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Bayesian Multimodel Estimation of global temperature Change based on the CMIP3 Data

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Introduction :

Outputs from Global Circulation Models (GCMs) form the main scientific basis for several climate change assessment reports sponsored by the Intergovernmental Panel on Climate Change (IPCC) and are widely used in global change research. GCMs can be used to simulate present-day and project future climate conditions under different scenarios, and hence inform decision makers regarding policy making such as potential mitigation measures and adaptation strategies. However, the theoretical description of the climate remains incomplete, and simplifying assumptions are inherent when building these GCMs. Various uncertainties in climate models introduce biases into GCM outputs, and so GCMs are unable to represent fully the intensity and frequency of observed climate characteristics. A good understanding of how these biases manifest in the 20th century climate simulation is necessary for us to understand how climate change may occur in the future.

Besides building better GCM models, many researchers found that multi-model ensemble prediction methods help reduce model biases and improve predictive skills of GCMS. This study presents results of a study that uses Bayesian Model Averaging method to estimate global temperature trend in the 20th century.

Objectives :

1.Assess the performance of the GCMs used in IPCC-AR4 when applied to the global temperature simulation (excluding Antarctica).

2. Conduct an inter-comparison of the temporal and spatial changes in global temperature using the SMA and BMA.

Bayesian Model Averaging (BMA) method :

The BMA method considers a predicted time-mean climatological variable y, the corresponding evidentiary target data y_T, and an ensemble of K model simulations $\{f_1, f_2, \ldots, f_K\}$ of variable :

$$p(y \mid f_1, f_2, \ldots, f_K) = \Sigma(k)\, p(y \mid f_k) \bullet p(f_k \mid y_T) \quad (1)$$

where, $p(y \mid f_k)$ is the probabilistic prediction given by simulation f_k, and $p(f_k \mid y_T)$ is the likelihood that this simulation is the best.

Identifying $p(f_k \mid y_T)$ as a fractional statistical weight w_k, whose magnitude reflects how well f_k matches the target data y_T, it follows that $\Sigma\, w_k = 1$, and (1) can be expressed as

$$p(y \mid f_1, f_2, \ldots, f_K) = \Sigma(k)\, w_k \bullet p(y \mid f_k) \quad (2)$$

The prediction $p(y \mid f_1, f_2, \ldots, f_K)$ is thus a weighted sum of the predictions of y provided by the individual simulations, and so will be referred to as the "multi-model consensus prediction".

It is computationally convenient to assume that $p(y \mid f_k)$ for each climatological simulation f_k can be represented by a Gaussian distribution that is defined by mean μ_k and variance σ_k^2. Denoting parameter vector $\theta_k = \{\mu_k, \sigma_k^2\}$ and $g(.)$ as the associated Gaussian PDF, it follows that

$$p(y \mid f_k) = g(y \mid \theta_k) \quad (3)$$

or, substituting (3) into (2),

$$p(y \mid f_1, f_2, \ldots, f_K) = \Sigma_{(k)}\, w_k \bullet g(y \mid \theta_k) \quad (4)$$

It is easier, however, to estimate unknowns w_k and θ_k, $k = 1, 2, \ldots, K$ by deriving a log likelihood function l from the Gaussian function g :

$$l(\theta_1, \theta_2, \ldots, \theta_K) = \Sigma_{(s)} \log\left(\Sigma_{(k)}\, w_k \bullet g(y_{Ts} \mid \theta_k)\right) \quad (5)$$

where $\Sigma_{(s)}$ denotes a summation over all spatial points s, and y_{Ts} denotes a target datum at location s.

The BMA method entails the estimation of the Bayesian weights w_k and statistical parameter vectors θ_K such that the log likelihood function l is maximized. For multimodel simulations of historical climate, it is straightforward to maximize the likelihood function (5), since climate observations can provide evidentiary target data y_T.

More details about BMA method can be found at (Duan & Phillips, 2010 JGR)

Data :

Climate variable: Surface Air Temperature
Duration: 1960~1999
Resolution: 0.5° ×0.5°
Observed data: CRUTS2p0, Climatic Research Unit
Simulated data: IPCC-AR4(24 GCMs) + SMA result + BMA result

The global climate models in IPCC-AR4

No.	Model	Source
1	bccr_bcm2_0	Bjerknes Centre for Climate Research, Norway
2	cccma_cgcm3_1	Canadian Centre for Climate Modelling and Analysis, Canada
3	cccma_cgcm_t63	Canadian Centre for Climate Modelling and Analysis, Canada
4	cnrm_cm3	Centre National de Recherches Meteorologiques, France
5	csiro_mk3_0	Australian Commonwealth Scientific and Research Organization, Australia
6	csiro_mk3_5	Australian Commonwealth Scientific and Research Organization, Australia
7	gfdl_cm2_0	Geophysical Fluid Dynamics Laboratory, United States
8	gfdl_cm2_1	Geophysical Fluid Dynamics Laboratory, United States
9	giss_aom	Goddard Institute of Space Studies(NASA), United States
10	giss_model_e_h	Goddard Institute of Space Studies(NASA), United States
11	giss_model_e_r	Goddard Institute of Space Studies(NASA), United States
12	iap_fgoals1_0_g	Institute of Atmospheric Physics, China
13	ingv_echam4	National Institute of Geophysics and Volcanology, Italy,
14	inmcm3_0	Institute for Numerical Mathematics, Russia
15	ipsl_cm4	Institut Pierre Simon Laplace, France
16	miroc3_2_hires	Center for Climate System Research, Japan
17	miroc3_2_medres	Center for Climate System Research, Japan
18	miub_echo_g	Meteorological Institute of the University of Bonn, Germany
19	mpi_echam5	Max-Planck-Institute for Meteorology, Germany
20	mri_cgcm2_3_2a	Meteorological Research Institute, Japan
21	ncar_ccsm3_0	NCAR Community Climate System Model, USA
22	ncar_pcm1	NCAR Parallel Climate Model, USA
23	ukmo_hadcm3	Hadley Centre for Climate Prediction, UK
24	ukmo_hadgem1	Hadley Centre for Climate Prediction, UK
25	SMA	
26	BMA	

Skill scores :

Root-mean-square (RMS) difference

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

Pearson correlation coefficient (R)

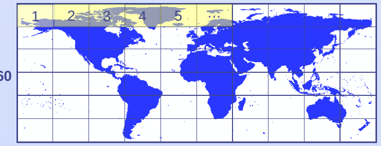
$$R = \frac{\sum_{i=1}^{n}(P_i - \bar{P})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2} \cdot \sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}}$$

Nash-Sutcliffe model efficiency (E)

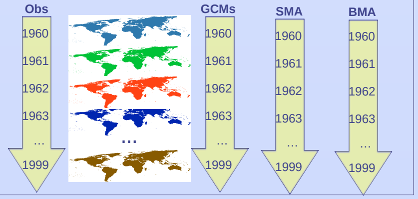
$$E = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$$

Evaluation objects :

Spatial simulation



Trend simulation

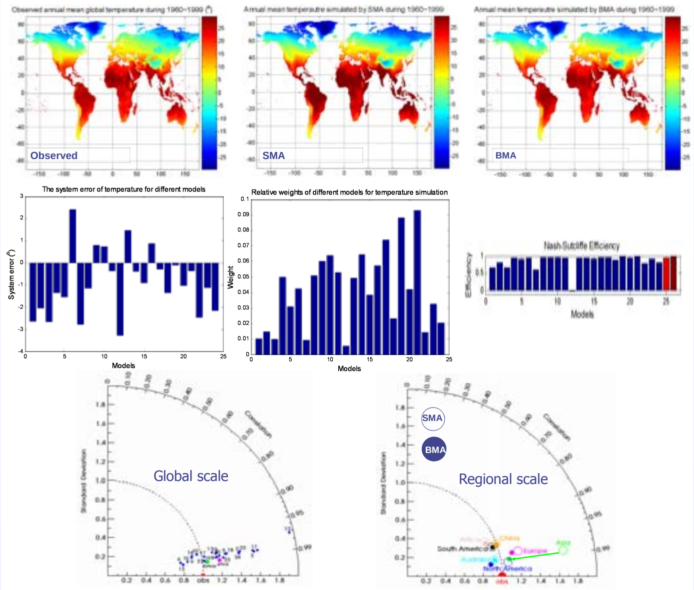


Results :

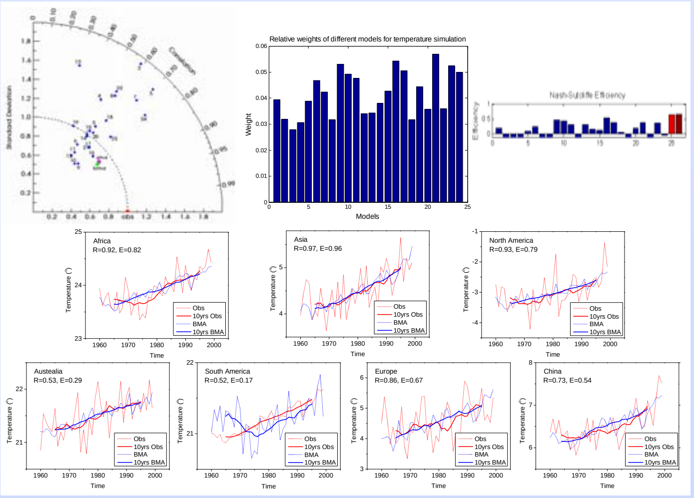
1. All simulations (24 AR4 GCMs + SMA + BMA) provide satisfactory results of the spatial distribution of annual mean temperature during 1960~1999.

2. AR4 GCMs give unsatisfactory simulations of the inter-annual temporal variability in global temperature.

3. BMA and SMA can improve simulations of temperature trend over 10 years, and the performance of BMA is better than SMA.



Spatial simulation



Trend simulation