Future Projections of East Asian Climate Change from Multi-AOGCM Ensembles of IPCC SRES Scenario Simulations

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Abstract

In this paper, future climate changes over East Asia (20–50°N, 100–145°E) are projected from multi-model ensembles (MMEs) of selected coupled atmosphere-ocean general circulation model (AOGCM) simulations based on Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) A2 and B2 scenarios. Analyzed variables include annual and seasonal near surface temperature and precipitation over East Asia. Before projecting future climate, model performances are evaluated on the simulation of the present-day climate (1961–1990) with bias, root-mean squared error (RMSE), and the Taylor diagram analysis. The result of model evaluation shows that CSIRO Mk2, ECHAM4/OPYC3, GFDL_R30_c, and HadCM3 exhibit higher performance. In order to test the sensitivity of projection results, four MMEs are defined: simple arithmetic averages of all seven AOGCM simulations (MME7) and four skillful AOGCM simulations (MME4), and skill-weighted averages of seven AOGCM simulations based on the skill scores of the Taylor diagram (MME_S1 and MME_S2). While the weighted MMEs (MME_S1 and MME_S2) have similar performances in the present-day climate simulation to that of MME7, MME4 constructed by four skillful models reveals higher performance than the other MMEs.

The overall projection results from four MMEs show that East Asia will experience warmer and wetter climate in the 21st century. The projection results are not sensitive to the MME method. Area-averaged temperature changes for three 30-year periods of 2020s, 2050s, and 2080s simulated by MME7 A2 [B2] scenario ensembles are 1.2 [1.4], 2.5 [2.4], and 4.1°C [3.2°C] increase, and precipitation changes are 0.4 [1.4], 2.2 [2.6], and 5.0% [4.0%] increase, respectively. Spatial patterns indicate that both temperature and precipitation increases are larger over the continental area than the oceanic area, and that the areas of larger inter-model variability are in accord with those of stronger climate change. The inter-model variability (noise) in precipitation changes is as large as that of ensemble mean (signal), whereas noise is much smaller than signal in the projection of temperature changes. It is demonstrated that MME4 reduces the inter-model uncertainty about a half of MME7 in the temperature projection of the late 21st century, but not in the precipitation projection. A significant difference in projected patterns between A2 and B2 scenario ensembles (defined as a potential impact of greenhouse-gas mitigation) appears in the 2080s temperature field over the southwestern part of East Asia. However, no significant differences can be found between precipitation patterns of A2 and B2 scenario ensembles because of the

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dominant inter-model variability. It is also shown that the climate change over East Asia has a characteristic seasonal dependence, that is, larger increases of wintertime temperature and summertime precipitation, which implicates the possible change of the East Asian monsoon system by global warming.

1. Introduction

Multi-model ensemble (MME) is defined as average of simulation results from multiple models. MME is used to reduce the effects of uncertainty originating from different initial conditions and characteristic biases of individual models. MME method has been applied to seasonal predictions from atmospheric general circulation models (AGCMs) (Krishnamurti et al. 2000; Kharin and Zwiers 2002; Yun et al. 2003; Yun and Kwon 2003), model evaluation or estimation of the climatology from coupled atmosphere-ocean GCMs (AOGCMs) (McAvaney et al. 2001), climate change projection from AOGCMs (Cubasch et al. 2001; Giorgi and Mearns 2002; Lal and Harasawa 2001), and climate change detection from AOGCMs (Gillett et al. 2002).

The AOGCMs have been used for projections of future climate change with spatial scales of hundreds of kilometers and larger. MMEs of AOGCM simulations were assessed by the Intergovernmental Panel on Climate Change (IPCC) for the period of 1990 to 2100 based on a range of emissions scenarios for greenhouse gases (GHGs) and sulfate aerosols. Total ten and eight AOGCMs were used for IPCC IS92a (Pepper et al. 1992) and the Special Report on Emissions Scenarios (SRES) (Nakicenovic and Swart 2000), respectively (data available from IPCC Data Distribution Center (DDC) at <http://ipcc-ddc.cru.uea.ac.uk>). For climate change detection and attribution problem, control simulations of AOGCMs are used to estimate internal variability (noise) of climate system and forced simulations of AOGCMs provide fingerprints (signal) of climate change (Mitchell et al. 2001).

Giorgi and Mearns (2002) introduced a kind of weighted MME, referred to as the Reliability Ensemble Average (REA), using the bias of the present climate simulation and the difference from ensemble mean in the future climate for the 22 continental regions. Lal and Harasawa (2001) projected climate change over the Asian continent from four skillful AOGCM simula-

tions based on the IPCC IS92a scenario selected by analyzing spatial pattern correlations and root-mean squared errors (RMSEs).

In this study, the projection results of the previous works focusing on the East Asian region are updated using seven AOGCM simulations based on the SRES A2 and B2 scenarios. More comprehensive method of model evaluation is introduced to construct MMEs with skillful AOGCMs and the affect of skillful models on the noise level in the projection result is assessed. Assuming that we can reduce GHG emissions by the level of the B2 scenario from that of the A2 scenario, a potential impact of GHG mitigation is estimated by comparing the MME results of the A2 and B2 scenarios. In addition, monthly and seasonal climate change is examined to see whether the annual cycle of temperature and precipitation over East Asia will be changed in the future.

Data and methodology are described in the next section. MME constructions from seven AOGCMs are explained along with model evaluation on their present-day climate simulations in section 3. Future projections of temperature and precipitation over East Asia are provided in section 4 with emphasis on inter-model uncertainty, a potential impact of GHG mitigation, and seasonal dependence of climate change. Conclusions are given with some discussions in the final section.

2. Data and methodology

The East Asian region is defined as the domain of 20–50°N and 100–145°E, which is the same as in Giorgi and Mearns (2002) and Lal and Harasawa (2000, 2001). Analysis variables include monthly to annual mean near surface temperature and precipitation. Table 1 summarizes the experiments of SRES A2 and B2 scenario simulations with seven AOGCMs with descriptions of atmospheric and oceanic resolutions, flux adjustments, cumulus convection schemes, aerosol forcing effects, and key references. Among seven AOGCMs, HadCM3, and DOE PCM do not use flux adjustments, and ECHAM4/OPYC3 has a distinct flux correction

Table 1. AOGCM experiments based on the IPCC SRES A2 and B2 scenarios used in this study.

Model name <i>Center</i> ^a	Starting and ending year	Atmospheric resolution ^b	Oceanic resolution ^c	Flux adjustment ^d	Cumulus convection scheme	Aerosol forcing effect ^f	References
CGCM2 <i>CCCma</i>	1900– 2100	T32 (3.8×3.8) L10	1.875×1.875 L29	H, W	Moist convective adjustment similar to Manabe et al. (1965)	D	Flato and Boer (2001)
CCSR/NIES2 <i>CCSR/NIES</i>	1890– 2100	T21 (5.6×5.6) L20	2.8×2.8 L17	H, W	Relaxed Arakawa- Schubert (Moorthi and Suarez 1992)	D, I1, I2	Nozawa et al. (2001)
CSIRO Mk2 <i>CSIRO</i>	1961– 2100	R21 (3.25×5.625) L9	3.25×5.625 L21	H, W, M	Modified Arakawa “soft” moist convective adjustment (Arakawa 1972) and mass flux scheme	D	Gordon and O’Farrell (1997)
ECHAM4/ OPYC3 <i>MPIfM</i>	1990– 2100	T42 (2.8×2.8) L19	$2.8 \times 2.8^{\#}$ L11	H*, W*	Mass flux scheme (Tiedtke 1989) with an adjustment closure based on CAPE ^e (Nordeng 1994)	D, I1	Stendel et al. (2002)
GFDL_R30_c <i>GFDL</i>	1965– 2104	R30 (2.25×3.75) L14	2.25×1.875 L18	H, W	Moist convective adjustment (Manabe et al. 1965)	D	Delworth et al. (2002)
HadCM3 <i>HCCPR</i>	1950– 2099	2.5×3.75 L19	1.25×1.25 L20	—	Mass flux penetrative convective scheme (Gregory and Rowntree 1990) and modification (Gregory et al. 1997)	D, I1	Johns et al. (2003)
DOE PCM <i>NCAR</i>	A2: 1981– 2099 B2: 2001– 2099	T42 (2.8×2.8) L18	$0.67 \times 0.67^{\#}$ L32	—	Simplified Arakawa- Schubert (Zhang and McFarlane 1995)	D	Washington et al. (2000) Dai et al. (2001)

a. Canadian Center for Climate Modelling and Analysis (CCCma), Center for Climate Research Studies (CCSR)/National Institute for Environmental Studies (NIES), Commonwealth Scientific and Industrial Research Organization (CSIRO), Max-Planck-Institute für Meteorologie (MPIfM), Geophysical Fluid Dynamics Laboratory (GFDL), Hadley Centre for Climate Prediction and Research (HCCPR), and National Center for Atmospheric Research (NCAR).

Table 1. (Continued)

- b. Atmospheric and oceanic resolutions are expressed as latitude ($^{\circ}$) $\times$ longitude ($^{\circ}$) with spectral truncations and 'L' + number of vertical levels.
- c. A sharp (#) depicts the use of equatorial refinement.
- d. H = heat flux; W = freshwater flux, M = momentum flux. An asterisk (*) indicates annual mean flux adjustment only.
- e. Convective available potential energy (CAPE).
- f. D: direct radiative cooling effect of the aerosols, I1: first indirect effect of the aerosols (cloud albedo effect), and I2: second indirect effect of the aerosols (cloud lifetime effect).

of annual mean values rather than monthly means. All model simulation data are interpolated into the same $5^{\circ} \times 5^{\circ}$ grids as the observations before analysis. We construct and use mainly two MMEs; one is the average of all seven AOGCMs, which is referred to as MME7, and the other is MME4 defined from four selected AOGCMs of higher performance. To select skillful AOGCMs their present-day climate is validated with bias, RMSE, spatial pattern correlation, and standard deviation. The pattern correlation and standard deviation is evaluated with the help of the Taylor diagram (Taylor 2001). Table 2 enlists the experiments of present-day climate simulations from three AOGCMs, A2 and B2 simulations of which exclude the present-day period (see Table 1).

After bias and RMSE are first analyzed to validate uncentered statistics in individual models, the Taylor diagram analysis is applied to evaluate centered statistics (pattern correlation and spatial variance). The Taylor diagram displays three pattern statistics on a 2-D plot (McAvaney et al. 2001; Taylor 2001): ratio of the variances of the two fields ($\tilde{\sigma}_f$), correlation between two fields (R), and centered root mean squared difference between two fields ($\tilde{E}'$). The Taylor diagram provides simple and easily interpretable results of model evaluation or inter-comparison and can be used to a number of applications (Taylor 2001). However, it has a shortcoming that it does not consider un-

centered statistics. Boer and Lambert (2001) suggested an alternative diagram to overcome the shortcoming in the Taylor diagram, but their diagram has disadvantages as using the “effective” correlation coefficient, which is defined as a weighted difference between two true correlation coefficients, so more difficult to interpret (Taylor 2001).

In order to evaluate quantitatively the model performance from the Taylor diagram, we use two skill scores S_1 and S_2 devised by Taylor (2001), although they were offered as illustrative examples to guide in developing better skill scores (Taylor 2001):

$$S_1 = \frac{4(1+R)}{(\tilde{\sigma}_f + 1/\tilde{\sigma}_f)^2(1+R_0)}, \quad (1)$$

$$S_2 = \frac{4(1+R)^4}{(\tilde{\sigma}_f + 1/\tilde{\sigma}_f)^2(1+R_0)^4}, \quad (2)$$

where R_0 is the maximum correlation attainable. As the model variance approaches the observed variance and the pattern correlation between model and observation approaches to R_0 , the scores approach unity. As the variance ratio approaches zero or infinite or as the correlation gets close to negative unity, skills approach zero. The score S_1 places emphasis on variance performance while pattern correlation between model and observation is more importantly treated in the score S_2 . Using the scores S_1 and S_2 as weighting factors in calculating model

Table 2. AOGCM experiments used for the present-day (1961–1990) climate validation.

Model name <i>Center</i>	Experiment name	Total period	References
ECHAM4/OPYC3 <i>MPIfM</i>	GSDIO	1860–2049	Roeckner et al. (1999) Stendel et al. (2002)
GFDL_R30_c <i>GFDL</i>	GS_C_1	1865–2089	Delworth et al. (2002)
DOE PCM <i>NCAR</i>	Historic Run	1960–1999	Washington et al. (2000)

averages, we define two additional MMEs, MME_S1 and MME_S2, which are weighted MMEs similar to Giorgi and Mearns (2002). However, there is a main difference between our weighted MMEs and those of Giorgi and Mearns (2002) in that we use pattern statistics of the present-day climate while they utilized area-averaged values in the present and future periods.

In the previous studies, model selection from AOGCMs or weighting factor calculation for each AOGCM has been evaluated in an independent way for each variable and/or region, e.g., for each grid point. This method might produce physically inconsistent projections and make it difficult to interpret the mechanism in future projection results. In this study, skillful models for construction of MME4 are selected simultaneously based on their performances of present-day climate simulation of both temperature and precipitation. Observational data, which are used for model climate validation, are 1961–1990 mean temperature from the Climate Research Unit (CRU) (Jones 1994; Jones and Moberg 2003) and 1979–1999 mean precipitation from the Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) (Xie and Arkin 1996, 1997).

Temperature and precipitation changes during the 21st century are projected with four MMEs (MME7, MME4, MME_S1, and MME_S2) and their differences are analyzed. Differences between ensemble means and intra-ensemble standard deviations of MME7 and MME4 are analyzed to examine if there is an advantage to use MME4 (MME from selected skillful models) over MME7 (simple average of total member of models) and those between the A2 and B2 results to assess a possible effect of greenhouse gas mitigation. To see whether there is seasonal dependence of climate change over East Asia, monthly and seasonal distributions of temperature and precipitation in the late 21st century are investigated.

3. Model evaluation

3.1 Bias and RMSE

Because the present-day climate fields of the A2 and B2 simulations with the same AOGCM are very similar to each other, only A2 scenario runs are used for validation. In the bias of the global temperature field, CSIRO Mk2 (+1.1°C),

DOE PCM (−1.7°C), and GFDL_R30_c (+1.8°C) have larger absolute value while CGCM2 (−0.1°C), CCSR/NIES2 (−0.1°C), and HadCM3 (−0.2°C) show smaller value. RMSEs of global temperature field have larger values with a range of 2.4–2.9°C except for ECHAM4/OPYC3 (1.7°C) and HadCM3 (1.9°C). In the global precipitation, DOE PCM has relatively large bias (+0.4 mm/day) and RMSE (1.8 mm/day) whereas other models have biases with a range of −0.2–+0.1 mm/day and RMSEs of 1.0–1.4 mm/day. Regional biases and RMSEs for the East Asian domain show different behaviors from global values.

Figure 1 shows bias and RMSE distributions of East Asian temperature and precipitation from seven AOGCMs and four MMEs. Most models have negative biases in temperature while positive biases in precipitation exist over East Asia. In the bias distribution (Fig. 1a,b) ECHAM4/OPYC3 has the best skill and other models show similar performances. CGCM2 represents stronger negative bias of −4°C in the temperature but the lowest bias in the precipitation. GFDL_R30_c has the largest precipitation bias but smaller temperature bias. Hence it is difficult to select models of lower performance in the bias field of temperature and precipitation. The RMSE distribution of temperature in Fig. 1c shows that CGCM2 has notably larger value of 6.4°C than other models. The RMSE in precipitation is grouped with a range of similar amplitude of 1.0–1.5 mm/day (Fig. 1d). In the model evaluation of East Asian climate simulation using two uncentered statistics (bias and RMSE), it is found that there is not large difference between model performances except for large RMSE and bias of CGCM2 temperature. As a result, the first selection is done as CGCM2 is removed from further consideration of skillful models. Figure 1 also shows that four MMEs have in general an increased performance than the individual models, and that, among four MMEs, MME4 has the best skill in near surface temperature. More comprehensive discussions of MME results are given below.

3.2 Taylor diagrams

The Taylor diagram analysis is applied to present-day climate patterns for temperature and precipitation field of seven AOGCMs in

Fig. 1. Bias and RMSE distributions of area-averaged near surface temperature ($^{\circ}\text{C}$) and precipitation (mm/day) over East Asia for the present-day climate (1961–1990 mean) from seven AOGCM simulations and four MMEs.

order to select skillful models. Figure 2 represents the result of the Taylor diagram analysis for the East Asian temperature and precipitation, and Table 3 lists values of normalized variance ratio ($\tilde{\sigma}_f$), pattern correlation with observation (R), normalized centered RMSE ($\tilde{E}'$), and skill scores S_1 and S_2 for seven AOGCMs and four MMEs. In the Taylor diagram the radial distance from the origin represents the standard deviation ratio of a tested pattern (model) to that of a reference pattern (observation), the pattern correlation between two fields is given by the azimuthal position, and the normalized centered RMSE of the tested pattern is given by the distance from the reference point of the observations (Taylor 2001). The results of MME_S1 and MME_S2 are not plotted in Fig. 2 because they are located very close to the point of MME7 results in both temperature and precipitation (see Table 3). CGCM2, which exhibited the lowest performance in the bias and RMSE (see Fig. 1), is analyzed in the Taylor diagram and it also reveals the lowest skill scores among seven models in both temperature and precipitation (see Table 3). Apart from CGCM2, CCSR/NIES2 has the lowest skill scores for the East Asian temperature, but the

difference from other models is not large (Table 3). The Taylor diagram in Fig. 2 shows that six models except for CGCM2 are positioned very close to each other in the temperature performance. On the other hand, precipitation evaluation result shows that, excluding CGCM2, CCSR/NIES2 and DOE PCM have a relatively low skill score in S_1 , and that DOE PCM has an outstandingly lower skill score in S_2 (Table 3). In the Taylor diagram (Fig. 2) one can see the lower performance in the precipitation of DOE PCM ('g' mark). Putting together the results of bias, RMSE, and Taylor diagram analyses, the second model selection is done as DOE PCM and CCSR/NIES2 are removed from models of high performance constituting MME4. Finally, skillful models for MME4 are selected as CSIRO Mk2, ECHAM4/OPYC3, GFDL_R30_c, and HadCM3.

In Table 3 the performances of four MMEs in the present-day climate simulation are compared with the individual models. Generally MMEs have better skills than the individual models. MME_S1 and MME_S2 show similar (or a little higher) performances to MME7, which implies that the weighted MMEs based on centered statistics in the present-day cli-

Table 3. The normalized standard deviation ratio ($\hat{\sigma}_f$), pattern correlation with observation (R), normalized centered RMSE ($\tilde{E}'$), and skill scores (S_1, S_2) in the Taylor diagram analysis for the East Asian temperature and precipitation from seven AOGCM simulations and four MMEs. The asterisks (*) indicate AOGCMs selected for MME4.

Models	Temperature					Precipitation				
	$\hat{\sigma}_f$	R	$\tilde{E}'$	S_1	S_2	$\hat{\sigma}_f$	R	$\tilde{E}'$	S_1	S_2
CGCM2	1.351	0.908	0.610	0.873	0.758	0.644	0.569	0.826	0.650	0.314
CCSR/NIES2	1.193	0.978	0.300	0.959	0.928	0.664	0.808	0.607	0.768	0.567
CSIRO Mk2*	1.178	0.977	0.293	0.962	0.930	0.748	0.811	0.588	0.833	0.619
ECHAM4/OPYC3*	1.101	0.988	0.191	0.985	0.967	0.810	0.750	0.664	0.837	0.561
GFDL_R30_c*	1.086	0.984	0.205	0.985	0.962	1.128	0.746	0.768	0.860	0.572
HadCM3*	1.144	0.987	0.225	0.976	0.957	1.246	0.893	0.572	0.902	0.765
DOE PCM	1.074	0.988	0.177	0.989	0.971	0.865	0.597	0.846	0.782	0.398
MME7	1.142	0.987	0.223	0.976	0.957	0.760	0.863	0.516	0.865	0.699
MME4	1.119	0.991	0.185	0.983	0.970	0.887	0.893	0.450	0.933	0.791
MME_S1	1.139	0.988	0.216	0.977	0.960	0.774	0.870	0.502	0.876	0.716
MME_S2	1.137	0.989	0.209	0.978	0.962	0.795	0.885	0.474	0.895	0.749

Fig. 2. Taylor diagram analysis for model-simulated near surface temperature and precipitation over East Asia for the present-day period (1961–1990) from seven AOGCM simulations, MME7, and MME4. Symbols [alphabets] depict temperature [precipitation] results.

Fig. 3. Time series of East Asian area-averaged temperature ($^{\circ}\text{C}$) and precipitation change (%) with respective to 1961–1990 mean in seven AOGCM simulations, MME7, and MME4 for the SRES A2 (upper panels) and B2 (lower) scenarios.

mate do not have significant advantage over the simple arithmetic averaging. It is notable that MME4 exhibits better skill than the other MMEs as in the bias and RMSE analysis in Fig. 1. The Taylor diagram in Fig. 2 supports the result showing that the position of MME4 is closer to the reference point than the individual models and other MMEs.

4. Projection results

4.1 Area average

a. Temperature

Figure 3a,c show the annual time series of area-averaged East Asian temperature change relative to 1961–1990 mean in the A2 and B2 scenario simulations of seven AOGCMs, MME7, and MME4. The results of MME_S1 and MME_S2 are omitted in Fig. 3 because they display very similar behavior to MME7 (compare mean values in Table 4). All model simulations and MMEs predict the temperature increase, which is larger than global mean and the internal and inter-model variabilities in

East Asian temperature are also larger than those in global mean (see Fig. 9.6a of Cubasch et al. 2001). Table 4 summarizes the temperature changes in the A2 and B2 simulations of seven AOGCMs and four MMEs for three 30-year periods of 2020s (2010–2039), 2050s (2040–2069), and 2080s (2070–2099) including intra-ensemble standard deviations for MME7 and MME4. MME7 of the A2 [B2] scenario indicates East Asian temperature increase of 1.2 [1.4], 2.5 [2.4], 4.1 $^{\circ}\text{C}$ [3.2 $^{\circ}\text{C}$] for 2020s, 2050s, and 2080s, respectively (for reference, global mean temperature increases are 1.0 [1.0], 1.9 [1.8], 3.3 $^{\circ}\text{C}$ [2.5 $^{\circ}\text{C}$]). The reason why the B2 temperature increase is 0.2 $^{\circ}\text{C}$ larger than the A2 scenario in 2020s might be because the aerosol cooling effect is larger in the A2 scenario than in the B2 for that period while GHG emissions are similar (Stendel et al. 2002; Cubasch et al. 2001). The similar result is obtained in the global temperature, but the global temperature increase in 2020s is 0.08 $^{\circ}\text{C}$ larger in the B2 scenario than in the A2. The distri-

Table 4. Area-averaged near surface temperature changes ($^{\circ}\text{C}$) over East Asia during 2020s (2010–2039), 2050s (2040–2069), and 2080s (2070–2099) from seven AOGCM simulations under the IPCC SRES A2 and B2 scenarios and four MMEs. The asterisks (*) indicate AOGCMs selected for MME4.

Model		2020s (2010–2039)		2050s (2040–2079)		2080s (2070–2099)	
		A2	B2	A2	B2	A2	B2
CGCM2		1.35	1.46	2.54	2.05	3.95	2.74
CCSR/NIES2		1.59	1.91	3.81	3.71	6.57	5.04
CSIRO Mk2*		1.04	1.35	2.25	2.17	4.04	3.05
ECHAM4/OPYC3*		1.67	1.63	2.85	2.91	4.68	3.63
GFDL_R30_c*		0.99	1.12	2.03	1.93	3.05	2.53
HadCM3*		1.09	1.22	2.36	2.08	4.12	2.94
DOE PCM		0.97	1.11	1.58	1.60	2.58	2.12
MME7	Mean	1.24	1.40	2.49	2.35	4.14	3.15
	Std Dev	0.29	0.29	0.71	0.72	1.28	0.95
MME4	Mean	1.20	1.33	2.37	2.27	3.97	3.04
	Std Dev	0.32	0.22	0.35	0.44	0.68	0.45
MME_S1	Mean	1.24	1.40	2.48	2.35	4.13	3.15
MME_S2	Mean	1.24	1.40	2.48	2.35	4.13	3.15

bution of aerosol emissions is spatially inhomogeneous in contrast to well-mixed GHGs and the East Asian region is one of large emission areas, so the aerosol cooling effect will be larger than the global mean (Mitchell and Johns 1997). The inter-model variability (intra-ensemble standard deviation) in the East Asian temperature change for the A2 [B2] scenario is 0.3 [0.3], 0.7 [0.7], and 1.3 $^{\circ}\text{C}$ [1.0 $^{\circ}\text{C}$] during 2020s, 2050s, and 2080s, respectively, which is almost twice larger than global values (not shown). However, ensemble mean change (signal) is three times larger than inter-model variability (noise) in the East Asian temperature projections.

In Fig. 3a,c, MME4 mean temperature series, depicted by thick dotted line, show little difference from MME7. Temperature changes of MME4 for the A2 [B2] scenario in 2020s, 2050s, and 2080s are 1.2 [1.3], 2.4 [2.3], and 4.0 $^{\circ}\text{C}$ [3.0 $^{\circ}\text{C}$], respectively, which are about 0.1–0.2 $^{\circ}\text{C}$ smaller than MME7 (Table 4). However, inter-model standard deviations of MME4 for 2050s and 2080s are about a half of those of MME7.

Figure 4a,c show the ensemble mean and standard deviation of MME7 and MME4 for East Asian temperatures based on the A2 and B2 scenarios. It is clearly shown that model uncertainties in the East Asian temperature change are smaller in MME4 than in MME7. This demonstrates that MME4 has an advantage of intensifying signal to noise ratio (SNR) twice of MME7 in 2050s and 2080s, and that the MME from skillful models can make more significant signals in the projection of area-averaged East Asian temperature change.

b. Precipitation

The time series of area-averaged East Asian precipitation changes (%) relative to the present-day climate (1961–1990 mean) in the A2 and B2 scenario simulations of seven AOGCMs, MME7, and MME4 are shown in Fig. 3b,d. The MME_S1 and MME_S2 results are left out since they are very close to the MME7 result in Fig. 3 (see also Table 5). The East Asian precipitation exhibits an increasing trend in most models, more dominantly in the

Fig. 4. East Asian area-averaged temperature ($^{\circ}\text{C}$) and precipitation changes (%) (bar) during 2020s (2010–2039), 2050s (2040–2069), and 2080s (2070–2099) and their inter-model variability (error bar) from MME7 and MME4 for the SRES A2 and B2 scenarios. Changes are relative to 1961–1990 mean.

Table 5. Same as Table 4 except for precipitation change (%).

Model		2020s (2010–2039)		2050s (2040–2079)		2080s (2070–2099)	
		A2	B2	A2	B2	A2	B2
CGCM2		0.40	1.60	−0.03	0.06	−2.37	0.65
CCSR/NIES2		1.49	2.92	4.44	7.21	7.33	8.98
CSIRO Mk2*		0.12	1.55	1.34	1.61	4.96	2.80
ECHAM4/OPYC3*		−2.05	−0.62	1.42	−0.65	2.71	2.43
GFDL_R30_c*		−1.06	−0.66	−0.73	0.87	2.51	1.57
HadCM3*		0.07	1.82	4.56	5.48	12.89	6.50
DOE PCM		3.55	2.86	4.03	3.65	6.99	4.85
MME7	Mean	0.36	1.35	2.15	2.60	5.00	3.97
	Std Dev	1.80	1.47	2.19	2.93	4.79	2.97
MME4	Mean	−0.73	0.52	1.65	1.83	5.77	3.33
	Std Dev	1.04	1.35	2.18	2.61	4.88	2.18
MME_S1	Mean	0.30	1.31	2.19	2.65	5.28	4.03
MME_S2	Mean	0.20	1.30	2.32	2.87	5.82	4.27

A2 scenario, but the trend is not clearer than the global precipitation increase (Fig. 9.6b of Cubasch et al. 2001). It might be caused by the fact that the internal and inter-model variabilities are larger in the regional precipitation than in the global precipitation. The increase of natural noise in the regional precipitation also appears more dominant than in the regional temperature. A2 scenario results in Fig. 3b show a little decreasing trend up to ~2035, which might be related to stronger aerosol forcing in the A2 scenario than in the B2, but further analysis is required (also see discussion below). Precipitation changes in the A2 and B2 simulations of seven AOGCMs and four MMEs for three 30-year periods are given in Table 5. The MME7 A2 [B2] result predicts East Asian precipitation increase of 0.4 [1.4], 2.2 [2.6], and 5.0% [4.0%] for 2020s, 2050s, and 2080s, respectively while global mean changes are 1.1 [1.4], 2.3 [2.6], and 4.4% [3.7%] increases. Precipitation increases in East Asia are 0.4–1.0% larger in the B2 scenario than in the A2 for the periods of 2020s and 2050s, which is consistent with the global result. This seems to be related to the enhanced direct cooling effect of aerosols in the A2 scenario compared with the B2 scenario in the mid 21st century (Cubasch et al. 2001). However, the indirect effect of aerosols on clouds can be another important factor (Penner et al. 2001), so more detailed analyses are required for future works. The inter-model standard deviations in the East Asian precipitation projections using the MME7 A2 [B2] scenarios are 1.8 [1.5], 2.2 [2.9], and 4.8% [3.0%] for 2020s, 2050s, and 2080s, which is more than twice of those in the global mean precipitation projections (not shown). This implies that noise is as large as signal in the East Asian precipitation change, indicating a very large model uncertainty in the projection of regional precipitation changes.

The MME4 mean precipitation shows a very similar trend to MME7 (Fig. 3b,d). Table 5 shows that precipitation changes of MME4 for the A2 [B2] scenario are –0.7 [0.5], 1.7 [1.8], 5.8% [3.3%] in 2020s, 2050s, and 2080s, respectively, which are about 0.5–1.1% smaller than MME7 except for the A2 result of 2080s. The precipitation projections of MME_S1 and MME_S2 reveal less difference (0.1–0.8%) from MME7. The comparison of inter-model stan-

dard deviations shows that MME4 has similar amplitude of inter-model uncertainty to that of MME7 but for the A2 scenario in 2020s and the B2 scenario in 2080s (Table 5). Figure 4b,d represent means and intra-ensemble standard deviations of MME7 and MME4 for East Asian precipitation changes for three 30-year periods. Both ensemble mean and inter-model variability of MME4 have little difference from those of MME7. The advantage of MME4 does not appear in the precipitation projections in contrast to the marked noise reduction in the temperature projections (Fig. 4a,c).

4.2 Spatial patterns

a. Temperature

Figure 5 shows spatial patterns of East Asian temperature change and inter-model variability for the three 30-year periods of 2020s, 2050s, and 2080s using MME7 for the A2 scenario. The ensemble mean value is defined as signal and the standard deviation is as noise following Cubasch et al. (2001). The area where signal is larger than noise ($\text{SNR} > 1$) is shaded in the mean field of Fig. 5a,c,e. Larger temperature increase appears in higher latitude than in lower latitude and in land than in ocean, which gets stronger as time. Horizontal patterns of the inter-model variability shown in Fig. 5b,d,f are also characterized by larger values in higher latitude, but more zonal pattern and smaller amplitude than ensemble means. The fact that all area of ensemble mean fields is shaded in all 30-year periods, represents that the GHG signal is larger than the inter-model uncertainty in the East Asian temperature projections. Spatial patterns of temperature change for the B2 scenario have similar spatial patterns to the A2 results except for a little different amplitude (figure not shown). More detailed analysis of comparing the A2 results with the B2 is done below.

b. Precipitation

Horizontal distributions of ensemble mean change and intra-ensemble standard deviation of the precipitation change for the MME7 A2 scenario are shown in Fig. 6. As in the temperature pattern of Fig. 5, the area where $\text{SNR} > 1$ is shaded in the mean field of Fig. 6a,c,e. Precipitation patterns are similar to temperature patterns in Fig. 5 showing that larger increase

Fig. 5. Multi-model ensemble mean of near surface temperature changes (left panels) and intra-ensemble standard deviations (SD) (right panels) in MME7 for the SRES A2 scenario for three 30-year periods of 2020s (2010–2039), 2050s (2040–2069), and 2080s (2070–2099). In the mean field, changes are relative to the 30-year mean of 1961–1990, the area where ensemble mean is greater than standard deviation (inter-model variability) is shaded, and area-averaged values are depicted at the right top.

in higher latitude land than in lower latitude ocean. Stronger inter-model variability appears in the continental area of 35–45°N in 2080s, which is known as one of active cyclogenesis in East Asia (Chen et al. 1991) and the entrance region of storm track in the North Pacific (Chang 2001; Harnik and Chang 2003). In contrast to the temperature field, notable signals

of precipitation change relative to the inter-model noise appear only in land area north of 30°N in 2080s, demonstrating the large uncertainty and the low reliability in the precipitation projections. The precipitation pattern of mean and variability for the B2 scenario is not largely different from the A2 result as in the case of temperature (figure not shown).

Fig. 6. Same as Fig. 5 but for precipitation (%).

c. Difference between MME4 and MME7 results

In order to see if MME4 constructed by selected skillful models has an advantage over MME7 in the pattern projections, we compare ensemble mean and inter-model variability of MME4 with those of MME7. The comparison of MME_S1 and MME_S2 mean with MME7 mean is not shown because their projection results are very close to MME7. Figure 7 represents temperature comparisons of MME4 with

MME7. The difference between MME4 and MME7 (MME4-MME7) is used for the ensemble mean comparison (Fig. 7a,c,e) while the ratio of standard deviation (MME4/MME7) is shown for the comparison of the inter-model variability (Fig. 7b,d,f). In the mean field MME4 and MME7 have a difference of amplitude from -0.4 to $+0.6^{\circ}\text{C}$ in 2080s (Fig. 7e), which is very small compared to the large temperature change of 2.5 – 6°C (Fig. 5e). Regional mean difference is also small with amplitude of

Fig. 7. Comparison of near surface temperature changes in MME4 with MME7 for the SRES A2 scenario simulations during 2020s (2010–2039), 2050s (2040–2069), and 2080s (2070–2099): Multi-model ensemble mean difference (MD) of temperature change (MME4 minus MME7, left panels) and intra-ensemble standard deviation ratio (SDR) (MME4 divided by MME7, right panels). Area-averaged values are depicted at the right top of the MD fields.

0.16°C in 2080s (Table 4). In the variability comparison the ratio of standard deviation has 0.4–0.8 in 2050s and 2080s (Fig. 7d,f). This indicates that the inter-model noise is reduced when skillful models are used to construct MME. The comparison of MME4 and MME7 for the B2 scenario shows very similar results to the A2 result except that the difference between MME4 and MME7 is reduced in the

mean field of 2020s and 2050s in the B2 scenario (figure not shown).

Precipitation changes of MME4 and MME7 are compared in Fig. 8. Difference of ensemble means (MME4–MME7) has a range from –2 to +10% in 2080s with larger values in southwest China and East Manchuria (Fig. 8e). This difference is not small considering that the amplitude of precipitation change is 0–20% in 2080s

Fig. 8. Same as Fig. 7 but for precipitation.

(Fig. 6e). The comparison of the standard deviation of MME4 with MME7 is represented by their ratio (MME4/MME7). The area of similar variability with ratios of 0.8–1.2 appears extensively in 2050s and 2080s (Fig. 8d,f). It means that there is no significant advantage of reducing the inter-model noise when using MME4 over MME7. The precipitation comparison result for the B2 result shows that the ensemble mean difference between MME4 and MME7 in 2050s and 2080s is a little bit smaller than the A2 result, but that overall patterns

are very similar to the A2 results (figure not shown).

4.3 Potential impact of GHG mitigation:

A2 minus B2

The difference between the simulations based on the A2 and B2 scenarios can provide a potential impact of GHG mitigation, especially in 2050s and 2080s because aerosols play a more important role than GHGs in making such a difference in 2020s (Stendel et al. 2002). Figure 9 shows the difference between temperature

Fig. 9. SRES A2 minus B2 scenario results for near surface temperature projections ($^{\circ}\text{C}$) in MME7 (left panels) and MME4 (right panels) for three 30-year periods of 2020s (2010–2039), 2050s (2040–2069), and 2080s (2070–2099). Light [dark] shadings indicate areas of statistically significant positive [negative] difference (one-sided T test at 95% confidence level). Area-averaged value is depicted at the right top of each panel.

projections from the A2 and B2 scenarios for MME7 and MME4. Statistically significant differences are searched for by one-sided T test with 5% significant level and are depicted by shadings. The A2-B2 result of MME7 shows negative values over all East Asia in 2020s, which is mainly caused by the stronger aerosol cooling in the A2 scenario (Fig. 9a) as discussed above, while positive values appear in 2050s

and 2080s (Fig. 9c,e). The temperature increase of the A2 scenario in 2050s is larger than the B2 scenario (area-average 0.1°C) but not statistically significant (Fig. 9c). The A2-B2 in 2080s is statistically significant over the central and southern China and the oceanic area south of 25°N with a regional average of 1.0°C (Fig. 9e). This demonstrates that the potential impact of GHG mitigation in the East Asian

Fig. 10. Same as Fig. 9 but for precipitation projections (%).

warming appears only in the late 21st century over the southern area if the concentrations of GHG are successfully controlled along the levels of the SRES B2 scenario. The A2-B2 results of MME4 are alike in the pattern and amplitude to those of MME7 (Fig. 9b,d,f). However, it is shown that the area of significant difference in 2080s of MME4 is broader than in MME7 (Fig. 9f), including almost all the continental area, which mainly results from the reduced inter-model variability in MME4 than in MME7 (Fig. 7f).

The A2-B2 in the precipitation change over East Asia is given in Fig. 10. The MME7 result in Fig. 10a,c,e shows that regional average value of A2-B2 is -1.0 , -0.5 , and 1.0% in 2020s, 2050, and 2080s, and that statistically significant difference cannot be found in all periods. It is shown that, unlike the temperature result in Fig. 9, the potential impact of GHG mitigation on the precipitation change is not clear because of the large inter-model difference. The MME4 result of A2-B2 in Fig. 10b,d,f shows that the amplitude of differences be-

Fig. 11. Monthly mean change of area-averaged near surface temperature ($^{\circ}\text{C}$) and precipitation (%) over East Asia during 2080s (2070–2099) in MME7 and MME4 for the SRES A2 and B2 scenarios. Changes are relative to 1961–1990 mean. Inter-model variability (intra-ensemble standard deviation) for each monthly mean is depicted by error bar.

comes larger than MME7 and the statistically significant area appears over southern China in 2050s and 2080s. Area-averaged precipitation differences of A2-B2 in MME4 are -1.3 , -0.2 , and 2.4% for 2020s, 2050s, and 2080s, respectively. This indicates the high dependence of future projections of precipitation change on the selected models and the necessity of efforts to improve models for better simulations of precipitation patterns. Relatively notable impact of GHG mitigation on precipitation change is the reduction of precipitation increase over the southern China region. It should be noted that, in the precipitation field, the area of notable change (continent north of 30°N , Fig. 6e) does not correspond to the area of significant GHG mitigation impact (southern China, Fig. 10f).

4.4 Seasonal dependence of climate change

In order to examine the seasonal dependence of the East Asian climate change, monthly distributions of area-averaged East Asian temperature and precipitation change in 2080s are

presented in Fig. 11 for MME7 and MME4. The A2 and B2 results are also compared and the error bars depict the range of uncertainty from model difference for each month. It shows that monthly mean temperature change and its uncertainty range are larger in December to April than in June to November, which is irrespective of selected scenarios and MMEs (Fig. 11a,c). As a whole, the A2 scenario results have larger temperature increases than B2 scenario results. As in the annual mean case in Fig. 4, MME4 has an advantage of less uncertainty range in monthly temperature change over MME7. However, this seasonal dependence in the temperature change is not clear because of a relatively large and overlapped inter-model variability between months. Monthly precipitation change shows more characteristic feature of seasonal dependence than temperature (Fig. 11b,d). Precipitation increases in the warmer season (April to September) while it decreases in the cooler season (November to February). Especially the precipitation increase in summer is a common characteristic through most

models, i.e. significant over inter-model noise, but precipitation decrease in the cooler season is not clear compared to the inter-model variability.

To search for geographical characteristics of seasonal climate change necessary to the impact assessment of regional climate change, horizontal patterns of temperature and precipitation changes are analyzed for each season. Figure 12 shows the MME7 result of seasonal change in 2080s for the A2 scenario. The area where $\text{SNR} > 1$ is depicted by shadings as in Fig. 5 and Fig. 6. The amplitude of temperature change (signal) is larger than the inter-model variability (noise) over East Asia and in all seasons (Fig. 12). It is worthwhile to note that the temperature change over the oceanic area is seldom varied with season, but the continental temperature increases more in winter and spring than in summer and autumn. Accordingly, the horizontal temperature gradient between ocean and continent gets weaker in 2080s than in the present-day (1961–1990), especially in winter and spring (Fig. 14), which may weaken East Asian winter monsoon system (Hu et al. 2000a).

In the seasonal precipitation patterns, strong GHG signal areas ($\text{SNR} > 1$) exhibit different features with season (Fig. 12). Area-averaged precipitation change is -2.8 , 4.5 , 10.5 , and 3.6% in winter, spring, summer, and autumn, respectively (also compare with monthly precipitation change of Fig. 11b,d). The precipitation in winter increases in the continental area north of 30°N while it decreases over the oceanic area south of Japan, suggesting the northward shift of the frontal zone by global warming (Hu et al. 2000a). The overall pattern of precipitation change in spring is similar to that in winter, but the amplitude of precipitation increase is smaller and the precipitation decrease of oceanic area moves toward the Philippine Sea. It should be noted that the real amount of precipitation increase would not be strong in winter and spring because the area of precipitation increase exhibits small precipitation in the present-day simulations (Fig. 14b).

The precipitation change in summer is positive over all East Asia with a maximum change of 30% near the Korean Peninsula and Yellow Sea (Fig. 12f). This area of large precipitation increase in summer is known to have a heavy

rainfall above 6 mm/day in the present-day observations (Fig. 13f), but most AOGCMs constituting MME7 produce much less precipitation (i.e. negative bias) over the area than observations (Fig. 14f). Therefore, the interpretation of the future precipitation increase in summer should be done very carefully although its signal is stronger than inter-model uncertainty. A strong signal cannot be found in the precipitation change in autumn relative to inter-model noise (Fig. 12h). In contrast to the low performance in summer precipitation, the performance of the MME simulation of seasonal temperature fields is quite good except for the notable cold bias in the northern continental area in winter and spring (Fig. 13, Fig. 14).

5. Conclusion and discussions

The 21st century climate changes over East Asia are projected from multi-model ensembles (MMEs) of seven AOGCM simulations based on IPCC SRES A2 and B2 scenarios. Analyses of East Asian climate change from MMEs show that East Asia is likely to experience warmer and wetter climate in the 21st century than present with larger amplitude than global mean. Temperature change signal is larger than inter-model noise while there is a large noise in the projection of precipitation change. The MME from four selected AOGCMs (MME4) does not provide different projection result from MME7, but reduces the inter-model uncertainties in temperature projections in the late 21st century. The skill-weighted MMEs based on centered statistics in the Taylor analysis exhibit very similar projection result to MME7. A potential impact of greenhouse gas mitigation inferred from A2 minus B2 results becomes more discernable in the temperature change during the late 21st century, but not in precipitation change. Monthly to seasonal dependence of climate change over East Asia is characterized by the larger increase of winter temperature and summer precipitation. Temperature increase in winter is dominated in the continental area north of 30°N , while summer precipitation increase appears along the coastal area with a maximum near the Korean Peninsula. However, it should be noted that large uncertainty remains in the projection results originating from the low model performance in the simulation of summer precipitation. Also it

MME7 A2 2080s

Fig. 12. Seasonal changes of near surface temperature (°C) and precipitation (%) in MME7 for the SRES A2 scenario during 2080s (2070–2099). Changes are relative to the 30-year mean of 1961–1990. Light [dark] shadings indicate areas of SNR > 1 for positive [negative] changes. Area-averaged value is depicted at the right top of each panel.

should be kept in mind that four AOGCMs selected for MME4 are not the best models in the world scientific community, since the samples are limited to the models available in IPCC DDC.

In the previous studies, MME method is normally constructed for each variable applied. In this study, we use more comprehensive method via selecting skillful model evaluating model performance simultaneously for temperature

Observations

Fig. 13. Seasonal mean near surface temperature ($^{\circ}\text{C}$) and precipitation (mm/day) distributions of the observations. Note that CMAP precipitations are interpolated into $5^{\circ} \times 5^{\circ}$ grids. Area-averaged value is depicted at the right top of each panel.

and precipitation simulations. However, spatial similarity is considered only, and the evaluation of space-time structure is necessary in the future study. This might be helpful to reduce uncertainties from inter-model variability, especially in the precipitation projection, and pro-

duce more reliable projections of future regional climate change.

The result of this study indicates a possible change of East Asian monsoon system by global warming. In the previous studies, an enhanced land-sea contrast and a northward shift of the

MME7 1961–1990

Fig. 14. Same as Fig. 13 but MME7 mean for the present-day period (1961–1990).

convergence zone are proposed as a possible mechanism of the intensified Asian summer monsoon (Hu et al. 2000b; Kitoh et al. 1997) and the northward and eastward shift and weakening of the East Asian trough are analyzed as the cause of the weakening of the Asian winter monsoon in the global warming scenario (Hu et al. 2000a). However, their re-

sults are based on the simulations from a single model and they can be different from model to model, that is, model-dependent. Mechanism of monsoon change should be more intensively investigated using MME methods in the context of seasonal cycle change in the future work. Especially, contributions of convective and large-scale precipitation to the total pre-

precipitation change should be analyzed over East Asia (e.g., Noda and Tokioka 1989).

In this paper, MME projections using AOGCMs with coarse resolution of $5^\circ \times 5^\circ$ are provided, so climate features of higher resolution such as an orographic effect on precipitation distribution cannot be analyzed in the results. In this context, the MME method can be applied to time-slice experiments using high-resolution AGCM (Cubasch et al. 1995; Timbal et al. 1997; May and Roeckner 2001) and simulations from various Regional Climate Models (RCMs) as a more promising way (e.g., Hirakuchi and Giorgi 1995; Kato et al. 2001 for East Asia). Finally, the change of pattern and intensity of extreme events including floods and droughts should be examined (e.g., Meehl et al. 2000; Kharin and Zwiers 2000; Palmer and Rälsänen 2002; Milly et al. 2002) considering its high impacts on society and spatial and temporal linkage within the East Asian region (Min et al. 2003; Qian et al. 2003).

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