Deterministic and Probabilistic Seasonal Prediction of Indian summer monsoon rainfall based on the APCC Multi-model system

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Abstract

Prediction of Indian summer monsoon rainfall (ISMR), from June to September, is always in high demand as its high variability has a significant impact on the economy of the country. The general circulation model (GCM) especially coupled General circulation model (CGCM) is an alternative approach over the existing empirical/statistical models in recent times for predicting ISMR. The Asia-Pacific Economic Cooperation Climate Center (APCC) is one of the leading centres for predicting seasonal outlook using CGCM's outputs on a real-time basis. A comprehensive assessment has been done for 24 years (1982-2005) hindcast runs of those CGCM in the context of ISMR. Duo to the intrinsic biases present in the CGCM, the performance of CGCM is not impressive and largely differs in spatial and temporal scale. Therefore, two different schemes of the multi-model ensemble (MME) have been implemented to improve the individual skill of CGCM. These schemes viz, simple composite method (SCM) and multi-model superensemble (SE), are different in nature of assigning the weights for combining CGCM. After a rigorous skill evaluation, it is established that the SE method is more superlative than SCM. Due to the enormous complexity characteristic of ISMR, probabilistic approaches are a new thought to disseminate forecast as they convey the inherent uncertainty of forecast that helps to manage the climate risk which has more potential to decision-makers than deterministic forecasts. Therefore, the present study gives special attention to converting the MME-based prediction into a probabilistic manner using the parametric approach. The skill of probabilistic prediction based on the SE method has also an improvement over SCM.

Key words: Indian summer monsoon rainfall, General Circulation Models, Multi-model ensemble, Probabilistic prediction.

1. Introduction

The major rainfall season for India is during the months of June to September which contributes almost 80% to the annual rainfall of the country. Rainfall during this season plays a vital role in economic development, disaster management, and hydrological planning in the country as the erratic nature of Indian summer monsoon rainfall (ISMR) directly affects agriculture, drinking water, transportation, health, power, and the very livelihood of more than 1 billion of people living in the country. Therefore, the enormous impact of monsoon rainfall on these sectors made the scientists make an attempt for the prediction of monsoon for more than a hundred years with the pioneering work done by [1]. Literature is available on the development of statistical/empirical forecast models for seasonal monsoon rainfall prediction [2-4]. These statistical models are based on the teleconnection of ISMR with global parameters (like sea surface temperature, wind, etc). Moreover, the predictability of such statistical models has limited the relationship between ISMR and those atmospheric parameters, being weaker in recent years [5].

An alternative avenue for the prediction of Indian Summer Monsoon rainfall (ISMR) has been opened by the development in the field of dynamic modeling using state-of-the-art General Circulation Models (GCMs). Significant work in this direction includes [6-10]. Nevertheless, studies show that due to the inherent bias GCMs has varying skills in the prediction of ISMR [9,10]. Multi-model ensemble (MME) has been considered to be a remedy for improving the prediction by GCMs [6,11-14]. Different types of MME techniques available in literature such as simple average [6,15-17], multiple regression method [11,12,18], singular value decomposition-based regression [19,20], canonical correlation analysis method [21] and artificial neural network [22].

Due to the immense intricacy characteristic of ISMR, prediction communicating the intrinsic uncertainty becomes more useful to the user community involved in agricultural/hydrological planning and climate risk management. A probabilistic forecast which can convey the uncertainty of the prediction can be thought to be a better way to disseminate a seasonal forecast [23]. Most of the MME techniques discussed in the previous paragraph are used to generate a deterministic prediction without a measure of its inherent uncertainty. Although probabilistic seasonal prediction using GCMs has been discussed by several works in literature [15,24-28], a very few studies [29-31] have addressed for the context of ISMR.

The Asia-Pacific Economic Cooperation (APEC) Climate Center (APCC) is one of the leading seasonal forecasting centers using GCM's outputs on a real-time basis. Since 2007, the APCC has continuously produced the seasonal outlook for rainfall and temperature using MME-based forecasts and disseminated it to APEC member economies [32]. Currently, 17 prominent operational climate centers and research institutes from 9 APEC member economies participate in the APCC operational MME prediction by routinely providing their predictions in the form of ensembles of global forecast fields.

With the above background, the prime objective of the current study is to examine the skill of MME-based prediction in a deterministic and probabilistic manner based on GCMs used in APCC. More specifically, the present works have the following three-fold objectives:

- At the outset, the performance evaluation of eight fully coupled general circulation models (CGCM) used in the climate prediction system at APCC will be done against observed features of ISMR.
- Two different MME techniques are employed for the improvement of the existing skill of individual GCMs. A comparative study of both the MME techniques is accomplished.
- The novelty of the present study lies in the fact that it gives special attention to probabilistic prediction. The deterministic forecast from MMEs is converted in probabilistic output by using the parametric approach.
- The layout of the present manuscript is as follows: A brief description of the hindcast run of GCM and observational references is presented in section 2. The Foundation of MME techniques and probabilistic prediction system is discussed in section 3. Section 4 contains the major findings results of the study. The work is finally concluded in section 5.

2. Data:

2.1 Coupled General Circulation Models (CGCM) products:

Eight fully coupled general circulation models (CGCM) used in this study are also used in the APCC. A brief summary of each CGCM including host organization, atmospheric and ocean component, members, resolution, and relevant citations are presented in Table 1. These CGCMs viz. CANCM3, CANCM4, NASA, NCEP, PNU, POAMA, SNU, and UH, shows a large range of model resolutions and ensemble sizes, and their retrospective forecast datasets match the requirements of the Seasonal Prediction Model Inter-comparison Project-2/Historical Forecast Project (SMIP2/HFP) [28]. For this study, we have used the lead-1 (initial conditions of May start) hindcast runs (1982-2005) of the ensemble mean of all CGCM for summer monsoon seasonal rainfall (i.e., mean rainfall of June-July-August-September).

2.2 Observational references:

The high resolution ($1^0 \times 1^0$) gridded rainfall data based on 2140 rain gauge stations are used in this study as an observational reference provided by the National Climate Centre of India Meteorological Department (IMD). The station data have been interpolated to the specific grid points using objective analysis by the methodology proposed by [33], where in addition to a distance factor a direction factor has also been introduced while defining

Model	Institution (Country)	Resolution	AGCM	OGCM	Ensemble Member	Reference
CANCM3	Meteorological Service of Canada (Canada)	T95 L27	AGCM2	CMC	10	http://www.ec.gc.ca/ccmac-cccma/default.asp?lang=En&n=1299529F-1
CANCM4	Meteorological Service of Canada (Canada	T32 L10	AGCM2	CMC	10	http://www.ec.gc.ca/ccmac-cccma/default.asp?lang=En&n=3701CEFE-1
NASA	National Aeronautics and Space Administration Goddard Space Flight Center (USA)	288x181 L72	GEOS-5	MOM4	9	http://www.gfdl.noaa.gov/ocean-model
NCEP	National Centre for Environmental Prediction (USA)	T126 L64	GFS (2009 version)	MOM4	20	[35]
PNU	Pusan national University (Korea)	T42 L18	CCM3	MOM3	10	[36]
POAMA	Bureau of Meteorology Research Centre (Australia)	T47 L17	ACOM2	MOM2	30	[37]
SNU	Seoul national University (Korea)	T42 L21	SNU	MOM2.2	6	[38]
UH	University of Hawaii (USA)	T31 L19	ECHAM4	UH Ocean	10	[39]

the weights for interpolation. The detailed methodology for the preparation of gridded data has been discussed by [34]. There are 357 grid points ($1^0 \times 1^0$) over the landmass of the country. The temporal resolution of this precipitation dataset is 1 day, i.e., this dataset is available for each day. For the present study, a seasonal mean (i.e., June-July-August-September) dataset has been created from the original daily data for the period 1982-2005 constrained by the availability of the GCMs. The individual GCM's product for rainfall is bilinearly interpolated at the observed data grid ($1^0 \times 1^0$).

Table 1: Description of 8 CGCM used in the study

3. Methodology:

The present section of the study deals with the short description of deterministic and probabilistic multi-model ensemble (MME) schemes used in this study. Two types of MME methods viz., the simple composite method (SCM) and multi-model super-ensemble (SE) are used to obtain a deterministic prediction. Apart from such a deterministic approach, one of the main objectives of the current study is to generate a probabilistic prediction based on this MME. Therefore, the methodology for probabilistic prediction approaches is also described in the current section. The entire methodology adopted in this work is summarized as in the flow chart shown in the figure 1.

3.1 Multi-model ensemble schemes

There is a plethora of studies that show that GCM has a large systematic and random bias for the prediction of ISMR [9;10]. Therefore, a proper approach is needed for the bias removal of each GCM before using it in the multi-model ensemble. [40] applied six statistical methods for bias correction to GCM's output for Indian summer monsoon rainfall. The study identified two methods viz. quantile mapping and standardized-reconstruction techniques to be the best for bias removal of GCM's prediction for ISMR. In view of the simplicity and importance, the standardized-reconstruction technique is used for this purpose. The bias-corrected GCM's prediction for ISMR is used as an input in the multi-model ensemble techniques which are described here.

3.1.a Simple Composite Method (SCM):

The simple method of MME schemes is the averaging of all bias-corrected individual GCMs where the contribution of each GCM is equally weighted [6; 15; 16; 17]. This method will be referred to as the simple composite method (SCM) in the present manuscript. This lucid scheme has the common benefit and constraint of the individual GCM predictions with the assumption that each model is comparatively independent of the other. For the seasonal prediction context, the rationale behind the success of such an MME method is explained by several studies. [9] showed that this simple MME technique has the better skill to predict ISMR than individual GCMs.

3.1.b Multi-model Superensemble (SE):

For carrying out weighted multi-model ensemble mean, the multiple linear regression method has been employed among the bias-corrected GCMs. This method is popular as 'superensemble' in the literature [11;12]. In general, the regression coefficients are obtained using Gauss-Jordan elimination with pivoting in regression. However, this method is not numerically robust due to the singularity problem i.e. the case where covariance matrix becomes singular ([19;20]. As a remedy, the singular value decomposition (SVD) method is employed for the estimation of regression coefficients as SVD removes the singular matrix problem while calculating the covariance [19;20]. The success of such MME schemes solely depends on the performance of individual GCM in the hindcast period. In other words, the weights assigned to each GCM depend on the estimates of covariance of the GCM with observation. Therefore, the estimation could be degraded if the training is executed with a GCM having low skill which may enhance in the case of a higher quality training dataset [19;20].

The above-stated statistical post-processing viz., bias correction, and MME methods have been done in a leave one out cross-validation method recommended by [41]. In the present study due to the short length of the training period, the data set cannot be divided into two independent parts viz. for estimation of unknown parameters and further for testing. Therefore, one year among the total dataset (consisting of 24 data) is reserved for "test" and residual dataset (consisting of 23 data) is used as a "training" dataset. The training dataset has been used for the calculation of all statistics. Now, the calculated statistics are implemented on the "test" year and evaluate the skill with the same year observations.

3.2 Probabilistic prediction based on MME:

Prediction by MME techniques discussed in the previous sections is used to generate a deterministic prediction system without a measure of its inherent uncertainty. The importance of probabilistic forecast is already discussed in section 1. In this section, a brief description regarding the development of probabilistic prediction is presented. Though probabilistic prediction based on GCM outputs products can be done both the parametric and non-parametric way. In the present study, the parametric method is executed assuming the Gaussian distribution for tercile-based category (namely below-normal (BN), near-normal (NN), and above-normal (AN)) [31]. These categories are defined from the climatological probability density function (pdf).

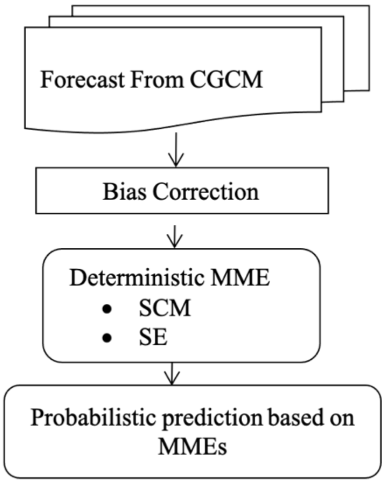

Figure 1. Schematic representation of implementation procedure of the present study.

The parametric method depends on the simple linear model where the observed variations of rainfall (X) are represented as the sum of potential predictable signal and non-predictable stochastic noise [24]. Both the signal and noise follow Gaussian distribution whereas; the mean of noise is zero. Therefore, the mean of forecast distribution depends on the signal (as the mean of the as stochastic noise zero), and variance can be represented by the sum of the variance of signal and variance of stochastic noise. The detailed mathematical foundation is described in [31]. There are several methods to estimate the variance of stochastic noise such as Ensemble Spread (ES), Error Residual (ER), and Correlation Method (CR) are well documented in the literature. In the ES method, the variance of stochastic noise is treated as an ensemble spread of GCM [24], whereas ER method uses the error between the mean of all GCMs and observation for estimation of the variance [42]. CR method uses the correlation between observation and signal from GCMs for the evaluation of variance [25]. [29] establish that among three methods, the CR method is the best in the case of ISMR. The justification behind the success of the CR method is discussed in detail in the study. In this case, when the correlation between observation and signal from GCM is positive, correlation can be used to define a positive linear regression coefficient [25]. In other words, the CR method estimates the forecast uncertainty by the standard error of a regression fit.

In the present study, we adopt the same CR method for the estimation of the variance of distribution and the MME-based predictions are used as a potential predictable signal. The performance of the CR method directly depends on the correlation between observation and potential predictability [31]. This approach is done in the above-mentioned leave one out cross-validation method where the correlation between MME prediction and observation in the "training" period is used to estimate the probability in the "test" period which is evaluated against the observation in the "test" period.

4. Result and Discussion:

This section focuses on the major findings of the study. It is already stated that the purpose of the present study is threefold. Therefore, the result part is organized in the following manner. Firstly, the performance of all CGCM is evaluated in detail. Secondly, a comparison has been done for deterministic prediction by the two MME schemes. Lastly, a detailed analysis is made on the probabilistic prediction by both of the MMEs.

4.1 Performance of individual GCM's prediction:

The 24 years of the hindcast runs (1982 to 2005) obtained from eight general circulation models (GCMs) for rainfall of June-July-August-September (JJAS) generated in May are used. The performance of individual GCM for the prediction of ISMR is examined against observation. For this purpose, initially, the climatology for JJAS are evaluated for observation with the GCMs prediction and shown in figure2 (in shading). The observed spatial distribution of seasonal mean rainfall/ climatology showed that most parts of the country get more than 4 mm/day rainfall during JJAS. The zones of maximum rainfall (more than 15 mm/day) in this season are located in the Western Ghats region and the northeastern part of India. However, some parts of northern and eastern India also receive more than 8 mm/day rainfall climatology. Whereas, the east coast area of the country doesn't receive much rain during the season. The region is the rain shadow area of the southern part of India where the rain is distracted from the mountains along the west coast of India. Over northern India, a minimum rainfall belt is found from Rajasthan to the central parts of West Bengal along the axis of the monsoon trough during JJAS. The GCM used in the study are having a large variation in the simulation of observed seasonal mean rainfall over India. However,

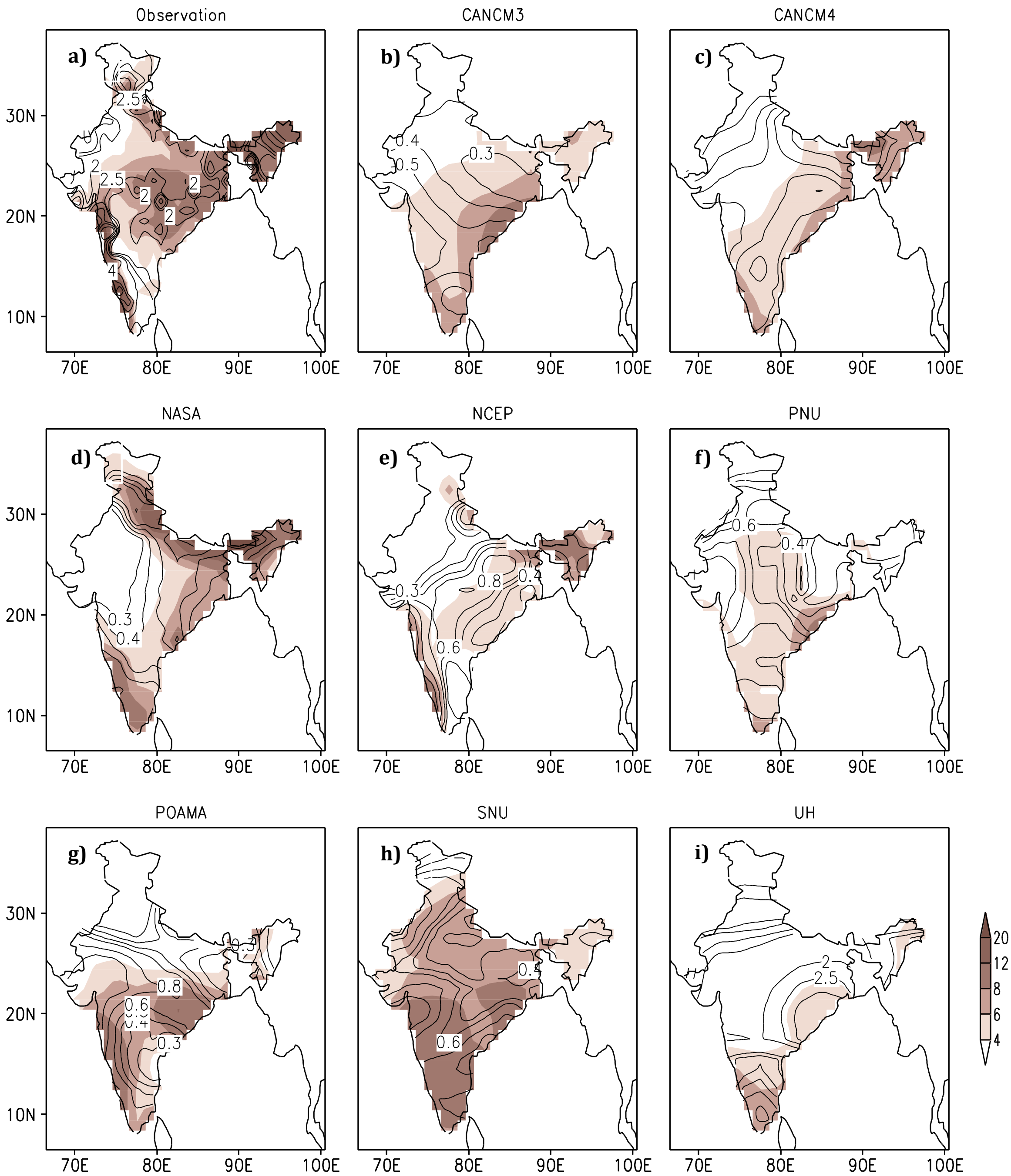

Figure 2. Climatology (in shading) and interannual variability (in contour) of rainfall over India in June-July-August-September from observed data and the participating GCMs during hindcast for 1982 to 2005.Rainfall areas with >4 mm/day climatology have been shaded.

the spatial pattern of climatology predicted by NASA, NCEP, and POAMA models are found closer to observation as compared to other GCMs though; the magnitude is less than the observation. On the other hand, the spatial patterns of rainfall climatology from CANCM3, CANCM4, PNU, and UH are found different from observed climatology. It is also noticed that the rainfall climatology in the SNU model is very less varied spatially. In fact, the predicted rainfall climatology by SNU is more than 6mm/day over the maximum part of the country. Therefore, it can be said that the amount of rainfall climatology and its spatial distribution varies largely from GCM to GCM. Further, the skill of GCMs for the prediction of the climatological pattern is measured by evaluating the pattern correlation which is presented in Table 2. Maximum GCMs fail to capture the observed climatological pattern as it can be observed from the correlation values. As an example, the pattern correlation of SNU (0.10) and PNU (0.15) is very less whereas, the NCEP model has the highest pattern correlation (0.71) among the GCMs.

The interannual variability/standard deviation (IAV) of observation and all GCMs are also shown in the same figure (in contour). It is noticed that the areas with maximum rainfall have maximum IAV in observation. The west coast, the northeastern region, the central parts of the country have IAV of more than 3 mm/day. The IAV of GCMs also follows the same spatial pattern as in climatology but the magnitude of IAV is much less than the observed. The GCM predicted IAV lies between 0.2 to 0.8 mm/day except for UH. The IAV of UH goes up to 3 mm/day but the spatial pattern is completely different as compared to the observation. The IAV of each GCM is calculated on their ensemble to mean therefore, it is expected that the magnitude of IAV will be highly underestimated (Acharya et al 2011). The climatology and IAV of rainfall from observation and individual GCMs are also calculated for the country as a whole which is presented in Table3. Based on 24 years study period the observed rainfall climatology is found to be 7.6 mm/day whereas IAV is 0.76 mm/day. Among the GCMs, rainfall climatology of NASA (6.38 mm/day) and SNU (6.85 mm/day) are found closer to the observation whereas, other models highly underestimated the observed climatology. On the other hand, except for UH (1.29 mm/day), the IAV predicted by all the GCMs is much less than that of observation.

Table2. Climatology, interannual variability (IAV) of observation and all participating GCM along with their correlation, root mean square error (RMSE) and mean anomaly correlation coefficient (ACC) for 24 years (1982-2005) hindcast run.

	Observation	**CANCM3**	**CANCM4**	**NASA**	**NCEP**	**PNU**	**POAMA**	**SNU**	**UH**
Climatology(mm/day)	7.67	4.88	4.09	6.38	3.99	3.79	4.71	6.85	2.93
IAV (mm/day)	0.76	0.28	0.36	0.27	0.35	0.41	0.38	0.39	1.29
Correlation		0.34	0.05	0.33	0.55	0.3	0.28	0.59	0
RMSE (mm/day)		2.87	3.67	1.47	3.73	3.94	3.05	1.01	4.96
Mean ACC		0.3	0.51	0.49	0.62	0.37	0.1	0.26	0.14

Table3. Pattern correlation of ISMR climatology between observation and all participating GCM for 24 years (1982-2005) hindcast run.

	Observation	**CANCM3**	**CANCM4**	**NASA**	**NCEP**	**PNU**	**POAMA**	**SNU**	**UH**
Observation	1	0.34	0.57	0.54	0.71	0.15	0.40	0.10	0.34
CANCM3		1	0.83	0.28	0.52	0.75	0.77	0.66	0.85
CANCM4			1	0.59	0.78	0.45	0.60	0.39	0.82
NASA				1	0.72	-0.01	0.08	0.02	0.25
NCEP					1	0.17	0.48	0.19	0.50
PNU						1	0.67	0.63	0.63
POAMA							1	0.65	0.68
SNU								1	0.58
UH									1

To get a clear picture of the predictability of ISMR in GCM, the temporal correlation coefficient (TCC) values between the observed rainfall and predicted rainfall by individual GCM has been calculated at each grid point for the 24 years of hindcast runs (Fig.2). According to Student's t-test, the expected magnitude of TCC should be at least 0.34 at a 5% level of significance for 24 years of data series. Therefore, the TCC values greater than the significance level (>0.34) is shaded in color (figure 3). The spatial pattern of GCM's TCC shows that the skill varies from GCM to GCM and also from region to region. The TCC value of the SNU model is found significant over the Western Ghats and the central part of the country. Whereas, the NCEP model also has significant TCC value over the northern region, some parts of Western Ghats, and southern part. NASA model is also having some significant skill over the entire domain mainly over the rain shadow region (southern part). Other GCMs are having poor skills in terms of correlation over most regions. The correlation coefficient (CC) between GCMs and observation is also calculated for the country as a whole (Table3). Among these eight GCMs, SNU (0.59) and NCEP (0.55) have superlative CC values. The CC value of CANCM3 (0.34) and NASA (0.33) is also very close to the statistically significant value. Details of individual GCM's TCC can be inferred from Fig.3. The root mean square error (RMSE) from individual GCM is also computed to quantify the inherent bias among them (figure not shown). This indicates that more or less all the GCMs have large errors in those parts of the country where the observed rainfall climatology is more especially Western Ghat, northeast region, and some part of central. The all-India level RMSE of all the GCMs is also shown in Table3. It is found that the SNU (1.01 mm/day) and NASA (1.47 mm/day) have less RMSE than others whereas UH (4.96 mm/day) possesses the highest RMSE at all India levels.

The observed time series of ISMR is very erratic in nature i.e., the year to variation is very high. To quantify the ability of GCM for predicting such random fluctuation of ISMR, the normalized rainfall anomaly at all India is plotted for observation as well as GCMs (Fig.4). In this study, the years having rainfall anomaly (normalized) less than -1 (greater than +1) are considered deficit (excess) monsoon years while years having anomalies between ±1 are considered as normal years. There are the years where the observed rainfall faces some extreme features with significantly less rainfall as compared to normal (1982, 1987, and 2002), and in some years, more than normal rainfall occurred (1983, 1988, and 1994). These years are closely linked with the ENSO phenomena. Four among the eight GCMs are able to capture the deficit rainfall in the year 1982 whereas SNU, NCEP, and POAMA models

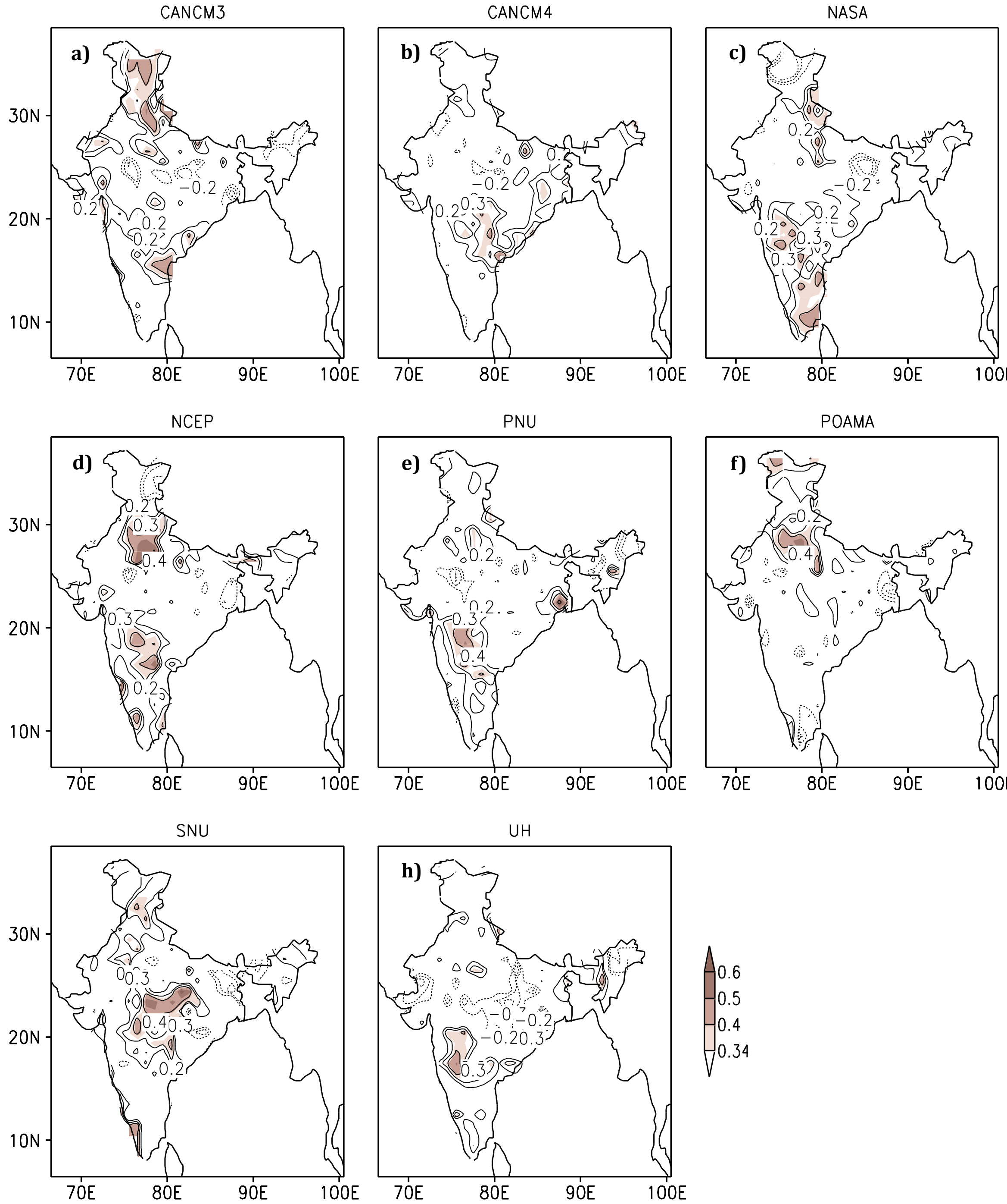

Figure3. The temporal correlation coefficient between observed rainfall and rainfall from all the participating GCMs for June-July-August- September during the hindcast period. Areas with a correlation value greater than 5% significance level (>0.34) have been shade.

are close to the observed anomaly in 2002. Some of the models are also able to capture the excess rainfall in the year 1988. Therefore, it can be concluded that monsoon years (except 1987) influenced by ENSO can be well predicted by GCM as they are more sensitive to ENSO. Generally, the GCM has a strong coupling with pacific

SST (ENSO region) but in recent years the association between Indian monsoon rainfall and ENSO is much weaker [5]. This affects the skill of prediction by GCMs. For instance, almost all models are showing deficit (excess) rainfall for 1997 (1998). These two years are an exception as a very strong El Nino event was observed but on the contrary, ISMR was normal.

For examining the skill of GCMs' prediction for capturing the year-to-year spatial pattern the anomaly correlation coefficient (ACC) is calculated for each year. ACC represents the spatial similarity between prediction and observation map for each year following the recommendations of the World Meteorological Organization Standardized Verification System for Long-Range Forecast (SVS-LRF; [41]). The anomalies of observation and each GCM are calculated as departures from their climatology over the training period in a leave one-year out cross-validation way. That is, the anomalies are estimated using climatology from the 23-year long training periods for the retrospective forecasts of 1982-2005. This implies that a new climatology is calculated at each cross-validation step, with the target year being withheld. It is seen that (figure not shown) UH and POAMA model's ACC is poorer than others for each year (less than 0.3 for almost all year). While NCEP is the best model as its ACC is greater than 0.6 for most of the year and the second-best model is CANCM4. The mean ACC of all the GCM periods has been calculated for the country as a whole for the entire period (Table3). The mean ACC of NCEP (0.62), CANCM4 (0.51), and NASA (0.49) are superlative to the other GCMs.

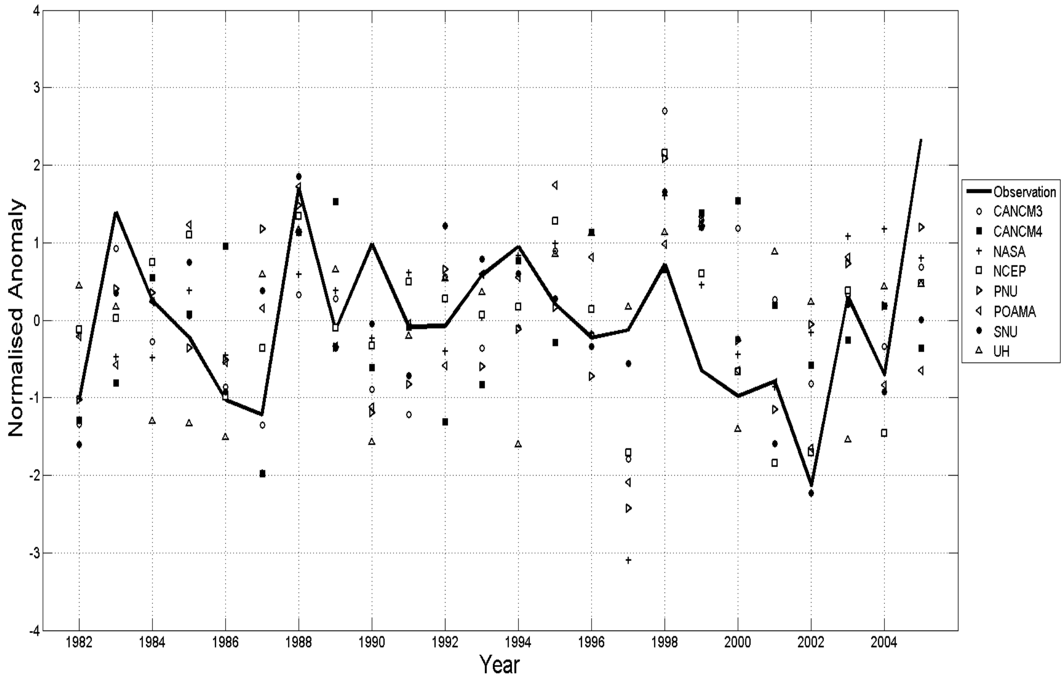

Figure 4. Normalised anomalies of rainfall from observed data and the participating GCMs for June-July-August-September for the country as a whole during 1982–2005.

The above discussions suggest that the prediction skill of Indian summer monsoon rainfall largely differs from individual GCM in spatial and temporal scales. For example, the TCC of SNU (0.59) at all India level is highest whereas, its mean ACC (0.26) is lesser than CANCM4 (0.51) which is having TCC (0.05) at all India level. Therefore, it is difficult to choose a particular GCMs output for a robust prediction system. Therefore, as a remedy, it is considered to use appropriate statistical post-processing techniques to properly correct the rainfall forecasts from these models and combine that GCM for a more reliable prediction. With the availability of a large number of GCM's predictions, in the recent decade, multi-model ensemble (MME) has been recognized as an effective tool to improve the existing model skill.

4.2 Performance of MME forecast:

4.2 (a) Deterministic forecast: assessment of SCM and SE prediction skill:

As discussed above, two different MME schemes are applied in the present study. Both the MME (SCM and SE) schemes are implemented on standardized rainfall anomaly of observation and GCMs. For examining the performance of such MME schemes, the grid point-wise temporal correlation coefficient (TCC) is calculated and presented in figure 5 where the TCC value greater than the significance level (>0.34) is shaded. A significant correlation is found in the northern part as well as some parts of the central to the southern part of the country in the SCM method. The skill in northern and some parts of central to southern India by SCM is achieved since most of the individual member models have positive skill scores over the same region (figure 3). Therefore, in all the areas where the maximum GCMs do not have any positive skill, the SCM scheme is not able to enhance the skill over the same region. The TCC of SE is also presented in the same figure. SE method as defined above is based on the multiple linear regression technique where weights are assigned to the models based on their skill in the training period (using leave one out cross-validation). Noticeably, the skill over the northern part and some parts of central to the southern part of the country which was obtained from the SCM scheme is enhanced in SE. Also, the north-east, eastern part, and some parts of Western Ghats are having significant skills in SE methods. To quantify the improvement of SE over SCM, the difference between TCC of both the MME is calculated (SE minus SCM) (Figure 4 c). More or less, most of the part of the country is improved in SE methods compared to SCM. However, the maximum improvement is coming from the eastern part and north-east part of the country (from negative skill in SCM to positive and significant skill in SE). The grid points having significant TCC are also more in SE (93 grid points) than SCM (74 grid points). The correlation coefficient (CC) between the MME schemes and observation is also calculated for the country as a whole. It is found that the CC of SE (0.42) is far better than the CC of SCM (0.36). The ACC also calculated for each year for SCM and SE. The mean ACC value for the SCM and SE are 0.53 and 0.88 respectively. Therefore, SE is also having more skill in pattern correlation or ACC. So, it can be concluded that the SE method is more skillful than simple averaging the GCMs for monsoonal rainfall (JJAS).

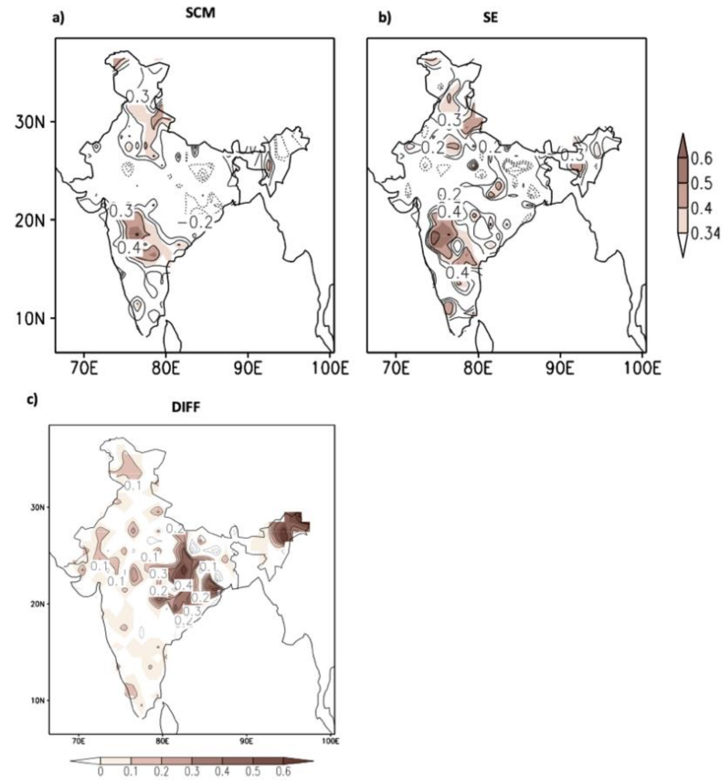

Figure5. Temporal correlation coefficient between observed rainfall and rainfall from the MME schemes viz. SCM (a) and SE (b) for June-July-August- September during hindcast period. Areas with correlation values greater than 5% significance level (>0.34) been shade. Difference (DIFF; SE minus SCM) of correlation of the two MME is plotted in (c).

However, the prediction of monsoonal rainfall becomes more useful if it conveys its intrinsic uncertainty to the user, especially in agriculture or hydrological sectors for planning climate risk management. All the GCM and MME techniques discussed in the previous sections are used to generate a deterministic prediction without a measure of its intrinsic uncertainty. As the seasonal prediction is inherently probabilistic, the probabilistic forecast has recently been thought to be a better way to disseminate a seasonal forecast as it represents the uncertainty of the prediction. Therefore, it is necessary to convert the above discussed deterministic MME prediction in terms of probabilistic approaches for the realistic application of seasonal prediction.

4.2 (b) Probabilistic forecast: assessment of probabilistic forecasts based on SCM and SE:

The predictions by both the MME schemes are converted in probabilistic space using the methods discussed in section 3.2 in the leave one out cross-validation procedure. The forecast from SCM and SE is regarded as a potential predictable signal for estimating the probabilities. The skill of such probabilistic prediction is assessed by different skill metrics described in the subsequent section. In the present study, we used Relative Operating Characteristic Score (ROCS) and Rank Probability Skill Score (RPSS) for evaluating the probabilistic prediction by SCM and SE. Both the skill metric is estimated in a leave one out cross-validation way for 24 years (1982-2005). The detailed discussion is presented below.

4.2. b.1*Relative Operating Characteristic Score (ROCS):*

The relative operating characteristic (ROC) curve is a common skill map for representing the quality of the probabilistic forecasts system in which the hit rate and the false-alarm rate are compared [43]. In other words, ROC is the signal detection curve obtained by plotting a graph of hit rate against false alarm rate over a range of different probability thresholds. Hit rate (false-alarm rates) indicates the proportion of events (nonevents) for which a warning is predicted correctly (incorrectly). Both ratios (hit rate and false-alarm rate) can be calculated simply from the contingency table. For a probabilistic system, the ROC curve describes the varying quality of the prediction system at different levels of confidence in the warning, i.e. the forecast probability which is helping to identify this optimum strategy in any specific application. ROC curve travels from the bottom left to the top left of the diagram, then across to the top right of the diagram. In this system, there is a skill only when the hit rate exceeds the false-alarm rate. A diagonal line indicates no skill, i.e. the hit rate and false-alarm rate are equal. Therefore, for a skillful forecast ROC will lie above the 45^0line. The ROC score (ROCS) is another way to quantify the ROC by estimating the area beneath the ROC curve. The ROCS is equal to 1 (unit area) for a perfect forecast

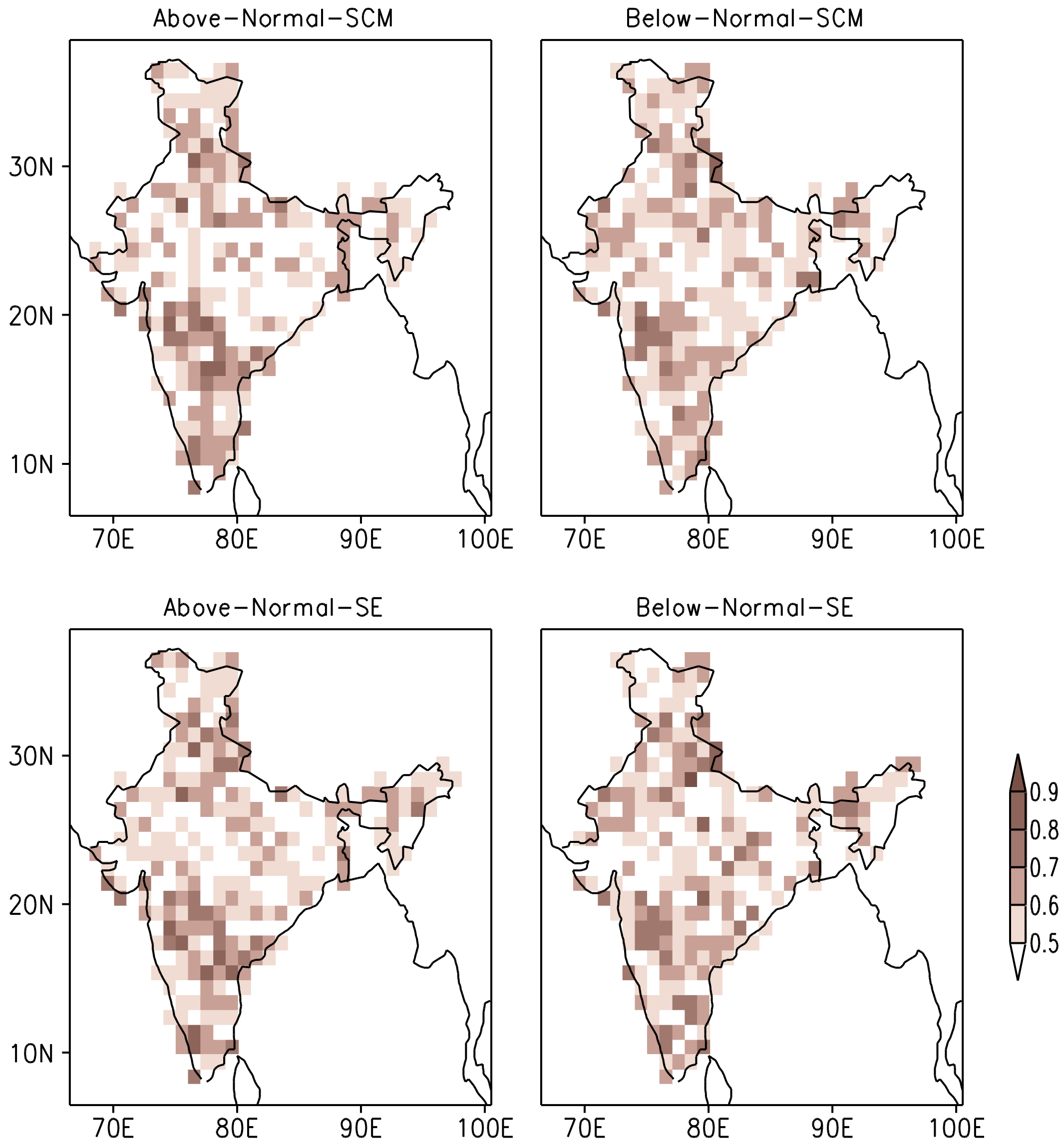

Figure6. Relative Operating Characteristic Score (ROCS)of the MME schemes viz. SCM and SE for AN and BN categories (for June-July-August- September during 24 year hindcast period. Areas with ROCS values greater than 0.5 been shade.

and 0.5 for a forecast that corresponds to the climatological forecast. If the ROCS is less than 0.5 (i.e. the same as a no-skill forecast), then the model is less skillful than a random or constant forecast. ROCS is calculated for each of the tercile categories (AN or BN or NN). The spatial patterns of ROCS for probabilistic forecast based on SCM and SE methods have been shown for the AN and BN category in figure 6. It is interesting to notice that maximum grid points over the study domain are having more skill (ROCS>0.5) than climatological forecast (i.e., 0.33 for each tercile category) in both of the MME techniques. The spatial pattern of ROCS (with higher magnitude) of SCM and SE almost resembles their TCC (with significant value). The ROCS of SE method is improved than the SCM method as SE method has more skill in the north-east, eastern part region with enhancing the skill over northern part and some parts of central to the southern part of the country which was obtained from the SCM. Therefore, the improvement in the predictable signal by the MME method improves the skill of probabilistic prediction with respect to climatological forecast.

The aggregated ROCS (pooled over 357 grid points) for the country as a whole was also calculated for SCM and SE schemes in AN and BN categories. The ROCS of SE (0.54) is little improved in the AN category over SCM (0.52) but for the BN category, both the MME methods have the same skill (0.53). Hence, aggregated ROC (pooled over 357 grid points) curves of both the MME are also calculated (figure not shown). ROC curve can be found by changing the different thresholds (11 thresholds or critical probability points between 0% to 100%) and plotting the leading hit rate against the false alarm rate. It is noticed that for a lower threshold of probabilities the false alarm rate is higher than the hit rate and reverse for higher critical probability for both the category and almost for both the MME methods. As a result, the ROC curve is laying not much far from the diagonal line. Therefore, it can be concluded that the improvement in the predictable signal by the MME method improves the skill of probabilistic prediction with respect to climatological forecasts.

4.2. b.2 ***Rank Probability Skill Score (RPSS):***

Another skill metric for evaluating probabilistic forecast is Rank Probability Skill Score (RPSS), which measures cumulative squared error between the categorical forecast probabilities and the observed categorical frequencies relative to a reference (or standard baseline) forecast [44]. The climatological forecast is considered as a reference forecast in general for seasonal prediction. The interpretation of RPSS and Brier Skill Score which is the mean squared error in probabilistic prediction is the same [45]. The advantage of RPSS is it can be estimated for all categories (above normal (AN), near normal (NN), or below normal (BN)) cumulatively, whereas BSS is calculated for each category. Therefore, RPSS represents the overall skill in each category at a time. RPSS is equal to 1 implies that the observed category is always predicted with 100% confidence. RPSS of score 0 implies that the prediction skill is the same as climatological prediction and a score of <0 means the forecast system performs worse than climatology. Figure 7 shows the spatial distribution of RPSS SCM and SE-based probabilistic forecast where the RPSS>0 is shaded. From this figure, it can be found that there are large numbers of grid points having skill better than climatological forecast by both the methods. Like ROCS, the spatial pattern of RPSS also exhibits a similar pattern of TCC of SCM and SE. There is a close relation between RPCC and TCC. RPSS of probabilistic prediction can be represented as a function of the square root of the correlation between the deterministic forecast and observation. Therefore, the region with a significant TCC value has higher RPSS in both MME schemes. Like other skill metrics, the skill improvement of SE w.r.t SCM is also noticed in RPSS. The difference in RPSS of SE and SCM (SE minus SCM) schemes is also plotted in the same figure (Figure. 6 c) to justify the improvement by

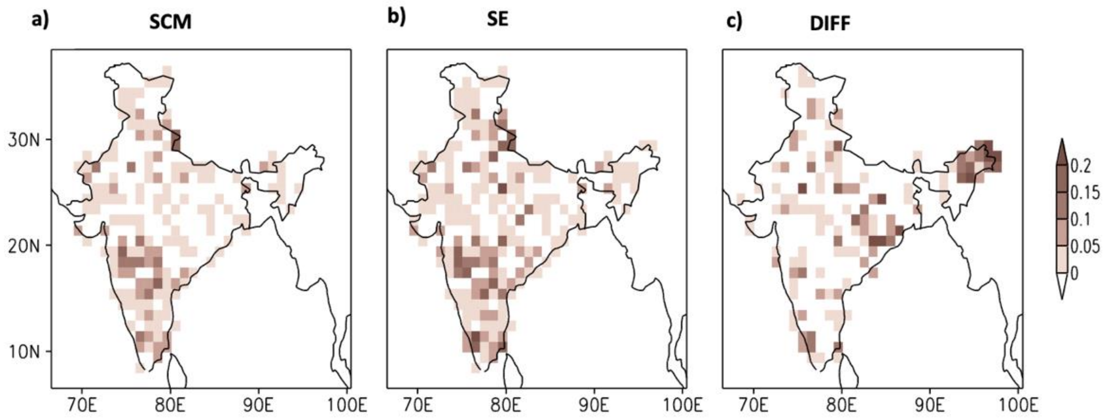

Figure7. Rank Probability Skill Score (RPSS) of the MME schemes viz. SCM (a) and SE (b) for June-July-August- September during 24 year hindcast period. Areas with RPSS values greater than 0 been shade. Difference (DIFF; SE minus SCM) of RPSS of the two MME is plotted in (c).

SE. The positive value of such difference is found in 259 grid points (among 357). Moreover, improvement is 72.5% found in most of the grid points of the study domain by SE method compared to SCM.

Therefore, from the above discussion, it can be concluded that the use of skillful MME methods in probabilistic prediction suggests a positive impact on probabilistic prediction. Although it is embellishing the skill of MME prediction, especially the SE method has also some limitations as the estimation of regression coefficients could be degraded if the training was executed with a poorer hindcast from the individual GCMs. The prediction skill of weighted MME is improved when the higher quality training dataset is organized for the evaluation of the multi-model bias statistics.

5. Concluding Remarks:

Prediction of the Indian summer monsoon rainfall (ISMR) is always one of the challenging problems because of the intrinsic multifariousness of the physical processes associated with it. The prime objective of the present study is to evaluate the multi-model ensemble (MME) based prediction based on eight coupled general circulation models (CGCMs) which are currently semi-operational at the Asia-Pacific economy Cooperation Climate Centre (APCC). As seasonal prediction is inherently probabilistic, an effort has been done to convert the MME-based prediction in a probabilistic manner. A rigorous examination of the performance of individual CGCM is done for JJAS (based on May initial condition) 24 years study period (1982-2005) before the development of prediction model. In summary, the following are the major conclusions of the study.

- Assessment of those CGCM revealed that the prediction skill of Indian summer monsoon rainfall largely differs from individual CGCM in spatial and temporal scales. Due to their inherent bias, CGCMs have varying skills in predicting the dominant characteristic of observed rainfall. Moreover, models are strongly coupled with the ENSO phenomena but in recent years the association between Indian monsoon rainfall and ENSO is much weaker [5]. This may be one of the possible reasons behind the poor performance of the skill of prediction by CGCMs.

- MME can be used as statistical post-processing to obtain an optimum prediction by a combination of all these available CGCMs. Two different MME schemes, viz., SCM and SE are deployed on the bias-corrected GCMs and further evaluated in a cross-validation manner. It is noticed that the skill in northern and some parts of central to southern India by SCM is achieved since most of the individual member models have positive skill scores over the same region.
- Noticeably, the skill of that region that was obtained from the SCM scheme is enhanced in the SE method which is based on the multiple regression techniques where weights are assigned to the models based on their skill in the training period. Though most of the part of the country is improved in SE methods compared to SCM, however, the maximum improvement is coming from the eastern part and north-east part of the country (from negative skill in SCM to positive and significant skill in SE). Moreover, the performance of SE methods is also superlative than SCM as the correlation coefficient of SE (0.42) is far better than CC of SCM (0.36) with observation. The potential improvement of SE is also found in terms of mean ACC values which are 0.53 and 0.88 respectively for the SCM and SE.
- Particular attention of this study is the probabilistic prediction based on the deterministic forecast. Therefore, both the MME-based prediction is individually used as a potential predictable signal for tercile category (viz., above normal (AN), near normal (NN), or below normal (BN)) based probabilistic prediction by parametric ways. After a critical examination of probabilistic prediction based on ROCS and RPSS, it can be concluded that both the prediction (based on SCM and SE respectively) are superior to climatological prediction (equal probability of each category). It is also noticed that the probabilistic skill enhanced in SE is similar to in the deterministic prediction skill compared to SCM.

Based on the above discussion, this present study concludes that regression-based MME is better than simple MME techniques for the prediction of ISMR in a deterministic as well as probabilistic manner. Although, it may be noted that the total period of data used in this study is from 1982 to 2005 which may not be very large for the stable estimation of regression coefficients. Another concerning issue is the prediction skill of weighted MME is improved when the higher quality training dataset is organized for the evaluation of the multi-model bias statistics.

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