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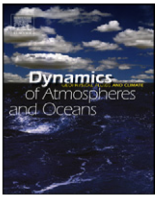

On the predictability of Indian summer monsoon rainfall in general circulation model at different lead time

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ABSTRACT

The objective of this present study is to analyze the predictability of all India summer monsoon rainfall (AISMR) and its dependence on lead time using general circulation model (GCM) output. For the purpose, six GCMs for the hindcast run from 1982 to 2008 are used at three different initializations viz. April (lead 2), May (lead 1), and June (lead 0) for seasonal mean rainfall of June–July–August–September (JJAS). Among these models, four of them are the coupled ocean–atmosphere GCMs (CGCMs) and the remaining two are the atmospheric GCMs (AGCMs). The analysis is made on the basis of statistical measures of predictability including climatology, interannual variability, root mean square error, correlation, signal to noise ratio, potential model predictability and index of agreement. On the basis of these measures it is found that all the GCM having the minimum prediction skill is at lead 2 compare to lead 1 and lead 0. It is also noticed that higher predictability in the lead-1 forecasts is found in coupled models whereas, the predictability of atmospheric models exhibit high in lead 0. Rather than rainfall, teleconnection of rainfall with large scale features (such as sea surface temperature, zonal wind at 850 hPa) and monsoon dynamic index (Indian monsoon index (IMI)) are also examined in GCMs. The results depicted that there is not much variation in the teleconnection pattern in two leads (lead 0 and lead 1) whereas; the dynamic index being predicted closer to the observed value

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at lead 1 in the CGCMs. The GCMs are also examined during four typical monsoon (excess/deficit) years, among which 1983 and 1988 are excess and 1987 and 2002 are deficit. Results indicate that the coupled (atmospheric) models capture the extreme rainfall signal in lead 1 (lead 0). The probabilistic prediction skill of GCM predicted rainfall is also evaluated which supports our initial analysis and results.

1. Introduction

The predictability of atmospheric variables for a longer time period (season as a whole) highly depends on the slowly varying boundary conditions that may provide its predictability (Charney and Shukla, 1981). Some studies have shown that the potential predictability of Indian summer monsoon rainfall (ISMR) not only depends on slowly varying surface boundary conditions, but also depends on internal dynamics, such as the eastward propagating Madden Julian oscillation (MJO) and the northward propagating intraseasonal oscillation, with a period from 30 to 60 days (Goswami, 1998; Ajaya Mohan and Goswami, 2003; Goswami and Xavier, 2003). Besides all the limitations prediction of summer monsoon rainfall is in focus ever since the pioneer works of Walker (1924). In the current scenario, India Meteorological Department (IMD) is responsible for issuing the operational forecast. The operational forecast is given in two phases viz. forecast issued in the middle of April using an eight parameter regression model and in the end of June using a 10 parameter regression model. These statistical models are based on the relationship of ISMR with several atmospheric variables like Nino 3.4 SST anomaly, North Atlantic surface pressure anomaly, Equatorial SE Indian Ocean SST anomaly, etc. (Rajeevan et al., 2006a,b). The predictability of these statistical models is limited due to variation in the relationship between All India Summer Monsoon Rainfall (AISMR) and most of the atmospheric parameters used in these statistical models (Mooley and Munot, 1993; Kumar et al., 1999).

On the other hand with the availability of the state-of-the-art general circulation models, some studies have investigated the predictability of ISMR using these dynamical models (Kang et al., 2004). These dynamical models are somewhat able to handle the linear and non-linear interactions of the atmosphere (van Oldenborgh et al., 2005). On the other hand, there are some cases where the statistical models have better prediction skill as compared to dynamical models (van Oldenborgh et al., 2005). The issue of predictability of south Asian summer monsoon precipitation is carried out in a recent study by Sohn et al. (2012). They examined long lead prediction skill of precipitation using statistical and dynamical models and found that the statistical forecast are more sensitive to the ENSO phase. However, the potential of multi-model ensemble based on dynamical models is observed during neutral years of ElNino which results in the better performance of these models. In view of the limitations and importance the present study is focused to analyze the predictability of dynamical models.

In the context of dynamical models Kang et al. (2004) evaluated the potential predictability using the ratio of external and internal components of seasonal variability. The external component in GCMs is assumed to be the variance of the ensemble mean, whereas the variance of noise (difference between individual member and ensemble mean) is termed as the internal component. The ratio of these two components is defined as the signal-to-noise ratio (SNR). In view of SNR, higher predictability is observed over tropical region. On the other hand, the predictability over the Indian domain was found very low. Phelps et al. (2004) have shown that atmospheric initial conditions did not play any important role in the predictability of 200-hPa geopotential heights on monthly or seasonal scales. Reichler and Roads (2005) evaluated the influence of initial conditions on several atmospheric variables including the precipitation for winter months. This study concludes that the initial conditions have an influence for the first three weeks and with some influence up to eight weeks. Specifically, the role of initial condition on the predictability of precipitation was strongest over Indian Ocean. Study by Chen et al. (2010) showed that the role of atmospheric initial conditions on the predictability of monthly mean temperature. They examined the prediction skill of National Centers for Environmental Prediction (NCEP) operational coupled model Climate Forecast System (CFS) at different lead times (initializations). They found that the lead 0 (same month atmospheric initial conditions) forecast skill of the model was highest and that the skill decreases rapidly over the extra tropics, while over the tropical region the skill decreases more slowly. As far as the summer monsoon season is concerned (JJA) in the tropical region the skill was found to be highest at lead 0. Peng et al. (2011) studied the impact of different initial conditions in coupled model for seasonal predictability of atmospheric variables. They analyzed that there are large spread in the ensemble members even for short lead time predictions. Also, for the SST prediction the signal to noise ratio remains high even for 6-month lead forecast.

Plethora of studies has shown the decrease in predictability of atmospheric parameters with longer lead time all over the globe. In other words, the seasonal predictability is generally found high at lead 0 (same month initial conditions) as compared to longer lead times whereas, it not is the case for every region. The study by Peng et al. (2011) described the lead time dependency of predictability over tropical region which also explains the degradation in signal to noise ratio for tropical SST and zonal wind at 800 hPa. The skill for precipitation is found almost constant at lead 0 and lead 1 over the tropical band. In the context of ISMR, no such study is available on lead time dependency of predictability.

In view of the above, the main focus of the present study is to examine the dependence of predictability of AISMR at different lead time in GCMs. For the purpose, six of the general circulation models (GCMs) are used among which two are the atmospheric GCMs (AGCMs) and four of them are coupled ocean–atmosphere GCMs (CGCMs). The predictability of JJAS rainfall at all three leads, i.e. initialized in the month of April (lead 2), May (lead 1), June (lead 0) is examined for all of the GCMs separately. These three initializations are considered for the evaluation of predictability at different leads.

The flow of this article is summarized here: Section 2 deals with the details of data sets and analysis procedures. The results are discussed in Section 3 and finally the entire study is summarized in Section 4.

2. Data and analysis procedures

Inherent components of the GCM along with the observed rainfall data are discussed in this section. Further, the details of various skill measures and analysis procedure which are used in this study are discussed.

2.1. GCM products and observed data

As discussed above the present study deals with predictability of AISMR in six of the GCMs initialized in three different lead times that are lead 2, lead 1, and lead 0. The lead 2 prediction for JJAS implies GCM's run using the initial conditions of April. Similarly, lead 1 and lead 0 corresponds to the GCM's initialization in the month of May and June respectively. Among these GCMs four of them are the CGCMs and the other two are the AGCMs as described above. Rainfall values from these GCMs are extracted for June–July–August–September (JJAS) for 27 years of the hindcast run (1982–2008). For the analysis purpose, other atmospheric parameters like sea surface temperature (SST), zonal wind at 850 hPa (U850) predicted by GCMs are also used in the study. Brief description regarding the GCMs used in the present study is given as below.

The first GCM used in the study is NCEP Climate Forecast System version1 (referred as CFS) which is a fully coupled atmosphere–ocean GCM (CGCM) (Saha et al., 2006). The atmospheric component is the NCEP Global Forecast System (GFS) and the oceanic component is Geophysical Fluid Dynamics Laboratory (GFDL) Modular Ocean Model version 3 (MOM3). The model runs is 9-month integration (9-month lead) initiated from 15 initial conditions centered on the pentad ocean initial condition. The ocean initial conditions are taken from the NCEP Global Ocean Data Assimilation (GODAS).

Rest of the coupled models are the product of International Research Institute for Climate and Society (IRI), Columbia University, USA. None of the IRI models are initialized using real-time land or atmospheric conditions. These variables are initialized from the long historical runs of the AGCM driven with observed SSTs, therefore it is essentially random. One of the coupled GCM from IRI is ECHAM4.5GML (referred as GML) which is a semi-coupled model having the European Centre-Hamburg Model (ECHAM version 4.5) as an atmospheric component which is coupled to slab-ocean mixed layer model with CFS-predicted SSTs prescribed over the tropical Pacific basin. In this case, forecasts are run for each calendar initial condition month for 12 ensemble members and having duration of eight months (Roeckner et al., 1996; Lee and De Witt, 2009). The other two products of IRI coupled models are the ECHAM4.5MOM3AC1 (referred as MOM3AC1) and ECHAM4.5MOM3DC2 (referred as MOM3DC2). Both the coupled models are having the same atmospheric (ECHAM4.5) and oceanic component Modular Ocean Model (MOM3). Although, the atmospheric and oceanic components are similar in both the GCMs but, the coupling system is different as MOM3AC1 is an anomaly coupled GCM while MOM3DC2 is a directly coupled (Roeckner et al., 1996; Pacanowski and Griffes, 1998).

The two atmospheric GCMs used in the study are also the product of IRI, Columbia University, USA. The atmospheric model namely ECHAM4.5casst (referred as ECHcasst) is already stated before which is taken as the atmospheric component in the IRI coupled GCMs. The retrospective forecasts are produced using the ECHAM4.5 AGCM, which is forced with Constructed Analogue (CA) SST (Roeckner et al., 1996; Van den Dool, 1994). On the other hand, another GCM used in the present study named as ECHcfssst is also having the same atmospheric component in which the CFS SST forecasts (Saha et al., 2006) is prescribed in the central and eastern Pacific.

The data description say though, the atmospheric initial condition is random according to their calendar date except of the coupled model CFS whose initial condition is fixed. However the coupling system of different models differs from each other which may affect the predictability of AISMR in different GCMs. All the above described GCMs are downloaded from IRI data library (http://iridl.ldeo.columbia.edu/). The details about the GCM's resolution and the ensemble members are summarized in Table 1. Rainfall, sea surface temperature (SST) and zonal wind at 850 hPa of above mentioned GCMs are used in the study.

The high resolution ($1^\circ \times 1^\circ$) gridded rainfall data based on 2140 rain gauge stations with minimum 90% data availability provided by India Meteorological Department (IMD) are used in this study as observational reference. The detailed methodology for the preparation of gridded data from the rain gauge stations has been discussed in Rajeevan et al. (2006a,b). The optimum interpolated SST (Reynolds and Smith, 1994) is used as observed reference of sea surface temperature while and the zonal wind data obtained from NOAA NCEP-NCAR reanalysis data sets (Kalnay et al., 1996) for this study.

2.2. *Measures for predictability*

In this section, some of the skill matrices which are used to examine the predictability of above stated GCM's output for AISMR are discussed. At first the climatological bias of each GCM is calculated to measure the difference of the model (ensemble mean) predicted rainfall climatology from observed climatology. It represents the model error of simulating the long term characteristic of observed rainfall. It is already stated that AISMR is highly variable from year to year. To quantify the model's variability we calculated interannual variability (IAV) of each GCM. Actually IAV is the standard deviation of GCM rainfall over year by pooling the entire ensemble member.

Further, the GCMs are analyzed with use of some of the predictability measures which are described as below.

2.3. *Root mean square error (RMSE)*

The root mean square error (RMSE) is a measure for the evaluation of error between predicted and observed values and is defined as below

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(P_i - O_i)^2}{n}} \qquad (1)$$

Table 1
GCM outputs used in the study.

Model	Resolution	AGCM	OGCM	Ensemble member	Reference
CFS	(T62) $\sim 1.8^{\circ} \times 1.8^{\circ}$	GFS(2003 version)	MOM3	15	Saha et al. (2006)
ECHAM-MOM3AC1	(T42) $\sim 2.7^{\circ} \times 2.8^{\circ}$	ECHAM4p5	MOM3 (anomaly coupled)	24	Roeckner et al. (1996), Pacanowski and Griffes (1998)
ECHAM-MOM3DC2	(T42) $\sim 2.7^{\circ} \times 2.8^{\circ}$	ECHAM4p5	MOM3 (direct-coupled)	12	Roeckner et al. (1996), Pacanowski and Griffes (1998)
ECHAM-GML	(T42) $\sim 2.7^{\circ} \times 2.8^{\circ}$	ECHAM4p5	CFS-predicted SSTs prescribed over the tropical Pacific basin (semi-coupled)	12	Roeckner et al. (1996), Lee and De Witt (2009)
E4p5 (casst)	(T42) $\sim 2.7^{\circ} \times 2.8^{\circ}$	ECHAM4p5	Constructed Analog SST	24	Roeckner et al. (1996)
E4p5-CFS	(T42) $\sim 2.7^{\circ} \times 2.8^{\circ}$	ECHAM4p5	CFS-predicted SST	24	Roeckner et al. (1996)

Here, P is the predicted value and O is the observed value. The RMSE is evaluated between the observed rainfall with the ensemble mean of GCM predicted rainfall.

2.4. Correlation coefficient (c)

Correlation coefficient is one of the basic measures for the evaluation of prediction skill. Therefore, in order to quantify the predictability correlation coefficient measure is used which is defined as below

$$C = \frac{Cov(P, O)}{\sqrt{Var(P)Var(O)}} \tag{2}$$

Here, the covariance between the two series is represented as $Cov(P,O)$ and the variance of individual series is denoted by Var. The correlation between observed rainfall and ensemble mean of each GCM is calculated in this study.

2.5. Signal-to-noise ratio (SNR)

Signal-to-noise ratio (SNR) is defined as the ratio of external and internal variability is another kind of measure of predictability in GCM. The external component is obtained as the variance of the ensemble mean and the internal component can be evaluated as the variance of noise (difference of individual members and ensemble mean). Therefore, SNR can be defined as

$$\mathrm{SNR} = \frac{\mathrm{Variance(ensemble\ mean)}}{\mathrm{Variance(noise)}} \tag{3}$$

2.6. Potential predictability measure

The potential predictability which is a well-defined measure of predictability (Kharin and Zwiers, 2003; Weigel et al., 2009) is defined as below

$$\rho_{pot} = \frac{1}{M}\sum_{i=1}^{M} \rho(P_i, O) \tag{4}$$

where $\rho(P_i, O)$ is the correlation coefficient between the ith ensemble member (f_i) and the observations (O) and M is the ensemble size (Weigel et al., 2009).

2.7. Index of agreement (d)

Some of the study (Willmott, 1982) mentioned that the correlation kind of skill measures is often misleading when a comparison is made between the predicted and the observed values. These measures are not related directly to the accuracy of prediction (Willmott, 1982) and they also have the limitation that they are not bounded and unstable for very small (near zero) climatology of observation. Further, Willmott (1982) suggested a new skill metrics called "index of agreement (d)" which is stated as below

$$d = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \tag{5}$$

Here, P_i and O_i are the predicted and observed variables. This skill metric is relative and bounded between 0 and 1 ($0 \le d \le 1$) where closer the value to 1 indicates the more efficiency of the forecast. This skill measure is also evaluated between the observed rainfall values with the ensemble mean of GCM predicted rainfall.

The above stated skill measures are evaluated for all GCMs in order to enlighten the issue of dependency of predictability at different leads.

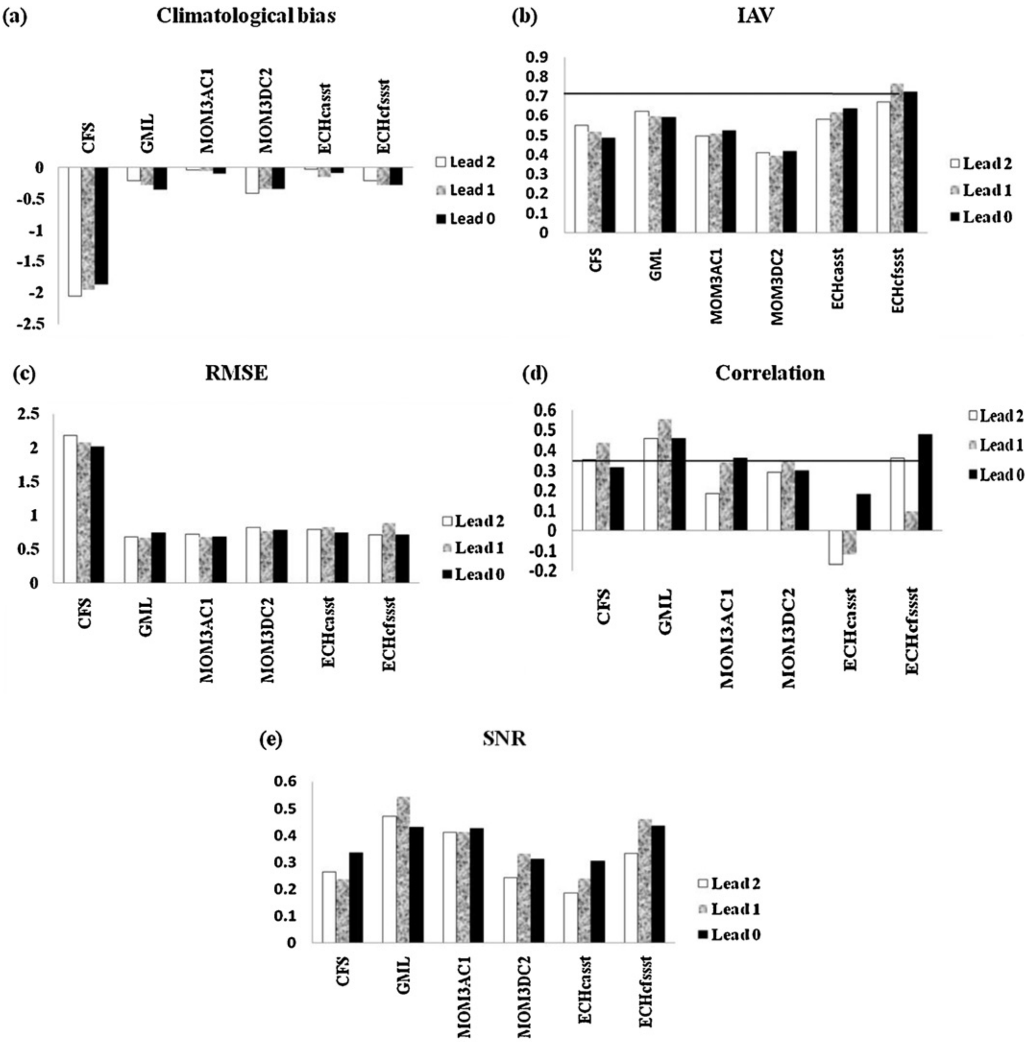

Fig. 1. Skill of the GCMs in April start (lead 2), May start (lead 1), June start (lead 2) on the basis of (a) Climatological bias in mm/day, (b) IAV in mm/day, (c) RMSE in mm/day, (d) correlation, (e) SNR (signal to noise ratio).

3. Results and discussion

As discussed above, the main focus of the present study is to evaluate the predictability of AISMR in GCMs at different lead time. For the analysis purpose, lead-2 (April start), lead-1 (May start) and lead-0 (June start) GCM prediction for JJAS at all India level is considered. The results related to the predictability measures are summarized as below.

3.1. Model biases at different lead times

To begin with, the climatological bias and interannual variability (IAV) is calculated for all of the GCMs at three lead times and shown in Fig. 1(a and b). It is already being discussed in some of the studies (Kang et al., 2004; Acharya et al., 2011; Kulkarni et al., 2012; Singh et al., 2012) that the

GCMs are able to capture the observed rainfall climatology at all India level to some extent. Therefore, climatological bias at all leads, for both the coupled and the atmospheric models is small except for CFS which exhibits large negative climatological bias at all leads (Fig. 1(a)). The large bias might be related to the bias from initial conditions as CFS is the only coupled GCM with real time initial conditions which also depends on the rainfall analysis used as observation. On the other hand, no such significant difference is observed in the prediction of climatology at different leads.

The model predicted IAV at all leads with the observed value are shown in Fig. 1(b). The IAV is evaluated by pooling all members of each GCM which contains the external and internal variability as described above. The solid black horizontal line in the figure represents the observed IAV of rainfall (0.74 mm/day) and bars representing the IAV for GCMs at each leads. It is seen that GCMs underestimates the observed IAV at all leads having negligible variation with lead time. The skill measure representing the error with respect to observed values viz. root mean square error (RMSE) is represented in Fig. 1(c). The subplot clearly shows large amount of error at lead 2 as compared to lead 0 and lead 1 in most of the GCMs. In coupled GCMs less amount of RMSE is observed at lead 1 whereas, less RMSE at lead 0 is observed in the case of atmospheric GCMs. Although, there is not much variation in RMSE at all leads similar to climatological bias whereas CFS exhibits maximum amount of error.

3.2. Predictability in GCMs at different lead times

The inherent bias in GCMs does not show noticeable changes in predicting the summer monsoon rainfall at all India level in terms of climatology, IAV and RMSE. Therefore, some other skill scores as described in Section 2.2 are evaluated which may enlighten on the predictability issue and its dependence on lead time in GCMs. For this purpose, the correlation is evaluated for GCM's forecast for JJAS and shown in Fig. 1(d). From the figure, it is clear that the skill for seasonal forecast in almost all GCMs (except CFS, GML, ECHcfssst) is found minimum at lead 2 (April start). Four of the GCMs used in the study are having significant (95% confidence interval) correlation skill in lead 1 (May start JJAS) which is mainly the coupled models. Among these CGCMs three of them are having highest skill at the same lead except MOM3AC1. On the other hand, significant skill is obtained in only three of the GCMs at lead 0 with the atmospheric GCMs having maximum skill in lead 0 (June start JJAS). Therefore, the correlation skill is found to be higher in lead 1 in majority of the CGCMs.

In support of the above analysis one of the basic measures of predictability is also evaluated that is the signal to noise ratio (SNR), which is defined as the ratio of external and internal component. In GCMs, the ensemble mean of all members is treated as the external component whereas, the deviation of members with the ensemble mean is treated as the internal component. If the value of SNR at a particular location is large (greater than 1) the signal is more as compared to noise which corresponds to higher potential predictability. In this study, SNR is evaluated at all leads which are shown in Fig. 1(e). From the figure, it can be observed that SNR for all the GCMs is relatively low, in the range 0.2–0.5 at all leads The only GCM showing large SNR (greater than 0.5) is GML at lead 1 which also exhibits maximum correlation at the same lead. On the other hand, two of the coupled GCMs other than GML shows high signal at lead 1 except of MOM3AC1 which shows maximum signal at lead 0 along with the atmospheric GCMs. An important point coming out from this analysis is that the atmospheric models which are having very low or sometimes even negative correlation values show high SNR. The high SNR indicates that the individual members are close to the ensemble mean of the GCM which reflects in high signal. On the other hand, the case when this ensemble mean behaves in the other direction as compared to the observation, the correlation may worsen.

The predictability measures as obtained from the above analysis suggest that the GCMs exhibit maximum skill either in the forecasts initialized in the month of May or in the month of June. In view of Fig. 1, the maximum prediction skill is observed at lead 1 in CGCMs whereas, at lead 0 in AGCMs therefore, further the analysis is focused on these two leads that is, lead 1 (May start) and lead 0 (June start). As discussed above, it is considered that mainly coupled model (CGCM) having higher skill in lead-1 and atmospheric model (AGCM) having higher skill in lead 0 on the basis of correlation. In the present study, in view of the importance of index of agreement (d) the corresponding skill metric is calculated for each GCM in these two leads (May start and June start JJAS) which is represented in Fig. 2(a). The figure shows that the skill is found minimum for the atmospheric model ECHcasst. On

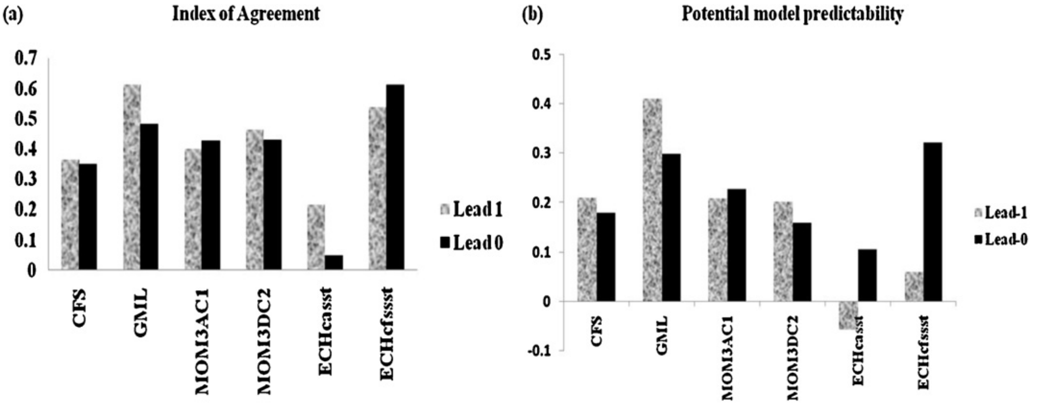

Fig. 2. Predictability measure of GCM in terms of (a) index of agreement and (b) the potential predictability.

the other hand, the coupled models exhibit maximum skill in terms of index of agreement (greater than 0.3). In view of our comparison of the model's ability to predict ISMR at an appropriate lead the index of agreement shows high value as compared to lead 0 for the coupled models having high statistical skills at the same lead. The skill for the anomaly coupled model MOM3AC1 is also supporting its behavior as observed above. The atmospheric GCM, ECHcfssst shows the high value for this index at lead 0 (0.53).

As discussed in the above section the potential predictability measure is another kind of measure which is used in the present study to strengthen the findings as obtained above. The potential predictability of the models (Fig. 2(b)) clearly shows that the predictability of coupled models is higher in lead-1 whereas, the atmospheric models show more predictability in lead-0. For example, the coupled models like CFS, GML and MOM3DC2 having higher ρ_{pot} in lead-1 while, ρ_{pot} of ECHcasst and ECHcfsst is higher in lead-0.

The results based on all the above statistical measures of predictability suggests that AGCMs are having higher predictability in lead-0 (June start) whereas, CGCMs in lead-1 (May start). These statistical measures are statistically significant as defined so one can rely on the conclusions as obtained from the analysis. Further, examination of some dynamic features is calculated in the GCMs in order to strengthen the analysis and results. For the purpose, large scale features like sea surface temperature (SST) and zonal wind at 850 hPa predicted by GCM in these two leads (i.e. lead 1 and lead 0) are analyzed.

3.3. SST teleconnection patterns

Fig. 3 shows the observed pattern for the teleconnection between AISMR and SST that is the correlation between SST (globally) and all India average rainfall. The significant correlation values (at 95% significance level) are shaded in Fig. 3. The solid contours in the figures show the positive correlations and the dashed contours correspond to negative correlation values. Some of the previous studies like Kumar et al. (1999), Mooley and Munot (1993) have examined the weakening of the teleconnection between AISMR and ENSO especially the NINO3 index. They have analyzed that in recent decades the relationship is decayed and the ENSO do not have any significant effect on AISMR. In this study, the figure supports those findings. Some negative patches are found in the Indian Ocean whereas, high negative correlation values are found from 30°S to 60°S. In the Western Pacific Ocean, the negative correlation is found from 0°N to 10°N. This teleconnection pattern indicates that the temporal variability of AISMR does not have a strong dependency on the slowly varying boundary conditions like SST from pacific.

The similar teleconnection are calculated between model predicted AISMR and SST for two initializations (lead-1 and lead-0) (Figs. 4 and 5). Fig. 4 shows the predicted teleconnection pattern at lead

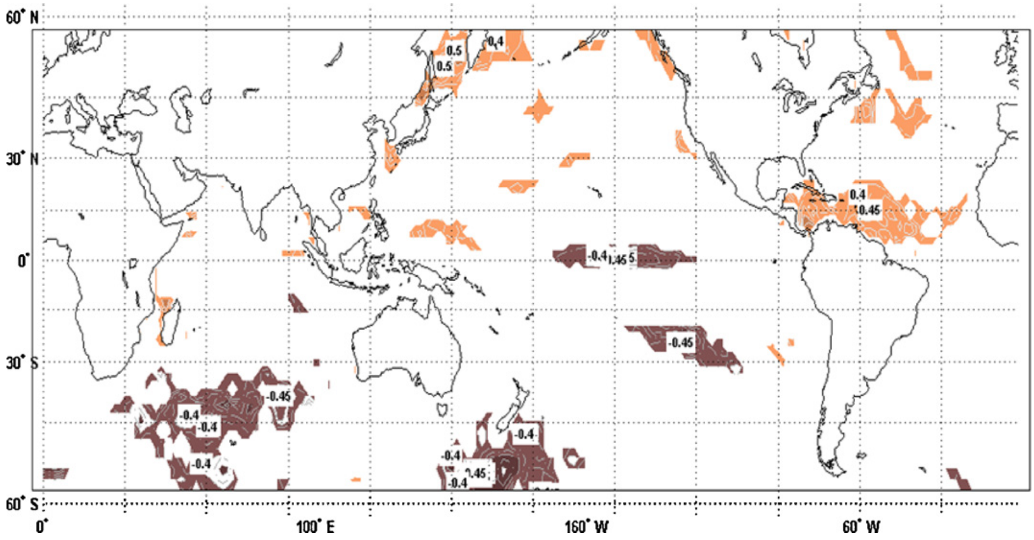

Fig. 3. The observed correlation pattern between SST and AISMR.

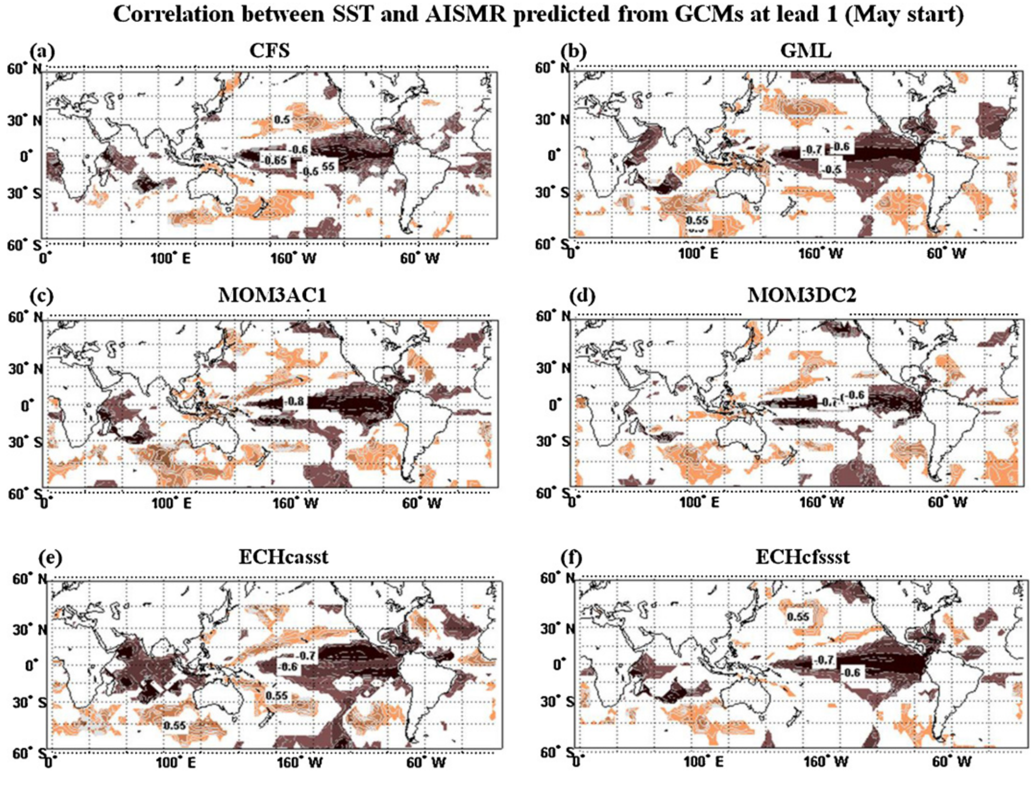

Fig. 4. The correlation pattern predicted by GCM at lead 1 (May start) for SST and AISMR.

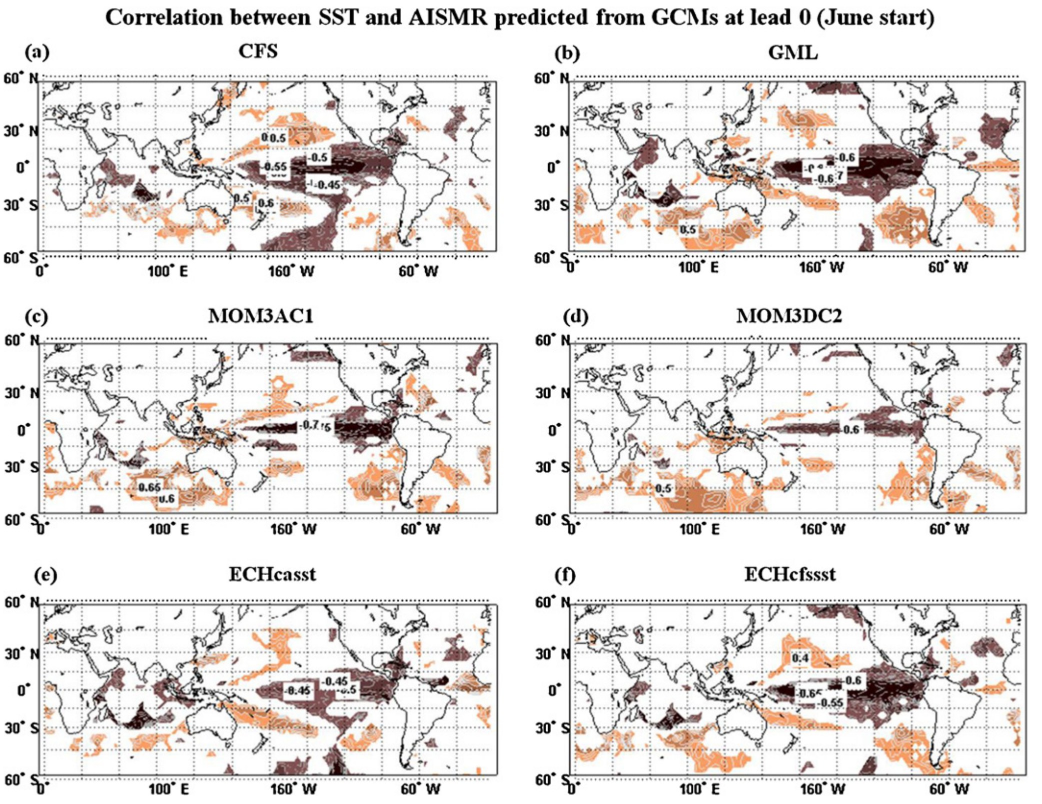

Fig. 5. Same as Fig. 4 but for lead 0 (June start).

1. Subplots (a) to (d) correspond to the coupled models whereas, subplots (e) and (f) to the atmospheric models. These teleconnection patterns are evaluated using the ensemble mean of SST at all grid points with the ensemble mean of model predicted AISMR considering the fact that averaging of ensemble member reduce the variability among the members. It can be clearly noticed that all the GCMs used in the present study overestimate the strength of SST teleconnection pattern with AISMR at both leads. The pattern for the forecast initialized in the month of May for the coupled models are showing very high correlation values over the NINO areas. In particular, the coupled models CFS and GML are showing very high correlation values over these areas with very high over estimation over the Indian Ocean. The other two coupled GCMs MOM3AC1 and MOM3DC2 are also showing almost similar kind of teleconnection pattern. These two models show very low correlation over the Indian Ocean which is also seen in the observed figure. As far as the atmospheric models are considered ECHcasst is not able to predict the observed teleconnection. The AGCM, ECHcfssst highly overestimates the correlation over the western pacific as well as over the Indian Ocean.

The correlation of AISMR with SST averaged in two boxes of Indian Ocean viz. West Indian Ocean 50E–70E, 10S–10N (WIO) and East Indian Ocean from 90E–110E, 10S–0 (EIO) are evaluated for both the lead times (i.e. lead 1 and lead 0) and presented in Fig. 6. From the figure (Fig. 6(a)), it can be observed that the correlation in observation over WIO is found positive but not significant (0.23). On the other hand, if the GCM's prediction is considered over the WIO box none of the GCM is able to predict correctly even the sign of relationship. Most of the GCMs prediction is found in opposite direction which is also discussed above in the spatial pattern for SST teleconnection. The second subplot (Fig. 6(b)) shows the relationship for SST averaged over the box of EIO. Over the EIO, observed correlation is found to be in negative direction with very less magnitude. In the same figure, the GCMs prediction shows very

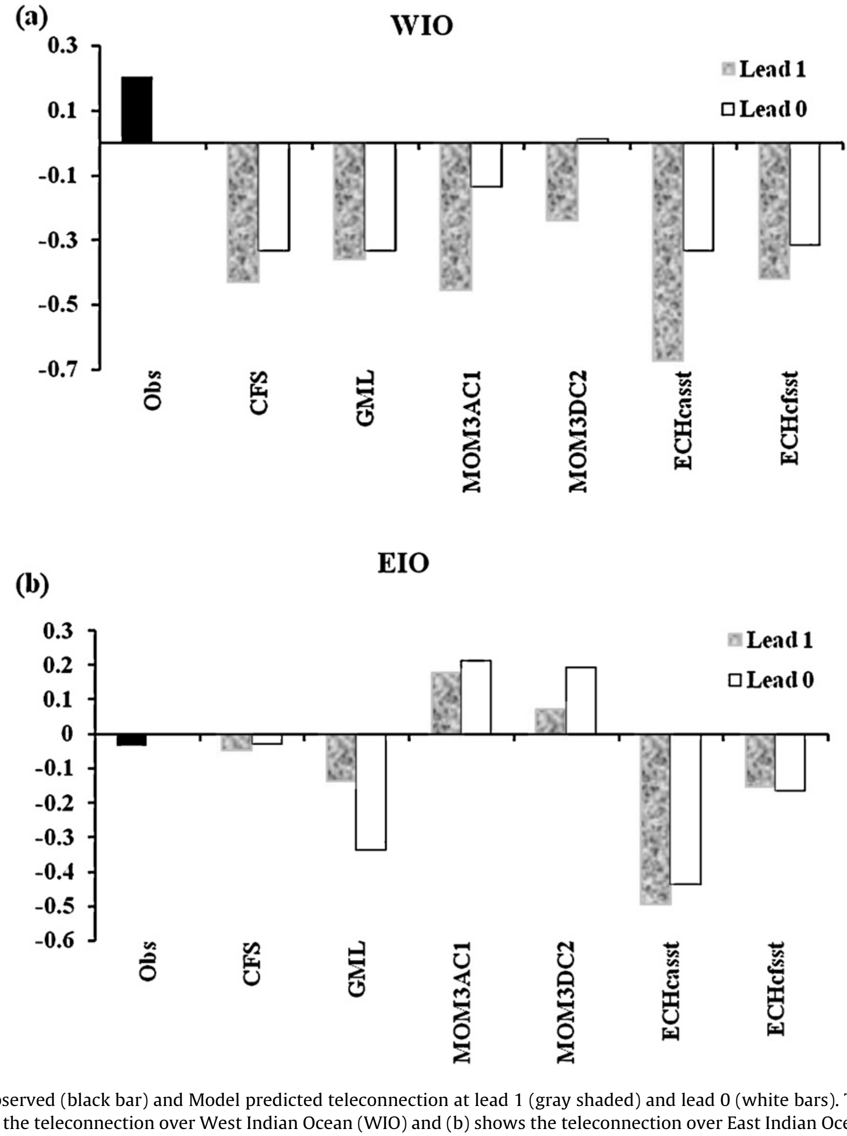

Fig. 6. Observed (black bar) and Model predicted teleconnection at lead 1 (gray shaded) and lead 0 (white bars). The subplot (a) shows the teleconnection over West Indian Ocean (WIO) and (b) shows the teleconnection over East Indian Ocean (EIO).

high and significant correlation as compared to observation. Over the EIO, the coupled GCM, CFS is able to predict observed relationship whereas other coupled models like MOM3AC1 and MOM3DC2 are having opposite relationship. Therefore, it can be seen that none of the GCM is able to predict observed correlation over the WIO and EIO which is highly over estimated in the opposite direction in most of the GCMs. The results clearly indicate that none of the GCMs is coupled properly over the Indian Ocean.

Similarly, the model predicted correlation pattern initialized in the month of June (lead 0) is shown in Fig. 5. Overestimation of teleconnection prediction is also observed in the June start remote forcing. The two figures for the remote forcing also suggests that the overestimation is less for lead 1 for the models CFS, GML, and MOM3DC2 as compared to the teleconnection patterns initialized at lead 0. Other models MOM3AC1 (anomaly coupled), ECHcasst, and ECHcfssst highly overestimates the correlation values over the Pacific Ocean as well as over the Indian Ocean. Although, the teleconnection is over

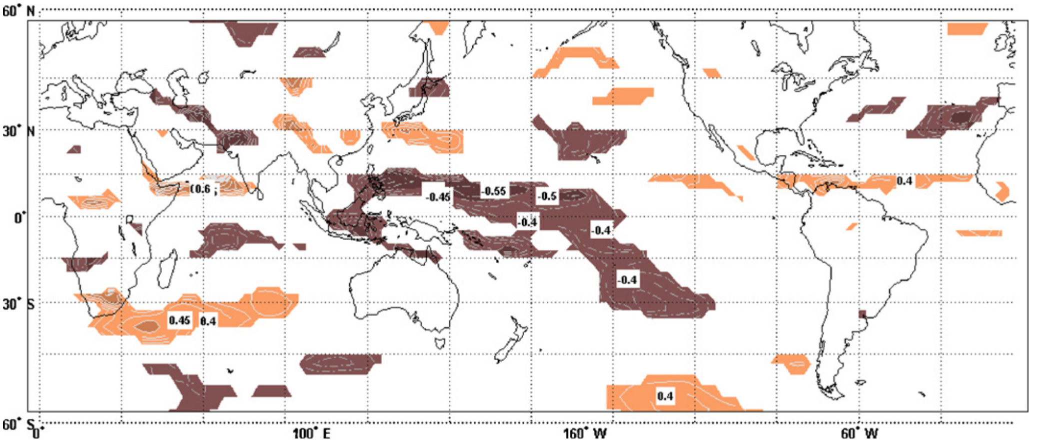

Fig. 7. The observed correlation between observed U850 and AISMR.

estimated over Pacific Ocean but over the Indian Ocean none of the GCMs any model is able to show even same sign of the correlation values.

3.4. Zonal wind at 850 hPa teleconnection pattern

This section deals with the observed and GCM predicted patterns of atmospheric circulation in both lead times. The inter-relationship between the observed zonal wind at 850 hPa and AISMR is shown in Fig. 7. The equatorial zonal wind over the Indian Ocean is negatively correlated with the AISMR whereas, the zonal wind over the Arabian Sea are highly positively related, albeit it over a small region. Strengthened easterly trade winds over the western equatorial Pacific are associated with higher summer monsoon rainfall and vice versa. Similarly, the strong winds coming from the northeast (mid-latitude) interacts with the monsoonal southwesterly winds which is associated with drought conditions for the Indian summer monsoon rainfall.

The corresponding correlations between GCM-predicted AISMR and zonal wind at 850 hPa are plotted in Figs. 8 and 9 for lead-1 (May) and lead-0 (June) starts respectively. Some of the GCMs like CFS and MOM3DC2 are able to simulate the spatial pattern of the observed relationship between AISMR and U850 hPa in the month of May (lead-1). Whereas, in CFS the positive relationship of the zonal wind over Mascarene high (MH) is underestimated, which is significantly related to the strong monsoon circulation as found in the observation. Over the Arabian Sea a small shift is observed in the simulated pattern by CFS, which is related to the Jet stream. On the other hand, the coupled GCM, MOM3DC2 is to an extent able to predict the observed teleconnection pattern over MH. Both the models (CFS and MOM3DC2) overestimate the U850-AISMR relationship over Tibetan High (TH). Although, the teleconnection of zonal wind with AISMR is highly over estimated but the spatial pattern is well captured by almost all GCMs. Similarly, it is observed for the model's prediction at lead 0. The overall pattern is found similar as observed in lead 1 prediction. The overestimation is high in lead 1 as compared to lead 0 for coupled GCMs except of MOM3AC1. MOM3AC1 is able to simulate the overall features of teleconnection pattern in this lead as compared to lead 1. The small differences in the overestimation in teleconnection pattern may influence the predictability.

As a summary, the teleconnection pattern (SST and U850 hPa) is highly overestimated by all GCMs whereas; CFS and MOM3DC2 along with GML are able to predict observed features at lead 1 as compared to lead 0. On the other hand, MOM3AC1 is able to predict observed features at lead 0 with more overestimation at lead 1.

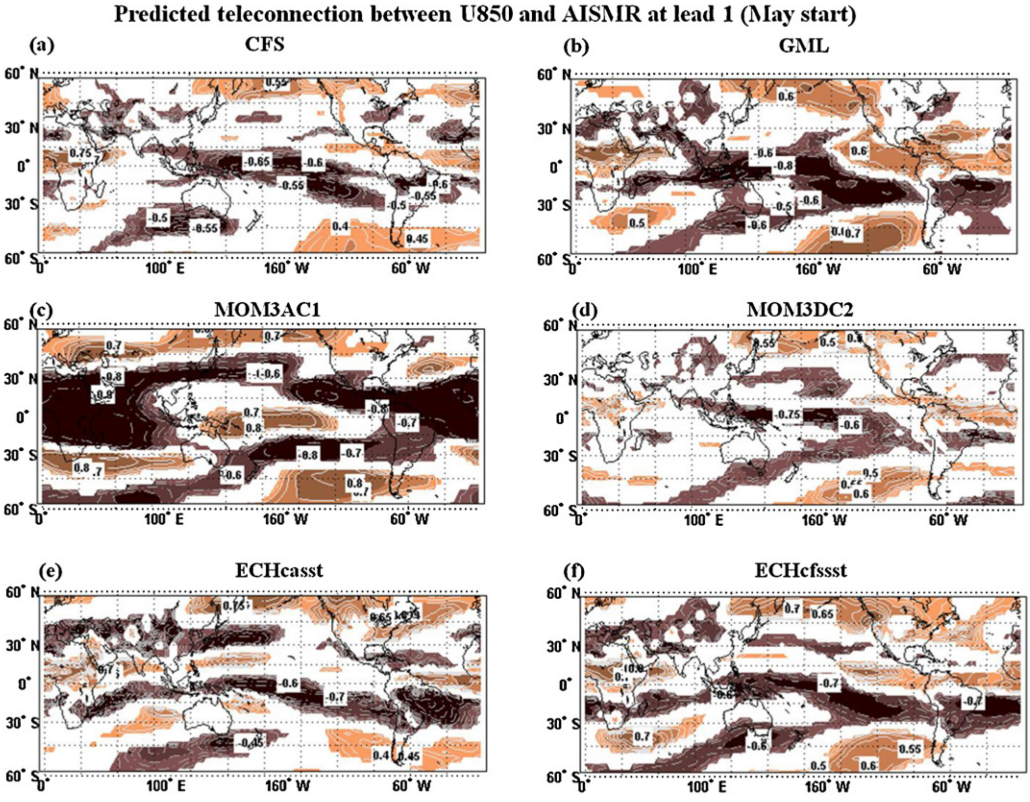

Fig. 8. The GCM predicted teleconnection pattern at lead 1 (May start).

3.5. Dynamic monsoon index

In this section a large-scale index of Indian summer monsoon circulation strength is analyzed. The Indian monsoon index (IMI) defined by Wang et al. (2001) reflects the strength of the monsoon circulation. The IMI is defined as the difference of zonal wind at 850 hPa over the area between 5–15°N, 40–80°E with the northern region which spans from 20–30°N, 70–90°E (Wang et al., 2001). The correlation between GCM's predicted IMI with the observed IMI is presented in Fig. 10(a) at lead 1 and lead 0. The figure clearly shows that except GML which shows highly significant correlation none of the model is able to predict the Indian monsoon wind strength with significant skill. On the other hand, the skill of IMI is found high in the coupled GCMs in lead 1 as compared to lead 0 (non significant). Similarly, the atmospheric GCMs also support our initial analysis which says that the predictability of AISMR is high at the model initialization in the month of June (lead 0).

From the above analysis, it is clear that the large differences in the predictability in these two leads are obtained in one of the coupled model GML and the atmospheric model ECHcfssst. Therefore, the behavior of these two GCMs during the extreme years in lead 1 and 0 is further analyzed in the next section.

3.6. Performance in extreme monsoon year

The performance of the above selected GCMs (GML and ECHcfssst) which are having the same atmospheric component, and have the same SST prescribed over the tropical Pacific. The only difference is that GML is a semi-coupled (coupled to slab-ocean mixed layer model with CFS-predicted

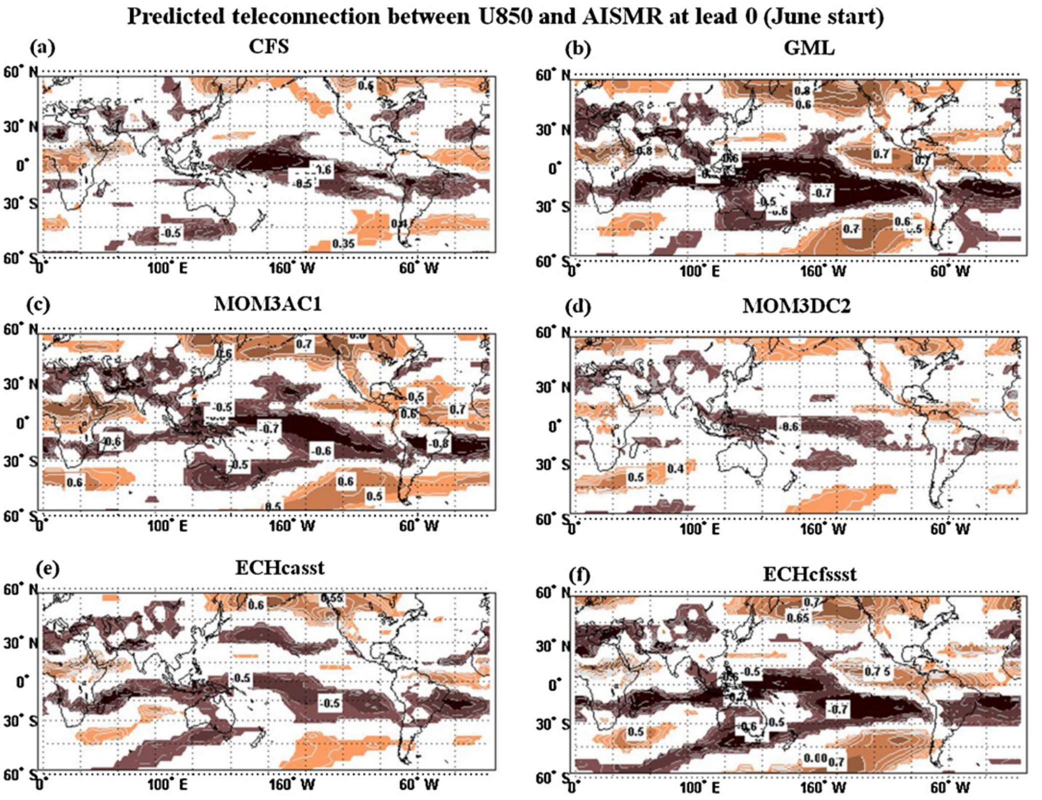

Fig. 9. Same as Fig. 7 but at lead 0 (June start).

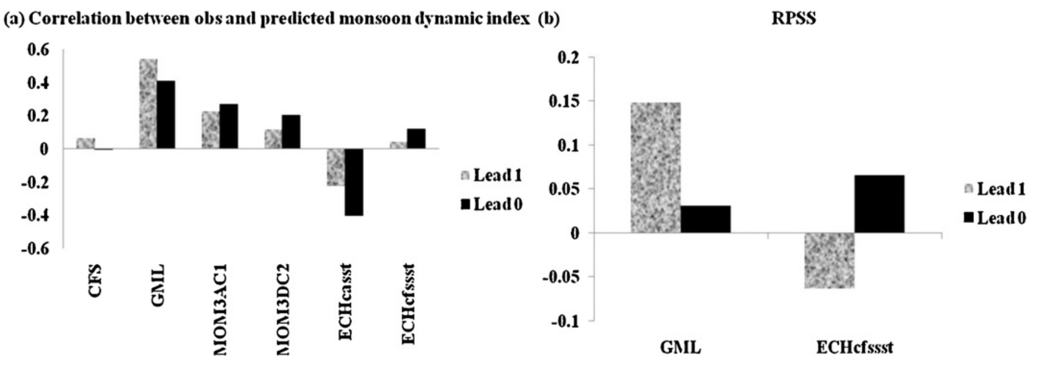

Fig. 10. The subplot in the figure is (a) correlation between observed and predicted monsoon dynamic index and (b) rank probability skill score (RPSS).

SSTs) model where ECHcfssst is an atmospheric model. In this section, the performance of both the models during the summer monsoon deficit/excess years is analyzed. For the purpose, two deficit (1987 and 2002) and two excess (1983 and 1988) years from the period of analysis are selected and represented in Table 2. During the selected deficit years the observed rainfall percentage departure was −13 for 1987 and in the year 2002 it was −21. Both the models show negative rainfall departure in both the leads. The observed magnitude for rainfall departure is much more captured in lead 0 in

Table 2
Performance of two GCMs during the extreme deficit and extreme excess years.

Years	Observed departure (%)	GML		ECHcfssst	
		May start (%)	June start (%)	May start (%)	June start (%)
1987	−13	−17	−14	−8	−15
2002	−21	−8	−6	−1	−9
1983	12	−6	−9	−18	−9
1988	15	2	4	3	7

Table 3
SST difference over the two boxes of Indian Ocean during the extreme deficit and extreme excess years.

Years	Observed SST difference (WIO–EIO)	GML		ECHcfssst	
		May start (%)	June start (%)	May start (%)	June start (%)
1987	−0.60	−0.63	−0.90	−0.49	−0.48
2002	−0.82	−1.2	−1.1	−1.31	−1.27
1983	−0.27	−0.97	−0.79	−0.88	−0.63
1988	−0.71	−1.12	−1.22	−1.29	−1.25

atmospheric model ECHcfssst as shown in the table. On the other hand, the performance of coupled model GML is found better in terms of rainfall departure in lead 1. During the excess years like in 1983 (observed rainfall departure was 12) none of the GCMs is able to predict the observed feature in any of the leads while during the year 1988 (observed rainfall departure was 15) the models are able to capture the observed feature, but the magnitude is very less. These results are supported by the recent study Acharya et al. (2012) in which they found that the GCMs are more efficient in the prediction of deficit as compared to excess years which may be due to the negative bias in the GCMs.

In view of the above discussion, it is already seen that the observed relationship between AISMR and Indian Ocean SST is not captured by most of the GCMs. Therefore, in the present section the role of Indian Ocean SST is analyzed during the extreme monsoon years considered in the study. For the purpose, the difference between the SST averaged over West Indian Ocean (WIO) and East Indian Ocean (EIO) is evaluated in the observation as well as for the two GCMs (Table 3). During 1987, the observed difference in SST over two regions is found to be −0.60 which is predicted well by the two GCMs. The coupled model GML predicted the difference as −0.63 (lead 1) and ECHcfssst as −0.48 (lead 0). During 2002, the difference is a bit over estimated by the two GCMs whereas; during the excess rain years none of the GCMs are able to predict the observed SST difference which is found far away from the observed difference. It is also noticed that the SST over EIO is highly over estimated that results in high negative difference as compared to observation during these years (figure not shown). The over estimation of SST over the Indian Ocean may affect the performance of GCMs during extreme years. It is already seen in Section 3.3 that the GCMs highly over estimate the observed relationship over the Pacific Ocean whereas; over Indian Ocean none of the GCM predicts the observed relationship. Therefore, during the year 1987 which was highly influence by Elnino almost all GCMs predicted the drought conditions at all leads which is not observed during other extreme years. In view of the importance of the probabilistic prediction schemes in the present scenario, the probabilistic skill of these models is also analyzed and discussed in detail in the forthcoming section.

3.7. Assessment of the probabilistic prediction skill in two leads (May start and June start)

From the above discussion it is concluded that among the six models some of them is more skillful in lead-1 (coupled) and some of them in lead-0 (atmospheric), especially, GML shows higher skill in lead-1 whereas ECHcfssst having more skill in lead-0. In the present section, it is quantified that whether the above conclusion is true in the case of probabilistic prediction. The main advantage of probabilistic prediction is that the intrinsic uncertainty of the prediction can be conveyed (Kulkarni et al., 2012). Some of recent study (Kulkarni et al., 2012), discussed the importance of probabilistic prediction for

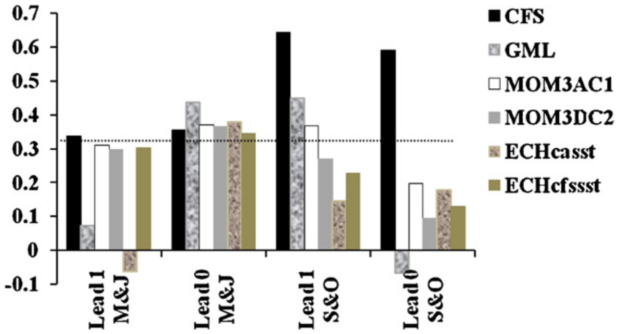

Fig. 11. The correlation skill of GCMs at lead 1 and lead 0 during early (M and J) and late (S and O) monsoon season.

AISMR using GCM outputs. They implemented the parametric method to calculate the uncertainty in the probability prediction for tercile categories viz. below normal, near normal and above normal. The skill of such prediction is measured by rank probability skill score (RPSS) (Weigel et al., 2007). RPSS represents whether a probabilistic prediction is better or worse than a climatological forecast of equal probabilities for each tercile category (i.e. 0.33 of each category). A positive (negative) value of RPSS means that the prediction is better (worse) than the climatological prediction, while zero means the skill of prediction is equal to the skill of the climatological prediction. The probabilistic prediction of the GML (having maximum skill at lead 1) and ECHcfssst (having maximum skill at lead 0) are calculated by the same procedure described by Kulkarni et al. (2012). Fig. 10(b) clearly shows that GML show a very clear increase in the probabilistic skill at lead 1 as compared to lead 0. RPSS value for GML is observed 0.15 at lead 1 and 0.03 at lead 0. On the other hand, ECHcfssst is having maximum probabilistic skill at lead 0 (0.07) which turn out to be negative at lead 0. This analysis clearly indicates that the coupled models having significant deterministic skill at lead 1 are also having maximum probabilistic skill at the same lead.

The above analyses conclude that the GCMs are having variable deterministic and probabilistic skill for the Indian summer monsoon rainfall prediction. The atmospheric GCMs are having maximum predictability at the model's initializations in the month of June whereas, coupled model are having highest predictability at the model's initialization in the month of May. The remote forcing predicted by GCMs does not show any significant changes in these leads may be the coupling of the GCMs is responsible for the dependence of predictability on leads. In other words, the relationship of Pacific Ocean SST with ISMR is decreased in recent decades whereas, the GCMs are still strongly coupled to the SST which may affect the predictability of rainfall. In a recent study, Rajagopalan and Molnar (2012) have shown that the relationship of early/late monsoon rainfall with Pacific SST is increased which may influence the predictability of early/late monsoon rainfall. Therefore, the skill of early/late monsoon season is also evaluated in the present study. For the purpose, average of rainfall during May and June (early monsoon), September and October (late monsoon) is evaluated for the observation which is correlated with that from the GCMs at two leads and the results are presented in Fig. 11. The correlation skill is found significant in almost all GCMs (lead 0) for early monsoon whereas, the skill is not significant in three of the coupled GCMs during late monsoon (lead 1). It is clearly observed from the figure that the skill is even larger than the correlation skill during JJAS which clearly supports the initial study and supports our analysis. In view of the figure, it can be said that the rainfall if associated with Pacific SST exhibits more predictability.

4. Summary and conclusion

The present study is focused to evaluate the predictability of all Indian summer monsoon rainfall (AISMR) in GCMs at different lead time. For the purpose, six of the GCM's output for rainfall for the time period of 27 years starting from 1982 to 2008 is used. The predicted rainfall from the GCM are extracted for June-July-August-September (JJAS) at three lead times viz. April (lead 2), May (lead 1), and June (lead 0). Not much variation is observed in the prediction of climatology, IAV and RMSE at different leads. On the other hand, the predictability on the basis of correlation and signal to noise ratio suggests that the coupled GCMs are having maximum skill at lead 1 (95% confidence interval) that is the GCMs initialized in the month of May whereas, the atmospheric GCMs shows high predictability in lead 0. Another skill measure, which is related directly to the accuracy of prediction and known as the index of agreement is also evaluated which says that the coupled models are having higher value of index of agreement at the model initialization in the month of May and atmospheric model having higher skill in June. Potential predictability of individual model, i.e. the correlation coefficient between the individual ensemble members and the observation also supports our analysis. The conclusions drawn from analysis based on the statistical measures say that the coupled GCMs contains more predictability in lead 1 and the atmospheric GCMs in lead 0. The variation in the predictability at lead 1 and lead 0 is may be due to the coupling of the GCMs. In other words, the coupled GCMs may take more spin up time which may affect the predictability of AISMR as compared to the atmospheric GCM. On the other hand, in the current study, some of the forecast members in lead 0 (initialized in June) contain the partial month information that is June start JJAS contains partial information for the month of June that might result in skill differences between the two leads (lead 0 and lead 1).

Further, the remote response from SST is analyzed at two leads in which high predictability is observed. The findings clearly show that the GCMs contain large bias in simulating the Indian monsoon rainfall response to SST at all leads. But as far as the comparison among the leads is considered the degree of overestimation is less at lead 0 in the atmospheric GCMs; whereas, for the coupled models it is found to be less. It should be noted that there is not much difference in the model simulation of SST response at lead 0 and 1. On the other hand, over Indian Ocean none of the GCMs are even able to predict sign of the observed relationship. Most of the GCMs show opposite correlation pattern over the Indian Ocean.

In order to study the GCM's prediction for monsoon circulation the zonal wind component at 850 hPa is also related with the AISMR and compared with the observed relationship. None of the GCM is found to capture the actual relationship between the AISMR and U850 hPa. In this case, the overestimation is found very high in case of atmospheric models as well as for the anomaly coupled model whereas, the spatial variation is almost captured by the GCMs. To support our analysis the dynamical index (IMI) for the summer monsoon rainfall is evaluated for observation and GCMs. These two time series of dynamic indices are correlated in two leads and found the similar results as obtained from the statistical analysis. The performance of these GCMs is analyzed during the selected extreme deficit/excess years which show that the observed features are well predicted during the deficit years. On the other hand, influence of Indian Ocean SST is also observed on the extreme summer monsoon years. It is seen that if the GCMs are able to predict the SST over WIO and EIO reasonably well the prediction of extreme year rainfall is comparable with observed figures which clearly indicates the importance of Indian Ocean SST for AISMR prediction. The present study is aware of the importance of the probabilistic prediction for the summer monsoon rainfall therefore the probabilistic skill is also evaluated for the two selected GCMs (an atmospheric with one of the coupled GCM) having maximum variation in skill between two leads. The rank probability skill score (RPSS) is found very high for the coupled model GML in lead 1 as compared to lead 0. Also, the atmospheric model is having highest probabilistic skill for lead 0. The deterministic and probabilistic skill measures with the teleconnection pattern suggest that the skill of AISMR is limited due to the strong forcing of SST in GCMs which may provide skill during the seasons highly related to Pacific SST. The hypothesis is well supported by the skill measures during early/late monsoon which are highly influenced by the Pacific SST.

However, the above study is limited due to inadequate length of study period which highly affects the confidence on the statistical skill measures of predictability. With the short length of time period, the above results clearly indicate that the models highly overestimate the observed relationship mainly over the Indian Ocean which is a kind of limitation in GCMs. On the other hand, the GCMs are still showing strong SST forcing over Pacific Ocean which was observed in earlier decades. Therefore, the study suggests improving the dynamical predictions by incorporating these issues will finally improve the predictability of AISMR in GCMs. Due to the limitation of both the model viz. statistical and dynamical model (in terms of GCM)-, the study may extend by combining both for a skillful prediction system.

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