Predictability Of Trend In Temperature Change In Eurasia Using Bayesian Multimodel Ensemble Approach

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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. A good understanding of how these biases manifest in the historical simulation is necessary for us to understand how climate change may occur in the future. However, existing research had indicated that GCMs from IPCC- AR4 (Fourth Assessment Report) are unable to represent fully the intensity and frequency of observed climate characteristics, due to the fact that a theoretical description of the climate remains incomplete, and simplifying assumptions are inherent when building these GCMs. It is expected that some of the scientific questions that arose during preparation of the IPCC-AR4 will be addressed through CMIP5 (Coupled Model Intercomparison Project Phase 5) in time for evaluation in the AR5. In addition, 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 the global average temperature trend during the 1901~2005 using CMIP5 data.

Objectives :

1.Assess the performance of the GCMs used in CMIP5 when focus on the global temperature simulation.

2. Conduct an inter-comparison of the temporal and spatial changes in global temperature using the Bayesian Model Averaging (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 $\{f_1, f_2, \dots, f_K\}$ of variable :

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

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

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

The prediction $p(y \mid f_1, f_2, \dots, f_K)$ 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),

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

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

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

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: 1901~2005

Resolution: 0.5° ×0.5°

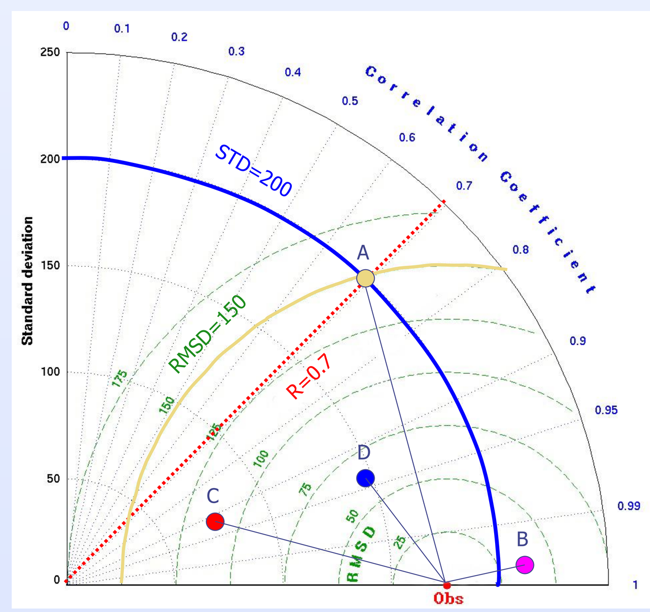
Observed data: CRUTS3p1, Climatic Research Unit

Simulated data: IPCC-AR5(7 GCMs) + BMA result

The global climate models in IPCC-AR5

No.	Model	Source
1	BNU-ESM	Beijing Normal University, China
2	CNRM-CM5	National Centre for Meteorological Research, France
3	CanESM2	Canadian Centre for climate modelling and analysis, Canada
4	FGOALS2-s	Institute of Atmospheric Physics, China
5	GISS-E2-H	NASA Goddard Institute for Space Studies, USA
6	GISS-E2-R	NASA Goddard Institute for Space Studies, USA
7	NorESM1-M	Norwegian Climate Centre, Norway
8	BMA	

Evaluation of simulation skill : Taylor diagram

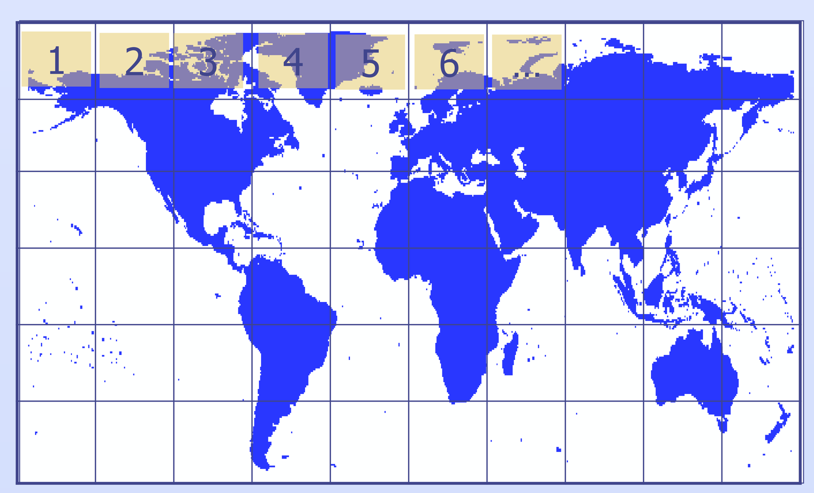


It is generally accepted that closer to observed point, more accurate simulation.
So, B>D>C>A

(Taylor, 2001 JGR)

Evaluation objects :

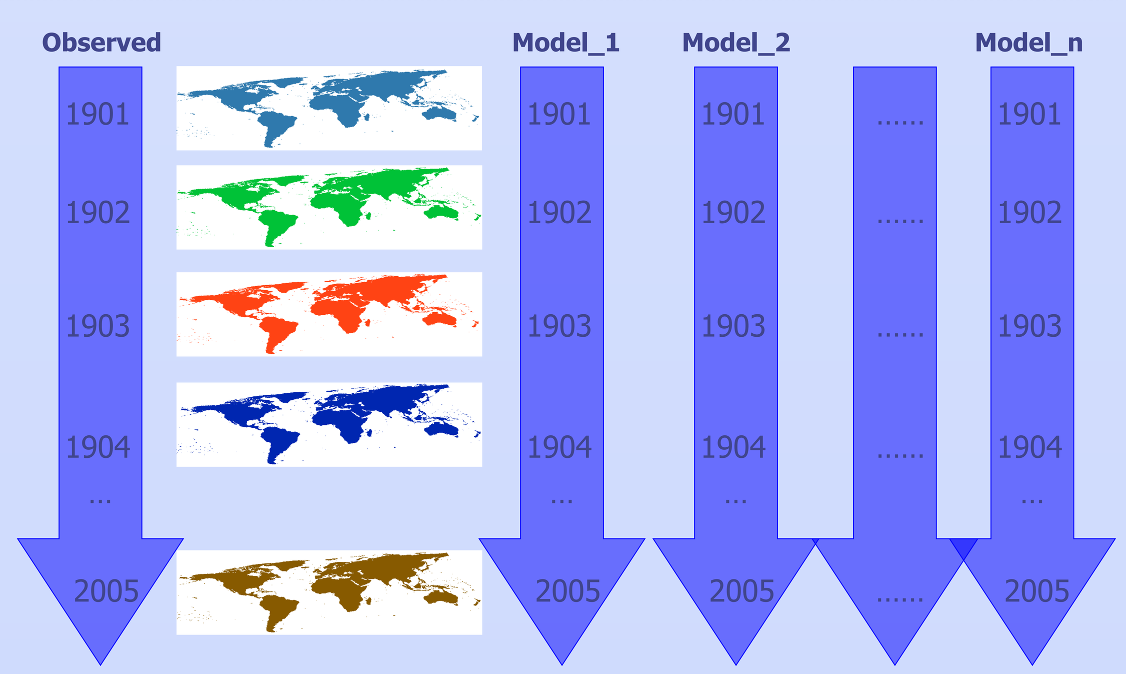
Spatial simulation



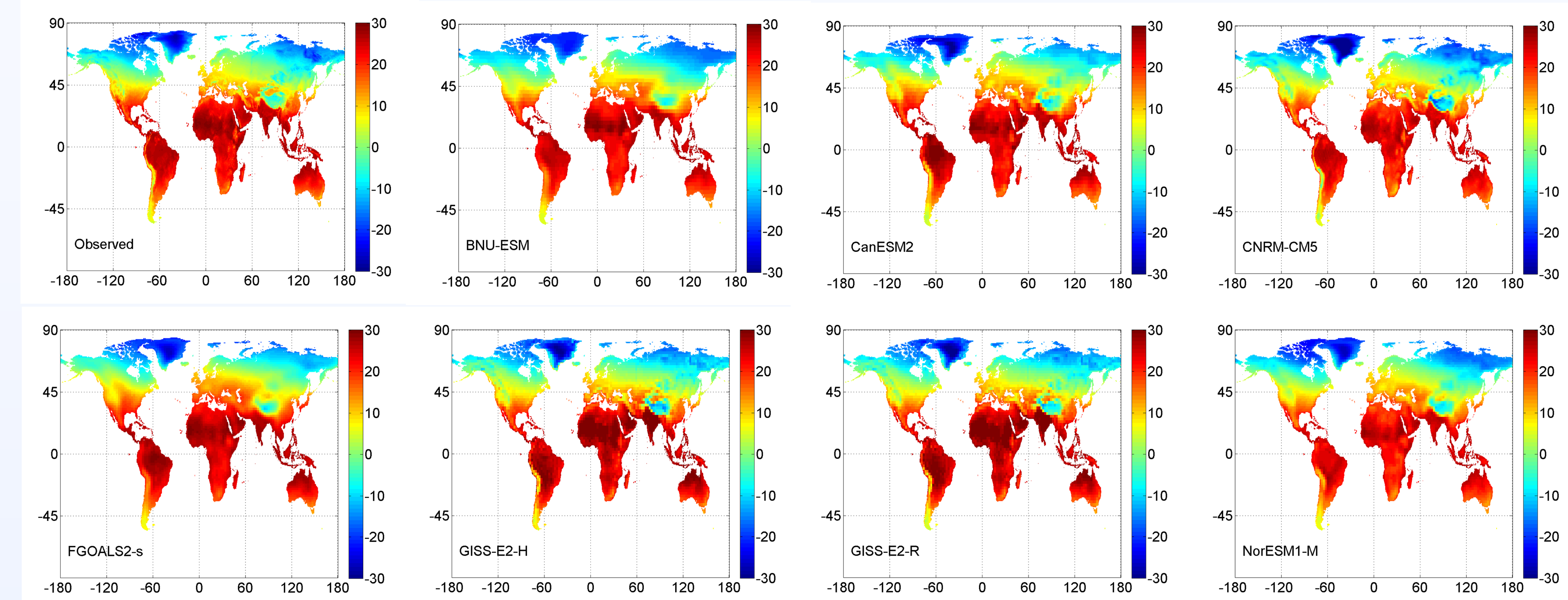
360

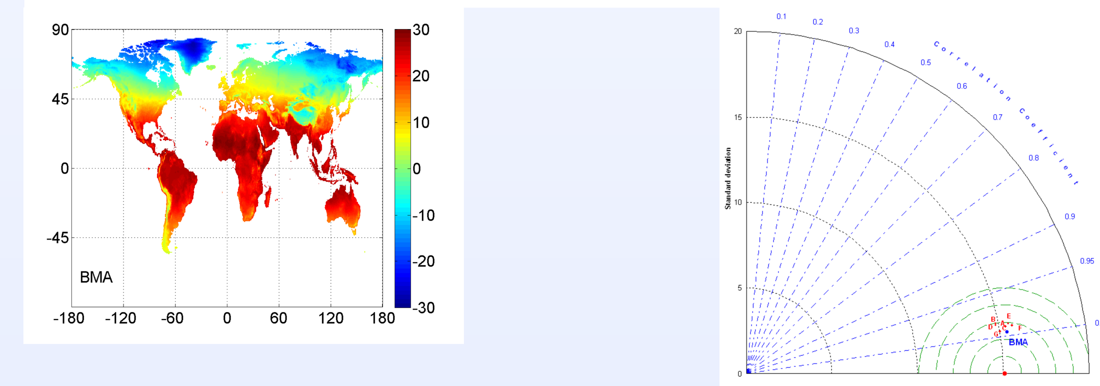
720

Trend simulation



Results :

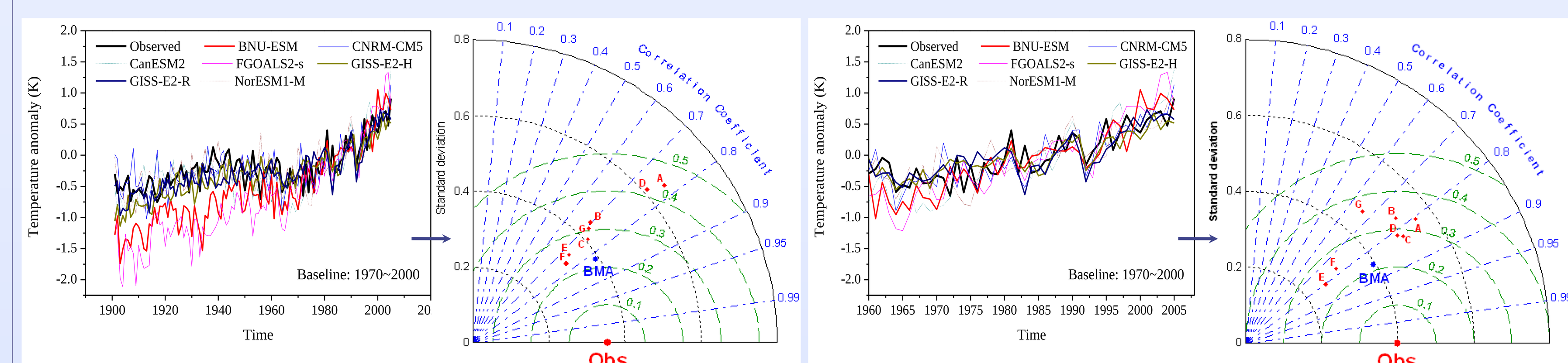




Symbol	model
A	BNU-ESM
B	CNRM-CM5
C	CanESM2
D	FGOALS2-s
E	GISS-E2-H
F	GISS-E2-R
G	NorESM1-M
BMA	Bayesian Model Averaging results

The spatial distribution of annual average observed and simulated TAS during 1901-2005 and its Taylor diagram evaluation

Spatial simulation



The temporal simulation of annual average observed and simulated TAS during 1901-2005 and its Taylor diagram evaluation

Temporal simulation

Discussion and summary:

- Model resolution

  It is generally believed that higher resolution does not automatically mean a better performance of the models. However, coarse resolution possibly have an effect on the accuracy of spatial simulation, even the model outputs were regrided into uniform resolution (0.5° ×0.5°) in this research.

- Models' shortage

  Although the 20th Century historical simulations in CMIP5 will use a much more diverse set of model types than did the similar simulations in CMIP3, some internal variability of the climatic itself is still not full considered due to our incomplete understanding on climate process.

- The quality of observed data

  The observed climate data (CRU 3.1) is generated by the meteorological station, however, the sparsity and uneven disiribution of stations in the world directly influence the accuracy of interpolated outputs.

- IPCC-AR5 simulates the spatial distribution of annual average temperature well.
- The performance of AR5 is weakened when facing the temporal simulation of annual average temperature.
- BMA method can improve the IPCC-AR5 GCMs performance effectively, especially for the temporal simulation.