Uncertainty quantification and reliability analysis of CMIP5 projections for the Indian summer monsoon[1]

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Abstract

A reliable Ensemble Averaging(REA) is a proposed technique which provides an 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^{0}C with an associated uncertainty range ($\pm\delta\Delta T$) of 0.22^{0}C, and an all-India precipitation increase by 7.109 mm/ month with an associated uncertainty (($\pm\delta\Delta$P) of 2.592 mm/month for 2021–2050. REA technique also shows a considerable reduction in the uncertainty range compared with the simple average ensemble approach and is characterized by consistently high reliability index in a comparative study with individual CGCMs. The results suggest achievability of REA methodology in constituting the realistic future Indian Monsoon Projections by preparing a performance model and a descriptive confluence criteria.

Introduction

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 CMIP5.An evaluation of historical as well as future (RCP4.5 scenario)simulations of ten CGMs in the REA technique projects a mean monsoon warming of 1.215 C, and an all India precipitation increase by 7.109 mm/ month with an associated uncertainty 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

The Summer monsoon in India spreads over a tenure of four months (June-September) and it accounts for more than 70 % of the annual rainfall of the country. And is characterized by prominent variability in its onset, pullback, rainfall's amount and extreme climatic conditions like flood or droughts . All these results have an effect on the water resource, agriculture and economy of the country. There is also an important parameter which has effect on agriculture and water resources which is temperature .under the scenario of increase in GHGs emission, the monsoon of India is sensitive to global warming. With increasing anthropogenic activities and industrial revolution, there is much concern about how increase in GHGs may effect the Indian monsoon circulation and rainfall. There is only single way to understand the effect of global warming on the monsoon of India and to assess future monsoon climate is to use climate models. This can be achieved based on historical counterfeiting and the new developed RCPs under the CPMIP5 . RCP represents the pathways of radiated forcing based on the concept that any one radiated forcing pathway can give consequence from a diverse range of socio-economic and technological scenes.

General Circulation Models(GCMs) are one of the basic tools for getting projections of future change in climate. For IPCC 5th assessment report (AR5) , which is set to be released shortly , the couples models of CMIP5 have been utilized. To asses the future change in climate, it is important to read the strength and weakness of climate models .

A detail study of CMIP3 and CMIP5 models is thus made to understand the ability of climate models in simulating the present day climate. Instead of branding climate models as good or bad , climate scientists use simulations of a range of coupled models to account for the pro and cons of individual GCMs. Since they are mostly qualitative, and such projections are characterized by high level of uncertainty and low level of confidence. Thus, quantification of uncertainty in projecting future scenario of climate for climate change effect assessment and possible mitigation forms a main research focus. More over, decision makers in a wide range of organizations, are increasingly searching quantitative climate prognosis, as the impact of change in climate are critical to many stakeholders, including adaptation researchers and resource managers, with a increasing and vulnerable population along with the modification in the usage of land and urbanization

In this article , we lay on a procedure which is quantitative and based on the model performance and model convergence criteria, known as REA . We use this method for decisiveness of uncertainty range and the dependence of climate change projections of ten different CMIP5 GCMs for 2 main variables , precipitation and temperature . In the whole article ., the term ensemble signifies to simulations of different GCMs and not to different realizations within the same model.

Here we analyze projection of climates for all the GCMs under the RCP4.5 scenario. The first criteria in this REA method, whose name is ‘model performance’ is based on the capability of GCMs to replicate the today’s climate. Thus, the better performance of model in this regard , the greater is the reliability of that climate change stimulation

The second criteria, namely ‘model convergence’ is expressed as deviation of individual projection of change with respect to the middle tendency of the ensemble. So a higher weightage is given to the GCMs with lower skill in reproducing the analyzed climate pattern and with lower skills with to respect to preponderance of the ensemble members get less weight

REA method is also considered as advantageous as it does not embed with prior assumptions regarding the shape distribution function of probability

Data and methodology

There are two variables i.e rainfall and temperature for which detailed analysis exist, which have been observed in the context of monsoon of India . This ongoing study analyses historical simulation as well as future projections of the ten GCMs which have been selected under the RCP5.4 . This represents a stabilization scenario where all the radiative forcing is stabilized before 2100 by laying on the strategies as well as range of technology for the purpose of curbing GHG emission. The model data are taken from CMIP5 for which the model details and data from the ECGF portal of the program PCMDI website maintain by the LawerenceLiverMore National laboratory ,USA.The future projection and historical projection for summer monsoon of India(June-September) are consider over India by masking out the oceans and territories outside the geographical outline of India. For validating the model simulations for precipitation, the use of Global Precipitation Climatology Project (GPCP) rainfall data have been done which is available 1979 to 2005. This project was initiated under WRCP tocalculate and provide global gridded data of monthly precipitation, depends on all appropriate observational techniques. In order to calculate surface temperature simulations of the CGCMs, we have taken all India regionally averaged surface temperature data from 1971 to 2000

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 past climate for summer monsoon of India .For comparison of our results from our suggested REA method, we have used a simpler averaging steps for development of climate change estimates associated uncertainty range. The approximate change is given by the average of all model simulations, that is

$$\Delta\mathrm{T} = \frac{1}{R}\sum_{i=1}^{R} \Delta Ti\,,$$

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

$$\delta\Delta\mathrm{T} = [\frac{1}{R}\sum_{i=1}^{R}(\Delta\mathrm{Ti} - \Delta\mathrm{T}')\text{^}2]\text{^}(1/2)$$

Reliability ensemble averaging methodology

This is a method for uncertainty quantification through a weighted average of each GCM simulations quantified by two prominent criteria, namely model bias and convergence, proposed by Giorgi and Mearns. In the present study, the two variables surface temperature and precipitation for all India monsoon rainfall are taken 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 the analysis of this method, keeping JJAS precipitation as the parameter of sample is following

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

$$\Delta P = \tilde{\mathrm{A}}(\Delta P) = \sum_{i=1}^{N} Ri\Delta Pi \Big/ \sum_{i=1}^{N} Ri$$

Where the operator A denotes REA averaging and Ri denotes the individual GCM reliability factor.

Step2- The GCM overall reliability factor Ri is defined as

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

$$= \{[\varepsilon_p/abs(B_{p,i})]^m [\varepsilon_p/abs(D_{p,i}]^n\}^{[\frac{1}{m\times n}]}$$

Here, model reliability factor RB,i is a function of the model bias (BP,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, RD,i is a factor that measures the GCM reliability in terms of the distance (DP,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, RB,i is a measure of the model performance criterion, while RD,i is a measure of the model convergence criterion, which are by far the governing criteria for the REA method.

Step3- An iterative procedure is then used to calculate distance parameter DP,i, starting with an initial guess value as the distance of each ΔPi from the ensemble average change , ΔṖas in eq. (1), i.e. [DP,i]1 = [ΔPi –ΔṖ]. P The first guess value is then used in eqs (3) and (4) to obtain a first-order REA average change $[\Delta\dot{P}]_1$, which isthen used to recalculate the distance of each individual model as [DP,i] 2 =$[\Delta P_i - [\Delta\dot{P}]_1]$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, RB and RD are set to 1 when B and D are smaller than 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 RB = RD = R = 1. Besides, as the bias and/or distance grows, the reliability of a given GCM simulation decreases.

Step 5- The parameter δ 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 δ, 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 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, P is to be obtained, defined by

$$\delta_{\Delta P} = [\tilde{A}(\Delta P_i - \Delta P)^2]^{\frac{1}{2}} = [\sum R_i(\Delta P_i - \Delta P)^2/\sum R_i]^{1/2}$$

And the total uncertainty range is given by

$$\Delta P_+ - \Delta P_- = 2\delta_{\Delta P}$$

.now,according to REA method, when the changes are divided following a Gaussian PDF, the rmsd is equivalent to standard deviation,so that the range would imply a 68.3% confidence to interval. For the uniform PDF, that is one in which each change has the equal level possibility of occurrence, the range implies aconfidence interval of about 58%. Moreover, in this REA method, the normalized factor of reliability of eq 4 are meant as the likelihood of the outcome of

GCM, that is, greater will be the likelihood attached with model stimulation.

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

ṗ=Ã(R)=$\sum R_i^2/\sum R_i$

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

This explanation or definition of reliability is thus consistent with the fact that different model simulations are weighted separately in the evaluation of the REA average, This method also incorporates a quantitative measure of the collective reliability of the GCMs with respect to model convergence and model bias criteria separately are following

$$\bar{Ṛ}_B = 1/N \sum_{i=1}^{N} R\,\mathrm{B}, i$$

$$\bar{Ṛ}_D = 1/N \sum_{i=1}^{N} R\mathrm{D}, i$$

Results

As a forerunner of our uncertainty quantification and reliability examination, the need of including of model performance criterion in the evaluation of GCM projections is examined . Figure 1 a and b shows the analyzed mean spatial pattern of rainfall and temperature , for the monsoon season (June–September). The distribution plots of monsoon temperatures averaged between 1971-2000, depending upon the historical simulations of the ten CMIP5 GCMs, can be shown in Figures 2 a-j, while figure 3 a-j describes the spatial mean rainfall of the monsoon season in mm/month pattern for the time period 1979-2005. These spatial plots are shown as illustrations in simulating monsoon climatology of Indian summer. However the only concern we have shown with getting individual GCM bias which shall act as our input parameters in the REA. The spatially distributed biases between simulated and observed rainfall have already been discussed in the earlier studies for the Indian monsoon1,3. 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 side , all models simulate the rainfall maximum over the Bay of Bengal. However, other details differ from model to model. Minimum five of the models in this study (NCAR , MPI , LASG, MIROC5, NorESM) capture the observed(GPCP)rainfall maximum over the west coast of Indiaand all the GCMs simulate meager amount rainfall over northwest India

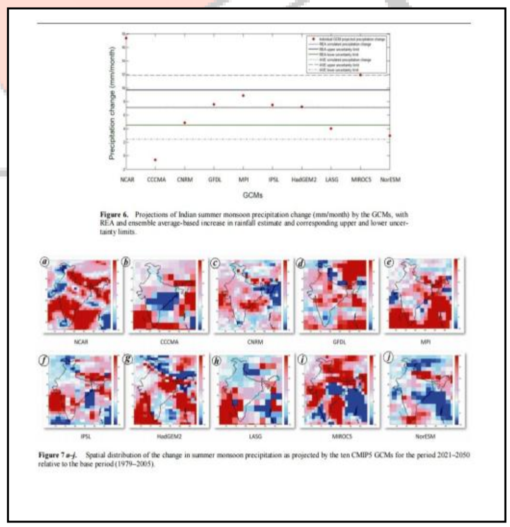
Models like CCCMA, IPSL, CNRM, HadGEM2 and LASG severely underestimate observed rainfall, whereas NCAR, MIROC5 and

NorESM provide an overestimated monsoon rainfall simulation. It can be noticed that the biases of GCMs are far more pronounced in case of precipitation, with widespread positive and negative biases(Table2)

In case of surface temperature, biases range from -3.94 C to 0.62 C when compared with 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 ($^{\circ}C$) 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 0.95–1.91C 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 (δ_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



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