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A Balanced Atmospheric Ensemble Forcing for Sea Ice Modeling in Southern Ocean

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Key Points:

- A multivariate balanced atmospheric ensemble forcing is developed for the Southern Ocean coupled sea ice-ocean model
- Adopting this new forcing can suppress model errors of sea-ice concentration and produce better estimates of simulation uncertainties
- The improvement is primarily caused by atmosphere-ocean and sea ice-ocean thermodynamic processes

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Abstract

To deal with the great challenges in simulating the highly non-linear physics of Antarctic sea ice, a multivariate balanced atmospheric ensemble forcing is developed based on the high-resolution component of ERA5, which considers the relationship between different variables and adjacent times. To validate the performance of this new forcing, experiments were conducted from 1 January 2016 to 28 February 2017. Compared to simulations forced with the ensemble component of ERA5, a more reasonable ensemble of simulations is produced by the atmospheric ensemble forcing developed in this study, which suppresses the sea-ice concentration (SIC) simulation errors and produces a better estimation of SIC simulation uncertainties. Further sea-ice thickness budget analysis reveals that this impact of atmospheric ensemble forcing on sea ice simulation is due to a modulation of atmosphere-ocean and sea ice-ocean thermodynamic processes. These results lay the foundation for further improvements in Antarctic sea ice data assimilation and probabilistic prediction.

Plain Language Summary

Antarctic sea ice plays an important role in the Earth system. However, its accurate simulation still faces many challenges. Considering the highly non-linear sea ice processes, adopting an ensemble simulation procedure is a way to improve Antarctic sea ice modeling skill. Perturbing the sea ice-ocean coupled model indirectly through the atmospheric ensemble forcing can ensure the dynamic consistency of model states. In this study, we developed a method to perturb high-frequency ERA5 reanalysis in a multivariate balanced way for the Southern Ocean coupled sea ice-ocean model. Results show obvious improvements in the Antarctic sea ice simulation with the newly developed atmospheric ensemble forcing from both deterministic and probabilistic perspectives, which is achieved by modulation of atmosphere-ocean and sea ice-ocean thermodynamic processes. This is an important step toward the development of a comprehensive reanalysis for the sparsely observed Antarctic sea ice, which should benefit the scientific research and human activities in the Southern Ocean.

1. Introduction

The Antarctic has experienced different changes in the sea ice extent (SIE) from the Arctic during the satellite era, and the underlying mechanisms are still disputed (Turner & Comiso, 2017). To understand these changes, many Antarctic sea ice studies often depend on models because of the scarcity of observations in the polar regions. However, accurately reproducing the Antarctic sea ice in models still faces many challenges (e.g., Massonnet et al., 2011; Shu et al., 2020). Therefore, the uncertainty of models cannot be ignored in these studies.

Due to the highly non-linear nature of sea ice physics (Carrieres et al., 2017), an ensemble of sea ice simulations can improve simulation accuracy and also provide an associated uncertainty estimate. Although many model perturbation methods have been proposed, such as perturbing initial conditions (e.g., Buizza & Palmer, 1995; Toth & Kalnay, 1997) or perturbing model parameters (e.g., Buizza et al., 2007; Evensen, 2003), here we focus on adopting an atmospheric ensemble to perturb sea ice-ocean coupled model runs for the following reasons. First, sea ice-ocean coupled models are strongly influenced by atmospheric forcing (e.g., Barthélemy et al., 2018; Marchi et al., 2020; Q. Wang et al., 2021), and the recent changes in the Antarctic sea ice may be related to atmospheric circulation anomalies (e.g., J. Wang et al., 2022; Z. Wang et al., 2019). Second, perturbing the sea ice-ocean coupled model indirectly through the atmospheric forcing can ensure the dynamic consistency of model states (Sakov et al., 2012).

As the latest generation of ECMWF atmospheric reanalysis, ERA5 provides not only hourly reanalysis but also a 10-member ensemble at three-hourly intervals (Hersbach et al., 2020). Studies on the intercomparison of atmospheric reanalysis reveal that ERA5 can reproduce the surface atmospheric condition over the Antarctic effectively (e.g., Dong et al., 2020; Gossart et al., 2019; G. J. Marshall et al., 2022; G. Wang et al., 2021), and ERA5 has been widely used in studies on the Antarctic climate (e.g., Christie et al., 2022; Chung et al., 2022; Neme et al., 2022; Shields et al., 2022). Furthermore, the uncertainty estimated by the ERA5 ensemble can identify the relative accuracy of the ERA5 data, though it is unable to directly describe all the uncertainties of ERA5, especially the systematic model errors. Luo et al. (2021) pointed out that the underestimation of sea ice simulation uncertainty is caused by adopting the ERA5 ensemble as the atmospheric forcing directly. Nevertheless, given the positive impacts of high-frequency atmospheric forcing in the Antarctic sea ice simulation (Wu et al., 2020), the hourly ERA5 reanalysis is still of great value. Although atmospheric forcing perturbation is adopted in many studies, enough attention is not paid to relationships between different variables. For instance, Sakov et al. (2012) considered the geostrophic balance between sea level pressure and wind in the perturbation, while ignoring the impact of air temperature perturbation on the circulation, which would increase the possibility that perturbations to the various forcing variables are not physical consistent and would reduce their effectiveness in maintaining ensemble spread. Thus, an open question is how to perturb hourly ERA5 reanalysis in a balanced way to maintain the physical relationships of different variables. In this paper, we develop a multivariate balanced atmospheric ensemble forcing and investigate its impact on the Southern Ocean coupled sea ice-ocean modeling.

2. Methodology

2.1. Model

The sea ice-ocean coupled model used in this study is the Massachusetts Institute of Technology general circulation model (MITgcm, J. Marshall et al., 1997) with the same regional Southern Ocean configuration as used in Verdy and Mazloff (2017). It has a 1/3° zonal spacing with equidistant meridional spacing, and 52 unevenly spaced vertical levels from the surface to 5800 m. The sea-ice component of the model is the viscous-plastic dynamic-thermodynamic sea-ice model (Losch et al., 2010). The dynamic part of the sea-ice model is solved by line successive over-relaxation (Zhang & Hibler, 1997) on a C grid, and the thermodynamic counterpart is a "zero-layer" model (Semtner, 1976). MITgcm also provides a diagnosis of the sea-ice thickness (SIT) budget, including the change rates of SIT due to the atmospheric heat flux at the ice surface, the oceanic heat flux at the ice bottom, the atmospheric heat flux at the sea surface in the open water area, the snow flooding, the zonal advection flux, and the meridional advection flux. The atmospheric forcing variables required by MITgcm consist of air temperature at 2 m, zonal and meridional wind speed at 10 m, surface downward shortwave and longwave radiation flux, surface pressure, specific humidity, and total precipitation.

2.2. Atmospheric Forcing Perturbation

To maintain the physical consistency between different variables induced by perturbing ERA5 reanalysis, a perturbation method proposed by Zheng and Zhu (2008) is adopted here, which is based on the multivariate empirical orthogonal function (MEOF) and a first-order Markov chain model. The detailed description is as follows,

$$P_i^t = D_i^t + \sum_{j=1}^{n\text{mode}} \text{MEOF}_j \cdot \sigma_j \cdot \omega_{ij}^t$$

$$\omega_{ij}^t = \alpha_j \omega_{ij}^{t-1} + \sqrt{1-\alpha_j^2} W_{ij}^t$$

$$i = 1, 2, \cdots, \text{nens}$$

where P_i^t denotes the atmospheric perturbation field for the ith ensemble member at time t, D_i^t denotes the ERA5 reanalysis field for ith ensemble member at time t, MEOF_j denotes the spatial pattern of the jth MEOF mode, and σ_j denotes the standard deviation for the principal component of the jth MEOF mode. ω_{ij}^t denotes a random normalized time coefficient of the jth MEOF mode for the ith ensemble member at time t, and α_j denotes the first-order autocorrelation of the principal component of jth MEOF mode. W_{ij}^t denotes the random number of

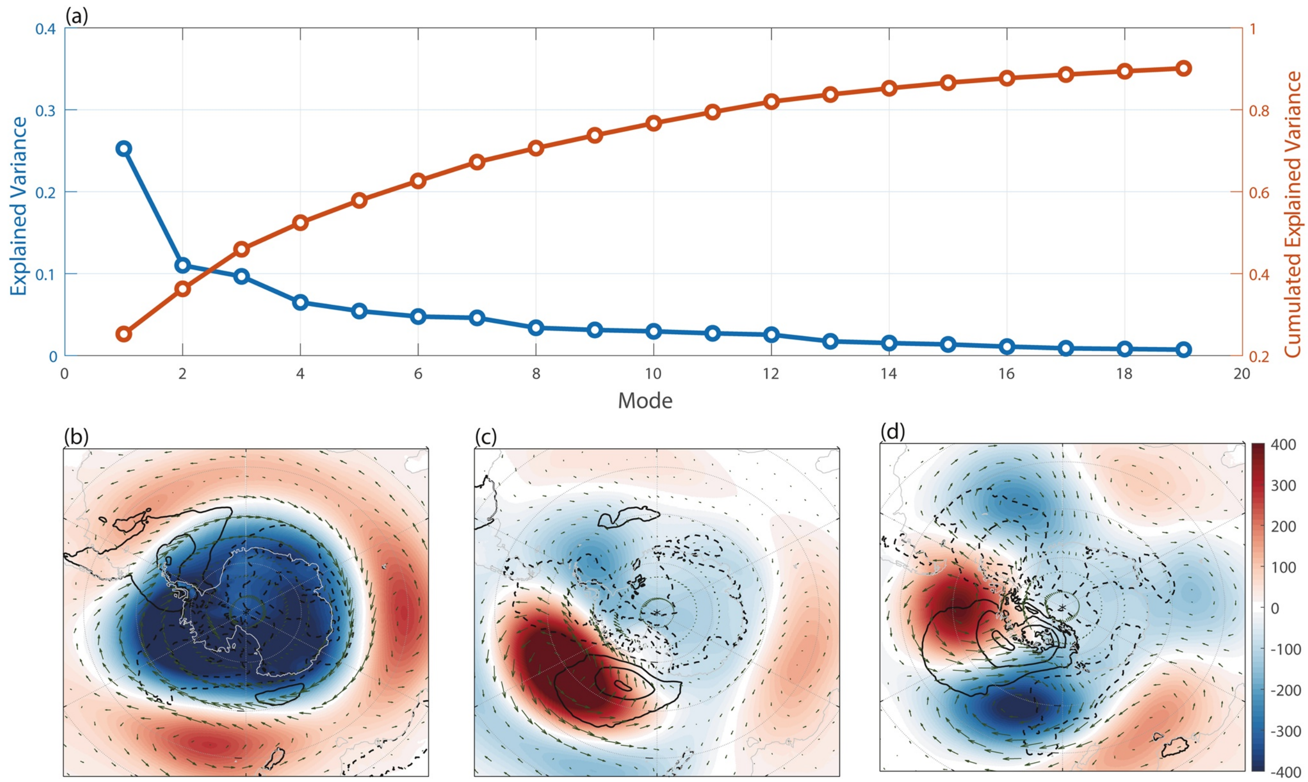

Figure 1. The multivariate empirical orthogonal function (MEOF) of atmospheric surface quantities for ERA5 reanalysis from 1979 to 2019. (a) Variance contributions of the first 19 modes from the MEOF. (b, c) The spatial pattern of the first 3 modes from the MEOF respectively. The shading is for surface pressure, the contours are for the air temperature at 2 m with the solid (dashed) line denoting the positive (negative) value, and the arrows are for horizontal wind at 10 m.

the *j*th MEOF mode for the *i*th ensemble member at time *t* with a mean equal to 0 and a variance equal to 1, and the correlations between the random vector of each mode should be zero to retain the orthogonality of each mode. It should be noted that W_{ij}^{t} changes with different time for the same mode and the same ensemble member. Therefore, this equation ensures that the variance in ω_{ij}^{t} i is equal to 1 as long as the variance of ω_{ij}^{t-1} is also equal to 1. *n*mode is the number of selected MEOF modes, and nens is the number of ensemble members. And the differences between variables in each mode are reflected by different but temporally covarying spatial patterns for the individual variables.

In this study, MEOF analysis is performed for anomalies of the required atmospheric forcing variables based on ERA5 reanalysis from 1979 to 2019. Notably, anomalies of different atmospheric variables are normalized with their standard deviation before MEOF analysis, and the atmospheric fields in the resulting modes are re-scaled to their original variability after MEOF analysis. Figure 1a shows the variance contribution of the first 19 MEOF modes. The first mode accounts for about 25.3% of the total variance, the second and third modes drop to 11.0% and 9.7% rapidly, and the variance contributions of the rest of the modes decrease gradually. For example, the difference in variance contributions between the 18th and 19th modes is less than 0.08%. The total variance contribution of the first 19 MEOF modes is more than 90%. Under affordable computing resources, therefore, we choose *n*mode to be 19 and nens to be 20 to achieve reasonable amplitudes and maintain the orthogonality of each mode. Considering the greater variance contribution of the first 3 modes, the corresponding spatial patterns for these modes are shown in Figures 1b–1d, respectively. The anomaly fields of the surface pressure field and the horizontal wind satisfy the quasi-geostrophic balance, and the air temperature anomaly can be regarded as the response to the surface pressure anomaly. The spatial pattern of the first mode resembles the Southern Annular Mode, and the second and third modes resemble the first and second Pacific–South American patterns. All these imply the physical consistency of atmospheric perturbation fields. Finally, we can apply these principal components and the corresponding spatial patterns derived from MEOF analysis to the above equation to generate an ensemble of atmospheric forcing.

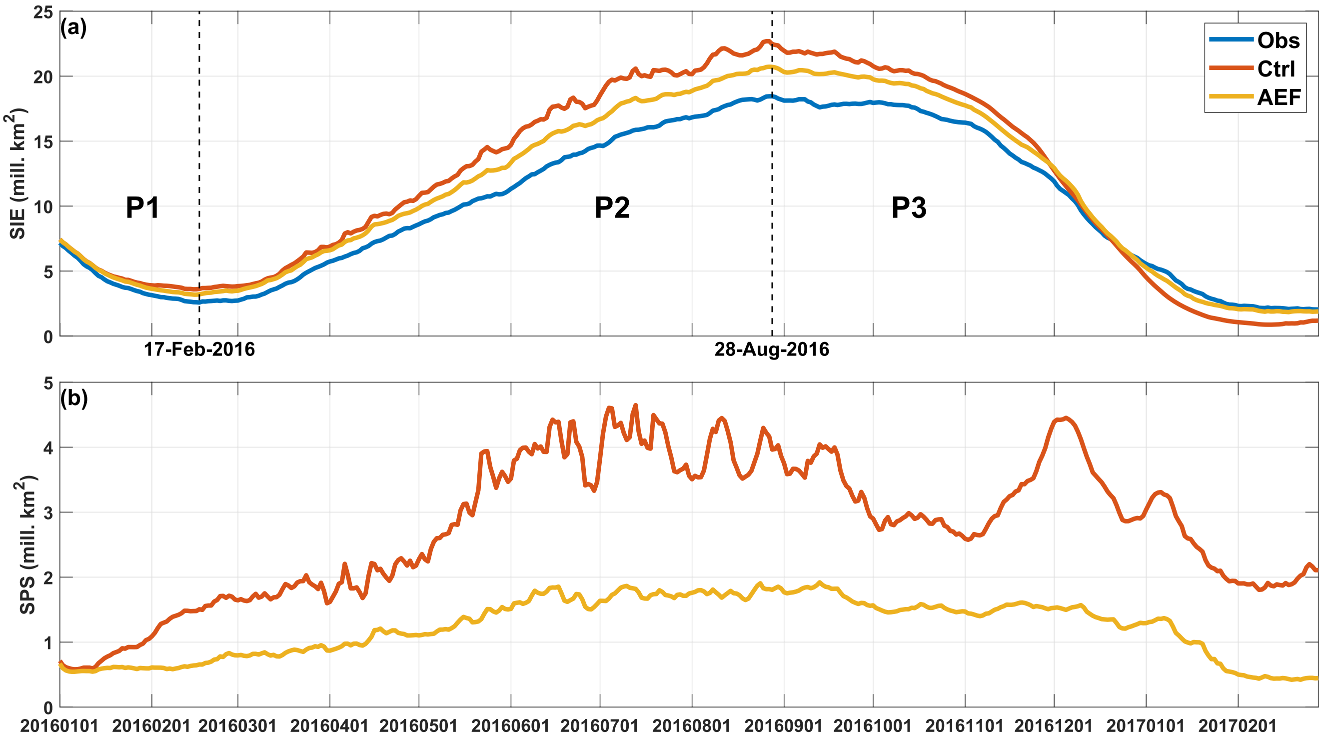

Figure 2. The deterministic and probabilistic evaluation of Antarctic sea ice simulation from 1 January 2016 to 28 February 2017. (a) The time series of sea ice extent (SIE) in the observation as well as in the ensemble mean of the simulations. (b) The time series of Spatial Probability Score in the ensemble of the simulations against the observation. The blue, orange, and yellow colors denote observations derived from Ocean and Sea Ice Satellite Application Facility, simulations from Ctrl, and AEF, respectively. Two vertical dashed lines indicate the time for the maximum and minimum SIE in 2016, and divide the whole experiments into three periods (i.e., P1 from 1 January 2016 to 17 February 2016, P2 from 18 February 2016 to 28 August 2016, and P3 from 29 August 2016 to 28 February 2017).

2.3. Experiment Design

To investigate the impact of atmospheric ensemble forcing on the simulation of Antarctic sea ice, two experiments are conducted with different ensembles of atmospheric forcing and the same initial conditions. These simulations run from 1 January 2016 to 28 February 2017, when an unprecedented retreat of Antarctic sea ice occurred in the melting season of 2016/2017. The initial conditions are from the Data Assimilation System for the Southern Ocean (DASSO, Luo et al., 2021) which assimilates sea ice concentration (SIC) from the Ocean and Sea Ice Satellite Application Facility (OSISAF, Lavergne et al., 2019) on 31 December 2015. The control experiment is forced by the ERA5 ensemble directly (denoted Ctrl), and the ERA5 ensemble is derived from the ensemble data assimilations component of ERA5 whose horizontal resolution is 0.5° and temporal resolution is 3 hr. The other experiment is forced by the atmospheric ensemble forcing based on ERA5 reanalysis and the perturb method described in Section 2.2 (denoted AEF), and the ERA5 reanalysis is from the high-resolution component of ERA5 whose horizontal resolution is 0.25° and temporal resolution is 1 hr. Thus, differences in atmospheric ensemble forcing between Ctrl and AEF can be found both in the ensemble mean and ensemble spread. By comparing Ctrl with AEF, we can determine whether the proposed atmospheric forcing perturbation method is beneficial and quantify the effects on the simulation. The results inform future studies on Antarctic sea-ice probabilistic prediction and data assimilation.

3. Results

Figure 2a shows the time evolution of SIE from 1 January 2016 to 28 February 2017. The observed SIE decreases from 1 January 2016 to 17 February 2016 (i.e., P1), then increases slowly from 18 February 2016 to 28 August 2016 (i.e., P2), and finally drops rapidly from 29 August 2016 to 28 February 2017 (i.e., P3), which reflects the asymmetry in the seasonal cycle of Antarctic SIE. Both simulations reproduce this asymmetric SIE evolution and capture the timing when the maximum/minimum SIE occurred, while the simulated maximum/minimum SIE is stronger than the observed ones. Notably, the SIE evolution of AEF is closer to the observation than that of Ctrl,

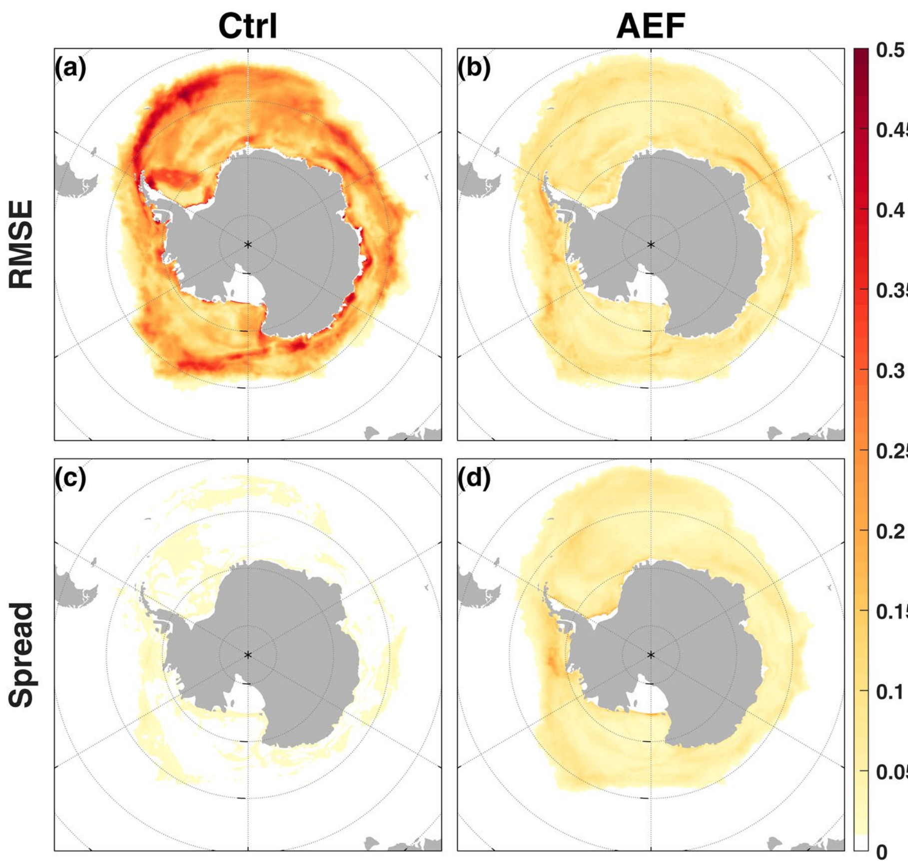

Figure 3. The spatial distribution of skill for Antarctic sea-ice concentration (SIC) simulations. (a, b) The root mean square error of the ensemble means of SIC simulations compared to the observation derived from OSI SAF. (c, d) The time-mean of ensemble spread of Antarctic SIC simulations. The 1st column is for Ctrl and the 2nd column is for AEF.

and the overestimation of the SIE change rates is suppressed in AEF to some extent, which implies the positive impact of atmospheric forcing with enhanced spatiotemporal resolution on the Antarctic sea ice modeling. To evaluate the spatial distribution of sea ice edge from a probabilistic perspective, the Spatial Probability Score (SPS, Goessling & Jung, 2018) is introduced as another verification metric, which is defined as follows,

$$\mathrm{SPS} = \int_A [P_s(x) - P_o(x)]^2 dA$$

$P(x)$ is the probability of SIC being above 15% at location x, A is the area of the grid cell, and the subscripts s and o denote simulation and observation respectively. Thus, $P_o(x)$ is a binary field (i.e., either 1 or 0) under the assumption that the observation is perfect, and $P_s(x)$ is generally a field of numbers in the continuous range [0, 1] and is defined as the relative frequencies of event occurrence derived from the ensemble. Figure 2b shows the variation of SPS with time. In Ctrl, the SPS increases quickly before mid-June, then remains at a high level until September, and decreases gradually to February of the next year except for the rise during November 2016, which is similar to the evolution of SIE simulation errors (Figure 2a). The SPS of AEF is relatively stable and less than that of Ctrl except at the start of integration, and the amplitude of high-frequency SPS fluctuation is much weaker in AEF, indicating a more reasonable probability distribution of the Antarctic sea ice edge can be estimated from the ensemble of AEF.

Given the distinct regional variation of Antarctic sea ice, the spatial distribution of skill for Antarctic SIC simulations is displayed in Figure 3. In Ctrl, the spatial mean of root mean square error (RMSE) of SIC is about 0.160, and the larger values of RMSE are mainly located at the sea ice edge and the coast of the Antarctic (Figure 3a). However, as Figure 3c shows, the spatial mean of the SIC ensemble spread is about 0.008 in AEF, which is far less than the RMSE of SIC in Ctrl. And the spatial pattern of ensemble spread is very different from that of RMSE. Thus, the ensemble of Ctrl is underdispersed, and the uncertainty of simulations cannot be represented

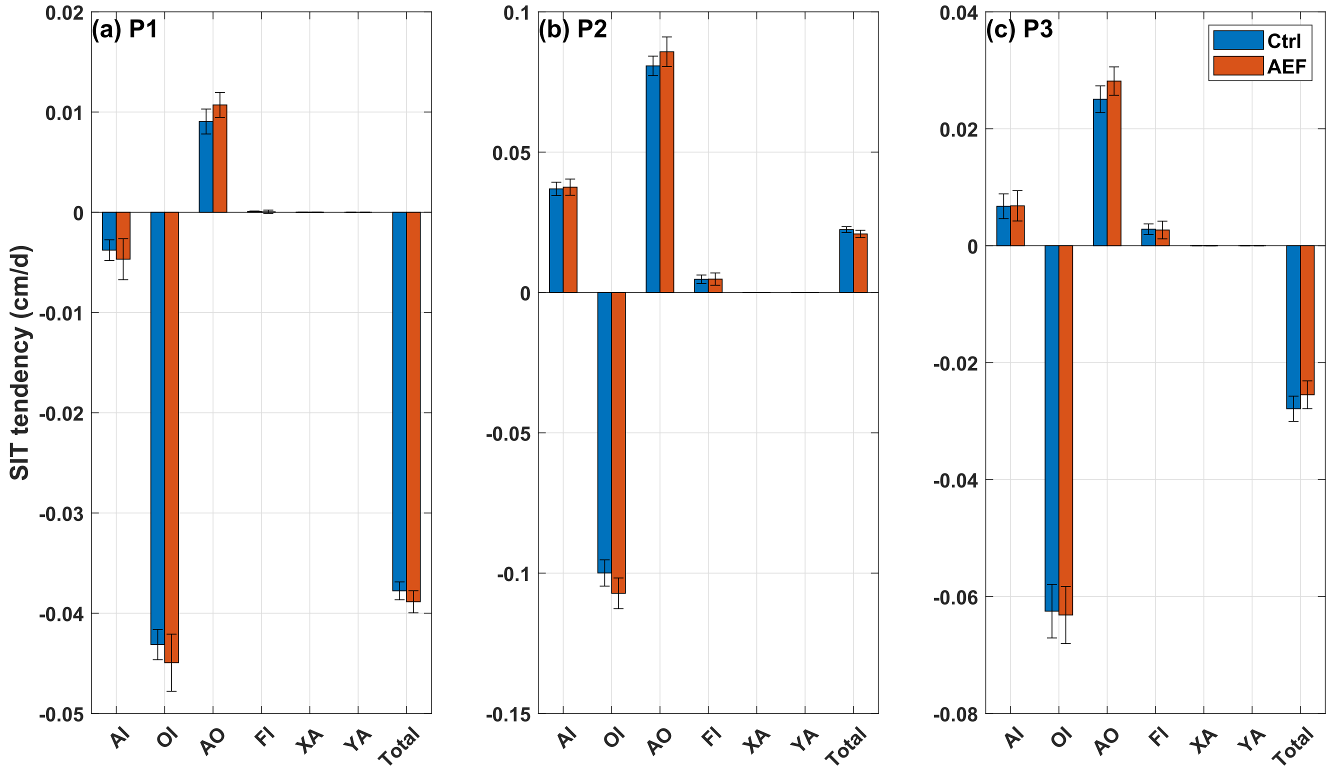

Figure 4. The mean sea-ice thickness (SIT) budget for Antarctic sea ice simulations during different periods, including (a) from 1 January 2016 to 29 February 2016, (b) from 1 March 2016 to 31 August 2016, and (c) from 1 September 2016 to 28 February 2017. The *X*-axis represents the processes related to the change rate of SIT involved in the SIT budget. AI is the atmospheric heat flux at the ice surface, OI is the oceanic heat flux at the ice bottom, AO is the atmospheric heat flux at the sea surface in the open water area, Fl is the snow flooding, XA is the zonal advection flux, YA is the meridional advection flux, and Total is the sum of the above processes. The blue and orange colors denote Ctrl and AEF, respectively.

by the ensemble of Ctrl. Although the spatial pattern of RMSE in AEF is similar to that in Ctrl, the spatial mean of RMSE of SIC is about 0.063 in AEF, and the RMSE is suppressed effectively at the sea ice edge as well as the coast of the Antarctic compared to Ctrl (Figure 3b). Besides, the spatial mean of the SIC ensemble spread is about 0.048 in AEF, which is close to the SIC RMSE of AEF. And the spatial pattern of ensemble spread resembles that of RMSE, which means the uncertainty of simulations can be well depicted by the ensemble of AEF.

To quantify the impact of atmospheric ensemble forcing on the ensemble of sea ice simulation, the SIT budget analysis is applied to the sea ice freezing and melting seasons individually (Figure 4). For the total change rate of SIT, the melting rate is faster than the growth rate, which is in line with the asymmetric evolution of SIE (Figure 2a). For the whole Antarctic, the dynamic processes (i.e., advection and diffusion) have almost no effect on the SIT changes, while thermodynamic processes play an important role. Among thermodynamic processes, the opposite effect of the oceanic heat flux at the ice bottom and the atmospheric heat flux in the open water area are the most important factors, and the contribution of flooding is weak. Compared to Ctrl, the total change rate of SIT in AEF is faster in P1 while slower in the rest time of the experiment, which is also consistent with the difference in the SIE evolution between Ctrl and AEF (Figure 2a). For the whole period of the experiment, this difference between Ctrl and AEF can be mainly attributed to their differences in the oceanic heat flux at the ice bottom and the atmospheric heat flux in the open water area. The difference in the atmospheric heat flux at the ice surface between Ctrl and AEF is also obvious during P1 (Figure 4a). The ensemble spread of thermodynamic processes in AEF is generally greater than that in Ctrl. These results indicate that the new multivariate balanced atmospheric ensemble forcing can not only perturb sea ice simulations effectively but also improve the accuracy of sea ice simulation.

4. Conclusions and Discussion

Accurate Antarctic sea ice simulations are still a scientific challenge. Considering the highly non-linear sea ice processes, an ensemble of sea ice simulations is a way to improve simulation accuracy and estimate simulation uncertainties. In this study, a multivariate balanced atmospheric ensemble forcing based on hourly ERA5 reanalysis is introduced to perturb a coupled sea ice-ocean model, which is a generalized application of the method proposed by Zheng and Zhu (2008), from constructing a model-error model to establishing atmospheric forcing as well as from single to multiple equilibrium relationships. In this atmospheric ensemble forcing, the balance between atmospheric forcing variables as well as the relationship between atmospheric forcings at an adjacent time is taken into account by MEOF and a first-order Markov chain model, respectively. To specify the influence of the atmospheric ensemble forcing on the Antarctic sea ice simulation, two experiments with different atmospheric ensemble forcings and the same initial condition are carried out from 1 January 2016 to 28 February 2017.

Generally, a more reasonable ensemble of Antarctic sea ice simulations can be achieved by adopting the newly developed multivariate balanced atmospheric ensemble forcing. From a deterministic perspective, although both experiments can capture the asymmetric evolution of SIE and the timing of SIE maximum/minimum, the overestimation of the SIE change rates can be suppressed in the simulation with a multivariate balanced atmospheric ensemble forcing, implying the advantage of atmospheric forcing with enhanced spatiotemporal resolution. From a probabilistic perspective, both experiments show a rise of SPS during the freezing season as well as a decline of SPS during the melting season in 2016/2017, and using a multivariate balanced atmospheric ensemble forcing can reproduce a more accurate simulation of the sea ice edge. The RMSE spatial distribution of SIC shows that the simulation with the multivariate balanced atmospheric ensemble forcing can suppress the error of SIC, especially at the sea ice edge as well as the coast of the Antarctic. And the comparison of spatial distribution between RMSE of SIC and ensemble spread of SIC suggests that a more reasonable simulation ensemble can be produced with AEF. Meanwhile, the SIT budget analysis reveals that the influence of atmospheric ensemble forcing on the Antarctic sea ice simulation is achieved mainly through the modulation of the opposite SIT change rates induced by the oceanic heat flux at the ice bottom and the atmospheric heat flux in the open water area. The more accurate simulation achieved in AEF rather than that in Ctrl can be owed to the higher spatiotemporal resolution of atmospheric forcing used in AEF. Previous studies highlighted the impact of transient atmospheric activities on the variation of ocean circulation and sea ice in the Southern Ocean through thermal and dynamic processes (e.g., Holland & Kwok, 2012; Stewart et al., 2021; Z. Wang et al., 2014; Wu et al., 2020). In this study, AEF stems from the ERA5 reanalysis with high resolution and thus can better depict the fine structure of high-frequency transient atmospheric activities, which is also found in the direct comparison between ERA5 reanalysis and ERA5 ensemble (Hersbach et al., 2020).

Although adopting a multivariate balanced atmospheric ensemble forcing can indeed improve the simulation of the Antarctic, the ensemble spread is still slightly less than the RMSE as shown in Figures 3b and 3d. A larger ensemble size of atmospheric forcing may relieve this issue, and the ensemble size should be increased if computational resources allow. Considering the long memory of sea ice and the same initial condition used in this study, the above under dispersion of the ensemble can be relieved by perturbing the initial condition. It also should be noted that considering higher MEOF modes in atmospheric forcing would certainly change the simulation of Antarctic sea ice, and further investigations on perturbating higher mode variability will be considered in our future studies. A more reasonable ensemble of sea ice simulations will contribute not only to a deeper understanding of model-based sea ice studies but also to the improvement of sea ice probabilistic predictions as well as sea ice data assimilation. And our preliminary result of the data assimilation experiment with this new forcing shows that compared with our previous study based on the ERA5 ensemble, this experiment can better reproduce the condition of Antarctic sea ice and decrease reliance on the forgetting factor significantly, implying the effectiveness of the new ensemble forcing. In future research, better estimations of background error and observation error can be achieved via an ensemble of simulation with the multivariate balanced atmospheric ensemble forcing, which is the foundation for further optimizations of DASSO and an important step to reconstruct the long-term Antarctic sea ice state through sea ice data assimilation.

Data Availability Statement

The ERA5 reanalysis is available from https://doi.org/10.24381/cds.adbb2d47. The daily OSISAF SIC data is available from http://doi.org/10.15770/EUM_SAF_OSI_NRT_2008.

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