Climate Sensitivity and Feedbacks of BCC-CSM to Idealized CO₂ Forcing from CMIP5 to CMIP6

Xueli SHI1, Xiaolong CHEN2-3*, Yunwei DAI4, and Guoquan HU1
1 National Climate Center, China Meteorological Administration, Beijing 100081
2 State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029
3 CAS Center for Excellence in Tibetan Plateau Earth Sciences, Chinese Academy of Sciences (CAS), Beijing 100101
4 Huafeng Meteorological Media Group, China Meteorological Administration, Beijing 100081

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ABSTRACT

Climate sensitivity represents the response of climate system to doubled CO₂ concentration relative to the preindustrial level, which is one of the sources of uncertainty in climate projections. It is unclear how the climate sensitivity and feedbacks will change as a model system is upgraded from the Coupled Model Intercomparison Project Phase 5 (CMIP5) to CMIP6. In this paper, we address this issue by comparing two versions of the Beijing Climate Center Climate System Model (BCC-CSM) participating in CMIP6 and CMIP5, i.e., BCC-CSM2-MR and BCC-CSM1.1m, which have the same horizontal resolution but different physical parameterizations. The results show that the equilibrium climate sensitivity (ECS) of BCC-CSM slightly increases from CMIP5 (2.94 K) to CMIP6 (3.04 K). The small changes in the ECS result from compensation between decreased effective radiative forcing (ERF) and the increased net feedback. In contrast, the transient climate response (TCR) evidently decreases from 2.19 to 1.40 K, nearly the lower bound of the CMIP6 multimodel spread. The low TCR in BCC-CSM2-MR is mainly caused by the small ERF over even though the ocean heat uptake (OHU) efficiency is substantially improved from that in BCC-CSM1.1m. Cloud shortwave feedback ($\lambda_{SWCL}$) is found to be the major cause of the increased net feedback in BCC-CSM2-MR, mainly over the Southern Ocean. The strong positive $\lambda_{SWCL}$ in BCC-CSM2-MR is coincidently related to the weakened sea ice-albedo feedback in the same region. This result is caused by reduced sea ice coverage simulated during the preindustrial cold season, which leads to reduced melting per 1-K global warming. As a result, in BCC-CSM2-MR, reduced surface heat flux and strengthened static stability of the planetary boundary layer cause a decrease in low-level clouds and an increase in incident shortwave radiation. This study reveals the important compensation between $\lambda_{SWCL}$ and sea ice-albedo feedback in the Southern Ocean.

Key words: Beijing Climate Center Climate System Model (BCC-CSM), climate sensitivity, cloud feedback, sea ice-albedo feedback, Coupled Model Intercomparison Project Phase 6 (CMIP6)

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1. Introduction

Climate sensitivity is defined to measure how sensitive a climate system model is to the external forcing of a doubled CO₂ concentration relative to the preindustrial level, which is an important indicator to describe the relationship between greenhouse gas increases and global temperature rise and is also related to some uncertainties of the model simulations and projections (Cess et al., 1993; Stocker et al., 2013; Chen and Zhou, 2015; Zhou et al., 2019). In addition to being an important metric widely used in the natural science community to investigate global warming, climate sensitivity is also a key factor in the cause-effect chains from CO₂ emissions to temperature increases described in the integrated assessment model used by the socioeconomic science com-
munity (Liu et al., 2019).

Two parameters are generally used to describe climate sensitivity in climate change studies. One parameter is the equilibrium climate sensitivity (ECS), defined as the global mean surface temperature (GMST) response to a doubled CO\textsubscript{2} concentration relative to the preindustrial level when the climate state reaches a new equilibrium and therefore accounts for the equilibrium change (Gregory et al., 2004; Forster and Taylor, 2006; Knutti et al., 2017). The other parameter is the transient climate response (TCR), defined as the GMST change relative to the preindustrial level at the time when the CO\textsubscript{2} concentration is doubled in an idealized scenario in which CO\textsubscript{2} increases 1% per year (Stocker et al., 2013). TCR accounts for the transient climate state with continuing climate change. The ECS is primarily determined by climate feedback, while TCR is also affected by the ocean heat uptake (OHU) efficiency (Li et al., 2013; Zhou and Chen, 2015).

Large uncertainties still exist in the estimation of ECS, with the range in IPCC AR5 (Intergovernmental Panel on Climate Change Assessment Report 5) being 1.5–4.5 K (Stocker et al., 2013; Cox et al., 2018), which is similar to that estimated by National Research Council (1979). The studies have shown that the ECS and its uncertainty are mainly determined by climate feedback processes, in which clouds are the major source of uncertainty, especially shortwave cloud feedback (Andrews et al., 2012a; Ceppi et al., 2017). The large model spread in cloud feedback has not been reduced substantially in recent decades because of complex interactions among factors such as radiation, microphysics, convective, and turbulent fluxes throughout the lifetime of various clouds, which has not been well represented in the current state-of-the-art models (Ceppi et al., 2017; Heinze et al., 2019). Clouds can both reflect solar radiation and absorb longwave radiation; thus, the responses of cloud properties, such as amount, height, particle phase, particle size, and thickness, to global warming determine the net effect after compensation between cloud shortwave and longwave feedbacks (\(\lambda_{SWCL}\) and \(\lambda_{LWCL}\)). Other feedback processes can also be involved in complex interactions, such as water vapor feedback, since moisture is necessary for cloud formation. In the Southern Ocean, strong interactions have been found between low-cloud boundary layer processes and sea ice during austral winter (Wall et al., 2017), implying the potential interaction between cloud and ice–snow albedo feedbacks under warming. Compensation between surface albedo feedback and cloud feedback at high latitudes was revealed in a very early study (Le Treut et al., 1994). Although the offsetting effect between \(\lambda_{SWCL}\) and ice-albedo feedback has also been observed in some models (Andrews and Forster, 2008; Chen et al., 2019), the underlying mechanism remains unclear. Comparing different versions of the same model is useful to better understand the uncertainty in cloud feedback.

The Beijing Climate Center Climate System Model (BCC-CSM) has participated in the Coupled Model Intercomparison Projects Phase 5 (CMIP5) and CMIP6. Simulations with BCC-CSM1.1 in CMIP5 have been widely used and have shown good performances in simulating the climate and carbon cycle (Wu et al., 2013). The CMIP6 simulation with the new BCC-CSM2-MR (medium resolution) is mostly completed and shared with all users through the Earth System Grid Federation (ESGF). Preliminary analyses show that the model exhibits better performances in representing climate systems than its previous version in CMIP5 (Wu et al., 2019). As key parameters of the model response to greenhouse gases, how will ECS and TCR change in the same model system that is updated from CMIP5 to CMIP6? Which physical processes or feedback would contribute to possible changes in the ECS? These are the questions that we will address by comparing the two BCC-CSM versions, i.e., BCC-CSM1.1m and BCC-CSM2-MR.

In the following sections, brief introductions of the BCC climate system model, CMIP experiments, and analysis method are provided in Section 2, followed by a simulation comparison and analysis in Section 3. The main conclusions are summarized in Section 4 with a brief discussion.

2. Models, experiment, and methods

2.1 BCC-CSM climate model

The BCC-CSM was developed by improving the process parameterization schemes primarily in atmosphere and land surface component models on the basis of CCSM (Community Climate System Model) /NCAR (Wu et al., 2013). The BCC-CSM is a fully coupled system of atmosphere, land surface, ocean, and sea ice component models that exchange fluxes of momentum, energy, and water through the coupler at the interfaces. The first model version, BCC-CSM1.1, has been applied for both climate change and short-term climate predictions (Wu et al., 2014). The new version model, BCC-CSM2, was frozen at the end of 2017 and participated in the CMIP6 experiments (Eyring et al., 2016). Most of the simulations have been completed and shared with global users.
Two model versions were included in the CMIP5 experiments, i.e., BCC-CSM1.1 and BCC-CSM1.1m. The only differences between them are the spatial resolutions T42 (∼300 km) and T106 (∼110 km). Three versions of the BCC model were included in CMIP6, i.e., BCC-CSM2-MR (T106), BCC-CSM2-HR (T266, ∼45 km), and BCC-ESM1 (T42). Here, we use two model versions with the same horizontal resolution in CMIP5 and CMIP6. The atmosphere and land surface model resolutions are approximately 110 km × 110 km, while the ocean and sea ice model resolutions are approximately 30 km × 30 km in tropical areas. Vertically, there are 46 layers (top at 1.459 hPa) in BCC-CSM2-MR and 26 layers (top at 2.917 hPa) in BCC-CSM1.1m.

For the schemes in the atmosphere component model of BCC-CSM2-MR and BCC-CSM1.1m, the prescribed aerosols are used in the two model versions, as well as a semi-Lagrangian tracer transport scheme for water vapor, liquid cloud water, and ice cloud water. The main physical scheme differences between the two model versions include deep convection, cloud microphysics, and radiative transfer. The cumulus convection parameterization scheme (Wu, 2012) in BCC-CSM1.1m is modified in BCC-CSM2-MR by connecting the deep convection to the instability of the boundary layer and lowering the nondivergence level (from 600 to 650 hPa) to improve the simulation of the diurnal cycle of precipitation and the Madden–Julian Oscillation. The cloud microphysics in BCC-CSM2-MR consists of calculating convective clouds and total cloud cover, which is different from that in BCC-CSM1.1m. Regarding the cloud microphysics, although the essential part of stratiform cloud microphysics remains the same and follows the framework of nonconvective cloud processes in the Community Atmosphere Model version 3.0 (CAM3.0; Collins et al., 2004), noticeable differences exist between the two model versions concerning the distinct treatments for indirect effects of aerosols through cloud and precipitation mechanisms. For the radiative transfer parameterization, the indirect aerosol effects are fully included in BCC-CSM2-MR, and the effective radius of droplets for liquid clouds is calculated by using the concentration of liquid cloud droplets. While the indirect aerosol effects are not considered in BCC-CSM1.1m, the effective radius of cloud droplets is only a function of temperature for cold clouds and is prescribed different values for maritime, polar, and continental cases for warm clouds (Wu et al., 2019).

2.2 Numerical experiments

The simulations used for the diagnostic climate sensitivity and feedback processes in BCC-CSM include the preindustrial control (named piControl) and two idealized benchmark CO₂ concentration forcing experiments. One simulation is named abrupt4×CO₂, with the abrupt instantaneous quadrupling of CO₂ and then holding it fixed. The other simulation is named 1pctCO₂, with a 1% increase per year in the CO₂ concentration until the value quadruples. Both experiments run for 150 yr (Taylor et al., 2012; Eyring et al., 2016).

2.3 Calculation methods for climate sensitivity and feedback

2.3.1 ECS and feedbacks

Climate sensitivity is assessed from the model energy conservation perspective (Andrews et al., 2012b; Vial et al., 2013; Zhou and Chen, 2015; Chen et al., 2019), which is expressed with a zero-dimensional relation between the net radiation at the top of the atmosphere (TOA), forcing, net feedback, and the response of the GMST (Gregory et al., 2004).

\[ N = F + \lambda T', \]

where \( N \) is the net radiation at the TOA, \( F \) is radiative forcing, \( \lambda \) is the feedback factor (the reciprocal of the climate sensitivity factor), and \( T' \) is the GMST changes relative to that of piControl. The variable \( \lambda \) is assumed to be a negative constant, while the others vary with time. According to the regression method proposed by Gregory et al. (2004), effective radiative forcing (ERF) is a constant under stable CO₂ concentration forcing, similar to the abrupt4×CO₂ experiment. Therefore, \( \lambda \) could be calculated from \( N \) and \( T' \) in abrupt4×CO₂ with the above formula. Here, we assume that \( F \) and \( \lambda \) are constants during the model integration. By linear fitting of \( \Delta T \) and \( N \), \( F \) can be obtained at the intercept of the \( N \)-axis where \( \Delta T = 0 \), and the corresponding equilibrium temperature can be obtained at the intercept of the \( \Delta T \)-axis where \( N = 0 \), indicating that a new equilibrium state is achieved. The slope of the fitting line is the feedback factor \( \lambda \). Strictly speaking, the climate feedback is nonlinear, increasing slowly with warming (Chen et al., 2014).

When the forcing term \( F \) remains constant, outward radiation ultimately compensates for the forcing that is \( N = 0 \); thus, a new equilibrium state is reached. Under the forcing of doubled preindustrial CO₂ concentrations, the GMST changes to a new equilibrium state and is defined as the ECS. Thus, the estimation formula for ECS is as follows:

\[ \text{ECS} = F_{2x}/(-\lambda). \]
To further understand the effects of different processes, the net radiative feedback is decomposed into four components, i.e., clear-sky longwave (\(\lambda_{\text{LWCS}}\)), clear-sky shortwave (\(\lambda_{\text{SWCS}}\)), cloud longwave (\(\lambda_{\text{LWCL}}\)), and cloud shortwave (\(\lambda_{\text{SWCL}}\)). The corresponding net radiation at the TOA is noted as \(\text{N}_{\text{LWCS}}\), \(\text{N}_{\text{SWCS}}\), \(\text{N}_{\text{LWCL}}\), and \(\text{N}_{\text{SWCL}}\), with the forcing being \(\text{F}_{\text{LWCS}}\), \(\text{F}_{\text{SWCS}}\), \(\text{F}_{\text{LWCL}}\), and \(\text{F}_{\text{SWCL}}\). Here, to maintain the linear additivity of feedbacks, the cloud feedback is calculated based on the cloud radiative effect rather than the radiative kernel approach. Thus, we can decompose Eq. (1) in the following form:

\[
\text{N}_{\text{LWCS}} + \text{N}_{\text{SWCS}} + \text{N}_{\text{LWCL}} + \text{N}_{\text{SWCL}} = \text{F}_{\text{LWCS}} + \text{F}_{\text{SWCS}} + \text{F}_{\text{LWCL}} + \text{F}_{\text{SWCL}} + (\lambda_{\text{LWCS}} + \lambda_{\text{SWCS}} + \lambda_{\text{LWCL}} + \lambda_{\text{SWCL}})T',
\]

(3)

where \(\lambda_{\text{LWCS}}\) reflects the net effect of negative Planck feedback and positive water vapor-lapse rate feedback, and \(\lambda_{\text{SWCS}}\) mainly represents positive snow and sea ice-albedo feedback. The geophysical pattern of feedback and its components can be obtained by using Eq. (3) through regressing onto the GMST change on each grid.

2.3.2 TCR and OHU efficiency

According to the definition, TCR is estimated directly from the GMST changes over the period of approximately 70 model years when the CO2 concentration doubled in the 1pctCO2 experiment. Here, following the method in IPCC AR5 (Flato et al., 2013), TCR is the 20-yr averaged GMST change from 60–79 model years when the CO2 concentration is doubled.

Since the heat capacity of the atmosphere and land (soil) is negligible compared with that of the ocean, the net TOA radiation was roughly equivalent to that absorbed by the ocean. In the 1pctCO2 experiment, the CO2 concentration linearly increased, and \(N\) and \(T'\) both changed with time; they could be considered linear relations and expressed as

\[N \approx \kappa T',\]

(4)

where \(\kappa\) is the OHU efficiency, with the same unit as that of climate feedback, and is estimated by the slope of the line (\(N\) and \(T'\) changes in the 1pctCO2 experiment). Under the condition of a constant \(\lambda\) or ECS, a higher \(\kappa\) indicates a smaller TCR because more heat is absorbed by the deep ocean than the surface.

3. Results

The two versions of the BCC-CSM for CMIP5 and CMIP6 are used to compare the ECS, TCR, radiative forcing and feedback processes. The analysis period includes all the integration periods (150 yr) of the two idealized experiments from which the results of the piControl run are subtracted in the corresponding time periods to reduce the effects of climate drift.

3.1 Responses in abrupt4×CO2 and 1pctCO2

The piControl simulation, as the baseline of abrupt4×CO2 and 1pctCO2, is first analyzed. As shown in Fig. 1, the global mean net TOA radiation and GMST in BCC-CSM2-MR are \(-0.51\) W m\(^{-2}\) and 14.4°C, respectively, with corresponding trends of 0.06 W m\(^{-2}\) per century and 0.02°C per century. The values in BCC-CSM1.1m are \(-0.76\) W m\(^{-2}\) and 14°C, with trends of 0.11 W m\(^{-2}\) per century and –0.17°C per century, respectively. BCC-CSM2-MR shows improvement in simulating the equilibrium states in piControl with smaller climate drifts than those in BCC-CSM1.1m.

The responses in abrupt4×CO2 and 1pctCO2 have different features. The net radiation at the TOA shows an approximately linear increase in 1pctCO2, whereas in the abrupt4×CO2 experiment, it quickly decreases in the first 30 years, and the rate of decline becomes very slow (Fig. 1a). Consistent with the responses of the net TOA radiation, the GMST linearly increases in 1pctCO2, while in the abrupt4×CO2 experiment, it increases quickly during the first 10–20 years and then slowly afterwards (Fig. 1b).
3.2 **ECS and TCR in the two versions of the BCC model**

Using the Gregory-style regression based on Eq. (1), the equilibrium GMST under abrupt quadrupling of CO₂ concentration forcing is estimated in the abrupt4×CO₂ experiments, as well as the corresponding ERF and net climate feedback ($\lambda$).

As shown in Fig. 2, the quadrupling forcing of BCC-ESM2-MR ($F_{4×}$) is 5.57 ± 0.24 W m⁻² (± 1σ), the equilibrium temperature change ($\Delta T_{eqm}$) is 6.08 ± 0.21 K, and the slope of the line, i.e., the feedback parameter, $\lambda$ is $-0.92\pm0.06$ W m⁻² K⁻¹ (Fig. 2a). The corresponding values for BCC-CSM1.1m are 6.90 ± 0.24 W m⁻², 5.83 ± 0.21 K, and $-1.18\pm0.04$ W m⁻² K⁻¹ (Fig. 2b). The ECS and ERF can be estimated as half of $\Delta T_{eqm}$ and $F_{4×}$, respectively, based on the logarithmic relation between CO₂ concentration and forcing (Myhre et al. 1998). The ECS derived from the quadrupled CO₂ scenario has been found to be underestimated compared to that from the doubled CO₂ scenario but may still underestimate the real ECS due to the strong positive feedback under a warming climate (Meraner et al., 2013; Rugenstein et al., 2020).

In addition to the results of BCC-CSM2-MR and BCC-CSM1.1m, 23 other CMIP5 (Chen et al., 2019) and 9 CMIP6 models are also used for references and comparisons. The climate sensitivity and feedback parameters of the CMIP6 models are listed in Table 1.

The ECS, TCR, ERF, and feedbacks are compared between BCC-CSM2-MR and BCC-CSM1.1m, as well as with the multimodel ensembles in CMIP6 and CMIP5. The ECS differs little in the two versions of the BCC model, that is, the values differ by 3.04 and 2.91 K in the BCC-CSM2-MR and BCC-CSM1.1m, respectively. The ECS values of the BCC models are slightly lower than the multimodel mean results, which are mostly evident for BCC-CSM2-MR due to an overall shift in the CMIP6 models to higher ECS values than those in the CMIP5 models (Fig. 3a). The small changes in the ECS from BCC-CSM1.1m to BCC-CSM2-MR result from compensation between the decrease in ERF (Fig. 3c) and positively increased net feedback (Fig. 3d). In contrast, the TCR is significantly different between the two versions. This value is 1.40 K in BCC-CSM2-MR, whereas it is 2.19 K in BCC-CSM1.1m (Fig. 3b). The distribution of TCR seems to follow that of ERF (Figs. 3b, c). The extremely small ERF in BCC-CSM2-MR (Fig. 3c) can explain the very low TCR, which is located at the lower bound of the CMIP6 model spread (Fig. 3b). Although the ERF of BCC-CSM1.1m is close to the CMIP5 multimodel mean (Fig. 3c), the TCR is slightly larger than the mean (Fig. 3b) due to an extremely low OHU efficiency ($\kappa$) with reference to the CMIP5 model spread (Fig. 3e), which is consistent with the evidently small ocean heat content that increases with global warming compared to that in BCC-CSM2-MR (Fig. 4). The OHU efficiency of BCC-CSM2-MR is close to the CMIP6 multimodel mean. The estimated $\kappa$ based on observational data indicates a value of at least 0.5 W m⁻² K⁻¹.

**Table 1.** Climate sensitivity and feedback indices of BCC-CSM1.1m (CMIP5) and 10 CMIP6 (including BCC-CSM2-MR) models, including ERF of doubled CO₂ concentration ($F_{2×}$; W m⁻²), ECS (K), net climate feedback ($\lambda$; W m⁻² K⁻¹), TCR (K), OHU efficiency ($\kappa$; W m⁻² K⁻¹), clear-sky/cloud and longwave/shortwave components of $\lambda$ ($\lambda_{SWCS}$, $\lambda_{LWCS}$, $\lambda_{SWCL}$, and $\lambda_{LWCL}$; W m⁻² K⁻¹), and cloud feedback ($\kappa_{CL} = \lambda_{SWCL} + \lambda_{LWCL}$; W m⁻² K⁻¹).

| Model             | $F_{2×}$ | ECS   | $\lambda$ | TCR   | $\kappa$ | $\lambda_{SWCS}$ | $\lambda_{LWCS}$ | $\lambda_{SWCL}$ | $\lambda_{LWCL}$ | $\kappa_{CL}$ |
|-------------------|----------|-------|-----------|-------|----------|------------------|------------------|------------------|------------------|---------------|
| BCC-CSM1.1m (CMIP5) | 3.45     | 2.91  | -1.18     | 2.19  | 0.25     | -1.97            | 0.76             | 0.16             | -0.13            | 0.03          |
| BCC-CSM2-MR       | 2.78     | 3.04  | -0.62     | 1.40  | 0.40     | -1.91            | 0.72             | 0.13             | 0.15             | 0.28          |
| CESM2             | 3.22     | 5.19  | -0.69     | 1.97  | 0.55     | -1.86            | 0.53             | 0.10             | 0.78             | 0.65          |
| CESM2-WACCM       | 3.27     | 4.72  | -0.69     | 2.26  | 0.48     | -1.76            | 0.82             | 0.31             | -0.11            | 0.20          |
| CNRM-CM6-1        | 3.66     | 4.88  | -0.75     | 2.26  | 0.48     | -1.76            | 0.82             | 0.31             | -0.11            | 0.20          |
| CNRM-ESM2-1       | 2.99     | 4.76  | -0.63     | 1.86  | 0.42     | -1.60            | 0.78             | 0.25             | -0.05            | 0.20          |
| GISS-E2-1-G       | 4.03     | 2.69  | -1.50     | 1.73  | 0.21     | -1.59            | 0.58             | 0.25             | -0.73            | -0.49         |
| GISS-E2-1-H       | 3.51     | 3.12  | -1.13     | 1.90  | 0.40     | -1.53            | 0.82             | 0.21             | -0.62            | -0.41         |
| IPSL-CM6A-LR      | 3.36     | 4.60  | -0.73     | 2.45  | 0.33     | -1.54            | 0.79             | 0.04             | -0.06            | 0.03          |
| MIROC6            | 3.72     | 2.58  | -1.44     | 1.59  | 0.53     | -1.94            | 0.78             | 0.05             | -0.24            | -0.29         |
| MRI-ESM2-0        | 3.44     | 3.13  | -1.10     | 1.70  | 0.60     | -1.94            | 0.83             | 0.02             | -0.01            | 0.01          |
| MME (CMIP6)       | 3.40     | 3.87  | -0.95     | 1.89  | 0.44     | -1.75            | 0.69             | 0.08             | 0.02             | 0.10          |
| StdDev (CMIP6)    | 0.36     | 1.94  | 0.33      | 0.31  | 0.12     | 0.17             | 0.17             | 0.17             | 0.55             | 0.43          |

Note: BCC-CSM1.1m: Beijing Climate Center Climate System Model version 1.1 with medium resolution; BCC-CSM2-MR: Beijing Climate Center Climate System Model version 2 with medium resolution; CESM2: Community Earth System Model version 2; CESM2-WACCM: CESM2 interactive with the Whole Atmosphere Chemistry Community Climate Model; CNRM-CM6-1: Centre National de Recherches Météorologiques Climate Model version 6.1; CNRM-ESM2-1: Centre National de Recherches Météorologiques Earth System Model version 2.1; GISS-E2-1-G: NASA Goddard Institute for Space Studies model version E2.1 with the GISS ocean model; GISS-E2-1-H: NASA GISS model version E2.1 with the Hybrid Coordinate Ocean Model; IPSL-CM6A-LR: Version 6 of the Institut Pierre-Simon Laplace (IPSL) climate model with low resolution; MIROC6: The sixth version of the Model for Interdisciplinary Research on Climate; MRI-ESM2-0: Meteorological Research Institute Earth System Model version 2.0.
Fig. 2. Linear fitting estimations of \(4 \times \text{CO}_2\) ERF \((F_{4\times}, y\text{-axis intercept}; \text{W m}^{-2}\), \(AT_{eqm}\) (i.e., \(2 \times \text{ECS, x-axis intercept; K}\), and \(\lambda\) (slope; \text{W m}^{-2} \text{K}^{-1}\) under constant forcing of quadrupled \text{CO}_2\) (abrupt4×CO\(_2\)) based on Eq. (1). (a) BCC-CSM2-MR in CMIP6 and (b) BCC-CSM1.1m in CMIP5.

(Watanabe et al., 2013). Hence, \(\kappa\) in BCC-CSM2-MR shows an evident improvement from BCC-CSM1.1m.

In summary, the two versions of the BCC model simulate different forcings and responses. The ECS in BCC-CSM2-MR is close to that in the previous version (Fig. 3a), whereas the TCR is evidently smaller than that in the previous version (Fig. 3b) due to a larger \(\kappa\) (Fig. 3e) and weaker ERF (Fig. 3c). The nearly unchanged ECS in BCC-CSM2-MR is the compensated result from more positive feedback (Fig. 3d) and evidently weakened effective forcing (Fig. 3c).

3.3 Decomposition of feedback

The four feedback components based on Eq. (3) are listed in Fig. 5 for the two BCC model versions, along with the multimodel results for CMIP5 and CMIP6. Consistent with Fig. 3d, the net feedback \(\lambda_{Net}\) exhibits a large spread across models, in which the two BCC-CSM versions are not located far from the multimodel mean. Evidently, the more positive net feedback in BCC-CSM2-MR \((-0.92 \text{ W m}^{-2} \text{K}^{-1}\) than that in BCC-CSM1.1m \((-1.18 \text{ W m}^{-2} \text{K}^{-1}\) mainly comes from \(\lambda_{SWCL}\) \((0.15 \text{ vs } -0.12 \text{ W m}^{-2} \text{K}^{-1}\)), which also has the largest uncertainty across models. Hence, understanding the changes in \(\lambda_{SWCL}\) is the key to explaining the changes in the net feedback of the BCC model system from CMIP5 to CMIP6.

To clearly show the contributions of regional processes to global mean feedbacks, the spatial distributions of longwave and shortwave components under clear-sky and cloud conditions are analyzed. Although the global means of \(\lambda_{LWCS, SWCS}\) and \(\lambda_{LWCL}\) change very slightly from BCC-CSM1.1m to BCC-CSM2-MR (Fig. 5), the regional variations may not be negligible. For example, as shown in Fig. 5d, the difference in \(\lambda_{SWCS}\) between BCC-CSM2-MR and BCC-CSM1.1m is only \(-0.04 \text{ W m}^{-2} \text{K}^{-1}\) for the global mean, which actually results from compensation for prominent increases in high latitudes in the Northern Hemisphere and decreases over the Southern Ocean around Antarctica.

The differences in \(\lambda_{LWCL}\) and \(\lambda_{SWCL}\) between the two BCC-CSM versions also have evident regional distribution features. Compared with BCC-CSM1.1m, \(\lambda_{LWCL}\) in BCC-CSM2-MR increases in the western Indo-Pacific and decreases in the central Pacific, which leads to a global mean difference of nearly zero \((-0.03 \text{ W m}^{-2} \text{K}^{-1}\); Fig. 6f). The pattern of the \(\lambda_{SWCL}\) changes between BCC-CSM2-MR and BCC-CSM1.1m is almost opposite to the global changes in \(\lambda_{LWCL}\), and the increasing \(\lambda_{SWCL}\) is stronger than the decreasing \(\lambda_{LWCL}\) in most regions (Figs. 6f, h). The changes in \(\lambda_{LWCL}\) and \(\lambda_{SWCL}\) reflect different cloud responses in the two BCC-CSM versions.

The variables \(\lambda_{LWCL}\) and \(\lambda_{SWCL}\) are mostly contributed by the responses of high-level and low-level clouds, respectively, because high-level clouds are effective in absorbing longwave radiation from the surface, while low-level clouds are good at reflecting incident solar radiation. For simplicity, we use the cloud ice path (CIP) and cloud water path (CWP) to represent high-level (cold and frozen) and low-level (warm and liquid) clouds, respect-
More high-level clouds under warming can lead to a positive $\lambda_{LWCL}$, whereas more low-level clouds cause a negative $\lambda_{SWCL}$. The patterns of the changes in CIP and CWP between the two BCC-CSM versions are similar (Figs. 7d, f), indicating that the responses of local high-level and low-level clouds are enhanced or weakened jointly in BCC-CSM2-MR, which is consistent with the opposite patterns of the $\lambda_{LWCL}$ and $\lambda_{SWCL}$ changes (Figs. 6f, h). As expected, a larger decrease in low-level clouds than in high-level clouds under warming (Figs. 7d, f) leads to a strengthened enhancement of the positive $\lambda_{SWCL}$ rather than the negative $\lambda_{LWCL}$ (Figs. 6f, h) in the BCC-CSM2-MR.

The compensation between the reduced ERF and enhanced $\lambda$ results in nearly no change in ECS from BCC-CSM1.1m to BCC-CSM2-MR. We mainly focus on the $\lambda$ differences in this study because the forcing components derived from the Gregory method show patterns similar to those of $\lambda$ but with the opposite sign (Fig. 8), with pattern correlation coefficients of approximately $-0.85$ globally (left columns in Figs. 6, 8). In fact, the ERF and $\lambda$ derived from the Gregory method are not independent since the intermodel correlation coefficient between the two quantities listed in Table 1 is $-0.69$, exceeding the 5% significance level. $F_{SWCL}$ also mainly contributes to the reduced ERF (Fig. 8h), suggesting that the changes in ERF and $\lambda$ may share similar mechanisms.

3.4 Physical mechanisms related to enhanced $\lambda_{SWCL}$ in BCC-CSM2-MR

Approximately 60% of the increases in $\lambda_{SWCL}$ (0.15 W...
m$^{-2}$ K$^{-1}$) in BCC-CSM2-MR are contributed by those in the Southern Ocean (Fig. 6h), which is caused by the decreasing CF and CWP with warming (Figs. 7b, d). It is interesting that the pattern of changes in $\lambda_{SWCL}$ around Antarctica is nearly identical to that of $\lambda_{SWCS}$ (Fig. 6d), suggesting a close relation between the changes in responses of sea ice and low clouds from BCC-CSM1.1m to BCC-CSM2-MR.

A previous study indicated that models with greater (lesser) ice coverage in piControl generally possess a colder (warmer) and drier (moister) climate, exhibit stronger (weaker) ice-albedo feedback and experience greater (weaker) warming under greenhouse gas forcing (Hu et al., 2017). We find that the control-run sea ice concentration (SIC) in the Southern Ocean in BCC-CSM2-MR is evidently less than that in BCC-CSM1.1m throughout an annual cycle, especially in the cold season (June–November), the period with maximum sea ice cov-
erage (solid lines in Fig. 9). As suggested by the above mechanism, the GMST in BCC-CSM2-MR is 0.4°C higher than that in BCC-CSM1.1m in piControl (Fig. 1b), and the positive ice-albedo feedback ($\lambda_{SWCS}$) is weakest in the Southern Ocean (Fig. 6d), corresponding to slow sea ice melting with warming (dashed lines in Fig. 9). However, in contrast to the weak warming expected from the weak ice-albedo feedback, the warming in BCC-CSM2-MR is increased (Fig. 1b) under the quadrupled CO$_2$ forcing because the weak ice-albedo feedback (Fig. 6d) is largely offset by the strong $\lambda_{SWCL}$ in the Southern Ocean (Fig. 6h).

To clarify the mechanism by which weakened $\lambda_{SWCS}$ could lead to positively strengthened $\lambda_{SWCL}$, the response differences between BCC-CSM2-MR and BCC-CSM1.1m are analyzed in the cold season (Fig. 10) when the sea ice responses are the most distinct (Fig. 9). The results are masked south of 66.5°S (Fig. 10) because the shortwave processes can be neglected due to the limited solar radiation in the cold season. The response of the Antarctic SIC to per 1-K global warming in BCC-CSM2-MR shows slower melting than that in BCC-CSM1.1m (Fig. 10b). The pattern is nearly identical to that of $\lambda_{SWCL}$ (Fig. 10a), indicating a strong linkage between sea ice response and cloud shortwave processes. When the sea ice melts slowly in BCC-CSM2-MR, more sensible and latent heat fluxes from the ocean to the atmosphere are inhibited (Fig. 10d). Meanwhile, the static stability in the boundary layer, represented by the air temperature difference between 925 and 850 hPa, is enhanced due to the cold surface (Fig. 10c). As a result, the CWP, representing low clouds, decreases around Antarctica (Fig. 10c) due to weakened vertical upward motion (Wall et al., 2017). The decreasing response of low clouds in BCC-CSM2-MR leads to increased shortwave radiation into the air-earth system to warm the climate, largely offsetting the relatively weak ice-albedo feedback in the Southern Ocean. Therefore, compared with BCC-

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**Fig. 7.** Geographical distributions of responses of cloud properties in BCC-CSM2-MR (left) and differences between BCC-CSM2-MR and BCC-CSM1.1m (right). (a, b) Cloud fraction (CF; % K$^{-1}$), (c, d) cloud water path (CWP; g m$^{-2}$ K$^{-1}$), and (e, f) cloud ice path (CIP; g m$^{-2}$ K$^{-1}$). Dotted shadings exceed the 5% significance level.
CSM1.1m, the strong positive $\lambda_{\text{SWCL}}$ around Antarctica in BCC-CSM2-MR and its close relation with weak ice-albedo feedback is well clarified, which can be attributed to the reduced sea ice coverage in the piControl simulation.

### 4. Conclusions and discussion

The climate sensitivity and feedbacks of two BCC-CSM versions participating in the CMIP6 (BCC-CSM2-MR) and CMIP5 (BCC-CSM1.1m) experiments are analyzed and compared by using two idealized CO$_2$ concentration forcing scenarios (1pctCO$_2$ and abrupt4xCO$_2$) and the corresponding piControl simulations. The main results show as follows.

1) The ECSs of BCC-CSM2-MR and BCC-CSM1.1m are 3.04 and 2.91 K, respectively. The small changes in ECS result from the compensation between the decreased ERF and increased feedback from the CMIP5 to
Fig. 9. Annual cycle of Antarctica sea ice concentration (SIC; %; left y-axis) in piControl (solid lines) and its response to per 1-K global warming (% K$^{-1}$; right y-axis) in abrupt4×CO$_2$ experiment (dashed lines) of BCC-CSM2-MR (red) and BCC-CSM1.1m (blue).

Fig. 10. Differences of (a) $\lambda_{SWCL}$ (W m$^{-2}$ K$^{-1}$), (b) response of SIC (% K$^{-1}$), (c) responses of CWP (g m$^{-2}$ K$^{-1}$; shadings) and static stability in the boundary layer (temperature difference between 925 and 850 hPa; K K$^{-1}$; contours drawn for ±0.2, ±0.6, and ±1.0), and (d) surface sensible (SH; W m$^{-2}$ K$^{-1}$; contours drawn for ±2, ±6, and ±10) and latent heat (LH) responses (shadings) in cold seasons (June–November) between BCC-CSM2-MR and BCC-CSM1.1m. The solid and dashed contours denote the positive and negative values. Dotted shadings exceed the 5% significance level.
CMIP6. In contrast, the TCR (1.40 K) of BCC-CSM2-MR is near the lower bound of the CMIP6 multimodel spread due to the too low ERF. The OHU efficiency in BCC-CSM2-MR is evidently improved from that in BCC-CSM1.1m with reference to the multimodel mean and observational estimation.

(2) The feedback coefficient $\lambda$ of BCC-CSM2-MR positively increases to $-0.92$ W m$^{-2}$ K$^{-1}$ from $-1.18$ W m$^{-2}$ K$^{-1}$ for BCC-CSM1.1m and is close to the CMIP6 multimodel mean. The strong positive $\lambda_{SWCL}$ in BCC-CSM2-MR accounts for the net feedback differences from BCC-CSM1.1m.

(3) The differences in $\lambda_{SWCL}$ between the two BCC-CSM model versions are significant around the Antarctic, where the sea ice-albedo feedback is weak. This result is related to the limited sea ice simulated in the piControl experiments in BCC-CSM2-MR. Reduced sea ice coverage leads to a decreased melting rate (per 1-K global warming) and weakened sea ice-albedo feedback. Therefore, the slow melt of sea ice in BCC-CSM2-MR inhibits the surface sensible and latent heat flux from the ocean to the atmosphere. The resulting limited moisture and more stable boundary layer due to the cold surface lead to reduced low-cloud formation and increased incident solar shortwave radiation. The strong $\lambda_{SWCL}$ in BCC-CSM2-MR caused by its weak sea ice-albedo feedback can in turn largely compensate for the latter locally, indicating complex interactions between different feedbacks. The compensation mechanism is summarized in Fig. 11.

Although a 60% increase in $\lambda_{SWCL}$ around Antarctica in BCC-CSM2-MR is well explained in this study, the remaining 40% is still unclear. For example, the increased $\lambda_{SWCL}$ (Fig. 6h) results from the decreasing response of low clouds in the tropical central Pacific and over the midlatitudes (Figs. 7b, d), which may be partly related to the indirect radiative effect of aerosols that are fully included in BCC-CSM2-MR (Wu et al., 2019). As shown in Fig. 12, more preindustrial clouds are simulated in BCC-CSM2-MR almost globally, which is expected from the increase in available condensation nuclei from aerosols. More clouds coincide with greater cloud decreases per 1-K global warming in abrupt4$\times$CO$_2$, especially in the central Pacific, which has the largest cloud response after that in the Southern Ocean (Fig. 7b), and thus a large $\lambda_{SWCL}$ (Fig. 6h). Physical processes in the BCC models underlying the apparent relationship require further study. The response differences between the two BCC-CSM versions to CO$_2$ forcing are related to improvements in the model system, especially upgrades of the processes schemes mainly in the atmosphere model. This study indicates that coupling between different model components is also very important to the integrated model properties. Compared with BCC-CSM1.1m, the modified schemes in BCC-CSM2-MR may benefit not only the performance in atmosphere and land models (Li et al., 2019; Wu et al., 2019) but also that in ocean and sea ice models. The two model versions of CMIP5 and CMIP6 simulate reasonable ECS and climate feedback processes within the multimodel ensemble bounds, indicating that the BCC-CSM model has good capability to describe the interactions between the atmosphere, ocean, sea ice, and land surface model components.

We currently adopt the methods following Gregory et
al. (2004). In fact, there have been some new achieve-
ments to find other approaches and new definitions to
investigate climate sensitivity, radiative forcing, and feed-
backs (e.g., Meraner et al., 2013; Chung and Soden, 2015; Murphy and Ravishankara, 2018; Soden et al., 2018). However, more detailed studies need to further in-
vestigate the forcing and feedbacks in BCC-CSM. Al-
though the ERF is defined as the forcing considering rapid
adjustments in the atmosphere without warming in sea
water, the ERF derived from the Gregory method could
still partly involve the effect of a slow response. Taking
$F_{SWCL}$ as an example, because of the limited sea ice cover
in the Southern Ocean in BCC-CSM2-MR in the piCon-
trol experiment, an increased cloud response to the ini-
tial surface warming under quadrupled CO$_2$ over more
open water can reflect more shortwave radiation, and
thus reduce the ERF (Fig. 8h). Nevertheless, the oppo-
site relationship between ERF and $\lambda$ deserves further
study. A better understanding of how feedback is relat-
ed to other feedbacks, how feedbacks and forcings interac-
t and how present-day climate determines feedbacks could
potentially help improve model performance on historical
simulations and future projections.

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REFERENCES
Andrews, T., and P. M. Forster, 2008: CO$_2$ forcing induces semi-
direct effects with consequences for climate feedback inter-
pretations. Geophys. Res. Lett., 35, L04802, doi: 10.1029/2007GL032273.

Andrews, T., J. M. Gregory, M. J. Webb, et al., 2012a: Forcing,
feedbacks and climate sensitivity in CMIP5 coupled atmo-
sphere–ocean climate models. Geophys. Res. Lett., 39,
L09712, doi: 10.1029/2012GL051607.

Andrews, T., J. M. Gregory, P. M. Forster, et al., 2012b: Cloud ad-
justment and its role in CO$_2$ radiative forcing and climate
sensitivity: A review. Surv. Geophys., 33, 619–635, doi:
10.1007/s10712-011-9152-0.

Ceppi, P., F. Brient, M. D. Zelinka, et al., 2017: Cloud feedback
mechanisms and their representation in global climate mod-
els. WIREs Climate Change, 8, e465, doi: 10.1002/wcc.465.

Cess, R. D., M. H. Zhang, G. L. Potter, et al., 1993: Uncertainties
in carbon dioxide radiative forcing in atmospheric general cir-
culation models. Science, 262, 1252–1255, doi: 10.1126/sci-
ence.262.5137.1252.

Chen, X. L., and T. J. Zhou, 2015: Distinct effects of global mean
warming and regional sea surface warming pattern on projec-
ted uncertainty in the South Asian summer monsoon. Geophys.
Res. Lett., 42, 9433–9439, doi: 10.1002/2015GL066384.

Chen, X. L., T. J. Zhou, and Z. Guo, 2014: Climate sensitivities of
two versions of FGOALS model to idealized radiative for-
cing. Sci. China Earth Sci., 57, 1363–1373, doi: 10.1007/s
11430-013-4692-4.

Chen, X. L., Z. Guo, T. J. Zhou, et al., 2019: Climate sensitivity
and feedbacks of a new coupled model CAMS-CSM to ideal-
ized CO$_2$ forcing: A comparison with CMIP5 models. J. Met-
eor. Res., 33, 31–45, doi: 10.1007/s13351-019-8074-5.

Chung, E. S., and B. J. Soden, 2015: An assessment of methods for
computing radiative forcing in climate models. Environ. Res.
Lett., 10, 074004, doi: 10.1088/1748-9326/10/7/074004.

Collins, W. D., P. J. Rasch, B. A. Boville, et al., 2004: Description of
the NCAR Community Atmosphere Model (CAM3.0).
NCAR, Boulder, Colorado, USA, 226 pp.

Cox, P. M., C. Huntingford, and M. S. Williamson, 2018: Emer-
gent constraint on equilibrium climate sensitivity from global
temperature variability. Nature, 553, 319–233, doi: 10.1038/
nature25450.

Eyring, V., S. Bony, G. A. Meehl, et al., 2016: Overview of the
Coupled Model Intercomparison Project Phase 6 (CMIP6) ex-
perimental design and organization. Geosci. Model Dev., 9,
1937–1958, doi: 10.5194/gmd-9-1937-2016.

Flato, G., J. Marozkze, B. Abiodum, et al., 2013: Evaluation of cli-
mate models. Climate Change 2013: The physical Basis. Con-
tribution of Working Group I to the Fifth Assessment Report
of the Intergovernmental Panel on Climate Change. T. F.
Stocker, D. H. Qin, G. K. Plattner, et al., Eds., Cambridge
University Press, Cambridge, United Kingdom and New
York, USA, 1535 pp.

Forster, P. M., and Taylor K. E., 2006: Climate forcings and cli-
smate sensitivities diagnosed from coupled climate model in-
tegrations. J. Climate, 19, 6181–6194, doi: 10.1175/JCLI3974.1.

Gregory, J. M., W. J. Ingram, M. A. Palmer, et al., 2004: A new
method for diagnosing radiative forcing and climate sensitiv-
ity. Geophys. Res. Lett., 31, L03205, doi: 10.1029/2003GL018747.

Heinze, C., V. Eyring, P. Friedlingstein, et al., 2019: ESD reviews:
Climate feedbacks in the earth system and prospects for their eval-
uation. Earth Syst. Dyn., 10, 379–452, doi: 10.5194/esd-
10-379-2019.

Hu, X. M., P. C. Taylor, M. Cai, et al., 2017: Inter-model warm-
ing projection spread: Inherited traits from control climate di-

Fig. 12. Difference of climatological cloud fraction (CF; %) in pi-
Control between BCC-CSM2-MR and BCC-CSM1.1m.
Stocker, T. F., D. Qin, G. K. Plattner, et al., 2013: Beyond equilibrium climate sensitivity. Nat. Geosci., 10, 727–736, doi: 10.1038/ngeo3017.

Le Treut, H., Z. X. Li, and M. Forichon, 1994: Sensitivity of the LMD General Circulation Model to greenhouse forcing associated with two different cloud water parameterizations. J. Climate, 7, 1827–1841, doi: 10.1175/1520-0442(1994)007 <1827:STOLS>2.0.CO;2.

Li, C., J. S. Von Storch, and J. Marotzke, 2013: Deep-ocean heat uptake and equilibrium climate response. Climate Dyn., 40, 1071–1086, doi: 10.1007/s00382-012-1350-z.

Li, W. P., Y. W. Zhang, X. L. Shi, et al., 2019: Development of land surface model BCC_AVIM2.0 and its preliminary performance in LS3MIP/CMIP6. J. Meteor. Res., 33, 851–869, doi: 10.1007/s11069-019-9016-y.

Liu, C. Y., X. L. Shi, G. Q. Hu, et al., 2019: A simple earth system model for C3IAM: Based on BCC_CSM1.1 and CMIP5 simulations. Nat. Hazards, 99, 1311–1325, doi: 10.1007/s11069-019-03640-1.

Meraner, K., T. Mauritzen, and A. Voigt, 2013: Robust increase in equilibrium climate sensitivity under global warming. Geophys. Res. Lett., 40, 5944–5948, doi: 10.1002/2013GL058118.

Murphy, D. M., and A. R. Ravishankara, 2018: Trends and patterns in the contributions to cumulative radiative forcing from different regions of the world. Pros. Natl. Acad. Sci. USA, 115, 13192–13197, doi: 10.1073/pnas.1813951115.

Myhre, G., E. J. Highwood, K. P. Shine, et al., 1998: New estimates of radiative forcing due to well mixed greenhouse gases. Geophys. Res. Lett., 25, 2715–2718, doi: 10.1029/98GL01908.

National Research Council, 1979: Carbon Dioxide and Climate: A Scientific Assessment. Washington D.C., The National Academies Press, 22 pp, doi: 10.17226/12181.

Rugenstein, M., J. Bloch-Johnson, J. Gregory, et al., 2020: Equilibrium climate sensitivity estimated by equilibrating climate models. Geophys. Res. Lett., 47, e2019GL083898, doi: 10.1029/2019GL083898.

Soden, B. J., W. D. Collins, and D. R. Feldman, 2018: Reducing uncertainties in climate models. Implementing accurate calculations of radiative forcing can improve climate projections. Science, 361, 326–327, doi: 10.1126/science.aau1864.

Stocker, T. F., D. H. Qin, G. K. Plattner, et al., 2013: Technical summary. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, T. F. Stocker, D. Qin, G. K. Plattner, et al., Eds., Cambridge University Press, Cambridge, United Kingdom and New York, USA, 1535 pp.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment design. Bull. Amer. Meteor. Soc., 93, 485–498, doi: 10.1175/BAMS-D-11-00094.1.

Vial, J., J. L. Dufresne, and S. Bony, 2013: On the interpretation of inter-model spread in CMIP5 climate sensitivity estimates. Climate Dyn., 41, 3339–3362, doi: 10.1007/s00382-013-1725-9.

Wall, C. J., T. Kohyama, and D. L. Hartmann, 2017: Low-cloud, boundary layer, and sea ice interactions over the Southern Ocean during winter. J. Climate, 30, 4857–4871, doi: 10.1175/JCLI-D-16-0483.1.

Watanabe, M., Y. Kamae, M. Yoshimori, et al., 2013: Strengthening of ocean heat uptake efficiency associated with the recent climate hiatus. Geophys. Res. Lett., 40, 3175–3179, doi: 10.1002/grl.50541.

Wu, T. W., 2012: A mass-flux cumulus parameterization scheme for large-scale models: Description and test with observations. Climate Dyn., 38, 725–744, doi: 10.1007/s00382-011-0995-3.

Wu, T. W., W. P. Li, and J. J. Ji, et al., 2013: Global carbon budgets simulated by the Beijing Climate Center climate system model for the last century. J. Geophys. Res. Atmos., 118, 4326–4347, doi: 10.1002/jgrd.50320.

Wu, T. W., L. C. Song, W. P. Li, et al., 2014: An overview of BCC climate system model development and application for climate change studies. J. Meteor. Res., 28, 34–56, doi: 10.1007/s13351-014-3041-7.

Wu, T. W., Y. X. Lu, Y. J. Fang, et al., 2019: The Beijing Climate Center Climate System Model (BCC-CSM): The main progress from CMIP5 to CMIP6. Geosci. Model Dev., 12, 1573–1600, doi: 10.5194/gmd-12-1573-2019.

Zhou, T. J., and X. L. Chen, 2015: Uncertainty in the 2°C warming threshold related to climate sensitivity and climate feedback. J. Meteor. Res., 29, 884–895, doi: 10.1007/s13351-015-0306-4.

Zhou, T. J., X. L. Chen, and B. Wu, 2019: Frontier issues on climate change science for supporting Future Earth. Chinese Sci. Bull., 64, 1967–1974, doi: 10.1360/N972018-00818. (in Chinese)