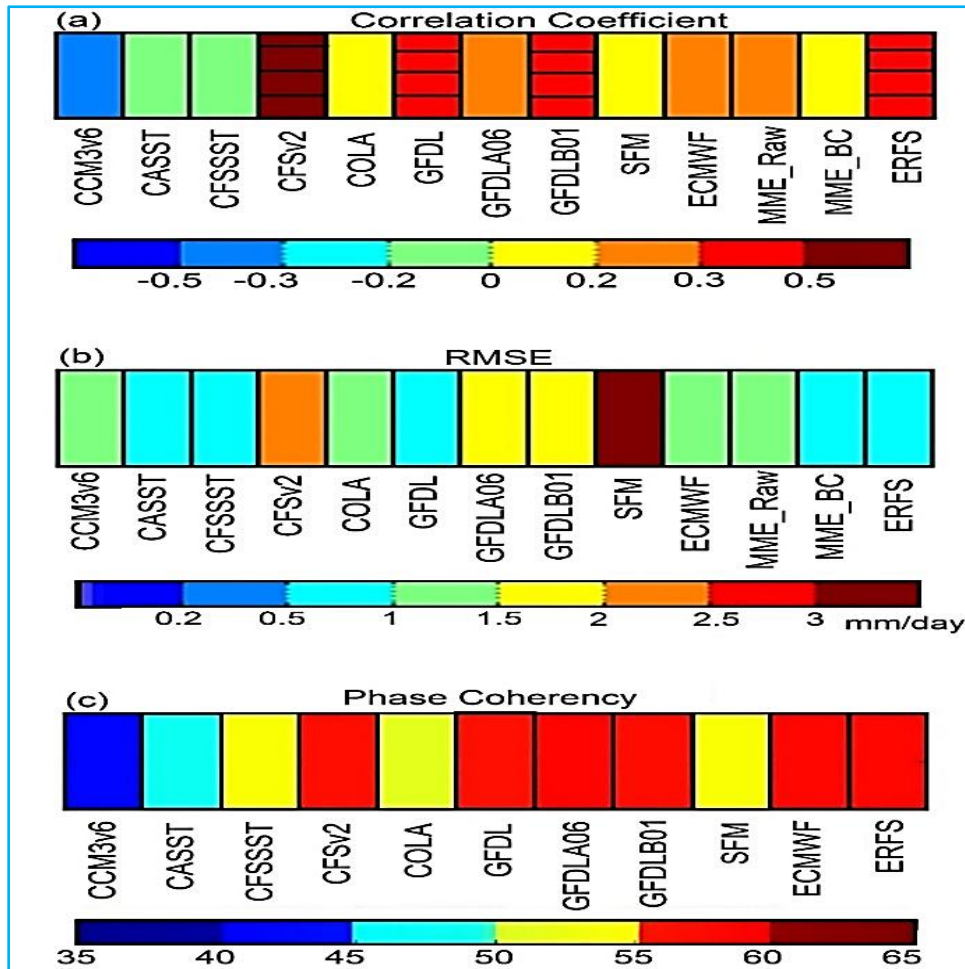
Figs. 9(a-c). (a) Correlation coefficient (b) Root mean square error (RMSE) and (c) Phase Coherency of GCMs, MME, MME BC and ERFS for JJAS seasonal rainfall in hindcast period 1982-2008 against IMD observation. The dashed lines on the Fig. 15(a) indicate significant positive correlations

techniques are further combined based on their hindcast skill in order to obtain the final consensus ERFS product (Mohanty *et al.*, 2013, 2019).

The all-India JJAS mean seasonal rainfall and its inter-annual variation for the individual GCMs, MME Raw (simple mean of GCM products), MME BC (weighted mean of bias corrected GCMs) and ERFS are shown in Table 4; it is clearly demonstrated that ERFS could able to adjust the mean and variability close to observations. Figs. 9(a-c) illustrates that the skills of atmospheric GCMs are not satisfactory in simulating the JJAS seasonal precipitation. It is noticed that three coupled GCMs are significantly (at 90% confidence level) correlated with fairly high values and the highest correlation is found in CFSv2 followed by the GFDL and GFDLB01. The skill of multi-model ensemble mean of these raw GCMs (MME Raw) and bias corrected GCMs (MME BC) have also been examined since this is now a common standard practice in seasonal scale forecasting. It is interesting to note that the MME Raw shows an insignificant skill. In the case of MME BC there is not much improvement in terms of correlation; while in RMSE, there is a slight depreciation indicating MME BC is better than MME Raw. Since, one individual GCM and the mean of ensemble members of that particular GCM, are not able to properly simulate the seasonal patterns, the multi-model ensemble mean through robust statistical technique is adopted in the ERFS. Figs. 9(a-c) clearly indicates that the ERFS show higher correlation and lesser RMSE value in JJAS than the individual GCMs, MME Raw and MME BC. It can be noticed that the skill of the ERFS is higher in representing the seasonal mean precipitation with the maximum skill in JJAS. The analysis on phase coherency (Sinha *et al.*, 2015) indicates that ERFS has a satisfactory skill compared to the individual GCMs, MME Rawand MME BC (Mohanty *et al.*, 2019).
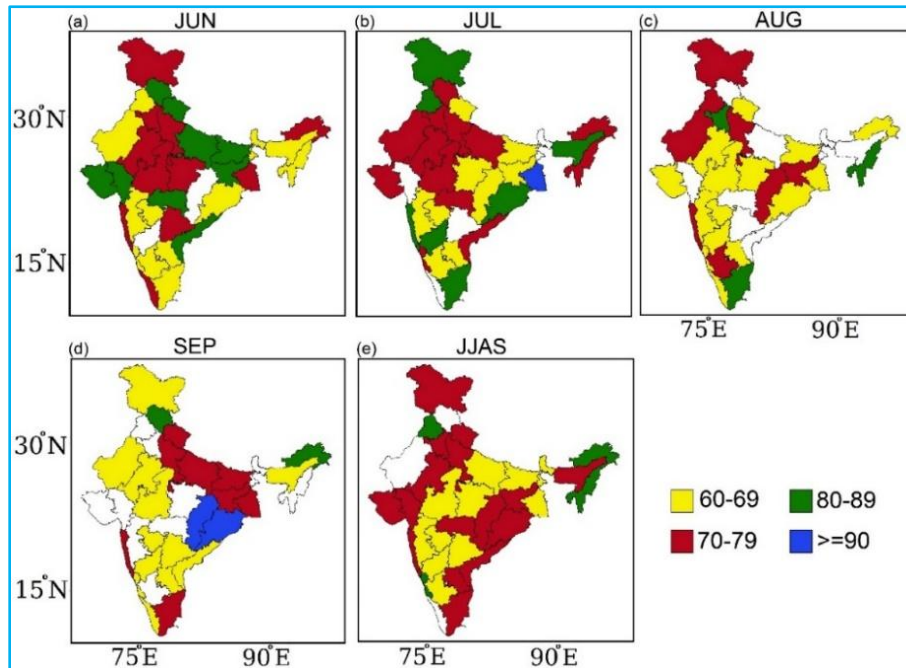
Figs. 10(a-e). Confidence map of real-time ERFS forecast (a) June, (b) July, (c) August, (d) September and (e) JJAS precipitation at each subdivision for the period 2009-2017

5.1. *Spatial skill of real-time ERFS with confidence maps*

The confidence maps as a percentage of success of the ERFS real-time forecasts of 9 years (2009-2017) are generated at a meteorological subdivision level to focus upon the spatial variation.

The confidence maps are evaluated as a number of forecast years that are same with the observed category to a number of years in consideration, multiplied by 100 [for all the seasons and presented in Figs. 10(a-e)]. From Figs. 10(a-e), it can be observed that the success of hits is highly significant in all the June and July months and the appreciation part is that the ERFS real-time forecast has high confidence during the peak monsoon month July. The confidence during August and September, more than 70% of the met-subdivisions have confidence more than 60%, which is encouraging. Further, the confidence for June and July is higher than the latter two months with more number of sub-divisions. During the southwest monsoon season (JJAS), the success rate ranges from 60% to 100% [Fig. 10(e)]. The hits in the Monsoon Core Zone (MCZ) are also higher and are greater than 60% in the met-subdivisions comprising the MCZ. The maximum precipitation zones *viz.*, Northeast and the Western Ghats are having a confidence of more than 70%. Interestingly, the confidence of the ERFS is notably high for JJAS scale [Fig. 10(e)]. The ERFS forecast has satisfactory confidence over the Indo-Gangetic plain and surrounding area of the monsoon trough, particularly near the Bay of Bengal.

5.2. *Application of ERFS real-time forecast in agriculture*

The beauty in the ERFS project is that they not only enhance the confidence in the forecast skill at met-subdivision scale, but they have also used the ERFS real-time forecast in the agriculture model to estimate the usability of the forecast.

The ERFS basically generates the monthly and seasonal forecasts, but it is needed to disaggregate into daily sequences as a requirement of CERES-rice crop model. The stochastic disaggregation of forecasts at seasonal and monthly scales to daily values by weather generator is based on statistical properties of climate series by manipulating input parameters to reproduce mean and variance. A number of studies are available to link the seasonal and monthly climate forecasts to crop simulation models for prediction of crop yield. Using this stochastic disaggregation, monthly data can be converted into daily values. But, it is always necessary to test the reliability of stochastic process. Reliable disaggregation process will build the confidence in disaggregating the total rainfall into frequency and intensity.
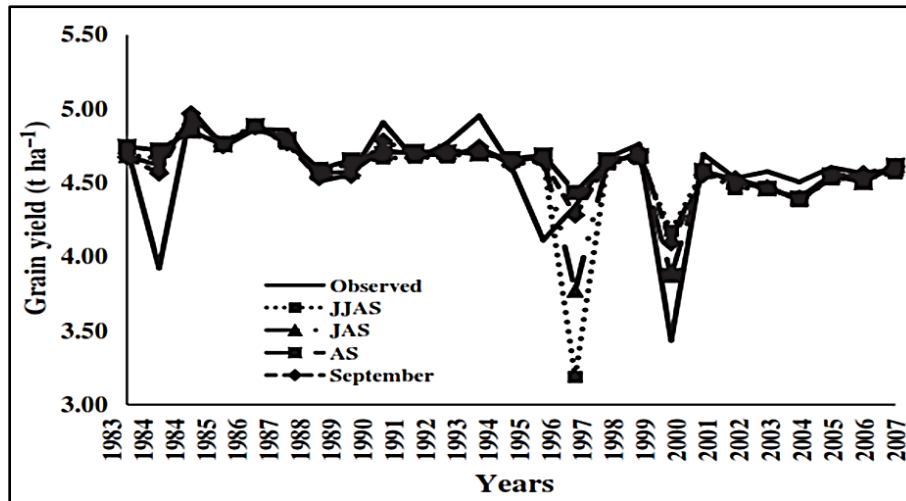
Fig. 11. Simulated grain yields using observed weather and disaggregated seasonal rainfall forecast (mean of simulated yields using 200 realizations) for June-September, July-September, July-August and September from 1983 to 2007 (*Ghosh et al.*, 2015)

Ghosh *et al.* (2015) tested the performance of stochastic disaggregation based on Markov chain model by disaggregating the observed monthly weather data into daily sequences and correlated with observed daily series. Rice is a major crop, grown under rainfed condition in most parts of the state of Orissa and West Bengal in India during summer monsoon months and thus exposed to uncertainties of monsoon rainfall in respect of onset of monsoon, long dry spell causing soil moisture stress or drought and extremely heavy rainfall leading to flood etc. In view of that, attempts have been made to evaluate performance of predicted kharif rice yields over West Bengal and Odisha from crop simulation models using ERFS seasonal and sub-seasonal rainfall forecast products with different initial conditions during summer monsoon, with the objective of providing advance information to the farming community and the decision makers to prepare for upcoming crop growing season. Crop productivity may be predicted, through linking climate forecasts to a crop yield model, at the beginning of the season or even long before the season starts. The ERFS forecast first disaggregated in daily sequence and then used in the crop model DSSAT for Kharif yield prediction at Bhubaneswar, Odisha. After rigorous evaluation, they have found that for all the time steps, more or less, mean and inter-annual variability of the observed rice yield have been predicted reasonably well. Further, some of the statistical skill measures such as MBE, correlation and index of agreement were evaluated to quantify the predictability of the crop yield. An improvement in these skills is noticed with the advancement of the season. The correlation (index of agreement) was found to be 0.45 (0.63) for June-September, 0.61 (0.73) for July-September, 0.73 (0.79) for August-September

and 0.79 (0.79) for September. The skill improves as the season advances and inter-annual variation is well captured at all time steps (Fig. 11). In a similar context, Dhekale *et al.* (2018) have also investigated the applicability of ERFS forecast for Kharif yield prediction over Kharagpur, West Bengal. They have also reported that the simulated rice yield corresponding to the realizations from the stochastic disaggregation are in good agreement in capturing the magnitude as well as year-to-year variations in the baseline yield.

Therefore, the ERFS forecast has significantly contributed in improving the monthly and seasonal scale forecast during the summer monsoon. More importantly, the ERFS has made a jump from all-India scale to met-subdivision scale with satisfactory prediction skill and higher confidence. The application of ERFS in agriculture for crop yield prediction is reasonably well which will be helpful to the agro-met advisory.

6.   Future challenges

The GCMs are the most important tools for advance intimation of the atmospheric conditions. However, it is already seen in a large number of research articles that the usefulness of GCM raw products is insignificant or may be worse for direct application in different sectors like hydrology, agriculture etc. In one hand, it is seen that application of multi-statistical techniques on multiple GCMs output can provide a robust and improve prediction of rainfall. On the other hand, dynamical downscaling of GCMs using regional climate model (RCM) can reproduce fine structure atmospheric state with higher accuracy. Therefore, dynamical downscaled products from

RCM can be further used in the statistical downscaling approaches (Hybrid Dynamical-Statistical approach; HDS) to improve prediction. Moreover, the advancement in the HDS system may provide district level forecast which will be adequate to use in the different sectors.

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