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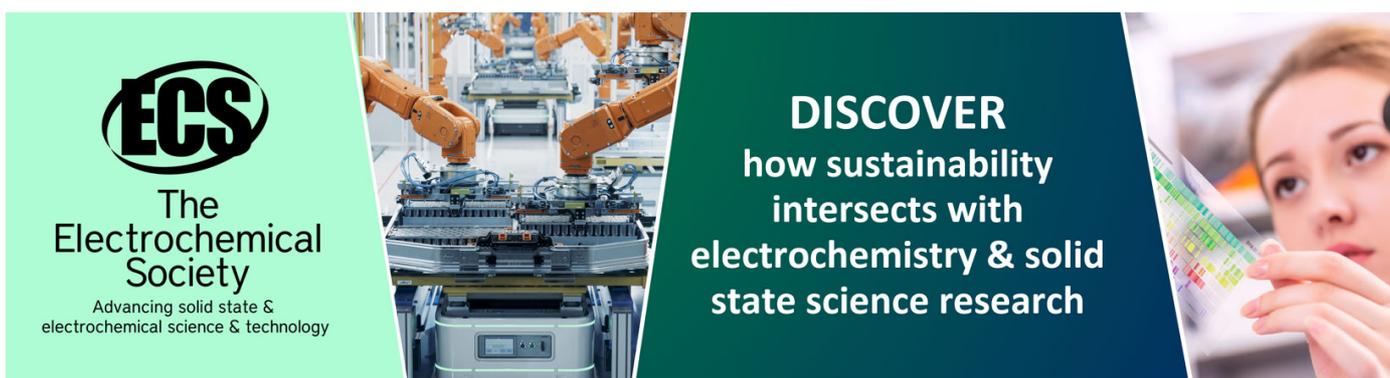
Probabilistic multi-model ensemble prediction of interdecadal variability of East Asian surface air temperature based on CMIP5 data

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Probabilistic multi-model ensemble prediction of interdecadal variability of East Asian surface air temperature based on CMIP5 data

Hongmei Zhou^{1,3}, Shusu Wang², Shuqin Wang¹ and Yue Mao¹

¹ Sheyang Meteorological Service, Yancheng, 224300;

² Haimen Meteorological Service, Nantong, 226100

³ Email:meizi_zhou2016@163.com

Abstract. Based on the CMIP5 runs of 10 models for climate hindcast of the surface air temperature, the prediction based on the method of Bayesian model average (BMA) has been conducted in the study. The results show that the ensemble system exhibited high performance in hindcasting the interdecadal (1981–2010) mean of temperature anomalies. In the RCP4.5 scenario, the decadal projection initialized on 2005 is used to estimate the temperature changes for the period from 2006 to 2035. Moreover, the temperature averaged over 2006-2035 increases conspicuously compared with 1961-1990. The results show that the temperature rising in the south is relatively slow, which reaches 0.7°C, while the temperature rises 1.3°C in the north. The temperature rise in the Western Pacific is fairly modest, while the temperature rise in the northwestern part of East Asia is more considerable, and the inland temperature rises more significantly than the coastal and offshore areas.

1. Introduction

The global warming has led to frequent occurrences of extreme weather and climate events such as floods and droughts, causing huge losses to people's production, life and socio-economic development. Therefore, it plays an important role in the study of the global climate change. The climate prediction of 10-30 years becomes more and more popular [1]. The prediction of the fully coupled model is the most promising method for the interdecadal climate prediction. The fifth phase of the coupled model Intercomparison Project (CMIP5) includes interdecadal experiments of the fully coupled model [2]. However, due to uncertainties such as the physical parameterization process of each model and future emission scenarios, there are great uncertainties in climate change returns and future climate change predictions. Therefore, how to reduce these uncertainties has become an important issue in the interdecadal climate prediction.

The generation of ensemble prediction techniques has helped to resolve the uncertainty of model prediction [3], and the multi-model results have a more reliable ability for simulating the climate in East Asian than a single model [4]. The probabilistic prediction can quantitatively assess the uncertainty and provide more accurate predictions for risk analysis and decisions about weather changes to achieve economic optimization [5]. The Bayesian Model Averaging (BMA) method produces a highly concentrated Probability Density Function (PDF). The probabilistic forecast for a particular variable is a weighted average of probability predictions for a single model after the bias correction, and the weight is the posterior probability of the corresponding model, representing the relative forecasting skill of each model in the model training phase. Probabilistic forecast is performed



on the PDF of the existing prediction effect. This predictive PDF is the weighted average of the probability density function (PDF) of each center subjected to the deviation correction.

The BMA method is originally used for variables with normal distribution of ground pressure and sea level pressure. Hoeting et al. [6] systematically described the BMA method and pointed out that BMA can quantitatively estimate the uncertainty of the model. Raftery et al. [7] used the BMA method for the probabilistic prediction of sea level pressure and surface air temperature at 48h. Zhi et al. [8] pointed out that the Bayesian model average probabilistic forecast can provide more accurate forecasting and provide more comprehensive forecasting information than deterministic forecasting. Peng et al. [9] used the BMA method to study the surface air temperature and precipitation in East Asia and concluded that the BMA method can effectively convert a single deterministic forecast into a continuous probabilistic forecast to fully reflect the uncertainty of the forecast and provide the more comprehensive forecast information. Zhao [10] used the BMA method to integrate and correct the quantitative precipitation in the Huaihe River Basin, and found that the forecasting ability of BMA is higher than the deterministic forecast. Zhi et al. [11] used the surface air temperature data of CMIP5 to study the BMA prediction method. The results show that the return effect of the ensemble method is better than that of 8 single modes, and BMA has the best return effect. Wang et al. [12] used the GED method to analysis the decadal variability of surface air temperature in East Asia. Zhi et al. [13] compared two different methods of the probabilistic prediction, and found that the variance of the probabilistic prediction by BMA method is small, which reduced the uncertainty of the forecast.

The paper is organized as follows. Firstly, the verification of the BMA forecast in the forecast period is conducted. Then the results of the RCP4.5 scenario are used for the probability prediction of the interdecadal variability of the surface air temperature in East Asia from 2006 to 2035.

2. Data and methods

2.1. Data

Table 1. Basic characteristics of the 10 CMIP5 coupled climate models.

Model name	Unit and country	Resolution (Nx×Ny)
BCC-CSM1-1	National Climate Center, China Meteorological Administration	128×64
CanCM4	Canadian Climate Model and Analysis Center, Canada	128×64
CMCC-CM	European Mediterranean Climate Change Center, Italy	480×240
FGOALS-g2	State Key Laboratory of Numerical Simulation of Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, China	128×60
FGOALS-s2	State Key Laboratory of Numerical Simulation of Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, China	128×108
IPSL-CM5A-LR	Pierre Simon Laplace Institute, France	96×96
MIROC4h	Institute of Atmospheric and Oceanography, Japan	640×320
MIROC5	Institute of Atmospheric and Ocean Research, University of Tokyo, National Institute of Environment, Japan Institute of Earth and Ocean, Japan	144×143
MPI-ESM-LR	Max Planck Institute for Meteorology, Germany	192×96
MRI-CGCM3	Japan Meteorological Institute, Japan	320×160

In this paper, the monthly average data of the interdecadal prediction of 10 climate models (Table 1) in the CMIP5 test is all initialized in 1960, 1965, 1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, and the forced fields under the RCP4.5 scenario are used after 2005. All data is interpolated to $2.5^{\circ} \times 2.5^{\circ}$, and the reanalysis monthly average data of surface air temperature from NCEP/NCAR is used as the observation. East Asia (15° - 55° N, 70° - 140° E) is the research area in this paper.

2.2. Method

2.2.1. *BMA*. For surface air temperature, the conditional probability density function can be well fitted with a normal distribution [14]. In the BMA, $h_k(y|f_k)$ is the probability density function when f_k is the best forecast in the ensemble.

$$p(y|(f_1, f_2, \dots, f_K, y^T)) = \sum_{k=1}^K \omega_k h_k(y|(f_k, y^T))$$

where ω_k is the weight that reflects the relative contribution of the Kth model during the training period. ω_k is non-negative and satisfies $\sum_{k=1}^K \omega_k = 1$. $h_k(y|f_k)$ is approximate to a normal distribution and the mean is a simple linear function of the original return result $a_k + b_k f_k$, σ is the standard deviation, i.e.:

$$h_k(y|f_k) \sim N(a_k + b_k f_k, \sigma^2)$$

The forecast mean of BMA is the deterministic result :

$$E(y|f_1, \dots, f_K) = \sum_{k=1}^K w_k (a_k + b_k f_k)$$

2.2.2. *Evaluation method*. In this paper, the results of BMA are evaluated by Rank Probability Score(RPS). The formulation of RPS is as follows:

$$RPS(p, d) = 1 - \frac{1}{k-1} \left[\sum_{i=1}^k \left(\sum_{n=1}^i p_n - \sum_{n=1}^i d_n \right)^2 \right]$$

Where $p : (p_1, p_2, \dots, p_k)$ and $d : (d_1, d_2, \dots, d_k)$ are the forecast and observed probabilities of different ranks k respectively. The member of d set is 1 or 0, and if $d_i = 1$, all the other $d_j (j \neq i, j = 1, 2, \dots, k) = 0$. The value of RPS is between 0 and 1. The more accurate the ensemble hindcast, the higher the value of the average RPS is.

3. Results

3.1. Evaluation of BMA skill

Before ensemble prediction, the skill of BMA over East Asia is evaluated by RPS. The probabilistic prediction of the annual mean temperature anomaly is divided into 10 ranks: $T \leq -0.2^{\circ}\text{C}$; $-0.2^{\circ}\text{C} < T \leq 0.0^{\circ}\text{C}$; $0.0^{\circ}\text{C} < T \leq 0.2^{\circ}\text{C}$; $0.2^{\circ}\text{C} < T \leq 0.4^{\circ}\text{C}$; $0.4^{\circ}\text{C} < T \leq 0.6^{\circ}\text{C}$; $0.6^{\circ}\text{C} < T \leq 0.8^{\circ}\text{C}$; $0.8^{\circ}\text{C} < T \leq 1.0^{\circ}\text{C}$; $1.0^{\circ}\text{C} < T \leq 1.2^{\circ}\text{C}$; $1.2^{\circ}\text{C} < T \leq 1.4^{\circ}\text{C}$; $T > 1.4^{\circ}\text{C}$. The results show that, BMA performs better at predicting the annual mean temperature anomaly. The values of RPS in East Asia reach 0.92. The

regional distribution of RPS by BMA reflected in Figure 1 can reach more than 0.85 in most areas, but the skill scores near Baikal Lake and near the Qinghai-Tibet Plateau in China are relatively low, with a minimum of 0.65. These two areas are the high-value area and low-value area of the 30-year surface air temperature anomaly from 1981 to 2010, that is, the BMA method still has problems for the simulation of extreme values.

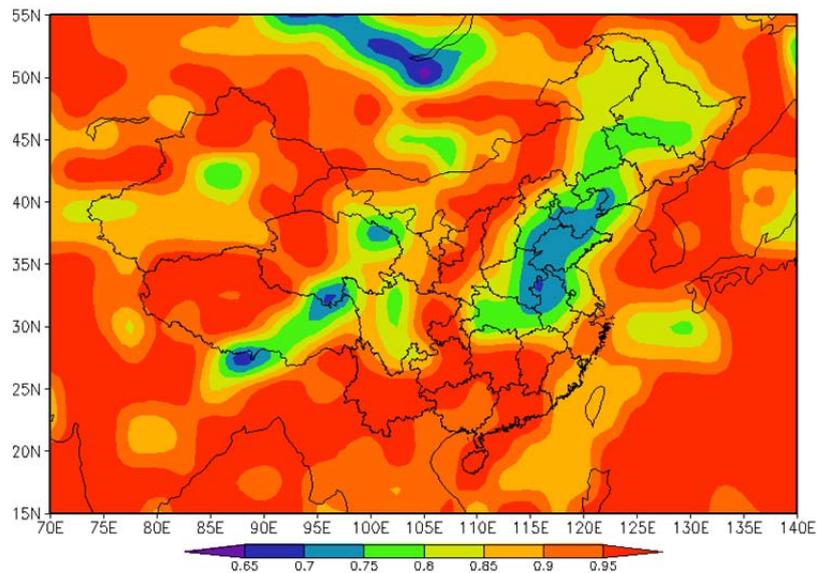


Figure 1. RPS of annual mean temperature (ANN) hindcasts over East Asia during 1981–2010 by BMA.

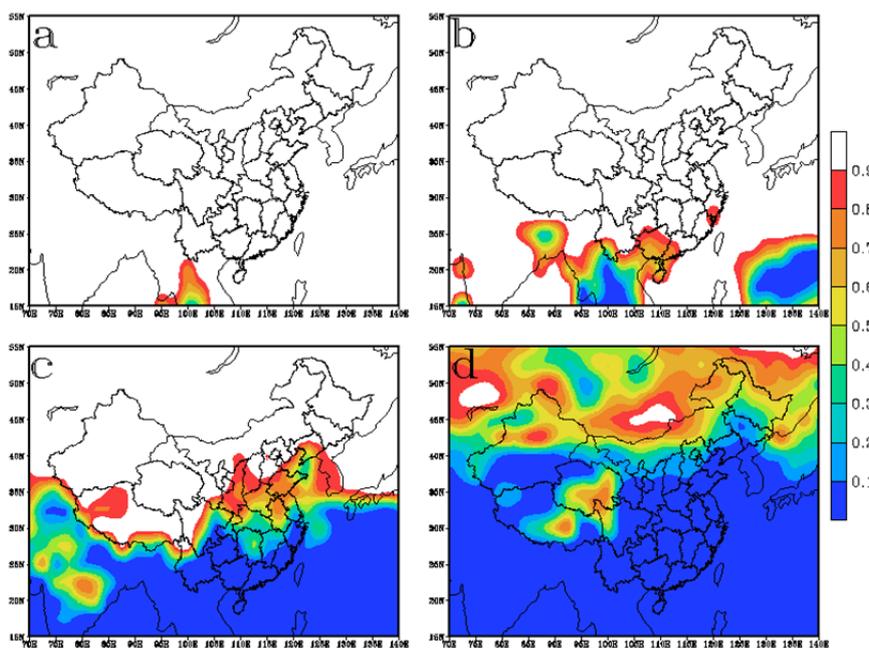


Figure 2. Probability maps exceeding prescribed values of -0.3°C (a), 0.5°C (b), 0.9°C (c), 1.3°C (d) for mean temperature in East Asia from 2006 to 2035.

3.2. Future surface air temperature estimate under medium emission scenarios

The probability maps reflect the spatial patterns of annual mean temperature anomaly exceeding prescribed values. Figure 2 shows the probability maps for the 30-yr mean in the period 2006-2035 for exceeding $-0.3^{\circ}\text{C}(30\text{ yr})^{-1}$, $0.5^{\circ}\text{C}(30\text{ yr})^{-1}$, $0.9^{\circ}\text{C}(30\text{ yr})^{-1}$ and $1.3^{\circ}\text{C}(30\text{ yr})^{-1}$. In general, all probability distributions show a north-south pattern, that is, the probability of the temperature greater than a certain value is greater in the north than in the south. According to IPCC-AR4, the probability of a future climate event is divided into five categories: >99% (virtually certain), >90% (very likely), >66% (likely), <33%(impossible) and <10%(unlikely). In general, the surface air temperature in East Asia rises in 2006-2035, and there is no negative area of the surface air temperature anomalies. In the northern part of East Asia, the possibility of surface air temperature rising above 0.9°C is far greater in the inland than in the oceans and in the eastern and southern coastal areas. The increase of surface air temperature in East Asia is increasing from southeast to northwest. Therefore, the temperature rise in the tropical northwestern Pacific is the least obvious, while the surface air temperature in northwestern China is the most significant.

Figure 3 shows the distribution of surface air temperature under different probabilities of BMA from 2006 to 2035. The north-south characteristic of the rise of the surface air temperature is also very obvious. The most obvious increase in surface air temperature is in the northwest and northeast regions, while the temperature in the central and southern peninsula of the western Pacific is not obvious.

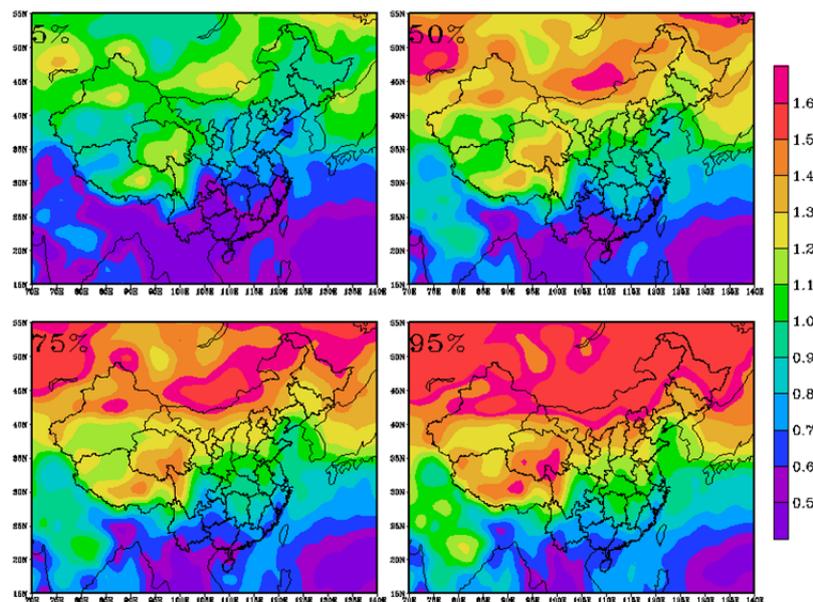


Figure 3. Temperature distribution under different probabilities of BMA (5%, 50%, 75%, 95%) during 2006-2035.

4. Summary

The result of BMA is evaluated by using the results of the CMIP5's 10 global climate system models. On this basis, some predictions are made by BMA in the RCP4.5 scenario from 2006 to 2035, and the main findings are concluded as follows:

The average surface air temperature anomalies in East Asia during the period 2006-2035 are about $1.0-1.1^{\circ}\text{C}$ with respect to 1961-1990. It is less likely that the temperature in the south of East Asia will rise more than the north. Moreover, in the north of East Asia, the probability of inland warming is greater than that of the coastal and offshore areas. In the south, inland warming is more pronounced than in the tropical northwestern Pacific, with greater warming. Therefore, the most obvious increase

in surface air temperature during 2006-2035 locates in the northwest and northeast regions, while the warming of the Indo-China Peninsula in the western Pacific is the least obvious.

Under the climate background of various changes [15-25], further contents with respect to experiments for precipitation and many other factors under different RCP scenarios need to be investigated with statistical methodology [26-30]. Improved prediction skills [31-32] will do a lot of favor for disaster preventions and social stability [33-34].

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