Uncertainty quantification and reliability analysis of CMIP5 projections for the Indian summer monsoon

Agniv Sengupta[1,]* and M. Rajeevan[2]

[1]Department of Civil Engineering, Jadavpur University, Kolkata 700 032, India
[2]Ministry of Earth Sciences, Earth System Science Organization, New Delhi 110 003, India

A 'reliability ensemble averaging (REA)' technique is proposed to provide a quantitative estimate of associated uncertainty range and reliability of future climate change projections for Indian summer monsoon (June–September), simulated by the state-of-the-art Coupled General Circulation Models (CGCMs) under Coupled Model Intercomparison Project 5 (CMIP5). An evaluation of historical as well as future (RCP4.5 scenario) simulations of ten CGCMs in the REA technique projects a mean monsoon warming of 1.215°C with an associated uncertainty range (± $\delta_{\Delta T}$) of 0.22°C, and an all-India precipitation increase by 7.109 mm/month with an associated uncertainty (± $\delta_{\Delta P}$) of 2.592 mm/month for 2021–2050. REA technique also reflects a reduction in uncertainty range compared to simpler ensemble average approach and is characterized by consistently high reliability index in a comparative study with individual CGCMs. These results suggest the viability of REA methodology in providing realistic future Indian monsoon projections by incorporating model performance and model convergence criteria.

Keywords: Climate change projections, monsoon, reliability analysis, uncertainty range.

THE Indian summer monsoon spread over a span of four months (June–September; JJAS), accounting for over 70% of the country's rainfall, is characterized by prominent variability in its onset, withdrawal, amount of rainfall and occurrences of extreme climatic events like floods and droughts. All these consequences have an impact on the country's water resources, agriculture and economy[1]. Temperature is also an important parameter which has an impact on agriculture and water resources. Under the increasing greenhouse gases (GHGs) emission scenario, the Indian monsoon is susceptible to global warming. With increasing anthropogenic activities and industrial revolution, there is much concern about how increase in GHGs may influence the Indian monsoon circulation and rainfall. The only way to understand the impact of global warming on the Indian monsoon and to assess future monsoon climate is to use climate models. This can be achieved based on historical simulations and the newly developed representative concentration pathways (RCPs) under the Coupled Model Intercomparison Project 5 (CMIP5)[2]. RCPs represent pathways of radiative forcing based on the concept that any single radiative forcing pathway can result from a diverse range of socio-economic and technological development scenarios[3].

General Circulation Models (GCMs) are one of the primary tools for deriving projections of future climate change. For the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5), which is scheduled to be released shortly, the coupled models of CMIP5 have been used. To assess the future climate change scenarios, it is necessary to understand the strength and weakness of the climate models. An analysis of CMIP3 and CMIP5 models is thus prepared to understand the capability of climate models in simulating the present-day climate[1,4]. Instead of branding climate models as 'bad' or 'good'[5], climate scientists use simulations of a range of coupled models to account for the merits and demerits of individual GCMs. Since they are mostly qualitative, such projections are characterized by low level of confidence and high level of uncertainty[6,7]. Thus, quantification of uncertainty in projection of future climate scenarios for climate change impact assessment and possible mitigation forms a prime research focus. Moreover, decision-makers in a wide variety of organizations are increasingly seeking quantitative climate predictions[8], as the effects of climate change are critical to multiple stakeholders, including resource managers and adaptation researchers, with a growing and vulnerable population along with changes in urbanization and land use[9].

In this article, we employ a quantitative procedure based on the model performance and model convergence criteria, known as 'reliability ensemble averaging' (REA)[10]. This method is used for the determination of uncertainty range and reliability of climate change projections of ten different CMIP5 GCMs for two main variables, surface temperature and precipitation. Throughout this article the term 'ensemble' refers to simulations of different individual GCMs and not to different realizations within the same

*For correspondence. (e-mail: agnivsengupta99@gmail.com)

model. Here, we analyse climate projections for all the GCMs under the RCP4.5 scenario. The first criterion in the REA method, namely 'model performance', is based on the ability of GCMs to replicate the present-day climate. Thus, the better the model performance in this regard, the higher is the reliability of that climate change simulation. The second criterion, namely 'model convergence', is defined as deviation of the individual projection of change with respect to the central tendency of the ensemble. Thus, a larger weightage is assigned to the GCMs with small bias and whose projections agree with the consensus, while GCMs with lesser skill in reproducing the observed climatology and with inferior skills with respect to majority of the ensemble members receive less weight. The REA method is also advantageous as it does not involve prior assumptions regarding the shape of probability distribution functions (for example, Jones[11] assumes uniform PDFs for both regional and global temperature changes in a study for the south Australian region) for major uncertainty factors like climate sensitivity, radiative forcing, etc. Moreover, the REA methodology has been highly acclaimed in the study by Tebaldi *et al.*[12] as a formal statistical model which justifies itself as an optimal procedure.

Data and methodology

Rainfall and temperature are the two variables for which detailed observations exist, which have been extensively studied in the context of Indian monsoon[9]. The present study analyses historical simulations as well as future projections of ten selected GCMs under the RCP4.5 scenario. The RCP4.5 scenario represents a stabilization scenario where total radiative forcing is stabilized before 2100 by employing a range of technologies and strategies for reducing GHG emissions. The model data are taken from CMIP5 for which the variables surface temperature and precipitation are readily available. The selected coupled GCMs are listed in Table 1. Model details and data are available from the Earth System Grid Federation (ESGF) portal of the Program for Climate Model Diagnosis and Intercomparison (PCMDI) website maintained by the Lawrence Livermore National Laboratory, USA. The historical and future projections for Indian summer monsoon (June–September) are considered over the Indian land mass, by masking out the oceans and territories outside the geographical borders of India. For validating the model simulations for precipitation, we have used the Global Precipitation Climatology Project (GPCP) rainfall data (available from 1979 to 2005)[13]. The GPCP project was initiated under WCRP to evaluate and provide global gridded datasets of monthly precipitation, based on all suitable observational techniques[1]. In order to evaluate surface temperature simulations of the CGCMs, we have used all-India regionally averaged surface temperature data from 1971 to 2000, available from the Indian Institute of Tropical Meteorology (IITM, Pune, http://www.tropmet.res.in).

For the quantification of model uncertainty, we considered the model-simulated changes in mean surface temperature and precipitation for the period 2021–2050 (under the RCP4.5 scenario) compared to the recent-past climate for Indian summer monsoon (June–September). For comparison of our results from our suggested REA method, we first use a simpler averaging procedure for development of climate change estimates and associated uncertainty range[10]. For introducing this approach, we take surface temperature T as an example. The estimated change is given by the average of all model simulations, that is

$$\Delta\bar{T} = \frac{1}{R}\sum_{i=1}^{R}\Delta T_i, \tag{1}$$

where R is the total number of GCMs, the bar indicates the averaging procedure and Δ indicates the model-simulated change.

In its generalized form, the uncertainty is measured by the corresponding root-mean-square difference (rmsd), or δ, defined by

$$\delta_{\Delta T} = \left[\frac{1}{R}\sum_{i=1}^{R}(\Delta T_i - \Delta\bar{T})^2\right]^{1/2}. \tag{2}$$

The uncertainty range is then given by $\pm\,\delta_{\Delta T}$ and is centred around $\Delta\bar{T}$. Thus, from a probabilistic point of view, if the changes followed a Gaussian probability distribution function, the rmsd would be equivalent to the standard deviation and $\pm\,\delta_{\Delta T}$ would approximately cover the 68.3% confidence interval. However, this direct model averaging procedure undermines the model reliability criteria and weighs all the ten GCM simulations equally.

Reliability ensemble averaging methodology

The REA is a method for uncertainty quantification through a weighted average of individual GCM simulations quantified by two major criteria, namely model bias and model convergence, proposed by Giorgi and Mearns[10]. In the present study, the two variables surface temperature and precipitation for all-India monsoon rainfall are considered to determine the fidelity of the ten selected CMIP5 GCMs in projecting future climate change through a quantitative assessment of the uncertainty associated with future climate model projections. Stepwise procedure for REA analysis, considering JJAS precipitation as the sample parameter, is as follows.

Step 1: The REA simulated precipitation change $(\widetilde{\Delta P})$ is given by the weighted average of the individual GCMs.

Table 1. List of CMIP5 GCMs used in this study with their modelling organization, spatial resolution and model designation

Modelling organization	GCM	Spatial resolution	Model designation
National Center for Atmospheric Research (USA)	CCSM4	0.942° × 1.25°	NCAR
Canadian Centre for Climate Modelling and Analysis (Canada)	CanESM2	2.79° × 2.8125°	CCCMA
Centre National de Recherches Meteorologiques/Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique (France)	CNRM-CM5	1.4008° × 1.4063°	CNRM
NOAA Geophysical Fluid Dynamics Laboratory (USA)	GFDL-CM3	2° × 2.5°	GFDL
Max Planck Institute for Meteorology (Germany)	MPI ESM-LR	1.865° × 1.875°	MPI
Institut Pierre-Simon Laplace (France)	IPSL-CM5A-MR	1.268° × 2.5°	IPSL
Hadley Centre for Climate Prediction and Research/ Meteorological Office (UK)	HadGEM2-AO	1.25° × 1.875°	HadGEM2
LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences (China)	FGOALS-G2	2.79° × 2.8125°	LASG
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology (Japan)	MIROC5	1.4° × 1.406°	MIROC5
Norwegian Climate Centre (Norway)	NorESM 1-M	1.895° × 2.5°	NorESM

$$\widetilde{\Delta P} = \tilde{A}(\Delta P) = \frac{\sum_{i=1}^{N} R_i \Delta P_i}{\sum_{i=1}^{N} R_i}, \quad (3)$$

where the operator $\tilde{A}$ denotes REA averaging and R_i denotes the individual GCM reliability factor.

Step 2: The GCM overall reliability factor R_i is defined as

$$R_i = [(R_{B,i})^m \times (R_{D,i})^n]^{[1/(m\times n)]}$$

$$= \left\{ \left[\frac{\varepsilon_p}{\text{abs}(B_{P,i})} \right]^m \left[\frac{\varepsilon_p}{\text{abs}(D_{P,i})} \right]^n \right\}^{[1/(m\times n)]}. \quad (4)$$

Here, model reliability factor $R_{B,i}$ is a function of the model bias ($B_{P,i}$) in simulating precipitation of the recent past, and bias is defined as the difference between the GCM simulated and observed GPCP mean JJAS precipitation for the recent past (1979–2005). Again, $R_{D,i}$ is a factor that measures the GCM reliability in terms of the distance ($D_{P,i}$) of the change calculated by a given model from the REA average change, and therefore, the distance is a measure of the degree of convergence of a given model with the others. In other words, $R_{B,i}$ is a measure of the model performance criterion, while $R_{D,i}$ is a measure of the model convergence criterion, which are by far the governing criteria for the REA method.

Step 3: An iterative procedure is then used to calculate distance parameter $D_{P,i}$, starting with an initial guess value as the distance of each ΔP_i from the ensemble average change $\Delta\bar{P}$, as in eq. (1), i.e. $[D_{P,i}]_1 = [\Delta P_i - \Delta\bar{P}]$. The first guess value is then used in eqs (3) and (4) to obtain a first-order REA average change $[\Delta\tilde{P}]_1$, which is then used to recalculate the distance of each individual model as $[D_{P,i}]_2 = [\Delta P_i - [\Delta\tilde{P}]_1]$ and the iteration is continued henceforth. Typically, this procedure converges quickly after several iterations.

Step 4: According to the REA method, the parameters m and n used in eq. (4) to weigh each criterion are assumed to be equal to 1, which gives equal weightage to both criteria. Also, R_B and R_D are set to 1 when B and D are smaller than ε respectively. Thus, eq. (4) states that a GCM projection is 'reliable' when both its bias and distance from the ensemble average are within the natural variability, so that $R_B = R_D = R = 1$. Besides, as the bias and/or distance grows, the reliability of a given GCM simulation decreases.

Step 5: The parameter ε used in eq. (4) is a measure of natural variability in 30-year average JJAS regional temperature and precipitation according to the REA method. In order to calculate ε, we compute the time series of observed, regionally averaged temperature and precipitation for JJAS monsoon from IITM data for 1901–2005. Then, 30-year moving averages of the series are calculated, and ε is estimated as the difference between the maximum and minimum values of these 30-year moving averages.

Step 6: In order to calculate the uncertainty range around the REA average change, the REA rmsd of the changes, $\widetilde{\delta_{\Delta P}}$ is to be obtained, defined by

$$\widetilde{\delta_{\Delta P}} = [\tilde{A}(\Delta P_i - \widetilde{\Delta P})^2]^{1/2} = \left[\frac{\sum R_i (\Delta P_i - \widetilde{\Delta P})^2}{\sum R_i} \right]^{1/2}. \quad (5)$$

The upper and lower uncertainty limits are defined as

$$\Delta P_+ = \widetilde{\Delta P} + \widetilde{\delta_{\Delta P}}, \quad (6)$$

$$\Delta P_- = \widetilde{\Delta P} - \widetilde{\delta_{\Delta P}}, \quad (7)$$

and the total uncertainty range is given by $\Delta P_+ - \Delta P_- = 2\widetilde{\delta_{\Delta P}}$. Now, according to the REA method, when the changes are distributed following a Gaussian PDF, the rmsd is equivalent to the standard deviation, so that the $\pm\,\delta$ range would imply a 68.3% confidence interval. For a uniform PDF, that is, one in which each change has the same probability of occurrence, the $\pm\,\delta$ range implies a confidence interval of about 58%. Moreover, in the REA method, the normalized reliability factors of eq. (4) are interpreted as the likelihood of a GCM outcome, that is, greater the factor, greater will be the likelihood associated with the model simulation.

Step 7: Finally, a quantitative measure of the collective reliability of the ten selected GCMs ($\tilde{\rho}$) in simulating future climate changes is obtained by applying the REA averaging operator to the reliability factor, that is

$$\tilde{\rho} = \tilde{A}(R) = \frac{\sum R_i^2}{\sum R_i}. \tag{8}$$

In other words, the collective reliability is given by the REA average of the individual GCM reliability factors.

This definition of reliability is thus consistent with the fact that different model simulations are weighted differently in the calculation of the REA average. The REA method also incorporates a quantitative measure of the collective reliability of the GCMs with respect to model bias and model convergence criteria separately as follows

$$\overline{R_B} = \frac{1}{N}\sum_{i=1}^{N} R_{B,i}, \tag{9}$$

$$\overline{R_D} = \frac{1}{N}\sum_{i=1}^{N} R_{D,i}. \tag{10}$$

Results

GCM historical simulations for the mean Indian recent past summer monsoon

As a precursor of our uncertainty quantification and reliability analysis, the need of inclusion of model performance criterion in evaluation of GCM projections is examined. Figure 1 *a* and *b* shows the observed mean spatial pattern of temperature and rainfall respectively, for the monsoon season (June–September). The spatial distribution plots for monsoon temperatures (°C) averaged for the period 1971–2000, based on historical simulations of the ten CMIP5 GCMs, are shown in Figures 2 *a–j*, while Figure 3 *a–j* shows the spatial mean monsoon seasonal rainfall (in mm/month) pattern for the period 1979–2005. These spatial plots are shown as illustrations in simulating Indian summer monsoon climatology. However, we are only concerned with obtaining individual GCM bias (difference between the spatially averaged model simulated and observed monsoon climatology for all-India monsoon rainfall) which will act as our input parameters in the REA methodology. The spatially distributed biases between simulated and observed rainfall have already been discussed in the earlier studies for the Indian monsoon[1,3]. We find here that the models simulate the spatial pattern of observed temperatures fairly well, marked by temperature maximum over parts of Thar Desert, Rajasthan and minimum over the Himalayan region. On the other hand, all the models simulate the rainfall maximum over the Bay of Bengal. However, other details vary from model to model. At least five of the models in this study (NCAR, MPI, LASG, MIROC5, NorESM) capture the observed (GPCP) rainfall maximum over the west coast of India reasonably well, and all the GCMs simulate scanty rainfall over northwest India. Models like CCCMA, IPSL, CNRM, HadGEM2 and LASG severely underestimate observed rainfall, whereas NCAR, MIROC5 and NorESM provide an overestimated monsoon rainfall simulation. We notice that the biases of GCMs are far more pronounced in case of precipitation, with widespread positive and negative biases (Table 2). In case of surface temperature, biases range from –3.94°C to 0.62°C when compared with the observed (IITrop-Met) regionally averaged temperature. Thus, widely variable bias exists in simulating present-day observed Indian summer monsoon climatology, as reflected in Table 2. This substantiates our claim to incorporate model performance criterion and proves the fact that a simple multi-model average may not be appropriate in the evaluation of future GCM climate change projections.

Projected temperature change for 2021–2050 All India Monsoon Rainfall (AIMR) and estimates of uncertainty range

Figure 4 shows the mean JJAS temperature change (°C) projected by the ten CMIP5 GCMs during 2021–2050 under the RCP4.5 scenario relative to the 1971–2000 base period. The REA and ensemble average-based temperature changes with corresponding upper and lower uncertainty limits are also shown in Figure 4. The all-India mean monsoon temperature increases by 0.95–1.91°C according to the CMIP5 GCM simulations (Table 3) relative to the 1971–2000 historical simulations, while the REA and ensemble average warming are 1.215°C and 1.297°C respectively. The JJAS natural variability (ε_T) in observed all-India temperature is computed as 0.11°C, while the GCM-projected and REA-based temperature increases are well above this natural variability estimate. The uncertainty range defined by the rmsd ($\pm\,\delta_{\Delta T}$), is 0.366°C for the ensemble average, while the use of REA methodology reduces the overall model uncertainty range

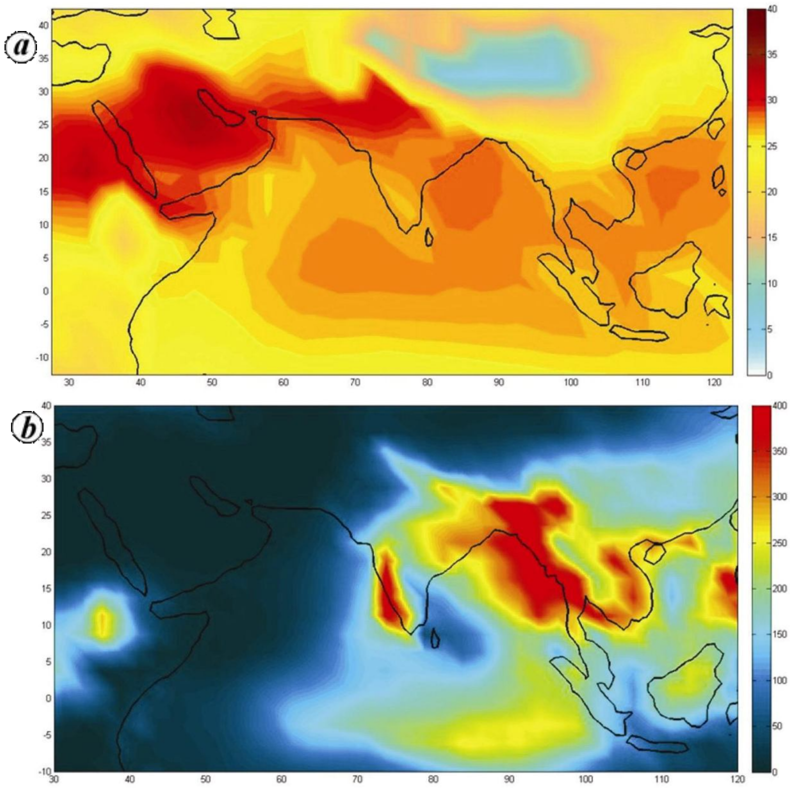

Figure 1. ***a***, Mean spatial pattern of observed temperature (°C) based on HadCRU data (obtained from http://www.cru.uea.ac.uk/cru/data/temperature) for the JJAS season. ***b***, Observed mean monsoon spatial rainfall (mm/month) pattern for the period 1979–2005 based on GPCP data.

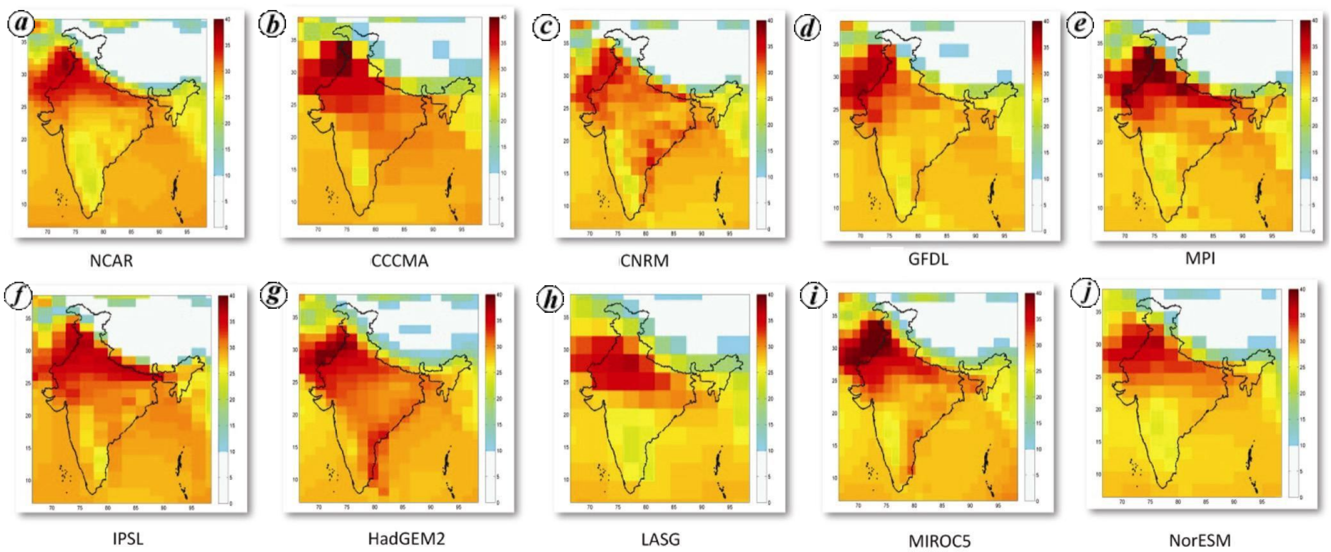

Figure 2 *a–j*. The spatial pattern of June–September mean surface temperature (°C) simulated by the ten CMIP5 GCMs for the period 1971–2000.

(as shown by the blue and green bold lines in Figure 4), since $\delta_{\Delta T}$ in this case is of the order of 0.22°C. This improvement in terms of uncertainty range results due to filtering out of highly biased model outliers by assigning proper weightage as stated in the REA methodology. Thus, under the assumption of a Gaussian PDF of the temperature changes, the REA-projected JJAS warming of 0.995–1.435°C (eqs (6) and (7)) with a mean value of 1.215°C and standard deviation of 0.22°C would cover a 68.3% confidence interval.

The spatial pattern of mean monsoon warming for the June–September period, projected by the ten CMIP5

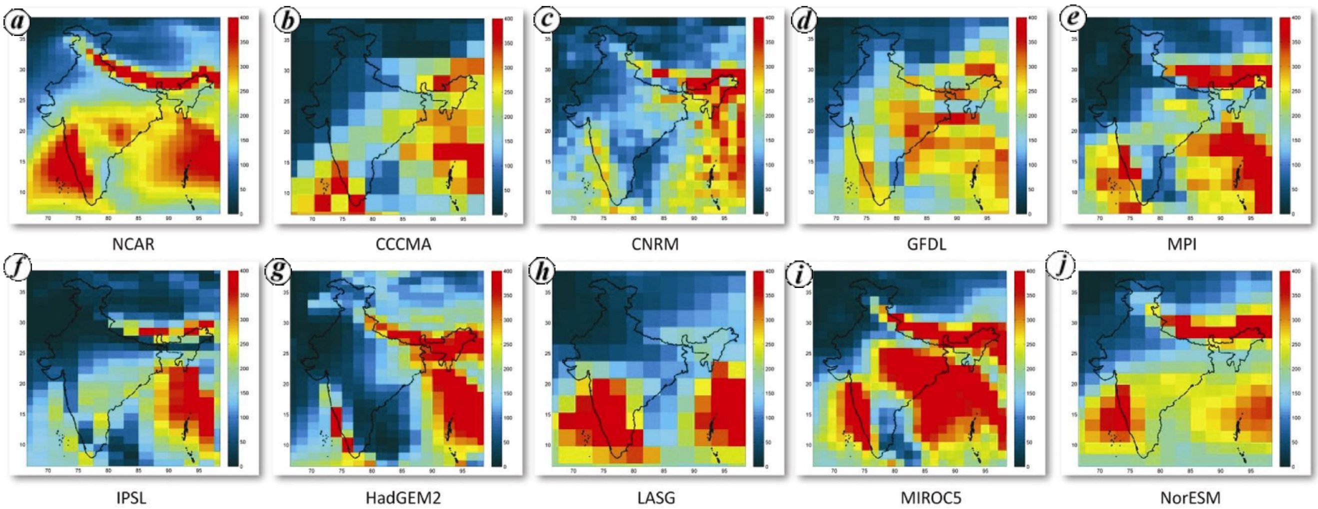

Figure 3 *a–j*. The spatial distribution of Indian summer monsoon seasonal (JJAS) precipitation (mm/month) as simulated by the ten CMIP5 GCMs for the period 1979–2005.

Table 2. List of CMIP5 GCMs with corresponding biases in simulating Indian summer monsoon mean observed surface temperature and precipitation climatology

CMIP5 GCM	Model bias in simulating temperature (°C)	Model bias in simulating precipitation (in mm/month)
NCAR CCSM4	–2.44	56.377
CCCMA CanESM2	0.62	–71.8
CNRM-CM5	–3.83	–33.14
NOAA GFDL-CM3	–3.94	0.8
MPI ESM-LR	–1.77	–17.88
IPSL-CM5A-MR	–1.11	–68.47
UKMO HadGEM2-AO	0.55	–45.78
LASG FGOALS-G2	–0.53	–32.62
MIROC5	–1.9	75.12
NorESM 1-M	–1.07	31.15

GCMs, are illustrated in Figure 5 *a–j*. The most significant aspect is the greater warming scenario projected over northern India compared to the rest of the country, especially for Jammu and Kashmir, and the Himalayan region, by the NCAR, CNRM, MPI, LASG, MIROC5 and NorESM models. On the other hand, CCCMA, GFDL, IPSL and HadGEM2 project a temperature increase of the order of 1.4–2°C over the eastern coast of India.

Projected precipitation change for 2021–2050 AIMR and estimates of uncertainty range

Figure 6 shows the mean JJAS precipitation increase (mm/month) projected by the ten CMIP5 GCMs during 2021–2050 under the RCP4.5 scenario relative to the 1979–2005 base period, along with REA and ensemble average-based change with corresponding upper and lower uncertainty limits. The change in the all-India mean monsoon precipitation varies from –0.59 to 17.39 mm/month according to CMIP5 GCM simulations (Table 3) relative to the 1979–2005 historical simulations. The REA and the ensemble-averaged projected future JJAS precipitation increase are 7.109 and 7.184 mm/month respectively. The precipitation increases differ by the order of a few tenths of a millimetre. The REA projected change can be interpreted as a 3.46% all-India precipitation increase from the observed (IITrop-Met) 1979–2005 Indian regionally averaged summer monsoon precipitation. The JJAS natural variability (ε_P) in observed rainfall is 4.667 mm/month, and GCM projections whose bias and convergence parameters lie within this natural variability range are considered as highly reliable. The uncertainty range estimates based on rmsd ($\pm\ \delta_{\Delta P}$) are large for ensemble average ($\pm\ \delta_{\Delta P}$ is 4.729 mm/month), as shown by the black dotted lines in Figure 6. This uncertainty range is reduced while using the REA method ($\pm\ \delta_{\Delta P}$ in this case is 2.592 mm/month) due to filtering out of highly biased model outliers. Thus, assuming a Gaussian PDF of the precipitation changes, the REA-projected JJAS precipitation increase of 4.517–

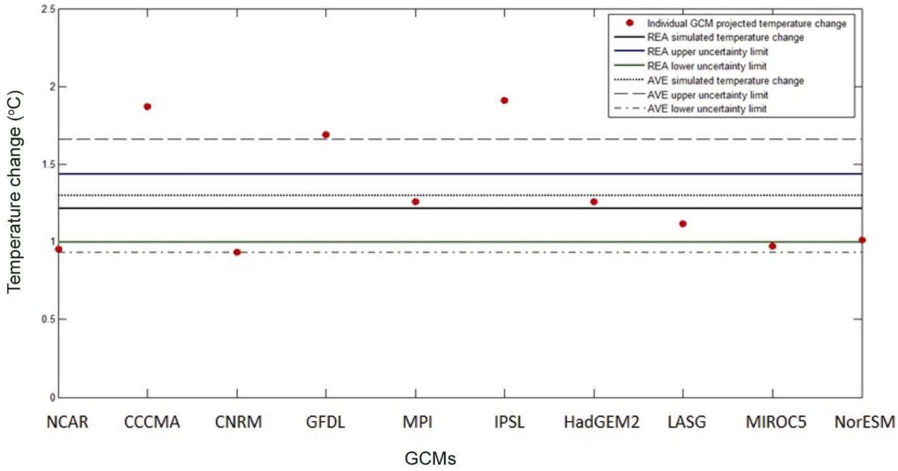

Figure 4. Change (°C) in June–September mean temperature as projected by the GCMs, with REA and ensemble average-based warming estimate and corresponding upper and lower uncertainty limits.

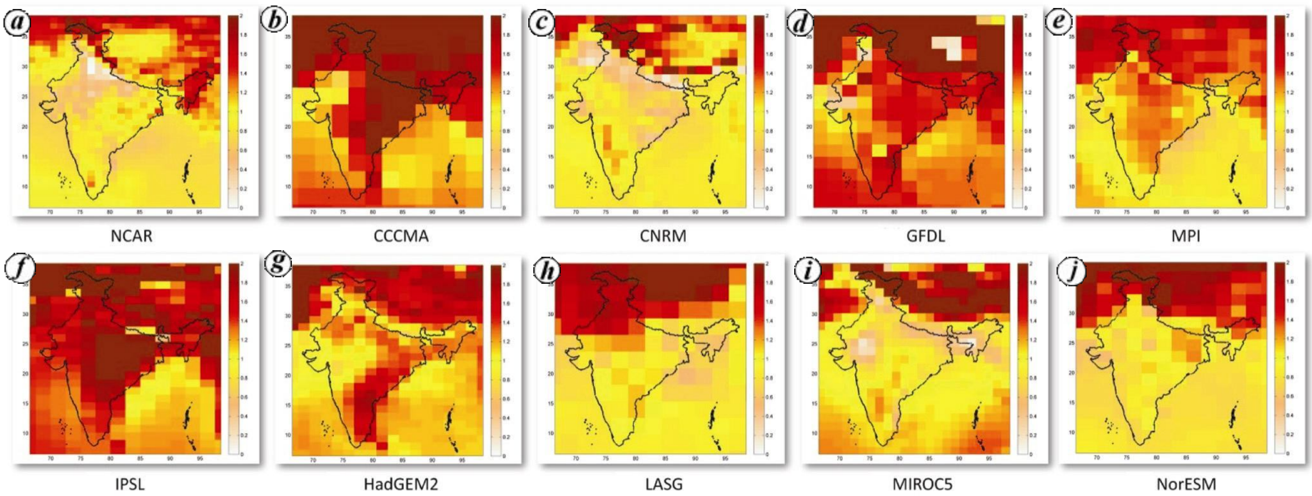

Figure 5 ***a–j***. Spatial distribution of the change in average surface temperature during June–September as projected by the ten CMIP5 GCMs for the period 2021–2050 relative to the base period (1971–2000).

Table 3. List of CMIP5 GCMs with projected changes in JJAS mean surface temperature (°C) and precipitation (mm/month) for 2021–2050 (under the RCP4.5 scenario) relative to recent-past simulations* of the models for all-India monsoon rainfall

CMIP5 GCM	ΔT (°C)	ΔP (mm/month)
NCAR CCSM4	0.95	17.39
CCCMA CanESM2	1.87	–0.59
CNRM-CM5	0.93	4.89
NOAA GFDL-CM3	1.69	7.61
MPI ESM-LR	1.26	8.89
IPSL-CM5A-MR	1.91	7.51
UKMO HadGEM2-AO	1.26	7.23
LASG FGOALS-G2	1.12	4.01
MIROC5	0.97	11.94
NorESM 1-M	1.01	2.96

*All the projected changes are for JJAS average of 2021–2050 relative to 1971–2000 in case of surface temperature, and relative to 1979–2005 in case of precipitation.

9.701 mm/month, with a mean of 7.109 mm/month and standard deviation of 2.592 mm/month would signify a 68.3% confidence interval. All these results are testimony to an intensification of summer monsoon precipitation over India.

Figure 7 *a–j* illustrates the spatial distribution plots for CMIP5 GCM projected JJAS precipitation change for 2021–2050 relative to the base period simulations. Wide regional variation exists in model projections for rainfall as is evident from the spatial patterns of this figure. Precipitation is likely to increase all over India, except for a few regions, as was also noticed by Chaturvedi *et al.*[3] for these short-term projections. In the CCCMA, IPSL, MIROC5 and NorESM models, there is marked decrease of JJAS precipitation up to –10 mm/month over parts of Bengal, Odisha, stretches of the eastern coast and over certain parts of Central India. On the other hand, the

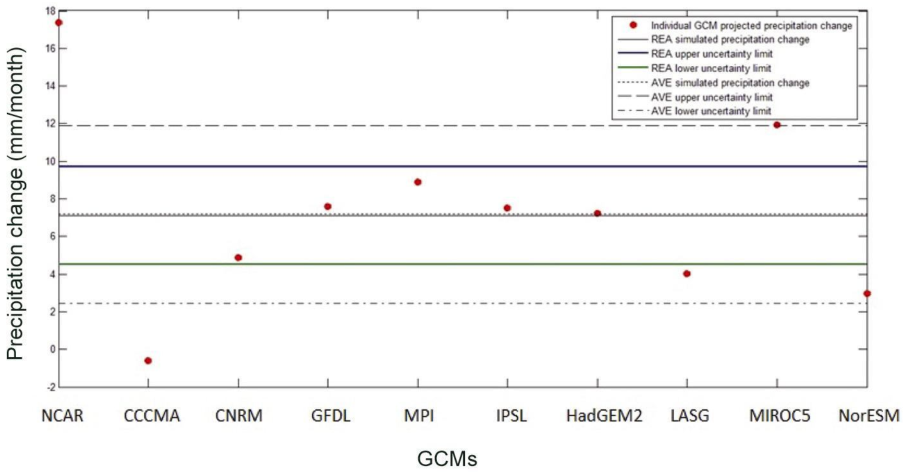

Figure 6. Projections of Indian summer monsoon precipitation change (mm/month) by the GCMs, with REA and ensemble average-based increase in rainfall estimate and corresponding upper and lower uncertainty limits.

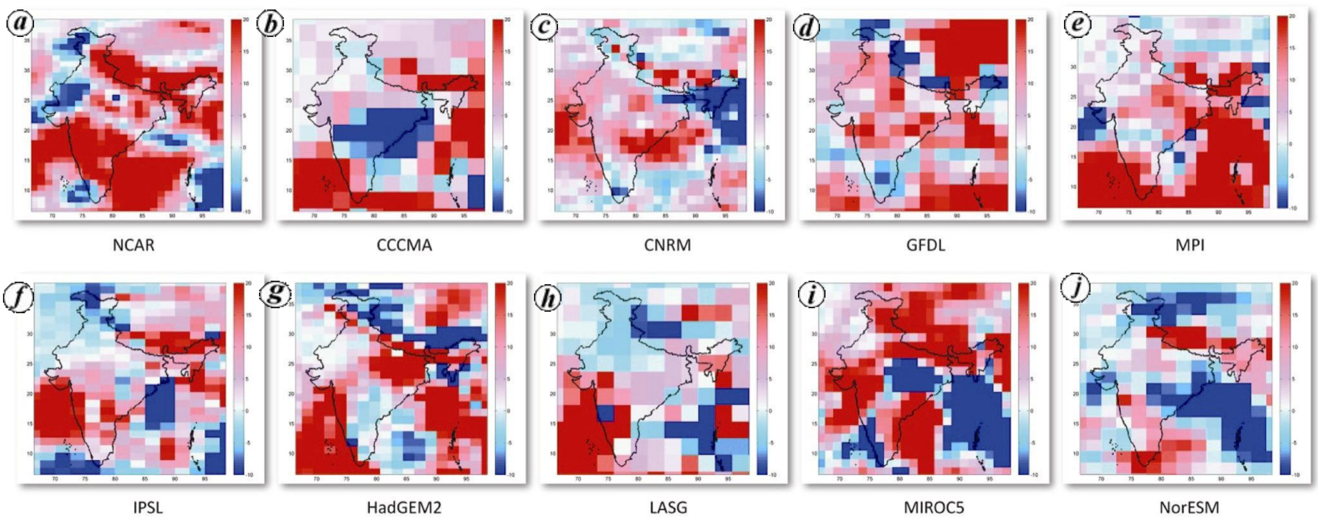

Figure 7 *a–j*. Spatial distribution of the change in summer monsoon precipitation as projected by the ten CMIP5 GCMs for the period 2021–2050 relative to the base period (1979–2005).

existing rainfall maximum trend over the west coast of the country is likely to intensify as predicted by most of the models, especially NCAR, GFDL, IPSL, HadGEM2 and LASG. Moreover, at least five of the GCMs (NCAR, IPSL, HadGEM2, LASG and NorESM) project a decreasing monsoon over Jammu and Kashmir.

However, instead of merely relying on this qualitative study, the fidelity of these regional climate change projections has been assessed in the next section to aid model selection strategies.

Reliability analysis of CMIP5 GCMs for surface temperature and precipitation projections

The performances of all the ten GCMs and the proposed REA methodology in terms of reliability metrics, namely model bias reliability factor ($R_{B,i}$), model convergence reliability factor ($R_{D,i}$) and collective model reliability factor (R_i), are presented in Tables 4 and 5 for surface temperature and precipitation respectively. The ranks obtained for these three criteria illustrate that with an exception of model bias reliability parameter for temperature, the REA technique consistently ranks within the top three (ranked two and three for precipitation and surface temperature variables respectively). The two GCMs which perform better than REA for temperature are LASG and HadGEM2; however, the poor performance of these models in case of precipitation projections is also noteworthy. GFDL-CM3, with the least bias (0.8 mm/month) in simulating present-day observed precipitation, ranks first among the GCMs for rainfall projections; however it fails in modelling surface temperature simulations properly.

Table 4. Performance evaluation and ranking of CMIP5 GCM in terms of model bias reliability factor, model convergence reliability factor and overall collective model reliability for temperature

GCM	Reliability factor for model bias ($R_{B,i}$)	Rank	Reliability factor for model convergence ($R_{D,i}$)	Rank	Overall collective model reliability (R_i)	Overall rank
NCAR	0.045082	9	0.41556479	5	0.018734478	8
CCCMA	0.177419	3	0.167862048	8	0.029781976	6
CNRM	0.028721	10	0.386371619	6	0.011096835	10
GFDL	0.027919	11	0.231432779	7	0.006461321	11
MPI	0.062147	7	1	1	0.062146893	4
IPSL	0.099099	6	0.158205091	9	0.015677982	9
HadGEM2	0.2	2	1	1	0.2	2
LASG	0.207547	1	1	1	0.20754717	1
MIROC5	0.057895	8	0.449530037	4	0.026025423	7
NorESM	0.102804	4	0.537371764	2	0.055243826	5
REA	0.10086	5	0.535	3	0.1459	3

Table 5. Performance evaluation and ranking of CMIP5 GCM in terms of model bias reliability factor, model convergence reliability factor and overall collective model reliability for precipitation

GCM	Reliability factor for model bias ($R_{B,i}$)	Rank	Reliability factor for model convergence ($R_{D,i}$)	Rank	Overall collective model reliability (R_i)	Overall rank
NCAR	0.082781986	8	0.453970663	5	0.037580593	11
CCCMA	0.065	10	0.606135384	4	0.0393988	10
CNRM	0.140826795	6	1	1	0.140826795	6
GFDL	1	1	1	1	1	1
MPI	0.261017897	2	1	1	0.261017897	3
IPSL	0.068161238	9	1	1	0.068161238	8
HadGEM2	0.10194408	7	1	1	0.10194408	7
LASG	0.143071735	5	1	1	0.143071735	5
MIROC5	0.062127263	11	0.966172574	2	0.060025658	9
NorESM	0.149823435	4	1	1	0.149823435	4
REA	0.207475	3	0.90263	3	0.57571	2

These results suggest the effectiveness and viability of the REA approach in judiciously combining multiple coupled model projections in obtaining future climate change estimates of the Indian monsoon.

The individual GCM-projected change and the corresponding GCM bias as a function of their reliability factor are plotted in Figures 8 and 9 for temperature and precipitation respectively. Note that LASG with a bias of only –0.53°C and GFDL with a bias of just 0.8 mm/month in simulating observed temperature and rainfall climatology respectively, attain the greatest reliability in the figures. Also, the consistently high reliability estimate of the REA technique in both cases is worth mentioning. The most noticeable aspect is, however, the progressively increasing model reliability with decreasing model bias, implying more likely future projections of the monsoon climate. However, there also exist cases (CCCMA in Figure 8) where in spite of having lower model bias (0.62°C), the models get lesser overall reliability due to poor model convergence criterion ($R_D = 0.168$).

Figures 10 and 11 show the overall reliability factor (R) along with the model reliability factors for model bias (R_B) and model convergence criteria (R_D) in case of the ten GCMs and the REA methodology for surface temperature and precipitation respectively. For temperature, the values of R_D are mostly in the range 0.4–1.0, with models like MPI, HadGEM2 and LASG having a model convergence reliability factor of 1.0 (Figure 10). For precipitation, model convergence criterion shows significant improvement, with seven GCMs attaining a R_D value of 1.0 (Figure 11), signifying the fact that the deviation of these individual GCM-projected changes from the REA-projected changes is within the natural variability estimate and hence 'highly reliable'. The values of R_B are generally lower, in the range 0.03–0.21 for temperature, and mostly 0.1–0.26 for precipitation. However, GFDL showing minimum bias in reproducing present-day monsoon precipitation with its deviation within the natural variability of the observed JJAS precipitation is attributed the highest model bias reliability factor of 1.0. The consistently greater R_D value compared to the R_B factor, portrayed in the figures, indicates that the convergence of GCMs in future monsoon climatology projections is more than the ability of the GCMs to reproduce the recent past climate. Also, the values of the individual GCM reliability factor (R_i) and the REA-based collective reliability factor ($\tilde{p}$) lie within their corresponding R_B and R_D values, ranging from 0.01 to 0.21 for surface temperature,

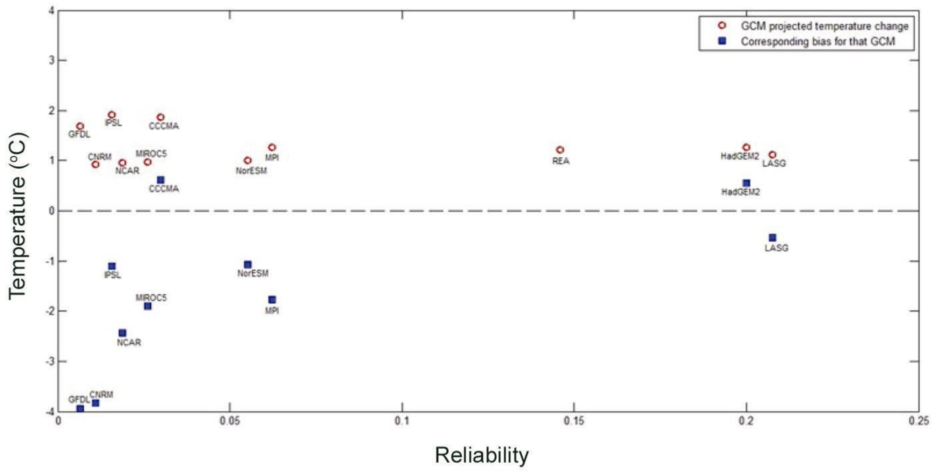

Figure 8. Change in June–September mean temperature (red circles) and corresponding bias (blue squares) as a function of reliability factor for different GCMs. Also shown is the REA simulated change. The dashed line represents the zero level.

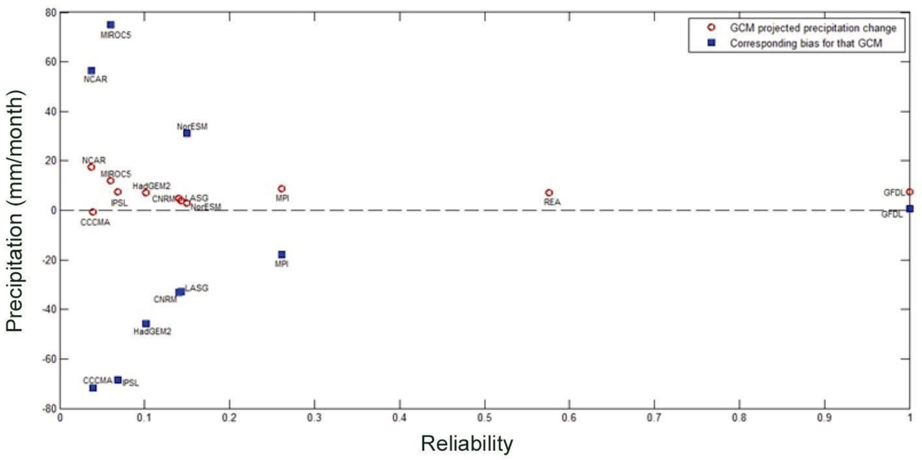

Figure 9. Change in June–September mean precipitation (red circles) and corresponding bias (blue squares) as a function of reliability factor for different GCMs. Also shown is the REA simulated change. The dashed line represents the zero level.

and from 0.04 to 1.0 for precipitation. This proves the fact that in spite of having higher model convergence reliability, the decrease in the overall reliability of the GCMs is due to their poor performance in reproducing recent past observed JJAS summer monsoon climatology due to existence of significant biases. Also, it is important to point out the effect of the natural variability estimate on the overall reliability of a model. Since the estimated natural variability in surface temperature is very small (0.11°C), the reliability factor also reduces. However, the use of REA metric maximizes the chances of obtaining a likely future climate change estimate of the Indian monsoon by minimizing the contribution of poorly performing models and by extracting the most reliable information from each model.

Discussions and conclusions

With climate change posing the biggest threat to our planet, quantitative assessment and possible reduction of the contribution of uncertainty in future climate predictions remains a potential research area. Thus, in the present study, we consider ten CMIP5 GCMs and introduce REA method for quantification of uncertainty and reliability associated with climate model projections of JJAS Indian summer monsoon climate. This exercise is needed as the consideration of model uncertainty by combination of model outputs provides confidence to decision-makers in formulating policies for climate change impact assessment[14]. Our results provide precipitation and surface temperature projections of the Indian summer monsoon

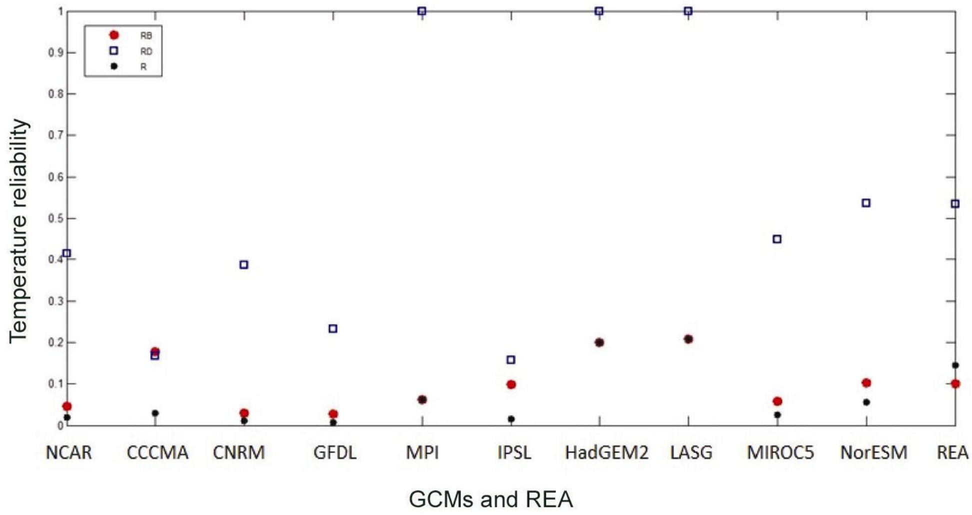

Figure 10. Overall GCM reliability, R_i (black circles), GCM performance reliability factor, R_B (red circles) and GCM convergence reliability factor, R_D (blue squares) for temperature projections of the Indian summer monsoon.

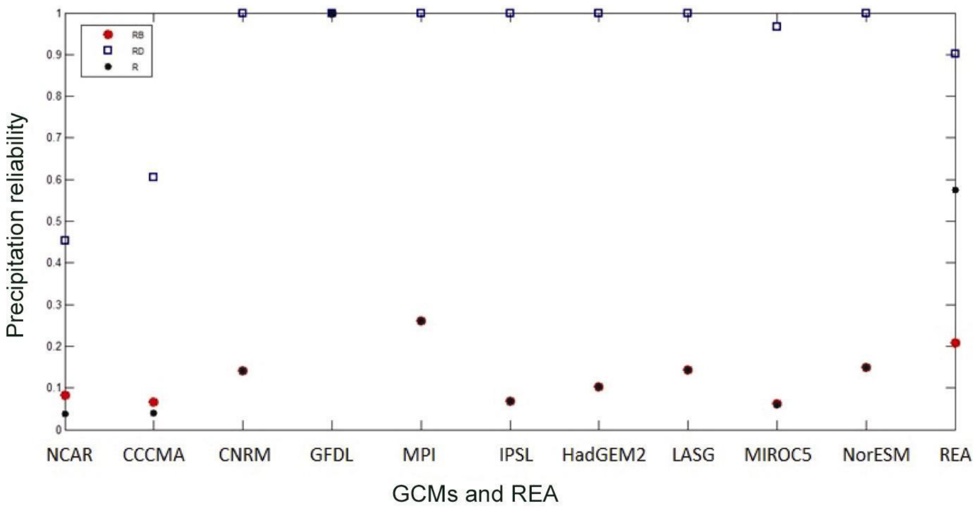

Figure 11. Overall GCM reliability, R_i (black circles), GCM performance reliability factor, R_B (red circles) and GCM convergence reliability factor, R_D (blue squares) for precipitation projections of the Indian summer monsoon.

for 2021–2050 for the individual GCMs and also using the REA technique. The following conclusions are drawn from this study.

(1) The use of REA technique, accounting for model performance and model convergence parameters, is highly beneficial with significant uncertainty reduction and high reliability index (ranking three and two for temperature and precipitation projections respectively) associated with climate predictions.

(2) The uncertainty range computed quantitatively using REA technique (0.22°C and 2.592 mm/month) is lower than that determined by the rmsd in an ensemble average approach. This uncertainty reduction suggests that REA is a viable technique for determining future Indian monsoon forecasts, by minimizing the contribution of poorly performing models or outliers.

(3) The comparative study of the individual GCMs with CMIP5 simulations and our proposed REA methodology for quantitative estimates of the reliability of climate model projections highlight that REA, with consistently high reliability values (overall reliability 0.146 and 0.576 for temperature and precipitation projections respectively), is a highly effective approach in determining long-term simulations of the Indian monsoon rainfall by combining multiple GCM outputs and assigning adequate weightage parameters.

(4) The performance of GCMs in simulating recent past Indian monsoon climatology is far inferior to the

convergence of GCMs in simulating projected monsoon changes, as is evident from the substantially lower R_B values compared with their R_D values. Thus, the prime requirement for improvement in reliability of GCM-simulated changes is the reduction of significant biases that exist in reproducing recent past monsoon climate.

(5) This study will aid policy-makers of India in assessment of future climate change impacts on water resources, agriculture, economy, etc. which depend upon all-India monsoon rainfall, by providing a reliable combination of CMIP5 outputs.

1. Rajeevan, M. and Nanjundiah, R. S., Coupled model simulations of twentieth century climate of the Indian summer monsoon. In *Current Trends in Science*, Platinum Jubilee Special Volume of the Indian Academy of Sciences, Bangalore, 2009, pp. 537–567.
2. Taylor, K. *et al.*, An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.*, 2012, **93**, 485–498.
3. Chaturvedi, R. K., Joshi, J., Jayaraman, M., Bala, G and Ravindranath, N., Multi-model climate change projections for India under representative concentration pathways. *Curr. Sci.*, 2012, **103**(7), 791–802.
4. Sperber, K. R. *et al.*, The Asian summer monsoon: an intercomparison of CMIP5 vs CMIP3 simulations of the late 20th century. *Climate Dyn*., 2012; doi: 10.1007/s00382-012-1607-6.
5. Knutti, R., Should we believe model predictions of future climate change? *Philos. Trans. R. Soc., London Ser. A*, 2008, **366**, 4647–4664.
6. Visser, H. *et al.*, Identifying key sources of uncertainty in climate change projections. *Climatic Change*, 2000, **45**, 421–457.
7. Giorgi, F. and Francisco, R., Evaluating uncertainties in the prediction of regional climate change. *Geophys. Res. Lett.*, 2000, **27**, 1295–1298.
8. Hawkins, E. and Sutton, R., The potential to narrow uncertainty in regional climate predictions. *Bull. Am. Meteorol. Soc*., 2009, **90**, 1095–1107.
9. Kodra, E., Ghosh, S. and Ganguly, A., Evaluation of global climate models for Indian monsoon climatology. *Environ. Res. Lett.*, 2012, **7**, 014012.
10. Giorgi, F. and Mearns, L. O., Calculation of average, uncertainty range, and reliability of regional climate changes from AOGCM simulations via the ‘reliability ensemble averaging’ (REA) method. *J. Climate*, 2002, **15**(10), 1141–1158.
11. Jones, R. N., Managing uncertainty in climate change projections – issues for impact assessment. *Climate Change*, 2000, **45**, 403–419.
12. Tebaldi, C., Smith, R. L., Nychka, D. and Mearns, L. O., Quantifying uncertainty in projection of regional climate change: a Bayesian approach to the analysis of multimodel ensembles. *J. Climate*, 2005, **8**, 1524–1540.
13. Adler, R. F. *et al.*, The Version-2 Global Precipitation Climatology Project (GPCP) monthly precipitation analysis (1979–present). *J. Hydrometeorol*., 2003, **4**, 1147–1167.
14. Knutti, R., The end of model democracy? *Climatic Change*, 2010, **102**, 395–404.

ACKNOWLEDGEMENTS. A.S. thanks IASc, INSA and NASI for support in the form of Summer Research Fellowship. We thank the WCRP’s Working Group on Coupled Modelling (WGCM) and the CMIP5 modelling organizations mentioned in Table 1 in making available their GCM outputs.

Competing Financial Interests: The authors declare no competing financial interests.

Received 15 July 2013; revised accepted 9 October 2013